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Fuzzy-Based Decision Support for Strategic Management: Evaluating Electric Vehicle Attractiveness in the Digital Era

Sónia Gouveia ^{1,2,*} , Daniel H. de la Iglesia ³ , José Luís Abrantes ^{1,2} , Alfonso J. López Rivero ⁴ 
and Eduardo Gouveia ^{1,2} 

¹ Superior School of Technology and Management, Polytechnic Institute of Viseu, 3504-510 Viseu, Portugal; jlabrantes@estgv.ipv.pt (J.L.A.); egouveia@estgv.ipv.pt (E.G.)

² CISED—Research Centre in Digital Services, Instituto Politécnico de Viseu, 3504-510 Viseu, Portugal

³ Faculty of Science, University of Salamanca, 37008 Salamanca, Spain; danihiglesias@usal.es

⁴ Computer Science Faculty, Universidad Pontificia de Salamanca, 37002 Salamanca, Spain; ajlopezri@upsa.es

* Correspondence: sgouveia@estgv.ipv.pt

Abstract: In an era marked by sustainability challenges and digital transformation, organizations face heightened uncertainty in strategic decision-making. This paper applies a conceptual tool, a fuzzy-based decision model, in the appraisal of the attractiveness of electric vehicle acquisition and navigates the multifaceted complexities of integrating economic, environmental, and infrastructural factors. A concise overview of fuzzy principles highlights their relevance to strategic management in uncertain contexts. The study uses a practical example to demonstrate how fuzzy set-based decision models assess EV attractiveness by synthesizing costs, environmental impact, vehicle depreciation, and energy independence variables. The findings reveal the fuzzy set-based decision model's potential to enhance decision clarity and efficiency, offering managers a simple but robust framework for navigating complex trade-offs. Implications for sustainable strategic management and suggestions for future research on advanced decision support systems are discussed.

Keywords: strategic; management; decision; environment; innovation; fuzzy; digital; EVs



Academic Editor: Antonio Gil Bravo

Received: 20 March 2025

Revised: 17 April 2025

Accepted: 22 April 2025

Published: 25 April 2025

Citation: Gouveia, S.; de la Iglesia, D.H.; Abrantes, J.L.; López Rivero, A.J.; Gouveia, E. Fuzzy-Based Decision Support for Strategic Management: Evaluating Electric Vehicle Attractiveness in the Digital Era. *Eng* **2025**, *6*, 86. <https://doi.org/10.3390/eng6050086>

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1. Introduction

In recent years, the trend towards electric vehicles (EVs) has been driven by a growing global focus on sustainability and technological development. Environmental concerns, economic viability, and the desire for energy independence increasingly influence the choices of governments, businesses, and consumers [1–3]. Despite the positive outlook, EV adoption continues to face significant strategic challenges. Under uncertainty, decision-makers must evaluate multiple and often conflicting criteria, from vehicle cost and maintenance to emissions and energy infrastructure [4–6].

Decision support models can be applied to respond to these challenges. Within these models, deterministic models often fail to adequately include the subjectivity and uncertainty inherent in real decision-making situations, especially for long-term investments such as automobile purchases.

Fuzzy tools present an accessible solution, allowing quantitative measures to be derived through the conversion of qualitative assessments and allowing strategic planning to be carried out under conditions of uncertainty [7–9]. Of the various fuzzy set-based decision-model-based methods, the Fuzzy Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) deserves special mention for its ability to efficiently evaluate and rank alternatives based on their similarity to an ideal solution [10,11]. It allows for a

comprehensive analysis of car alternatives by incorporating linguistic variables, informed data, and flexible weighting measures, eventually leading to decisions that prove to be more realistic and achievable [12–14].

Although fuzzy tools have been widely applied in the electric vehicle (EV) domain—particularly in areas such as charging infrastructure, route optimization, and smart grid system integration [15–17]—most existing studies remain focused on highly technical or operational aspects. For example, fuzzy approaches have been used to optimize charging schedules [8] and to identify suitable charging stations along travel routes [18].

However, few models address the broader question of EV attractiveness in a way that supports strategic decision-making across the value chain. For manufacturers, understanding which EV configurations appeal most to users is critical to aligning product development with market expectations. For sellers and commercial operators, comparing EV types based on value-added criteria such as energy independence or cost of ownership can inform marketing and investment strategies. Finally, end users face increasing pressure to make sustainable mobility choices, often without access to practical and uncertainty-aware tools to compare options.

The present study addresses this gap by proposing a fuzzy model based on TOPSIS that integrates economic, technical, and environmental criteria in a flexible framework to assess the relative attractiveness of EV alternatives, including those with solar integration.

This research study presents an approach based on applying Fuzzy TOPSIS for measuring five different automotive options: pure electric vehicles (with or without the option of recharging via an external photovoltaic power source), Hybrid Electric Vehicles, and diesel and gasoline vehicles (Fuzzy TOPSIS implemented in MATLAB R2023a). The comparison is made based on six key decision-making factors: the overall cost, utilization of energy/fuel, carbon dioxide emissions, maintenance cost, depreciation rates, and the Energy Independence Index.

This research investigates improving strategic decision-making methods by applying fuzzy theory to a multi-criteria system tailored for sustainable transportation mode comparison.

The paper continues with Section 2, where the literature review and conceptual framework are presented. Section 3 describes the methodology. Section 4 provides a case study and results. Section 5 provides a discussion, followed by the limitations and conclusions in Sections 6 and 7.

2. Literature Review and Conceptual Framework

2.1. Electric Vehicle Adoption: Key Drivers and Challenges

There is a rising trend of electric cars as a greener alternative to internal combustion engine cars, and the factors behind the adoption of electric vehicles have drawn great attention [1]. The appeal of electric cars depends on numerous factors that generally fall into technical, economic, environmental, and social considerations [2]. Since the decision-making process inherently encompasses subjective elements, such factors tend to be analyzed using fuzzy decision approaches to achieve a more subtle evaluation.

Technical factors such as range, charging time, and vehicle efficiency play a central role in evaluating the viability of electric vehicles. Studies employing the fuzzy Analytic Hierarchy Process have identified range and charging time as key technical considerations influencing consumer purchasing behavior [19,20], while other research using fuzzy-rough methods has emphasized the combined importance of range and price in the selection of electric delivery vehicles [21].

Economic factors, including initial investment costs, operating costs, and government incentives, play a significant role in EV adoption [5,6]. A study combining fuzzy logic with

the Delphi method [12] identified initial investment costs as a significant barrier to battery electric truck procurement [22,23].

Environmental factors, such as greenhouse gases and energy consumption, increasingly shape consumer attitudes toward electric cars [3]. A study that used a combination of fuzzy logic and the Unified Theory of Acceptance and Use of Technology highlighted the roles of environmental factors in consumers' intentions to buy electric cars [23]. An alternative study that used fuzzy set qualitative comparative analysis presented insights into consumer choices regarding electric cars, especially the roles of environmental attitudes in consumers' decision-making process [4].

Social factors, including perceived social benefits and government policies, also influence the attractiveness of electric vehicles [24]. Additional studies using fuzzy set analysis revealed that attitudes toward EVs differ across age groups, emphasizing the need for targeted policies to promote EV adoption [4]. Fuzzy logic is utilized in several applications to support decision-making regarding electric cars. These include the evaluation of the suitability of electric cars for specific use situations and developing expert systems that match electric cars with customer needs.

In addition to influencing EVs' initial adoption, technical, economic, environmental, and social factors also affect long-term user engagement, particularly the likelihood of BEV repurchase and the phenomenon of electric vehicle (EV) owner dropout. Dissatisfaction with key aspects—such as limited driving range, slow or unavailable charging infrastructure, or high ownership costs—can discourage repeat purchases and even lead former adopters to return to internal combustion engine (ICE) vehicles [25,26]. On the other hand, positive experiences with vehicle reliability and access to public incentives may reinforce loyalty to electric mobility and increase the probability of BEV repurchase [27].

These referred elements reflect the dynamic nature of EV ownership. For instance, battery technology—initially a driver of adoption—can become a reason for abandonment if user expectations regarding lifespan or degradation are not met. Additionally, concerns about resale value, maintenance costs, or the ecological impacts of battery production may evolve over time, influencing whether users remain committed to electric vehicles or revert to conventional alternatives [28,29]. Thus, understanding the factors that attract first-time buyers and those that sustain long-term commitment is essential for designing effective EV strategies and policy interventions.

2.2. Fuzzy Sets in Strategic Multi-Criteria Decision-Making

Fuzzy set theory offers a powerful decision-making tool that is able to handle uncertainties and vagueness [7]. In this research, the application of fuzzy set-based methods to determine the attractiveness of electric cars is explored by relying on past research that uses the method to articulate complex decision-making problems.

