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THE SELECTION OF INDICATORS AND MODELLING OF THE CREDITWORTHINESS OF LEGAL ENTITIES USING THE THEORY OF FUZZY LOGIC

This article presents a new approach of selection, which would allow choosing the most informative indicators when calculating the creditworthiness of legal entities. The real data of domestic companies are processed and those indicators are selected, which can define creditworthiness of the legal entities the most efficiently. Moreover, the fuzzy logic model is built, which shows the 77% efficiency of prediction.

Keywords: creditworthiness, coefficients, bankrupt, stable company, legal entity, financial indicators, borrower, theory of fuzzy logic, term, rule base.

Паламарчук О.В. ВІДБІР ПОКАЗНИКІВ ТА МОДЕЛЮВАННЯ КРЕДИТОСПРОМОЖНОСТІ ЮРИДИЧНИХ ОСІБ З ВИКОРИСТАННЯМ ТЕОРІЇ НЕЧІТКОЇ ЛОГІКИ

У цій статті подано новий підхід відбору коефіцієнтів, який дозволить обрати найбільш інформативні показники при розрахунку кредитоспроможності юридичних осіб. В роботі було оброблено реальні дані вітчизняних компаній та обрані ті показники, які найбільш ефективно визначають кредитоспроможність юридичних осіб. Крім того, була побудована модель нечіткої логіки, яка показує 77% ефективності прогнозування.

Ключові слова: кредитоспроможність, коефіцієнти, банкрут, стабільна компанія, юридична особа, фінансові показники, позичальник, теорія нечіткої логіки, терм, база правил.

Паламарчук О.В. ОТБОР ПОКАЗАТЕЛЕЙ И МОДЕЛИРОВАНИЕ КРЕДИТОСПОСОБНОСТИ ЮРИДИЧЕСКИХ ЛИЦ С ИСПОЛЬЗОВАНИЕМ ТЕОРИИ НЕЧЕТКОЙ ЛОГИКИ

В этой статье представлен новый подход отбора коэффициентов, который позволит выбрать наиболее информативные показатели при расчете кредитоспособности юридических лиц. В работе были обработаны реальные данные отечественных компаний и выбраны те показатели, которые наиболее эффективно определяют кредитоспособность юридических лиц. Кроме того, была построена модель нечеткой логики, которая показывает 77% эффективности прогнозирования.

Ключевые слова: кредитоспособность, коэффициенты, банкрот, стабильная компания, финансовые показатели, юридическое лицо, теория нечеткой логики, заемщик, терм, база правил.

The posing of problems. Today, as in prior years, determining the probability of loan default when a customer refers to the bank is a relevant topic. Moreover, there could be several appeals. Conclusions on possible lending for a legal entity for each appeal may differ.

It depends on the current financial status of a legal entity since the main source of information is their financial reports.

All known approaches to the analysis of the creditworthiness of legal entities based on the study of enterprise financial condition of the borrower and consideration of his credit history. An analysis of financial condition usually comes down to using discriminant and regression models. It is based on financial data and includes the manipulation by quantitative indicators, such as the Altman Z-factor [1]. This approach has become widespread and has been applied in many countries for different years in models of Toffler and Tishaw for the UK [2], Beermann for Germany [3], Davidova and Belikov for Russia [4], Tereshchenko [5], Cherniak [6], Matviychuk [7] and discriminant models approved by the National bank of Ukraine on 25.01.2012 № 23 [8], for Ukraine, and many others.

However, a comparison of data obtained for a number of countries shows that weighting coefficients in the Z-convolution and limiting standards vary greatly not only from country to country but also depending on the year in the same country [5, 9, 10].

Classic numerical methods for diagnosing bankruptcy, which are based on work only from financial indicators, have resistance to variations in the output and cannot effectively handle qualitative indicators. Therefore, it becomes important to consider the additional expert-analytical information when analysing because the outcome of bank's decision to grant or to refuse the credit is also influenced by such factors as the reputation of the company, the authority of the head of the company, his personal qualities, ownership of the company etc. These figures cannot be quantitatively described always. That is why a problem of interpretation and processing of ambiguous linguistic information arises.

