International Journal of Economics, Commerce and Management
United Kingdom ISSN 2348 0386 Vol. X, Issue 4, April 2022

http://ijecm.co.uk/

MULTICRITERIA CLASSIFICATION MODEL FOR STUDENT ASSIGNMENT IN E-LEARNING MODULES

Georgios Rigopoulos

Department of Digital Innovation Management

Royal Holloway University of London

Surrey TW20 0EX, United Kingdom

georgios.rigopoulos@rhul.ac.uk

Nikolaos Karadimas

Div. of Mathematics and Engineering Science

Dept. of Military Sciences

Hellenic Army Academy

Evelpidon Av., 16673, Greece

nkaradimas@sse.gr

Abstract

E-learning programs in higher education require the student assignment in groups or teams, either ad hoc or permanent based on a number of predefined criteria, educational or not. The assignment of students into appropriate competency teams is time consuming when the number of criteria is large and executed manually. Here, we propose a model for the assignment based on the application of NexClass methodology. The approach is based on the utilization of multicriteria analysis in order to assign students into a number of predefined categories according to specific criteria. The methodology is presented along with an illustrative example with the usage of the relevant decision support system. The specific approach can be utilized in a variety of settings, especially when student assignment decisions must be taken. The method is simple enough to allow for easy interpretation and and the decision support system allows for easy implementation.

Keywords: Multicriteria classification, student assignment, NexClass decision support system

INTRODUCTION

E-learning programs in higher education often enroll students of varied competency levels and skills. On the other hand lecturers do not meet students so as they do not have direct view of them as in traditional courses. In order to maximize student performance and learning output it is necessary to build appropriate competency teams and assign students in them instead of mass approach. So, in practice, several teams are formed, either ad hoc or permanent, and students are assigned to the most suitable for them. The inclusion criteria may vary from generic to very specific ones. Several factors influence the selection of criteria, such as program preferences, student skills and knowledge. Although, no set can be wide enough to fit all the variations, however the more refined the criteria are, the better the assignment and the learning outcome will be. When the student assignment is executed manually by lecturers or program leaders the assignment problem can be a very time consuming task, especially in cases of large groups of teams and students. In addition it is an error prone task, subject to biases and is also less objective approach. For the above reasons, there is need for an automated and objective assignment approach, especially for large numbers of students.

Multicriteria analysis is a wide area of operations research which offers a variety of methodologies and tools to solve assignment, sorting problems as well as choice and ranking ones [1], [2], [3], [4], [5], [6], [7], [18], [19]. It has been applied to numerous problems with success and research continuous to develop novel methods. In this work, we present the application of multicriteria analysis for the assignment problem of students. Our focus is the problem of assigning a number of students to a small number of classes. The methodology is extending previous research on multicriteria assignment, especially the NexClass method which is used for multicriteria classification [10], [11], [12], [13].

In brief, NeXClass is a classification algorithm and a decision support system for classification problems based on multicriteria analysis, which solves classification problems to predefined non-ordered categories [8], [9], [14], [15], [16], [17]. The overall approach in NexClass is to form a number of ordered categories, then a number of criteria with their associate weights are introduced and the students are scored on each criterion. Next, according to the aggregate scores students are assigned to classes.

In the following sections, the basic terminology of the NexClass multicriteria methodology is introduced and an illustrative example in student assignment is provided along with the NexClass decision support system. The method is presented in its basic terms and the interested reader can refer to relevant literature for a detailed theoretical presentation [9], [10].

METHODS

NexClass algorithm overview

NexClass algorithm supports classification decisions to predefined categories and is based on multicriteria analysis and outranking relations. It utilizes outranking relation principles as well as concordance and discordance indexes as follows. Given a set of alternatives, a set of predefined ordered categories and a set of evaluation criteria, the algorithm classifies an alternative to a specific category with respect to alternative's performance to the evaluation criteria.

The 'non-excluding principle' is the basic rule for the classification of alternatives to categories and is defined as follows:

An alternative 'a' is assigned to a category if it is 'not excluded' or 'roughly not excluded' according to the threshold entrance of this category.

