A Fuzzy Knowledge-Based Decision Aiding Method for the Assessment of Financial Risks: The Case of Corporate Bankruptcy Prediction

ARTICLE · FEBRUARY 2001

Source: CiteSeer

4 AUTHORS, INCLUDING:


Georgios Dounias
University of the Aegean


Nikolaos Matsatsinis
Technical University of Crete

A Fuzzy Knowledge-Based Decision Aiding Method for the Assessment of Financial Risks: The Case of Corporate Bankruptcy Prediction

Spanos Michael, Dounias Georgios*, Matsatsinis Nikolaos and Zopounidis Constantin
Technical University of Crete
Dept. of Production Engineering and Management
Financial Engineering Laboratory,
University Campus, Kounoupidiana, 73100 Chania, Greece
*Phone: +30-821-37323, Fax: +30-821-69410
email: dounias@dpem.tuc.gr

ABSTRACT: In many applications it is rather difficult to find dependencies between the variables of a process or more general of a system, dependencies which can be used for controlling a plant, forecasting a value or classifying a group of objects into pre-defined classes. Since in many cases, analytic dependencies are unknown or very difficult to set up, the formulation of dependencies with the help of fuzzy rules offers a useful alternative. This paper presents the combine use of a fuzzy rule generation method and a data mining technique for the assessment of financial risks. The case of business failure is considered here and the classification of the firms into two classes is sought. Initially, a method for the generation of fuzzy rules is used. Then these rules are imported to a data mining technique so as a certain number of objects (firms) can be classified into two classes (bankrupt and non- bankrupt firms). The fuzzy method supports the discovery of relevant dependencies by the automatic generation of if/then rules on the basis of expert knowledge, while the data mining technique, with the help of a fuzzy rule-based classifier, assigns an object to different classes on the basis of various different characteristics (financial ratios). Finally a thorough comparison with Discriminant Analysis, Logit and Probit Analysis takes place based on the same sample and financial ratios. Results indicate that the combination of the fuzzy rule generator and the data mining technique constitutes a powerful tool and a reliable alternative in the assessment of financial risks and more specifically in the two-group classification of firms involved in liable bankruptcy.

Keywords: Fuzzy set theory, Corporate bankruptcy prediction, Data mining, Multivariate statistical analysis, Decision support systems

INTRODUCTION

One of the most important new trends in information technologies is data mining, which can be defined as extracting valuable and relevant information from data, as well as gaining insights and knowledge into information hidden within data. Since this knowledge can be a key competitive advantage, this creates an important need for powerful tools, for analyzing and modeling this data, and for using the extracted knowledge into decision support systems. The situation in real world problems and especially in the financial risk assessment is very specific to this respect. Data per se can not be considered as a competitive advantage, since the same information is available to all competitors. Only the knowledge extracted from this data is. The knowledge extraction and model building is rather challenging in financial risk assessment and particularly in corporate bankruptcy prediction since bankruptcy itself concerns a considerable number of people (owners, managers, shareholders, creditors, competitors, clients, etc.).

Financial risk assessment problems are characterized by the complexity they entail, the variety of factors of both qualitative and quantitative nature that must be examined, and the difficulty of determining a specific decision procedure. In some financial risk assessment problems, such as bankruptcy risk assessment, credit granting, portfolio selection and management, etc., ranking the alternatives from the best to the worst does not always provide a solution to the problem. In such cases, it would be more preferable to classify the alternatives (firms, loans, portfolios, etc.) into homogeneous predetermined classes, in order to make the appropriate decisions.

The techniques already applied in financial risk assessment problems that require a classification of the considered alternatives, include mainly statistical and econometric methods like discriminant analysis, both linear (LDA) and quadratic (QDA), logit analysis (LA), probit analysis (PA), the linear probability model, etc. Such methods were the first and most popular approaches in studying financial classification problems, which took into consideration the multi-dimensional nature of financial problems, combining different decision variables into the same classification model. However, they were severely criticised mainly due to the statistical limitations they incorporate (Eisenbeis, 1977).

