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MULTIMETHOD AND MULTICRITERIA DECISION ANALYSIS OF OBJECTS IN A COMPUTERIZED DECISION SUPPORT SYSTEM

A multimethod approach to the multicriteria analysis and assessment of objects (rankings, grouping, econometric assessments) have been presented. This issue is a field of research and engineering associated with the construction and application of a computerized decision support system (DSS 2.0). In terms of the proposed approach, the functionality of the developed prototype has been illustrated based on a practical example of the assessment of employees and the analysis of remuneration. The Electre TRI method of grouping derived from a relational model complements ranking methods well (e.g., AHP) based on the functional model. Grouping reveals cases, where all or the vast majority of objects in a ranking were clustered within one class (e.g., in the best or the worst one).

Keywords: *multicriteria decision analysis, ranking, grouping, allocation of resources, computerized decision support system (DSS)*

1. Introduction

The complexity of the description of any practical decision problem makes it highly difficult to design a method so universal that it will enable obtaining the best solution for many different decision problems. The literature, e.g., [9, 13, 17], contains a variety

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of procedures and methods for multiple criteria decision making (MCDM). They can be divided into methods based on a functional model (American school) and those based on a relational model (European school) [9]. The creation of hybrid approaches, which combine the application of different methods for solving a decision-making problem, has led to a few interesting approaches being proposed. For example, the use of the AHP procedure and preference ranking organization method for enrichment evaluations (PROMETHEE) as a hybrid method to select the outsourcing strategy of a computer system was presented in [19]. A similar hybridisation of the technique for order of preference by similarity to ideal solution (TOPSIS) method with the AHP method was proposed in [12]. A practical combination of the relational model (elimination and choice expressing reality, the ELECTRE method) with a functional model (MAUT) was presented in [7]. Another interesting approach was presented in [4], the authors used the PROMETHEE II method and linear programming.

The prototype of the DSS 2.0 computerized decision support system [5], whose elements are presented in this paper, is an original solution. The structures of the databases and models used in this system are based on the approach adopted by the multicriteria linear programming (MLP) method [2]. This system has been developed for the purposes of the analysis of complex, multi-faceted decision-making. The subject of such problems may include many categories of object – understood as decision-making variants (e.g., grant applications, the purchase of products and services, the ranking of companies, the hiring of employees, etc.). The attributes of objects, assessment criteria and preferences can be expressed using numeric values, linguistic descriptions (expert opinions) or in a mixed manner. Due to the use of various methods, data on an object may sometimes be inputted in a simple form (e.g., as elements of a vector, or rows of a matrix or decision-making table) and sometimes in a complex form – e.g., using partial MLP models, which after combination create a so-called multimodel. DSS 2.0 is designed for the multicriteria analysis of objects, focusing on: optimal selection, ranking and grouping. In addition, objects can be subjected to econometric evaluation and it is possible to search for selection rules using the method of approximate set theory (algorithm LEM2 [10]). This system allows the presentation of detailed results separately for each method and overall on a decision desktop, where appropriate methods are applied on the basis of expert consultation, diagnosing the condition of a given object. This desktop presents the results in a cognitive form (using simple linguistic descriptions and a spectrum of colours). The methodological and design foundations for the construction of this system were described in [2]. This is presented in the broader context of DSS 2.0, namely the integration of knowledge sources – measurement data, expert opinions, unified structures of mathematical models and collections of methods – at an important time in the information and decision process, i.e. the decision game, whose purpose is the selection of the best solutions from the available ones.

The aim of this article is to present the multimethod, multicriteria decision analysis of objects (rankings, grouping, econometric assessments) which is part of the functionality of the DSS 2.0 prototype. An example of objects subjected to analysis included employees of a company. Their identity data has been coded due to the confidential nature of the study.

2. The multimethodical approach to the multicriteria analysis of objects in the decision support system

The DSS system assumes that each analysed object, a_t (t = 1, 2, ..., n), is a partial MLP model (Fig. 1) and at the same time a record in the database table. Any collection of partial MLP models (representing objects) is connected and creates a so-called multimodel. This constitutes a form of linear programming task, which maximizes an additive utility function (taking into account the criteria and preferences of the decision-maker), in order to find objects which are preferred the most among the available objects. An interesting example of the use of an optimisation procedure for the multi-parametric auction of objects is given in [1]. The system supports the decision-making participants of such a game (represented in the system as objects) by answering the question: What should be done to be found on specific ranking lists at the lowest cost?

