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# COMPARISON OF THE METHODS USED IN MULTICRITERIA DECISION-MAKING TO DETERMINE THE VALUES OF THE COEFFICIENTS OF IMPORTANCE OF INDICATORS THAT CHARACTERIZE A COMPLEX SYSTEM

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**Abstract.** *This paper provides a general description of the following typical methods that are used in multicriteria decision-making to determine the values of the coefficients of importance of indicators that characterize a composite system: the analytic hierarchy process, the methods of critical distance, of pairwise comparison, and of rank, the Fishburn, the CRITIS, and the entropy methods. The features of these methods are determined and calculations are carried out that illustrate the differences in the values of the coefficients of importance of the obtained indicators with their use. The recommendations on the practical application of these methods are provided.*

**Keywords:** *analytic hierarchy process, critical distance method, pairwise comparison method, rank method, Fishburn method, CRITIS method, coefficients of indicator importance, entropy method.*

## INTRODUCTION

It is common knowledge that multicriteria decision-making methods are widely used when investigating complex systems. The analysis results of a number of these methods, including TOPSIS [1], ELECTRE II [2], taxonomy [3], ARAS [4], WS [5], SAW [6], WASPAS [7], PROMETHEE [8], TODIM [9], VIKOR [10], MOORA [11], COPRAS [12], OCRA [13] methods, etc., attest to the fact that one of their integral output data types is the value of importance coefficient indicators that characterize the complex system under study. A comparison of its alternative variants is performed by using these values.

To obtain the values of the indicator importance coefficients, there exists a number of methods that are fundamentally different from each other in the principal ideas they are based upon; therefore, we surmise that a comparison of the methods used during multicriteria decision-making to obtain these coefficients is a currently important scientific assignment.

## REVIEW OF METHODS USED TO OBTAIN THE VALUES OF INDICATOR IMPORTANCE COEFFICIENTS

As is known, a typical decision-making problem statement where the above-mentioned methods are used is as follows.

Let there be the number $n$ of alternative variants of a certain system, each of them characterized by the indicator value $m$ upon which the systems performance is assessed. These values are specified by a matrix with the elements $E_{ij}$ $(i = 1, \dots, n;$

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$j = 1, \dots, m$). Furthermore, there are $m$ importance coefficients whose values characterize the importance of each of the indicators with consideration to the objective of the performance of the system under study. Therewith, an optimization criterion (maximization or minimization) is specified for each indicator. A priority order of the given alternative system variants has to be formed according to this output data.

Note that the problem of choosing a method for obtaining the values of importance indicator coefficients is not new. A description of around 20 methods that can be used to reach this objective has been presented in 1997 in [14]. Not every one of these methods stood the test of time. The methods used in practice today are described in [15–17]. The analysis of scientific literature attest to the fact that depending on the approach to the process of obtaining the values of importance coefficients of the indicators, the available methods can be divided into the following two groups: expert methods (enlisting expert opinion) and numerical methods (with no expert opinion). Expert methods can also be divided into two subgroups depending on the amount of consultations with experts.

The defying feature of expert methods lies in the fact that they do not need a direct application of the values $E_{ij}$ for the comparison of alternative variants of the system under study. On the other hand, numerical methods are oriented towards performing computations using the values of these indicators. Depending on the amount of consultations with experts, expert methods are divided into the ones based on the pairwise comparison of indicators and into the ones where a direct arrangement of indicators according to their importance is provided for. It is obvious that the first subgroup of expert methods is characterized by a much deeper level of expert comparisons, and that has a positive effect on the quality of its results. On the other hand, an expert arrangement of indicators according to their importance and the application of certain dependences to the changes of the respective coefficients that can be agreed upon with the experts is provided for the other subgroups. Such a simplification of the expert survey is characterized by much lesser difficulties as a result of exclusion of the pairwise comparison, but can also lead to lower accuracy of the obtained results. Naturally, the presented classification is quite conventional, yet it is enough to compare the typical specification methods of the values of the importance coefficients.

The analytic hierarchy method described in detail in specialized scientific literature (for example, in [18]) is the most well-known one among the expert method subgroup for which the pairwise indicator comparison is provided for. This method implies the construction of a corresponding hierarchy, filling out the pairwise comparison matrix by experts (using the nine-level comparison scale), and calculating the values of the importance indicator coefficients. This method contains processes that ensure the alignment of expert estimates not only for each of the pairwise comparison matrices but for the hierarchy as a whole.

