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Application of Self-Organizing Maps for Risk Assessment of Mining and Metallurgical Enterprises

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Abstract

Investigation of risk factor assessment and grouping is relevant because ranked risk groups help companies to navigate achieving their strategic development goals while minimizing the impact of external risk factors. Grouping, carried out with neural network modelling, enables the formation of a self-learning model that can be changed by rearranging the vectors of cluster groups under the influence of turbulent external factors. The aim of this research was to develop a risk factor-prioritizing neural network model for a vertically integrated mining and metallurgical company. To attain this goal, the authors identified risk factors by the mining and metallurgical enterprises' key activities and allocated them into key groups by forming a risk register. In accordance with the risk register, the degree of influence and probability of each risk factor was assessed using the expert assessment method that allows for calculating the significance of each risk factor. The formation of risk factor groups by significance was carried out using the method of Kohonen self-organizing maps. The DataBase Deductor Studio Academic 5.3 software was used to simulate the results and build the artificial two-layer neural network. The study proved to be effective for (1) identifying the major risks and risk factors inherent in vertically integrated mining and metallurgical companies based on annual company reports; (2) assessing the impact and probability of risk factors using an expert computational method; (3) graphically presenting a two-layer neural network for further simulation; (4) forming five groups using neural simulation based on Kohonen networks; and (5) interpreting the simulation results, identifying the most significant risk in management decision-making and putting forth brief recommendations on using artificial neural networks for risk analysis and assessment. Based on the research results, recommendations on the use of artificial neural networks for risk analysis and assessment for vertically integrated mining and metallurgical companies are provided. The proposed algorithm allows large vertically integrated companies with a complex organizational structure and technological processes, as well as a wide list of risks affecting their activities, to quickly identify the most significant risks.

Keywords: risk management, neural networks, mining and metallurgical industry, digital transformation, risk analysis

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Применение Самоорганизующихся Карт для Оценки Рисков Предприятий Горно-металлургической Отрасли

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Аннотация

Изучение вопроса оценки и группировки факторов риска является актуальным, так как ранжированные группы рисков в дальнейшем помогают ориентироваться компаниям при достижении стратегических целей развития, минимизируя влияние внешних факторов риска. Группирование, выполнено с применением нейросетевого моделирования, позволяет сформировать самообучающуюся модель, которая сможет изменяться, перестраивая векторы кластерных групп при влиянии действующих внешних факторов. Целью исследования является разработка нейросетевой модели приоритезации факторов рисков для вертикально-интегрированной горно-металлургической компании. Для достижения поставленной цели в статье идентифицированы факторы рисков в ключевых сферах деятельности предприятий горно-металлургической отрасли и распределены по ключевым группам – сформирован реестр рисков. В соответствии с реестром рисков произведена оценка степени влияния и вероятности каждого фактора риска посредством метода экспертных оценок, что позволило рассчитать значимость каждого фактора риска. Формирование групп факторов рисков по значимости осуществлено с помощью метода самоорганизующихся карт Кохонена. Для моделирования результатов использован функционал программного обеспечения DataBase Deductor Studio Academic 5.3, с помощью которого строится искусственная нейронная сеть с двумя слоями. На основе результатов исследования сформулированы рекомендации по использованию искусственных нейронных сетей в целях анализа и оценки рисков для вертикально-интегрированных горно-металлургических компаний.

Ключевые слова: управление рисками, нейронные сети, горно-металлургическая отрасль, цифровизация, анализ рисков

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1. Introduction

Uncertainties are growing, and the external environment is rapidly changing. Today, enterprises have to use modern and powerful analytical tools that allow them to consider risks and make management decisions quickly. Risk is one of the most important economic phenomena. In current circumstances, risk management to minimize possible financial losses is paramount. The economy as a whole is affected by various factors, such as globalization, recurring global crises, the economic downturn of recent years, increased competition, the destruction of national borders, and the COVID-19 pandemic, which has become a turning point for the economy and society as a whole. In terms of market relations, these are key external factors influencing enterprises' operations. Modern companies need to quickly adapt their management objectives and functions, including production methods, given the volatile business environment (Pukała, 2016). Consequently, the growth potential of enterprises in each specific case depends on the effectiveness of this adaptation to the new externalities and internalities, including the needs of a market economy.

