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# Paraconsistent and fuzzy logic applied to company profitability analysis

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## Abstract

This study proposes an application of two models based on non-classical logic, the paraconsistent logic and the fuzzy logic, in company profitability analysis. We conduct interviews with market specialists in order to identify the main explanatory variables related to company profitability and apply the paraconsistent model in order to classify the data and to attribute a degree of favorable evidence and of contrary evidence to each profitability ratio. In the fuzzy model, the collected data is analyzed and classified using inference rules and membership functions, thus assigning a qualitative variable to each profitability index. The empirical implementation indicates that both models can be used as tools for assistance and validation of opinions of specialists in the analysis of a company's profitability.

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# 1. Introduction

In this study, we have proposed conceptual models for company profitability analysis using the concepts of Paraconsistent Annotated Evidential Logic and of Fuzzy Logic along with market specialists about the most relevant indices for the analysis of profitability of the company. In addition to that, we have developed a specific software for the implementation of both models, and provided an empirical evaluation. Our results support the use of both non-classical logics as tools for assistance and validation of opinions of specialists in the analysis of a company's profitability.

This paper is organized as follows. Section 2 reviews the main aspects related to financial statements and profitability analysis. Sections 3 and 4 detail the main theoretical aspects of the paraconsistent and fuzzy models, respectively. Section 5 explains the methodology for implementing both models. Section 6 presents an empirical evaluation. Finally, Section 7 brings conclusion remarks.

# 2. Financial statements and profitability analysis

The process of analyzing financial statements usually starts with the calculation of a set of economic and financial indices that could reveal strong and weak points of the company. Indices are usually a ratio of two quantities, and are assumed that there is a relationship between both elements. According to Stolowy and Lebas (2006), the methods of calculation and interpretation of the significance of any data relationship are more or less homogeneous across countries.

There are hundreds of different possible indices, as the number of combinations of all the items of financial statements, as well as the possibility to relate the descriptions of business activity (such as number of employees, sales volume, market share, etc.), is almost unlimited. As a result, the indices are frequently classified into categories that reflect a particular aspect of the economical and financial performance of a company. Stolowy and Lebas (2006) pointed out that the most common categories are: (a) assessment of short-term liquidity and solvency; (b) assessment of long-term solvency and financial leverage; (c) assessment of profitability and of profitability generation; and (d) measures of shareholder return. This study is mostly concerned with profitability ratios. The justification for this choice is the fact that the financial statement analyses usually present profitability indices, being used from the point of view of both investors, creditors, and managers and also by researchers, market analysts, and consultants in financial accounting.

## 2.1 Profitability ratios

The value of a company is partly determined by its profitability and growth, which are influenced by the market and by the strategies that it adopts. The objective of profitability analysis, although it cannot give all the answers, it serves to assess the efficiency of the company's policies (Penman, 2004). The profitability ratios measure the result of business policies and decisions. In other words, profitability is the main indicator of survival and success of a company. These quotients can also be identified as indices that show the level of economic success of the company. As a whole, these measures allow the assessment of the profit of the company in comparison with a given level of sales, a certain level of assets, with prior investment or with the value of the share itself.

Different authors present a set of ratios that are considered ideal for demonstrating the profitability of a company. However, it is necessary to bear in mind that the analysis of financial statements should be treated carefully, as there is no standard script. Brealey, Myers, and Allen (2008) highlight that "*there is no international standard for the ratios, and there is a need for a baseline that would allow assessment of the economic and financial situation of a company.*"

Table 1 describes the main profitability ratios based on Brealey, Myers, and Allen (2008), Stolowy and Lebas (2006), Gitman (2002), Iudicibus (1998), and Penman (2004). *Asset Turnover* is an index that measures sales efficiency in relation to the total assets. *Earnings per Share* represents the income earned by shareholders in relation to the number of shares issued. *Gross Margin* measures the percentage of each monetary unit of remaining sales after the company has paid for raw materials. *Net Margin* measures the efficiency of the company in making profit through its sales, which is calculated in net terms. *Operating Margin* measures the efficiency of the company in making profit from its sales, which is calculated in operating terms. *Return on Assets* (ROA) is the measure of returns produced by the total investment realized by a company on its assets. *Return on Investment* (ROI) measures the returns produced by the total resources invested by shareholders (equity) and creditors (debt) in the business. *Return on Equity* (ROE) is the ratio of net income by the average shareholder's equity, and it measures the rate of returns of shareholders' investment.

