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INCLUDING INTANGIBLE ASSETS IN RATES TO ESTIMATE THE RISK OF BANKRUPTCY

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Abstract:
The purpose of this paper is to show that an economic entity's intangible assets play an important role in predicting the risk of bankruptcy of the company and at the same time in its evolution. Based on benchmarking and on appeal to the experience and intuition of available human expert it can be shaped a credible model and, based on this model can be projected the future course of a business organization. Among other issues, we note that the intangible assets of a company can and should be entered into the equation for estimating the risk of bankruptcy whether it avails or not to artificial intelligence (AI) techniques to solve this problem (values lead to bankruptcy and the graphics functions differ majorly when the analysis includes the Rhine rate which takes into account intangibles of firms). From the structure of the paper we can see that whatever the type of model used in predicting the risk of bankruptcy at either classic or using artificial intelligence techniques (AI) a leading role in the evolution and the value of the company represents intangible.

Key words: intangible assets, knowledge, neural network, predicting the risk, score

JEL classification: M1, M15

1. LITERATURE REVIEW

The innovation capacity has been and continues to be a fundamental component that differentiates the competition and better meets the requirements and market needs. The knowledge society is based on human intelligence and creativity and intangible assets such as knowledge and information and knowledge management skills *are becoming the new kernel*. Intellectual property assets include know-how, trade secrets, copyright, patent or other intellectual property rights.

Richard Crawford, in his studies showed that 70% of resources of firms, represent investments in human capital. *Thomas Davenport's* views on human capital refer to the value represented by investment in human capital *"human capital means all intangible assets that people bring to their jobs."*

In the literature (Malhotra, 2003), it is shown that the analysis of existing models for measuring knowledge as assets highlights the fact that despite the abundance of such measurement models, there is a strong need to connect the measurement process of knowledge as active with their management.

Measuring knowledge as assets relates to the evaluation, growth, monitoring and management of business success through a number of increasingly large intangible factors. In the context of knowledge assets, knowledge represents the collective part of intangible assets, identifiable and measurable. This interpretation of knowledge is different from the concept of knowledge (Luban and Breazu, 2000), as knowledge and learning, which refers to how organizations acquire, distribute, and use knowledge - is supported by technology and organizational processes.

Most of the papers consider intellectual capital as something that is not visible, including value incorporated in skills of employees, an organization's processes and its relations with customers. In (Malhotra, 2003) these models are grouped into four categories: models based on the method of scoring, models based directly on components of intellectual capital, models based on market capitalization (market value of the company) and methods based on return on assets.

When assessing the risk of bankruptcy some researchers have used multiple discriminate analysis (Altman 1968; Altman, Haldeman and Narayanan, 1977), the conditional probability (Martin 1977 Ohlson, 1980; Zmijewski, 1984), recursion (Frydman, Altman and Kao, 1985) and expert systems applications and artificial neural networks (Messier and Hansen, 1988; Bell, Ribar and Verchio, 1990; Hansen and Messier, 1991; Serrano Martin del Brio, 1993; Koh and Tan, 1999; Brockett et al ., 2006). Some of these models are built on fuzzy set theory and fuzzy logic (Dubois and Prade, 1992; Slowinski and Zopounidis, 1995; McKee and Lensberg, 2002).

The successful application of neural networks is present in many areas. Here are a few examples: detecting explosives in baggage at airports, identifying the types of cloud-based satellite imagery, signal processing, eg for detecting radar, speech recognition using integrated neural networks, applications for trading on the stock exchange, risk assessment, and so on.

Based on models provided by Altman (1968), Conan-Holder and Rating research concentrated on predicting the risk of bankruptcy using advanced artificial intelligence (AI) techniques. The aim is to introduce a new rate in the score function of patterns mentioned above to build a predictive model.

