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# Multicriteria Decision Aid Methods and portfolio selection: case study

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**Abstract**

This article focuses on some problems in finance that have a multi-criteria character, such as the prediction of bankruptcy, the credit risk and the constitution of the stock portfolio (the latter which will be the subject of a case study). Tunis Stock Exchange-), from this it evokes some existing studies in terms of solving the problems in finance by means of multi-criteria methods. From the point of view of the large number of criteria to be taken into consideration for the evaluation of titles, it is in this perspective that this article falls , devoted to the application of multicriteria methods in an attempt to evaluate shares with a view to constituting a portfolio of shares in the Tunisian stock market, the use of UTA + was intended to lead to a classification of actions according to their marginal utilities, this same classification has been refined thanks to the use of ELECTRE TRI.

*Keywords: Tunis Stock Exchange, Multi-Criteria Character, Multi-Criteria Method, Problems in Finance*

## 1. Introduction

The use of multi-criteria analysis has become a necessity because of the multi-criteria nature of decision-making problems in finance, a nature that could not be understood by a single-criteria or even classic analysis, this inability is because the perception of risk is reduced to its probabilistic dimension, thus denying the various sources of influence that affect returns and gives risk its multidimensional character.

In the light of all this we were able to formulate the following problem “How does multi-criteria analysis contribute to financial decision-making with application to the Tunisian stock market for the case of the constitution of a portfolio of shares on the stock market?”

To answer this problem, we have relied on two main hypotheses which are:

1. Multi-criteria decision support provides the necessary and most adequate methodological framework for solving financial decision problems.
2. Efficient management of the equity portfolio requires the joint use of the classical theoretical criteria of return and risk and of criteria generated by the valuation models of fundamental analysis (the purpose of these models is to study the ability to the beneficiary of the issuing firm - they are at the origin of a certain number of criteria for evaluating a share or a portfolio commonly used).

This progression of ideas leads us to articulate this present work around three parts. Before illustrating the cases studied (the Tunis stock exchange) which will be the subject of a third party, we will present first a literature review then the methodology, application case with results and discussion; at last, a conclusion.

## 2. Literature Review

### *2.1. Multi-criteria decision support in finance [Micheal Doumpos. 2004]*

#### *2.1.1. Bankruptcy prediction*

The interest in analyzing the performance and viability of the business under review has been explored by researchers, from different perspectives, considering different forms of financial distress, including default, insolvency, and bankruptcy. The term "bankruptcy" refers to the termination of the operation of the business after filing for bankruptcy due to the business's severe financial difficulties in meeting its financial obligations to its creditors. Other forms of financial distress do not necessarily lead to the termination of the business operation [Altman (1993), and Zopounidis Dimitras (1998)]. The consequences of bankruptcy are not limited to individuals, businesses or organizations that have



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an established relationship with the bankrupt business; they often extend to the entire economic and social environment of the country or region. For example, developing countries are often very vulnerable to business failures, moreover, given the globalization of the economic environment, it is becoming clear that such a case can also have global implications. This demonstrates the need for the development and implementation of effective procedures for bankruptcy prediction, these procedures are necessary for financial institutions, individual and institutional investors, as well as for companies themselves and even for decision makers (e.g. , government officials, central banks, etc.). The main objective of default prediction procedures is to discriminate between companies that are susceptible to bankruptcy from healthy ones. It is a problem of classification into two groups. We often see the addition of an additional group (a third group) : the international group Amy includes companies for which it is difficult to draw a clear conclusion, some researchers have placed them (such a group of intermediary companies) in the category of companies in distress, despite this these same companies have finally survived thanks to restructuring plans (Theodossiou et al., 1996). The classification of companies into groups according to their risk of bankruptcy is carried out based on their financial characteristics using information obtained from available financial statements (such as balance sheet and income statement). The financial ratios calculated by the accounts of the financial statements are the criteria most widely used in the prediction of default. Nevertheless, the prediction of bankruptcy based on financial ratios alone has been criticized by several researchers (Dimitras et al, 1996. Laittinen, 1992). Critics have focused on the fact that financial ratios are only symptoms of the operating and financing problems that the company is facing rather than the cause of those problems. To overcome this drawback, several researchers have noted the importance of considering additional qualitative information in anticipation of failure. This qualitative information involves criteria such as the management of companies, their organization, market trends, their competitive advantages, etc. (Zopounidis, 1987).However, this information is not publicly available and therefore quite difficult to collect. This difficulty justifies the fact that most of the existing studies on bankruptcy prediction are based only on financial ratios. The first approaches used for bankruptcy prediction were empirical. Most of the well-known approaches of this type include the "5C method" (character, capacity, capital, hedging conditions), the "lab" method (liquidity, activity, profitability, potential), and the "Creditmen" (Zopounidis, 1995). Later, more sophisticated statistical approaches univariate was introduced in this area, these approaches are studying the discriminated financial ratios to distinguish between bankrupt companies and healthy ones (Beaver, 1996). However, the real push in the field of bankruptcy prediction was given by the work of Altman (1968) on the use of linear discriminated analysis (LDA), some researchers thought of the development of a bankruptcy prediction model and this by exploring statistical and econometric techniques. Some studies include the characteristics of the work of Altman et al. (1977) on the use of QDA (quadratic discriminant analysis), avaux de Jensen (1971), Gupta and Huefner (1972) on typological analysis, the work of Vranas (1992) on the linear probability model, the words of Martin (1977), Ohlson (1980), Zavgren (1985), Peel (1987), Keasey et al. (1990) on logit analysis, the works of Zmijewski (1984), Casey et al. (1986), Skogsvik (1990) on probit analysis, the work of Luoma and Laitinen (1991) on survival analysis, and the work of Scapens et al. (1981) on the theory of catastrophes. Over the past two decades, new non-parametric approaches have attracted the interest of researchers in the field. These approaches include, among others, mathematical programming (Gupta et al, 1990.), expert systems (Elmer and Borowski, 1988; Messier and Hansen, 1988), machine learning (Frydman et al, 1985.), sets approximate (Slowinski and Zopounidis, 1995; Dimitras et al, 1999), neural networks (Wilson and Sharda, 1994; Boriz and Kennedy, 1995), and MCDA (Zopounidis, 1987; Andenmatten, 1995; Dimitras et al, 1995); Zopounidis and Dimitras, 1998). The results of these studies have shown that the aforementioned new approaches are well suited to the problem of bankruptcy prediction, providing satisfactory results with respect to bankruptcy statistics and econometric techniques.

