Journal of Applied Sciences

ISSN 1812-5654

science alert

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Journal of Applied Sciences 8 (3): 443-452, 2008
ISSN 1812-5654

A Decision Support System for Supervised Assignment in Banking Decisions

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Abstract: This study presents a Decision Support System (DSS) which supports assignment of actions (e.g., numbers, projects, people etc.) into predefined categories according to their score on evaluation criteria. It implements a novel classification algorithm based on multicriteria analysis and fuzzy preference relations. More detailed, assignment to classes is based on the concept of category threshold, which defines at what degree an alternative can be included in a specific category. For each category a threshold is defined by the corresponding decision maker, which indicates its lower limit with respect to the evaluation criteria. Actions are then evaluated according to the criteria and fuzzy inclusion degrees are calculated for each category. Finally, an action is assigned to the category for which the inclusion degree is the maximum. The DSS implements the above classification algorithm, providing a user-friendly interface, which supports decision makers to formulate and solve similar problems. In addition to the DSS, we present a real world application at a classification problem within the environment of a Greek bank. Results derived from evaluation experiments in the business environment provide evidence that the proposed methodology and the DSS can effectively support decision makers in classification decisions. The methodology as well as the proposed DSS can be used to classification problems not only in financial domain but to a variety of domains such as production, environmental, or human resources.

Key words: Fuzzy preference, ELECTRE III, multicriteria classification

INTRODUCTION

Classification has been active research topic during the past decades with wide range of applications. Assignment of actions (numbers, people, projects etc.) to categories is common objective in decision-making problems to a variety of fields (Doumpos and Zopounidis, 2001). Algorithms and methodologies to solve such problems come from operations research, neural networks, mathematics and machine learning, reflecting active research interest. Computational complexity of classification problems has been reduced due to developments in information technology, resulting to Decision Support Systems which implement resource intensive classification algorithms.

Classification can be divided in, (a) supervised, which requires decision maker's contribution and refers to predefined categories which depending on whether they are ordered or not is referred as sorting or classification and (b) unsupervised, which does not require decision maker's contribution, is executed automatically mostly based on appropriate algorithms, categories are not predefined and is referred as clustering. Multicriteria analysis offers a variety of methodologies and tools to solve sorting and classification problems (Figueira *et al*., 2005). However, existing multicriteria methodologies and decision support tools focus mostly on ordered categories, resulting in relative lack for classification in non-ordered categories.

Within this framework, we present NeXClass, a novel supervised classification algorithm as well as a decision support system based on multicriteria analysis, which solves classification problems to predefined non-ordered categories. The classification algorithm is based on the concept of category entrance threshold. The problem that we want to solve is to classify an action to a specific category with respect to action's score to the evaluation criteria, considering a set of actions, a set of predefined non-ordered categories and a set of evaluation criteria. In general, for each predefined category, the decision maker defines an entrance threshold. This threshold represents the minimum requirements for an action in terms of performance on the evaluation criteria in order to be included in this category. Decision maker defines actions' score on the criteria as well as all required parameters' values. For each action, its performance on the criteria is compared with the entrance threshold of every category and finally the action is assigned to the category for

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which it has the maximum distance from the entrance threshold, in terms of a fuzzy inclusion degree.

In this study, we present the algorithm and the decision support system, which implements it, as well as a real world case study demonstrating its usage. Initially, we introduce the basic definition of NeXClass algorithm and the integrated classification methodology. Next, we present the architecture and major functionalities of NeXClass DSS. Finally, a real world case study is presented in order to demonstrate the methodology and DSS usage. Following the application of DSS, evaluation results from DSS usage provide evidence for DSS efficiency and applicability to classification problems. Although we focus on financial classification problems, the proposed DSS can be utilized to support decision makers at a variety of fields, such as human resources, production and environment where similar assignment problems can occur.

MATERIALS AND METHODS

NeXClass methodology: The proposed methodology NeXClass (Non Excluding Classification) for multicriteria classification is based on the concept of inclusion (non exclusion) to a category. Inclusion (non exclusion) of an action is determined by the value of actions' fuzzy inclusion degree which is calculated following concordance/non-discordance concepts generalizing ELECTRE III method (Roy, 1991). In NeXClass categories are defined by an entrance threshold, which can be considered as a virtual action that marginally satisfies inclusion requirements. The objective of the methodology is to classify actions to categories considering the inclusion (non exclusion) concept.

In the following we present the definition of fuzzy inclusion degree and the methodology which utilizes it to classify actions to categories. The following notations will be used:

- A = $\{a_1, a_2,..., a_n\}$ is a set of actions for assignment to categories.
- C = $\{C^1, C^2,..., C^h\}$ is a set of categories, defined by their least typical representatives referred as entrance thresholds.
- G = $\{g_1, g_2,..., g_m\}$ is a set of evaluation criteria.
- W = $\{w(g_1), w(g_2),..., w(g_m)\}$ is the set of criteria importance weights.
- B = $\{b^1, b^2, ..., b^h\}$ is the set of entrance thresholds per category.
- Action's a_i score on the evaluation criteria g_j is defined as $g_j(a_i)$.
- Entrance threshold's b^h score on the evaluation criteria g_j is defined as $g_j(b^h)$, where b^h is the threshold of category $C^k \in C$.

