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Multicriteria Approach to Sustainable Transport Evaluation under Incomplete Knowledge: Electric Bikes Case Study

Wojciech Sałabun [1,*], Krzysztof Palczewski [1] and Jarosław Wątróbski [2]

[1] Department of Artificial Intelligence Methods and Applied Mathematics, Faculty of Computer Science and Information Technology, West Pomeranian University of Technology in Szczecin ul. Żołnierska 49, 71-210 Szczecin, Poland; krzysztof.palczewski@zut.edu.pl

[2] Department of Information Systems Engineering in the Faculty of Economics and Management, University of Szczecin, Mickiewicza 64, 71-101 Szczecin, Poland; jaroslaw.watrobski@usz.edu.pl

* Correspondence: wojciech.salabun@zut.edu.pl; Tel.: +48-9144-955-80

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Abstract: The problem of sustainable city transport is a growing field of study, and will be addressed in this paper. With the rising significance of present transportation systems' negative externalities on the environment, such as the unavoidable increase of air pollution levels, cities seek sustainable means of transport and reduction of combustion cars' utilization. Moreover, improvements in the area of renewable energy sources have led to rising trends in sustainability, driving the usage and production of electric vehicles. Currently, there is an increasing tendency of looking for more sustainable transport solutions, especially in highly congested urban areas. It seems that in that case, electric bicycles can be a good option, as they yield more benefits in comparison to cars, especially combustion cars. In this paper, we identify an assessment model for the selection of the best electric bicycle for sustainable city transport by using incomplete knowledge. For this purpose, the Characteristic Objects METhod (COMET) is used. The COMET method, proven effective in the assessment of sustainable challenges, is a modern approach, utterly free of the rank reversal phenomenon. The evaluated model considers investigated multiple criteria and is independent of chosen alternatives in the criteria domain. Hence, it can be easily modified and extended for diverse sets of decisional variants. Moreover, the presented approach allows assessing alternatives under conditions of incomplete knowledge, where some data are presented as possible interval numbers.

Keywords: sustainability; city transport; decision-making; multi-criteria decision analysis; rank reversal; fuzzy logic; incomplete knowledge

1. Introduction

More than 50% of the world's population lives in urban areas, and it is estimated that by 2045 the number of people living in cities will increase up to 1.5 times—which is around 6 billion people [1]. There are more than 1 billion motorized vehicles worldwide, and with rising income levels, one should expect continuous expansion [2,3]. As a result of high flows of people into cities, transport systems are on the verge of transformation. With rising numbers of people dwelling in urban areas, many challenging needs and problems arise regarding sustainable development, where the critical element is the sustainable transport. The importance of this issue is not only proven by the critical postulates of the Sustainable Development Goals [4], but also by negative aspects current urban transport poses, such as elevated levels of air pollution or more frequent premature deaths from human exposure to harmful pollutants [5]. Diseases caused by pollution were responsible for an estimated 9 million premature deaths in 2015 three times more deaths than from AIDS, tuberculosis, and malaria combined and 15 times more than from all wars and other forms of violence [6].

Sustainable urban transport has become more complex and more significant to sustainability policies [6]. Thus researchers investigate this ongoing challenge through diverse and innovative means [7,8]. This problem is examined not only concerning modern metropolitan areas [9], but also to cities in developing countries [10,11]. The vital role of transport in the sustainability of the cities has been ascertained in previous papers, motivating researchers to explore new solutions in the area [12]. Consequently, new approaches have been proposed that aim to improve current transportation systems and solve prevailing environmental and economic aspects concerned with currently unsustainable transportation [13,14]. However, the previous works examine the problem of transport systems as a whole, often only regarding the supply chain, entirely omitting or briefly investigating specifically urban transportation [15]. Furthermore, researchers in the sustainable city transport discipline need to consider a broad spectrum of criteria, such as environmental, economic, social, legal and political issues [16]. Such multidimensional matter requires the use of various techniques to address this problem, such as fuzzy logic or multi-criteria decision analysis (MCDA) methods [17–19]. Currently, the evaluation of sustainable transport is an emerging area that researchers handle more frequently with the use of MCDA methods, proven to be effective in such challenges [20–22], as well as in evaluating other sustainable decision problems [23,24]. With growing attention towards sustainability assessment, one should also consider renewable energy sources, which is a popular subject in many kinds of research. Studies have shown that zero-emission energy sources, highly demanded by modern cities, are tending to be more accessible and cleaner [25,26]. Researchers have used various methods to investigate renewable energy sources problems, such as evaluating locations for offshore wind farms using PROMETHEE for Sustainability Assessment (PROSA) method [27,28], or investigating the design of wind farms using Analytic Network Process (ANP) and Analytic Hierarchy Process (AHP) methods [29]. Consequently, with greener energy, studies showed that there is a rising interest in sustainable means of transport, such as electric vans or public city buses [30,31].

The key to sustainable urban transport is finding optimal means of transport, which would satisfy both the needs of the present and the future. In this area, multiple various research and practical initiatives undertaken in the recent years can be indicated [32–34]. They include both works focused on formulating a strategy of building and developing sustainable city transport [35–37], as well as papers of tactical [38–40] and operational [41] scope, focused for example on selection and evaluation of selected variants of sustainable city logistics [42–44]. It should be pointed out that the dynamic development of technology allows to undertake new attempts in searching for new and updating the existing sustainable options in city logistics and transport (for example the search for a portfolio of apropriate variants of sustainable city transport should be conducted in multiple layers [45] with the use of the complete set of available transport options [46]. As other types of solutions, such as car sharing, proved to be promising sustainable transport fields, it should be pointed out that their optional coexistence in a single unified system of sustainable city logistics [47–50] should be considered with other pro-ecological variants of city logistics such as ebikes, emotors, bikes. Naturally, a holistic approach to sustainable city transport requires to take into account a set of external conditions (e.g., climate conditions), technical or urbanistic options, which condition obtaining the desired effects [51] while sustaining an appropriate level of safety. As indicated, the coexistence of different modes of sustainable transport is therefore essential and in this context, the use of e-bikes may fill this gap. Electric bicycles are relatively cheap, and their cost of use is significantly lower compared to, e.g., fuel-powered personal cars [52]. Furthermore, they create a great opportunity concerning more rapid movement around the city, especially in congested city centers and are more comfortable than other ecological means of transport, such as traditional bicycles. Electric bikes are less safe (higher speed of movement) and do not require any physical activity compared to traditional bikes. However, they empower many positive externalities such as negligible emissions of pollutants, reduction in harmful noise levels and impacting overall awareness towards a sustainable future, to name a few. Today, many modern cities are limiting the usage of combustion vehicles and some are planning to completely withdraw existing ones or ban future sales [53]. With the encouragement of sustainable means of transport, one can expect an increasing trend towards electric vehicles in the foreseeable future [54]. The dynamically developing technology causes that the set of available sustainable transport variants (e.g., ebikes, electric powered or hybrid cars, emotors) grows rapidly. In such context, it becomes necessary to develop methodological foundations for the evaluation of sustainable transport options. The specifics of this problem, implicating the natural lack of selected data (e.g., malfunction reports data, loss of value of newly-introduced variants over a few-year time span), result in the necessity to develop the methodological guidelines in the environment of incomplete knowledge in the model.

