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SELECTION OF DATA CONVERSION TECHNIQUE VIA SENSITIVITY-PERFORMANCE MATCHING: RANKING OF SMALL E-VANS WITH PROBID METHOD

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Abstract. *Sensitivity analyses are frequently performed to determine the robustness of MCDM methods, of which there are more than 200 types. In the past, rankings were compared to each other rather than to an external ranking. Thus, the direction and meaning of sensitivity can become unclear and complex. In addition, sensitivity analysis is usually performed only based on weight coefficients, but the effect of the normalization type is neglected. In this study, the most appropriate data conversion technique was investigated through an innovative sensitivity procedure to select the Small electric Van, which is an environmentally friendly logistics and transportation vehicle. Seven different normalization types based on the PROBID method (and two additional alternative MCDM methods) were used as parameters, resulting in 105 different MCDM rankings. According to the findings, MCDM rankings, which have low sensitivity, were also the performing methods that produced the highest correlation with price. What is striking is that careless choice of normalization type can be so effective as to manipulate the results. Although the most appropriate technique may vary depending on the data type, the fixed gold standard we recommend offers a flexible solution for all applications. A suitable data converter will result in the choice of a reliable electric vehicle.*

Key words: *Normalization Technique, MCDM, Sensitivity Analysis, Electric Vehicles, Logistics, Transport*

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1. INTRODUCTION

The transportation sector has been a sector that has especially triggered commercial growth since the beginning of human history. Transport has played a key role in determining the location of industries and cities and shaping the prosperity of regions. Moreover, in many industrialized countries, transportation has established itself as an important industry and has therefore become a complex sector. The belief that the increasing travel demand in the world's major cities can be met by building more highways has had to change due to the resulting congestion. Humanity quickly embraced the freedom of movement opened up by motor vehicles. But it was only realized over time that this also led to urban sprawl, air pollution, traffic noise and accidents. It was a known fact that the use of oil would not continue forever due to limited fossil fuel resources and the need to reduce greenhouse gas emissions. The fact that the current situation in transportation is not sustainable has led to the idea that fundamental changes are required in the technology of transportation systems [1]. This led to the production of more environmentally friendly electric vehicles, whose development continues to this day. However, in a short time, performance types of these (like gasoline-powered ones) were produced under very different brands. Moreover, choosing a suitable electric vehicle has become an important selection and ranking problem due to the abundance of different alternatives, performance criteria, weight methods, and normalization techniques.

In daily life, we encounter different problems that require choosing the most suitable one among alternatives. It is not easy for the average person to immediately visualize, calculate and conclude a decision matrix to solve a multi-criteria and multi-alternative decision problem. Therefore, in such problems, people may make regrettable decisions based on only a few criteria. In addition, the Multi-Criteria Decision Making (MCDM) methodology is frequently used in solving such problems where the weight importance of the criteria is different and the approach to them can be focused on maximum benefit and minimum cost [2-8].

MCDM methods also normalize different units of different criteria and are successfully used in solving problems in many application areas. Moreover, the original calculation algorithm of each MCDM method is unique. This also means that different MCDM methods may produce different rankings for a given problem [9]. When the input variables or parameters of MCDM methods change, the ranking results may also change. For example, when weight coefficients and normalization techniques change, the ranking results produced by some MCDM methods often change depending on the situation. This situation is expressed by sensitivity analysis in the literature [10-14]. The MCDM holistic algorithm consists of some additional input parameters. And these may include data type, number of alternatives, number of criteria, problem type, normalization technique, weighting method, even threshold values and preference function in the initial decision matrix. The final rankings produced by the MCDM integrity are affected by different inputs at different rates. Of course, since there are so many parameters or input types in the MCDM architecture, understanding how they affect the final sensitivity of the MCDM method is a very complex issue and it is very difficult to solve the problem in one go. For example, normalization, weight coefficients and the MCDM basic equation interact simultaneously and affect each other to certain extent, which in turn affects the final result.

There is no consensus on how to determine the quality of an MCDM method or the reliability of the results it produces, and moreover, there is no consensus on exactly what the limits of sensitivity analysis are and how to determine them [15]. A classical criterion emphasized for sensitivity analysis in MCDM methods is that the best ranked alternative expresses the stability conditions [16]. In fact, we can think that this determination is a partial solution, that is, it is not sufficient. Because what is important is not just the change in the position of one alternative, but the degree to which the ranking of all alternatives changes, which can be easily measured with any rank correlation analysis. As it is known, the number of inputs of a decision-making problem is very high, and this further increases the complexity. Thus, it becomes difficult to verify precise model recommendations. For example, when it comes to alternatives with close values, changing the criterion weight coefficients as a parameter can easily change the position of the alternatives, which is natural. Thus, focusing on the stability of the ranking of all alternatives rather than the stability of the alternatives may provide a more holistic and robust view.

Although there is no objective guarantee, many authors have recently described the comparison of the sensitivities of the results obtained using many different MCDM methods as "accuracy" and "robustness" analysis [17]. It is a controversial issue whether the concept of "accuracy" is actually measured here. On the other hand, what is meant by robustness is low sensitivity, that is, minimal fluctuation of the ranking results. However, in our opinion, this is a judgment or inference that is open to criticism in terms of the semantics of the methodology. Identification of classical sensitivity analysis with the concepts of "robustness" or "accuracy" in a direct approach without being subjected to a reasonable cost-benefit analysis requires evidence. Of course, excessive sensitivity can be harmful in the sense of "unnecessarily affecting the rankings", but in our opinion, it is a controversial claim that all types of sensitivity are harmful.

According to many research results, sensitivity is actually affected by the chosen MCDM method, the characteristics of the problems, the data type, and many components, parts or parameters in the MCDM integrity such as normalization and weight coefficient. Because of this dependence on input variables, the results of each study are often empirical (i.e., relevant only to the observed sample). And it has not been possible to generalize them with a framework. Performing a sensitivity analysis beforehand for the selection of an MCDM method, which is a complex problem, of course gives an idea, which is actually useful. But first of all, it may be useful to objectively evaluate what the results of classical sensitivity analysis for MCDM methods mean from a different perspective. For example, it is important to consider which direction sensitivity goes and to what extent this involves robustness or verification. Of course, it is an expected result that an MCDM method will be affected by the change in input parameters. However, in order to understand change and give meaning to change, we need a fixed base or a solid reference point. This can be difficult to formulate clearly in MCDM methods. However, by taking advantage of data analytics and with a rational approach, we need to create a static, somewhat similar and natural external order against the dynamic MCDM results. Thus, we compare the dynamic and refreshed MCDM results with a static sequence and observe the sensitivity. This approach has previously been successfully applied in the comparative capacity assessment of MCDM methods by taking advantage of the natural relationship of financial performance and stock return [8,9,18]. Moreover, there are authors who suggest that this may mean a sensitivity analysis approach from a different perspective [19]. Essentially, when considered well, this type of approach can be applied to all commercial products with a price-performance relationship.

The performance of commercial products can already be calculated with MCDM using different criteria and alternatives. It is already known that there is a reasonable level of relationship between performance and price, which companies fine-tune. We can take advantage of the relationships that static price produces with dynamic MCDM-based performance. Thus, it can be easily observed how and to what extent the change in MCDM input parameters affects the statistical relationship with price, provided that other factors are kept constant. The MCDM components (criteria, alternatives, weight coefficient, normalization, MCDM basic algorithm, threshold values, preference function, etc.) essentially have the same purpose in all MCDM methods (in terms of each task type allocated). This means that if an MCDM component reduces or increases an existing relationship with the other party, it can be described as a different indicator of sensitivity. In this study, we measure sensitivity through the relationship with a static and external factor and strive to discover the degree, direction and nature of sensitivity. In our study, we examine normalization types as the determining parameter in sensitivity, which is rare. Not only that, we also measure how sensitivity is determined when we change the weight coefficient and MCDM basic algorithms.

In this study, we measure how changing the input parameter of an MCDM method specifically for a new method, PROBID, affects the final ranking sensitivity produced, roughly using the "price-performance relationship". We apply the selection of the Small commercial transportation and logistics electric vehicle to our case. The PROBID original equation or method may have a special empirical situation that prevents justified generalization. And avoiding this risk, the well-known SAW and CODAS methods will also be tested in comparative analyses. It is known how normalization affects sensitivity in MCDM studies, but this is an issue that has not been adequately conceptualized. Generally, to understand sensitivity, criterion weighting coefficients are changed and the results are monitored. In fact, the sensitivity of the normalization method used may be a more determining parameter. In this study, the selection of an appropriate normalization method based on the sensitivity-MCDM performance special relationship will be evaluated through the Small Electric Van selection.

