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The Use of Multicriteria Knowledge-based Systems in Financial Risk Management

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Abstract

This paper investigates the contribution of knowledge-based decision support systems in the modeling of financial decision problems. Knowledge-based decision support systems (KBDSSs) originated from the combination of decision support systems (DSSs) with the expert systems' (ESs) technology, and they have recently started to attract the interest of financial and operational researchers, as well as professionals financial and credit analysts, managers of firms and banks, investors, stockbrokers, etc. The paper discusses the general methodological framework of KBDSSs, illustrates their relative advantages and benefits as opposed to the classical DSS and ES framework, and presents the FINCLAS DSS and the FINEVA KBDSS for the modeling of financial decision problems regarding the assessment of corporate performance and viability.

Keywords: Financial modeling, decision support systems, expert systems, knowledge-based decision support systems, multicriteria decision aid

1. Introduction

Financial management includes a wide variety of significant decisions regarding three crucial issues: investment, financing and dividend policy (Lee, 1985). Financial theory constitutes an essential framework describing in general the effect of financial decisions, on the operation of a firm or an institution, or on the wealth of an investor. This general framework is necessary for understanding the nature of financial decisions as well as the operation of financial markets. However, a precise framework is required for supporting financial decision making in a more specific context.

The determination of such a decision support framework is the aim of financial modeling. The term of financial modeling has been used by several researchers to describe every quantitative analysis of a financial or economic system. This is a rather ambiguous and general definition which does not comprise the basic aim of financial modeling. Spronk and Hallerbach (1997) on the other hand propose a more specific definition: "financial modeling is concerned with the development of tools supporting firms, investors, intermediaries, governments, etc. in their financial-economic decision making, including the validation of the premises behind these tools and the measurement of the efficacy of these tools". This definition is clearly decision support oriented focusing on the particular financial decision problem that is faced, the methodologies which are the most appropriate for solving this problem, as well as the way that the obtained solution can be successfully implemented.

According to this decision support orientation of the aforementioned definition of financial modeling, its role involves all the phases of a decision support process beginning from designing and generating decision alternatives, until making the most appropriate decision and implementing it. Specifically, the first phase (design and generation of alternatives) is very close related to another form of financial modeling: financial engineering. Finnerty (1988) and Mulvey et al. (1997) define financial engineering as "the design, development and implementation of innovative financial instruments and processes and the formulation of creative solutions to problems in finance".

The combination of financial modeling and financial engineering provides a wide set of operations research tools, including simulation, optimization, decision support systems, expert systems, neural networks, stochastic processes, for effective financial decision making, taking advantage of the basic concepts and notions that financial theory provides, in order to support well defined, specific, financial decision problems.

This paper focuses on the contribution of knowledge based decision support systems (KBDSSs) in financial modeling. KBDSSs technology integrates the traditional decision support systems (DSSs) framework with expert systems (ESs) to provide enhanced decision support capabilities which are essential for real time financial decision making. The contribution of KBDSSs in financial modeling is examined from the data base and model base management point of view, the user interface point of view, and of course from the overall system's capabilities in supporting financial decision making point of view.

Initially, section 2 provides a brief description of DSSs and ESs technologies (as KBDSSs originate from these two approaches), outlining their basic features and limitations. Section 3 illustrates how the integration of DSSs and ESs in the KBDSSs framework can be achieved, as well as the expected benefits in financial modeling of such integration. Sections 4 and 5 present the FINCLAS (FINancial CLASsification) and the FINEVA (FINancial EVAluation) systems respectively. This presentation will depict how DSSs and KBDSSs technologies contribute in the modeling and the analysis of corporate performance and viability, one of the most essential decision problems in financial management. Finally, section 6 discusses the basic conclusions and findings of this research and outlines some possible future perspectives.

2. Decision Support Systems and Expert Systems

Among the tools used in financial modeling and financial engineering, DSSs and ESs constitute two essential approaches in supporting financial decision making. Both DSSs and ESs provide the means for implementing sophisticated decision support methodologies to make decisions in real time, taking advantage of the increasing processing power of modern computers.

The concept of DSSs was introduced, from a theoretical point of view, in the late sixties. Klein and Methlie (1995), define a DSS as a computer information system which provides information in a specific problem domain using analytical decision models as well as techniques and access to databases, in order to support a decision maker in making decisions effectively in complex and ill-structured problems. Thus, the basic goal of a DSS is to provide the necessary information to the decision maker, in order to help him get a better understanding of the decision environment and the alternatives he faces.

DSSs have been developed in several fields of financial management including financial planning (Eom et al., 1987-1988; Hayen, 1982; Jenkins, 1973; Sprague, 1972), financial analysis (Mareschal and Brans, 1991; Siskos et al., 1994; Zopounidis et al., 1992), portfolio management (Gerrity, 1971; Singh and Cook, 1986, Zopounidis et al., 1995) and banking (Langen, 1989; Mareschal et al., 1992; Sprague and Watson, 1976) among others. The criticism on DSS development has been focused mainly on the assumptions underlying the structure and the operation of a DSS; the overlooking of these assumptions, either by the developer who does not make them clear to the user or by the user who does not pay attention to them, may lead to improper use of the system and to misinterpretation of the obtained results (Klein and Methlie, 1995; Turban, 1993).

Except for the DSSs approach, ESs constitute a significant contribution from the field of artificial intelligence to financial modeling and financial decision making. The aim of ESs' development in the field of financial management is to represent and exploit the knowledge of experts financial/credit/investment analysts in a computerized system which will be able to draw conclusions and provide decision makers with recommendations on a specific financial problem at hand. Thus, an ES can be defined as a computer program that represents the knowledge and inference procedures of an expert to solve complicated problems, providing possible solutions or recommendations (Klein and Methlie, 1995). The main characteristic and basic goal of an ES is its ability to simulate the human logic and reasoning, to draw conclusions and to provide the corresponding explanations in an easily understandable form.