The application of fuzzy set theory in investigating the choice to adopt electric vehicles has proven to be an efficient tool to overcome the inherent uncertainties and subjective judgments involved in the choice to adopt EVs [4,8,30].

By transforming qualitative assessments into quantitative analyses, this approach provides a structured model for considering multiple criteria, such as cost, range, charging infrastructure, and environmental impact [31,32]. An example is a study that combined fuzzy logic with the Delphi method to identify critical factors in acquiring battery electric trucks, highlighting aspects such as the initial investment cost and the clarity of current legislation [12,33]. Similarly, another study integrated fuzzy logic with the Analytic Hierarchy Process (AHP) and Multi-Attributive Border Approximation Area Comparison (MABAC) to evaluate electric vehicle selection, considering criteria such as cost, range, and environmental impact [15,28].

Fuzzy logic excels in handling the uncertainty and vagueness inherent in decision-making processes. For example, a study used fuzzy PIPRECIA and CRADIS methods to rank electric vehicles based on criteria such as price and fuel consumption, highlighting the importance of fuzzy logic in criteria weighting and ranking [9,34].

Integrating fuzzy numbers with other multi-criteria decision-making (MCDM) techniques has further enhanced its applicability. For instance, a study combining fuzzy set theory with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) introduced a novel correlation coefficient measure in Fermatean fuzzy contexts, providing a robust framework for evaluating EVs [13,35].

Fuzzy models are particularly useful in evaluating the popularity of electric cars, but with some limitations and constraints. Some of the significant limitations concerning fuzzy models include the complexity of fuzzy models, the need for expert knowledge in a specific field to design membership functions, and the possibility of data loss in the aggregation process [13,35].

The complexity of fuzzy models can make them challenging to interpret and apply, particularly for decision-makers without a strong background in fuzzy set theory. For instance, research employing q-rung ortho-pair fuzzy numbers highlighted the need for simplifying fuzzy models to enhance their applicability in real-world decision-making scenarios [35,36]. Applying fuzzy models often requires expert knowledge in defining membership functions and handling linguistic assessments.

The future development of fuzzy set-based methods for evaluating the popularity of electric cars depends on their capability to solve the issues and limitations of their use. Among the most important areas that need more research include the betterment of the interpretability of fuzzy set-based models, integrating fuzzy set theory with other decision-making approaches, and developing more robust approaches to handling uncertainty.

There is a need to enhance the explainability of fuzzy set-based models to support more extensive decision-making framework integration. Simplifying these models and providing simple approaches to determining the membership function allows for more widespread access to fuzzy set-based methods for decision-makers with minimal technical background [37].

Advanced methods of handling uncertainty need to be defined to address the shortcomings of fuzzy set-based approaches in decision-making. Adopting tools based on fuzzy set theory, such as fuzzy MCDM methods, has proven essential in enhancing strategic decision-making processes within organizations. These tools enable the management of uncertainties and subjectivities inherent to the corporate environment, providing a more precise and reliable evaluation of multiple criteria, including technical, economic, and social factors [38–40]. At the same time, digital transformation plays a crucial role in the evolution of these processes. Integrating emerging technologies, such as artificial intelligence, big data, and the Internet of Things (IoT), has facilitated the creation of data-driven business models, fostering innovation and market competitiveness [41].

Digital transformation involves changes in business models, organizational activities, and processes through various digital technologies, accelerating results across all sectors in a strategic and prioritized manner [42,43].

Fuzzy set-based methods became an important tool for analyzing the attractiveness of electric cars across modern digital environments. Through resolving the uncertainties and subjective judgments usually present in decision-making, fuzzy set theory presents a methodical model for examining various factors, such as technical, economic, environmental, and social [44]. In addition, integrating fuzzy set-based approaches with other decision-making approaches has diversified their use across different situations, from evaluating electric cars for applications to developing expert systems to assist consumers.

Still, with their broad applicability, factors such as model complexity, the requirement of expert knowledge, and possible information loss make it necessary to conduct more research to fully exploit the capacities of fuzzy set-based methods in promoting electric vehicle consumption [39].

2.3. Conceptual Framework

MCDM methods have been broadly used to help solve challenging decision problems with several conflicting criteria. These approaches enable decision-makers to assess options in several areas—including economics, engineering, and strategic management—and to rank them. Among the many MCDM techniques, the Technique for Order Preference by Simplicity to Ideal Solution (TOPSIS) is among the most powerful ranking methods.

Originally suggested by Hwang and Yoon in 1981 [10], the TOPSIS approach is based on the idea that the best alternative should be situated near to an ideal solution—defined as the best performance on all criteria—and far away from an anti-ideal solution, representing the poorest performance on all criteria.

Nevertheless, conventional TOPSIS relies on precise numerical values, a constraint that can occur with uncertain, ambiguous, or subjective information. To solve this limitation, using fuzzy set theory, as introduced by Zadeh (1965) [45], in Fuzzy TOPSIS enables the effective handling of uncertainty in decision-making using linguistic variables and fuzzy numbers.

The Fuzzy TOPSIS method improves the classical TOPSIS method by allowing the expression of criterion values and weights as fuzzy numbers [11,46]. Such a modification is particularly relevant to expert decision-making situations that require subjective judgments.

Fuzzy set theory can be applied through the Fuzzy TOPSIS methodology by converting crisp input values into Triangular Fuzzy Numbers (TFNs), enabling the representation of inherent ambiguity in vehicle evaluation. Each decision criterion and its relative weight may be expressed as fuzzy sets, allowing for the use of linguistic terms that better reflect expert opinions and real-world uncertainty. For example, the cost may not be represented as a fixed value but, rather, as a range (e.g., “low to moderate cost”), incorporating variability related to acquisition, maintenance, and operational expenses.

Although Fuzzy TOPSIS itself is not a fuzzy logic technique per se, its adaptation using fuzzy sets allows the method to operate within the fuzzy set-based decision-making paradigm. The role of fuzzy sets here is to fuzzify inputs and weights and support the more nuanced ranking of alternatives. The methodology is particularly useful when traditional crisp methods cannot account for subjectivity in data or expert judgment. By integrating fuzzy set theory with a well-established MCDM technique, this study leverages both the interpretability of fuzzy systems and the ranking strength of TOPSIS in a practical, replicable model.

The decision problem is structured by defining a set of m alternatives $A = \{A_1, A_2, \dots, A_m\}$ and a set of n criteria $C = \{C_1, C_2, \dots, C_n\}$, each with an assigned weight $\tilde{w}_j$ indicating its relative importance.

A decision matrix $\tilde{X} = (\tilde{x}_{ij})$ is then created, where $\tilde{x}_{ij}$ represents the performance of alternative A_i in criterion C_j . Since fuzzy set theory is used, the values x_{ij} and weights w_j are fuzzy numbers, often represented as triangular or trapezoidal fuzzy numbers.

The crisp values in the decision matrix are transformed into fuzzy numbers using membership functions. This corresponds to the fuzzification of the decision matrix step.

Fuzzy numbers can be represented as Triangular Fuzzy Numbers (TFN) or Trapezoidal Fuzzy Numbers (TrFN) ($\tilde{x} = (a, b, c)$ and $\tilde{x} = (a_1, a_2, a_3, a_4)$, respectively).

The membership function $\mu_A(x)$ of a trapezoidal fuzzy number is defined as (1):

$$\mu_A(x) = \begin{cases} 0, & x \leq a_1 \\ \frac{x-a_1}{a_2-a_1}, & a_1 < x \leq a_2 \\ 1, & a_2 < x \leq a_3 \\ \frac{a_4-x}{a_4-a_3}, & a_3 < x \leq a_4 \\ 0, & x > a_4 \end{cases} \quad (1)$$

where a_1, a_2, a_3 , and a_4 describe the shift points of the function.

The triangular function is a particular case where there is only one central point of maximum relevance, defined as (2):

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x < b \\ \frac{c-x}{c-b}, & b \leq x < c \\ 0, & x > c \end{cases} \quad (2)$$

where a, b , and c determine the function's structure, b represents the highest membership point, a is the lower bound, b is the most likely value, and c is the upper bound.

Consider, for instance, the assessments provided by two domain experts. The first expert stated the following: "In most cases, the maintenance cost is around EUR300, although it can vary between €250 and €400 depending on usage". This type of evaluation can be modeled using a triangular fuzzy number (TFN), where EUR 300 represents the most likely value, and EUR 250 and EUR 400 define the lower and upper bounds of uncertainty.