To overcome these limitations several alternative approaches have been proposed by researchers working in the fields of operations research and artificial intelligence (Zopounidis, 1998). Among these new alternative approaches that have received significant attention during the last two decades in the study of classification problems, such as corporate bankruptcy, are survival analysis (Lane et al.,1986), recursive partitioning algorithm (Frydman et al., 1985), goal programming (Doumpos et al, 1999), multicriteria decision/support methods (Zopounidis, 1987), rough sets methods (Dimitras et al., 1999), expert systems (Messier and Hansen, 1988 and Matsatsinis et al., 1997), neural networks (Tam et al., 1992) etc. Dimitras et al.(1996) provide a thorough review of these methods with an emphasis on the corporate bankruptcy prediction case.

In many cases analytic dependencies between the considered variables are unknown or very difficult to set up. So is the case for corporate bankruptcy prediction. The formulation of dependencies with the help of fuzzy rules offers a useful alternative. This paper presents the use of a fuzzy rule generator and a data mining technique for the corporate bankruptcy prediction problem in comparison to three widely used statistical and econometric methods: discriminant analysis (DA), logit analysis (LA) and probit analysis (PA). The results obtained from the four methods are important in drawing useful conclusions for resolving complex financial risk assessment problems like the corporate bankruptcy prediction one.

The rest of the paper is organized as follows. In section 2, a presentation of the methodology adopted in this paper is given, along with some transformations that data require. Section 3 is devoted to a brief description and analysis of the data, while in section 4 the results are discussed. Finally in section 5, the conclusions of this research are briefly stated and points for further research are proposed.

METHODOLOGY

The aim of the proposed methodology (Figure 1) is to classify a number of objects (firms) into two predefined classes (bankrupt and non bankrupt). Data are transferred from a database into the data mining technique, most commonly in form of matrices. Rows represent the number of objects to be classified and columns represent the characteristics (criteria) for classification. In the next step, data are being analyzed. This stage is often called "data preprocessing" and its purpose is to select data which can be operated by the data mining technique and a further rule generating process at a later level. This stage involves characteristics selection and handling of possible missing values which could be either deleted or filled by deleting the entire rows or by using mean, previous or following values. Moreover, the user should check and possibly delete certain characteristics that are largely dependent of one another. Eventhough this analysis might lead to better results it was not adopted by this research, due to the fact that all 12 characteristics are considered important for the classification of the firms. In our approach, data preprocessing also entails normalization of the data which transforms data into the [0,1] interval, avoiding different weightings being attributed to different characteristics simply on the basis of the scaling involved (MIT GmbH, 1997(a)). After the data analysis process, data are ready to be exported to the automatic fuzzy rule generator. The aim of using fuzzy systems is to make qualitative knowledge useful. Experience shows that it is easy to formulate this knowledge in the form of rules (Zimmermann, 1991). The dependence between an input situation and a conclusion is represented in the following form:

IF { input situation } THEN { conclusion }

Here is an example of a fuzzy rule:

$$\text{IF}\{a_2 = 1, a_7 = 3 \text{ and } a_8 = 2\} \text{ THEN } \{\textit{Firm-Status} = \textit{Bankrupt}\} \quad \text{with } 0.985$$

