

Received November 29, 2021, accepted December 27, 2021, date of publication January 7, 2022, date of current version January 14, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3141329

# Swimmer Assessment Model (SWAM): Expert System Supporting Sport Potential Measurement

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The work of Wojciech Sałabun was supported by the National Science Centre under Grant 2018/29/B/HS4/02725. The work of Jarosław Wątróbski was supported in part by the National Science Centre under Grant 2018/29/B/HS4/02725; and in part by the Minister of Science and Higher Education through the Project “Regional Excellence Initiative,” in the years 2019–2022 (the amount of financing: PLN 10.684.000,00), under Project 001/RID/2018/19.

**ABSTRACT** A swimmer’s potential can be exploited to the full if an individual approach is applied to training early enough. In the initial stage of a competitor’s career, it is hard to say whether the person will reach the world level. It is influenced by factors related to physical and mental characteristics, swimming technique, or the current skills level of the athlete. Some of them cannot be improved by swimmers; however, a few of these factors can be affected and upgraded by working on them. The data from 30 swimmers were collected in the research. Then, adopting the COMET method, the values of attributes characteristic for the athletes were entered into the proposed model to determine the predispositions of each of them. The applied method proved to be effective in assessing the parameters of competitors, and at the same time, it is a modern approach free of the rank reversal phenomenon. In addition, the model obtained allows for the study of input data to check how the change of a given criterion will affect the overall rating. The model developed is forward-looking. The results are satisfactory but can be improved to analyze somatic traits better and achieve more accurate predictions.

**INDEX TERMS** COMET, decision analysis, decision support systems, decision theory, expert systems, fuzzy systems, knowledge based systems, TOPSIS.

## I. INTRODUCTION

Swimming is an individual sport that is treated as a niche by many sports fans. Most of them find it not very spectacular and attractive [1]. Still, there are also those for whom the opportunity to watch the competition of swimmers on television or from the stands of the swimming pool is an unforgettable experience. Only a few are aware of each swimmer’s vast sacrifices and effort into achieving success. Hours spent in the pool and on functional land training during the week are counted in dozens. By devoting so much time and commitment to our passion, we hope that our efforts will be rewarded to some extent [2]. As we know, many swimmers aim for the most outstanding achievements, namely the medal of the Olympic Games, which can be treated as the top of

the mountain they are aiming for. However, not everyone will be given this honor, and the vast majority of them will have to content themselves with just improving their life records, which is also quite an achievement. In swimming, the most important aspect of progress is training [3]. Some part of how good we will be is our talent and physical predisposition. One should take into account such elements as weight, height, flexibility, arm length to height ratio, or maximum heart rate [4]. Some of them are in the group of features we influence. The rest of them are independent of us. However, each of these factors has an impact on the results achieved. Moreover, they can be used to determine whether a given swimmer has better predispositions to swim at the world level than a teammate [5], [6].

The choice, skills assessment, and prediction of the performance of athletes in competitions are the issues on which all coaching teams work [7]. The best football clubs employ

The associate editor coordinating the review of this manuscript and approving it for publication was Giovanni Pau<sup>1</sup>.

many people responsible for analyzing players, who pay attention to many aspects such as football skills, physical and mental conditions. However, still, many of them have problems with the selection of the best line-up and the correct evaluation of potential transfer targets [8]–[10]. The situation is similar in swimming, where the selection of swimmers is crucial nowadays. There are more and more people willing to train. Unfortunately, coaches training swimmers at a high level do not receive any help finding talents. They look for them among the groups assigned to them by the club's management. Therefore, there is a problem with choosing the most flourishing and most likely swimmers to be at the top of the world [11]. Those who have the most desirable qualities should form the core of the training groups, and it is around them that the trainer's attention should focus on fully exploiting their potential. Nowadays, such a choice is not easy [12]. Trainers often lead groups with 15 or more members, where the amount that allows focusing entirely on the needs of individual swimmers should not exceed 5. Therefore, a system of recommendations for the selection of swimmers, created with the use of multi-criteria decision support methods, indicating which of the candidates has better predispositions to train and succeed, would be helpful for the trainers and would allow seeing people with potential [13].

The key to finding future world champions in the swimmers' environment is to determine which features of the athletes have the greatest influence on their performance. Numerous sports institutions and clubs use data on somatic traits [14] or anthropological characteristics [15], [16] of the competitors to determine on their basis what chances for progress a given person has [17]. Multi-criteria decision support has also been applied to other sports competitions such as basketball and football. The most popular rating system for basketball players is based on efficiency and performance statistics [18]. The system uses data on the physicality of players or effectiveness in particular match elements. In football, it works similarly, but apart from the evaluation of players, such systems are also used to predict the growth of the market value of a player shortly. The examples mentioned above are characterized by different approaches to analyzing a player's appearance and assessing his chances for progress using decision support methods. In this paper, the Characteristics Object METHod (COMET) [18]–[20] was used due to the simplicity and flexibility of the method and the possibility of using a hierarchical structure that significantly reduces the number of comparisons. Moreover, the decision to use the mentioned method was dictated by the conducted analysis in the MCDA field [21], which shows that the COMET is suitable for designing complex systems performed based on expert knowledge. This method is also much more resistant to the mistake made by the decision-maker, and therefore it was decided to use it in the design of one's prediction model. Swimmer Assessment Model (SWAM) is available on-line at: <http://comet.edu.pl/SWAM>. The main contributions of this work are:

- Decision Support System (DSS) based on the COMET method;
- Validation the proposed DSS with the TOPSIS method;
- Presented the different strategies to obtain ranking from interval data.

The COMET method has a couple of significant advantages that make it suitable for use in DSS. It is a simple approach based on distances from reference points, similar to TOPSIS. However, it incorporates more characteristic points and thus more accurately models the nonlinearity typical of real-life problems. This method works by comparing characteristic objects instead of alternatives, which is easier for the decision-maker and has an entirely independent complexity of the number of alternatives being evaluated. Moreover, it is a method constantly developed by adding new modifications and extensions, making it possible to eliminate limitations identified in MCDM methods. The algorithm of the COMET method consisting of interconnected independent modules gives vast possibilities of combining this method with other mathematical models and MCDM methods. The described advantages make the COMET method suitable as a DSS engine due to its innovative approach that eliminates the previous limitations of MCDM, compatibility with other techniques, and its develop-ability. It gives the opportunity of creating a full-domain system based on COMET and its extensions. The COMET method has been improved a lot since its development and inspired the development of its extensions, in which calculations are based on interval arithmetic, hesitant fuzzy sets [22]–[24] and intuitionistic fuzzy sets [25].

The rest of the paper is organized as follows: the next section explains the Fuzzy Set Theory. Section 3 describes how COMET works and why the chosen method is helpful for evaluating the multi-criteria decision-making model. The validation approach is shown in Section 4. The next step, in Section 5, is to conduct an experiment on a previously built model of a recommendation system for the selection of swimmers, describe its successive stages, summarize the results, and present them. The short discussion is presented in Section 6. The last Section 7, includes a summary and concluding the conducted research.

## II. FUZZY SET THEORY: PRELIMINARIES

Zadeh developed the fuzzy set theory as the approach to handling uncertainty and introduced this idea in [26]. The growing significance of the Fuzzy Set Theory in model identification in numerous scientific fields has proven to be an effective way to approach and solve multi-criteria decision problems [4], [27]–[29]. The necessary concepts of the Fuzzy Set Theory are recalled as follows [9], [22], [30], [31]:

*Definition 1 (The Fuzzy Set and the Membership Function):* the characteristic function  $\mu_A$  of a crisp set  $A \subseteq X$  assigns a value of either 0 or 1 to each member of  $X$ , as well as 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 [32], [33].

**Definition 2 (The Triangular Fuzzy Number (TFN)):** a fuzzy set  $\tilde{A}$ , defined on the universal set of real numbers  $\mathbb{R}$ , is told to be a triangular fuzzy number  $\tilde{A}(a, m, b)$  if its membership function has the following form [32], [33] (1):

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

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

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

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

**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 [32], [33] (4):

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

**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 [32], [33] (5):

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

**Definition 5 (The Fuzzy Rule):** the single fuzzy rule can be based on the Modus Ponens tautology [32], [33]. 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 [33], [34].

**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 property: boundary (6), monotonicity (7), commutativity (8), and associativity (9) (for any  $a, b, c, d \in [0, 1]$ ).

$$T(0, 0) = 0, \quad T(a, 1) = T(1, a) = a \quad (6)$$

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

$$T(a, b) = T(b, a) \quad (8)$$

$$T(a, T(b, c)) = T(T(a, b), c) \quad (9)$$

In this paper, the product is used as the T-norm operator [32]–[34] (10):

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

**Definition 8 (The S-Norm Operator (Union), or T-Conorm):** the S-norm operator is a  $S$  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 property: boundary (11), monotonicity (12), commutativity (13), and associativity (14) (for any  $a, b, c, d \in [0, 1]$ ).

$$S(1, 1) = 1, S(a, 0) = T(0, a) = a \quad (11)$$

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

$$S(a, b) = S(b, a) \quad (13)$$

$$S(a, S(b, c)) = S(S(a, b), c) \quad (14)$$

In this paper, the bounded sum is used as the S-norm operator [32]–[34] (15):

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

### III. THE CHARACTERISTIC OBJECTS METHOD

In the many MCDM methods, the rank reversal phenomenon is observed. However, the Characteristic Objects Method (COMET) is completely free of this problem. In previous works, the accuracy of the COMET method was verified [35]. The formal notation of the COMET method should be briefly recalled according to [22], [30], [31]. The whole decision-making process using the COMET method is presented in the Figure 1.