The second expert noted the following: "Energy consumption typically ranges from 12 to 14 kWh/100 km, but it may go as low as 10 or as high as 16 in certain conditions". This statement can be represented using a trapezoidal fuzzy number (TrFN), where the core interval [12,13] reflects the most plausible values and defines the overall support.

Figures 1 and 2 illustrate, respectively, the triangular and trapezoidal fuzzy numbers corresponding to these expert inputs.

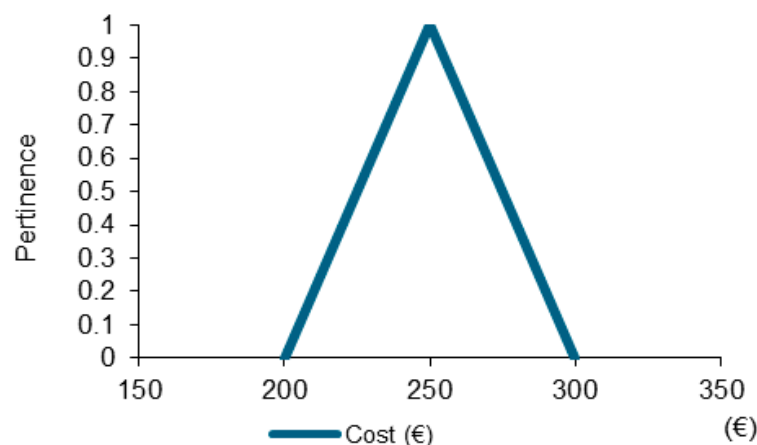


Figure 1. Triangular fuzzy number representing an expert's estimation of maintenance cost (EUR) (source: authors' own creation).

Since different criteria may have different units and scales, the decision matrix must be normalized (Normalization of the Decision Matrix step). For the benefit criteria, where higher values are preferred, the normalized value is obtained by (3) and (4), respectively, for TFN and TrFN.

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{C_j^{max}}, \frac{b_{ij}}{C_j^{max}}, \frac{c_{ij}}{C_j^{max}} \right) \quad (3)$$

$$\tilde{r}_{ij} = \left(\frac{a1_{ij}}{C_j^{max}}, \frac{a2_{ij}}{C_j^{max}}, \frac{a3_{ij}}{C_j^{max}}, \frac{a4_{ij}}{C_j^{max}} \right) \quad (4)$$

For the cost criteria, where lower values are preferred, the normalized value is obtained by (5) for TFN and (6) for TrFN:

$$\tilde{r}_{ij} = \left(\frac{C_j^{min}}{C_{ij}}, \frac{C_j^{min}}{b_{ij}}, \frac{C_j^{min}}{a_{ij}} \right) \quad (5)$$

$$\tilde{r}_{ij} = \left(\frac{C_j^{min}}{a4_{ij}}, \frac{C_j^{min}}{a3_{ij}}, \frac{C_j^{min}}{a2_{ij}}, \frac{C_j^{min}}{a1_{ij}} \right) \quad (6)$$

where c_j^{max} and c_j^{min} are the maximum and minimum values for criterion C_j across all alternatives.

Each normalized value is then multiplied by its respective fuzzy weight $\tilde{w}_j$, resulting in a weighted normalized decision matrix $\tilde{v}_{ij}$. This procedure corresponds to the calculation of the Weighted Normalized Decision Matrix step. This procedure ensures that criteria with higher importance (higher weights) have a stronger impact on the ranking.

$$\tilde{v}_{ij} = \tilde{r}_{ij} \times \tilde{w}_j \quad (7)$$

The determination of weights in fuzzy multi-criteria decision-making has been addressed through various approaches. These include methods based on interval-valued hesitant fuzzy information [47], interval intuitionistic trapezoidal fuzzy numbers [48], and intuitionistic fuzzy sets with scoring functions [49]. Other techniques incorporate fuzzy Pythagorean sets [50] or vague sets [51], or combine fuzzy set theory with optimization models such as the Fuzzy TOPSIS–CRITIC approach [52].

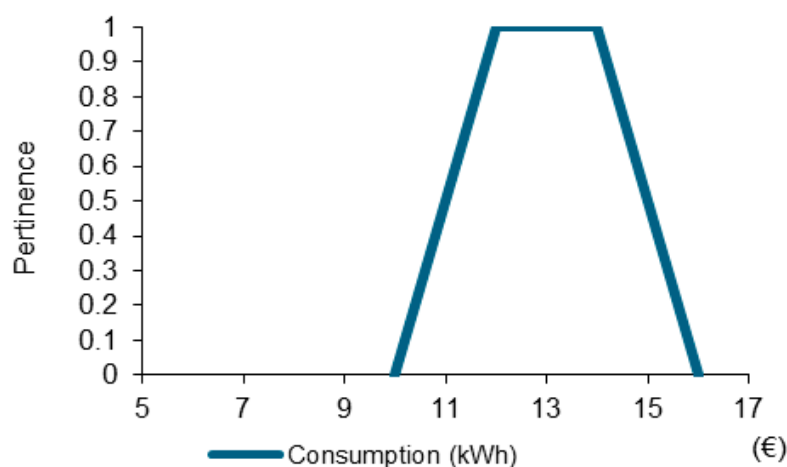


Figure 2. Trapezoidal fuzzy number representing an expert's estimation of energy consumption (kWh/100 km) (source: authors' own creation).

In the next step, fuzzy ideal and anti-ideal solutions are determined. The Fuzzy Positive Ideal Solution (FPIS) represents the best possible values for each criterion, provided by (8) and (9), respectively, for TFN and TrFN.

$$\tilde{A}^{+} = ({}_i^{max} c_{.ij}, {}_i^{max} b_{.ij}, {}_i^{max} a_{.ij}) \quad (8)$$

$$\tilde{A}^{+} = ({}_i^{max} a4_{.ij}, {}_i^{max} a3_{.ij}, {}_i^{max} a2_{.ij}, {}_i^{max} a1_{.ij}) \quad (9)$$

Similarly, the Fuzzy Negative Ideal Solution (FNIS) represents the worst possible values, provided by (10) and (11), respectively, for TFN and TrFN:

$$\tilde{A}^{-} = \left(\min_i c_{ij}, \min_i b_{ij}, \min_i a_{ij} \right) \quad (10)$$

$$\tilde{A}^{-} = \left(\min_i a_{4ij}, \min_i a_{3ij}, \min_i a_{2ij}, \min_i a_{1ij} \right) \quad (11)$$

The final step corresponds to the Computation of Distance Measures and Similarity Index. The distance of each alternative from the FPIS and FNIS is calculated using the Euclidean distance for fuzzy numbers. The distance to the FPIS is given by (12):

$$D_i^{+} = \sum_{j=1}^n d \left(\tilde{v}_{ij}, \tilde{A}^{+} \right) \quad (12)$$

Similarly, the distance to the FNIS is given by (13):

$$D_i^{-} = \sum_{j=1}^n d \left(\tilde{v}_{ij}, \tilde{A}^{-} \right) \quad (13)$$

The final Relative Closeness (RC) to the ideal solution is then computed using (14):

$$RC_i^{-} = \frac{D_i^{-}}{D_i^{+} + D_i^{-}} \quad (14)$$

where higher values of RC_i indicate better alternatives.

Fuzzy TOPSIS is a powerful decision-making method that utilizes fuzzy set theory to deal with the fuzziness and subjectivity of multi-criteria issues. Through the combination of fuzzy numerical values with linguistic assessments, the method enables the more versatile and practical ranking of alternatives concerning the optimal solution.

Fuzzy TOPSIS, within the context of electric vehicle rollout, allows for the evaluation of multiple factors, such as cost, range, environmental considerations, and technology, thus allowing for a complete and dynamic examination that better reflects consumer behavior and the state of the markets.

3. Methodology

The decision to purchase a vehicle involves a series of criteria, such as total cost of ownership (TCO), energy consumption, CO₂ emissions, maintenance costs, depreciation, and energy independence. All of these factors are subject to the uncertainties and variability introduced by economic, technological, and regulatory factors. The price of an automobile could change due to promotion campaigns, inflationary forces, or government offers. Driving behavior, geographical conditions, and meteorological conditions also influence energy consumption. Maintenance costs depend on component wear, unexpected repairs, and manufacturer recommendations. CO₂ emissions are influenced by fuel quality, engine efficiency, and driving conditions. Traditional decision-making models rely on deterministic values, assuming fixed inputs that do not account for real-world fluctuations. The Fuzzy TOPSIS method addresses this limitation, converting crisp numeric inputs into Triangular Fuzzy Numbers (TFNs). This transformation improves the model's ability to capture inherent uncertainties, leading to a more realistic and robust assessment framework.