The considered variables as well as the linguistic values with their membership functions are defined by the decision maker (user/operator), mainly based on already existing, qualitative knowledge (Dimitras et al., 1999). For instance a_2=1means that a_2 lies in the 1 interval specified by the expert or the decision maker. In practice, complex real problems require the close involvement of field experts when defining the membership functions. This reflects their valuable practical experience in the most proper way. The recorded data of the process are as learning data the basis of the way of action that follows (Figure 2). First of all, hypotheses in the form of if/then rules are generated. They describe possible dependencies between the input and output variables of the process. In case of small search spaces all possible hypotheses are considered, in case of larger search spaces only promising hypotheses are generated with the help of search methods (like the evolutionary search method which is adopted here). Every single hypothesis is checked for relevance and evaluated with a rating index [0…1], (Krone and Kiendl, 1994, Krone and Kiendl, 1996 and MIT GmbH, 1997(b)). A rule reduction procedure might follow as the number of the rules sometimes can be quite big. Afterwards, in the fuzzy rule-based classification model, the rating index is used as certainty factor for approximate reasoning. According to the decision maker's preferences, a fuzzy rule set is exported to the fuzzy rule-based classification model and the classification of the objects is carried out. The classifier assigns every object to the two classes with a membership degree varying from 0 to 1. Figure 1 presents the basic functions of the proposed methodology, while Figure 2 represents graphically the methodological steps of the fuzzy rule generating process.

Figure 1: Basic Functions of the Fuzzy Knowledge-Based Decision Aiding Method

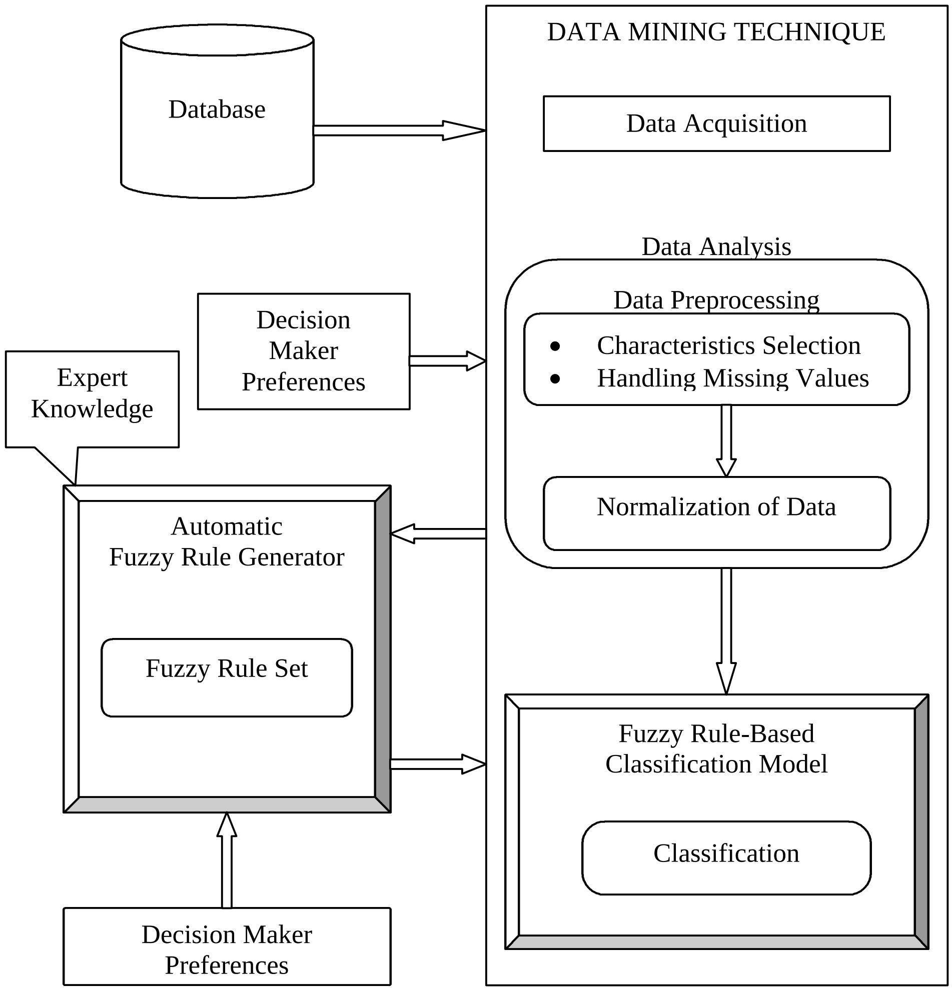
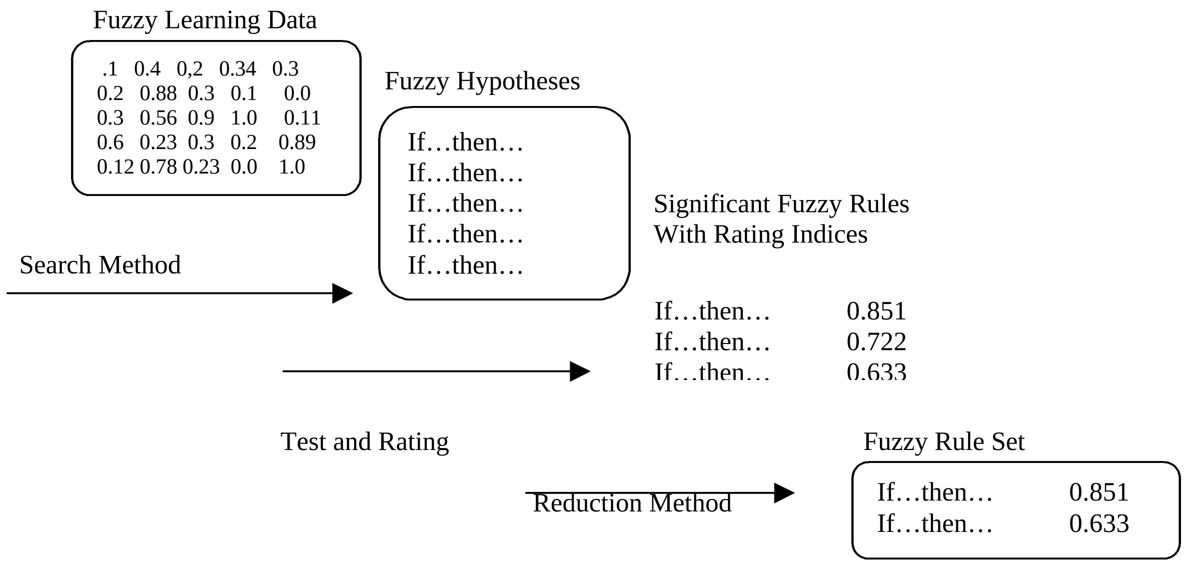


