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Decision-Making on Green Vehicles Using a Hybrid Taxonomy Approach with Reference-Based Methods

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Abstract

Nowadays, decision-making in the selection of green vehicles in Iran has become a major challenge, as choosing an appropriate vehicle has a significant impact on fuel consumption, air pollution, and environmental protection. Therefore, the use of suitable Multi-Criteria Decision-Making (MCDM) algorithms in this field appears to be essential. This study aims to analyze and propose an effective and efficient approach for decision-making related to the selection of green vehicles. In this research, a framework combining three MCDM methods, EDAS, VIKOR, and Taxonomy, has been employed to achieve optimal selection and facilitate the process of choosing green vehicles. By utilizing the characteristics of all three decision-making algorithms, the proposed algorithm enables accurate analysis through assigning weights to each criterion, thereby contributing to more intelligent economic and environmental decision-making in the selection of green vehicles. Based on the conducted analyses and the results obtained from the proposed EDAS–VIKOR–Taxonomy MCDM method, Plug-In Hybrid Electric Vehicles (PHEVs) were identified as the best green vehicles for entering the Iranian automotive market. The production of this type of vehicle in Iran's automotive industry can represent an effective and significant step toward environmental protection, air pollution control, and fuel consumption management.

Keywords: Green vehicles, Multi-criteria decision-making, VIKOR decision-making method, EDAS decision-making method, Taxonomy decision-making method.

1 | Introduction

Air pollution and fuel consumption in Iran have become fundamental and critical issues that each year impose irreparable impacts on the lives of thousands of people. Reports from the Ministry of Health indicate that

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more than 45,000 people die annually due to air pollution. According to the national air quality monitoring system, in 2022 (1401), Tehran experienced more than 130 days with unhealthy, very unhealthy, and hazardous air conditions, which is considered a new record. Meanwhile, reports from the Air Pollution Control Organization and the Statistical Center indicate that one of the main contributors to air pollution is mobile sources such as vehicles, to the extent that vehicles account for more than 80% of pollutant gas emissions. Moreover, reports from the National Iranian Oil Products Distribution Company show that average gasoline consumption in August 2023 reached 122 million liters per day, while Iran's refineries, even operating at maximum capacity, produced only 117 million liters per day. Consequently, sufficient imports of gasoline and diesel fuel are required to meet domestic demand. Studies and research indicate that with population growth and the increasing number of vehicles, the use of green and low-emission vehicles is one of the most important solutions for reducing air pollution and fossil fuel consumption. Such vehicles can be considered suitable alternatives to conventional fuel-powered vehicles and play a significant role in improving air quality and reducing fuel consumption. In this regard, green vehicles equipped with modern and sustainable technologies represent innovation and progress in the automotive industry [1].

Given the importance of selecting green vehicles, this study proposes a novel decision-making approach for selecting the most desirable green vehicle using Multi-Criteria Decision-Making (MCDM) criteria. MCDM comprises a set of methods and procedures that provide appropriate analytical frameworks for selecting an alternative based on multiple, often conflicting, criteria. In fact, MCDM focuses on problems involving a limited number of alternatives and criteria under conditions of uncertainty [2]. Accordingly, the main objective of this research is to introduce a new decision-making method for selecting the optimal green vehicle by leveraging the analytical features of three well-established MCDM methods: EDAS, VIKOR, and Taxonomy.

This study seeks to combine the advantages and limitations of each of these methods in order to offer a more comprehensive and effective solution than each method individually. The resulting method, referred to as EDAS–VIKOR–Taxonomy (EDAVIKORONOMY), is applied to the most desirable green vehicle among battery electric vehicles, PHEVs, hybrid electric vehicles, flexible-fuel vehicles, fuel-cell electric vehicles, and natural gas vehicles in Iran. To achieve this goal, the most influential criteria are identified and weighted. Subsequently, Section 2 reviews the literature on MCDM and its methods. Section 3 presents the theoretical foundations of the decision-making methods. Section 4 describes the research methodology, including the EDAVIKORONOMY method and the results obtained for green vehicles. Finally, Section 5 presents the conclusions and suggestions for future research.

2 | Literature Review

MCDM refers to a set of methods that provide an appropriate analytical framework for selecting an alternative from a set of available options by considering multiple, often conflicting, criteria related to the decision problem. MCDM essentially consists of two main branches: multi-objective optimization and MCDM. MCDM focuses on problems involving multiple criteria and a finite number of alternatives under conditions of uncertainty. In contrast, multi-objective optimization addresses problems that can be formulated within a mathematical optimization framework and involve multiple objective functions.

The concept of MCDM was first introduced in the 1960s, and since then, numerous theories and algorithms have been developed and presented in various articles and books. These contributions have played a significant role in advancing operations research, particularly in decision analysis. It should be noted that in multi-criteria decision analysis, comparisons among potential actions must be comprehensive and inclusive, taking into account all relevant criteria. Accordingly, various methods have been proposed to achieve this objective, among which the EDAS, VIKOR, and Taxonomy methods can be mentioned. In the following sections, the literature related to these methods is reviewed.