Defining decision-making problems (tasks) in the system is inseparable from determining the structure of a template for a mathematical model in the module specially developed as an MLP model generator [2] (see the example of describing the object a_t in Fig. 1). The functioning of this module has been divided into thematic groups (described in [1]) that determine the following for all objects a_t (t = 1, 2, ..., n): the number and types of variables $x_j^{(t)}$ (j = 1, 2, ..., s), values defining local constraints B_i' (i = 1, 2, ..., m) and global constraints C_g' (g = 1, 2, ..., h), as well as values of partial objective functions D_k' (k = 1, 2, ..., r).

The proposed multimethod, multicriteria object analysis includes three issues: ranking, grouping and econometric evaluations (Fig. 1). The parameters $d_k^{(t)}$ and $c_g^{(t)}$ defining the values of the objectives functions and the global constraints, D_k' and C_g' create the matrices of input data for the analysis

$$\mathbf{D} = [d_k^{(t)}]_{n\times r}, \qquad \mathbf{C} = [c_g^{(t)}]_{n\times h}. \tag{1}$$

In order to rank or group objects, we only use the **D** matrix, whose elements play the role of values with respect to various criteria. The procedure for the econometric assessment of objects uses the elements of the **D** matrix as the values of explanatory (exogenous) variables and the elements of a selected column vector from the **C** matrix as the values of the explained (endogenous) variable.

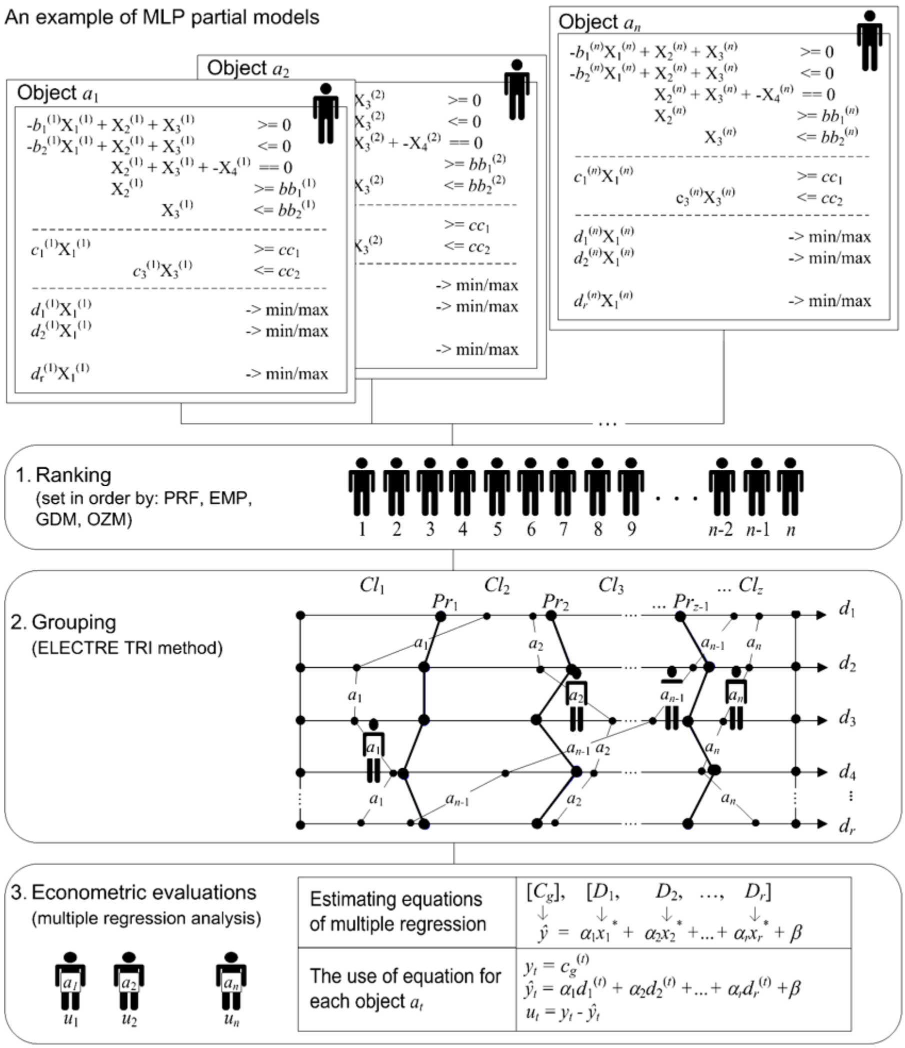


Fig. 1. Multimethod approach to multicriteria object analysis (source: authors' own study)

