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A dynamic model of corporate bankruptcies with a combination of structural synthesis of the neural network and the regularization of its training

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ABSTRACT

The object of the study is the problem of financial management, in particular, the problem of forecasting the stage of developing bankruptcy of corporations-loaners and decision-making on the restructuring of credit debt. The solution of such problems is also important for assessing the solvency of counterparties in transactions, resolving issues of the illegal bankruptcies, economic security and for other areas of the economy. The subject of the research is the development of a dynamic model of bankruptcies with continuous time in conditions of high uncertainty and noise data, which allows diagnosing the stages of bankruptcy of the simulated object at any time (between the "time slices" in the data), as well as to predict the probability of bankruptcy in time ahead for a given horizon. The purpose of the study is to create an effective mathematical tool for predicting corporate bankruptcy to support decision-making on the financial management of corporations, which is focused on complex real-world modelling conditions. On the basis of system-wide laws for reducing entropy when combining rationally interacting subsystems and the law of temporary inertia of a simulated economic object, a conceptual basis (CB) of neural network modelling of bankruptcy dynamics has been developed. The design bureau serves as a methodological basis for the proposed original neuro logistic dynamic method (NLDM), which allows us to eliminate the incompleteness and uncertainty noted in the training sample and to operate with continuous time in the procedures for diagnosing and predicting the stages of the bankruptcy of borrowing corporations. The NLDM method, including the previously published monograph (Beloliptsev I.I., et al.) of the authors of the article, is distinguished by a new algorithm for regularizing the model integrated with the structural synthesis of the neural network.

KEYWORDS: neural network, optimal factor selection algorithm, conceptual basis, factor compression in clusters, Harrington function, dynamic bankruptcy model, regularization of the model integrated with structural synthesis, testing, model adequacy.

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Un modelo dinámico de quiebras corporativas con una combinación de síntesis estructural de la red neuronal y la regularización de su formación

El objeto del estudio es el problema de la gestión financiera, en particular, el problema de pronosticar la etapa de desarrollo de la bancarrota de las empresas prestamistas y la toma de decisiones sobre la reestructuración de la deuda crediticia. La solución de tales problemas también es importante para evaluar la solvencia de las contrapartes en las transacciones, resolver problemas de quiebras ilegales, seguridad económica y otras áreas de la economía. El tema de la investigación es el desarrollo de un modelo dinámico de quiebras con tiempo continuo en condiciones de alta incertidumbre y datos de ruido, que permite diagnosticar las etapas de quiebra del objeto simulado en cualquier momento (entre los "segmentos de tiempo" en los datos), así como para predecir la probabilidad de quiebra a tiempo para un horizonte determinado. El propósito del estudio es crear una herramienta matemática efectiva para predecir la bancarrota corporativa para apoyar la toma de decisiones sobre la gestión financiera de las corporaciones, que se centra en condiciones complejas de modelado del mundo real. Sobre la base de las leyes de todo el sistema para reducir la entropía cuando se combinan subsistemas que interactúan racionalmente y la ley de la inercia temporal de un objeto económico simulado, se ha desarrollado una base conceptual (CB) de modelado de redes neuronales de dinámica de bancarrota. La oficina de diseño sirve como base metodológica para el método dinámico neurológico logístico (NLDM) original propuesto, que nos permite eliminar el estado incompleto y la incertidumbre observados en la muestra de capacitación y operar con tiempo continuo en los procedimientos para diagnosticar y predecir las etapas de La quiebra de las empresas prestatarias. El método NLDM, que incluye la monografía publicada previamente (Beloliptsev I.I., et al.) De los autores del artículo, se distingue por un nuevo algoritmo para regularizar el modelo integrado con la síntesis estructural de la red neuronal.

PALABRAS CLAVE: red neuronal, algoritmo óptimo de selección de factores, base conceptual, compresión de factores en grupos, función de Harrington, modelo dinámico de bancarrota, regularización del modelo integrado con síntesis estructural, pruebas, adecuación del modelo.