However, ESs have been criticized mainly due to two significant limitations: (i) it is often very difficult to elicit precise knowledge from expert analysts and to represent it in an appropriate manner in the knowledge base of an ES, and (ii) ESs' flexibility is limited, since they employ shallow knowledge (knowledge which is suitable only in specific and narrowly defined problem domains), while once this knowledge has been incorporated in the knowledge base it is very difficult to be updated.

In the international literature, during the last decade, several studies have been conducted trying to investigate possible connections and relationships among DSSs and ESs. Ford (1985) in his study examined the similarities and differences between DSSs and ESs from the objectives and intents points of view, the operational point of view, the user point of view, as well as the development methodology point of view. According to the author, as far as the objectives and intents are concerned, although the fundamental goal of DSSs and ESs is basically the same (the improvement of the quality of decisions), their underlying philosophies and objectives differ. Concerning the operational point of view, DSSs allow the user to confront a decision problem in a personal manner, providing the ability to manipulate data and models in different ways. On the other hand, ESs provide little flexibility in the way the decision problem is analyzed. As far as the users are concerned, Ford argues that DSSs are primarily applied in the business or organizational fields, while ESs are typically associated with scientific research. The users of DSSs are involved in the development of the system, while the users of ESs do not participate in the development process. Finally, according to the development methodology, both DSSs and ESs are designed through an iterative or prototyping approach.

Doukidis (1988) carried out a survey on 67 ESs to investigate whether they employ DSS concepts. The survey was based on a questionnaire model composed of a list of key concepts of DSSs, such as their role, their design features, their components, the phases of the decision they support. The results of this survey show that three fundamental issues of DSSs are employed in ESs: semi-structured task, support, and effectiveness. The main differences concern the boundary of the problem space and the way that the problem is solved. Henderson (1987) investigated the existence of synergy between the DSSs and the ESs research. He concluded that in many respects, the similarities between these areas appear to dominate the differences. Finally, a critical review of DSSs and ESs can be found in the studies of Klein and Methlie (1995) and Zopounidis et al. (1997).3

3. Knowledge-based Decision Support Systems

According to the brief description of DSSs and ESs in the previous section, it is clear that actually DSSs are commonly used to perform a quantitative analysis of the decision problem under consideration (in this case the term quantitative is used to describe the mathematical formulation of the problem), while ESs are mainly oriented in employing a qualitative form of reasoning to address decision problems. However, financial decisions are usually too complex and ill-structured, so that their modeling requires both a qualitative approach to understand the problem under consideration, its characteristics and basic features, as well as a mathematical formulation to describe the problem and obtain “optimal” or generally “satisfying” solutions.

To address this twofold nature of financial decisions and in the light of the ongoing research in both DSSs and ESs, financial and operational researchers, as well as computer scientists have exploited the combination of DSSs and ESs in the framework of an integrated computerized system. The term “knowledge-based decision support system” (KBDSS) has been consecrated and it is being used to describe this new type of system which integrates the data base and model based management capabilities of DSSs with the inference and explanations abilities of ESs.

3.1 Integrating DSSs with ESs

The integration of DSSs with ESs technology can be achieved in two ways: either by incorporating several ESs in the different modules of a DSS (data base, model base, user interface), or by considering an ES and a DSS as two distinct but complementary parts of an integrated KBDSS.

In the former case the DSS is the key component in the KBDSS framework, while the role of the ESs is rather supportive. More specifically, the ESs interact with the several modules of the DSSs helping the decision maker (financial/credit analyst, investor, portfolio manager, etc.) to use as effectively and appropriately as possible the data base and model base management capabilities, while furthermore the ESs facilitate the development of user friendly interfaces.

On the contrary, in the second approach for integrating DSSs and ESs, the structure of the KBDSS in considered as the combination of two major modules: an ES module and a DSS module. Both of these parts are used separately to support the financial modeling process, taking advantage of the specific characteristics and capabilities that each one can provide. Nevertheless, besides this separate use of the DSS and the ES, there can be a link between them, enabling the transfer of the obtained results among the two modules: the results obtained through an inference procedure carried out by the ES can be used as inputs for further analysis by the DSS component and vice versa.

3.2 Benefits of integrating DSSs and ESs in the KBDSS framework

Both DSSs as well as ESs have already been applied with relative success in the last three decades to the study and modeling of financial decision problems. Consequently, it would be of major interest to examine the possible advantages and benefits that are expected to come from their integration in the context of an integrated KBDSS. This has been an issue that has attracted the interest of researchers in the fields of DSSs and ESs.