In this paper, the ongoing challenge of sustainable transport will be addressed, which is the selection of the most rational electric bicycle. The paper shows step by step how to identify multi-criteria decision-making assessment model. For this purpose, the Characteristic Objects METhod (COMET) is used, which was proven successful in other sustainable development problems [55]. The COMET method, as one of the multi-criteria decision-analysis technique based on a rule set, is completely free of the rank reversal paradox, which is a key in a proper analysis [56,57]. The obtained model is used to rank the considered bicycles and choose the most rational from the set of ten proposed products. Methodically, work presents a successful attempt of building integrated, inference based model, that aggregates full data with incomplete expert knowledge. In a practical sense, the authors' contribution is an attempt to build a reference ranking of ebikes for a carefully selected extensive set of ebikes, which can provide useful knowledge both for particular decision makers as well as for local communities and policy makers, where the evaluation and selection of sustainable transport variants is at stake.

The rest of the paper is organized as follows: in the next section, the Fuzzy Set Theory preliminaries are outlined. In Section 3, the COMET method is described as a useful tool to identify multi-criteria decision models. Subsequently, in Section 4, an experiment to build a decision model for an assessment of electric bicycles is described step by step, and the results are presented. The conclusions and the possible future directions are presented in Section 5.

2. Fuzzy Set Theory: Preliminaries

The fuzzy set theory was developed by Lofti Zadeh, who introduced the idea of fuzzy sets in [58]. The growing importance of the Fuzzy Set Theory in model creation in numerous scientific fields has proven to be an effective way to approach and solve multi-criteria decision problems [59–61]. The necessary concepts of the Fuzzy Set Theory are described as follows [62–64]:

Definition 1. *The fuzzy set and the membership function—the characteristic function μ_A of a crisp set $A \subseteq X$ assigns a value of either 0 or 1 to each member of X, and the crisp sets only allow a full membership ($\mu_A(x) = 1$) or no membership at all ($\mu_A(x) = 0$). This function can be generalized to a function $\mu_{\tilde{A}}$ so that the value assigned to the element of the universal set X falls within a specified range, i.e., $\mu_{\tilde{A}} : X \rightarrow [0, 1]$. The assigned value indicates the degree of membership of the element in the set A. The function $\mu_{\tilde{A}}$ is called a membership function and the set $\tilde{A} = (x, \mu_{\tilde{A}}(x))$, where $x \in X$, defined by $\mu_{\tilde{A}}(x)$ for each $x \in X$ is called a fuzzy set [65,66].*

Definition 2. *The triangular fuzzy number (TFN)—a fuzzy set $\tilde{A}$, defined on the universal set of real numbers $\Re$, is told to be a triangular fuzzy number $\tilde{A}(a, m, b)$ if its membership function has the following form [65,66] (1):*

$$\mu_{\tilde{A}}(x, a, m, b) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{m-a} & a \leq x \leq m \\ 1 & x = m \\ \frac{b-x}{b-m} & m \leq x \leq b \\ 0 & x \geq b \end{cases} \tag{1}$$

and the following characteristics, Equations (2) and (3):

$$x_1, x_2 \in [a, b] \wedge x_2 > x_1 \Rightarrow \mu_{\tilde{A}}(x_2) > \mu_{\tilde{A}}(x_1) \tag{2}$$

$$x_1, x_2 \in [b, c] \wedge x_2 > x_1 \Rightarrow \mu_{\tilde{A}}(x_2) > \mu_{\tilde{A}}(x_1) \tag{3}$$

Definition 3. *The support of a TFN—the support of a TFN $\tilde{A}$ is defined as a crisp subset of the $\tilde{A}$ set in which all elements have a non-zero membership value in the $\tilde{A}$ set [65,66], Equation (4):*

$$S(\tilde{A}) = x : \mu_{\tilde{A}}(x) > 0 = [a, b] \tag{4}$$

Definition 4. *The core of a TFN—the core of a TFN $\tilde{A}$ is a singleton (one-element fuzzy set) with the membership value equal to 1 [65,66], Equation (5):*

$$C(\tilde{A}) = x : \mu_{\tilde{A}}(x) = 1 = m \tag{5}$$

Definition 5. *The fuzzy rule—the single fuzzy rule can be based on the Modus Ponens tautology [65,66]. The reasoning process uses the $IF–THEN, OR$ and AND logical connectives.*

Definition 6. *The rule base—the rule base consists of logical rules determining the causal relationships existing in the system between the input and output fuzzy sets [66,67].*

Definition 7. *The T-norm operator (intersection)—the T-norm operator is a T function modelling the AND intersection operation of two or more fuzzy numbers, e.g., $\tilde{A}$ and $\tilde{B}$. Basic requirements for a function T is described by four properties: boundary Equation (6), monotonicity Equation (7), commutativity Equation (8), and associativity Equation (9) (for any $a, b, c, d \in [0, 1]$).*

$$T(0, 0) = 0, T(a, 1) = T(1, a) = a \tag{6}$$

$$T(a, b) < T(c, d) \quad \Leftrightarrow \quad if \quad a < c \quad and \quad b < d \tag{7}$$

$$T(a, b) = T(b, a) \tag{8}$$

$$T(a, T(b, c)) = T(T(a, b), c) \tag{9}$$

In this paper, the product is used as the T-norm operator [65–67], Equation (10):

$$\mu_{\tilde{A}}(x) AND \mu_{\tilde{B}}(y) = \mu_{\tilde{A}}(x) \cdot \mu_{\tilde{B}}(y) \tag{10}$$

Definition 8. *The S-norm operator (union), or T-conorm—the S-norm operator is an S function modelling the OR union operation of two or more fuzzy numbers, e.g., $\tilde{A}$ and $\tilde{B}$. Basic requirements for a function S is described by four properties: boundary Equation (11), monotonicity Equation (12), commutativity Equation (13), and associativity Equation (14) (for any $a, b, c, d \in [0, 1]$).*

$$S(1, 1) = 1, S(a, 0) = T(0, a) = a \tag{11}$$

$$S(a, b) < S(c, d) \quad \Leftrightarrow \quad if \quad a < c \quad and \quad b < d \tag{12}$$

$$S(a, b) = S(b, a) \tag{13}$$

$$S(a, S(b, c)) = S(S(a, b), c) \tag{14}$$

In this paper, the bounded sum is used as the S-norm operator [65–67], Equation (15):

$$\mu_{\tilde{A}}(x) OR \mu_{\tilde{B}}(y) = (\mu_{\tilde{A}}(x) + \mu_{\tilde{B}}(y)) \wedge 1 \tag{15}$$

3. The Characteristic Objects Method

Many MCDM methods exhibit the rank reversal phenomenon; however, the Characteristic Objects Method (COMET) is completely free of the this problem. In previous works, the accuracy of the COMET method was verified [68]. The formal notation of the COMET method should be briefly recalled [62–64]. The whole decision-making process by using the COMET method is presented in Figure 1.

