Adaptive Approach to Building Risk Models of Financial Systems

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Abstract. The paper outlines the main issues of developing an adaptive approach to financial systems risk management based on the adaptive risk management principle and the method of structural parametric adaptation. The adaptive risk management principle provides an opportunity to assess and adapt risks during the system operation through the usage of adaptive methods and models, refinement of the best model, its parameters and structure, application of adaptive forecast estimates, usage of the lot of comprehensive criteria to assess the structure quality and model parameters. The method of structural parametric adaptation of the mathematical models and the scheme of its realization are illustrated. It involves the implementation of two contours of adaptation: internal and external, which provides a dynamic assessment of financial risks in real time through the probabilistic and cost component. The use of two adaptation loops allows you to immediately partially overcome the risk, as well as adjust the solution if it is not effective enough. We suggest a neuro-fuzzy method of supplementing rejected applications in financial risk modelling which allows us to take into account the information on existing risks and their influences on the financial system, and to improve techniques for preventing and decreasing the risks which are used in risks management. Additional adaptation contour makes it possible to consider new observations, information, updated data, new variables in existing scoring model. The creation of a generalized information system for decision support is proposed, its architecture is given, the main components are identified.

Keywords: adaptive risk management, neuro-fuzzy method of supplementing rejected applications, decision support information system, structural-parametric adaptation, scoring models.

1 Introduction

Decision-making under various types of uncertainty is quite a difficult task, because some information may not just be omitted but even be completely opposite to the information, decision-maker was counting on. The main risk is to make the wrong decision that could lead to a new risk. In fact, there is an ongoing search for some compromise in making a better decision in the case when available information is inaccurate or incomplete. It also leads to the emergence of several types of risks at the same time, and therefore can lead to certain losses. Financial systems are inherently related to other systems, so decision-making is carried out in conditions dependent on other persons, systems, countries. They are also acting in accordance to their own tasks and external conditions, making appropriate management decisions, also in conditions of uncertainty.

During dynamic development and interconnection with other systems it is important not only to make decisions but also to be able to clarify and refine them in case of a sharp change in conditions, external influences, emergencies or as a reaction to competitors' actions. The most vulnerable to any economic, social, environmental, global crisis are financial systems which are somehow related to the systems that suffer the most from the crises. Systems' losses are described in monetary terms and are determined as income which haven't been received by the system due to the above phenomena.

The Covid-19 crisis has become a significant indicator for all systems that operate in the modern world. The rapid change and break of chains between systems, countries, continents, the industry, companies and factories cessation, transport locking, borders closure, restrictions on freedom of movement and logistics have revealed the same close interconnectedness, influence and symbiosis of systems which haven't been noticed at first sight. All systems were forced to respond to new circumstances and challenges, to search for the compromises, to adapt to changes, to identify for themselves new ways for development, taking into account new circumstances. In fact, now we are witnessing the adaptation and development of new strategies and decisions, dynamic response and consideration of new factors, decision-making in conditions of uncertainty. In fact, the system effectiveness in such realities will be determined by how effectively management has analyzed all possible ways of the situation and developed effective alternative management solutions in case of adverse developments i.e., how the system is prepared and adjusted and able to adapt.

A method based on the principle of adaptive management has been developed. It allows us to take into account new data, criteria and even the emergence of new risks, refining existing models by adapting the structure and parameters [1-5] or choose an alternative method. Thus, alternative method makes it possible to create a new model that takes into account both historical data and new data related to critical changes in external conditions. It will reduce the risks of making erroneous management decisions regarding further management actions and provide an effective tool for making management decisions in real systems when external conditions change.

2 Problem statement

Research objectives are as follows: to propose the adaptive approach based on the complex using of adaptive principle, structural-parametric method of mathematical models for evaluating and forecasting the risks; to develop the scheme of the structural parametric method for implementation in the information technology; to give the mechanisms for including new information from rejected application and adaptation of existing model to the real data. To complete these tasks, the neuro-fuzzy method of supplementing rejected applications in financial risk modelling has been developed.

