Assessing Risk of Enterprise Bankruptcy by Indicators of Financial and Economic Activity Using Bayesian Networks

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Abstract. Financial problems and business failures can lead to a waste of resources and loss of investment opportunities. Forecasting bankruptcy will alert companies to the problem so they can take appropriate action to prevent bankruptcy. The purpose of this study is to develop a model for predicting the financial problems of enterprises. A Bayesian network has been developed for analyzing and predicting the financial condition of industrial enterprises. Financial statements were used to analyze 3000 industrial enterprises in Ukraine. Five integral financial indicators were identified for building Bayesian networks (maneuvering coefficient, debt-to-equity ratio, the coefficient of autonomy, current liquidity ratio, financial stability ratio). The developed banking network allows for situational analysis "What… if". The results obtained in the study show the forecast of the quality and the practical application possibility of the developed Bayesian network in the decision support system for an intelligent assessment of forecasting bankruptcy probability of an enterprise.

Keywords: Bankruptcy Prediction; Financial Distress; Bayesian Networks; "What-if" analysis.

1 Introduction

Determining the bankruptcy risk of an enterprise is an important stage in the analysis of the enterprise financial condition. But usually this analysis is based only on the clear method of Altman and derivatives from it. Now all the enterprises activities take place in conditions of uncertainty, so it is more expedient to use fuzzy methods.

There is also a problem that some enterprises may not fully accurately reflect their activities in the annual financial statements, but using fuzzy methods, these inaccuracies are partially smoothed out. In practice, probabilistic methods give more accurate results, which is why building systems based on Bayesian methods is so important now. Risks can have different meanings and can be assessed in different ways according to different typologies of activities and priorities.

In general, risk is measured in terms of the probabilistic combination of an event (frequency) and its consequences (impact). Expert opinions (both qualitative and quantitative) are used to assess the frequency and impact (severity) of historical data. Moreover, the quality data must be converted to numerical values to be used in the model.

In the case of assessing economic risks, the considered risks are, for example, strategic, operational, legal and image, which in many cases is difficult to quantify. So in most cases, only expert data collected through scorecards is available for risk analysis.

The Bayesian Network is a useful tool for integrating various information and, in particular, for studying joint risk distribution using data from experts.

In this paper, we want to show one of the possible approaches for building a Bayesian network based on the calculated integral economic indicators. Causal networks explain waste in terms of random variables sequence. Each variable itself can be called by a combination of other variables.

The aim of this work is to develop a methodology for constructing a Bayesian network to assess the probabilistic risk of an enterprise bankruptcy.

The rest of the paper is organized as follows. Section 2 provides an overview of the literature on existing methods for predicting bankruptcy. In Section 3 we discuss the general formulation of the solution to the problem. In Section 4, we describe the input data and methods for obtaining integral economic indicators. After that, we describe the sequence of building and validating a Bayesian network. Section 4 describes the research process and presents its results. Section 6 summarizes and completes.

2 Literature Review

The first research results were published in [1]. In this paper, the author proposed to use 29 financial coefficients calculated using multiple discriminant analysis (MDA). In [2] proposed a bankruptcy forecasting model, which is a function of indicators characterizing the economic potential of an enterprise and the results of its work over the past period. In the initial study, when constructing the index, 66 industrial enterprises were surveyed, half of which went bankrupt in the period 1946-1965, and half of which worked successfully, 22 analytical coefficients were examined that could be useful for predicting possible bankruptcy. From these indicators, the 5 most significant indicators for the forecast were selected and a multivariate regression equation was constructed. The Altman index allows us to assess the degree of the enterprise bankruptcy risk, the level of the enterprise financial stability, the enterprise safety margin, the activities of the enterprise management, to compare with other enterprises, regardless of their size and industry. The built-in weights in the index allow taking into account the multidirectional indicators of the enterprise economic efficiency.

In [3], a neural network was used to solve the problem of predicting bankruptcy for the first time. In this work, comparative studies of the neural network and the model proposed by Altman in the form of a multivariate regression equation obtained as a result of multivariate discriminant analysis were carried out. The study used the same dataset. The results show that neural networks provide more accurate and robust results.

