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Application of neural network technologies to assess the competence of personnel in the tasks of controlling the operational risk of a credit institution

Ekaterina V. Chumakova
E-mail: catarinach@yandex.ru

Dmitry G. Korneev
E-mail: korneev.dg@rea.ru

Mikhail S. Gasparian
E-mail: gasparian.ms@rea.ru

Ilia S. Makhov
E-mail: ilya.makhov.98@list.ru

Plekhanov Russian University of Economics, Moscow, Russia

Abstract

The article is devoted to issues of controlling the operational risks of a credit institution associated with the actions of personnel. Operational risk control is an important aspect of a credit institution's business. Despite the fact that the Bank of Russia in regulatory documents described in detail the set of actions that banks should take to control operational risks, in practice credit institutions experience serious difficulties in dealing with operational risk associated with the actions of personnel. This may be explained, first, by the difficulty of identifying and formalizing the specified risk. One of the main sources of operational risks associated with personnel actions is employees' lack of qualifications. This can lead to reduced availability and quality of services provided by credit institutions, as well as possible financial and reputational losses. The purpose of the research conducted by the authors is to improve the system of control of operational risks in a credit institution using artificial intelligence technologies, including the development of tools for assessing in an automated mode the level of criticality of the influence of personnel competence on the occurrence of operational risk events. To achieve this goal, an artificial neural network (ANN) was developed using the high-level Keras library in Python. This paper defines a set of key indicators that have the most significant impact on the possibility of operational risk associated with the actions of the personnel in a credit institution. The article presents the results of checking the generated sets of training and test data using application software packages that implement mathematical methods to assess the consistency of the generated data sets. The paper presents graphs showing the results of training and testing of the artificial neural network that has been constructed. The results obtained are new and may allow credit institutions to significantly increase the efficiency of their work by digitalizing the solution of tasks to control the level of operational risk associated with the actions of personnel.

Keywords: operational risks, personnel competence, artificial neural network, machine learning, direct distribution neural network, high-level Keras library

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Introduction

The concept of operational risk is defined by the Bank of Russia as the risk of direct and indirect losses as a result of imperfections or erroneous internal processes of a credit institution, actions of personnel and other persons, failures and deficiencies of information, technological and other systems, as well as a result of external events [1].

In [2, 3], the authors proposed methods for using neural networks to control the operational risks of a credit institution that arise in the process of using information technologies. This paper examines the operational risks associated with the actions of the staff of a credit institution, such as unintentional errors, intentional actions or inaction.

In the field of personnel management, it has long been common practice to use competency models (maps) describing the required knowledge, skills, and behavioral indicators necessary to perform specific duties when seeking employees of the right professional level. Such maps are developed for certain positions or functions, as well as for departments or even organizations as a whole [4].

However, once an employee appears as an executor of a business process, an employee who fully meets all the requirements may, due to various circumstances, demonstrate a level of competence lower than expected. The presence of such a factor will have a negative impact on the outcome of the business process and lead to operational risk events that may entail financial or reputational losses [5].

To identify inconsistencies in the demonstrated level of competence by an employee or a team of employees in a timely manner, it is convenient to have a common universal tool for evaluating staff actions. As a rule, point systems are used within organizations [6] which, unfortunately, do not always show problem areas due to imperfection of the assessment scales. Also, competence assessment is often replaced by disciplinary control [7], which, of course, is important, but still is not a comprehensive assessment that determines the operational risks associated with personnel actions.

In recent years, the use of neural networks to assess the competence of employees has been gaining popularity, in particular on the basis of assessments made by heads of departments [8]. There is a significant drawback in this approach — the possibility of obtaining biased assessments due to the influence of interpersonal relationships. Another group of approaches is related to the use of test systems and systems of compliance with required competencies [9, 10]. However, such systems are usually used either for pre-selection of candidates, or to assess the need to improve and update the knowledge and skills of employees. It should also be noted that there is no single approach to the development of a scale for assessing the level of competence of an employee.

Each employee is an executor of the business process and has an impact on its functioning. This impact can be assessed by a fairly large set of indicators characterizing, in particular, the professional competence of employees and their non-specialized supra-professional skills (soft skills).

The purpose of the study, as mentioned earlier, is to determine, based on the use of neural network technologies, the level of criticality of the influence of personnel competence on the occurrence of operational risk events in a credit institution.

To achieve this goal, it is necessary to solve the following tasks:

1. Analyze the indicators of employee competence in terms of their impact on the possibility of operational risk events during the execution of business processes.
2. Identify the key indicators characterizing the level of competence of the employee which will be the input parameters of the ANN.
3. Define the architecture (topology) of the ANN.
4. Create training and test datasets for the ANN.
5. Train various neural network architectures and perform their comparative analysis.

In accordance with the set goal and the tasks to be solved, the structure of the work includes an introduction, the main part, conclusion and a list of literature used.