3 The principle of adaptive risk management of financial systems

The risks of financial systems are essentially non-systemic risks and are not explicitly defined. They can be even a consequence of other risks or a combination of them. Therefore, the principle of risks assessment should allow not only to take into account changes in the level and degree of the system risk but also to predict, model, and reduce new risks that may arise during the system operation. Main features of financial systems' risks are that they are measured in monetary terms, associated with financial processes that can vary from stationary to non-stationary, from homoskedastic to heteroskedastic, significantly depend on financial markets, economic components, policy decisions and even cannot be clearly defined and classified into groups. New currencies, new monetary equivalents, payment systems and payment methods [6], digital signatures, non-cash and PayPal settlements appear. They generate optimal states' estimates with short-term forecasts under the influence of external stochastic perturbations and measurement noise. However, such methods require estimates of statistical parameters of random perturbations and noise measurements in real time. It creates additional overload and errors for forecasting procedures.

The principle of adaptive risk management which gives the possibility to assess and adapt risks during the system the operation through the usage of adaptive methods and models, refinement of the best model, its parameters and structure, application of adaptive forecast estimates, usage of the lot of comprehensive criteria to assess the structure quality and model parameters. It also gives the opportunity to introduce the new criteria for solution quality assessment and impute new statistics. To implement this principle, it is necessary to involve modern data mining methods, information technology with extensive computing capabilities and also special new method of structural-parametric adaptation.

An important opportunity for adaptation is the usage of combined and integrated methods and models that overcome the existing limitations for standard methods and obtain higher estimates of forecasts quality for financial risks modelling. For example, such methods as logistic regression or classification methods require the existence of a limited number of classes, which may not be initially specified for input data. However, it is known that these methods provide the best opportunities for solving the classification problem so it makes sense to use a combination of several methods. Another serious limitation for statistical methods is the need for a balanced sample (ideally 50/50), but for risk analysis tasks this limitation is critical, as the sample size for different types of risks can be significantly smaller.

Correct application of modern models and adaptive methods for estimation, probabilistic and statistical data analysis allows to receive higher quality of forecast estimations in conditions of structural, parametric and statistical uncertainties. Possibilities for adaptation are provided by methods based on the Kalman filter [7] which generates optimal state estimates together with short-term forecasts under the influence of external stochastic perturbations and measurement noise. However, such methods require estimates of statistical parameters of random perturbations and noise measurements in real time. It creates additional overload and some errors for forecasting procedures.

The idea of model adaptation for dynamic processes forecasting provides hierarchical approach to modelling and forecasting procedures. Such procedures are taking into account structural, parametric and statistical uncertainty, mathematical models' adaptation to possible changes in learning process and using alternative methods of parameters estimation for modelling and improving the forecasts estimation.

The adaptive risk management principle is based on the adaptive approach and structural-parametric adaptation of the mathematical models. It assumes the implementation of two contours of adaptation: internal and external and provides financial risks dynamic assessment in real time through probabilistic and cost component. Usage of two adaptation loops allows you to immediately partially overcome risk (while it reduces the uncertainty that causes risks, due to new statistics and perturbations), as well as adjust the decision if it is not effective enough. The sequence of realization of two contours of adaptation for credit risks on the example of scoring models adjustment and structural-parametric adaptation is given in figure 1.

The method allows both the use of expertise in risk management and the use of pre-collected statistics, which are combined into a single knowledge and data base. Initial data for risk modeling is submitted to the input in the first step.

Step 1. Pre-processing of input data.

Step 2. Statistical analysis of data and construction of a set of candidate models.

Step 3. Choosing the best model for assessing financial risks.

Step 4. Forming a decision regarding risk management.

Step 5. Analysis of the quality of the solution.

Step 6. Real-time financial risk management based on the chosen model.

The chosen best model is implemented in a real decision support system for risk assessment of a real financial enterprise. Statistics are collected based on forecast estimates for risks according to the best model compared to the actual results of modeling [8], the so-called samples of rejected applications are formed and solutions and strategies to deal with risk in case of its transition from acceptable to critical.

Step 7. Analysis of the effectiveness of real-time risk management decisions.