Turban and Watkins (1986) provide an excellent comprehensive discussion of this issue. More specifically, the authors discuss the benefits of integrating ESs with DSSs, in terms of their possible contribution in data base management, model base management, user interface as well as in the overall capabilities of the resulting KBDSS. In particular, as far as the database and database management (DBMS) are concerned, DSSs provide database capabilities to ESs, while on the other hand ESs improve the construction, operation, and the overall capabilities of DBMS, as well as the accessibility to large databases. Concerning the model base and the model base management system (MBMS), DSSs provide an initial problem structuring through standard models and computations, and also provide data to models, as well as storage of models developed by the decision makers in the model base. The use of ESs improves the model base management, by supporting the generation of alternatives, the selection of the appropriate models according to the available data, as well as the structuring of the problem analysis process. Furthermore, ESs contribute to the interpretation of the results of the models, provide guidance to decision makers through the basic assumptions underlying the application of these models, and finally improve the sensitivity analysis and trial-error processes. The contribution of DSSs in the design of user friendly interfaces, mainly focuses on the incorporation of the appropriate presentation means which match the requirements of the decision maker. On the other hand ESs provide explanations concerning the use of the system, communication with the decision maker using natural language, interactivity in the problem solving process, and tutoring capabilities. Finally, concerning the overall system capabilities, DSSs help the decision maker to get experience in data collection, as well as in the implementation of several sophisticated decision models, and they also incorporate the preferences and decision policy of the decision maker in the decision making process. ESs using the knowledge and experience of experts can provide intelligent advice as well as explanations concerning their estimations and conclusions.

On the basis of these contributions of DSSs and ESs in the development of integrated KBDSSs, one could distinguish the new possibilities, perspectives and contribution of KBDSSs development and implementation, in the improvement of the decision making process, especially in the field of financial modeling, in the following three main aspects:

- *Understanding the operation and the results of the system*: incorporating a knowledge base in a DSS can help the decision makers to understand the results of the mathematical models. The knowledge base provides the necessary explanations concerning the reasoning process of the system, its basic assumptions, and its operation. Thus, the methodology used by the system can be clearly presented to the decision makers, helping them to learn the decision analysis process of the problem under consideration. At the same time the interpretation of the results is achieved, avoiding their misunderstanding and misinterpretation. The quantitative results are transformed into qualitative explanations, which are easiest to understand, and are often of greater significance to the decision makers. Specifically, in the field of financial management, the significance of the decisions taken, necessitates their full justification. For instance, in the credit granting problem, the credit analyst should be able to argue upon the rejection of a loan application to the applicant, while on the other hand he/she should be able to justify the granting or rejection of a credit to the top managers of the bank or the credit institution. Although a mathematical model could be used to derive a credit granting decision, the credit analyst can hardly use the score of a credit application obtained through a credit scoring system to justify the acceptance/rejection of the application either to the applicant or to his/her senior officers. The justification must be based upon the special characteristics of the applicant (weaknesses or strengths on each evaluation criterion) and the way that these characteristics affect the final decision. A knowledge base incorporating the expertise of credit granting experts, as well as knowledge on the mathematical models which are used, can provide a qualitative interpretation of the quantitative results and support the credit analyst in implementing the final decision.

The objectiveness and the completeness of the results is ensured: the combination of the ES's results with those derived from mathematical models and analytical techniques, increases the objectiveness of the final results. The subjective results of the ES (which depend on the expert's knowledge) are not the final estimations of the system. The decision maker except for the expert's knowledge, represented in the ES's results, is also provided with the results derived from mathematical models from the fields of multicriteria analysis, multivariate statistical analysis, and mathematical programming. The results of this combination correspond not only to the expert's opinion, but also to the preferences and the policy of the decision maker. For instance, consider the portfolio selection problem, where the objective of the investor is initially to identify the stocks, bonds or mutual funds which constitute the best investment opportunities; then taking into consideration his/her risk aversion policy as well as the available amount of money that he/she is willing to invest, the objective is to determine the "optimal" or more generally the "most satisfying" portfolio. An ES incorporating the knowledge of expert portfolio managers can be used to examine the current economic and stock exchange condition as well as the financial and stock market behavior of the stocks, bonds and mutual funds and provide an evaluation of the available investment opportunities. However, an ES is difficult to encompass an analysis of all the special characteristics, behavior and preferences of an investor. On the other hand a sophisticated mathematical model can consider these key factors in portfolio selection, and can be used to determine the efficient set of portfolios (considering the alternatives which have been identified in the previous stage as the most appropriate investment opportunities) and finally to select from this set, the portfolio that meets the preferences of the investor and the constraints that he/she poses.

The structuring of the proper decision analysis is achieved: the usefulness and the suitability of the decision analysis techniques often vary, depending on the available data of the examined decision problem. According to the existing data, the use of a certain analysis or a mathematical model may be unnecessary or even inappropriate, and consequently the decision maker could be led to incorrect estimations and conclusions. The knowledge concerning the problem domain represented in a knowledge base can be used to face such problems, recommending the decision analysis process and the appropriate analytical models, which correspond to the available data. Thus, the structuring of the decision analysis process is achieved, ensuring the effectiveness, the applicability, and the validity of the decision analysis models and techniques. A common problem of this type which is often being overlooked in real world financial applications involves the application of multivariate statistical methods which are based on specific statistical assumptions. For instance, applying linear discriminant analysis to predict business failure when qualitative variables should be considered, violates the assumption that the variables follow a multivariate normal distribution. In this case a quadratic discriminant analysis would be more appropriate to use. Similarly, when the equal variance-covariance matrices assumption is violated, a logit or probit analysis should be applied instead of discriminant analysis (linear or quadratic). Using a knowledge base and according to the specific nature of the data which are considered in financial decision problems such as business failure, recommendations can be provided on the methods and models which should be used to reach a decision. Furthermore, the ES can be used as a data mining tool to analyze the characteristics of the alternatives which are considered (firms, investment projects, countries, loan applications, etc.), to determine their specific features, and even to identify possible outliers which are common in finance (as much as 10% of financial data may consist of outliers; Duarte Silve and Stam, 1994) and which should be studied in more detail by the analyst.

