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TODIM-FSE: A MULTICRITERIA CLASSIFICATION METHOD BASED ON PROSPECT THEORY

Abstract

This paper introduces TODIM-FSE, a multicriteria method for classifying alternatives based on Prospect Theory. TODIM-FSE therefore relies on the TODIM method combined with the Fuzzy Synthetic Evaluation approach. TODIM-FSE makes use of the innovative "contribution" concept, not used previously for multicriteria classification purposes. This notion is central to the classification procedure of TODIM-FSE as it is associated to the contribution of each criterion to the classification of a given alternative in a predefined category. The TODIM-FSE method is explained in this paper by means of an application example and its steps are outlined. The application example has to do with the selection of trainee candidates for a company in the area of information technology. The classification of the candidates allows to identify the best of them, which is typically done at the first stage of the selection process. Some of the evaluation criteria considered in the study were: computers skills, mastery of technical English, and previous working experience in the field. In the second stage of that process another procedure ranks the best candidates. TODIM-FSE can be easily programmed in spreadsheets so as to be made available to professionals without a sound knowledge of either Multiple Criteria Decision Analysis or Prospect Theory. Currently the authors are working on a series of applications for validating TODIM-FSE in a broader way.

Keywords: TODIM-FSE method, Prospect Theory, Multicriteria classification of candidates, Multiple Criteria Decision Analysis.

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1. Introduction

This paper presents a new method for multicriteria classification of alternatives inspired by the TODIM method (Gomes and Lima, 1991, 1992; Gomes et al., 2009; Gomes and Rangel, 2009; Rangel et al., 2011; Moshkovitch et al., 2011; Gomes and González, 2012; Gomes et al., 2013). The TODIM-FSE method is also based on Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) and Fuzzy Synthetic Evaluation or FSE (Lu et al., 1999; Onkal-Engin and Demir, 2004; Chang et al., 2001; Sadiq et al., 2004; Kuo and Chen, 2006). While the TODIM method is a multicriteria method for ranking alternatives well established in the scientific literature, FSE, although not known as a multicriteria method has already been used as such (Kuo and Chen, 2006).

This paper intends to merge important features of both methods, TODIM and FSE to present an innovative multicriteria classification procedure. The classification is based on the "contribution" concept not used previously in MCDA, and along with other characteristics constitutes the body of the method. The role of Prospect Theory in TODIM-FSE is represented by the aggregation functions adapted in this paper to classify the alternatives.

The operation of the TODIM-FSE method is shown in this paper through a case study in human resources evaluation. The purpose of this evaluation is to select trainees for an information technology company. The company is highly rated in the labor market and offers attractive job opportunities for new professionals. Because of high demand, the process was divided in two stages. In the first stage the candidates are screened and the best ones identified. In the second stage the candidates selected in the first stage are evaluated in greater detail and rigor. This paper approaches the first stage of the process, where the candidates answer questions and take computerized tests. This information is used to classify them into four categories: excellent, very good, good or bad. Three evaluation criteria are used: computer skills, English language skills and working experience.

There exist few multicriteria methods to classify discrete alternatives. The book by Doumpos and Zopounidis (2002) gives detailed information on methods and techniques of multicriteria classification available in literature. The most widely known methods according to Zopounidis and Doumpos (2002) are ELECTRE TRI and UTADIS. Thus, TODIM-FSE is an option for typical applications for alternative classification using multiple sorting criteria.

This paper is divided in the following way: Section 2 gives a brief description of Prospect Theory taking into account the relevant aspects for the understanding of TODIM-FSE. Section 3 describes all the stages of the method. In section 4 these stages are used in a case study. Finally, the conclusions are presented.