The introduction presents the purpose of the study, provides a generalized description of the subject area, and describes the relevance and significance of the problem under study.

The main part of the article is devoted to the study of the possibility of using neural network technologies to assess the competence of personnel in the tasks of controlling the operational risk of a credit institution and consists of several sections. The Methods section includes a description of the design and stages of the study. The Results section includes a description of the ANN model, an analysis of the training sample and the results of experiments on teaching the ANN to determine competence the employee. The Discussion section includes an assessment and interpretation of the results obtained, as well as a summary of the research carried out.

The conclusion contains conclusions and recommendations on the implementation of the research results to create intelligent systems for monitoring operational risks associated with personnel actions both in credit institutions and in organizations of other sectors of the economy.

1. Methods

1.1. Research design

This study analyzed the factors influencing the occurrence of operational risks associated with personnel actions. First, the factors that are usually analyzed in works on this topic were considered: education and professional skills, career growth indicators, punctuality, initiative, commitment and responsibility, sociability in a team, work experience, striving to achieve goals, age, workload of employees [11]. Additionally, the following factors were identified that have a different level of impact on business processes in terms of the possibility of operational risk events, namely:

- leadership and leadership in the project,
- engagement and motivation,
- self-control and self-organization,
- confidence and persuasiveness,
- stress relief,
- stress tolerance,
- creativity,
- result orientation,
- the ability to coordinate interests,
- negotiating,
- the ability to manage conflicts and crises,
- reliability,
- understanding the values of the organization and the project,
- ethics of behavior,
- problem solving,
- communication skills,
- customer orientation,
- ability to work in a team,
- leadership,
- ability to organize work,
- business knowledge,
- adaptability to change,
- ability to help other employees in professional development,
- ability to effectively solve problems,
- analytical thinking,
- loyalty to the organization.

Due to the large number of indicators, the main part of them was divided into two groups according to the nature of the impact: a group combining professional criteria (competence) and a group of supra-professional skills (soft skills).

The competence of the personnel involved in the business process is an aggregated value of the competence of each employee. During the study, the most significant indicators of professional competencies were identified which have a significant impact on the possibility of operational risk events. At the same time, it is assumed that an employee cannot hold a position without having a certain (basic) set and level of competencies.

To determine the level of influence of personnel competence on the operational risks of the business process, the method of assigning the criticality status "red (critical) – yellow (medium) – green (weak)" was used ("red – amber – green" (RAG)) [12].

During the research, a database was formed with indicators of employee competence and with a final assessment of his or her competence (green, yellow, and red zones). The prototype of the data for the formation of the training sample was data on 4800 employees in an impersonal form which were provided by two Russian banks. Preliminary data processing was carried out, namely: determining the presence of common significant indicators and depersonalizing them, clearing data from omissions, thinning out redundant data to evenly represent classes of objects, clearing outliers, etc. As a result, 2688 records with depersonalized employee data were obtained which were later used for training and testing of the ANN.

The assessment of the employee's impact on the level of criticality of emerging operational risk events was carried out by three experts in the field of risk management working in the Risk Control Department of

Russian Banks and who provided the data included in the sample. During the evaluation, consultations were also held with employees of the HR department of the relevant bank. The study considered the possibility of increasing the size of the expert group. It was considered that experts evaluating input data are required to adhere to the same views on the data being evaluated. Otherwise, several different opinions on the same type of events may lead to conflicting data in the training sample. A way out of such a situation could be a joint decision on each of the disputed objects. However, the process of agreeing on the opinions of a large number of experts can be quite time-consuming and take considerable time. It should be noted that the sample formed on the basis of the opinions of the three experts involved turned out to be sufficient to achieve the set goal of the study.

It was decided to make an assessment based on the following categorical indicators: general experience in the field of the position held, current experience in the organization, level of education, completion of additional advanced training courses, violations of technological discipline and their consequences, promotions and incentives, as well as the frequency of change of the company that is the place of work. It was also decided to take into account one continuously changing parameter, namely: the average score of the document confirming the level of education.

Analysis of the received training sample was performed from the point of view of the presence of dependencies between the identified features, as well as the presence of the influence of independent input variable features on the dependent output. To qualitatively characterize the closeness of the relationship between the factors in the data set, Spearman's rank correlation coefficient was used [13], which was estimated in accordance with the Cheddock scale [14]. The quantitative determination of Spearman's rank correlation coefficient was performed using statistical analysis tools of the Loginom analytical low-code platform. It was also decided to evaluate the set of input parameters in terms of the impact on determining whether objects belong to one of the classes. To identify redundant independent parameters for each input characteristic, either bar charts or a probability density graph were constructed; these allow one to display a smoother distribution by smoothing parameter changes. Graph visualization was performed using the Plotly and Seaborn libraries in Python [15].