Recently, several KBDSSs have been proposed in the modeling of financial decision problems: The ISPMS (Intelligent Stock Portfolio Management System) system (Lee et al., 1989) the PMIDSS (Portfolio Management Intelligent Decision Support

System) system (Lee and Stohr, 1985) and the Investment Portfolio Selection Decision Support System (Shane et al., 1987) for portfolio selection and management; the LASS (Lending Analysis Support System) system (Duchessi and Belardo, 1987), the CGX system (Srinivasan and Ruparel, 1990), and the CREDEX (CREDit EXpert) system (Pinson, 1989; 1992) for credit granting problems; the FINEVA (FINancial EVAluation) system (Zopounidis et al., 1996a; 1996b) and the KABAL (Kabal is the Norwegian word for patience) system (Hartvigsen, 1990) for financial analysis, the INVEX (Investment Advisory Expert System) system (Vranes et al., 1996) and the CASH MANAGER system (McBride et al., 1989) for capital investments.

The following two sections illustrate two systems for modeling financial decision problems regarding the assessment of corporate performance and viability. The first one, namely the FINCLAS system (FINancial CLASsification; Zopounidis and Doumpos, 1998) is based on the DSS context. Its aim is to exploit the capabilities of the preference disaggregation approach of multicriteria analysis (Jacquet-Lagrèze and Siskos, 2001) in order to provide support in the study of financial classification problems involving the assessment of corporate performance and viability. On the other hand, the second system, namely the FINEVA system (FINancial EVAluation; Zopounidis et al., 1996a; 1996b) is based on the KBDSS approach. The system combines an expert system, with a multivariate statistical analysis method (principal components analysis) and with a multicriteria decision aid method to provide integrated estimations regarding the evaluation of corporate performance.

4. The FINCLAS System

The FINCLAS system is the outcome of an attempt to integrate powerful methodologies from the preference disaggregation approach of MCDA with decision support systems technology, in order to provide financial/credit analysts with a user friendly but powerful tool to study financial classification decision problems efficiently in real time.

The structure of the system is similar to the general structure of a decision support system as proposed by Sprague and Carlson (1982). The basic modules of the system include the data base, the model base (financial and multicriteria model base), and the user interface (Figure 1). There is a complete interaction and integration of these modules. The data base management as well as the model base management are close related to the friendly window-based user interface of the system, which enables the financial/credit analyst to access and handle easily the data of the firms, and to exploit the financial modeling tools as well as the MCDA methodologies which are incorporated in the model base.

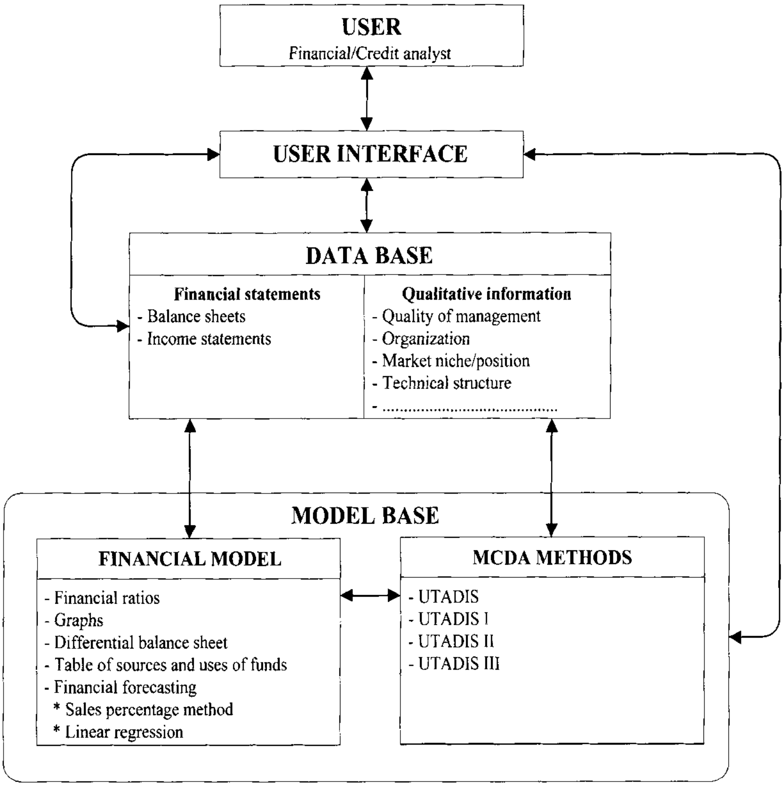

Figure 1. *Structure of the FINCLAS system*

4.1 Data base

To perform a detailed in depth analysis of corporate performance and viability, two types of information is required: financial data and non financial data regarding key factors for the operation of the firm, such as its management and organization, its technical structure, its market niche/position, the market trend, etc. This information is included in the data base of the FINCLAS system.

The financial data of firms are drawn from their financial statements (i.e. the balance sheet and the income statement) for a five years period, which is commonly considered as a pertinent time period to derive reliable estimations for the evolution of the basic financial characteristics of a firm. The financial data are further used by the financial model base of the system for the calculation of several financial ratios (profitability ratios, solvency and liquidity ratios, managerial performance ratios) which are used as evaluation criteria for the classification of the firms. No specialized knowledge is needed to insert and handle the financial data of the firms in the data base of the system. The system using a user friendly spreadsheet type of communication enables the financial/credit analyst to easily perform the basic data base management activities, such as editing, storage and retrieval of data.

In addition to the financial data of the firms, qualitative information is also included in the data base of the FINCLAS system. This information involves the quality of management, the technical structure of the firm, its market position, its organization, the special know-how that the firm possesses concerning its production methods, the market trend, etc. These variables affect both the long term and short term operation of the firm, and they can be of even greater significance than the financial characteristics of the firms for the evaluation of corporate performance and viability. A different module of the data base of the system is used to input such type of information to the system.