In [4] made a statistical prediction of bankruptcy using a sample of 80 companies that combined hotel, restaurant and entertainment companies. In this work, a comparative assessment of the logistic regression model predictive ability and neural networks was carried out. The authors concluded that neural networks have better predictive power within the sample, but the accuracy of both models predictive power in the external sample is the same. In [5] logistic regression, random forest models and neural networks were used to define the model with the highest accuracy in predicting the financial problems of industrial bankruptcy. The best results were obtained with neural network models.

The first results on the application of Bayesian networks for predicting bankruptcy were published in [6]. The study demonstrated how probabilistic models can be used for early warning of bank bankruptcy. In [7, 8] Bayesian networks were used to predict bankruptcy, while a methodological issues number of their application for solving this class of problems were considered.

In the works [9,10] models of static Bayesian networks were developed for solving problems of credit risk and credit scoring.

In [11], it is shown how the Bayesian network can be used to represent the traditional financial model of portfolio returns, while it is demonstrated how expert subjective assessment can be included in the Bayesian network model. The output of the model is the posterior probability distribution of portfolio returns. In [12,13], a new Bayesian optimization procedure is proposed to detect variances in the capital asset pricing model. The authors showed that the returns follow independent normal distributions and the partition structure is superimposed on the parameters of interest. The methodology is illustrated on a real dataset for which a microeconomic interpretation of the detected outliers was provided.

[14] describes a method for evaluating Japanese energy companies using Bayesian networks. A method of data preprocessing is proposed, including clustering of expert assessments further of economic variables assessments based on data, the use of a naive Bayes classifier, followed by the use of an improved naive Bayes classifier. This is accomplished by adjusting its conditional density for each characteristic variable taking into account the class variable, which are initially obtained by estimating the maximum likelihood. The adjustment is made using simulated annealing optimization.

[15] presents the results of applying an extended Bayesian network to simulate and analyze chain disturbances. In the methodology proposed by the authors, supply chains are presented as interconnected components that can be complex and dynamic. Disruptions in one subnet of a system can reverse impact other subnets, disrupting the

supply chain. When a failure occurs, the speed at which the problem is detected becomes critical.

The most popular are BN developed in the field of risk management and assessment [16]. In this work, the Bayesian network is used to assess the risk profiles of firms operating within the construction industry.

Risk prediction modeling using BN has a number of advantages over regression-based approaches that address common problems in risk prediction, but we will focus here on three important aspects: (1) they generate network structures so that the underlying causality the structure between the variables can be visualized and easily seen; (2) they can be used to conduct what-if scenario analysis and risk prediction at an individual level, and (3) they can be converted to decision models in a relatively simple way.

The general problem of research is that none of the studies evaluated the validity of the developed networks, and the resulting models were not used to analyze "what-if" scenarios [17,18]. The scenario involves adding additional information to the model, more specifically, adding node observation. In this way, uncertainty is removed and the consequences for other nodes can be calculated. In a Bayesian network, you can do both forward and backward inference, i.e. information can be added to any node, and the effect is calculated in any direction of the graph.

This problem has been repeatedly solved in a number of our works using static and dynamic Bayesian networks [19-23].

3 Problem statement

Having a set of economic indicators known data, it is necessary to determine the calculated parameters influence on the risk parameter of the enterprise bankruptcy. The main task is to select an algorithm for constructing a network structure, taking into account the relationship nature between nodes and a preliminary determination of the conditional probabilities of the network ancestor nodes. The stages of the Bayesian network development are shown in Fig. 1.

