# USEFULNESS AND CREDIBILITY OF SCORING METHODS IN CONSTRUCTION INDUSTRY

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**Abstract.** The methods presented in the paper clarify the route of a company towards bankruptcy. The information comes from the so called early warning systems, among which a special attention has been paid to statistical scoring methods. A review of scoring methods informing about the financial standing of a company has been made. Examples have been selected among construction companies listed on Warsaw Stock Exchange. Credibility of models and results has been highlighted. Results point at the fact that the synthetic *Z-score* index should be adjusted to economic conditions of a given country, or even to an industry.

**Keywords:** early warning systems, scoring methods, financial standing of a company, credibility of methods.

## 1. Introduction

Construction industry, though quite specific, obeys the same laws of economy as other sectors. Building companies, just like many others, operate on the market and can go bankrupt.

Operating in the marketplace requires some knowledge of areas generating critical situations and insolvency. It is necessary to learn about factors determining both development and downfall of a company. There is a number of factors influencing development, there are many influencing decline. Usually there are symptoms of worsening the situation, but symptoms ought to be separated from causes of the changing standing.

The symptoms of the crisis are usually noticed by managers and employees first. Later on, those who obtained a delayed information, for example, through media, or the subcontractors who are not paid in due time learn about it too (cf Antonowicz 2006; Hamrol 2007; Jaselskis 1992; Kangari 1987; Kapliński 2007; Mączyńska 2005a, b; Zdyb 2006a)**.** Financial analysis of the company is the most natural and objective identification of crisis symptoms.

Observing the economy, one can draw a conclusion that, more than anything else, economic relationships influence insolvency of Polish. Political forces and the negotiating pressure of unions and employees themselves are no longer influential. Simultaneously, there is a better understanding of the company's financial situation. It has been understood that, after a time, poor financial standing of a company results in its bankruptcy.

Financial standing of a company primarily depends on:
- the company's financial structure,
- financial liquidity,
- solvency,
- the company's capability to adapt,
- economic resources, including production potential,
- capability to generate profit,
- capability to maximise the company's market value.

Financial standing should be referred to a given time span.

Change in the financial standing over time is presented in Fig. 1. It is a classic case of a company's downfall: it can be supposed that a set of characteristic symptoms presented itself; further, the symptoms have not been noticed in time, and no adequate steps have been taken to amend the situation. The symptoms listed above can only "set a red alert" and inform about the reasons of the crisis, but say nothing about what steps ought to be taken in order to prevent bankruptcy! Evident attempts to take preventive steps (saving against the downfall) are to be seen in Fig. 2. Both examples have been taken from the construction sector.
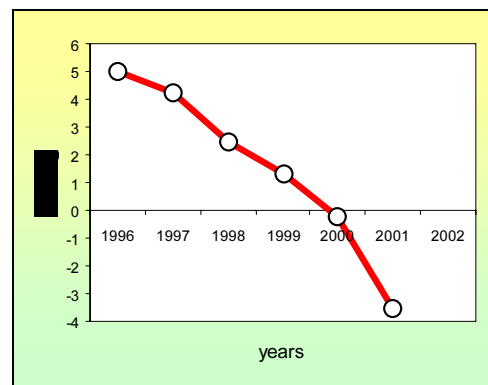


**Fig. 1.** Scoring used to illustrate the financial standing of a building company, using an example of Euro-Bud-Inwest

**Fig. 2.** The route to insolvency for BETONSTAL, a construction and assembly company

## 2. Early warning systems

Crises and bankruptcies of many companies in the 1930s, and in the 1960s both caused and increased interest in the so-called early warning systems, including a number of different indicators (cf Antonowicz 2007a and 2007b; Boguszewski & Gelińska 2004; Ginevičius & Podvezko 2006; Hamrol *et al.* 2004a, b; Karol 2004; Mączyńska & Zawadzki 2006; Nowak 1998).

There is an ample research pointing at methodologies using indices, eg in the USA, Austria, Germany, Holland, France, Ireland, Italy, Turkey (cf Abidali & Haris 1995; Aksoy 2003; Altman 2005; Altman & Pasternak 2005; Falta 2006; Koh & Killough 1990; Kralicek 1991; Schwarzecker 1992; Szczepankowski 2006; What 2005; Yang *et al.* 1997), in Lithuania (Ginevičius and Podvezko 2006; Ustinovicius and Zavadskas 2004;

Zavadskas *et al.* 2004). There is also ample Polish literature covering this area (Antonowicz 2006a; Czarny 2004; Gawrońska 2005; Mączyńska 2005; Niedziela 2005; Nowak 1998; RAKSSQL 2006; Rogowski 1999; Ryś 2003; Staniec *et al.* 1998; Stasiewski 1996; Szczepankowski 2006; Zaleska 2002). In (Staniec 2000) as many as 322 quoted bibliographical sources are to be found. The discussion presented in this article is a continuation of work done under the auspices of the Chair of Construction Engineering and Management (CE&M) at the Poznań University of Technology. Fig. 3 presents an attempt of categorising early warning systems into a coherent entity. Due to editing constraints, the article does not present a discussion of methods mentioned there, such as the Quick Test, the Wilcox Method, the Logit Analysis. It is reasonable to assume that quantitative methods, primarily scoring methods, may be rewarding in examination of financial standing, and further in formulating the so-called early warning indicators.