In order to utilize the rule to assign alternatives to categories the 'excluding degree' is defined as the degree of validation of the statement:

Alternative 'a' is not-excluded or roughly not-excluded.

'Excluding degree' measures at what degree the alternative is not excluded from a category or equivalently at what degree the alternative's performance overcomes the category entrance threshold. Calculation of the degree results in the following cases:

The more the alternative performance overcomes the entrance threshold, the more likely it can be assigned to the category and 'excluding degree' is minimized.

The less the alternative performance overcomes the entrance threshold, the less likely it can be assigned to the category and 'excluding degree' is maximized.

Finally, an alternative is assigned to the category for which the 'excluding degree' is the minimum.

For classification problems the methodology is distinguished in three phases:

Problem formulation, where the decision maker defines all parameters.

NexClass algorithm application, where the algorithm classifies the alternatives.

Result validation, where the results are examined according to the parameters.

NexClass Algorithm Notations

$A=\{a_1,a_2,...,a_m\}$: a set of alternatives for classification in a number of categories, $G=\{g_1,g_2,...,g_n\}$: a set of evaluation criteria, $C=\{C^1,C^2,...,C^h\}$: a set of categories, $B^h=\{b_1^h,b_2^h,...,b_k^h\}$: a set of prototypes for category h, where $B^h=\{b_i^h \mid i=1,..k,h=1,...L_h\}$ and

b_i^h is the i$_{th}$ prototype of h$_{th}$ category. These prototypes define the category as thresholds of entrance to category.

Alternatives' performance on criteria is calculated in way such that $\forall a, g(a) = (g_1(a), g_2(a),..., g_n(a))$ and $\forall b_i^h, g(b_i^h) = (g_1(b_i^h), g_2(b_i^h),..., g_n(b_i^h))$.

Excluding degree definition

In order to estimate the degree of validation of the statement

'Alternative $a \in A$ is not excluded or is not roughly excluded',

or the equivalent

'Alternative $a \in A$ is preferred or roughly preferred over the entrance threshold',

the preference degree of an alternative $a \in A$ over the category C^h entrance threshold b_i^h can be calculated.

Thus, an alternative is preferred over the entrance threshold if $aPb_i^h \Leftrightarrow aSb_i^h \wedge \neg b_i^h Sa$.

The degrees of validation of aSb_i^h and $b_i^h Sa$ are given by the credibility indexes $\gamma_i\,(a, b_i^h)$ and $\gamma_i\,(b_i^h, a)$.

So, maximization of preference of alternative $a \in A$ over the entrance threshold b_i^h occurs when $\gamma_i\,(a, b_i^h) \longrightarrow 1$ and $\gamma_i\,(b_i^h, a) \longrightarrow 0$. On the other hand, minimization of preference of alternative $a \in A$ over the entrance threshold b_i^h occurs when $\gamma_i\,(a, b_i^h) \longrightarrow 0$ and $\gamma_i\,(b_i^h, a) \longrightarrow 1$.

In order to estimate the degree of preference of alternative $a \in A$ over the entrance threshold b_i^h the 'excluding degree' is defined as $\gamma_i^{tot} = \dfrac{\gamma_i\,(b_i^h, a)}{1 + \gamma_i\,(a, b_i^h)} \in [0,1]$ where $\gamma_i\,(a, b_i^h)$ and $\gamma_i\,(b_i^h, a)$ are the degrees of validation of aSb_i^h and $b_i^h Sa$ statements.

When $\gamma_i^{tot} \longrightarrow 0$ 'excluding degree' of alternative $a \in A$ over the entrance threshold b_i^h is maximized, while when $\gamma_i^{tot} \longrightarrow 1$ 'excluding degree' of alternative $a \in A$ over the entrance threshold b_i^h is minimized.

When the excluding degree is maximized, alternative is less preferred over the entrance threshold and excluded, while when it is maximized alternative is more preferred over the entrance threshold and included.