The possibilities of using a multilayer perceptron with two and three hidden layers (DNN) were examined as ANN models in the study of learning effectiveness. At the same time, network architectures were analyzed, considered, in particular, in [3], which showed the best results in solving similar problems. The presence of similar ANN in topology will make it possible to use the proposed ANN as one of the unified modules within the framework of an intelligent system for identifying operational risks associated with personnel actions. Neural network modeling and training were carried out using the high-level Keras library in Python.

1.2. Stages of the study

At the initial stage of the study, the indicators traditionally used for personnel assessment were analyzed [16]. Their impact on business processes was studied in terms of the possibility of operational risk events, as well as the use of various units of measurement to assess these indicators. Among the considered indicators of professional skills assessment, the following were highlighted: work experience in the current position, general work experience in the field, the level of education (exceeding the requirements/required), passing additional advanced training courses, the average score of a document confirming education, the level of labor and technological discipline, making mistakes that led (or could lead) to financial and/or reputational losses. Among the additional factors for assessing competence, the following were highlighted: the availability of debt obligations and the conscientiousness of their repayment (percentage of monthly payments relative to salary), cash dependents, age of the employee, health group. A group of criteria was also considered to determine supra-professional skills (soft skills), such as communication skills, loyalty to the company, managerial skills, stress tolerance, efficiency of thinking, creativity, responsibility [17].

In this paper, a study was conducted on the possibility of using the ANN to assess the level of competence of personnel as a factor influencing the occurrence of operational risk events. The construction of an ANN to assess the impact of supra-professional skills (soft skills) was proposed to be included in a separate study and described in a separate paper.

When determining the list of input parameters of the ANN to assess the level of competence of the staff, it was assumed that the organization hires employees who fully meet all the requirements for the skills and competencies of the applicant. In addition, the organization strictly monitors the level of competence of its employees, organizing regular refresher courses with monitoring the level of knowledge and skills acquired [18]. From this point of view, all employees should have a sufficient level of knowledge to perform their official duties, and the level of competence of the employee is proposed to be considered as the level of influence on the possibility of operational risk events of the business process: "red (critical, exposure required) – yellow (medium) – green (weak)." Thus, 10 input parameters (neurons of the input layer) were identified, namely:

- current work experience in the organization and in the field of activity,
- exceeding the required level of education,
- the average score of the education document,
- the availability of certificates of advanced training provided they are optional,
- the frequency of violations of technological and labor discipline,
- the presence of commendations / incentives,
- the presence of penalties,
- promotions over the past 5 years,
- the frequency of job changes.

It was decided to set all parameters except the average grade of the educational document with categorical values.

At the next stage, data sets were formed and based on the values of these competence indicators, an expert assessment of the level of competence was performed in terms of its impact on the possibility of operational risk events. Next, a statistical analysis of the obtained sample was carried out for the presence of a relationship between independent characteristics, as well as the presence of their influence on the dependent output indicator. Identifying the relationship between the input parameters will allow us to talk about data redundancy. The correlation between the features in the data set was estimated using Spearman's rank correlation coefficient, which refers to indicators for assessing the closeness of the relationship. The Spearman coefficient was determined in pairs for each of the parameters using the low-code Loginom platform. The quantitative measure of the tightness of the connection was evaluated on the Cheddock scale, according to which the coefficient value in the range from 0.1 to 0.3 indicates a weak connection, and in the range from 0.3 to 0.5 indicates a moderate connection.

Further analysis of the received training sample was reduced to assessing the influence of each of the input parameters on the values of the aggregated employee competence indicator (the output parameter of the ANN with the values "red" – "yellow" – "green"). For categorical parameters, bar charts were constructed with the color division of the column of each class in proportion to the number of dependent values. To estimate the continuous parameter, a probability density graph was constructed; this allows display of a smoother distribution by smoothing the parameter changes. Visualization of diagrams and graphs was performed using the Plotli and Seaborn libraries in Python [19–21].

In accordance with the results obtained at the previous stages, it was proposed to train several models of neural networks with 2–3 hidden layers, of the form 10–m–3 and, in accordance with general heuristic recommendations, m (the number of neurons in the hidden layer) was assumed to be equal to m = 15, 20, 25. Training was conducted during 200 epochs. Using the results obtained in [3], Adam, implemented in the Keras software library, was used as an optimizer to determine the competence of an employee as a component of assessing the occurrence of operational risk. The functions “sigmod” and “tanh” (hyperbolic tangent) were compared as the activation function of the hidden layer, and “softmax” as the activation function of the output layer. Together with the optimizer, the MSE loss function (RMS error) was used. The training was carried out on a general sample divided into a training sample, which made up 80% of the total number of training sets (2150 sets), validation and test samples, each making up 10%.

2. Results

2.1. The ANN model

One of the factors leading to the occurrence of operational risk is the actions committed (or inaction) of personnel when performing business tasks. These actions are largely determined by the professional skills of the participants in the business process. Organizations have been monitoring the level of knowledge and competence of employees for a long time, conducting interviews and various knowledge tests when applying for a job, as well as organizing various advanced training courses during their working life.