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

$$\begin{aligned} C_1 &= \{\tilde{C}_{11}, \tilde{C}_{12}, \dots, \tilde{C}_{1c_1}\} \\ C_2 &= \{\tilde{C}_{21}, \tilde{C}_{22}, \dots, \tilde{C}_{2c_2}\} \\ &\dots \\ C_r &= \{\tilde{C}_{r1}, \tilde{C}_{r2}, \dots, \tilde{C}_{rc_r}\} \end{aligned} \quad (16)$$

where  $C_1, C_2, \dots, C_r$  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 (17):

$$CO = C(C_1) \times C(C_2) \times \dots \times C(C_r) \quad (17)$$

As a result, an ordered set of all  $CO$  is obtained (18):

$$\begin{aligned} CO_1 &= C(\tilde{C}_{11}), C(\tilde{C}_{21}), \dots, C(\tilde{C}_{r1}) \\ CO_2 &= C(\tilde{C}_{11}), C(\tilde{C}_{21}), \dots, C(\tilde{C}_{r2}) \\ &\dots \\ CO_t &= C(\tilde{C}_{1c_1}), C(\tilde{C}_{2c_2}), \dots, C(\tilde{C}_{rc_r}) \end{aligned} \quad (18)$$

where  $t$  is the count of  $CO$ s and is equal to (19):

$$t = \prod_{i=1}^r c_i \quad (19)$$

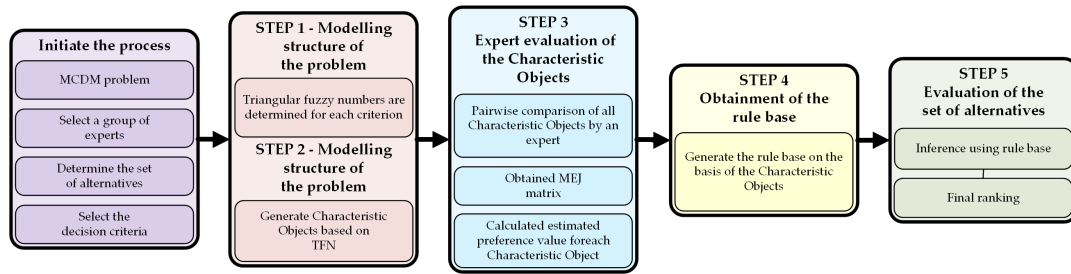


FIGURE 1. The procedure of the COMET method to identify decision-making model.

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 (20):

$$MEJ = \begin{pmatrix} \alpha_{11} & \alpha_{12} & \dots & \alpha_{1i} \\ \alpha_{21} & \alpha_{22} & \dots & \alpha_{2i} \\ \dots & \dots & \dots & \dots \\ \alpha_{i1} & \alpha_{i2} & \dots & \alpha_{ii} \end{pmatrix} \quad (20)$$

where  $\alpha_{ij}$  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 (21):

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

After the MEJ matrix is prepared, a vertical vector of the Summed Judgments (SJ) is obtained as follows (22):

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

Eventually, the values of preference are approximated for each characteristic object. As a result, a vertical vector  $P$  is obtained, where the  $i$ -th 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 (23):

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

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.  $A_i = \{\alpha_{i1}, \alpha_{i2}, \alpha_{ir}\}$ . This set corresponds to the criteria  $C_1, C_2, \dots, C_r$ . 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.

#### IV. THE TECHNIQUE FOR ORDER OF PREFERENCE BY SIMILARITY TO IDEAL SOLUTION

The TOPSIS technique is a popular MCDA approach used in many practical problems. It is widely used in solving multi-criteria problems in a different areas. We recall its

algorithm according to [36]. Let us suppose that we have a decision matrix with  $m$  alternatives and  $n$  criteria, and it is represented as  $X = (x_{ij})_{m \times n}$ .

Step 1: Calculate the normalized decision matrix. The normalized values  $r_{ij}$  calculated according to equation (24) for profit criteria and (25) for cost criteria. We use this normalization method, because [37] shows that it performs better than classical vector normalization.

$$r_{ij} = \frac{x_{ij} - \min_j(x_{ij})}{\max_j(x_{ij}) - \min_j(x_{ij})} \quad (24)$$

$$r_{ij} = \frac{\max_j(x_{ij}) - x_{ij}}{\max_j(x_{ij}) - \min_j(x_{ij})} \quad (25)$$

Step 2: Calculate the weighted normalized decision matrix  $v_{ij}$  according to equation (26).

$$v_{ij} = w_i r_{ij} \quad (26)$$

Step 3: Calculate Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS) vectors. PIS is defined as maximum values for each criteria (27) and NIS as minimum values (28). We don't need to split criteria into profit and cost here, because in step 1 we use normalization which turns cost criteria into profit criteria.

$$v_j^+ = \{v_1^+, v_2^+, \dots, v_n^+\} = \{\max_j(v_{ij})\} \quad (27)$$

$$v_j^- = \{v_1^-, v_2^-, \dots, v_n^-\} = \{\min_j(v_{ij})\} \quad (28)$$

Step 4: Calculate distance from PIS and NIS for each alternative. As shows equations (29) and (30).

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (29)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (30)$$

Step 5: Calculate each alternative's score according to equation (31). This value is always between 0 and 1, and the alternatives which got values closer to 1 are better.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (31)$$

## V. SWAM SYSTEM FOUNDATIONS

This paper presents an evaluation model concerning the system of recommendations for selecting swimmers, including the male gender. Considering the number of athletes in groups and the problem with selecting units that stand out from others, it is difficult to select those to whom the coach should devote his attention. This choice is influenced by many factors related to somatic traits, and based on expert knowledge, 11 criteria were selected, which will be the core of attributes determining the swimmer's predispositions. Thus, the space of the solving problem is equal to  $r = 11$ . The criteria are the following:

- $C_1$  - weight of the swimmer, expressed in kilograms (kg);
- $C_2$  - height of the swimmer, expressed in centimeters (cm);
- $C_3$  - age of the swimmer, expressed in years (yr);
- $C_4$  - length of foot, expressed in centimeters (cm);
- $C_5$  - arms-height-ratio, expressed in units;
- $C_6$  - swimming technique, expressed in units;
- $C_7$  - flexibility of the swimmer, expressed in units;
- $C_8$  - maximum heart rate, expressed in heart beats per minute;
- $C_9$  - fat index, expressed in units;
- $C_{10}$  - fat-muscle-ratio, expressed in units;
- $C_{11}$  - best FINA result, expressed in units.

The choice of criteria was dictated by the importance of the indicated characteristics in the discipline of swimming. Body length, shoulder width, and foot length have a significant impact on the driving force generated by the player while swimming [38]. Bodyweight, fat and muscle levels, on the other hand, have an impact on how hard it will be for us to overcome the next meters and what ballast we will have to set in motion while swimming [39]. Age is an important factor that indicates how long the athlete will still be able to continue his career and still be at good disposal to improve or develop [40]. Based on the maximum heart rate, the coach and the player can determine the individual heart rate values for different training intensities [41]. In turn, technique and mobility play an important role because they directly affect the quality of movements in the water [42], [43]. The FINA points obtained by the contestant allow the comparison of all swimmers, regardless of the style of the distance [44].

This study has decomposed the problem into subproblems, as shown in Figure 2. In this way, we need to identify seven interrelated models, where each of them requires a lot less queries number. The decision model can be demonstrated as the following modules:

- $P_1$  - metric assessment model (27 characteristic object and 351 pairwise comparisons are needed);
- $P_2$  - additions body parameter model (9 characteristic object and 36 pairwise comparisons are needed);
- $P_3$  - metrics model (9 characteristic object and 36 pairwise comparisons are needed);

- $P_4$  - skills model (9 characteristic object and 36 pairwise comparisons are needed);
- $P_5$  - body and fitness assessment model (27 characteristic object and 351 pairwise comparisons are needed);
- $P_6$  - physical condition and skills assessment model (27 characteristic object and 351 pairwise comparisons are needed);
- $P$  - comprehensive assessment model (9 characteristic object and 36 pairwise comparisons are needed).

It is worth noting that without using a structural approach (hierarchical approach), the number of characteristic objects according to eq. (19) will be 177,147. However, with the decomposition of the problem, according to Figure 2., the total number of characteristic objects will be only 117. This reduction has a huge impact on the number of queries to the expert that have to be made to identify the MEJ matrix. There are only 1197 queries to the expert in the proposed approach, while in the monolithic approach, it would be more than 13 million times more questions. So, the emerging curse of dimensionality can be easily solved by introducing the structural approach in the comet method.

Table 1 shows the listed criteria and their linguistic values, and Table 2 provides information on all these attributes of the designed model for 30 young swimmers. Before determining the final comprehensive assessment model, individual criteria with the most significant impact on the selection of swimmers should be defined, e.g., best FINA result, arm length to height ratio, flexibility, and technique or maximum heart rate.

### A. BEST FINA RESULT

One of the criteria taken into account when assessing the predisposition of a competitor in the proposed model is the best FINA (fr. Fédération Internationale de Natation) result obtained by a given swimmer in his entire career [45]. FINA is a global water sports organization that sets the standard for competition regulations. The so-called FINA score is used to classify the result against the world record in a given competition in swimming. It means that if the world record for a 25-meter swimming pool (short course) over a distance of 50 meters in freestyle is 20 seconds and 26 hundredths, the result will be 1000 FINA points [46], [47]. When a competitor achieves a time better than the world record, the score exceeds 1000 points. When the time is slower, which happens much more often, the result is placed in the table between the nearest times in the FINA table, and the number of points he has achieved is determined. The FINA table containing the times includes a summary of the times and a corresponding number of points [48]. For example, at the same distance mentioned above, time 21.60 gives 825 points, while 22.70 gives 711 points. The characteristic values for criterion  $C_{11}$  and related to them the triangular fuzzy number are depicted in Figure 3. The space of the problem, including characteristic objects and alternatives, is presented in Figure 4. The MEJ matrix is presented in Figure 5. The values of

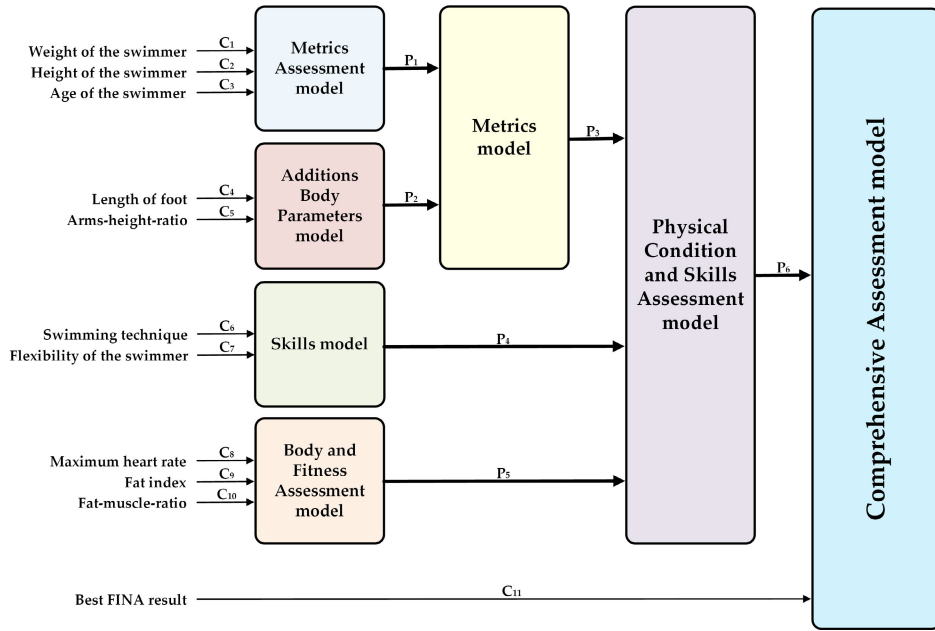


FIGURE 2. Hierarchical structure for the problem of comprehensive assessment of the swimmers.