Excluding degree calculation

Calculation of excluding degree $\gamma_i^{tot} = \dfrac{\gamma_i\,(b_i^h, a)}{1+\gamma_i\,(a, b_i^h)}$ is based on outranking relations. Expressions $\gamma_i\,(a, b_i^h)$ and $\gamma_i\,(b_i^h, a)$ are the degrees of validation of the statements aSb_i^h and $b_i^h Sa$ respectively, and are calculated by the concordance and discordance indexes [$C(a,b_i^h)$, $C(b_i^h,a)$] and [$d(a,b_i^h)$, $d(b_i^h,a)$] . Total concordance index is calculated as $C(a,b_i^h)=\sum_{i=1}^{n} w_i c_i(a,b_i^h)$ and $C(b_i^h,a)=\sum_{i=1}^{n} w_i c_i(b_i^h,a)$ from partial concordance and discordance indexes,

Fuzzy excluding degree calculation

The fuzzy excluding degree of an alternative $a \in A$ over a category $C^h \in \Omega$ is defined as $\gamma(a,C^h)=P(a,b^h)=\gamma^{tot}$ for the case of one entrance threshold for the category.

In the case of more than on entrance thresholds, expression $\gamma_i^{tot} = \dfrac{\gamma(b_i^h, a)}{1+\gamma(a, b_i^h)}$ is calculated for every threshold for the category b_i^h and the fuzzy excluding degree is defined as

$$\gamma(a,C^h)=\min\{P(a,b_1^h),P(a,b_2^h),...,P(a,b_k^h)\}=\min\{\gamma_1^{tot},\gamma_2^{tot},...,\gamma_k^{tot}\}$$

Assignment to categories

Having calculated the fuzzy excluding degree of an alternative $a \in A$ for every category $\{C^1, C^2, ..., C^h\}$, assignment to one category is based on the following rule

$$a \in C^h \Leftrightarrow \gamma(a,C^h)=\min\{\gamma(a,C^i)/\,i \in \{1,...,k\}\}$$

which states that alternative $a \in A$ is assigned to the category $C^h \in \Omega$ for which the excluding degree over the entrance threshold is minimum.

RESULTS AND DISCUSSION

Overview

In the following, we present the application of NeXClass classification methodology as well as the usage of NeXClass decision support system to the student assignment problem. The application of the algorithm for classification problems is comprised of the following phases:

Problem definition.

The Decision Maker (DM) formulates the problem, setting all appropriate parameters. In details, DM defines the set of categories $\Omega = \{C^1, C^2, ..., C^h\}$ for the classification of alternatives, the set of evaluation criteria $F = \{g_1, g_2, ..., g_n\}$, the criteria weights, the set of alternatives $A = \{a_1, a_2, ..., a_m\}$ for classification, and their performance on the evaluation criteria $\forall a, g(a) = (g_1(a), g_2(a), ..., g_n(a))$. Next DM defines appropriate entrance thresholds for each category $\Omega = \{C^1, C^2, ..., C^h\}$ and for each threshold defines preference, indifference and veto thresholds.

NeXClass application

Following the formulation, NeXClass algorithm is applied and results are evaluated by the DM. In case of misclassifications, DM redefines parameters in order to calibrate the model. When training set classification is acceptable, the entire set of alternatives is classified.

Result assessment

The DM assesses the results, and in case of major misclassifications, modifies the parameters accordingly and runs the model again. The desirable output is the classification of students to a number of predefined groups according to specific criteria, so NeXClass method was selected as the most appropriate for the analysis and construction of the decision process.

Student assignment methodology

According to the steps of NexClass methodology, we developed a methodology for the student assignment problem. A classification problem was formulated and the required parameters were defined reflecting decision preferences. Based on the method the following steps were followed:

Definition of categories C and evaluation criteria G: The categories were defined in ordered form.

Definition of decision maker's preferences: The criteria weights for each category were set.
Alternative set A: A set of alternatives was defined correspond to the students to be assigned.
Alternatives' performance: Performance on the criteria were evaluated for each student.
Classification: Classification results were derived.
Results assessment: The results were assessed.

Student assignment

Initially, a specific academic program was selected as the target program for the student assignment. The decision maker was the lecturer of the program and the students were selected randomly from the pool of students enrolled to the program. Two categories were defined in order to reflect specific competency skills and desired knowledge attitudes. These were associated to two training profiles so as to achieve the maximum outcome from the program and at the same time to increase student commitment. Based on the desired profiles, two classes were defined (Table 1) and linked to specific course delivery model each.

