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Multi-Criteria Stochastic Selection of Electric Vehicles for the Sustainable Development of Local Government and State Administration Units in Poland

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Abstract: Increasing the popularity of electric vehicles is one way of reducing greenhouse gas emissions and making the economy more sustainable. In Poland, the use of electric vehicles is to be increased by the adoption of the Act on Electromobility and Alternative Fuels. This Act obliges local government units and state administration to expand the electric vehicle fleet. The expansion of the fleet should be carried out on a planned basis, based on rational decisions supported by economic analyses. Therefore, the aim of this article is to provide a recommendation of an electric vehicle that meets the needs of local and state administration to the greatest extent possible. The aim has been achieved using the multi-criteria decision analysis method called PROSA-C (PROMETHEE for Sustainability Assessment—Criteria) combined with the Monte Carlo method. The PROSA-C method allows promoting more sustainable vehicles with high technical, economic, environmental and social parameters. The Monte Carlo method, on the other hand, is a stochastic simulation tool that allows for taking into account the uncertainty of parameters describing vehicles. As a result of the research, the most and least attractive vehicles were identified from the perspective of the needs of local government units and state administration. Moreover, the conducted research allowed confirming the effectiveness and usefulness of the research methodology proposed in the article and the procedural approach combining the PROSA-C and Monte Carlo methods.

Keywords: electric vehicles; PROSA; PROMETHEE for Sustainability Assessment; MCDA; Multi-Criteria Decision Analysis; stochastic analysis; Monte Carlo; uncertainty

1. Introduction

Global energy demand is almost steadily increasing, the only exception being the global lockdown in the first half of 2020, which caused a temporary drop in demand for energy production [1]. Together with increased energy production, the number of greenhouse gases emitted into the atmosphere is also increasing: at present, more than 25 billion tons of CO_2 are released annually as a result of human activity [2]. One of the most important options for reducing CO_2 emissions into the atmosphere is the development of electric vehicles [3], because, according to the International Energy Agency, around 14% of greenhouse gases in the world are produced by the transport sector [4]. Therefore, the electrification of transport, together with an increase in the use of renewable energy sources, offers the possibility of significantly reducing greenhouse gas emissions [3]. Of course, the development of electric vehicles is not the only option for reducing CO_2, emissions associated with transport. Another interesting option is, for example, the design of urban space in such a way as to maximize the possibility of walking [5,6]. However, the need to use the vehicle cannot always be eliminated, so electrifying transport remains the main way to reduce emissions contributing to the sustainability of the transport system.

In order to increase the share of electric vehicles in transport, the Polish government has adopted the Act on Electromobility and Alternative Fuels [7] imposing obligations on state and local government units in terms of:

- the percentage of battery electric vehicles in the fleet of used vehicles,
- the percentage of zero-emission buses in the fleet of vehicles in use,
- the minimum number of charging points in municipal districts.

According to this legal act, state administration authorities and local government units with more than 50,000 inhabitants must gradually increase the share of electric vehicles in the vehicle fleet. For state administration bodies, the share of battery electric vehicles in the fleet of used vehicles should be: from 1 January 2022 at least 10%, from the beginning of 2023 at least 20%, and in 2025 at least 50%. For larger municipal districts and counties, i.e., with more than 50,000 inhabitants, the share should be at least 10% from 1 January 2022, and at least 30% in 2025. In addition, local government units are obliged to provide public transport services using a fleet partly composed of zero-emission buses: from the beginning of 2021 such buses are to constitute 5%, from 2023 10%, from 2025 20%, and on 1 January 2028 it is to be 30% of the bus fleet. As far as the expansion of the electric vehicle charging network is concerned, the number of charging points required in 2021 depends on the number of inhabitants and the number of cars in each municipal district. The detailed requirements are shown in Table 1 [7,8].

Table 1. Required number of electric vehicle charging points installed by 31 March 2021 depending on the size of the municipal district.

Number of Inhabitants of the Municipal District	Number of Motor Vehicles in the Municipal District	Number of Motor Vehicles per 1000 Inhabitants	Required Number of Charging Points
≥100,000	≥60,000	≥400	≥60
≥150,000	≥95,000	≥400	≥100
≥300,000	≥200,000	≥500	≥210
≥1,000,000	≥600,000	≥700	≥1000

Increasing the share of electric vehicles in the fleets of state and local government units is expected to contribute to the number of 1 million electric vehicles in use in Poland in 2025 [9]. Therefore, a critical problem is the appropriate expansion of the fleets of state and local administration vehicles. The expansion of fleets should be well thought-out and carried out in a planned manner, and decisions taken in this area must be rational and supported by analyses. The expansion of fleets of electric vehicles cannot take place chaotically, without a plan and research, because this can lead to wasteful spending of state and local government funds, with criminal sanctions associated with this. This is all the more important because the cost of purchasing electric vehicles is much higher than that of conventional vehicles, so ill-considered purchases of electric vehicles result in greater financial losses than conventional vehicles. Selecting suitable vehicles to expand the fleet is even more difficult due to the fact that electric vehicles, even belonging to the same class, differ in a number of parameters. It is important to properly select such vehicles in order to minimize the inconvenience associated with, among other things, the low range and long charging time of such vehicles, while maintaining a reasonable price of expanding the fleet of electric vehicles.

The research problem addressed in the article, and at the same time its practical objective, is to analyze the electric vehicles available in Poland and to present recommendations of vehicles with the highest utility for institutional users (state and local government bodies). This is of particular importance in the context of the previously indicated statutory obligation of state and local government units to expand the fleet of electric vehicles and the expected increase in demand for such vehicles.

The methodological contribution is the use of MCDA (Multi-Criteria Decision Analysis) method called PROSA-C (PROMETHEE for Sustainability Assessment–Criteria) [10,11], which allows taking

into account the sustainability of decision-making alternatives in the solution of a decision problem. In the case of electric vehicles, the PROSA-C method allows promoting vehicles with more balanced economic, technical, social and environmental characteristics. What is important, in this article the method has been developed with elements of a stochastic simulation, which takes into account the uncertainty of individual parameters of electric vehicles. This uncertainty should be taken into account in the solution of the decision problem and is due, among other things, to the fact that certain operational parameters depend on the user and how the vehicle is used, e.g., the same vehicle may have different energy consumption and range depending on the driving style.

Section 2 contains a literature discussion on the applications of MCDA methods in decision-making problems related to electric vehicles. Section 3 discusses the PROSA-C method, a stochastic analysis using the Monte Carlo method, and a research procedure based on these methods. Section 4 presents the results of research on the selection of electric vehicles for local government units and state bodies in Poland. The article ends with a summary and indication of further research directions.