On the other hand, we think that the findings obtained from our study can be a solution to the data conversion problem not only for the MCDM family but in every field (for example in machinery, automotive, energy and industry engineering, artificial intelligence, machine learning or finance, etc.) and will be remarkable. The data preprocessing phase is an advancement where information can be parsed more easily. Normalization is the best technique for pre-processing data before the data training phase. Normalization is a process where data within a model is categorized to increase attribute connectivity [20]. The interesting point is that only a few techniques, especially Min-Max and Z-Score, are widely used in artificial intelligence or machine learning studies. [20-24]. We think that the adequacy of this choice may be a research gap open to question. According to the expertise and insights of MCDM methods, which are known to focus more on the problem of normalization selection than many other disciplines, using a random or static normalization technique is an objectionable choice. It can greatly influence, change, and even manipulate the final results. For example, a statistical relationship or causality investigated between two factors such as x and y may increase, decrease, or become meaningless depending on normalization [25]. This situation will question the reliability of the analysis results. As a matter of fact, in this study, we will show that the normalization technique can directly affect or mislead the relationship between price and MCDM final rankings that measure performance. In other words, the normalization method can reach a level that can manipulate the price-performance relationship. On the other hand, for example in machine learning, the subject is generally viewed in terms of prediction verification performance. However, we think that the results found (even if they are low or high) may be misleading because the wrongly chosen normalization type transforms the data incorrectly. Working with an arbitrary and incorrectly chosen type of normalization can be the same as working with a different data set.

In this study, we focus on the literature in the first part. The literature consists of two parts. First, we focus on the importance of electric transport vehicles in the transportation and logistics industry and investigate the importance of choosing a commercial logistics transport vehicle with a good price-performance ratio. In the second part, we focus on the literature on normalization and sensitivity analysis. In the third part, the application part, we conduct an innovative sensitivity analysis for PROBID, VIKOR and CODAS methods in order to choose the most suitable/best Small e-Van among 51 alternatives. Here, we also try different weighting methods as in the literature. Thus, we observe how three MCDM basic algorithms, seven normalization techniques, and five weighting method parameters individually affect the sensitivity of MCDM final results. MCDM sensitivity analysis in this study was analyzed with a total of 105 different alternative methodological scenarios, based mainly on the performance-price relationship. Finally, we evaluate our findings in the discussion section and make final inferences and recommendations based on the available evidence in the conclusion section.

2. Literature Overview

In this study, we select Small electric Van, commercial vehicle category, with MCDM methodology. To understand the nature of MCDM methods and, according to some, "sensitivity analysis", which means validation and robustness, has become popular and widespread in recent years. It is known that in recent years, sensitivity analysis has been used as a criterion in choosing a good MCDM method. However, sensitivity analysis is generally done by changing the weighting coefficient. Normalization methods are also a strong sensitivity indicator. Normalization methods can change the ranking results just like the weight coefficients. The individual effects of the original MCDM equation, normalization and weighting methods on the final result of the MCDM methods are significant. A comprehensive sensitivity framework for this, through a fixed external factor (e.g. price), has not been addressed before to such a scope as in this study. This study approaches classical sensitivity analysis with critical thought, improves it, and proposes an alternative sensitivity approach. In this study, we investigate whether an MCDM has low sensitivity but also shows high performance (by observing the relationship between price and MCDM).

Therefore, we examine the literature in three parts. First, we emphasize the undeniable importance of electric vehicles in terms of transportation, logistics, environment, and sustainability, based on the literature. Secondly, we review past studies on Electric Vehicles and MCDM methods. Third, we provide a framework for the reader by summarizing the existing literature on sensitivity analysis and normalization, an important topic within the methodology of evaluating MCDM methods.

2.1 Sustainable Transportation

The transportation sector is seen as the sector that contributes the most to carbon dioxide emissions. Because the operating system of the vehicles used on the roads is mostly powered by fossil fuels. The rapid development of technology significantly affects all countries in the world. Technological development and environmental awareness have given birth to electric and alternative energy vehicles in the global transportation system. It is estimated by the International Energy Agency that, with the more intensive use of such vehicles, the emission rate will drop below 50% by the 2050s, especially in developed countries such as the USA [26]. In the World Energy Outlook Special Report published by the Agency in December 2023, it was stated that if countries fully implement their national energy and climate commitments, oil and gas demand will be below the current level, that is, 45%, before 2050. It has been stated that if emissions from the sector reach net zero, oil and gas use will decrease by 75% by 2050 [27].

Sustainable transportation, also often referred to as green transportation due to its emphasis on sustainable transportation or environmental aspects, stems from sustainable development. According to the OECD's definition, sustainable transportation is defined as transportation that does not harm human health and the ecosystem and includes the use of renewable and non-renewable energy resources at an acceptable level. Sustainable transportation narrowly focuses only on resource depletion or air pollution problems. Social and economic welfare in a broad sense is also included in the content [28]. Black [29] claimed in his study that the transportation system is not sustainable due to reasons such as limited oil reserves, air quality problems, global atmospheric problems, excessive deaths, traffic congestion and urban sprawl. Nakamura, Hayashi [30] discussed different strategies used to reduce carbon emissions in the transportation sector. He compared the policies followed in different cities with the double classification they created. It has been revealed that each city has its own solutions to reduce carbon emissions. Within the strategy expressed as Improve, electric vehicles are mentioned as the next generation of the low-emission vehicle class. Sustainable transportation policy covers many interrelated issues such as climate, air quality, safety, traffic safety and health [31].

Some countries in the EU tax vehicles annually based on the pollution they emit. For this purpose, Germany has created annual taxes for different automobile classes and has especially exempted electric vehicles from tax for 5 years after they enter the traffic. Tax rates are offered at a significant discount for environmentally friendly and energy efficient vehicles. On the other hand, the tax rates applied to large vehicles that do not save energy and cause more harm to the environment are quite high. In order to encourage the purchase of more efficient and cleaner vehicles, the UK taxes vehicles annually according to six-band carbon emission figures [32]. Additionally, free charging stations have been created in London to encourage people to purchase electric vehicles [33].

2.2 Electric Vehicles and MCDM Methods

Since batteries are used as the power source in electric vehicles, they do not create exhaust emissions and effectively reduce dependence on fossil fuels and air pollution. Since renewable energy can be used when charging electric vehicles, energy consumption decreases. Thus, it prevents the decrease in energy resources. However, today, efforts are being made to develop the technology of high-performance electric vehicles and improve their costs [34]. The use of electric vehicles in traffic is accepted as a part of the sustainable transportation system planned in cities. Electric vehicles have many advantages compared to motor vehicles. It reduces operating costs, users feel less noise and vibration inside the car, it accelerates better at low speeds, has appropriate charging systems, and has zero exhaust emissions [35].

2022 has been a difficult year for the automobile industry due to different factors (wars, the ongoing impact of the coronavirus pandemic, increasing energy-fuel costs, increase in inflation). 14% of new cars sold in 2022 are electric vehicles. This rate is expected to reach 18% by the end of 2023. 60% of world electric car sales occur in China. While the EU ranks second, it is reflected in the data as the USA third [36]. According to the statement of the European Automobile Manufacturers Association, alternative energy vehicles had a share of more than half of the EU automobile market in 2022. While petroleum-powered cars have a share of 36.4% and diesel-powered cars have a share of 16.4%, battery electric vehicles (BEV) have a share of 12.1%, hybrid electric vehicles 22.6% and plug-in hybrid vehicles (PHEV) 9.4% [37]. This situation was realized as 6.7% for battery electric vehicles, 7.2% for hybrid electric vehicles and 1.7% for plug-in hybrid vehicles in the USA [38]. As of the third quarter of 2023, the share of these vehicles has increased to 18% in total. The share of other internal combustion engine vehicles in the USA is around 82% [39].

Small electric vans are the subject of this study. Small vans have a small and economical structure and are the vehicles preferred by SMEs and tradesmen for product deliveries within the city. It moves easily through the narrow streets and bends of cities, is easily parked, and provides convenience by reducing costs. The biggest reason for choosing small vans is the need to carry loads of a certain size and weight. For this, the powerful engine and torque it will have and the speed and acceleration it will use when carrying loads in the city are important [40].

The sales share of electric light commercial vehicles worldwide was 3.6%, accounting for one quarter of passenger cars. Battery electric vehicles (BEV) constitute 98% of electric light commercial vehicle sales. There are reasons for this situation, such as intensive use, driving range, wide geographical coverage, lower maintenance and service costs, and the promotion of BEVs. Among light commercial vehicles sold globally, Korea had the largest share of electric vehicles with 27%. This situation was realized as 15% in China. In the EU and US markets, the share of electric light commercial vehicles in sales remained below 10%. Countries regarding light commercial vehicles have made changes to their incentive plans and reduced their support per vehicle. Despite this, world light commercial vehicle sales have continued to increase [36].

Choosing the most suitable electric transportation vehicle is important, especially from the perspective of cost-benefit analysis and price-performance. Electric vehicles have different performance characteristics based on multiple criteria. A significant number of Multi-Criteria Decision Making (MCDM) methods have been used in the past. Moreover, we come across thousands of examples of modified versions of methods with the authors' intention of improvement. Kijewska et al. [41] evaluated the electric freight vehicles used in city logistics within the framework of their technical specifications using the PROMETHEE method. It was evaluated according to engine, battery, price and performance and sub-factors. Price and engine were the most influential factors. EVI Walk-In Van and MT-EV WIV vehicles according to engine factor features; According to the price factor, eWolf Omega 0.7, Motorcars SUV and Zero Truck vehicles were chosen as the best. Ecer [42] used MCDM techniques (SECA, MARCOS, MAIRCA, COCOSO, ARAS and COPRAS) to evaluate battery electric vehicles (BEV) such as battery, acceleration, range, price, etc. It tried to identify the best one by sorting it according to its technical features such as. The most important features were found to be price, allowable load and energy consumption, and as a result of the sensitivity analysis, Tesla Model S was chosen as the best BEV.