However, a sufficient level of knowledge of an employee cannot guarantee the complete exclusion of the possibility of operational risk associated with his actions as a participant in the business process. Very often, the occurrence of operational risk events is influenced not only by the low level of professional knowledge of the staff, but also by indicators indirectly related to it and affecting the effectiveness of the application of this knowledge. The indicators of the level of education, general health, financial independence, marital status and personal qualities were considered as such parameters in the work. Some of the considered parameters have a very insignificant effect, and sometimes may not affect the possibility of operational risk events at all [16]. As a result of the analysis, the indicators that have the greatest impact on the possibility of operational risk events were selected and these were used as input parameters of the ANN:

1. Work experience in the organization in the field of activity (performance of functionality within the framework of the business process).
2. General work experience in the field of activity (performance of functionality within the framework of the business process).
3. Education (in accordance with the requirements, exceeds the requirements);
4. The average score of the document confirming education.
5. Availability of certificates, provided they are optional.
6. Violation of technological discipline.
7. The presence of penalties.
8. Availability of thanks/rewards.
9. Promotion in the last 5 years.
10. Frequent job changes (more than once a year).

Quantitatively, the average score of an educational document is set as a continuously changing value, the remaining parameters are usually set as elements of a finite set. So, for example, for the parameters: the presence of certificates, the presence of penalties, the presence of commendations/rewards, promotion over the past 5 years, the frequency of job changes was determined by the values “yes” (presence) or “no” (absence). The level of education was considered as meeting the requirements of the business process or exceeding these requirements. The length of service was set in ranges of values (years), based on the fact that it cannot be less than the value required for the position, but can only meet or exceed the requirements (for example, “more than 2 years” or “more than 5 years”). To quantify the indicator of violation of technological discipline, gradations were used: “rarely,” “periodically” and “constantly.”

Thus, a generalized ANN model for determining the impact of the competence of business process participants on the possibility of operational risk events can be described by an input layer containing 10 neurons and 3 neurons in the output layer (risk level) with the values “low (green)”, “medium (yellow)" and "high (red)". The total size of the general sample formed by the experts was 2688 sets.

2.2. Analysis of the training sample

To analyze the created data sets for the possibility of their use in the process of training and testing of the INS, a quantitative assessment of the Spearman correlation coefficient for pairs of parameters each with each was used. The assessment showed that the value of Spearman's correlation coefficient varies in the range from 0.26 to 0.34, which, in accordance with the Cheddock scale, indicates a weak bond strength for the qualitative characterization of the tightness of the rank correlation coefficient. *Figure 1a* shows the dependence of the correlation coefficient of the average score on all others. The trend shown in *Figure 1a* is typical for almost all parameters. The exception is the parameter characterizing the frequency of job changes (*Fig. 1b*), which shows a moderate dependence on work experience in the current position (the correlation coefficient is 0.65).