To test the effectiveness of the proposed model and the decisions made on its basis, the model is tested in practice, taking into account new data, perturbations, external influences. The effectiveness of risk management is assessed by a set of the following characteristics [8]:

$$E = < A, F, C, D, I >,$$

where A - the adequacy of the constructed model,

F - forecast of acceptable quality, C - reasonable computing costs, D - the decision formed on the basis of the developed model and the forecast, I - consistency with the data,

$$I = \begin{cases} 1 – \text{the data is consistent with the model}, \\ 0 – \text{the data is not consistent with the model.} \end{cases}$$

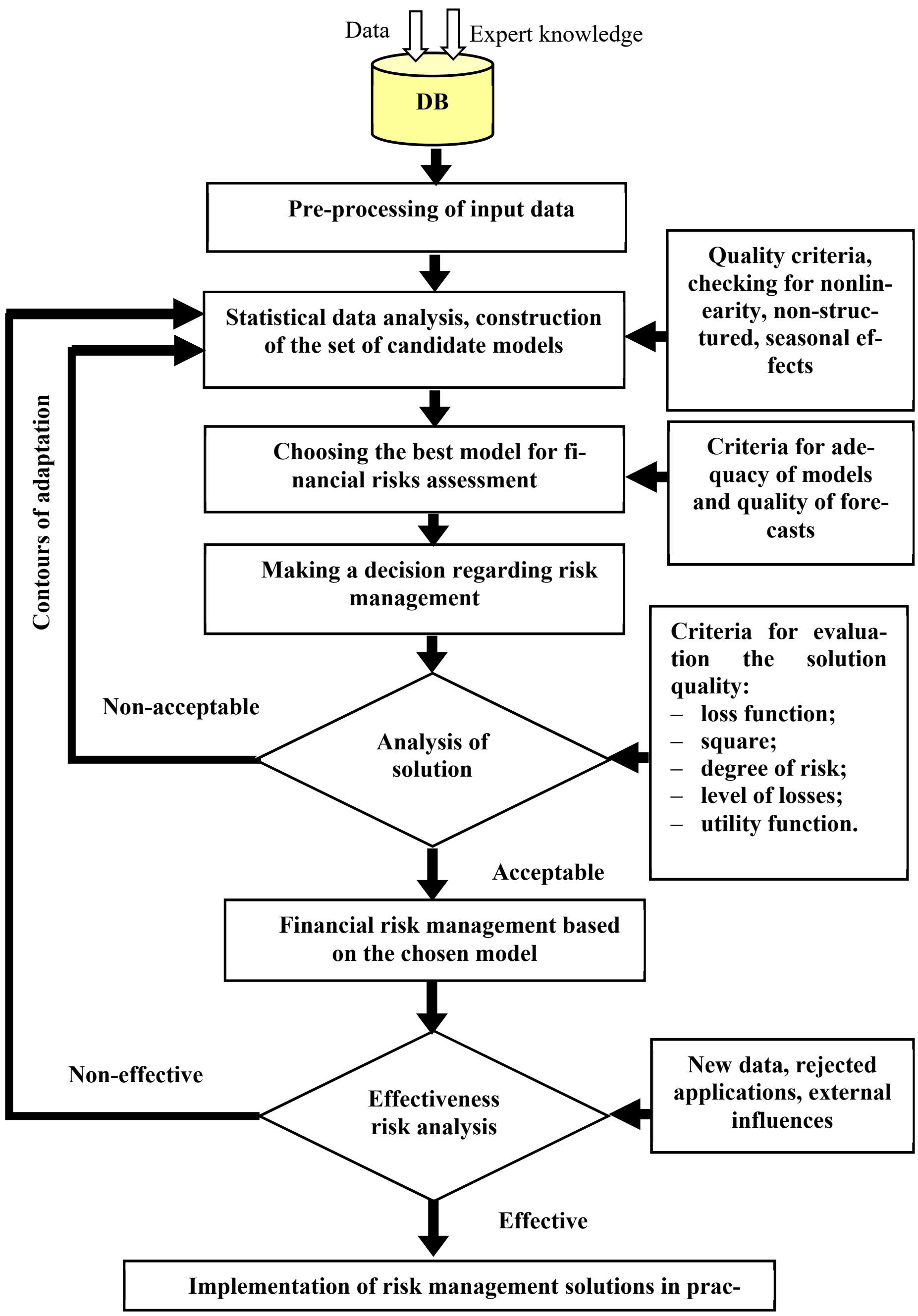

Fig. 1. Algorithm of the structural parametric adaptation of models for risk management.