Another conventional approach to evaluating the possibility of bankruptcy, such as the Argenti method [11], based on the work with quality indicators. However, this approach has its own drawbacks. In particular, the problem of this approach to analyse the risk of bankruptcy caused by lack of widely recognized measuring instruments of a quality factor and these parameters have not been classified in terms of actual deviations of their values from some admissible norms. Accordingly, this approach is characterized by a large proportion of subjectivity and does not provide optimization of the model on real data.

A significant increase in the effectiveness of analysis of the financial capacity of the borrower can be achieved by a combination of quantitative (financial) and qualitative indicators. However, the above approaches do not provide such possibilities for analysts. To avoid these limitations, Nedosyekin has developed a methodological approach to risk assessment of bankruptcy on grounds of the theory of fuzzy logic that provides an opportunity to carry out integrated diagnostics of bankruptcy based on quantitative and qualitative factors [12]. However, this method is, in fact, the interval analysis, which means that the set of possible values of all indicators are divided into clearly defined intervals. And elements of the theory of fuzzy logic are used only to convert qualitative indicators in numerical form. This approach is devoid of flexibility and disables optimization of model based on retrospective data.

Ease of use. Thus, the analysis of existing methods of credit analysis and diagnosis of the financial condition of the borrower leads to the conclusion that there is a need to build a number of adaptive mathematical economic models, which would be based on the theory of fuzzy logic that allow avoiding the above restrictions. This instrument has been chosen as the mathematical basis, as it enables to form a model, which take into account Ukrainian specifics of doing business. It also allows you to use the expert knowledge of subject area and imposes no restrictions on the nature of incoming data, while providing the ability to customize the model parameters in real terms of activities of creditors and companies that do not fulfil their obligations, taking into account the data of the previous financial operations available to banks.

Accordingly, the aim of this research is the development of an economic and mathematical model of credit analysis based on tools of fuzzy logic and detection of the financial problems of Ukrainian companies at an early stage. It will provide the management of banks and other lending institutions with a tool, which could justify adoption of effective solutions towards avoiding unnecessary risk that will increase the stability and balance of the economy as a whole.

The main material research. Stage 1. The selection of data. To analyse the creditworthiness of legal entities, we offer to determine based on data (calculated economic factors) derived from the income statement and balance sheet, whether a potential borrower is bankrupt, or is it a stable company, to whom we can give a credit.

To solve this problem, there were selected 49 real financial statements of Ukraine, 25 of which are potential bankrupts, and 24 – enterprises, which have no problems with the business.

For a detailed assessment of the financial condition of the company, we can calculate a large number of basic financial indicators [11]. Later it was calculated the 60 basic financial indicators [14]. But such an analysis is rather unwieldy and may contain duplication or redundant data, which instead of helping, will only hinder to perform an adequate assessment of creditworthiness.

So after calculating basic financial indicators, we have selected the most informative of them to solve the current task.

Indicators of share capital were rejected because they are not necessary to solve the problem.

The selection took place in two stages:

1) Selection of parameters by graphical methods in terms of information content;

2) Among the selected indicators, we calculate the correlation dependence between all pairs of indices to eliminate duplication.

At first, just build schedules for each factor that will contain all 49 indicators of enterprises. Those that will show more or less clear boundary between stable and bankrupt enterprises will be selected to build the economic and mathematical models. For example, we select current assets turnover ratio, which is shown in Fig. 1:

Conditionally, we divide the picture into 4 zones. Before light vertical line (Zones 1 and 3), there is data of bankrupt enterprises after that (Zones 2 and 4) – stable. For the current assets turnover ratio, we set limit value 1.2. (In Fig. 1, we can see that the most concentrated area of enterprises-bankrupts is at Zone 3, and at Zone 1, there is very small amount of them. Thus, this value will be considered exceptional for this situation. And vice versa – at Zone 2, there are more stable businesses and at Zone 4 – less). That is, all values below 1.2 may indicate a possible bankruptcy, and above 1.2 – the stable position of the company.