Table 1 – Profitability ratios

| **Profitability Ratios** | **Definition** |
|---|---|
| Asset Turnover | $\frac{Sales}{Total\ Asset}$ |
| Earnings per Share | $\frac{Net\ Income}{Number\ of\ Shares\ Issued}$ |
| Gross Margin | $\frac{Gross\ Income}{Sales}$ |
| Net Margin | $\frac{Net\ Income}{Sales}$ |
| Operating Margin | $\frac{Operating\ Income}{Sales}$ |
| Return on Assets (ROA) | $\frac{Net\ Income}{Total\ Assets}$ |
| Return on Investment (ROI) | $\frac{Net\ Income}{(Interest\ bearing\ debt + Equity)}$ |
| Return on Equity (ROE) | $\frac{Net\ Income}{Equity}$ |

## 3. Paraconsistent logic

Classical logic is considered binary, that is, a declaration is either false or true; it cannot be partially true and partially false at the same time. With this supposition and the law of non-contradiction, where one declaration cannot contradict the other, all the possibilities are covered by the laws of classical logic, thus forming the basis of occidental logical thinking. In classical logic, every theory that is inconsistent is trivial and vice versa. However, there is no distinction between inconsistent and trivial theories.

In the real world, not all the situations can be simply classified as being true or false. When we need to precisely describe something, it is hard to establish limits that allow affirmatives or negatives regarding the quality of things. Almost always, the limits between the "false" and "true" are undefined, uncertain, ambiguous, and even contradictory.

Based on the seminal theoretical results achieved by the Brazilian logician Newton C. A da Costa, Paraconsistent Logic has become a progressive and promising field of research. In recent years, various studies related to the application of Paraconsistent Annotated Evidential Logic in different areas have emerged, such as, for example, construction and implementation of electronic circuits (Da Silva Filho and Abe, 2000), intelligent systems for the control of autonomous mobile robots (Torres et al., 2011), electroencephalography analysis (Abe et al. 2011), and cephalometric diagnosis (Mario et al., 2010), among others. However, application of Paraconsistent Annotated Evidential Logic $E\tau$ to the company profitability evaluation is still an unexplored problem.

According to Da Costa et al. (1991), in Paraconsistent Annotated Evidential Logic, propositional formula[1] are followed by annotations. These formula are of the $p(\mu_1, \mu_2)$ type, where

[1] A phrase consists of propositional formulae when one of the two logic values is admited: true or false.

$(\mu_1, \mu_2) \in [0, 1]$, $p$ is the propositional variable, and $\mu_1$ and $\mu_2$ are the values of annotation that can be obtained by measurements, statistics, or probabilities.

The formulae $p(\mu_1, \mu_2)$ can be read intuitively as follows: "I believe in the proposition $p$ with favorable evidence degree $\mu_1$ and contrary evidence $\mu_2$." Thus, we have:

- $p(1.0, 0.0)$ can be read as a true proposition (total favorable evidence and null contrary evidence);
- $p(0.0, 1.0)$ can be read as a false proposition (null favorable evidence and total contrary evidence);
- $p(1.0, 1.0)$ can be read as an inconsistent proposition (total favorable evidence and total contrary evidence);
- $p(0.0, 0.0)$ can be read as a paracomplete[2] or unknown proposition (null favorable evidence and null contrary evidence); and
- $p(0.5, 0.5)$ can be defined as an indefinite proposition (favorable evidence equal to the contrary evidence).

Taking into consideration that $0 \leq \mu_1, \mu_2 \leq 1$, the following concepts can be introduced:

- Degree of contradiction: Gct $(\mu_1, \mu_2) = \mu_1 + \mu_2 - 1$;
- Degree of certainty: Gce $(\mu_1, \mu_2) = \mu_1 - \mu_2$;
- Order relation defined on the interval [0, 1]: $(\mu_1, \mu_2) \leq (\lambda_1, \lambda_2) \Leftrightarrow \mu_1 \leq \lambda_1$ e $\mu_2 \leq \lambda_2$, constituting the reticle that is symbolized by $\tau$.

Based on degrees of contradiction and certainty, it is possible to obtain $N$ regions that represent $N$ possible logic states. In this article, we choose 12 possible states, according to those presented in Table 2.

Table 2 – Legend for the extreme and non-extreme logic states

| **Logic State** | **Symbol** |
|---|---|
| False | F |
| True | V |
| Inconsistent | T |
| Paracomplete | $\perp$ |
| Quasi-true, tending to be inconsistent | QV$\rightarrow$ T |
| Quasi-true, tending to be paracomplete | QV$\rightarrow\perp$ |
| Quasi-false, tending to be inconsistent | QF$\rightarrow$ T |
| Quasi-false, tending to be paracomplete | QF$\rightarrow\perp$ |
| Quasi-inconsistent, tending to be true | QT$\rightarrow$V |
| Quasi-inconsistent, tending to be false | QT$\rightarrow$F |
| Quasi-paracomplete, tending to be true | Q$\perp\rightarrow$V |
| Quasi-paracomplete, tending to be false | Q$\perp\rightarrow$F |

For the complete definition of the reticle associated with this logic, it is still necessary to define certain control values that will delimit the regions of the reticle associated with the logic values. The control values are presented in Table 3.