2.1 | EDAS Method

The Evaluation based on Distance from Average Solution (EDAS) method, as a compensatory approach, was introduced in 2015 by Keshavarz Ghorabaee et al. [3]. This method is particularly applicable when multiple criteria exist, especially in the presence of conflicting criteria. Based on the distance of each alternative from the average solution, the best alternative is selected. Moreover, EDAS demonstrates high compatibility with the complexities of decision-making processes. For this reason, in 2023, a modified EDAS method was adapted for MCDM in the field of robotic agriculture. By managing the unique challenges of robotic agriculture, such as dynamic environmental conditions and diverse decision criteria, the modified EDAS method provides practical solutions for improving operational efficiency and productivity [4].

According to the EDAS literature, in 2021, the EDAS method was used to evaluate the admission of COVID-19 patients to intensive care units. This study facilitated rational decision-making in the selective admission of COVID-19 patients during ICU bed shortages [5]. In another study, a conventional fuzzy EDAS approach was employed to evaluate energy alternatives in Turkey by considering MCDM aspects. The objective was to provide insights into the most suitable renewable energy options for Turkey, taking into account factors such as environmental impacts, economic feasibility, and technological readiness [6].

2.2 | VIKOR Method

The VIKOR method was developed to solve discrete decision-making problems involving conflicting and incommensurable criteria. This method emphasizes selecting from a set of alternatives and achieving a compromise solution for problems with conflicting criteria. In a study conducted in 2024, the authors applied the VIKOR approach to evaluate and select the most appropriate smart vehicle transportation system by considering multiple criteria in decision-making processes. The study highlighted the importance of multiple criteria in decision-making, particularly in complex systems such as intelligent transportation systems [7]. Based on existing literature, another study carefully compared the VIKOR and TOPSIS methods under different conditions by examining their characteristics, advantages, and disadvantages. The results indicated that the VIKOR method performed significantly better than the TOPSIS method [8].

In another article, appropriate dispute resolution methods for airport projects were investigated by considering multiple criteria, with an emphasis on the fuzzy VIKOR method. The findings demonstrated that the fuzzy VIKOR approach can be effectively used to prioritize dispute resolution methods for airport projects [9].

2.3 | Taxonomy Method

Taxonomy analysis is widely used in various classification contexts. A specific type, numerical taxonomy, focuses on the quantitative evaluation of similarities and proximities among the studied units and classifies elements into taxonomic groups. In a study conducted in 2022, a new decision support system based on the taxonomy method was proposed to assist in recommending and selecting MCDM methods. The taxonomy introduced in this study was presented as an effective tool for categorizing existing concepts and methods under different conditions in multi-criteria decision analysis [10].

In another study, an improved numerical taxonomy method was combined with the Analytic Network Process (ANP), a hybrid model, and a mathematical dispersion model to select suitable locations based on passive defense considerations. As a result, sensitive centers were classified into three categories: public facilities, undesirable facilities, and critical facilities [11]. Due to certain shortcomings associated with the taxonomy method, Faraji and his colleagues proposed a modified taxonomy model in which the criteria were no longer considered equal, significantly improving the method's accuracy. In addition, the positive and negative nature of the criteria was taken into account in this new approach, leading to more reliable results [12].

2.4 | Review of Decision-Making Criteria Literature

One of the critical stages in the MCDM process is identifying appropriate criteria for comparing different alternatives. To select suitable criteria, previous research articles published in this field were utilized. This section reviews the literature of several studies conducted in the area of MCDM and other decision analysis methods related to green vehicles.

The first study analyzed different types of sustainable vehicles within a sustainable road transportation system. In this research, the economic, environmental, and technical impacts of each vehicle type were evaluated and compared [13]. In this context, another study aimed to identify barriers to the widespread adoption of electric vehicles. The results indicated that consumer perceptions play a significant role in the adoption of electric vehicles, and several barriers exist, including trust in technology, access to charging infrastructure, high initial costs, and concerns related to vehicle performance and economics [14].

Another study examined the economic and environmental impacts associated with conventional, hybrid, and electric vehicles, employing various analytical methods to assess the advantages and limitations of each vehicle type [15]. A further study analyzed consumer attitudes toward purchasing electric vehicles, focusing on technological threats and trust in vehicles. The criteria used in this research included initial purchase cost, charging infrastructure, environmental aspects, and technical performance characteristics [16].

In another article, the energy, environmental, and economic performance of electric vehicles was evaluated through empirical assessment. Various criteria were used to measure energy performance, including energy consumption, greenhouse gas emissions, and financial costs associated with electric vehicles [17]. In a case study, pollutant emissions and energy requirements related to electric vehicles were assessed, considering criteria such as energy consumption, charging infrastructure, and vehicle performance [18].

Another study aimed to examine the adoption of electric vehicles and the impact of local policy instruments. The findings showed that local policy tools can significantly influence the increased adoption of electric vehicles by society by providing facilitators that support consumer decision-making [19].