2. Literature Review

Electric vehicles are characterized by many parameters, such as: electric motor size, weight, range, battery capacity, energy consumption, charging time, etc. [12,13]. These parameters are often in conflict with each other, so improving one of them causes deterioration of another, e.g., higher battery capacity means longer charging time. Moreover, many parameters are characterized by uncertainty, e.g., charging time depends on the charger used. Therefore, the comparison and recommendation of electric vehicles is a multi-criteria problem characterized by uncertainty and consisting in the search for pareto-optimal solutions. MCDA methods are used to solve these types of decision-making problems [14]. These methods are used both to solve decision-making problems at the strategic level (e.g., selecting policies for the development of electric vehicles and their infrastructure) and at the tactical and operational level (e.g., selecting specific vehicles or locations of charging stations). Barfod et al. [15] studied the opportunities, risks and policies for the widespread use of commercial electric vehicles in Denmark. Adhikari et al. [16] examined the limitations and challenges of using electric vehicles in the context of Nepal. Both Zhang et al. [17] and Liu and Wei [18] examined the risk factors for building an electric vehicle charging infrastructure in a public-private partnership, with Zhang et al. [17] conducting the study from a Chinese perspective, and Liu and Wei [18] considered the three Chinese provinces separately, building their ranking. Fazeli et al. [19] assessed the potential impact of various fiscal policies on the acceptance of electric vehicles by consumers and the Government of Iceland over the next 30 years. Erbas et al. [20] and Ju et al. [21] examined the potential locations of electric vehicle charging stations and built a ranking, with Erbas et al. [20] conducting a survey for Ankara and Ju et al. [21] examining the locations in Beijing. Xu et al. [22] ranked the various electric vehicle sharing programs used in Beijing. Sałabun, Karczmarczyk [13] and Wątróbski et al. [23] compared different electric cars in their rankings. The decision-making problems considered in individual studies and the MCDA methods used are presented in Table 2.

In the above mentioned works, various MCDA methods were used, starting from methods based on single synthesizing criterion: AHP and Fuzzy AHP, TOPSIS and Fuzzy TOPSIS, VIKOR, SMARTER, DEMATEL, COMET, and ending with the outranking PROMETHEE II method. It should be noted here that the AHP method in each of the quoted tests was only used to determine the weights of the criteria. A detailed review of these and many other MCDA methods can be found, for instance, in the papers of [14,24]. In the context of the research objective, it should be noted that MCDA methods may have high or low compensation of criteria and therefore a correspondingly weak and strong sustainability. Depending on the adopted paradigm (strong or weak sustainability), different MCDA methods can be used to solve sustainability decision-making problems. Generally speaking, it is recognized that methods based on a single synthesizing criterion, such as AHP, SMARTER, TOPSIS, VIKOR, DEMATEL, COMET, among others, are characterized by high compensation and therefore only allow for weak sustainability. On the other hand, methods based on outranking, thanks to the use of indifference,

preference and sometimes also veto thresholds, are characterized by lower compensation and thus stronger sustainability [25,26]. In the light of the purpose of the research, in addition to the degree of compensation, another important feature of MCDA methods is their ability to take into account the uncertainty of the criteria. The MCDA methods are often used to deal with *ex-ante* decision-making problems, so the decision-maker or analyst is not able to fully and certainly foresee all its consequences at the time of the decision. So this is a decision taken in conditions of uncertainty. A natural tool for taking into account uncertainty in decision making problems is fuzzy MCDA methods [27]. In turn, the MCDA methods using crisp data can take into account uncertainty by using a stochastic approach, such as the Monte Carlo method [28].

Table 2. Decision-making problems related to electric vehicles and MCDA methods used.

Decision Problem	Location	MCDA Method	No. of Alternatives/Criteria	Reference
Analysis of the challenges related to the widespread use of commercial electric vehicles	Denmark	SMARTER	-/25	[15]
Analysis of obstacles related to the use of electric vehicles	Nepal	AHP	-/17	[16]
Risk analysis of the development of electric vehicle charging infrastructure in public-private partnership	China	2-tuple DEMATEL	-/22	[17]
Risk assessment of the development of electric vehicle charging infrastructure in public-private partnership	China	Fuzzy TOPSIS	3/17	[18]
Assessment of the impact of fiscal policy on the acceptance of electric vehicles	Iceland	TOPSIS	6/4	[19]
Evaluation of the locations of electric vehicle charging stations	Ankara, Turkey	Fuzzy AHP + TOPSIS	12/15	[20]
Evaluation of the locations of electric vehicle charging stations	Beijing, China	Fuzzy AHP + PFWIG + GRP	6/14	[21]
Ranking of electric vehicle sharing programs	Beijing, China	VIKOR	3/22	[22]
Electric vehicle selection	Poland	COMET	9/6	[13]
Electric vehicle selection	Poland	PROMETHEE II, Fuzzy TOPSIS	36/9	[23]

Analyzing the quoted articles, several important research gaps can be observed in the studies on the selection of electric vehicles for public administration and local authorities. First of all, the presented literature review indicates a small number of works in which electric vehicles were compared in a multi-criteria way. It can also be noted that to the best of the author's knowledge, no scientific research on the selection or recommendation of electric vehicles for administrative and local government units has been published so far. On the other hand, the quoted research on the Polish electric vehicle market is out of date, because this market is changing dynamically and new vehicle models appear on it every year, and current vehicles are updated. As regards the MCDA methods used, it should be noted that among the approaches taking into account the uncertainty of parameters of electric vehicles, the only methods used are Fuzzy TOPSIS and COMET, operating on fuzzy sets. Unfortunately, both methods are characterized by high compensation [24] and therefore weak sustainability [14]. This means that a high

value of one of the vehicle's parameters can fully compensate for a low value of another parameter [29], so, for example, a high maximum speed can compensate for high energy consumption. In other words, in the case of high compensation, a profit for one criterion may compensate for losses for another criterion, while low or no compensation reduces or eliminates this possibility altogether [30]. There is another research gap here, because the use of highly compensated MCDA methods results in solutions obtained using the indicated methods are not sustainable.

The research gaps identified directly determine the objectives and contribution of this research. The aim is a multi-criteria analysis of electric vehicles currently available in Poland, which meet the needs of state and local administration bodies. The practical effect will be to identify the most useful vehicles for these administrative units. As far as the scientific contribution is concerned, in this article, the PROSA-C method was used to evaluate electric vehicles available in Poland. It is a method designed to solve multi-criteria decision-making problems, enabling sustainable solutions. It allows adjusting the balance between the criteria influencing the expected degree of sustainability of the solution. This article develops the PROSA-C method by introducing elements of a stochastic analysis, thanks to which the uncertainty of data describing characteristics of electric vehicles is taken into account.

3. Materials and Methods

3.1. PROSA-C Method

PROSA is used to consider discrete decision-making problems, where a set of $A = \{a, b, \ldots\}$ consisting of m alternatives is considered. Alternatives are considered in terms of n criteria belonging to a set $C = \{c_1, c_2, \ldots, c_n\}$. The calculation procedure of the PROSA-C method [10,11] consists of 7 stages, with the initial 4 stages taken directly from the PROMETHEE method [31,32], on which the PROSA method is based. These steps are based on the approach using single criterion net flows [33] (pp.161–162) [31] (pp.200). The subsequent stages are written below using mathematical formulas.

1. Determination of deviations based on pair-wise comparisons:

$$d_j(a,b) = c_j(a) - c_j(b) \tag{1}$$

where $d_j(a,b)$ denotes the difference between the performances of a and b on a j-th criterion.

