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Prediction of Financial Crisis Using Imperialist Competitive Algorithm: Evidence from Tehran Stock Exchange

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ABSTRACT

Since the accuracy of corporate financial crisis prediction is very important for financial institutions, investors and governments, many methods have been employed for developing effective prediction models. The aim of this research was twofold: (1) propose a new classification method following the artificial intelligence, which employs an Imperialist Competitive Algorithm (ICA) to the problem, (2) predict the financial crisis in Iranian firms listed inTehran stock exchange (TSE) using principal component analysis Imperialist Competitive Algorithm (PCAICA) model and its related financial ratios.For this purpose the sample was 60 registered firms in Tehran Stock Exchange and the financial information was gathered with use of their financial reports within 21 years beginning from 1991 and ending to 2012 and desired financial ratios were extracted. The experimental results show that the proposed model is good alternative for financial crisis prediction.

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INTRODUCTION

The current financial crisis has already thrown many companies out of business all over the world. All this happened because they were not able to face the challenges and the unexpected changes in the economy. Over the past decade or so a number of studies have appeared on corporate bankruptcy. The first attempts, in the U.S., to use publicly available data with various statistical techniques in order to predict business failure were

Made by Beaver (1967) and Altman (1968). Since then a growing number of related studies have tested bankruptcy prediction models in several industrial countries such as Germany, England, Ireland, the Netherlands, France, Japan, Australia, Canada and Brazil. This widespread interest in predicting financial distress is understandable. Identifying impending financial crisis is very important to analysts, stockholders and creditors of business firms as well as to the firm’s managers. The bankruptcy models can be used as early signals warning management that, unless corrective action is undertaken, the firm may be faced with financial crisis.

Creditors, auditors, stockholders and senior management are all interested in bankruptcy prediction because it affects all of them alike. For reduction of the undesirable bankruptcy effects for financial statement user, bankruptcy prediction models have been made. [Wilson, Sharda 1994]

The bankruptcy prediction models can be divided into two main streams. The first one is based on statistical techniques. Among statistical techniques, the methods covered are: linear discriminant analysis (LDA)(Altman,Marco&Varetto1994)multivariate discriminate analysis (MDA) Altman (1968), quadratic discriminant analysis (QDA)(Michael, Georgios, Nikolaos, & Constantin 1999), logistic regression (logit)(Andres, Landajo & Lorca 2005; Ohlson 1980) and factor analysis (FA)(West 1985). The second one is employing artificial intelligence (AI) methods, The intelligent techniques covered in the study belong to (i) different neural network (NN)architectures including multi-layer perception (MLP) (Cinca 1998; Rumelhart, Hinton Williams 1986) probabilistic neural networks (PNN)((Yang, Platt, & Platt,1999), auto-associative neural network (AANN) (Baek& Cho 2003), self-organizing map (SOM) (Kaski, Sinkkonen, &Peltonen, 2001; Lee, Booth, & Alam, 2005), learning vector quantization (LVQ) (Gersho Gray 1992; Gorzalczany, Pista 1999) and cascade correlation neural network (Cascor) ((Lacher, Coats, Sharma, & Fantc, 1995), (ii) decision trees (Frydman, Altman, & Kao, 1985; Marais, Patel, &Wolfson, 1984 ; . Lacher, Coats, Sharma &Fantc 1995), (iii) case-based reasoning (Bryant 1997) , (iv) evolutionary approaches (Varetto 1998; Etemadi, Anvary Rostamy, Farajzadeh

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Dehkordi 2009), (v) rough sets (Dimitras, Slowinski, Susmaga, Zopounidis 1999), (vi) soft computing (hybrid intelligent systems) (Zadeh 1994), (vii) operational research techniques including linear programming (LP) (Cielen, Peeters, Vanhoof, 2004), data envelopment analysis (DEA) (Cielen, Peeters, Vanhoof 2004) and quadratic programming (QP) (Tseng Lin 2005), (viii) other intelligent techniques including support vector machine (Min, Lee 2005), fuzzy logic techniques (Zadeh 1965). (Kumar and Ravi 2007; Min, Jeong 2009).

In this paper, proposed a new classification method following the artificial intelligence, which employs an Imperialist Competitive Algorithm (ICA) to the problem. Imperialist Competitive Algorithm is a new socio-politically motivated global search strategy that has recently been introduced for dealing with different optimization tasks. (Atashpaz-Gargari, 2007).