In another study, the energy consumption and greenhouse gas emissions of a hydrogen fuel cell electric vehicle were compared with those of a conventional gasoline-powered vehicle. Criteria such as purchase cost, fuel efficiency, and fuel availability were used to assess energy consumption and emissions across both energy production and vehicle usage phases [20]. Another article applied both the Analytic Hierarchy Process (AHP) and a matrix-based MCDM approach. This integrated framework enabled the evaluation and selection of electric vehicles based on various criteria, including performance, cost, energy consumption, and environmental impact [21].

Another study examined the market acceptability of electric vehicles by simultaneously considering economic, technical, environmental, and social factors to facilitate effective decision-making regarding the development of this technology [14]. In [22], a study employing a multi-criteria approach simultaneously considered stochastic and fuzzy uncertainties in selecting electric vehicles with high social acceptance, using criteria such as price, fuel efficiency, and environmental impacts.

The results obtained from these studies and the selected articles are summarized in *Table 1*. It should be noted that, for the purpose of advancing the present research, all criteria are considered independent of one another, such that no overlap exists among them

Table 1. Criteria.

Authors	Vehicle supply time	Fuel cost	Flexiability	Fuel recovery time	Life cycle analysis and environmental sustainability of the vehicle	Vehicle performance in different weather conditions	Vehicle support	Access to the charging network and fuel supply stations	Technical and functional limitations of the vehicle	Maintenance and repair costs	Fuel consumption	The views of society and different groups towards cars	Vehicle Brand	Vehicle lifespan and quality	Customer satisfaction	Reliability	Type of technological advancement and productivity increase	Vehicle appearance and design	Driving system	Ease of repair and maintenance	Environmental health	Battery charging time	Purchase cost	security
[15]		*		*				*	*					*		*					*	*	*	*
[16]					*	*		*															*	
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[18]							*	*	*	*	*													
[1]			*																				*	
[19]												*	*	*	*	*	*							
[20]							*	*							*				*				*	*
[21]							*	*	*		*					*				*	*		*	
[14]																		*	*	*	*	*	*	*
[22]	*	*				*		*	*							*				*		*	*	*
[23]							*	*		*	*			*				*			*			*
Current research								*	*	*		*				*					*	*	*	*

Numerous studies to date have addressed issues related to green vehicles and MCDM methods separately, considering various criteria. By reviewing the existing literature summarized in *Table 1*, the most effective and frequently cited criteria were selected based on expert opinions. These criteria include vehicle reliability, public acceptance and societal attitudes toward the vehicle, accessibility to charging networks and fuel supply stations, safety, technical and performance limitations of the vehicle, environmental sustainability, fuel efficiency, the time required for charging or refueling, maintenance and repair costs, and the vehicle purchase price. These criteria have been employed for the evaluation and decision-making process concerning green vehicles. Based on the steps conducted in the present study, the operational framework illustrated in *Fig 1.* has been developed for decision-making on green vehicles using the IDA–VIKOR–Taxonomy (IDAVIKORONOMY) method. This framework can serve as a comprehensive guideline for implementing and conducting similar research in other locations or at different points in time.

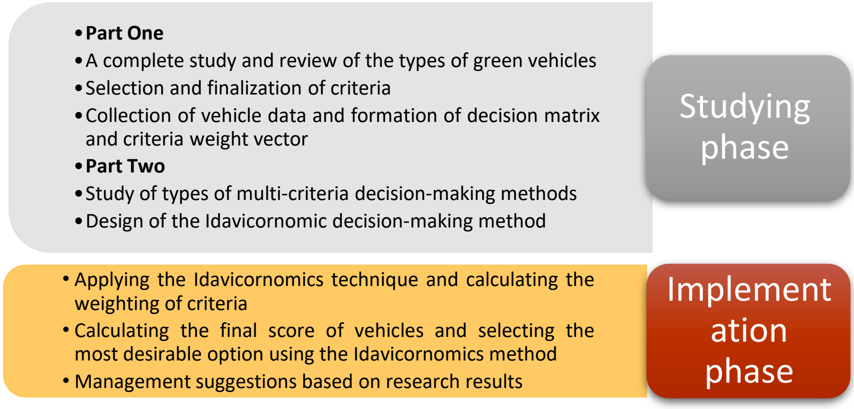

Fig. 1. Research implementation structure.

3 | Theoretical Foundations

In the MCDM process, selecting an appropriate decision-making method or methods is a fundamental step. In this study, after extensive examination, three methods (Taxonomy, VIKOR, and EDAS) were selected as the basic methods for developing a new decision-making approach. To properly understand the EDAS, VIKOR, and Toxonomy methods, it is necessary to be familiar with the steps of each of these methods. Therefore, the following introduces the three decision-making methods of EDAS, VIKOR, and Taxonomy.

3.1 | Taxonomy Method

In this section, the steps of the Taxonomy algorithm are examined.

First, the alternatives and the different criteria involved in the decision-making problem must be clearly defined. For this purpose, it is assumed that the decision-making problem consists of m alternatives (A_1 to A_m), which are evaluated by decision-makers based on n criteria (C_1 to C_n).