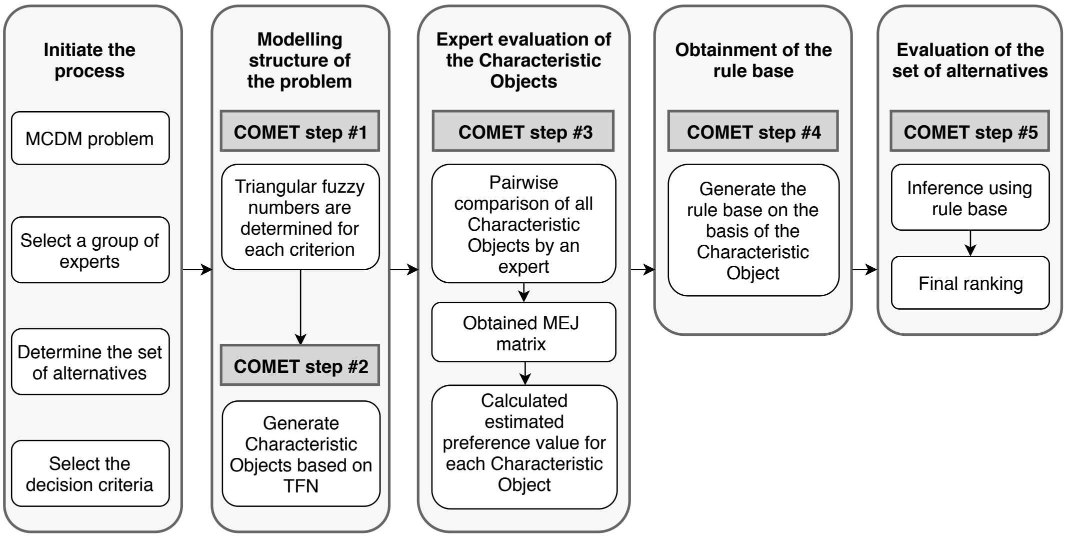

Figure 1. The procedure of the Characteristic Objects Method (COMET) to identify decision-making model.

Step 1. *Definition of the space of the problem*—the expert determines the dimensionality of the problem by selecting r criteria, $C_1, C_2, \cdots, C_r$. Then, a set of fuzzy numbers is selected for each criterion C_i, e.g., $\{\tilde{C}_{i1}, \tilde{C}_{i2}, \cdots, \tilde{C}_{ic_i}\}$ (16):

$$\begin{array}{l} C_1 = \{\tilde{C}_{11}, \tilde{C}_{12}, \ldots, \tilde{C}_{1c_1}\} \\ C_2 = \{\tilde{C}_{21}, \tilde{C}_{22}, \ldots, \tilde{C}_{2c_2}\} \\ \cdots \\ C_r = \{\tilde{C}_{r1}, \tilde{C}_{r2}, \ldots, \tilde{C}_{rc_r}\} \end{array} \tag{16}$$

where $C_1, C_2, \cdots, C_r$ are the ordinals of the fuzzy numbers for all criteria.

Step 2. *Generation of the characteristic objects*—the characteristic objects (CO) are obtained with the usage of the Cartesian product of the fuzzy numbers' cores of all the criteria:

$$CO = C(C_1) \times C(C_2) \times \cdots \times C(C_r) \tag{17}$$

As a result, an ordered set of all CO is obtained:

$$\begin{array}{l} CO_1 = C(\tilde{C}_{11}), C(\tilde{C}_{21}), \ldots, C(\tilde{C}_{r1}) \\ CO_2 = C(\tilde{C}_{11}), C(\tilde{C}_{21}), \ldots, C(\tilde{C}_{r2}) \\ \cdots \\ CO_t = C(\tilde{C}_{1c_1}), C(\tilde{C}_{2c_2}), \ldots, C(\tilde{C}_{rc_r}) \end{array} \tag{18}$$

where t is the count of COs and is equal to:

$$t = \prod_{i=1}^{r} c_i \tag{19}$$

Step 3. *Evaluation of the characteristic objects*—the expert determines the Matrix of Expert Judgment (MEJ) by comparing the COs pairwise. The matrix is presented below:

$$MEJ = \begin{pmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1t} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2t} \\ \cdots & \cdots & \cdots & \cdots \\ \alpha_{t1} & \alpha_{t2} & \cdots & \alpha_{tt} \end{pmatrix} \quad (20)$$

where α_{ij} is the result of comparing CO_i and CO_j by the expert. The function f_{exp} denotes the mental judgement function of the expert. It depends solely on the knowledge of the expert. The expert's preferences can be presented as:

$$\alpha_{ij} = \begin{cases} 0.0, & f_{exp}(CO_i) < f_{exp}(CO_j) \\ 0.5, & f_{exp}(CO_i) = f_{exp}(CO_j) \\ 1.0, & f_{exp}(CO_i) > f_{exp}(CO_j) \end{cases} \quad (21)$$

After the MEJ matrix is prepared, a vertical vector of the Summed Judgments (SJ) is obtained as follows:

$$SJ_i = \sum_{j=1}^{t} \alpha_{ij} \quad (22)$$

Eventually, the values of preference are approximated for each characteristic object. As a result, a vertical vector P is obtained, where the ith row contains the approximate value of preference for CO_i.

Step 4. *The rule base*—each characteristic object and its value of preference is converted to a fuzzy rule as:

$$IF\ C(\tilde{C}_{1i})\ AND\ C(\tilde{C}_{2i})\ AND\ \ldots THEN\ P_i \quad (23)$$

In this way, a complete fuzzy rule base is obtained.

Step 5. *Inference and the final ranking*—each alternative is presented as a set of crisp numbers, e.g., $A_i = \{\alpha_{i1}, \alpha_{2i}, \alpha_{ri}$. This set corresponds to the criteria $C_1, C_2, \cdots, C_r$. Mamdani's fuzzy inference method is used to compute the preference of the $i-th$ alternative. The rule base guarantees that the obtained results are unequivocal. The bijection makes the COMET completely rank reversal free.