The problem that we want to solve is defined as follows: Having a set of actions (e.g., projects, people, numbers etc.), a set of non-ordered categories which are defined by their least typical representative (entrance threshold) and a set of evaluation criteria, assign actions to categories with respect to their score on the evaluation criteria and the inclusion (non exclusion) concept.

Fuzzy inclusion degree: In order to utilize the inclusion (non exclusion) concept for the classification of actions an appropriate method is needed to quantify actions' inclusion degree to a category. To support this, we introduce the fuzzy inclusion relation P(a, b) as a binary relation between an action a_i and a category threshold b^h.

The relation P(a, b) states that an action a_i is preferred over a threshold b^h (and can be thus included in the category C^h) if there is a majority of evaluation criteria supporting preference of action a_i over threshold b^h and there is no strong opposition to this. In order to evaluate the relation P(a, b) we utilize concordance/non-discordance principle, defining appropriate inclusion/non-inclusion indexes and calculate action's fuzzy inclusion degree for a category.

Partial inclusion index: A criterion is said to be concordant if it expresses agreement about the assertion that action a_i is preferred over threshold b^h or equivalently $g_j(a_i)>g_j(b^h)$ for the specific criterion. However, in order to overcome imprecision in definition of data, we define two discrimination thresholds $q(g_j)$ and $p(g_j)$ (indifference and preference thresholds respectively) for each criterion, resulting in three areas of inclusion (no inclusion, weak inclusion and strong inclusion). Considering these areas, we define the partial inclusion index Cj (a, b^h) for the evaluation of concordance per criterion as follows:

$$C_j(a_i,b^h)=\begin{cases}0, & g_j(a_i)\le g_j(b^h)+q(g_j)\\ \dfrac{g_j(a_i)-g_j(b^h)-q(g_j)}{p(g_j)-q(g_j)}\in[0,1], & g_j(b^h)+q(g_j)\le g_j(a_i)\le g_j(b^h)+p(g_j)\\ 1, & g_j(a_i)\ge g_j(b^h)+p(g_j)\end{cases} \quad (1)$$

Comprehensive inclusion index: For the evaluation of concordance degree of all criteria on the assertion that a_i is preferred over threshold b^h, we define the comprehensive inclusion index for action a_i aggregating partial inclusion indexes as:

$$C(a_i,b^h)=\sum_{j=1}^{m} w_j * C_j(a_i,b^h) \quad (2)$$

Where, w_j is the importance weight of criterion g_j.

Non-inclusion index: In some cases a criterion can express negative judgment about classification of action a_i to a class C^h. More specifically, a criterion g_j can express a significant opposition (or is discordant) to assertion that action a_i is preferred over threshold b^h. In order to measure the discordance degree we define the non-inclusion index $D_j(a_i, b^h)$ for every criterion. To handle imprecision, we define a veto threshold $v(g_j)$ for each criterion as the minimum value which is incompatible with the assertion that the criterion is discordant, resulting in three areas of non-inclusion as follows:

$$D_j(a_i,b^h)=\begin{cases}0, & g_j(a_i)\le g_j(b^h)+p(g_j)\\ \dfrac{g_j(a_i)-g_j(b^h)-p(g_j)}{v(g_j)-p(g_j)}\in[0,1], & g_j(b^h)+p(g_j)\le g_j(a_i)\le g_j(b^h)+v(g_j)\\ 1, & g_j(a_i)\ge g_j(b^h)+v(g_j)\end{cases} \quad (3)$$

Comprehensive fuzzy inclusion relation: In order to evaluate the assertion 'a_i is preferred over a threshold b^h (and can be thus included in the category C^h)' appropriate consideration of all concordant and discordant criteria should be executed aggregating inclusion and non-inclusion indexes (Eq. 2, 3) into a comprehensive relation. Among other aggregation operators that have been proposed, we follow the ELECTRE III method and define the comprehensive fuzzy inclusion relation aggregating the inclusion relations (Eq. 2) weakened by non-inclusion (Eq. 3) as:

$$P(a_i,b^h)=C(a_i,b^h)*\prod_{j=1}^{m}\left(\frac{1-D_j(a_i,b^h)}{1-C(a_i,b^h)}\right) \quad (4)$$

Fuzzy inclusion degree: Finally, in order to measure the credibility degree of the comprehensive fuzzy inclusion relation (Eq. 4) we define the fuzzy inclusion degree of each action $a_i \in A$ for every category $C^h \in C$, as:

$$\gamma(a_i,C^h)=P(a_i,b^h) \quad (5)$$

Classification methodology: The classification procedure using the fuzzy inclusion degree as defined above (Eq. 5) is comprised of the following phases.

Problem definition: Decision maker formulates the problem, setting all appropriate parameters. In details:

- **Categories:** Decision Maker (DM) defines the set of categories $C = \{C^1, C^2, ..., C^h\}$ for the classification of actions reflecting problem requirements.
- **Evaluation criteria:** DM defines the set of evaluation criteria $G = \{g_1, g_2, ..., g_m\}$ according to problem requirements.
- **Criteria weights:** DM defines importance weights $W = \{w(g_1), w(g_2), ..., w(g_m)\}$ of criteria.
- **Actions:** DM defines the set of actions $A = \{a_1, a_2, ..., a_m\}$ for classification and scores them on the evaluation criteria $\forall a, g(a) = \{g_1(a), g_2(a), ..., g_m(a)\}$.
- **Entrance thresholds:** DM defines appropriate entrance thresholds b^h for each category $C = \{C^1, C^2, ..., C^h\}$ and scores them on the evaluation criteria $g_j(b^h)$.
- For each criterion DM defines preference $p(g_j)$, indifference $q(g_j)$ and veto $v(g_j)$ thresholds respectively.