In their study to rank electric vehicles with the MCDM method and select the best among them, Sonar, Kulkarni [43] used the AHP method to determine the weights of the criteria and the MABAC method to select electric vehicles. As a result, Hyundai Kona was chosen as having the best performance among all the selected alternatives. Tata Tigor model is also suitable for those looking for a low-priced vehicle. Chawla et al. [44] selected the best electric scooter according to five criteria: price, engine power, driving range, maximum speed and battery charging time, using the integrated MCDM model. Fuzzy AHP was used to calculate the weights, and the TOPSIS method was used to rank the alternatives. According to the results, battery charging time was determined to be the feature with the most weight, and engine power was found to be the feature with the least weight. If all criteria are weighted equally, Ola S1 Pro is found to be the best model, and according to AHP's weighting, Simple One is found to be the best model. Pradhan et al. [45] introduced a model that allows consumers to choose the most suitable electric vehicle based on two sets of criteria using the MCDM method. The Quality Function Distribution (QFD) model was used to weight the criteria. Hyundai Kona Electric was chosen as the most suitable model with the highest score.

Puška et al. [46] evaluated 9 small vans according to 12 criteria using a mixed method consisting of Entropy, CRITIC and MEREC weight determination methods. Charging time and cargo volume were determined as the most important criteria. According to most conditions, the Toyota Proace City Verso Electric L2 model was chosen as the most suitable model. In the evaluation made with the MEREC method, the Renault Kangoo E-Tech model came to the fore. Saxena, Yadav [47] used the Fuzzy Analytic Hierarchy Process (FAHP) to determine the importance levels of factors for the adoption of electric light commercial vehicles in India. A telephone survey was administered to 32 logistics operators and their opinions on the impact of the selected factors were obtained. High capital costs, driving range concerns and long charging times have been found to be the most important negatives in the adoption of electric light commercial vehicles.

Tian et al. [48] determined the weights and importance levels of the criteria that are important in the selection of electric vehicles with the MCDM method based on sensitivity analysis. It made weighting by combining the best-worst method and the deviation maximization method. The ranking of electric vehicles was carried out with the extended ORESTE based on HIFS. In the evaluation made based on comfort, cost performance, appearance, interior space, fuel consumption, space, handling and power criteria and consumer comments, Toyota's LEVIN HEV E+ was determined as the most superior model among the alternatives. While consumers were very satisfied with the appearance criterion, they expressed more negative statements about fuel consumption. Wang et al. [49] tried to identify electric distribution vehicles with the best features in urban logistics by using fuzzy-coarse SWARA and MARCOS methods. According to the fuzzy-rough SWARA method, the most important features in choosing an electric distribution vehicle were found to be the range and price of the vehicle. According to the fuzzy-coarse MARCOS method, in line with the opinions of experts, Kangoo E-Tech Electric was determined as the vehicle with the best features and was confirmed by sensitivity analysis.

2.3 Normalization, MCDM and Sensitivity Analysis

The word 'sensitivity' is derived from the Latin 'sensibilitas' meaning 'capacity to feel'. Over time, the term has evolved in both meaning and usage. For example, this concept also includes some meanings related to awareness, reaction, and response. As in many scientific fields, sensitivity analysis in the MCDM methodology is more concerned with the degree to which the change of a certain input affects the final results [10,50]. So, in general terms, sensitivity analysis is about the relationship between the influencer and the affected. It is a comparative study of why the affected are affected too much, too little, or at average levels, rather than the influencer. The general judgment or acceptance on this issue is that high sensitivity for MCDM methods is considered to be a negative situation because it means being easily affected by an impact factor. It is claimed that an overly sensitive MCDM sequence also reduces quality because it deviates from the ideal more easily and is damaged more quickly. Although this determination seems reasonable and correct in general, sometimes it is useful to determine whether the sensitivity of an MCDM can be positive or not. A positive sensitivity cannot be considered negative. To give real-life examples, it is sometimes desirable for a sensor device to be extremely sensitive, and this is beneficial. Therefore, when you change the weight coefficients of an MCDM method (perhaps because it is the right thing to do), it may be positive that the rankings change a lot. Especially if sensitivity is measured with the help of a specific reference point, the results can be interpreted more meaningfully.

As explained above, sensitivity analysis for MCDM methods generally refers to the degree to which a final ranking is affected by one or more inputs [51]. Frequently, attempts have been made to measure the effect of changing weight coefficients on the sensitivity of the ranking [52,53]. However, for example, normalization may also be a determinant of sensitivity. It can be said that sensitivity has not been examined systematically and in-depth. In studies where robustness evaluation is made, the effect of the change in weights on sensitivity is meant. However, the effect of other components on the change of MCDM results seems to be generally neglected [54]. The concept of sensitivity should not be understood as just changing a few MCDM components. It can be easily observed how changing any MCDM input component affects the results, provided that other factors are kept constant. These MCDM components include data type, criteria, alternatives, weight coefficient, normalization techniques, MCDM basic algorithm and even threshold values, preference function, etc. It might even happen. Moreover, changing the MCDM basic equation itself and evaluating the ranking results is a common sensitivity analysis. Of course, not every impact factor changes the rankings in the same direction and degree. For example, in PROMETHEE, a threshold value or preference function parameter may not affect MCDM results as much as changing the weight coefficients.

The intention and purpose behind performing the sensitivity analysis of MCDM is related to the choice of the best of the alternatives for the decision-maker. In other words, decision-makers perform sensitivity analysis to make a sound decision or avoid a wrong choice. In this context, choosing a reliable and robust MCDM tool is useful in choosing the most appropriate alternative for a problem. [54,11-14]. Therefore, the health of a measurement can also ensure the reliability of the decision. On the other hand, the sensitivity level of an MCDM method may vary depending on the conditions, especially the data and the problem. Many influencing factors such as what the problem is, data type, number of alternatives and criteria, weight coefficients, normalization, and the basic

MCDM equation can explain this situation. Therefore, to keep the work more robust, authors have used more than one method simultaneously for a given problem in the past. Instead of choosing the most appropriate alternative using a single method, it is suggested to compare the procedures applied and the results obtained with the results obtained by other methods [55]. According to the highlighted definition, sensitivity analysis can be performed depending on any parameter or input change.

As a different example, Triantaphyllou and Mann [16] also pointed out the normalization technique and "rank reversal", which means that the change of alternatives disrupts consistency. On the other hand, among the sensitivity analysis techniques for MCDM methods, even the Monte Carlo simulation method has been used on initial data [56]. On the other hand, if you look carefully, the fact that normalization techniques have different calculation procedures and, as a result, produce different ranking results (provided that other MCDM components are kept constant) is a source of concern for the decision-maker. These procedures mean that very different sequences or alternative solutions are produced even when tested in a fixed MCDM method. There is almost a consensus in the literature that normalization or data transformation techniques directly affect the results. Moreover, the best method for all scenarios cannot be mentioned for now [24,57-63]. The findings in the literature are quite controversial in terms of whether the answer sought regarding the choice of normalization is correct or appropriate. Although some normalization techniques are rejected and some are highlighted depending on the data structure or statistical tools such as standard deviation and entropy, it can be said that there is not yet a solid, consistent, and reliable objective criterion required for normalization selection [24].

According to the general opinion in past studies, a low-sensitivity MCDM method that maintains the order of all alternatives by changing the weight coefficients and prevents drift is consistent and acceptable [54]. Even if this is generally true, it is problematic to understand sensitivity only by changing the best alternative. Because hypothetically, when you choose the wrong weighting method, there is the possibility of choosing the wrong alternative, and when you choose the right weighting method, there is a possibility of choosing a correct and different alternative. Therefore, the best alternative may change as the weight inputs change. We think that it is useful to observe the ranking of all alternatives statistically, rather than observing one alternative as in the study here.

3. Methods and Materials

In this study, we provide the selection of the best Small Electric Van alternative, one of the environmentally friendly mobile vehicles, with MCDM, based on an innovative sensitivity model analysis based on the selection of an appropriate normalization. And we show methodologically whether this choice is a reasonable choice. As it is known, there are at least 200 MCDM methods available, and moreover, there is no common trend regarding which one to choose. Recently, many authors have been trying to legitimize their chosen or newly produced MCDM algorithms with sensitivity analysis. We would like to demonstrate the degree of verifiability of these efforts with the model we propose here. Additionally, in this study, we showed that classical sensitivity analysis can be objectively criticized, and then we focused on developing an alternative sensitivity analysis. Some information about the methodological framework we used in the selection of an Small electric Van is included in Table 1 below.

Table 1 Normalization methods, MCDM Methods, Performance Criteria and Weighting Technique used in this Study

Normalization Method	***Weighting Method***	***MCDM Methods***	***Performance Criteria***
Sum, Vector, Min-Max, Max, Rank Based, Z-Score, Decimal	Entropy, Equal, CRITIC, SD, Subjective	PROBID, SAW and CODAS	Acceleration, Electric Range, Total Power, Fastcharge Time, Efficiency, Useable Battery, Weight Unladen, Cargo Volume, Total Torque, Top Speed

The phases shown in Fig. 1 were used during the implementation of this research.