Scoring methods, which allocate points, emerged from the merger of indication analysis and discriminative methodology.

Scoring can be defined as a way (a system) of research object assessment, introduced on the basis of research, and justified with statistics. A score is generated, which estimates the weight of future factors and outlines the probability of future events. The scoring model gives scores to specific categories, and those scores form a foundation on which operational decisions are taken in the course of further analysis. The core of such models is a division of measurable features into two separate groups (eg solvent or insolvent). A dichotomic division is used most often. A polytochomic division, on the other hand, is used in polynominal logit models.
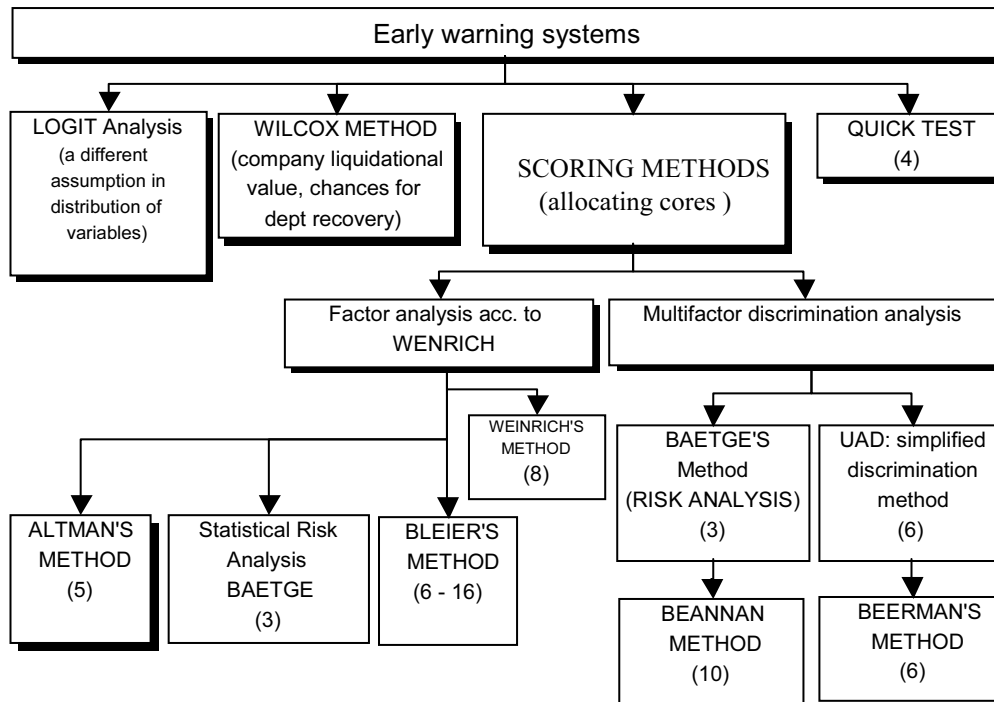


**Fig. 3.** Position of scoring methods in early warning systems. In brackets: numbers of indicators in use

The method of classifying object into known classes (based on historical data) is called a discriminant analysis. There are several discriminative methods which often have some limitations.

Using scoring method entails:

- choice of a set of indicators, most suitable from the viewpoint of the aim of an analysis, and reduction of potential indicators,
- defining weight of particular indicators,
- setting up a synthetic indicator (an index),
- defining the critical value of the index, based on which it can be predicted whether an assumed occurrence will or will not be present.

Until recently, only statistical/mathematical methods (eg linear regression, probit regression, classification trees, closest neighbourhood methods) have been used in scoring. In the 1990s, a number of non-statistical methods emerged, though quite interesting, such as artificial neural networks and expert systems.

It is believed, that from the point of view of forecast capabilities, multidimensional methods are more useful (multiple discriminant analysis) which analyse a number of indicators at a time, and at least two form a given model. Fig. 3 gives (in brackets) numbers of indicators in use.

The discriminant function can be defined using the following formula (Altman 2005; Altman and Pasternak 2005):

$Z = W_1 X_1 + W_2 X_2 + ... + W_n X_n$, where: Z – is the value of the discrimint function, $W_i$ – weights of $i^{th}$ variable (e.g. financial indicators), $X_i$ – variables clarifying the nature of the model.

Such a model is also known as *Zeta function* or a *Z-score* model.