**Table 1.** List of financial ratios used for bankruptcy prediction

| Ratio | Calculation method | Ratio | Calculation method | Ratio | Calculation method |
|---|---|---|---|---|---|
| G1 | Net profit / Gross profit | G5 | Current assets / Current liabilities | G9 | Net income / Net fixed assets |
| G2 | Gross profit / Total assets | G6 | Current assets / Current liabilities | G10 | Stocks / Working capital |
| G3 | Net income / total assets | G7 | Total Assets / Total Liabilities | G11 | Current liabilities / total assets |
| G4 | Net Profit / Net Worth | G8 | Net Worth / (Net Worth + long-term liabilities) | G12 | Working capital / Net income |

**Source**: Micheal Doumpos and all. 2004, op. cit, p200

Finally, it would be useful to consider the failure prediction problem in a dynamic rather than a static context. As already mentioned, bankruptcy is an event that evolves over time. Therefore, it might be useful to consider all available information relating to bankruptcy, in order to develop more reliable early warning models for bankruptcy prediction. Kahya and Theodossiou (1999) followed this approach and modeled the failure prediction problem in a time series context.

*2.1.2. Credit risk assessment*

Credit risk assessment refers to the analysis of the probability that the debtor (company, organization or individual) will not be able to meet its debt obligations to its creditors (by default). This incapacity can be temporary or permanent. This problem is often related to the prediction of bankruptcy. In fact, default prediction models are often used in the context of credit risk assessment. However, the two issues are slightly different: bankruptcy has primarily a legal interpretation, rather than a financial default. Indeed, most authors consider that the company is in a situation of default when the book value of its liabilities exceeds the book value of its assets (Altman, 1993).

The trade-off between estimated losses and profits is a key issue in deciding whether to accept or reject credit as well as the amount of credit that will be granted.

The implementation of this context assumes that the problem of granting credit (and therefore the assessment of credit risk) is a multi-period problem. It is true that the loan repayment condition is made through a series of interest payments (monthly, semi-annual) spanning a period (usually several years). During this period, the credit institution has the possibility of extending its cooperation with the firm. In this regard, the benefits are not only derived from the interest that the company pays for the loan, but they can also be obtained through the extended cooperation between the bank and the company.

At the research level, there has been a wide use of statistical approaches until today. An analytical presentation of the relevant applications is described in the book by Altman et al. (nineteen eighty-one). There has recently been a spread of alternative approaches such as machine learning and expert systems (Cronan et al 1991; Tessmer, 1997; Matsatsinis et al, 1997.), decision support systems (Srinivasan and Ruparel, 1990; Duchessi and Belardo, 1987; Zopounidis et al, 1996; Zopounidis and Doumpos, 2000b), genetic algorithms and neural networks (Fritz and Hosemann, 2000), multicriteria analysis (Bergeron et al, 1996; Zopounidis and Doumpos, 1998; Jablonsky, 1993; Lee et al, 1995; Khalil et al, 2000), etc.

*2.1.3. Stocks Evaluation: selection and portfolio management*

The selection and portfolio management were one of the main areas of interest in the financial field for nearly 50 years. In general terms, portfolio selection and management consist of building a portfolio of securities (stocks, bonds, treasury bills, mutual funds, pensions, financial derivatives, etc.) that maximizes utility of the investor. The term "portfolio construction" refers to the allocation of a known amount of capital to the securities under review. Portfolio construction can be accomplished as a two-step process:

1. Initially, in the first step of the process, the investor must assess the available securities, which constitute investment opportunities based on their prospects. This evaluation leads to the selection of reduced game composed of the best titles. Considering the large number of securities that are traded in international financial markets today, the importance of this step becomes apparent. It is very difficult for the investor to be able to manage a portfolio made up of a large number of securities. Such a portfolio is quite rigid since the investor will need to be able to collect and analyze a huge amount of daily information about the securities in the portfolio. It is a difficult and tedious process. Therefore, portfolio updates will be difficult to perform (in order to adapt) as market conditions change rapidly. Furthermore, a securities portfolio imposes trading costs which are often a deciding factor in portfolio investment decisions. Therefore, a compact set of securities should be formed for the purpose of portfolio construction.