TABLE 1. Selected criteria  $C_1 - C_{11}$  and their characteristic values {low, medium, high}.

$C_i$	name	unit	low	medium	high
$C_1$	weight	kg	73	82	88
$C_2$	height	cm	175	188	200
$C_3$	age	years	15	18	24
$C_4$	length of foot	cm	28	29.5	32
$C_5$	arms-height-ratio	units	95	101	104
$C_6$	swimming-technique	units	1	8	10
$C_7$	flexibility	units	1	7	10
$C_8$	maximum heart-rate	HB/min	185	195	210
$C_9$	fat-index	units	4	8	12
$C_{10}$	fat-muscle-ratio	units	5	9	15
$C_{11}$	best FINA result	units	650	740	1000

$\alpha_{ij}$  of either 0, 0.5, or 1 are represented by white, black, and gray boxes, respectively.

**B. ARMS-HEIGHT-RATIO**

Another factor worth noting is the arms-height ratio. It is an important element of an athlete’s assessment and belongs to the group of criteria which are not influenced by the trainee [49]. Longer arms mean that the hand will have to travel a long way when making a move, it will result in more captured water, so it also affects the greater distance we will travel with each movement [50]. When strokes are dynamic and energetic, they are the most effective. A person with longer arms will work with a lower frequency of movements during one pool than a person with shorter arms [51]. This results in less fatigue and more energy, for example, at the distance’s end. A swimmer who is 185 centimeters tall with an arms-height-ratio of 101 has a arms length of 186.85 centimeters, so the shoulder length is greater than the body length. On the other hand, a swimmer of the same height with a ratio of 96 has an arms length of 177.6 centimeters.

As we can see, this is a significant difference that affects the assessment of a swimmer’s predisposition. The triangular fuzzy number of criteria  $C_5$  is depicted in Figure 3. The MEJ matrix is presented in Figure 5. The domain space, including characteristic objects and alternatives, is presented in Figure 8.

**C. FLEXIBILITY AND SWIMMING TECHNIQUE**

Criteria that are closely related to each other are the assessment of flexibility and swimming techniques. Flexibility is an element on which competitors can work and improve [52], [53]. Stretching is a tedious and lengthy process, bringing the desired results. The more flexible the body is, the easier it will be to make movements in the water to give optimal results. For example, high shoulder mobility is very important when swimming in a butterfly. The smaller the range of shoulder movement, the more difficult it is to maintain a correct position in the water and a proper flow rate. In the breaststroke, while making legs move, it is important that the groin is stretched as much as possible and does not restrict

**TABLE 2.** The performance table of the alternatives  $A_1 - A_{30}$  and body parameters for considered criteria.

$A_i$	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$	$C_6$	$C_7$	$C_8$	$C_9$	$C_{10}$	$C_{11}$
$A_1$	75.53	198.7	20.8	29.2	0.994	9	6	197	7.75	0.054	731
$A_2$	81.54	190.3	18.1	29.8	0.967	7	2	192	4.76	0.139	652
$A_3$	87.73	185.6	21.4	29.0	0.968	2	2	188	11.60	0.078	734
$A_4$	73.08	190.6	22.7	30.4	1.016	6	3	185	4.12	0.091	730
$A_5$	83.25	190.0	22.1	30.8	0.993	9	6	208	10.32	0.122	961
$A_6$	80.68	191.3	16.3	30.2	0.966	6	8	189	6.42	0.146	682
$A_7$	73.41	183.7	17.1	28.7	0.995	8	7	199	8.74	0.110	846
$A_8$	75.91	178.8	21.5	28.4	1.038	4	6	201	11.26	0.143	751
$A_9$	73.29	190.7	16.0	28.5	0.996	8	1	202	8.70	0.134	677
$A_{10}$	77.70	198.4	19.5	29.0	0.973	5	4	194	7.23	0.135	931
$A_{11}$	73.56	187.8	20.8	28.2	0.976	3	5	203	8.43	0.066	781
$A_{12}$	75.88	179.7	21.8	31.6	0.962	2	9	203	7.26	0.104	661
$A_{13}$	87.64	192.2	20.3	32.0	1.026	4	6	196	5.32	0.109	935
$A_{14}$	82.01	195.7	20.9	28.9	0.957	1	1	207	10.48	0.070	841
$A_{15}$	87.92	198.1	19.0	31.3	0.969	2	7	199	4.42	0.147	778
$A_{16}$	81.47	180.7	23.2	29.8	1.035	1	8	186	9.00	0.052	813
$A_{17}$	78.94	187.2	18.2	28.0	0.966	2	3	196	5.29	0.149	843
$A_{18}$	80.03	175.1	20.3	31.7	1.012	3	3	208	4.46	0.059	864
$A_{19}$	85.83	185.9	17.2	31.7	0.999	1	6	204	8.02	0.056	740
$A_{20}$	86.78	198.0	17.0	28.9	0.965	9	6	196	8.28	0.134	653
$A_{21}$	78.55	196.2	20.2	29.2	0.992	6	1	204	4.98	0.098	832
$A_{22}$	86.50	175.7	17.2	30.7	1.010	1	7	189	8.07	0.072	709
$A_{23}$	85.13	192.7	18.3	29.8	1.017	6	7	193	5.71	0.059	815
$A_{24}$	74.01	195.3	18.4	30.0	0.986	2	3	201	4.11	0.061	846
$A_{25}$	85.96	183.0	16.0	30.1	1.014	7	4	198	8.70	0.112	951
$A_{26}$	74.34	197.0	19.8	29.1	0.982	1	7	193	4.92	0.074	676
$A_{27}$	82.90	179.9	17.6	28.2	0.971	9	6	192	11.08	0.080	667
$A_{28}$	78.79	184.1	17.8	30.9	0.993	9	7	205	4.44	0.118	985
$A_{29}$	73.42	176.5	19.9	30.4	1.027	7	1	200	8.76	0.128	804
$A_{30}$	73.20	179.0	22.2	31.6	0.972	8	1	191	5.38	0.089	935

the range of movement of the legs [54]. This will ensure a more effective pushback, so it will also improve the result. What is more, whatever a swimmer style is, it is a good idea to stretch his ankle joints. The feet are one of the main engines of the float. They constantly work over a distance [55]. When making a move, a stiff foot will not allow effective pushback and will make it much more difficult to compete with the best. To sum up, the more flexible the body, the easier it will be to make a given movement according to the correct pattern. The swimming technique is largely an individual issue. Fine-tuning the details of the movements performed requires determining the characteristics of each part of the body and selecting the most effective solutions to achieve the best results. However, the whole process is based on the ability to swim according to the correct pattern of each style, which is continuously analyzed and enhanced to improve swimming ergonomics. The triangular fuzzy numbers of criteria  $C_6$  and  $C_7$  are depicted in Figure. 3. The space of the problem, including characteristic objects and alternatives, is presented in Figure. 10. The MEJ matrix is presented in Figure. 6.

**D. MAXIMUM HEART RATE**

The heart rate is the number of beats the heart does during one minute. The maximum average heart rate is the number of beats per minute during exercises. We can estimate it for people who are not athletes by subtracting their age from 220. During intensive exercise, the heart rate is much higher than at rest. Moreover, the heart rate of a professional athlete is different from that of an average person not connected with sport. In the case of people who train, some adaptations force

them to get used to working at high intensity, which means that while performing a given effort, the athlete will have a much lower heart rate than a person who does not train at the same activity. The maximum heart rate is determined during the test, where the person is attached to an oxygen mask and a heart rate monitor and runs subsequent sections on the treadmill at the given speed. The treadmill is inclined at an angle of 3 degrees, the speed is increased regularly, and the test takes place until the person cannot continue the effort. The oxygen mask in the test is used to check the amount of oxygen taken in when inhaling and excreted carbon dioxide when exhaling. Based on this, we can determine what swimmer oxygen consumption looks like. The heart rate monitor allows us to check your heart rate at each stage of the test and at a critical point where the person can no longer continue the test. It also allows us to capture a heart rate that will most likely determine that person’s maximum possible heart rate. The higher the maximum heart rate, the greater the body’s endurance, which results in training at higher intensity over a longer time. The TFN of criteria  $C_8$  are depicted in Figure 3. The MEJ matrix is presented in Figure 6. The space of the problem, including characteristic objects and alternatives, is presented in Figure 11.

**E. FINAL RANKING**

The final preference and considered ranking of all athletes are presented in Table 3. When considering the case in which we know the values of all the criteria taken into account in the proposed model, the person with the most favorable parameters is the athlete  $A_{28}$  (preferential value