The pairwise method presented in [15] also belongs to this group. This method implies the pairwise comparison using the three-level scale without constructing a hierarchy. The values of importance coefficients for the indicators under study are obtained according to the result of expert estimates. However, this method does not include processes allowing the evaluation of the alignment of expert estimates according to the results of the pairwise comparison, which can have a negative effect on the accuracy of the obtained results.

We believe that typical examples of the expert method subgroup for which expert arrangement of indicators is provided for are the rank method [3] and the Fishburn method [15, 17]. In the case of the use of the rank method [3], experts form a priority order of indicators where the best one is assigned the value of one, and the worst one is assigned the value of $m$. It is considered that there exist a linear dependence between the indicator rank and its importance.

In this case, the unnormalized value of the importance coefficient of the $j$th indicator is calculated as

$$C_j = 1 - (R_j - 1) / m,$$

where $R_j$ is the rank of the $j$th indicator according to the priority order constructed by the experts.

The normalization of the importance coefficient values is performed by the formula

$$k_j = C_j / \sum_{j=1}^{m} C_j,$$

where $k_j$ is the normalized value of the importance coefficient of the $j$th indicator.

The experts construct the priority order of coefficients and specify the dependence characterizing the changes of importance coefficient values in the form of an arithmetic or a geometric progression in accordance with the Fishburn method [15, 17]. Herewith, the sum of importance coefficients of all indicators has to be equal to one.

For the arithmetic progression, the values of the importance indicator coefficients in the priority order is calculated according to [15, 17]

$$k_j = \frac{2(m-j+1)}{m(m+1)}. \tag{1}$$

The obtained values of $k_j$ are considered as corresponding to the maximum of the entropy of the information uncertainty with respect to the objects to be compared.

For the geometric progression, the values of the importance indicator coefficients in the priority order are calculated by the formula [17]

$$k_j = \frac{2^{m-j}}{2^m - 1} \tag{2}$$

or by the formula [15]

$$k_j = \frac{\omega^{j+1}}{1-\omega^m}, \tag{3}$$

where $\omega = 0.618$ is the number corresponding to the “golden ratio.”

A fundamental difference between the calculations by formulas (2) and (3) results is the fact that in the case of using (2), the condition $k_j > \sum_{g=j+1}^{m} k_g$, $j = 1, \dots, m-1$, is satisfied for all the values of importance coefficient.

Thus, the expert models under study numerically reflect the idea of experts in respect to the relative importance of indicators to some extent.

The entropy method [19–21], the critical distance method [3], and the CRITIS method [22] belong to the group of typical numerical methods for which the involvement of the experts are not provided for.

The entropy method [19–21] is as follows.

At the first stage, the output indicator values are normalized by one of the following formulas:

- when normalized according to [19],

$$x_{ij} = E_{ij} / \sum_{i=1}^{n} E_{ij}^2, \; i = 1, \dots, n, \; j = 1, \dots, m; \tag{4}$$

- when normalized according to [20, 21],

$$x_{ij} = E_{ij} / \sum_{i=1}^{n} E_{ij}, \; i = 1, \dots, n, \; j = 1, \dots, m. \tag{5}$$

At the second stage, the entropy values are calculated by the formula

$$E_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} x_{ij} \ln(x_{ij}), \; j = 1, \dots, m.$$

At the third stage, the entropy deviation from the value of one is estimated by the formula

$$d_j = |1 - E_j|, \; j = 1, \dots, m.$$

At the fourth stage, the normalized values of importance coefficients are calculated by the formula

$$\beta_j = d_j / \sum_{j=1}^{m} d_j, \; j = 1, \dots, m.$$

As is evident from (4) and (5), the entropy method has two variants depending on the variant of normalization of output indicator data being used and can stipulate the appearance of different importance coefficient values.

The critical distance method is performed in a few stages according to [3].