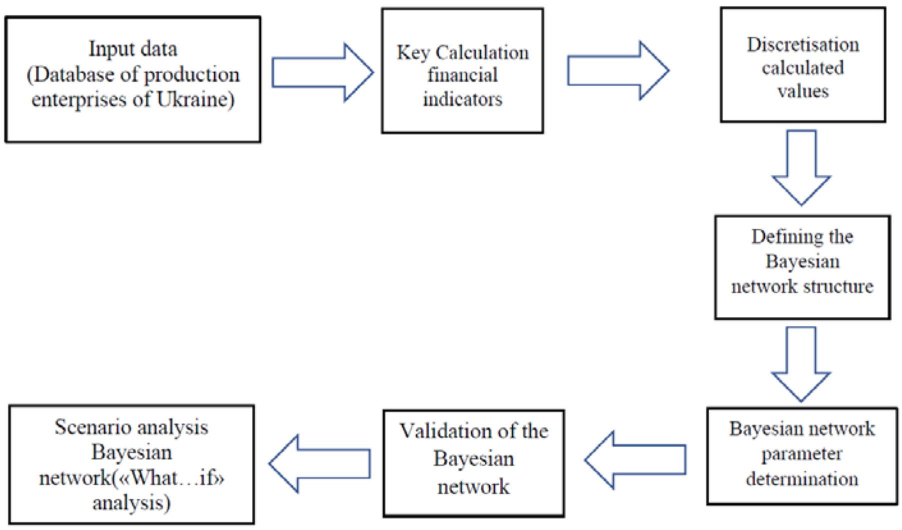

Fig. 1. Stages of a Bayesian network development for modeling the states of change in the bankruptcy risk of an enterprise.

4 Materials and Methods

4.1 Data

To build the model, an industrial enterprises database in Ukraine was used. When constructing the model, a training set of 3000 records was used, which contains information about the company (Balance Sheet, Statement of Financial Results, Statement of Cash Flows) and information about whether the company is bankrupt or not (0 - solvent company, 1 - insolvent company).

In the training sample, 75% (2250 enterprises) are solvent, and 25% (i.e. 750 enterprises) are insolvent. The constructed model is tested on a sample of 300 records, of which 75% are solvent enterprises, 25% are bankrupt. For the test sample for each enterprise, we calculate the bankruptcy probability and compare the predicted values with actual information (0 - if the enterprise is solvent, 1 - otherwise). Regardless of which simulation technology is used, the result will be the probability of bankruptcy (default) calculated for each enterprise. The developed BN was used to analyze the solvency of selected manufacturing enterprises. The following attributes are selected as process variables:

1) maneuvering coefficient, 2) leverage coefficient (debt-to-equity ratio); 3) the coefficient of autonomy; 4) current liquidity ratio; 5) financial stability ratio; 6) bankruptcy probability.

(1) **Maneuvering coefficient** shows how much of the own working capital is in circulation. The maneuverability factor should be high enough to provide flexibility in using your own funds:

$$M_c = \frac{O_{wc}}{E_q}, \quad (1)$$

where M_c is maneuvering coefficient, O_{wc} is owned working capital, E_q is equity.

The standard value of the maneuverability coefficient is in the range from 0.2 to 0.5. The value of the indicator below the norm indicates the insolvency risk and financial dependence of the company. It would seem that the higher the value of the coefficient, the more financially stable the company is. However, these values may indicate an increase in long-term liabilities and a decrease in financial independence.

(2) **Leverage coefficient** (debt-to-equity ratio) is calculated by dividing a company’s total liabilities by its shareholder equity. The ratio is used to evaluate a company's financial leverage. The D/E ratio is an important metric used in corporate finance. It is a measure of the degree to which a company is financing its operations through debt versus wholly-owned funds. More specifically, it reflects the ability of shareholder equity to cover all outstanding debts in the event of a business downturn. D/E ratio formula and calculation is:

$$D/E = \frac{T_L}{T_{ShE}}, \quad (2)$$

where D/E is the debt-to-equity (D/E) ratio, T_L is the total liabilities, T_{ShE} is total share holds equity. The information needed for the D/E ratio is on a company's balance sheet. This formula also reflects the financial risks of the enterprise. The optimal value of the coefficient ranges from 0.5 to 0.8.