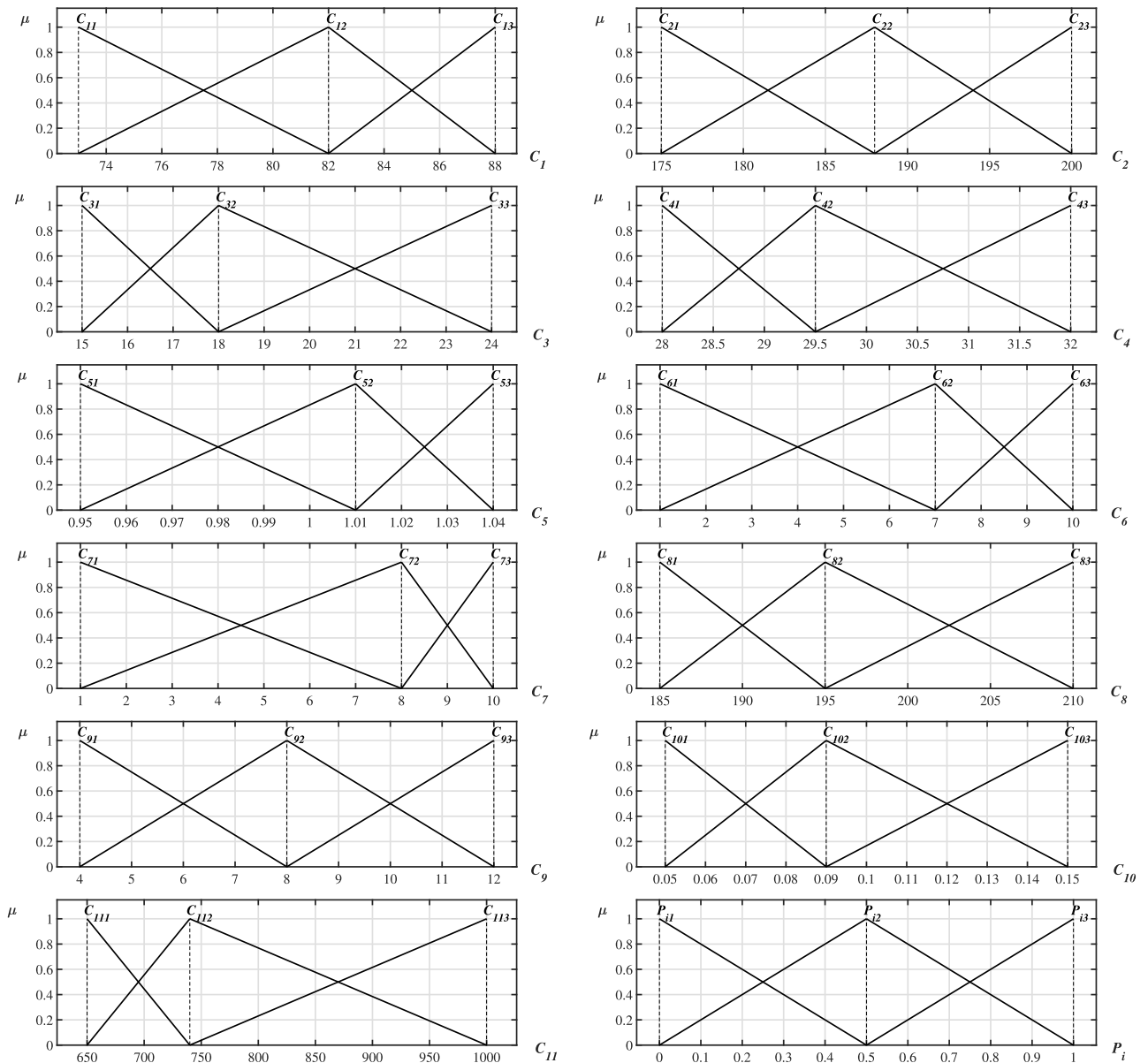


FIGURE 3. The set of the triangular numbers for the criteria  $C_j$  and  $P_j$ .

0.926), followed by the athlete  $A_5$  (preference value 0.882). On the other hand, the worst alternative is  $A_2$  (preference value 0.208). Athletes  $A_{26}$ ,  $A_{12}$  and  $A_3$  (preference values of 0.244, 0.255 and 0.260 respectively) have a slightly better, but not significantly different, overall rating. The  $A_{26}$  competitor, despite obtaining a high score in the  $P_5$  module (0.717), was one of the worst-rated athletes.  $A_{13}$  obtained a very high rating in modules  $P_2$  and  $P_3$  (0.924 and 0.891 respectively), but this ensured him only fourth place in the overall rating. It is also worth noting that competitor  $A_5$  (second most recommended) has a lower rating than competitor  $A_{13}$  in 4 modules ( $P_1$ ,  $P_2$ ,  $P_3$ ,  $P_5$ ), but module  $P_4$  is more than twice as good as competitors  $A_5$  score, which resulted in a better overall rating. In the case of competitor  $A_{14}$ , who received 0.000 rating in

module  $P_4$  (flexibility and swimming technique rated at value 1), thanks to high factors in modules  $P_1$ ,  $P_5$  and average in the others, was not among the worst proposed competitors, which proves that person having deficiencies in one of the fields can be classified better than a person with non-zero ratings in all modules.

The analysis of similarity coefficients  $WS$  and  $r_w$  [56] for the final ranking concerning intermediate rankings is presented in Tables 4 and 5. According to the  $WS$  coefficient, the most similar ranking to the final ranking was  $P'_6$ , followed by  $P'_3$  and  $P'_4$ . A similar ranking is obtained by applying  $r_w$  coefficient, but with the difference that  $P'_3$  is not such an important parameter. This shows that aggregation of models was a desirable element and each of the partial models carries



**TABLE 3.** The obtained preference results for determined submodels  $P_i$  and their corresponding positions in general ranking  $P_i^r$ .

$A_i$	$P_1$	$P_2$	$P_3$	$P_4$	$P_5$	$P_6$	$P$	$P_1^r$	$P_2^r$	$P_3^r$	$P_4^r$	$P_5^r$	$P_6^r$	$P^r$
$A_1$	0.426	0.476	0.490	0.698	0.782	0.756	0.610	18	17	16	2	4	2	11
$A_2$	0.673	0.307	0.456	0.360	0.260	0.406	0.208	7	23	17	12	25	21	30
$A_3$	0.524	0.244	0.359	0.077	0.329	0.195	0.260	14	25	26	29	21	29	27
$A_4$	0.293	0.761	0.543	0.339	0.534	0.536	0.491	25	5	11	13	15	10	16
$A_5$	0.644	0.639	0.692	0.698	0.424	0.720	0.882	8	12	6	2	17	4	2
$A_6$	0.747	0.379	0.538	0.524	0.137	0.485	0.330	5	20	12	7	30	15	22
$A_7$	0.386	0.385	0.390	0.625	0.419	0.601	0.693	21	19	25	6	18	5	7
$A_8$	0.286	0.690	0.496	0.310	0.183	0.350	0.402	26	10	15	16	29	25	20
$A_9$	0.431	0.355	0.400	0.375	0.319	0.421	0.280	17	22	22	10	23	20	26
$A_{10}$	0.586	0.279	0.406	0.312	0.224	0.334	0.621	11	24	21	15	27	26	10
$A_{11}$	0.368	0.175	0.229	0.214	0.757	0.374	0.460	22	27	29	20	6	22	17
$A_{12}$	0.295	0.520	0.408	0.280	0.578	0.452	0.255	24	15	20	18	13	16	28
$A_{13}$	0.769	0.924	0.891	0.310	0.502	0.576	0.805	4	1	1	16	16	7	4
$A_{14}$	0.723	0.148	0.333	0.000	0.697	0.242	0.427	6	28	27	30	9	28	19
$A_{15}$	0.939	0.525	0.711	0.196	0.278	0.352	0.438	2	14	5	21	24	24	18
$A_{16}$	0.352	0.828	0.632	0.167	0.590	0.434	0.551	23	2	8	22	10	19	13
$A_{17}$	0.544	0.087	0.230	0.101	0.207	0.131	0.336	12	30	28	27	28	30	21
$A_{18}$	0.223	0.822	0.518	0.161	0.952	0.491	0.671	29	4	14	23	1	14	8
$A_{19}$	0.643	0.754	0.757	0.104	0.848	0.496	0.497	9	6	3	26	3	13	15
$A_{20}$	0.940	0.212	0.450	0.698	0.226	0.558	0.301	1	26	18	2	26	8	24
$A_{21}$	0.587	0.459	0.561	0.268	0.715	0.522	0.642	10	18	10	19	8	12	9
$A_{22}$	0.131	0.748	0.397	0.125	0.559	0.324	0.297	30	7	23	24	14	27	25
$A_{23}$	0.774	0.728	0.780	0.482	0.775	0.751	0.716	3	9	2	8	5	3	6
$A_{24}$	0.453	0.513	0.538	0.101	0.893	0.444	0.605	16	16	12	27	2	17	12
$A_{25}$	0.536	0.731	0.713	0.437	0.397	0.592	0.832	13	8	4	9	19	6	3
$A_{26}$	0.412	0.363	0.393	0.125	0.717	0.363	0.244	19	21	24	24	7	23	29
$A_{27}$	0.404	0.147	0.225	0.698	0.395	0.539	0.325	20	29	30	2	20	9	23
$A_{28}$	0.481	0.647	0.639	0.750	0.581	0.776	0.926	15	11	7	1	12	1	1
$A_{29}$	0.279	0.823	0.567	0.321	0.320	0.437	0.541	27	3	9	14	22	18	14
$A_{30}$	0.262	0.582	0.414	0.375	0.582	0.529	0.790	28	13	19	10	11	11	5

**TABLE 4.** Comparing the similarity of partial rankings with the final ranking using WS coefficient.

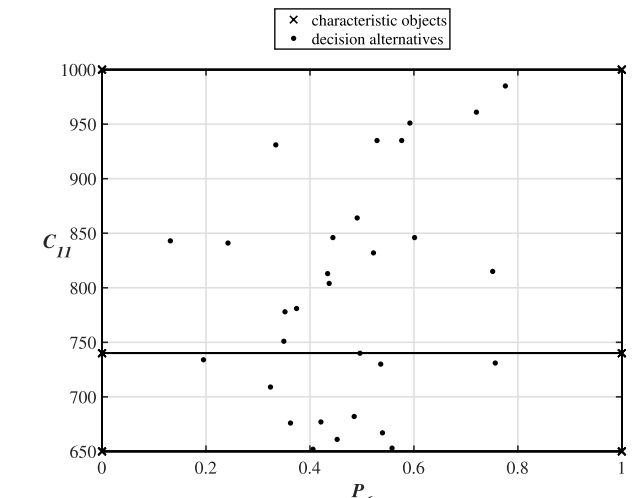
$WS$	$P_1^r$	$P_2^r$	$P_3^r$	$P_4^r$	$P_5^r$	$P_6^r$	$P^r$
$P_1^r$	1.0000	0.3863	0.6409	0.7378	0.2921	0.6421	0.4072
$P_2^r$	0.5522	1.0000	0.8778	0.4364	0.5545	0.6316	0.7616
$P_3^r$	0.8772	0.8951	1.0000	0.5409	0.6437	0.8064	0.8320
$P_4^r$	0.3794	0.1348	0.3262	1.0000	0.2655	0.8608	0.5277
$P_5^r$	0.3119	0.7506	0.6307	0.2628	1.0000	0.5693	0.7000
$P_6^r$	0.5770	0.6203	0.7297	0.9636	0.7195	1.0000	0.8908
$P^r$	0.6190	0.6893	0.8209	0.9311	0.5590	0.9484	1.0000

**TABLE 5.** Comparing the similarity of partial rankings with the final ranking using  $r_w$  coefficient.

$r_w$	$P_1^r$	$P_2^r$	$P_3^r$	$P_4^r$	$P_5^r$	$P_6^r$	$P^r$
$P_1^r$	1.0000	-0.2478	0.3883	0.1097	-0.2218	0.1482	0.0608
$P_2^r$	-0.2478	1.0000	0.7289	-0.1280	0.2745	0.2905	0.4776
$P_3^r$	0.3883	0.7289	1.0000	0.1015	0.1770	0.4920	0.5991
$P_4^r$	0.1097	-0.1280	0.1015	1.0000	-0.3127	0.7656	0.3267
$P_5^r$	-0.2218	0.2745	0.1770	-0.3127	1.0000	0.2526	0.3132
$P_6^r$	0.1482	0.2905	0.4920	0.7656	0.2526	1.0000	0.6926
$P^r$	0.0608	0.4776	0.5991	0.3267	0.3132	0.6926	1.0000

some information, and similarity results are not unambiguous with the coefficients used.

To sum up the presented assessments of individual modules and the comprehensive assessment, it can be observed that the most optimal and promising opportunity for achieving the most significant progress is to have attributed at a balanced level or insignificantly different from each other. However, weaker results in individual modules do not disqualify and are not associated with having the worst comprehensive factor,



**FIGURE 4.** The space of the problem for the identification of P considering submodel  $P_6$  and criterion  $C_{11}$ .

as confirmed by the example above representing the athlete  $A_{14}$ .