In this study, financial crisis prediction model is compiled by use Imperialist Competitive Algorithm (artificial intelligent technique) and financial ratio (loss & profit and balance sheet).

1. Explanation of tools and modeling technique:

1. 1. principal component analysis(PCA):

Principal component analysis, or PCA, is a technique that is widely used for applications such as dimensionality reduction, lossy data compression, feature extraction and data visualization (Jolliffe, 2002).

PCA can be defined as the orthogonal projection of the data onto a lower dimensional linear space, known as the *principal subspace*, such that the variance of the projected data is maximized (Hotelling, 1933). Equivalently, it can be defined as the linear projection that minimizes the average projection cost, defined as the mean squared distance between the data points and their projections (Pearson, 1901). Geometrically, principal components analysis can be thought of as a rotation of the axes of the original coordinate system to a new set of orthogonal axes that are ordered in terms of the amount of variation of the original data they account for. (A.R Webb & K.D. Copsey).

1. 2. Imperialist Competitive Algorithm(ICA):

Imperialist Competitive Algorithm (ICA) is a new socio-politically motivated global search strategy that has recently been introduced for dealing with different optimization tasks (Atashpaz- Gargari & Lucas, 2007). This method has been inspired by imperialistic competition. It has shown great performance in both convergence rate and better global optima achievement (Atashpaz-Gargari & Lucas, 2007; Rajabioun, Hashemzadeh, Atashpaz-Gargari, Mesgari, & Rajaei Salmasi, 2008b; Biabangard-Oskouyi, Atashpaz-Gargari, Soltani, & Lucas, 2009; Sepehri Rad & Lucas, 2008; Atashpaz-Gargari, Hashemzadeh, Rajabioun, & Lucas 2008; Rajabioun, Atashpaz-Gargari,& Lucas, 2008a).

Fig 1 shows the flowchart of the ICA. This algorithm starts with an initial population. Each member of the population is called a country. Some of the best countries (in this paper, countries with the least cost) are selected to be the imperialist states and the rest form the colonies of these imperialists. All the colonies of initial countries are divided among the mentioned imperialists based on their power. The power of each country, the counterpart of fitness value in the GA, is inversely proportional to its cost. The imperialist states together with their colonies form some empires.

After forming initial empires, the colonies in each of them start moving toward their relevant imperialist country. This movement is a simple model of assimilation policy which was pursued by some of the imperialist states. The total power of an empire depends on both the power of the imperialist country and the power of its colonies. This fact is modeled by defining the total power ofan empire as the power of imperialist country plus a percentage of mean power of its colonies.

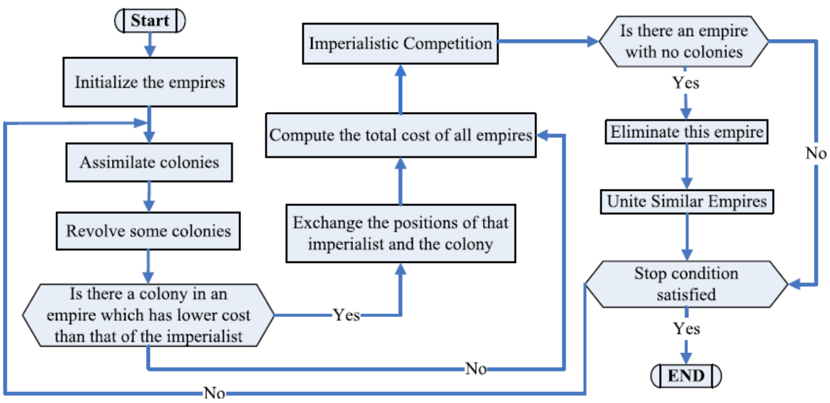

Fig. 1: Flowchart of the Imperialist Competitive Algorithm.