2. Once this compact set of the best securities is determined after the evaluation of the first step, the investor must decide on the allocation of the available capital to these securities. Allocation should be done so that the resulting portfolio meets the investor's best policy, goals, and objectives. Since these goals / objectives are often diversified in nature (some are linked to the expected return, while others are linked to the risk of the portfolio), the resulting portfolio may not be an optimal solution, at least in the sense that the term "optimal " has, in the classical optimization framework, only one objective assumed. Instead, the constructed portfolio will be a satisfactory solution, that is, a portfolio that satisfactorily (but not necessarily optimally) meets all the investor's goals and objectives.

The implementation of the two processes (previous steps) is based on the clear specification of how the terms “best stocks” and “satisfactory portfolio” are defined. Financial market theory assumes that investor policy can be represented by a utility function of some unknown form. This function is implicitly used by the investor in his decision making. The pioneer of modern portfolio theory, Harry Markowitz assumes that this unknown utility function is a function of two variables / criteria: the expected return of the portfolio and the risk of the portfolio (Markowitz, 1952, 1959). These two criteria define the two main objectives of portfolio selection and its management, namely: to maximize the expected return and minimize the risk of the investment. Markowitz proposed two well-known statistical metrics for considering portfolio return and risk. He proposed the use of a quadratic programming formulation to specify an efficient portfolio that minimizes risk (variance) for a given level of return (mean).

### *2.2. Previous Studies (Multicriteria) on the Constitution of an Equity Portfolio*

Two distributions are necessary; by field of interest and by a group of multicriteria methods used:

#### *2.2.1. Breakdown by area of interest*

Typical examples of extensions made in the Markowitz mean-variance model, including single and multi-index models, mean correlation models, mixed models, utility models, as well as models based on the geometric mean, on stochastic dominance, on the asymmetry of Elton and Gruber (1995), while Pardalos et al. (1994) provide a review on the use of optimization techniques in portfolio selection and management. Generally, the existing research on portfolio selection and management issues can be organized into three broad categories:

- **Studies on the characteristics of securities risk / return characteristics**

These studies are carried out by researchers specializing in finance in order to clarify the determinants of risk and return in securities investment decisions. The best-known examples of studies within this category include Sharpe's study on the capital asset pricing model (CAPM; Sharpe, 1964), Ross in his study on Arbitrage Pricing Theory (APT; Ross, 1976) and the study by Black and Scholes on the pricing of options (Black and Scholes, 1973).

Studies on mathematical modeling (in a functional form) and representation of investor policy aggregate all relevant factors describing the performance of securities that are following this policy. The model developed generally takes the form of a utility function following the general framework of portfolio theory, according to which the investor intends to construct a portfolio that maximizes its utility. Thus, making explicit the form of this utility function contributes significantly to the choice and management of the portfolio, both as a safety evaluation mechanism and as a good used in the construction of the portfolio. Some studies use ADMC methods (MCDA : multicriteria model), characteristic of the political model of the investor in the work of Saaty et al. (1980), Rios-Garcia and Rios-Insua (1983), Evrard and Zisswiller (1983), Martel et al. (1988), Szala (1990), Khoury et al. (1993), Dominiak (1997), Hurson and Ricci (1998), Zopounidis (1993), and Zopounidis Hurson (1995,1996, 1997), Zopounidis et al. (1999). A comprehensive review of the use of ADMC techniques in portfolio selection and management is presented in the book by Hurson and Zopounidis (1997) as well as in the studies by Spronk and Hallerbach (1997) and Zopounidis (1999).

- **Studies relating to the development of methodologies for evaluating the performance of securities**

These studies include studies on forecasting securities prices. The goal of this forecast-based approach is to develop models that will be able to provide accurate predictions on future securities prices. Since reliable predictions can be obtained from time series data, the investor can choose the securities with the highest upward trend and anticipate the future of their price. These securities are then used for portfolio construction. The development of such forecasting models has traditionally been a major focus of interest for researchers in econometrics and statistics. However, recently, interest in the use of artificial intelligence techniques has increased dramatically. This is mainly due to the flexibility of these modeling techniques and the representation of the complexity of financial markets by describing the movements of the prices of securities and the highly (strongly) non-linear behavior of these markets. Some examples based on this new approach, notably neural networks (Wood and Dasgupta, 1996; Trippi and Turban, 1996; Kohara et al, 1997; Steiner and Wittkemper, 1997), machine learning (Tam et al, 1991; John and Lee and Kim,1997), expert systems (Lee et al, 1989; Lee and Jo, 1999; Liu and Lee, 1997), fuzzy set theory (Wong et al, 1992. Jog et al., 1999). Regarding the contribution of these new techniques in the choice and management of portfolio, it is important to note that their use is not dictated only by academic research, but they have become a daily practice of the investors of the whole world.