At the first stage, the indicator output values are normalized by the following formulas:

$$Z_{ij} = (E_{ij} - E_{jcp}) / S_j,\ i = 1, \dots, n,\ j = 1, \dots, m,$$

$$E_{jcp} = \frac{1}{n}\sum_{i=1}^{n} E_{ij},\ S_j = \left[\sum_{i=1}^{n} (E_{ij} - E_{jcp})^2 / n\right]^{1/2},\ j = 1, \dots, m.$$

At the second stage, the elements of the matrix of distances between the indicators are calculated as follows:

$$C_{rs} = \frac{1}{n}\sum_{i=1}^{n} | Z_{ri} - Z_{si} |,\ r, s = 1, \dots, m.$$

At the third stage, the critical distance is calculated using the following dependence:

$$C_k = \max_r \min_s C_{rs},\ r, s = 1, \dots, m,\ r \neq s.$$

At the fourth stage, all distances are found for each indicator that do not exceed the following critical one:

$$\rho_{js} = \{C_{js} \leq C_k\},\ j = r = 1, \dots, m,\ s = 1, \dots, m.$$

At the fifth stage, all the found distances of each indicator are added using the following formula:

$$Q_j = \sum_{s=1}^{m} \rho_{js},\ s = 1, \dots, m.$$

The importance of the indicator is considered to be the greater, the greater the sum of its distances to the neighboring indicators. Thus, at the sixth stage, among all of the obtained values of $Q_j$ the greatest one is determined by formula

$$Q_m = \max_j Q_j,\ j = 1, \dots, m.$$

At the seventh stage, the unnormalized values of importance coefficient are calculated by the following formula:

$$\lambda_j = Q_j / Q_m,\ j = 1, \dots, m.$$

At the last stage, the obtained values of $\lambda_j$ are normalized as follows:

$$\lambda_j^{\mathrm{n}} = \lambda_j / \sum_{j=1}^{m} \lambda_j,\ j = 1, \dots, m.$$

The CRITIS method according to [22] is as follows.

At the first stage, the normalization of indicator output values is performed by the formula

$$r_{ij} = \frac{E_{ij} - \min\limits_{i=1,\dots,n}(E_{ij})}{\max\limits_{i=1,\dots,n}(E_{ij}) - \min\limits_{i=1,\dots,n}(E_{ij})},\ i = 1, \dots, n.$$

At the second stage, the mean square deviation $S_j$ of each indicator is calculated, and at the third stage, the importance of indicators is estimated by the formula

$$C_j = S_j \sum_{i=1}^{n} (1 - r_{ij}),\ j = 1, \dots, m.$$

At the last stage, to ensure the satisfaction of the condition $\sum_{j=1}^{m} C_j = 1$, the obtained values are normalized by the formula

$$w_j = C_j / \sum_{j=1}^{m} C_j,\ j = 1, \dots, m.$$

TABLE 1. Output Data from [3] and the Calculation Results by the Rank and Fishburn Methods

| Number of the Indicator $j$ | Rank of the Indicator | Importance Coefficient Values Obtained by | | | |
|---|---|---|---|---|---|
| | | the rank method | the Fishburn method according to formula (1) | the Fishburn method according to formula (2) | the Fishburn method according to formula (3) |
| 1 | 7 | 0.036 | 0.036 | 0.008 | 0.022 |
| 2 | 4 | 0.147 | 0.143 | 0.063 | 0.093 |
| 3 | 5 | 0.106 | 0.107 | 0.031 | 0.058 |
| 4 | 2 | 0.215 | 0.214 | 0.252 | 0.244 |
| 5 | 1 | 0.250 | 0.250 | 0.504 | 0.396 |
| 6 | 3 | 0.179 | 0.179 | 0.126 | 0.151 |
| 7 | 6 | 0.071 | 0.071 | 0,016 | 0.036 |
| Range of changes of coefficient values | | 0.036–0.250 | 0.036–0.250 | 0.008–0.504 | 0.022–0.396 |
| The relation between the neighboring coefficient values in the priority order | | 1.16–2 | 1.16–2 | 2 | 0.62 |

## EXAMPLES OF CALCULATIONS BY THE CONSIDERED ABOVE METHODS OF OBTAINING IMPORTANCE COEFFICIENT VALUES

Let us evaluate the influence of the chosen method of obtaining importance coefficient values on the calculation results using a couple of examples. We surmise that the comparison of the results obtained using expert methods based on the indicator arrangement, as well as numerical methods are the most informative ones.