[2] A logic system is paracomplete when it derogates the law of excluded middle. In this logic, it is possible for both the formula and its denial to be false.

Table 3 – Control values

| |
|---|
| $V_{CVE} = C_1$ = Truthfulness control value, $0 \leq V_{CVE} \leq 1$ |
| $V_{CFA} = C_2$ = Falsehood control value, $-1 \leq V_{CFA} \leq 0$ |
| $V_{CIC} = C_3$ = Inconsistency control value, $0 \leq V_{CIC} \leq 1$ |
| $V_{CPA} = C_4$ = Paracompleteness control value, $-1 \leq V_{CPA} \leq 0$ |

Therefore, with the 12 extreme and non-extreme logic states plus the control values just defined, we can build the reticle shown in Figure 1. The horizontal and vertical axes represent the degrees of certainty and contradiction, respectively. The format of the regions can vary in terms of the adopted control values.

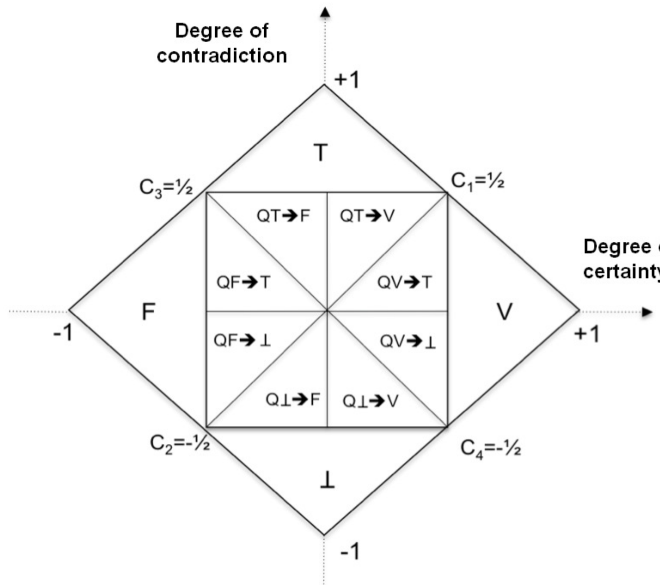


Figure 1 – Reticle with 12 logic states
(Four extreme values and eight non-extreme values).

## 4. Fuzzy Logic

Fuzzy Logic is an important approach that is capable of capturing vague, ambiguous, or inaccurate information mainly described in natural language, and transforming it into numerical form, thus allowing a wide range of applications in computing environments and in artificial intelligence. The proposal of Fuzzy Logic is to take a premise that varies in the degree of membership, in the range of 0 to 1, which assumes the element of the fuzzy set to be partially true or partially false.

The fuzzy controllers consist of an input stage (discrete inputs tied to some sort of a numeric scale), a processing stage, and an output stage. The input stage maps the input data in such a way that is appropriate to the consecutive functions. The processing stage aims at achieving a solution for the problems and can be divided into three phases: fuzzification, evaluation rules, and defuzzification (Von Altrock, 2002, p.37). Figure 2 depicts the phases of the processing stage.

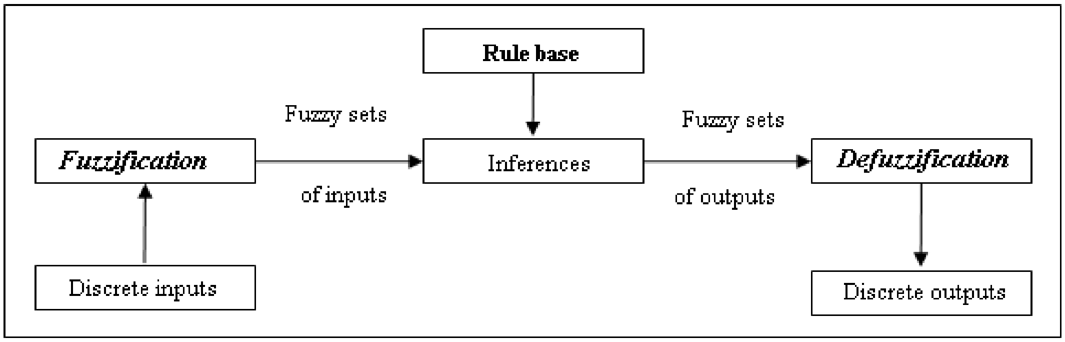


Figure 2 – Structure of a fuzzy logic controller

The second phase of the processing stage is the assessment of rules. The fuzzy rules are *if – then* statements that describe the action to be performed in response to various fuzzy inputs. Finally, the third and last phase of the processing stage is the defuzzification, although the name is not exactly the reverse process of fuzzification. Other methods have been proposed in literature; see Zimmermann (2001).

