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# Application of Accounting Information System to Predict Bankruptcy and Financial Crises in Tehran Stock Exchange

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**Abstract:** The high social costs associated with bankruptcy have spurred for better theoretical understanding and prediction capability. From initial developments such as Beaver and Altman, the interest of experts, academics and others regarding models of bankruptcy prediction, has intensified, also in the light of the recent global economic-financial crisis. Bankruptcy of companies appears because of different reason, one of that is financial and economic crisis. In this paper, I investigated application of Genetic Algorithm (GA) as tools of accounting information systems in predicting companies' bankruptcy. So doing, having read the review of literature, I found a complete list of financial proportions that showed high capabilities the predicting bankruptcy These variables include measures of liquidity, market-based growth, leverage, and variables related to short-term debt obligations. Then, GA was applied to classify 140 bankrupt and non-bankrupt Iranian firms listed in Tehran stock exchange (TSE) for the period 2012 to 2016.

**Keywords:** Bankruptcy, Financial Crisis, Genetic Algorithm, Tehran Stock Exchange.

## Introduction

The recent economic crisis is the first major Global Economic Management Disaster of the 21st century according to Ivashina and Sharfstein (2010). The Euro fund's European Restructuring Monitoring reports the number of bankruptcies peaked in many countries in 2008 and 2009 as the global recession spread. For example, in Denmark, commercial firms filed 85% more bankruptcies in 2008 and in Belgium 239% more firms filed for bankruptcy in 2009. The global crisis is a major reason for these filings. Sachs (1995) calls for the formation of an international bankruptcy court to reduce global financial instability. Due to the global financial crisis of 2007–2009, numerous countries' economies plummeted into a severe recession, destabilizing firms within a cross-section of industries and, thus, increasing bankruptcy filings. Therefore, management's contingency turnaround plans rest on a strategic knowledge of bankruptcy laws. In particular, bankruptcy outcomes and decisions affect corporations' resources and their ability to repay domestic and international creditors. Yet, to date, few studies evaluate how the design of an international bankruptcy law affects turnaround strategies or a firm's decision to participate in a business relationship with a foreign firm.

The economic crisis of the 1930s necessarily led financial studies to final saving aspects for the companies and the issues such as liquidity, bankruptcy, liquidation and refunding the companies (Gordon, 1971). The world economy has become aware of the risk within the capital structure of the companies especially after the bankruptcy of some huge companies such as WorldCom and Enron (Newton, 1998). Because of the radical change in global economy, corporate financial bankruptcy prediction is playing an increasingly important role. Financial bankruptcy often occurs when a firm has serious losses and/or when the firm becomes insolvent with liabilities that are disproportionate to assets (Gestel et al., 2006). Widely identified cause and symptoms of financial bankruptcy include poor management, autocratic leadership and difficulties in operating successfully in the Stock Exchange. Corporate bankruptcy does not only cause substantial losses to the business community, but also to the society as a whole. Therefore, accurate bankruptcy prediction models are of critical importance to various stakeholders, i.e. management, investors, employees, shareholders and other interested parties, as the models provide them with timely warnings. Bankruptcy predicting models can be divided into two main groups. The first group is those models that predict bankruptcy using information of the market and analyzing them and the 2nd group refers to these ones that predict bankruptcy using financial ratios. The 2nd group models can be divided using modeling method into statistical models, models based on artificial intelligence and theoretical models. The statistical methods include regression, discriminate analysis, logistic models, factor analysis etc. The artificial intelligence techniques include decision trees, fuzzy logic, neural networks (NNs), genetic algorithm, support vector machine etc. The prediction is a kind of binary decision, in terms of two class pattern recognition.

Early studies of bankruptcy prediction used statistical models. Recently, however, numerous studies have demonstrated that artificial intelligence can be alternative methodology for classification problems to which traditional statistical method have long been applied (Barniv et al., 1997; Beaver, 1966; Bell, 1997; Boritz & Kennedy, 1995; Chung & Tam, 1992; Etheridge & Sariram, 1997; Fletchera & Goss, 1993; Jo et al., 1997; Odom & Sharada, 1990; Salchenberger et al., 1992; Tam & Kiang, 1992). Considering all the research done, it can be understood that although the statistical models could predict the bankruptcy well, some limiting assumptions such as linearity, Normality and independent relation among the variables could affect the efficiency of these models. Therefore, other methods have been introduced to overcome some or even all of these limitations to improve the predicting performance (Garkaz & Abdollahi, 2010).