2. Application of the preference function:

$$P_j(a,b) = F_j\Big[d_j(a,b)\Big] \tag{2}$$

where $P_j(a,b)$ denotes the preference of alternative a with regard to alternative b on each criterion, as a function F of $d_j(a,b)$.

3. Calculation of a single criterion net outranking flow:

$$\phi_j(a) = \frac{1}{m-1}\sum_{i=1}^{m}\Big[P_j(a,b_i) - P_j(b_i,a)\Big] \tag{3}$$

where $\phi_j(a)$ denotes the criterion net flow of a over any other alternative, and m describes the number of alternatives.

4. Calculation of a global (overall) net outranking flow:

$$\phi_{net}(a) = \sum_{j=1}^{n}\phi_j(a)\, w_j \tag{4}$$

where $\phi_{net}(a)$ is the weighted sum of net flow for each criterion, w_j is the weight of j-th criterion, and weights are normalized to 1 ($\sum_{j=1}^{n} w_j = 1$). The above steps allow obtaining the PROMETHEE II solution, while the subsequent steps lead to the PROSA-C solution.

5. Determination of a single criterion absolute deviation:

$$AD_j(a) = \left|\phi_{net}(a) - \phi_j(a)\right| s_j \tag{5}$$

where s_j denotes the sustainability (compensation) coefficient for a j-th criterion. As it can be easily noticed, s_j is a sort of a weight coefficient, and $AD_j(a)$ is a weighted distance of a solution $\phi_{net}(a)$ from solutions $\phi_j(a)$ obtained for individual criteria. The greater the value s_j, the more preferred are alternatives strongly sustainable with regard to the j-th criterion, therefore, the compensation degree for the criterion $c_j(a)$ is smaller.

6. Calculation of a single criterion PROSA net sustainable value:

$$PSV_j(a) = \phi_j(a) - AD_j(a) \tag{6}$$

where $PSV_j(a)$ describes the sustainability of alternative a and with regard to the j-th criterion.

7. Calculation of a global PROSA net sustainable value:

$$PSV_{net}(a) = \sum_{j=1}^{n} PSV_j(a)\, w_j \tag{7}$$

where $PSV_{net}(a)$ is the weighted sum of the PROSA net sustainable value for each criterion.

The PROSA-C method allows conducting an analysis of the sustainability of criteria for individual decision alternatives. It distinguishes three sustainability/compensation relationships.

1. The relation of being sustainable ($\approx$)–takes place when $\phi_j(a) \approx \phi_{net}(a)$ and it means that the alternative a is sustainable in terms of a j-th criterion.
2. The relation of being compensated (Cd)–takes place when $\phi_j(a) \ll \phi_{net}(a)$ and it means that the low performance of the criterion $c_j(a)$ is compensated by another criterion or other criteria ($\exists \phi_{j'}(a) : \phi_j(a)\ Cd\ \phi_{j'}(a)$).
3. The compensation relationship (Cs)–occurs when $\phi_j(a) \gg \phi_{net}(a)$ and it means that the high performance of the criterion $c_j(a)$ compensates for lower performance on another criterion or other criteria ($\exists \phi_{j'}(a) : \phi_j(a)\ Cs\ \phi_{j'}(a)$).

Relations Cd and Cs are relations indicating the unsustainability of the alternative a with regard to the criterion $c_j(a)$. The << and >> operators denote contractual relations "much less than" and "much greater than", expressing the subjective views of the decision-maker about the difference between the compared values. These relations can provide a hint to the decision-maker about the expected values of the coefficient s_j. For example, if the decision-maker wants to increase the impact of sustainability on the obtained solution, a lower s_j value can be adopted for more sustainable criteria, and higher s_j values can be adopted for less sustainable criteria.

3.2. Stochastic Analysis

A stochastic analysis is based on random variables defined in the probability space. In this article, a stochastic simulation based on the Monte Carlo method is used. In the Monte Carlo method, K iterations are carried out, and during each of them L independent random variables r with a specific distribution D are drawn [34]:

$$r_l^k \overset{i.i.d.}{\sim} D(v) \tag{8}$$

where r_l^k is an l-th independent random variable (l = 1,2, ... ,L) drawn in a k-th iteration (k = 1,2, ... ,K), v is a set of distribution parameters D (e.g., range of values), *i.i.d.* means independent and identically distributed. This approach allows considering solutions based on different values of random variables, covering the whole probability space, including the specified distribution.

In this article, the Monte Carlo method has been used to generate various possible values for criteria describing uncertain parameters of electric vehicles. Random variables represent the values of individual criteria for each of the alternatives $c_j(a)$. Therefore, the number of random variables generated in each iteration should be equal to the product of the number of criteria and alternatives considered ($L = n * m$). However, each random variable may have a different distribution and distribution parameters, depending on which alternative and which criterion it represents. Therefore, in this article, the stochastic simulation is based on a formula:

$$c_j(a_i)^k = r_l^k \overset{i.i.d.}{\sim} D(v)_{i,j} \tag{9}$$

where $D(v)_{i,j}$ denotes the distribution and parameters adopted for a j-th criterion of an i-th alternative.

Further elements of the stochastic analysis are based on elements of SMAA (Stochastic Multicriteria Acceptability Analysis) [35]. On the basis of random variables generated in each iteration, rankings of alternatives are built using the PROSA-C method. The results obtained in subsequent iterations allow us to determine the statistic B_{ir} indicating the number of iterations, in which the i-th alternative obtained an r-th position in the ranking. On this basis, after K iterations, rank acceptability indices [35] are estimated:

$$b_i^r \approx \frac{B_{ir}}{K} * 100\% \tag{10}$$

In practice, the rank acceptability indices b_i^r show the probability that the i-th alternative will get the r-th position in the ranking. This probability is, of course, determined by random variables generated on the basis of the specified distributions $D(v)_{i,j}$. The obtained values of the rank acceptability indices are characterized by a certain precision and an assumed confidence interval, depending on the number of iterations. The expected precision of the rank acceptability indices can be determined from the formula [36]:

$$\varepsilon = \frac{z_\alpha}{\sqrt{4L}} \tag{11}$$

where z_α denotes a standard score for a confidence level $1 - \alpha$. In the SMAA method and Monte Carlo simulations 10^4–10^6 iterations [36,37] are usually used, which gives a precision of 0.01–0.001 for 95% confidence respectively.

3.3. Research Procedure

Some elements of the research procedure have already been mentioned in Section 3.2, while this section discusses the complete procedure applied to the decision-making problem of recommending electric vehicles for state and local authorities. A diagram of the procedure is presented in a graphical form in Figure 1.