4. Study Case

This paper presents the assessment model of decision-making concerning sustainable city transport. Selecting an optimal electric bike, especially considering multiple criteria, is a complex challenge. Such compound problems require the expert's knowledge to establish the requirements for the model and therefore, based on the expert's opinion, eight criteria were selected. Hence, the space of the investigated problem is equal to 8. Based on [69–80], the following criteria are specified:

- C_1—battery capacity, expressed in Ampere hours (Ah) [73];
- C_2—charging time of the battery, expressed in hours (h) [73,74];
- C_3—number of gears (derailleur), expressed in units [75];
- C_4—power of the engine, expressed in Watts (W) [74,76];
- C_5—the maximum speed reached solely by electric mode, expressed in kilometers per hour (km/h) [78];
- C_6—driving range of the bicycle by electric mode using fully loaded battery, expressed in kilometers (km) [77,78];
- C_7—weight of the bicycle, including battery expressed in kilograms (kg) [78];
- C_8—price in US dollars [74,79].

In this study case, the considered problem is simplified to a simple structure which is presented in Figure 2. In that way, we have to identify four related models, where each one requires a lot smaller number of queries. The decision model can be presented as the following models:

- battery effectiveness assessment model with two inputs (9 characteristic objects and 36 pairwise comparisons are needed);
- engine assessment model with two inputs (9 characteristic objects and 36 pairwise comparisons are needed);
- drive system assessment model with three inputs (27 characteristic objects and 351 pairwise comparisons are needed);
- comfort of usage assessment model with two inputs (9 characteristic objects and 36 pairwise comparisons are needed);
- electric bicycle assessment model with three inputs (36 characteristic objects and 351 pairwise comparisons are needed).

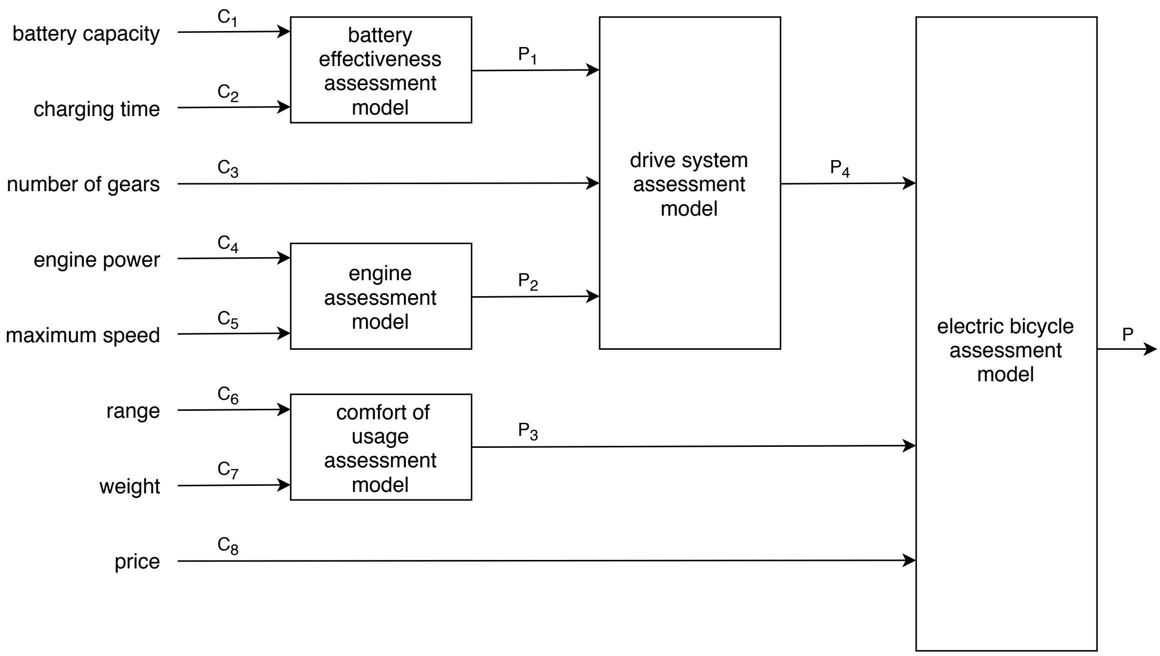

Figure 2. The hierarchical structure of the electric bicycle assessment problem.

In Table 1, criteria are presented along with their respective linguistic values. Table 2 presents 10 exemplary ebikes along with the explanation of the model foundations, whereas the complete model for 64 bikes is presented in Section 4.7.

Table 1. Selected criteria C_1–C_8 and their characteristic values {low, medium, high}.

C_i	Name	Unit	Low	Medium	High
C_1	battery capacity	Ah	4	9	15
C_2	charging time	hours	3	5	8
C_3	number of gears	units	1	7	21
C_4	engine power	W	250	350	500
C_5	maximum speed	km/h	20	27	35
C_6	range	km	20	60	100
C_7	weight	kg	10	20	25
C_8	price	USD	300	2500	6300

Table 2. The performance table of the alternatives A_1–A_{10}.

A_i	Name	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	Emu Crossbar	14.5	[6, 8]	7	250	25	[55, 100]	23	1560
A_2	Xiaomi QiCycle	5.8	3	3	250	20	45	14.5	950
A_3	ANCHEER Plus	8	5	21	250	25	[25, 50]	23	615
A_4	ECOTRIC	12	[5, 8]	7	500	32	55	24.9	999
A_5	Merax 26″ Aluminum	8.8	[5, 6]	7	350	32	[35, 45]	22	690
A_6	Kemanner	8	[4, 6]	21	250	25	[35, 70]	20	[615, 700]
A_7	Rattan	10.4	[4, 5]	7	350	32	50	23.5	740
A_8	Aceshin	8	[4, 6]	21	250	30	40	22.2	730
A_9	Shaofu 6AH	4.4	3	1	350	25	20	12	390
A_{10}	Carrera Crossfuze	11	[6, 7]	9	400	25	80	20.3	2300

In order to identify the final model for the electric bicycle assessment, we first have to determine the following assessment models, i.e., battery effectiveness, engine, drive system and comfort of the usage.

4.1. Battery Effectiveness Assessment Model

The expert identified two important criteria for the battery effectiveness assessment model, battery capacity, expressed in Ampere-hours [Ah] and charging time expressed in hours [H]. The former is a profit type criterion; hence the value increase implies the preference increase, whereas the latter is a cost-type criterion; hence the value increase implies the preference decrease. It should be noted that the relationship is rarely linear in such complex problems. The triangular fuzzy numbers of criteria C_1 and C_2 are depicted in Figure 3. The characteristic objects CO_1–CO_9 are created using the Cartesian product of the fuzzy numbers' cores of criteria C_1 and C_2 and are presented in Table 3. The space of the problem, including characteristic objects and alternatives, is presented in Figure 4.