The Fuzzy TOPSIS model developed in this study is designed to be flexible and adaptable to different decision-making contexts. The set of evaluation criteria (input variables) can be defined according to the data available and the specific objectives of the analysis. These may include, for example, economic indicators (e.g., acquisition cost, operating

cost), environmental factors (e.g., emissions, energy source), or technical characteristics (e.g., vehicle range, maintenance needs). Once defined, these criteria are represented using fuzzy numbers to capture uncertainty and subjectivity and processed through the Fuzzy TOPSIS procedure to rank the available alternatives. This structure allows the model to be reused in different scenarios, including sustainable mobility planning, strategic investment, and technology selection. Unlike traditional deterministic approaches, fuzzy set theory allows the incorporation of human-like reasoning into multi-criteria analysis. In this study, fuzzy sets are not used generically but operationalized through the definition of fuzzy numbers for both criteria and weights, enabling the model to reflect real-world ambiguity and stakeholder preferences with greater accuracy.

- Fuzzy set-based model follows structured process explained in Section 2.3.
- Definition of Alternatives and Criteria—Selection of EVs and conventional vehicles along with relevant decision factors.
- Fuzzification of Input Data—Conversion of deterministic values into TFNs to account for uncertainty.
- Weight Assignment—Criteria are weighted based on relative importance.
- Fuzzy Decision Matrix—Structuring of fuzzy values into decision matrix.
- Fuzzy TOPSIS Computation—Calculation of ideal and anti-ideal solutions based on fuzzy distances.
- Defuzzification and Ranking—Conversion of fuzzy results into crisp values for final decision-making.

Figure 3 illustrates the Fuzzy TOPSIS method.

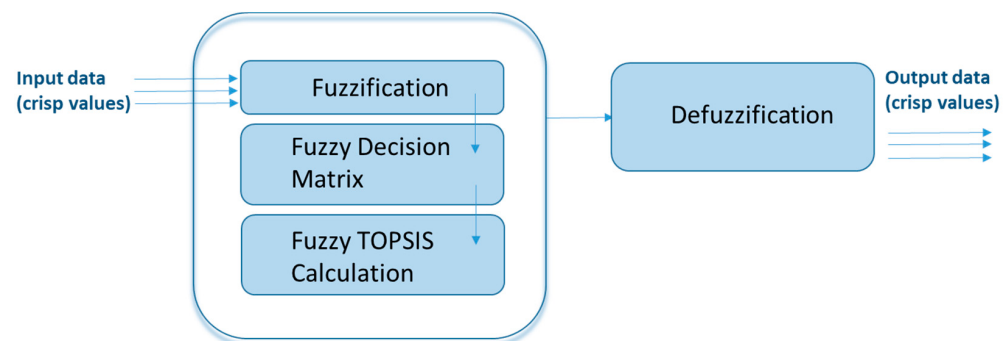


Figure 3. General structure of a Fuzzy TOPSIS-based model (source: authors' own creation).

4. Case Study and Results

In this study, fuzzy set theory is concretely applied to model the uncertainty associated with each evaluation criterion. Each input variable—such as global cost (GC), energy/fuel consumption (EFC), and Energy Independence Index (EI)—was translated into Triangular Fuzzy Numbers (TFNs) to reflect variations and subjective estimates. This fuzzification was based on a $\pm 10\%$ range around the base value, representing optimistic and pessimistic scenarios. The transformation of crisp values into fuzzy intervals enables more realistic modeling of data affected by price volatility, consumption variability, and policy uncertainty. Once fuzzified, these values are processed using the Fuzzy TOPSIS method, which supports ranking alternatives under imprecise and multidimensional conditions. This approach not only distinguishes the role of fuzzy sets (capturing uncertainty and subjectivity) from the TOPSIS technique (prioritizing alternatives), but also ensures that strategic decisions can be supported by flexible, data-informed insights.

4.1. Input Data

Electric cars (EVs) are included in a broad range of vehicles aiming to reduce greenhouse gas emissions and become free of fossil fuel dependence. Among the major kinds of EVs are Battery Electric Vehicles (BEVs), Plugin Hybrid Electric Vehicles (PHEVs), and Hybrid Electric Vehicles (HEVs). Because they use every available technology, every type of engine poses different challenges and opportunities [53].

BEVs generate no emissions and rely exclusively on rechargeable batteries for energy storage [54]. In contrast, PHEVs combine an electric motor, a rechargeable battery, and an internal combustion engine that enables brief all-electric driving before switching to fuel-based propulsion [55]. HEVs, which lack external charging capabilities, also integrate an internal combustion engine with an electric motor, relying primarily on regenerative braking to recharge their batteries [56].

This research focuses only on Hybrid Electric Vehicles (PHEVs) and EVs (BEVs). The decision model's vehicles are grouped using Pure EVs (Without Solar), Pure EVs (With Solar), and Hybrid EVs. Pure EVs (Without Solar) and Pure EVs (With Solar) represent BEVs in this categorization, varying in terms of their energy sources. Using a battery storage device coupled with a photovoltaic (PV) system to capture solar power during the day, the Pure EV (With Solar) reverts the car overnight, cutting off or eradicating the electricity requirement from the grid. Dependent entirely on energy provided by the electrical grid, the Pure EV (Without Solar) has a carbon footprint indirectly shaped by the energy mix of the national grid.

The data used in this study (Table 1) are values commonly available from commercial sources, representing a realistic estimate of the typical costs and performance of the vehicles analyzed. The main objective is not to provide an exact market assessment, but to establish a working hypothesis for applying the Fuzzy TOPSIS method in comparing alternatives. Any other data set could have been used as long as the defined criteria structure was maintained. Thus, the proposed approach remains valid regardless of specific variations in the values used. The data considered for the analysis, adapted from Gouveia et al. [57], are presented in Table 1.

Table 1. Data source: authors' own creation.

Parameter	Pure EV (Without Solar)	Pure EV (With Solar)	Hybrid EV	Diesel	Gasoline
Vehicle Price (EUR)	EUR 40,000	EUR 40,000	EUR 30,000	EUR 26,000	EUR 25,000
Wall Box Cost (EUR)	EUR 800	EUR 800	EUR 800	N/A	N/A
Wall Box Installation Cost (EUR)	EUR 100	EUR 100	EUR 100	N/A	N/A
Solar Panel System Cost (EUR)	N/A	EUR 5000	N/A	N/A	N/A
Battery Storage System Cost (EUR)	N/A	EUR 2000	N/A	N/A	N/A
Electricity Consumption (kWh/100 km)	21 kWh/100 km	21 kWh/100 km	10 kWh/100 km	N/A	N/A
Daily Distance (km/day)	100 km/day	100 km/day	100 km/day	100 km/day	100 km/day
Electricity Price (EUR per kWh)	EUR 0.18/kWh	N/A (Covered by Solar)	EUR 0.18/kWh	N/A	N/A
Fuel Consumption (liters/100 km)	N/A	N/A	500 L (5 L/100 km)	2920 L (8 L/100 km)	4015 L (11 L/100 km)
Fuel Price (EUR per liter)	N/A	N/A	EUR 1.80/liter	EUR 1.80/liter	EUR 1.80/liter
Maintenance Cost (EUR per year)	EUR 400/year	EUR 400/year + Solar and Battery Maintenance (EUR 100/year)	EUR 800/year	EUR 1000/year	EUR 1000/year
Vehicle Depreciation Rate (per year)	10%	10%	10%	15%	15%

The parameters used in this study, such as vehicle price, energy/fuel consumption, maintenance costs, and depreciation rates, are influenced by multiple market variables and the actual use of vehicles. Traditionally, this information was obtained from static reports

and market averages, but digital transformation allows access to dynamic and personalized data, improving the accuracy and relevance of analyses.

4.2. Input Variables

4.2.1. Global Cost (GC)

GC reflects the total outlay needed to buy the vehicle, including the initial cost and further infrastructure expenditures. This comprises expenses connected with wall box chargers (EUR 800), installation (EUR 100), and, occasionally, solar panel systems (EUR 6000) and battery storage (EUR 5000) for electric vehicles (EVs). These extra expenses are unnecessary for traditional cars, including diesel and gasoline. This element significantly affects the general economic feasibility of car ownership and is shaped by market price changes, tax rules, and manufacturer incentives.

4.2.2. Energy/Fuel Consumption (EFC)

EFC assesses the efficiency of each vehicle type in terms of energy used per 100 km driven. Hybrid electric cars run at roughly 21 kWh/100 km, and hybrid EVs run on electricity (10 kWh/100 km) and gasoline (5 L/100 km). With petrol vehicles running solely on fossil fuel and diesel, using 8 L/100 km, these values differ. Driving style, terrain features, and energy management systems affect this efficiency.