The most popular, and one of the first methods is a set of E. I. Altman models. Results obtained using such a method will be used further in the paper. The first model was developed in 1968. It helped predict bankruptcy of a stock exchange trading company. E. I. Altman encased his model in the following formula:

$$Z = 1,2\,X_1 + 1,4\,X_2 + 3,3\,X_3 + 0,6\,X_4 + 0,999\,X_5. \quad (1)$$

As we can see, the equation contains parameters in the form of weights determined on the basis of multiple discriminant analysis, while the value of Z informs about the level of risk of bankruptcy. Because it was possible to predict pending financial problems on the basis of this model and define the risk related to bankruptcy, the methods stirred much interest at the time. In view of the needs of model (1), the following 5 indicators have been chosen:

$$X_1 = \frac{\text{turnover capital}}{\text{assets}},$$

$$X_2 = \frac{\text{retained profit}}{\text{assets}},$$

$$X_3 = \frac{\text{profit before tax and interest repayment}}{\text{assets}},$$

$$X_4 = \frac{\text{market value of share capital}}{\text{accounted value of liabilities}},$$

$$X_5 = \frac{\text{sales income}}{\text{assets}}.$$

Depending on the value of *Z-score* index, a company being assessed can be categorised into one of three groups:

- $Z > 2,99$ companies free of bankruptcy risk,
- $1,81 < Z < 2,99$ the "grey zone" – the area where both companies free of bankruptcy risk and bankrupt companies can easily find themselves,
- $Z < 1,80$ bankrupts (insolvent companies).

It is clear from the above comparison that companies for whom the value of Z index exceeds 2.99 have good financial standing. On the other hand, those for whom the value of $Z < 1,80$ went bankrupt. Graphic interpretation of thresholds was presented in Fig. 2. The method is believed to be credible, especially regarding one year forecasts (over 90 % accuracy).

The model developed on the basis of (1) helps predict bankruptcy of a stock exchange trading company. This was another reason, why in 1984, E. I. Altman published an equation describing the condition of companies traded in the stock exchange:

$$Z = 0,717X_1 + 0,847X_2 + 3,107X_3 + 0,420X_4 + 0,998X_5 \;(2)$$

In case of this index, if the value of Z exceeds 2.9, the company is believed to have good financial standing, whereas if the value of Z is below 1.2, there is a high risk of bankruptcy.

Another version of *Z-score* emerged, when $X_5$ indicator was eliminated, and discriminant values were changed. Also this version is quite universal:

$$Z = 6,56\,X_1 + 3,26{\cdot}X_2 + 6,72{\cdot}X_3 + 1,05{\cdot}X_4. \quad (3)$$

X indicators refer to the same parameters as in model (1), while borderline values are as follows: 1,10 and 2,60.

The significance of those methods may be highlighted by the fact that in construction work public tender announcements in Poland there is a requirement (condition) which must be met in order to participate in the tender. In the Public Orders Bulletin # 140, Section III: concerning legal, economic, financial, and technical information, paragraph 5 says: „Shall, in the 2003 report, show that the value of Altman's index, calculated according to the formula $Z = 6,56X_1 + 3,26X_2 + 6,72X_3 + 1,05X_4$, is not less than 2.99, where: $X_1$ = turnover capital/total assets, $X_2$ = net profit/total assets, $X_3$ = EBIT*/total assets, $X_4$ = own capital/total liabilities, *EBIT = Earnings Before Interest & Taxes (regards every company participating in the tender jointly)", (cf Bulletin 2004).

These methods are developed constantly. For example, E. I. Altman, in his lecture (2007) quotes 12 new variants of his models. Whereas, Fig. 4 presents a comparison of most popular Polish methods of bankruptcy prediction. These are scoring methods. They are discussed or commented in dispersed reference sources: Antonowicz 2006b; Czarny 2004; Gawrońska 2005; Hamrol *et al.* 2004b; Moskwa 2004; Niedziela 2005; Nowak 1998; Prusak 2002 and 2005; Rogowski 1999; RAKSSQL 2006; Ryś 2003; Staniec *et al.* 1998; Stasiewski 1996; Zaleska 2002). We should turn the

special attention to models presented by Hołda (2001) because of potential usefulness in the building industry.

## 3. Examples of applications of *z-score* models in construction industry in Poland

Now, on this background, a question arises: does the question concern only a risk of bankruptcy, or perhaps a risk of credibility of assessment models? A tricky question comes up: what is credibility of bankruptcy?

In order to answer those questions, let us use some examples the first of which have been selected among construction companies listed on Warsaw Stock Exchange. Using the Warsaw Stock Exchange data is quite important; it is the matter of availability of data. For a few decades, economists all over the world have been trying, based on external financial reports (balance sheet and balance of income and loss) to define more or less precisely future development chances or forecast company bankruptcies (cf Mączyńska 2005b).

The examples use data from the Chair of CE&M research work done by Meszek and Polewski (2006), Central Statistical Office (GUS), available company financial reports (Warsaw Stock Exchange, www.parkiet.com.pl),

and first of all from research work done by Zdyb (2006a, 2006b, 2007a, 2007b).

Figs 1 and 2 based on this data present financial standing of two construction and assembly companies gone bankrupt in 1996–2002. The definition of financial standing has been, in this case, stated using E.I. Altman *Z-score* synthetic index, according to Eq (1).

Fig. 5 presents the financial standing of (chosen) companies trading at Warsaw Stock Exchange, at risk of bankruptcy in 2003.

The results do not represent individual occurrences, but occurrences over a decade (Zdyb 2006a, 2006b). Therefore the calculations are much more time consuming, but the benefit is that it is possible to obtain information about development tendencies, and insolvency in particular. One time assessments are used most often when research objects are compared (e.g. companies), and first of all when potential loan customer solvency is assessed by a bank.