***Previous Research***

A large stream of research focuses on the determinants and predictability of companies' failures. A small but growing set of studies have begun to apply these techniques to more recent data on bank failures during the financial crisis. One of the central findings is that not much has changed.

The seminal contribution in the literature to address the issue of bankruptcy was written by Altman (1968). Altman (1968) was the first to introduce a bankruptcy prediction model using the discriminant analysis technique. He uses a linear combination (referredtoas ‘‘Z-score’’) of financial variables to obtain a score for each firm in the sample, which discriminates bankrupt firms from non-bankrupt firms using a cutoff point of 0.5. Altman's model produces adequate results within sample, but its performance out of sample is very poor. Subsequently, Eisenbeis (1977) and, more recently, Grice and Ingram (2001) use the Altman model for predicting bankruptcy with a more recent data set and find some inadequacies in the discriminant analysis approach. Grice and Ingram (2001) re-tested Altman's (1968) model on a more recent sample and find that its predictive ability of bankrupt companies fell from 83.5% to 57.8%. Eisenbeis (1977) had previously outlined various statistical problems associated with the discriminant analysis approach, but in this study he demonstrates that for matched pair sampling the approach may be adequate. However, in the case of a random sample of firms where the potential failed firms' are not around 50%, the predictive ability could seriously be affected. The literature is rich with studies that have used logistic or probit regression in predicting bankruptcy, for example (Premachandra et al., 2009; Keasey & Watson, 1987; Mensah, 1983; Ohlson, 1980; Zavgren, 1985). The traditional approach in using these techniques is to use half of the data sample (estimation sample) for estimating the model and the other half for prediction purposes. These models compute a conditional probability of an observation belonging to a particular category, such as bankrupt or non-bankrupt, and a cutoff point of 0.5 is used to classify the observations. A number of previous studies have shown that the logistic regression approach provides accurate classification within sample, but out-of-sample prediction is very poor. Among other approaches recently developed that all play an important role in evaluating corporate failures are neural networks (Tam, 1991), CUSUM methodology (Kahya & Theodossiou, 1999), multidimensional scaling (MDS) techniques (Molinero & Ezzamel, 1991). However, numerous studies have demonstrated that artificial intelligence such as genetic algorithm and support vector machine can be alternative methodology for classification problems to which statistical method have long been applied.

Varetto (1998) suggested two different models based on genetic algorithm, one of which is a linear model estimating the constant and the variable coefficients of the discriminant function to maximize its discriminant power using genetic algorithm. The other one is a rule based model, which classifies firms according to their respective discriminant scores called GSR (genetic score by rules) using genetic algorithm. Genetic algorithm can also be used to produce a set of rules based on the tests deriving the signs and the cutoff values of selected ratios, and in this regard, Shin and Lee (2002) suggested a rule inducing model to maximize its prediction power using genetic algorithm. Also, they presented a model beside on genetic algorithm that showed how this algorithm could be used in modeling predicting the bankruptcy. They investigated 528 producing comprised of 264 bankrupted and 265 not bankrupted from 1995 to 1997. Their results showed that the designed model could predict bankruptcy one year in advance its occurrence with the accuracy of 80% (Shin & Lee, 2002). Min and Jong suggested a new classification based on the genetic algorithm to predict bankruptcy. The proposed method was also flexible and was able to be applied in other fields such as predicting the purchase of the products or risk management of the project. The financial ratios of 2542 small and middle audited producing companies and the same number not bankrupted one were used as the data of this research (Min & Jong, 2008).

In previous literature as described in the above examples, genetic algorithm has played a role complementing the existing statistical methods and AI methods rather than a standalone method for bankruptcy prediction. In this study, genetic algorithm is also used as a medium of designing a new binary classification method. Specifically, it is used to estimate the weights and the values of the classification variables of the firms representing bankrupt firms and non-bankrupt ones, respectively.