4.2.3. CO₂ Emissions (CO)

CO quantifies the environmental impact of each vehicle type. Electric vehicles (EVs) loaded by PV systems with battery banks have zero direct emissions and a minimal carbon footprint. EVs (Without Solar) depend on the electricity grid, meaning their emissions depend on the grid's energy mix. Hybrid, diesel, and gasoline vehicles emit CO₂ in proportion to their fuel consumption, with gasoline cars producing the highest emissions, followed by diesel and hybrid vehicles.

4.2.4. Maintenance Cost (MC)

MC accounts for annual maintenance expenses. Pure EVs have lower maintenance costs (EUR 400/year), while EVs (With Solar) incur an additional EUR 100/year for solar and battery upkeep. Hybrid vehicles require more frequent servicing, leading to EUR 800/year in maintenance costs. Diesel and gasoline vehicles have the highest maintenance costs (EUR 1000/year) due to engine servicing, oil changes, and brake replacements.

4.2.5. Depreciation (D)

D represents the vehicle's value reduction over time, expressed as a yearly percentage. All electric and hybrid vehicles depreciate at a rate of 10% per year. Diesel and gasoline vehicles experience a higher depreciation rate of 15% per year, as their resale value is more affected by market trends and emission regulations.

4.2.6. Energy Independence Index (EI)

EI measures the degree of the vehicle's dependence on renewable energy sources. Vehicles that use solar energy or operate within sustainable electricity grids have higher rates. In contrast, those powered by gasoline and diesel have zero energy independence, as they depend entirely on fossil fuels. EVs (With Solar) achieve 100% energy independence. EVs (Without Solar) rely on the grid, so their independence is estimated to be 50%, assuming a partial mix of renewable energy in electricity generation. Hybrid vehicles use electricity and fuel and have 25% energy independence. Diesel and gasoline vehicles entirely depend on fossil fuels, meaning their electrical energy independence is 0%.

A summary of the input variables can be found in Table 2. The Energy Independence Index is not naturally defined commercially and is considered in these terms by the authors.

Table 2. Input variables. Data source: authors' own creation.

Variable	Symbol	Unit	Description
Global Cost	GC	EUR	Total vehicle acquisition cost, including infrastructure.
Energy/Fuel Consumption	EFC	kWh/100 km, L/100	Energy/fuel used per 100 km.
CO ₂ Emissions	CO	g CO ₂ /km	Environmental impact in CO ₂ emissions.
Maintenance Cost	MC	EUR per year	Annual maintenance expenses.
Depreciation	D	% per year	Annual vehicle value loss.
Energy Independence Index	EI	%	Dependence on renewable energy.

Regarding the CO variable, some considerations must be made. Environmental CO₂ emissions are calculated based on the annual fuel and electricity consumption of different vehicle types, as presented in Table 3. The emissions factors used for conversion are derived from the studies [58,59], indicating that diesel emits approximately 2.68 kg CO₂ per liter, while gasoline emits approximately 2.31 kg CO₂ per liter. For electric vehicles, the emissions factor is based on the EU energy composition, with an average value of 0.4 kg CO₂/kWh [60]. Pure EVs (With Solar) are assumed to have zero emissions during the operational phase.

Table 3. Environmental CO₂ emissions. Data source: authors' own creation.

Parameter	Pure EV (Without Solar)	Pure EV (With Solar)	Hybrid EV	Diesel	Gasoline
Annual Fuel Consumption (liters)	N/A	N/A	1460	2920	4015
Annual Electricity Consumption (kWh)	7665	7665	3650	N/A	N/A
Conversion Factor KgCO ₂ /liters (diesel/gasoline)	N/A	N/A	2.68	2.68	2.31
Conversion Factor KgCO ₂ /kWh	0.4	N/A (solar covered)	0.4	N/A	N/A
Estimated Annual Emissions (kgCO ₂)	3586.0	N/A (solar covered)	6598.6	7825.6	9274.7

The final values used as input for the Fuzzy TOPSIS model are presented in Table 4.

Table 4. Input variable summary. Data source: authors' own creation.

Variable (Symbol, Unit)	Pure EV (Without Solar)	Solar	Pure EV (With Solar)	Hybrid EV	Diesel	Gasoline
Global Cost (GC, EUR)	40,900		47,900	30,600	26,000	25,000
Energy/Fuel Consumption (EFC, EUR)	1379.7		0.0	3285.0	5256.0	7227.0
CO ₂ Emissions (CO, g CO ₂ /km)	3066.0		0.0	5372.8	7825.6	9274.7
Maintenance Cost (MC, EUR per year)	400.0		500.0	800.0	1000.0	1000.0
Depreciation (D, EUR per year)	4000.0		4000.0	3000.0	3900.0	3750.0
Energy Independence Index (EI, %)	50		100	30	0	0

4.3. Input Variable Fuzzification

Traditional decision-making models often rely on fixed, deterministic inputs that fail to reflect real-world variability. To address this limitation, the Fuzzy TOPSIS method is employed to convert crisp numerical values into fuzzy representations. Specifically, this study adopts Triangular Fuzzy Numbers (TFNs), as introduced by Chen-Tung [11], due to their flexibility in modeling uncertainty through adjustable bounds. While other fuzzy number types—such as rectangular—could also be used, TFNs provide a practical balance between simplicity and expressiveness for capturing variability in input data. Regarding data variability, a variation of $\pm 10\%$ was chosen in the fuzzification of input values in the Fuzzy TOPSIS method. This variation is based on the need to represent the uncertainties inherent in the data used. Several factors can influence the input variables, such as vehicle price fluctuations, energy and fuel consumption variations, unpredictable maintenance costs, and depreciation affected by market changes. Therefore, it is essential to incorporate a margin of uncertainty to ensure that the analysis reflects realistic conditions [11]. The choice of $\pm 10\%$ achieves a balance between precision and robustness of the analysis. If the uncertainty adopted is too small (for example, $\pm 5\%$), the modeling may not capture real variations in the data, making the analysis excessively rigid. On the other hand, if the uncertainty is too large (such as $\pm 20\%$), there is a risk of distortions in the results, reducing the reliability of the comparison between alternatives. Therefore, the choice of $\pm 10\%$ ensures that uncertainties are represented without compromising the stability of the decision-making. As a result, each fixed value provided by the user (Table 1) is transformed into a fuzzy triangular number, represented as a triplet of values:

- b: original value (most likely estimate).
- a: lower bound (optimistic scenario for cost criteria and pessimistic scenario for benefit criteria).
- c: upper bound (pessimistic scenario for cost criteria and optimistic scenario for benefit criteria).

Considering the above assumptions, the input variables are fuzzified (Table 5).

As an example, Figure 4 illustrates the membership functions for the input variable GC.

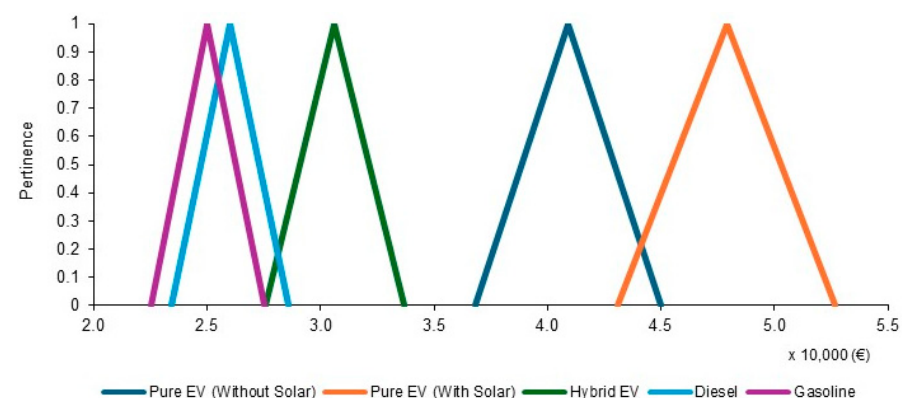


Figure 4. Membership functions for the global cost (GC) variable (source: authors' own creation).

Table 5. Input variables after fuzzification. Data source: authors' own creation.

Variable (Symbol, Unit)	Pure EV (Without Solar)	Pure EV (With Solar)	Hybrid EV	Diesel	Gasoline
Global Cost (GC, EUR)	(36,810.0, 40,900.0, 44,990.0)	(43,110.0, 47,900.0, 52,690.0)	(27,540.0, 30,600.0, 33,660.0)	(23,400.0, 26,000.0, 28,600.0)	(22,500.0, 25,000.0, 27,500.0)
Energy/Fuel Consumption (EFC, EUR)	(1241.7, 1379.7, 1517.7)	(0.0, 0.0, 0.0)	(2956.5, 3285.0, 3613.5)	(4730.4, 5256.0, 5781.6)	(6504.3, 7227.0, 7949.7)

Table 5. Cont.