The bold line marks the tendencies in average value for the entire construction sector at the stock exchange at a given time. The most dramatic decrease is to be observed in 2001. It was the worst period for construction industry, to be precise – May 2001. The Building index
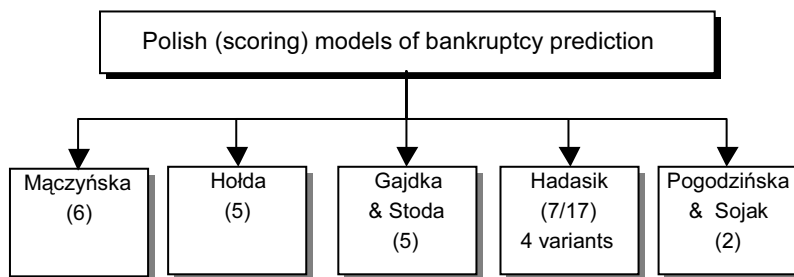


**Fig. 4.** The most popular Polish methods of bankruptcy prediction. In brackets: numbers of indicators in use
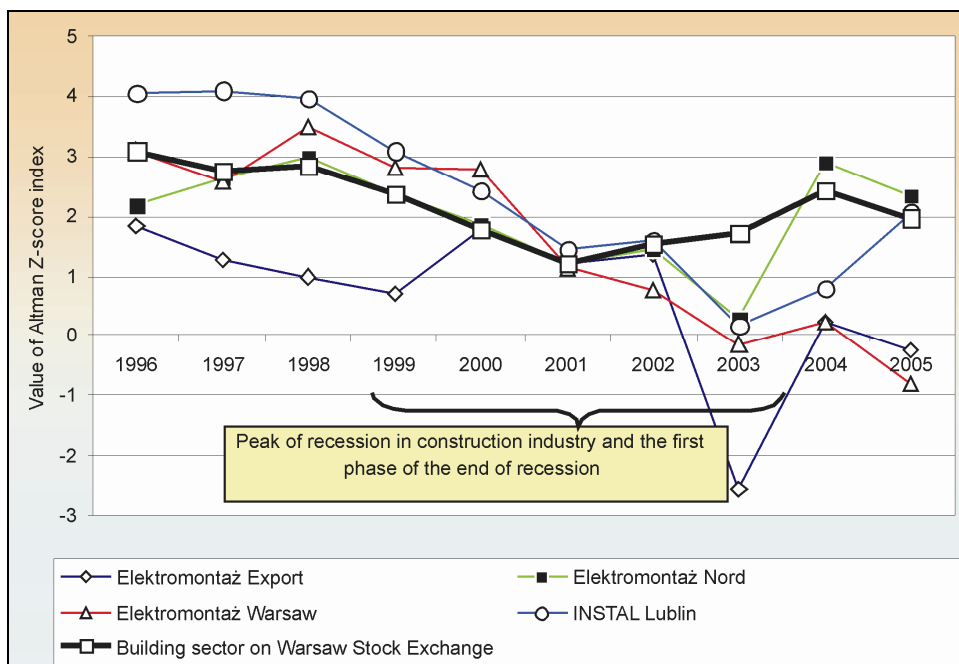


**Fig. 5.** Altman Z-scores for companies at risk of bankruptcy in 2003

**Table 1.** Prediction coherence in the original E. I. Altman model, according to formula (1)

| Number of years before bankruptcy | Original attempt used with the assessed model 33 companies, % | Tests performed by Altman on another sample of companies, % | Test performed 1969–75 a sample of 86 companies, % | Test performed 1976–98 (a sample of 110 companies), % | Test performed 1997–99 (a sample of 120 companies), % |
|---|---|---|---|---|---|
| 1 | 94 (88) | 96 | 82 | 85 | 94 |
| 2 | 72 | (92) | (75) | (78) | (84) |
| 3 | 48 | 80 | 68 | 75 | 74 |
| 4 | 29 | – | – | – | – |
| 5 | 36 | – | – | – | – |

After: B. Caouette, E. I. Altman, P. Narayanan, Managing Credit Risk. John Wiley & Sons, 1998, p. 22. Quoted after Prusak (2007) and Wudarczyk & Kieszkowski (2004).

**Table 2.** Prediction errors in the K. Beerman model

| Number of years before loss of solvency | Prediction error, % |
|---|---|
| 1 | 9,5 |
| 2 | 19,0 |
| 3 | 29,0 |
| 4 | 38,0 |

Reference source: Olszewski D. W. (1993)

(WIG-Budownictwo) increased as much as by 900 % (between May 2001 and April 2007)! On the other hand, the Building index increased by 122 % between May 2006 and May 2007.

The graphs do not provide an answer to the question what generated the critical situation and company insolvency. The reasons, which usually operate in groups, vary. Nonetheless, they can be categorised into external and internal. There is a whole range of internal causes of insolvency: from bad management, unskilled turnover capital management, lack of control, through mistaken assessment of operating potential to erroneous risk diversification. What is interesting is the fact that, regardless of the country where research is done, the size of a company counts in the assessment of bankruptcy tendencies (see Szczepankowski 2006; Hamrol *et al.* 2004a; Wędzki 2004; Zdyb 2007b). External causes have more of a macroeconomic and legal/administrative character.