"Black swans" affect all enterprises, including vertically integrated mining and metallurgical companies (VIMMCs) (Taleb, 2009), which need to structure their various business practices in a timely and transparent manner. The mining and metallurgical industry is one of the key sectors of the modern global economy (Korneeva, 2016). The metallurgical sector consists of enterprises engaged in the extraction, enrichment, and processing of ferrous and non-ferrous ores and is a type of heavy industry that negatively influences the environment. The environmental impact can worsen VIMMCs' reputation if their management does not take swift actions to alleviate the negative impact. In addition, now, the metallurgical industry is influenced by some downward trends, including high depreciation of fixed assets, strict environmental requirements for products, insufficient supply of the domestic market, high production costs of metals and metal products, a high level of production concentration, and underdevelopment of the system of small and medium-sized enterprises (Pishchalkina, 2021). It should be noted that today, as the flow of information is practically unlimited, any enterprise that tries to increase its competitiveness or maintain its current position in the market must be constantly involved in technical improvements. Most VIMMCs define the following main objectives of risk management: (1) increasing the probability of achieving the company's strategic and operational goals; (2) improving the efficiency of resource allocation; and (3) increasing the company's investment attractiveness and shareholder value.

The scale of the mining and metallurgical industry and the specifics of the vertically integrated technological process of metal production result in the formation of "big data" that must be analysed promptly and accurately. Advanced digital technology can be used to algorithmize the analysis and evaluation processes, including processing a large array of corporate data. In addition, digitalization transformation helps to speed up information processing and expand the methods used (for example, simulation modelling, The program evaluation and review technique (PERT) analysis, fuzzy sets, neural networks, RiskMetrics, CorporateMetrics, heuristic methods, Bayesian analysis, Markov chains, etc.) (Damodaran, 2017).

However, large amounts of data are not always the key to resolving all problems and making the right management decisions. In many cases, statistical methods can hardly be used for risk assessment, even with the necessary amount of information collected. This is due to several factors: (1) Linear modelling methods are not applicable (for example, the simplex method) to most risk analysis problems; and (2) it is assumed that to assess risks, a multivariate statistical model with a Gaussian distribution of observations is built, but this is not common when solutions to practical economic problems are sought (Strebkova, 2014).

In risk analysis, it is necessary to identify non-linear dependencies, and one of the promising approaches to risk management is using neural networks (for example, for predicting or classifying risks). Artificial neural networks are used in many scientific fields, and because they are based on a large amount of data with non-linear dependencies and implicit relationships, they can help to determine the nature of these interdependencies and create the necessary models.

2. Literature review

The literature review reveals that researchers from all over the world use neural networks for risk assessment and apply self-learning models with a set of various factors.

Neural network modelling is actively used in medicine (Hosny et al., 2018a, 2018b; Shankarapillai et al., 2010); the automotive industry, including for crash assessment (Chinea and Parent, 2007; Elhag and Wang, 2007); the wind energy industry (Pinson and Kariniotakis, 2003); project activities, for investment risk assessment (Gaber et al., 1992; Jiang, 2009); the banking industry, for credit risk assessment (Li et al., 2017; Mohammadi and Zangeneh, 2016; Oreski et al., 2012; Yang et al., 2001). For example, Yang et al. (2001) considered artificial neural networks used in an early warning credit risk system for a commercial bank. Jiang (2009) used an artificial neural network to create a new risk assessment model for assessing investments to be made in high-tech projects and MATLAB software for performing exemplary simulations, with the BP neural network model and the RBF neural network model, respectively.

Neural network forecasting has become widespread at the level of enterprises and organizations, which model artificial neural networks to conduct an analysis of risk factors affecting the company's operations and the forecasts of its development. Ramamoorti et al. (1999), Kiseleva and Simonovich (2014), Novikov et al. (2013), Bataev et al. (2019), and Demidova (2020) described modern approaches to risk assessment and reviewed the architecture of a neural network according to different models and methods of neural network interpretation.

Some studies have focused on developing a mathematical framework for risk management of software projects (Lebedeva and Guseva, 2020) and considered various mathematical models for neural network modelling (Schwartz et al., 2004; Zhao et al., 2009). For example, in their study, Lebedeva and Guseva (2020) developed software for assessing the risks of project deadline extension, predicting the future performance of a project, and building scenarios to support decision-making.