After forming the decision matrix, the mean and standard deviation of the data related to each criterion in the decision matrix are calculated using *Eqs. (1)* and *(2)*:

$$\bar{r} = \frac{1}{m}\sum_{i=1}^{m} r_{ij}\,, j = 1, \dots, n, \tag{1}$$

$$S_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(r_{ij} - \bar{r}_j\right)^2}\,, j = 1, \dots, n, \tag{2}$$

In the third step, it is necessary to form a standard matrix using *Eq. (3)*.

$$z_{ij} = \frac{r_{ij} - \bar{r}_j}{s_j}. \tag{4}$$

In the fourth step, the composite distance between the options must be determined. For this purpose, using the standard matrix, the distance of each option to the other options is calculated through the Euclidean equation, which is obtained through *Eq. (4)*.

In the fifth step, it is necessary to determine the minimum distance of each row of the matrix and then obtain the average distance of the options and their standard deviation. For this purpose, *Eqs. (5)-(7)* are used.

$$\bar{o} = \frac{1}{m}\sum_{i=1}^{m} O_i\ , \tag{5}$$

$$S_O = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(O_i - \bar{O})^2}, \tag{6}$$

$$O = \bar{o} \pm 2S_O. \tag{7}$$

This operation is performed to homogenize the options. As a result, if an option does not fall within a certain distance, it is heterogeneous, and this step must be repeated after its removal.

In this step, it is necessary to calculate the distance of each option from the ideal option. For this, *Eq. (8)* can be used.

$$C_{io} = \sqrt{\sum_{j=1}^{n}(z_{ij} - z_{oj)})^2}\ , \qquad i = 1,\ldots,m, \tag{8}$$

Z_{oj} represents the best option under the j-th criterion in the standard matrix, depending on whether the criterion is positive or negative. In addition, it is necessary to obtain the mean and standard deviation of the obtained C_{io}. 7. In the last step, it is necessary to first obtain the maximum possible distance through *Eq. (9)*, and finally, to obtain the taxonomic rank, *Eq. (10)* can be used [24].

$$C_O = \overline{C_{10}} + 2S_{C_{io}}\ , \qquad i = 1,\ldots,m, \tag{9}$$

$$F_i = \frac{C_{io}}{C_O}, \tag{10}$$

$$(\sum_{j=1}^{n} w_j = 1). \tag{11}$$

3.2 | VIKOR Method

The steps of the VIKOR algorithm are discussed below.

I. As in the first step of the taxonomy method, it is necessary to form a decision matrix.

II. In addition to the decision matrix, it is also necessary to form a weight vector matrix. According to *Eq. (11)*, wj represents the weight of the jth criterion. It should also be noted that the sum of all weights must be equal to 1.

III. In this step, it is necessary to determine the best and worst options for each criterion according to the decision matrix. As a result, for each positive criterion, we will have:

$$\begin{cases} f_j^* = \max_i f_{ij} \\ f_j^- = \min_i f_{ij} \end{cases}, \qquad i = 1,\ldots,m\ , j = 1,\ldots,n, \tag{12}$$

and for each negative criterion, we will have:

$$\begin{cases} f_j^* = \min_i f_{ij} \\ f_j^- = \max_i f_{ij} \end{cases}, \qquad i = 1,\ldots,m\ , j = 1,\ldots,n, \tag{13}$$

IV. In this step, the utility value (S_i) and the regret value (R_i) will be determined according to *Eqs. (14)* and (*15)*.

$$S_i = \sum_{j=1}^{n} w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)}, \qquad i = 1, \dots, m, \tag{14}$$

$$R_i = \max_j \left[w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)} \right], \qquad i = 1, \dots, m, j = 1, \dots, n, \tag{15}$$

V. In the fifth step, it is necessary to calculate the VIKOR index using *Eq. (16)*.

$$Q_i = v[\frac{(S_i - S^*)}{(S^- - S^*)}] + (1 - v)[\frac{(R_i - R^*)}{(R^- - R^*)}], \tag{16}$$

Subject to

$$S^* = \min_i S_i, \qquad S^- = \max_i S_i, \qquad R^* = \min_i R_i, \qquad R^- = \max_i R_i,$$

VI. During this step, the results obtained from S, R, and Q are sorted in ascending order. Option a_1, which has the lowest value in the list Q, is selected, and option a_2 is considered as the second-best option after a_1 in the list Q. Option a will be selected as the best option if it satisfies the following two conditions:

   I. $Q(a_2) – Q(a_1) \geq DQ$.

   II. Option a_1 is the best option in both S and R lists.

In the first condition, m is the number of options, and we will have:

$$DQ = \frac{1}{m - 1}. \tag{17}$$

If one of the two aforementioned conditions is not satisfied, the procedure will be carried out as follows:

I. If only the second condition is not satisfied, a_1 and a_2 will be selected as the best alternatives.

II. If the first condition is not satisfied, a set of alternatives corresponding to the maximum value will be selected as the most preferable alternatives, such that they satisfy the following equation [24].

$$Q(a_z) - Q(a_1) < DQ. \tag{18}$$

3.3 | EDAS Method

The EDAS algorithm is as follows.

I. As in the taxonomy and VIKOR methods, it is necessary to create a decision matrix. In addition to the decision matrix, it is necessary to form a weight vector matrix such that w_j represents the weight of the j-th criterion.