Recently SVM which was developed by Vapnik (1995) is one of the methods that is receiving attention with remarkable results. The main difference between NN and SVM is the principle of risk minimization. While NN implements empirical risk minimization to minimize the error on the training data, SVM implements the principle of Structural Risk Minimization by constructing an optimal separating hyper plane in the hidden feature space, using quadratic programming to find a unique solution. Originally SVM was developed for pattern recognition problems and it has been used for time series prediction such as stock prince indexing (Kim, 2004; Tay & Cao, 2002) and classification such as credit rating and bankruptcy (Fan & Palaniswami, 2000; Shin et al., 2005).

SVM has been studied as bankruptcy prediction tool quite often in past (Hardle et al., 2005; Kay & Titterington, 2000; Kumar & Ravi, 2007; Min et al., 2006; Ravi et al., 2007; Ravi et al., 2008; Shin et al., 2005). It is a classification method based on Statistical Learning (SL) theory. It has already been successfully applied to optical character recognition, medical diagnostics and text classification. Two applications where SVM outperformed other methods are electric load prediction (EUNITE, 2001) and optical character recognition (Vapnik, 1995). SVM are most widely used nonparametric technique in ANN and are deemed to be most accurate. SVM classification exercise finds hyper plane in possible space for maximizing the distance from hyper plane to data points. This is equivalent to solving a quadratic optimization problem. The solution of strictly convex problems for SVM is unique and global. SVM implements Structural Risk Minimization (SRM) principle that has high generalization performance. As complexity increases by number of support vectors, SVM is constructed through trading off decreasing number of training errors and increasing the risk of over fitting data. However, data dependent SRM for SVM does not rigorously support the argument that good generalization performance of SVM is attributable to SRM (Vapnik, 1995). Since SVM captures geometric characteristics of feature space without deriving weights of networks from the training data, it is capable of extracting optimal solution with small training set size. They have flexible structure and produce better classification results than parametric methods. SVM have attractive properties and give single solution characterized by global minimum of optimized functional and not multiple solutions associated with local minima. They do not rely on heuristics and thus are an arbitrary choice to model various problems.

***Genetic Algorithm***

The Genetic algorithm (GA) is an artificial intelligence procedure based on the theory of natural selection and evolution. GA uses the idea of survival of the fittest by progressively accepting better solutions to the problems. It is inspired by and named after biological processes of inheritance, mutation, natural selection, and the genetic crossover that occurs when parents mate to produce offspring (Huang ety al, 2004). GA differs from conventional non-linear optimization techniques in that it searches by maintaining a population (or data base) of solutions from which better solutions are created rather than making incremental changes to a single solution to the problem. GA simultaneously possesses a large number of candidate solutions to a problem, called a population. The key feature of GA is the manipulation of a population whose individuals are characterized by possessing a chromosome.

Therefore, GAs is distinct from many conventional search algorithms in the following ways:

1. GAs considers not a single point but many points in the search space simultaneously reducing the chance of converging to local optima;

2. GAs work directly with strings of characters representing the parameter set, not the parameters themselves;

3. GAs use probabilistic rules, not deterministic rules, to guide their search.

Two important issues in GA are the genetic coding used to define the problem and the evaluation function, called the fitness function. Each individual solution in GA is represented by a string called the chromosome. The initial solution population could be generated randomly, which evolves into the next generation by genetic operators such as selection, crossover and mutation that means GAs perform the search process in four stages: initialization, selection, crossover, and mutation. Fig. 1 shows the basic steps of GAs. The solutions coded by strings are evaluated by the fitness function. The selection operator allows strings with higher fitness to appear with higher probability in the next generation. Crossover is performed between two selected individuals, called parents, by exchanging parts of their strings, starting from a randomly chosen crossover point. This operator tends to enable to the evolutionary process to move toward promising regions of the search space. Mutation is used to search for further problem space and to avoid local convergence of GA (Tang et al, 1996). GA has been extensively researched and applied to many combinatorial optimization problems. Furthermore GA has been increasingly applied in conjunction with other AI techniques such as NN and CBR. Various problems of neural network design have been optimized using GA. GA has also been used in conjunction with CBR to select relevant input variables and to tune the parameters of CBR. But, few studies have dealt with integration of GA and SVM, though there is a great potential for useful applications in this area.