## 5. Methodology

The first step for implementing the models consists of determining the importance of each profitability ratio in the opinion of financial analysts (experts). A research questionnaire was sent via e-mail to financial analysts of the Regional Bank for Far-South Development – BRDE, Florianopolis Unit, Brazil, containing all the indices defined and researched by the authors such as profitability ratios. A total of 20 experts responded to the request. In order to verify whether the choice of experts was adequate, their profiles were evaluated. Among the interviewed, 80% have a degree in management, accounting, or economics, 45% have an MA or a PhD, and 45% have more than ten years of experience in financial analysis.

The experts answered their degree of “agreement” or “disagreement” regarding the importance of each index for measuring the profitability of companies in the food sector in a category of five possible answers ranging from 1 to 5, with 5 being the higest importance. Table 4 reports the total score of the profitability ratios. We observe that the operating margin is the index of higher importance, highlighted in the analysis of answers, presenting an average of 4.40. It is also important to point out the return on equity (ROE) and the return on investment (ROI), both with an average of 4.20, and the net margin with an average of 4.05.

Table 4 – Profitability ratios assessment: per total and average points, based on the 20 respondents

| | **Sum** | **Average** | **Standard Deviation** | **CV*** |
|---|---|---|---|---|
| **Operating Margin** | **88** | **4,40** | **0,99** | **22,61** |
| **Return on Equity (ROE)** | **84** | **4,20** | **0,83** | **19,85** |
| **Return on Investment (ROI)** | **84** | **4,20** | **0,62** | **14,66** |
| **Net Margin** | **81** | **4,05** | **0,69** | **16,95** |
| Return on Assets (ROA) | 74 | 3,70 | 0,80 | 21,66 |
| Gross Margin | 73 | 3,65 | 1,09 | 29,85 |
| Asset Turnover | 71 | 3,55 | 0,83 | 23,26 |
| Earnings per Share | 66 | 3,30 | 0,98 | 29,66 |

* CV is the coefficient of variation that shows the variability around the average. The maximum of admitted variability for the average to be considered representative was 30%.

As the second step, the database maintained by the financial newspaper *Valor Economico* was used to evaluate the financial indicators of companies in the food sector. This database gathers data on a thousand companies in diverse sectors; Appoximately eighty of them were from the food sector. Based on this sample, the deciles of the selected profitability ratios were extracted and reported in Table 5.

Table 5 – Distribution of the deciles ratios of 80 companies from the food sector

| Decile | Operating Margin | Return on Equity (ROE) | Return on Investment (ROI) | Net Margin |
|---|---|---|---|---|
| 1º | ≤ -2,58 | ≤ -5,70 | ≤ -4,73 | ≤ -1,30 |
| 2º | ≤ -0,04 | ≤ 1,90 | ≤ 0,92 | ≤ 0,40 |
| 3º | ≤ 1,72 | ≤ 6,10 | ≤ 3,35 | ≤ 0,90 |
| 4º | ≤ 3,04 | ≤ 10,10 | ≤ 4,30 | ≤ 1,60 |
| 5º | ≤3,69 | ≤ 11,50 | ≤ 6,25 | ≤ 2,00 |
| 6º | ≤4,86 | ≤ 13,80 | ≤ 7,44 | ≤ 2,60 |
| 7º | ≤6,33 | ≤ 15,60 | ≤ 9,68 | ≤ 4,00 |
| 8º | ≤7,59 | ≤ 26,50 | ≤ 11,55 | ≤ 5,10 |
| 9º | ≤9,98 | ≤ 35,40 | ≤ 14,22 | ≤ 6,20 |
| 10º | 9,98 < | 35,40 < | 14,22 < | 6,20 < |

### 5.1 Implementation of the paraconsistent model

The first step is to assign degrees of favorable evidence ($\mu_1$) and contrary evidence ($\mu_2$) to each of the profitability ratios. The degree of favorable evidence is obtained through division by 10 of the decile to which a determined profitability value belongs. The degree of contrary evidence is obtained through subtraction of 1.0 from the degree of favorable evidence ($\mu_2 = 1 - \mu_1$).

The second step is to apply the connective and to identify the degree of favorable evidence ($\mu_{1R}$) and contrary evidence ($\mu_{2R}$). This connective selects the highest values of the degree of favorable and contrary evidence. During the third step, the degree of favorable evidence of profitability ($\mu_R$) is calculated using the basic structural equation that assesses and makes the processing of signals in paraconsistent artificial neural networks within a real, closed interval between zero and one. Finally, the degree of favorable evidence resulting from profitability (values between 0 and 1) is multiplied by 10 ($\mu_R \times 10$) to enable a comparison with the experts' notes. Figure 3 summarizes the three steps of the implementation of the paraconsistent model.