Figure 2: Principles of the Automatic Fuzzy Rule Generator, (MIT GmbH, 1997(b))



DATA

The case study on corporate bankruptcy prediction involves data of Greek firms (Dimitras et al., 1999). The data include two samples of firms. The first sample (the basic sample) consists of 80 firms (40 bankrupt and 40 non-bankrupt). For these firms their financial data were collected up to five years before bankruptcy. The first year prior to bankruptcy (year –1) is used to develop the bankruptcy prediction model through the fuzzy rule generation method. The previous four years prior to bankruptcy are used to evaluate the discriminating ability of the developed model. The second sample (holdout sample) consists of 38 firms (19 bankrupt and 19 non-bankrupt). In the holdout sample the financial data of the firms concern a three-year period before bankruptcy. The aim of the control sample is to evaluate the predictive ability of the developed bankruptcy evaluation methodology. In the case study the analysis of the financial risk assessment problem involves only the financial data of the firms. Information on strategic variables of qualitative nature that affect the internal operation of the firms and their relation with their external environment was not available. According to the available financial data, some financial ratios are formed that serve as evaluation characteristics (criteria) in the corporate bankruptcy prediction problem (Table 1).

Table 1: Financial ratios used as evaluation characteristics (criteria)

Codification	Financial Ratios
a_1	Net income/Gross profit
a_2	Gross profit/Total assets
a_3	Net income/Total assets
a_4	Net income/Net worth
a_5	Current assets/Current liabilities
a_6	Quick assets/Current liabilities
a_7	(Long term debt+current liabilities)/Total assets
a_8	Net worth/(net worth+long term debt
a_9	Net worth/Net fixed assets
a_{10}	Inventories/Working capital
a_{11}	Current liabilities/Total assets
a_{12}	Working capital/Net worth

RESULTS

As already mentioned in the corporate bankruptcy prediction application, the most recent year is used to apply the knowledge-based fuzzy rule generator and develop the classifier that assigns the firms into the considered classes. The fuzzy rule generator produced the fuzzy rule base presented in Table 2. The rating index denotes the probability of the correctness of a rule. The higher the index the better is the rule. Remarkable is the substantial number of rules having rating indices in the intervals (0.0,0.1) and (0.9,1.0), which means that there is a considerable number of rules having high and low certainty factors. Another point to discuss is that the total number of rules is uniformly distributed in the two classes satisfying the classification of both bankrupt and non-bankrupt firms.

The corresponding results for the bankruptcy prediction problem are presented in Table 3. The type I error is defined as the classification of a bankrupt firm into the non-bankrupt class, whereas type II error refers to the classification of a non-bankrupt firm into the bankrupt class. The total error type is the average of type I and type II errors. When types of error have a different impact on the decision to be taken, ‘costs’ can be determined for each type of error.

A significant conclusion that emerges from these classification results is the low type II error rates in comparison to the type I error rates, especially in the basic sample. This result indicates that the proposed classifier is able to correctly evaluate firms that do not face financial problems, in a large extent, while in the holdout sample the classifier appears to be constant in its evaluation. Finally, the overall error rate of the classifier is 26.16%, referring to all years and both types of classification error.

Table 2: Analysis of the Fuzzy Rule Set

Intervals of Rating Index	Both Classes	Bankrupt Class	Non-Bankrupt Class
0.0-0.1	349	170	179
0.1-0.2	21	6	15
0.2-0.3	26	14	12
0.3-0.4	18	5	13
0.4-0.5	23	4	19
0.5-0.6	23	9	14
0.6-0.7	34	11	23
0.7-0.8	41	12	29
0.8-0.9	46	19	27
0.9-1.0	511	253	258
Total Number of Rules	1092	503	589

Table 3: Classification Results of the Fuzzy Rule Based Classifier

	Year of Analysis								Overall
	Basic Sample					Holdout Sample			
Error	-1	-2	-3	-4	-5	-1	-2	-3	Error
Type I	0.00%	2.50%	2.50%	2.50%	5.00%	21.05%	10.52%	15.78%	7.48%
TypeII	2.50%	30.00%	50.00%	52.50%	50.00%	52.63%	63.15%	57.89%	44.83%
Total	***1.25%***	***16.25%***	***26.25%***	***27.50%***	***27.50%***	***36.84%***	***36.84%***	***36.84%***	***26.16%***

COMPARISON TO MULTIVARIATE STATISTICAL AND ECONOMETRIC TECHNIQUES

On the same financial risk assessment problem, three well-known multivariate statistical and econometric methods were applied: the linear discriminant analysis (LDA), the logit analysis (LA) and the probit analysis (PA). Many researchers have already used these techniques in the past for the study of financial classification problems (Altman et al., 1981, Altman, 1968, Ohlson, 1980, and Zavgren, 1985). They are still used by many researchers to perform comparative studies in order to evaluate the classification performance of new classification techniques that are proposed. This is also the purpose of the use of these techniques in this research, that is, to compare the results obtained through the fuzzy rule based classifier, with well-known methods receiving significant recognition among financial researchers and financial risk analysts. The methodology used to apply the LDA, LA and PA techniques is the same with the one employed in the application of the fuzzy rule based classifier, that is, the most recent year is used for model development, and the previous years are used for model extrapolation and evaluation of the classification performance. Table 3 illustrates the obtained classification results in bankruptcy prediction.

