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Multi-criteria evaluation of urban battery electric vehicles for sustainable transport decision-making

Daniel Jan Marcasii[1], Krzysztof Krystosiak[2,3*], Anita Ilska[4*], Tadeusz Sałaciński[2]

[1] MARCASII (independent research initiative), Poland
[2] Faculty of Mechanical and Industrial Engineering, Warsaw University of Technology, ul. Narbutta 85, 02-524 Warsaw, Poland
[3] Faculty of the Creative School, Toronto Metropolitan University, 350 Victoria St., Toronto Ontario M5B 2K3, Canada
[4] Łukasiewicz Research Network – Lodz Institute of Technology, ul. Maria Skłodowska-Curie 19/27, 90-570 Łódz, Poland
* Corresponding author's e-mail: krzysztof.krystosiak@pw.edu.pl

ABSTRACT

This study evaluates urban battery electric vehicles (BEVs) by integrating economically non-measurable technical-operational parameters with economically measurable operational effects to support evidence-based selection. We compare 15 models across 13 parameters prioritized by a panel of 10 electromobility experts and apply weighted aggregated performance (WAP) for linear ordering; measurable effects are analysed using one-year operational data from a fleet of 15 BMW i3 vehicles. The greatest inter-model variability is observed for home-socket charging time (X4), while energy consumption (X5) and 0–100 km/h acceleration (X8) vary least. In the WAP ranking, Opel Corsa-e ranks first, followed by Hyundai Kona 64 kWh and Peugeot e-208; BMW i3 is seventh, and Volkswagen e-Up! ranks last. In real-world operation, the BMW i3 fleet shows an average single-charge range of 185 km (manufacturer WLTP 260 km) and average energy use of 15.8 kWh/100 km over a total distance of 124,766 km. Under the study assumptions, electricity costs are ~2.5× lower than estimated fuel costs for comparable combustion vehicles. These findings indicate that combining WAP-based technical-operational assessment with operational data yields a transparent, replicable comparison of urban BEVs and highlights charging-related parameters as priority targets for optimization, while underscoring the need to evaluate range and costs under actual use conditions.

Keywords: battery electric vehicles, technical-operational parameters, weighted aggregated performance, operational costs, charging time, urban mobility.

INTRODUCTION

The global agenda/idea pursues sustainable development [1], while geopolitical instability and armed conflicts introduce uncertainty into economic, technological and social systems. The growth in fossil fuel extraction, including oil production by the world's largest economies [2], and the withdrawal of some countries from selected climate targets [3] underscore the complexity of adapting environmental goals with national interests and economic competitiveness [4]. This may be due to the fact that some ecological solutions exhibit lower competitiveness compared to traditional technologies or due to conflicting interests of countries possessing key resources [5].

Therefore, in this context, a comprehensive assessment of innovation is necessary, enabling the measurement of monetary and non-monetary effects [6], the assessment of the level of sustainability [7] and the indication of directions for dissemination. These factors influence the acceptance or rejection of given solutions in accordance with the idea of sustainable development [8]. A comprehensive approach can enable a more complete assessment of the actual value of the innovation under analysis, considering economic, ecological, technological, legal, and social aspects [9].

It is important that the innovations developed and implemented are not only competitive and economically viable but also generate measurable ecological and social benefits [10]. Decision-makers from the public and private sectors are faced with the need to select optimal technologies and strategies, considering economically measurable (economic) and non-measurable (technical and operational) aspects [11], as well as factors that are part of the concept of sustainable development [12]. This process is complicated but essential for making informed decisions, especially in sectors that are critical to the global economy and natural environment [13]. An area where an interdisciplinary approach to innovation plays a fundamental role is electromobility, perceived as a key strategy for sustainable transport [14], offering reduced emissions and greater energy efficiency [15]. Electric vehicles, compared to conventional internal combustion engine units, are characterized by a simpler design, associated with fewer components requiring maintenance and potentially lower operating costs [16,17]. The dynamic development of lithium-ion battery technology allows for the gradual increase of their efficiency, extension of vehicle range and reduction of charging time [18]. However, battery production raises environmental and ethical concerns due to intensive resource extraction (lithium, cobalt and nickel) and recycling challenges [19]. There is also a lack of a unified methodology for selecting the best recycling technology [20,21].

Moreover, the ecological efficiency of electric vehicles depends on the energy mix – in countries where fossil fuels dominate, the reduction of CO_2 emissions may be smaller than assumed [22,23].

The literature on the subject also suggests that preferred green technologies – such as renewable energy sources or electric vehicles – do not always develop at a sufficiently fast pace to enable their full market adaptation [24]. Attempts to impose them administratively, without a comprehensive assessment of their actual effectiveness, may lead to serious environmental and economic consequences. The lack of a reliable assessment of innovations may result in:

- high operating and infrastructure costs,
- lack of adaptation of the charging network to the energy systems,
- a paradoxical increase in environmental burdens (e.g. CO_2 emissions in the battery production process).

At the same time, any technological transformation requires a period of adaptation and gradual improvement in competitiveness, and the resistance encountered often results not only from technical barriers but from entrenched interests of groups associated with traditional technologies. Therefore, an objective and scientifically grounded assessment of new technologies is key in guiding decision-making and avoid both premature implementation of costly, immature solutions and rejection of innovations due to market biases [25].

In this context, an important research issue becomes the assessment of electric vehicles, discussed in this article, both in terms of economically measurable effects (e.g. operating costs, energy consumption) and non-measurable effects (technical and operational parameters such as range in the WLTP cycle – mixed cycle, charging time with alternating current (AC) up to 7.4 kW in (h), in order to select the optimal transport solution. This evaluation involves considering many different, often conflicting criteria, which can be complicated but is essential to making informed decisions.

The method of multi-criteria decision analysis (MCDA)/multi-criteria decision-making (MCDM), which is a set of techniques used for evaluating and prioritizing options in situations where there are various, often conflicting criteria, may prove helpful in making a choice [26], particularly in the context of information system evaluation [27], business process composition [28], and public decision-making frameworks as demonstrated by the decision-support software developed by 1000minds, which applies MCDA/MCDM principles in various sectors [1000 minds, 2025]. This method includes four main elements [29]:

- alternatives (or people) from which a ranking or selection will be made;
- criteria (quantitative or qualitative) by which the alternatives are assessed and compared,
- weights representing the relative importance of the criteria. There are many methods for determining the weight of individual criteria, reflecting their relative importance, among which classical and alternative methods can be distinguished,
- decision-makers and stakeholders whose preferences will be represented [30].