Variable (Symbol, Unit)	Pure EV (Without Solar)	Pure EV (With Solar)	Hybrid EV	Diesel	Gasoline
CO ₂ Emissions (CO, g CO ₂ /km)	(2759.4, 3066.0, 3372.6)	(0.0, 0.0, 0.0)	(4835.5, 5372.8, 5910.1)	(7043.0, 7825.6, 8608.16)	(8347.2, 9274.7, 10202.2)
Maintenance Cost (MC, EUR per year)	(360.0, 400.0, 440.0)	(450.0, 500.0, 550.0)	(720.0, 800.0, 880.0)	(900.0, 1000.0, 1100.0)	(900.0, 1000.0, 1100.0)
Residual Value (RV, EUR)	(3600.0, 4000.0, 4400.0)	(3600.0, 4000.0, 4400.0)	(2700.0, 3000.0, 3300.0)	(3510.0, 3900.0, 4290.0)	(3375.0, 3750.0, 4125.0)
Energy Independence Index (EI, %)	(45.0, 50.0, 55.0)	(90.0, 100.0, 110.0)	(27.0, 30.0, 33.0)	(0.0, 0.0, 0.0)	(0.0, 0.0, 0.0)

4.4. Definition of Criteria Weights

The assignment of weights to the criteria is an essential factor in the analysis, as it determines the relative influence of each variable in the final decision. In the present study, the weights were defined considering the importance of each criterion in choosing the most suitable vehicle, balancing economic, environmental, and operational factors. The criterion with the most significant weight is the total cost, reflecting its direct influence on the financial viability of purchasing and operating the vehicle. Energy/fuel consumption and CO₂ emissions also have significant weights, impacting operating costs and environmental sustainability. In addition, maintenance costs, vehicle depreciation over time, and the degree of energy independence, which measures dependence on fossil fuels or renewable sources, were considered. The definition of weights must be carried out by experts.

The authors defined the weights applied to the evaluation criteria in this study based on their domain expertise in sustainable mobility, electric vehicle systems, and decision support modeling. While the expert panel involved in the weighting process was relatively small, this approach is consistent with the practice in the recent literature on structured expert judgment, where small samples are often considered valid in exploratory or early-stage models [61–63]. Moreover, the current configuration is presented as a replicable methodological prototype, which can be easily extended in future applications to include inputs from broader stakeholder groups, such as policymakers, fleet managers, and end users. This flexibility ensures that the model remains adaptable to various decision contexts and levels of participatory engagement.

The weights assigned to each criterion are presented in Figure 5.

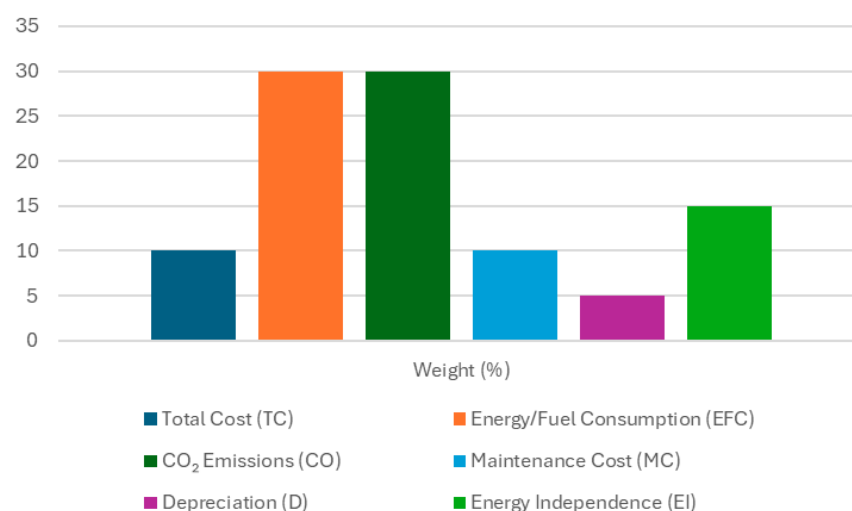


Figure 5. Criteria weights: distribution of weights assigned to each criterion (source: authors' own creation).

Although this study does not include a detailed sensitivity analysis of expert weighting schemes, future work could benefit from exploring alternative approaches to assess the robustness of the results. Common strategies include equal weighting, experience-based weighting, and familiarity-based weighting, each with distinct implications for decision-making under uncertainty.

In equal weighting, each expert is assigned the same level of influence, regardless of background or expertise. This approach, often used to ensure balanced consensus, avoids subjective bias in weight assignment but may overlook differences in expert competence or relevance. It is widely adopted due to its simplicity, despite its limitations in more heterogeneous panels [64].

Experience-based weighting allocates more importance to experts with longer professional or academic involvement in the field. For instance, those with over ten years of experience may receive a weight of 0.4, compared to 0.2 for those with less than five years [65,66]. While this method often correlates expertise with decision quality, it can introduce bias if not properly calibrated [64].

Familiarity-based weighting relies on the experts' self-assessed familiarity with the specific evaluation criteria or alternatives. Weights can be derived using a Likert scale, assigning higher influence to experts more confident in their knowledge. This approach is particularly effective in fuzzy MCDM settings, where nuanced judgments are crucial [67].

Sensitivity analysis can then be applied to test how variations in expert weights influence the final rankings or the selection of the top alternative. By examining a range of weighting scenarios, researchers and decision-makers can validate the stability and reliability of the model under different assumptions [68].

4.5. Output Variable

The output variable represents the attractiveness index (AI), which quantifies the suitability of each vehicle alternative based on the criteria evaluated and is obtained through the Fuzzy TOPSIS method, which considers the normalized and weighted fuzzy decision matrixes. The Attractiveness Index ranges from 0 to 1, where higher values indicate a more favorable alternative.

The Attractiveness Index (AI) (14) is computed as the Relative Closeness (RC) to the ideal solution, as defined in Equation (15):

$$A_i = RC_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (15)$$

where

- A_i represents the final output variable, indicating how close each alternative is to the ideal solution.

Higher values of A_i suggest better alternatives, meaning that the vehicle performs well across all considered criteria. This index enables a ranked comparison of the evaluated alternatives, integrating economic, environmental, and operational factors into a single decision-making metric.

4.6. Results

The results obtained through the Fuzzy TOPSIS method provide a structured and multi-criteria evaluation of vehicle alternatives, considering economic, environmental, and operational aspects. The ranking of alternatives is as follows (Figure 6):

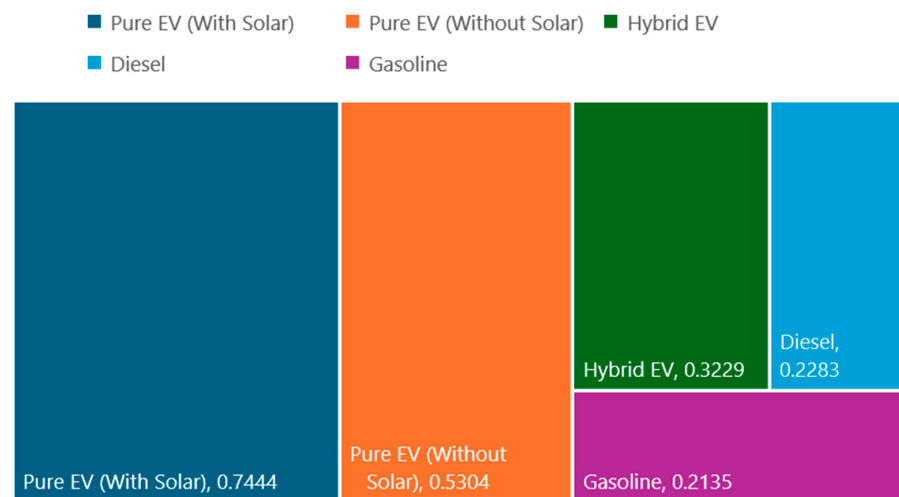


Figure 6. Attractiveness Index (AI) results (source: authors' own creation).

4.7. Sensitivity Analysis

The Fuzzy TOPSIS model used in this study allows for comprehensive sensitivity analyses by enabling the adjustment of input values and weights. Rather than being limited to predefined ranges around central values, the model supports the direct manipulation of each criterion. For instance, a user may change the maintenance cost of a specific vehicle or adjust the Energy Independence Index to reflect different scenarios or expert insights. This flexibility enables tailored assessments, such as adjusting the CO₂ emission value of a vehicle from 0.4 to 0.3 to evaluate its impact on final rankings. This feature enhances the model's applicability in real-world contexts where variables often change due to policy shifts, market conditions, or technological updates.