(3) **The coefficient of autonomy** (concentration of equity capital, property of the enterprise) illustrates the independence degree of the organization from creditors. It is defined as the equity ratio to the value of all assets. That is, it shows the share of equity in the aggregate of assets, own and borrowed. The coefficient of autonomy (financial independence) is used in the analysis of enterprise financial condition by managers.

$$C_a = \frac{Eq_r}{A} \quad (3)$$

where C_a - the coefficient of autonomy, Eq_r - equity and reserves, A - asses.

In fact, we need numbers from the balance sheet liability. Thus, this ratio is used by financial analysts for their own diagnostics for financial stability of their company.

(4) **Current liquidity ratio** is a liquidity ratio that measures a company's ability to pay short-term obligations or those due within one year. It

tells investors and analysts how a company can maximize the current assets on its balance sheet to satisfy its current debt and other payables.

To calculate the ratio, analysts compare a company's current assets to its current liabilities. Current assets listed on a company's balance sheet include cash, accounts receivable, inventory and other assets that are expected to be liquidated or turned into cash in less than one year. Current liabilities include accounts payable, wages, taxes payable, and the current portion of long-term debt:

$$C_R = \frac{C_a}{C_l} \tag{4}$$

where C_R is current ratio, C_a is current assets, C_l is current liabilities.

(5) **Financial stability ratio** is the financial stability indicator, which indicates the company's ability to meet its obligations in the medium and long term. The indicator value indicates how many hryvnias of equity account for each hryvnia of the company's liabilities. The high value indicates a low level of financial risks.

$$F_{SR} = \frac{Eq}{L_{tl} + S_{tl}} \tag{5}$$

where F_{SR} is financial stability ratio, L_{tl} is long-term liability, S_{tl} is short-term liability.

The normative value of the indicator is in the range of 0.67-1.5. Values below 0.67 indicate a high level of financial risk. A value above 1.5 can means additional efficiency reserves to calculate the positive funds attraction.

4.2 Bayesian network

A Bayesian network (BN) is a pair <G, B>, in which the first component G is a directed acyclic graph corresponding to random variables [24, 25]. Each variable is independent of its parents in G. So, the graph is written as a set of independence conditions. The set of parameters defining the network is the second component B. It contains parameters $Q_{x^i|pa(X^i)} = P(x^i \mid pa(X^i))$ for each possible x_i value from X_i and $pa(X^i)$ from $pa(X^i)$, where $pa(X^i)$ denotes the set of parents of the variable X_i in G [26]. Each variable X_i is represented as a vertex. We use the notation to identify the parents $pa^G(X^i)$ if we consider more than one graph. The total joint probability of BN is calculated by the formula $P_B(X^1,...,X^N) = \prod_{i=1}^{N} P_B(X^i \mid pa(X^i))$.

BN is a probabilistic model for representing probabilistic dependencies, as well as the absence of these dependencies. At the same time, the A→B relationship is causal, when event A causes B to occur, that is, when there is a mechanism whereby the value accepted by A affects the value adopted by B. BN is called causal, when all its connections are causal.

Discretization of the computed values of economic data. One of the approaches to the formation of the BN output is the preliminary discretization of continuous variables. The domain of each continuous variable is divided into some definite finite number of sets (Fig. 2). Then the conditional probability distributions are discretized and as a result we get a discrete model, with which it is much easier to work [27]. From the existing sampling methods (hierarchical sampling, sampling by the same class width, sampling by the same number of points within the classes), the hierarchical sampling method was chosen for the existing dataset.