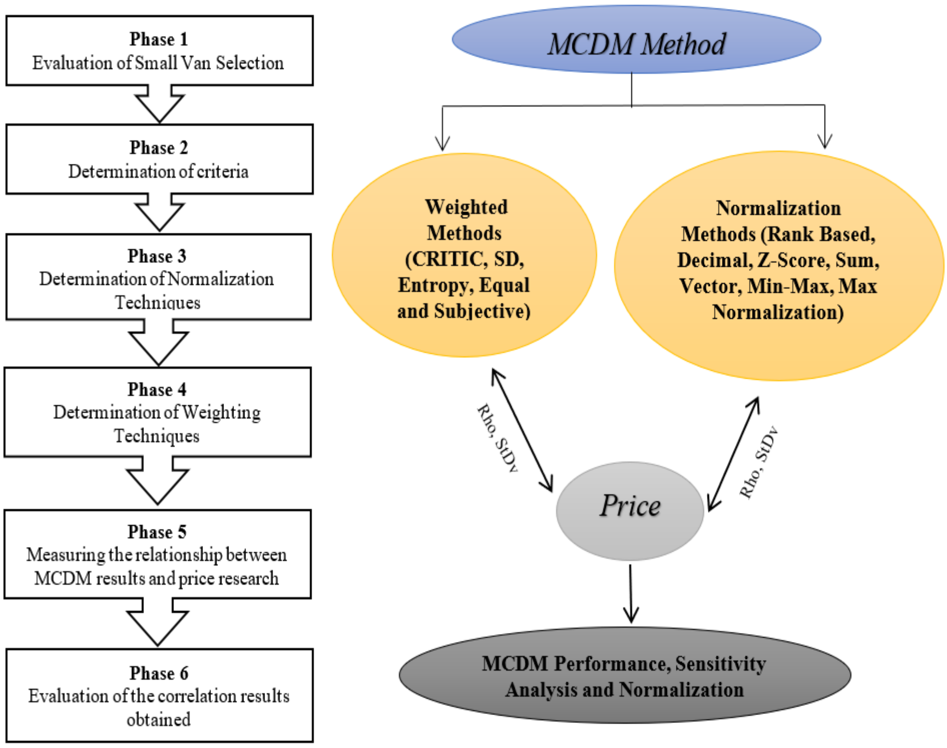

Fig. 1 Flow diagram of the study

We aim to provide a gold standard insight into which data transformation/normalization technique should be chosen for the best Small e-Van selection (and other MCDM problems) through the performance-sensitivity pattern matching proposed in Figure 1. We measure how the sensitivity of an MCDM method is affected by changing the weight coefficients and normalization techniques individually each time.

3.1 Performance Criteria

Although Small e-Van have many technical features, detailed explanations based on the literature of the technical criteria used in the analysis part of the study are mentioned below.

Acceleration (C1 Criteria): It shows how many seconds the vehicle can reach 100 kilometers. As it is known, in current technology, "acceleration" is a factor that increases energy consumption. A small amount of acceleration increases energy consumption by several hundred percent [64]. In their study, Sovacool et al. [65] found that, as an interesting finding, male participants gave more importance to "acceleration" than women.

Electric Range (C2): The Range criterion is an element that shows how many kilometers the electric vehicle can travel with a full battery. Electric vehicles find a place in the market mostly due to their high level of acceleration. However, this reduces energy efficiency and shortens the range distance [64]. The issue of range is expressed as the biggest problem in electric vehicles. It is estimated that the range limitation problem will be solved by developing battery technology [66].

Total Power (C3): Total Power is the motive power of the vehicle, which expresses the horsepower in internal combustion engine vehicles [66]. As the weight of the battery in electric vehicles increases, it increases the total power demand and decreases its efficiency [65,64].

Fastcharge Time (C4): As a feature that increases the preference for electric vehicles, "fastcharge time" ensures that the range barrier is ignored in the purchasing choice. [67], who examined the relationship between daily driving distance and standard and fast charging mechanisms, found that fast charging is more effective. Nilsson, Nykvist [68] stated that charging technology should be improved, long-range vehicles should be charged very quickly, and this will reduce the current charging time by half.

Efficiency (C5): It refers to the fuel efficiency of electric vehicles, that is, the efficiency of the battery system. Therefore, the performance of batteries is very important for electric vehicles. The efficiency of the battery is also expressed by power density. It shows the amount of power the battery can transmit without being damaged [69]. In the study by Egbue, Long [66], participants stated that electric vehicles save fuel and are more efficient than motor vehicles.

Useable Battery (C6): The battery technology of electric vehicles continues to be developed today. The usable battery is the capacity that indicates that 95%-99% of it can be used even though it shows 100% on the vehicle's dashboard. Vehicle manufacturing companies use software that prevents the battery from charging up to 100% to keep it healthy [70]. Agrawal et al. [71] described the useable battery as "the duration within which the maximum EV battery capacity gradients below a certain threshold of its original capacity and needs to be replaced for regular use".

Weight Unladen (C7): It refers to the weight of the vehicle without a load. Curb weight is the weight of a vehicle that includes all its equipment, tires, other in-vehicle accessories, and at least 90% energy filling required during production [72]. The share of batteries in the weight of electric vehicles is large. As electric vehicle technology develops, the weight of the battery should be reduced without reducing the performance of the vehicle [42].

Cargo Volume Max. (C8): It refers to the load that the vehicle can carry if the rear seats are folded or completely removed. The highest cargo volume affects the vehicle's energy consumption. Therefore, the range that the vehicle can travel may vary depending on the battery capacity [73]. Aiello et al. [74] stated that the maximum carrying capacity should be taken into account when comparing vehicles that will perform urban distribution activities.

Total Torque (C9): It refers to the rotational power of the vehicle's engine. Direct-current electric motors are used for the movement of electric vehicles. Although these engines have different features, the torque required in the vehicles is the same. Torque constitutes part of the power that enables the wheels and also the vehicle to move [75].

Top Speed (C10): It refers to the highest speed level reached by the electric vehicle. Jensen et al. [76] found that participants' opinions about top speed changed before and after using an electric vehicle. Electric vehicles with a maximum speed below 120 km/h were not accepted by the participants.

3.2 Normalization Methods

The sensitivity of an MCDM method to the type of data normalization is not an issue that is often addressed in sensitivity analyses. We propose a rare use case in sensitivity analysis. Below is information about normalization types and equations [77,78,61,25].

For Sum normalization:

$$F_{ij}=\frac{f_{ij}}{\sum_{k=1}^{m} f_{kj}} \qquad i\in\{1,2,\ldots,m\};\ j\in\{1,2,\ldots,n\} \tag{1}$$

For Vector normalization:

$$F_{ij}=\frac{f_{ij}}{\sqrt{\sum_{k=1}^{m} {f_{kj}}^2}} \qquad i\in\{1,2,\ldots,m\};\ j\in\{1,2,\ldots,n\} \tag{2}$$

For Minimum-Maximum normalization:

$$\begin{aligned} F_{ij}&=\frac{f_{ij}-\min_{i\in m} f_{ij}}{\max_{i\in m} f_{ij}-\min_{i\in m} f_{ij}} \qquad i\in\{1,2,\ldots,m\};\ j\in\{1,2,\ldots,n\} \text{ for benefit objectives} \\ F_{ij}&=\frac{\max_{i\in m} f_{ij}-f_{ij}}{\max_{i\in m} f_{ij}-\min_{i\in m} f_{ij}} \qquad i\in\{1,2,\ldots,m\};\ j\in\{1,2,\ldots,n\} \text{ for cost objectives} \end{aligned} \tag{3}$$

For Maximum normalization:

$$\begin{aligned} F_{ij}&=\frac{f_{ij}}{\max_{i\in m} f_{ij}} \qquad i\in\{1,2,\ldots,m\};\ j\in\{1,2,\ldots,n\} \text{ for benefit objectives} \\ F_{ij}&=\frac{\min_{i\in m} f_{ij}}{f_{ij}} \qquad i\in\{1,2,\ldots,m\};\ j\in\{1,2,\ldots,n\} \text{ for cost objectives} \end{aligned} \tag{4}$$

For Ranking based data conversion:

For each criterion, the best value is assigned first rank, while the worst value is assigned *n* rank. Thus, the weighted preference function for the unit cell in each criterion column is calculated as follows:

$$F_{ij}= r_{ij}\times w_j \tag{5}$$

where r_{ij} is the rank of solution *i* for criteria *j*. This data conversion method is recommended as an alternative to the normalization method. This method is used instead of normalization techniques in the FUCA method.

For Z-score normalization:

$$n_{ij}=\frac{x_{ij}-\mu_j}{\sigma_j}=\frac{x_{ij}-\frac{\sum_{i=1}^{m}x_{ij}}{m}}{\sqrt{\frac{\sum_{i=1}^{m}(x_{ij}-\mu_j)^2}{m}}} \quad n_{ij}=-\frac{x_{ij}-\mu_j}{\sigma_j} \tag{6}$$

Z-score refers to the measurement of the standard deviation of a value from the mean of a given distribution.