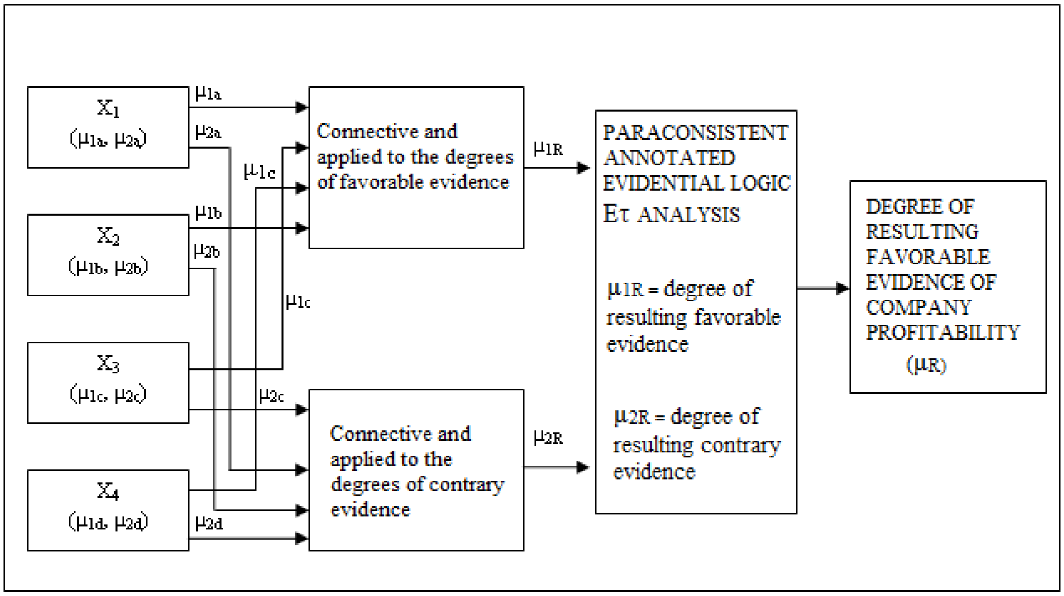


Figure 3 – Conceptual paraconsistent model for profitability analysis

As for the implementation of the paraconsistent model, we have developed a tool named as *Paraconsistent Analyzer*. Figure 4 displays a template of that tool and exemplifies the input of the values of a company with an operating margin equal to 7.60, ROE equal to 5.80, ROI equal to 3.60, and a net margin equal to 0.80. The tool classifies to which decile it belongs and calculates the degree of favorable and contrary evidence of each of the input values. Thus, the operating margin receives $\mu_1$ equal to 0.90 and $\mu_2$ equal to 0.10, ROE receives $\mu_1$ equal to 0.30 and $\mu_2$ equal to 0.70, ROI receives $\mu_1$ equal to 0.40 and $\mu_2$ equal to 0.60, and the net margin receives $\mu_1$ equal to 0.30 and $\mu_2$ equal to 0.70. Then, the degree of the resulting favorable evidence (0.90) and of the contrary evidence (0.70), the degree of favorable evidence of profitability (0.60), and, finally, the profitability assessment of the company (6.00) are calculated.

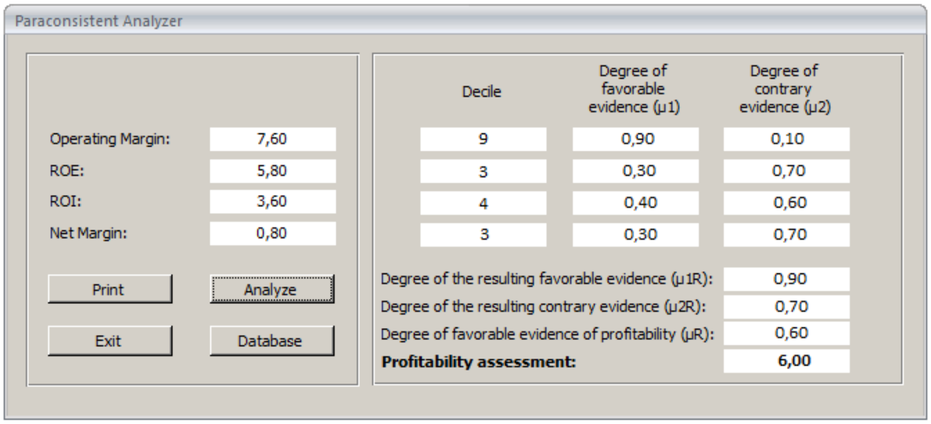


Figure 4 – Paraconsistent analyzer.

### 5.2 Implementation of the fuzzy model

The implementation of the fuzzy model was performed using a Matlab-based toolbox for fuzzy systems. The software requires the definition of the decision tree that the system will use, that is, what are the linguistic input variables, the output variables, what is the scale of values assigned to each variable, the rules of conduct, and the inference method to be used. As Figure 5 shows, the decision tree of the model is composed of four inputs (operating margin, return on equity (ROE), return on investment (ROI), and net margin), one base rule, and one output (final assessment).