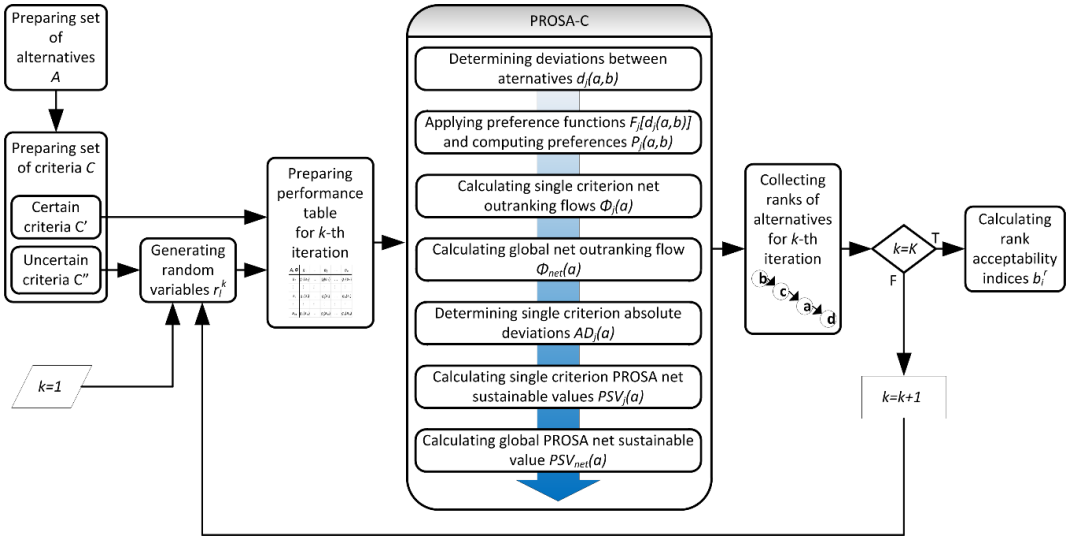


Figure 1. Research procedure.

1. At the beginning, an analysis of electric vehicles available in Poland was carried out and a review of sources describing usual needs of the state administration and local government in relation to electric vehicles was conducted. Data on electric vehicles available on the Polish market were obtained from the database of the Polish Alternative Fuels Association [38]. On the other hand, the needs of administration units with regard to electric vehicles were determined on the basis of information on tenders for such vehicles announced by administration units and information on purchases made by local government units and public administration units [39–42]. This information was also verified by consulting local government experts. On this basis, vehicles applicable in local government units and state authorities were selected, obtaining a set of decision-making alternatives A.
2. The vehicle characteristics were then considered and a set of criteria C was obtained. The set of criteria was established on the basis of the data on electric vehicles obtained in step 1, with the reservation that these must be measurable and, at least to some extent, objective criteria. For this reason, criteria such as the appearance of the vehicle were not taken into account. The selection of the set of criteria was also based on other studies on vehicle recommendations, including electric vehicles [12,13,23]. The following criteria were taken from these publications: Top speed [23], Power [13,23], Torque [13,23], Cargo capacity [23], Battery capacity [12,13,23], Price [13,23], Range [12,13,23], Consumption [12], Charging time [13,23], Fast charging time [23]. This collection was supplemented with the criteria obtained in an expert interview: Acceleration, Seats, and Safety. This set of criteria was divided into certain criteria, the values of which for each alternative are crisp numbers, and uncertain criteria, the values of which may vary according to different factors. In addition, ranges of uncertain criteria were established.
3. In the next stage, based on the Monte Carlo simulation, random variables were generated to determine the values of uncertain criteria.
4. A performance table with values for the certain criteria and simulated crisp values for the uncertain criteria was constructed.
5. On the basis of the performance table, calculations were carried out using the PROSA-C method, thereby obtaining a ranking of alternatives.
6. The procedure of generating random numbers and building the ranking of alternatives was repeated K-times (the study assumed the number K = 1,000,000 iterations).
7. After all iterations of the calculation procedure were performed, the rank acceptability indices b_i^r were calculated for each alternative.

4. Results

At the outset, the most frequent needs of state and local government units with regard to electric vehicles were identified. The analysis of Internet sources [39–42] as well as the expert interview revealed that both the state administration and local government in Poland most often use electric hatchback, B-segment (small cars), C-segment (medium cars) and J-segment (SUVs) cars with appropriate electric motor power, energy consumption and range. Therefore, electric cars of these segments with electric motor power of not less than 130PS, a range of at least 200 km and energy consumption of not more than 250 Wh/km are considered in this research. Moreover, only electric vehicles available on the Polish market were considered [38]. The vehicles concerned and their characteristics are shown in Table 3.

Table 3. Characteristics of the electric vehicles concerned [38,43,44].

	Parameter	A1-DS 3 CROSSBACK E-TENSE	A2-Hyundai KONA Electric 39.2 kWh	A3-Hyundai KONA Electric 64 kWh	A4-Hyundai IONIQ Electric	A5-Nissan LEAF	A6-Nissan LEAF e+	A7-BMW i3	A8-BMW i3s	A9-Mini Cooper SE	A10-Opel Corsa-e	A11-Peugeot e-208	A12-Renault ZOE R135
	Segment	JB	JB	JB	C	C	C	B	B	B	B	B	B
	Top speed [km/h]	150	155	167	165	144	157	150	160	150	150	150	140
	Acceleration 0–100 km/h [s]	8.7	9.9	7.9	9.7	7.9	7.3	7.3	6.9	7.3	8.1	8.1	9.5
	Total power [PS]	136	136	204	136	147	218	170	184	184	136	136	136
	Total torque [Nm]	260	395	395	295	320	340	250	270	270	260	260	245
	Cargo volume [L]	350	361	361	357	435	420	260	260	211	309	265	338
	Cargo volume–seats folded [L]	1050	1143	1143	1417	1176	1161	1100	1100	731	1118	1106	1225
	Seats [people]	5	5	5	5	5	5	4	4	4	5	5	5
	Battery capacity-useable [kWh]	45	39.2	64	38.3	36	56	37.9	37.9	28.9	45	45	52
Price [PLN th.]	Min equipment	159.9	158.4	182.4	184.5	155.5	164	169.7	184.2	139.2	128.9	124.9	135.9
	Max equipment	199.9	185.3	232.6	204	195.5	211.1	233.7	242.6	173.4	171.9	155.7	165.6
Range [km]	EVDB range	250	255	400	250	220	325	235	230	185	275	275	310
	WLTP range	320	305	484	311	270	385	308	283	234	330	339	385
	City–cold weather	250	250	390	235	215	320	235	230	180	270	270	305
	City–mild weather	375	385	595	365	325	485	365	355	280	410	415	465
	Highway–cold weather	175	180	280	175	155	230	165	160	130	195	195	220
	Highway–mild weather	225	230	365	230	200	300	215	205	170	250	255	280
	Combined–cold weather	210	215	335	205	185	275	200	195	155	230	230	260
	Combined–mild weather	285	295	460	290	250	375	275	265	215	315	320	355
Energy consumption [Wh/km]	EVDB vehicle consumption	180	154	160	153	164	172	161	165	156	164	164	168
	WLTP rated consumption	176	143	147	138	206	180	153	161	152	170	164	177
	WLTP vehicle consumption	141	129	132	123	133	145	123	134	124	136	133	135
	City–cold weather	180	157	164	163	167	175	161	165	161	167	167	170
	City–mild weather	120	102	108	105	111	115	104	107	103	110	108	112
	Highway–cold weather	257	218	229	219	232	243	230	237	222	231	231	236
	Highway–mild weather	200	170	175	167	180	187	176	185	170	180	176	186
	Combined–cold weather	214	182	191	187	195	204	190	194	186	196	196	200
	Combined–mild weather	158	133	139	132	144	149	138	143	134	143	141	146
Charging time [m]	Wall plug (2.3 kW)	1395	1215	1965	1185	1110	1725	1170	1170	900	1395	1395	1605
	1-phase 16A (3.7 kW)	870	750	1230	735	690	1080	735	735	555	870	870	1005
	1-phase 32A (7.4 kW)	435	375	615	375	390 [5]	600 [2]	375	375	285	435	435	510
	3-phase 16A (11 kW)	300 [6]	255	420	735 [1]	690	1080 [1]	255	255	195	300 [6]	300 [6]	345
	3-phase 32A (22 kW)	300 [6]	255 [4]	420 [4]	375 [3]	390 [5]	600 [2]	255 [4]	255 [4]	195 [4]	300 [6]	300 [6]	180