For decimal normalization:

This method moves the decimal point of series values. The movement of decimal points depends on the number of digits of the maximum value in the series. Decimal scaling produces a normalized series with values in the range 0 to 1; where *d* is the number of digits of the maximum value.

$$F_{ij}=f_{ij}/10^d \qquad i\in\{1,2,\dots,m\};\ j\in\{1,2,\dots,n\} \tag{7}$$

3.3 MCDM Methods

3.3.1 Preference Ranking on the Basis of Ideal-Average Distance (PROBID) Method

In this study, a new MCDM method, PROBID, (and CODAS as an alternative) were used. In 2021, Wang et al. [77] developed the PROBID method, which follows a similar methodology to the distance-based TOPSIS and VIKOR methods. The mathematical stages of the PROBID method can be followed below. The basic idea of the PROBID method is that it covers ideal solutions from the most positive ideal solution (PIS) to the most negative ideal solution (NIS). In this respect, PROBID is actually similar to methods such as TOPSIS and VIKOR. The PROBID calculation comprises six steps [77]:

Phase 1. By applying Vector transformation, an initial decision matrix containing *m* rows and *n* columns is obtained.

$$F_{ij}=\frac{f_{ij}}{\sqrt{\sum_{k=1}^{m}f_{kj}^{\ 2}}} \qquad i\in\{1,2,\dots,m\};\ j\in\{1,2,\dots,n\} \tag{8}$$

Phase 2. A weighted decision matrix is obtained by multiplying each column by a determined weight coefficient:

$$v_{ij}=F_{ij}\times w_j \quad i\in\{1,2,\dots,m\};\ j\in\{1,2,\dots,n\} \tag{9}$$

Phase 3. The highest value PIS is determined ($A_{(1)}$), 2nd PIS ($A_{(2)}$), 3rd PIS ($A_{(3)}$), …, and m^{th} PIS ($A_{(m)}$) (i.e., the most NIS).

$$A_{(k)}=\{\left(\mathrm{Large}(v_j,k)\middle|j\in J\right),\ \left(\mathrm{Small}(v_j,k)\middle|j\in J'\right)\}=\{v_{(k)1},v_{(k)2},v_{(k)3},\dots,v_{(k)j},\dots,v_{(k)n}\} \tag{10}$$

Where, $k\in\{1,2,...,m\}$, J= set of benefit objectives from *{1, 2, 3, 4, …, n}*, J' = set of cost objectives from {1, 2, 3, 4, …, n}, Large (v_j,k) means the k^{th} largest value in the j^{th} weighted normalized objective column (i.e., v_j) and Small (v_j,k) means the k^{th} smallest value in the j^{th} weighted normalized objective column (i.e., v_j). Then, find the average value of each objective column.

$$\bar{v}_j=\frac{\sum_{k=1}^{m}v_{(k)j}}{m} \qquad \text{for } j\in\{1,2,\dots,n\} \tag{11}$$

The average solution is then:

$$\overline{A}=\{\bar{v}_1, \bar{v}_2, \bar{v}_3,\ldots,\bar{v}_j, \ldots, \bar{v}_n\} \tag{12}$$

Phase 4. Calculate the Euclidean distance of each solution to each of the *m* ideal solutions as well as to the average solution:

$$S_{i(k)}=\sqrt{\sum_{j=1}^{n}(v_{ij}-v_{(k)j})^2} \quad i\in\{1,2,\ldots,m\};\ k\in\{1,2,\ldots,m\} \tag{13}$$

Then, the distance to average solution is found as:

$$S_{i(avg)}=\sqrt{\sum_{j=1}^{n}(v_{ij}-\bar{v}_j)^2} \quad i\in\{1,2,\ldots,m\} \tag{14}$$

Phase 5. At this stage, the overall positive-ideal distance, which is the weighted total distance of a solution to the first half of the ideal solutions, is determined:

$$S_{i(PIS)}=\begin{cases}\sum_{k=1}^{\frac{m+1}{2}}\frac{1}{k}S_{i(k)} & i\in\{1,2,\ldots,m\} \text{ when } m \text{ is an odd number}\\ \sum_{k=1}^{\frac{m}{2}}\frac{1}{k}S_{i(k)} & i\in\{1,2,\ldots,m\} \text{ when } m \text{ is an even number}\end{cases} \tag{15}$$

And, determine the overall negative-ideal distance, which is essentially the weighted sum distance of one solution to the second half of ideal solutions.

$$S_{i(NIS)}=\begin{cases}\sum_{k=\frac{m+1}{2}}^{m}\frac{1}{m-k+1}S_{i(k)} & i\in\{1,2,\ldots,m\} \text{ when } m \text{ is an odd number}\\ \sum_{k=\frac{m}{2}+1}^{m}\frac{1}{m-k+1}S_{i(k)} & i\in\{1,2,\ldots,m\} \text{ when } m \text{ is an even number}\end{cases} \tag{16}$$

Here, weight is increasing with the ideal solution number (i.e., k increasing to m). Overall positive-ideal and negative-ideal distances of each solution (i = 1, 2, ..., m) are thus calculated by equations 8 and 9 respectively.

To better visualize the calculations of ideal and non-ideal distances, a small dataset with 4 Pareto-optimal solutions (S_1, S_2, S_3, S_4) and 2 objectives (F1 and F2) is plotted in Fig. 2. As shown, the green (continuous) arrowed line $S_{4(3)}$, for example, represents the Euclidean distance between optimal solution S_4 to the 3rd PIS ($A_{(3)}$). Following equations (8) and (9), $S_{4(pos\text{-}ideal)} = S_{4(1)} + (1/2)\ S_{4(2)}$ and $S_{4(neg\text{-}ideal)} = (1/2)\ S_{4(3)} + S_{4(4)}$.

Phase 6. Calculate the *PIS/NIS* ratio (R_i) and then performance score (P_i) of each solution as follows:

$$R_i=\frac{S_{i(pos\text{-}ideal)}}{S_{i(neg\text{-}ideal)}} \quad i\in\{1,2,\ldots,m\} \tag{17}$$

$$P_i=\frac{1}{1+R_i^2}+S_{i(avg)} \quad i\in\{1,2,\ldots,m\} \tag{18}$$

On the other hand, the MCDM method called sPROBID is a simple variation of PROBID. The first 4 steps of sPROBID are the same as those of PROBID. In stage five, instead of using the first half of ideal solutions to find $S_{i(PIS)}$ and the second half of ideal solutions to find $S_{i(NIS)}$, sPROBID considers only the top and bottom quarters of ideal solutions for finding $S_{i(PIS)}$ and $S_{i(NIS)}$, respectively.

$$S_{i(\text{pos-ideal})}=\begin{cases}\sum_{k=1}^{m\backslash 4}\frac{1}{k}S_{i(k)} & i\in\{1,2,\ldots,m\} \text{ when } m\geq 4\\ S_{i(1)} & i\in\{1,2,\ldots,m\} \quad \text{when } 0<m<4\end{cases} \tag{19}$$

Here, m\4 is the integer quotient of *m* divided by 4, which discards the remainder and retains only the integer portion. In case the number of Pareto-optimal solutions is smaller than 4, only the Euclidean distance between optimal solution S_i and the most PIS is taken.

$$S_{i(\text{neg-ideal})}=\begin{cases}\sum_{k=m+1-(m\backslash 4)}^{m}\frac{1}{m-k+1}S_{i(k)} & i\in\{1,2,\ldots,m\} \text{ when } m\geq 4\\ S_{i(m)} & i\in\{1,2,\ldots,m\} \quad \text{when } 0<m<4\end{cases} \tag{20}$$

Where, m+1-(m\4) gives the starting position of calculating negative-ideal distance. If fewer than 4 non-dominated solutions exist, only the Euclidean distance between optimal solution S_i and the m^{th} PIS (i.e., most NIS) is taken.

In step six of sPROBID, the final score is simplified to the ratio of negative-ideal distance over positive-ideal distance.

$$P_i=\frac{S_{i(NIS)}}{S_{i(PIS)}} \quad i\in\{1,2,\ldots,m\} \tag{21}$$

The farther a solution is from NIS and the closer it is from PIS, the higher the performance score P_i. The solution with the highest P_i is recommended to the decision maker.

3.3.2 Combinative Distance-Based Assessment (CODAS)

In the CODAS method, which has become popular in the last five years, the ranking performance of an alternative is measured by its distance from the negative ideal point [77]. Each pair of alternatives is compared according to their distance from this ideal value. Here, the superiority of the alternatives over each other can be determined by two criteria. The priority criterion is the Euclidean distance of the considered alternatives to the negative ideal (in cases where the Euclidean distance cannot be used, taxi distance is preferred as an alternative). This distance-based method, somewhat similar to TOPSIS, is actually preferred in cases where the best alternative has the farthest distance from the negative ideal [79].

3.3.3 Simple Additive Weighting (SAW)

The score for each alternative is calculated as follows: The final score is the sum of the normalized value multiplied by the predetermined weight coefficient across the entire row for each criterion. In other words, it represents the weighted total score for each alternative. Among the selected alternatives, the one with the highest score is considered the best solution [80].

3.3.4 Weighted Methods

The most common use of sensitivity analysis is the sensitivity of an MCDM to weight coefficients. Below is information about five different weight coefficient assignment methods [77,80,81].

The Entropy approach involves the subsequent three stages.