To define the structure of the decision problem and to determine the preferences of a user or group of users based on the criteria adopted, the AHP method has been used [16]. This enables the decomposition of the criteria vector into the form of a multi-level hierarchy. The DSS prototype has introduced only two levels, each criterion d_k can be determined by any number of subcriteria $d_{k,1}$, $d_{k,2}$, ..., $d_{k,r*}$. AHP supports the articulation of the decision-maker's preferences in this form and validation of the cohesion of the expressed judgments. Evaluation of the criteria based on pairwise comparison is compiled in the form of square matrices. In the case of determining group preferences, the results of the comparisons made by each individual are aggregated into one matrix using the geometric mean. To determine the normalised vector of weight coefficients at the level of main criteria and subcriteria, we use Saaty's method [16].

The possibility of analysing a very large number of objects a_t excludes the practical use of Saaty's method to compare objects according to a given criterion. It has been assumed that the values according to each criterion ($d_k^{(t)}$) and other parameters ($b_i^{(t)}$, $bb_i^{(t)}$, $c_g^{(t)}$, cc_g) describing the objects take the form of accurate numeric values or imprecise terms of an ordinal nature (e.g., low, average, high) articulated by experts or respondents. In order to standardise and use them as the inputs for different methods, we use two-way data conversion based on the linguistic quantifiers, which are presented in the form of fuzzy, ordinal profiles of the grading scale (more in [2, 5]).

The DSS 2.0 prototype can apply five different procedures for ranking objects. Objects are ordered according to vectors with increasing components:

- $\mathbf{PRF} = [prf_1, ..., prf_n]^T$ – a measure taking into account both criteria and preferences, the elements of the vector are calculated according to the formula

$$prf_t = r\sum_{k=1}^{r} w_k d_k^{(t)}$$

where: prf_t – a multicriteria grade for object t in the ranking, $d_k^{(t)}$ – value of the t-th object according to the k-th criterion, w_k – value of the weight coefficient (strength of preference) for the k-th criterion, r – number of criteria,

- $\mathbf{EMP} = [emp_1, ..., emp_n]^T$ – a multicriteria, empirical measure for ranking which does not take into account preferences, the elements of the vector are calculated as sums of the values according to the individual criteria $\left(emp_t = \sum_{k=1}^{r} d_k^{(t)} \right)$,

- $\mathbf{GDM} = [gdm_1, ..., gdm_n]^T$ – a generalised measure of distance, taking into account both criteria and preferences; the structure of the measure uses the idea of the general correlation coefficient (a generalisation of both the Pearson coefficient of linear correlation and the tau Kendall coefficient for ordinal variables); the values based on this method, gdm_t, are in the range $\langle 0, 1 \rangle$ ($gdm_t = 1$ means that the object a_t is aligned with the object $a_{\max}$, which has maximal values $d_k^{(t)}$ (or, equivalently, products $w_k d_k^{(t)}$) according to each criterion $k = 1, 2, ..., r$); more on **GDM** can be found in [18],

• **OZM** $= [ozm_1, ..., ozm_n]^T$ – the components of this vector are equal to the corresponding components from a selected column vector from the matrix **C** ($ozm_t = c_g^{(t)}$), it is worth mentioning that from the records on the global constraints C'_g ($g = 1, 2, ..., h$), it is possible to determine the number of parameters required in the study $c_g^{(t)}$ ($h = 99$), most often, these parameters express the demand reported by objects (e.g., requested amount of funding, monthly remuneration, etc.), the total values of these demands are bound by the parameter value cc_g given in the records of C'_g.

In the case of the occurrence of different units of measures or different directions of impact according to the criteria (e.g., criteria based on costs or profits), the system automatically conducts normalisation, thus a given method. Specific requirements in this regard are possessed by the **GDM** measure. It can be used when the objects are described using data measured according to the following scales: quotient, interval, ordinal or nominal [18]. The system applies data transformation to a quotient scale adopting a value from the range of $\langle 0, 10 \rangle$.

