Models for Default Risk Analysis Focus on Artificial Neural Networks, Model Comparisons, Hybrid Frameworks

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ABSTRACT. During the last three decades various models have been proposed by the literature to predict the risk of bankruptcy and of firm insolvency.
In this work there is a survey on the methodologies used by the author for the analysis of default risk, taking into account several approaches suggested by the literature.
The focus is to analyse the Artificial Neural Networks as a tool for the study of this problem and to verify the ability of classification of these models.
Finally, an analysis of variables introduced in the Artificial Neural Network models and some considerations about these.

KEYWORDS: Artificial Neural Networks, Hybrid neural network models Expert Systems, Default, Bankruptcy, Rating Systems, Credit scoring models

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INTRODUCTION

This paper is a survey of neural networks and techniques used for the default risk analysis.

The analysis of default risk is very interesting mainly after the agreement of Basel2 in January 2001. In this year the Basel's committee defines the "The New Basel Capital Accord" that is a document where a new regulation about patrimonial requirements of banks.

The aim of this document can be analysed under a three fold perspective:

- A definition of minimal patrimonial requirements;
- The control of Central Banks;
- Market discipline and financial/economic liberalization.

For the first goal the committee sanctions that the banks must elaborate internal rating systems to evaluate the credit risk. This reason induced the researchers to study many analysis systems of risk and default risk for firms.

Moreover, it is necessary to define a clear definition of default otherwise it will be impossible to build an effective model for analysis and forecasting of default.

In the literature a default definition doesn't exist but the need of this is clear to all.

Altman (1993) defines between static and dynamic insolvency: the first one happens when the equity is negative and the second one when the cash flow of firm doesn't exceed the payment on maturity. Also Wruck (1990) defines the financial distress as dynamic Altman definition.

The Standard & Poor's (2003), rating agency, affirms that the default occurs when the debtor is not able to keep his financial commitments, meeting the deadlines.

Today, each financial institution can to decide the default definition to use but, in this way, there isn't the possibility to compare the results and the opinions on the same firms or credits.

In this work, we give some considerations about the models used in the literature for the default analysis. It is a part of a larger project where we study the determinants of insolvency and the better model for the classification of firms on a base of their solvency capacity.

The first section is dedicated to the analysis of methods used in literature for the study of default risk focusing on the Artificial Neural Network methodologies. Then, hybrid Neural Network models will be presented and, finally, in the section 4, the variables to be introduced in the network will be studied.

1. A SURVEY OF DEFAULT RISK METHODOLOGIES

In the literature there are many classification ways for the analysis of default risk. In this se ction, we analyse three types of models for the credit risk measurement (Georgakopoulos, 2004):

1. *The traditional models*. These models estimate the default probability (PD) rather than the losses related to default event (LGD: loss given default[1]). These methodologies don't consider the downgrades and upgrades in credit quality that are studied by market models, but they analyse the "failure" like the bankruptcy, the default or liquidation.
2. *Modern credit risk measurement methodologies*. These methods are two alternative classes of models respect the relationship with the finance literature.
3. *Proprietary credit risk measurement approaches.* These are models built by the financial institution to forecast the default of firms and their solvency.

1.1 Traditional models

The three models used for the default probability assessment are the expert systems, the rating systems and the credit scoring models.

The first ones take into account decision trees, genetic algorithms, fuzzy logic methods and artificial neural network models. For neural networks a section is dedicated because these are the most used tools in the last decades.

The rating systems are the second models

[1] LGD (Loss Given Default): is the proportion of exposure that is lost.

analysed. These techniques give a score to each firm considered and this score depend to the default risk. In this way, the goal of this system is the definition of default probability.

The last methodologies are the credit scoring model where the most famous is the Z-score analysis of Altman (1968). This technique finds a z-level that distinguishes the firms between failed and not failed one.

1.1.1 Expert Systems

The bankers use expert systems to assess credit quality. Particularly, they introduce different variables like Character (reputation), Capital (leverage), Capacity (earnings volatility), Collateral and macroeconomic variables to evaluate the economic cycle and the macroeconomic conditions.

Very interesting expert systems are artificial neural networks that will be discussed below.

The other models used are genetic algorithms, decision trees and fuzzy logic methodologies.

In the work of Varetto (1998) Decision Trees and Genetic Algorithms are used to discriminate between failed and not failed firms.

The *Decision Tree* model is a system allowing to create a classification of considered elements on a base of their determinant variables. In the paper of Varetto firms are discriminated through the financial framework variable. This is the most important determinant of default. The output of this methodology is a decision tree like that below (fig.1).

The tree before is an example of model result where there are the analysis of firms analysed in the sample. From this tree it is possible to see that in the considered sample there are two firms with robust financial framework. The firms with mean financial framework are one with good liquidity and the other one with scarce one whereas with fragile financial framework there are one firm with high profitability, two with modest one and one with insufficient profitability.

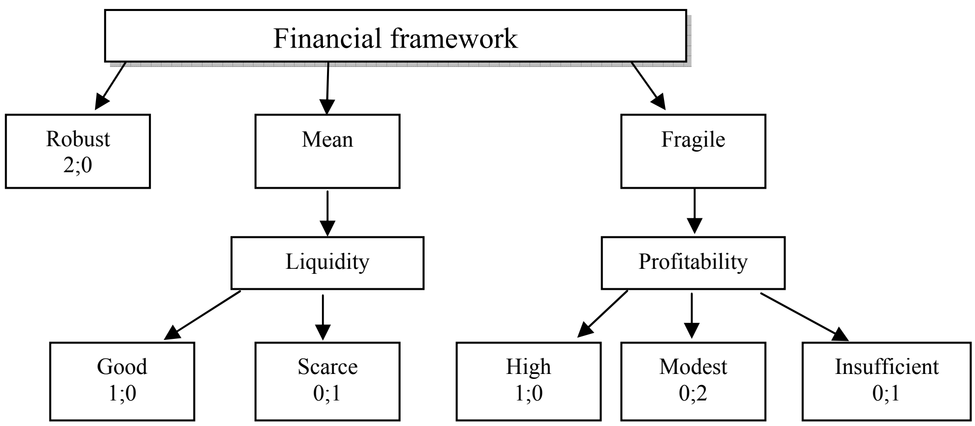
From this we see that four firm are healthy (robust, good and high) and four are odd (scarce, modest and insufficient).

The results can be simplified "pruning the tree". This step is necessary when the considered reality is complex.

At the end, analysing the result dependence from the selection criterion of variables based on the entropy, the indexes below are used:

- Gini's index;
- Herfindal's index;
- Breinman's Twoing-rule (Breiman L. et al., 1984).

Figure 1: Decision Tree



Source: Varetto, april 1998

The Decision Trees aren't expensive models and haven't strong methodological hypothesis but the optimum obtained is local and not global.

Another weakness of this technique is the dichotomous result and the impossibility of multiple results.

The *Genetic Algorithm* (Varetto, 1998) represents a powerful tool of optimisation. The AG, developed by Holland in the decade of 1960, is inspired by the principles of the Darwin's natural evolution. The principles processes are the genetic selection and the reproduction.

The first identifies which population elements survive reproducing and thereby it means the genetic recombination.

The genetic mutation introduces other changes happening rarely on the genes; hence the reproduction mechanism with genetic recombination determines a swifter evolutive process respect to simple mutation.

The selective process is based on the individual ability to adequate at needs imposed by the external world: the "most adapt" survives. In the evaluation concept, there is the implicit idea of specie improvement respect to the generations below.

The fundamental AG's operators are.

- The *selection* and the *reproduction*. The first is made with a help of a function (fitness) evaluating the people adequateness. During the reproduction it happens the process of:
- *Genetic recombination* (*crossover*): the genes of two individuals selected for the reproduction are exchanged so that the population evolves and allows the exploration of new space pieces.
- The *mutation* is a process interesting the crossover and it happens with low probability to not destroy the genetic property cumulated in the precedent selections. Hence the people are more varied and it is able to evolve.

The steps of AG's procedure are:

1. It creates randomly the initial population of individuals (genomes),
2. For each individual, it calculates the fitness function (the goodness of hypothetic solutions);
3. It calculates the homogeneity degree of all population (bias);
4. It sorts the individuals on a base of their fitness and it selects the ablest generating the following population;
5. It generates the following population on a base of to the reproduction of new individuals starting to those selected in the precedent population;
6. In the new population, it repeats the sequence starting from the second step.

For the default risk problem, the AG is used:

- To generate linear functions;
- To generate scores on rules based.

The Genetic Algorithms start from linear optimized functions independent from normality hypothesis and this is a strong strength of this model. Nevertheless, the results aren't very exact and the methodology is not too easy to build.