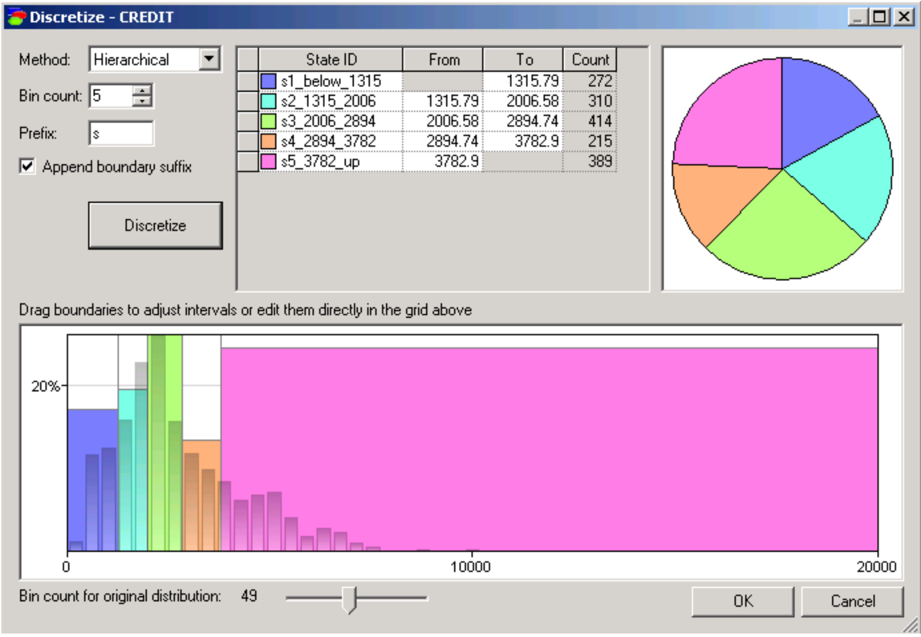

Fig. 2. Process of hierarchical data sampling.

Determining the structure of a Bayesian network. Our research uses the PC algorithm. The essence of the PC algorithm for constructing a BN structure is as follows. There is a set of variables X = (X1, ..., Xn) with a global distribution of probabilities about them P and A, which we will denote as a subset of variables X. By the expression I (A, B | C) we will assume that the sets A and B are conditionally independent in C. The PC algorithm assumes the presence of confidence probabilities. This means that there is a directed acyclic graph G such that the independence relations between the variables in X are exactly the ones represented by G using the d-separation criterion. The PC algorithm provides for a procedure that can recognize when the expression I (A, B | C) is verified (tested) on the graph G. The algorithm starts with finding an undirected graph, and at the last step determines the orientation of the edges.

The goal of parameter learning is to find the most probable θ that explain the data. Let D={D_1,D_2,…,D_N} - be a training data where D_1={$x_1[l]$,$x_2[l]$,…,$x_n[l]$} consists of instances of the Bayesian network nodes. Parameter learning is quantified by the log-likelihood function denoted as $L_D(\theta)$. When the data are complete, we get the following equations:

$$L_D(\theta) = \log\left\{\prod_{l=1}^{N} P\left(\mathrm{x}_1[l], \mathrm{x}_2[l], ..., \mathrm{x}_\mathrm{n}[l] : \theta\right)\right\} \tag{6}$$

$$L_D(\theta) = \log\left\{\prod_{i=1}^{n}\prod_{l=1}^{N} P\left(\mathrm{x}_i[l] \mid pa\left(\mathrm{x}_i[l]\right) : \theta\right)\right\} \tag{7}$$

In the case where all variables are observed, the simplest method and the most used is the statistical estimation. It estimates the probability of an event by the frequency of occurrence of the event in the database. This approach (called maximum likelihood (ML)) then gives us:

$$P\left(\mathrm{X_i} = x_k \mid pa\left(\mathrm{X_i}\right) = x_j\right) = \theta_{\mathrm{i,j,k}} = \frac{\mathrm{N_{i,j,k}}}{\sum_k \mathrm{N_{i,j,k}}} \tag{8}$$

where $N_{i,j,k}$- is the number of events in the database for which the variable X_i is in the state x_k, and his parents are in the configuration x_j. The principle, somewhat different, the Bayesian estimation is to find parameters most likely knowing that the data were observed. Using a Dirichlet distribution as a priori parameters which are written as:

$$\mathrm{P}(\theta) \infty \prod_{i=1}^{n}\prod_{j=1}^{qi}\prod_{k=1}^{ri} \theta_{i,j,k}\left(\alpha_{i,j,k} - 1\right) \tag{9}$$

where $\alpha_{i,j,k}$ - are the parameters of the Dirichlet distribution associated with the prior distribution. The approach to maximum a posteriori (MAP) gives us:

$$P\left(\mathrm{X_i} = x_k \mid \mathrm{pa}\left(\mathrm{X_i}\right) = x_j\right) = \theta_{\mathrm{i,j,k}} = \frac{\mathrm{N_{i,j,k}} + \alpha_{\mathrm{i,j,k}} - 1}{\sum_k \mathrm{N_{i,j,k}} + \alpha_{\mathrm{i,j,k}} - 1} \tag{10}$$

Validation of the developed network was carried out according to the algorithm of maximizing the expectation, which was proposed for the first time in 1977 in [28,29]. The algorithm finds local optimal estimates of the maximum likelihood of parameters.