The other important view on the considered problem is that it includes numerous criteria making it more difficult to obtain a golden standard between determined submodels assessments. It is worth noticing that regarding the post-Pareto optimality analysis [57], objectives multiobjective optimization conflict with each other, which means

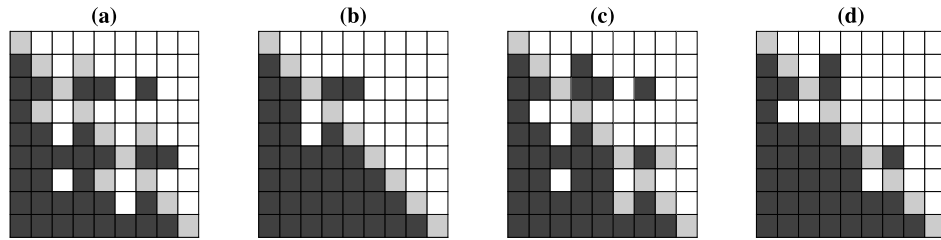


FIGURE 5. The matrix of expert judgement for  $P_2$  (a),  $P_4$  (b),  $P_3$  (c), and  $P$  (d).

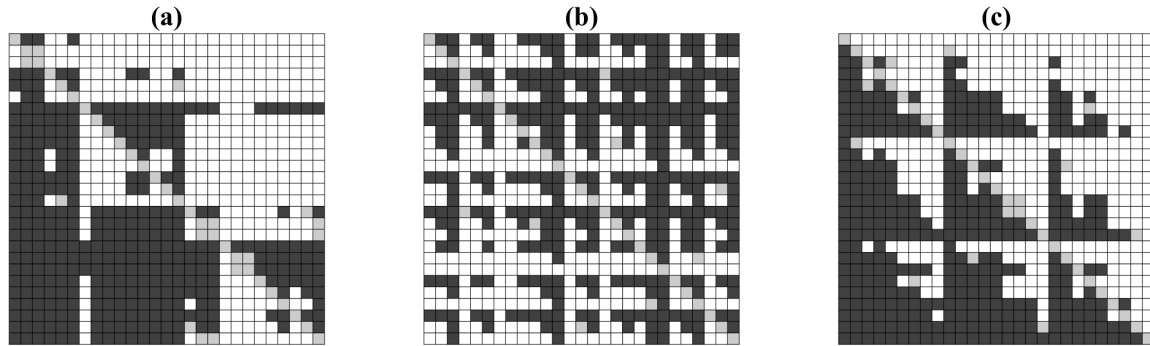


FIGURE 6. The matrix of expert judgement for  $P_1$  (a),  $P_5$  (b),  $P_6$  (c).

TABLE 6. The decision matrix after normalization by using the TOPSIS method.

	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$	$C_6$	$C_7$	$C_8$	$C_9$	$C_{10}$	$C_{11}$
$A_1$	0.1651	1.0000	0.6667	0.300	0.4568	1.000	0.625	0.5217	0.4860	0.0206	0.2372
$A_2$	0.5701	0.6441	0.2917	0.450	0.1235	0.750	0.125	0.3043	0.0868	0.8969	0.0000
$A_3$	0.9872	0.4449	0.7500	0.250	0.1358	0.125	0.125	0.1304	1.0000	0.2680	0.2462
$A_4$	0.0000	0.6568	0.9306	0.600	0.7284	0.625	0.250	0.0000	0.0013	0.4021	0.2342
$A_5$	0.6853	0.6314	0.8472	0.700	0.4444	1.000	0.625	1.0000	0.8291	0.7216	0.9279
$A_6$	0.5121	0.6864	0.0417	0.550	0.1111	0.625	0.875	0.1739	0.3084	0.9691	0.0901
$A_7$	0.0222	0.3644	0.1528	0.175	0.4691	0.875	0.750	0.6087	0.6182	0.5979	0.5826
$A_8$	0.1907	0.1568	0.7639	0.100	1.0000	0.375	0.625	0.6957	0.9546	0.9381	0.2973
$A_9$	0.0142	0.6610	0.0000	0.125	0.4815	0.875	0.000	0.7391	0.6128	0.8454	0.0751
$A_{10}$	0.3113	0.9873	0.4861	0.250	0.1975	0.500	0.375	0.3913	0.4166	0.8557	0.8378
$A_{11}$	0.0323	0.5381	0.6667	0.050	0.2346	0.250	0.500	0.7826	0.5768	0.1443	0.3874
$A_{12}$	0.1887	0.1949	0.8056	0.900	0.0617	0.125	1.000	0.7826	0.4206	0.5361	0.0270
$A_{13}$	0.9811	0.7246	0.5972	1.000	0.8519	0.375	0.625	0.4783	0.1615	0.5876	0.8498
$A_{14}$	0.6018	0.8729	0.6806	0.225	0.0000	0.000	0.000	0.9565	0.8505	0.1856	0.5676
$A_{15}$	1.0000	0.9746	0.4167	0.825	0.1481	0.125	0.750	0.6087	0.0414	0.9794	0.3784
$A_{16}$	0.5654	0.2373	1.0000	0.450	0.9630	0.000	0.875	0.0435	0.6529	0.0000	0.4835
$A_{17}$	0.3949	0.5127	0.3056	0.000	0.1111	0.125	0.250	0.4783	0.1575	1.0000	0.5736
$A_{18}$	0.4683	0.0000	0.5972	0.925	0.6790	0.250	0.250	1.0000	0.0467	0.0722	0.6366
$A_{19}$	0.8592	0.4576	0.1667	0.925	0.5185	0.000	0.625	0.8261	0.5220	0.0412	0.2643
$A_{20}$	0.9232	0.9703	0.1389	0.225	0.0988	1.000	0.625	0.4783	0.5567	0.8454	0.0030
$A_{21}$	0.3686	0.8941	0.5833	0.300	0.4321	0.625	0.000	0.8261	0.1162	0.4742	0.5405
$A_{22}$	0.9043	0.0254	0.1667	0.675	0.6543	0.000	0.750	0.1739	0.5287	0.2062	0.1712
$A_{23}$	0.8120	0.7458	0.3194	0.450	0.7407	0.625	0.750	0.3478	0.2136	0.0722	0.4895
$A_{24}$	0.0627	0.8559	0.3333	0.500	0.3580	0.125	0.250	0.6957	0.0000	0.0928	0.5826
$A_{25}$	0.8679	0.3347	0.0000	0.525	0.7037	0.750	0.375	0.5652	0.6128	0.6186	0.8979
$A_{26}$	0.0849	0.9280	0.5278	0.275	0.3086	0.000	0.750	0.3478	0.1081	0.2268	0.0721
$A_{27}$	0.6617	0.2034	0.2222	0.050	0.1728	1.000	0.625	0.3043	0.9306	0.2887	0.0450
$A_{28}$	0.3848	0.3814	0.2500	0.725	0.4444	1.000	0.750	0.8696	0.0441	0.6804	1.0000
$A_{29}$	0.0229	0.0593	0.5417	0.600	0.8642	0.750	0.000	0.6522	0.6208	0.7835	0.4565
$A_{30}$	0.0081	0.1653	0.8611	0.900	0.1852	0.875	0.000	0.2609	0.1696	0.3814	0.8498

that the specific optima cannot be achieved simultaneously. In the practical dimension, translating the presented formula to swimming means it is impossible to achieve the best

results in all presented submodels by the particular swimmer. The diversity in results can be seen in Table 3, where the obtained preferences are presented. Keeping higher positions

TABLE 7. The alternatives  $A_1 - A_8$  presented partly as uncertain data.

$A_i$	$C_1$	$C_2$	$C_3$	$C_4$	$C_5$	$C_6$	$C_7$	$C_8$	$C_9$	$C_{10}$	$C_{11}$	$C_{12}$
$A_1$	79.7	186	18	29	[1.01, 1.03]	[7, 9]	[8, 10]	[205, 209]	6.3	0.084	717	23.32
$A_2$	87.9	194	18	31.5	[1.00, 1.04]	[6, 8]	[5, 7]	[208, 210]	9.6	0.129	697	23.46
$A_3$	87.4	188	17	29.5	[1.00, 1.03]	[8, 10]	[6, 8]	[205, 210]	7.8	0.104	787	22.61
$A_4$	73.5	186	18	29	[1.00, 1.04]	[8, 10]	[6, 8]	[200, 208]	6.6	0.091	757	22.87
$A_5$	81.2	184	16	29	[0.99, 1.02]	[7, 9]	[7, 8]	[195, 205]	11.9	0.141	661	23.70
$A_6$	78.5	182	18	28.5	[0.98, 1.01]	[6, 8]	[5, 7]	[200, 208]	7.2	0.101	682	24.44
$A_7$	84.6	187	24	30	[1.01, 1.04]	[8, 10]	[5, 8]	[208, 210]	7.3	0.094	773	23.11
$A_8$	82.8	188	17	30	[0.97, 1.01]	[5, 7]	[5, 7]	[198, 204]	9.9	0.136	619	25.20

TABLE 8. The interval preferences of alternatives  $A_1 - A_8$ .

$A_i$	$P_1$	$P_2$	$P_3$	$P_4$	$P_5$	$P_6$	$P$
$A_1$	0.536	[0.556, 0.704]	[0.614, 0.698]	[0.595, 0.875]	[0.766, 0.817]	[0.748, 0.884]	[0.576, 0.653]
$A_2$	0.873	[0.739, 0.967]	[0.815, 0.945]	[0.411, 0.625]	[0.420, 0.453]	[0.603, 0.765]	[0.444, 0.545]
$A_3$	0.762	[0.583, 0.778]	[0.694, 0.805]	[0.583, 0.917]	[0.588, 0.659]	[0.733, 0.891]	[0.674, 0.746]
$A_4$	0.396	[0.481, 0.778]	[0.469, 0.641]	[0.583, 0.917]	[0.652, 0.758]	[0.684, 0.874]	[0.613, 0.705]
$A_5$	0.617	[0.407, 0.630]	[0.526, 0.679]	[0.554, 0.792]	[0.088, 0.236]	[0.470, 0.667]	[0.265, 0.401]
$A_6$	0.422	[0.250, 0.444]	[0.313, 0.462]	[0.411, 0.625]	[0.559, 0.669]	[0.513, 0.669]	[0.348, 0.471]
$A_7$	0.540	[0.700, 0.867]	[0.697, 0.792]	[0.542, 0.917]	[0.709, 0.735]	[0.742, 0.902]	[0.661, 0.736]
$A_8$	0.723	[0.389, 0.700]	[0.540, 0.750]	[0.345, 0.554]	[0.206, 0.307]	[0.396, 0.624]	[0.198, 0.343]

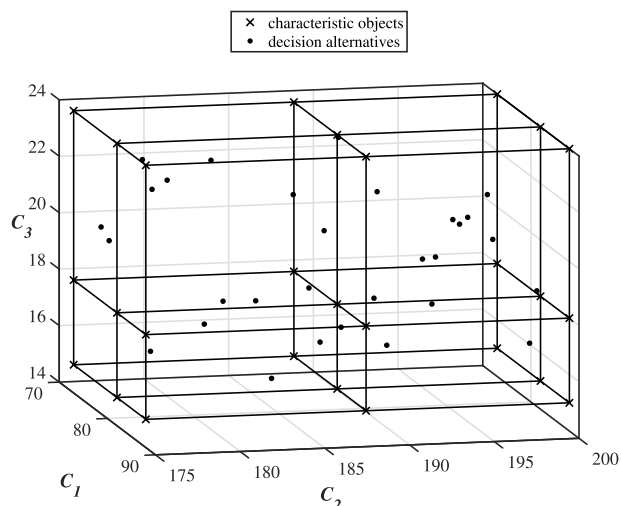


FIGURE 7. The space of the problem for the identification of  $P_1$ .

in the given submodels causes the lower positions in other assessments, and this phenomenon can be observed within all swimmers. Based on the post-Pareto rule, it can be concluded that one athlete cannot be the best in all submodels. However, one area and obtained assessment can be more valuable than the other, so observed differences impact the final results.