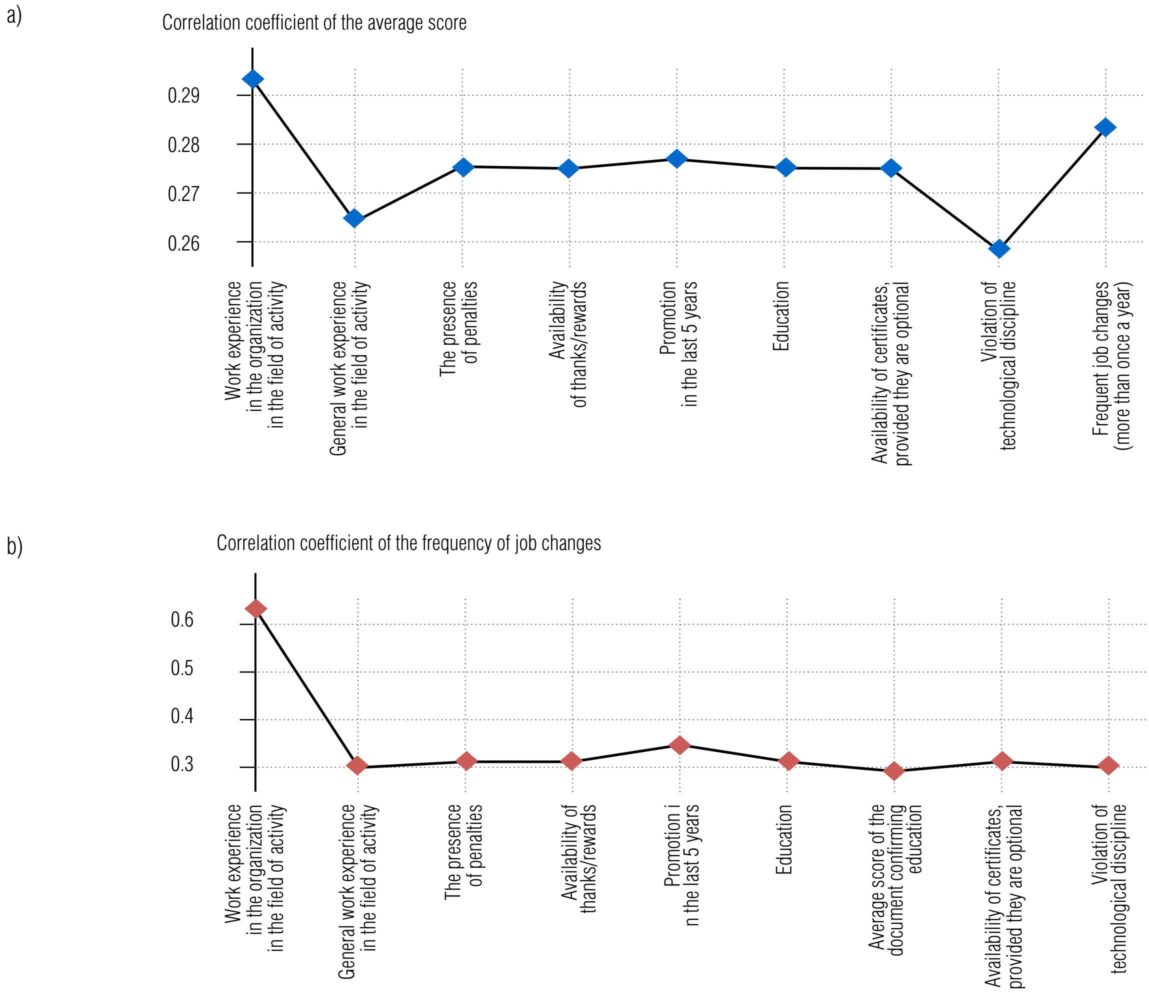

Fig. 1. Change in Spearman's correlation coefficient
a) the average score of the education document, b) the frequency of job changes.

The influence of each of the defined independent input parameters on the output was also analyzed. For categorical parameters, bar charts were constructed indicating the number of values of this parameter included in a certain class. *Figure 2* shows a diagram for the frequency of violations of technological discipline in the workplace.

It can be seen from the diagram in *Fig. 2* that the distribution of input values between output classes is fairly uniform, that is, there is no direct dependence on only one of the parameter values.

Figure 3 shows a diagram for the general work experience in the field of activity, from which it can

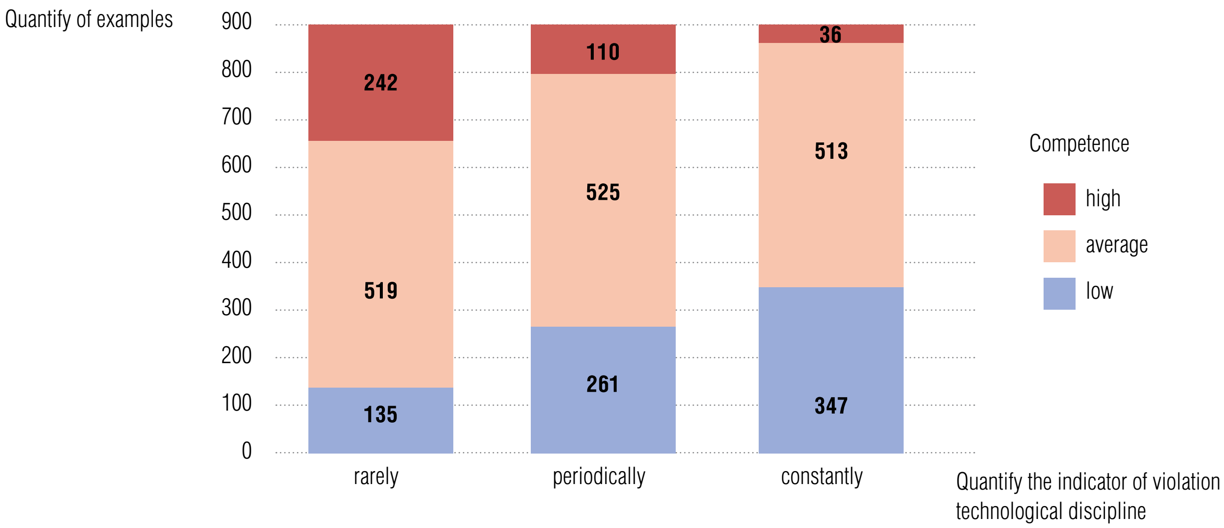

Fig. 2. Diagrams of the level of competence depending on the frequency of violation of technological discipline.