This approach to using artificial neural networks can be applied to forecast both financial and economic indicators and to assess the degree of risk (Strebkova, 2014), which confirms the above analysis of the studies conducted by domestic and foreign researchers. Various numerical and textual data, such as estimates, expert opinions, and probabilistic estimates, can be used as input parameters of the neural network.

Compared with traditional technologies, neural networks have the following advantages (Korneev, 2017): (1) They do not depend on the properties of the input data; (2) they do not require a certain type of initial data distribution or linearity of the objective functions (these can be either linear or non-linear) (Haikin, 2006); (3) they are relatively simple, and no special training is needed to apply them in practice; (3) they solve the dimensional problem of linear modelling and are suitable for modelling dependencies with many variables; (4) they speed up the process of finding dependencies because all the neurons process data simultaneously; (5) they can learn; (6) they are suitable for representing nonlinear dependencies and solving problems where cause-and-effect relationships are difficult to establish; and (7) they have a relatively high resistance to measurement errors.

However, neural networks have some constraints (Ivanov, 2013): (1) They do not have a template solution, and a separate modelling algorithm must be found for each particular task (the type of network, the number of neurons, and the network layers must be selected specifically); (2) a neural network is a "black box", and interpreting the results is difficult; (3) the model can be retrained, after which its ability to generalize the input information is reduced; and (4) they are inclined towards "network paralysis during learning", which can occur when too much significance is attached to one of the weights.

Despite the constraints of neural networks, they have proven themselves well in solving problems related to classification, prediction, encoding, and decoding of information (Strebkova, 2014). Neural networks are mostly used if the exact type of connection between the input and output is not known but there is a known connection between the input and output data. In this case, the dependence itself will be identified by the neural network in the process of its learning. The main advantage of neural networks might be their suitability for representing non-linear dependencies and solving problems if there are difficulties in determining cause-and-effect relationships. These features make them helpful in optimizing risk management in enterprises operating in the mining and metallurgical industry. Kohonen's method of self-organizing maps (Haykin, 2006; Kohonen, 1982a, 1995b) was chosen due to the simplicity of analysing the obtained graphical information. The proposed tool makes it possible to identify the most significant risks that should be paid special attention when implementing the enterprise strategy and operational plans.

The aim of this research was to develop a neural network model for clustering risk factors to determine the impact of the key risk factors and the most significant risks for a VIMMC.

To achieve this goal, the following objectives were pursued: (1) identify risk factors in the core activities of VIMMCs; (2) make an expert assessment of the degree of influence and probability of each risk factor; (3) graphically represent a two-layer neural network of corporate risk clustering of VIMMCs; (4) cluster the risks using neural networks; and (5) make recommendations for how artificial neural networks can be used for analysis and risk assessment.

3. Materials and Methods

3.1. Rationale for the applied research methods

Neural network modelling was applied as the research method, which is suitable for clustering the risk factors faced by VIMMCs with a two-layer neural network. Clustering is widely applied to various objects and subjects of research (Babkin et al., 2020; Kudryavtseva et al., 2020; Schepinin et al., 2018; Victorova et al., 2020), but this type of grouping seems particularly effective for substantiating risk factor groups (Er Kara and Oktay Fırat, 2018; Izmalkova and Leontiev, 2018; Panjehfouladgaran and Lim, 2020; Yeo et al., 2001). In this study, clustering was used as a means for ordering and grouping. Neural network modelling is widespread, so there are many studies by domestic (Kiseleva and Simonovich, 2014; Lebedeva and Guseva, 2020; Novikov et al., 2013) and foreign authors (Elhag and Wang, 2007; Jiang, 2009; Li et al., 2017; Yang et al., 2001). This is one of the most effective ways to expand analytical capabilities when studying problems that do not have a standard solution algorithm (Zaentsev, 1999). Neural networks do not require programming but envisage that learning is done on specially selected examples (Debok and Kohonen, 2001). Neural networks are great at solving problems that are somehow related to the processing of data images. The list of typical tasks for neural networks is as follows (Zaentsev, 1999): (1) regression (approximation of functions according to a set of points); (2) recognition (classification of data according to a given set of classes); (3) data clustering and identification of previously unknown prototype classes; (4) information compression; (5) lost data recovery; and (6) associative transformation of information.