2. Prospect Theory

Prospect Theory belongs to the field of cognitive psychology and describes how people make decisions under conditions of risk. Through a set of experiments performed in the 1970s Daniel Kahneman and Amos Tversky discovered previously unknown behavior. They observed that in situations involving gains people tend to be more conservative as regards risk, while in situations involving losses they are more prone to risk. Therefore, when people have a chance of winning, they prefer a lower but certain gain, than to risk for higher although uncertain gains. When a situation involves losses, people prefer to risk losing more but with the possibility of losing nothing than to suffer a smaller but certain loss. Additionally, the researchers noticed that situations involving losses are usually more relevant and striking than situations involving gains. This behavior is graphically represented in their seminal paper (Kahneman and Tversky, 1979) by a value function which is extremely relevant to understand the equations used in the TODIM-FSE method. Figure 1 illustrates this behavior. From the use of this value function within a multicriteria context, people's satisfaction can be quantitatively measured by entering into the model the characteristics of risk aversion and risk seeking, natural to people.

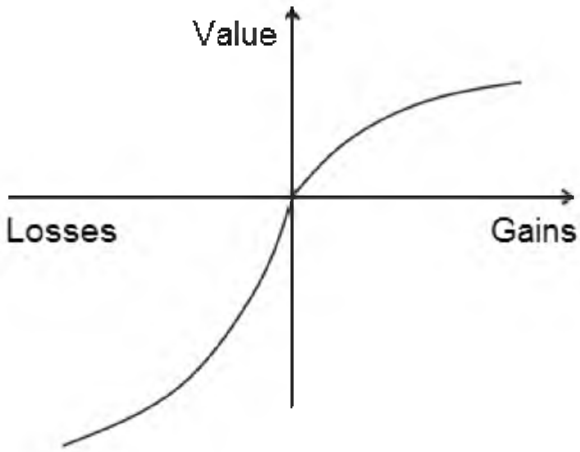

Figure 1. Value function of Prospect Theory

Although when ranking alternatives in the presence of multiple criteria we are not necessarily dealing with lotteries, the idea of being risk-averse in the domain of gains and risk-prone in the domain of losses is subject to the mathematical description by the value function of TODIM. This value function is built step-by-step as it will be shown in section 3.6. A detailed explanation of the TODIM method can be found, for example, in Gomes et al. (2009; 2013).

3. The TODIM-FSE method

As previously mentioned, TODIM-FSE is a method for multicriteria classification of discrete alternatives inspired by the TODIM method and by the Fuzzy Synthetic Evaluation (FSE).

In order to facilitate the understanding and use of the method, TODIM-FSE is described here step-by-step following the example of Goodwin and Wright (2004) when they described the SMART method (Edwards, 1977). However, the steps below do not need to be strictly followed in the sequence proposed.

Step 1: Determining decision makers and decision analysts.
Step 2: Analyzing and structuring the decision making problem.
Step 3: Defining the relevant criteria of the problem.
Step 4: Defining categories and contribution functions.
Step 5: Defining the relative weights of the criteria.
Step 6: Classifying each alternative to one of the categories.
Step 7: Validation Analysis.

Each stage is described in detail below.

3.1. Step 1: Determining decision makers and decision analysts

This stage is used to determine the persons involved in the decision making process. Decision makers are the individuals who actually make decisions regarding the problem. They define the criteria to be used and their judgments (criteria weights, evaluation of the alternatives according to the criteria, etc.) contribute to construct the final result. The decision analysts are individuals who know the decision aiding methods and therefore support the development of the decision making process.

3.2. Step 2: Analyzing and structuring the decision making problem

It is very important to analyze the problem and discuss it thoroughly, to be certain that the right problem is being addressed. Ill-defined problems often lead to good decisions for the wrong problem. In this way, all the effort undertaken becomes useless. References on the subject can be found in Belton and Stewart (2010).

3.3. Step 3: Defining the relevant criteria of the problem

The construction of the decision making model begins in this step. The decision makers suggest the criteria to be considered for classifying the alternatives through brainstorming. The criteria are then screened, combined or eliminated to meet the recommendations of Keeney and Raiffa (1976) for the construction of a good set of criteria. According to those two authors, the criteria set must present the following characteristics: operationality, decomposability, minimum size, completeness and non-redundancy.