An expert is involved to check the effectiveness. If the model remains effective and the decisions made are correct, then this model is still applied in practice. If the solution is incorrect then the external contour of adaptation is performed [8].

At the same time, new data are added to the historical data on which the initial model was built, taking into account the rejected applications, estimates obtained by our model, external data, and re-construction of candidate models and evaluation of their parameters.

Step 8. Implementation of the solution for risk management in practice.

Structural adaptation by itself involves adding of new parameters to the model, changing the model order as well as choosing a new model from the set selected at the initial stage of probabilistic-statistical models.

The developed scheme of structural-parametric adaptation is universal and can be used for analysis and forecasting of risks of different types. The proposed approach was tested on common financial risks, including credit, as well as to forecast stock prices in financial markets. The only limitation was more related to the type of tasks (risk assessment) that were solved during this research. It was necessary to ensure the usage of such methods that allow obtaining accurate estimates of the factors that characterize the risk: probability and loss. The use of methods that only calculate losses and do not estimate probability (for example the method of linear regression) is incorrect while it will provide an incomplete risk assessment and form only a partial decision for risk management.

Consider the implementation of the method of structural-parametric adaptation in the practice of a real bank. Figure 2 shows that the sample used to construct the scoring map is evaluated by the Score component in the SAS Enterprise Miner analytical environment [8, 9].

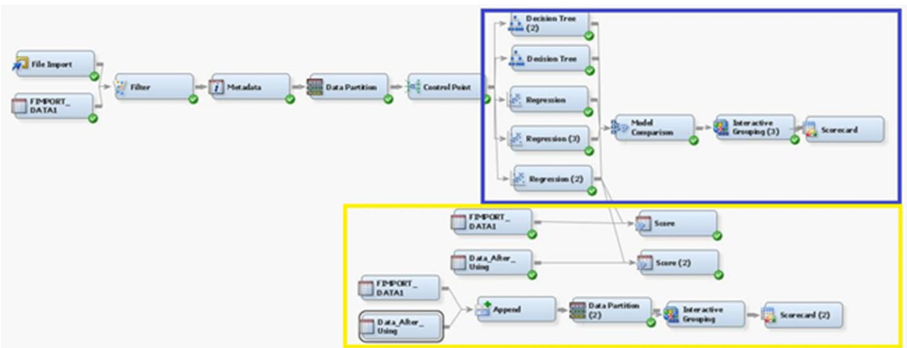

Fig. 2. Structural and parametric adaptation in the scoring card development

Next, the probability of default is predicted and compared with the cut-off threshold and the actual state of whether the loan was repaid. The percentage of incorrect classification (first and second kind of errors) is calculated. For the test sample, it was 11%. For the new sample obtained after usage on practice developed scoring card, we also calculate the probability and check the percentage of mismatch for a known cut-off threshold. It is 15% but for the bank it is really high result. This means that the model needs to be adapted to the new statistics. Thus, we need to implement the second contour of adaptation which provides uploading rejected applications by existing in bank scoring model, made credit decisions etc. A new scoring card will be built on the outer adaptation contour. For this task after applying the structural-parametric adaptation of the model, the share of incorrect classification was obtained as 12.5% for a new data set. It is lower than the original model and acceptable to the bank so this model was used to build a new scoring card.

Adaptation involves both adjusting the parameters of the model itself and adapting and adjusting the parameters and weights for the scoring card which is based on the selected model. Structural and parametric adaptation in the credit risk management tasks continues also after the re-introduction of the updated scoring card. Then the process of monitoring and analysis of the scoring card effectiveness, clarification and adjustment of its parameters is carried out. Due to such adaptation, there is a possibility of periodic updating and further application of a scoring card in real time. It is important for the financial institution which continues to carry out the financial activity and has to analyze credit histories and make decisions without stopping the activity waiting for development of new method and corresponding models for financial risks assessment.

4 Information decision support system (IDSS) based on the method of adaptive risk management

An information system was developed to implement described above idea. It provides powerful functionality and the usage of the large set of methods for dynamic risk assessment, development of the integrated models and usage of special tools for adaptive risk management. The developed IDSS should provide for decision maker a full range of mechanisms for modelling, evaluation and forecasting of financial risks and criteria for assessing the data and models quality. It also has the possibility of adaptive response to prevent and reduce financial risks taking into account new evidence, data and challenges in the modelling process [5]. IDSS architecture should be based on the principles of functionality, modularity, scalability, interactivity, etc.