Another methodology very interesting is the *Fuzzy Logic* method (Mileno). The model must be created for a specific credit institute. Using the fuzzy logic, it's possible to take into account the characteristics of the credit applicant, creating several systems, taking care the retail or corporate applicants.

There are 6 steps:

- *Variables definition*. The selected indexes are those important for the default risk definition. In this method it is possible to add qualitative variables as the entrepreneurship ability, the industrial relationship, the market visibility, the contractual policy with the customers.
  At this point, it is necessary to create a decision tree to cluster the variables into homogeneous groups on a base of the economic relationship.
- *The fuzzy logic applied to variables selected*. Inputs and outputs are transformed in languages variables through the language attributes (labels) and through the fuzzy set assignments to each inputs and outputs.
  For each variable it is necessary to locate a range. (Mamdami, Assilian, 1975) to assign some languages assessments "good" or "sufficient" to range of ROI or current liquidity values.
  At this point, it is necessary to define the membership functions showing the proximity degree between the ROI value and the labels.

The choice of function is context-dependent and it is just the analyst who judges. This step is very ticklist since the effected choice will determinate the activation degree of rules affecting the output results.

- *Determination of rules*. This step is dedicated to rules determination for establishing the model strategy. I.e. considering this rule:

IF x is A_i AND y is B_j THEN z is C_{ij}

Given A and B, the rule number to manage the decisional process is *mxn*, where n and m are the variable label number. At this point, it is the economic experience that will determinate the value combinations between inputs and outputs:

- IF ROI is low AND LIQUIDITY is low THEN RATING is low;
- IF ROI is low AND LIQUIDITY is medium THEN RATING is low;
- IF ROI is low AND LIQUIDITY is high THEN RATING is medium;
- IF ROI is medium AND LIQUIDITY is low THEN RATING is medium;
- IF ROI is medium AND LIQUIDITY is medium THEN RATING is high;
- IF ROI is medium AND LIQUIDITY is high THEN RATING is high;
- IF ROI is high AND LIQUIDITY is low THEN RATING is medium;
- IF ROI is high AND LIQUIDITY is medium THEN RATING is medium;
- IF ROI is high AND LIQUIDITY is low THEN RATING is high.

- *Choice of aggregation procedure*. In this step, it makes an assessment of results and for achieving this goal it uses the Mandani procedure.
- *Data inference*. Given two values of ROI and of current liquidity, these are inserted in the membership function plots and thereby it calculates if these values satisfy the expressed concepts of labels.
- *Result decodification*. It calculates the maximum between the rules used in the model. The output must be "defuzzyfied" to compare it with the initial input values. For this conversion it uses the centroid or the maximum mean methods.

The output model is a rating to insert into a merit class system better defined.

The Fuzzy Logic is a very good technique for representing the complex reality but the rules are created for a specific problem and these are not objective.

The methodology isn't general and isn't able to solve each problem.

1.1.2 Survey on Artificial Neural Networks[2]

About artificial neural networks we make a specific analysis because these are tools most used recently and ours next researches will be based on these techniques.

A neural network is a set of processing units (neurons) linked through connexions.

The figure below (fig.2) shows what a neuron is.

Each i unit is represented by its activation state x_i propagating to other neurons through connexions w_i that slows down or accelerates the signal passage.

When the activity states reach at a particular unit, these are jointed in an only value expressing the total quantity of signal reached: if this exceeds a determined threshold (related to this neuron), then this unit is activated, otherwise inhibited.

In the artificial neuron the activation state x_i is a number value and the connexions w_i are mathematical weights.

The only value of total activation is the linear combination of activation states x_i for correspondent weights w_i.

The net activation state is equal to the total activation state minus the threshold value. The net state is elaborated by a non linear function f (.) and the output value y is the activation state of single neuron.

There are neurons receiving signal x from the external environment (input units or input layer), they propagate the signal through w connexions to other internal units (hidden units or hidden layers) that elaborate sending the signal, through other w connexions, to the units special-

[2] For a deeper technical overview about Artificial Neural Networks see: Haykin S., Neural Networks: a comprehensive foundation, Prentice Hall, 1999.

ized in the signal communication (output units or output layer).

The activation state of input units is determined by the external, whereas the output activation state is red by the external environment.

The connexion links have a feed forward framework, that is, the signal can be propagated only one direction.

The mathematical weights have an important role because they determine the connexions and because they represent what the system knows.

The figure 3 represents the neural network used and the connexions

The input units have connexions starting but not in arriving, contrary to, the output neurons have connexions arriving and not starting.

The hidden units have connexions arriving from the input layer and starting to the output neurons and this layer don't have relationships with the external environment.

This neural network architecture works in this way:

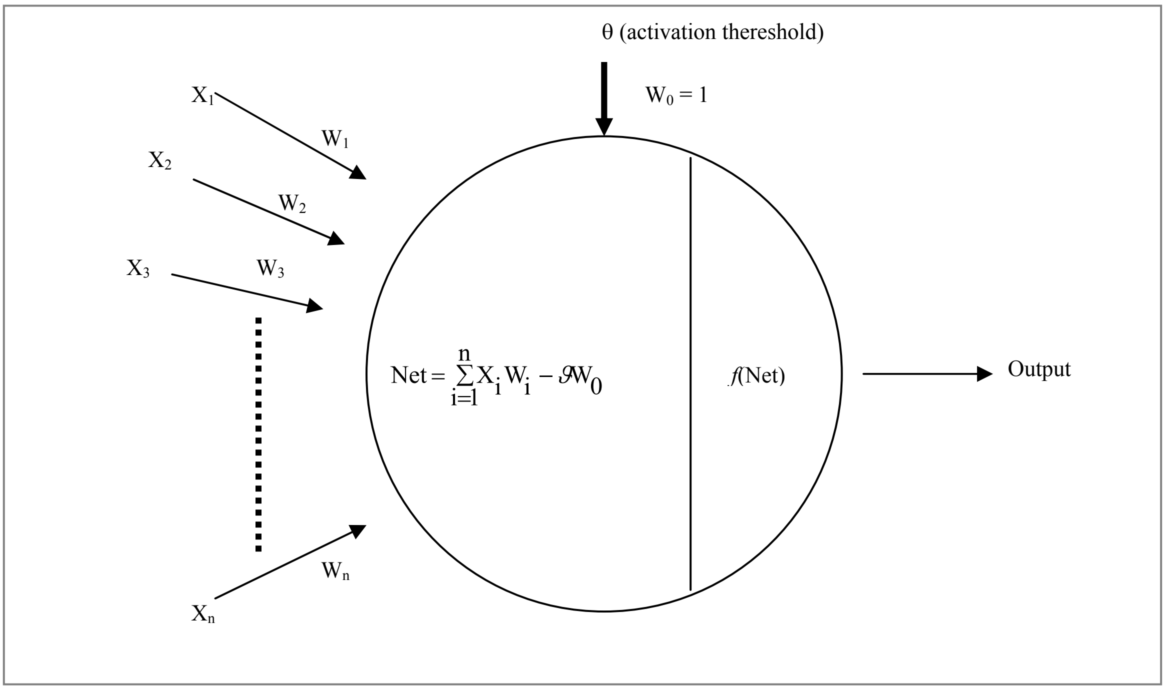
- In the input layer, balance sheet data are inserted;
- In the hidden layer, it calculates the activation state of each neurons;
- At the end, the output units express a result easy to interpret.

The network is able to generate a good answer (output unit) because it has a training phase.

This step is regulated by training laws fixing rules for updating the network weights. There are two types of neural network training:

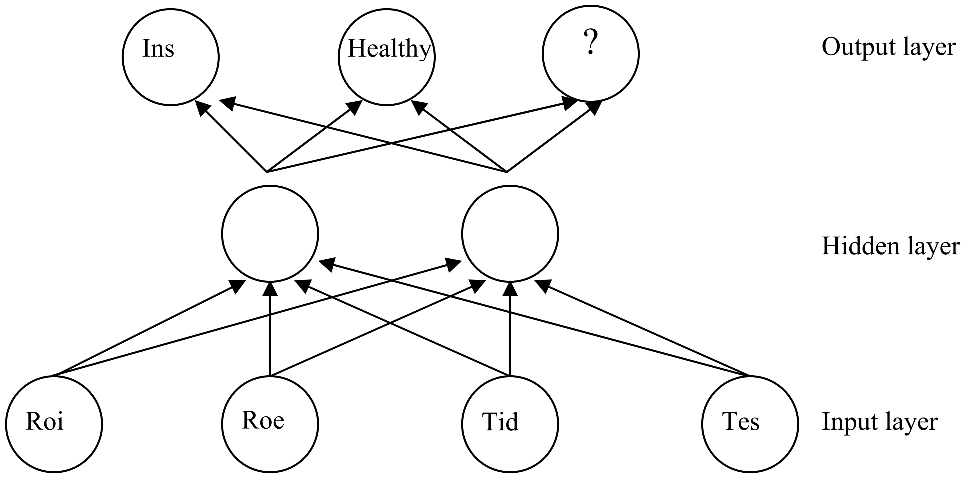
- *Supervised training*: the current output is compared to the desired one (target). The weights are adjusted for minimizing the error between the current output and the target.
- *Unsupervised output*: there are only the inputs and there isn't output information. The network self-organizes with the connexion weights calculated through the Kohonen, Hebbian and Grossemberg training rule.