II. To obtain the average solution, we act according to *Eq. (19)*.

$$AV_j = \frac{\sum_{i=1}^{m} r_{ij}}{m}, \qquad j = 1, \dots, n. \tag{19}$$

III. After calculating the mean solution, it is necessary to calculate the values of the positive distance from the mean and the negative distance from the mean. For this purpose, if the criterion is of the positive type, *Eqs. (20)* and *(21)* can be used.

$$PDA_{ij} = \frac{\max\left(0, (r_{ij} - AV_j)\right)}{AV_j}, \qquad i = 1, \dots, m, j = 1, \dots, n, \tag{20}$$

$$NDA_{ij} = \frac{\max(0, (AV_j - r_{ij}))}{AV_j}, \qquad i = 1, \dots, m, j = 1, \dots, n, \tag{21}$$

If the criterion is negative, *Eqs. (22)* and *(23)* can be used.

$$PDA_{ij} = \frac{\max\left(0, \left(AV_j - r_{ij}\right)\right)}{AV_j}, \qquad i = 1, \dots, m, j = 1, \dots, n, \tag{22}$$

$$NDA_{ij} = \frac{\max(0, (r_{ij} - AV_j))}{AV_j}, \qquad i = 1, \dots, m, j = 1, \dots, n, \tag{23}$$

4. As mentioned in the first step, in the EDAS method, the weights of different criteria are not the same; therefore, in this step, it is necessary to consider the weight of each criterion. For this purpose, *Eqs. (24).* and *(25)* are used.

$$SP_i = \sum_{j=1}^{n} PDA_{ij}.w_j, \qquad i = 1, \dots, m, \tag{24}$$

$$SN_i = \sum_{j=1}^{n} NDA_i.w_j, \qquad i = 1, \dots, m, \tag{25}$$

IV. In the fifth step, it is necessary to standardize and normalize the values obtained in the fourth step, which is done through *Eqs. (26).* and (27*).*

$$NSP_i = \frac{SP_i}{\max_i(SP_i)}, i = 1, \dots, m, \tag{26}$$

$$NSN_i = \frac{SN_i}{\max_i(SN_i)}, i = 1, \dots, m, \tag{27}$$

V. In the final step, the final score of the options can be calculated and ranked using the following equation. The final option is obtained through *Eq. (28).*

$$AS_i = \frac{1}{2}(NSP_i + NSN_i), i = 1, \dots, m, \tag{28}$$

The option with the highest AS_i is the one with the highest utility [24].

4 | Research methodology

The EDAVIKORONOMY method is an approach that exploits the positive features of three methods (EDAS, VIKOR, and Taxonomy) and compensates for their respective strengths and weaknesses. Accordingly, this method benefits from the classification of alternatives based on their characteristics, as in the Taxonomy method; the comparison of alternatives with the average solution, as employed in the EDAS method; and the normalization techniques used in the VIKOR method.

As mentioned earlier, the prominent and important feature of the Taxonomy method is the classification of alternatives based on their attributes; however, since this method does not take the weights of criteria into account, it is not a suitable algorithm for decision-making and ranking alternatives. In the VIKOR method, each alternative is compared with a positive ideal solution and a negative ideal solution. This issue may negatively affect the final results, because these ideal solutions can be far removed from the best alternative or, in general, from the set of alternatives. In contrast, this drawback does not apply to the comparison of alternatives with the average solution used in the EDAS method. A positive feature of the VIKOR method is the use of relative normalization techniques, which have not been adequately considered in the EDAS method.

Therefore, by combining these methods, their weaknesses are mutually compensated, and the Idavikoronomy method is free from the shortcomings identified in the three aforementioned methods. The steps of the Idavikoronomy MCDM method are described as follows.

4.1 | First Step

First, as in the first step of the methods mentioned, it is necessary to clearly identify the various options and criteria in decision-making. Each of these criteria can be positive or negative, which needs to be identified at this stage.

Table 2. Decision matrix.

Alternative	(+)	(+)	(+)	(+)	(-)	(+)	(+)	(-)	(-)	(-)
	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Criterion 8	Criterion 9	Criterion 10
BEV	7	7	4	8	3	9	9	508	2	47046
PHEV	8	6	5	7	2	7	7	245	3	45430
HEV	9	7	8	7	1	6	6	0	4	35375
FFV	6	3	7	6	6	4	5	4	5	32945
FCV	7	2	3	7	3	5	8	4	4	60880
NGV	8	8	9	6	2	6	4	7.5	5	35522

According to *Table 2*, the decision matrix consists of six alternatives and ten criteria. The first criterion is vehicle reliability; the second criterion is public acceptance and societal perception of the vehicle; the third criterion is accessibility to charging networks and fuel supply stations; the fourth criterion is safety; the fifth criterion refers to the vehicle's technical and performance limitations; the sixth criterion is environmental sustainability; the seventh criterion is fuel efficiency; the eighth criterion is the time required for charging or refueling; the ninth criterion represents maintenance and repair costs; and the tenth criterion is the vehicle purchase price.