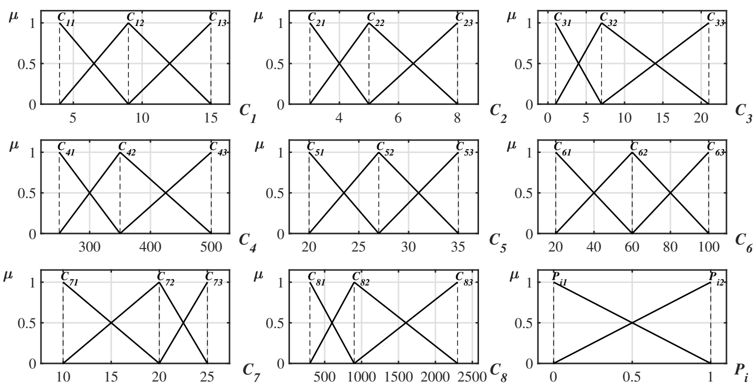

Figure 3. The sets of triangular numbers for each considered criterion C_j and the aggregated criteria P_i, where $i = 1, 2..., 4$; $j = 1, 2..., 8$.

Table 3. The results for criteria C_1 (battery capacity), C_2 (charging time), and P_1 values for each CO_i.

CO_i	C_1	C_2	P_1
CO_1	4	3	0.3333
CO_2	4	5	0.1667
CO_3	4	8	0.0000
CO_4	9	3	0.8333
CO_5	9	5	0.5000
CO_6	9	8	0.1667
CO_7	15	3	1.0000
CO_8	15	5	0.6667
CO_9	15	8	0.5000

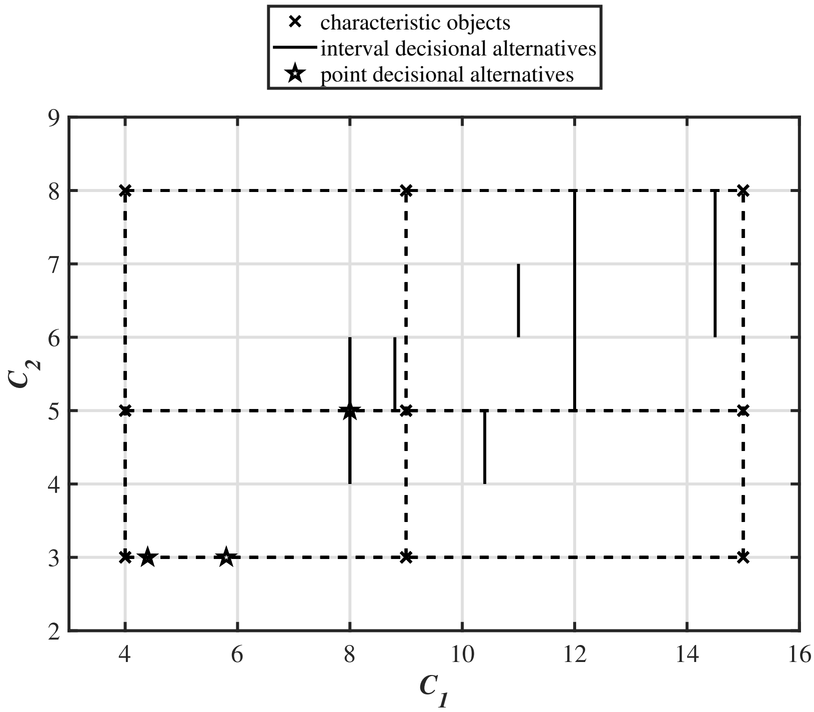

Figure 4. The space of the problem for the identification of P_1.

The expert performed 36 pairwise comparisons of the characteristic objects. As a result, the Matrix of Expert Judgment (MEJ) was determined, where each α_{ij} value was calculated using the Equation (21). The MEJ matrices are presented in Figures 5 and 6, where the α_{ij} values of either 0, 0.5 or 1 are represented by white, black and gray boxes, respectively. Consequently, the vector of the Summed Judgements (SJ) was calculated using Equation (22), and hence, it was to used to calculate the values of preference (P), presented in Table 3.

4.2. Engine Assessment Model

The expert identified two criteria for the engine assessment model, namely engine power, expressed in Watts [W] and maximum speed reached by electric bicycle in electric mode expressed in kilometers per hour [km/h]. Both are profit type criteria, hence as stated before, with the increase in values, preference increases. The triangular fuzzy numbers of criteria C_4 and C_5 are depicted in Figure 3. The characteristic objects CO_1–CO_9 are created using the Cartesian product of the fuzzy numbers' cores of criteria C_4 and C_5 and are presented in Table 4. The space of the problem, including characteristic objects and alternatives, is presented in Figure 7.

Table 4. The results for criteria C_4 and C_5 and their characteristic objects' values of preference P for CO_i.

CO_i	C_4 Engine Power	C_5 Maximum Speed	P_2
CO_1	250	20	0.0000
CO_2	250	27	0.3750
CO_3	250	35	0.7500
CO_4	350	20	0.1250
CO_5	350	27	0.5000
CO_6	350	35	0.8750
CO_7	500	20	0.2500
CO_8	500	27	0.6250
CO_9	500	35	1.0000

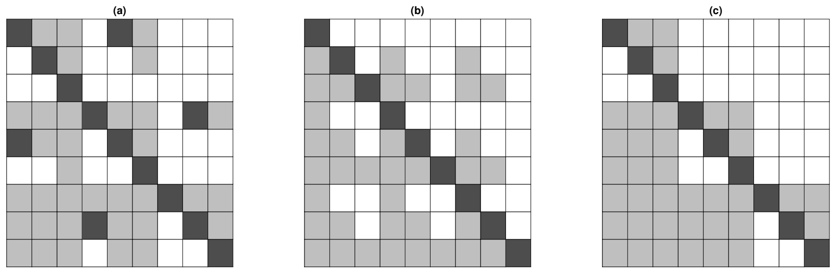

Figure 5. The matrix of expert judgement for P_1 (**a**), P_2 (**b**), and P_3 (**c**).

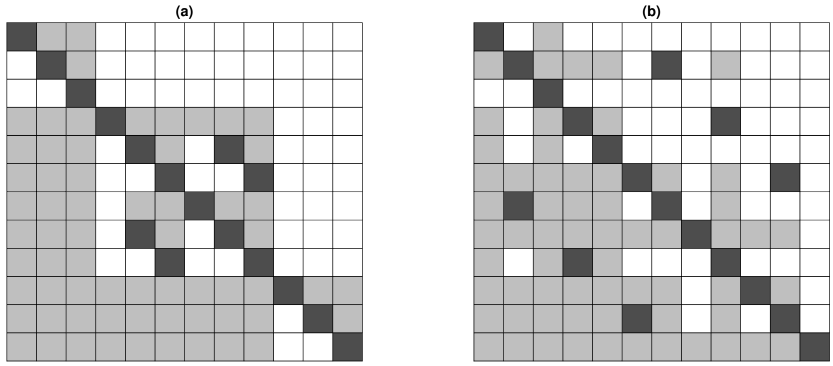

Figure 6. The matrix of expert judgement for P_4 (**a**), and P (**b**).