2. WORKING METHODOLOGY

Expert systems and systems artificial neural have in common the idea of using knowledge to support electronic computer, however being different but essentially, in terms of how to store that knowledge (for systems expert storage, predominant explicit and comprehensible to the user, for neural artificial systems a default storage (defined as weight thresholds) and unintelligible to the human subject). Therefore, knowledge acquisition is more complex for expert systems and simpler if neural networks are used. Changing knowledge is direct for expert systems, for artificial neural networks adding a new element of knowledge may require completion of training users. Artificial neural networks are proving faster, more robust in making approximate judgments and less susceptible to interference than expert systems (Wang, 1997), but they lack in explicit facilities.

Artificial neural networks, also called connectionist systems appear as a smart solution of last resort, where other methods of computer assistance are difficult to apply due to the poor structuring of the decision-making problem. These so called connectionist models were considered by some researchers as "direct competitors" to traditional models (Russell, 2003 pp.25). What can neural networks do today? A concise answer is difficult to give because there are so many activities in so many subfields that it is hard to say. From the point of view of our research we mentioned that expert systems (ES) and neural network (NN) are suitable for assessing the risk of bankruptcy of a firm by appealing to models Altman, Conan-Holder etc (it is difficult to say which of the two tools would be appropriate to Economic resolve this issue, some opinions on this subject will result implicit in our study of applied research).

3. RESULTS AND DISCUSSION

To achieve the main objective of the research was left from the financial statements of company A1 and the company A2 (which is public data, according to www.bvb.ro site). A1 is one of the leading Romanian, with a market share of 10.22%. Regarding the company A2, we remember that it also has a significant market position in Romanian (until its listing on the Bucharest Stock Exchange the company studied resorted to a coherent strategy to strengthen its market position, including mergers, expanding primary domain etc.; from 2009 was admitted to listing on the stock exchange).

The working mechanism for enforcement of ES and NN in the two companies is relatively complex and requires several intermediate steps to achieve a rate value and function score associated to each calendar year and each of the three business models (Altman, Conan- Holder, rating).

The recourse to the NN, which we will call Reform is a program developed in Visual Basic for Application in Excel and uses a multilayer perceptron with error retro-propagation (similar mechanism applied to NN).

The figure no.1 present for illustrative purposes the results to be obtained by recourse to the ES for A1 case for the entire period; the score function values are illustrated graphically showing the evolution of the function based on ES (Chart A) and based on NN (Chart B); All three business models are found in this comparative analysis confirming again that both techniques of AI lend themselves quite well to solve the bankruptcy risk of a company.

A – Score function obtained through ES

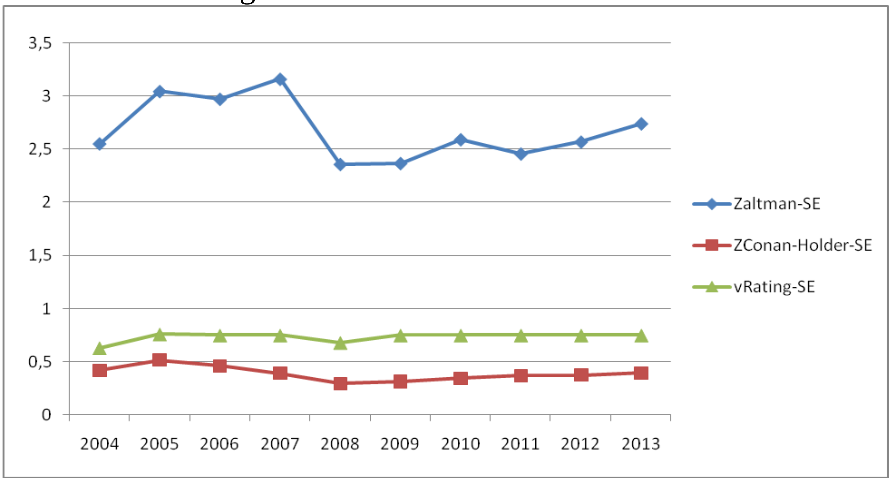

Figure no 1. The Evolution of Score function based on ES SysEXP for Company A1

Source: Iancu E. (2016) - *Aplicarea tehnicilor de inteligenţă artificială pentru estimarea riscului de faliment al firmelor*, Ed. Prouniversitaria, Bucureşti