To illustrate model robustness, sensitivity analyses were performed with a variation of $\pm 15\%$ for all input values. The AI values obtained with these inputs were as follows, and are presented through a graphical representation in Figure 7: Pure EV (With Solar) = 0.7996; Pure EV (Without Solar) = 0.6151; Hybrid EV = 0.3047; diesel = 0.1842; and gasoline = 0.1345. These values confirm the consistency of the model, as the ranking of the alternatives remains unchanged compared to the baseline and $\pm 10\%$ scenarios. This stability under varying degrees of uncertainty reinforces the reliability of the proposed approach for strategic decision-making, particularly in contexts that demand robust prioritization under evolving conditions.

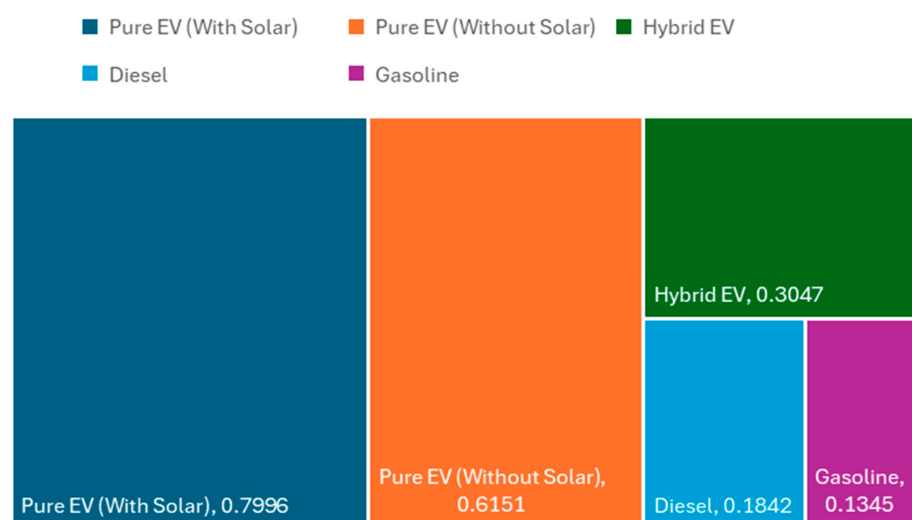


Figure 7. Attractiveness Index (AI) values for $\pm 15\%$ variation in input variables (source: authors' own creation).

Overall, this analysis confirms that the Fuzzy TOPSIS method is adaptable to specific evaluation contexts and resilient to moderate variations in input assumptions. It thus provides a dependable foundation for decision-makers seeking to evaluate sustainable mobility alternatives under uncertainty.

5. Discussion

5.1. Comparison with Previous Studies

The decision model proposed in this study builds upon a growing frame of research that applies fuzzy set theory and multi-criteria decision-making (MCDM) methods to evaluating electric vehicles (EVs). While other studies have employed fuzzy-based techniques—such as fuzzy AHP, fuzzy PROMETHEE, or fuzzy-rough integrations—to support EV selection, most have focused on narrowly defined objectives such as cost optimization, range maximization, or emissions reduction [2,14,20].

In contrast, the model presented here emphasizes strategic comprehensiveness by integrating technical, economic, environmental, and long-term autonomy considerations into a unified framework. Specifically, including an Energy Independence Index, alongside classical criteria like CO₂ emissions and total cost of ownership, represents a novel attempt to operationalize sustainability and resilience in mobility decisions. This complements approaches such as that of Coşkun et al. [8], who focused on charging systems using fuzzy logic, or Golui et al. [13], who applied Fermatean fuzzy methods but did not explicitly address strategic energy autonomy.

Compared to fuzzy-rough methodologies like those used by Wang et al. [21], which excel in incorporating subjective expert preferences and data uncertainty, the Fuzzy TOPSIS approach used here offers a more intuitive and computationally efficient alternative, particularly suited for organizations with limited analytical resources. This simplicity does not come at the expense of rigor; as noted by Krohling and Campanharo [46], Fuzzy TOPSIS has proven effective in group decision contexts involving high uncertainty and multiple stakeholders—a characteristic often present in EV-related investments.

Additionally, the model distinguishes itself by offering a flexible, transparent decision-making structure that can be adapted to various organizational contexts. While hybrid approaches such as those proposed by Auer [18] offer advanced analytical depth by combining multiple MCDM techniques, the Fuzzy TOPSIS model stands out for its balance between methodological rigor and ease of implementation. Its straightforward structure and compatibility with widely available tools make it particularly attractive for organizations seeking rapid and transparent decision support without requiring specialized computational resources. Also, this study distinguishes itself from prior research by introducing a solar “integrated” EV alternative, allowing for the evaluation of energy-autonomous mobility solutions (regarding the energy source), and proposing a novel Energy Independence Index as a strategic evaluation criterion. These additions expand the scope of traditional EV assessments, aligning the model more closely with the long-term goals of sustainable development and energy transition, which are increasingly relevant in both corporate and policy-driven decision contexts.

In sum, this study contributes to the literature by proposing a decision model that is not only grounded in fuzzy theory but also designed with strategic usability in mind. It complements and extends prior research by offering a framework that balances analytical robustness with practical applicability, making it suitable for guiding EV-related strategic decisions in both private and public sectors.

5.2. Interpretation of Findings (Main Case Study)

Among the evaluated options, the Pure EV (With Solar) emerged as the most attractive, achieving an AI of 0.7444. This preference is primarily attributed to its lack of fuel costs, negligible CO₂ emissions, and complete autonomy from the electricity grid, as the vehicle is recharged via a PV-powered battery bank. Although the initial investment in solar panels and battery storage is substantial, the resulting savings in energy consumption validate the long-term economic viability of this solution.

The Pure EV (Without Solar) came second (0.5304) due to its low maintenance costs and lack of direct CO₂ emissions. Its reliance compromises the sustainability score on the electricity grid, as its overall carbon footprint depends on the actual mix of energy types used to produce electricity. Although it is still a very efficient option, its operating costs are not as favorable as those of the option that integrates PV systems with battery banks.

Significantly less attractive than the pure EV, the hybrid EV came in third with an Attractiveness Index of 0.3229. This balance between electric and fuel-based mobility shows its function as a transition technology. Nevertheless, its reliance on fossil fuels and increased maintenance costs makes it less appealing than fully electric cars. Hybrids could lose more appeal over time and become less strong rivals as battery technology improves and charging choices abound.

The diesel vehicle came in fourth place (0.2283), mainly due to higher CO₂ emissions and operating costs. Despite lower fuel consumption than gasoline vehicles, diesel vehicles' high depreciation rate (15%) and total dependence on fossil fuels negatively impact their attractiveness. Their lack of energy independence further reinforces their limited long-term viability in sustainable mobility policies.

The gasoline vehicle came last, with a rating of 0.2135, therefore making it the least attractive. Its high operating costs and carbon dioxide emissions come from its high fuel consumption (11 L/100 km). Additionally, its high maintenance cost and rapid depreciation help justify its low rating. These results correspond with international standards that support electric mobility instead of fossil fuel-powered cars.

The classifications derived from the Fuzzy TOPSIS approach are consistent with the current shift towards green transportation through the gradual replacement of internal combustion engine (ICE) vehicles with electric vehicles (EVs), recognized for their economic and environmental advantages. The increased efficiency demonstrated by electric vehicles when powered by PV systems with battery banks is a strong signal of the potential ability of renewable resources to reduce dependence on fossil fuels and save costs in the long term.

The scope of this analysis identifies the most balanced alternative considering multiple factors. Even if a vehicle option has the lowest total cost, it may perform worse in terms of other crucial aspects such as CO₂ emissions, energy consumption, or energy independence. A traditional cost-minimization approach might favor vehicles with lower acquisition and operational costs, but this would overlook critical sustainability and energy efficiency concerns. The Fuzzy TOPSIS method addresses this issue by incorporating conflicting criteria, adjusting the weight of each factor, and allowing a fair comparison between different technologies. The Attractiveness Index analysis conducted in this study can be valuable for academic and policy discussions and serves as a strategic decision-making tool for key stakeholders in the automotive and energy markets.

The results of this study emphasize the increasing importance of energy independence, which could drive further investment in solar-integrated EVs and battery advancements. Furthermore, important for increasing consumer trust is the need to improve battery life and second-life applications (for example, using EV batteries for grid storage), reducing depreciation rates.