The main idea of the algorithm is that if we knew the values of all nodes, then training (at some step M) would be simple, since we already have all the necessary information.

Therefore, at stage E, calculations of the expected likelihood value (expectation of the likelihood) are made, including latent variables, as if we were able to observe them. In step M, the maximum likelihood values of the parameters are calculated (maximum likelihood estimates) of the parameters using the maximization of the expected likelihood values obtained in step E. Next, the algorithm again performs step E using the parameters obtained in step M and so on.

Based on the algorithm of maximizing the expectation, a whole series of such algorithms was developed [30]. For example, the structural algorithm for maximizing the mathematical expectation (structural EM algorithm) combines a standard algorithm for maximizing the mathematical expectation to optimize parameters, and an algorithm for the structural search of a selection model. This algorithm builds networks based on penalty probabilistic values, which include values, obtained by using Bayesian information criteria, the principle of minimum description length, and others.

5 Results of experiments and discussions

To develop the Bayesian network, the GeNie 2.4 Academic software environment was used. This software environment provides an opportunity not only to develop BN on the basis of statistical data, but also to carry out situational modeling of the “What… if” type, which in general makes it possible to evaluate all possible situations when changing certain parameters of the modeled system. Figure 3 shows the developed Bayesian network that allows you to assess and analyze the likelihood of bankruptcy. Our coefficients are:

- maneuvering coefficient: Kmanev
- leverage coefficient (debt-to-equity ratio): Klever
- the coefficient of autonomy: Kavt
- current liquidity ratio: Kpot_likv
- financial stability ratio: Kstab

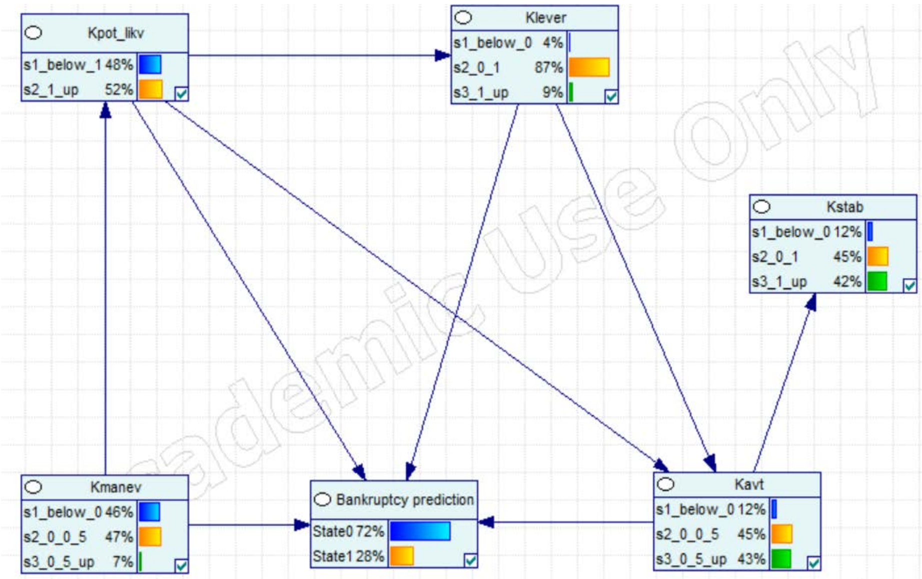

Fig. 3. The original Bayesian network derived from experimental data.

Now let's identify the trends and conditions that will help the company to avoid bankruptcy and increase the level of its solvency in the process of its activities.