Artificial intelligence-based clustering is possible with genetic algorithms (Kalmykov et al., 2011; Sastry et al., 2005; Sivanandam and Deepa, 2008), the C-means fuzzy clustering method (Bezdek, 1981; Jang et al., 1997; Wu and Yang, 2002); the Kohonen neural network (Gorshkov et al., 2009; Haikin, 2006; Kohonen, 1982a, 1995b), and random forest (Shi and Horvath, 2006; Speiser et al., 2019). It is worth highlighting clustering approaches that are not based on artificial intelligence: the probabilistic approach, logical approach (Rakićević et al., 2019), k-means discriminant analysis (Lloyd, 1982; MacQueen, 1967), k-medians (Bradley et al., 1997; Pandit et al., 2011), the EM algorithm (Dempster and Laird, 1977; Zhong and Ghosh, 2003), the hierarchical approach (Pestunov et al., 2015; Zhang et al., 2018), and the graph-theoretic approach (Koontz et al., 1976; Pavan and Pelillo, 2003). Neural network modelling implies choosing a method based on artificial intelligence and able to self-learn. The Kohonen self-organizing map method was chosen to group the risk factors (Haikin, 2006; Kohonen, 1982a, 1995b). Kohonen maps organize data in such a way as to identify unknown structures, serve as a clustering tool, and allow for identifying patterns, as well as visually presenting the data. A self-organizing map consists of components called nodes or neurons. The analyst sets the number of neurons. Each node is described by two vectors (Kohonen, 1982a, 1995b): (1) the M-vector, with the same dimensions as the input data, and (2) the R-vector, representing the coordinates of the node on the Kohonen map.

The Kohonen map can be visually displayed using rectangular or hexagonal cells (Kohonen, 1995b). A hexagonal Kohonen map is built in the paper so that the distance between the centres of neighbouring cells is the same, and the interpretation of the map result is the most correct.

The self-organizing map method has a number of advantages if it is used for solving a specific problem of clustering the risk factors by significance (W): (1) Unlike other networks devised for solving problems with supervised learning, the method is suitable for solving problems with unsupervised learning ("without a teacher"), where the learning outcome depends only on the structure of the input data; and (2) input learning data is sufficient for modelling (output values are not required or, if present, are ignored).

For neural network modelling, we used the free functionality of DataBase Deductor Studio Academic 5.3 to build an artificial neural network with two hidden layers.

3.2. Research algorithm

In this study, to solve the economic and statistical problem, we sequentially modelled an artificial neural network based on a two-layer model of risk clustering factors, in which the input is the risk register of the VIMMCs and the output is a map of neurons with cluster groups of the risk factors. Thus, the following logical steps were taken in the study:

Stage 1. Determine the total number of risk factors that can characterize the analysed VIMMCs, based on the following sub-stages:

1.1. Analyse the annual reports of the mining and metallurgical companies, in particular the risk analysis section.

1.2. Group the risk factors according to their semantic load and form a consolidated register of the risks faced by the VIMMCs.

Stage 2. Form a learning sample for the neural network that includes the values of the indicators generated at the previous stage for a period of time. The corporate risk factors of the VIMMCs are ranked given the estimated significance of each risk factor; the significance is based on the impact and probability of the risk factor. The estimator algorithm involves the following steps:

2.1. Prepare a questionnaire.

2.2. Carry out an online survey of respondents.

2.3. Analyse and rank the results of the survey by risk factors in accordance with the impact and probability assessments.

Stage 3. Form a self-organizing Kohonen map and cluster the risk factors.

3.1. Prepare the input parameters for data clustering.

3.2. Build a Kohonen map using the free version of DataBase Deductor Studio Academic 5.3.

3.3. Interpret the results.

4. Results and Discussion

In the mining and metallurgical industry, risks are inherent in all operations due to the complex organization and scale of production. Companies have to be very careful at the risk identification stage. The best method for identifying risks is to create a risk map based on risk analysis carried out by internal risk managers or risk controllers of the company.