In classical MCDA methods, such as:

- Analytic hierarchy process (AHP),
- Technique for order of preference by similary to ideal solution (TOPSIS),

- Elimination and choice translating reality (ELECTRE),
- Preference ranking organization method for enrichment evaluations (PROMETHEE),
- Multi-attribute utility theory/utilités additives (MAUT/UTA),
- Simple additive weighting (SAW),

which are based on weighted criteria, there are aspects that are difficult to precisely define and identify [31], such as:

- determining appropriate weights for different criteria, which often have to be established based on a consensus between objective and subjective methods [32],
- combining qualitative and quantitative criteria into a unified evaluation model,
- in the case of more advanced MCDA methods, such as AHP or PROMETHEE [33], computational complexity may require advanced tools and techniques [34],
- MCDA results may be unstable depending on changes in the weights in the criteria or in the criteria themselves,
- interactions between criteria, which are difficult to consider in standard MCDA methods.

In response to the above challenges related to the limitations of classical methods [35] such as sensitivity to the normalization method, compensability problems, or lack of stability in the ordering of alternatives, their versions were improved, and new methods (so-called alternatives) were developed, such as:

- an alternative to the SAW compensatory method - the WAP (Weighted Aggregated Sum Product Assessment) weighted aggregation method,
- an alternative to the TOPSIS distance method, newly developed (2020) by Dezert et al., the stable preference ordering towards ideal solution (SPOTIS) method,
- other: ARAS, COPRAS, MOORA, MABAC, EDAS, which may prove to be valuable substitutes depending on the characteristics of the problem.

One of the approaches that uses weighting of criteria to evaluate alternatives is the WAP method, often used in comparative analyses, such as the assessment of the financial situation of enterprises, the creation of municipal rankings or the analysis of investment risk. This technique has many advantages, such as simplicity, intuitiveness, flexibility, and wide application in various fields, but also limitations [36], such as:

- the possibility of subjective determination of criteria weights, which affects the objectivity of the results,
- computational complexity in the case of a large number of criteria and alternatives,
- possibility of unstable results depending on changes in the criteria weights or the criteria themselves.

Another example of a method that is of relevant importance in the decision-making process in complex problems is the SPOTIS method, which is flexible and objective [37], as it allows for an assessment without prior determination of criteria weights [38], is based on comparisons with the ideal solution, and not on direct comparisons between alternatives, and can be used in various fields, such as the evaluation of technical devices, the selection of suppliers, or risk analysis [39,40]. At the same time, this method has less flexibility in adapting users' preferences compared to other MCDA methods [41] and limitations in practical application related to specific data requirements and calculations and their complexity [42].

The choice of the appropriate approach and method should take into account the specific context of the analysis and the availability of computational resources [43].

In relation to the process of evaluating electric vehicles undertaken in this article, the key factor determining the reliability of the results is the appropriate selection of evaluation criteria. An imprecise definition of the purpose of the analysis leads to incorrect weight assignments and subjective judgments, irrespective of the decision-making method used. For example, in analysis urban electric vehicles, acceleration and torque may be the top priorities, while for long-distance transport, range and battery capacity will be key. In the absence of a unequivocal definition of the purpose of the vehicle, experts may assign excessive importance to universal parameters, which leads to incorrect hierarchization of features and incorrect assignment of weights to criteria and thus lowering the accuracy of the analysis. Therefore, in the case of using expert methods, e.g. within the WAP method, which are necessary to assess technical and operational parameters and which use flexibility in shaping the weights of criteria, it is important to avoid bias, ensure consistency of the assessment and minimize the impact of incorrect hierarchization of features and incorrect allocation of weights by precisely defining the criteria and adapting them to the context of use. This is particularly important in the case of means of transport with electric drive, which are available in different markets and differ in terms of the technological solutions used and access to charging infrastructure [44].

In order to properly select a vehicle for the operating conditions, it is important to take into account the type of electric drive and the parameters related to the charging power, because they affect operational efficiency. The crucial criterion for classifying electric vehicles is the division based on the method of generating and storing energy, which distinguishes the following categories: HEV, PHEV, EREV, BEV, FCEV. Each of these types is characterized by unique technological features that determine their use in various operating conditions. Due to the variety of technologies used in electric vehicles, their proper selection should take into account not only the method of generating and storing energy, but also the technical parameters related to the charging power [45], i.e. vehicles: small 50 ≤150 kW, mid-range 120 – 150 kW, luxury ~300/350 kW. These aspects are crucial for practical operation and the effectiveness of use under different operating conditions and their intended purposes. In response to the above challenges of assessment reliability which constitute a significant problem in the context of assessing electric vehicles and innovations related to sustainable development, covering:

- lack of standardized assessment methods,
- lack of complete and easily accessible data regarding the entire vehicle life cycle,
- variable technical and operational conditions,

A comprehensive method for assessing technological innovations and services was developed. In its basic version, which is the subject of this article, it takes into account both measurable and economically non-measurable effects and can be extended to include another stage of multidimensional assessment of the level of multidimensional sustainability and directions of dissemination. The article presents a basic variant of the developed method using an electric vehicle as an example, which can be adapted to other sectors such as textiles, printing, aviation or defence.

This research is not limited to identifying the "best" electric vehicle based on a set of technical and operational parameters and the analysis and evaluation of the selected vehicle model. Instead, they focus on analyzing the relationships and discrepancies between multiple vehicle models, using an orderly multi-criteria evaluation model and taking into account the operating conditions and costs characteristic to a specific user group.

The aim is to formulate generalized conclusions on how the selected parameters affect user decisions, performance expectations and trade-offs in a systemic approach. In this context, it is also to consider that depending on the adopted important evaluation criteria, the selection of technical and operational parameters and destination of vehicles, hierarchization may change, which may significantly affect the interpretation of the results.

The paper was sought answers to the following research questions:

1. What are the key differences between selected models of electric vehicles?
2. How do changes in the values of individual technical and operational parameters affect the reduction of discrepancies between models of electric vehicles?
3. What are the possibilities of hierarchizing electric cars from the urban segment in terms of technical and operational parameters?
4. How does the analysis of measurable and non-measurable economic effects affect the holistic assessment of electric vehicles?