## 4. Credibility of insolvency prediction

What is important apart from the credibility of data, is the credibility of the method itself: the bottom line is that they are based on a better or worse synthesis of other indicators. Due to the fact that we are dealing with the so-called early warning systems, the methods become even more valuable when the synthetic *Z-score* index reflects a high probability of an occurrence. The initial prediction coherence tests were made for E. I. Altman models. His model became so popular that its application was tested

on different samples. Table 1 lists the results (after: Prusak 2002; Wudarczyk & Kieszkowski 2004).

The major disadvantage of the model is its low credibility (efficiency) in estimating the risk of bankruptcy 3 or more years before insolvency. In practice, credibility at the level lower than 50 % for 3 and more years before insolvency makes the effort of building the model pointless! Good results are achieved when the risk of insolvency is tested 2 years on 1 year before a company goes bankrupt.

References to testing other models, such as: ZETA, Springate, Fulmer, CA-score, Taffler, Keasy, McGiuness, Bilderbeek, Ooghe-Veber and others, can be found in paper: Prusak (2002).

On the background of Altman models, the results of prediction credibility based on the Beerman model (Table 2) seem quite wrong.

What followed, was a comparative analysis of Altman index mean values for insolvent and solvent companies. Countries with similar economic systems were taken into account. The results are in Table 3.

Results presented in Table 3 indicate that there are major differences between those values. Credibility of the same models in other countries if doubtful. What becomes important is the so-called cut off point of the models for variants existing in a given country. In Polish conditions, it is suggested to lower the threshold value (ie. the value of *Z-score*) from 1.8 to 1.0. The above was suggested by Zdyb (2006a, 2006b), and it regards building companies, as in other cases quite a few of scrutinised companies should be coming close to insolvency in spite of their potential existence.

**Table 3.** Compared mead values of Z-scores for insolvent and solvent companies

| *Z-score* index/ Companies | USA Altman 1968 | USA Altman 1977 | Australia Castagna & Matolesy 1981 | Brazil Altman 1979 | Japan Ko 1981 |
|---|---|---|---|---|---|
| Insolvent companies | –0,258 | 1,271 | 1,707 | 1,124 | 0,667 |
| Solvent companies | 4,885 | 3,878 | 4,003 | 3,053 | 2,070 |

Reference source: Rzeczpospolita nr 10, 13 May 1996, p. 19. Quoted after: Prusak (2002)

**Table 4.** Comparison of credibility of results arrived at via neural networks

| Model | Neural networks, % | Discriminant analysis, % |
|---|---|---|
| Sharda and Odom (1990) | | |
| a) Efficiency I (companies gone bankrupt) | 77–81,5 | 59,3–70,4 |
| b) Efficiency II (companies not gone bankrupt) | 78,6–85,7 | 78,6–85,7 |
| Sharda and Wilson (1992) | 96 | 91 |
| Coats and Fand (1993) | 95 | 87,9 |
| Serrano and Cinca | 91–96 (SOM) | 90 |
| Kiviluoto (1998) | 81–86 (SOM) | 81–86 |

While comparing construction companies to industrial or trading companies, it is not so much the changeability of portfolio should be taken into account, but the fact that there are seasons in construction work. Therefore, the period of gathering information about indicators is important. The data must originate from repeatable time spans.

## 5. Usefulness of neural networks in defining insolvency risk

The analysed insolvency risk resulting from growing economisation of social and economic life and rigorous economic criteria require even more precision and credibility in its definition if we want to take a proper action. In the last decade of the 20th century, some new solutions emerged which define the probability of bankruptcy even better. Those methods are based on artificial neural networks. A number of research works in this area have already been written (e.g. Baetge & Krause 1993; Domaradzki 2004; Kieszkowski & Wudarczyk 2005; Najman & Najman 2001; Staniec *et al.* 1998; Staniec 1999; Wudarczyk & Kieszkowski 2004). The comparison of initial results, arrived at via neural models based on discriminant analysis, is in Table 4. The results of quoted research works have been taken into account. Focusing on this type of research, including the application of artificial neural networks results from the fact that, generally, there is non-linearity of relationships due to the multiplicative character of some relationships between indicators, and the possibility of bankruptcy.

At the very beginning of financial standing analysis and classifying objects (e.g. from the viewpoint of their condition), it appears that using a linear discriminant function is impossible (this regards a dichotomous division of objects into classes). Two types of mistakes are often made. The first type of mistake is categorising a company close to insolvency (or an incredible loan applicant) to a class of prosperous companies (or credible loan applicants). A reverse case is the second type of error.