3.4. Step 4: Defining categories and contribution functions

Once the criteria are established, the next step is defining the number of categories (denoted below by “cat”) to be used in the model. As a rule of thumb, no more than five categories should be used. In this manner, the model becomes simpler, more attractive and easy to use. Once the number k of categories is defined, the contribution values (represented by μ) that each criterion provides to classify an alternative within a certain category must also be defined. The concept of contribution in the sense used in TODIM-FSE is, to the best of our knowledge, innovative.

Contribution values should vary continuously between 0 (zero) and 1 (one), with the value 1 (one) indicating that the criterion has the greatest contribution to the classification of an alternative within a given category. The value 0 (zero) indicates that the criterion does not contribute to the classification of an alternative within a given category. Intermediate contribution values are also allowed. It is important to note the similarity to the concept of values of membership functions in fuzzy set theory (Mendel, 1995; Zadeh, 2008). The contribution values are defined in a different way for qualitative and quantitative criteria. If the criterion is qualitative, we expect that its evaluation γ is done on a scale with discrete values. The contribution values for each category are defined for each verbal value γ of the scale, in the form of contribution tables, as shown in Table 1. A set of contributions, represented by the corresponding row in the table, is defined for each possible evaluation γ assigned to criterion i.

Table 1

Contributions table for qualitative criterion *i*

	Categories				
Evaluation	**Cat $_1$**	**Cat $_2$**	**...**	**Cat $_{k-1}$**	**Cat $_k$**
γ_1	μ_{11}	μ_{12}	...	μ_{1k-1}	μ_{1k}
γ_2	μ_{21}	μ_{22}	...	μ_{2k-1}	μ_{2k}
...	...	...	...	...	...
γ_m	μ_{m1}	μ_{m2}	...	μ_{mk-1}	μ_{mk}

A quantitative criterion can take continuous values. In this case contributions are represented by contribution functions, which are similar in shape and construction to membership functions in fuzzy set theory. However, one important point to highlight is that, despite the fuzzy set similarity, that is an unnecessary knowledge to the method's users once they don't need to know what are these sets to build the contribution functions. Figure 2 illustrates an example of contribution functions described with sigmoid functions for the three categories. For the value 42 of the criterion the following contribution vector associated to each category is obtained: [0.19 0.78 0]. Thus, when the criterion j takes the value 42 it is contributing with 0.19 to the classification of the alternative in the first category, 0.78 to the classification of the alternative in the second category and with 0 to the classification of the alternative in the third category.

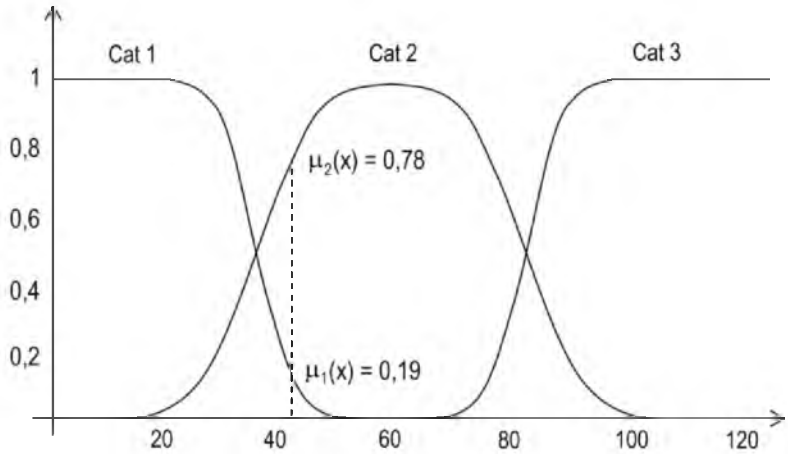

Figure 2. Contribution functions for quantitative criterion *j* in a problem with three categories