4.2 Financial model base

The financial model base module of the FINCLAS system provides the financial/credit analyst with an arsenal of well known financial modeling tools including advanced graphical illustrations of the evolution of the financial ratios of the firms for the time period under consideration, the structure of the balance sheet and the income statement, statistical information regarding the special characteristics of each class of firms (mean, variance, etc.), the table of sources and uses of funds, and financial forecasting methods such as the sales percentage method and linear regression. These tools are necessary in order to perform an initial, descriptive financial analysis of the firms.

4.2.1 Graphical illustrations

The financial model base of the FINCLAS system includes 30 financial ratios, which enable the financial/credit analyst to perform an extensive analysis of the financial characteristics of firms, concerning their financing, investment, dividend and credit policies. Following the methodology proposed by Courtis (1978), these ratios are categorized in three major groups: (a) profitability ratios, (b) solvency ratios (including liquidity), and (c) managerial performance ratios. Based on the financial data of the firms, the financial ratios are computed for a five years period (a shorter period can also be considered in case of lack of data).

The financial model base of the system provides a variety of graphical illustrations of the evolution of financial ratios, as well as of the structure of the balance sheet and the income statement. This type of descriptive analysis is commonly used by financial/credit analysts as a preliminary, elementary but useful examination of the financial characteristics of firms, in order to derive an overall view of their financial situation.

4.2.2 The table of sources and uses of funds

The table of sources and uses of funds constitutes a tool for the dynamic analysis of the inflows and the outflows of the firm and their uses that affect its financial position, in order to examine the investment and financing policy of a firm. Any decrease in assets or increase in total liabilities and stockholders' equity constitutes a source of funds, while any increase in assets or decrease in total liabilities and stockholders' equity constitutes a use of funds. Based on the changes in the accounts of the balance sheet for two successive years and using some additional information (i.e. purchases and sales of fixed assets, depreciation policy, possible increase in capital stock by incorporation of retained earnings), the construction of the table of sources and uses of funds is achieved.

4.2.3 Financial forecasting methods

The sales percentage method and linear regression are two simple financial forecasting methods which are commonly used in corporate finance. The aim of the sales percentage method is to forecast the external financing required for a given increase in sales, as well as the percentage of the increase in sales that should be financed by external funds, according to the changes of the accounts of the balance sheet with regard to the increase in sales. On the other hand, the linear regression method can be used to forecast the accounts of the balance sheet with regard to sales.

4.3 Preference disaggregation sorting methods

Although all the financial modeling techniques which are incorporated in the financial model base of the FINCLAS system can provide useful information on the basic financial characteristics and policy of a firm, more sophisticated tools are needed to support financial/credit analysts in making a reliable estimation of corporate performance and viability. For this reason, an arsenal of multicriteria decision aid (MCDA) methods is also included in the model base of the system. These methods are originated from the preference disaggregation approach. The preference disaggregation approach refers to the analysis (disaggregation) of the global preferences of the decision maker to deduce the relative importance of the evaluation criteria, and develop the corresponding preference model as consistently as possible with the global preferences of the decision maker. This is achieved through ordinal regression techniques based mainly on linear programming formulations.

More specifically, the model base of the FINCLAS system incorporates the UTADIS method (UTilités Additives DIScriminantes; Jacquet-Lagrèze and Siskos, 1982; Jacquet-Lagrèze, 1995; Zopounidis and Doumpos, 1999) and three of its variants, referred as UTADIS I, UTADIS II and UTADIS III. The UTADIS method coming from the family of UTA methods (Jacquet-Lagrèze and Siskos, 1982; 2001), is an ordinal regression method, based on the preference disaggregation approach of MCDA.

Given a predefined classification of the alternatives (i.e. firms) in classes, the objective of the UTADIS method is to estimate an additive utility function and the utility thresholds that classify the alternatives in their original classes with the minimum misclassification error. The estimation of both the additive utility function and the utility thresholds is accomplished through linear programming techniques.

$$\text{Minimize } F = \sum_{a \in C_1} \sigma^+(a) + \ldots + \sum_{a \in C_k} \left[\sigma^+(a) + \sigma^-(a)\right] + \ldots + \sum_{a \in C_q} \sigma^-(a)$$

s.t.

$$\sum_{i=1}^{m} u_i[g_i(a)] - u_1 + \sigma^+(a) \geq 0 \qquad \forall a \in C_1$$

$$\left.\begin{aligned} &\sum_{i=1}^{m} u_i[g_i(a)] - u_{k-1} - \sigma^-(a) \leq -\delta \\ &\sum_{i=1}^{m} u_i[g_i(a)] - u_k + \sigma^+(a) \geq 0 \end{aligned}\right\} \qquad \forall a \in C_k$$

$$\sum_{i=1}^{m} u_i[g_i(a)] - u_{q-1} - \sigma^-(a) \leq -\delta \qquad \forall a \in C_q$$

$$\sum_{i=1}^{m} \sum_{j=1}^{b_i - 1} w_{ij} = 1$$

$$u_{k-1} - u_k \geq s \qquad k = 2, 3, \ldots, q-1$$

$$w_{ij} \geq 0, \ \sigma^+(a) \geq 0, \ \sigma^-(a) \geq 0$$

where C_1, C_2, …, C_q are the q ordered predefined classes (C_1 the best, C_q the worst), u_1, u_2, …, u_{q-1} are the corresponding utility thresholds which distinguish the classes (i.e. the utility threshold u_k distinguishes the classes C_k and C_{k+1}, $\forall k \leq q-1$), σ^+ and σ^- are two misclassification error functions, s is a threshold used to ensure that $u_{k-1} > u_k$ ($s>0$), and δ is a threshold used to ensure that $u[g(\alpha)] < u_{k-1}$, $\forall a \in C_k$, $2 \leq k \leq q-1$ ($\delta > 0$). b_i is the number of subintervals $[g_i^j, g_i^{j+1}]$ into which the range of values of criterion g_i is divided, and w_{ij} is the difference $u_i(g_i^{j+1}) - u_i(g_i^j)$ of the marginal utilities between two successive values g_i^j and g_i^{j+1} of criterion i ($w_{ij} \geq 0$).