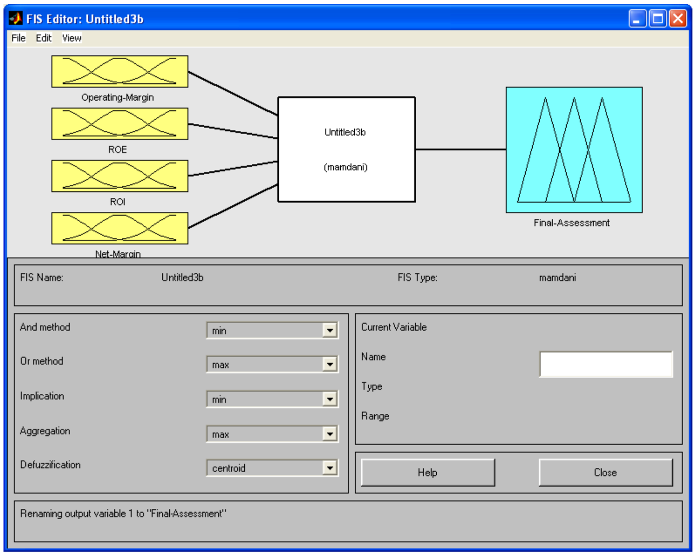


Figure 5 – Decision tree for the fuzzy model

***Building the input and output variables***

Each input variable "*operating margin*", "*return on equity (ROE)*", "return *on investment (ROI)*", and "*net margin*" along with the output variable "*final assessment*" were labeled according to seven qualitative terms (*Very bad*, *Very poor*, *Poor*, *Fair*, *Satisfactory*, *Good*, and *Excellent*) according to the correspondent decile. Each set received a range of values corresponding to the name that was given to it. This value is called *membership degree*.

Figure 6 illustrates the construction of the input variable operating margin, where the label "Very bad" has a membership degree equal to any value lower than -2.58, and from it to -0.04 membership down to zero. "Very poor" has a membership increasing from -2.58 to -0.04 and decreasing from -0.04 to 1.72. "Poor" has a membership increasing from -0.04 to 1.72 and decreasing from 1.72 to 3.04. "Fair" has a membership increasing from 1.72 to 3.04 and decreasing from 3.04 to 3.69. "Satisfactory" has a membership increasing from 3.04 to 3.69 and decreasing from 3.69 to 7.59. "Good" has a membership increasing from 3.36 to 7.59 and decreasing from 7.59 to 9.98. "Excellent" has a membership increasing from 7.59 to 9.98 and a membership equal to the one above this value.

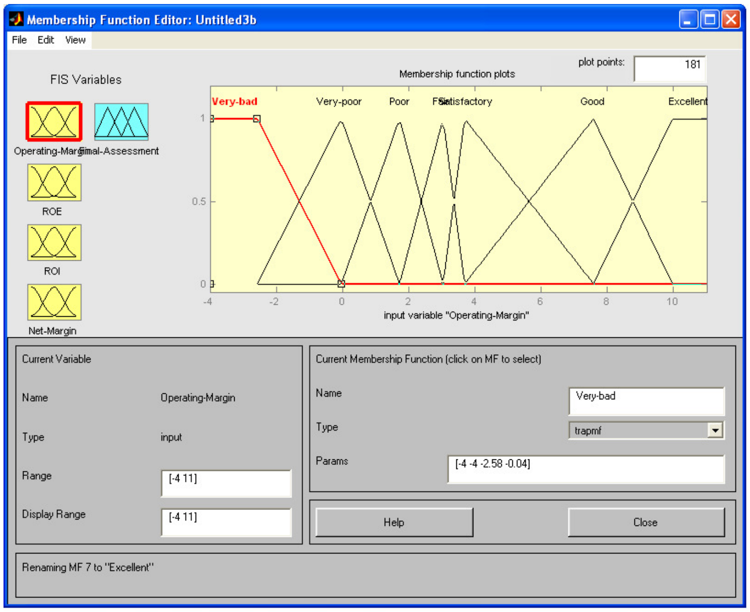


Figure 6 –Fuzzy function input: *Operating margin*.

When all the stages of construction of the fuzzy model are complete, the system presents the discrete outputs. Figure 7 shows the inputs inserted in the system, the activated rules, and the discrete output. Thus, taking as an example a company with the following profitability ratios: operating margin = 5.4, return on equity (ROE) = 16.0, return on investment (ROI) = 9.6, and net margin = 3.5, the system returns a discrete output for the "assessment" equal to 6.26.