A juxtaposition of the expert methods based on pairwise comparison, in particular, the hierarchy analysis method and pairwise comparison method, continues to be quite problematic due to the differences in the structure of their output data. However, they are quite extensively described in the specialized scientific literature. The results of their comparison attest to the fact that the existence of multilevel hierarchy reflecting the connection between the objective of the system creation, the factors influencing its performance, and the indicators characterizing the factors under study, as well as the system itself, makes the hierarchy analysis method the most advantageous, despite its relative complexity and substantial labor intensity.

To perform the calculations using the rank and Fishburn methods for which the expert arrangement of indicators is provided for, we will use an example from [3], according to which we obtained a priority order for seven indicators based on the results of the expert survey (Table 1).

The analysis of the calculation results presented in Table 1 has attested the fact that the results obtained according to the rank and Fishburn methods (using formula (1)) are practically identical. In other words, in the case of absence of equal in their importance indicators, the rank method presents a counterpart to the Fishburn method under the assumption that the importance coefficients form an arithmetic progression. In the case of presence of equal in their importance indicators, the use of the rank method is possible; however, the use of the Fishburn method is problematic since the progression cannot contain multiple equal elements.

Moreover, from Table 1, we can conclude that the importance coefficient values decrease with the decreasing their rank in all the variants of the Fishburn method. However, there exist fundamental differences in the variation ranges of the coefficient values and the relations between their neighboring values in the priority order.

Let us employ two following examples when performing calculations using the numerical methods for which the expert intervention is not needed. First of all, let us consider an example from [3], the output data for which are presented in Table 2. As we can see from the table, ten variants of a certain system are given and characterized by six indicators. The calculation results of their importance coefficients performed using the above numerical methods are presented in Table 3.

TABLE 2. Output Data for Example 1 [3]

| Number of the Alternative $i$ | Indicator Values | | | | | |
|---|---|---|---|---|---|---|
| | $E_{i1}$ | $E_{i2}$ | $E_{i3}$ | $E_{i4}$ | $E_{i5}$ | $E_{i6}$ |
| 1 | 0.852 | 0.903 | 0.724 | 0.085 | 0.216 | 0.102 |
| 2 | 0.741 | 0.935 | 0.827 | 0.064 | 0.177 | 0.245 |
| 3 | 0.815 | 0.839 | 0.896 | 0.106 | 0.118 | 0.143 |
| 4 | 0.778 | 0.806 | 0.689 | 0.128 | 0.255 | 0.163 |
| 5 | 0.926 | 0.742 | 0.862 | 0.043 | 0.098 | 0.082 |
| 6 | 0.741 | 0.871 | 0.827 | 0.085 | 0.137 | 0.225 |
| 7 | 0.667 | 0.903 | 0.793 | 0.064 | 0.235 | 0.123 |
| 8 | 0.852 | 0.839 | 1.000 | 0.128 | 0.275 | 0.143 |
| 9 | 0.667 | 0.806 | 0.896 | 0.106 | 0.294 | 0.266 |
| 10 | 0.778 | 0.903 | 0.965 | 0.177 | 0.059 | 0.184 |

TABLE 3. Calculation Results of the Importance Coefficient Values with the Use of the Output Data from Table 2

| Number of the Indicator | Calculation Results According to | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | the critical distance method | | the entropy method | | | | CRITIC | |
| | $\lambda_j^{\mathrm{n}}$ | rank | normalization according to formula (4) | rank | normalization according to formula (5) | rank | $w_j$ | rank |
| 1 | 0.108 | 3 | 0.183 | 2 | 0.021 | 5 | 0.184 | 2 |
| 2 | 0.093 | 5 | 0.185 | 1 | 0.009 | 6 | 0.132 | 6 |
| 3 | 0.088 | 6 | 0.183 | 2 | 0.026 | 4 | 0.159 | 5 |
| 4 | 0.407 | 1 | 0.151 | 4 | 0.298 | 2 | 0.177 | 3 |
| 5 | 0.104 | 4 | 0.142 | 5 | 0.388 | 1 | 0.163 | 4 |
| 6 | 0.200 | 2 | 0.156 | 3 | 0.258 | 3 | 0.185 | 1 |

The analysis of the data presented in Table 3 attests to the fact that the importance ranks of the indicators obtained using different methods are highly contradictory. This inconsistency appears even when using a single method for different normalization variants of the indicator output data. In particular, the importance of the indicator 2 for the entropy method with the normalization in form (4) is the greatest, while it is the smallest (or approaching it in the case of critical distance method) with the normalization in form (5).