Classification: After problem formulation, the following steps are followed for the classification:

- For each action a_i fuzzy partial inclusion relations (Eq. 1) are calculated over all thresholds b^h and categories C^h.
- For each action a_i comprehensive inclusion relations (Eq. 2) and non-inclusion indexes (Eq. 3) are calculated over all thresholds b^h and categories C^h.
- For each action a_i fuzzy inclusion degree is calculated for every category C^h (Eq. 4).
- Action a_i is assigned to the category for which fuzzy inclusion degree is maximum $a_i \in C^h \Leftrightarrow \gamma(a_i, C^h) = \max\{\gamma(a_i, C^i) \ / \ i \in [1,h]\}$.

Results assessment: DM assesses the results and in case of major misclassifications, modifies the parameters accordingly and reruns the model.

NeXClass DSS: The above algorithm and methodology is implemented in NeXClass DSS, a Decision Support System which was developed in order to support decision makers to interactively solve classification problems (Fig. 1). The DSS was developed in C++ and is running under Windows OS.

DSS architecture: The DSS is oriented towards usage from single decision makers. Thus, it was developed as stand alone application, which can be installed and executed in Windows workstations. Since data necessary for classification can reside in several data sources, DSS supports XML, text files and RDBMS as data sources. For the development of the DSS we followed a N-tier architecture model, defining the following major layers: data layer, application layer and presentation layer. Every layer comprises from appropriate modules which implement the above presented methodology phases. Below we present the basic operations of major modules (Fig. 2).

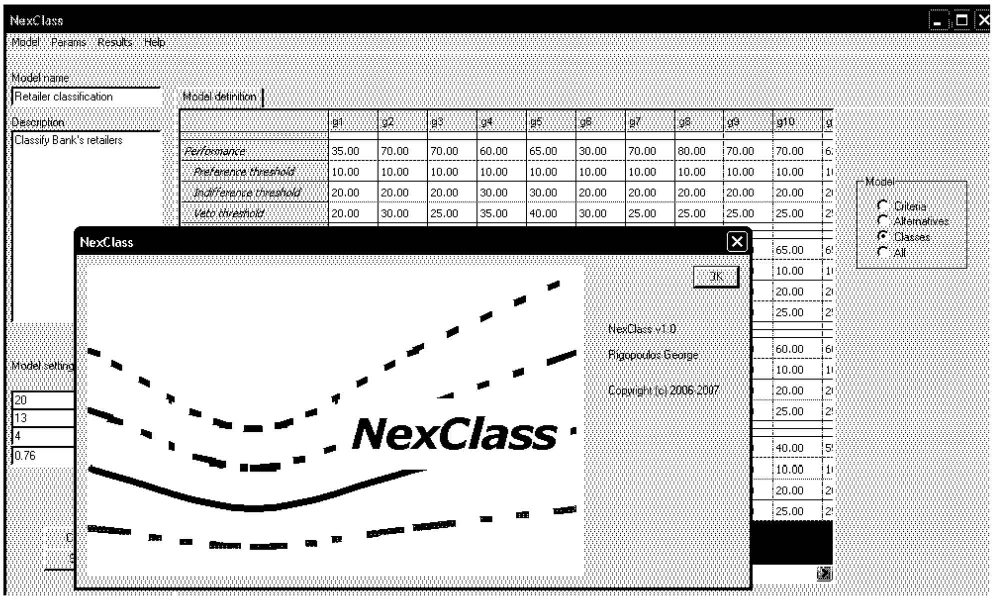

Fig. 1: NeXClass DSS

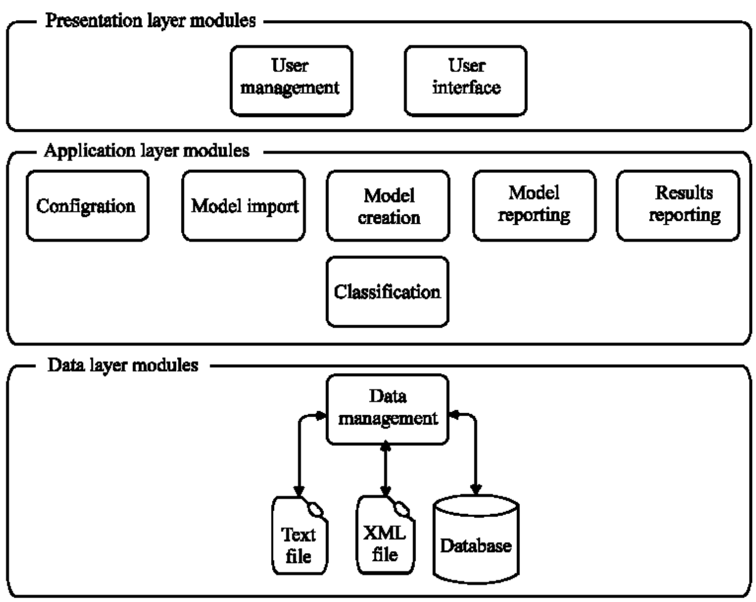

Fig. 2: DSS modules

Presentation layer: This layer includes the user interface, which supports user operations. Design follows the methodology and it was based on the required functionalities. It provides a flexible guided interface for the formulation of classification problems reducing thus complexity for users. Layers's modules are:

- **User management:** Since it is possible that a classification model handles confidential data, (such as financial data including costs, budgets etc.) and classification results may be confidential, it is imperative to protect usage of DSS from unauthorized users. This module provides user authentication procedure and in the case of multiple users, restricts access only to user's own models.
- **User interface:** This module provides all the necessary screens to user in appropriate format according to the methodology.

Application layer: Within this layer, basic operations as well as the classification algorithm takes place. As described earlier, the entire methodology is separated in 3 main phases. Application layer is responsible for the implementation of these phases. Layers's modules are:

- **Configuration:** This module provides general configuration capabilities to user to customize the DSS interface, such as font selection, sizing, colour and other interface parameters.
- **Model import:** In the case of large quantities of data, a user can import a model from a data source, instead of inserting all the values manually. In this case the module imports all the data from the external source and formats the classification model.
- **Model creation:** In the general case, a user creates a new model from scratch. This module provides all the functionality to create a new model following the steps of the problem definition phase of the methodology.
- **Model reporting:** After the model creation/import, this module provides overview of the model, allowing corrections to it.
- **Classification:** This is the module which implements the classification algorithm, either on a training set or the entire set of the alternatives.
- **Results reporting:** After the classification, this module presents the results in appropriate format. Results include not only the alternatives' assignment to classes, but evaluations of inclusion degrees, concordance and discordance indexes as mentioned in the methodology.

Data layer: This layer includes the data model necessary for the application. All data are stored in appropriate format in database tables, within a relational database. Since, decision support problems may require relative large amount of data, we have included the capability to import data from XML files or text files with appropriate format. Layers's basic module is:

- **Data management:** This module is responsible for handling the data operations from and to data sources. This module is responsible to support data operations to data stored in text files, XML files and RDBMS in appropriate formats.

RESULTS AND DISCUSSION

Here, we present a real world application of the proposed methodology and the DSS in order to demonstrate its applicability in classification problems within business environment. The specific problem refers to a top Greek bank, which aims to reorganize its electronic payment network, consisted of retail companies that are equipped with terminals for online electronic payments. Electronic payments between retail companies and consumers are executed mostly through appropriate terminals (EFTPoS/Electronic Fund Transfer at Point of Sale), which form a network connecting banks, retailers and consumers in a triangular relationship. Banks or financial organizations are usually the owners of such networks, charging users of network services with transaction fees (Alexander *et al*., 1992). During the early development of payment networks, such terminals were offering basic payment services. However, today's EFPoS terminals, which have evolved technologically and are capable for advanced payment services, can be utilized by banks as point of differentiation to competitors, offering a set of value added services to both retailers and individual consumers (Smith, 1987; Alexander *et al*., 1991). Although in several countries ownership of network is separated from service provision, in Greece, due to market particularities, several private EFTPoS networks owned by banks coexist, resulting in increased competition that suppresses banks' revenues. Retailer evaluation is thus a critical issue for network viability.

Problem definition: The bank's payment network has currently an extended installed base of more than 5.000 EFTPoS devices located at several retailer stores. However, analysis posed several inefficiencies, which in combination with high investment and operational costs as well as technical and support issues result in low profitability of the payment network. In addition, advanced capabilities and enhancements of EFTPoS devices are not efficiently deployed to support customers' needs. Trying to minimize network inefficiencies, the bank decided to follow a renovated customer centric approach and consider its EFTPoS devices not as dummy terminals for payment execution, but as points to deliver added value payment services to its customers. Following this strategic approach, the bank's objective is the assignment of EFTPoS retailers to appropriate categories reflecting differentiated development strategies. A retailer will be assigned to a specific category if he satisfies the minimum entrance requirements for inclusion to this, considering bank's preferences as expressed by bank's expert. Based on the above requirements, the proposed NeXClass methodology was applied in order to support the entire decision process. Below, we present the assignment procedure for a subset of 20 retailers following the steps of the methodology.

Table 1: Defined categories for retailer classification

Category specification	Category C1	C2	C3	C4
Definition	Retailers with relative low potential and medium to high profitability	Retailers with relative high potential and medium to high profitability	Retailers with medium to high potential and medium to low profitability	Retailers with medium to low potential and low profitability
Strategy	Bank will allocate substantial resources to strengthen retailer's potential	Bank will allocate maximum resources to provide high added value innovative services.	Bank will minimize resource allocation and focus to top retailers of the category.	Bank will screen retailers for potential development, allocating a minimum level of resources.