It is worth quoting some interesting research by Wudarczyk and Kieszkowski (2004). The research is based on multi-layered networks. Two types of networks were used, according to representation of key features. SOM (Self – Organising Map according to Kohonen 1995), and RBF (Radial Basis Functions – Kohonen 1988). In the following research work, fuzziness of data was also accounted for, therefore the networks were supplemented with neural-fuzzy network. The research took into account 20 companies close to insolvency and 40 with sound financial standing. From the IT point of view, the models ought to be perfect regarding the influence of learning coefficients on network oscillation, and it can increase the range of analysis error. Work quoted under (Najman & Najman 2001) presents some interesting conclusions in this respect. It transpires that, from our point of view, results are promising despite the small sample. All networks reached classification error at 20–30 %, while in the Altman model – for the same data - the error was at 40–25 %. The influence of input data is also quite clear, in this case fuzzy data, which ameliorates the total result (credibility) but makes the results nearly impossible to compare. What should also be mentioned that another of Altman's model was chosen for comparison, ie the model based on Eq (3).

## 6. Conclusions

Judging from the review of problems concerning the risk of insolvency and credibility of bankruptcy prediction models, some specific conclusions can be drawn – which have been presented in the text, and some more general – are presented below.

1. There is an urgent need to quite precisely define future development or bankruptcy of a company. The early warning systems presented in the article best serve this purpose.

2. The knowledge of symptoms of worsening financial condition is crucial. This knowledge can be obtained from external financial reports. Knowing the symptoms is not equal to actions aimed at preventing insolvency.

3. If it is assumed that the indicators presented in the text are helpful in assessing the symptoms of financial condition, it may be difficult to use them on the daily basis not only due to the labour consuming procedure, but also due to the ambiguous manner of accounting. The quality of data is the most important factor influencing the credibility of discussion.

4. Comparing the credibility of some methods leads to a conclusion that the synthetic *Z-score* index should be adjusted to economic conditions of a given country of even sector.

5. There is a problem of usefulness of models in a longer time scope (parameter stability; besides - attention on the influence of seasonal character of a production in construction industry). Changing operational conditions results in other relationships being used as standards. It pertains, for example, crediting periods for customers, profitability levels, liabilities. Moreover, sensitivity of companies to changes in macroeconomy may differ.

## References

Abidali, A. F. and Haris, F. C. 1995. A methodology for predicting companies in the construction industry, *Construction Management and Economics* 13: 189–196.

Aksoy, H. 2003. *A discrimination analysis for the performance prediction of the industrial companies in the Istambul Stock Exchange* [cited Dec 2007]. Available from Internet: <http://mfs.rutgers.edu/MFC/MFC11/mfcindex/files/MFC-091%20Aksoy.DOC>.

Altman, E. I. 2005. *Current credit conditions and the link between default and recovery rates.* Lecture: Dec 5 2005: Warsaw School of Economics SGH, Warsaw. Available from Internet: <E_Altman_prezentacja_SGH.ppt>.

Altman, E. I. 2007. *Revisiting credit scoring models in a Basel 2 environment.* Lecture at National Taiwan University. Available from Internet: <www.fin.ntu.edu.tw/~hwang-dar/94emba19.ppt>.

Altman, E. I. and Pasternack, B. 2005. *Special Report on High Yield and Distressed Debt Default and Return Report*: Third-Quarter 2005 Update. New York University Salomon Center, Leonard N. Stern School of Business. Nov 2005. Available from Internet: <Altman_raport_ Third-Quarter-Q3-2005-SC.pdf>.

Antonowicz, P. 2006b. Verification of prediction capabilities of chosen models of insolvency prediction in companies based on discriminant analysis, in Romanowska M., Wachowiak P. (eds.). *Concepts and tools of strategic management* Warszawa: SGH, 477–494.

Antonowicz, P. 2006a. *Early warning systems in predicting company insolvency*: PhD thesis, Gdańsk University.

Antonowicz, P. 2007a. *Assessment methods of company economic and financial standing and prediction.* ODDK, Gdańsk, 207 p.

Antonowicz, P. 2007b. Scoring methods of assessment of perspectives of company operation in the marketplace, in *Safety in administration and business,* Gdynia: WSAiB, 317–326.

Baetge, J. and Krause, C. 1993. The classification of companies by means of neural networks, *Journal of Information Science and Technology* 3(1): 96–112.

Boguszewski, L.; Gelińska, B. 2004. Statistical and universal foundations of scoring, in *Proc. Confer. Interdisciplinary utilization of quantitative methods.* Szczecin [cited Nov 2007]. Available from Internet: <http//knmi.wzr.pl/dok/scoring.pdf>.

Bulletin 2004. *Public Orders Bulletin*, Nr. 140, from 2004.08.18 (POZYCJA 40548).

Czarny, A. 2004. *Using selected scoring methods in assessing financial standing of companies, based on the example of confectionery industry* [cited Dec. 2006]. Available from Internet: <http://156.17.80.146:8080/konferencje/referaty/czarny_a.pdf.>.

Domaradzki, R. 2004. *Neural networks as investmet decision aid.* AGH [cited July 2007]. Available from Internet: <http://bossa.pl/analizy/techniczna/elementarz/sieci_neuronowe/>/.

Falta, M. 2006. *Modelling construction business performance. Literature review (Project: 2005-017-A)*. Cooperative Research Center for Construction Innovation. Brisbane Qld, Australia, 52 p.