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2.2.1. Creation of initial empires:

The *goal* of optimization is to find an optimal solution in terms of the variables of the problem. We form an array of variable values to be optimized. In the GA terminology, this array is called ‘‘chromosome”, but in ICA the term ‘‘country” is used for *this* array. Inan Nvar-dimentional optimization problem, a country is a 1× Nvar array. This array is defined as following:

Country= [p_1; p_2; p_3; . . . ; p_{Nvar}],

Wherep_{is} are the variables to be optimized. The cost of a country is found by evaluation of the cost function *f* at variables (*p1, p2, p3, . . . ,pNvar*). So we have:

Cost=*f* (country) = *f* (p_1; p_2; p_3; . . . ; p_{Nvar})

To start the optimization algorithm, initial countries of size *NCountry*is produced. We select *Nimp* of the most powerful countries to form the empires. The remaining Ncol of the initial countries will be the colonies each of which belongs to an empire.

To form the initial empires, the colonies are divided among imperialists based on their power. That is, the initial number of colonies of an empire should be directly proportionate to its power. To proportionally divide the colonies among imperialists, the normalized cost of an imperialist is defined by

$$C_n = c_n - \max_i\{c_i\}$$

Where *cn* is the cost of the *n*th imperialist and *Cn* is its normalized cost. Having the normalized cost of all imperialists, the normalized power of each imperialist is defined by

$$p_n = \left|\frac{C_n}{\sum_{i=1}^{N_{imp}} C_i}\right|$$

The initial colonies are divided among empires based on their power. Then the initial number of colonies of the *n*th empire will be:

$$N.{C_{\cdot n}} = \text{round}\{p_n . N_{col}\},$$

Where $N.{C_{\cdot n}}$is the initial number of colonies of the *n*th empire and *Ncol*is the total number of initial - colonies. To divide the colonies, $N.{C_{\cdot n}}$of the colonies are randomly chosen and given to the nth imperialist. These colonies along with the *n*th imperialist form the *n*th empire. Fig. 2 shows the initial empires. As shown in this figure, bigger empires have a greater number of colonies while weaker ones have less. In this figure imperialist 1 has formed the most powerful empire and consequently has the greatest number of colonies.

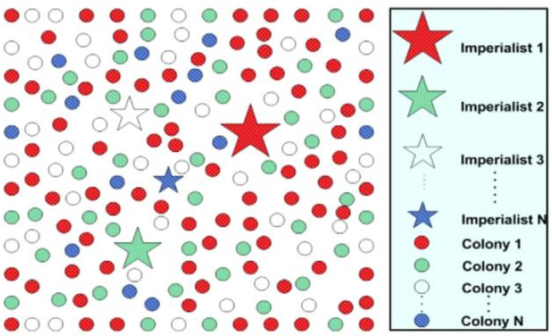

Fig. 2: Generating the initial empires: The imperialist with more colonies, has shown with a bigger star.

2.2.2. Assimilation: movement of colonies toward the imperialist:

Pursuing an assimilation policy, the imperialist states tried to absorb their colonies and make them a part of themselves. More precisely, the imperialist states made their colonies to move toward themselves along different socio-political axis such as culture, language and religion. In the ICA, this process is modeled by moving all of the colonies toward the imperialist along different optimization axis. Fig. 4 shows this movement. Considering a 2-dimensional optimization problem, in this figure the colony is absorbed by the imperialist in the *culture* and *language* axes. Then colony will get closer to the imperialist in these axes. Continuation of assimilation will cause all the colonies to be fully assimilated into the imperialist.

In the ICA, the assimilation policy is modeled by moving all the colonies toward the imperialist. This movement is shown in Fig. 3 in which a colony moves toward the imperialist by x units. Thenew position of the colony is shown in a darker color. The direction of the movement is the vector from the colony to the imperialist.

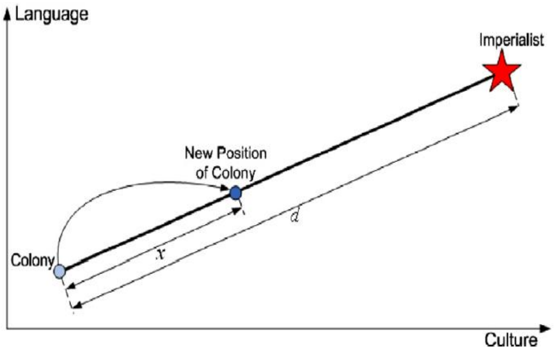

Fig.3: Movement of colonies toward their relevant imperialist.