The decision support system generates a lot of alternatives for making recommendations to the decision maker. IDSS should contain a set of functions and procedures to implement sufficient completeness of decisions. The functional completeness of IDSS for risk management can be represented as follows:

$$IDSS = \{DKB, DP, IR(MS, MMP, EMP), RE(SRE, DRE, SC), MR(DQ, MAQ, FQ, DE, SPA)\}.$$

It involves the implementation of the entire sequence of risk management procedures in the form of appropriate modules: identification, modeling, assessment and minimization of risks, containing functions for data processing and accounting for uncertainties and other risks, static and dynamic risk assessment, forecasting probabilities and consequences, building a scoring map as measures of risk, adaptation and verification of the quality and effectiveness of the proposed solutions. Here DKB is data and knowledge base; DP is a set of procedures and functions of preliminary preparation, consolidation and data processing using the proposed methods of filling in incomplete or lost data; IR are risk identification procedures, which involve development of the model that describes the change in risk, assessing its structure and parameters, forecasting the consequences and probability of risk.

The procedures IR contain the following elements: MS are procedures for data preparation and evaluation of the structure of the mathematical model (for example, based on Bayesian networks); MMP is a unit for estimating the parameters of the mathematical model; FMP is a module for estimating forecasts of losses (consequences) and the probability of risk on the basis of the selected mathematical model. $RE(SRE, DRE, SC)$ denote the procedures for static SRE and dynamic DRE risk evaluation; construction of risk scoring cards SC. $MR(MAQ, FQ, DE, SPA)$ is the risk management module based on the criteria of adequacy of mathematical models MAQ, accuracy of forecasts FQ, efficiency of decisions DE and functions of structural-parametric adaptation of risk assessment models SPA.

Each module of IDSS represents its separate functional element which implements all set of procedures, functions and classes for integration with DKB, other modules and users. It is clear that IDSS must meet the general requirements for decision support systems [5]: contain modern databases, models, criteria and the necessary computational procedures; have a convenient and simple interface; the sequence of performance functions must correspond to human perception and representation; to accumulate knowledge and adapt during the process of its functioning; have the necessary speed of procedures and calculations and the necessary accuracy; generate the forms and reports necessary for decision maker; provide interactive interaction with other users; exchange data and knowledge with other information processing systems using computer networks; be able to add new procedures, functions and modules.

The simplified architecture of IDSS is quite complex and could be represented in understandable way as a set of modules (blocks) presented in figure 3.

It can be represented as a set of sequentially combined modules and applications based on system methodology, in particular:

- ❖ Module for processing uncertainties and incomplete data and knowledge implements such main features;
- ❖ The scoring card development module as a measure of risk performs;
- ❖ The module of financial risks dynamic assessment;
- ❖ The module for evaluating the quality of data and solutions;
- ❖ Risk management module which includes:
  - calculation the real losses of possible risk realization;
  - management modules: calculation the investments; compensatory losses for risks combat; setting limits and restrictions for the level of losses and the risk realization probability;
  - recommendations for choosing a risk reduction strategy.
- ❖ Adaptation module which allows:
  - introduction of new data and knowledge, criteria, restrictions;

• behavioral risk assessment (risk assessment in the process and verification of its degree and level compared to the initial state);
• execution of structural-parametric adaptation with two contours of adaptation and use of rejected applications.