To identify the risks specific to the industry, we analysed the annual reports of metallurgical companies, such as PJSC Norilsk Nickel[1], PJSC RUSAL[2], PJSC EVRAZ[3], PJSC NLMK[4], PJSC Severstal[5], Glencore Plc.[6], Vale S.A.[7], and China Hongqiao Group Ltd.[8] These companies were selected as major VIMMCs, some of which have been operating successfully in the ferrous and non-ferrous metallurgical sector for more than half a century.

The risk factors (x1-x37) were grouped according to the key risks specific to the VIMMCs (N1-N12). The resulting indicator is the corporate risk (R), which considers the impact of all risk factors, given their significance. The impact of corporate risk can be assessed on EBITDA (Earnings Before Interest, Taxes, Depreciation), FCF (Free Cash Flow), or SVA (Shareholder Value Added), as well as on changes in investment attractiveness that depend on the goals of each company. The weight (rank of significance) was estimated using an expert calculation method so that the possible impact of each risk factor on the entire activity of the enterprise could be measured. To assess the significance of risk factors (W.N), expert assessments were considered in terms of the degree of influence of the factor (x.n.i), as well as the probability of the occurrence of the risk (x.n.p).

Three experts in the field of corporate risks of the mining and metallurgical industry were involved in the expert assessment. They were asked to assess the degree of influence and probability for each risk factor that was chosen from VIMMCs' annual reports. Table 2 shows the expert assessment scale.

Table 1. Scale of impact and probability of risk factors for VIMMCs

Expert assessment scale	Impact	Probability
1	1	0.95
2	0.7	0.7
3	0.4	0.3
4	0.1	0.05

After assigning scores to all risk factors, an average score was calculated for each risk. Furthermore, the average values were converted into more accurate values of impact and probability in accordance with the ranges proposed in Table 2. The ranking range for impact was from 0.1 to 1.00, with a minimum progressive step of 0.1; for probability, it varied from 0.05 to 0.95, with a minimum progressive step of 0.01. The averaged expert assessments were converted into updated values of the impact and probability of the risk factors using an interpolation method. The calculation was made using the MS Excel FORECAST function.

Table 2. Scale for assessing the impact and probability of risk factors faced by VIMMCs

Range	Range validation
Graded impact	
1-0.7	It is assumed that 70% to 100% of the assessed risk indicators (in monetary terms) have the greatest impact on the enterprise operations.
0.7-0.4	It is assumed that 40% to 70% of the assessed risk indicators have an average impact on the enterprise operations.
0.4-0.1	The lowest limit is defined by the materiality threshold. Values in monetary terms below this threshold are not included in the scope of the detailed analysis.

[1] Annual report 2021 Nornickel. December 18, 2022. Available at: https://ar2021.nornickel.ru/
[2] Annual report 2021 RUSAL. December 14, 2022. Available at: https://rusal.ru/investors/financial-stat/annual-reports/
[3] Annual report 2021 EVRAZ. December 11, 2022. Available at: https://ar2021.evraz.com/en
[4] Annual report 2021 NMLK. December 11, 2022. Available at: https://nlmk.com/ru/ir/results/annual-reports/
[5] Annual report 2021 Severstal. December 18, 2022. Available at: https://www.severstal.com/files/55799/Annual_Report_2020_RUS.pdf
[6] Annual report 2021 Glencore. December 18, 2022. Available at: https://www.glencore.com/.rest/api/v1/documents/ce4fec31fc81d6049d076b15db35d45d/GLEN-2021-annual-report-.pdf
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[8] Annual report 2021 China Hongqiao Group. December 11, 2022. Available at: http://en.hongqiaochina.com/Uploads/File/2022/04/13/E1378-AR.20220413163757.pdf

Range	Range validation
Graded probability	
0.95-0.7	Risk is assumed to represent uncertainty, so the upper limit is 95%.
0.7-0.3	If the occurrence of an event is expected within the range of 30% to 70%, it is an event of medium probability.
0.3-0.05	If the occurrence of an event is expected within the range of 5% to 30%, it is an event of low probability. If the probability of a risk event is below 5%, the risk is not within the perimeters of a detailed analysis.

After this stage, the final assessment of the weight of each risk factor (W1-W37) is calculated according to Formula 1:

$$W_n = x_{ni} * x_{np} \tag{1}$$

where x_{ni} is the impact of each risk factor and x_{np} is the probability of each risk factor.