Subject of research

The subject of the research are electric vehicles selected based on the following assumptions:

- Type of BEV drive (battery-powered electric vehicle),
- Classification based on charging power: small vehicles (urban segment) with charging power in the range of 50 <150 kW,

A set of technical and operational parameters was selected taking into account the actual needs of enterprises, organizations and individual users as well as the existing charging infrastructure (e.g. density of public charging stations in each city or country). This approach allows for reliable prioritization of vehicle features and the process of weighting the assessment criteria, directing the analysis in line with the expectations of stakeholders and decision-makers. The identification of economically non-measurable effects was carried out using comparative analysis on a set of 15 most popular urban electric vehicles available on the Polish market, including the following models:

- Skoda CITIGOe iV
- Volkswagen e-UP!
- Opel Corsa-e
- Peugeot e-208
- Renault Zoe R110
- Renault Zoe R135
- Renault R135
- Nissan Leaf
- Nissan Leaf e+
- Hyundai Kona 39.2 kWh
- Hyundai Kona 64 kWh
- BMW i3
- BMW i3s
- Hyundai Ioniq
- Mini Cooper SE Electric.

In order to determine the economically measurable effects associated with the operation of an electric vehicle (BEV), the analysis was carried out on the example a fleet of 15 electric vehicles - the BMW i3 model, introduced in the organizational unit at the end of 2018. BMW i3 vehicles were operated by 15 units of a specific organization with headquarters located throughout Poland (location signature M1-15). The study was conducted based on operational data collected during one year of fleet use for administrative purposes and for travel between unit locations.

The organization whose vehicles were researched works for sustainable development, and its employees at the time of the research had both theoretical and practical knowledge from the scope of sustainable development and electromobility.

Assessment of economically measurable and non-measurable features

The main objective of the research was to assess the non-measurable features (technical and operational parameters) and economically measurable features of electric vehicles. The first analysis of individual vehicles and their technical and operational parameters was carried out on the basis of data from publicly available technical specifications of electric cars from their manufacturers, catalogues of individual models and official websites of manufacturers. Missing data was supplemented through direct interviews with electric vehicle dealers. The second stage was based on the actual operating results of the BMW i3 fleet purchased by the organizational unit, which were compared with the technical data provided by the manufacturer of this model.

Selection and hierarchy (weighting) of technical and operational parameters of urban electric vehicles

The analysis directed on assessing non-measurable features, due to the wide range of technical and operational parameters of electric vehicles, required the selection of those most crucial for assessing their performance and usefulness in practical operation.

In order to ensure the reliability and credibility of the analysis, expert research was conducted with the participation of specialists* from the automotive sector (electromobility). The experts were presented with an extensive set of technical and operational parameters, from which those of key importance to the individual customer were jointly selected, taking into account the charging infrastructure and the place of use of the vehicle. Detailed opinions were collected from all users. Each stage of the study was supervised by the researcher controller, which enabled full identification and hierarchization of research problems. Hierarchization and weights for each technical-utility parameter are presented in Table 1. It should be emphasized that it is important that the adopted ranks reflect the actual impact of individual features on the functionality of the assessed vehicles, as their values are crucial for the final ranking of the set.

The above hierarchization of individual technical and operational parameters together with the assigned rank coefficients may suggest that the total weight of an electric vehicle has not been considered a key parameter in the assessment of operational efficiency. However, it is a feature with a significant impact on key operational aspects, such as range, energy consumption or vehicle dynamics, which directly affects operational efficiency [46]. The selection of the parameters subjected to analysis was based on their importance both from the perspective of the end user and the actual technical conditions and availability of charging infrastructure in Poland in the analyzed period.

In the process of classifying parameters and allocation weights to individual parameters, potential correlations between them were taken into account to ensure their adequacy for the target group of individual users. This approach allowed for a structured and objective assessment, minimizing the risk influence of subjective opinions. This task required a thorough understanding of the objects being assessed. If respondents were not adequately prepared, there would be a risk of incorrectly allocation ranking coefficients to individual features, which could affect the reliability of the results. In order to identify a vehicle that stands out from the competition or to conduct a comparative analysis aimed at improving a given product, it is necessary to conduct a detailed analysis of the technical and operational parameters of the selected vehicle in relation to other models with similar characteristics. A comprehensive assessment of the non-measurable effects was conducted in a representative group of 15 electric vehicle models and their corresponding 13 technical and operational parameters arranged in Table 2. Each of the selected vehicles is characterized by different data regarding selected technical and operational parameters. Based on the collected data, in addition to a detailed analysis of technical and operational parameters, key factors determining purchase decisions were also identified. The most important include:

- purchase price,
- technical and operational parameters, especially operating range and charging time,
- operating costs.

Identification of these factors allows for a better understanding of the expectations and priorities of users when choosing an electric vehicle, which is necessary for further analysis and assessment of the competitiveness of models available on the market.

Analysis of economically non-measurable features – weighted aggregated performance

This article presents the weighted aggregated performance (WAP) multidimensional comparative analysis method, but depending on the nature of the problem, at this stage of the evaluation, it is possible to select the optimal multi-criteria decision analysis technique from among the MCDA/MCDM methods. The comparison of the impact of the variables listed in Table 3 was carried out based on the following calculation procedure, which enabled the ordering of all analyzed vehicle models in terms of the level of importance (from the highest to the lowest) of all selected technical and operational parameters (Table 10).

Table 1. Hierarchization of individual technical and operational parameters of urban BEVs with assigned rank coefficients

No.	Feature	Ranks
1.	Range in WLTP cycle - Combined cycle (km)	11.55
2.	Charging time with alternating current (AC) up to 7.4 kW (h)	11.04
3.	Battery capacity (kWh)	10.02
4.	Home charging socket (h)	9.52
5.	Energy consumption (kWh/100 km)	9.27
6.	Fast charging (DC) three-phase current (h)	9.01
7.	Electric motor power (kW)	7.74
8.	Acceleration 0-100 km/h (s)	7.36
9.	Boot capacity (L)	6.98
10.	Maximum speed on electric drive (km/h)	6.22
11.	Charger power (kW)	5.97
12.	Electric engine: max torque (Nm)	4.18
13.	Current weight (kg)	1.14

Note: * The evaluation process involved 10 experts in the field of electromobility, representing the leading manufacturers of electric cars in Poland. The panel of experts was selected in a way that ensured representativeness and a high level of expertise. Their assessments were verified based on actual operational data, which minimizes the risk of subjective bias and increases the reliability of the analyzed parameters.