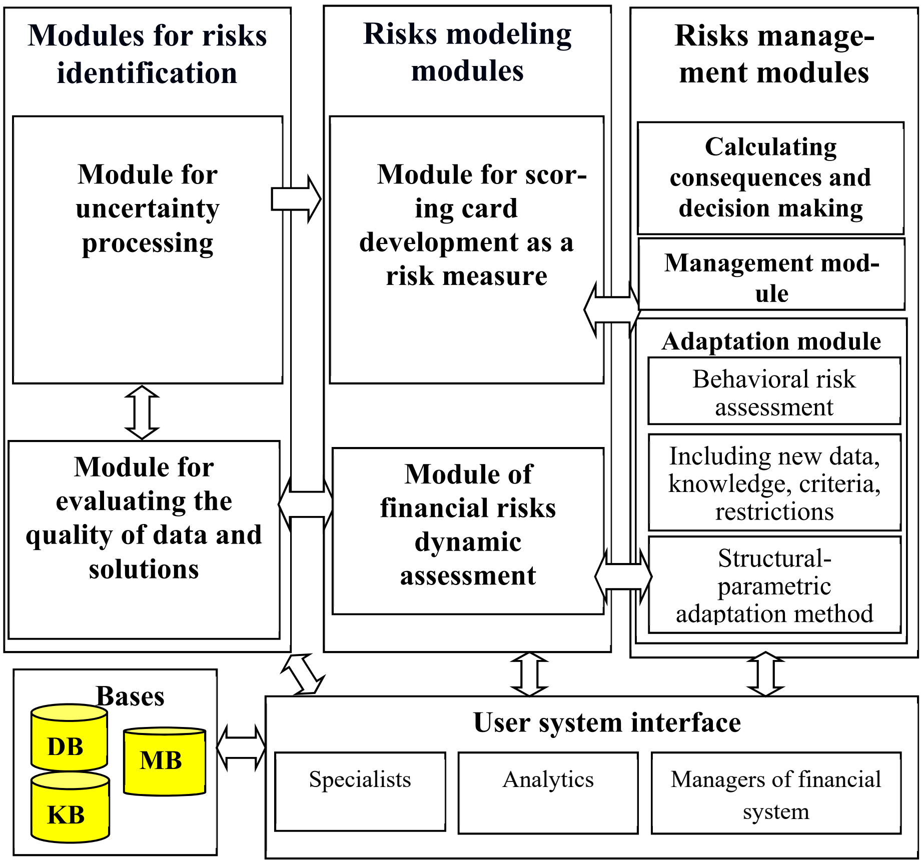

Fig. 3. Structure of the informational decision support system for financial risk management

The system can be represented in different modifications and content depending on the needs of the financial enterprise but this architecture is the new type of system which reflects the concept of system methodology for analysis, assessment and management of financial risks. IDSS database consists of the database by its own and knowledge and model bases (MB) where the best models built to solve problems of static and dynamic risk assessment stores. Each module of IDSS is its separate functional element which implements all set of procedures, functions, classes for integration with DKB, other modules and users. The module of uncertainty processing includes operations: pre-processing and consolidation of data, filling in missing / lost data, information risk assessment, uncertainty processing [10]. Scoring card development module implements statistical data analysis, model structure formation and scoring parameters evaluation.

An important opportunity to adapt the models is to take into account historical experience and new information, the results of scoring models, identified errors of the first and second kind, taking into account the experience gained on current stage in financial system model, information and statistics on risk cases [11, 12], which systems have already been identified, anti-risk methods and strategies applied.

As it was shown on example of the scoring card, the process of adaptation is really widespread and needed during the operation with banking risks. The adaptation by itself could be made in the way of correcting (adaptation) the scoring model, parameters scores or developing the new scoring model. Next cycle of the adaptation is including the new observations, information, data in existing scoring model. For this reason, it was proposed to develop approach which gives the opportunity to take into account the information of existing risks and their influences of the financial system, and also techniques for preventing and decreasing the risks which were used for risks management. Let's consider such approach of the neuro-fuzzy method of supplementing rejected applications for scoring card adaptation.

5 Application of neuro-fuzzy method of supplementing rejected applications in financial risk modelling

For developing scoring maps, it is important to use as a training sample not only data characterizing the occurrence of risks, but also to analyze rejected applications. Rejected applications are such elements which were defined by existing scoring model as high-risk applications (for examples, such applicants didn't receive the credit), and that's why the binary value of the target variable is unknown. For such rejected elements of the sample, it should be assigned some special value for target and after that they should be included in the training sample for ensuring the stability of the final model relative to the general population [10].