Table 3 presents the results of the risk analysis given in the annual reports. A risk register illustrates the types of risks associated with the operation of VIMMCs. The names of the risks and the key risk factors are the compilation of the most mentioned risks in the reviewed annual reports of the firms analysed earlier. The risk register was chosen as a method for structuring and ranking risks, approved by the National Standard of the Russian Federation, "Risk Management. Risk Register. Construction Rules"[9]. The risks were grouped according to the proposed categories, and each one's the degree of influence on the whole company was determined.

Table 3. Key business risks of VIMMCs

Risk (N)	Major risk factors (x)		Significance (W)
Price risk (N1)	- Falling demand for metals	x1	0.59
	- Slowdown of global economy as a whole and in countries consuming metals	x2	0.36
	- Imbalanced supply and demand in metal markets	x3	0.69
Market risk (N2)	- Stricter requirements for environmental, social, and corporate governance and product quality on the part of the consumer and the market	x4	0.78
	- Competition from other manufacturers of metal products that sell metals at a lower price	x5	0.68
	- Changing patterns in consumption of high-tech products	x6	0.39
	- Limitation of product exports due to an increasing intensity of decarbonization programs	x7	0.78
	- Introduction of foreign trade restrictions by foreign regulators: tariff and non-tariff regulation	x8	0.87
FX risk (N3)	- Increase in Russia's balance of payments, increasing stock oil prices and decreasing imports	x9	0.13
	- Change in country macroeconomic indicators	x10	0.22
	- Changing rankings	x11	0.13

[9] GOST R 51901.22-2012. December 05, 2022. Available at: https://docs.cntd.ru/document/1200100075

Risk (N)	Major risk factors (x)		Significance (W)
	- Decreasing volatility in the financial markets of Russia, as well as in the markets of other developing countries	x12	0.07
Tighter environmental regulations (N4)	- Greater focus of the international and domestic communities on sustainable development and the environment	x13	0.33
More rigorous environmental standards (N4)	- Stricter environmental supervision and active law-making in the environmental field	x14	0.52
	- Introduction of technological restrictions associated with industrial wastewater and mine water treatment	x15	0.26
Climate change risk (N5)	- Climate changes leading to abnormal natural phenomena (droughts), an increasing average annual temperature over the past 15–20 years, and a growing depth of seasonal thawing	x16	0.13
Investment risk (N6)	- Changes in the deadlines of investment projects	x17	0.39
	- Changing budgets of investment projects and revisions of technological indicators in the process of project implementation	x18	0.22
	- Changes in forecasts for the volume, quality, and properties of ores during supplementary exploration	x19	0.33
Work-related injury risk (N7)	- Unsatisfactorily organized execution of work	x20	0.17
	- Disrupted technological process and impact of hazardous factors	x21	0.22
	- Failure to comply with the legal requirements for occupational health and safety	x22	0.14
Epidemic risk	- Spread of virus infections	x23	0.26
(N8)	- Restrictive anti-epidemic measures taken by international, federal, and regional government bodies	x24	0.34
Information security and	- Growing external threats, including unfair competition	x25	0.27
digital efficiency risks (N9)	- High growth rates of the IT infrastructure of the mining and metallurgical complex and automation of business processes	x26	0.39
	- Illegal actions on the part of employees of enterprises and (or) third parties aimed at obtaining material gain or influence	x27	0.07
	- Failure to introduce new IT capacities in due time	x28	0.07
Technical and production risk	- Difficult natural and climatic conditions: low temperature, storm wind, snow load	x29	0.22
(N10)	- Unscheduled shutdowns of the main equipment caused by depreciation of fixed assets, collapse of buildings and structures, or failure of infrastructure facilities	x30	0.24
	- Emission of explosive gases and flooding of mines	x31	0.10
Risk of changing legislation and	- Instability of the legal system and the lack of consistent regulatory legal acts in various fields	x32	0.05
law enforcement	- Frequency of changes in legislation	x33	0.14
practice (N11)	- Complex foreign political situation	x34	0.28
	- Deficit of the budget system (the need to increase revenues through tax and other deductions)	x35	0.17

Risk (N)	Major risk factors (x)		Significance (W)
Compliance risk	- Inconsistency in legislation	x36	0.11
(N12)	- Scope of power and special attention on the part of oversight bodies	x37	0.10

Next, a graphical interpretation of the two-layer neural network of clustered corporate risks of VIMMCs was formed (see Figure 1).