Statistical analysis

For the individual technical and operational parameters X_{ij} of the analyzed electric car models (CAR), the following were calculated:

a) arithmetic mean expressed by the formula

$$\bar{X}_i = \frac{1}{n}\sum_{\substack{i=1\\j=1}}^{n} X_{ij} \tag{1}$$

b) standard deviation $s_{\bar{X}_i}$

$$s_{\bar{X}_i} = \sqrt{\frac{\sum_{\substack{i=1\\j=1}}^{n}(X_{ij}-\bar{X}_i)^2}{n(n-1)}}$$

(Gaussian distribution for n > 11) (2)

c) range R_i

$$R_i = X_{i\,max} - X_{i\,min} \tag{3}$$

where: $X_{i\,max}$ – maximum value for i-th parameter, $X_{i\,min}$ – minimum value for i-th parameter.

d) coefficient of variation of the standard deviation V_i

Table 2. Breakdown of technical and operational parameters of electric vehicles

No.	Electric vehicles	Product designation	Features (1–7)						
			Range in WLTP cycle - Combined cycle (km)	Charging time with alternating current (AC) up to 7.4 kW (h)	Battery capacity (kWh)	Home charging socket (h)	Energy consumption (kWh/100 km)	Fast charging (DC) three-phase current (h)	Electric motor power (kW)
1	Skoda CITIGOe iV	CAR 1	265	248	36.8	757	14.6	60	61
2	Volkswagen e-UP!	CAR 2	258	327	32.3	972	14.4	60	61
3	Opel Corsa-e	CAR 3	330	325	50.0	1680	16.9	30	100
4	Peugeot e-208	CAR 4	340	440	50.0	1443	13.8	25	100
5	Renault Zoe R110	CAR 5	395	513	52.0	2233	15.0	65	80
6	Renault Zoe R135	CAR 6	386	513	52.0	2233	15.0	65	100
7	Volkswagen e-Golf	CAR 7	233	320	35.8	1020	15.3	45	100
8	Nissan Leaf	CAR 8	270	450	40.0	1260	20.6	60	110
9	Nissan Leaf e+	CAR 9	385	690	62.0	1920	18.5	90	160
10	Hyundai Kona 39,2	CAR 10	289	575	39.2	1140	15.0	57	99
11	Hyundai Kona 64	CAR 11	449	370	64.0	1860	15.4	75	150
12	BMW i3	CAR 12	260	258	42.2	900	15.8	42	125
13	BMW i3s	CAR 13	260	258	42.2	900	16.4	42	135
14	Hyundai Ioniq	CAR 14	331	365	38.3	2130	15.5	57	100
15	Mini CooperSE E.	CAR 15	216	265	28.9	1200	18.0	35	135

No.	Electric vehicles	Product designation	Features (8–13)					
			Acceleration 0–100 km/h (s)	Boot capacity (L)	Maximum speed on electric drive (km/h)	Charger power (kW)	Electric engine: max torque (Nm)	Current weight (kg)
1	Skoda CITIGOe iV	CAR 1	12.5	250	130	40	210	1160
2	Volkswagen e-UP!	CAR 2	11.9	250	130	40	210	1235
3	Opel Corsa-e	CAR 3	8.1	267	150	100	260	1455
4	Peugeot e-208	CAR 4	8.1	265	130	100	260	1455
5	Renault Zoe R110	CAR 5	11.4	388	135	50	225	1502
6	Renault Zoe R135	CAR 6	9.5	388	140	50	245	1502
7	Volkswagen e-Golf	CAR 7	9.6	341	150	40	290	1615
8	Nissan Leaf	CAR 8	7.9	435	144	50	320	1594
9	Nissan Leaf e+	CAR 9	6.9	420	157	50	340	1723
10	Hyundai Kona 39,2	CAR 10	9.7	332	155	50	395	1535
11	Hyundai Kona 64	CAR 11	7.6	332	167	50	395	1685
12	BMW i3	CAR 12	7.3	260	150	50	250	1343
13	BMW i3s	CAR 13	6.9	260	160	50	270	1365
14	Hyundai Ioniq	CAR 14	9.9	357	165	50	295	1527
15	Mini CooperSE E.	CAR 15	7.3	211	150	100	270	1365

Note: Own research based on catalogue data from manufacturers [47].

Table 3. List of variables indicating individual features (technical and operational parameters) of objects

Variable designation	Unit of measurement	Variable name	Type of feature	Type and name of measurement scale
X_1	[km]	Range in WLTP cycle - Combined cycle	Quantitative continuous	Strong ratio
X_2	[min]	Charging time with alternating current (AC) up to 7.4 kW	Quantitative continuous	Strong ratio
X_3	[kWh]	Battery capacity	Quantitative continuous	Strong ratio
X_4	[min]	Home charging socket	Quantitative continuous	Strong ratio
X_5	[kWh/100km]	Energy consumption	Quantitative continuous	Strong ratio
X_6	[min]	Fast charging (DC) three-phase current (h)	Quantitative continuous	Strong ratio
X_7	[kW]	Electric motor power	Quantitative continuous	Strong ratio
X_8	[s]	Acceleration 0-100 km/h	Quantitative continuous	Strong ratio
X_9	[L]	Boot capacity	Quantitative continuous	Strong ratio
X_{10}	[km/h]	Maximum speed on electric drive	Quantitative continuous	Strong ratio
X_{11}	[kW]	Charger power	Quantitative continuous	Strong ratio
X_{12}	[Nm]	Electric engine: max torque	Quantitative continuous	Strong ratio
X_{13}	[kg]	Current weight	Quantitative continuous	Strong ratio

$$V_i = \frac{s_{X_i}}{\bar{X}_i} \times 100\% \tag{4}$$

where: $\bar{X}_i \neq 0$, s_{X_i} is the standard deviation of the sample, $\bar{X}_i$ is the arithmetic mean of the sample.

The coefficient of variation was estimated to illustrate the differentiation of individual features (technical and operational parameters) of the tested electric car models. The results of the above calculations are presented in Table 4. The above shows that:

- among the models included in the study, the greatest variation in values occurs for charging time from a household socket (X4), while the most similar values occur for energy consumption (X5) and acceleration (X8).
- the greatest variability occurs sequentially in the following parameters: charger power (X11), charging time using a household socket (X4), and AC charging time up to 7.4 kW (X2). This indicates that manufacturers are advised to implement measures to reduce the observed discrepancies.
- the fast-charging time of an electric vehicle depends not only on the available charging infrastructure, but primarily on the maximum power accepted by the vehicle.

Even if the user connects the vehicle to a high-power charging station, the charging process will be limited to the maximum value supported by the built-in on-board charger (for AC charging) or the battery system (for DC charging). This is particularly important during travel, when the limited charging power of the vehicle can affect the efficiency of the energy replenishment process. Additionally, the charging management strategies implemented by manufacturers – including among others battery temperature control, power limitations at high charge levels, and differences in the architecture of charging systems – can affect the charging time and explain some discrepancies in the analyzed data [48].