In this figure x is a random variable with uniform (or any proper) distribution. Then $x \sim U(0, \beta \times \boldsymbol{d})$,

Where β is a number greater than 1 and d is the distance between the colony and the imperialist state. $\beta > 1$ causes the colonies to get closer to the imperialist state from both sides.

Assimilating the colonies by the imperialist states did not result in the direct movement of the colonies toward the imperialist. That is, the direction of movement is not necessarily the vector from the colony to the imperialist. To model this fact and to increase the ability of searching more area around the imperialist, a random amount of deviation is added to the direction of movement. Fig. 4 shows the new direction. In this figure θ is a parameter with uniform (or any proper) distribution.

$\theta \sim U(-\gamma, \gamma)$

Then Where$\gamma$is a parameter that adjusts the deviation from the original direction? Nevertheless the values of β and $\gamma$are arbitrary, in most of implementations a value of about 2 for $\beta$and about π/4 (Rad) for γresults in good convergence of countries to the global minimum.

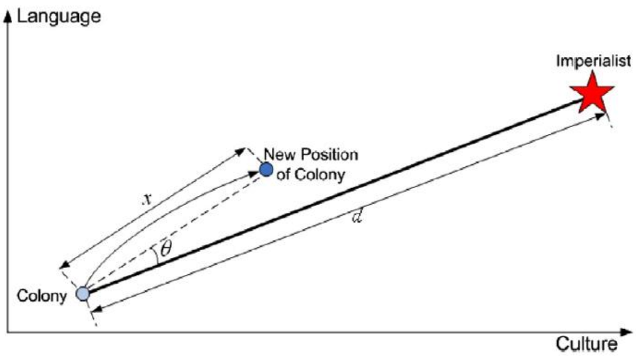

Fig. 4: Movement of colonies toward their relevant imperialist in a randomly deviated direction.

2.2.3. Revolution: a sudden change in socio-political characteristics of a country:

Revolution is a fundamental change in power or organizational structures that takes place in a relatively short period of time. In the terminology of ICA, revolution causes a country to suddenly change its socio-political characteristics. That is, instead of being assimilated by an imperialist, the colony randomly changes its position in the socio-political axis. Fig. 5 shows the revolution in Culture-Language axis. The revolution increases the exploration of the algorithm and prevents the early convergence of countries to local minimums. The revolution rate in the algorithm indicates the percentage of colonies in each colony which will randomly change their position. A very high value of revolution decreases the exploitation power of algorithm and can reduce its convergence rate.

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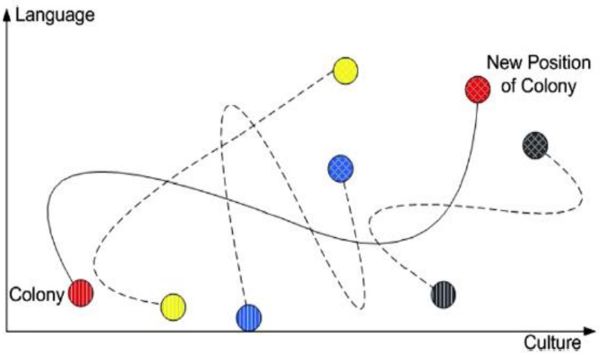

Fig. 5: Revolution: a sudden change in socio-political characteristics of a country.

2.2.4. Exchanging positions of the imperialist and a colony:

While moving toward the imperialist, a colony might reach to a position with lower cost than the imperialist. In this case, the imperialist and the colony change their positions. Then the algorithm will continue by the imperialist in the new position and the colonies will be imitated by the imperialist in its new position. Fig. 6a depicts the position exchange between a colony and the imperialist. In this figure the best colony of the empire is shown in a darker color. This colony has a lower cost than the imperialist. Fig. 6b shows the empire after exchanging the position of the imperialist and the colony.

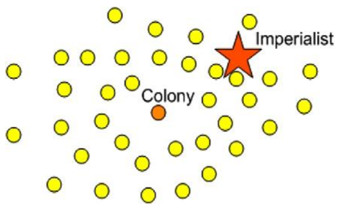

Fig. 6a: Exchanging the positions of a colony and the imperialist.

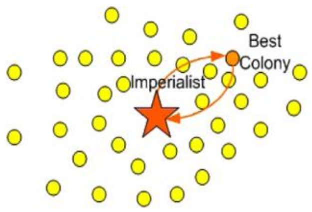

Fig. 6b. The entire empire after position exchange.