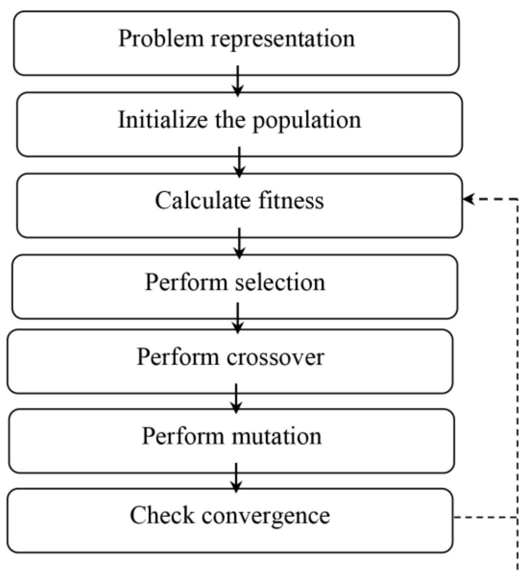


**Figure 1.** Basic steps of Gas.

***Rule extraction using GA***

Although numerous experimental studies reported the usefulness of NNs in classification studies, there is a major drawback in building and using a model in which the user cannot readily comprehend the final rules that NN models acquire. An advantage of present approach using GAs is that it is capable of extracting rules that are easy to understand for users like expert systems. In extracting bankruptcy rule, I use the similar approach that suggest in their stock selection applications. I apply GA to find thresholds (cutoffs) for one or more variables, above or below which a company is considered 'dangerous'. For instance, if the model's structure consists of two variables representing a particular company's quick ratio and a debt ratio, the final rule the GA returns might look like the following:

IF (Debt ratio > 1:50 and Quick ratio < 0:35) THEN Dangerous.

In many cases, the simplistic rule like the above example is insufficient to model relationships among financial variables. Our rule structure contains five conditions using 'AND' relations. The general form of the rule that GAs generate is as follows:

IF (the VAR1 is GREATER THAN OR EQUAL TO (LESS THAN) C1,
AND the VAR2 is GREATER THAN OR EQUAL TO (LESS THAN) C2,
AND…,
AND the VAR9 is GREATER THAN OR EQUAL TO (LESS THAN) C9)
THEN Prediction is Dangerous.

If all of the nine conditions are satisfied, then the model will produce ‘dangerous’ signal for an evaluated company. C1 to C9 denote the cutoff values which are found through genetic search process. The cutoff values range from 0 to 1, and represent the percentage of the data source’s range. This allows the rules to refer to any data source, regardless of the values it takes on. Above rule structure is summarized in Table 1. In the table, ‘which data’ means data source the rule refers to.

**Table 1.** The general rule structure.

| Description | Cond 9 | Cond 8 | Cond 7 | Cond 6 | Cond 5 | Cond 4 | Cond 3 | Cond 2 | Cond 1 | Number (j) |
|---|---|---|---|---|---|---|---|---|---|---|
| $VAR_{ji}$ (i= var. number, j= condition number) | $VAR_{9i}$ | $VAR_{8i}$ | $VAR_{7i}$ | $VAR_{6i}$ | $VAR_{5i}$ | $VAR_{4i}$ | $VAR_{3i}$ | $VAR_{2i}$ | $VAR_{1i}$ | Which data |
| $L/G_{jk}$ (k= 1: less than / 2: greater than or equal to) | $L/G_{9k}$ | $L/G_{8k}$ | $L/G_{7k}$ | $L/G_{6k}$ | $L/G_{5k}$ | $L/G_{4k}$ | $L/G_{3k}$ | $L/G_{2k}$ | $L/G_{1k}$ | Less than/ Greater than or equal to |
| Cutoff $C_j$ (j= condition number) | $C_9$ | $C_8$ | $C_7$ | $C_6$ | $C_5$ | $C_4$ | $C_3$ | $C_2$ | $C_1$ | Cutoff value |

The string encoded for the experiments is as follows:

String {$VAR_{1i}$; $VAR_{2i}$; $VAR_{3i}$; $VAR_{4i}$; $VAR_{5i}$; $VAR_{6i}$; $VAR_{7i}$; $VAR_{8i}$; $VAR_{9i}$; $L/G_{1k}$; $L/G_{2k}$; $L/G_{3k}$; $L/G_{4k}$; $L/G_{5k}$; ; $L/G_{6k}$; ; $L/G_{7k}$; ; $L/G_{8k}$; ; $L/G_{9k}$; $C_1$; $C_2$; $C_3$; $C_4$; $C_{5;}$ $C_6$; $C_7$; $C_8$; $C_9$}.