Let us consider an example from [21] next with its output data presented in Table 4. As we can see in the table, 22 variants of a certain system are given and characterized by 9 indicators. The results of calculations of their importance using numerical methods are presented in Table 5.

The data analysis from Table 5 leads to the same appropriate conclusion concerning the contradictory nature of the indicator ranks obtained using different methods as the result analysis from Table 3.

Summarizing the obtained results, a conclusion can be reached that numerical methods under study give different (sometimes fundamentally different) estimates of the indicator importance in the general case.

TABLE 4. Output Data for Example 2 [21]

| Number of the Alternative $i$ | Indicator Values | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $E_{i1}$ | $E_{i2}$ | $E_{i3}$ | $E_{i4}$ | $E_{i5}$ | $E_{i6}$ | $E_{i7}$ | $E_{i8}$ | $E_{i9}$ |
| 1 | 291 | 185 | 351 | 187 | 36 | 147 | 4902.74 | 96.89 | 94.43 |
| 2 | 413 | 113 | 211 | 293 | 62 | 195 | 5732.71 | 93.95 | 82.91 |
| 3 | 335 | 258 | 228 | 316 | 63 | 222 | 9085.19 | 97.47 | 94.68 |
| 4 | 376 | 111 | 361 | 368 | 51 | 124 | 5027.69 | 94.71 | 92.75 |
| 5 | 371 | 77 | 231 | 244 | 49 | 89 | 5989.66 | 96.50 | 91.35 |
| 6 | 427 | 544 | 216 | 419 | 54 | 421 | 11924.22 | 97.49 | 93.44 |
| 7 | 217 | 146 | 118 | 233 | 21 | 228 | 20958.38 | 95.05 | 93.79 |
| 8 | 151 | 48 | 121 | 186 | 12 | 123 | 30542.34 | 94.19 | 92.72 |
| 9 | 71 | 44 | 61 | 65 | 13 | 53 | 3852.83 | 92.10 | 90.56 |
| 10 | 141 | 26 | 74 | 155 | 14 | 115 | 43835.97 | 93.13 | 90.49 |
| 11 | 137 | 117 | 111 | 121 | 97 | 187 | 24796.49 | 94.07 | 92.65 |
| 12 | 131 | 124 | 172 | 75 | 133 | 279 | 16427.02 | 90.73 | 93.78 |
| 13 | 163 | 57 | 95 | 132 | 18 | 116 | 16946.48 | 94.98 | 92.65 |
| 14 | 166 | 49 | 152 | 141 | 14 | 82 | 23354.20 | 94.03 | 94.47 |
| 15 | 211 | 33 | 176 | 178 | 38 | 85 | 15698.32 | 90.09 | 92.72 |
| 16 | 117 | 72 | 127 | 118 | 21 | 69 | 15998.30 | 88.62 | 42.90 |
| 17 | 138 | 45 | 115 | 111 | 82 | 56 | 36574.57 | 87.34 | 89.54 |
| 18 | 152 | 77 | 141 | 89 | 31 | 51 | 3877.13 | 89.55 | 91.24 |
| 19 | 65 | 12 | 61 | 64 | 7 | 21 | 5614.43 | 87.59 | 92.63 |
| 20 | 185 | 119 | 162 | 96 | 27 | 62 | 5197.18 | 91 | 91.31 |
| 21 | 71 | 56 | 59 | 31 | 19 | 44 | 927.84 | 94.71 | 90.27 |
| 22 | 41 | 31 | 65 | 26 | 6 | 12 | 8624.92 | 95.52 | 89.43 |

