Bank Creditworthiness Using Fuzzy Systems:
A Comparison with a Classical Analysis Approach

By

Gisella Facchinetti*
Stefano Bordoni**
Giovanni Mastroleo***

April 2000

Università degli Studi di Modena e Reggio Emilia
Dipartimento di Economia Politica
Via Berengario, 51
41100 Modena (Italy)
* e-mail: facchinetti@unimo.it
** e-mail: bordoni@unimo.it
*** e-mail: mastroleo@unimo.it
Abstract

In the last decades, the problem of measuring credit risk has been the object of analysis by researchers. Financial organisations, banks, credit institutions, clients, suppliers, etc., need prediction of failure for firms in which they have any kind of interest. The most widely used methods are based on econometric analysis, which estimates the probability of clients' insolvency (default). Often they do not show a satisfactory ability to discriminate between creditworthy and non-creditworthy clients. This situation is often due to the use of unrealistic assumptions of statistical hypotheses and to the complete lack of communication with the decision makers. The aim of this research is to overcome these limitations. In this paper a fuzzy logic approach, an alternative method, is used to provide a system able to evaluate bank creditworthiness. The financial data of 400 clients, offered by the Bank of Sardinia\(^2\) and relating to small businesses are used to compare the econometric and fuzzy approaches\(^3\). The results are really interesting and show how the fuzzy system may offer better solutions to the problem of bank creditworthiness.

1. Introduction

In the recent years there has been an increase of bank competition in the activity of credit grants. This induces banks to assume higher risks in order not to lose clients and money. It thus becomes all the more necessary to use subtler tools as decision supports. These problems are typical not only of banks but also of financial organisations, credit institutions, clients, suppliers, insurance, which need predictions of credibility for firms or persons in which they have any kind of interest.

In the last decades, the problem of measuring of credit risk has been the object of

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1 This research work is financed by Modena University (project “Fuzzy logic prototype of a scoring for bank creditworthiness” 1999).
2 We thank the Bank of Sardinia for the data offered and for all the time their experts dedicated us. In particular, we thank again the Bank’s President, Prof. Sebastiano Brusco, who believed in this research and supported us.
3 The fuzzy system is built with the support of “fuzzyTECH” by INFORM.
analysis by researchers and credit operators. The more widely used methods are based on econometric models, which estimate the probability of clients’ insolvency (default) and are used in the screening and monitoring phases. They produce a score and are based on accounts and financial data of the client requesting money. The analysis results in a positive or negative client judgement. Among these methods are “linear probability” analysis, logit [8] and probit analysis [14] and discriminant analysis [1]. In particular, Altman’s Z-score has, in the past, given some good performances. Recent studies have shown the disadvantages of this approach, [4], [6] and to provide a higher level of prediction accuracy new methods have been proposed. They use methodologies like neural networks [2], expert system [7], and fuzzy logic. [9],[12]. These methodologies fall under the rubric of “soft computing”.

In this paper a fuzzy logic system is built for evaluation of bank creditworthiness, and the results are compared with what is obtained by classic methods such as a multivariate approach. This is the first paper in which two such different methods are compared on the same data and even though not all the power of the fuzzy inference system is exploited, the results obtained show that this new approach offers a better performance than the classic one.

2. The soft computing approach

Loﬁ A. Zadeh in the foreword of [9] writes: “The heart of the applications of quantitative methods to business and finance is decision analysis. The pioneer searchers of this field are mathematicians like von Neumann, Morgenstern, Wald. They thought that it is possible to construct a theory of decision-making that has an axiomatic foundation. With the passage of time and accumulation of experience, it is becoming increasingly clear that the real-world decision-making is much too complex, too uncertain, and too imprecise to lend itself to precise, prescriptive analysis. It is this realization that underlies the rapidly growing shift from conventional techniques of decision analysis to techniques based on fuzzy logic, neurocomputing, genetic computing, more in general “Soft Computing”. Soft Computing is a consortium of methodologies that are tolerant of imprecision, uncertainty, and partial truth.”