The GA maintains a population of strings which are chosen at random. This initialization allows the GAs to explore the range of all possible solutions, and this tends to favor the most likely solutions. Generally, the population size is determined according to the size of the problem, i.e. bigger population for larger problem. The common view is that a larger population takes longer to settle on a solution, but is more likely to find a global optimum because of its more diverse gene pool. We use 100 strings in the population. The task of defining a fitness function is always application specific. In this study, the objective of the system is to find a rule which would yield the highest ratio if rules are fired across the company. Thus, we define the fitness function to be the ratios of the rule. The genetic operators such as crossover and mutation which are described in Section 3 are used to search for the optimal solutions. Several parameters must be defined for the above operators, and the values of these parameters can greatly influence the performance of the algorithm. The crossover rate ranges from 0.6 to 0.8 and the mutation rate ranges from 0.08 to 0.14 for our experiment. As a stopping condition, we use 3000 trials. These processes are done by the GAs toolbox in MATLAB software.

***Data***

I use the same nine financial variables that proxy for the financial strength/weakness and potential insolvency of firms. These financial ratios have commonly been used in past bankruptcy literature and are considered to be the most efficient ones. These variables include measures of liquidity, market-based growth, leverage, and variables related to short-term debt obligations. This variables show in table 2.

**Table 2.** Variables.

| Variable | Abbreviation | GA |
|---|---|---|
| total debt/total assets | TDTA | * |
| current liabilities/total assets | CLTA | * |
| cash flow/total assets | CFTA | * |

| Variable | Abbreviation | GA |
|---|---|---|
| net income/total assets | NITA | * |
| working capital/total assets | WCTA | * |
| current assets/total assets | CATA | * |
| earnings before interest and taxes/total assets | EBTA | * |
| earnings before interest and taxes/interest expense | EBIE | * |
| market value of equity/book value of common equity | MVCE | * |

TDTA indicates the long-term financial obligations of a firm. An increase in this variable would lead to higher probability of financial distress.

A firm with high CLTA indicates that the firm does not have sufficient cash flow to continue its day-to-day operations, i.e., such firms would find it difficult to fulfill short-term debt obligations and therefore would become financially distressed.

The following input variables are considered in such a way that smaller values for these variables would result in a firm to become more probable for bankruptcy. It can be seen that the following input variables are functions of liquidity measures, such as net income, working capital, current assets, cash flows, operating earnings, etc. Firms with smaller values for such liquidity measures are more probable for bankruptcy.

The above inputs and outputs are used in models (1) and (2) to compute the efficiency score $\theta_1$ and the corresponding bankrupt frontier.

To obtain $\theta_2$ and identify the success frontier, we use TDTA and CLTA as the two inputs. Firms with small TDTA and CLTA are less likely to go bankrupt and would appear close to the success frontier. The inputs of the bankruptcy frontier model are used as outputs in the success frontier model, i.e., in this case, large values on CFTA, NITA, WCTA, CATA, EBTA, EBIE, and MVCE indicate better financial performance of a firm.

According to the information and data available in library of Tehran Stock Exchange, in that span of time only 70 companies were in accordance with article 141 of Business law over the period 2012-2016 across a full spectrum of industries. To compare with bankrupt companies, some 70 non-bankrupt companies were also chosen via random sampling.

## Results

In this section, I will present the result of GA and SVM in prediction of bankruptcy in bankrupt and non-bankrupt firms. I use the follow phrases to show the result in the models:

(i) P (PBR|BR): percentage of bankrupt firms predicted as bankrupt.