Figure 2: The neuron of artificial neural network



Source: Chilanti, 1993

Figure 3: The neural network layers



Roi=Return on Investment; Roe=Return on Equity, Tind=Leverage, Tes=Tresury margin.

Source: Chilanti, 1993

In the paper of Chilanti (1993), the sample used is represented by north-Italia limited liability companies and public companies extracted by Chamber of Commerce in the 1986.

The results of this paper are the neural network model is able to generalize and classify the firms on a base of to the input variables.

In this way, these are good tools to analyse the default risk and the determinant of this.

In the study of Abid and Zouari nine neural network models[3] are created considering:

- The impact of the time varying information structure prior the distressed situation using first, independent annual financial ratios (four models) and second, different panel data sets (three models);
- The influence of time varying probability estimates of financial distress in panel data set (two models);
- The goal achieved is it isn't necessary having complex neural network architecture to predict the firm bankruptcy. Moreover, the forecasting neural network capability is better when more the predictability horizon is shorter and the input information is more recent.

The data set used for this research is based on financial statement data[4] and the financial ratios between 1993 and 1996 on annual basis are calculated.

The set of firms are randomly subdivided into two sub samples: the first with 57 for the training and the second with 30 firms for the testing set. Healthy and distressed are the categories which the firms are classified. The classification criterion is the value-at-risk approach using Black and Scholes (1973) formula extended to corporate finance. To define the classification criteria it needs to determine the probability that the firm will be distressed at the given likelihood probability value (= 0.01).

The target (output desired) is a binary value: 1 for healthy firms and 0 for distressed ones.

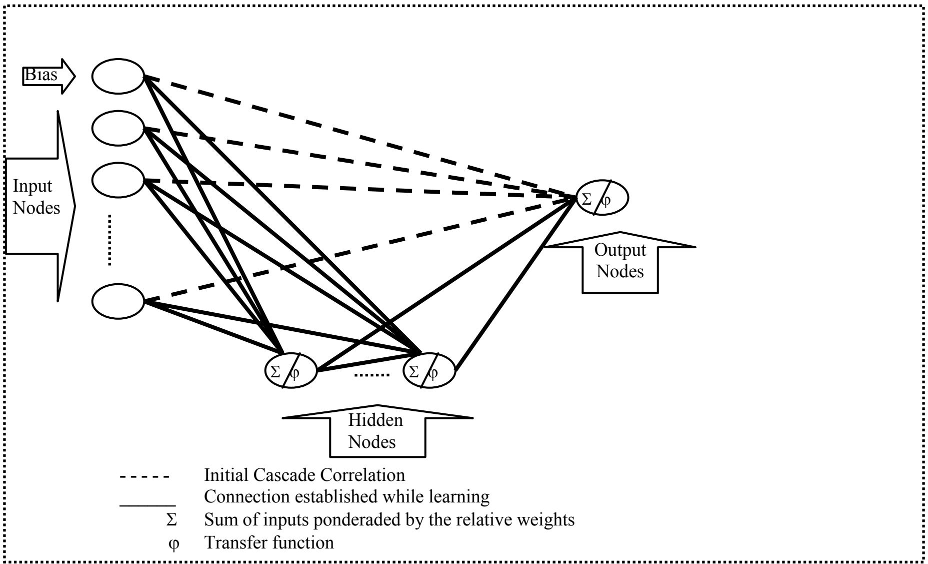
Firstly a big number of financial variables are selected and, using a linear regression approach, 15 different ratios are extracted. To classify the firms into two groups, healthy and distressed, the Black and Scoles (1973) formula is used and on 87 firms, 70 are judged healthy firms and 17 distressed.

To perform the neural network is used a Fahlman and Labiere (1990) cascade correlation architecture because this framework determines his structure by itself and because this is a faster architecture (fig.4).

[3] There are many frameworks of neural networks beyond the presented one.

[4] That is: balance sheet, result account and cash flow statement.

Figure 4: Neural Network framework



Source: Abid, Zouari, 2000

A hardlim function is used as a transfer function.

The ANN models created use these data:

- Independent years: 1993, 1994, 1995, 1996;
- Panel: 1993-1996, 1994-1996, 1995-1996;
- Panel with desired output time varying: 1994-1996, 1995-1996.

During the training phase, the neural network determines the weights set that, combined with the inputs, defines the output values on a base of to established rules.

These results will be compared with the targets to calculate the correct classification perceptual of training and testing phase. The testing is determined dividing the observation number correctly classified with the total observation number into the training subset.

The results are that the perceptual of correct classification test increases from the 70% to the 83.33% with the input data of 1993 and 1996 respectively.

Hence, the best model of neural network to forecast is obtained when the information consequently of two years (panel data: 1995-1996) is used.

The choice of best model is based on four competitive criteria that are:

- Best percentage of correct classification of training, conditioned by;
- Best percentage of test of correct classification, both conditioned by;
- Minimum difference between training and testing correct classification percentage, all conditioned by;
- The simplest neural network structure (minimum of hidden nodes).

In the Atiya's work (2001) are used variables extracted from the stock price of the firm (like Merton). These variables are good predictor of shortfalls (or improvements) in the performance of a firm. The indexes tested are: volatility, change in volatility, change in price, absolute price, price-cash flow ratio, etc.

The authors created two models: one based only on financial ratios (financial ratio system) and another one based on financial ratios and price-based indicators (financial ratio and equity-based system).

The sample considers 120 variables (financial statement data, ratios, stock price data, and transformation of these).

Using a preprocessing data, the authors selected 5 or 6 indicators most important:

1. Book value/total assets: BV/TA;
2. Cash flow/total assets: CF/TA;
3. Rate of change of cash flow per share: ROC(CF);
4. Gross operating income/total assets: GOI/TA;
5. Return on assets: ROA.

The 6 variables are:
1. Book value/total assets: BV/TA;
2. Cash flow/total assets: CF/TA;
3. Price/cash flow ratio: P/CF;
4. Rate of change of stock price: ROC(P);
5. Rate of change of cash flow per share: ROC(CF);
6. Stock price volatility: VOL

In this work 716 not failed firms are considered and 195 failed ones. The results are shown in the table below (tab.1).

It's possible to see that the results are best when also market variables are used.

The market indexes are predictive because reflect the firm quality seen by the external environment.

From the correlation matrix of indexes it is possible to see that the volatility index is negatively correlated with other indexes. This is a clear sign of discriminant power of volatility variable.

In the Charalambous *et al*. (2000), the Kohonen learning vector quantization (LVQs) is used to train algorithms (Kohonen 1990), the Radial basis function (RBF) network (Broomhead and Lowe, 1988) and the feed forward network minimizing the Least Squares Error Function (LSEF) with and without a penalty term using conjugate gradient optimization algorithms (Charalambous, 1992), in addition to the common feed forward network trained by the back propagation algorithm (Rumelhart *et al.*, 1986). Moreover, it compares the results of this ANN methdos with the Logistic regression model.

The sample is composed by 139 matched-pairs of bankrupt and not bankrupts US firms for the period 1983-1994. The data used are extracted by Compustat database. For the training set, 192 firms, failed or not failed, are used for the period 1983-1991. The testing set includes 86 firms for the period 1992-1994.

For inputs, 27 financial variables used in the literature as significant are selected.

With an unvaried regression analysis the indexes selected are 7:
- CHETA: Cash and equivalents/Total assets;
- CLTA: Current Liabilities/Total assets;
- DAR: Change in Accounts Receivables;
- DER: (Debt due in one year + Long term debt)/Total assets;
- OPN12N: Dummy for Operating Income, 1 if negative for the last two years and 0 otherwise;
- UCFFOM: Change in Cash flow from operations/Market value;
- WCFOM: Working Capital from operations/Market value of equity at fiscal year end.