Table 2: Defined criteria for the evaluation of retailers

Criterion	Definition	Scale	Weight
G1	Retailer Size (Based on average daily sales in 1.000Euros)	1-100(asc)	10
G2	Intensity of EFT/POS usage (Based on percentage of daily sales through EFT/POS)	1-100(asc)	12
G3	Average value per EFT/POS transaction (in Euros)	1-100(asc)	4
G4	Average cost per EFT/POS Terminal (in Euros)	1-100(asc)	13
G5	EFT/POS Terminal profitability. Average monthly revenue per terminal (in Euros)/Average monthly cost per terminal (in Euros)	1-100(asc)	13
G6	Average growth rate. Indicator showing monthly increase in transaction ratio	1-100(asc)	8
G7	Merchant category. Based on bank's merchant type definition according to merchant activity	1-100(asc)	10
G8	Collaboration efficiency. Index based on merchants calls to bank support centre	1-100(asc)	4
G9	Exclusivity. Index based on retailer's exclusive collaboration (Normally, a retailer has installed at the same place EFT/POS terminals from several competing banks)	1-100(asc)	4
G10	Location. Index based on retailer's distance factors from areas with high traffic (Location and accessibility influence customers to buy a product or service at a specific place. Appropriate locations increase EFT/POS transaction volume)	1-100(asc)	8
G11	Opening hours. Index based on retailer's opening hours	1-100(asc)	4
G12	Training of employees. Index expressing employees' expertise on EFT/POS	1-100(asc)	8
G13	Alternative channels. Index expressing usage degree of bank's alternative payment channels from retailer	1-100(asc)	2

Methodology and DSS application: Initially, the bank formed a two-dimensional conceptual evaluation framework comprised of retailer's site potential and profitability indicators. The EFTPoS domain was thus segmented into four partitions. The classification categories were defined, relying on this segmentation. For the sake of simplicity, bank's expert defined 4 categories depicting the relevant importance of retailer for the bank (Table 1). The categories are also linked to a marketing strategy that the bank will follow for the retailers classified to each one.

The next step was the definition of a set of appropriate evaluation criteria to represent both profitability and site's potential factors, according to the segmentation. Criteria selection was based on relevant studies (Abdul-Muhmin and Alzamel, 2001; Ironfield and McGoldrick, 1988; McFayden, 1987) and availability of data for easy quantification. In total, thirteen criteria were defined satisfying bank's requirements and Simos procedure was followed (Figueira and Roy, 2002) for the definition of importance weights, since it is straightforward and decision maker can easily understand the process. Scoring of retailers on each criterion was executed by bank's expert, based on data collection from bank's resources. Decision maker scored each retailer according to its performance on each criterion and values were converted to 1-100 scale using appropriate procedure for each criterion.

Criteria are presented in Table 2, along with the defined scales and importance weights. Criteria parameters were imported by DM to the DSS using the appropriate form as shown in Fig. 3.

Following the methodology, appropriate values were defined for the required parameters. Entrance thresholds for the categories were defined by bank's expert DM setting values for each criterion in the scales defined previously. For simplicity, the expert defined low indifference and preference zones. In addition, veto thresholds were set in relative high values in order to restrict exclusions only for extreme cases. Threshold values were imported by DM to the DSS using the appropriate forms as shown in Fig. 4, Table 3.

Next, a subset of 20 retailers was selected from the existing customer base as alternatives for classification and expert evaluated their scores on criteria using bank's data (Table 4). As mentioned earlier, expert initially scored retailers with respect to bank's resources and values were normalized in 1-100 scale with appropriate functions for uniformity. Score values were imported by DM to the DSS in the appropriate forms as shown in Fig. 5.

Finally, the model was executed and classification results were derived. Calculated inclusion degrees and classification results are shown in Table 5, 6, respectively. We also include in Table 6 classification of this set from expert using existing procedure. As it can be seen from this set, the model is in accordance with