A function of the DSS system, complementary in relation to ranking, is multicriteria object grouping using the ELECTRE TRI method (for examples of applications, see [11, 14, 8, 7]). This method is founded on the method proposed by Roy in 1990 [15]. It is based on a preference model in the form of an outranking relation, which is constructed as a form of compliance and non-compliance test. This relation is used to estimate the degree of the superiority of objects a_t over profiles $Pr_{k,l}$, ($l = 1, 2, ..., z - 1$), which separate classes Cl_l ($l = 1, 2, ..., z$) from each other based on criteria d_k ($k = 1, 2, ..., r$). Classes are defined independently of the objects and must be compared from the point of view of the decision-maker's preferences. It is assumed that the decision-maker prefers objects from higher classes to those from lower classes (Fig. 1). ELECTRE TRI is initialized in the system when the matrix **D** and vector **W** are defined. Defining the profiles which separate classes involves the determination of values according to each criterion separately. Using DSS, based on the defined interval of acceptable values $\langle d_{k,\min}, d_{k,\max} \rangle$ and the selected number of classes (z), the algorithm calculates the initial values of profiles separating the classes ($Pr_{k,l}$). These profiles are determined on the basis of the equal section division $(d_{k,\max} - d_{k,\min})/(z)$ and can be modified by the user. The next step involves thresholds of: indiscernibility ($q_{k,l}$), preferences ($p_{k,l}$) and veto ($v_{k,l}$), which are focused around the profiles and are used to describe the type of preferences. The strength of preference according to a given criterion is given by the absolute difference between the value taken by the object and the profile for that criterion. For example: $\langle 0; q_{k,l} \rangle$, $(q_{k,ip}; p_{k,ip} \rangle$, $(p_{k,ip}; v_{k,ip} \rangle$, $(v_{k,ip}; \infty)$ may correspond to: indiscernibility, weak preference, strong preference and veto, respectively. The system calculates the initial values of thresholds according to a simple relationship $\{q_{k,l} = \alpha_q Pr_{k,l},\ p_{k,l} = \alpha_p Pr_{k,l},\ v_{k,l} = \alpha_v Pr_{k,l}\}$, where $0 < \alpha_q < \alpha_p < \alpha_v < 1$ (initial values: $\alpha_q = 0.03$, $\alpha_p = 0.20$, $\alpha_v = 0.40$). These thresholds can then be customised by the user. The latter element that needs to be determined is the cut-off threshold $\lambda \in (0.5; 1\rangle$. This determines the level of credibility for a claim concerning an outranking relation ($\lambda = 0.76$ is a commonly used value). An object surpasses another at the first degree if such a preference is expressed according to all the criteria.

Using the ELECTRE TRI method, the allocation of options to the defined classes is implemented according to two complementary procedures: optimistic and pessimistic (the details are described in [8, 11]). If an object is incomparable with at least one profile, then as a result of the pessimistic allocation, it will be found in a worse class compared to the result of the optimistic procedure. Otherwise, the results of grouping will be the same. This issue is illustrated and interpreted in Sections 3 and 4 of this article.

Another function of the DSS system expanding the scope of information about the objects is econometric analysis of effectiveness (Fig. 1, econometric evaluation). With a suitably defined econometric model of the behaviours of objects a_t ($t = 1, 2, ..., n$), it is possible to determine the rating of each object by taking into account factors which have significant impacts [6]. For this purpose, you should calculate for each a_t the residual $\hat{u}_t = y_t - \hat{y}_t$, which is the difference between the empirical value of the explained variable and the theoretical value obtained from the regression function [3]. In the context of the analysis of the object a_t, the residual $\hat{u}_j$ is understood as a measure of its effectiveness, y_t as the real value obtained by the given object, and $\hat{y}_t$ as the value according to the model, i.e. the value achieved by the object a_t according to the tendency determined by the regression function estimated based on the studied set of objects.

The procedure of the econometric analysis of objects uses the elements of the **D** matrix as values of the explanatory variables and elements of a selected column vector from the **C** matrix as values of the explained variable. The form of the multiple regression equation is given in Fig. 1. The least squares method (LSM) [3] was used to estimate the unknown structural parameters $\{\alpha_1, \alpha_2, ..., \alpha_r, \beta\}$ of the econometric model. The LSM algorithm and the remaining part of the procedure are implemented if the number of observations (objects) exceeds the number of estimated coefficients of the independent variables ($n > r$). The initial model is subjected to assessment, which includes: assessment of how the model fits the empirical data, examination of the significance of structural parameters and examination of the properties of random deviations. If the results of this verification confirm that the assumptions of the regression model are satisfied, then econometric assessment of the objects is performed, otherwise, the appropriate message is broadcast.