Table 1 Student classes

	C1	**C2**
Definition	**High**	**Low**
course delivery model	Teaching level 1 (advanced group)	Teaching level 2 (medium/low group)

The second step was to define a set of evaluation criteria. The criteria and their scale were based on lecturer's knowledge reflecting the most important aspects of students' profiles (Table 2).

Table 2 Criteria

	Definition	**Scale**
G1	Competency level 1	1-100
G2	Competency level 2	1-100
G3	Competency level set 3	1-100
G4	Knowledge set 1	1-100
G5	Knowledge set 2	1-100
G6	Personal profile	1-100

Based on the above, the lecturer defined criteria weights (Table III) and set the values to the DSS (Fig. 1).

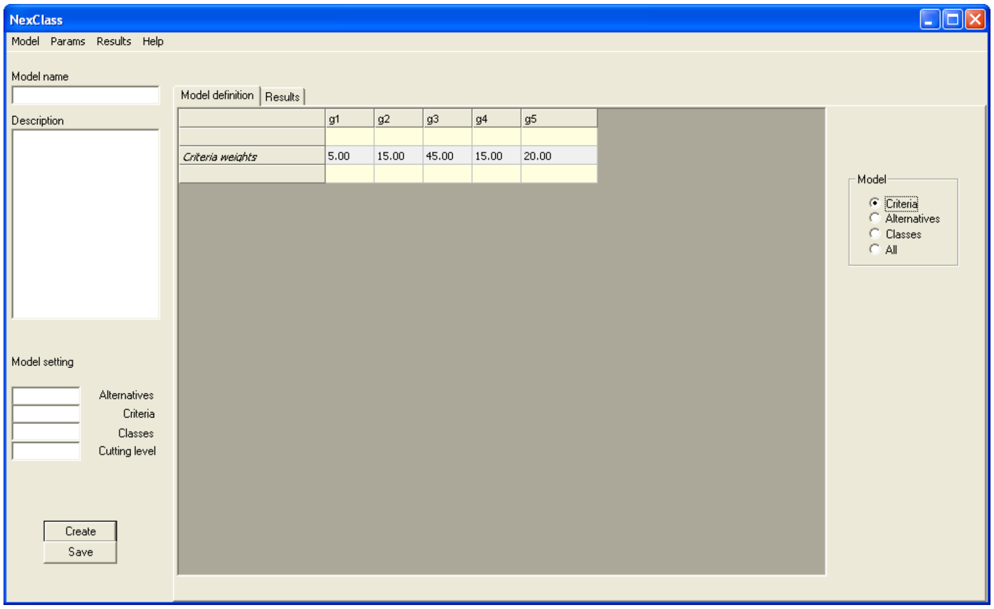

Figure 1 Criteria definition

Table 3 Criteria weights

	G1	G2	G3	G4	G5
Weights	5.00	15.00	45.00	15.00	20.00

Next, the lecturer defined the limits of the categories setting appropriate values for each criterion in the scales defined previously. (Table IV) and set the values to the DSS (Fig. 2).