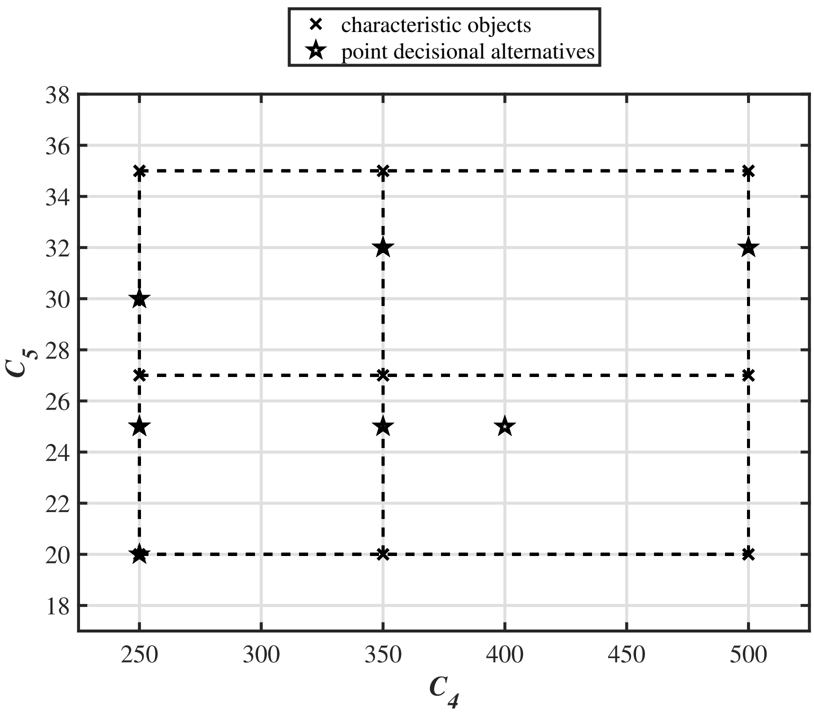

Figure 7. The space of the problem for the identification of P_2.

4.3. Comfort of Usage Assessment Model

Two important criteria were selected for the engine assessment model, range, expressed in kilometers [km] and weight of the bicycle in kilograms [kg]. The first one is a profit type criterion and the second one is a cost-type criterion. The triangular fuzzy numbers of criteria C_6 and C_7 are shown in Figure 3. The characteristic objects CO_1–CO_9 are created using the Cartesian product of the fuzzy numbers' cores of criteria C_6 and C_7 and are presented in Table 5. The space of the problem, including characteristic objects and alternatives, is presented in Figure 8.

Table 5. The results for criteria C_6 (range) and C_7 (weight) and their characteristic objects' values of preference P for CO_i.

CO_i	C_6	C_7	P_3
CO_1	20	10	0.2500
CO_2	20	20	0.1250
CO_3	20	25	0.0000
CO_4	60	10	0.6250
CO_5	60	20	0.5000
CO_6	60	25	0.3750
CO_7	100	10	1.0000
CO_8	100	20	0.8750
CO_9	100	25	0.7500

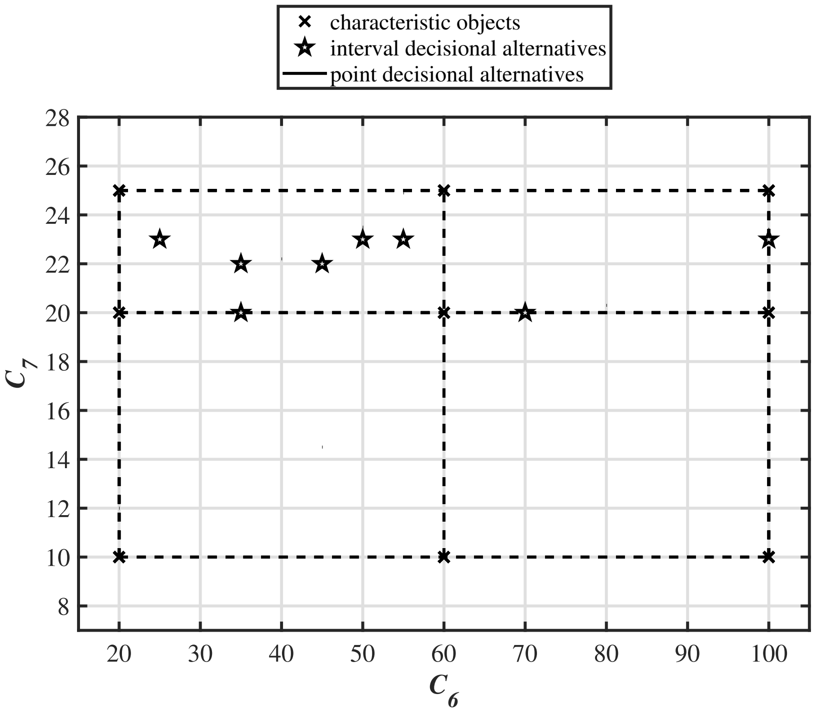

Figure 8. The space of the problem for the identification of P_3.

4.4. Drive System Assessment Model

For the model of drive system assessment, the variables from previous models are used, namely battery effectiveness assessment model and the engine assessment model, P_1 and P_2 respectively. Additionally, the third criterion is included—the number of gears available in the bicycle derailleur system C_3. The aggregated variables P_1, P_2 and criterion C_3 are all profit type. The triangular fuzzy numbers of criterion C_3 is presented in Figure 3. The characteristic objects CO_1–CO_{12} are presented in Table 6.

Table 6. The results for P_1 battery assessment, C_3 number of gears and P_2 engine assessment and their corresponding characteristic objects' values of preference P for O_i.

CO_i	P_1	C_3	P_2	P_4
CO_1	0	1	0	0.0000
CO_2	0	1	1	0.3750
CO_3	0	7	0	0.2500
CO_4	0	7	1	0.6250
CO_5	0	21	0	0.1250
CO_6	0	21	1	0.5000
CO_7	1	1	0	0.3750
CO_8	1	1	1	0.7500
CO_9	1	7	0	0.6250
CO_{10}	1	7	1	1.0000
CO_{11}	1	21	0	0.5000
CO_{12}	1	21	1	0.8750

4.5. Electric Bicycle Assessment Model

The final model for the electric bicycle assessment has three input variables. Two aggregated variables were used, the output variable from the drive system assessment and the output variable from the comfort of usage assessment. Moreover, we include the third input—the criterion price C_7. The aggregated variables P_1, P_2 are both profit type, whereas the criterion C_7 is cost type. The triangular fuzzy numbers of criterion C_7 is shown in Figure 3. The characteristic objects CO_1–CO_{12} are presented in Table 7.

Table 7. The results for P_3 (drive system assessment), P_4 (comfort of usage assessment) and their corresponding characteristic objects' values of preference P for CO_i.