Using the multiple regression equation for each object a_t ($t = 1, 2, ..., n$), the value of object a_t is estimated using

$$\hat{y}_t = \alpha_1(d_1^{(t)}) + \alpha_2(d_2^{(t)}) + ... + \alpha_r(d_r^{(t)}) + \beta \tag{2}$$

To test the hypothesis that the theoretical value, $\hat{y}_t$, is significantly different from the real value, y_t, it is possible to use a statistical test using the specification of efficiency classes described in [6].

3. An example of the multicriteria assessment of employees

Let us consider an example of the multicriteria assessment of 17 employees in a company. They are employed in three branches in the position of locksmith. Let us assume that the company management wants to assess the current level of remuneration and distribute additional cash resources in the form of awards. The test procedure in the DSS 2.0 system included:

1) determination of the decision task template, criteria and preferences,
2) inputting of data on the employees (values according to criteria, Fig. 2A),
3) ranking of employees and analysis of the level of remuneration (Fig. 2B, C),
4) complementary analyses – employee grouping, additional rankings (Fig. 3).

In the DSS 2.0 system, each employee a_t (t = AA0001, AA0002, ..., AA0017) is represented by a partial mathematical model based on linear programming. It consists of one variable of the binary type $x_j^{(t)}$ and a vector of technical-economic parameters, $[c_1^{(t)},\ cc_1,\ d_1^{(t)},\ d_2^{(t)},\ d_3^{(t)},\ d_4^{(t)}]$, where: $c_1^{(t)}$ – the hourly rate of the employee's remuneration a_t, cc_1 – bound on the sum: $\sum_{t=1}^{n} c_1^{(t)} x_1^{(t)}$, $d_k^{(t)}$ – numerical assessment of employee a_t according to main criteria $k = 1, ..., 4$.

The employees are evaluated on their work performance. Three groups of criteria are used during this operation, namely: a) efficiency criteria related to performance, e.g., the number of items made in one month and the proportion of products with defects (d_1 – work performance, $w_1 = 0.45$), b) eligibility criteria depending on the job, e.g., work experience, familiarity with the devices, physical condition (d_2 – professional qualifications, $w_2 = 0.35$), c) behavioural criteria – e.g., accountability, initiative, discipline (d_3 – professional attitudes, $w_3 = 0.15$). Additionally, the extra skills criterion was introduced into the system, for example: driver's license, certificates, courses and foreign language skills (d_4 – additional skills, $w_4 = 0.05$) [1]. All the weighting factors were determined by Saaty's method (the CR convergence coefficient for the criteria was 0.068).

As a result of these calculations, we obtained a base ranking of employees (Fig. 2) based on PRF, i.e. taking into account the preferences of decision-makers (weighted sums of assessments according to the criteria), and two control orders, which do not consider preferences (Fig. 3), EMP – non-weighted sum of assessments according to the criteria and GDM – distances of non-weighted vectors of the assessments of each employee with respect to a “model employee”.

A. Input data | B. Ranking | C. Estimation

ID	Object name	$y=c_1$	d_1	d_2	d_3	d_4	No.	PRF	$\hat{y}$
AA0011	Employee 1 – Branch 3	9,80	6,80	9,00	7,60	5,00	1	30,400	10,240
AA0002	Employee 2 – Branch 1	12,10	8,60	6,20	7,70	7,00	2	30,180	10,800
AA0005	Employee 5 – Branch 1	9,10	6,90	7,30	10,00	6,00	3	29,840,	10,168
AA0001	Employee 1 – Branch 1	9,30	7,50	6,10	7,70	8,00	4	28,260	9,973
AA0009	Employee 3 – Branch 2	13,40	8,00	6,50	6,80	2,00	5	27,980	11,084
AA0007	Employee 1 – Branch 2	10,40	5,60	8,50	8,40	4,00	6	27,820	9,646
AA0008	Employee 2 – Branch 2	10,50	7,60	6,50	6,80	3,00	7	27,460	10,699
AA0013	Employee 3 – Branch 3	9,60	7,90	6,10	5,60	2,00	8	26,520	10,894
AA0010	Employee 4 – Branch 2	12,60	8,40	4,80	4,30	2,00	9	24,820	10,976
AA0006	Employee 6 – Branch 1	10,80	8,50	2,52	8,60	3,00	10	24,588	10,984
AA0012	Employee 2 – Branch 3	9,40	8,40	4,40	4,40	2,00	11	24,320	10,943
AA0003	Employee 3 – Branch 1	9,30	6,70	3,80	5,60	7,00	12	22,140	9,232
AA0014	Employee 4 – Branch 3	9,00	6,90	4,20	4,30	3,00	13	21,480	9,852
AA0004	Employee 4 – Branch 1	8,80	5,50	6,20	3,10	2,00	14	20,840	9,241
AA0016	Employee 6 – Branch 3	8,30	4,10	6,50	2,80	1,00	15	18,360	8,524
AA0015	Employee 5 – Branch 3	8,30	3,90	4,50	3,10	1,00	16	15,380	8,220
AA0017	Employee 7 – Branch 3	8,20	3,60	3,10	3,10	5,00	17	13,680	7,342