Not for all factors, we can clearly draw one horizontal line that would show the division of companies into two groups. Sometimes you need to split the plane not into 4 but into 6 zones.

For example, for payables turnover ratio, there is no one clear boundary between stable and bankrupt enterprises. In Fig. 2, we can see that at Zones 3 and 5 much more points of bankrupt enterprises are focused than at Zone 1. Moreover, at Zone 5, there are more enterprises than at Zone 3. And vice versa – at Zone 2 more stable companies are concentrated than at Zone 4. And at Zone 6, there are only a few. So, for this factor, we have the following situation: at Zones 5-6, bankrupt enterprises are situated, at Zones 3-4 we have average values, and at Zones 1-2, there are stable enterprises. The value below 0.8 indicates a probable bankruptcy, values between 0.8 and 2.2 points to the uncertain status, and above 2.2 – the stable position of the company.

All inaccuracies of classification of enterprises in terms of one indicator should be eliminated as a result of the economic and mathematical models that will implement the resulting index calculation based on many financial ratios simultaneously.

As a result of the graphical analysis, 13 most informative factors were selected. But this amount of data is quite excessive for the analysis.

So, let us go to the second stage of selection.

For the selected coefficients, we calculated the correlation dependence (pairwise each coefficient of each).

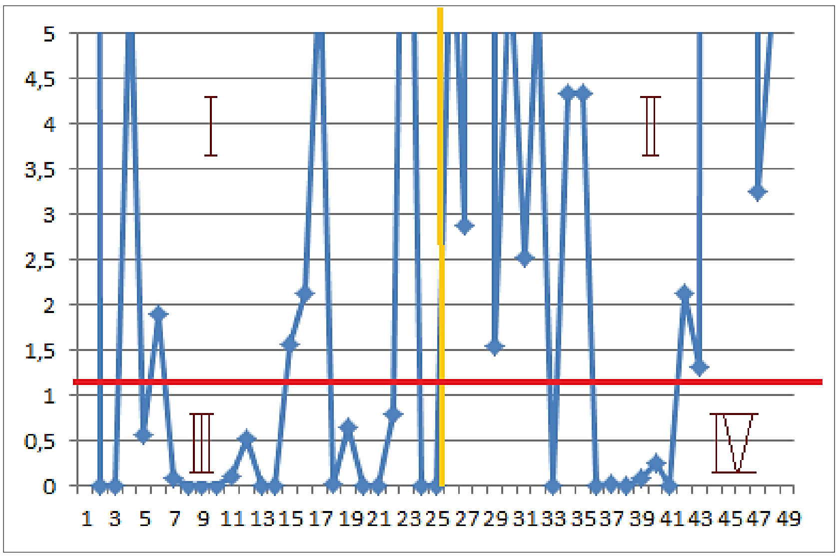

Fig. 1. Data of turnover ratio of current assets

Among the group of indicators with a close dependence, the only one was chosen – on the basis of the first stage. This means that if two or more indices have close relationship – we looked at informativeness of each of their charts. For which coefficient the boundary between enterprises bankrupt and stable company was expressed in the best way – that coefficient we have included.

As a result of the analysis, seven coefficients were selected. It will be used as a basis economic and mathematical model and related to decision-making support system for providing or not providing a loan to borrower – legal entity. For the convenience, the selected indicators are summarized in Table 1.

Stage 2. The formation of linguistic variables. To build models based on fuzzy logic, let us use three linguistic terms for each variable, for which we can distinguish three more or less clear zones of possible values for the available statistics. For these indices, we form a single scale with three qualitative terms: L – low, M – medium level, H – high indicator. If the actual value of the input parameter wisely to group in two classes with one line of separation between them, its linguistic assessment is carried out by two terms: L – low and H – high indicator.