CO_i	P_3	P_4	C_8	P
CO_1	0	0	300	0.2222
CO_2	0	0	2500	0.1111
CO_3	0	0	6300	0.0000
CO_4	0	1	300	0.6667
CO_5	0	1	2500	0.5556
CO_6	0	1	6300	0.4444
CO_7	1	0	300	0.6667
CO_8	1	0	2500	0.5556
CO_9	1	0	6300	0.3333
CO_{10}	1	1	300	1.0000
CO_{11}	1	1	2500	0.8889
CO_{12}	1	1	6300	0.7778

4.6. Final Ranking

The final preference and the ranking for the ten considered alternatives of electric bicycles are presented in Table 8. Concerning the case with the full knowledge, when we always assume the best value of the interval, then the best variant is bicycle Emu Crossbar (preference value 0.6119), slightly exceeding the Rattan bicycle (preference value 0.6056). Undoubtedly, the worst alternative is the ANCHEER Plus model (preference value 0.3752). The second worst, however, not that close to the least optimal one, is the Xiaomi QiCycle model (preference value 0.4063). The Emu Crossbar scored such high results due to the fact, that has the most extended range (up to 100 km) and the highest battery capacity (14.5 Ah), which outweighs its disadvantages, such as high price. However, when considering Rattan model (second best), it is worth stating that, although it has lower battery capacity than Emu Crossbar, it has also lower charging time (which is cost type), hence the overall preference for battery assessment is greater in Rattan model. Compared to Emu, Rattan is also two times cheaper and has a higher preference regarding engine assessment. However, its rather average range contributed to only second place.

Table 8. Considered alternatives and their results A_1–A_{10}.

A_i	P_1	P_2	P_3	P_4	P
A_1	[0.4722, 0.5926]	0.2679	[0.5275, 0.5727]	[0.3781, 0.8000]	[0.4219, 0.6119]
A_2	0.5133	0	0.2758	0.4281	0.4063
A_3	0.4333	0.2679	0.3880	[0.0969, 0.3313]	[0.3752, 0.4693]
A_4	[0.3333, 0.5833]	0.8594	[0.6973, 0,7910]	0.3306	[0.5308, 0.5686]
A_5	[0.3778, 0.4867]	0.7344	[0.6671, 0.7079]	[0.2156, 0.3094]	[0.5264, 0.5778]
A_6	[0.3333, 0.5833]	0.2679	[0.3505, 0.4442]	[0.2656, 0.5938]	[0.4116, 0.5959]
A_7	[0.5389, 0.7055]	0.7344	[0.7275, 0.7900]	0.3188	[0.5800, 0.6056]
A_8	[0.3333, 0.5833]	0.5156	[0.4433, 0.5371]	0.2575	[0.4414, 0.4804]
A_9	0.3733	0.3929	0.2873	0.225	0.4261
A_{10}	[0.3704, 0.4630]	0.4345	[0.5340, 0.5687]	0.6800	[0.4802, 0.4918]

However, these were the rankings under assuming full knowledge as the best value from the uncertainty intervals. When we do take them into account, the final ranking has to be interpreted differently—taking into example the Emu Crossbar, which the final preference interval is equal to [0.4219, 0.6119]. While considering the highest values from intervals made Emu clearly the the first, it is worth noticing how broad the interval is, mainly due to the fact that his range C_6 and his preference value for comfort of usage assessment P_4 have extensive intervals, 55–100 (km) and [0.3781, 0.8000], respectively. Thus, under some degree of uncertainty, the final ranking varies greatly. Hence, the Emu still might be first, but one has to be aware of the fact that considering the lowest values from the interval, Emu belongs closer to the end of the ranking.

On the contrary, the Rattan bicycle (second place), which also exhibits the problem of uncertainty, has a much lower range of the interval [0.5800, 0.6056]. Even with the lowest value, Rattan still has a high preference value ($P = 0.5800$), whereas Emu had ($P = 0.4219$). Therefore, interval numbers can be a useful indicator of the stability of the final ranking, under conditions of incomplete knowledge, which can easily change the definitive ranking of alternatives.

4.7. Practical Exploitation of the Identified Model

The proposed methodological aspects of the identification of the assessment model in the conditions of incomplete knowledge are presented on a set of 10 arbitrarily selected decision variants. In practice, the number of possible decision options is often much higher. Therefore, as a result of the analysis of literature and websites [81–87], the set of evaluated variants was extended by another 54 decision alternatives. The extended set was assessed using the identified model and decision-making system available on wwww.comet.edu.pl. Table 9 presents the analyzed set together with the determined assessments of preferences (P). The worst option was the California Bicycle Factory Retro S bike (with 0.3669 point). It had a low battery capacity (it was 8 ah), which was not compensated by charging time (it was 4 hours), low number of gears, low engine power, high weight, high price ($2499) and average maximum speed. The next variant was only improved by 0.0229 of point. On the other hand, the best option was the Blix Sol bike, which was rated 0.687 of point. The parameters were mostly medium; however, the low price and big range were crucial to the victory of this option.

Table 9. The results of the model for a wider domain of e-bikes according to [81–87].