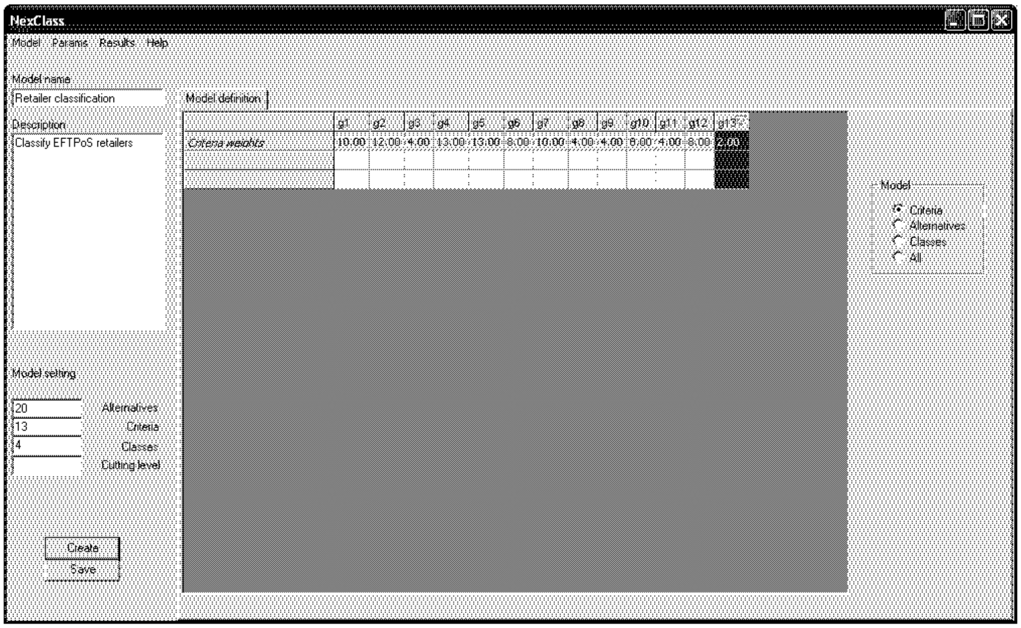

Fig. 3: DSS screen for criteria definition

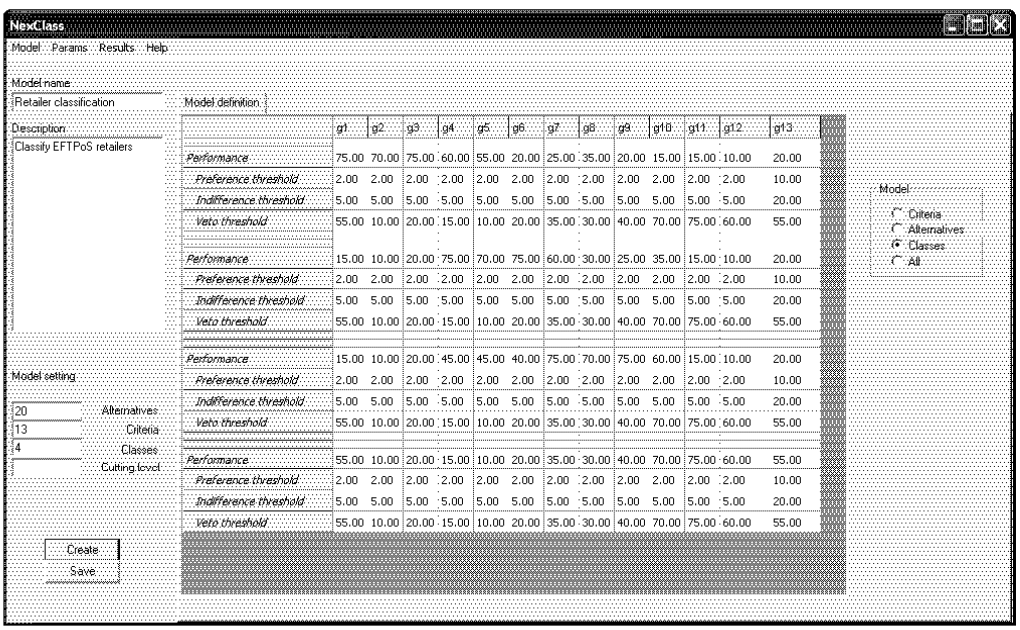

Fig. 4: DSS screen for category threshold definition

Table 3: Categories' entrance thresholds

	Criterion												
Category	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13
C1	75	70	75	60	55	20	25	35	20	15	15	10	20
C2	15	10	20	75	70	75	60	30	25	35	15	10	20
C3	15	10	20	45	45	40	75	70	75	60	15	10	20
C4	55	10	20	15	10	20	35	30	40	70	75	60	55

Table 4: Retailers' performance on criteria

Retailer	Criterion G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13
R1	29	22	28	25	69	25	61	52	25	39	58	61	68
R2	80	78	88	69	59	30	50	45	48	42	22	15	27
R3	77	90	88	61	63	28	35	33	51	33	22	28	33
R4	16	39	26	25	55	25	50	51	43	65	37	38	73
R5	28	56	51	21	34	8	37	61	30	37	55	66	98
R6	79	75	80	65	60	25	30	34	22	19	22	18	21
R7	50	6	54	25	38	21	47	41	40	57	65	65	88
R8	44	19	31	55	49	29	80	70	73	55	48	29	45
R9	49	43	28	29	61	22	67	42	25	39	51	62	55
R10	30	25	30	51	55	44	82	84	90	74	32	15	32
R11	30	29	32	87	86	80	77	46	28	49	25	29	33
R12	49	17	54	25	37	21	47	39	42	54	65	55	98
R13	42	14	27	51	43	22	74	67	69	53	40	25	92
R14	25	19	26	90	81	79	70	44	32	45	28	24	30
R15	42	14	27	51	56	46	81	78	82	53	40	25	33
R16	80	77	79	69	65	22	31	37	28	22	19	21	29
R17	21	15	22	86	79	83	68	40	30	41	20	19	25
R18	18	12	25	82	81	79	64	38	29	39	19	15	27
R19	22	18	26	49	51	41	80	80	86	69	24	11	26
R20	41	35	44	29	34	21	47	61	50	57	62	61	98