Once the contribution tables or contribution functions for each criterion are defined, it is possible to group the first data set relevant to the model, here called the *table of criteria grouped contributions*. Each row of this table is obtained from the evaluation of an alternative using each criterion. For the qualitative criteria they represent a row in Table 1. For the quantitative criteria they represent the value of the contribution function associated with the quantitative value assigned to the criterion *j*. Table 2 shows an example of such a table. Note that each row of this table is formed by the contributions associated with the evaluation made for each criterion. For a qualitative criterion the row associated with the evaluation is extracted from its contributions table. The extracted row is copied in the corresponding row of Table 2. For a quantitative criterion, the contribution vector obtained is copied on the corresponding row of Table 2.

Table 2

Table of criteria grouped contributions

	Categories				
Criterion	**Cat $_1$**	**Cat $_2$**	**…**	**Cat $_{k-1}$**	**Cat $_k$**
crit$_1$	μ_{11}	μ_{12}	…	μ_{1k-1}	μ_{1k}
crit$_2$	μ_{21}	μ_{22}	…	μ_{2k-1}	μ_{2k}
…	…	…	…	…	…
crit$_n$	μ_{n1}	μ_{n2}	…	μ_{nk-1}	μ_{nk}

One important point is that the decision maker must evaluate each alternative according to each criterion, by determining the contribution values for each category. This information must be generated and will serve as an input to the rank procedure that will fit the alternative (and the classification itself) in the best category, described later in step 6. For this reason, in the table of criteria grouped contributions, the same number of categories for different criteria is assumed.

3.5. Step 5: Defining the relative weights of the criteria

The second and last data set relevant for the model is defined in this step: the weights of criteria. Those weights are interpreted as measures of relative importance of criteria and must add up to 1.0. Therefore, the simplest way to obtain those weights is by direct assignment of values on a preset scale, followed by normalization. The result of both procedures is a weight vector W shown in (1) and (2).

$$W = [w_1 \; w_2 \; \dots \; w_{n-1} \; w_n] \text{ and} \tag{1}$$

$$\sum_{i=1}^{n} w_i = 1 \tag{2}$$

The weights of criteria in TODIM or in its extension TODIM-FSE are measures of relative importance of criteria. By criteria importance we understand the power of the criteria in discriminating the overall desirability of the alternatives, as explained by Choo et al. (1999). In other words, the relative importance of a given criterion is a measure of the extent to which the rankings of the alternatives under that particular criterion are the same as their overall ranking.

3.6. Step 6: Classifying each alternative to one of the categories

For this step the two data sets relevant for the classification are already defined: the table of the criteria grouped contributions (Table 2) and the weights of the criteria (1). Once we know the contribution of each criterion to the classification of an alternative in a given category, we use the trade-offs between the criteria weights and aggregate everything to find the category in which the alternative has the highest score (i.e., the class in which each alternative fits). This is done using the TODIM method. At this point n matrices of partial dominance Φ_c are being constructed, one for each criterion c. The elements of each matrix are given by (3):

$$\Phi_c(cat_i, cat_j) = \begin{cases} \sqrt{\dfrac{w_{rc}(\mu_{ic} - \mu_{jc})}{\sum_{c=1}^{n} w_{rc}}} & , \mu_{ic} - \mu_{jc} > 0 \\ 0 & , \mu_{ic} - \mu_{jc} = 0 \\ -\dfrac{1}{\theta}\sqrt{\dfrac{(\sum_{c=1}^{n} w_{rc})(\mu_{jc} - \mu_{ic})}{w_{rc}}} & , \mu_{ic} - \mu_{jc} < 0 \end{cases} \quad (3)$$

In (3) we have:

$\Phi_c(cat_i, cat_j)$ – measure of dominance of category *i* (cat_i) over category *j* (cat_j) with respect to the criterion c;

w_{rc} – tradeoff between a pre-chosen criterion r (denoted here as reference criterion) and the criterion c;

$\mu_{ic} - \mu_{jc}$ – difference between the contributions to the classification of the *i*-th and the *j*-th evaluations in the criterion c (extracted from Table 2);

$\sum_{c=1}^{n} w_{rc}$ – sum of the tradeoffs over all criteria;

θ – a loss aversion parameter (i.e., attenuation factor of the losses);

$\mu_{ic} - \mu_{jc} > 0$ .... measure of the gain, if this value is positive;

$\mu_{ic} - \mu_{jc} = 0$ .... no gain and no loss reference point;

$\mu_{ic} - \mu_{jc} < 0$ .... measure of the loss, if this value is positive.

The matrix Φ_1, for instance, is constructed using only the contribution values associated with the criterion 1, that is, only the first rowof the table of the criterion grouped contributions. The differences $\mu_{i1} - \mu_{j1}$ are seen as gains or losses associated with the value function of Prospect Theory, as represented graphically in Figure 1. If the difference is positive (indicating a dominance gain of the category *i* over the category *j*, in this case in the criterion 1) the value of the generic element a_{ij} of the matrix Φ_1 is given by the first segment of (3); if the difference is negative (indicating a dominance loss of the contribution of the category *i* over the category *j*) the value of the same element a_{ij} is given by the second segment of (3); and it is 0 if the difference is 0, corresponding to the second segment of (3). The values w_{rc} represent the weight of the criterion c divided by the weight of a reference criterion r (i.e. $w_{rc} = w_c/w_r$). In this case, the latter can be for example the criterion with the highest weight. It is easy to verify that it makes no difference which one is the reference criterion. The value θ is the attenuation factor of the losses. Different choices of this value lead to different forms of the value function of Prospect Theory in the negative quadrant (Figure 1). Note, therefore, that the matrix Φ_c displays a set of dominance values of the categories with respect to each criterion.

Once the matrices of partial dominance for each criterion are calculated, the matrix of dominance $\delta(cat_i, cat_j)$ is calculated as shown in (4):

$$\delta(\mathrm{cat_i,cat_j}) = \sum_{c=1}^{n} \Phi_c\,(\mathrm{cat_i,cat_j}) \qquad \forall(i,j) \tag{4}$$

Each element of the dominance matrix $\delta(cat_i, cat_j)$ sums all the partial dominances obtained previously from each criterion. The final result is obtained by calculating the vector Ξ with the general element ξ_i shown in (5):

$$\xi_i = \frac{\sum_{j=1}^{k} \delta(\mathrm{cat_i,cat_j}) - \min \sum_{j=1}^{k} \delta(\mathrm{cat_i,cat_j})}{\max \sum_{j=1}^{k} \delta(\mathrm{cat_i,cat_j}) - \min \sum_{j=1}^{k} \delta(\mathrm{cat_i,cat_j})} \tag{5}$$

The term $\sum_{j=1}^{k} \delta(\mathrm{cat_i,cat_j})$ represents the sum of the elements from the i-th row of the matrix δ, the term $\min \sum_{j=1}^{k} \delta(\mathrm{cat_i,cat_j})$ represents the least of these sums, and the term $\max \sum_{j=1}^{k} \delta(\mathrm{cat_i,cat_j})$ represents the greatest sum. For this reason, according to (5), the vector Ξ will always have a component with value 1 (one) representing the most appropriate category for the classification, as well as another with value 0 (zero), representing the least adequate category for the classification. Intermediate values are assigned to the remaining categories.

3.7. Step 7: Validation analysis

The validation analysis is important for creating a good model to support decision making. The alternatives previously classified in each of the proposed categories are used as reference to adjust the classification produced by TODIM-FSE. These adjustments can be made in the criterion weights or in the contribution tables or functions.