Existing methods of analysis of rejected applications can be classified as methods: assigning a negative result to rejected applications; adding them in the form of proportions; equal ratio for accepted applications; complete disregard for rejected applications; temporary approval of all applications for data collection; usage the similar data of the banks or credit bureaus; simple addition ("hard cut-off"); additions for the expert decision-making process [11]; additions based on the probabilities of approved applications; risk groups division for rejected applications; fuzzy addition. In this paper it is offered to develop a special method based on improving the fuzzy addition technique by usage a neural network as a model of estimation the set of the accepted applications.

For each score interval, a certain addition factor F_k is calculated for accepted applications, A_k, which is defined as the ratio of the number of all applications to the number of accepted applications (within one interval): $F_k = \frac{A_k + R_k}{A_k}$, where R_k – applications are rejected. The formation of a new supplemented sample is carried out by selecting from the original sample only accepted applications with their target behavioural result (good / bad) n_i times, where the number of occurrences is equal to or proportional to the complement factor. Then the dependence of the odds ratio of the supplemented sample is a convex combination of the original odds ratio of the accepted applications and the obtained ratio of rejected applications ($\alpha \in [0;1]$): $\frac{AG}{AB} = \alpha \frac{G}{B} + (1-\alpha)\frac{AG-G}{AB-B}$. Usually $\frac{odds_{accepted}}{odds^{*}_{rejected}} = \frac{AG(AB-B)}{AB(AG-G)} \in [1,5;4,0]$.

On the next step it is proposed to build a neural model on the set of received applications to determine the weight of each received application $w_i = p_i(NN(accepted|\mathbf{x}))$. The supplemented sample consists of accepted applications included in proportion to the non-standardized weight $w_j(\mathbf{x}) = p_j^{-1}(NN(accepted|\mathbf{x}))$, calculated as separate w_i for each accepted application, which is included with this weight in the new supplemented sample [10].

During the next step each accepted application is evaluated by the neural network with a single weighting factor and each rejected application is included in the sample twice: with a weight equal to the probability of a "good" indicator $p_{i1} = p(y_i^{NN} = 1|\mathbf{x})$ with a *one target result*, and with a weight equal to the probability of a negative target indicator $p_{i0} = p(y_i^{NN} = 0|\mathbf{x}) = 1 - p(y_i^{NN} = 1|\mathbf{x}) = 1 - p_{i1}$ with *zero target result*. Predicted probabilities (weights) are obtained using a model based only on accepted applications (known good / bad). The main stages of the neuro-fuzzy method for supplementation dataset by rejected application is shown in figure 4.

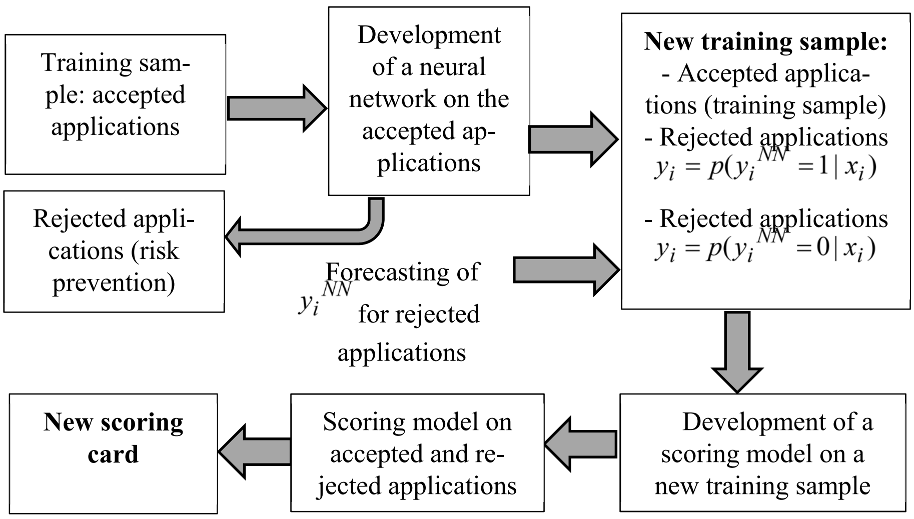

Fig. 4. The main idea of the neuro-fuzzy method for supplementation.

Modification of the method is the recalculation of the weights by taking into account the ratio of rejected and accepted applications:

$$r = \frac{N_R}{N_A + N_R},$$

where N_R - the number of rejected applications, N_A - the number of agreed applications.