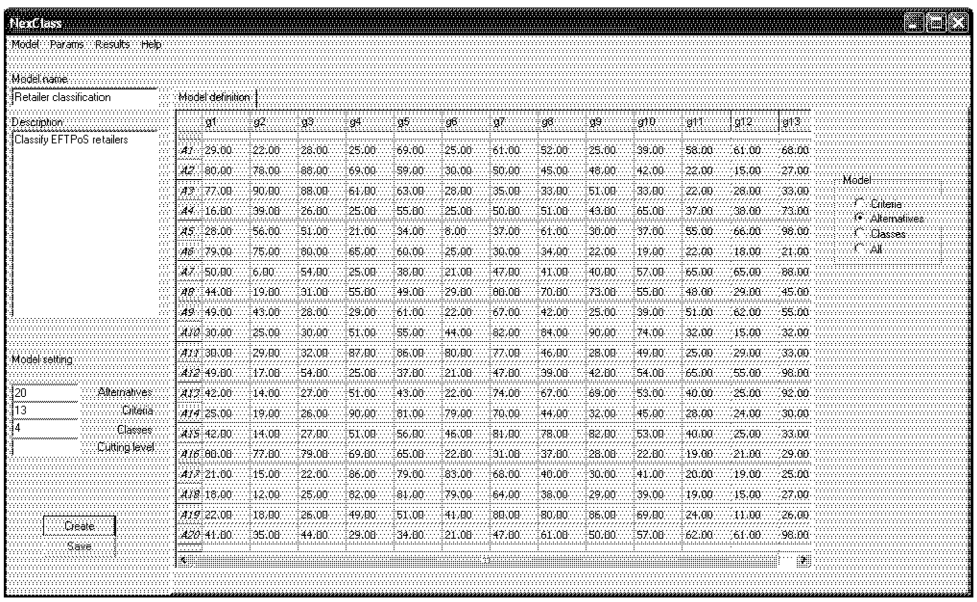

Fig. 5: DSS screen for scores' definition

experts' opinion using existing procedure except some misclassifications in categories C3 and C4. In Fig. 6 and 7, the degrees as well as the classification results are depicted in screens of the DSS.

Validation of NeXClass: In order to validate the NeXClass methodology, we executed a number of experiments, testing the validity of results on the one hand, as well as functionality from decision maker's point of view. Validation testing, measured the correctness of the results and the accuracy of the algorithm. Since, supervised classification incorporates decision maker's preference there is no absolute solution set to classification problems. For the specific bank setting, we considered a number of solution sets as defined by the expert following the traditional decision making procedure. These sets were used as benchmarks for methodology and DSS evaluation and a number of tests were executed in order to verify methodology's classification accuracy. Below we present the results from a number of experiments regarding classification accuracy according to existing procedure (Table 7).

As it can be seen, at the initial run DSS presents a percentage of misclassifications. Existing procedure is