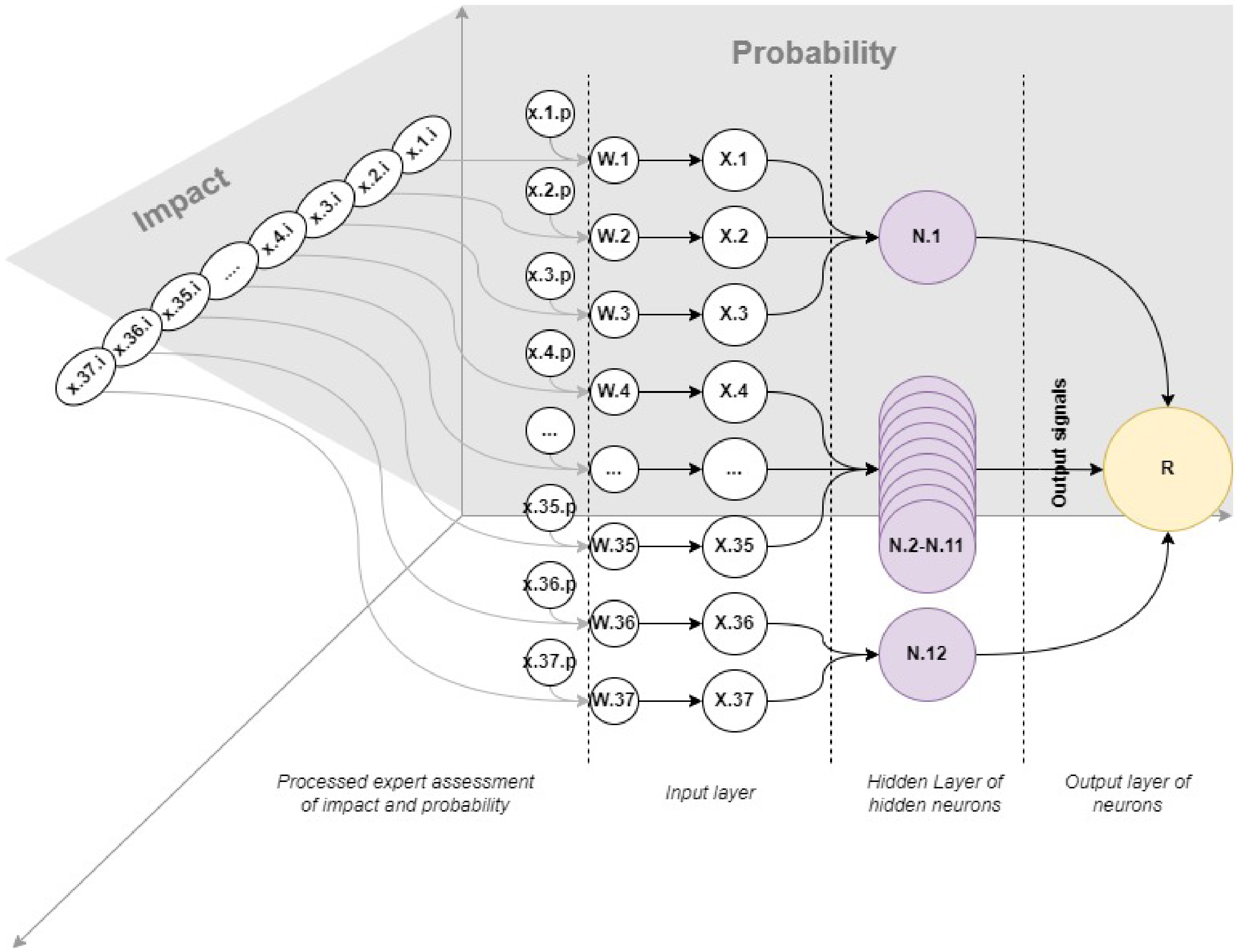

Figure 1. Two-layer neural network of clustered corporate risks of VIMMCs

Figure 1 shows distinctive neuron layers: a layer of hidden neurons and an output layer of neurons[10]. With output signals, the output layer of neurons forms the corporate risk of VIMMCs (R). Corporate risk represents a complex risk that is aimed at protecting the company's assets and also combines all types of risks inherent in the VIMMCs and discussed in Table 1. The layer of latent neurons forms cluster groups of the risk factors for VIMMCs (G1-G5) in accordance with the levels shown in Table 4. The input layer is formed by processing expert assessments on the impact and probability indicators of a particular risk factor (x1-x37). The risk factors of the input layer (see Table 1) belong to the corresponding risk groups (N1-N12). The aggregated data will be used as input (vector) data for further analysis, which is performed using artificial neural networks. The input data collected at the level of the input layer of neurons represent a combination of the influence and probability degree of the identified risk factors in Table 1, which reflect the significance of risk factors.

It follows from the above study that there are 37 types of risk factors inherent in mining and metallurgical enterprises (Table 1). In addition, all the identified risk factors are divided into 12 risk groups. Furthermore, an artificial neural network is modelled to formalize the description of the risk assessment

[10] How to configure the number of layers and nodes in a neural network. December 05, 2022. Available at: https://www.machinelearningmastery.ru/how-to-configure-the-number-of-layers-and-nodes-in-a-neural-network/

of VIMMCs (Kachalov et al., 2019). At the first stage of modelling, the designations of the variables (N1-N12) are introduced to characterize an event as a manifestation of the risk factor of the corresponding group, which has a significant impact on the corporate risk of VIMMCs (R), and the risk factors themselves (x1-x37).