The TOPSIS method was used to validate the obtained results within the usage of the COMET method. TOPSIS also belongs to the MCDA distanced-based methods and is eagerly used to solve multi-criteria problems. All criteria were taken into account by using the TOPSIS method because considering the presented structure for handling the problem in the COMET method and the differences between those methods, solving the presented problem with the TOPSIS method was carried with a monolithic structure. All crite-

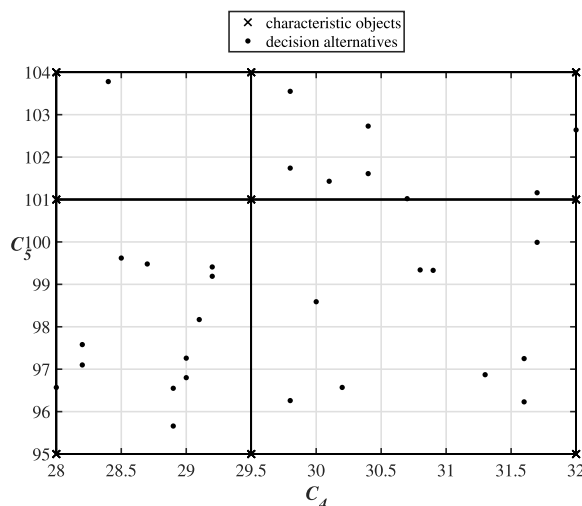


FIGURE 8. The space of the problem for the identification of  $P_2$ .

ria were on the same level, and the same characteristics did not group them into submodels as it was done in the COMET method. Table 6 presents the partial results by using the TOPSIS method (for this purpose, library pymcda: <https://pypi.org/project/pymcda/>). Obtained preferences were used to calculate the positional ranking, and then both rankings were compared with the weighted Spearman correlation coefficient. The high similarity could be observed by the correlation coefficient equaling 0.8834. It shows that simplifying the base model with a hierarchical structure makes it possible to achieve strongly correlated results using another MCDA method.

VI. DISCUSSION

The condition of a sportsman in the given period of the season depends on many factors. This is influenced by the

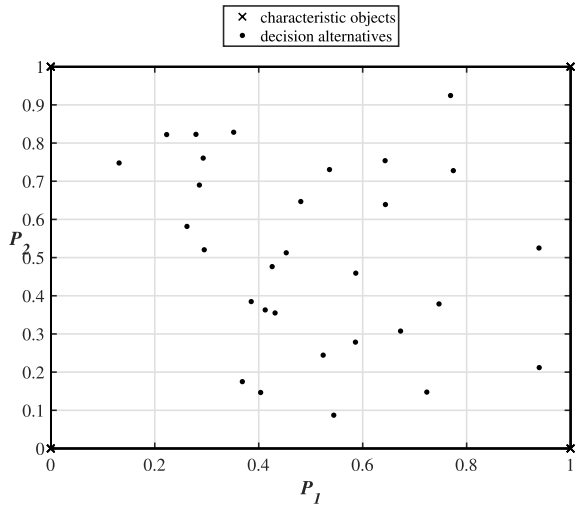


FIGURE 9. The space of the problem for the identification of  $P_3$ .

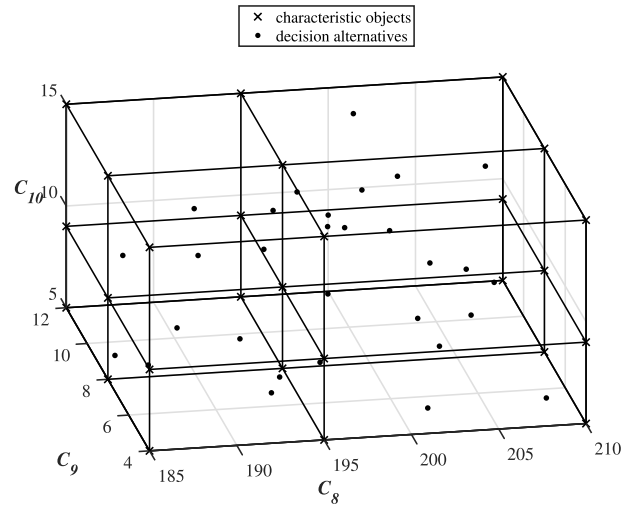


FIGURE 11. The space of the problem for the identification of  $P_5$ .

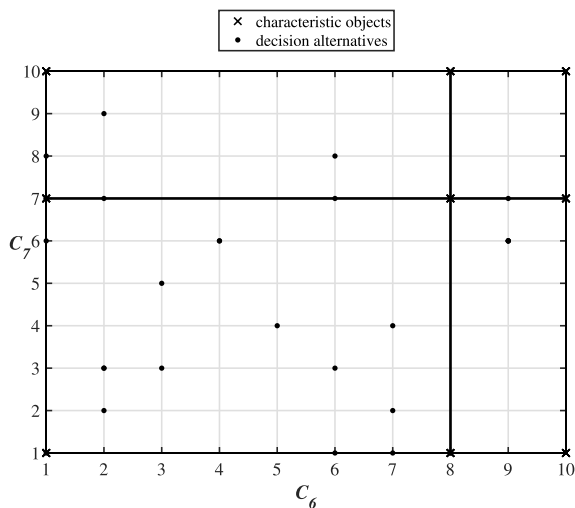


FIGURE 10. The space of the problem for the identification of  $P_4$ .

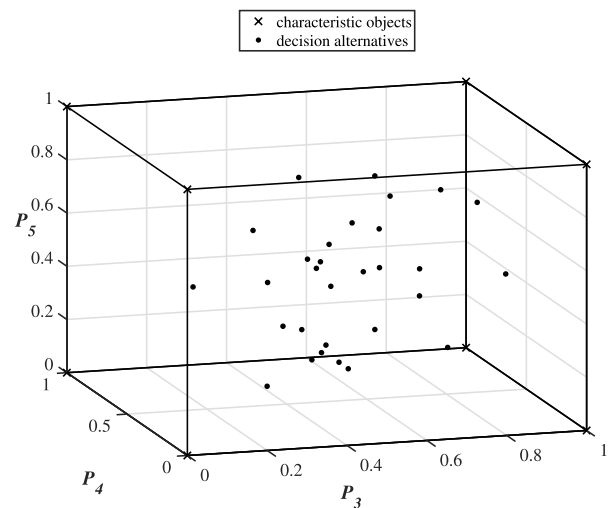


FIGURE 12. The space of the problem for the identification of  $P_6$ .

type of preparation training phase, the intensity of training, the quality of recovery and physiotherapy treatments and even the availability of the day or the number of calories consumed. In addition, each of the competitors taking part in the competition is characterized by a different swimming style, somatic features, or level of training. These differences give some athletes better opportunities for high performance in some fields than others. These factors determine whether on a given day, in a given competition, in a given event, a contestant will use his full potential and whether the effort made in training will bring the expected result, which can be to achieve a medal position or to improve the best result in his career.

Some of the factors that influence the final result obtained during the competition are influenced by the athlete, and he can work on improving them. An example is the level of flexibility of the competitor, which with regular stretching will gradually improve, allowing for better mobility dur-

ing the swim. Important factors are the amount of sleep and the number of calories consumed. With two swimmers of similar build, the quality of their training was at the same level. Their results also indicate a very even level. The day's disposition can determine the final competition between them at a given event. Despite the same starting point, if one of them neglects the appropriate amount of sleep and calories consumed, this may lead to the fact that during the race, he will not have enough glycogen in his muscles to allow him to compete with his rival in whom these two factors have been maintained at an appropriate level. As we can see, the final result is influenced by many, even the most minor factors, so it is worth taking care of every element to avoid weakening one's position before the race.

We also extend our study to using the resulting system for computations on uncertain data. To this end, we present a table of interval data for eight athletes and then subject

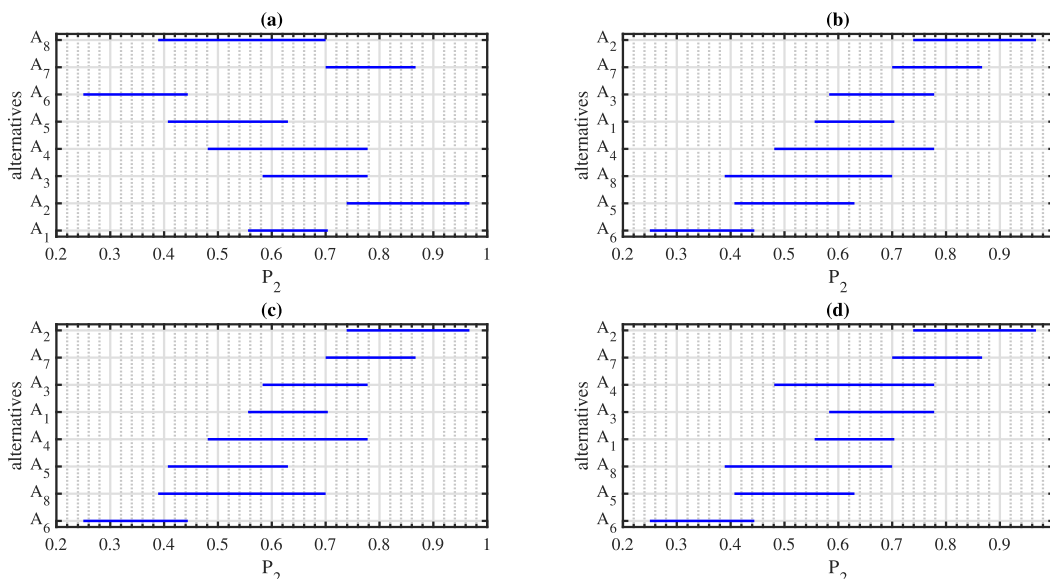


FIGURE 13. Comparison of the ranking of alternatives in terms of preference  $P_2$ .