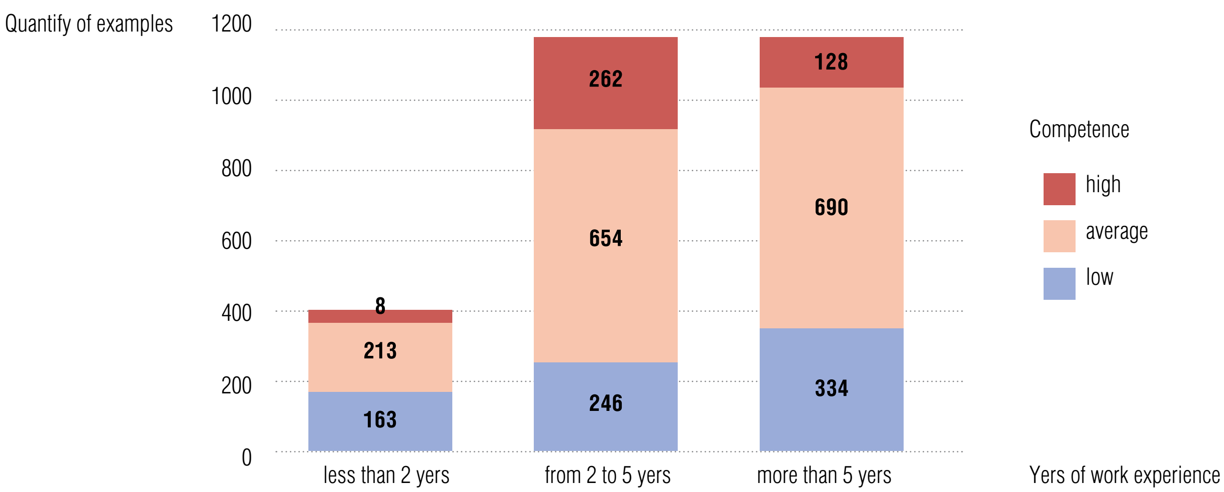

Fig. 3. Diagrams of the level of competence depending on the general experience in the current direction.

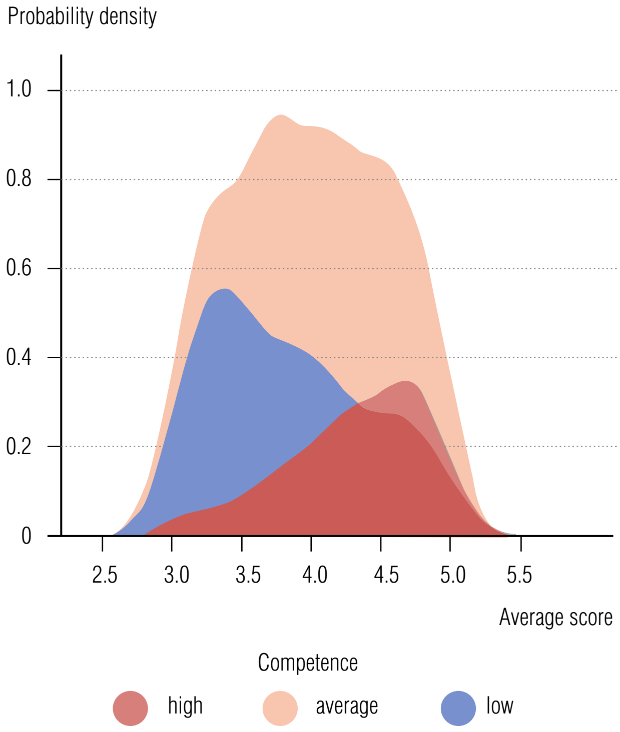

Fig. 4. Graph of the probability density distribution of the average score.

be seen that there is a shift towards more experienced personnel, which is quite consistent with the desire to hire more experienced workers, but there is no unambiguous dependence.

For a single continuously changing parameter of the assessment of the average score of an educational document, a graph of the probability density distribution of a random continuous value was constructed (*Fig. 4*).

Figure 4 shows that employees with a higher score are more likely to be found in a group with high competence and vice versa. However, there is no complete alignment of the graphs, which indicates that the average score of the education document has an impact on the assessment of competence and can be used as an input parameter of the projected neural network.

2.3. ANN training to determine employee competence

During the study of various network options, the choice of the number of layers and the number of neurons was carried out based on the well-known recommendation that the size of the training sample should be at least twice the number of configurable parameters. For the smallest of the considered networks (with a structure of 10–15–15–3), this ratio is 4, and for the largest (with a structure of 10–25–25–25–3) it is 2. Larger networks in this case were not studied due to the limited sample size. The volume of the sample used turned out to be sufficient to investigate the fundamental possibility of applying the proposed approach to assessing the impact of personnel on the occurrence of operational risk based on the results of training and testing of the ANN.

To determine the optimal network structure, training experiments were conducted for direct propagation networks with a different number of hidden layers and neurons in the hidden layer, as well as with various learning parameters: activation functions and algorithms for updating weights (optimizers). The results are summarized in *Table 1*. The loss function MSE (RMS error) was used for the Adam optimizer.