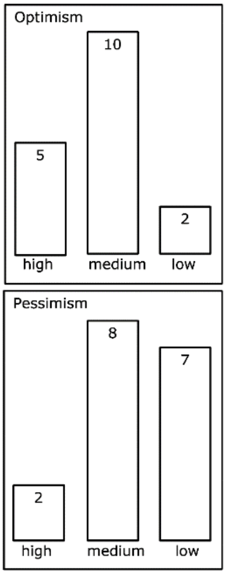
Fig. 2. Remuneration analysis (c_1) based on employee ranking calculated in DSS 2.0

A comparison of the results of the ranking based on PRF with those obtained using EMP highlights the strategy of personnel development approved by the employer. For example, the employee with No. AA0005 obtained first place in the ranking where each criterion was given the same weight (emp_5 = 30.2), but third position in the ranking taking into account the varying importance of the criteria (prf_5 = 29.84). The direction of the professional development of this employee slightly deviates from the priorities defined by the company management. The opposite situation is represented by the employee with No. AA0011, who obtained first place in the PRF ranking and fourth position in the EMP ranking.

The analysis of the GDM ranking results (Fig. 3) and values of the general correlation coefficient illustrate the distances of the assessments of individual employees from the top pole of development a_{max} which has components [d_1 = 8.6, d_2 = 9.0, d_3 = 10, d_4 = 8.0], where gdm_{max} = 1. All of the factors are stimulants. Hence, each of these coordinates is the maximal assessment according to the appropriate criterion. It is worth noting that the employee with No. AA0002 is the closest to the “model employee” (Fig. 3). This can be interpreted as having travelled 82% of the path (gdm_2 = 0.82) from an employee without talent or experience to the synthetic ideal outlined by the maximal, based on the results from these employees. The last employee with No. AA0015 has barely travelled 13.6% of this path to the top pole of development.

D. Grouping of ELECTRE TRI methods

ID	Cl	Opt	Pes	Cl
AA0005	DE	high	high	DE
AA0007	DE	high	medium	CD
AA0011	DE	high	high	DE
AA0006	DE	high	low	BC
AA0002	DE	high	medium	CD
AA0009	CD	medium	medium	CD
AA0008	CD	medium	medium	CD
AA0013	CD	medium	medium	CD
AA0001	CD	medium	medium	CD
AA0016	CD	medium	low	BC
AA0010	CD	medium	medium	CD
AA0012	CD	medium	low	BC
AA0004	CD	medium	medium	CD
AA0014	CD	medium	low	BC
AA0003	CD	medium	low	BC
AA0015	BC	low	low	BC
AA0017	BC	low	low	BC



E. Other rankings

ID	GDM	EMP	ID	No.
AA0002	0,820	30,200	AA0005	1
AA0005	0,785	29,500	AA0002	2
AA0001	0,702	29,300	AA0001	3
AA0011	0,692	28,400	AA0011	4
AA0007	0,667	26,500	AA0007	5
AA0008	0,618	23,900	AA0008	6
AA0006	0,592	23,300	AA0009	7
AA0009	0,588	23,100	AA0003	8
AA0013	0,468	22,620	AA0006	9
AA0003	0,454	21,600	AA0013	10
AA0010	0,436	19,500	AA0010	11
AA0012	0,429	19,200	AA0012	12
AA0014	0,359	18,400	AA0014	13
AA0004	0,284	16,800	AA0004	14
AA0017	0,229	14,800	AA0017	15
AA0016	0,229	14,400	AA0016	16
AA0015	0,136	12,500	AA0015	17