The NN algorithms used in this study are:
- Kohonen's SOM plus three Learning Vector Quantization (LVQ1, LVQ2 and LVQ3);
- The radial basis function, with optimization;
- The feed forward network with:
  - Back propagation algorithm;
  - Conjugate gradient optimization algorithm.

The results of neural networks are better than those of logistic regression and the back propagation algorithm is the best.

Table 1: Results for the Neural Network Default Prediction Model: Financial Ratio and Equity-Based Model

Time to default	*# Correct (in sample)*	*# in sample*	*% Correct (in sample)*	*# Correct (out of sample)*	*# out of sample*	*% Correct (out of sample)*
5 month or less	35	38	92.11	56	65	86.15
6 to 12 month	43	61	84.31	44	54	81.48
12 to 18 month	33	37	89.19	47	43	74.80
18 to 24 month	33	37	89.19	26	22	78.13
More than 24 month	19	25	75.00	28	42	56.57
Total defaulted	163	188	86.70	200	256	78.13
Solvent	278	303	91.09	372	413	90.07
Total	439	491	89.41	572	589	85.50

Source: Atiya, 2001

1.1.3 Rating Systems

There are some specialists in credit analysis firms that give a credit rating about firm solvency. These firms are large and publicly traded.

The rating opinions take into account the loss given default and default probability, particularly the expected loss. Hence, these methods study both default prediction and exposure models.

The banks made a rating system in according with the BIS New Capital Accords that will come into force at 2005.

The rating system has one-dimensional or two-dimensional architecture. In the first case, at each loan is assigned a rating score based on default probability, whereas, in the last case, each borrower's default probability is calculated separately from loss severity of individual loan (LGD).

Treacy and Carey (2000) compare both one-dimensional and two-dimensional architecture and they find the two-dimensional is the best solution.

These authors and BIS (2000) find that many different models for the internal rating system in banks exist.

Treacy and Carey (2000) find that, whereas for the small and medium-sized firms the qualitative factors play a bigger role to determine the loans rating system, for the large-sized firms the quantitative methods are more used for rating system. Generally, the rating scores are calculated with one-year time horizon.

These models are used frequently and are very performing for the default risk problem. The goal of these methodologies is not to classify but to determine the default probability.

1.1.4 Credit scoring models

The most important methodology is the multiple discriminant analysis studied by Altman (1968). This approach is the "Z-Score Model".

The model takes into account the values of ratio-level and the categorical measures.

The goal of this method is the discrimination between defaulted and not defaulted firms.

Particularly, the Z-score model is a multivariate approach that studies the variables for maximizing the between-group and minimizing the within-group variance. On a base of several statistical criteria, it chooses the best indexes to introduce as inputs in the model.

In this way, it calculates a z-value representing the boundary between failed firms and not failed ones.

In the introduction of paper, Altman makes considerations on the variables that are more mentioned in the literature. The results are that the largest indexes used are the profitability, the liquidity and the leverage.

The multiple discriminant analysis is a statistic methodology used to classify prior an observation into one or more groups depending to characteristics of single observation.

Mainly, this approach is used to classify and to forecast in a problem where the independent variable is qualitative, i.e. male/female, defaulted/healthy firm.

The MDA discriminates within firms on a base of some variables determining the solidity or not-solidity of firms.

The MDA's strengths are:

- It reduces the dimensional space of analysis. It decreases the number of several independent variables at G-1 where G represents the number of groups. The discriminant function is:

  $Z=v_1x_1+\ldots+v_nx_n$
  $v_1\ldots v_n$: *discriminant coefficients*
  $x_1\ldots x_n$: *indipendent variables*

- The result is the Z-Score and it defines the classification of firm. The MDA calculates the discriminant coefficients v_j $(j = 1,\ldots,n)$, whereas the independent variables x_j $(j = 1,\ldots,n)$ are the current values. This model has the advantage that is simple but it incorporates many pieces of information. These pieces of information are determinant in the definition of differences between the groups but it is more important to verify if these differences are significant.
- The MDA method analyses simultaneously all the variables of firm rather than to examine the firm in their characteristics.

The initial sample is made by 66 firms: 33 faulted and 33 not faulted. The failed companies are failed between 1946 and 1965. Mean assets value is \$6.4 millions with a range of \$0.7 and \$25.9 millions. In this set the firms deferrer by the industry and the size. The not failed firms have an asset range between \$1 and \$25 millions. These companies are present till 1966.

The variables are selected by the balance sheet and the indexes are 22 divided into 5 principle groups: liquidity, profitability, leverage, solidity and others ratios created to solve the problem.

There are 5 indexes extracted to introduce in the model because these have a forecasting power. To select these ratios Altman follows this step:

- Statistical analysis of significant function to use in the model;
- Assessment of correlation between the variables;
- Observation of forecasting accuracy;
- Analyst evaluation.

Altman choose, from 22 initial variables, five indexes that today are more frequently used. The Z-Score and the ratios chosen are:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$$

where:

X_1 = working capital/total assets,

X_2 = retained earnings/total assets,

X_3 = earnings before interest and taxes/total assets,

X_4 = market value equity/book value of total liabilities,

X_5 = sales/total assets, and

Z = overall index.

The variables used are:

- Working Capital/Total Assets: measures the liquidity net of firms related of total capitalization. The working capital statement is determined like a difference between the current assets and the current liabilities.
- Retained Earnings/Total Assets: this is a "new" index that considers the firm's age. A young firm will have a low value because it will have a time to build a bigger revenue reserve.
- Earnings before interest and tax/Total Assets: measures the productivity of firm, taking into account tax and leverage factors related.
- Market Value Equity/Book Value of Total Debt: the equity is measured as the market value of all the equity shakes. The debt is medium-long time. Also this index is a "new" index.
- Sales/Total Assets: measures the competitiveness of firm.

It is necessary to take into account that these variables are the most used in the literature.

To test the discriminant ability of all variables an F-Test has been made. The first four indexes are all significant and it means there are many differences for these variables into the two groups.

The better contributions to discriminate are due by the variables 3, 4 and 5.

At one year precedent to bankruptcy the model is able to classify correctly the 95% of sample.

At two years precedent this perceptual is 83%.

An extent of this model is to verify the forecasting ability. To do this, the variables at three, four and five year's precedent to default have been got.

The results aren't good and the model is able to forecast and classify at 2 years at maximum to bankruptcy but this is a very good result respect to those of artificial neural networks as described below.

It has been defined a discriminant Z value able to divide the defaulted firms by not defaulted.

If Z-score of firm is greater of 2.99, the company is not failed, whereas the firms showing a Z lower to 1.88 are failed.

The "zone of ignorance" or "grey area" is defined between 1.81 and 2.99. Hence, there is a big probability to fall in misclassification errors. For the classification in this area has been made tests to define a discriminant value and this is: 2.675. This Z-score is able to discriminate between failed and not failed firms.

The Multiple Discriminant analysis can give continuum results not as the Decision Tree technique. Moreover, this model is more performing than Genetic Algorithms and DecisionTrees methodologies. Nevertheless, the stronger weakness is the normality hypothesis of financial data and the variance matrix equal to the covariance matrix.

The MDA is the technique most used in the hybrid models because the results are more performing.

Mester (1997) studies the applications of rating systems and he analyses four multivariate credit scoring approaches:

1. The linear probability model;
2. The logit model;
3. The probit model;
4. The multiple discriminant analysis.

These several methods identify the variables explaining better the differences between the defaulted and not defaulted firm. All these methods achieve this goal with statistical analysis.

The credit scoring approaches don't suffer of subjectivity or inconsistency of expert systems and are quite simple and inexpensive to apply.

Martin (1977) uses both the logit analysis and the discriminant analysis to study the bankruptcy between the 1975 and 1976 when 23 banks defaulted. Both the models achieve at equal results.

West (1985) describes a logit model to measure the economic situation of financial institution (FIs) and for determining the default probability of FIs.

Platt and Platt (1991) use a logit model to test if, in an industry, the balance sheet ratios are the best predictor of default. The results are that the model for the single firm is more effective than that for the industry.

1.2 Modern credit risk measurement methodologies

The modern approaches are the option-theoretic structural approaches, the reduced form approaches and other methods.

The first models are all based on the Merton methodology (1974) that considers balance-sheet indexes but also market variables and defines the distance to default as variable to investigate.

The reduced form approaches study the process underlying the default and the risk of debt.

1.2.1 Options-theoretic structural approach

The *options-theoretic structural approach* by Merton (1974) analyses the economic process of default.