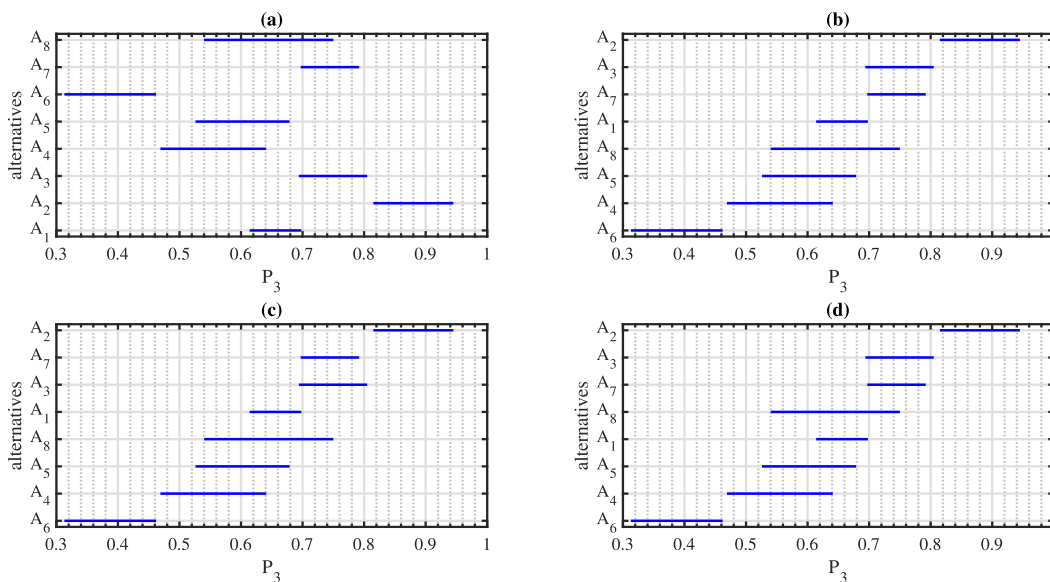


FIGURE 14. Comparison of the ranking of alternatives in terms of preference  $P_3$ .

them to analysis. The athletes’ data are presented in Table 7, and the data of their evaluations obtained with the discussed system are presented in Table 8. Unfortunately, interpreting such results is quite challenging, so we perform a ranking analysis in the following.

Figure 13 presents a ranking of interval values for alternatives to the  $P_2$  model, which describes additional body parameters. Figure (b) shows the ranking taking into account the average value of the interval, while (c) and (d) represent the pessimistic and optimistic possibles of this interval. Despite the large range of the interval value for the alternatives  $A_8$  and  $A_4$ , none of them was classified higher than the 3rd position when the optimistic limit of the interval was respected. The disadvantage of such a range value divergence is that when average and pessimistic values were taken into account, the

$A_8$  alternative was classified as 6 and 7, respectively, while  $A_4$  was classified as 5 and 4.

It is worth noticing that the values of the athlete represented by the alternative  $A_2$  allow him to take the ranking regardless of the type of interval value comparison. It shows that even in the worst-case scenario, and without obtaining favorable values for these criteria, he is still rated better than any other swimmers in this category. On the other hand, the  $A_6$  competitor is rated the worst of all the swimmers, which shows that his predisposition disqualifies him from getting a high rating from the model that evaluates additional body parameters. It does not mean that he will not get higher marks in other sub-models and thus will be placed in a better position in the final ranking. Foot length and shoulder-length to height ratio are important aspects of swimming, as longer

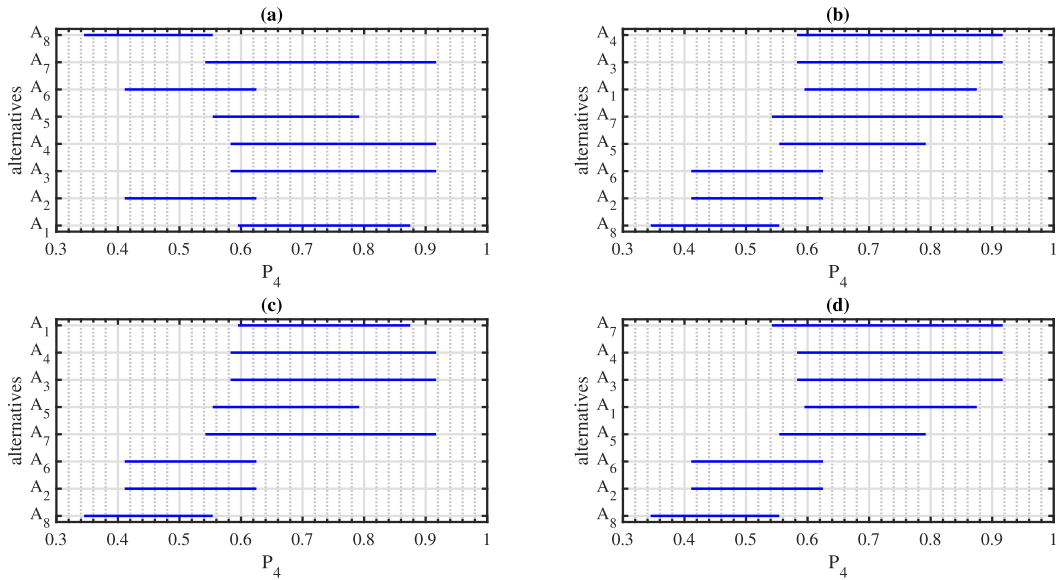


FIGURE 15. Comparison of the ranking of alternatives in terms of preference  $P_4$ .

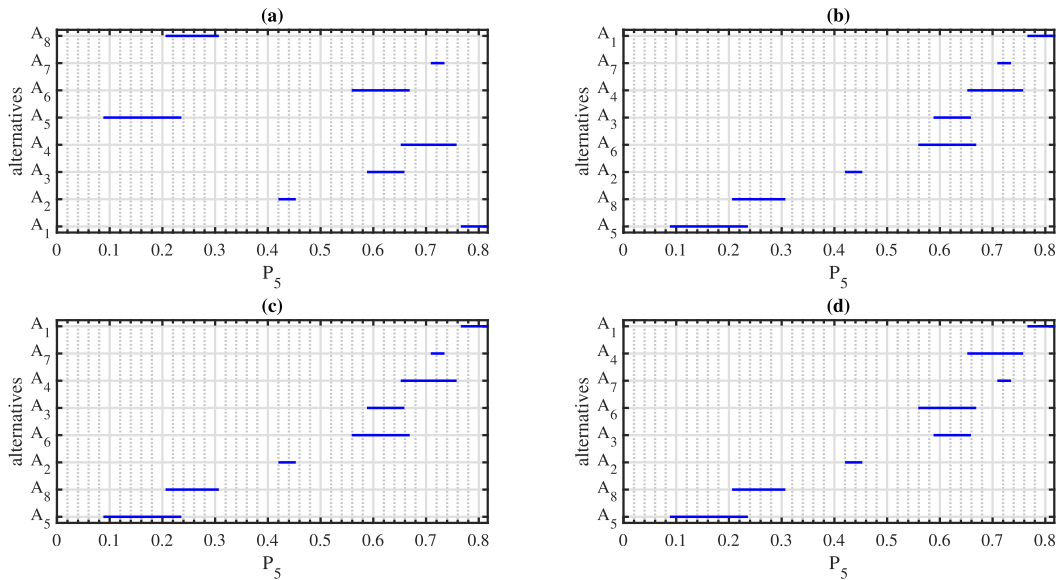


FIGURE 16. Comparison of the ranking of alternatives in terms of preference  $P_5$ .

feet provide more power during leg work, while longer arms will allow more effective movements at a race distance.

The next Figure 14 shows a ranking of interval values for alternatives to the  $P_3$  model describing the athlete’s metric, whose input includes preference values from the  $P_1$  and  $P_2$  sub-models. This model is the least dependent on the effort made by the sportsman. It evaluates his somatic features, which are beyond his control. Competitors with more height, longer feet, or a better shoulder-to-height ratio will get higher assessments from the model. The parameter on which they have the greatest influence is weight, where they can maintain an appropriate weight-to-height ratio. The highest rating of the model is the  $A_2$  player, who is the highest from compared swimmers and also has long feet and shoulders. In addition,

his age is relatively low, which is another advantage to his overall performance as he has a better chance of developing and improving his rating on these criteria.

Athlete represented by the alternative  $A_7$ , although is the oldest of the compared competitors and has the least chance of improving the preference rating of the model, has the somatic characteristics that have allowed him to be classified in the 3rd position when taking into account the average of the interval value and when considering the optimistic limit of this interval. On the other hand, comparing the pessimistic limit of this range, he was placed in the 2nd position, thus overtaking a  $A_3$  swimmer who has similar values to him. Furthermore, he is younger, which is in his favor, while minimal differences in other aspects make him lower-rated overall.

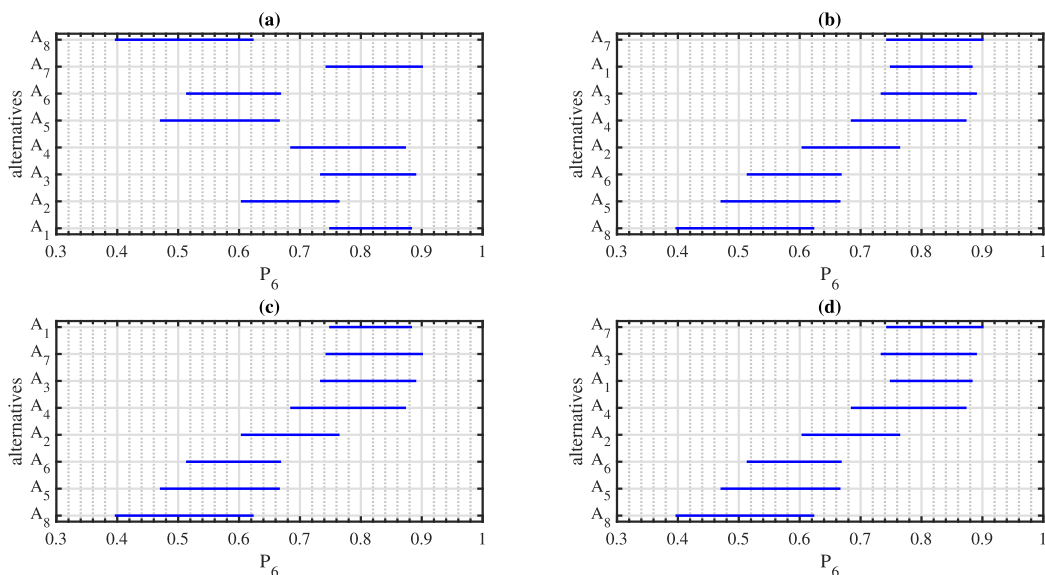


FIGURE 17. Comparison of the ranking of alternatives in terms of preference  $P_6$ .