Using the UTADIS method, the minimization of the total misclassification error is achieved in terms of the distances of the misclassified alternatives from the utility thresholds using the two error functions $\sigma^+(a)$ and $\sigma^-(a)$. However, this objective may lead in placing some correctly classified alternatives very close to the utility thresholds, resulting in poor generalizing (predicting) ability of the model. On the contrary, UTADIS I method aims at minimizing the total misclassification error and at the same time maximizing the distances of the global utilities of the alternatives from the utility thresholds.

Both methods, UTADIS and UTADIS I, minimize the number of misclassified alternatives in an indirect manner, through the minimization of the magnitude of the misclassification errors. A more direct approach would be to minimize the number of the misclassified alternatives using the UTADIS II method. In this case the LP model of the UTADIS method is transformed into a mixed integer one using two boolean variables $M^+(a)$ and $M^-(a) \in \{0,1\}$ to indicate the misclassification of the firms. If an alternative is correctly classified then $M^+(a)$=0 and $M^-(a)$=0, otherwise, if $M^+(a)$=1 or $M^-(a)$=1 then the alternative is misclassified. Consequently, the objective is to minimize the sum of $M^+(a)$ and $M^-(a)$. Finally, UTADIS III combines the objective functions of UTADIS I and II. Therefore, its aim is to minimize the number of classifications and maximize at the same time the distances of the correctly classified alternatives from the utility thresholds.

In addition to the classification of the firms the financial/credit analyst through the UTADIS method and any of its variants can determine the competitive level between the firms of the same class (i.e. which are the best and the worst), according to their global utilities. Figure 2, illustrates the presentation of the classification results obtained through the preference disaggregation methods in the FINCLAS system. The original and the estimated class are presented, as well as the global utilities of the firms, the utility thresholds which distinguish the classes, the weights of the evaluation criteria, the total number of misclassifications, and the accuracy rate. The developed additive utility model can be stored so that it can be used to evaluate new firms which are inserted in the data base of the system (extrapolation).

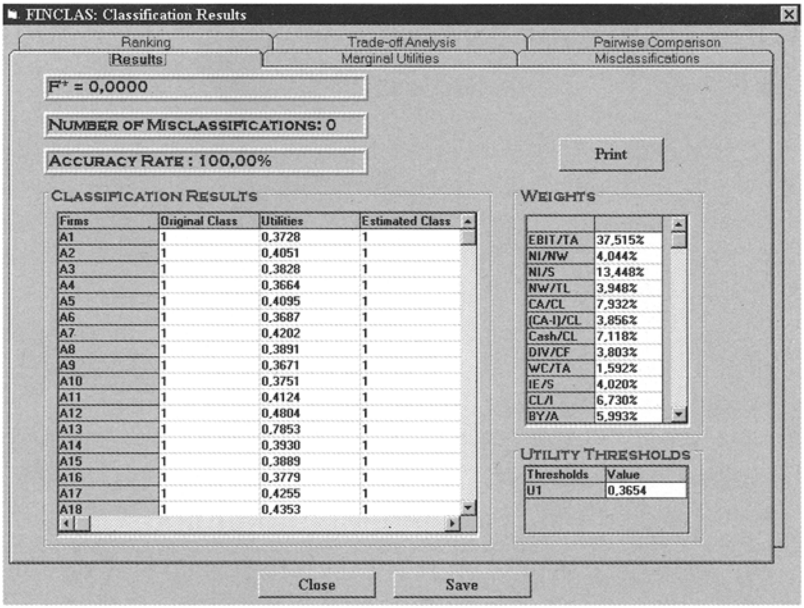

Figure 2. Presentation of the classification results

5. The FINEVA System

The FINEVA system is a multicriteria knowledge-based decision support system for the assessment of corporate performance and viability. The basic characteristic of the FINEVA system is the combination of an ES with a multivariate statistical method (principal components analysis) and a multicriteria method, to estimate the corporate performance and the viability of firms. The basic parts of the FINEVA system and the way they interact, are described in Figure 3.