In order to evaluate green vehicles in Iran, due to the lack of reliable and comprehensive data, a combination of desk research, public surveys, and expert opinions was employed. Technical characteristics of vehicles, such as environmental performance, reliability, charging time, fuel efficiency, and similar attributes, were extracted from reputable international sources, including the Alternative Fuels Data Center, under the supervision of the United States Department of Energy, as well as official vehicle technical manuals. To assess public acceptance, a questionnaire was designed and distributed among experts, academics, and other respondents, and the survey results were analyzed using specified weighting coefficients. It should be noted that the vehicle purchase price corresponds to the average factory-gate price of vehicles in the year 2022.

4.2 | Second Step

In this step, after forming the decision-making matrix, it is necessary to calculate the mean and standard deviation of the data related to the criteria in the decision-making matrix in accordance with *Eqs. (29)* and *(30)*

$$\bar{r} = \frac{1}{m}\sum_{i=1}^{m} r_{ij}, \qquad j = 1,\ldots,n, \tag{29}$$

$$S_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(r_{ij} - \bar{r_j}\right)^2}, \qquad j = 1,\ldots,n. \tag{30}$$

Table 3. Mean and standard deviation of criteria.

Statistic	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Criterion 8	Criterion 9	Criterion 10
Mean	7.5	5.5	6	6.83	2.83	6.17	6.5	128.08	3.83	42866.3
Standard Deviation	0.96	2.22	2.16	0.69	1.57	1.57	1.71	191.37	1.07	9635.23

The mean and standard deviation of each option are in *Table 3*.

4.3 | Third Step

In the third step, it is necessary to form a standard (normalized) matrix. Each criterion in the decision-making matrix has different scales and units of measurement; therefore, it is necessary to eliminate the units and scales in this step, which is done using *Eq. (31)*.

$$z_{ij} = \frac{r_{ij} - \overline{r_j}}{s_j}, \tag{31}$$

Table 4. Standard matrix.

Alternative	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Criterion 8	Criterion 9	Criterion 10
BEV	-0.522	0.676	-0.926	1.698	0.106	1.802	1.464	1.985	-1.718	0.434
PHEV	0.522	0.225	-0.463	0.243	-0.53	0.53	0.293	0.611	-0.781	-0.266
HEV	1.567	0.676	0.926	0.243	-1.166	-0.106	-0.293	-0.669	0.156	-0.777
FFV	-1.567	-1.127	0.463	-1.213	2.014	-1.378	-0.878	-0.648	1.093	-0.03
FCV	-0.522	-1.578	-1.389	0.243	0.106	-0.742	0.878	-0.648	0.156	1.87
NGV	0.522	1.127	1.389	-1.213	-0.53	-0.106	-1.464	-0.63	1.093	-0.762

4.4 | Step Four

In the fourth step, the composite distance between the options must be determined. For this purpose, using the standard matrix, the distance of each option to the others is calculated through the Euclidean equation *Eq. (32)*.

$$C_{ab} = \sqrt{\sum_{j=1}^{n} \left(z_{aj} - z_{bj}\right)^2}. \tag{32}$$

Table 5. Composite distance matrix.

Alternative	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	Alternative 6
BEV	0	3.133	5.503	7.139	5.171	6.627
PHEV	3.133	0	5.503	5.237	3.55	3.995
HEV	5.503	5.503	0	5.331	5.021	2.506
FFV	7.139	5.237	5.331	0	4.822	4.337
FCV	5.171	3.55	5.021	4.822	0	5.687
NGV	6.627	3.995	2.506	4.337	5.687	0

According to *Eq. (33)*, a and b are two options to be evaluated. The distance of each option to itself is equal to zero, and the distance of option a to option b is equal to the distance of option b to option a. Therefore, the composite distance matrix of the options is as shown in *Table 5*, whose main diagonal is equal to zero.

4.5 | Fifth Step

In this step, it is necessary to determine the minimum distance of each row of the matrix. Then, the average distance of the options and their standard deviation should be calculated. For this purpose, *Eqs. (33)-(35)* are used.

$$\bar{o} = \frac{1}{m}\sum_{i=1}^{m} o_i, \tag{33}$$

$$S_O = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(O_i - \overline{O})^2}, \tag{34}$$

$$O = \bar{o} \pm 2S_O, \tag{35}$$

Table 6. Mean, standard deviation, and bounds of shortest distances.

Parameter	Value
Mean of shortest distances	3.194
Standard deviation of shortest distances	0.631
Lower bound	1.933
Upper bound	4.456

A heterogeneous option is an option that does not fall within the above limit. Therefore, if an option is heterogeneous, we eliminate it and reform the decision matrix with the remaining options.

Table 7. Shortest distance.

Alternative 6	Alternative 5	Alternative 4	Alternative 3	Alternative 2	Alternative 1	
2.506	3.550	4.327	2.506	3.133	3.113	Shortest distance

4.6 | Step 6

In addition to the decision matrix, it is also necessary to form a weight vector matrix. According to *Table 8*, wj represents the weight of the jth criterion. It should also be noted that the sum of all weights must be equal to 1.

Table 8. Criteria weights.