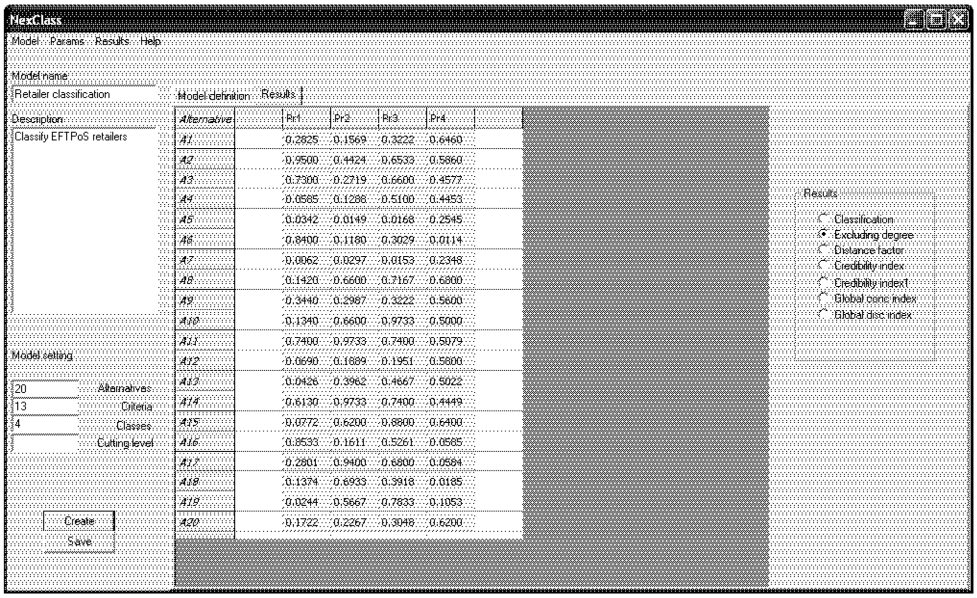

Fig. 6: DSS screen for inclusion degrees result

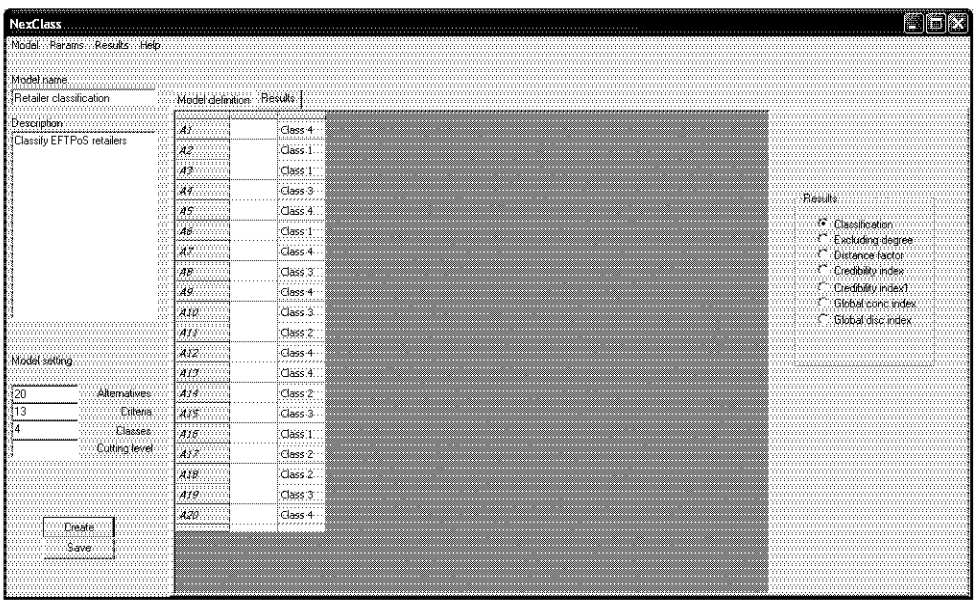

Fig. 7: DSS screen for classification results

heuristic based and definition of category thresholds is not a straightforward process. So we tuned the thresholds and after a second run misclassification percentage was reduced proving thus that these misclassifications were due to inappropriate parameter definition.

Our findings from DSS application and interaction with decision makers provide valid evidence that the proposed methodology and DSS can provide sufficient support for classification problems. It formulates the entire problem in a structured way, enhancing decision makers understanding, reducing thus misclassifications derived by existing heuristics. However, some limitations and issues for future study exist. Deriving parameters is a time consuming and relative complex procedure, which

Table 5: Inclusion degrees per category

	Category			
Retailer	C1	C2	C3	C4
R1	0.282	0.156	0.322	0.646
R2	0.950	0.442	0.653	0.586
R3	0.730	0.271	0.660	0.457
R4	0.058	0.128	0.510	0.445
R5	0.034	0.014	0.016	0.254
R6	0.840	0.117	0.302	0.011
R7	0.006	0.029	0.015	0.234
R8	0.142	0.660	0.716	0.680
R9	0.344	0.298	0.322	0.560
R10	0.133	0.660	0.973	0.500
R11	0.740	0.973	0.740	0.507
R12	0.069	0.188	0.195	0.580
R13	0.042	0.396	0.466	0.502
R14	0.613	0.973	0.740	0.444
R15	0.077	0.620	0.880	0.640
R16	0.853	0.161	0.526	0.058
R17	0.280	0.940	0.680	0.058
R18	0.137	0.693	0.391	0.018
R19	0.024	0.566	0.783	0.105
R20	0.172	0.226	0.304	0.620

Table 6: Classification results (Retailers per category)

Category	NeXClass	Existing procedure
C1	{R2, R3, R6, R16}	{R2, R3, R6, R16}
C2	{R11, R14, R17, R18 }	{R11, R14, R17, R18 }
C3	{R4, R8, R10, R15, R19}	{R1, R8, R10, R15, R19, R13}
C4	{R1, R5, R7, R9, R12, R13, R20}	{R4, R5, R7, R9, R12, R20}

Table 7: Misclassification results from DSS validation experiments

No. of Alternatives	No. of categories	NeXClass misclassifications (first run)	NeXClass misclassifications (second run)
10	4	1	0
20	4	4	1
25	4	6	3
50	4	8	4

requires decision maker to be familiar enough with the methodology. As a future enhancement, we plan to extract parameters from past decisions, in order to minimize decision maker's effort. From the above experience, we believe that both methodology and DSS can become a valuable tool for decision makers, in similar classification problems in a variety of domains, including production, human resources and environment to mention a few.

REFERENCES

Abdul-Muhmin, A.G. and I.A. Alzamel, 2001. Retailers' experiences with and attitudes toward the Saudi Arabian EFTPoS system. Int. J. Retail Distrib. Manage., 29 (4): 188-199.

Alexander, N., J. Hine and J. Howells, 1991. EFTPoS, before and after: Retailer reaction. Int. J. Retail Distrib. Manage., 19 (5): 10-16.

Alexander, N., J. Howells and J. Hine, 1992. EFTPoS: Impact on channel relationships. Int. J. Bank Mar., 10 (6): 38-44.

Doumpos, M. and C. Zopounidis, 2001. Multicriteria classification methods in financial and banking decisions. Int. T. Operat. Res., 9 (5): 567-581.

Figueira, J. and B. Roy, 2002. Determining the weights of criteria in the ELECTRE type methods with a revised Simos' procedure. Eur. J. Operat. Res., 139: 317-326.

Figueira, J., S. Greco and M. Ehrgott, 2005. Multiple Criteria Decision Analysis: State of the Art Surveys. Springer Verlag, Boston, Dordrecht, London.

Ironfield, C.E. and P.J. McGoldrick, 1988. EFTPoS systems determinants of shoppers' awareness and usage. Int. J. Retail., 6 (6): 60-61.

McFayden, E., 1987. Retailers' attitudes to EFTPoS. Int. J. Retail Distrib. Manage., 15 (4): 19-20.

Roy, B., 1991. The outranking approach and the foundations of ELECTRE methods. Theor. Decis., 31: 49-73.

Smith, C., 1987. Will EFTPoS really help the retailers improve service at the checkout desk? EFTPoS Int. Bull., 5: 6-9.