Introduction

In Russian and foreign practice, the indicators of solvency and financial stability are calculated to assess the risk of bankruptcy. In accordance with the guidelines for the analysis of the financial condition of organizations, these indicators relate to indicators of the first class and have corresponding regulatory values. Despite the fact that the analysis of solvency and financial stability indicators is carried out in comparison of the data obtained over time, and in comparison with the standards, an objective assessment is not always possible. Since the frequency of generating such reports is 12 months, a lot of factors varying during the year, including various kinds of uncertainties not taken into account in the reports, influence the obtaining of reliable data (Moiseenko, 2017; Vernigor, 2017).

With regard to the activities of modern financial and economic objects, in which there is the above uncertainty in the characteristics of these objects and the conditions of their functioning, the construction of a dynamic model of bankruptcies cannot be performed by known methods of diagnosis of bankruptcies: Altman's Z-account, Beaver's model, Taffler test, Savitskaya's discriminant model, R-model of the Irkutsk State Economic Academy, the Saifullin-Kadykov's medium-term rating forecast. To fend off the manifestations of uncertainty in the training set and in the process of object functioning is possible only in the adaptive (intelligent) model, the means of rapid adjustment of model parameters to changing the current situation. Intelligent neuro net methods are well suited here (Haikin, 2006; Beloliptsev et al.; Gorbatkov et al., 2018).

However, the effective application of neuro net methods for building dynamic bankruptcy models directly to the original "raw" data is hardly possible. It is necessary to develop a formalized procedure for structuring the training sample and the optimal selection of factors, as well as their subsequent compression.

In other words, by the content informativeness of the data set, we mean the requirement of adequate reflection in ordered sets (tuples)

$$\langle y_{g,t}; \vec{x}_{g,t} \rangle,\ g \in \overline{1,G}\ ;\ t\ \in\ [t_o,T];\ \vec{x} = (x_1, \dots, x_j, \dots, x_n) \in X \qquad (1)$$

for "input-output" patterns of simulated objects that need to be restored using a neural network model (NNM). Here $y_{g,t}$ – NNM output value for g-th object at time t; $\vec{x}_{g,t}$ – the values of the vector of input factors on the model; t_0 – initial time; T – retrospective observation period during data generation; X – space of quantitative and qualitative factors. In addition to this requirement of "adequate reflection", it is necessary to meet the requirement of the data sufficiency contained in the set for training and testing of the NNM, which with the required level of accuracy could reproduce the behavior of the dynamic system (DS) in the entire range of possible values for the simulated generalized characteristics – the probability of bankruptcy $P(y(\vec{x}(t))) \in [0; 1]$.

The questions of a selection of factors in the formation of training samples for dynamic NNM are poorly investigated, more precisely among several hundred works on bankruptcies, a review of which is given in (Gorbatkov et al., 2018; Rissanen, 1978) a theoretically substantiated general approach (concept) to the formation of factor space has not been developed. The exceptions are the works of J. Rissanen (1978) and S.A. Shumsky (2002) where, based on the Kullback-Leibler information criterion, an important generalized theoretical conclusion is made: the shorter the total length of the data description and model (and, accordingly, the number of variables in the model), the better the generalizing ability of the NNM, i.e. its prognostic properties. From the point of view of this recommendation, it is rational in the initial expertly formed system of factors to carry out optimal selection (Gorbatkov and Polupanov, 2018), and then perform the operation of factor compression if their number is too large, for example, more than 50.

It is widely known that all the characteristics of the developed neural network model depend on its structure, especially on the number of hidden layers and the degree of connectivity of the structure. There are various approximate, iterative approaches to the problem of synthesizing the rational structure of a neural network, mainly based on minimizing the average experimental risk (Gorbatkov and Polupanov, 2018). However, a formalized mathematical method for solving this problem has not yet been developed.

An important and little-studied issue of constructing a dynamic NNM of bankruptcies is the justification of the adequacy of the model and the regularization of its training in the difficult conditions of data incompleteness noted above and the lack of a priori information about the form of the law of the distribution of measurement noise in the data. Here, the authors of the article deliberately refuse to embarrass the model being developed to make assumptions about any form of the noise distribution law, like (Shumsky, 2002) which brings our model closer to practice.

The study of the above poorly studied issues of developing methods for constructing a dynamic neural network model of bankruptcies in difficult conditions of data uncertainty served as the message to write this article.