In the result of analysis of available statistical base, the area of possible values of coefficient of payables turnover X_1 was decided to divide into three levels. It was decided to put the value between the terms L and M = 0.8 and between the terms M and H = 2.2. For the current assets turnover ratio X_2, there were found two quite separate areas, the boundary between which was estimated at 1.5. For equity turnover ratio X_3 and financial risk X_4 limits were set at 0.6 and 1.7 for X_3 and 0.6 and 1.95 for X_4 respectively. For the concentration of involved capital X_5 – at 0.8 and 1.6. the coefficient of providing debt by X_6 has limits 0.18 and 0.55, and the payback of assets X_7 is divided into two subsets with the level of separation between them at 1.2.

Moreover, belonging the indicator to one of prescribed for it zones in a certain way indicates the level of the financial condition of the company.

To evaluate the value of output linguistic variable Z, which indicates the level of creditworthiness of the borrower, we will use terms: L – which characterizes high risk of bankruptcy and, therefore, a low credit standing (in his appearance, a decision is not to issue a loan); H – which indicates high creditworthiness of the borrower and indicates the advisability of issuing credit.

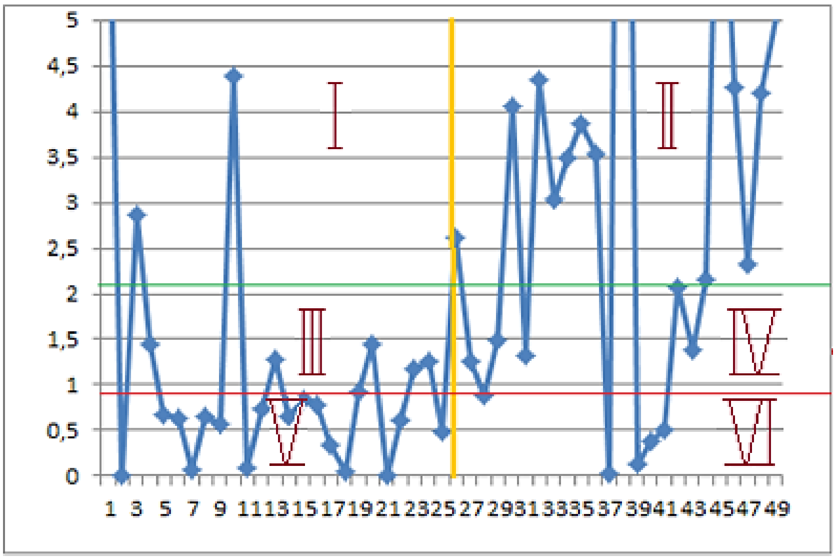

Fig. 2. Data of accounts payable turnover ratio

Stage 3. Construction of the membership functions. Unclear descriptions of the structure of the method of financial and economic analysis occur due to the uncertainty of the expert that arises in the classification of various kinds, such as when an expert can distinguish clearly between medium and high values of some parameters. In this case, it is necessary to build membership functions of fuzzy terms as the input and output variables to be able to perform an adequate classification of levels of all indicators.

The Gauss function is applied for the model membership function formation. The main advantages of this function are as follows: (i) simplicity (as soon as only two parameters determine its form), (ii) convenience of these parameters settings, because the functional derivative is enough simple. Furthermore, this function does not come down directly to zero being only zero asymptotically approximate. It possesses additional advantages in the resulting index values calculations of the models in fuzzy logics [9].

The Table 1 data are used for the membership functions of all initial variables construction. Hence, the payables convertibility coefficient membership functions to the three linguistic terms (L – low, M – middle, H – high) will take the form given in Fig. 3. The membership functions of all other variables are obtained similarly. The resulting variable is presented by two terms L and H with the centres of the membership functions in the points 0 and 1, which intersect at the level 0,5.