4. Application example: evaluation of trainees for an information technology company

The IT Company operates in the area of computational technology and looks for young people with computer skills, among other requirements, to be trainees of the company. The company therefore wants to perform an initial screening of the best candidates. This stage is to be entirely performed through the company's web site. Each registered candidate has to answer a questionnaire and take tests to have his knowledge in the relevant areas assessed. From the responses to the questionnaire and the test scores obtained by the candidate, it is possible to classify him according to the TODIM-FSE method. In this manner, the score obtained by the candidate classifies him in one of the pre-established categories. This way, the TODIM-FSE method produces the desired screening of all candidates.

4.1. Determining decision makers and decision analyst

Decision makers are the senior executives of the IT company responsible for the selection process and the decision analyst is the manager of that process.

4.2. Analyzing and structuring the decision making problem

To better understand the work to be undertaken it is important to present a summary of the practical use of the TODIM-FSE method, and the type of inputs to be supplied from the senior executives. Then, the senior executives explained their goals, the desired type of professional and the plans for those professionals. In this way, the problem was well understood by the decision makers and the decision analyst, ensuring reliability in the evaluation process.

4.3. Defining the relevant criteria of the problem

After discussing the desired profile of the new trainees it was possible to define the criteria to be taken into consideration in the selection process, which are: a) Computer knowledge, b) English language skills, c) Working experience d) Interpersonal relationship skills. These criteria are described in more detail below:

a) *Computer knowledge*: the IT company needs candidates with an extensive knowledge in computer science, familiar with both office applications and programming languages. A multiple choice test will be used to evaluate the candidate's knowledge including several questions on computer topics deemed important by the company.
b) *English language skills*: the company believes that it is very important that the candidate read and speak English. However, at this stage only reading and understanding skills will be evaluated. Again, a multiple choice test will be used.
c) *Working experience*: working experience will be assessed by a questionnaire which tries to identify the quality of the candidate's working experience. The candidates should be young, and for this reason not much is expected in this respect. It will be used as a differential.
d) *Interpersonal relationship skills*: this criterion is considered very important: personal relationships, teamwork, and verbal communication skills should be taken into consideration. However, as this criterion requires personal contact with the candidate, it will be left to the next stage of the evaluation.

Therefore only the first three criteria will be used at this stage of the evaluation: a) Computer knowledge, b) English language skills, c) Working experience. It is worth noting that these three criteria meet almost all the characteristics that Keeney and Raiffa (1976) suggest for a criterion set, particularly non-redundancy. They do not meet the completeness requirement because it is not possible to evaluate "Interpersonal relationship skills" at this stage.

4.4. Defining categories and contribution functions

Four (4) evaluation categories were defined for this problem: excellent, very good, good and bad. The contributions of each criterion are determined from these categories. *Computer knowledge* and *English language skills* are handled as quantitative criteria because they are scored based on the result of a test. As described previously, in this step it is necessary to build the range of contribution values (μ) for each category (represented by contribution functions), that allow to determine the contribution of each criteria evaluation to the classification of the alternative in each category. Thus, contribution functions using trapezoidal functions are defined for them as shown in Figure 3. Figures 3 and 4 were created using Microsoft Excel, which was also used to obtain the results of this example. It is possible to see (looking at Figure 3) that, according to the decision maker's judgments, for example, a candidate who obtains a grade between 0 (zero) and 5 (five) in both tests, may receive the greatest contribution value (1) to the "bad" category, and zero to other categories. If the candidate receives a grade greater that 6 (six) in both tests the contribution values for the "bad" category will be zero, and for grades between 5 (five) and 6 (six) we obtain contribution values within the interval (0,1). The same contribution functions are used for both criteria. Since we know the score obtained by the candidate in the multiple choice tests, the contribution of each criterion to the classification the candidate in a given category is obtained.