The comparison of these results with those of the fuzzy rule based classifier illustrates the ability of the fuzzy rule based classifier to provide results that are at least competitive to those of the multivariate statistical and econometric techniques. More specifically in the basic and holdout sample the fuzzy rule based classifier is compared favorable to PA. Worth of noticing is the remarkably low error rates of the fuzzy rule based classifier in the year –1 of the basic sample. The comparison with LDA and LA indicates that in many cases the fuzzy rule based classifier provides superior results.

As far as the basic sample is concerned, in year –1 and year –2 the fuzzy rule based classifier performs better in comparison to the total error rate, LDA and Logit perform better in year –3, while Logit gives better results in years –4 and years –5 with slight difference. On the other hand, the fuzzy rule based classifier provides similar classification results in the control sample apart from the year –3 where its results outperform. Finally, as far as the overall error rate is concern, it is clearly demonstrated that the fuzzy rule-based classifier provides the best results. This is a very positive result on the classification performance of the fuzzy rule based classifier in the study of financial risk assessment problems.

Table 4: Classification results of the multivariate statistical and econometric methods

		Basic Sample (Years)					Holdout Sample (Years)			Overall
Methods	Error	–1	–2	–3	–4	–5	–1	–2	–3	Error
LDA	Type I	12.50%	25.00%	32.50%	45.00%	45.00%	36.84%	57.89%	63.16%	39.74%
	Type II	7.50%	12.50%	12.50%	15.00%	20.00%	31.58%	26.32%	26.32%	18.97%
	Total	***10.00%***	***18.75%***	***22.50%***	***30.00%***	***32.50%***	***34.21%***	***42.11%***	***44.74%***	***29.35%***
Logit	Type I	7.50%	22.50%	22.50%	35.00%	32.50%	36.84%	57.89%	63.16%	34.74%
	Type II	12.50%	12.50%	20.00%	15.00%	17.50%	32.11%	10.53%	26.32%	18.31%
	Total	***10.00%***	***17.50%***	***21.25%***	***25.00%***	***25.00%***	***39.47%***	***34.21%***	***44.74%***	***27.15%***
Probit	Type I	12.50%	27.50%	37.50%	50.00%	37.50%	42.11%	63.16%	73.68%	42.99%
	Type II	12.50%	10.00%	17.50%	15.00%	17.50%	31.58%	15.79%	26.32%	18.27%
	Total	***12.50%***	***18.75%***	***27.50%***	***32.50%***	***27.50%***	***36.84%***	***39.47%***	***50.00%***	***30.63%***

CONCLUSIONS

In this paper, the implementation of a fuzzy knowledge-based decision aiding method was presented as an alternative for the assessment of financial risks and especially for corporate bankruptcy prediction. This method, which is a combination of a fuzzy rule generator and a data mining technique that utilises a fuzzy rule-based classifier, aims at the classification of firms into two classes according to the financial risk that they incorporate. The comparison of our methodology to multivariate statistical and econometric methods that was carried out, showed that the results obtained by the knowledge-based method are at least competitive, indicating that such an approach can be considered as an alternative to existing parametric techniques that are subject to specific limitations and problems.

Nevertheless, the knowledge-based method entails limitations and restrictions as well. This method comprises of a substantial number of parameters and options that should be clarified and properly chosen (like the search method, the setting of the membership functions, the choice of the rule set, etc). Further examination should be focused on the possible reduction of the number of rules and the implementation of a rule base consisting of rules having only high rating indices. Therefore, extreme caution of the modelling of the problem is required as well as the assistance of a financial risk assessment expert.

However, it is necessary that the method proposed in this paper should be further applied in other financial decision problems requiring classification of a set of alternatives, such as the assessment of credit or country risk, acquisition of firms, portfolio selection and management, credit cards assessment, etc. Moreover, it would be of great usefulness the implementation in real world problems that require classification in more than two classes (some financial problems require classification in at least three classes) as well as the performance of experimental studies on the comparison with multivariate statistical methods and other classification techniques from the fields of multicriteria analysis, expert systems, rough sets, neural networks etc.