B –score function obtained through NN

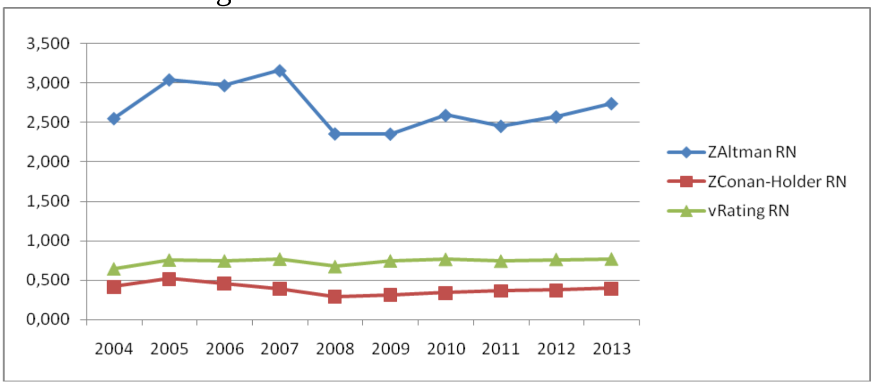

Figure no. 2. The Evolution of Score function based on NN for Company A1

Source: Iancu E. (2016) - *Aplicarea tehnicilor de inteligenţă artificială pentru estimarea riscului de faliment al firmelor*, Ed. Prouniversitaria, Bucureşti

So whatever the type of NN operated by the user, it is finally reached a very close value for estimating the risk of bankruptcy for a period of 5 or more years that define the past of a company. Also, these values of the bankruptcy risk score based on NN - figure 2 are very close to the values that are obtained by an appeal to the ES – figure 1.

From the perspective of our research, we determined a separate rate (RIN) given by the ratio of "Concessions, patents, licenses, trademarks, similar rights and assets and other intangible assets" and "Total tangible assets"; this rate was determined on the basis of accounting in both companies researched by us (RIn rate value is shown by us in Figure 3). Subsequently, the rate given by the inclusion of intangible assets was in turn included in the structure of the models used, i.e. Altman, Conan-Holder and Rating (without establishing a weighting function or weighting the score of each model).

Company A1

Anul	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
RIn	0,095643	0,132467	0,834507	0,747102	0,333451	0,301614	0,797502	0,568663	0,695884	0,616578

Company A2

Anul	2007	2008	2009	2010	2011	2012	2013
RIn	0,216438	1,135163	0,618491	0,341212	0,066183	0,0822	0,099298

Figure no. 3. RIn rate value for the two companies (the inclusion of intangible assets)

By way of example, we present below the new values for the score function based on ES for company A1 and A2; these values drive a different contour of CAF for both companies analyzed in the study periods, as shown in figure 4 and figure 5.

The graphics for the score function based on ES, including intangible assets for Company A1:

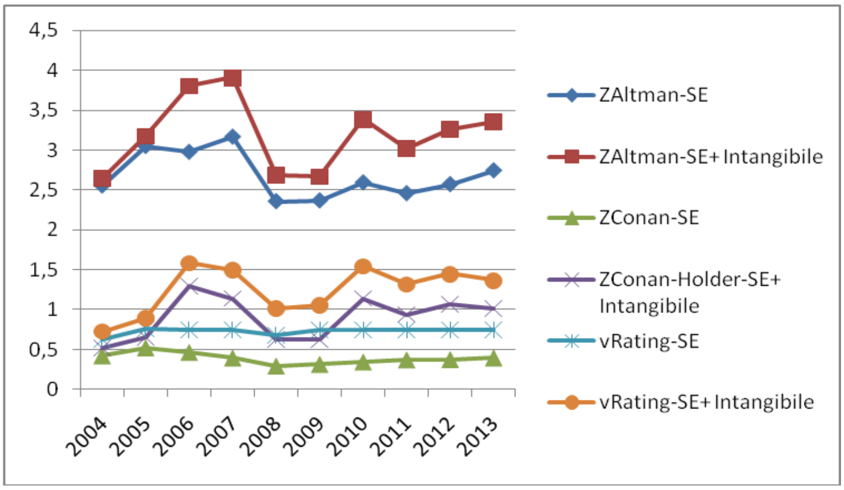

Figure no. 4 The graph of function score which takes into account intangible assets for Company A1

Source: Iancu E. (2016) - *Aplicarea tehnicilor de inteligenţă artificială pentru estimarea riscului de faliment al firmelor*, Ed. Prouniversitaria, Bucureşti

The graphics for the score function based on ES, including intangible assets for Company A2:

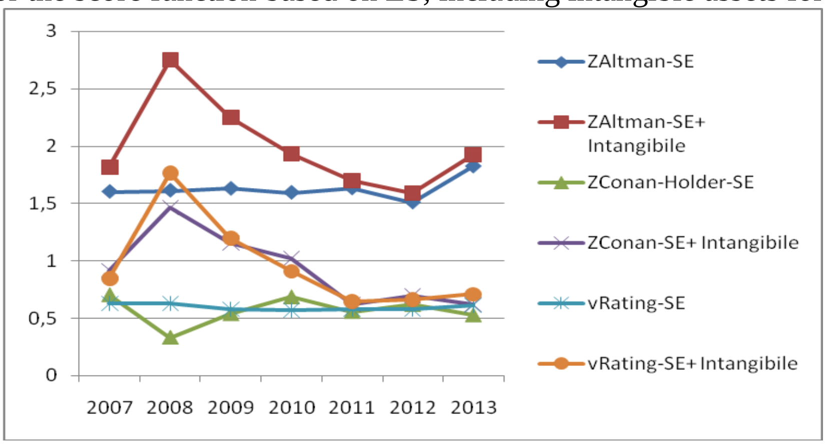

Figure no. 5. The graph of function score which takes into account intangible assets for Company A2

Source: Iancu E. (2016) - *Aplicarea tehnicilor de inteligenţă artificială pentru estimarea riscului de faliment al firmelor*, Ed. Prouniversitaria, Bucureşti

Assessments made by us up to this point are based on the ES appeal and RIn rate inclusion as a share estimated for intangible assets of the two companies studied.

When using NN for estimating the risk of bankruptcy based on a model that takes into account the intangible assets of a company, accounting data analyzed by us *conclude that the final score of bankruptcy and graphic model of these functions remain highly close / similar to the results based on ES.*

4. CONCLUSION

In our opinion, it would be ideal if the next annual financial statements communicated by public company (balance sheet, profit and loss, etc.) would include information / data that reflects the value of its intangible assets that stock all the knowledge available to it; obviously based on such data on intangible assets any potential investor will have information on which to assess realistic account of the situation of the organization at that time. Equally, publication of data by companies on intangible assets would be likely to give the public a clear picture of the organization's long-term prospects.

So, inclusion in the equation to estimate the risk of bankruptcy of a firm of intangible assets available to the entity leads to relatively significant conclusions from theoretical and pragmatic view, among which:

- For both companies analyzed by us, the graphics which renders the evolution of the score bankruptcy is much different when account is taken of intangible assets compared to the same graph when they are not included in calculating this indicator; This statement applies when using ES and NN as well;
- It must be concluded that the CAF model (business cycle of the company) resulted by using ES or NN and including intangible assets of the two companies is closer to the situation known on the business environment in Romania and the relative positioning of the two companies;
- The value of intangible assets of a company and the "stock" of knowledge available to the organization is directly related to the market value of this entity, however the reflection of this relationship is limited by how it is organized the accounting of the firm.

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