This model is based on the asset value model, studied by Merton (Merton R., 1974). The approach proposes the default process endogenous and related to the capital structure of the firm. When the value of the assets of a firm goes down a given critical level, the default happens.

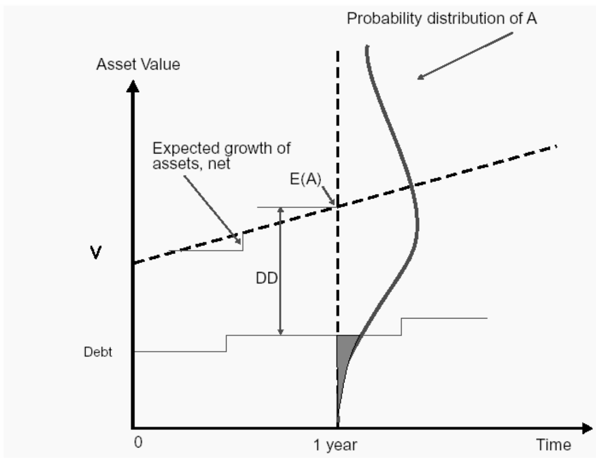
Merton (1974) considers the firm's equity as a call option on the firm's assets (A) and the strike price is considered equal to the liabilities of the firm (D). To expiration[5] if the firm's assets market value is greater than the value of its debt, the shareholders of firm will exercise the option for the firm's assets repayment the debt. If A<D, the shareholders will not exercise the option and they will go in bankruptcy.

Until the expiration, the default probability is equal to the probability that the option will expire unexercised and for evaluating the default probability he calculates the call option value. To do it, he determines the market value of assets (A) and its volatility (σ_A). The amount of debt liabilities (D) and the values of A and σ_A are combined to calculate the Distance to Default (DD):

$$DD = \frac{(\textit{Market Value of Assets}) - \textit{Debt}}{(\textit{Market Value of Assets}) \cdot (\textit{Volatility of Assets})} = \frac{A - D}{A - \sigma_A}$$

The σ_A represents the number of standard deviation between current asset value and the debt liabilities as shown in the figure (fig. 5) below.

Figure 5: The probability of default



Source: Crouhy *et al*., 2000

[5] The expiration coincides to the maturity of the firm's liabilities that comprise the pure discount debt instruments.

The default probability is proportional to the height of Distance to Default. The higher this is and lower is the default probability.

Merton (1974) assumes the asset values are lognormals distributed to convert the Distance to default into a default probability estimate.

The proprietary structural models use different methods for converting the DD in default probability estimate.

The KMV[6] have a KMV's Credit Manager and he uses a historical database of default rates for estimating the default probability and this estimate is named "Expected Default Frequency" (EDF). Particularly the DD is related to default probability by the likelihood that the assets of firm will traverse the DD during the credit horizon period.

The weakness of these methods is that they are sensitive to financial circumstances respect to external rating criteria since these are calculated by balance sheet ratios.

For the private firms there aren't the equity prices for estimating the asset values. Hence, the KMV's Private Firm Model adds four steps to determinate the Distance to Default:

1. Computation of Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) for the private firm P in industry I;
2. Determination of the average equity multiple for industry I. To do this, it divides the industry average market value of equity by industry average EBITDA;
3. Obtain an estimate of the market value of equity for the private firm P by multiplying the industry equity multiple from step 2 by firm P's EBITDA;
4. Firm P's asset equals the step 3 estimates of the market value of equity plus the book value of firm P's debt. Once the private firm's asset values can be estimated, then the public firm model can be utilized to evaluate the call option of the firm's equity and obtain the KMV EDF score.

1.2.2 Reduced form approach or intensity-based model

The *reduced form approach* or *intensity-based model* by Jarrow and Turnbull (1995), Jarrow *et al*. (1997), Duffie and Singleton (1998, 1999).

This model estimates the random intensity process underlying of default on a base of risky debt prices.

In these models, the default is considered as a sudden event and the economic process leading to default is not specified. The default occurs with probability given by the "hazard function".

The reduced form models analyse the observed credit spreads on in default debt to determinate the default probability and the LGD[7].

Hence, the observed credit spread is a measure of the expected cost of default and it is.

CS (Credit Spreads on risky debt) = PD x LGD

where:
CS = risky debt yield minus the risk-free rate;
PD = probability of default;
LGD = loss given default = 1 – recovery rate

Das and Tufano (1996) use a deterministic intensity function for calculate the PD and the LGD is assumed correlated with the default risk-free spot rate.

Longstaff and Schwartz (1995) use a model with two factors for specifying a negative relationship between the stochastic processes that determinate credit spreads and default-free interest rates.

Jarrow and Turnbull (1995) define the recovery rate as a known fraction of the bond's face value at maturity date and Duffie and Singleton (1998) assume the recovery rate is a known fraction of the bond's value just prior to default.

For Duffie and Singleton (1999) the PD and LGD are considered as a function of economic state variables.

At the end, Madan and Unal (1998) and Unal *et al*. (2001) determine the recovery rates on junior and senior debts.

These methods use as input-variables probabilities that are not easy to determine as the probability of default. Nevertheless these are very interesting model because, like the previous ones, take into account the risk probability to fail.

1.2.3 Other modern models

A table (tab.2) below presents some models less used. It is interesting to analyse these methods because it is possible linking these to the methods presented in this work for obtaining good results.

[6] In the summer of 2001, Moody's has bought KMV.

[7] LGD = 1 – recovery rate.

Table 2: Other methods

Exposure approaches These methodologies determine the credit exposure conditional of the default event. These models include also the estimation of the recovery rate due by collateral type, seniority and industry.
Portfolio methodologies For this model it is necessary calculate the default probability and the exposure for each transaction in a portfolio. Do this, it makes a summing up and this isn't a straightforward due to correlations and the asymmetry of debt payoff. Using the correlations of the exposures it calculates the portfolio valuation.
Risk of ruin methods A firm fails if the market value of assets (A) falls below the value of them bonds (B). The Black-Scholes-Merton model defines the default probability of firm is related to the market value of initial assets (A) related to external debt (B) and to market value volatility of firm assets (σ_A). Thereby, it links the risk of ruin model and the Merton's methodology. The KMV model is based on these rules. Particularly A and σ_A are important to define the default probability and they are the parameters to estimate. The theoretical relationship is: • The equity value is considered as a call option of firm assets; • There is a theoretical link between the observable volatility of equity value of firm and the not observable volatility of value assets of firm.
Non parametric frontiers In the paper of Caporaletti *et al*. (1999), the authors affirme the problem to analyse the default and credit risk of firm is there isn't a defined way to weight the factors determining the default situation. This paper proposes a classification of entities described by multiple performances attributes into "performer" and "underperformer". To do this, the authors use a framework based on nonparametric frontiers to rate. The approach used is equivalent to Data Envelopment Analysis (DEA) where the weights for each attribute are selected to maximize each entity's performance score.
Gambler's ruin theory model (G.R.M.) The default risk in this model is linked to the trend of wealth used by a subject in the economic dangerous activity. Considering a time range between 0 and N where it defines an increasing trend with probability P of an amount S of risked wealth. In the case of decreasing dynamic, the probability happens be Q = 1 – P and the reduction is S. Thereby, there are two types of subjects: • For the first type, the default probability is certain and they are qualified on a base of at time period dividing them to the insolvency event; • For the second type, the survival probability is nothing. In this case it is necessary identifying the default risk. Wilcox underlines the importance of these variables: the solvability (wealth at the start of the game), the average value of risky bet and her volatility.
Sandberg-Lewellen-Stanley (S.L.S.) In this method it's assumed a normal distribution of ROA (return on assets). The way is to research the probability that the ROA will be lower to the value assuring the coverage of liabilities related to the leverage expressed as a part of assets. Particularly it calculates. $$\frac{(\text{Average ROA} - \text{Liabilities/Assets})}{\Delta \text{ROA}}$$
Assurance theory based models The economic and financial variables can be expressed as random variables. If U_r is the minimum reserve assuring the solvency, Pi is: $$Pi = Pi\ (U \geq U_r) = prob\ (\Sigma I - \Sigma O + U_r > 0)$$ Where the financial difficulties are related to probability of the difference between the financial input flows (ΣI) and the output flows (ΣO). The result is summed with the current funds (U) and is lower to the sum of minimum reserve of financial resources assuring the solvency (U_r). It uses hence this technique for underlining the number of "break down" of the security frontier anticipating the financial difficulties.

*RAPD model Risk analysis probability of defa*ult

This method (Montesi and Papiro, 2003) represents a new model to the assessment of default probability. Particularly, the PD is estimated with a forward looking technique and through the Monte Carlo Simulation. The default probability is the probability that the firm in the future isn't able to face up to payments.