Stage 1. Normalize the first decision matrix:

$$F_{ij}=\frac{f_{ij}}{\sum_{k=1}^{m} f_{kj}} \qquad i\in\{1,2,\ldots,m\};\ j\in\{1,2,\ldots,n\} \tag{22}$$

Stage 2. Calculate the Entropy of values of each criterion:

$$E_j=-\frac{1}{\ln(m)}\sum_{i=1}^{m}(F_{ij}\ln F_{ij}) \qquad j\in\{1,2,\ldots,n\} \tag{23}$$

Stage 3. Determine the weight for each criterion:

$$w_j=\frac{1-E_j}{\sum_{j=1}^{n}(1-E_j)} \qquad j\in\{1,2,\ldots,n\} \tag{24}$$

for benefit and cost criteria

$$F_{ij}=\frac{f_{ij}-\min_{i\in m} f_{ij}}{\max_{i\in m} f_{ij}-\min_{i\in m} f_{ij}},\ F_{ij}=\frac{\max_{i\in m} f_{ij}-f_{ij}}{\max_{i\in m} f_{ij}-\min_{i\in m} f_{ij}} \tag{25}$$

According to that, calculate the *Standard Deviation* method of values of each criterion:

$$\sigma_j=\sqrt{\frac{\sum_{i=1}^{m}(F_{ij}-\overline{F_j})^2}{m}} \tag{26}$$

CRITIC Weighted Method (Criteria Importance Through Intercriteria Correlation) has three phases.

Phases 1: “m” is the number of rows and “n” is the number of columns;

$$F_{ij}=\frac{f_{ij}-\min_{i\in m} f_{ij}}{\max_{i\in m} f_{ij}-\min_{i\in m} f_{ij}} \qquad i\in\{1,2,\ldots,m\};\ j\in\{1,2,\ldots,n\} \text{ If it is beneficial} \tag{27}$$

$$F_{ij}=\frac{\max_{i\in m} f_{ij}-f_{ij}}{\max_{i\in m} f_{ij}-\min_{i\in m} f_{ij}} \qquad i\in\{1,2,\ldots,m\};\ j\in\{1,2,\ldots,n\} \text{ If it is cost-oriented} \tag{28}$$

Phases 2: A binary correlation matrix is created to measure the dependency/correlation between two criteria.

$$\rho_{jk}=\frac{\sum_{i=1}^{m}(F_{ij}-\overline{F_j})(F_{ik}-\overline{F_k})}{\sqrt{\sum_{i=1}^{m}(F_{ij}-\overline{F_j})^2}\sqrt{\sum_{i=1}^{m}(F_{ik}-\overline{F_k})^2}} \qquad j,k\in\{1,2,\ldots,n\} \tag{29}$$

Phases 3: The standard deviation of the criteria is calculated.

$$\sigma_j=\sqrt{\frac{\sum_{i=1}^{m}(F_{ij}-\overline{F_j})^2}{m}} \qquad j\in\{1,2,\ldots,n\} \tag{30}$$

Here, $\overline{F_j}=\frac{1}{m}\sum_{i=1}^{m}F_{ij}$. It is the arithmetic mean of the j^{th} normalized objective values. Finally, the weight coefficients for each criterion are determined as follows.

$$c_j=\sigma_j\sum_{k=1}^{n}(1-\rho_{jk}) \quad j\in\{1,2,\ldots,n\},\ w_j=\frac{c_j}{\sum_{k=1}^{n}c_k} \qquad j\in\{1,2,\ldots,n\} \tag{31}$$

Mean/Equal Weighting Method: The equal weighting method is the simplest way to create weights for each criterion. It is based on the assumption that all *n* criteria are of equal importance. It is based on the assumption that all *n* criteria are of equal importance and therefore equal weight coefficients are assigned to each: wj= 1/n j = ∈{ 1, 2, ...n}

Finally, subjective weighting was also used in practice. Weight coefficients are assigned high by the author, especially for some criteria, to better understand the sensitivity of MCDM and to show it to the reader.

3.3.5 Statistical Method Used

In this study, the relationship between MCDM performance results and price was obtained by Spearman Rank Correlation. We should emphasize that our aim here is part of sensitivity analysis. We would like to remind you that as MCDM results change, the existing relationships with the fixed reference point also change. This change means sensitivity. The Spearman rank correlation coefficient measures the statistical dependence between two ranking-based variables [82,83]:

$$r_s = 1 - \frac{6\sum di^2}{n\,(n^2\ -1)}$$

Here, r_s is the symbol for Spearman's Rho coefficient. *di* is the symbol for the difference between pairwise rankings. And *n* represents the number of alternatives in the formula.

4. Application

When purchasing an small e-van in transportation and logistics, people also pay attention to the technical features of the vehicles. This situation becomes more prominent when purchasing an electric vehicle because it is difficult to choose the best alternative for matrix problems where the alternatives and criteria are numerous. Moreover, evaluation methodologies such as weighting coefficient, normalization selection and sensitivity analysis are also used for this selection. We rather help them by guiding them to make a reasonable decision. There are 51 Small e-Van categories for our study. The data regarding the brands, models, 10 different criteria and price amounts of the vehicles in this category were obtained from the open access web address ‘https://ev-database.org/’ [84]. The price of each Small electric Van is in euro currency.

It is a known fact that normalization affects MCDM results [85,86]. We show how this affects sensitivity in the following application from an innovative gold standard perspective. The matrix in Table 2 shows the alternatives (Small electric Van models and brands), criteria (performance dimensions), and price information.

The small e-van used in the study are all brands and models between 2020-2023. Tables 3-5 show the Spearman Correlation (rho) results between price and MCDM rankings for a total of 105 different scenarios with PROBID, SAW, and CODAS methods. While reading the table, we can read from two different perspectives: row and column. If we read along the lines, this means that we must first assume that the normalization method will be constant. On the other hand, when we read from the column, this means that we act with the assumption that the weight assignment method will be constant. Thus, we can see from the table that the relationship levels with price always change. In other words, provided that all components remain constant, either the weight coefficient or the normalization type is changed and the correlation results are monitored.

Table 2 Alternatives (A), performance criteria (C) and price information for Small Electric Van selection

	C1	*C2*	*C3*	*C4*	*C5*	*C6*	*C7*	*C8*	*C8*	*C10*	*PRICE*
A1	135	11.7	205	100	26	226	46.3	1739	2126	260	*32790*
A2	135	11.7	205	100	26	226	46.3	1813	2693	260	*43640*
A3	130	12.1	185	100	26	250	46.3	1969	3061	260	*51940*
A4	130	13.3	265	100	38	257	68	2131	3061	260	*57940*
A5	130	12.1	180	100	26	257	46.3	1989	3497	260	*52730*
A6	130	13.3	260	100	38	262	68	2161	3497	260	*58730*
A7	130	12.1	185	100	26	250	46.3	1969	3061	260	*53640*
A8	130	13.3	265	100	38	257	68	2131	3061	260	*59640*
A9	130	12.1	180	100	26	257	46.3	1989	3497	260	*54430*
A10	130	13.3	260	100	38	262	68	2161	3497	260	*60430*
A11	130	12.1	185	100	26	250	46.3	1969	3061	260	*55990*
A12	130	13.3	265	100	38	257	68	2140	3061	260	*61990*
A13	130	12.1	180	100	26	257	46.3	1989	3497	260	*56990*
A14	130	13.3	260	100	38	262	68	2167	3497	260	*62990*
A15	180	9.2	345	180	50	261	90	2385	2179	350	*68990*
A16	132	12.6	225	90	40	200	45	1874	1979	245	*49445*
A17	160	12	210	150	44	286	60	2531	5010	362	*68949*
A18	160	12	210	150	44	286	60	2501	4630	362	*68056*
A19	160	12.1	310	150	41	290	90	2660	5010	362	*72519*
A20	160	12.1	310	150	41	290	90	2635	4630	362	*71626*
A21	160	12	205	150	28	293	60	2405	4990	366	*61571*
A22	160	12	305	150	41	295	90	2555	4990	366	*65140*
A23	160	12	210	150	28	286	60	2380	4630	366	*60678*
A24	160	12	310	150	41	290	90	2530	4630	366	*64248*
A25	132	12.6	225	90	40	200	45	1872	1730	245	*39990*
A26	135	11.7	205	100	26	226	46.3	1739	2126	260	*43050*
A27	135	11.7	200	100	26	232	46.3	1813	2693	260	*44750*
A28	130	12.1	180	100	26	257	46.3	1989	3497	260	*51825*
A29	130	13.3	260	100	38	262	68	2161	3497	260	*57775*
A30	130	12.1	185	100	26	250	46.3	1969	3061	260	*50992*
A31	130	13.3	265	100	38	257	68	2131	3061	260	*56942*
A32	130	12.1	180	100	26	257	46.3	1989	4900	260	*64075*
A33	130	13.3	260	100	38	262	68	2161	4900	260	*70075*
A34	130	12.1	185	100	26	250	46.3	1969	4900	260	*63250*
A35	130	13.3	265	100	38	257	68	2131	4900	260	*69250*
A36	130	13.1	185	100	26	250	46.3	1989	3497	260	*52730*
A37	130	14.3	260	100	38	262	68	2161	3497	260	*58730*
A38	130	13.1	185	100	26	250	46.3	1969	3061	260	*51940*
A39	130	14.3	265	100	38	257	68	2131	3061	260	*57940*
A40	135	11.7	200	100	26	232	46.3	1841	2693	260	*42440*
A41	135	11.7	205	100	26	226	46.3	1765	2126	260	*41240*
A42	130	13.1	185	100	26	250	46.3	1989	3497	260	*54430*
A43	130	14.3	260	100	38	262	68	2161	3497	260	*60430*
A44	130	13.1	185	100	26	250	46.3	1969	3061	260	*53640*
A45	130	14.3	265	100	38	257	68	2131	3061	260	*59640*
A46	132	12.6	220	90	40	205	45	1870	2500	245	*39300*
A47	135	11.2	210	100	26	220	46.3	1739	2126	260	*37800*
A48	135	11.2	205	100	26	226	46.3	1813	2693	260	*40150*
A49	130	13.1	260	100	38	262	68	2161	3497	260	*65385*
A50	130	13.1	265	100	38	257	68	2131	3061	260	*64530*
A51	145	10.2	345	150	30	223	77	2459	2123	310	*64581*

If the correlation results are very volatile or have high variability, it means that the sensitivity of that MCDM ranking will be high. So, the table below primarily shows that each of the 7 different normalization types and 5 weighting methods are used in different scenarios together with CODAS, PROBID, and SAW. In addition, the degree of relationship between 105 different MCDM rankings and price was obtained. The variation of all correlations in the table (on a methodological basis) can be measured by "standard deviation", thus providing an innovative measure of sensitivity. What we mean by the concept of average here is the average correlations between price and a method or technique. Standard deviation is the measure of the degree of change in the correlations produced by the same MCDM sequence, that is, it expresses the degree of sensitivity of the PROBID, CODAS, and SAW methods. Table 3 shows the Spearman Correlation (rho) and standard deviation results between price and PROBID rankings for a total of 35 different scenarios.