Criterion 10	Criterion 9	Criterion 8	Criterion 7	Criterion 6	Criterion 5	Criterion 4	Criterion 3	Criterion 2	Criterion 1
0.09	0.1	0.09	0.08	0.11	0.07	0.12	0.14	0.09	0.11

4.7 | Seventh Step

In this step, it is also necessary to obtain the average solution. For this, *Eq. (36)* is used. The result is shown in *Table 9*.

$$AV_j = \frac{\sum_{i=1}^{m} r_{ij}}{m}, \qquad j = 1,\ldots,n, \tag{36}$$

Table 9. Mean solution of criteria.

Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Criterion 8	Criterion 9	Criterion 10
7.5	5.5	6	6.833	2.833	6.167	6.5	128.083	3.833	42866.33

4.8 | Step 8

After calculating the mean solution, it is necessary to calculate the values of the positive distance from the mean and the negative distance from the mean. For this purpose, if the criterion is positive, *Eqs. (37)* and *(38)* can be used

$$PDA_{ij} = \frac{\max\left(0, \left(r_{ij} - AV_j\right)\right)}{AV_j}, \quad i = 1, \dots, m, j = 1, \dots, n, \quad (39)$$

$$NDA_{ij} = \frac{\max(0, (AV_j - r_{ij}))}{AV_j}, \quad i = 1, \dots, m, j = 1, \dots, n. \quad (38)$$

If the criterion is negative, *Eqs. (39)* and *(40)* are used.

$$PDA_{ij} = \frac{\max\left(0, \left(AV_j - r_{ij}\right)\right)}{AV_j}, \quad i = 1, \dots, m, j = 1, \dots, n, \quad (39)$$

$$NDA_{ij} = \frac{\max(0, (r_{ij} - AV_j))}{AV_j}, \quad i = 1, \dots, m, j = 1, \dots, n. \quad (40)$$

The results obtained from the above relationships are shown in *Tables 10* and *11*.

Table 10. Calculating the positive distance from the mean.

Alternative	(+) Criterion 1	(+) Criterion 2	(+) Criterion 3	(+) Criterion 4	(-) Criterion 5	(+) Criterion 6	(+) Criterion 7	(-) Criterion 8	(-) Criterion 9	(-) Criterion 10
BEV	0	0.273	0	0.091	0	0	0	0	0.091	0
PHEV	0.067	0.091	0	0.273	0.2	0	0.333	0	0.273	0.2
HEV	0.2	0.273	0.333	0	0	0.333	0.167	0.333	0	0
FFV	0	0	0.167	0	0	0.167	0	0.167	0	0
FCV	0	0	0	0	0.067	0	0	0	0	0.067
NGV	0.067	0.455	0.5	0.067	0	0.5	0	0	0.067	0

Table 11. Calculation of the negative distance from the mean.

Alternative	(+) Criterion 1	(+) Criterion 2	(+) Criterion 3	(+) Criterion 4	(-) Criterion 5	(+) Criterion 6	(+) Criterion 7	(-) Criterion 8	(-) Criterion 9	(-) Criterion 10
BEV	0.07	0	0.33	0	0.33	0	0	0	0.33	0.1
PHEV	0	0	0.17	0	0.17	0	0	0.45	0.17	0.05
HEV	0	0	0	0	0	0	0.45	0.64	0	0
FFV	0.2	0.45	0	0.12	0	0.12	0.64	0	0	0
FCV	0.07	0.64	0.5	0	0	0	0	0	0	0.42

4.9 | Step 9

In this step, using the criteria weight vector and *Eqs. (41)* and *(42)*, the values of SPi and SNi are calculated, and using *Eq. (43)*, the values of SPi and SNi are relatively normalized, and Si is obtained

$$SP_i = \sum_{j=1}^{n} PDA_{ij}.w_j, \quad i = 1, \dots, m, \quad (41)$$

$$SN_i = \sum_{j=1}^{n} NDA_i.w_j, \quad i = 1, \dots, m, \quad (42)$$

$$S_i = \frac{SP_i - SP*}{SP^- - SP*} + \frac{SN_i - SN*}{SN^- - SN*}, \quad (43)$$

In the above equations, we have:

$$SP^* = \max_i SP_i, \quad SN^- = \min_i SN_i,$$

In addition, the values of RP_i and RN_i are calculated using *Eqs. (44)* and *(45)* and normalized using *Eq. (46)*. The results obtained from the following equations are given in *Table 12*.

$$RP_i = Max(PDA_{ij}.w_j), \quad i = 1, \dots, m, \quad (44)$$

$$RN_i = MAX(NDA_{ij}.w_j), i = 1, \dots, m, \quad (45)$$

$$R_i = \frac{RP_i - RP*}{RP^- - RP*} + \frac{RN_i - RN*}{RN^- - RN*}, \quad (46)$$

In the above equations, we have:

$$RP^* = \max_i RP_i, \quad RN^- = \min_i RN_i,$$

Table 12. Utility and regret values.