The Monte Carlo method used here is made by 3 steps that are:

- Forecasting method to economic financial firm trend;
- A focused uncertainty modelization of forecasting;
- A determined default state definition.

Through this model it is possible to verify the solvency conditions of firm simulating all the possible scenarios, determining in this way the frequency of default states expected by the firm.

The model is made by these steps:

- *Forecasting model building.*
  This tool must be an economic and financial model able to analyse the balance sheet variables. It is necessary to introduce in the model the relevant indexes, thereby to reduce the distortions in the obtained results.
- *Definition of default state.*
  The default state analysis can happen through the solvency margin study. If this variable is negative the firm is in an insolvency condition since the company isn't able to face up the maturing liabilities.
- *Uncertainty modelization.*
  To achieve this goal it is necessary to follow the subsequent procedure:
  - Choice of doubtful variables. The remaining is considered as not-stochastic.
  - Assessment of probability of forecasting errors.
  - Determination of interdependences.
- *Monte Carlo simulation and Probability of default assessment*
  It is possible creating forecasting scenarios where the stochastic variables are changed simultaneously randomly. For each test it is created a firm's scenario composed by a provisional balance sheet for each forecasting prevision. Through this, it is possible to determinate the Solvency Margin value. The PD is determined by the frequency of default event.

Extreme value theory

The goal of this model is to determinate a correct measure of credit portfolio risk through the Extreme Value Theory (EVT) model. The traditional approaches assess, the distribution of portfolio returns or earnings and losses is normal. In this way, mean and standard deviation are good measure using to evaluate the portfolio risk-return on an efficient boundary[8].

This isn't a good model assessing the credit risk because the credit losses are asymmetrically distributed. In the last years, we studied some models for the Value-at-Risk assess of a credit portfolio, that is, the maximum probable loss implicit in the bank credit framework.

The VAR is a probabilistic distribution of portfolio earnings and losses profile. To do this it is necessary to assess correctly the distribution.

This theory allows evaluating the distribution queue optimally, using a generalized distribution also if the data don't allow making hypothesis about the underlining distribution form.

To use this approach it is necessary to have a data base including the portfolio losses for a certain period. To do this, if it's impossible to have all the data, we uses a Monte Carlo Simulation.

1.3 Proprietary credit risk measurement approaches

The models presented below are created by the most important financial institutes for determining the default risk of their credits:

– *Moody's RiskCalc for Public firms* (Sobehart and Stein, 2000).

This approach combines two credit risk methodologies: the structural based model based on Merton's options-theoretic view of firms and the statistical model determined through empirical analysis of historical data.

The steps of this model are:

- Agency rating when available;
- Modified version of Merton model;
- Company financial statement information;

[8] This is a method for find a portfolio set risk minimizing, given the expected return.

- Additional equity market information;
- Macroeconomic variables that represent snapshot of the state of the economy or of specific industries, which are used for pre-processing, model inputs.

– *Moody's RiskCalc for private Companies* (Falkenstein *et al.*, 2000).
This model is not structural approach and its first step is to choose the input variables.
Since the Moody's database offers a big umber of variables, Falkenstein *et al.* (2000) use the common relations and define six big categories: profitability, leverage, liquidity, size, inventories and growth. Within these categories they exclude some ratios and they choose 8 indexes to use in RiskCalc.
Falkenstein *et al.* (2000) find there are many differences between the variables for the public and private companies. The current financial indexes are multiplied by the weights to determine one of five year expected default frequencies.
For each country, Moody's compiles a specific Credit Research Database and also a separate model

– *Moody's KMV EDF RiskCalc v3.1* (Dwyer *et al.*, 2004).
This is a new technique for assessing middle market credit risk. This approach combines the RiskCalc framework, the industry's leading middle market modelling approach and the Moody's KMV distance-to-default value.
Today, this methodology gives good results.

– *Actuarial approach proposed* by Credit Suisse Financial Product (CSFP) with CreditRisk+.
This approach focuses on default. An exogenous Poisson process is followed by the default for individual loans and bonds.

– *CreditPortfolioView by McKinsey.*
This model uses also macroeconomic variables like unemployment, the growth rate in the economy, etc. Particularly, the default probabilities are conditional on these macro variables.

– *Credit migration approach* proposed by JP Morgan with Credit Metrics.
This framework considers the probability of moving from one credit quality to another, taking into account the default situation.

2. A COMPARISON BETWEEN ARTIFICIAL NEURAL NETWORKS AND OTHER METHODOLOGIES

Odom and Sharda (1990) use the Altman indexes and make a comparison between the two methodologies (neural networks and MDA). The sample is formed by 128 USA firms and neural network model generates best results.

Tam (1991, 1994) and Tam and Kiang (1990, 1992) compare MDA, LR[9], ID3[10] and several models of neural networks that generate best results. Also Salchenberg *et al.* (1992) compares NN with LR and the results are the same of Tam.

Coats and Fant (1992, 1993)) compare NN with MDA like Kerling and Podding (1994) and the results confirm the goal of Tam.

The Altman *et al.* (1994) work considers the MDA results better than the NN ones.

Back *et al.* (1996) propose the genetic algorithms for selecting the inputs. The results are very good compared those of MDA or LR.

Kiviluoto (1998) uses a SOFM NN and compares them with MDA and LVQ obtaining good results.

Yang *et al.* (1999) use probabilistic neural networks on Bayes based. They use the MDA technique for the preprocessing phase and the results are very good.

Kim and Scott (1991) use a neural network to predict the default risk and they use a sample of 190 Compustat firms. At the year of bankruptcy, the model generates good results (87% prediction rate) but the accuracy decreases one year prior, two years prior and three years prior to default (75%, 59%, and 47%).

Podding (1994) uses a sample of 300 French firms and he finds neural networks outperform credit scoring model for the analysis of default prediction.

[9] The LR is a linear regression model.
[10] The ID3 is a decision tree model.

Yang *et al*. (1999) shows that the backpropagation neural network models generate best results for the classification accuracy.

The paper of Adya and Collopy. (1998) is a survey on the neural network model to forecast.

For the authors there are two questions to take into account for the model assessment:
- The first is if the model evaluates correctly the predictive ability of network used;
- The second is if the study uses neural network model really able to represent well the reality considered.

The criteria used to assess are extracted from Adya *et al*. (1994) work:
- Comparison with more used models;
- Use of validation process ex ante;
- Use of correct prediction sample.

To define the effectiveness which a neural network is created and tested, criteria take into account to assess the neural network performances suggested by Refenes (1995).

Nevertheless the criteria used by the authors are:
- Convergence. It analyses the network ability of classification;
- Generalization. It assess the network ability of recognize the data out of the training sample;
- Stability. This variable identifies the results consistency during the validation phase, with several data sample.

The criteria are quite general to can apply to each neural network architecture or learning mechanism.

Hence, the works are classified into three groups.
- Those are well implemented and validated;
- Those are well validated but aren't effective in the implementation phase;
- Those aren't able to make forecasting.

In the table below (tab.3) the validity results on the studies are shown:
- 11 studies satisfy both the criteria;
- 16 are validated but have problems in the implementation phase. Nevertheless, 11 of these studies use neural networks generating the best results respect to the other comparable models;
- 22 studies generate results relevant in the evaluation of neural network to forecast the default;
- 5 studies satisfy the validation criteria but in the implementation phase generate some problems.

Table 3: Number of paper analyzed

	NN better	*NN worse or inconclusive*	*Not compared*
Problems with validations	11	3	7
Problems only with implementations	11	5	0
No problems either criteria	8	3	0

Source: Adya and Collopy, 1998

Wilson and Sharda (1994) compare the neural networks with the multiple discriminant analysis. The authors make three experiments on the sample used and particularly test three subdivisions:
- 50% failed and 50% not failed;
- 80% not failed and 20% failed;
- 90% not failed and 10% failed.

The neural networks are the most performing model.

Salchenberger *et al*. (1992) compare the neural networks with a logit model and the first is the best model. The subdivision is at 50% between failed and not failed firms.

Coats and Fant (1993) use a Cascade Correlation algorithm. The neural networks, compared with the multiple discriminant analysis, generate best results when the sample contains more firms failed than not failed. If the sample is subdivided at 50% between healthy firms and not healthy, the multiple discriminant analysis is the best model.

Tam and Kiang (1990, 1992) compare the neural networks with:
- Regression;
- Multiple discriminant analysis,
- Logit analysis,
- K-nearest neighbour[11];
- ID3.

The authors obtain that, at one year before the event, the neural networks are the best model but at two years before the bankruptcy, is the multiple discriminant analysis generating the best performances.