A_i	Name	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	P
A_1	2017 Raleigh Detour iE	11.6	4	9	250	32	80	21.7	2399	0.5779
A_2	Aceshin	8	[4, 6]	21	250	30	40	22.2	730	[0.4414, 0.4804]
A_3	ANCHEER Plus	8	5	21	250	25	[25, 50]	23	615	[0.3752, 0.4693]
A_4	BESV CF1	8.4	5	10	250	28.8	64	22.4	1799	0.4810
A_5	BESV PSA1	10.5	5	7	250	30.4	72	19.5	1999	0.5569
A_6	Blix Aveny	11	3	7	350	32	96	23.5	1899	0.6849
A_7	Blix Sol	11	3	7	350	32	88	22	1599	0.6870
A_8	California Bicycle S	8	4	1	250	32	56	22.6	2499	0.3669
A_9	Cannondale E-Rigid	11	3.5	8	350	32	100	22.6	3490	0.6280
A_{10}	Carrera Crossfuze	11	[6, 7]	9	400	25	80	20.3	2300	[0.4802, 0.4918]
A_{11}	Coboc ONE Soho	9.6	2.5	1	250	24.8	88	13.1	5520	0.4016
A_{12}	CUBE Cross Pro 400	11	3.5	9	250	32	96	22.7	2599	0.6236
A_{13}	Desiknio Pinion Classic	7	3	6	250	24.8	80	15.7	6135	0.3945
A_{14}	Desiknio Single Urban	7	3	1	250	24.8	80	13.1	4415	0.3898
A_{15}	EcoMotion Tour e-Road	10.4	4	7	350	32	83	20.2	1299	0.6763
A_{16}	E-Glide SS	10.4	5	1	350	32	56	17.1	1099	0.4893
A_{17}	E-Glide ST	11.4	6	10	500	32	80	24.4	1699	0.5838
A_{18}	e-Joe Gadis	11	5	7	350	32	72	24.9	1699	0.5555
A_{19}	E-Lux Monaco	10.5	6	9	500	32	88	24.8	1995	0.5912
A_{20}	ECOTRIC	12	[5, 8]	7	500	32	55	24.9	999	[0.5308, 0.5686]
A_{21}	Emazing Coeus 73h3h	8.7	4	7	350	32	88	20.2	1800	0.6591
A_{22}	Emazing Selene 73h3h	8.7	4	7	350	32	88	21.9	2000	0.6336
A_{23}	Emu Crossbar	14.5	[6, 8]	7	250	25	[55, 100]	23	1560	[0.4219, 0.6119]
A_{24}	Espin Flow	11.6	4.5	8	350	35	80	24.3	1888	0.6095
A_{25}	EUNORAU E-TORQUE	12.5	5	7	350	32	72	24.6	1599	0.5694
A_{26}	eVox KAB 375	7.8	4	8	350	35	100	20.4	2199	0.6831
A_{27}	Gazelle Avenue C8	14	4	8	250	32	100	23.8	2999	0.6167
A_{28}	Gazelle CityZen C8 HM	11	3.5	8	350	32	94	23.1	2999	0.6204
A_{29}	Gazelle CityZen T9 HMB	13.4	4	9	350	32	100	24.1	3499	0.6089
A_{30}	GenZe 200 Series	9.6	3.5	8	350	32	56	22.6	1899	0.5399
A_{31}	IZIP E3 Brio	11.6	5.5	7	250	32	80	25	1699	0.5600
A_{32}	IZIP E3 Loma	11	5.5	7	250	32	80	24.9	1699	0.5582
A_{33}	Juiced OceanCurrent	8.8	4	8	500	35	64	23.1	1299	0.6144
A_{34}	Junto Gen 1	11.6	6	11	350	32	96	22.1	2222	0.6140
A_{35}	Kalkhoff Agattu B7	11	3.5	7	250	32	100	24	2499	0.6353
A_{36}	Kemanner	8	[4, 6]	21	250	25	[35, 70]	20	[615, 700]	[0.4116, 0.5959]
A_{37}	Merax 26″ Aluminum	8.8	[5, 6]	7	350	32	[35, 45]	22	690	[0.5264, 0.5778]
A_{38}	Optibike Rocky Mount.	11.6	5	11	500	35	96	24.4	3995	0.5768
A_{39}	Orbea Katu-E 10	11	3.5	8	250	32	96	22.9	2999	0.6114
A_{40}	Populo Lift V2	8.7	4.5	7	250	32	56	22.1	1399	0.5273
A_{41}	Populo Scout	13	4.5	8	350	32	80	24.7	1699	0.6010
A_{42}	Populo Sport	10.4	3	1	250	32	48	15.7	999	0.5028
A_{43}	Populo Sport V3	8.7	4.5	1	250	32	56	16.7	999	0.4813
A_{44}	Propella 2.2 7-Speed	6.8	2.5	7	250	28.8	56	16.8	1299	0.5486
A_{45}	Propella V2.0 Single-Speed	6.8	2.5	1	250	25.6	56	13.6	1199	0.4495
A_{46}	PUBLIC D8 Electric	8.8	4.5	8	350	32	88	24.8	2199	0.5841
A_{47}	Pure Cycles Volta 8-Speed	5.8	4	8	250	32	40	17	1999	0.4433
A_{48}	Rattan	10.4	[4, 5]	7	350	32	50	23.5	740	[0.5800, 0.6056]
A_{49}	Raleigh Sprite iE	8.8	5	7	350	32	64	24.5	1899	0.5116
A_{50}	Raleigh Superbe iE	8.8	4.5	7	350	32	64	22.7	1799	0.5450
A_{51}	Riese & Müller Mixte	13.4	3.5	10	350	32	100	21.9	3879	0.6238
A_{52}	Riese & Müller NuVinci	11	3.5	1	250	32	100	24.8	4489	0.4592
A_{53}	Schwinn Monroe 250	11.6	4.5	1	250	32	72	18.8	1199	0.5335
A_{54}	Schwinn Monroe 350	14	6	1	350	32	88	20.4	1499	0.5732
A_{55}	Scott E-Sub Evo	11	3.5	8	350	32	100	22.4	4199	0.6060
A_{56}	Shaofu 6AH	4.4	3	1	350	25	20	12	390	0.4261
A_{57}	Specialized Como 2.0	12.8	3.5	9	250	32	96	21.5	2600	0.6411
A_{58}	Specialized Como 3.0	12.8	4	9	250	32	80	20.7	2950	0.5711
A_{59}	Specialized Vado 3.0	12.5	3.5	10	250	32	100	24.5	3200	0.6027
A_{61}	Trek Lift+ Lowstep	11.6	4	10	250	32	80	20.3	2799	0.5718
A_{62}	Trek Neko+	11.6	4	10	250	32	80	19.1	2999	0.5717
A_{63}	VoltBike Urban	13	5.5	6	350	32	80	23.4	1199	0.6085
A_{64}	Xiaomi QiCycle	5.8	3	3	250	20	45	14.5	950	0.4063

It can often happen that some parameters describing variants are uncertain, e.g., the maximum distance may depend on the weight of the passenger, orography of the city and the climate (cold climate shorter distance). The given catalog values are very often averaged experimental results, therefore it seems justified to use interval numbers. It is difficult to assume that the vehicle will be moved in the same conditions as in laboratory tests.

5. Conclusions

Sustainable development is becoming a more complex problem, one that requires a modern approach with the use of various methods. In this paper, the sustainable city transport challenge was addressed in the context of selecting the electric bicycle. Methodically, the paper presents a successful attempt to adapt an MCDA method called COMET to the needs of evaluation of sustainable transport.

The fuzzy set theory with the COMET method was used to investigate and create the decision model under the condition of full knowledge and with some degree of uncertainty, using the interval numbers. As a result of the preformed research, also a practical contribution in the sustainable transport domain was obtained. The presented model for ebikes evaluation based on an extensive set of available options contains important domain knowledge supporting the decision makers in the process of evaluation and selection of proper variant of sustainable transport. Eight criteria were taken into consideration (battery capacity, charging time, number of gears, engine power, maximum speed, range, weight, and price); however, to reduce the amount of pairwise comparison, the final assessment model was restructured into sub-models, significantly reducing the complexity of the problem and restructuring the criteria into groups. Ten alternatives to electric bicycles were examined in details (from an extensive set of bikes presented in Table 9. The practical implications in the domain of sustainable transport provide a reference model for ebikes. It is worth adding that the proposed approach has considerable practical usability. The freely available software on the comet.edu.pl website results in the model being easy to validate even for non-experienced users.

For further study, it would be valuable to extend this model with additional criteria and sub-models, creating an even more detailed selection of electric bicycles. Additionally, further works concerning the incomplete knowledge case could be performed.

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