Gawrońska, A. 2005. *Early warning systems of E .I. Altman* [15 Dec 2006]. Available from Internet: <cited www.centrumwiedzy.edu.pl >.

Ginevičius, R.; Podvezko, V. 2006. Assessing the financial state of construction enterprises, *Technological and Economic Development of Economy* 12(3): 188–194.

Hadasik, D. 1998. The bankruptcy of enterprises in Poland and the methods of prognosis, *Zeszyty Naukowe AE-Poznań* 153, series II, 176 p.

Hamrol, M. (Ed.). 2007. *Financial analysis of a company – a situational approach.* Economic Academy in Poznań Press, Poznań, 314 p.

Hamrol, M.; Czajka, B.; Piechocki, M. 2004a. Company bankruptcy – a discriminant analysis model, *Przegląd Organizacji* 6: 35–39.

Hamrol, M.; Czajka, B.; Piechocki, M. 2004b. Discriminant analysis. Review of the most important models, *Przegląd Organizacji* 4: 34–37.

Hołda, A. 2001. Prognosis of the bankruptcy of the unit in the conditions of the Polish economy with utilisation of the discriminatory $Z_H$ function, *Rachunkowość* 5: 306–310.

Jaselskis, E. J. 1992. Risk analysis approach to selection of constructor evaluation methods*, Journal of Construction Engineering and Management* 188(4): 814–821.

Kangari, R. 1987. Business failure in construction industry, *Journal of Construction Engineering and Management* 114(2): 172–190.

Kapliński, O. 2007. Risk of the fall, in J.Bizon-Górecka (ed.). *Strategies of risk management in enterprise.* Ciechocinek-Bydgoszcz, TNOiK, 21–34.

Karol, T. 2004. Tools in back office, in *Proc of 10$^{th}$ International Baltic Forum*, University of Applied Sciences, Stralsund, 54–66.

Kieszkowski, D.; Wudarczyk, M. 2005. *Comparing the efficiency of classic and non-classic methods of assessing solvency and financial standing of companies.* Available from Internet: <http://www.mini.pw.edu.pl/~mandziuk/26-01-05.ppt>.

Koh, H.; Killough, L. 1990. The use of multiple discriminate analysis in the assessment of the going concern status of an audit client, *Journal of Business Finance and Accounting* 17: 179–191.

Kohonen, T. 1995. *Self-organizing mamps.* Springer Series in Information Sciences, Vol. 30, Berlin, Heidelberg, New York: Springer-Verlag. 501 p.

Kohonen, T. 1988. *Self-organization and associative memory.* New York: Springer-Verlag. 312 p.

Kralicek, P. 1991. *Grundlagen der Finanzwirtschaft: Bilanzen, Gewinn-und Verlustrechnung, Cash-flow, Kalkulationsgrundlagen, Fruehwarnsysteme, Finanzplanung,* Vien: Überrauter. 111 p.

Mączyńska, E. (Ed.). 2005a. At risk of bankruptcy, *Materiały i Prace IFGN,* XCIII, Warsaw: SGH. 265 p.

Mączyńska, E. 2005b. *Early warning systems* [cited 23 Oct. 2005]. Available from Internet: <www.centrumwiedzy.edu.pl>.

Mączyńska, E.; Zawadzki, M. 2006. Discriminative methods of company bankruptcy prediction, *Ekonomista* 2: 205–235.

Männasoo, K. 2007. Determinants of firm sustainability in Estonia. *Working Paper Series,* Nr. 4, Eesti Pank, Bank of Estonia, 30 p.

Meszek, W.; Polewski, M. 2006. Certain aspects of working capital in a construction company, *Technological and Economic Development of Economy* 12(3): 222–226.

Moskwa, M. 2004. Using discriminant analysis to predict corporate bankruptcy, in *Proc of 10th International Baltic Forum*, University of Applied Sciences, Stralsund, 84–95.

Najman, K. M.; Najman, K. 2001. *Using SOM type of neural networks to select the most attractive Warsaw Stock Exchange companies, based on fundamental analysis indices*. Gdańsk University, Faculty of Management. Sopot [cited July 2007]. Available from Internet: <panda.bg.univ.gda.pl/~prezes/WWW_SIECI_NEURONOWE_analiza_fundamentalna.pdf>.

Niedziela, J. 2005. Early warning system of J. Gajdka and D. Stody, *Encyklopedia Zarządzania*. M-files Wiki [cited 20 Dec. 2005]. Available from Internet: <mfiles.ae.krakow.pl>.

Nowak, M. 1998. *Practical assessment of company financial standing. Methods and limitations*. Fundacja Rozwoju Rachunkowości w Polsce, Warszawa, 295 p.

Olszewski, D. W. 1993. The payment ability of the enterprise - assessment conceptions and methods, *Bank i Kredyt* 6.

Prusak, B. 2002. *How to recognise a potential bankrupt? Assessment of company insolvency risk, based on multiple discriminant analysis*. Available from Internet: <www.zie.pg.gda.pl/~pb/jrpb.pdf>.