Data standardization

Data normalization using the standardization method was performed to determine the discrepancies in the values of individual technical and operational parameters in relation to the average result. The standardization process, the results of

Table 4. Statistical analysis

Variable	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}
$\bar{X}_i$	311	394	44	1443	16	54	108	9	317	148	58	282	1471
s_{Xi}	69	132	10	523	2	17	29	2	70	12	22	58	157
$X_{i\,min}$	216	248	29	757	14	25	61	7	211	130	40	210	1160
$X_{i\,max}$	449	690	64	2233	21	90	160	13	435	167	100	395	1723
R_i	233	442	35	1476	7	65	99	6	224	37	60	185	563
V_i	22.2	33.5	22.7	36.2	12.5	31.5	26.9	22.2	22.1	8.1	37.9	20.6	10.7

which are presented in Table 5, is presented by the equation:

$$Z_{ij} = \frac{x_{ij} - \bar{x}_j}{S_{xj}} \tag{5}$$

Determining the nature of variables (stimulants, nominants, destimulants)

Based on the content analysis, the nature of variables was identified. These included stimulants and destimulants (Table 6). No nominant features were identified.

Determination of a development benchmark

Benchmark z0 = [z_{01} z_{02} … z_{0m}]

where:

$$z_{0j} = \begin{cases} \max\limits_{i} z_{ij} & for\ stimulant \\ \min(i)\limits_{i} z_{ij} & for\ destimulant \end{cases} \tag{6}$$

and anti-pattern z_{-0} = [z_{-01} z_{-02} … z_{-0m}],

where:

$$z_{-0j} = \begin{cases} \min\limits_{i} z_{ij} & for\ stimulant \\ \max\limits_{i} z_{ij} & for\ destimulant \end{cases} \tag{7}$$

The obtained data are summarized in Table 7. In this study, the following variables were identified as stimulants of the technical and operational development of electric vehicles:

- X1 – driving range: The best result (2.00) was achieved by CAR 11, the worst (1.38) by CAR 15.
- X3 – battery capacity: The best result (1.91) was achieved by CAR 11, the worst (1.50) by CAR 15.
- X7 – motor power: The best result (1.80) was achieved by CAR 9, the worst (1.61) by CAR 1 and CAR 2.

Table 5. Standardization

Electric car	Variable												
	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}
CAR 1	-0.67	-1.11	-0.74	-1.31	-0.78	0.35	-1.61	1.91	-0.95	-1.41	-0.81	-1.24	-1.98
CAR 2	-0.77	-0.51	-1.17	-0.90	-0.89	0.35	-1.61	1.59	-0.95	-1.41	-0.81	-1.24	-1.50
CAR 3	0.27	-0.53	0.55	0.45	0.49	-1.37	-0.27	-0.47	-0.71	0.20	1.90	-0.38	-0.10
CAR 4	0.42	0.34	0.55	0.00	-1.22	-1.66	-0.27	-0.47	-0.74	-1.41	1.90	-0.38	-0.10
CAR 5	1.22	0.90	0.74	1.51	-0.56	0.64	-0.95	1.31	1.01	-1.01	-0.36	-0.98	0.20
CAR 6	1.09	0.90	0.74	1.51	-0.56	0.64	-0.27	0.29	1.01	-0.61	-0.36	-0.64	0.20
CAR 7	-1.14	-0.56	-0.83	-0.81	-0.39	-0.51	-0.27	0.34	0.34	0.20	-0.81	0.13	0.92
CAR 8	-0.60	0.42	-0.43	-0.35	2.54	0.35	0.08	-0.58	1.68	-0.28	-0.36	0.64	0.78
CAR 9	1.07	2.23	1.71	0.91	1.38	2.07	1.80	-1.12	1.46	0.76	-0.36	0.99	1.60
CAR 10	-0.32	1.36	-0.50	-0.58	-0.56	0.18	-0.30	0.39	0.21	0.60	-0.36	1.93	0.41
CAR 11	2.00	-0.18	1.91	0.80	-0.34	1.21	1.45	-0.74	0.21	1.57	-0.36	1.93	1.36
CAR 12	-0.74	-1.03	-0.21	-1.04	-0.12	-0.68	0.59	-0.91	-0.81	0.20	-0.36	-0.55	-0.81
CAR 13	-0.74	-1.03	-0.21	-1.04	0.19	-0.68	0.94	-1.12	-0.81	1.00	-0.36	-0.21	-0.67
CAR 14	0.29	-0.22	-0.59	1.31	-0.28	0.18	-0.27	0.50	0.57	1.41	-0.36	0.22	0.36
CAR 15	-1.38	-0.98	-1.50	-0.47	1.10	-1.08	0.94	-0.91	-1.51	0.20	1.90	-0.21	-0.67

Table 6. Summary of variables representing the technical and operational parameters of the analyzed electric vehicle models

Variable	Description	Nature of the variable
X_1	Range in WLTP cycle - Combined cycle (km)	Stimulant
X_2	Charging time with alternating current (AC) up to 7.4 kW (h)	Destimulant
X_3	Battery capacity (kWh)	Stimulant
X_4	Home charging socket (h)	Destimulant
X_5	Energy consumption (kWh/100 km)	Destimulant
X_6	Fast charging (DC) three-phase current (h)	Destimulant
X_7	Electric motor power (kW)	Stimulant
X_8	Acceleration 0-100 km/h (s)	Destimulant
X_9	Boot capacity (L)	Stimulant
X_{10}	Maximum speed on electric drive (km/h)	Stimulant
X_{11}	Charger power (kW)	Stimulant
X_{12}	Electric engine: max torque (Nm)	Stimulant
X_{13}	Current weight (kg)	Destimulant

Table 7. Benchmark i anti-pattern for individual variable

Variables	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
Benchmark	2.00	-1.11	1.91	-1.31	-1.22	-1.66	1.80	1.91	1.68	1.57	1.90	1.93	-1.98
Anti-pattern	-1.38	2.23	-1.50	1.51	2.54	2.07	-1.61	-1.12	-1.51	-1.41	-0.81	-1.24	1.60

- X9 – trunk capacity: The best result (1.68) was achieved by CAR 8, the worst (1.51) by CAR 15.
- X10 – Maximum speed: The best result (1.57) was achieved by CAR 11, the worst (1.41) by CAR 1, CAR 2, and CAR 4.
- X11 – charger power: The best result (1.90) was achieved by CAR 3, CAR 4, and CAR 15, the worst (0.81) by CAR 1, CAR 2, and CAR 7.
- X12 – maximum torque: The best result (1.93) was achieved by CAR 10 and CAR 11, the worst (1.24) by CAR 1 and CAR 2.