ACKNOWLEDGEMENTS

The authors would like to thank MIT GmbH for allowing the use of the software DataEngine® and WINROSA® for the realisation of this paper, as well as Doumpos M. for making useful comments on the present study.

REFERENCES

Altman, E.I., Avery, R., Eisenbeis, R., and Stinkey, J.: *Application of Classification Techniques in Business, Banking and Finance*, Contemporary Studies in Economic and Financial Analysis, Vol. 3, 1981, Greenwich, JAI Press.

Altman, E.I.: «Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy», *The Journal of Finance*, Vol. 23, 1968, 589–609.

Dimitras, A.I., Slowinski, R., Susmaga, R., and Zopounidis, C.; «Business Failure Prediction Using Rough Sets», *European Journal of Operational Research*, 114, 1999, 263-280.

Dimitras, A.I., Zanakis, S.H., and Zopounidis, C.: «A survey of business failures with an emphasis on prediction methods and industrial applications», *European Journal of Operational Research,* 90 / 3, 1996, 487–513.

Doumpos, M., Spanos, M. and Zopounidis, C.: «On the Use of Goal Programming Techniques in the Assessment of Financial Risks», *Journal of Euro-Asian Management*, 1999, (in press).

Eisenbeis, R.: «The Pitfalls in the Application of Discriminant Analysis in Business, Finance and Economics», *The Journal of Finance*, Vol. 32, 1977, 723–739.

Frydman, H., Altman, E.I. and Kao, D.L.: «Introducing recursive partitioning for financial classification: The case of financial distress», *The Journal of Finance*, 15 (1), 1985, 269-291.

Krone, A. and Kiendl, H.: *Automatic Generation of Positive and Negative Rules for Two-Way Fuzzy Controllers*, EUFIT '94, Aachen (Germany), 1994, 438-447.

Krone, A. and Kiendl, H.: *Rule-based decision analysis with Fuzzy-ROSA method*, EFDAN'96, Dortmund (Germany), 1996, 109-114.

Lane, W.R., Looney, S.W. and Wansley, W. «An application of the Cox proportional hazards model to bank failure», *Journal of Banking and Finance*, 10, 1986, 511-531.

Matsatsinis, N.F., Doumpos, M. and Zopounidis, C.: «Knowledge acquisition and representation for expert systems in the field of financial analysis», *Expert Systems with Applications: An International Journal*, 12 (2), 1997, 247-262.

Messier, W.F. and Hansen, J.V.: «Including rules for expert system development: An example using default and bankruptcy data», *Management Science*, 34 (12), 1988, 1403-1415.

MIT GmbH : *DataEngine: Overview and User Manual*, Aachen, Germany, 1997(a).

MIT GmbH : *WINROSA: Handbook*, Aachen, Germany, 1997(b).

Ohlson, J.A.: «Financial Ratios and the Probabilistic Prediction of Bankruptcy», *Journal of Accounting Research*, Spring 1980, 109-131.

Tam, K.Y., and Kiang, M.Y.: «Managerial applications of neural networks: The case of bank failure predictions», *Management Science*, 38/7, 1992, 926-947.

Zavgren, C.V.: «Assessing the Vulnerability to Failure of American Industrial Firms: A Logistic Analysis», *Journal of Business Finance and Accounting*, Vol. 12, No. 1, 1985, 19–45.

Zimmermann, H.J.: *Fuzzy set theory – and its applications*. Kluver-Verlag, Boston, 1991.

Zopounidis, C.: «A multicriteria decision making methodology for the evaluation of the risk of failure and an application», *Foundations of Control Engineering*, 14 (1), 1987, 45-67.

Zopounidis, C.: *Operational Tools in the Management of Financial Risks*, Dordrecht, Kluwer Academic Publishers, 1998.