Stage 4. The set of rules formulation. The expert system based on fuzzy knowledge should contain the decision-making procedure, giving the possibility to

Table 1

Indexes of assessment of creditworthiness

Index	Coefficient	The values which indicate the potential bankrupt	Indefinite condition	The values which indicate the stable condition of the borrower
X_1	Payables turnover ratio	Below 0,8	0,8-2,2	Above 2,2
X_2	Turnover of current assets	Below 1,5	-	1,5 and above
X_3	Equity turnover	Below 0,6	0,6-1,7	Above 1,7
X_4	Financial risk	Below 0,6	0,6-1,95	Above 1,95
X_5	Concentration of involved capital	Above 1,6	0,8-1,6	Below 0,5
X_6	Providing debt by equity	Below 0,18	0,18-0,55	Above 0,55
X_7	Payback of assets	Above 1,2	-	1,2 and below

come to a conclusion on the borrower creditworthiness level. For example, the enterprise has a high level of bankruptcy danger and, therefore, the low creditworthiness (Z = "L") if its coefficients (of payables convertibility, of convertible assets reversibility, of own capital convertibility, of financial risk and covering of debts by own capital) are given by low values (can be interpreted by the term "L"), not a matter of fact that coefficients of applied capital concentration and assets payback are high (associated with the term "H"). Such a combination of financial coefficients values that characterize the low creditworthiness of businesses is given in the first row of the corresponding database, which is presented in Table 2. Other rules of the enterprises' creditworthiness expertise, which are collected in Table 2, are formulated similarly.

The analytical form of decision-making rules presentation from Table 2 in terms of membership functions and weight coefficients, corresponding to the low risk of bankruptcy and, therefore, high creditworthiness of businesses H, is given by:

$$\mu^H(X_1,\dots,X_7) = w_1^H\left[\mu^H(X_1)\cdot\mu^H(X_2)\cdot\mu^H(X_3)\cdot\mu^H(X_4)\cdot\mu^L(X_5)\cdot\mu^H(X_6)\cdot\mu^L(X_7)\right] \vee w_2^H\left[\mu^H(X_1)\cdot\mu^H(X_3)\cdot\mu^M(X_4)\cdot\mu^L(X_5)\cdot\mu^M(X_6)\cdot\mu^H(X_7)\right] \vee w_3^H\left[\mu^M(X_1)\cdot\mu^H(X_2)\cdot\mu^H(X_3)\cdot\mu^H(X_4)\cdot\mu^M(X_5)\cdot\mu^H(X_6)\right], \quad (1)$$

where $\mu^{d_j}(X_1,\dots,X_N)$ is the function of belonging of initial variables X_i, $i=\overline{1,N}$, to the j value of initial variable Z (a linguistic term from the set $d_j \in$ {L, H});

N – amount of initial factors (in this problem N = 7);

$\mu^{a_i^{jp}}(X_i)$ – the membership function of initial variable X_i for the linguistic term a_i^{jp}, $j=\overline{1,m}$, $i=\overline{1,N}$, $p=\overline{1,k_j}$ $w_p^{d_j}$ – weight of p rule among rules, which correspond to d_j term of output variable;

m – amount of values of output variable Z (in this problem m=2);

k_j – amount of rules in the knowledge base, which corresponds to j term of output variable Z (in this problem $k_1 = k_2 = 3$).

Stage 5. Model optimization for the real data. It is useful to hold a tuning of the model using the data of