The following variables were identified as destimulants of technical and operational development:

- X2 – AC charging time: The best result (-1.11) was achieved by CAR 1, the worst (2.23) by CAR 9.
- X4 – household socket charging time: The best result (-1.31) was achieved by CAR 1, the worst (1.51) by CAR 5 and CAR 6.
- X5 – energy consumption: The best result (-1.22) was achieved by CAR 4, the worst (2.54) by CAR 8.
- X6 – fast DC charging time: The best result (-1.66) was achieved by CAR 4, the worst (2.07) by CAR 9.
- X8 – acceleration (0–100 km/h): The best result (-1.12) was achieved by CAR 8 and CAR 13, the worst (1.91) by CAR 1.
- X13 – curb weight: The best result (-1.98) was achieved by CAR 1, the worst (1.60) by CAR 9.

Higher values of stimulants indicate a better technical and operational evaluation of the vehicle, suggesting greater competitiveness, for example, in terms of driving range per charge. Conversely, lower values of destimulants indicate greater competitiveness, for example, in terms of shorter AC charging time.

Determination of the distance of each object from the benchmark using the Euclidean metric

The estimation results are presented in Table 8.

$$d_{i0} = \sqrt{\sum_{j=1}^{k} (Z_{ij} - Z_{0j})^2} \tag{8}$$

Determining the development measure z_i used to rank the studied objects

$$z_i = 1 - \frac{d_{i0}}{d_0} \tag{9}$$

Table 8. Comparison of electric vehicle models based on the relative taxonomic development measure and identification of the smallest and largest data discrepancies: max = 9.06; min = 1.02

Electric car	CAR 1	CAR 2	CAR 3	CAR 4	CAR 5	CAR 6	CAR 7	CAR 8	CAR 9	CAR 10	CAR 11	CAR 12	CAR 13	CAR 14	CAR 15
CAR 1	0.00	1.04	5.69	5.48	5.26	5.62	4.52	6.56	9.06	5.68	8.27	4.39	5.18	5.54	5.90
CAR 2	1.04	0.00	5.43	5.12	4.83	5.15	4.07	6.18	8.66	5.18	8.04	4.21	5.01	5.09	5.62
CAR 3	5.69	5.43	0.00	2.57	4.78	4.29	4.18	4.84	6.49	4.70	5.55	3.40	3.56	3.85	3.33
CAR 4	5.48	5.12	2.57	0.00	4.63	4.28	4.57	5.87	7.14	4.82	6.30	4.03	4.59	4.89	4.51
CAR 5	5.26	4.83	4.78	4.63	0.00	1.35	4.71	5.16	5.62	4.66	5.58	5.50	5.96	3.58	6.91
CAR 6	5.62	5.15	4.29	4.28	1.35	0.00	4.32	4.58	4.67	4.13	4.65	4.86	5.20	3.01	6.34
CAR 7	4.52	4.07	4.18	4.57	4.71	4.32	0.00	3.80	6.43	2.99	5.72	2.86	3.10	3.04	4.45
CAR 8	6.56	6.18	4.84	5.87	5.16	4.58	3.80	0.00	4.66	4.06	5.69	4.64	4.58	4.21	5.20
CAR 9	9.06	8.66	6.49	7.14	5.62	4.67	6.43	4.66	0.00	5.27	3.72	6.82	6.56	5.36	7.77
CAR 10	5.68	5.18	4.70	4.82	4.66	4.13	2.99	4.06	5.27	0.00	4.78	4.30	4.28	3.21	5.40
CAR 11	8.27	8.04	5.55	6.30	5.58	4.65	5.72	5.69	3.72	4.78	0.00	5.86	5.52	4.37	7.19
CAR 12	4.39	4.21	3.40	4.03	5.50	4.86	2.86	4.64	6.82	4.30	5.86	0.00	1.02	4.03	3.15
CAR 13	5.18	5.01	3.56	4.59	5.96	5.20	3.10	4.58	6.56	4.28	5.52	1.02	0.00	3.97	3.11
CAR 14	5.54	5.09	3.85	4.89	3.58	3.01	3.04	4.21	5.36	3.21	4.37	4.03	3.97	0.00	5.14
CAR 15	5.90	5.62	3.33	4.51	6.91	6.34	4.45	5.20	7.77	5.40	7.19	3.15	3.11	5.14	0.00

where: $d_0 = \bar{d}_0 + 2S_0$ (10)

$$\bar{d}_0 = \frac{1}{m}\sum_{i=1}^{m} d_{i0} \quad (11)$$

$$S_0 = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(d_{i0} - \bar{d}_0)^2} \quad (12)$$

where: z_i – synthetic development measure, d_0 – distance of the object from the benchmark, $\bar{d}_0$ – arithmetic mean of the calculated distances from the development benchmark, S_0 – standard deviation of the calculated distances from the development benchmark.

The summary of the obtained data is presented in Table 9.

Linear ordering of city electric car models based on estimated development measure

The developed ranking of the analyzed city electric car models in terms of technical and operational parameters is presented in Table 10.

Analysis of measurable features of an economically selected vehicle model – BMWi3

The analysis of the economic efficiency related to the operation of an electric vehicle based on a fleet of 15 electric vehicles – the BMW i3 model, was carried out based on descriptive statistics in the form of a tabular description. The study omitted the costs of registration, periodic technical inspections, third-party liability and AC insurance, and replacement or repair of damaged traction batteries for the following reasons:

- the process of registering an electric vehicle is analogous to combustion vehicles,

Table 9. Summary of the analyzed electric vehicle models, their distances from the benchmark, and the synthetic development measure

Electric vehicle models	Vehicle-to-benchmark distance	Distance d_0	Measure of development z_i
CAR 1	7.95	11.85	0.33
CAR 2	8.19		0.31
CAR 3	6.14		0.48
CAR 4	6.46		0.45
CAR 5	7.28		0.39
CAR 6	6.96		0.41
CAR 7	7.02		0.41
CAR 8	7.79		0.34
CAR 9	8.15		0.31
CAR 10	6.50		0.45
CAR 11	6.32		0.47
CAR 12	6.66		0.44
CAR 13	6.55		0.45
CAR 14	6.49		0.45
CAR 15	7.52		0.37

- new vehicles do not require periodic technical inspections for the first three years,
- third party liability insurance premiums are similar to combustion vehicles,
- contradictory information on the procedure for replacing or repairing damaged traction batteries and the costs associated with them.