(ii) P (PNBR|NBR): percentage of non-bankrupt firms predicted as non-bankrupt.

(iii) Percentage of total correct predictions: the mean of (i) and (ii) .

Our genetic search process finally extracts one bankruptcy prediction rule. This rule generated and the corresponding description is illustrated in Table 3.

**Table 3.** The description of rule generated.

| | Con 1 | Con 2 | Con 3 | Con 4 | Con 5 | Con 6 | Con 7 | Con 8 | Con 9 |
|---|---|---|---|---|---|---|---|---|---|
| Variable code | 2 | 7 | 6 | 9 | 1 | 3 | 4 | 8 | 5 |
| > / < code | 2 | 2 | 1 | 1 | 2 | 1 | 1 | 2 | 1 |
| Cutoff | 0.8746 | 0.595 | 0.082 | 0.4261 | 0.3112 | 0.3604 | 0.631 | 0.6653 | 0.4535 |
| Description | IF current liabilities to total assets greater than or equal to 0.8746 AND earnings before interest and taxes to total assets greater than or equal to 0.595 AND current assets to total assets less than 0.082 AND market value of equity to book value of common equity less than 0.4261 AND total debt to total assets greater than or equal to 0.3112 AND cash flow to total assets less than 0.3604 AND net income to total assets less than 0.631 AND earnings before interest and taxes to interest expense greater than or equal to 0.6653 AND working capital to total assets less than 0.4535 | | | | | | | | |

The general goal in optimization is to find the best solution to a problem. Since GAs try to find out the optimal or near optimal combination of above searching parameters, the final solution is one.

The average ratio if the rules are fired is 88.2% of training and validation sets, respectively. This means if the financial variables of a company are within the feature ranges of derived rules, the probability of bankruptcy is about 80% of cases. Table 4 show the result of GA in training set and validation set.

**Table 4.** Test result of GA model.

| Samples* | Real group membership | Predicted group GA model | | |
|---|---|---|---|---|
| | | 0 | 1 | Total |
| Training Set | 1 (Count) | 14 | 56 | 70 |
| | 0 (Count) | 68 | 2 | 70 |
| | 1 (%) | 20 | 80 | 100 |
| | 0 (%) | 97.1 | 2.9 | 100 |
| Validation Set | 1 (Count) | 16 | 54 | 70 |
| | 0 (Count) | 69 | 1 | 70 |
| | 1 (%) | 22.8 | 77.2 | 100 |
| | 0 (%) | 98.6 | 1.4 | 100 |

*Group 1: bankrupt firms; Group 0: non-bankrupt firms.

## Conclusion

The global financial crisis was brought on by the collapse of a small number of now (in) famous systemically important financial institutions. The high social costs associated with bankruptcy have spurred for better theoretical understanding and prediction capability. From initial developments such as Beaver and Altman, the interest of experts, academics and others regarding models of bankruptcy prediction, has intensified, also in the light of the recent global economic-financial crisis. Bankruptcy of companies appears because of different reason, one of that is financial and economic crisis. Bankruptcy is a highly significant worldwide problem that affects the economic well being of all countries. So, we can protect our investment against financial and economic crisis. The high social costs incurred by various stakeholders associated with bankrupt firms have spurred searches for better theoretical understanding and prediction capability. Bankruptcy prediction is an important and widely studied topic since it can have significant impact on bank lending decisions and profitability. Recently, the support vector machine has been applied to the problem of bankruptcy prediction. The GA-based model has been compared with other methods such as the neural network and logistic regression, and has shown good results. However, few studies have dealt with comparing of GA although there is a great potential for useful applications in this area. This paper focuses on the accuracy of the genetic algorithm and support vector machines in identifying and medicating bankruptcy of the companies. The findings show that the models can be used in Tehran Stock  Besides, based on the research findings, those companies that enjoy less profit and most their assets are obtained though liabilities are more in danger of bankruptcy than other companies. Meanwhile, the liquidity is one of factors that are of adverse relationship with bankruptcy. To protect against financial crisis and decrease bankruptcy, the companies should use more conservative strategies that lead to a decrease in liabilities and financial leverage and try to control the expenses more.

***Conflict of interest***

The authors declare no conflict of interest

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