2.2.5. Uniting similar empires:

In the movement of the colonies and imperialists toward the global minimum of the problem some imperialists might move to similar positions. If the distance between two imperialists becomes less than threshold distance, they both will form a new empire which is a combination of these empires. All the colonies of two empires become the colonies of the new empire and the new imperialist will be in the position of one of the two imperialists. Figs. 7a and b show the uniting process of two empires before uniting andresulting from uniting two empires, respectively.

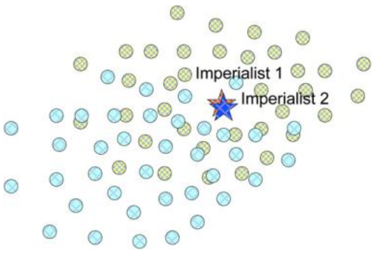

Fig. 7a: The empires before uniting.

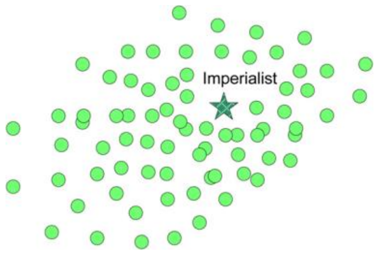

Fig. 7b: The empire resulting from uniting two empires.

2.2.6. Total power of an empire:

The total power of an empire is mainly affected by the power of an imperialist country. However the power of the colonies of an empire has an effect, albeit negligible, on the total power of that empire. This fact is modeled by defining the total cost of an empire by:

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$T.C. = Cost\ (Imperialist_n) + \xi\ mean\{\ Cost(\ colonies\ of\ empire_n)\}$

Where T.C.n is the total cost of the *n*th empire and ξ is a positive small number. A little value for ξ causes the total power of the empire to be determined by just the imperialist and increasing it will increase to the role of the colonies in determining the total power of an empire. The value of 0.1 for ξ has shown good results in most of the implementations.

2.2.7. Imperialistic competition:

All empires try to take the possession of colonies of other empires and control them. The imperialistic competition gradually brings about a decrease in the power of weaker empires and an increase in the power of more powerful ones. The imperialistic competition is modelled by just picking some (usually one) of the weakest colonies of the weakest empire and making a competition among all empires to possess these (this) colonies. Fig. 8 shows a big picture of the modelled imperialistic competition. Based on their total power, in this competition, each of empires will have a likelihood of taking possession of the mentioned colonies. In other words, these colonies will not definitely be possessed by the most powerful empires, but these empires will be more likely to possess them.

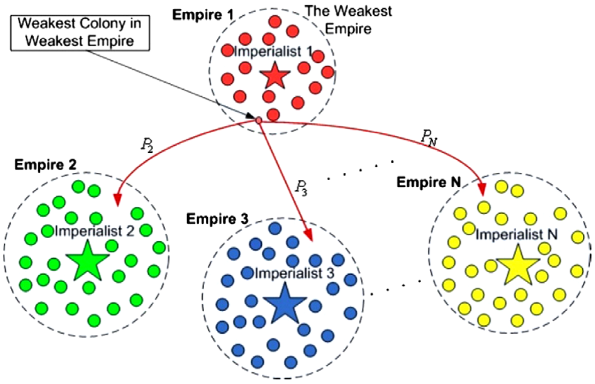

Fig. 8: Imperialistic competition: The more powerful an empire is, the more likely it will possess the weakest colony of the weakest empire.

To start the competition, first a colony of the weakest empire is chosen and then the possession probability of each empire is found. The possession probability $P_P$is proportionate to the total power of the empire. The normalized total cost of an empire is simply obtained by:

$$N.T.C._n = T.C._n - \max_i\{T.C._i\}$$

Where, T.C.nand N.T.Cnare the total cost and the normalized total cost of *n*th empire, respectively. Having the normalized total cost, the possession probability of each empire is given by:

$$P_{P_n} = \left|\frac{N.T.C._n}{\sum_{i=1}^{N_{imp}} N.T.C._i}\right|$$

To divide the mentioned colonies among empires vector **P**is formed as following:

$\mathbf{P}=\left[\ P_{P_1}, P_{P_2}, P_{P_3}, \dots P_{P_{N_{imp}}}\ \right]$

Then the vector **R**with the same size as **P**whose elements are uniformly distributed random numbers is created,

$$\boldsymbol{R} = \left[r_1, r_2, r_3, \dots, r_{N_{imp}}\right] r_1, r_2, r_3, \dots, r_{N_{imp}} \sim U(0,1)$$

Then vector **D**is formed by subtracting **R**from **P**

$\boldsymbol{D} = \boldsymbol{R} - \boldsymbol{P} = \left[D_1, D_2, D_3, \dots, D_{N_{imp}}\right] = \left[\ P_{P_1} - r_1, P_{P_2} - r_2, P_{P_3} - r_3, \dots P_{P_{N_{imp}}} - r_{P_{N_{imp}}}\right].$

Referring to vector **D** the mentioned colony (colonies) is handed to an empire whose relevant index in **D**is maximized.

The process of selecting an empire is similar to the roulette wheel process which is used in selecting parents in GA. But this method of selection is much faster than the conventional roulette wheel. Because it is not required to calculate the cumulative distribution function and the selection is based on only the values of probabilities. Hence, the process of selecting the empires can solely substitute the roulette wheel in GA and increase its execution speed.

The main steps of ICA are summarized in the pseudo-code are given in Fig. 10. The continuation of the mentioned steps will hopefully cause the countries to converge to the global minimum of the cost function. Different criteria can be used to stop the algorithm. One idea is to use a number of maximum iteration of the algorithm, called maximum decades, to stop the algorithm. Or the end of imperialistic competition, when there is only one empire, can be considered as the stop criterion of the ICA. On the other hand, the algorithm can be stopped when its best solution in different decades cannot be improved for some consecutive decades.

```
1) Select some random points on the function and initialize the empires.
2) Move the colonies toward their relevant imperialist (Assimilation).
3) Randomly change the position of some colonies (Revolution).
4) If there is a colony in an empire which has lower cost than the
   imperialist, exchange the positions of that colony and the
   imperialist.
5) Unite the similar empires.
6) Compute the total cost of all empires.
7) Pick the weakest colony (colonies) from the weakest empires and give
   it (them) to one of the empires (Imperialistic competition).
8) Eliminate the powerless empires.
9) If stop conditions satisfied, stop, if not go to 2.
```

Fig. 10: Pseudo code of the Imperialistic Competitive Algorithm.

2. Development of models:

2. 1. Statistical society:

The research statistical society is Iranian firms listed inTehran stock exchange (TSE) , that have given their financial statement from 1992 to2011.

The data set used for this research consists of 124. 62 companies went bankrupt under paragraph 141 of Iran Trade Law1 from 1992 through 2011.The other 62 companies are ‘‘matched” companies, from the same period of listing on the TSE.

2. 2. *Sample selection:*

The financial statement of the all companies listed in stock exchange is extracted from 1992 to 2011 by using the Rahavard Novin software. Then, using Article 141 of Iran’s the commercial law, all companies are classified into two categories: the companies having financially healthy and companies having financially distressed.According to this article the companies are known as bankrupt whose retained losses are more than 50% of their capital in companies having financially healthy, randomly selection in two steps are made, in first step, sample companies are selected among total samples and after selecting the samples , the desired fiscal year, from 1993through 2011 was randomly selected.

In companies having financially distressed, with respect to the limitation of the companies, it is impossible to select randomly, so all companies that are included in commercial law 141for three consecutive years and their all financial information has completely been available, are in this sample.After choosing the sample companies, each of these two kinds of companies were randomly separated again into two groups: training and hold out, as in table 1.

Table 1: Sample separation.

Companies	Training samples	Hold-out samples	Total samples
financially healthy	50	12	62
financially distressed	50	12	62
Total samples	100	24	124

Finally, by determining the sample and desired fiscal year. The desired financial ratios (a year before occurrence) were extracted for modeling.

2. 3. Selected financial ratios:

A common approach to bankruptcy prediction is to review the literature to identify a large set of potential predictive financial and/or non-financial variables and then develop a reduced set of variables, through some combination of judgmental and mathematical analysis that will predict bankruptcy (Lensberg, Eilifsen, & McKee 2006; Etemadi, Anvary Rostamy, Farajzadeh Dehkordi 2009).