To do this, a special weight correction is introduced:

$$W = \frac{r}{1-r}\frac{N_A}{N_R} = \frac{N_R/(N_A+N_R)}{1-(N_R/(N_A+N_R))}\frac{N_A}{\sum_{i:\,Rejects}(p_{i0}+p_{i1})}.$$

The new values of the revalued weights are determined as follows:

$$w_{i1}^{*} = p_{i1} \cdot W \cdot EventRateIncrease,$$

$$w_{i0}^{*} = p_{i0} \cdot W.$$

Thus, the main idea of the neuro-fuzzy method and improvement to the existed fuzzy method is the usage of a neural network based on a training sample to predict the probability value for rejected applications. Scales for Good / Bad are determined by a fuzzy approach. Using this approach for the credit risk assessment allowed obtaining more accurate forecasts estimates for the rejected applications sample and scoring estimates in general for the entire sample.

The following characteristics are used to assess the quality of the built scoring card: errors of the first and second kind, ROC-curve or Lorentz curve, cost of incorrect classification (losses due to loans to “bad” customers and lost opportunities due to non-loans to “good” customers) etc. [10]. Significant at the stage of development and subsequent application of the scoring card is the correct choice of the model cut-off threshold, i. e. such as an assessment which is calculated in total for all client characteristics.

The stage of scoring card validation involves comparing statistics for developed versions of cards and comparing the positive and negative cases distributions for developed versions, choosing the best one for further usage. Particular attention is on the percentage of incorrect classification, the “predictive power” of the card- the information criterion of Akaike, the Bayesian information criterion or Schwarz information criteria, the Kolmogorov-Smirnov statistic and others [10].

It should be noted that even after the scoring card involving the process of the scoring cards effectiveness monitoring continues, as in the process of its operation may change the factors and characteristics that were included, change legislation or key assessment factors. In practice the usage of scoring cards is an effective tool for risk managers while it gives a clear idea of the risk level of a client or product.

In some cases, it makes sense to set checkpoints in accordance with credit policy rules. For example, if a company’s policy requires that loans with a service ratio of more than 42% be submitted for consideration, it is necessary to group the debt service ratio and set the threshold at 42%. The advantage of such grouping is that it minimizes the distortion of the scoring card caused by such a rule of credit policy and allows you to identify the customers who are affected by this rule. In addition, such grouping allows you to check the existing view and the policy rules that have been valid so far. For example, it allows you to understand whether it makes sense to set the control point at 42% or move it to a higher level to increase the differentiation of levels.

6 Conclusion

The ability of systems to adapt to new data, significant changes in external conditions, taking into account new requirements, determines not only their resilience to new risks, but also the future existence of such systems and their ability to survive even after systemic, economic, social, environment crises, dynamic updating and modification, and hence adaptation, to new conditions of their functioning.

Proposed adaptive approach for risk management and the method of structural-parametric adaptation of mathematical models involves the implementation of two contours of adaptation: internal and external, which provides dynamic assessment of financial risks in real time through probabilistic and cost component. The use of two adaptation loops allows you to immediately partially overcome the risk (because it reduces the uncertainty that causes risks due to new statistics and perturbations), as well as adjust the decision if it is not effective enough. The developed scheme of structural-parametric adaptation is universal and can be used for analysis and forecasting different types of risks. The proposed approach was tested on common financial risks, including credit, as well as to forecast stock prices in financial markets. The only limitation that was imposed was more related to the class of tasks (risk assessment) that were solved during the research process. It was necessary to ensure the use of such methods that allow obtaining accurate estimates of the factors that characterize the risk: probability and loss. The use of methods that only calculate losses and do not estimate probability (for example, the method of linear regression) is incorrect, as it will provide an incomplete risk assessment and form only a partial solution for risk management. The proposed stages of preliminary preparation of data and models, the method of structural and parametric adaptation are implemented in the form of separate applications in the created information system for decision support.

The next possibility for adaptation is developed neuro-fuzzy method for rejected applications with gives the possibility to set more accurate the model according to the included information of caused risks applications which were rejected by existing model. Such technique gives the possibility to balance the preliminary dataset in accordance to the distribution in general set and also to check the effectiveness of existed policy of risk management.

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