As a result of the reconnaissance conducted with the manufacturer of the BMW i3 electric vehicle during the course of the study, it was not possible to determine whether post-warranty repair or replacement of the traction battery is feasible. The inability to repair the battery in the BMW i3 would classify the vehicle as non-repairable. The lack of a unequivocal response from the manufacturer prevented this aspect from being included in the analysis, which in turn makes it impossible to definitively assess whether the vehicle, after battery degradation, should be classified as repairable or non-repairable. This information would also have an impact on, among others, the technological, economic, and environmental dimensions in the subsequent stage of the evaluation method, which – due to the limited scope of this study – has not been presented in its entirety. The inclusion of a hypothetical battery replacement scenario could have influenced the final conclusions of the analysis; however, due to incomplete data, such an analysis was not carried out.

Descriptive statistics

he use of descriptive statistics results from the possibility of clear and structured presentation of data, ensuring their transparent interpretation and identification of key relationships, which is important for further analysis and formulation of conclusions. As a tool for the analysis of empirical data, descriptive statistics allows for the systematic development of information regarding the studied population without the need to refer to probabilistic methods. The research used data obtained from the organizational unit, which together with their analysis are included in Table 11.

Costs of purchasing electric vehicles – the lowest cost of purchasing a BMW i3 was PLN 154,000, while the highest was PLN 179,878.02. The total cost of purchasing 15 vehicles was PLN 2,557,698.19.

The actual range of the vehicle on a single charge – the average actual range, determined on the basis of the measurements carried out, was 185 km. The range declared by the manufacturer in the WLTP mixed cycle is 260 km. The difference of 75 km may result from, among other things, operating conditions, driving style and environmental factors affecting energy consumption.

Table 10. Ranking of city electric car models

Place	CAR	Measure of development z_i
1	CAR 3	0.482
2	CAR 11	0.467
3	CAR 4	0.455
4	CAR 14	0.452
5	CAR 10	0.451
6	CAR 13	0.447
7	CAR 12	0.438
8	CAR 6	0.412
9	CAR 7	0.408
10	CAR 5	0.385
11	CAR 15	0.358
12	CAR 8	0.343
13	CAR 1	0.329
14	CAR 9	0.312
15	CAR 2	0.309

Unit price of energy – the lowest unit cost of energy was recorded in the city M5 (PLN 0.48/kWh), while the highest in the local units M11 and M12 (PLN 0.80/kWh). The average unit price of energy was PLN 0.68/kWh.

Total energy consumed during the year – the lowest annual energy consumption was recorded for the vehicle from the local unit M2 and amounted to 717 kWh, while the highest consumption was recorded for the vehicle from the local unit M5 at 2467 kWh. The total annual energy consumption for the entire fleet of 15 electric vehicles was 19,528 kWh.

Average energy consumption during the year – average energy consumption values for individual vehicles were in the range of 11–23 kWh/100 km, with the average energy consumption for the entire fleet being 15.8 kWh/100 km, which is in line with the values declared by the manufacturer.

Annual mileage – the smallest annual distance travelled by a single vehicle was 3769 km (vehicle from the local unit M8), while the largest recorded mileage was 14,899 km (vehicle from the local unit M5). In total, the fleet of 15 electric vehicles travelled 124,766 km in a year, which is more than three times the circumference of the Earth (40,075 km).

Table 11. Values of individual parameters along with the inclusion of costs

Parameters and costs of electric vehicles													
No	City	Brand Model	Purchase - gross amount [PLN]	Actual vehicle range on a single charge [km]	Gross unit price of energy [PLN]	Total energy consumed for one year [kWh]	Average energy consumption for one year [kWh /100km]	Distance traveled in 1 year [km]	Energy cost during one year of operation [PLN]	Additional operating costs for one year [PLN]	Service costs for one year [PLN]	Total energy costs, additional operating and service costs for one year [PLN]	Total costs [PLN]
1	M 1		175476.52	170.00	0.74	1586.00	13.00	11788.00	1173.64	0.00	0.00	1173.64	176650.20
2	M 2		154000.00	185.00	0.67	717.00	13.00	5553.00	480.39	0.00	0.00	480.39	154480.40
3	M 3		173514.22	200.00	0.67	913.00	18.00	5194.00	611.71	11297.83	0.00	11909.54	185423.80
4	M 4		174711.01	220.00	0.57	966.00	14.00	6830.00	550.62	0.00	0.00	550.62	175261.60
5	M 5		168364.21	170.00	0.48	2467.00	17.00	14899.00	1184.16	11257.00	0.00	12441.16	180805.40
6	M 6		168723.52	170.00	0.69	1868.00	17.00	11185.00	1288.92	6683.38	0.00	7972.30	176695.82
7	M 7		168347.21	160.00	0.72	962.00	12.00	7937.00	692.64	18595.00	0.00	19287.64	187634.90
8	M 8	BMW i3	179878.02	155.00	0.65	732.00	19.00	3769.00	475.80	3813.00	0.00	4288.80	184166.80
9	M 9		175476.52	200.00	0.74	1586.00	13.00	11788.00	1173.64	0.00	0.00	1173.64	176650.20
10	M 10		165063.54	202.00	0.70	1239.00	18.00	7001.00	867.30	9635.00	0.00	10502.30	175565.80
11	M 11		173316.72	170.00	0.80	1894.00	23.00	8334.00	1515.20	4423.00	0.00	5938.20	179254.90
12	M 12		173316.72	180.00	0.80	843.00	11.00	7673.00	674.40	0.00	0.00	674.40	173991.10
13	M 13		165063.54	180.00	0.58	1275.00	18.00	6906.00	739.50	4643.00	0.00	5382.50	170446.00
14	M 14		173316.72	220.00	0.61	1576.00	18.00	8899.00	961.36	16561.00	0.00	17522.36	190839.10
15	M 15		169129.72	200.00	0.75	904.00	13.00	7010.00	678.00	10274.00	0.00	10952.00	180081.70
			Total	Average	Average	Total	Average	Total	Total	Total	Total	Total	Total
			2557698.19	185.00	0.68	19528.00	15.80	124766.00	13067.28	97182.21	0.00	110249.49	2667947.72

Energy cost during operation for a year – the lowest annual energy cost was incurred by the vehicle from the local unit M8 and amounted to PLN 475.8, while the highest cost was recorded for the vehicle from the local unit M11 at PLN 1,515.2. Total electricity costs for the entire fleet of 15 electric vehicles amounted to PLN 13,067.28.

In order to compare with combustion vehicles, a fuel cost analysis was carried out, assuming an average fuel consumption of 6 l/100 km and 95-octane fuel prices of PLN 5/l (2019) and PLN 4.45/l (2020).

In order to analyze the operating costs of electric vehicles compared to combustion vehicles, the following assumptions were made for electric vehicles, an annual mileage of 124,766 km and an average unit price of electricity of PLN 0.68/kWh were taken into account. For combustion vehicles, the same annual distance (124,766 km) and an average price of 95-octane fuel of PLN 5/l were assumed.