TABLE 5. Calculation Results of the Importance Coefficient Values of Indicators from Table 4

| Number of the Indicator | Calculation Results According to | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | the critical distance method | | the entropy menthod | | | | CRITIC | |
| | $\lambda_j^n$ | rank | normalization according to formula (4) | rank | normalization according to formula (5) | rank | $w_j$ | rank |
| 1 | 0.099 | 7 | 0.115 | 4 | 0.096 | 6 | 0.127 | 4 |
| 2 | 0.131 | 4 | 0.071 | 8 | 0.219 | 1 | 0.124 | 5 |
| 3 | 0.142 | 2 | 0.121 | 3 | 0.078 | 7 | 0.135 | 1 |
| 4 | 0.098 | 8 | 0.109 | 5 | 0.114 | 5 | 0.124 | 6 |
| 5 | 0.105 | 5 | 0.090 | 7 | 0.168 | 3 | 0.133 | 2 |
| 6 | 0.160 | 1 | 0.096 | 6 | 0.149 | 4 | 0.120 | 7 |
| 7 | 0.027 | 9 | 0.090 | 7 | 0.171 | 2 | 0.131 | 3 |
| 8 | 0.138 | 3 | 0.154 | 1 | 0.001 | 9 | 0.092 | 8 |
| 9 | 0.100 | 6 | 0.152 | 2 | 0.005 | 8 | 0.014 | 9 |

TABLE 6. Results of the Arrangement of Alternatives over the Different Importance Indicator Coefficient Values (in Accordance with the Data from Tables 2 and 3)

| Number of the Alternative $i$ | All the Indicators Are Equally Important | | The Results of the Arrangement of Alternatives According to the Taxonomy Method when the Indicator Importance is Evaluated According to | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\beta_i$ | rank | the critical distance method | | the entropy method and the normalization process according to function (4) | | the entropy method and the normalization process according to function (5) | | CRITIC | |
| | | | $\beta_i$ | rank | $\beta_i$ | rank | $\beta_i$ | rank | $\beta_i$ | rank |
| 1 | 0.633 | 3 | 0.395 | 3 | 0.645 | 3 | 0.532 | 4 | 0.592 | 3 |
| 2 | 0.707 | 6 | 0.468 | 4 | 0.709 | 7 | 0.544 | 5 | 0.722 | 6 |
| 3 | 0.524 | 1 | 0.515 | 6 | 0.535 | 1 | 0.373 | 2 | 0.498 | 2 |
| 4 | 0.929 | 9 | 0.734 | 9 | 0.945 | 9 | 0.754 | 8 | 0.872 | 9 |
| 5 | 0.604 | 2 | 0.235 | 1 | 0.665 | 4 | 0.123 | 1 | 0.476 | 1 |
| 6 | 0.691 | 5 | 0.507 | 5 | 0.706 | 6 | 0.461 | 3 | 0.695 | 5 |
| 7 | 0.755 | 8 | 0.368 | 2 | 0.783 | 8 | 0.569 | 6 | 0.752 | 8 |
| 8 | 0.680 | 4 | 0.684 | 7 | 0.632 | 2 | 0.796 | 9 | 0.646 | 4 |
| 9 | 1.007 | 10 | 0.725 | 8 | 0.997 | 10 | 0.904 | 10 | 0.996 | 10 |
| 10 | 0.716 | 7 | 1.025 | 10 | 0.681 | 5 | 0.663 | 7 | 0.736 | 7 |

## SUGGESTIONS ON PRACTICAL APPLICATION OF METHODS OF OBTAINING THE VALUES OF IMPORTNACE INDICATOR COEFFICIENTS

Giving a general estimate to the methods of obtaining the values of importance indicator coefficients taking into account the obtained calculation results and the data from the specialized scientific literature, we have to note the following. The highest estimate accuracy of the values of importance indicator coefficients is insured by the hierarchy analysis method since it allows for the most informative analysis of relations between the importance levels of indicators and the objective of the system creation; therefore, it is expedient to use this method if there is a possibility for a close cooperation with the experts.

In the case of using the simplified expert survey methods, for which only the indicator arrangement according to their importance level is provided, there arises a need in additional consultations with the experts in order to determine the dependence form describing the character of relations between the importance coefficient values; therefore, these methods are expedient to use if the possibility of a close cooperation with the experts is limited.

The numerical methods where expert involvement is not necessary have to be used with caution, as there is no possibility to reach a justified conclusion as to which of them is more preferable. The calculation results attest to the fact that the importance indicator series obtained using these methods have differences that condition the differences in the results when solving decision-making problems.

At the same time, the application of these methods can be useful to assess the stability of decision-making against possible change of importance indicator coefficient values conditioned by errors in expert judgment. In this case, numerical models can be viewed as a certain type of expert models. Let us demonstrate it on an example with the output data presented in Table 2. Note that in [3], it was solved using the taxonomy method with its indicator importance being equal to 0.167.