Prusak, B. 2005. *Modern methods of predicting financial risk in companies*. DIFIN, Warszawa, 208 p.

RAKSSQL. 2006. *Financial analyses, budgeting and controlling*. Chapter 10 [cited 12 Dec. 2006]. Available from Internet: <http://download.raks.pl/rakssql/instrukcje/10-rakssql-analizybudzetowaniekontroling.pdf>.

Rogowski, W. K. 1999. Chances of early recognition of company insolvency risk symptoms, *Bank i Kredyt* 6: 56–72.

Ryś, M. 2003. Strategies of financial liquidity and company bankruptcy prediction, *Bank i Kredyt* 11–12: 101–111.

Schwarzecker, J. 1992. *Bilanzanalyse nach den neuen Rechnungslegungsbestimmungen: Bilanzierung fűr 1992*; Österreich, BRD, Grossbritanien, Frankreich, Niederlande und Ireland. Wien: Überreuter-Wirtschafts. 309 p.

Staniec, I. 1999. *Zastosowanie sztucznych sieci neuronowych i wybranych metod statystycznych do wspomagania decyzji kredytowych*. Łódź: Technical University of Łódź. 310 p.

Staniec, I. 2000. *Bibliografia* [cited 2007]. Available from Internet: < www.oizet.p.lodz.pl/istan/pdf/Bibliografia.pdf>.

Staniec, I.; Witkowska, D.; Górecka, A.; Kompa, K. 1998. *Using artificial neural networks in economic research*. Laboratory of Quantitative Methods in Management,

Chair of Management, Faculty of Organisation and Management, Technical University of Łódź. Grant KBN 1 HO2B 016 102, Łódź.

Stasiewski, T. 1996. *Z-Score* – a company insolvency predictor, *Rachunkowość* 12: 7–8.

Szczepankowski, P. 2006. *Assessing company operational risk based on financial reports* (American, European Community and Polish methodologies) [cited 8 Dec. 2006]. Available from Internet: <www.studenci.pl/ekonomia/finanseprzds/semeko_85.html>.

Ustinovicius, L.; Zavadskas, E. K. 2004. *Statybos investicijų efektyvumo sistemotechninis įvertinimas*. Vilnius: Technika. 220 p.

Wędzki, D. 2004. Threshold values of financial indicators in examining company bankruptcies, *Zeszyty Teoretyczne Rachunkowości* 19(75): 139–160.

What. 2005. What's the financial viability (*Z-score*) of your company? *The Business Owner* May/June: 7.

Wudarczyk, M.; Kieszkowski, D. 2004. *Neural networks in financial analyses*. Bankruptcy prediction. Available from Internet: <http://www.mini.pw.edu.pl/~mandziuk/02-06-04.ppt>.

Yang, Z. R.; James, H.; Packer, A. 1997. *The failure prediction of UK private construction companies* [cited 1 Jan. 1997]. Available from Internet: <http://www.rics.org/RICSWEB/getpage.aspx?p=BkobTbQfdECBNch3UIk8bA>.

Zaleska, M. 2002. *Identyfication of insolvency risk of a company or bank*. DIFIN. 104 p.

Zavadskas, E. K.; Kaklauskas, A.; Banaitis, A.; Kvederytė, N. 2004. Housing credit assess model: the case for Lithuania, *European Journal of Operational Research* 155: 335–352.

Zdyb, M. W. 2006a. What to do to stay solvent, *Builder* 12: 24–27.

Zdyb, M. W. 2006b. *Financial conditions of companies trading in building materials and constructions and assembly companies GPW 1996 – 2005* [cited 25 May 2007]. Available from Internet: <www.osrodekbadania.freehost.pl/33.pdf.>.

Zdyb, M. W. 2007a. New method of assessment of share attractiveness based on construction industry traded shares, *Materiały Budowlane* 7: 94–98.

Zdyb, M. W. 2007b. Reasons of company bankruptcies in Poland [cited 5 Apr. 2007]. Available from Internet: <.ttp://finanse.wp.pl>.

**TAŠKŲ SKAIČIAVIMO METODŲ NAUDINGUMAS IR PATIKIMUMAS STATYBOS PRAMONĖJE**

**O. Kapliński**

S a n t r a u k a

Metodai, pateikiami straispnyje, atskleidžia kompanijos kelią į bankrotą. Informacija gaunama iš vadinamųjų išankstinio perspėjimo sistemų, kuriose daugiausia dėmesio skiriama statistinio taškų (balų) skaičiavimo metodams. Pateikiama taškų skaičiavimo metodų, atskleidžiančių finansinę įmonės padėtį, apžvalga. Pavyzdžiai paimti iš Varšuvos biržos statybos kompanijų sąrašo. Nustatytas modelių ir rezultatų patikimumas. Rezultatai rodo, kad sintetinė Z reikšmė turi būti koreguojama pagal ekonomines konkrečios šalies arba pramonės sąlygas.

**Reikšminiai žodžiai:** ankstyvaus perspėjimo sistemos, taškų (balų) skaičiavimo metodai, finansinė kompanijos padėtis, metodų patikimumas.

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