Alternative	SP	SN	S	RP	RN	R
BEV	0.174	0.334	0.441	0.478	2.966	0.739
PHEV	0.082	0.111	1.696	0.294	0.913	1.711
HEV	0.247	0.013	1	1	0.077	1
FFV	0.131	0.243	0.983	0.969	1.18	0.684
FCV	0.109	0.202	1.25	0.969	0.636	0.851
NGV	0.239	0.079	0.846	0.941	0.385	0.976

4.10 | Step 10

In this step, the Idavicoronomi index is calculated through *Eq. (47)*.

$$Q_i = v[\frac{(S_i - S^*)}{(S^- - S^*)}] + (1 - v)[\frac{(R_i - R^*)}{(R^- - R^*)}], \quad (47)$$

Subject to;

$$S^* = \min_i S_i, \quad S^- = \max_i S_i, \quad R^* = \min_i R_i, \quad R^- = \max_i R_i,$$

During this step, the results obtained from S, R, and Q are sorted in ascending order. Option a_1, which has the highest value in the list Q, is selected, and option a_2 is considered as the second-best option after a1 in the list Q. Option a will be selected as the best option if it satisfies the following two conditions:

I. $Q(a_2) - Q(a_1) \geq DQ$

II. Option a is the best option in both lists S and R. In the first condition, m is the number of options, and we have:

$$DQ = \frac{1}{m - 1}, \quad (48)$$

If one of the two above conditions is not met, then the following procedure will be followed:

I. If only the second condition is not met, a and b will be selected as the best options.

II. If the first condition is not met, a set of options will be selected as the most desirable options for the maximum value that meets the condition.

$$Q(a_z) - Q(a_1) < DQ,. \quad (49)$$

Based on the results obtained from the output of the EDA–VIKOR–Taxonomy (EDAVIKORONOMY) method for ν=0.4, as reported in *Table 13*, the acceptability conditions of this method are examined. Given that there are six alternatives, the value of DQ is 0.2. Therefore, the difference between the Q_i values of the two alternatives with the highest Q_i scores must be greater than 0.2. Since PHEVs and hybrid electric vehicles (HEVs) have the highest EDAVIKORONOMY index values, respectively, and the difference between their index values is 0.637, the first condition is satisfied. According to the second condition, the R_i and S_i values for PHEVs are the highest; therefore, it can be concluded that PHEVs are selected as the most preferable alternative. It is while, in the VIKORONOMY and taxonomy methods, hybrid vehicles were selected as the top alternatives; however, in the EDAS method, similar to the EDAVIKORONOMY method, plug-in hybrid vehicles are selected as the best option.

Table 13. EDAVIKORONOMY index.

Alternative	Qi	Ri	Si
BEV	0.032	0.739	0.441
PHEV	1	1.711	1.696
HEV	0.363	1	1
FFV	0.173	0.684	0.983
FCEV	0.355	0.851	1.25
NGV	0.3	0.976	0.846

To examine and analyze the results of the Idavicornomy ranking and the results obtained from this method, the Taxonomy and VIKOR MCDM methods were used alone. In the VIKOR method, plug-in hybrid vehicles (PHEV) were selected as the most desirable option, while in the Taxonomy method, hybrid vehicles (HEV) were ranked first and plug-in hybrid vehicles (PHEV) were ranked second with a very small difference; therefore, it can be claimed that the results obtained from the Idavicornomy MCDM method can be confirmed and cited.

5 | Conclusion

The present study introduces the EDAS-VIKOR-Toxonomy method as a significant innovation in MCDM. By integrating three MCDM methods (EDAS, VIKOR, and Taxonomy), this approach provides a comprehensive and efficient framework for evaluating and selecting the optimal green vehicles. Applying this method, while considering multiple criteria and their respective weights, led to the identification of the Plug-in Hybrid Electric Vehicle (PHEV) as the best alternative. This method not only enhances the accuracy and reliability of decision-making processes but can also be generalized as a practical model for other selection problems and complex decision-making contexts. To advance future research, it is recommended that other types of green vehicles be examined to enable broader comparative analyses. Moreover, identifying the factors that influence and encourage Iranian consumers to purchase and use green vehicles, and incorporating them into the decision-making process, is strongly recommended. In the present study, the criteria were considered independent; therefore, future studies should take into account the interdependencies among criteria. In addition, using alternative methods to determine criterion weights may yield more precise and robust results. For managers and policymakers, the findings of this study provide practical and applicable guidance for developing effective strategies to promote the adoption of green vehicles. The first step involves educating and raising public awareness about the economic and environmental benefits of green vehicles, which can be achieved through educational programs and information campaigns.

Furthermore, offering tax incentives and purchase subsidies can help reduce the initial cost of acquiring green vehicles and serve as a motivating factor for consumers. Developing and improving essential infrastructure, such as charging stations for electric and hybrid vehicles, is also crucial. In addition, investing in research and development to enhance green vehicle technologies and improve their efficiency can significantly contribute to the advancement of this industry. Finally, market analysis and identifying the key factors that motivate consumers to purchase green vehicles, and using this information to design effective advertising and marketing campaigns, are among the operational measures that can lead to reduced environmental pollution and improved public health.

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Data Availability

Relevant data supporting the conclusions of this study can be obtained from the corresponding author upon reasonable request.

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