Table 6 presents the arrangement results of the alternatives presented in the example with the equal indicator importance provided by Table 3. Herewith, the alternative arrangement is performed according to the generalized advantage indicator $\beta_i$ characterizing the Euclidean distance of the $i$th alternative from the “standard.”

The analysis of the calculation results presented in Table 6 shows that in the case of the summarized importance of indicators 4–6 (corresponding to the CRITIS method and the method of entropy with the normalization process according

TABLE 7. Ranks of Alternatives Averaged According to all Calculation Variants

| Number of the Alternative | All Indicators are equal in Importance | Alternative Rank in Case of Application of | | | | Rank | | |
|---|---|---|---|---|---|---|---|---|
| | | the critical distance method | the entropy method with the normalization process according to formula (4) | the entropy method with the normalization process according to formula (5) | CRITIC | summarized | averaged | generalized |
| 1 | 3 | 3 | 3 | 4 | 3 | 16 | 2.7 | 3 |
| 2 | 6 | 4 | 7 | 5 | 6 | 28 | 4.7 | 6 |
| 3 | 1 | 6 | 1 | 2 | 2 | 12 | 2 | 2 |
| 4 | 9 | 9 | 9 | 8 | 9 | 44 | 7.3 | 9 |
| 5 | 2 | 1 | 4 | 1 | 1 | 9 | 1.5 | 1 |
| 6 | 5 | 5 | 6 | 3 | 5 | 24 | 4 | 4 |
| 7 | 8 | 2 | 8 | 6 | 8 | 32 | 5.3 | 7 |
| 8 | 4 | 7 | 2 | 9 | 4 | 26 | 4.3 | 5 |
| 9 | 10 | 8 | 10 | 10 | 10 | 48 | 8 | 10 |
| 10 | 7 | 10 | 5 | 7 | 7 | 36 | 6 | 8 |

to formula (5)) it is greater than the summarized importance of indicators 1–3, and the leading arrangement alternatives (alternatives 3 and 5) stay the same when compared to the initial variant. In the other case (corresponding to the entropy method with the normalization process according to (4)), alternative 3 stays in the first place, but alternative 8 takes the second place. If the summarized importance of indicators 1, 4, and 6 (corresponding to the critical distance method) is greater than the summarized importance of other indicators, alternative 5 takes the first place, and the previously leading alternative 3 moves to the sixth place. In other words, the arrangement presented in [3] is unstable and can change depending on the expert estimates.

The generalized alternative ranks presented in Table 7 attest to the fact that the leading alternatives are 5 and 3, while alternatives 4 and 10 are the most disadvantageous. These results can serve as the basis for the proposals to a decision maker.

Numerical methods, besides being used for the stability verification, can be recommended as tools for preliminary (estimate) arrangement of alternatives by generalizing the alternative ranks and are suitable for when there is no possibility to involve experts.

## CONCLUSIONS

The present paper provides a description of typical methods of obtaining the values of the importance indicator coefficients characterizing the complex system under study.

The calculation examples show the differences between the results obtained using the above-mentioned methods.

It has been shown that the use of methods for which expert involvement is provided for is most expedient when determining the importance indicator coefficients characterizing a complex system. It is primarily the hierarchy analysis method that ensured the highest accuracy of the analysis of relations between the indicator importance and the objective of the creation of the system under study.

The use of the numerical methods for which expert involvement is not accounted for is more expedient when we are estimating the stability of a decision-making problem solution against the change of values of the importance indicator coefficients. They can also be used to estimate the averaged alternative ranks when expert involvement is not possible.

The future development of the performed investigations provides for the influence analysis of different normalization possibilities of indicator output data on solutions to multicriteria decision-making problems.