1. Research problem statement

Let us consider in more detail the problem of data incompleteness and uncertainty specific to the problems of bankruptcies. Data are usually formed as "time slices" (1), in which $t = t_0, t_1, t_2, \ldots, t_N$, where N – the number of slices for the observation period of each g-th object of financial management. Moreover, as noted above, in time slices, only the boundary points of the range of possible values of the probability of bankruptcy of the corporation-borrower are indicated: $P = 1$ ("bankrupt" corporation) and $P = 0$ ("non-bankrupt" corporation). There is no information about intermediate values of P in the interval [0; 1], which characterize different stages of the developing bankruptcy process. Incomplete data in time slices is related to the uncertainty caused by the legal reasons noted above. At the same time, an artificial "asymmetry" is introduced into the model: the information on the recognition of the bankruptcy of the corporation is fairly reliable, but the information on assigning the label "non-bankrupt" ($P = 0$) contains a high degree of uncertainty caused by the deformation of the model by the legal features of the bankruptcy procedure.

Let there be retrospective data of the form (1). Moreover, in the last time slice ($k = N$) is usually known as vectors of the values of factors $\{\vec{x}_{gN}\}$, so are the values of the output variable $y = \arg(P(\vec{x}_{gN}, t_N))$. This allows you to train NNM and assess the probability of bankruptcy P in the last time slice ($t = t_N$). However, for some of the previous time slices $(t_1, t_2, \ldots, t_{N-1})$ output (endogenous) variable $y_{gk} = \arg(P(X_{gk}, t_k))$, $k = \overline{1, N-1}$ values may not be known, since by the time $t \leq t_N$ in some of the borrowing corporations, the crisis process is developing and they have not yet been declared bankrupt.

Hence the conclusion: regardless of the method used to build the bankruptcy model, the negative manifestation of the noted incompleteness, uncertainty and asymmetry of information in the data must be somehow eliminated, or at least significantly weakened. This conclusion formed the basic idea of the proposed iterative NMDM.

Now we state the information-mathematical statement of the research problem. We consider the inverse problem (IP) of restoring the dependence of the probability of bankruptcy P on the vector of exogenous variables $\vec{x}$ hidden in the data. We will determine this dependence in the form of a logistic function proposed by Olson (1980):

$$P(t) = 1/[1 + \exp(-\hat{y}(\vec{x}(t), t))],\ P \in [0; 1]. \qquad (2)$$

The exponent $\hat{y}(\vec{x}(t), t)$, which plays the role of an argument in (2), is restored using a neural network mapping from the data:

$$\hat{y}(\vec{x}, t) = F(\vec{x}, \mathrm{W}, t); \quad F: \vec{x} \in R^{(n)} \to \hat{y} \in R^{(1)}, \qquad (3)$$

where W – a set of synaptic weights and displacements in neurons; $F(\cdot)$ – NN-mapping operator.

We note a feature of the logistic function that is important for constructing a dynamic neural network model: the map (2) is contracting in the sense that the interval for the argument of the function (2) $\hat{y}(\vec{x}, t) \in [-6; 6]$ is displayed in the corresponding interval of the function value $P \in [0; 1]$, i.e. compression ratio is approximately 12. Therefore, if NNM (2) - (3) is already trained, tested and examined, then errors in defining the vector of factors $\vec{x}$ will be "reduced" by the operator of the logistic mapping (2) when calculating the probability P.

However, for the neural network model (3) the task of training, i.e. finding the synaptic balance W of the neural network is an inverse problem which is set incorrectly according to Hadamard (Tikhonov and Arsenin, 1979); therefore, it requires special measures to regularize its solution, which was noted in the works (Beloliptsev et al.; Gorbatkov et al., 2018). In this article, based on the Bayesian approach, the original regularization algorithm, integrated with the synthesis of the rational structure of the neural network and the simultaneous selection of activation functions in the intermediate layers is described in detail. This result is central in the article (see below).