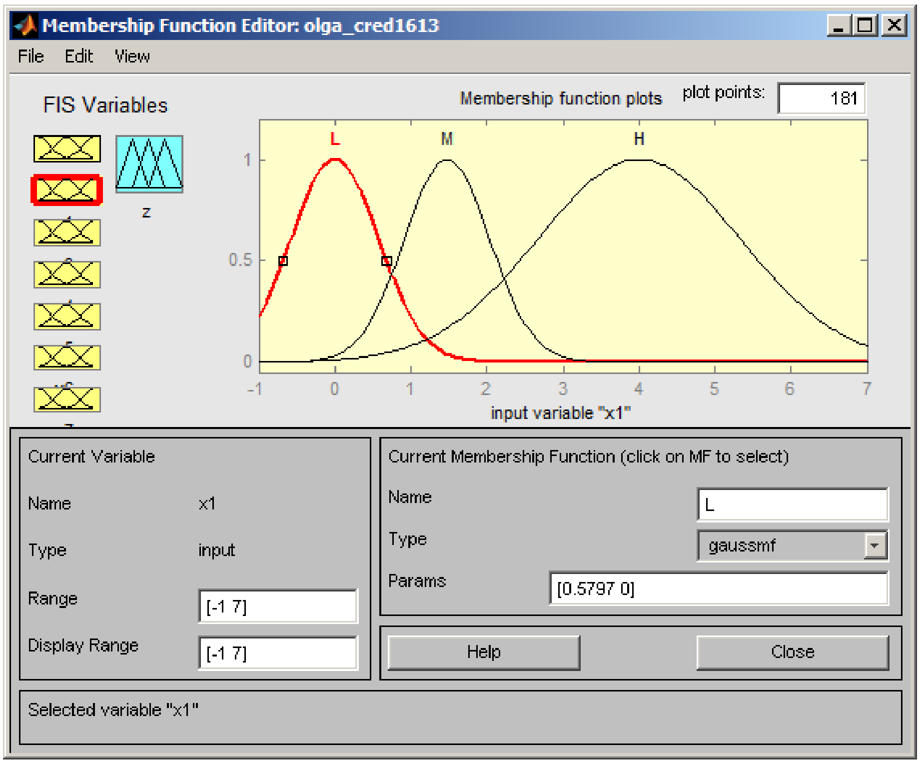

Fig. 3. Membership functions of the linguistic variable X1

Table 2

The knowledge base for the company creditworthiness determining

Linguistic value of input indicators							Weight of rules	Output variable
X_1	X_2	X_3	X_4	X_5	X_6	X_7	w	Z
L	L	L	L	H	L	H	w_1^L	L
L	None	L	M	H	M	L	w_2^L	L
M	L	M	L	H	L	None	w_3^L	L
H	H	H	H	L	H	L	w_1^H	H
H	None	H	M	L	M	H	w_2^H	H
M	H	H	H	M	H	None	w_3^H	H

bankrupted companies and financial stable enterprises before making the company financial condition expertise. In order to hold the optimization of the model, the mistake back propagation algorithm, being adapted for the models based on fuzzy logic or genetic algorithms [13], should be used. In principle, a tuning of an economic and mathematical model is not necessary because the model can give the solutions for arbitrary controlled parameters and their values if the basis rules are given. Nevertheless, the quality of the logical conclusion of the model can be improved essentially if a tuning of the model's parameters on the basis of existing statistical materials is carried out.

For the statistical materials, the data of already bankrupted companies and financial stable enterprises are used. The analysis of already bankrupted companies' data is carried out in different time intervals before bankruptcy. The reason is in companies' insolvency symptoms, which start a long time before the real financial problems and bankruptcy. The sooner the possibility to recognize the danger will appear, the more chances will have the credit organization to avoid unnecessary losses due to loan default.

Stage 6. Decision making. The final decision for the model is chosen in the form, where the membership function of the output variable Z has a maximum for the given values of controlled parameters X_i, $i=\overline{1,N}$:

$$Z = \arg \max_{j=\overline{1,m}} \left[\mu^{d_j}(X_1,\ldots,X_N) \right]. \qquad (2)$$

As soon as the values of the membership functions of the output variable according to any rule are calculated as the product of the membership functions of all initial variable and the operation of the output maximization among all rules is used to determine the term of resulting indicator Z, then the output variable of the model is calculated in general form according to the formula:

$$Z = \arg \max_{p=\overline{1,k_j},\, j=\overline{1,m}} \left\{ w_p^{d_j} \prod_{i=1}^{N} \mu^{a_i^{jp}}(X_i) \right\}. \qquad (3)$$

After the construction of the model and its tuning, the model can be used for the creditworthiness assessment of the company Z on the basis of the indicators X_i, $i=\overline{1,N}$.

The result of such a model application is not only the linguistic description of the bankruptcy risk but also the degree of confidence in the correctness of classification, which is determined by the resulting variable phase cut operation. Therefore, the conclusion about the bankruptcy risk degree of the company takes not only the linguistic form but the quality characteristic of the found assertions as well.