These methodologies are complementary rather than competitive. It is often useful to employ them in combination, giving rise to “hybrid systems”, like neurofuzzy computing. They have become very widespread, for two principal reasons. The first is that they are more effective in dealing with problems in which the dependencies between variables are too complex or too ill defined to admit a characterization by models, which are linear or quadratic. Such problems are the norm in economics and financial fields. The second is the progress in electronic data processing. Till a few decades ago with the first batch processing systems, users had to wait a long time before they got the output of their computations. The introduction of time-sharing systems has given users the benefit of accessing their
data in real time. Although, engineering applications of soft computing have gained much more public interest than business and financial applications, an even larger potential exists here.

The development in computer and information sciences has made the world of business and finance a magnet for methodologies that can exploit the ability of modern information systems to process huge volumes of data at high speed and with high reliability. Fuzzy logic has the benefit of enabling software to make human-like decisions. Zadeh himself, founder of fuzzy logic, contends that a computer cannot solve problems as well as human experts unless it is able to think in the characteristic manner of human beings [9]. Enabling software to make human-like decisions yields many benefits:

- For decisions that need to be made in large quantities, such as buy or sell decision in a stock-trading system, automation of decision-making greatly expands capacity at low cost.
- Complex decision-making processes become transparent and can thus be explicitly evaluated and optimized.
- The experience of more than one single person can be agglomerated into one system.

Fuzzy logic, introduced by Lofti Zadeh [10], has attracted the attention of many researchers, who have contributed to its development and applications to language, automata theory, and learning systems. In the early seventies, however, the introduction of linguistic variable and fuzzy if-then rules opened the door to many other applications like control theory. In the absence of complete and precise information, fuzzy logic and fuzzy sets are effective tools for modelling complex business, finance and management systems. The subjective judgement of experts who have used fuzzy logic techniques produces better results than the objective manipulation of inexact data [3]. Fuzzy logic exceeds the inability of classical logic to capture the vague language, common sense reasoning used by people every day. It deals with objects that have all the possible grades of truth between “yes” and “no”.

A fuzzy expert system applied to decision-making problems is defined in the same way as ordinary expert systems, but here the methods of fuzzy logic are applied. Fuzzy expert systems use fuzzy data, fuzzy rules, and fuzzy inference, in addition to the standard ones implemented in the ordinary expert systems. The following are the main stages of a fuzzy system design. [5]

1. Identifying the problem and choosing the type of fuzzy system which best suits the requirements of the problem. A modular system can be designed consisting of several fuzzy modules linked together. A modular approach, if applicable, may greatly simplify the design of the whole system, dramatically reduce its complexity and make it more comprehensible.
2. Defining the input and output variables, their linguistic attributes (fuzzy values) and their membership function (fuzzification of input and output).
3. Articulating the set of heuristic fuzzy rules. (IF-THEN rules).
4. Choosing the fuzzy inference method (selection of aggregation operators for precondition and conclusion).
5. Translation of the fuzzy output in a crisp value (defuzzification methods).
6. Experimenting with the fuzzy system prototype; drawing the goal function between input and output fuzzy variables; changing membership functions and fuzzy rules if necessary; tuning the fuzzy system; validation of the results.

3. The creditworthiness expert system

The building of a fuzzy expert system has two main problems: the fuzzification and the construction of blocks of fuzzy rules. These two steps are obtained in different ways. One approach is the interview with experts of the problem. Another is the use of the methods of machine-learning, neural networks and genetic algorithms to learn membership functions and fuzzy rules. The two approaches are quite different. The first approach does not use the past history of the problem and allows a real contact with the experts who may permit all the experience matured in years of work in that field to enter the study. The second is based only on the past data and transfers for the future the same structure as the past.