Data are usually based on annual financial statement information (Grice & Ingram, 2001). The required data to calculate the ratios have been gathered from companies' balance sheets and income statements.

In this paper, we apply two stages predictive variable selection process. In first step, list of variables based on bankruptcy prediction literature that is given by Kumar and Ravi is provided in 2007and by comparison assessment with commercial environment and researches done in this field(Anvary, Etemadi, Farajzadeh Dehkordi 2009and Rostamy, Bostanian 2011, Manzari, Mokhatab Rafiei) 23financial ratios were selected, as described in table 2.

Table 2: shows the selected variables.

Variables	financial ratios	variables	financial ratios
X1	Working capital to Shareholders' equity	X13	Total liabilities to Retained earnings
X2	Working capital to Sales	X14	Total liability to total assets
X3	Working capital to Total liabilities	X15	Retained earnings to Total assets
X4	Working capital to Total assets	X16	Operational income to sales ratio
X5	Earnings before interest & taxes to Shareholders' equity	X17	Interest expense to gross profit
X6	Earnings before interest & taxes to Sales	X18	Quick assets to total assets
X7	Earnings before interest & to Total liabilities	X19	Current assets to Current liabilities
X8	Earnings before interest & to Total assets	X20	Net income to Sales
X9	Shareholders' equity to Total liabilities	X21	Net income to Total assets
X10	Shareholders' equity to Total assets	X22	Current liabilities to Total assets
X11	Sales to Total liabilities	X23	Current liabilities to Shareholders' equity
X12	Sales to Total assets		

3. Experimental results:

3. 1. Data pre-processing using the component analysis:

Data pre-processing is a useful step before classification. In general pre-processing includes three stages; data transformation, data cleaning, and data selection (Han & Kamber, 2001).

For this purpose, principle component analysis and data normalizing techniques are used.The principal component analysis is a traditional multivariate statistical analysis method primarily meant for dimensionality reduction of the feature space in large datasets. Hence, it is widely used in data mining.(Ravi , Pramodh, 2008)

Normalizing is to re-write all factors in a known range for example [0, 1]. Normalization prevents elimination of the effect of small inputs by effects of large inputs. There are two main normalizing methods; linear and stochastic (Nguyen and Chan, 2004).

Linear normalization into [a, b] range that is done with following Eq. (1):

$(b-a)(x-x_{min})/(x_{max}-x_{min})+ a$ (1)

Stochastic normalization or $x_n=(x\text{-mean})/std$ (2)

In this study23input variables are reduced to 6variables by using main component analysis, then data in[0, 1] range is normalized, by using the linear normalization.

3. 2. ICA model:

Our problem consists of seven parameters, each of which is a real number between -10 and 10. The object is to minimize the error of the linear discriminant function. To use ICA algorithm to solve this problem, at first a proper definition of *county* should be stated. in this problem *county* include seven parameters as following: County=$[a_1, a_2, a_3, a_4, a_5, a_6, a_7]$ and Output variables form PCA are $[x_1,x_2,x_3,x_4,x_5,x_6]$. Z-score is used to predict the probable financial collapse of companies:

$$Z = a_1 \times x_1 + a_2 \times x_2 + a_3 \times x_3 + a_4 \times x_4 + a_5 \times x_5 + a_6 \times x_6 + a_7$$

So if Z is Positive the company is financially healthy, and if Z is negative the company will know as bankrupt. The Train and Test data are used to computer the classification error rate. We use ICA algorithm to minimize the classification error rate by finding optimal value for *County* which has the Minimum of classification error in Train, Test and total data.

The ICA algorithm will find a country which has the minimum value of the cost function. This algorithm starts by generating a set of random solutions (random countries). After calculating the costs of all countries, countries with least values are chosen as imperialists, other countries are divided among the imperialists as described earlier in section X. The parameters of ICA are shown in Table 3. The results show that 89% of train data and 79.17% of test data are classified correctly.

Table 3: Parameters of ICA approach.