2. Conceptual basis and neural network logistic dynamic method for building a bankruptcy model

Three concepts have been developed as a methodological basis for building a dynamic bankruptcy model:

- **Concept 1**: A carrier of indirect, but sufficiently reliable information about the dynamics of the bankruptcy process in the financial management system, i.e. in a dedicated cluster of borrowing corporations, there are many exogenous variables $\{\vec{x}_{g,t}\}$ that change over time ($g \in \overline{1,G}$, $t \in [t_k , t_N]$). Moreover, the information about $\{\vec{x}_{g,t}\}$ is known in advance in all time slices of the data, i.e. is complete.
- **Concept 2:** Using the law of time inertia of financial management objects, it is possible to use specially constructed iterative procedures with the help of the neural network to extract knowledge about the process dynamics from the indirect information contained in the time slices of factors $\{\vec{x}_g, t_k\}$, $k=1,2,\ldots,N$, specified in concept 1, and to restore incomplete, uncertain and asymmetric information about the values of the endogenous variable $\{y_g , t_k\}$ in time slices.
- **Concept 3:** Based on the system-wide law of reducing entropy when rationally interacting subsystems are combined into a common system, a concept of regularization of a dynamic neural network bankruptcy model is proposed, characterized by introducing into a Bayesian ensemble of neural networks with various structures and various activation functions, followed by a posteriori filtering of these structures according to the direct criterion of the number of identification errors on test set and then averaging the design characteristics on the filtered networks. The achieved the emergent effect is a formalized obtaining simultaneously with the regularization of the model of rational neural network structures and the type of activation structures of the neural network and the type of activation functions, synthesis of the structure of the neural network.

We now consider the specific NLDM algorithm that implements the concepts 1, 2, 3 and includes four subtasks:

A. Formalization and optimization of the factor selection for the formation of the training sample.

B. The study of the possibility of effective use of bankruptcies of aggregating generalized Harrington desirability functions (Gorbatkov and Polupanov, 2018) for construction of NNM.

C. Data recovering in time slices from incomplete, indefinite and asymmetric information about the values of endogenous variables $\{y_g, t_k\}$ in all time slices $t_k = t_1, t_2, \dots, t_N$.

D. Development of an algorithm for regularizing the solution of the inverse problem of learning NN integrated with a formalized choice of its structure and activation functions in the intermediate layers.

Algorithms for solving subtasks A, B, and C are described in detail in (Beloliptsev et al.; Gorbatkov et al., 2018; Gorbatkov and Polupanov, 2018). Therefore, we will not dwell on these subproblems in detail, but we will focus on subproblem D, which was not considered anywhere else.

3. Algorithm for solving subtask G

Suppose that sufficiently homogeneous clusters are formed in the retrospective data sample, and the grouping criterion includes only significant factors according to the solution of subtask A from (Gorbatkov and Polupanov, 2018).

The algorithm for solving subtask B is implemented by introducing two iterative cycles that implement concepts 1 and 2: “external” iterations by the index k-number of the temporary “slice”, which serve to restore incomplete data in time slices; “Internal” iterations over the index m, which serve to correct data recovery errors, i.e. more "fine-tuning" dynamic NNM.

External iterations are implemented according to the formulas:

$$F^{(k-1)}(\vec{x}_{k-1}, \mathrm{W}_k, s) \approx F^{(k)}(\vec{x}_k, \mathrm{W}_k, s) \Longrightarrow \hat{y}_{k-1,\mathrm{g}} \approx F^{(k)}(\vec{x}_{\mathrm{g,k-1}}, \mathrm{W}_k, s), \quad (4)$$

$$\varepsilon = \max_{\mathrm{g}\in\overline{1,G}} |y_{\mathrm{g},k-1} - F^{(k)}\left(\vec{x}_{\mathrm{g},k-1}, \mathrm{W}_k, s\right)| \ ; \ \ \varepsilon > 0. \quad (5)$$

where F(·) – neural network mapping in form (3); k = N-1, N-2,…,1; ε – data recovery error.

In other words, as, the NNM for the slice $(k - 1)$ uses the already trained and tested network obtained in the previous slice $k = N$, etc.

Internal iterations over the index m serve to reduce the error ε in (5) and uses already complete (reconstructed) data:

$$\{\hat{y}_{g,k}^{(m)}(\vec{x}_{g,k}) = F^{(m)}(\vec{x}_{g,k}W^{(m)}, s)\}; m = 1, 2, \ldots, k, \ldots, N. \qquad (6)$$

Comment. With high demands on the quality of the forecast, it is possible to organize several runs on the index *m* in (6).