Fig. 3. Multicriteria grouping of employees and complementary rankings
(source: calculated in DSS 2.0)

As part of the analysis of remuneration level based on the input data contained in Fig. 2 (A. Input data), the estimation of the unknown structural parameters has been performed for the multiple regression equation. As a result of these calculations we obtained: $\alpha_1 = 0.617$, $\alpha_2 = 0.101$, $\alpha_3 = 0.073$, $\alpha_4 = -0.138$, $\beta = 5.271$ and the value of the multiple correlation coefficient $R = 0.723$. This value indicates a significant correlation between the assessments of the employees according to the individual criteria and their hourly remuneration rate (c_1). It should be noted that an increase in an employee's assessment based on criterion d_4 (additional skills) by 1 point is associated with a drop in the hourly rate of remuneration by 0.138 monetary units (given the other assessments remain unchanged). A negative value of the partial regression coefficient α_4 may result from the fact that criterion d_4 is the least preferred by the employer ($w_4 = 0.05$) and has not been taken into account when determining remuneration.

Using the stepwise elimination approach to multiple regression, the theoretical value of the hourly rate of remuneration $\hat{y}_t$ has been calculated for each employee (Fig. 2). A comparison of the real rates y_t with these theoretical values $\hat{y}_t$ gives an answer to the question: What are the wage rates and what should they be? (in the light of the existing regression dependence between remuneration and employee assessment). Because of the negative impact of the regression parameter α_4, this equation for the remuneration rate can be considered inappropriate. In the next step of the analysis, we should estimate the multiple regression equation ignoring the influence of this factor and again calculate the theoretical values.

At the last stage of the multimethod analysis, using the ELECTRE TRI method, we have grouped the abilities of employees from the point of view of the adopted criteria and preferences into five assessment categories ($z = 5$): AB – very low, BC – low, CD – medium, DE – high, EF – very high. The study was performed using the default values of the parameters set in the DSS 2.0 system: profiles, thresholds and cut-off coefficient (Sect. 2).

The resulting allocations of employees to these classes (Fig. 3, optimistic and pessimistic) are somewhat different from each other. According to the optimistic classification, we assessed 5 employees as being of high ability, 10 average and 2 low. While according to the pessimistic division, only 2 people were assessed as having high ability, 8 average and 7 low. Nobody was classified into either of the extreme classes (AB and EF). These different allocations signal the occurrence of some ambiguities. For example, the employee with No. AA0006 was classified as being of high ability by the optimistic approach, but as of low ability by the pessimistic approach. This means that he is incomparable to the designated profiles separating the classes and indirectly to the employees, for whom such a comparison takes place. This is a strange starting-point for a decision-maker (employer) when carrying out a thorough analysis of the assessments of this employee. Especially since full comparability of the employees is assumed in the rankings obtained. In addition, the classifications of two employees are on the border of the high ability class (optimism) and average ability one (pessimism), and four between the average ability class (optimism) and low ability (pessimism). Ten employees obtained the same classification in both procedures. Overall, the structure of allocations to these classes, in order from high to low, corresponds to the order obtained according to the PRF ranking. This mainly concerns the 10 employees who were characterized by full comparability to the profiles separating classes.

4. Summary

The ELECTRE TRI grouping method based on a relational model well complements ranking methods (e.g., AHP) based on a functional model. Based on methods of ordering which use a utility function, we exclude the possibility of the incomparability of the decision variants (objects). However, in practice, in particular when analysing a large number of objects, it is difficult to precisely place objects in a ranking. Such rankings are to some degree different and incomparable and show various ambiguities in terms of the studied population. The ELECTRE TRI method signals this fact when the two described allocations of objects to classes, optimistic and pessimistic, are significantly different. Besides this, grouping reveals cases where all, or the vast majority, of the objects assessed are classified into a single class (e.g., either the best or the worst one).

This approach to the multimethod analysis of objects (rankings, grouping, econometric assessments) presented here based on the example of employee assessments, does not exhaust all the possibilities of the applied decision support system (prototype DSS 2.0). Due to limits on space, we have omitted several interesting areas of the system's functionality, e.g., group assessments, competence of experts, multi-parameter auctions of objects, induction of decision-making rules, cognitive synthesis of the results obtained using different methods (decision-making panel).

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