The aim of this paper is to produce a method to evaluate the creditworthiness of a client and to forecast its good performance. Usually the historical data offered by the bank are relative only to credits granted (we have no information about clients who have not been granted credit) and those granted several years previously. For to have complete historical data it is necessary to analyse positions that have started and ended. For these reasons, we have preferred the first approach. We can formalize the steps in the following manner.

For each linguistic variable, input $x_i (i=1...m)$ and output $y$, we must fix the one's range of variability $U_i$ and $V_i$.

$$\forall i, (i=1...m), n_i$$ is the number of the linguistic attributes of the variable $x_i$ and $\hat{n} = \max_{i\in[1,m]} n_i$, we define the set

$$A' = \{A'_1, A'_2, ..., A'_j, ..., A'_{\hat{n}}\}$$

where $\forall j_i \in [1, n_i], \forall n_j \in [1, \hat{n}]$ $A'_j$ are the fuzzy numbers that describe the linguistic attributes of the input variable $x_i$.

In the same way we define the set

$$B = \{B_1, B_2, ..., B_k, ..., B_{\hat{b}}\}$$
where \( \forall k \in [1, r] \) \( B_k \) are the fuzzy numbers which describe the linguistic attributes the output variable \( y \).

With every elements of \( A^i \) and \( B \) a membership function

\[
\mu_{A^i_k}(x): U_i \rightarrow [0,1] \quad \text{and} \quad \mu_{B_k}: V \rightarrow [0,1]
\]

is associated.

The elements of \( A^i \) and \( B \) are overlapped in some “grey” zones in which they are not easy to characterize precisely. Most things in the world do not fall clearly into one crisp category or another. Experts who use abstraction as a way of simplifying the problem identify the location of these “grey” zones.

The choice of the slopes of the elements of \( A^i \) and \( B \) is a mathematical translation of what the experts think about the single terms.

The second step is the construction of block rules.

We define the set \( \Psi \) of \( h \) fuzzy rules, where \( h \leq \prod_{i=1}^{m} n_i \), \( \forall \ n_i \in [1, n] \) of this type:

\[
\forall i \in [1,m], \ \forall \ j_i \in [1, n_i], \ \forall k \in [1, r] \\
\text{IF } (x_1 \text{ is } A_{j_1}^i) \otimes (x_2 \text{ is } A_{j_2}^i) \otimes \ldots \otimes (x_m \text{ is } A_{j_m}^i) \text{ THEN } (y \text{ is } B_k),
\]

\[ (5) \quad \text{and} \quad \text{(6)} \]

The relation (5) is called “precondition” and the symbol \( \otimes \) represents one of the possible aggregation operators. The ones most widely used in practical applications are the MIN and the MAX operators, or a convex combination of them

\[
\gamma \text{MIN} + (1-\gamma) \text{MAX}
\]

with \( \gamma \in [0,1] \)

where \( \gamma \in [0,1] \) could be interpreted as the “degree of positive compensation”.

If, instead of Min and Max, other t-norms or conorms are used, “negative”, or “positive” compensation will occur for different value of \( \gamma \). One can also choose different ways of linking the “and” with the “or”. If we start with a multiplicative coupling, we define:

\[
\mu_{\mathcal{A} \Theta \mathcal{B}} = \mu_{\mathcal{A} \land \mathcal{B}}^{1-\gamma} \ast \mu_{\mathcal{A} \lor \mathcal{B}}^\gamma
\]

with \( \gamma \in [0,1] \)

where \( \mu_{\mathcal{A} \Theta \mathcal{B}} \) is the membership of the aggregated set \( \mathcal{A} \Theta \mathcal{B} \), and \( \mu_{\mathcal{A} \land \mathcal{B}} \) and \( \mu_{\mathcal{A} \lor \mathcal{B}} \) are general memberships of the intersection and the union.
If the intersection and the union are algebraically represented by the product and the algebraic sum, we obtain the $\cdot$-operator \[ \mu = \left( \prod_i \mu_i \right)^{(1-\gamma)} \star \left( 1 - \prod_i (1 - \mu_i) \right)^{\gamma} \] (7)

If $\gamma = 0$, then:

$$\mu_\cap = \prod_i \mu_i$$

if $\gamma = 1$, then:

$$\mu_\cup = 1 - \prod_i (1 - \mu_i)$$

The $\cdot$-operator is pointwise injective, continuous, monotonous and commutative.