Table 3. *Cont.*

	Parameter	A1-DS 3 CROSSBACK E-TENSE	A2-Hyundai KONA Electric 39.2 kWh	A3-Hyundai KONA Electric 64 kWh	A4-Hyundai IONIQ Electric	A5-Nissan LEAF	A6-Nissan LEAF e+	A7-BMW i3	A8-BMW i3s	A9-Mini Cooper SE	A10-Opel Corsa-e	A11-Peugeot e-208	A12-Renault ZOE R135
Fast charging time [m]	CHAdeMO 50 kW DC					40	62						
	CCS 50 kW DC	50	50	63	50 [7]			36	36	29	50	50	56 [9]
	CHAdeMO 100 kW DC						35						
	CCS 175 kW DC	27 [12]	50 [10]	44 [11]	47 [8]			36 [10]	36 [10]	29 [10]	27 [12]	27 [12]	56 [9]
	CCS 350 kW DC	27 [12]	50 [10]	44 [11]	47 [8]			36 [10]	36 [10]	29 [10]	27 [12]	27 [12]	56 [9]
Safety [%]	Adult occupant	87	87	87	91	93	93	86	86	79	79	91	89
	Child occupant	86	85	85	80	86	86	81	81	73	77	86	80
	Pedestrian	54	62	62	70	71	71	57	57	66	71	56	66
	Safety assist	63	60	60	82	71	71	55	55	56	56	71	85

[1] 3.7 kW max; [2] 6.6 kW max; [3] 7.4 kW max; [4] 11 kW max; [5] optional 6.6 kW On-board Charger (3.6 kW is standard); [6] optional 11 kW On-board Charger (7.4 kW is standard); [7] 40 kW max; [8] 44 kW max; [9] 46 kW max; [10] 50 kW max; [11] 77 kW max; [12] 100 kW max.

On the basis of Table 3, the decision-making criteria were defined, which were: C1–Top Speed, C2–Acceleration, C3–Total Power, C4–Total Torque, C5–Cargo Volume, C6–Cargo Volume–Seats Folded, C7–Seats, C8–Battery Capacity, C9–Price, C10–Range, C11–Energy Consumption, C12–Charging Time, C13–Fast Charging Time, C14–Safety. It is easy to notice that criteria C9–C14 are uncertain and their values may vary depending on the situation. The other criteria (C1–C8) are certain and their values remain constant. Based on Table 3, the ranges of uncertain criteria values are defined in Table 4. Table 4 therefore shows the distribution parameters $D(v)_{i,j}$ used in the Monte Carlo simulation.

In subsequent iterations of the procedure, new values for uncertain criteria were generated on the basis of Table 4, using continuous uniform distribution for each criterion. These values, together with the values of the certain criteria, were recorded in the performance table and constituted the input for the PROSA-C method. In the PROSA-C method, in each iteration the same preference model was used, specifying the functions and directions of preferences and the weights of criteria. The weights may be defined directly or relative to other criteria [45], with the PROSA-C method expressing them directly. In the preference model, the most difficult to build is to select the preference function and set the values of the indifference and preference thresholds [46,47]. It is assumed that for quantitative criteria one of the functions should be used: V-shape criterion, V-shape criterion with indifference area, or Gaussian criterion. For qualitative criteria, the Usual criterion or Level criterion is most often used [48]. As regards the values of indifference (q) and preference (p) thresholds used in the V-shaped functions, Roy states that the threshold values should be between reliable minimum and maximum values for a given criterion. He also suggests that the values of these thresholds may be based on certain characteristics of the value of the criteria, such as mean value, standard deviation, minimum, maximum, etc. [49]. Deshmukh, on the other hand, notes in the context of the Gaussian criterion that the Gaussian threshold (σ) should be placed between the values of thresholds q and p [48]. Amponsah et al. interpret the threshold σ as the standard deviation of the value of a given criterion [50]. Based on these observations, it can be assumed that the threshold q should be less than the standard deviation of the criterion value and the threshold p should be greater than the standard deviation. In addition, Podvezko and Podvezko propose an approach where the values of thresholds q

and p should be between a minimum and a maximum value for the gap between the values of the alternatives on a given criterion [51,52]. The last parameter of the preference model in the PROSA-C method is the values of sustainability coefficients. Research on the PROSA-C method has shown that in order to maintain the performance scale [−1.1] in accordance with the classic PROMETHEE II method for a problem consisting of 14 criteria, sustainability coefficients with values no greater than 0.3 should be used [10]. Taking into account the above observations, a preference model presented in Table 5 was defined. The weights and functions of preferences were expertly defined taking into account assumptions about the applicability of the preferences function [48]. The preference thresholds were based on the population standard deviation σ_j calculated from all the values of a given criterion (for certain criteria) and all the minimum values of a given criterion (for uncertain criteria). The indifference threshold was set at $q = 0.5\sigma_j$ whereas the preference threshold at $p = 2\sigma_j$ [53]. Such threshold values are in line with previous considerations, and at the same time meet the request of Podviezko and Podviezko for threshold values to be included between a minimum and a maximum range of alternatives for a given criterion. Moreover, based on the analysis in [10], the values of sustainability coefficients were set as $s_j = 0.3$ for each criterion.

Table 4. Ranges of uncertain criteria.

Criterion		A1-DS 3 CROSSBACK E-TENSE	A2-Hyundai KONA Electric 39.2 kWh	A3-Hyundai KONA Electric 64 kWh	A4-Hyundai IONIQ Electric	A5-Nissan LEAF	A6-Nissan LEAF e+	A7-BMW i3	A8-BMW i3s	A9-Mini Cooper SE	A10-Opel Corsa-e	A11-Peugeot e-208	A12-Renault ZOE R135
C9–Price [PLN thousand]	min	159.9	158.4	182.4	184.5	155.5	164	169.7	184.2	139.2	128.9	124.9	135.9
	max	199.9	185.3	232.6	204	195.5	211.1	233.7	242.6	173.4	171.9	155.7	165.6
C10–Range [km]	min	175	180	280	175	155	230	165	160	130	195	195	220
	max	375	385	595	365	325	485	365	355	280	410	415	465
C11–Energy Consumption [Wh/km]	min	120	102	108	105	111	115	104	107	103	110	108	112
	max	257	218	229	219	232	243	230	237	222	231	231	236
C12–Charging Time [m]	min	300	255	420	375	390	600	255	255	195	300	300	180
	max	1395	1215	1965	1185	1110	1725	1170	1170	900	1395	1395	1605
C13–Fast Charging Time [m]	min	27	50	44	47	40	35	36	36	29	27	27	56
	max	50	50	63	50	40	62	36	36	29	50	50	56
C14–Safety [%]	min	54	60	60	70	71	71	55	55	56	56	56	66
	max	87	87	87	91	93	93	86	86	79	79	91	89

Table 5. Preference model.