When the coefficient of liquidity is minimal: the coefficient of stability and the coefficient of autonomy decrease by 20% (from 42% to 22%), the coefficient of leverage is reduced by 3% (from 9% to 6%), the coefficient of maneuvering is reduced by 6% (from 7% to 1%). The likelihood of bankruptcy increases by 10% compared to the baseline (from 28% to 38%). This is a situation, that should be avoided (fig.4).

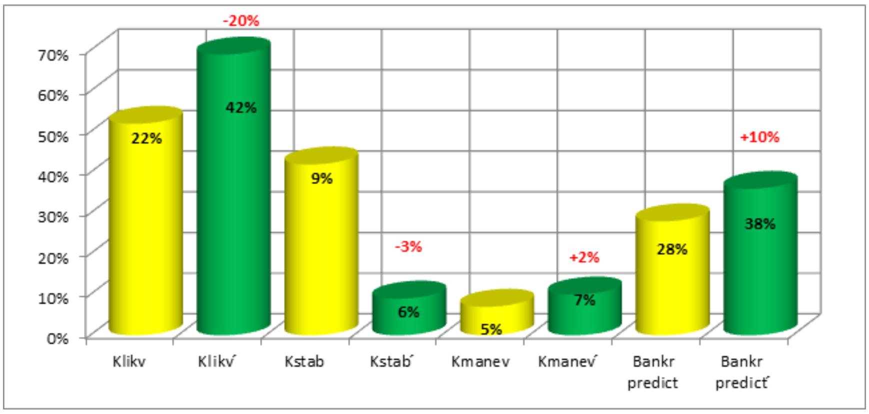

Fig. 4. Diagram of changes in the main economic indicators and the probability of bankruptcy when minimizing the liquidity coefficient.

With an increase in the liquidity ratio by 7% (from 7% to 14%), the leverage ratio increases by 3% (from 9% to 12%), the coefficient of stability and the coefficient of autonomy grow by 20% (from 41% to 61% and from 43% to 63%respectively). At the same time, the level of solvency increases by 8% (from 72% to 80%) compared with the initial one, and the probability of bankruptcy, respectively, decreases by 8% (from 28 % to 20%). All this is shown in the Figure 5.

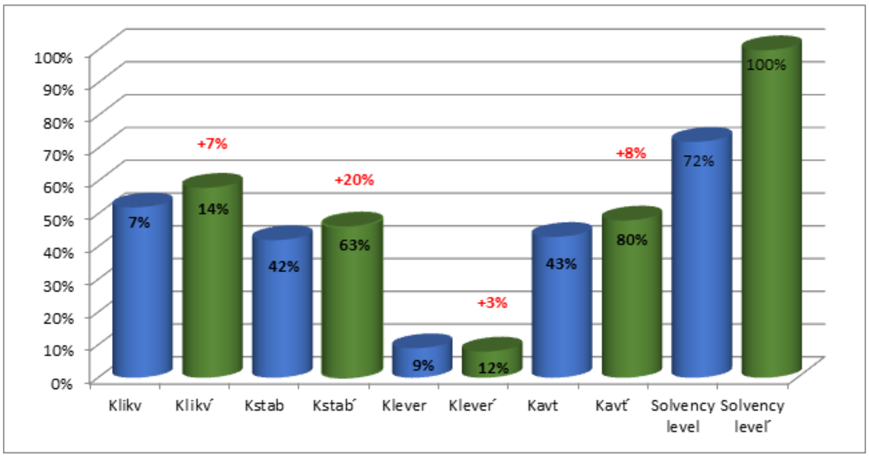

Fig. 5. Diagram of changes in the main economic indicators and the probability of bankruptcy with an increase in the Ratio of liquidity

In accordance with Fig. 6, the leverage coefficient should not be maximum, because along with a slight increase in the liquidity coefficient (by 17%) and the maneuvering coefficient (by 3%), the stability coefficient and the autonomy coefficient decrease by 34% (from 42% to 9% respectively). This will lead to an increase in the probability of bankruptcy by 8% (from 28% to 36%) and a corresponding decrease in the level of solvency. This happens because the enterprise has much more borrowed funds than its own funds, and this should not be so. For successful economic and financial activities, you need to strive for balance.