Table 3 Sensitivities of the PROBID Method to Weights and Normalization Types

	Entropy	*SD*	*CRITIC*	*Equal*	*Subjective*	**StDv**	**Average**
Sum	0.918	0.93	0.24	0.92	0.329	**0.314**	**0.667**
Vector	0.917	0.929	0.24	0.92	0.329	**0.314**	**0.667**
Min Max	0.897	0.877	0.863	0.878	0.762	**0.048**	**0.855**
Max	0.889	0.875	0.847	0.876	0.843	**0.018**	**0.866**
Rank Based	0.765	0.73	0.742	0.159	0.21	**0.276**	**0.521**
Decimal	0.917	0.891	0.877	0.909	0.892	**0.014**	**0.897**
Z-Score	0.762	0.318	0.021	0.207	0.277	**0.245**	**0.317**
StDv	**0.066**	**0.204**	**0.338**	**0.325**	**0.275**		
Average	**0.866**	**0.793**	**0.547**	**0.696**	**0.520**		

Table 3 clearly shows that in general, low sensitivity (standard deviation) in an MCDM ranking is matched to produce high correlation (rho) with price. For example, when we change the weight method, provided that the other components are constant, we see that the methods that provide the lowest standard deviation and the highest relationship with the price are the Decimal and Maximum methods. On the contrary, it is clear that Sum, Vector, Rank Based and Z-Score methods produce high sensitivity and low correlation with price. On the other hand, when we take a reading from the column, that is, when we keep the weight method constant and change the normalization method, we see that the Entropy method clearly produces the lowest sensitivity and the highest correlations with price. On the other hand, it can also be seen that the CRITIC method produces high sensitivity and low correlation with price. In other words, Decimal achieved the highest correlation average and the lowest sensitivity degree in normalization and Entropy in weighting. Additionally, when we create a combination of successful techniques, we notice that the Decimal/Entropy/PROBID combination produces one of the highest correlations with 92 %. While this is the case for the PROBID method, it is a matter of curiosity what the findings are for other methods. Because the MCDM basic algorithm may have special cases that prevent us from generalizing, we wanted to test the pattern matching (low sensitivity-high MCDM performance) we obtained here in other methods. For this purpose, we added the distance-based CODAS and the aggregation-based SAW method to this study. As can be clearly seen in the tables below, low sensitivity-high performance (or vice versa) patterns match here. Although the MCDM basic equation changes the results slightly, the general trend is the same. Table 4 shows the *rho* and standard deviation results between price and CODAS rankings for a total of 35 different scenarios. Also, shows that for CODAS, in general, the low sensitivity (standard deviation) in an MCDM ranking is matched by producing a high relationship (rho) with price. Accordingly, it can be said that Entropy techniques are more successful in weighting and Sum and Vector techniques are more successful in normalization. On the other hand, it can also be seen that the CRITIC method and the Subjective weight coefficient assignment by the authors produce high sensitivity and low correlation with price. Additionally, when we create a combination of the most successful techniques, we note that it is not a coincidence that the Sum&Vector /Entropy/CODAS combination produces the highest correlation with 92.5%.

Table 4 Sensitivities of the CODAS Method to Weights and Normalization Types

	Entropy	*SD*	*CRITIC*	*Equal*	*Subjective*	**StDv**	**Mean**
Sum	0.925	0.916	0.881	0.919	0.845	**0.030**	**0.897**
Vector	0.925	0.916	0.881	0.919	0.837	**0.033**	**0.896**
Min Max	0.773	0.384	0.289	0.359	0.105	**0.219**	**0.382**
Max	0.832	0.569	0.098	0.429	0.273	**0.251**	**0.440**
Rank Based	0.732	0.55	0.186	0.519	0.163	**0.221**	**0.43**
Decimal	0.924	0.905	0.884	0.912	0.898	**0.013**	**0.905**
Z-Score	0.911	0.907	0.887	0.907	0.82	**0.034**	**0.886**
StDv	**0.075**	**0.210**	**0.346**	**0.241**	**0.335**		
Mean	**0.860**	**0.735**	**0.587**	**0.709**	**0.563**		

Table 5 shows the *rho* and standard deviation results between price and SAW rankings for a total of 35 different scenarios. The same seems to be true for the SAW method. Table 5 clearly shows for the SAW method that in general the low sensitivity (standard deviation) of an MCDM ranking is matched by producing a high correlation (rho) with price. Accordingly, it can be said that Entropy techniques are more successful in weighting and Sum and Vector techniques are more successful in normalization. On the other hand, it can also be seen that the CRITIC method and the Subjective weight coefficient assignment by the authors produce high sensitivity and low correlation with price.

Table 5 Sensitivities of the SAW Method to weights and normalization types

	Entropy	*SD*	*CRITIC*	*Equal*	*Subjective*	**StDv**	**Mean**
Sum	0.913	0.908	0.886	0.911	0.89	**0.011**	**0.902**
Vector	0.913	0.907	0.886	0.911	0.89	**0.011**	**0.901**
Min Max	0.932	0.867	0.363	0.754	0.254	**0.274**	**0.634**
Max	0.935	0.896	0.378	0.82	0.328	**0.263**	**0.671**
Rank B	0.726	0.546	0.284	0.507	0.226	**0.182**	**0.458**
Decimal	0.909	0.914	0.889	0.912	0.899	**0.009**	**0.905**
Z-Score	0.909	0.908	0.893	0.907	0.835	**0.028**	**0.890**
StDv	**0.068**	**0.125**	**0.272**	**0.139**	**0.303**		
Mean	**0.891**	**0.849**	**0.654**	**0.817**	**0.617**		

When we create a combination of successful techniques, we notice that the SUM&Vector/Entropy/CODAS combination produces one of the highest correlations with 91.3%. Although the general trend points to this combination, the actual record was produced by a specific slightly different combination: the Max/Entropy/CODAS combination produced the best correlation at 93.5%. Although entropy is effective, the interaction seems to extract the first one from a different combination.

5. Results and Discussion

In this study, low sensitivity and high correlation production with price (and vice versa) seem to be a kind of "pattern matching", which we encounter in the three methods used. In fact, we can see and interpret the above findings better by means of Fig. 2 (for PROBID).

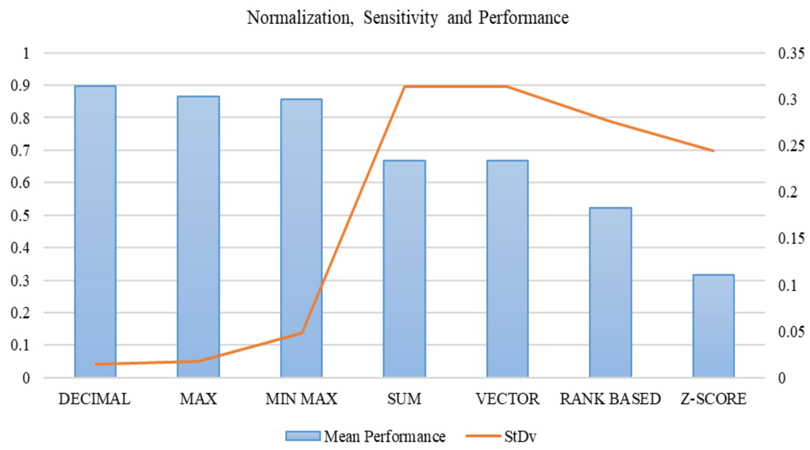

Fig. 2 Normalization, sensitivity and performance relationship for PROBID method

The better MCDM rankings have lower sensitivity and develop a good relationship with price. This situation emerges as an infallible feature in all possible scenario sets, as can be observed in Fig. 2 and Fig. 3 (for CODAS).