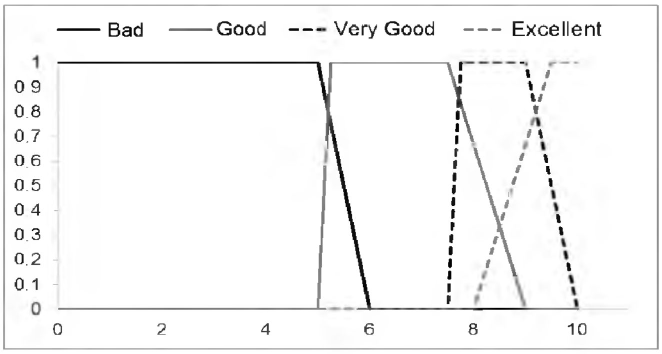

Figure 3. Contribution functions for *Computer knowledge* and *English language skills* criteria

The criterion *Working experience* is handled as a qualitative criterion and thus a contribution table, as shown in Table 3, can be defined. From the answers to this criterion questionnaire it is possible to assess whether the candidate has previous working experience and, in this case, whether the experience is related to the position to be filled.

Table 3

Contribution table for the *Working experience* criterion

	Categories			
Assessment	**Bad**	**Good**	**Very good**	**Excellent**
Worked in the computer science area	0	0.5	0.8	1
Worked in a technical area different from computer science	0.5	0.8	1	0.8
Worked in a non-technical area	0.8	1	0.8	0
Has no working experience	1	0	0	0

4.5. Defining the relative weights of the criteria

The relative weights of criteria are determined from direct assignment on a scale from 0 to 100. After normalization the following weights are obtained: w_{Ck} = = 0.605; w_{ME} = 0.283; w_{We} = 0.112.

4.6. Classifying each alternative in one of the preset categories

To evaluate and classify candidates, it is necessary to obtain the scores and the answers of a given candidate, as previously explained. With this information it is possible to obtain input data for the classification using TODIM-FSE, as shown in Table 4.

Table 4

Results of the scores obtained by the candidate in both tests (*Computer knowledge* and *Mastering of the English language*) and the questionnaire on working experience

Criterion	Candidate evaluation
Computer knowledge	8.5
Mastering of the English language	9.0
Working experience	Has no experience

The *table of criteria grouped contributions* (represented by Table 5, for this particular candidate) is obtained from that input data. The first and the second rows were extracted from the contribution functions defined in Figure 3. The third row was obtained from the last row of Table 3. With Table 5 and the criterion weights it is possible to classify the candidate by using equations (3), (4) and (5).

Table 5

Table of criteria grouped contributions for a particular candidate

Criterion	Bad	Good	Very Good	Excellent
Computer knowledge	0.00	0.33	1.00	0.33
Mastering of the English language	0.00	0.00	1.00	0.67
Working experience	1.00	0.00	0.00	0.00

Table 6 shows the candidate's final classification. All the categories will receive a score. However, only the category with the highest score will be chosen.

Table 6

Final classification of the "very good" candidate

Final Classification	
Bad	0.25
Good	0.00
Very Good	1.00
Excellent	0.43

4.7. Validation analysis

The validation analysis is then performed aiming at checking if the tests have indeed properly classified the candidates. Note that if the tests are too easy, even not well qualified candidates can obtain a good evaluation. Conversely, if the tests are too difficult, very good candidates may be incorrectly classified as "bad". For this reason, before placing the model in the automatic evaluation system, the test was applied to employees considered "very good" or "excellent" in the *Computer knowledge* and *English language skills* areas to allow for adapting the contribution functions to the test level. This means that if the tests are too difficult the contribution functions can be modified to classify candidates with lower score in higher categories. Conversely, if the tests are too easy, the contribution functions may be modified to classify only the candidates with very high score in the best categories.

It is important to stress that only the criteria with judgment values defined by the test were subject to this type of analysis. This is not really necessary for the *Working experience* criterion.