- **Studies on the development of methodologies for the construction of the portfolio .**

These methodologies follow an optimization perspective in a multi-objective context. This is consistent with the nature of the portfolio building problem. Indeed, portfolio construction is a multi-objective optimization problem, even if it is considered in the Markowitz mean-variance framework. It is an optimization problem with two objectives. Moreover, since both return and risk are multidimensional, it is possible to extend the traditional mean-variance framework, so that all relevant risks and return factors are taken into account. . The traditional mean-variance framework only considers non-systemic risk, while in a broader framework systemic risk (beta coefficient) can also be considered (for example, building the portfolio with a pre-specified beta). Such a framework can examine any goal / objective optimization as perceived by investors and not necessarily following a probabilistic approach such as that of the mean-variance model. In fact, as noted by Martel et al. (1998), measuring the risk and the return in a probabilistic context is not always consistent with investors' perception of these two key concepts. This finding has motivated several researchers to introduce additional goals, goals in the portfolio building process (e.g., market value, dividend yield, net earnings per share, price / earnings ratio, etc.)

Following this current of research, the constitution of portfolio can be carried out by techniques of multi-objective mathematical programming. Studies following this approach were presented by Lee and Chesser (1980), Nakayama et al. (1983), Rios-Garcia and Rios-Insua (1983), Colson and De Bruyn (1989), Tamiz et al. (1997), Zopounidis et al. (1998), and Zopounidis Hurson (1995,1996, 1997), Bertsimas et al. (1999), and Zopounidis Doumpos (2000).

The use of the classification techniques in the portfolio building process discussed at the outset. First, it requires an estimate of stocks, for example, in the case of stock valuation most investment analysts and financial institutions publish their work to periodically estimate the performance of securities in the form of recommendations such as "buy", "market execute", etc. Smith (1965) at the beginning used a classification method (LDA) in order to develop a model that can reproduce the recommendations of these experts. A similar study was compiled by Blanc (1975). Some more recent studies such as those by C. Hurson and C. Zopounidis (1995, 1996, 1997), Zopounidis et al . (1999) use ELECTRE TRI multi-criteria classification methods and in particular UTADIS for the development of securities classification models taking into account the investor's policy and his preferences. Surely, except for evaluation and classification based on expert judgment, other classification systems can also be considered. For example, Klemkowsky and Petty (1973) used LDA to develop a model for classifying securities such as those classified in risk classes based on their historical return volatility, or those classified on the basis of their expected future return, Jog et al. (1999) adopted this approach and used rough set theory to develop a model based on data from the past to classify securities into classes based on their expected future performance, such as top performers (securities with return highest to come), intermediate securities and low securities (securities with the lowest expected return in the future). A similar approach was used by John et al. (1996) who employed a machine learning methodology, while Liu and Lee (1997) developed an expert system that provides buy and sell recommendations (a two-group classification system) based on technical analysis indicators for stocks (Murphy, 1995). The results obtained through these classification models can be integrated at a later stage of the analysis with an optimization methodology (programming by objectives, multi-objective programming) to carry out the constitution of the most appropriate portfolio.

*2.2.2. Breakdown by group of methods used ( C. Hurson ; C. Zopounidis, 1997)*

**Table 2.** Some works

| Theories | The works |
|---|---|
| Utility multiattribute | Saaty, Rogers and Pell (1980)<br>Evrard and Zisswiller (1983)<br>Garcia and Rio-Rio -Insua (1983) |
| The upgrade methods | Mariel, Khoury and Bergeron (1988)<br>Khoury, Martel and Veilleux (1993)<br>Szala (1990) |
| Interactive methods | Nakayama, Takegushi and Sono<br>Lee and Chesser (1980)<br>Colson and de Bruyn (1989) |
| The approach of the disintegration of preferences | Colson and Zeleny (1980)<br>Zopounidis , Despotis and Kamaratou(1993) |

**Source**: Established by the researcher based on C. Hurson and Constantin Zopounidis, 1997

## 3. Methodology, Application, Results and Discussion

### *3.1. Work Methodology*

In what follows we will represent the application of the UTA + and ELECTRE TRI method, for a storage problematic we will apply UTA + and the ELECTRE TRI method, which are over-classification and sorting methods; These two methods belong to the constructive approach ; this is one of the main reasons for their choice. It should be noted that this is a multi-criteria decision support methodology for stock selection and not a yield forecasting model such as the CAPM (Financial Assets Valuation Model) or the APT (Arbitrage pricing theory).

### *3.2. Construction of Evaluation Criteria*

The database includes 54 Tunisian companies, stock market and financial data (balance sheet, income statement, share price, dividends, etc.) cover a period from December 2009 to July 2013. A From this database we will proceed the evaluation of a certain number of criteria. Seven criteria were retained, including four scholarship recipients (annual or monthly as the case may be) and three others for financial analysis (annual).