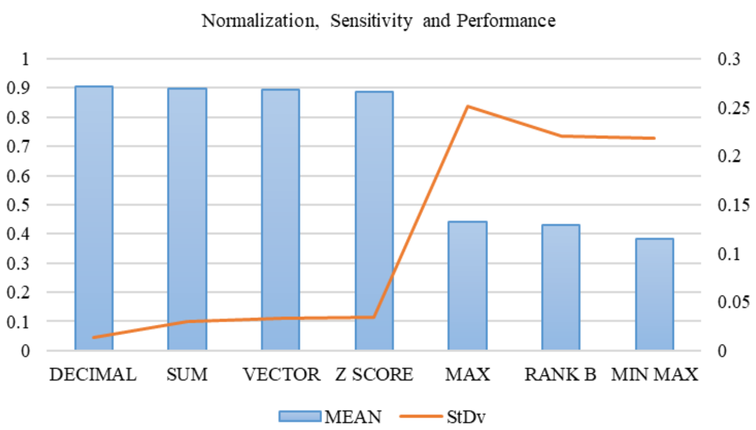

Fig. 3 Normalization, sensitivity and performance relationship for CODAS method

An MCDM method with low sensitivity has higher performance. In this study, we adjusted the sensitivity by the weight coefficient and by changing the normalization techniques. So, as a result, decimal-based MCDM methods gave better results. This interesting aspect can be easily observed in the Figs. 2 and 3, and in Fig. 4 (for SAW).

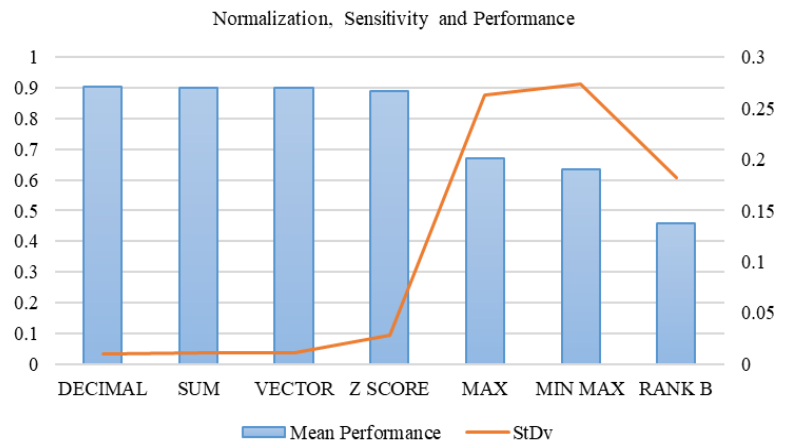

Fig. 4 Normalization, sensitivity and performance relationship for SAW method

As can be clearly seen from the graphs above, one of the determinants of sensitivity, regardless of the MCDM method, is the normalization techniques used. We can summarize other findings as follows:

- The lowest sensitivity and highest performing data transformation tool for all three MCDM methods is the Decimal scaling technique.
- On the other hand, in the opposite case, the data conversion technique that improves the highest sensitivity and lowest performance for an MCDM is Z-Score for PROBID, Min-Max for CODAS and Rank Based conversion technique for SAW. This shows that the interaction of the basic MCDM equation with normalization techniques also affects the result to some extent.
- Max, Rank Based or Min-Max techniques appear to reduce the performance of the SAW method, while others result in high performance. A similar situation also applies to the CODAS method. For both methods, Decimal, Sum and Vector seem to be the best techniques.
- It is noteworthy that the Min-Max method, which is most commonly used in the data pre-processing stage in artificial intelligence and machine learning algorithms, fails in the CODAS and SAW methods. This shows that the interaction of a calculation format with the type of normalization is important. In addition, although the other commonly used Z-Score technique performs relatively better, it is not the data conversion technique that produces the best performance. In fact, the worst case scenario for PROBID is produced with Z-Score. This shows that we need to question the widespread use of Min-Max and Z-Score techniques, especially in AI and ML applications. Sum and Vector techniques, which are two successful methods even though they are not used much in AI and ML studies, produced almost the same result, which is interesting.

- Undoubtedly, the best method for weighting was determined to be Entropy. Because Entropy produced the lowest sensitivity and highest correlation with price.
- When we cluster among 105 matrices, it can be seen that the most efficient results are as above. However, when we only search for the combination that provides high correlation without classifying or clustering the 105 matrices, we reach an interesting result. The Max/Entropy/SAW combination was able to produce a record correlation of 93.5%. Let us remind here that the Entropy method generally provides the lowest sensitivity and highest correlation average. Thus, we can say that general trends and record results may differ to a certain extent.
- As a result, it can be said that the Decimal method is the best data converter in terms of average relationship generation performance and low sensitivity, and on the other hand, the Entropy method is the best weighting method.
- It is clear that the normalization method can bring the price-performance relationship to a level that can be manipulated. For example, when you choose the Decimal technique, it can be seen that all three MCDM methods produce a statistical relationship of over 90% with the price. On the other hand, tragically, when you use Z-Score for PROBID, you may not even produce a relationship that is significant on average. When you use Min-Max converter for CODAS or Rank Based converter for SAW, low correlations such as 38.2% and 45.78% are produced on average.
- A much more tragic situation is this: If the CRITIC/Z-Score/PROBID combination is used, almost no relationship with the price can be produced (0.021%). In other words, if the normalization technique is chosen correctly, you will get a 90% relationship with the price, and if it is chosen incorrectly, you will get a 0% relationship. This shows how normalization and weighting coefficient combined manipulate the results.
- Another meaning of this is the following: If we look at the situation in the example of ML or AI studies, to look for a relationship between two variables such as *x* and *y*, let us assume that the relationship is detected in the first case. In another normalization case, there may be no relationship at all. This strange situation will also affect causality analyses.
- The sensitivity rating-performance level coupling for MCDM in this study appears to be a unique pattern matching discovery.
- We propose an alternative framework on how to determine the best alternative for PROBID, SAW and CODAS: If we look at the overall performance results, it is a fact that the three methods jointly produce the most efficient results with Decimal scaling & Entropy weight coefficient. In this case, the best alternative for all three MCDMs is common: the "Mercedes EQV 300 Extra-Long", which is the A19 alternative.
- When we look at the ranking of other alternatives for PROBID, the second alternative is the A22 model and the third alternative is the A24 model. The A46 alternative is in last place.
- When we look at the ranking of other alternatives for CODAS, the second alternative is A22 and the third alternative is A20. The A26 alternative is in last place.
- When we look at the ranking of other alternatives for the SAW method, the second alternative is A8 and the third alternative is A31. A1 and A26 are in the last place.
- The second option we recommend for the selection of the best alternatives is this: The MCDM rankings that provide the highest correlation among 105 matrices, regardless of sensitivity, is the Sum&Vector/SD combination for PROBID. The best alternative here is

"Mercedes eVito Tourer Extra-Long 90 kWh" (A22). For CODAS, Sum&Vector/Entropy is the most performant. And the best alternative here is the "Mercedes EQV 300 Extra-Long" (A19). For SAW, Sum&Vector/Entropy is the most performant. The best alternative here is "Mercedes EQV 300 Extra-Long" (A19). The common best alternative for CODAS and SAW is the same. We obtained the same results in the evaluation above. But it is noteworthy that the result changed for PROBID here.
- The most striking finding of this research is that we recommend that decision-makers be careful when choosing an electric vehicle, as choosing an incorrect or random normalization/data transformation technique may distort the ranking results.
- Wrong selection of the most suitable small e-Van may mean increased costs for the decision-maker. A good and low-risk choice can be possible with a good methodology selection. It should be noted that the choice of a good normalization technique is highly dependent on the data, MCDM method, weight coefficient and conditions.
- The choice of normalization technique is dynamic. A suitable MCDM configuration with all its components will result in a good electric vehicle choice.

6. Conclusion

In this study, a sensitive MCDM evaluation methodology was made to find the best alternative among Small electric Van types, which is an electric environmentally friendly transportation and transport vehicle. As it is known, sensitivity analysis in terms of the selection and robustness of MCDM methods is a subject that has been studied extra in recent years. The research gap in these studies is multifold. First, precision is often measured by weighting methods. However, the results of this study also showed that normalization also affects sensitivity. Second, there is no external reference point for sensitivity in other studies. A controversial benchmarking methodology is used as there is no reference point, meaning that the sentiment measurement in the MCDM rankings produced is novel. Thirdly, sensitivity analysis is generally done by only looking at whether the best alternative has changed. However, the entire ranking needs to be evaluated from a holistic perspective. On the other hand, sensitivity can also affect an MCDM's external relationships. In other words, normalization or weighted method sensitivity is decisive. Normalization-based sensitivity can distort or even manipulate correlations between MCDM performance and prices of Small electric Van alternatives when we approach the issue in this study example. At this point, choosing the appropriate weight coefficient and normalization technique is extremely critical. According to the findings obtained in this study, the relationship between price and performance can vary between ninety percent and zero percent, depending on the choice of normalization technique. In other words, while there is a very strong relationship between two factors, the relationship disappears with an incorrect normalization choice. This interesting result clearly showed decision-makers that the type of normalization can have a manipulative aspect if not chosen carefully in all data processing procedures. The selection of normalization technique is dynamic. A suitable data converter with all its components will result in the choice of a reliable electric vehicle.

Finally, so far the selection of optimal components for e-vehicles was mainly based on established engineering criteria, such as demonstrated by Kalmaganbetov et al. [87] regarding the selection of planetary transmission for light e-vehicle main gearbox. In the future work, the methods presented here should be applied for this purpose as well.

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