Criterion	Weight	Preference Direction	Preference Function	Indifference Threshold (q)	Preference Threshold (p)
C1–Top Speed [km/h]	3	Max	5	4	16
C2–Acceleration 0–100 km/h [s]	2	Min	5	0.5	2
C3–Total Power [PS]	1	Max	5	15	61
C4–Total Torque [Nm]	1	Max	5	27	108
C5–Cargo Volume [L]	3	Max	5	34	136
C6–Cargo Volume –Seats Folded [L]	3	Max	5	77	309
C7–Seats [people]	5	Max	1	-	-
C8–Battery Capacity [kWh]	4	Max	3	-	19.4
C9–Price [PLN thousand]	5	Min	3	-	42.4
C10–Range [km]	5	Max	3	-	80

Table 5. *Cont.*

Criterion	Weight	Preference Direction	Preference Function	Indifference Threshold (q)	Preference Threshold (p)
C11–Energy Consumption [Wh/km]	3	Min	5	3	10
C12–Charging Time [m]	4	Min	5	57	230
C13–Fast Charging Time [m]	5	Min	3	-	20
C14–Safety [%]	5	Max	3	-	14

Preference function: 5–V-shape with indifference, 1–Usual criterion, 3–V-shape criterion.

Based on the conducted simulation, the rank acceptability indices b_i^r contained in Table 6 were calculated. Additionally, the values of the rank acceptability indices are graphically shown in Figure 2. One million iterations allowed obtaining accuracy of results at 0.1% with 95% confidence level.

Table 6. Rank acceptability indices for individual alternatives.

Rank	Rank Acceptability Index [%]											
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12**
1 (b_i^1)	3.6	2.3	15.1	3.0	6.7	37.4	0	0	0	10.3	18.0	3.4
2 (b_i^2)	5.7	5.4	14.8	6.9	11.6	19.1	0	0	0	13.4	16.5	6.6
3 (b_i^3)	6.9	7.7	13.4	9.9	13.7	12.9	0.1	0.1	0	13.3	13.5	8.4
4 (b_i^4)	7.9	9.6	12.3	12.2	14.3	9.5	0.4	0.4	0	12.5	11.4	9.6
5 (b_i^5)	8.9	11.1	11.2	13.8	13.8	7.2	0.8	0.8	0	11.7	10.0	10.6
6 (b_i^6)	10.2	12.4	10.2	14.5	12.8	5.4	1.6	1.5	0	10.7	8.8	11.8
7 (b_i^7)	11.7	13.6	8.8	14.4	11.0	3.9	3.0	3.0	0.1	9.8	7.7	13.0
8 (b_i^8)	13.6	14.6	7.1	12.7	8.6	2.6	5.6	5.6	0.6	8.5	6.5	13.9
9 (b_i^9)	15.7	13.6	4.8	8.8	5.3	1.5	11.6	11.4	2.7	6.4	4.9	13.3
10 (b_i^{10})	9.7	6.9	1.8	3.1	1.7	0.4	26.3	26.1	12.6	2.6	2.1	6.7
11 (b_i^{11})	4.5	2.3	0.4	0.7	0.3	0.1	28.3	28.8	31.0	0.7	0.6	2.3
12 (b_i^{12})	1.5	0.5	0	0.1	0	0	22.2	22.2	52.9	0.1	0.1	0.4

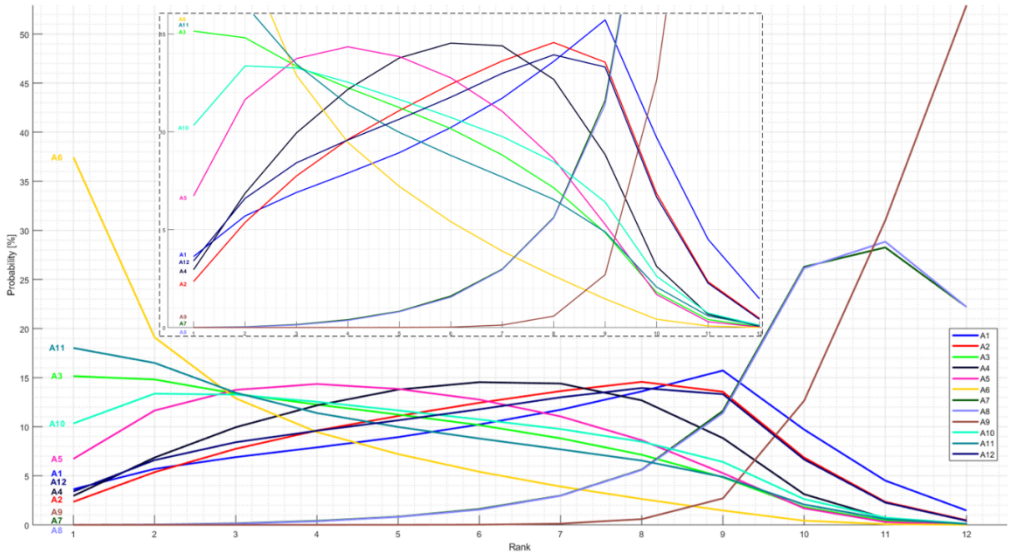


Figure 2. Plot of rank acceptability indices for individual alternatives A1–A12 (and zoomed fragment of the plot).

The analysis of Table 6 and Figure 2 shows that the best alternative, which most often comes first in the simulations, is A6, i.e., Nissan LEAF e+. Slightly worse results are obtained by the group of alternatives A11 (Peugeot e-208), A3 (Hyundai KONA Electric 64 kWh), A10 (Opel Corsa-e), but they are also in the lead and their profiles, determined by the ranks obtained in the simulations, are

similar. The rankings are usually followed by the A5 (Nissan LEAF) and A4 (Hyundai IONIQ Electric) alternatives, which are followed by a group of alternatives with similar ranks: A1 (DS 3 CROSSBACK E-TENSE), A2 (Hyundai KONA Electric 39.2 kWh), A12 (Renault ZOE R135). The last positions in the rankings are usually very similar to A7 (BMW i3), A8 (BMW i3s) and A9 (Mini Cooper SE) alternatives, with Mini Cooper SE achieving the worst rank in over half of the simulation. The results obtained are, of course, still uncertain, i.e., it is impossible to determine the order of alternatives with unknown values for uncertain criteria. However, this order is largely predictable. Furthermore, it is possible to identify a group of vehicles whose purchase is worthwhile and a group of vehicles which should not be taken into account. The first group certainly includes A6—Nissan LEAF e+, and the following vehicles can also be considered: A3—Hyundai KONA Electric 64 kWh, A10—Opel Corsa-e and A11—Peugeot e-208. The second group should certainly include the following: A1—DS 3 CROSSBACK E-TENSE, A2—Hyundai KONA Electric 39.2 kWh, A12—Renault ZOE R135, A7—BMW i3, A8—BMW i3s, A9—Mini Cooper SE.