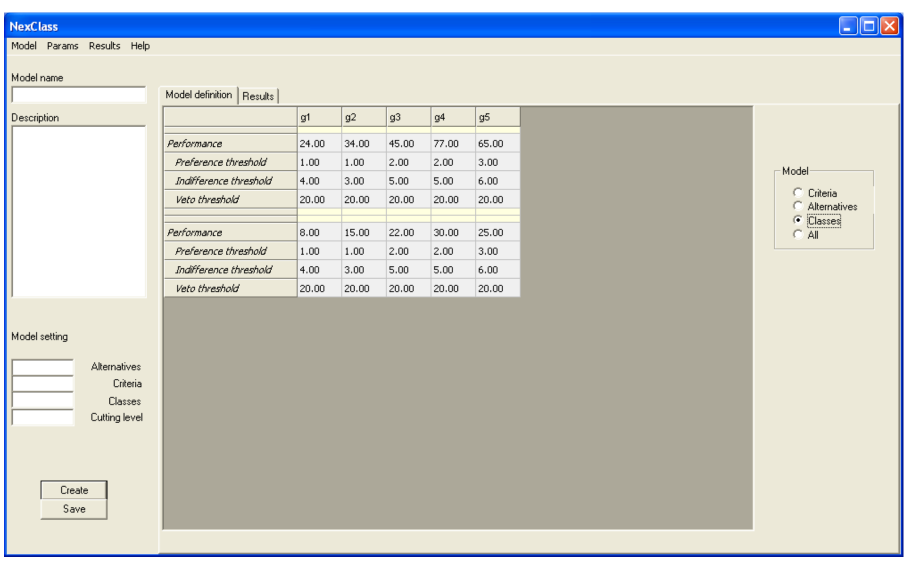

Figure 2 Categories definition

Table 4 Category profiles

	G1	G2	G3	G4	G5
C1	24.00	34.00	45.00	77.00	65.00
Indiff	1.00	1.00	2.00	2.00	3.00
Pref	4.00	3.00	5.00	5.00	6.00
Veto	20.00	20.00	20.00	20.00	20.00
C2	8.00	15.00	22.00	30.00	25.00
Indiff	1.00	1.00	2.00	2.00	3.00
Pref	4.00	3.00	5.00	5.00	6.00
Veto	20.00	20.00	20.00	20.00	20.00

Next, a subset of 20 target students was selected as training set. The selection was random not following any pattern. Their performance on the evaluation criteria was defined by the lecturer (Table 5) and was set to the DSS (Fig. 3).

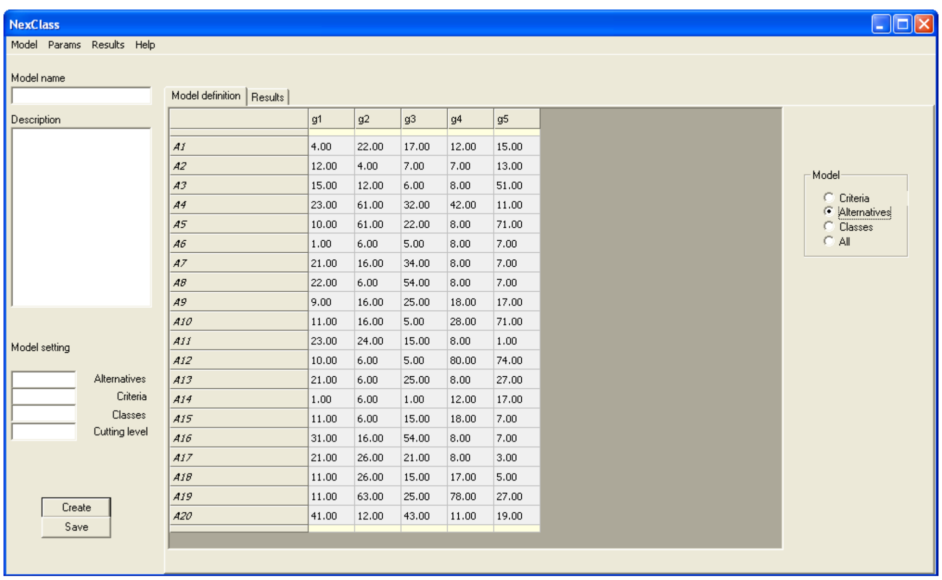

Figure 3 Alternatives performance definition

Table 5 Students' performance to evaluation criteria

	G1	G2	G3	G4	G5
a1	4.00	22.00	17.00	12.00	15.00
a2	12.00	4.00	7.00	7.00	13.00
a3	15.00	12.00	6.00	8.00	51.00
a4	23.00	61.00	32.00	42.00	11.00

a5	10.00	61.00	22.00	8.00	71.00
a6	1.00	6.00	5.00	8.00	7.00
a7	21.00	16.00	34.00	8.00	7.00
a8	22.00	6.00	54.00	8.00	7.00
a9	9.00	16.00	25.00	18.00	17.00
a10	11.00	16.00	5.00	28.00	71.00
a11	23.00	24.00	15.00	8.00	1.00
a12	10.00	6.00	5.00	80.00	74.00
a13	21.00	6.00	25.00	8.00	27.00
a14	1.00	6.00	1.00	12.00	17.00
a15	11.00	6.00	15.00	18.00	7.00
a16	31.00	16.00	54.00	8.00	7.00
a17	21.00	26.00	21.00	8.00	3.00
a18	11.00	26.00	15.00	17.00	5.00
a19	11.00	63.00	25.00	78.00	27.00
a20	41.00	12.00	43.00	11.00	19.00