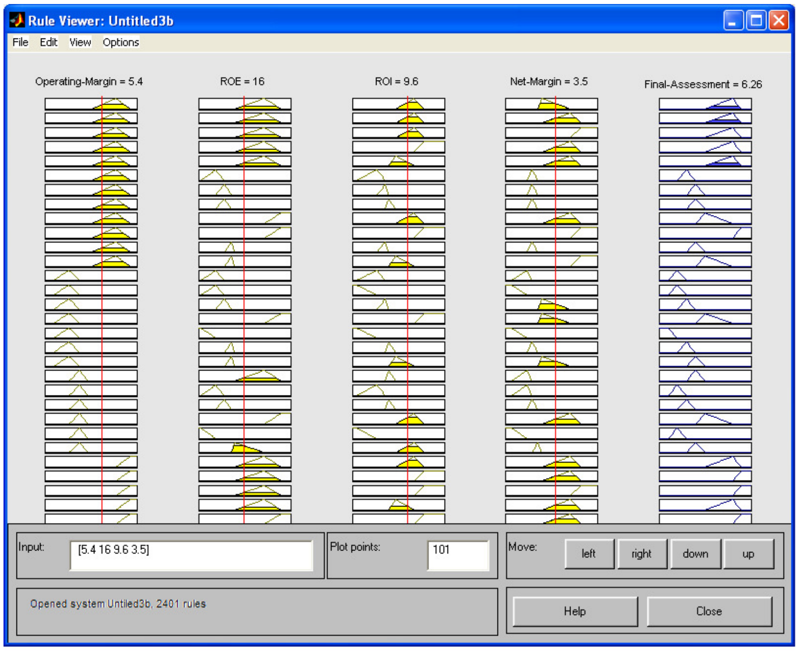


Figure 7 – Discrete values of inputs and outputs

## 6. Empirical evaluation of the paraconsistent and fuzzy models

The proposed models for analysis of company profitability were tested by financial analysts on their capacity to provide answers that are consistent with the objectives for which they were conceived. Among the financial analysts, according to the profile raised in the study, 11 have experience in financial analysis of companies in the food sector. Thus, contact with these ones was realized by asking for their participation in this stage, where four of the analysts agreed to participate. In this form, data on five companies were sent to each analyst. The number of five companies per analyst was stipulated by them according to their availability.

Twenty companies were randomly selected (five per each analyst) from the database. The selection process occurred in the following manner: The companies were listed in classification order according to the *Valor Economico* database ranking and divided into 16 groups of four companies (the last group had three companies). Within each group, the companies were numbered from 1 to 4. A number was drawn up, and the companies falling under this number were selected. In this process, three more companies were missing to complete the total twenty. Another number was drawn up, and the first three were selected. Then, the companies were classified in alphabetical order; the first specialist analyzed the first five companies; the second specialist analyzed from the sixth to the tenth; and, thus, consecutively.

The most relevant profitability ratios were extracted from these 20 companies, and a research tool was built for the analysts to assign quantitative notes between 0 and 10 to each company's profitability. In the referred research tool, the name of the company was excluded, as it could in some way influence the experts' analysis. Table 6 shows the 20 selected companies, the notes assigned by the experts, the notes assigned by the paraconsistent model, the notes assigned by the fuzzy model, and the difference between the notes of the experts and those of the models.

The results of the paraconsistent and fuzzy models are observed in Table 6 in a comparative form, using three methods of defuzzification, in relation to the analyses made by the experts. The paraconsistent model in six companies (E, F, G, I, O, and U), that is, 30% of the companies, assigns a note that is identical to that of the experts. In the fuzzy model, the method Middle of Maxima obtained the highest number of agreements with the experts. This method obtained agreement in four companies (A, C, M, and N) followed by the methods Center of Area and Center of Middle with two agreements each (A and N companies).

The negative divergence of notes assigned by the fuzzy model ranged from -2.32 and -2.85 points, where the paraconsistent model obtained a negative divergence of only -0.50 points. On the other hand, the paraconsistent model obtained the highest positive divergence of 2.00 points, although very close to the divergence obtained by the fuzzy model that ranged between 1.55 and 1.83 points.

Using the average difference and the standard deviation for analyzing the performance of each of the defuzzification methods used in the fuzzy model, it was observed that the Center of Area obtained an average difference of -0.21 points and a standard deviation equal to 0.99 points. Thus, it can be said that in 68% of the realized analyses, it varied between -1.21 and 0.78 points. The method Center of Maxima obtained an average difference that was equal to -0.25 points and a standard deviation of 1.00 points, which means that in 68% of the analyses, the difference was between -1.25 and 0.75 points. The method Middle of Maxima obtained an average difference of -0.44 points and a standard deviation of 1.07 points; thus, it can be stated that in 68% of the analyses, the difference varied between -1.51 and 0.63 points. The paraconsistent model obtained a positive average difference that was equal to 0.45 points and a standard deviation which was equal to 0.69 points; thus, it can be stated that in 68% of the analyses, the difference was between -0.24 and 1.14 points.