In later empirical studies it was shown that this aggregator concept represents the human decision process more accurately than the others. \[ \dagger \]

When we have decided what type of precondition aggregator $\otimes$ to use, we begin with the introduction of the inputs values $x_i^0 \ \forall i \in [1,m]$. This fact produces that only a subset $\Omega$ of the rules set $\Psi$ is involved. The elements of this subset are the rules in which are present in the IF part the fuzzy numbers $A_i^j$ that have $x_i^0$ in its domain. Every element of $\Omega$ produces a numerical values of this type:

$$\alpha_{i_1, i_2, \ldots, i_m} = \mu_{A_{i_1}}(x_{i_1}^0) \otimes \mu_{A_{i_2}}(x_{i_2}^0) \otimes \cdots \mu_{A_{i_m}}(x_{i_m}^0) \tag{8}$$

This value produces the strength of the rule involved and gives its level of “firing” (activation). At this step we must check, in $\Omega$, what are the $B_k$ involved.

The “conclusion” (6) is obtained by:

$$\left[ \mu_{A_{i_1}}(x_{i_1}^0) \otimes \mu_{A_{i_2}}(x_{i_2}^0) \otimes \cdots \mu_{A_{i_m}}(x_{i_m}^0) \right] \land \mu_{B_k}(y) \tag{9}$$

The result of (9) is a fuzzy set $\tilde{B}_k$ obtained by $B_k$ cut off at the level $\alpha_{i_1, i_2, \ldots, i_m}$.

When the same $B_k$ is affected by different rules, we must choose what will be the level of cut off to consider. We have several methods available. The choice depends on the type of application. The most used are the MAX and the BSUM method. The MAX has the meaning of keeping as “winner” the strongest rule, in
the sense that if a rule is "firing" more than one time, the result is the maximum level of firing. In the BSUM case, all the firing degree is considered and the final result is the sum of the different level of activation (not more than one). The aggregation of the control outputs produces a fuzzy set, with membership function $\mu_{\text{agg}}(y)$, obtained by the union of the different $\tilde{B}_k$. We now have a result of the fuzzy inference system, which is a fuzzy replay. We need to return to a "crisp" value, a step that is called "defuzzification". This operation produces a "crisp" action $y$ that adequately represents the output fuzzy set defined by its membership function $\mu_{\text{agg}}(y)$. There is no single way to perform this operation. To select the proper method, it's necessary to understand the linguistic meaning that underlies the defuzzification process. Two of these different linguistic meanings are of practical importance: the "best compromise" and the "most plausible result". One of the first type methods is the Centre of Area (CoA) that produces the abscissa of the centre of gravity of the fuzzy output set

$$y = \frac{\int y \mu_{\text{agg}}(y) dy}{\int \mu_{\text{agg}}(y) dy}$$

One of the methods of the second type is the "Mean of Maximum" (MoM) that, rather then balancing out the different inference results, selects the typical value of the terms that is most valid. [9]

4. Classical econometric methods

At the end of 1998, the Bank of Sardinia ordered a study of a system of Small Business Scoring from a well-known software house. This product should enable the criteria of evaluation for the screening moment to be automatic. Here, we present the results of their study. Before passing to the fuzzy approach, we used the same approach as theirs, in order to be sure that the initial data, offered by the bank, were the same. This approach uses a classical discriminant and logistic analysis, but we were requested by the Bank not to specify the exact model used. The study begins with the analysis of the bank data. This entails reducing the number of clients and identifying some statistical indicators that led to a reduction of the variables. A scorecard is constructed in which, for every selected variable, the range of variation is decided. This range is divided into some intervals and a score value is assigned to each interval. The final score is obtained by the sum of the values that every client obtained using the selected variables. As a last step, some measurements of the discriminant power of the model are presented.
The target is the type of Small Business that, for the Bank of Sardinia, is:

- Individual firms, personal society or capital society with a turnover of less than 1.5 million Ecu.
- Credit up to 100,000 ECU

4.1. Classical Environment Analysis

- Population of reference.