5.3. Implications for Strategic Management

The proposed Fuzzy TOPSIS-based decision model presents a significant contribution to strategic management in the context of sustainable mobility. In contrast to traditional deterministic or cost-only analyses, this model integrates economic, technical, environmental, and strategic dimensions using a fuzzy set-based framework that accommodates uncertainty, expert judgment, and linguistic assessments. This allows decision-makers to holistically evaluate complex investment scenarios—such as electric vehicle (EV) acquisition—where trade-offs between multiple often conflicting criteria must be considered.

Strategically, the model offers a replicable and adaptable methodology for organizations seeking to align their operational choices with long-term value creation. In contexts where sustainability, energy autonomy, and digital transformation are growing priorities, the model provides decision-makers with a structured yet flexible tool to compare vehicle technologies under realistic conditions. As demonstrated in recent studies [1,7,9], fuzzy multicriteria methods are increasingly seen as essential for strategic planning in uncertain environments.

The model also responds to a critical gap identified in the literature: the lack of decision support tools capable of integrating energy independence and carbon neutrality into mobility strategies [2,21]. By incorporating criteria such as an Energy Independence Index and maintenance costs—alongside more conventional metrics like CO₂ emissions and total cost—the proposed model allows organizations to operationalize sustainability in their asset selection and procurement decisions.

At the private business level, most importantly with respect to small and medium-sized enterprises (SMEs), this framework allows for designing mobility policies that are coordinated with overall strategic priorities, including cost-effectiveness, resilience to fuel price volatilities, and compliance with Environmental, Social, and Governance (ESG) requirements. The studies of Gouveia et al. [57] and Imran et al. [29] have highlighted the importance of coordinated decision-making models for helping SMEs adopt modern fleets and bolster their competitiveness while operating under a sustainable economic scenario.

In the public sector, the model has further implications. It offers a foundation for transparent and participatory decision-making regarding public fleet upgrades, infrastructure investment, or incentive design. Its fuzzy structure allows for the incorporation of expert input and contextual variables, making it adaptable to local realities and evolving policy frameworks [5,8].

Importantly, the model supports knowledge transfer and strategic communication. Because the method produces clear, justifiable rankings and visualizable outcomes, it facilitates internal alignment among stakeholders and supports external accountability—two crucial factors in strategic implementation. This aligns with findings from Bressane et al. [31], who point out that decision models that bridge technical, social, and behavioral perspectives are more likely to be accepted and implemented in practice.

Ultimately, the proposed Fuzzy TOPSIS model advances the integration of sustainability, digitalization, and strategic foresight into practical decision-making processes. It serves as a blueprint for organizations seeking to transition from reactive compliance-based strategies to proactive, value-driven approaches to sustainable mobility and beyond.

5.4. Practical Implications

Beyond strategic alignment, the proposed Fuzzy TOPSIS model offers practical advantages for decision-makers facing the operational complexities of sustainable mobility planning. Its flexibility allows it to be applied in different organizational environments—

such as SMEs, municipalities, or public agencies—helping to evaluate vehicle options based on real-world constraints and preferences.

The model's capacity to incorporate quantitative and qualitative performance measures based on expert opinions enables it to consider criteria often overlooked by classical analyses, such as expected maintenance needs, charging infrastructure accessibility, and user-dependent usage patterns. Its integration creates more advanced and situationally oriented evaluations, especially where several different goals must be satisfied simultaneously.

By establishing a ranked list of options, with attractiveness scores assigned to each, the model supports transparent and logical decision-making for vehicle acquisition or investment priority. In addition, it acts as an efficient communication tool to justify decisions internally—across different departments—as well as to outside parties like funding bodies and others.

Additionally, because it relies upon fuzzy set theory and available software, its operation does not require advanced computational facilities. Such a feature makes it suitable for bodies with limited analytical capacities, enabling broader applicability and thoughtful involvement at planning stages. Finally, the suggested framework can enhance planning effectiveness and policy coherence by enabling robust, transparent, and flexible appraisals that align with sustainability goals and energy transition's evolving targets.

6. Limitations and Future Research

While this study provides a comprehensive multi-criteria analysis based on fuzzy set theory, there are several limitations that should be acknowledged, along with suggestions for future research avenues.

The analysis assumes a fixed value for electricity-related CO₂ emissions based on an average grid intensity. However, this intensity can vary significantly across regions and time periods. Future versions of the model could allow users to adjust this value according to the national context or most recent energy data, making the analysis more locally relevant.

Although the current model includes a sensitivity analysis using $\pm 15\%$ variation across all input values, future studies could explore more detailed approaches, such as changing one criterion at a time or assigning different weights based on user profiles, expert familiarity, or level of experience. This would allow for more customized and realistic scenarios, particularly if applied to different types of decision-makers.

This study relies on standardized data for energy consumption and vehicle performance, which may not fully capture the variability observed in real-world use. In future applications, the model could be integrated with real-time or region-specific data, for example, from actual vehicle usage, driving conditions, or charging behavior.

In terms of cost-related variables, the model accounts for operational and maintenance costs but does not include full life-cycle elements. Expanding the analysis to cover battery degradation, second-life uses, or resale value could provide a more complete view of economic viability over time.

Finally, the model was applied here in a generic decision-making context, but it could be adapted to reflect different user profiles, including public sector planners, fleet operators, or private consumers. It could also be adjusted for different countries and policy settings, or integrated with digital platforms to support dynamic and data-driven decision-making. These potential developments would enhance the model's flexibility and strengthen its contribution to sustainable mobility planning.

7. Conclusions

Organizations are experiencing growing difficulty in decision-making regarding adopting electric vehicles (EVs) in this age of digital transformation and sustainability problems. By incorporating one decision support system that considers economic, ecological, and technical elements, Fuzzy TOPSIS and other tools could give a more organized rating. This method enables the acceptance of ambiguity and personal judgments, therefore offering a more flexible and open way of evaluating various vehicle possibilities that assist interested parties in negotiating the challenges of the shift to sustainable transportation.

From a strategic management viewpoint, Fuzzy TOPSIS—a decision-making approach—can help synthesize several criteria and provide valuable information for many market participants. Based on these observations, companies can change their production methods so that car features match consumer demands and meet standards. Car rental businesses and fleet management firms can improve their capital decisions by maximizing vehicle choice based on operational costs and sustainability. Similarly, consumers can use these models to make more informed choices that match their personal goals, while auto dealers might profit from knowing which features to highlight when counseling clients.

Further improving the accuracy and speed of decisions can be achieved by integrating data-driven methods with decision support systems as digital transformation continues to shape the mobility sector. Using predictive modeling, AI-based analytics, and real-time data can improve the efficiency of classification systems, providing companies with more flexible and targeted insights. By aligning strategic planning more closely with changing trends in the energy and automotive sectors, these developments can help companies anticipate shifts in consumer behavior, infrastructure upgrades, and legislative changes.

Although no techniques can exactly capture the complexity of strategic decision-making, systems like Fuzzy TOPSIS would be valuable instruments for businesses trying to balance several goals, lower volatility, and improve clarity in the assessment of EV acceptance. Continuous improvement of decision support systems will help companies and customers better negotiate the difficulties and possibilities of a sustainable mobility ecosystem that is becoming more digital.

Finally, the decision framework presented in this study may contribute to supporting organizational and policy actors in navigating complex mobility-related decisions. By framing vehicle selection as a strategic process influenced by uncertainty, competing priorities, and long-term sustainability goals, the model may align with concepts from innovation adoption and strategic decision-making theory. Its flexibility may allow decision-makers—from corporate managers to public administrators—to explore scenarios, evaluate trade-offs, and structure decisions that are not only technically informed but also potentially aligned with broader transformation agendas, such as energy autonomy, digital innovation, and climate policy.

Author Contributions: Conceptualization, S.G., D.H.d.I.I., J.L.A. and A.J.L.R.; Methodology, S.G., D.H.d.I.I. and J.L.A.; Validation, J.L.A. and A.J.L.R.; Formal Analysis, D.H.d.I.I., J.L.A. and A.J.L.R.; Investigation, S.G.; Data Curation, E.G. and S.G.; Writing—Original Draft, S.G.; Writing—Review and Editing, S.G.; Supervision, D.H.d.I.I. and J.L.A.; Project Administration, J.L.A. and E.G. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by National Funds through the FCT (Foundation for Science and Technology), I.P., within the scope of the project Ref. UIDB/05583/2020.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: We would like to thank the Research Centre in Digital Services (CISeD) and the Instituto Politécnico de Viseu for their support. Regarding the authors Sónia Gouveia, Daniel H. de la Iglesia, and José Luís Abrantes, this research work was conducted as part of the University of Salamanca PhD Programme on Education within the scope of Knowledge Society.

Conflicts of Interest: The authors declare no conflicts of interest.

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