The above results were obtained during training for 200 epochs; an increase in the number of training epochs did not lead to an increase in network accuracy. The training accuracy indicators shown in the table were obtained with the size of the batch of examples (batch_size), after which the weight coefficients are updated to 32. Increasing and decreasing the batch size of the weight coefficient updates led to a decrease in accuracy. At the same time, there was no effect of retraining.

From the results of the training cycles conducted (*Table 1*) it can be seen that the best accuracy indicators are given by a network with a 10–25–25–3 architecture and using the hyperbolic tangent activation function. The graph of the learning curve is shown in *Fig. 5*.

Table 1.

Network accuracy on a test sample

		Activation function							
		sigmoid				tanh			
DNN models		Acc.	Valid.	Test	mse	Acc.	Valid.	Test	mse
2 hidden layers	10–15–15–3	96.65	92.22	92.54	0.04	98.14	93.0	94.03	0.03
	10–20–20–3	98.33	93.74	92.54	0.04	99.4	93.48	94.4	0.03
	10–25–25–3	99.35	94.37	93.66	0.03	99.86	94.33	95.9	0.023
3 hidden layers	10–15–15–15–3	95.86	91.78	92.91	0.04	98.7	94.07	96.64	0.022
	10–20–20–20–3	98.23	93.48	92.16	0.036	98.74	95.7	94.4	0.032
	10–25–25–25–3	98.88	94.59	94.03	0.033	99.21	95.7	94.5	0.038

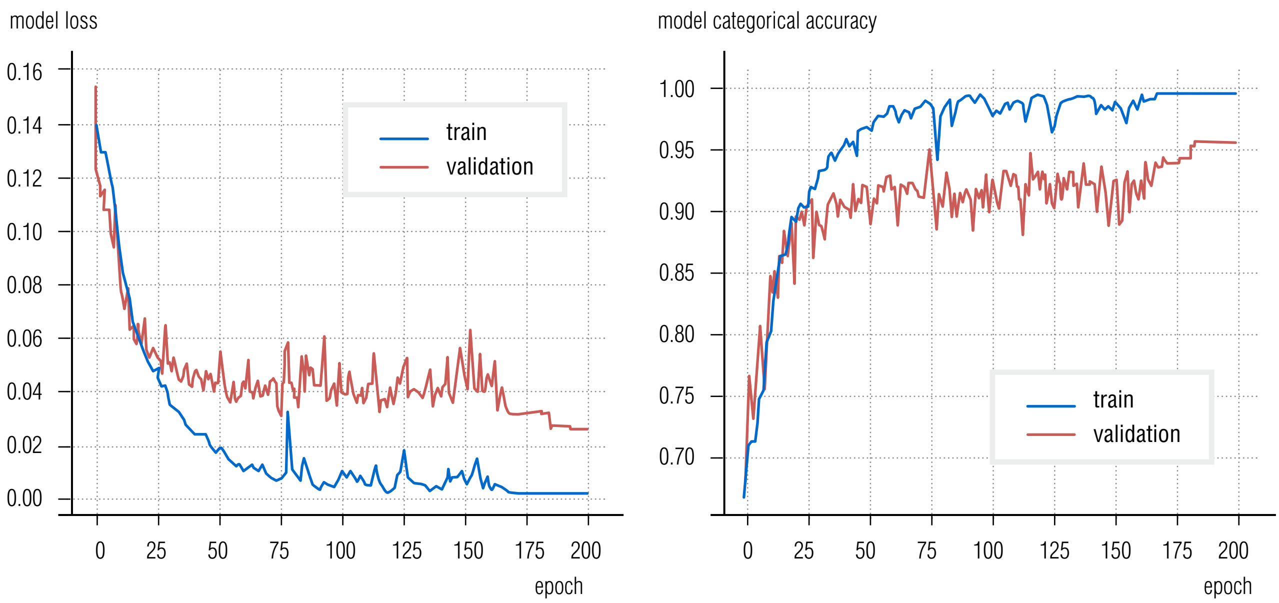

Fig. 5. Learning curves of Direct Distribution ANN with architecture 10-25-25-3.

In general, *Table 1* shows that the accuracy of the network model is higher than the estimate of the resulting model on the test set. The trend continued even after repeated mixing of data between and within samples.

3. Discussion

The paper describes an approach to building a neural network that can be used to assess the operational risks of a credit institution associated with the actions of personnel involved in business processes.

The following methods are usually used to assess the competence of employees in organizations: survey (testing, execution of business cases) an employee on a pre-determined range of issues; evaluation of an employee by his colleagues according to certain criteria. These methods do not sufficiently allow us to assess the impact of the employee's level of competence on the possibility of operational risk when performing the business process of a particular credit institution. For a more correct assessment, it is necessary to take into account statistical data on incidents related to the actions of personnel involved in this business process, and on the set of values of the characteristics of this personnel according to certain criteria.