**Table 3.** Evaluation criteria

| Criteria | Financial analysis criteria | Stock market criteria |
|---|---|---|
| The average monthly return | | Which is a stock market criterion |
| The monthly price earnings ratio to be minimized | | In the event of losses this criterion is negative which places the action at the top of the ranking so it would be more judicious to maximize the inverse of this criterion 1 / PER. |
| Annual earnings per share | | Or EPS : earnings per share to be maximized. |
| The return on equity | Which a criterion of profitability of equity to be maximized. | |
| Current ratio | Where liquidity criterion in the strict sense which must be maximized. | |
| The cash flow / debt ratio | Which is a criterion of solvency to be maximized | |
| The ß ê ta-1 | | Minimization of the absolute value of this criterion which represents a portfolio manager who prefers ßeta stocks close to 1 and follows a passive management strategy (the cautious attitude) |

**Source**: Established by the researcher

### *3.3. The application of the methods UTA +, ELECTRE TRI*

#### *3.3.1. Classification of actions by their degree of utility*

1. **Methodology:** This method is based on the search for a utility function allowing the storage of shares, two situations can be faced :
   a) There is an additive separable utility function which respects the order established by the decision maker, then F = 0. In this case, there is in fact an infinity of utility functions which respect this order, and a post-optimality analysis makes it possible to select an “ average ” function to represent it.
   b) There are no additive separable utility functions that respect the order, so F> 0. In this case, the role of the difference variables σ is to make it possible to estimate a utility function. The solution of the program is unique, and we obtain a utility function which best respects the preferences of the decision maker according to the criterion in question.
2. **Application and results:** In the present case (the studied case) the search for a utility function which best respects The preferences of the decision maker. This research is based on the hypothesis of the existence or not of a set of actions for which there is or not a utility function, this according to the Kendall coefficient τ, if it is less than 0.7 the function utility (which best represents the preferences of the decision maker) does not exist, if the coefficient is equal to or greater than 0.7 (approaching 1) there is a utility function which best respects the preferences of the decision maker. We therefore carried out a series of tests each time verifying the value of this coefficient, which remains greater than 0.7 for all the 54 companies. For the set of 54 alternatives the Kendall coefficient τ = 0.82 for which there is an additive utility function, the results are as follows:

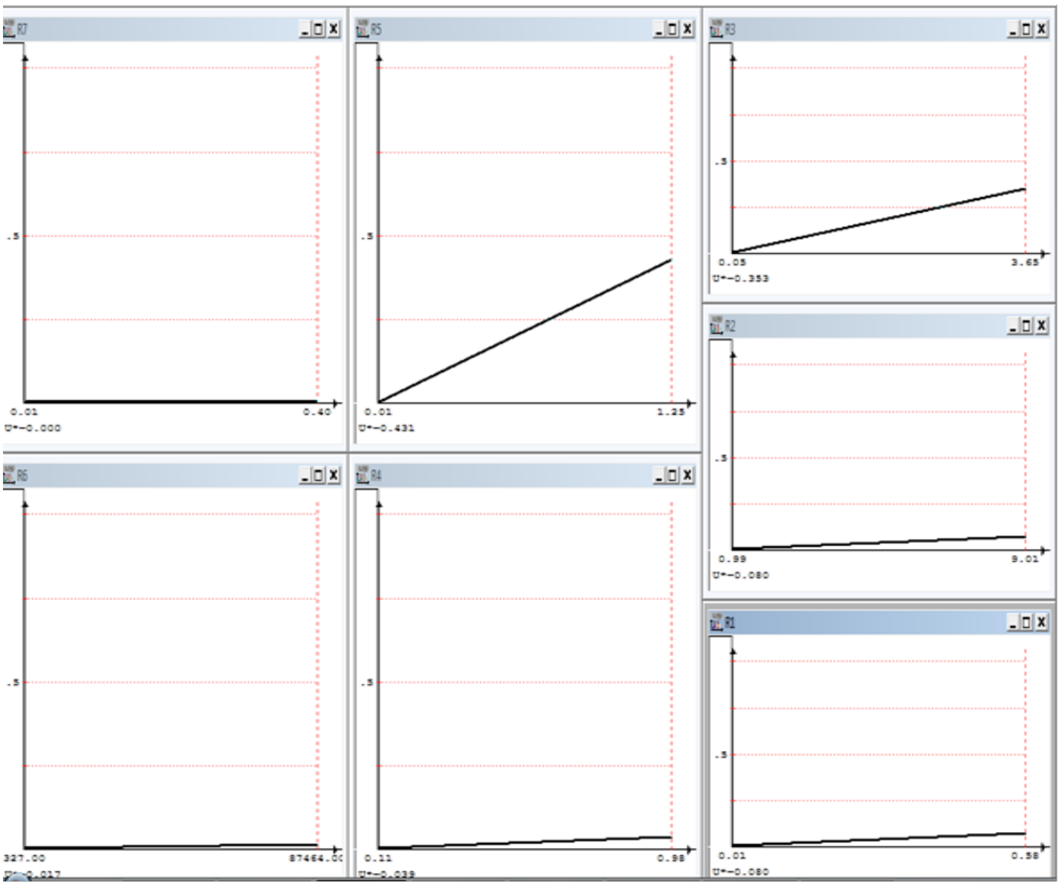

**Fig. 1.** Marginal utility of the seven ratios

DR is the portfolio ranking by the manager and MR : is the ranking in relation to the overall utility of each benchmark share. The value of the Kendall coefficient $\tau = 0.82$ shows that the estimated utility function respects at best and not perfectly the order established by the portfolio manager. The marginal utility curves of the eight criteria are shown in the following figures, given that the portfolio manager's ranking is in accordance with the model, we can move on to the total and final ranking phase:

**Table 4.** Final ranking

| MR | DR | Global Utility | Actions | MR | DR | Global Utility | Actions | 35 | 34 | 0.153 | AST |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 23,786 | AMEN BANK | 18 | 18 | 0.338 | PGH | 36 | 35 | 0.151 | STAR |
| 2 | 2 | 1,152 | SCB | 19 | 19 | 0.328 | ATL | 37 | 36 | 0.148 | TJARI |
| 3 | 3 | 0.986 | TJL | 20 | 20 | 0.312 | SIAME | 38 | 37 | 0.140 | TAIR |
| 4 | 4 | 0.641 | GIF | 21 | 20 | 0.312 | PLTU | 39 | 38 | 0.136 | SITS |
| 5 | 5 | 0.607 | SPDIT | 22 | 21 | 0.310 | ASSAD | 40 | 39 | 0.129 | UIB |
| 6 | 6 | 0.557 | BT | 23 | 22 | 0.308 | STEQ | 41 | 40 | 0.118 | WIFAK |
| 7 | 7 | 0.542 | ARTES | 24 | 23 | 0.275 | MNP | 42 | 41 | 0.113 | MGR |
| 8 | 8 | 0.469 | SOTET | 25 | 24 | 0.253 | ALKIM | 43 | 42 | 0.111 | SALIM |
| 9 | 9 | 0.460 | TLNET | 26 | 25 | 0.235 | ATB | 44 | 43 | 0.097 | SIMPA |
| 10 | 10 | 0.434 | STPIL | 27 | 26 | 0.228 | STB | 45 | 44 | 0.091 | NAKL |
| 11 | 11 | 0.433 | TINV | 28 | 27 | 0.204 | THE ADWYA LABS | 46 | 45 | 0.084 | SIPHA |
| 12 | 12 | 0.413 | TLAIT | 29 | 28 | 0.200 | SFBT | 47 | 46 | 0.050 | ML |
| 13 | 13 | 0.410 | TLS | 30 | 29 | 0.182 | BNA | 48 | 46 | 0.050 | AL |
| 14 | 14 | 0.407 | TREJ | 31 | 30 | 0.172 | BIAT | 49 | 47 | 0.045 | ICF |
| 15 | 15 | 0.362 | EYELASH | 32 | 31 | 0.166 | SOKNA | 50 | 48 | 0.043 | BH |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 16 | 16 | 0.356 | TPR | 33 | 32 | 0.163 | SOMOC | 51 | 49 | 0.032 | BTE |
| 17 | 17 | 0.355 | SOPAT | 34 | 33 | 0.161 | LSTR | 52 | 50 | 0.023 | UBCI |

**Source:** Established by the researcher using the UTA + software

*3.3.2. The use of the ELECTRE TRI method for the assignment of actions in predefined categories*

**1. Methodology of work**

a) Overview on the ELECTRE TRI method The ELECTRE TRI method which relates to the problem β (assignment procedure) poses the problem in terms of attribution of each action to a predefined category. Benchmarks are used to segment the criteria space into categories. Each category is bounded below and above by two reference actions and each reference action therefore serves as a limit for two categories, one is upper and the other is lower.

b) Design of the reference profiles We have designed border reference profiles such as Pro01> Pro02 and therefore three ordered categories of performances 3> 2> 1. The pessimistic assignment procedure proceeds to the classification as follows:

i. Ai S Pro01 then Ai is assigned to category 3 : the Ai share outclasses profile 01 which is the highest profile or higher than the action will be assigned to category 3 which represents all the attractive actions.

ii. Ai S Pro02, but not Ai S Pro01 then Ai is assigned to category 2 : the Ai action outclasses profile 02 which is the lowest or lower profile but does not outclass profile 01 which is high or higher profile, then the action will be assigned to category 2 which represents all the actions to be analyzed.

iii. No Ai S Pro02 then Ai is assigned to category 1 : the Ai action does not outclass profile 02 which has a low or lower profile then the action will be assigned to category 1 which represents all the actions to be rejected.

It is necessary to have the inter-criteria information which is the relative importance of the criteria and their veto thresholds. The latter will have the effect of prohibiting in the pessimistic procedure, the sorting of an alternative in a category if for at least one criterion, the evaluation is in favor of the low profile of this category with a difference greater than the value of the corresponding veto threshold. As the cut threshold λ represents the minimum number of criteria which must be favorable to over-classification, the reasonable cut threshold is therefore located in the range which goes from (0.55, 0.64, 0.73, 0.82, 0.91, 1) representing successively 6 favorable criteria, 7, 8, 9, 10 criteria and unanimity. We think that taking the default threshold given by the software as the basic threshold λ = 0.76 would be quite wise.

2. **Application of the ELECTRE TRI method and analysis of the results:**

a) **Application of the ELECTRE TRI method:** We only retain the pessimistic assignment procedure for the following good reason: it will only affect the good categories in actions whose qualities are firmly established, rejecting those which may present a doubt in the wrong categories. Its use is of interest to a decision maker who wishes to remain cautious. In our opinion, the pessimism of the decision-maker (investor) must be based on the following postulate: "listed companies tend to dress their balance sheets better and present a good image compared to what it really appears ", therefore c is the pessimistic affectation that will do the trick. The results of the pessimistic assignment procedure to the categories and to the reference cut threshold λ = 0.76 are as follows:

**Table 5.** Reference profiles

| | Profil haut (Pr01) | Profil bas (Pr02) | **Profil haut** | Poids | Seuil d'indifférence | Seuil de préférence | Seuil de veto | **Profil bas** | Poids | Seuil d'indifférence | Seuil de préférence | Seuil de veto |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R1 | 0.18 | 0.14 | R1 | 1 | 0.02 | 0.05 | 0.1 | R1 | 1 | 0.02 | 0.05 | 0.5 |
| R2 | 1.5 | 1 | R2 | 1 | 0.1 | 0.3 | 0.75 | R2 | 1 | 0.1 | 0.3 | 2.88 |
| R3 | 1 | 0.6 | R3 | 1 | 0.1 | 0.3 | 0.6 | R3 | 1 | 0.1 | 0.3 | 9.4 |
| R4 | 0.011 | 0.004 | R4 | 1 | 0.001 | 0.003 | 0.011 | R4 | 1 | 0.001 | 0.003 | 0.11 |
| R5 | 0.08 | 0.041 | R5 | 1 | 0.01 | 0.03 | 0.08 | R5 | 1 | 0.01 | 0.03 | 1.235 |
| R6 | 800 | 200 | R6 | 1 | 50 | 150 | 700 | R6 | 1 | 50 | 150 | 10762 |
| R7 | 0.19 | 0.09 | R7 | 1 | 0.02 | 0.05 | 0.26 | R7 | 1 | 0.02 | 0.05 | 5 |

**Source:** Established by the researcher

The results of the pessimistic and optimistic assignments (by category, by the most interesting alternatives for that matter) are represented in the following:

**Table 6.** Allocation by alternatives

| Categories | λ = 0.76 |
|---|---|
| 3 | X3, X7, X15, X24, X25 |
| 2 | X2, X4, X5, X6, X8, X9, X10, X13, X14, X17, X19, X23, X26, X27, X28, X29, X31, X35, X37, X39, X41, X43, X44, X45, X47, X49, X52, X53 |
| 1 | X1, X11, X12, X16, X18, X20, X21, X22, X30, X32, X33, X34, X36, X38, X40, X42, X46, X48, X50, X51 |

**Source:** Established by the researcher

The following conclusions can be drawn:

1. 1.Five stocks can be qualified as an attractive stock (stocks X3, X7, X15, X24, X25).
2. Category 2 includes X2, X4, X5, X6, X8, X9, X10, X13, X14, X17, X19, X23, X26, X27, X28, X29, X31, X35, X37, X39, X41, X43, X44, X45, X47, X49, X52, X53.
3. 3.Category 1 includes : X1, X11, X12, X16, X18, X20, X21, X22, X30, X32, X33, X34, X36, X38, X40, X42, X46, X48, X50, X51.

b) **Analysis of sensitivity of the results:** Variation of cut threshold consists of an analysis of the sensitivity of the results obtained if certain parameters of the problem are modified. We carried out a sensitivity analysis by not modifying the criteria weights, but by using pseudo criteria without veto on all profiles, pseudo-criteria with veto only on the high profile, real criteria. Among the different types of change that can occur those which consist of moving from the third category to the first category, or the opposite, are more troublesome than any other type of change, we distinguish two types of changes :

- Type I changes : correspond to a deviation from one category, a change from category 3 to 2 or from 2 to three or vice versa.
- Type II changes : correspond to a difference between two categories, a change from category 3 to 1 or vice versa.

The results as well as the magnitude of the changes in relation to the variation in cut thresholds were found to be more stable with pessimistic assignments.

**Table 7.** Summary of the different assignments according to the different cutting thresholds

| | λ = 0.5 | λ = 0.55 | λ = 0.6 | λ = 0.65 | λ = 0.75 | λ = 0.85 | λ = 0.9 | λ = 1 |
|---|---|---|---|---|---|---|---|---|
| C3 | X3, X4, X6, X7, X15, X24, X25, X28, X37, X45, X47 | X3, X6, X7, X15, X24, X25, X28, X37, X45, X47 | X3, X6, X7, X15, X24, X25, X28, X45, X47 | X3, X6, X7, X15, X24, X25, X28, X45, X47 | X3, X6, X7, X15, X24, X25, X28 | X3, X15, X25 | X3, X25 | X3 |
| C2 | X1, X2, X5, X8, X9, X10, X11, X12, X13, X14, X16, X17, X19, X21, X22, X23, X26, X27, X29, X30, X31, X32, X33, X34, X35, X38, X39, X41, X43, X44, X48, X49, X50, X51, X52, X53 | X1, X2, X4, X5, X8, X9, X10, X11, X12, X13, X14, X16, X17, X19, X22, X23, X26, X27, X29, X30, X31, X32, X33, X34, X35, X38, X39, X41, X43, X44, X48, X49, X50, X51, X52, X53 | X1, X2, X4, X5, X8, X9, X10, X11, X13, X14, X16, X17, X19, X22, X23, X26, X27, X29, X30, X31, X32, X33, X34, X35, X37, X38, X39, X41, X43, X44, X48, X49, X50, X51, X52, X53 | X1, X2, X4, X5, X8, X9, X10, X11, X13, X14, X16, X17, X19, X22, X23, X26, X27, X29, X30, X31, X33, X34, X35, X37, X38, X39, X41, X43, X44, X48, X49, X50, X51, X52, X53 | X2, X4, X5, X8, X9, X10, X13, X14, X17, X19, X23, X26, X27, X29, X30, X31, X35, X37, X39, X41, X43, X44, X49, X50, X52, X53 | X2, X4, X5, X6, X7, X9, X13, X17, X24, X26, X27, X28, X29, X31, X37, X41, X43, X45, X47, X52 | X6, X7, X13, X24, X37, X41, X43, X45, X47, X52 | X6, X7, X24, X25, X45, X47 |
| C1 | X18, X20, X36, X40, X42, X46 | X18, X20, X21, X36, X40, X42, X46 | X12, X18, X20, X21, X36, X40, X42, X46 | X12, X18, X20, X21, X32, X36, X40, X42, X46 | X1, X11, X12, X16, X18, X20, X21, X22, X30, X32, X33, X34, | X1, X8, X10, X11, X12, X14, X16, X18, X19, X20, X21, X22, X23, | X1, X2, X4, X5, X8, X9, X10, X11, X12, X14, X15, X16, X17, X18, X19, X20, X21, X22, X23, | X1, X2, X4, X5, X8, X9, X10, X11, X12, X13, X14, X15, X16, X17, X18, X19, X20, X21, X22, X23, X26, X27, X28, X29, X30, |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | X36, X38, X40, X42, X46, X48, X51 | X32, X33, X34, X35, X36, X38, X39, X40, X42, X44, X46, X48, X49, X50, X51, X53 | X26, X27, X28, X29, X30, X31, X32, X33, X34, X35, X36, X38, X39, X40, X42, X44, X46, X48, X49, X50, X51, X53 | X31, X32, X33, X34, X35, X36, X37, X38, X39, X40, X42, X43, X44, X46, X48, X49, X50, X51, X52, X53 |