After selection of the 8020 initial cases, 2557 positions are analysed.

- Performance definition

The clients' performance at the end of 1998 is the following:

<table>
<thead>
<tr>
<th>Situation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;Bad&quot; Customers</td>
<td>nonperforming, nonaccrual, bad loans, good</td>
</tr>
<tr>
<td>&quot;Good&quot; Customers</td>
<td></td>
</tr>
<tr>
<td>Bad rate</td>
<td>100*Bad/(Bad+Good)</td>
</tr>
</tbody>
</table>

- Selection of the sample

From the population they chose by lot a random sample of 26% of the total population which comprised 330 good and 330 bad clients. The documents offered by bank were not completed for all the clients identified by sampling, so they considered only 284 good and 199 bad clients.

4.2. Data analysis report

The data analysis report studies the trend of the risk of the variables that are eligible to enter the score grid. For every variable used by the bank for clients' creditworthiness (about 130), a table was constructed in which two statistics are produced:

- Bad rate: measures the risk and represents the percentage of bad clients out of the total.
- Power statistic: measures the level of separation between bad and good clients. Large values of the power statistic identify the variables that are predictive in the identification of the bad clients.

Some variables are presented in a collected form. These clusters are made by using their experience and to satisfy the following objectives:
• To collect classes with similar bad rate.
• To smooth, where possible, the risk trend and remove statistical anomalies.
• To use intuition and logic in the clustering of the variables.

4.3. The evaluation of the variables

The 130 variables that the bank uses for client creditworthiness were analyzed. Using the two indexes previously described, 22 most predictive ones were obtained. Among these, nine were considered most interesting. There are no explanations for this choice. The selected variables are:

• Legal structure (type of legal structure of the Company)
• Branch economic activity (line or branch of economic activity)
• Available assets (total available assets: commercial credits + other activities at short run + partner’s withdrawal)
• Total equity (economic wealth + year-end profit and loss picture)
• Number of employees
• Debts at short (debt with suppliers + other short term debts + short-term debts to banks)
• Variation of turnover (\[
\frac{\text{turnover}(t) - \text{turnover}(t-1)}{\text{turnover}(t-1)}*100\]
• Profit and loss (year-end profit and loss picture)
• Risky data base registration (possible position: yes or no)

5. The Fuzzy inference system

The goal of this research is to show the different improvements that a fuzzy inference system may offer in building a score for bank creditworthiness, as compared to the use of a classical scorecard. To reach this result, we built a model for every phase of the development.

The first phase: we used a neuro-fuzzy approach to reproduce the classic scorecard results. For the training of the network we used all the disposable knowledge, as it is typical of the hybrid approach.

The experts have decided the inputs aggregation schema and the numbers of the linguistic attributes. As we have nine input variables, we have built three aggregation blocks, with three variables each. The system produces three intermediate variables \(i_1,i_2,i_3\) that are outputs for the first rule-blocks and inputs for the next rule-block. The result obtained is a fuzzy algorithm that approximates the scorecard results but has at its core some expert knowledge.

The second phase: we optimised the first system erasing the rules with Degree of Support (DoS) near zero. The back testing on the data with this second system produced better results in comparison to the scorecard results.

The third phase: we built a new fuzzy system, adding four new inputs. This
decision was due to the participation of the experts. They decided that the nine variables proposed by the classical approach were not sufficient to describe the problem. They suggested four new variables, their aggregation, their fuzzification and the relative rule block.