More accurate estimates of the impact of an employee's level of competence on the possibility of operational risk can be obtained using statistical methods of data analysis. Having statistics on incidents and personnel characteristics, which were mentioned above, you can use, for example, the methods of classical (based on the calculation of proximity measures between sample elements) cluster analysis to identify employee profiles, whose actions during this business process most often lead to operational risk events. It should be noted, however, that the application of statistical methods gives good results on sets of discrete quantities and simple (usually linear) dependencies between them and is difficult if continuous quantities and complex nonlinear dependencies between sample elements are present in data sets. In our case, in particular, it is necessary to take into account the total work experience, work experience in the specialty, the score of the education document, which are continuous values.

In recent years, attempts have been made to use artificial intelligence methods, in particular, fuzzy logic and neural networks to solve problems related to assessing the level of competence of personnel. These methods make it possible to largely avoid the disadvantages inherent in the above-mentioned traditional assessment methods. Analyzing the methods listed above, it can be noted that the complexity of using fuzzy algorithms lies in the difficulty of compiling a rule base due to the exponential growth in the number of rules with an increase in the number of input parameters [11].

Perhaps the only drawback of neural network technology is the difficulty in interpreting the results obtained. A neural network simulates expert responses to a certain situation described by a set of network input parameters. This raises questions of trust in the experts whose assessments were involved in the training of the ANN. In this case, organizations can be invited to conduct additional training on the network using the opinion of experts from this organization, whose assessments can be fully trusted. In this case, when forming additional training and test samples, it is necessary to analyze the consistency of the data using the mathematical methods described in this article.

Based on the conducted research, it is possible to talk about the possibility of using the ANN in the system of indicating the occurrence of operational risk events related to the competence of personnel. The obtained test accuracy of the constructed ANN has a fairly high value equal to 95%.

The network model that showed the best results is almost similar to the model obtained in [3], for the preventive indication of the occurrence of operational risk events associated with the use of information technologies. The difference lies in the activation function used, although in both cases the accuracy indicators are very close and do not differ by more than 2%.

The uniformity of the models obtained allows us to make an assumption about the possibility of implementing a unified modular (homogeneous in module architecture) system of interconnected neural networks for the preventive indication of all types of events and sources of operational risks.

As a direction for further research, it is proposed to consider the possibility of building an ANN to assess the level of supra-professional competencies (soft skills) of employees and propose an ANN architecture for a comprehensive assessment of the personnel of a credit institution in terms of the possibility of operational risk events associated with the actions of employees involved in the business process.

Conclusion

Based on the use of the ANN, a method is proposed for assessing the level of competence of employees in terms of its impact on the possibility of operational risk events associated with the actions of the personnel in a credit institution (unintentional errors, intentional actions or inaction). The ANN models that have shown the best results in relation to assessing the level of personnel competence are similar to the models described by the authors in [3] for assessing operational risks arising in the process of using information technologies. This allows us to conclude that a system of unified network modules can be used for a comprehensive assessment of the operational risks of a credit institution, taking into account all possible sources of operational risk: imperfections or erroneous internal processes of a credit institution; actions of personnel and other persons; failures and deficiencies of information, technological and other systems, as well as a result of the implementation of external events.

The research results described in the paper are new and can serve as a basis for creating intelligent systems for monitoring operational risks associated with the actions of the personnel in a credit institution. Taking into account the adaptation, the proposed solutions can be used by companies in various sectors of the economy, including those not related to the financial sector. ■

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About the authors

Ekaterina V. Chumakova

Cand. Sci. (Phys.-Math.);

Associate Professor, Department of Applied Informatics and Information Security, Plekhanov Russian University of Economics, 36, Stremyanny Ln., Moscow 115054, Russia;

E-mail: CatarinaCh@yandex.ru

ORCID: 0000-0001-7231-9502

Dmitry G. Korneev

Cand. Sci. (Econ.);

Associate Professor, Department of Applied Informatics and Information Security, Plekhanov Russian University of Economics, 36, Stremyanny Ln., Moscow 115054, Russia;

E-mail: Korneev.DG@rea.ru

ORCID: 0000-0001-7260-4768

Mikhail S. Gasparian

Cand. Sci. (Econ.);

Associate Professor, Department of Applied Informatics and Information Security, Plekhanov Russian University of Economics, 36, Stremyanny Ln., Moscow 115054, Russia;

E-mail: Gasparian.MS@rea.ru

ORCID: 0000-0002-6137-7587

Ilia S. Makhov

Doctoral Student, Department of Applied Informatics and Information Security, Plekhanov Russian University of Economics, 36, Stremyanny Ln., Moscow 115054, Russia;

E-mail: ilya.makhov.98@list.ru

ORCID: 0000-0002-5096-8867