Two (2) experienced employees (here denoted as Employee 1 and Employee 2) who are generally considered excellent by the company are chosen to test the level of the *Computer knowledge* and *English language skills* tests. These employees took the tests without any prior preparation and obtained the scores shown in Table 7.

Table 7

Results of the scores obtained by the two employees in the *Computer knowledge* and *English language skills* tests

Tests	Employee #1	Employee # 2
Computer knowledge	8.0	7.5
English language	8.5	8.0

As these 2 employees were considered excellent both in *Computer knowledge* and *Mastering of the English language*, the scores that they obtained were considered low, indicating the high level of both tests. Thus, to properly classify the prospective candidates the contribution functions shown in Figure 3 were modified. Their modifications are shown in Figure 4.

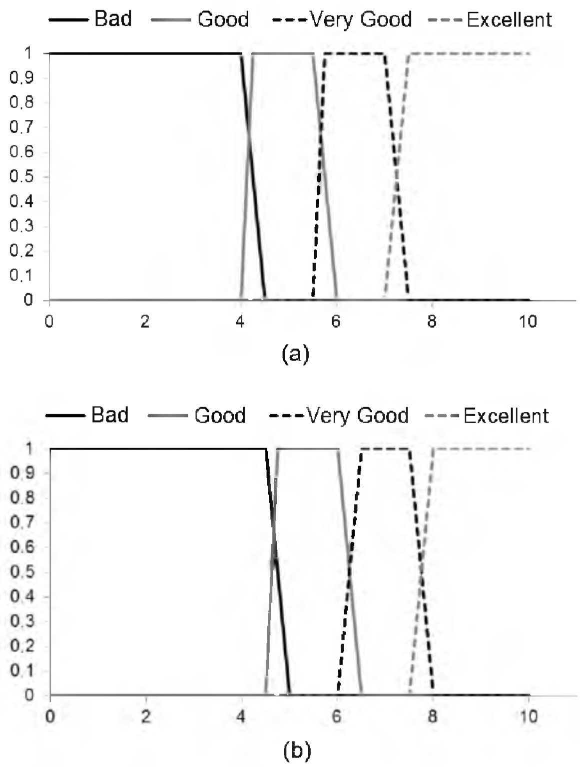

Figure 4. Contribution functions modified for the criteria (a) *Computer knowledge* and (b) *English language skills*

The modification brought a direct impact on the classification of the candidate evaluated. He was previously considered "very good" and after the modification he was considered "excellent". Table 8 shows the new scores of the candidate in each category.

Table 8

The new score of the candidate formerly considered "very good" ("excellent") after the validation analysis

Final Classification	
Bad	0.56
Good	0
Very Good	0
Excellent	1.00

5. Conclusions

TODIM-FSE proved to be effective for classifying the prospective candidates in the study case. An important characteristic of the method is its simplified mathematical formulation, without pre-requirements as in the UTADIS classification method (Zopounidis and Doumpos, 2002), which uses linear programming in its formulation. This enables users with little training to use it without difficulty. The validation analysis, last step of the process is not required in the classification process; and it is not performed in widely used classification methods such as UTADIS and ELECTRE TRI (Doumpos and Zopounidis, 2002). However, it was very important in obtaining the final result because it corrected the candidate's classification. But the validation analysis may not be important for some criteria used in the classification process.

The main differentials of the method are: (1) use of the "contribution" concept indicating the contribution of a criterion to the classification of the alternative in a given category and (2) consideration of the Prospect Theory, embedded in the TODIM method equations used in TODIM-FSE. Strictly speaking, it would be possible to use another method for ranking categories, substituting the TODIM method in step 6. However, the last differential would be lost.

Although the contribution functions described in Figures 3 and 4 are similar to fuzzy sets, it is worth noting that this knowledge is not necessary to construct them.

The consolidation of the method still demands a large number of applications to test and improve TODIM-FSE.

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