5. Discussion

The high rankings achieved by alternatives A3 and A6 are due to their good performance in terms of numerous criteria. The values of the criteria for the individual alternatives are shown in Figure 3. Bearing in mind that the preference direction for C1, C3–C8, C10, C14 is maximum and for C2, C9, C11–C13 the minimum is preferred, it is easy to observe that alternatives A3 and A6 have relatively high values of criteria C1–C8, C10, C14. The results are worse for criteria C12–C13 and values for the other criteria are average for the alternatives discussed. This allows alternatives A3 and A6 to obtain high values for ϕ_{net} (compare formula 4). Moreover, these alternatives are relatively balanced on criteria (C12–C13 is an exception). This results in low absolute deviation values (compare formula 5), so they do not receive large penalties for not reaching a sustainable balance of criteria. As a result, they have high PSV values.

As far as the highly rated alternatives A10 and A11 are concerned, they also score well on criteria C7, C9-C10, C13 and, for most of the other criteria, do not deviate significantly from the average. This gives them quite high scores for ϕ_{net}, but they gain higher profits in the PROSA-C method because they are more sustainable than alternatives A3 and A6. This observation can be confirmed by comparing the ranking of acceptability indices obtained in the PROSA-C method (Table 6) with the values obtained with the same assumptions (1 million iterations, accuracy 0.1%, 95% confidence level) in the classic PROMETHEE II method, presented in Table 7.

Comparing Tables 6 and 7, it is easy to see that in the case of alternatives A3 and A6, the PROSA-C sustainability study makes them ranked first less frequently compared to PROMETHEE, while alternatives A10 and A11 are more likely to win the PROSA-C rankings than in PROMETHEE II. Tables 8 and 9 show the rank acceptability indices obtained in the PROSA-C method with sustainability coefficients values of $s_j = 0.5$ and $s_j = 1$ respectively. The aim of this study was to check whether the results would change as the impact of the sustainability of alternatives on the achieved solution increased.

The analysis of Tables 6–9 shows that as the value of the sustainability coefficient increases, the alternatives A10 and A11 as well as A1, A2, A5 gain. In turn, the alternatives A3, A4, A6, A7, A8, A9, A12 lose. This comparison therefore allows dividing the alternatives into two groups, which include more and less sustainable alternatives.

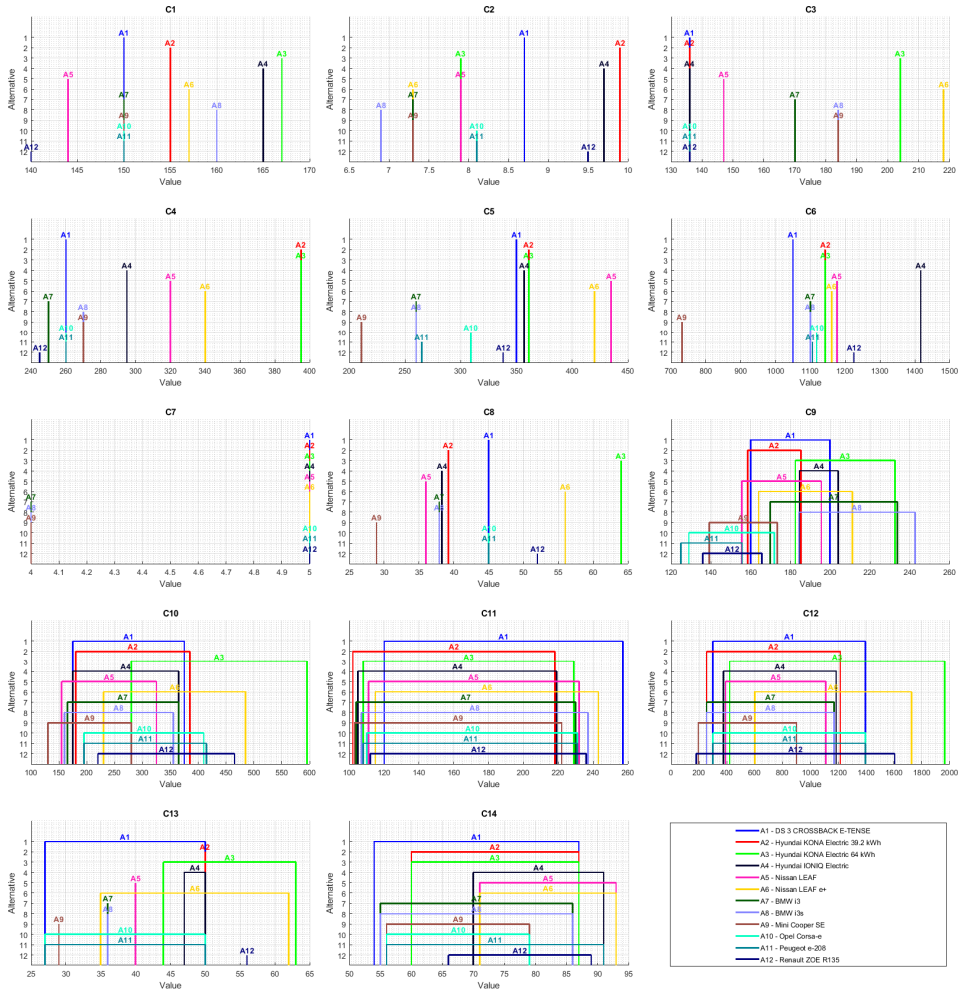


Figure 3. Values of the criteria C1-C14 for the different alternatives A1–A12.

Table 7. Rank acceptability indices for individual alternatives obtained by the PROMETHEE II method.

Rank	Rank Acceptability Index [%]											
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12**
1 (b_i^1)	1.9	1.6	22.8	3.7	4.3	37.5	0.0	0.0	0.0	7.2	16.0	5.0
2 (b_i^2)	3.6	3.9	20.3	8.0	8.9	21.3	0.1	0.1	0.0	10.4	15.3	8.2
3 (b_i^3)	5.0	6.0	16.2	11.2	12.2	13.9	0.2	0.3	0.0	11.6	13.4	10.0
4 (b_i^4)	6.3	8.0	12.7	13.2	14.1	9.6	0.5	0.6	0.0	12.1	11.7	11.1
5 (b_i^5)	7.7	9.8	9.9	14.2	14.8	6.8	0.9	1.2	0.1	12.2	10.5	11.8
6 (b_i^6)	9.4	11.9	7.5	14.4	14.3	4.7	1.7	2.1	0.3	11.9	9.4	12.3
7 (b_i^7)	11.5	13.8	5.3	13.4	12.7	3.1	3.1	3.8	1.0	11.3	8.3	12.6
8 (b_i^8)	14.1	15.6	3.2	11.0	9.9	1.9	5.7	6.8	2.8	10.2	6.9	12.0
9 (b_i^9)	16.7	14.7	1.5	7.2	5.9	0.9	10.7	12.4	8.0	7.6	5.0	9.4
10 (b_i^{10})	12.3	9.0	0.4	2.9	2.2	0.2	19.6	21.9	20.4	3.7	2.4	5.0
11 (b_i^{11})	7.6	4.3	0.1	0.8	0.6	0.0	24.7	24.7	32.9	1.4	0.9	2.0
12 (b_i^{12})	3.9	1.5	0.0	0.1	0.1	0.0	32.8	26.1	34.4	0.4	0.2	0.5

Table 8. Rank acceptability indices for individual alternatives obtained by the PROSA-C method, $s_j = 0.5$.