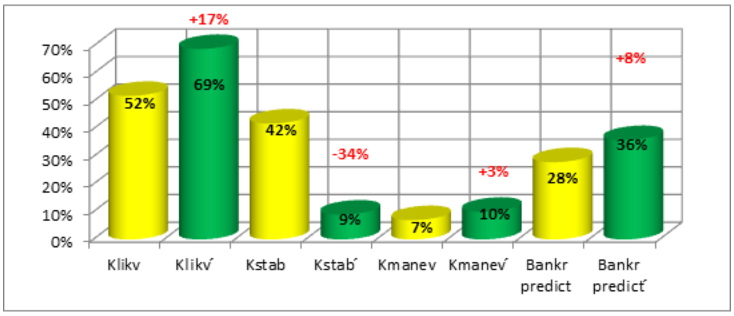

Fig. 6. Diagram of the influence of the maximum change in the leverage coefficient on economic indicators

In this experiment, the optimal indicators of economic indicators were determined with the maximum value of the solvency. In order for the level of the company's solvency to be maximum, the following conditions must be met:

- the liquidity ratio needs to be increased by 6% from the baseline (52% to 58%)
- the leverage ratio must be reduced by 1% (from 9% to 8%)
- coefficient of stability to increase by 4% (from 42% to 46%)
- increase the autonomy coefficient by 5% (from 43% to 48%)
- increase the coefficient of maneuvering by 1% (from 7% to 8%).

In this case, the level of the company's solvency will have a steady upward trend and reach a maximum (fig.7).

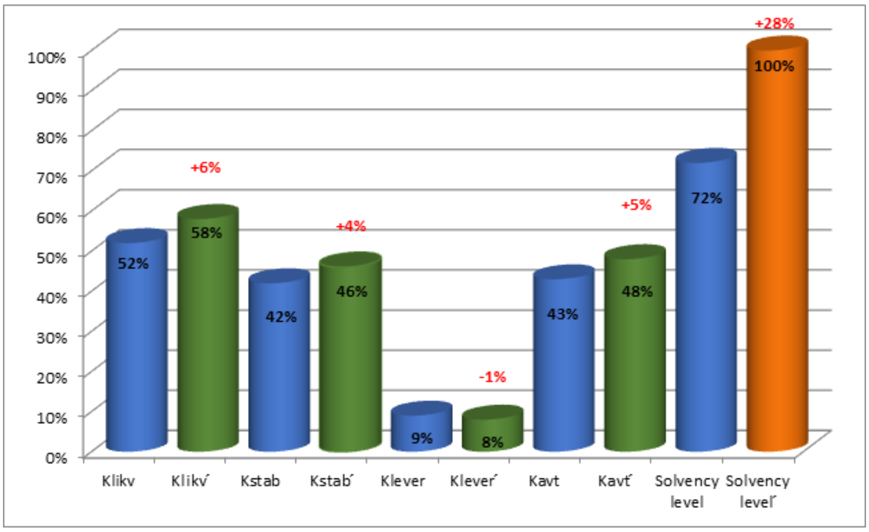

Fig. 7. Diagram of the increase in the level of the company's solvency to a maximum.

6 Conclusion

The main contribution of this study was to demonstrate how automated probabilistic models, which include a formal belief revision mechanism, can be used in problems of assessing the likelihood of an enterprise bankruptcy. We have narrowed the parameters number for assessing the financial condition of an enterprise to five, through the use of integral calculated economic indicators.

We have developed and tested a Bayesian network, which allows us to assess the financial viability of an enterprise, as well as to determine the optimal value of economic indicators to minimize the bankruptcy risk. The work also carried out various scenarios modeling like “What… if” to assess the economic parameters impact on the enterprise bankruptcy risk. In this context, four different probabilistic models were considered.

Our results are important for business economists, as they can now independently simulate different situations when making financial decisions.

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