**REFERENCES**


1. A. Z. Sarraf, A. Mohaghar, and H. Bazargani, “Developing TOPSIS method using statistical normalization for selecting knowledge management strategies,” J. of Industrial Engineering and Management, Vol. 6, No. 4, 860–875 (2013).
2. O. I. Larichev, Theory and Methods of Decision Making [in Russian], Logos, Moscow (2000).
3. O. M. Zagorka, S. P. Mosov, A. I. Sbitnev, and P. I. Stuzhuk, Elements of the Analysis of Complex Military-Oriented Systems [in Ukrainian], NAOU, Kyiv (2005).
4. P. Chatterjee and S. Chakraborty, “Flexible manufacturing system selection using preference ranking methods: A comparative study,” Intern. J. of Industrial Engineering Computations, Vol. 5, Iss. 2, 315–338 (2014).
5. S. Hajkowicz and A. Higgins, “A comparison of multiple criteria analysis techniques for water resource management,” Europ. J. of Operational Research, Vol. 184, Iss. 1, 255–265 (2008).
6. W. Deni, O. Sudana, and A. Sasmita, “Analysis and implementation fuzzy multi-attribute decision making SAW method for selection of high achieving students in faculty level,” Intern. J. of Computer Science Issues, Vol. 10, Iss. 1, No. 2, 674–680 (2013).
7. M. Madić, V. Gecevska, M. Radovanović, and D. Petković, “Multi-criteria economic analysis of machining processes using the WASPAS method,” J. of Production Engineering, Vol. 17, No. 2, 79–82 (2014).
8. G. Anand and R. Kodali, “Selection of lean manufacturing systems using the PROMETHEE,” J. of Modelling in Management. Vol. 3, Iss. 1, 40–70 (2008).
9. L. F. A. M. Gomes, L. A. D. Rangel, and F. J. C. Maranhãoc, “Multicriteria analysis of natural gas destination in Brazil: An application of the TODIM method,” Mathematical and Computer Modelling, Vol. 50, Iss. 1–2, 92–100 (2009).
10. M. F. El-Santawy, “A VIKOR method for solving personnel training selection problem,” Intern. J. of Computing Science, Vol. 1, No. 2, 9–12 (2012).
11. W. K. Brauers and E. K. Zavadskas, “Robustness of the multi-objective MOORA method with a test for the facilities sector,” Technological and Economic Development of Economy,” Vol. 15, Iss. 2, 352–375 (2009).
12. T. Poklepović and Z. Babić, “Stock selection using a hybrid MCDM approach,” Croatian Operational Research Review, Vol. 5, No. 2, 273–290 (2014).
13. M. Madić, D. Petković, and M. Radovanović, “Selection of non-conventional machining processes using the OCRA method,” Serbian J. of Management,” Vol. 10, No. 1, 61–73 (2015).
14. A. M. Anokhin, V. A. Glotov, V. V. Pavel’ev, and A. M. Cherkashin, “Methods for determination of criteria importance coefficients,” Avtomat. i Telemekh., No. 8, 3–35 (1997).
15. V. M. Postnikov and S. B. Spiridonov, “Selecting methods of the weighting factors of local criteria,” Science & Education of the Bauman MSTU, No. 6, 267–287 (2015).
16. G. A. Mirskikh and Y. Y. Reutskaya “Combined methods for determining the weighting coefficients in optimization problems and evaluate the quality of objects,” Visnyk NTUU “KPI,” Ser. Radiotekhnika, Radioaparatobuduvannia, No. 47, 199–211 (2011).
17. I. L. Makarova, “Analysis of methods for determining weight coefficients in the integral indicator of public health,” Intern. Sci. J. “Symbol of Science,” No. 7, 87–94 (2015).
18. T. L. Saaty and K. Kearns, Analytical Planning: The Organization of Systems, Pergamon Press, Oxford (1985).
19. J. Martínez and R. A. C. Narváez, “Use of multicriteria decision making (MCDM) methods for biomass selection aimed to Fischer Tropsch processes,” Intern. J. of Engineering Trends and Technology, Vol. 34, No. 6, 266–272 (2016).
20. A. Ceřeška, V. Podvezko, and E. K. Zavadskas, “Operating characteristics analysis of rotor systems using MCDM methods,” Studies in Informatics and Control, Vol. 25, No. 1, 59–68 (2016).
21. M. Moghimi and M. T. Yazdi, “Applying multi-criteria decision-making (MCDM) methods for economic ranking of Tehran-22 districts to establish financial and commercial centers (Case: city of Tehran),” Urban Economics and Management, Vol. 5, No. 4 (20), 43–55 (2017).
22. M. D. Vujičić, M. Z. Papić, and M. D. Blagojević, “Comparative analysis of objective techniques for criteria weighing in two MCDM methods on example of an air conditioner selection,” Tehnika — Menadžment, Vol. 67, No. 3, 422–429 (2017).