Table 5…

Solution

Finally, the model was executed, and classification results were derived NeXClass method. Results are depicted in Table 6. Excluding degrees and distance factors are also included for each class.

Table 6 Alternatives' assignment and excluding degrees

Alternative	**Class**	**Excluding degree for C1**	**Excluding degree for C2**	**Distance factor for C1**	**Distance factor for C2**
a1	Class 2	13.515	10.610	351.500	61.000
a2	Class 2	14.310	11.405	431.000	140.500
a3	Class 2	13.445	10.540	344.500	54.000
a4	Class 1	0.1790	0.8885	179.000	-111.500
a5	Class 1	0.1615	0.8710	161.500	-129.000
a6	Class 2	14.530	11.625	453.000	162.500
a7	Class 2	12.975	10.070	297.500	0.7000
a8	Class 1	-0.0883	0.9315	222.000	-68.500
a9	Class 2	13.090	10.185	309.000	18.500
a10	Class 1	0.1122	0.9845	275.000	-15.500
a11	Class 2	13.332	10.915	382.000	91.500

a12	Class 1	-0.0411	0.9160	206.500	-84.000
a13	Class 2	13.130	10.225	313.000	22.500
a14	Class 2	14.450	11.545	445.000	154.500
a15	Class 2	13.880	10.975	388.000	97.500
a16	Class 1	-0.1308	0.9120	202.500	-88.000
a17	Class 2	13.490	10.585	349.000	58.500
a18	Class 2	13.635	10.730	363.500	73.000
a19	Class 1	0.1275	0.8370	127.500	-163.000
a20	Class 1	0.2158	0.9340	224.500	-66.000

Table 6…

In Table 7, we depict the comparison of the above assignment to the classification of the same set of students executed by the lecturer using an existing manual procedure. As it can be seen from this reference set, the model is in accordance with lecturer's opinion using existing procedure except one misclassification in C1 and C2. The DSS provides classification the results in a convenient way along with the various degrees calculated by the algorithm.

Table 7 Assignment comparison

Category	NeXClass	Existing procedure
C1	{a4, a5, a8, a10, a12, a16, a19, a20}	{a4, a5, a6, a8, a10, a16, a18, a19, a20}
C2	{a1, a2, a3, a6, a7, a9, a11, a13, a14, a15, a17, a18}	{a1, a2, a3, a7, a9, a11, a12, a13, a14, a15, a17}

CONCLUSIONS

In this paper, we presented an approach for multicriteria assignment to ordered categories using NeXClass DSS which implements the methodology. For illustration purposes, we presented a real world application of NeXClass DSS, within higher education setting setting for student assignment to predefined classes. The specific approach can be utilized in a variety of settings, especially when student assignment decisions must be taken. The method is simple enough to allow for easy interpretation and demonstration and the decision support system allows for easy implementation. Given the increasing number of students for elearning modules and programs during the past years, it is becoming quite necessary to provide decision makers with tools that allow for automated decisions. In the future, we plan to extend the system in a web version to increase its user friendliness.