ICA parameter	Value	ICA parameter	Value
Number of initial countries	200	a_1	1.789514
Number of initial imperialists	15	a_2	0.600353
Number of decades	300	a_3	-0.40363
Revolutionrate	0.6	a_4	-0.01975
β	2	a_5	0.333445
γ	0.6	a_6	0.315955
ξ	0.05	a_7	-0.74388
Uniting threshold	0.01		

Fig. 9 shows the convergence of the ICA algorithm to the optimal solutionwhich has the least error rate. In this figure the red line shows the minimum error rate of the imperialists and the blue line concern with an average error rate of all imperialists.

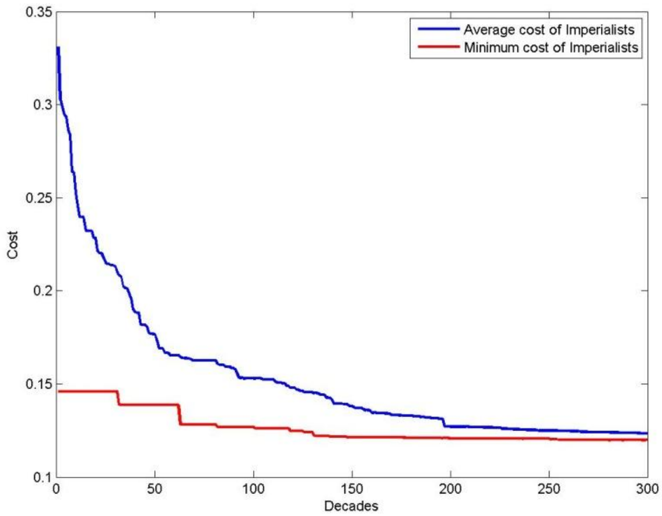

Fig. 9: Convergence of ICA to minimum error rate.

3. 3. Ability of the prediction model:

Table 4 represents the obtained results from the empirical test of ICA model for prediction of financial crisis. This model succeeded in correct classification of the firms present in the training, hold-out, and total sample into financially healthy and distressed firms with a general accuracy of 89%, 79.17% and 87.10%, respectively.

Study of the results obtained from this model in the training data indicates that ICA model had an accuracy of 92% in correct classification of financially distressed firms in this set (i.e. from50 financially distressed firms present in this set, 46 firms have been correctly classified). In addition, this model had an accuracy of 86% in correct classification of financially healthy firms in this set (i.e. from among 50 financially healthy firms in this set, 43 firms have been correctly classified).

Study of the results obtained from this model in the Hold-out data indicates that ICA model had an accuracy of 83% in correct classification of financially distressed firms in this set (i.e. from12 financially distressed firms present in this set, 10 firms have been correctly classified). In addition, this model had an accuracy of 75% in correct classification of financially healthy firms in this set (i.e. from among 12 financially healthy firms in this set, 9 firms have been correctly classified).

Table 4: Results ica model.

result	Training samples			Hold-out samples			Total samples		
	0	1	correct	0	1	correct	0	1	correct
Number 1	7	46	46	3	10	10	10	56	56
Number 0	43	4	43	9	2	9	52	6	52
Total	50	50	89	12	12	19	62	62	108
Percentage 1	%14	%92	%92	%25	%83.33	%83.33	%16.13	%90.32	%90.32
Percentage 0	%86	%8	%86	%75	%16.67	%75	%83.87	%9.68	%83.87
General percentage	%100	%100	%89	%100	%100	%79.17	%100	%100	%87.10

Study of total results from this model (in training and hold-out sets) indicates that ICA model has an accuracy of 90.32% in correct classification of financially distressed firms in this set (from among 62

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financially distressed firms in this set, 56 firms have been correctly classified). In addition, this model has an accuracy of 83.87% in correct classification of financially healthy firms in this set (from 62 financially healthy firms in this set, 52 firms have been correctly classified).

4. Summary and conclusions:

Financial crisis prediction models are among the techniques and tools used for prediction of firms' future state through calculation of financial crisis by combining a group of financial ratios. Financial and commercial prediction power from perspective of both private investor and society is of importance, since it is an evident signal to incorrect resource allocation. The early warning on bankruptcy probability by prediction of financial crisis enables management and investors to take preventive actions and to distinguish desirable investment opportunities from the undesirable ones. (Mehrani, Bahramfar & Ghayour, 2005).

In this paper Imperialist Competitive Algorithm (ICA) technique using the financial ratios for training and hold out samples could correctly and efficiently be classified.

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