- Cashflow (year-end profit and loss + depreciation + allocations)
- Financial costs / Turnover (financial charges / turnover)
- Used credit / Granted credits
- ROI ( [turnover ± stocks - raw materials costs - operating costs - wage costs - depreciation - allocations] / Total Assets)

This addition produced the new intermediate output $i_4$, which with the input ROI was been added to $i_1, i_2, i_3$ to build the five new inputs of the system, which produces the final valuation.

In the figure we have the schema of the system as described in the foregoing explanations. This project editor is built with the software “fuzzyTECH” by Inform. On the left we have four groups of three variables each. The first three groups generate the intermediate variables $i_1, i_2, i_3$, the fourth group is made with three of the four new variables and generates the intermediate variable $i_4$. The last variable ROI and the others produce the output Valuation. We have used the MIN operator for the aggregation of the precondition, the BSUM for the conclusion, and CoA for the defuzzification.
6. Compared Result

In order to compare the classical and the fuzzy logic approach, we present the two scores and two indexes of discriminant power of the models, as Maximum Spread and Span Area. The two scores give an evaluation of creditworthiness and offer different levels of "cut-off", that are the thresholds of the scoring under which the bank decide to refuse requests. In the first column are present the score values; in the "Good" Customers column is present the cumulate percentage of Good; the same for the column of "Bad" Customers. The Maximum Spread measures the maximum distance between the cumulated distributions of the "Good" and the "Bad" Customers. Higher this value is and higher the model discriminant capacity is. The Span Area is the area between the same distributions. Even in this case higher values correspond higher model discriminant capacity.

In Tab. 1 there is the classical score and the corresponding Maximum Spread and Span Area. The two values are:

Maximum Spread = 48.20
Span Area = 19.3%

<table>
<thead>
<tr>
<th>Score</th>
<th>&quot;Good&quot; Customers</th>
<th>&quot;Bad&quot; Customers</th>
</tr>
</thead>
<tbody>
<tr>
<td>29</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>31</td>
<td>0.00%</td>
<td>0.50%</td>
</tr>
<tr>
<td>41</td>
<td>0.00%</td>
<td>1.20%</td>
</tr>
<tr>
<td>51</td>
<td>0.00%</td>
<td>2.00%</td>
</tr>
<tr>
<td>61</td>
<td>0.00%</td>
<td>4.50%</td>
</tr>
<tr>
<td>71</td>
<td>0.00%</td>
<td>7.50%</td>
</tr>
<tr>
<td>81</td>
<td>0.00%</td>
<td>12.10%</td>
</tr>
<tr>
<td>91</td>
<td>0.40%</td>
<td>19.10%</td>
</tr>
<tr>
<td>101</td>
<td>4.00%</td>
<td>26.60%</td>
</tr>
<tr>
<td>111</td>
<td>4.20%</td>
<td>34.20%</td>
</tr>
<tr>
<td>121</td>
<td>6.00%</td>
<td>42.20%</td>
</tr>
<tr>
<td>131</td>
<td>10.60%</td>
<td>51.80%</td>
</tr>
<tr>
<td>141</td>
<td>16.50%</td>
<td>61.80%</td>
</tr>
<tr>
<td>151</td>
<td>24.30%</td>
<td>72.50%</td>
</tr>
<tr>
<td>161</td>
<td>31.30%</td>
<td>78.40%</td>
</tr>
<tr>
<td>171</td>
<td>41.20%</td>
<td>86.60%</td>
</tr>
<tr>
<td>181</td>
<td>50.70%</td>
<td>92.00%</td>
</tr>
<tr>
<td>191</td>
<td>59.50%</td>
<td>94.00%</td>
</tr>
<tr>
<td>201</td>
<td>71.10%</td>
<td>99.00%</td>
</tr>
<tr>
<td>211</td>
<td>80.60%</td>
<td>99.50%</td>
</tr>
<tr>
<td>221</td>
<td>86.60%</td>
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<td>231</td>
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<td>100.00%</td>
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<td>241</td>
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<td>100.00%</td>
</tr>
<tr>
<td>251</td>
<td>95.40%</td>
<td>100.00%</td>
</tr>
<tr>
<td>261</td>
<td>97.50%</td>
<td>100.00%</td>
</tr>
<tr>
<td>271</td>
<td>98.60%</td>
<td>100.00%</td>
</tr>
<tr>
<td>281</td>
<td>98.60%</td>
<td>100.00%</td>
</tr>
<tr>
<td>291</td>
<td>98.60%</td>
<td>100.00%</td>
</tr>
<tr>
<td>301</td>
<td>98.60%</td>
<td>100.00%</td>
</tr>
<tr>
<td>303</td>
<td>100.00%</td>
<td>100.00%</td>
</tr>
</tbody>
</table>
In Tab. 2 there is the score obtained with the fuzzy approach. In this case the two indexes are:

\[ \text{Maximum Spread} = 61.81 \]
\[ \text{Span Area} = 43.5\% \]

### Tab. 2

<table>
<thead>
<tr>
<th>Score</th>
<th>&quot;Good&quot; Customers</th>
<th>&quot;Bad&quot; Customers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Customers</td>
<td>Customers</td>
</tr>
<tr>
<td>29</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>31</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>41</td>
<td>0.00%</td>
<td>0.53%</td>
</tr>
<tr>
<td>51</td>
<td>0.00%</td>
<td>1.66%</td>
</tr>
<tr>
<td>71</td>
<td>0.00%</td>
<td>3.19%</td>
</tr>
<tr>
<td>81</td>
<td>0.00%</td>
<td>4.79%</td>
</tr>
<tr>
<td>91</td>
<td>0.00%</td>
<td>6.51%</td>
</tr>
<tr>
<td>101</td>
<td>0.00%</td>
<td>39.36%</td>
</tr>
<tr>
<td>111</td>
<td>0.92%</td>
<td>44.15%</td>
</tr>
<tr>
<td>121</td>
<td>2.29%</td>
<td>56.38%</td>
</tr>
<tr>
<td>131</td>
<td>7.24%</td>
<td>63.30%</td>
</tr>
<tr>
<td>141</td>
<td>12.84%</td>
<td>71.91%</td>
</tr>
<tr>
<td>151</td>
<td>20.04%</td>
<td>82.45%</td>
</tr>
<tr>
<td>161</td>
<td>31.85%</td>
<td>86.70%</td>
</tr>
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<td>171</td>
<td>45.87%</td>
<td>90.96%</td>
</tr>
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<td>181</td>
<td>58.09%</td>
<td>97.67%</td>
</tr>
<tr>
<td>191</td>
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### 7. Conclusion and remarks

In this paper, we propose a fuzzy expert system for bank creditworthiness. Comparison and implementation are performed with classical econometric techniques. The classical approaches and results were proposed to the Bank of Sardinia by a well-known software house. The results obtained show that this fuzzy expert system offers a better measurement of the discriminant power of the model. This happens even if we have not used the real capability of a fuzzy inference system that does not need to reduce the number of variables. Owing to its nature, it has the possibility to work with a great number of inputs. We think that the combination of the strong structure of a fuzzy system with the background knowledge of the decision-makers is a correct way to obtain good results. In addition, this type of method offers other advantages:

1. It offers transparency of classification decisions.
2. It does not use past data for the construction of the scoring.

These two facts are really interesting tools. For the variable fuzzification and the
rule blocks are completely readable at any moment by the users of the system. They may decide to change some of those without destroying the system, but in a very simple way. The past data are used only for tuning of the system, not for building it. In addition, this fact enables a good method of gauging creditworthiness to be constructed even in the absence of sufficient historical data, a situation that not infrequently occurs.

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