Table 6 – Comparison between the models and the experts

| **Company** | **Experts' opinion** | **Paraconsistent model** | | **Fuzzy model** | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $\mu_R$ *10 | Differ. | C-o-A | Differ. | C-o-M | Differ. | M-o-M | Differ. |
| A | 3.00 | 3.5 | 0.5 | 3.00 | 0.00 | 3.00 | 0.00 | 3.00 | 0.00 |
| B | 10.00 | 9.5 | -0.5 | 9.16 | 0.84 | 9.20 | 0.80 | 9.30 | 0.70 |
| C | 5.00 | 5.5 | 0.5 | 5.67 | -0.67 | 5.50 | -0.50 | 5.00 | 0.00 |
| D | 6.00 | 6.5 | 0.5 | 6.23 | -0.23 | 6.20 | -0.20 | 5.75 | 0.25 |
| E | 5.00 | 5.0 | 0.0 | 5.69 | -0.69 | 5.60 | -0.60 | 5.20 | -0.20 |
| F | 1.00 | 1.0 | 0.0 | 0.75 | 0.25 | 0.70 | 0.30 | 0.50 | 0.50 |
| G | 2.00 | 2.0 | 0.0 | 1.14 | 0.86 | 1.00 | 1.00 | 0.70 | 1.30 |
| H | 7.00 | 9.0 | 2.0 | 7.25 | -0.25 | 7.30 | -0.30 | 7.60 | -0.60 |
| I | 5.00 | 5.0 | 0.0 | 5.67 | -0.67 | 5.60 | -0.60 | 5.10 | -0.10 |
| J | 8.00 | 7.5 | -0.5 | 5.68 | 2.32 | 5.60 | 2.40 | 5.15 | 2.85 |
| L | 4.00 | 6.0 | 2.0 | 5.82 | -1.82 | 5.80 | -1.80 | 5.55 | -1.55 |
| M | 4.00 | 4.5 | 0.5 | 3.62 | 0.38 | 3.70 | 0.30 | 4.00 | 0.00 |
| N | 3.00 | 3.5 | 0.5 | 3.00 | 0.00 | 3.00 | 0.00 | 3.00 | 0.00 |
| O | 5.00 | 5.0 | 0.0 | 4.00 | 1.00 | 4.00 | 1.00 | 4.00 | 1.00 |
| P | 7.00 | 7.5 | 0.5 | 6.34 | 0.66 | 6.20 | 0.80 | 5.50 | 1.50 |
| Q | 3.00 | 3.5 | 0.5 | 4.00 | -1.00 | 4.00 | -1.00 | 4.00 | -1.00 |
| R | 7.00 | 8.5 | 1.5 | 5.74 | 1.26 | 5.70 | 1.30 | 5.00 | 2.00 |
| S | 9.00 | 9.5 | 0.5 | 9.13 | -0.13 | 9.10 | -0.10 | 9.25 | -0.25 |
| T | 1.00 | 1.5 | 0.5 | 0.79 | 0.21 | 0.80 | 0.20 | 0.60 | 0.40 |
| U | 6.00 | 6.0 | 0.0 | 4.00 | 2.00 | 4.00 | 2.00 | 4.00 | 2.00 |
| **Negative difference** | | | -0.50 | | -2.32 | | -2.40 | | -2.85 |
| **Positive difference** | | | 2.00 | | 1.82 | | 1.80 | | 1.55 |
| **Average difference** | | | 0.45 | | -0.21 | | -0.25 | | -0.44 |
| **Standard deviation** | | | 0.69 | | 0.99 | | 1.00 | | 1.07 |

## 7. Concluding remarks

The purpose of this study was to apply the two models to conduct an analysis of a company's profitability using approaches based on the paraconsistent annotated evidential logic and the fuzzy logic. For simulation and testing of the paraconsistent model's functioning, specific tool was developed, and the fuzzy model was implemented with specific tool. The operational validation of the models was realized through interviews that were applied by the experts, as well as by using a database for processing and a comparative analysis of the results realized by the experts. The topics selected based on this study as well as suggestions are as follows:

The evidence collected during the applied tests allows an acceptance of the proposed models, as well as shows that the paraconsistent model obtained higher results compared with the fuzzy model. Both conceived models contemplate the ambiguous and uncertain aspects inherent to the analysis of a company's profitability. It is also concluded that the models offered solution to the problems related to the financial analysis of companies through most appropriate analysis in a non-trivial form.

The models were shown to be totally operational and, therefore, applicable to the activity of companies' profitability analysis. The potential of the application of extended and improved versions of the models in question and other quantitative methods can be taken for signalization of unvoluntary deviations of the analysts in measuring company profitability, or even in identifying fraud occurrences.

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