Moreover, Tam and Kiang find that, at one and two years before the event, the neural network with an only one hidden layer generates better results than the linear networks without hidden layer.

Fletcher and Goss (1993) compare the neural networks with logit model and find the first model has best results concerning error and variance.

On 48 studies analysed, 44 (88%) use the back propagation. Nevertheless, this technique suffers from some problems:
- It doesn't exist a unique configuration able to represent all the domain or the single representations of the reality in the same domain;
- This algorithm find a minimum but it doesn't know if this is a local or global minimum;
- There are overfitting problems.

Refenes (1995) suggests 5 control parameters using to assess the efficacy.

The authors verify the efficacy of 27 studies for evaluating the validation criteria:
- Network architecture;
- Descendent gradient;
- Cross-validation;
- Cross-function;
- Transfer function.

In conclusion, if the neural networks are well implemented and validated the generated results are very effectiveness.

[11] The k-nearest neighbour is a cluster analysis model.

Nevertheless, the studies analysed suffer from implementation and validation problems.

Only 22 of 48 studies used generate good results for the forecasting problem. In 19 studies, the neural networks prevail over other models but in 5 of these, there are some uncertainties for the implementation phase.

This study compares several models for the bankruptcy prediction. These methodologies are:
- The prediction through the time series;
- The prediction based on the regression,
- The decision models based on the regression.

Moreover, the authors analyse the precedent works comparing the neural networks with the discriminant analysis.

At the end, the authors examine the types of neural network models better performing in the forecasting and in the determination of default risk.

Sharda and Patil (1990) use 75 time series extracted from a 111 time series sample and find that the neural network model are more performing than the time series elaborated through the Box.-Jenkins procedure.

Sharda and Patil (1990), Tang *et al.* (1991) find using the time series with a long memory, neural networks and time series elaborated with the Box-Jenkins procedure generate similar results.

If time series with short memory are used, Tang *et al.* (1991) obtain best results from neural networks.

Tang *et al.* (1991) and Kang (1991) find the neural networks generate best performances when the prevision is made not long before the event.

Hill *et al.* (1993) define two neural networks models:
- The first is like the Foster *et al.* (1991), Kang (1991), Sharda and Patil (1990, 1992) models. This network framework predicts all the period in a forecasting horizon simultaneous. In this case the neural networks give the same results as the statistical methods.
- In the second architecture is generated a prevision for the first period of the forecasting horizon. The obtained result is introduced newly in the provisional model to forecast the second period of provisional horizon. In this case, the results underline the neural networks as a best methodology.

At the end, the neural networks generate the best results if the forecasting horizon is short but if it is one year before the event the time series are the best model.

Dutta and Shekhar (1988) use 10 factors to forecast the corporate bond ratings. They evaluate the neural network models and the regression using a sample of 30 bonds randomly extracted from Standard and Poor's and from Valueline. They find the neural networks generate best results respect to the regression model.

Duliba (1991) compares the neural network model with four regression model in the prediction of financial performances. Considering the random effects, the neural network model generates best results but considering the fix effects, the regression is the winner.

Bell *et al*. (1989) compare the back propagation neural network with a logit regression methodology to forecast the bankruptcy in the commercial banks. The neural networks are the best model.

Roy and Cosset (1990) compare the same models but they use the country risk policy and economic variables to forecast. The networks have a lower absolute mean error whereas they are more sensitive at changes in the country risk, respect to the logistic model.

In the work of Sexton *et al*., a genetic algorithm is used to select neural network architecture. Particularly, the neural network is optimized using the genetic algorithm.

To achieve this goal, a Monte Carlo simulation on a base of 7 tests is made.

To compare the errors, a root mean square error (RMS) is made and it is possible to compare the performances between the back propagation and the genetic algorithm.

From the table below (tab.4) it is clear that the RMS is smaller for the genetic algorithm than for the back propagation model. This is a very good signal of genetic algorithm effectiveness but also neural networks have good results. A good idea is to use the genetic algorithm as preprocessing system for the variables to introduce in the network.

The back propagation algorithm is used very frequently but there are many problems related to this technique. It is possible to solve these details with other methods as genetic algorithms that assure a good choice of network architecture.

In Altman *et al*. (1994), the authors compare the linear discriminant analysis with the neural networks.

For the authors the discriminant analysis is able to generate financial results easy to interpret and there is the problem of overfitting.

At the end, the neural networks are able to generate best results but if increasing the architecture complexity, it's difficult to analyse the results.

Table 4: Comparison of RMS for different functions

Parameters from Training Run	$X_1 + X_2 + e^*$				$X_1^* + X_2 + e^{**}$			
	Interpolation		*Extrapolation*		*Interpolation*		*Extrapolation*	
	BP	*GA*	*BP*	*GA*	*BP*	*GA*	*BP*	*GA*
1	4.14	1.27	36.65	3.47	16.02	1.66	1303.61	8.58
2	2.85	1.56	32.24	3.89	215.97	1.75	2037.61	8.97
3	2.82	1.82	34.28	5.12	49.27	1.67	1460.35	8.67
4	2.93	1.48	30.73	4.15	50.82	1.88	1399.33	8.84
5	6.95	1.57	34.27	9.38	30.56	1.64	1479.32	8.50
6	2.90	1.30	38.37	3.70	15.96	2.00	1321.45	9.52
7	2.80	2.03	34.59	5.87	19.73	2.13	1317.33	9.80
8	3.11	1.47	33.43	4.17	21.35	1.85	1322.68	9.79
9	2.99	1.50	34.33	3.50	29.86	1.75	1348.10	9.24
10	2.71	1.60	34.02	3.69	19.48	1.65	1307.22	8.48

* error was drawn from a normal distribution (μ=0, s^2 = 5)
** error was drawn from a normal distribution (μ=0, s^2 = 10)

Source: Sexton *et al.*

3. HYBRID ANNS MODELS

In the last decades the hybrid models are the most used systems to solve the default risk problem.

Yim and Mitchell (2002) study if two neural networks, multilayer perceptron nets and hybrid models can generate better results than those obtained by the statistical models used to forecast at one or two years before to the event of bankruptcy.

There are two approaches at the hybrid models using:

- Statistical models to select the variables utilised as inputs in the artificial neural networks;
- An estimated probability of output, introduced as a network input.

The neural networks linked at statistical models can give some problems because the networks suffer from overfitting when the variables to use are many.

To avoid this problem, the method is made into two steps:

- Use a statistical methods to select the variables for decreasing the overfitting risk and, at the same time, it decreases the time defined to select the model;
- Use the output of a statistical model as neural network input.

At this point, the authors define three hybrid models:

- The logit and discriminant analysis (DA) methodologies are used in the pre-processing phase to select the variables (ANN-Logit and ANN-DA);
- The bankruptcy probability calculated by the Logit or DA model is introduced as a input in the network (ANN-Plogit and ANN-PDA);
- The Logit and DA model are used in the pre-processing phase to select the variables and the probability of predicted bankruptcy by the Logit and DA models is used as input in the network (ANN-Logit-Plogit; AMM-Logit-PDA; ANN-DA-PDA and ANN-DA-Plogit).

In the table (tab.5) below, the author compares the results obtained on the training sample and it shows that the hybrid models generate best results.

Table 5: Result one and two years before the default

Best Model	*1 year before*		*2 years before failure*	
	Non failed firms correctly classified (%)	*Failed firms correctly classified (%)*	*Non failed firms correctly classified (%)*	*Failed firms correctly classified (%)*
DA	86	75	86.3	60
Logit	91	80	91.2	55
ANN	94	80	95.0	65
ANN-DA	98	75	96.2	65
ANN-PDA	96	80	95.0	75
ANN-DA-PDA	93	75	96.2	65
ANN-Logit	98	70	96.2	65
ANN-Plogit	96	85	95.0	75
ANN-Logit-Plogit	93	85	97.5	65
ANN-DA-Plogit	93	85	97.5	65
ANN-Logit-PDA	91	80	95.0	65

Source: Yim and Mitchell, 2002

In the table below (tab.6) are shown the results accuracy and it's possible to see the hybrid model best performances.

Table 6: Comparison between the models

Best Model	*1 year before*	
	Non failed firms correctly classified (%)	*Failed firms correctly classified (%)*
DA	86	60
Logit	89	60
ANN	94	50
ANN-DA	92	50
Hybrid (ANN-PDA)	94	50
Hybrid (ANN-DA-PDA)	92	60
ANN-Logit	94	50
Hybrid (ANN-Plogit)	89	60
Hybrid (ANN-Logit-Plogit)	89	60
Hybrid (ANN-Logit-PDA)	94	80

Source: Yim and Mitchell, 2002

The author compares the results obtained on the training sample and he shows that the hybrid models generate the best results.