**Source:** Established by the researcher

The X3 alternative remains constantly at the top of the list by preserving its presence in category 3 and this even if we demand a better performance of the alternative on all the criteria (λ = 1), this alternative is gradually being joined. the alternatives X25 (from C2 to C3 for a cutting level of 0.9), X15 (from C1 to C3 for λ = 0.85), X6, X7, X24, X 28 (from C2 to C3 for λ = 0.75), X45 and X47 (from C2 to C3 for λ = 0.65), no change for a cut level λ = 0.6, X37 (from C2 to C3 for λ = 0.55) and X4 (from C2 to C3 for λ = 0.5).

These alternatives which have migrated to other categories can be considered as alternatives coming in second position except the case of the alternative X15 which has migrated to a better category (from C1 to C3) and this thanks to the relaxation of the conditions d. assignment. Category C2 contains the alternatives X6, X7, X24, X25, X45, X47 (for λ = 1), these alternatives will migrate for a relaxation of the conditions of assignment towards a better category (C3) gradually giving way to other alternatives which will be lodged (from category C1) and this always because of the drop in the cutting level λ, X13 (from C1 to C2 for λ = 0.9), the same for X37, X41, X43, X52.

For λ = 0.85 we have X2, X4, X5, X9, X17, X26, X27, X28, X 29 and X 31 which migrate from category C1 to C2, for λ = 0.75 : X8, X10, X14, X19, X23 , X30, X35, X39, X44, X49, X50, X53 (from C1 to C2), for λ = 0.65 : X1, X11, X16, X22, X33, X34, X38, X48, X51 (from C1 to C2), for λ = 0.6 : X32 (from C1 to C2), for λ = 0.55 : X12 (from C1 to C2), for λ = 0.5 : X21 (from C1 to C2).

For category C1 : this category includes many alternatives for a cut level λ = 1 (unanimously), these alternatives will gradually migrate (the majority) to the higher categories for more flexible cut levels λ.

**Table 8.** Types of errors

| Type of error | λ = 1 | λ = 0.9 | λ = 0.85 | λ = 0.75 | λ = 0.65 | λ = 0.6 | λ = 0.55 | λ = 0.5 |
|---|---|---|---|---|---|---|---|---|
| I | 31 | 27 | 22 | 12 | 11 | 3 | 2 | 1 |
| II | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Total change | 31/53 | 27/53 | 23/53 | 12/53 | 11/53 | 3/53 | 2/53 | 1/53 |

**Source:** Established by the researcher

The decrease in the value of λ corresponds to 9 type I changes and 0 type II changes according to the pessimistic procedure. This presents fairly good results since the sensitivity of the result remains low for cut-off values of less than 0.6, compared to the increase in the value of λ the number of changes made which becomes important especially with a type II change, the sensitivity of the result becomes important since most alternatives undergo changes which is quite reasonable since the higher the cut level is, the higher the over-classification condition is. We can therefore say that the sensitivity of the assignment depends on the initial value of λ, this denotes a stability of the results and a robustness of the methodology.

## 4. Conclusion

The dynamic nature of the stock markets in combination with the plethora of internal and external factors that affect stock performance, as well as the huge volume of financial and stock information that is available to investors and stock analysts, all contribute to the complexity of the problem of evaluation of titles. From the point of view of the large number of criteria to be taken into consideration for the evaluation of titles, it is in this perspective that this article falls , devoted to the application of multicriteria methods in an attempt to evaluate shares with a view to constituting a portfolio of shares in the Tunisian stock market, the use of UTA + was intended to lead to a classification of actions according to their marginal utilities, this same classification has been refined thanks to the use of ELECTRE TRI.

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