The constructed model is realized in Matlab medium. As the result of modelling experiments, carrying out the accuracy of the bankruptcies predictions among the financially unable companies is found as 89%, the accuracy of the classification of the financially stable companies is equal to 68%, which gives 77,8% about all group of enterprises under consideration, see Fig. 4.

In the carried out experiments, the parameters of the system are optimized, the base of decisive rules is clarified, on the basis of selected indicators, the possibility of effective fussy model construction is confirmed. As it is shown in Fig. 3 before the system tuning, nearly each second company was diagnosed as stable among the possible bankrupt, since after tuning only one bankrupt from 25 was considered as a stable one. Moreover, 7 stable companies were diagnosed by

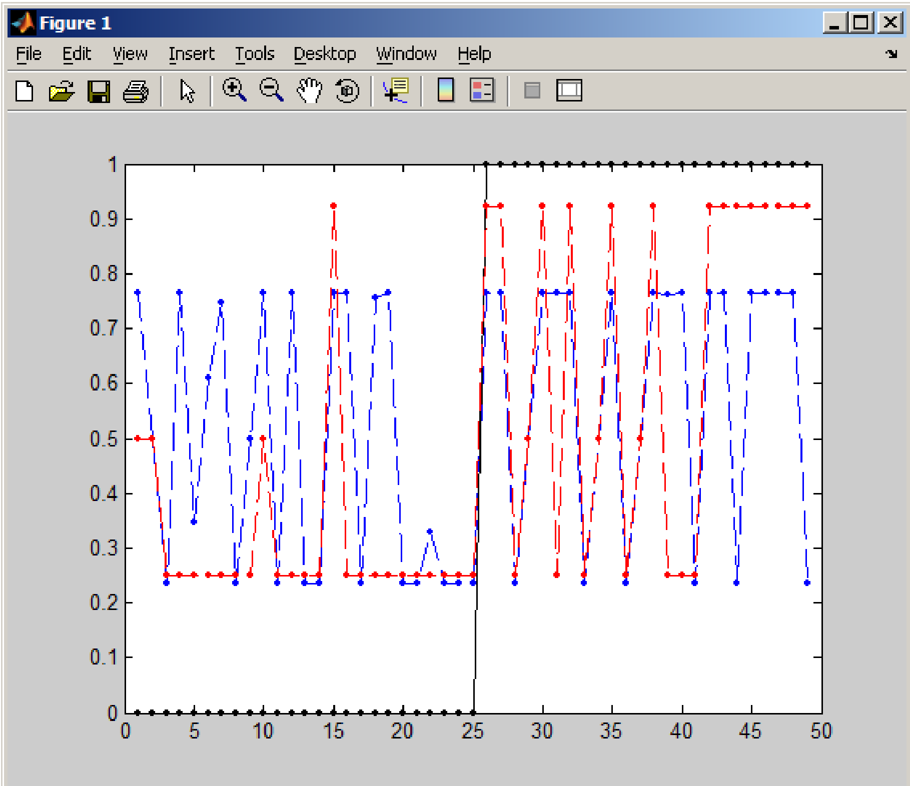

Fig. 4. The result of the modelling in Matlab medium (line 1 is the real values of the resulting indicator for the analysed companies; line 2 is the result of modelling to the model's tuning; line 3 is the result of modelling after model's parameters optimization in the real data)

the model as potential bankrupts, not a matter of fact that before the optimization their number was 6.

Note that it is possible to regulate the suspiciousness of the model from the fussy logics. However, with a decrease of alpha-error of classification (definition of bankrupt enterprises as a potential financial stable company) the beta-error simultaneously is increased (stable company diagnostic as a potential bankrupt). Moreover, the low value of alpha-error of classification may be considered as a positive characteristic of the model's work results, even not taking into account enough big beta-error. It indicates the possibility of profit shortfall from some false-classified stable companies. Nevertheless, the creditor has a possibility to obtain the same profit from other deposits (even from other credit correctly identified stable enterprises). Furthermore, the creditor does not suffer significant losses from potential bankruptcy loan (the modelling with the real data shows that only every 25th credit may suffer no return).