The criterion for stopping the iterations of the correction ε from (9) - (10) is the condition for stabilization of the restored values $\{\hat{y}_{g,k}^{(m)}\}$:

$$I^{(m)} = \max_{m \in \overline{1,N}} \left\{ \max_{k,m \in \overline{1,G}} \left[\frac{\hat{y}_{g,k}^{(m)}(\vec{x}_{g,k}) - \hat{y}^{(m-1)}(\vec{x}_{g,k})}{\hat{y}_{g,k}^{(m)}(\vec{x}_{g,k})} \right] \right\} \leq \xi, \ m=1, 2, \ldots, N. \qquad (7)$$

In practice, one or two back-and-forth runs in (7) are usually sufficient.

Now we present the proposed NNM regularization algorithm integrated with the structural synthesis of the network based on concept 3, which uses the same paradigm of regularization of the inverse problem solution as in A.N. Tikhonov (1979). The solution is based on a narrowing of the space of the desired solutions $Z' \subset Z$, where Z' is some "compact". However, the method of narrowing Z to the compact Z' in our case is different from the construction of Tikhonov's stabilizers.

- Firstly, due to the mechanism of a posteriori filtering of neural networks – $\{h_q\}$ hypotheses on the Bayesian ensemble and subsequent averaging of the model characteristics on the filtered ensemble.

- Secondly, due to the optimal selection of factors and their aggregation in subtasks A and B.

4. Assessment of quantitative results

First, we indicate the general moments of the organization of computational experiments. As the initial data D, we used the retrospective data of borrowing corporations of one of the most common sectors of the economy, the construction industry, obtained by Bereua Van Dijk (Makeeva and Neretina, 2013). The database contained 136 observations.

A system of 15 specific indicators was applied, which are widely used in bankruptcy assessment tasks (Kupryushin and Chernyatina, 2017): L_1 – quick liquidity ratio; L_2 – stock coverage ratio; P_1 – current liquidity ratio; F_1 – financial ratio; F_2 – equity ratio; F_3 – security of stocks with own working capital; F_4 – fixed asset index; R_1 – overall profitability; R_2 – return on assets; R_3 – return on equity; R_5 – return on current assets; A_2 – asset turnover; A_4 – accounts payable turnover; A_5 – accounts receivable turnover; A_6 – inventory turnover.

Calculating formulas for these specific indicators are contained in (Beloliptsev et al.; Gorbatkov et al., 2018) and operate with the data of standard financial statements. An algorithm was implemented from (Gorbatkov and Polupanov, 2018) for the optimal selection of factors using regularization in the Bayesian ensemble of auxiliary neural network models.

Ensemble characteristics: Ω - MLP-BP meta-hypothesis implemented on the NeuroSolutions 5.0 software product (demo version). From the initial 14 factors, 11 were selected corresponding to the values $\overline{\Theta} \leq 0{,}0444$, i.e. the average identification error on the auxiliary NNM ensemble equal to 4.44%;

$$\Theta_{qj} = (N^{(\mathrm{I})}/\ N) + \left(N^{(\mathrm{II})}/N\right)\ ; \overline{\Theta}_j = \left[\sum_{q=1}^{Q^*} \Theta_{qj}\right]/N, j = \overline{1,n}. \qquad (8)$$

Here Θ – quality criterion for identifying examples of a test set using the auxiliary NNM ensemble; j - the factor number; q – the number of auxiliary NNM in the ensemble; $N^{(\mathrm{I})}, N^{(\mathrm{II})}$ - the number of type I and type II errors in the identification of test sample objects; N - the total number of objects.

Comment. To solve the problem of formalized selection of the St structure of the "working" NNM (after selecting factors) integrated with the regularization of the NNM in the Bayesian ensemble, we used the same direct criterion for the synthesis quality St of the form (8) and activation functions (hyperbolic tangent and sigmoid) in hidden network layers :

$$f(s) = th(bs),\ b > 0;\ f(s) = 1/[1 + \exp(-as)],\ a, b > 0. \qquad (9)$$

where S – state of the neurons. The selection rule of the rational structure of the NN is described as: $St^*\colon \Theta_q \leq \eta$; where η – a predetermined small number, for example 0.01; an asterisk indicates that the structure has been successfully filtered.

Table 1 presents the Bayesian ensemble of the analyzed NN structures.