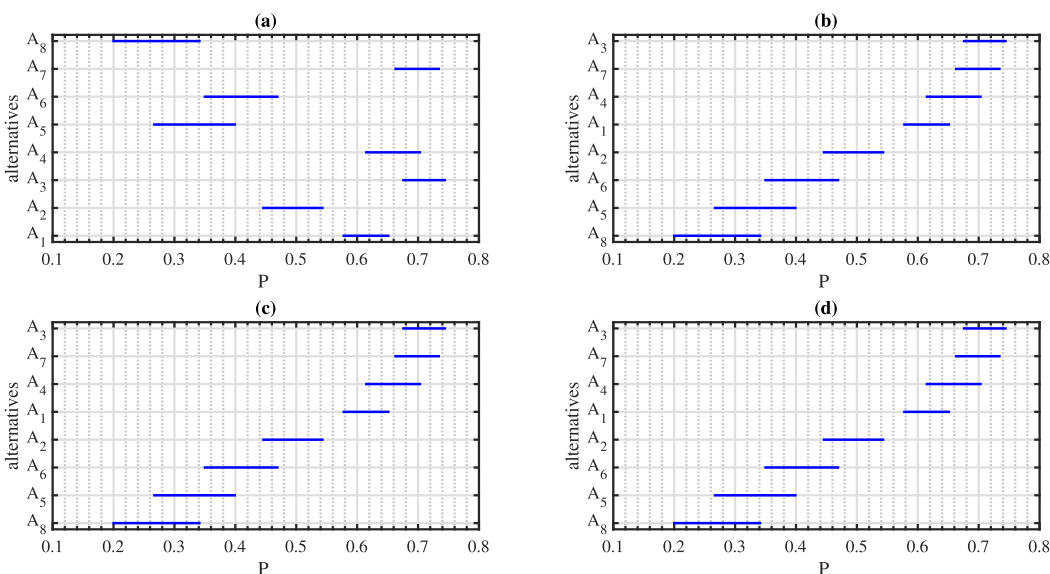


FIGURE 18. Comparison of the ranking of alternatives in terms of preference  $P$ .

In each case of analyzed ranking of interval range, the  $A_5$ ,  $A_4$  and  $A_6$  alternatives were 6th, 7th, and 8th respectively. Lower positions of these alternatives were determined by, among other things, too low weight in relation to height, the average height in relation to the athletes being compared, and low arm’s length in relation to height. Furthermore, in the figures (b), (c), and (d), which show the ranking for the average interval value, the pessimistic interval value, and the optimistic interval value, respectively, the  $A_6$  alternative stands out significantly from the rest of the swimmers, which is influenced by the lowest height, the low ratio of the arms-length to height, and the lowest foot length.

Figure 15 shows a ranking of interval values for alternatives to the  $P_4$  model describing skills, comparing preference values in order of:

- occurrence of alternatives (a),

- sorting alternatives by the middle of the interval value range (b),
- the smallest value of the interval range (c) and
- the largest value of this range (d).

Stretch level and swimming technique are highly influenced by the athlete, and spending much time improving these things can result in better and better results in the competition.

It is worth noticing that the victory was recorded by a different alternative in each of the compared cases. For the average value from the interval, it was the alternative  $A_4$ , for the lowest value from this interval, the alternative  $A_1$  won, while comparing the biggest value from the interval range, the alternative  $A_7$  was classified highest, slightly defeating the alternatives  $A_4$  and  $A_3$ . Athlete  $A_1$  could not be ranked highest, despite being the most flexible of all swimmers, in each of the rankings compared due to a slightly lower rating

of the swimming technique, compared to the alternatives  $A_3$ ,  $A_4$  and  $A_7$ . This shows that focusing on the technique and improving this aspect would allow him to get the highest preference ratings from this model. The swimming technique greatly influences the efficiency of movement in the water, which leads to a higher speed while preserving more power.

Figure 16 shows a ranking of interval values for alternatives to the  $P_5$  model of body and fitness of the athlete. Sportsmen very much influence the values of these criteria because, with a balanced diet, they can take care of low body fat levels. With adequately planned strength training and an increased amount of protein in their diet, they can increase their muscle mass, which will result in a reduced fat to muscle ratio. The least impact the athletes have on the maximum heart rate achieved, which can be increased by training at the appropriate intensity, while this progress will end when the maximum level, which is limited by the athlete's body structure, is reached.

The compared rankings show that swimmer  $A_1$  wins significantly against the other players, and this is influenced by the lowest fat percentage, the lowest body fat-to-muscle ratio, and a very high maximum heart rate threshold. In addition, athletes  $A_7$  and  $A_4$  have been placed on medal positions. For the first one of them, the interval value range was much narrower than for the second, which was due to the lower range of maximum heart rate values. This resulted in him winning  $A_4$  when comparing the mid-range and pessimistic value of the interval. The  $A_4$  won the ranking with an optimistic interval value. This shows that training at the appropriate intensity can move the limit of his heart rate to such an extent that he will evaluate his preference from this model very highly.

On the other hand, the alternatives  $A_2$ ,  $A_8$ , and  $A_5$  have been ranked 6th, 7th, and 8th respectively in each of the rankings compared. The main reason for the lower rating of these alternatives was a higher percentage of body fat and a higher fat to muscle ratio. In the case of the  $A_2$ , the very high maximum heart rate range was not able to provide compensation for the losses caused by the rest of the criteria and only allowed for a 6th place in these rankings. However, he can get much higher scores in this submodel with more attention to diet and training.

The next Figure 17 presents a ranking of interval values for alternatives to the  $P_6$  model, which contains assessments from the  $P_3$ ,  $P_4$  and  $P_5$  sub-models and evaluates the physical condition and skills of the player. The first three places in the ranking for averages in the interval range were taken by the  $A_7$ ,  $A_1$ , and  $A_3$  alternatives. The oldest of the competitors was best ranked, which shows that time spent on improving form, physical condition, and kilometers swam has influenced the highly rated swimming technique, high maximum heart rate, and low-fat percentage.

However, when we look at the ranking analysis with the pessimistic values of the intervals, we can see that the winner is a swimmer  $A_1$  who is younger, has a similar height and shoulder to height ratio, but is more stretched and has a lower percentage of fat. The next two alternatives  $A_7$  and  $A_3$  are

slightly worse in the ranking under consideration. While comparing the next two alternatives, significant differences can be seen assuming lower values from the designated ranges.

The ranking sorting the alternatives by the optimistic value of the interval range provided a victory for the alternative  $A_7$ . This shows that, despite his age, he has the desired characteristics taken into account in the sub-models, and the time worked for his career was not wasted, and he has been well trained. Younger rivals, defined by the alternatives  $A_3$ ,  $A_1$  and  $A_4$ , lose slightly in the ranking to a more experienced player, but this shows their great potential to develop and achieve even better results. Starting from a 4th position in ranking to 8th position, all rankings were followed by the same alternatives, which shows their balanced rating in the criteria under consideration.

Figure 18 shows a ranking of interval values for alternatives to the  $P$  model of the overall assessment. This ranking takes into account the overall score of all sub-models. Additionally, it includes the best FINA score in career, which is a reliable indicator of the swimmer's level and how good his performance can be. Comparison of the ranking by mean values in the interval range (b), pessimistic values in the interval range (c), and optimistic values in the interval range (d) show that the best-scored swimmer is  $A_3$ , who despite a lower score in the  $P_5$  sub-model, achieved higher assessment value than the swimmer  $A_7$  and it was influenced by a higher best score provided by FINA points. As we can see, despite the extent of training of an athlete  $A_7$ , a  $A_3$ , despite young age and less time working in the water, can have great potential, because at such a young age he achieves higher best scores according to FINA points.

Athlete  $A_1$ , on the other hand, was only ranked 4th, despite a very high rating from the  $P_5$  sub-model, his lower best point score FINA, did not allow him to take a higher position. This shows that he has the potential for better results, but he has not yet reached a level that would allow him to compete against the best. Nevertheless, consistent work will allow him to progress in his best results, which will lead to an increased preference rating from the model.

Moreover, it is important to mention that each of the compared rankings provided the same rating of alternatives. It shows that regardless of whether the athletes would have progressed or regressed in the values of the criteria under consideration, the ranking would not have changed. The rankings are the same as the highest number of FINA points achieved in a career, which is confirmed by the fact that even less trained players, less stretched and shorter than their rivals, can achieve better results in competitions, and this can be influenced by the talent that is difficult to quantify, but certainly many swimmers have it.

## VII. CONCLUSION

The selection of swimmers with the best chances of achieving world-class standards is becoming an increasingly complex problem, requiring the use of a variety of methods. The number of swimmers is growing, but not all of them have



the most valuable qualities for swimming. In this paper, the selection of swimmers is limited to a choice of male athletes. To solve the problem, for the needs of the defined topic, an adapted MCDA method called COMET was used, and this attempt proved to be effective. Finally, we have proposed a new decision support system, i.e., SWAM.

The theory of fuzzy numbers, together with the COMET method, was used to explore and create a decision model with full knowledge and uncertainty. Besides the research results, a practical system was developed to support the trainers in evaluating the athlete's predisposition and their selection. In addition, the system allows predicting and checking how a change of a specific attribute will affect the final result. Eleven criteria were taken into account (weight, height, age, foot length, arms-height-ratio, swimming technique, flexibility, maximum heart rate, fat index, fat-muscle-ratio, best FINA result); however, to reduce the number of necessary pairwise comparisons, the final model was divided into sub-models, significantly reducing the complexity of the problem and dividing the criteria into groups. Thirty alternatives for athletes were studied in detail (from the set of athletes presented in Table 3). The results obtained are the reference model for the selection of male swimmers. It is worth noting that the proposed approach can find practical implementation to support the trainers. In our work, it was also shown that the model is not limited to certain data and can also handle uncertain data in the form of interval data. It is especially important in the problem of potentiometric evaluation of athletes because some values can change quite often. Then the interval approach is much more accurate than working with average values. In the future, we may extend the interval value analysis with the possibility degree, which seems to have good generalization properties instead of the positive pessimistic and average strategy. It is worth considering extending the model with additional criteria and sub-models for further research, which would create an even more detailed recommendation system for selecting swimmers. In addition, further works may be carried out to consider the case of incomplete knowledge in this area.

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