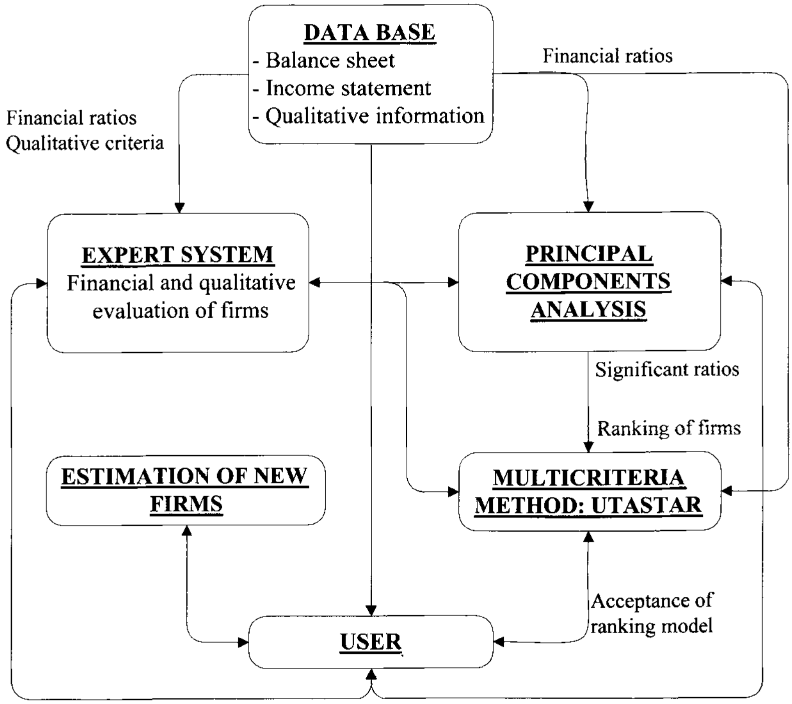

Figure 3. *Structure of the FINEVA system*

5.1 The data base

The data base includes all the financial information necessary for the computation of financial ratios. This information can be drawn from balance sheets and income statements of the examined firms. A number of consecutive basic financial statements could be also included in the data base to help the decision maker to form important trends for some classes of items of the balance sheet and the income statement. In addition to the financial information necessary for the estimation of the financial status of a firm, some qualitative information is also significant and therefore, they are also included in the data base of the system. A spreadsheet type of communication (similar to the FINCLAS system) based on several menus and buttons (tools) is used to facilitate the efficient use of data base management as well as of the overall system capabilities.

5.2 The expert system

The ES part offers an initial evaluation and segmentation of the firms based on the examination of some financial ratios and qualitative criteria. The firms are distinguished in those whose financial status is very satisfactory, satisfactory, medium and not satisfactory.

The knowledge that is used by the ES was drawn from the international literature, as well as from experts in financial analysis, from the academic and the banking field, through a series of meetings. The knowledge acquired is represented in the knowledge base through the production rules of the form: **IF** *conditions* **THEN** *conclusion* (Matsatsinis et al., 1997). The conditions part of a production rule may include one simple condition or a number of simple conditions combined with the logical operators AND, OR and NOT. If all the conditions are fulfilled, then the rule is verified and the actions in the conclusion part of the rule are carried out.

Based on experts' experience, in the field of financial analysis, limits concerning the possible values of each ratio and qualitative criterion, have been set. Each financial ratio and qualitative criterion can be characterized as not satisfactory, medium, satisfactory, very satisfactory or perfect, according to the corresponding limits posed.

Two rule examples that the knowledge base includes are presented below. The first rule concerns the profitability of total assets and stockholder's equity, and the second rule concerns the estimation of a firm based on qualitative criteria.

if	financial profitability = very-satisfactory	**and**
	industrial profitability = not-satisfactory	**or**
	industrial profitability = medium	
then	profitability of total assets and stockholders' equity = satisfactory.	

if	managers' work experience = medium	**and**
	firm's market niche/position = medium	**and**
	firm's technical structure = satisfactory	**and**
	firm's organization = satisfactory	**and**
	firm's special competitive advantages = medium	**and**
	market trend = satisfactory	
then	qualitative evaluation = satisfactory.	

The inference engine of the ES utilizes both the backward and the forward chaining methods (Klein and Methlie, 1995; Turban, 1993). The combination of both forward and backward chaining, provides the capability of confronting problems derived by incomplete information. The forward chaining method is very useful in cases where the inference process should be controlled and guided to specific sets of rules in the knowledge base. On the other hand the backward chaining method is quite efficient in cases where some hypotheses should be examined. Thus, the forward chaining method is used to guide the inference process to a set of rules, and the backward chaining method is applied within this set to derive a conclusion. This inference methodology is well suited to the human logic and decision making. Moreover, through the inference engine the ES part of the FINEVA system provides explanations concerning the reasoning that was employed to reach a specific conclusion/estimation.

Figure 4 illustrates the communication between the ES part and the user (financial/credit analyst) during the estimation procedure of firms' performance and viability. The ES poses questions to the user, together with the necessary explanations concerning all possible answers. In the case of Figure 4, the ES did not find any information in the data base concerning the special competitive advantages of the examined firm. Thus, it poses the corresponding question to the decision maker. There are five possible answers: not satisfactory, medium, satisfactory, very-satisfactory, and unknown. For each of these answers the corresponding explanations are provided, in order to help the decision maker understand the modelling of the criterion. In this specific example, the ES explains that the special competitive advantages of a firm are not satisfactory when the firm does not possess any expertise for its production methods, the special competitive advantages of a firm are medium when the firm possesses a small amount of expertise for its production methods, etc.