Table 1. Bayesian NNM ensemble

№ NNM	Number of hidden layers	Type of activation function in hidden layers
1	1	(9)
2	2	(9) in both layers
3	2	(9) in the first layer, (10) in the second layer
4	1	(10)
5	2	(10) in both layers
6	2	(10) in the first layer, (9) in the second layer

Table 1 corresponds to the optimal set of 10 factors as a result of solving problem A: $L_1, L_2, F_1, F_2, R_1, R_2, R_3, A_2, A_4, A_6$. The structure of ensemble №2 was eliminated at $\overline{\Theta}_2 = 0{,}166 > \eta = 0{,}01$. The accepted level η = 0.1 corresponds to a 90% correct identification of the test sample.

5. Convergence evaluation for endogenous variables restoration and adjustment of restored values iterative processes

For the proposed NLDM construction of a dynamic bankruptcy model, the convergence of iterative processes (4) - (5) is central. The data on the convergence of these processes are shown in Fig. 1.

From Fig. can be seen that the recurrent iterative process (4) - (5) of restoring the endogenous variables $\{\hat{y}_{g,k}\}$ when moving from the time slice k = 5 to the slice k = 3 leads to an improvement in the quality criterion (8) with $\overline{\Theta}$ = 0.2417 to 0.05, i.e. 4.83 times. Therefore, the recovery quality of endogenous variables $\{\hat{y}_{g,k}\}$ by the finish criterion $\overline{\Theta}$ from (8) is very high.

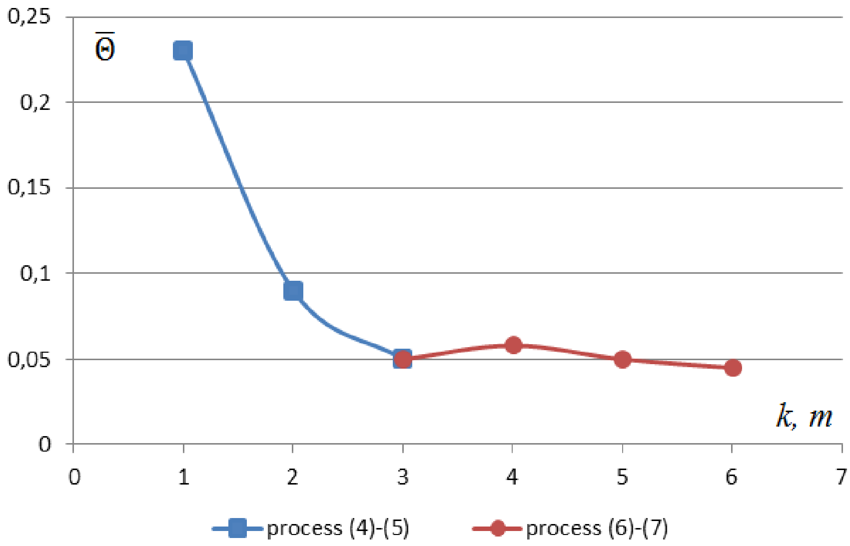

Fig. 1. Changes of the quality criterion $\overline{\Theta}$ for object identification by process steps *k* (4)-(5) and by process steps *m* of (6)-(7)

Subsequent iterations *m* = 4, 5 and 6 in Fig. 1 correspond to the correction process ε according to (6) - (7). Here, the convergence is oscillatory in nature with a residual between the steps of iterations not exceeding 0.0276. The reason for the variability of the residual with small deviations of the order of 2.76%, the authors of the article consider the «unimprovable» noisiness of the training data sample.

Thus, computational experiments on the convergence of the recovery process for endogenous variables (4) - (5) and their further correction (6) - (7) confirmed the efficiency of the proposed concepts 1, 2 and 3 of building NLDM bankruptcies.

Estimates of the change in the bankruptcy probability *P* in time *t* calculated by NLDM for 7 construction companies according to data from (Makeeva and Neretina, 2013) are shown in Fig. 2.