Assuming an average fuel consumption of combustion vehicles of 6 l/100 km, total fuel consumption over the distance travelled was 7,485.96 liters. At an average fuel price of PLN 5/l, the total fuel cost for 15 combustion vehicles per year was PLN 37,429.80. On the other hand, taking into account the average fuel price in 2020 of PLN 4.45/l, the annual fuel cost for the same group of vehicles was PLN 33,312.52.

In turn, the cost of electricity used by the fleet of electric vehicles per year amounted to PLN 13,279.04, which means savings of PLN 20,033.48 compared to fuel costs in 2020. The analysis showed that the operating costs associated with powering electric vehicles are on average about 2.5 times lower compared to their counterparts with combustion engines, which is a significant economic advantage of this means of transport. These values are illustrated in Figure 1. It should be noted, however, that taking into account both higher energy prices at commercial fast charging stations and cases of free charging, the ranking could change.

Additional operating and service costs - annual additional operating costs included, among others, the purchase of three-phase chargers, tires, air filters and wipers. The analysis showed that five locations (M1, M2, M4, M9 and M12) did not incur any additional operating costs during

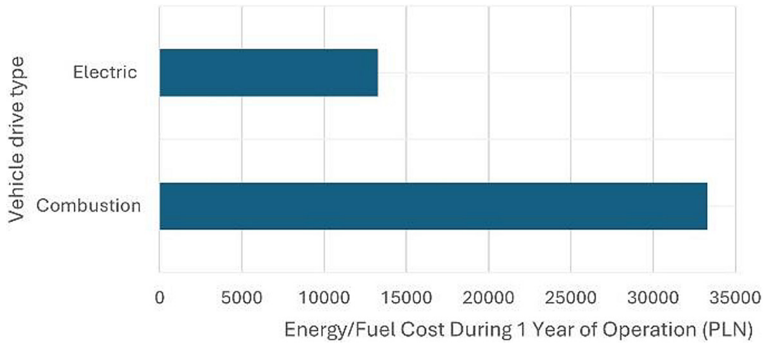

Figure 1. Comparison of operational energy and fuel costs for 15 electric and combustion vehicles

the period under review. The lowest documented annual additional operating costs amounted to PLN 3,813 (local unit M8), while the highest was PLN 18,595 (local unit M7). In terms of service costs, non-terms of service costs, none of the surveyed local units incurred expenses related to servicing 15 BMW i3 electric vehicles during one year of operation.

Total operating and service costs – the lowest total annual cost of energy, additional operation and service was PLN 480.39 (local unit M2), while the highest was PLN 19,287.64 (local unit M11). The total sum of energy, operating and service costs incurred by the fleet of 15 electric vehicles during the year was PLN 110,249.49. Total operating costs – the lowest total annual cost of using the vehicle (including energy, operation and service) was PLN 154,480.4 (local unit M2), while the highest was PLN 190,839.1 (local unit M14). The total cost of purchasing and operating a fleet of 15 BMW i3 electric vehicles in the period under review was PLN 2,667,947.72.

The analysis of costs and operating parameters of BMW i3 electric vehicles showed that despite the high purchase cost, these vehicles are characterized by relatively low operating costs, mainly in terms of electricity consumption. During the year of operation, no cases of failure or the need for repairs were recorded, which confirms the high reliability of the tested vehicles in the analyzed period.

Additional operating costs resulted primarily from the need to purchase portable chargers, which was the result of limited availability of public charging stations. This is an important aspect, which is a challenge for users, requiring additional financial outlays. In addition to purchasing chargers, there were other expenses related to supplementing the vehicle equipment, such as the purchase of windshield wipers; however, these were not related to vehicle failures.

CONCLUSIONS

The method of assessing electric vehicles presented in the article showed significant differences in the scope of non-measurable (technical and utility) effects in the scope of charging times, especially using a home socket, which was the most diverse parameter among the models tested. The smallest differences between the utility parameters of the models tested were observed in the scope of energy consumption and acceleration. The results indicate that the variability of parameters such as charger power, charging time with alternating current AC up to 7.4 kW and charging time using a home socket requires optimization actions by manufacturers in order to reduce the occurring discrepancies.

The classification of vehicles according to the analysed features showed that the Opel Corsa-e S (CAR 3) received the highest score in terms of technical and utility parameters, the BMW i3 (CAR 12) was in 7th place, while the Volkswagen e-UP! (CAR 2) received the lowest score. It should be emphasized, however, that the presented hierarchy refers only to a specific set of parameters and does not constitute an unambiguous recommendation of the best electric vehicle. Depending on the adopted assessment criteria, priority technical and utility features and the target purpose of the vehicles, the classification results may change.

Analysis of economically measurable effects on the example of the BMWi3 electric vehicle model, including the actual range on a single charge, showed a discrepancy in values from the values declared by the manufacturer, which emphasizes the need to take into account actual operating conditions in the technology assessment process. This deviation may result from actual operating conditions, driving style and environmental factors influencing energy consumption. The energy consumption analysis obtained values consistent with the manufacturer's data. Analysis of economically measurable effects on the example of the BMWi3 electric vehicle model, including the actual range on a single charge, showed a discrepancy in values from the values declared by the manufacturer, which emphasizes the need to take into account actual operating conditions in the technology assessment process. This deviation may result from actual operating conditions, driving style and environmental factors influencing energy consumption. The energy consumption analysis obtained values consistent with the manufacturer's data.

The results obtained are significant to potential buyers, because the technical and operational parameters of vehicles affect operating costs and the purchase decision. Differences between the actual and declared range may affect the selection of a vehicle appropriate for the individual needs of the user. Providing values by the manufacturer that deviate from reality may result in an incorrect choice of vehicle, especially in terms of cost – vehicles with larger battery capacities are usually more expensive, which may lead to unfavourable purchasing decisions.

The analysis of the operating costs of the BMW i3 electric vehicle showed that despite the high purchase price, the operating costs are relatively low, especially in terms of electricity consumption and servicing and repairs, as no failures or repairs were recorded during the period of operation under review. The limited availability of charging infrastructure at that time resulted in the need to purchase portable chargers, which was an additional cost for users.

The identified economic advantages of electric vehicles in the form of lower energy costs and no need for repairs may be a significant factor in users' purchasing decisions. However, a full assessment of this solution requires taking into account not only economic aspects (both measurable and unmeasurable), but also the impact on the environment, legal regulations, technological advancement and social aspects. These conclusions may be an important point of reference for further research on the optimization of electric drive technology and for manufacturers striving to increase efficiency and standardize key operating parameters.

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