Rank	Rank Acceptability Index [%]											
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12**
1 (b_i^1)	5.0	2.9	11.6	2.4	8.3	36.1	0.0	0.0	0.0	12.5	18.7	2.5
2 (b_i^2)	7.2	6.4	11.9	6.1	13.0	18.1	0.0	0.0	0.0	14.9	16.9	5.6
3 (b_i^3)	8.1	9.0	11.3	9.2	14.4	12.5	0.1	0.1	0.0	14.0	13.7	7.5
4 (b_i^4)	9.0	10.7	11.2	11.7	14.4	9.5	0.4	0.3	0.0	12.6	11.4	8.8
5 (b_i^5)	9.7	11.9	11.0	13.6	13.4	7.5	0.9	0.6	0.0	11.4	9.9	10.1
6 (b_i^6)	10.7	12.8	10.8	14.7	12.0	5.9	1.7	1.3	0.0	10.1	8.6	11.5
7 (b_i^7)	11.7	13.4	10.4	14.9	10.2	4.5	3.1	2.7	0.0	8.8	7.4	12.9
8 (b_i^8)	12.9	13.5	9.6	13.6	7.8	3.2	5.9	5.2	0.2	7.4	6.2	14.6
9 (b_i^9)	13.8	11.9	7.8	9.7	4.8	1.9	12.3	10.8	1.2	5.5	4.7	15.5
10 (b_i^{10})	8.0	5.6	3.5	3.4	1.5	0.6	30.0	27.2	8.1	2.1	1.9	8.1
11 (b_i^{11})	3.3	1.6	1.0	0.7	0.2	0.1	30.0	33.1	26.3	0.5	0.5	2.7
12 (b_i^{12})	0.7	0.2	0.1	0.0	0.0	0.0	15.6	18.7	64.2	0.0	0.1	0.3

Table 9. Rank acceptability indices for individual alternatives obtained by the PROSA-C method, $s_j = 1$.

Rank	Rank Acceptability Index [%]											
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12**
1 (b_i^1)	9.0	4.2	6.1	1.3	11.6	31.4	0.0	0.0	0.0	17.0	18.6	0.8
2 (b_i^2)	10.5	9.1	7.2	4.3	14.9	16.2	0.0	0.0	0.0	17.4	17.2	3.2
3 (b_i^3)	10.7	11.7	7.6	7.7	15.1	12.0	0.1	0.0	0.0	14.9	14.3	5.8
4 (b_i^4)	11.0	13.1	8.2	10.7	14.3	9.9	0.5	0.1	0.0	12.8	12.1	7.4
5 (b_i^5)	11.2	13.7	9.1	13.2	12.8	8.4	1.2	0.5	0.0	10.8	10.2	8.9
6 (b_i^6)	11.3	13.5	10.0	15.1	11.0	7.0	2.3	1.2	0.0	9.0	8.7	10.8
7 (b_i^7)	11.0	12.4	11.3	16.3	8.8	5.8	4.2	2.5	0.0	7.3	7.2	13.2
8 (b_i^8)	10.3	10.7	12.6	15.3	6.5	4.6	8.0	5.2	0.0	5.5	5.7	15.8
9 (b_i^9)	8.5	7.6	13.5	10.8	3.6	3.1	16.1	11.2	0.3	3.5	3.9	17.9
10 (b_i^{10})	4.6	3.2	9.4	4.4	1.1	1.3	32.9	25.6	2.7	1.4	1.7	11.6
11 (b_i^{11})	1.7	0.8	4.6	0.9	0.2	0.3	29.2	42.4	14.8	0.3	0.4	4.4
12 (b_i^{12})	0.1	0.0	0.5	0.0	0.0	0.0	5.6	11.2	82.2	0.0	0.0	0.3

6. Conclusions

The article considers the problem of analyzing and recommending electric vehicles which are most useful for local government and state administration units. For this purpose, based on publicly available information about tenders for local governments and state administration, the most typical demand of such units for electric vehicles was determined. Next, the vehicles available on the Polish market were analyzed, indicating vehicles meeting the needs of local and state units. Based on the relatively new MCDA method called PROSA-C and on the Monte Carlo method, the most useful vehicles were identified, taking into account the uncertainty of parameters describing individual vehicles. The conducted research indicated that the best choice, based on a defined preference model, is currently Nissan LEAF e+.

As regards the generalized conclusions of the studies carried out, there is a wide range of electric vehicles in B, C and J segments. Twelve such vehicles were included in the studies carried out, but a few others were initially rejected on the grounds that they did not meet the requirements for electric motor power or range. In addition, it is easy to see that many of the parameters characterizing electric vehicles are uncertain and dependent on the use of the vehicles or on external factors such as consumption or the types of charging station available. In relation to the methodological approach used in the studies, its usefulness is obviously not limited to electric vehicles, but the methodology is much more universal. The methodological contribution of the article consists in developing the PROSA method by

a stochastic analysis based on the Monte Carlo method. This allows the PROSA method, naturally designed to work on crisp data, to take into account the uncertainty of the input data. In addition, the PROSA method, indicating the most useful solution, takes into account the sustainability of the alternatives considered and through the option of changing the values of the sustainability coefficients s_j allows seeking more or less sustainable solutions.

The limitations of the studies presented in the article are mainly related to the fact that one preference model, presented in Table 5, has been applied. Therefore, the study presented captures the uncertainty of the parameters of electric vehicles, but does not take into account the possible uncertainty of the weights of the criteria, as well as the possibility of applying other preference functions and other values of the indifference and preference thresholds. Another limitation refers to the constant changes on the Polish electric vehicle market. These changes are related, among other things, to the development of the electric vehicle market and the introduction of new vehicle models on it, and to changes in the legal environment of that market. These restrictions result in further directions of research.

An important methodological research direction will be to develop the PROSA method into Fuzzy PROSA, capable of capturing uncertainty by means of fuzzy numbers, as other MCDA fuzzy methods do [54–56]. As far as practical aspects are concerned, it should be noted that subsidies for individual users have been introduced in Poland for the purchase of electric vehicles [57,58]. This may significantly change the situation on the vehicle market and make electric vehicles more attractive and accessible to the public. It would be interesting to carry out a study to address this situation and consider the attractiveness of electric and hybrid vehicles compared to conventional (combustion) vehicles for individual users.

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