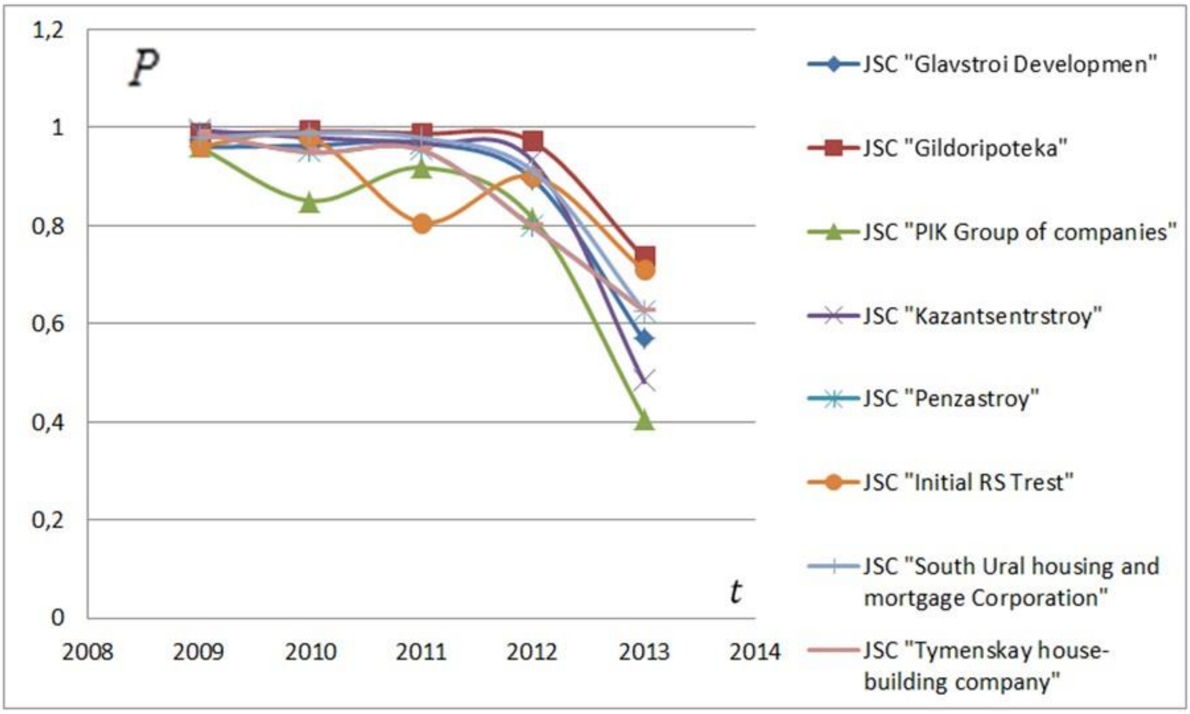

Figure 2. Dynamics of the probability of corporate bankruptcy

2013 in this study is a forecast year. It can be seen that the dynamic bankruptcy model built on the basis of NLDM provides valuable forward-looking information for making management decisions on financial management. Thus, PIK Group of Companies OJSC and Kazancentrostroy OJSC have positive dynamics (bankruptcy development scenario). Thanks to anti-crisis measures: the forecast values of the probability of bankruptcy P from the value of 0.98 decreased to (0.40, ... , 0.45). In relation to other corporations, the forecast gives unfavourable values (P > 0.56, ..., 0.76), which indicates the ineffectiveness of the anti-crisis measures taken in these corporations from 2009 to 2012 (insufficient revenue and profit).

Conclusions

1. As applied to the complex modelling conditions characteristic of bankruptcy tasks, in which, in addition to the usual noisy data, there are specific properties of uncertainty (asymmetry) and incomplete data. Therefore, the construction of dynamic bankruptcy models using traditional econometric methods is very difficult. The use of intelligent neural network modelling methods is promising here.

2. A conceptual basis was developed and the original iterative neural network logistic dynamic method (NLDM) for building bankruptcy models is implemented. Its main idea is to use indirect information about all the nuances of the dynamics of the developing bankruptcy process, contained in the values of the factor vectors $\vec{x}_{g,k}$ for the data "temporary slices". Moreover, the NLDM in the process of building the model restores incomplete data in the slices and corrects their asymmetry.

3. The new version of NLDM contains, in addition to the procedure for recovering incomplete data, an algorithm for integrating the regularization of the NNM on the Bayesian ensemble which is integrated with a formalized procedure for synthesizing the rational structure of the neural network.

4. The authors see the direction of further research in improving the quality of the medium-term and short-term bankruptcy forecast based on the proposed NLDM.

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