REFERENCES

1. Belacel, N., (2000), Multicriteria assignment method PROAFTN: Methodology and medical applications, European Journal of Operational Research, 125, 175-183.
2. Dias, L.C., V. Mousseau, (2005), IRIS: A DSS for Multiple Criteria Sorting Problems, Journal of Multi-Criteria Decision Analysis, Vol. 12, 285-298.
3. Doumpos, M., and C. Zopounidis, (2001), Multicriteria classification methods in financial and banking decisions, International Transactions in Operational Research, 567- 581.
4. Figueira, J., Y. De Smet, and J.P. Brans, (2004), MCDA methods for sorting and clustering problems: Promethee TRI and Promethee CLUSTER. Technical Report TR/SMG/2004-002, SMG, Universitı Libre de Bruxelles.
5. Greco, S., B. Matarazzo, and R. Slowinski, (2002), Rough sets methodology for sorting problems in presence of multiple attributes and criteria. European Journal of Operational Research, 138:247-259.
6. Karadimas N.V., Doukas N. and Papastamatiou N.P., Risk Preparedness and Management Scheme for Military Units. In Mastorakis N.E., Poulos M., Mladenov V., Bojkovic Z., Simian D., Kartalopoulos S., Varonides A. and Udriste C. (eds): MAMECTIS 2008 – 10th World Scientific and Engineering Academy and Society, International Conference on Mathematical Methods, Computational Techniques and Intelligent Systems, Corfu, Greece, ISBN: 978-960-474-012-3, 26-28 October 2008, pp. 481-485.
7. Karadimas N., Rigopoulos, G., Orsoni, A., (2008), A Decision Model for Group Assessment of Credit Applications, in Proceedings of the 10th International Conference on Computer Modelling & Simulation (IEEE), Page(s):319-323, Cambridge, England
8. Marichal, Jean-Luc, Patrick Meyer and Marc Roubens, (2005), Sorting multi-attribute alternatives: The TOMASO method, Computers and Operations Research, vol. 32, no 4, 861-877.
9. Rigopoulos, G., Anagnostopoulos, K, (2010), Fuzzy Multicriteria Assignment for Nominal Classification Methodology and Application in Evaluation of Greek Bank's Electronic Payment Retailers, International Journal of Information Technology & Decision Making, 9(3):1-18
10. Rigopoulos G., Anagnostopoulos K., Fuzzy Multicriteria Assignment for Nominal Classification Methodology and Application in Evaluation of Greek Bank's Electronic Payment Retailers, International Journal of Information Technology & Decision Making, Vol.9, No.3, 2010, pp.1-18
11. Rigopoulos, G., Askounis, D., Metaxiotis, K., NeXCLass: A Decision Support System for non-ordered Multicriteria Classification, International Journal of Information Technology & Decision Making, Vol.9, No.1, 2010, pp.53-79.
12. Rigopoulos, G., Karadimas N., (2011), Military staff assignment approach utilizing multicriteria analysis, in Proceedings of 15th WSEAS International Conference on COMPUTERS, pp: 107-110, Corfu, Greece, ISBN: 978-1-61804-018-3
13. Rigopoulos, G., Karadimas N., Preference Aggregation for Collaborative Multicriteria Assignment, Proceedings of the 1st National joint Conference of Hellenic Mathematical Society and Hellenic Operational Research Society, Athens, Greece, 24-25 June 2011.
14. Rigopoulos, G., Psarras, J., Askounis, D. (2008), Fuzzy Assignment Procedure based on Categories' Boundaries, American Journal of Applied Sciences, 5(7):844-851, 2008
15. Rigopoulos, G., Psarras, J., Askounis, D. (2008), An Aggregation Approach for Group Multicriteria Assignment, American Journal of Applied Sciences 5(8):952-958, 2008
16. Rigopoulos G., Psarras J., Karadimas N.V. and Orsoni A., Facilitatitng Group Decisions Through Multicriteria Analysis & Agent based Modeling. IEEE – AMS '07 First Asia International Conference on Modelling and Simulation, Phuket, Thailand, ISBN: 0-7695-2845-7, 27-30 March 2007, pp. 533-538.
17. Rigopoulos, G., Psarras, J., Askounis, D., Fuzzy Assignment Procedure based on Categories' Boundaries, American Journal of Applied Sciences, Vol.5, No.7, 2008, pp.844-851.
18. Rocha, C., and Dias, L., (2005), An idea for ordinal sorting based on electre without category limits, INESC Coimbra working paper: ISSN : 1645-2631.
19. Yu, W., (1992), ELECTRE TRI: Aspects methodologiques et manuel d'utilisation, Document du Lamsade No 74, Universite de Paris-Dauphine. Document du Lamsade No 74, Universite de Paris-Dauphine, 1992.