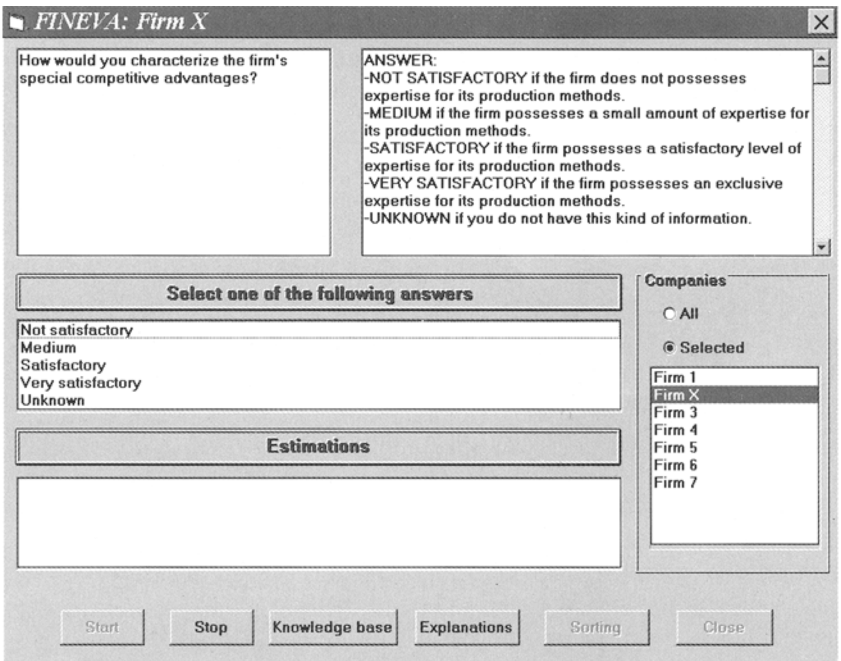

Figure 4. *The communication between the ES and the user during the estimation procedure*

5.3 Principal components analysis

Principal components analysis is included to assist the user in selecting the significant financial ratios. The principal components analysis is a factor method of descriptive character. In the case of corporate assessment, the principal components analysis shows the financial ratios which are the most important and which best describe the financial behavior of firms. The principal components analysis can also be used to classify firms in relevant categories, meaning that firms belonging to the same group have similar behavior and characteristics.

5.4 The multicriteria method

The FINEVA system also incorporates a multicriteria method in order to improve the system's capabilities in the evaluation of firms. The criteria used by this method are both financial ratios and qualitative variables which are chosen by the user (decision maker). The multicriteria method used by the system is called UTASTAR (Siskos and Yannacopoulos, 1995), an improved variant of the UTA method. Unlike the UTADIS method and its variants which are incorporated in the FINCLAS system, the UTASTAR method is oriented in the study of ranking problems. Consequently, instead of performing comparisons between the global utilities of the alternatives and the utility thresholds, in the UTASTAR method pairwise comparisons between the alternatives (firms) are performed in order to develop a ranking additive utility model to reproduce a predefined preordering (ranking) of the alternatives as consistently as possible.

More specifically, in the case of the evaluation of corporate performance, once the decision maker has expressed his judgement in the form of a ranking of the firms according to classes of risk, the system, by means of the ordinal regression method UTASTAR optimally estimates the multicriteria additive utility functions (similarly to the UTADIS method) which are as consistent as possible with the decision maker's ranking. The preordering of firms required by the UTASTAR method, is provided by the decision maker (sometimes with the help of the expert system's results). Through the UTASTAR method, the financial/credit analyst can determine a personal estimation model, which can be used as basic knowledge in the ES part (as a production rule based on the ranking or segmentation model) for the evaluation of new firms which are inserted in the data base of the system.

The FINEVA system using the multicriteria method UTASTAR can also provide a segmentation (sorting) of firms into three predefined classes. In this case, the decision maker can propose two fictitious firms with their multicriteria evaluations in order to discriminate the set of firms (reference firms or reference profiles). These reference profiles are easy to determine on the basis of the past experience of the decision maker and of the repetitive character of financial decisions related to the assessment of corporate performance and viability. Thus, for a given firm (a), there are three possibilities:

$$
\begin{array}{lll}
u[g(a)] \geq u_1 & \Rightarrow a \in \mathrm{A}_1 & \text{(acceptable)} \\
u_2 \leq u[g(a)] < u_1 & \Rightarrow a \in \mathrm{A}_2 & \text{(uncertain)} \\
u[g(a)] < u_2 & \Rightarrow a \in \mathrm{A}_3 & \text{(unacceptable)}
\end{array}
$$

where $u[g(a)]$ is the global utility of the firm (a), u_1 and u_2 are the global utilities of the two reference profiles called utility thresholds, all calculated by the UTASTAR method. The utility threshold u_1 distinguishes the firms among those which can be characterized as dynamic (acceptable) from those which need further study (uncertain). The utility threshold u_2 distinguishes the firms among those which need further study (uncertain) from those which can be characterized as bankrupt (unacceptable). Then, the system by using the UTASTAR method, classifies the firms into these three classes.

6. Concluding Remarks and Perspectives

The modeling of financial decision problems generally involves a complex process regarding both the qualitative description of the problem under consideration using the basic concepts and notions of financial theory, as well as the development and implementation of mathematical formulations to achieve problem structuring and solution. On the other hand, since financial decisions are essential on a daily basis for banks, credit institutions, firms, investors and stockbrokers, a powerful and efficient tool is required to derive real time decisions.

This is the issue on which the major contribution of KBDSSs can be located. KBDSSs take advantage of the increasing capabilities provided by information technology and computer science, to integrate the mathematical modeling and database management capabilities which characterize the DSSs framework, with the inference procedures and explanations capabilities of ESs. This integration provides new enriched capabilities in financial modeling, and facilitates the use of the system by professionals which are not always familiar with the necessary mathematical tools to address financial decisions in an efficient and sophisticated manner.

This paper examined how the integration of ESs and DSSs can be achieved in the KBDSSs framework, and analyzed the main benefits and contributions of this integration in financial modeling. The FINCLAS and the FINEVA systems which have been described, are two representative examples of how DSSs on the one hand and KBDSSs on the other can be used to improve financial modeling in order to support financial decisions in the field of corporate risk assessment.

As new technological advances are achieved in several fields of operations research such as multicriteria decision making, artificial intelligence, fuzzy sets and optimization, embedding them in the existing framework of KBDSSs could considerably increase the effectiveness of the provided decision support.

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