Conclusions. The constructed economic and mathematical model based on fuzzy logic shows the sufficiently high precision of diagnostics of the bankruptcy of native enterprises and may be used as an effective method to identify risky borrowers, which enable to minimize the risk of loan defaults and to improve as a result the stability of the financial system in general.

The model may be applied in commercial banks with the goal to assess the creditworthiness of borrowers, legal entities, as well as the main program or useful supplement to the existing programs, which the commercial banks of Ukraine are guided by when making decisions on granting loans to legal entities.

REFERENCES:

1. Altman E. I. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy // The Journal of Finance. – 1968. – No. 4. – P. 589-609.
2. Toffler R., Tishaw H. Going, going, gone – four factors which predict // Accountancy. – 1977. – March. – P. 50-54.
3. Beermann K. Prognosemöglichkeiten von Kapitalverlusten mit Hilfe von Jahresabschlüssen // Schriftenreihe des Instituts für Revisionswesen der Westfälischen Wilhelms-Universität Münster. – 1976. – Düsseldorf. – Band 11. – S. 118-121.
4. Davidova G. V., Belikov A.Yu. The method of quantitative assessment of the risk of bankruptcy of enterprises // Risk management.– 1999. – № 3. – P. 13-20.
5. Tereschenko O. O. Anticrisis financial management of the company – Kyiv: Kyiv National Economics University, 2004.– 268 p.
6. Chernyak O. I., Krekivskiy V. O., Monakov V. O., Yaschyk D. V. Detecting signs of company insolvency and possible its bankruptcy // Statistics of Ukraine. – 2003. – № 4. – P. 87-94.
7. Matviychyk A. V. Discriminant model of estimate of the bankruptcy probability // Modeling and information systems in the economy.– Kyiv: Kyiv National Economics University, 2006. – Vol. 74.– P. 299-314.
8. Resolution of the National Bank of Ukraine of 25 January 2012 № 23 « On approval of the procedure of formation and the use by banks of Ukraine reserves for compensation of possible losses on active banking operations».
9. Matviychyk A. V. Artificial intellect in the economy: neural networks, fuzzy logic. – Kyiv: Kyiv National Economics University, 2011. – 439 p.
10. Matviychyk A. V. Modeling the financial stability of enterprises using the theory of fuzzy logic, neural networks and discriminant analysis // NAS of Ukraine Herald. – 2010. – № 9. – P. 24–46.
11. Eytingtton V., Anohin S. Bankruptcy prediction: Basic methods and problems. – [Electronic resource]: http://www.iteam.ru/articles.php?tid=2&pid=1&sid=&id=141.
12. Nedosekin A. O. Fuzzy-multiple risk analysis of equity investments. – SPb.: Sezam, 2002. – 181 p.
13. Rotshtein A. P. Intellectual identification technologies: fuzzy sets, genetic algorithms, neural networks. – Vinnytsa: Universum – Vinnytsa, 1999. – 320 p.
14. Podderyogin A. M. Finance Companies: Tutorial. / A. M. Podderyogin, L. D. Buryak, G. G. Num et al. / Kyiv: Kyiv National Economics University – 2001. – 460 p.
15. Palamarchuk O.V. The selection of indicators for determining the creditworthiness of legal entities // Economic Analysis: collected works. – Ternopil, 2013. – Vol. 12. – Part. 1. – 292 p. – P. 266-268.
16. Matviychyk A. V., Palamarchuk O.V. Modeling creditworthiness of legal entities using the metod of fuzzy logic theory // Information technology and modeling in economic: towards interdisciplinarity: / Edit by V.M. Solovyov et al. – Cherkassy: Brama-Ukraine, 2013. – 408 p. – P. 23-33.
17. L.Dolinsky, Building Integrated credit rating of the banking system of Ukraine / L. Dolinsky, A. Kovalchuk // Bulletin of the NBU. – 2012. – № 6 (196). – P. 36-38.
18. Organizational development company, textbook [electronic resource]. – Access: http://library.if.ua/books/28.html