In the work of Chang Lee *et al*. (1996), the authors study three hybrid neural network models that are:

- MDA-assisted neural network (MDA-ass NN);
- ID3 assisted neural network (ID3-ass NN);
- SOFM (Self Organizing feature map)-assisted neural network (SOFM-ass NN). This model links the SOM neural networks and the LVQ (linear Vector Quantization) framework.

In this study, the algorithm used is the back propagation for the supervised neural network, whereas, the SOM network is used as an unsupervised model and this is utilized as a data preprocessing. The MDA and ID3 methods are used like benchmarking tools.

The data are related to the failed Korea firms and they are subdivided into:

- Training data,
- Hold-out data.

Moreover, a cross-validation method is used to perform the neural network architecture.

The MDA method is based on the Fisher procedure, which maximizing the ratio of between-groups and within-groups variance for constructing a discriminant function.

The conditions for this method are:

- Each group must be normally distributed (here, log transformations are used to guarantee the normality of distribution);
- The covariance matrix of groups must be equal;
- Mean vectors, covariance matrix and prior probabilities to mistake the classifications must be known.

The independent variables are the financial ratios, whereas the dependent variable is a bankruptcy state.

Through the ID3 method a decision tree is created for classifying the sample (training data). This methodology minimizes the entropy (quantity of information transmitted by a message) subdividing the sub samples.

The *MDA-assisted neural network* method don't command any input variables assumptions unlike the MDA methodology.

The MDA technique is used as a preprocessing method and particularly the more significant input variables are selected.

The *ID3-assisted neural network* method tests the input variables for the neural network. The entropy measure is the crucial index for this model.

In the *SOFM-assisted neural network* model the neural network updates the connexion weights when there are external inputs.

In this model, it links sequentially an unsupervised method (SOM) and supervised one (LVQ). In this way, input data clusters are created. A single cluster represents a rule describing the complex of data.

The Kohonen neural networks (SOM) have these characteristics:

- An array of neurons receiving coherent inputs and computing a simple output function;
- A mechanism for comparing the neuronal outputs to select the neuron producing maximum output;
- A local interaction between the selected neuron and its neighbours;
- An adaptive updating that updates the interconnection weights.

The input layer of neuron is completely interconnected to the hidden layer. The SOM principle is: "an input pattern is presented sequentially to the input layer, and then the best matching neurons are found in the competitive layer through learning. Later on, the best matching neurons activate their neighbours to classify the same input patterns" (Chang Lee *et al.*,1996). This neural network model transforms the input layer into a map of competitive neurons and the similarities in the input are mapped into the same clusters.

In the competitive layer each neuron is called quantization and computes how its quantization vector is close to the input vector.

The LVQ (Linear vector quantization) model is a supervised method that assigns the quantization vector to each class.

The SOFM-LVQ (SOFM-ass NN) is a methodology two stages based and these are:

- Clustering NN stage (CNN),
- Output NN stage (ONN).

In the Stage CNN the clusters are expressed as rules.

This is composed by three steps:

- *SOFM model application*. Through this method the inputs are divided in clusters. Each cluster represents a rule set describing the inputs.
- *Refine with LVQ methodology*. The LVQ method is used to define the boundaries between clusters created by SOFM model. The cases which the model isn't able to classify are included into particular clusters. Hung (1993) uses a learning control system based on neuron-fuzzy methodology and he shows that the combination of SOFM model with the LVQ methods is really efficient.
- *Train the clusters through the back propagation neural network model*. The back propagation model is applied to the input data samples with cluster outputs given by the SOFM and LVQ methodologies.

Hence, the CNN model is a method that finds an appropriate cluster for each sample.

At the ONN step the back propagation neural network model is applied at each cluster. ONN is a function defining a map between the input sample and the output state desired (bankruptcy or not).

The sample includes Korean failed firms between 1979 and 1992 extracted by the Korea Stock Exchange.

The bankruptcy state is defined by:

- Firms under the process of corporate clearance;
- The firms which quit or closed business,
- The firms which had losses for the consecutive three years and are currently under legal control;
- The firm witch reported the withdrawal of listing or terminated to be listed by the Korea Stock Exchange.

On a base of these criteria 83 firms are selected.

Each failed firm is linked to a not failed firm on a base of these variables:

- Asset size,
- Capital size,
- Number of employees,
- Age.

Hence, 166 firms are selected and the training set is subdivided into three subsets on a base of the period.

- Group I: 1979-1984,
- Group II: 1979-1990,
- Group III: 1979-1991.

Each group contains training data and hold-out data.

Financial variables significant for the default forecasting are 57 and into 6 categories are grouped:
- Growth;
- Profitability;
- Stability;
- Cash flow;
- Activity;
- Credibility.

In the neural network model the input layer is created by 10, 18 and 17 neurons for the group I, II and III.

In the hidden layer there is the same number of neurons than in the input layer.

In the output layer, there are two neuron: one for the bankruptcy firms and the other for the not failed firms.

The neural network architectures (MDA-ass NN) are three and there are these groups:
- Group I: 10 input-neurons, 10 hidden-neurons and 2 output-neurons;
- Group II: 18 input-neurons, 18 hidden-neurons and 2 output-neurons;
- Group III: 17 input-neurons, 17 hidden-neurons and 2 output-neurons.

The ID3-ass NN shows a neural network model operating with the variables extracted through the decision tree. The neural network architecture changes for the neuron number in the layers. In fact, the back propagation algorithm is used in these methodologies.

The models SOFM (MDA)-ass NN and SOFM (ID3)-ass NN use the MDA and ID3 techniques for the selection of input variables but there is a change in the architecture of neural network. In this case, the network used is the Self Organizing Map with Linear Vector Quantization and the authors don't use the back-propagation algorithm. In the table below (tab.7) there are the results.

Table 7: The results (percentage values)

Group	*MDA*	*ID3*	*MDA-ass NN*	*ID3-ass NN*	*SOFM(MDA)-ass NN*	*SOFM(ID3)-ass NN*	*Total*
Group I	68.00	74.00	70.00	73.00	84.00	74.00	73.83
Group II	68.57	77.86	80.00	81.43	74.30	80.00	76.19
Group III	70.00	77.50	80.00	82.50	82.50	77.50	78.33
Total	68.57	74.29	75.24	77.62	80.48	76.67	75.00

Source: Chang Lee *et al*., 1996

The SOFM (MDA)-assNN give the best performances because the MDA is the best method for preprocessing the data. This model is able to well discriminate.

At the end, the authors made a z test to evaluate the predictive accuracy of hybrid models and the best method is the SOFM(MDA)-ass NN because the MDA technique is able to discriminate between variables.

4. THE VARIABLES FOR ANNs

One of problems of neural networks is the introduction in the model of input variables.

These are balance sheet indexes or financial market variables and in the last years there is a large use of market indexes. These variables show the idea of market about the considered firm.

All the authors start in their works from the Altman (1968) indexes built for the MDA method.

On this way there is a survey very intresting, made by Altman and Narayan (1997) where several papers are grouped on a base of input variables. The indexes selected are all extracted by the balance sheet data.

From this work we see that the most used variables are the EBIT to sales, debt or interest ratio; the retained earnings to asset ratio; the working capital to debt or sales ratio; the sales to asset ratio; the market value equity to debt ratio and profitability, leverage and liquidity indexes. These are the best indexes to discriminate between failed and healthy firms.

For these approaches there is a limited economic theory in the choice of significant variables, whereas the modern credit risk models are based on the financial theory.

For these approaches there is a limited economic theory in the choice of significant variables, whereas the modern credit risk models are based on the financial theory.

Hence, the principle problem of ANNs is to know the variables to be introduced as inputs in the model and nevertheless the most used variables are those of Altman (1968). In this step, it is necessary to create a preprocessing model able to determine the significant variables to introduce in the artificial neural networks.

CONCLUSIONS

The Artificial Neural Networks are tools used in literature for the analysis of default risk and several authors think they are the best models for the study of bankruptcy risk of a firm.

In most cases the results obtained with the networks are the best and especially for the hybrid model developed in the last decades. In these methodologies two techniques are used for the analysis and study of problems. The results are very good particularly for the genetic algorithm and multivariate discriminant analysis.

Finally, artificial neural networks had many technical problems but these were solved in time and these tools are considered very well.

This work wants to supply a significant survey about the methods so that it is possible to create a good system able to analyse correctly a complex reality as that of a firm or an industry.

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