As part of the study, the method of self-organizing Kohonen maps (Kohonen networks) was applied. The network formed with DataBase Deductor Studio Academic 5.3 can be defined as having the following parameters: 1) 37 values of weights (W) of factors were taken as input parameters, and the information layers are risk groups (N1-N12) and risk factors (x1-x37); 2) the sample is broken down into training and test subsets in the following proportions: 95% of the weights of risk factors were included in the training subset, and 5% were included in the test sample; 3) the size of the map was set according to the software developer's recommendation as 12*9; 4) the number of clusters was 5, which corresponds to the following ranking of levels of risk impact on the activities of VIMMCs: low, below average, medium, above average, and high; and 5) the defined conditions for stopping training were 500 by the number of iterations (epochs), the average normalized error for the training set does not exceed 0.05, and the average normalized error for the test set is not higher than 0.05.

The self-organizing map method enabled visualization of the clustering of the initial set of risk factors (Figure 2).

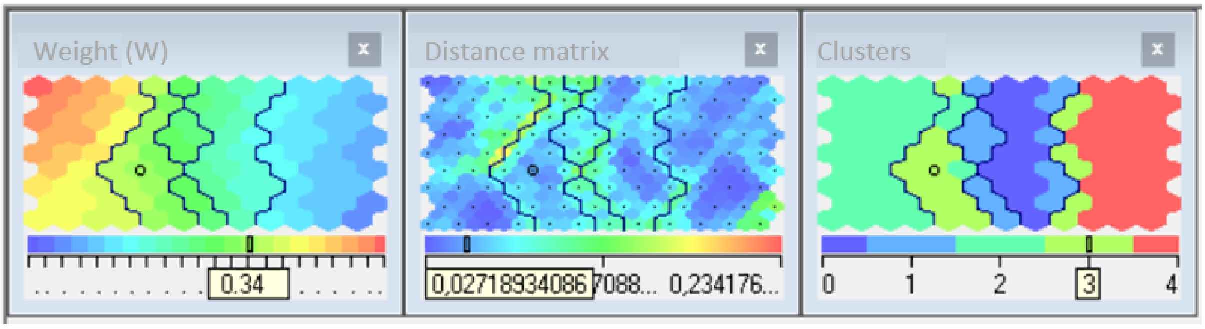

Figure 2. Clustering of risk factors of VIMMCs

The colour of a cell indicates the approximate value of the objects that fall into it. On the component projections, red is the highest value, blue is the lowest, and the intermediate values are represented by a colour gradient. In the context of the self-organizing map method, clusters are the collections of vectors, with the distance between them being less than the distance to the vectors of neighbouring groups. All elements of the map that fall into an area of the same colour (cluster) have similar properties. Based on the maps, it can be inferred which objects have the highest values of a particular indicator (a group of objects, marked in red) and which have the smallest values (a group of objects, marked in blue).

Table 4 shows the results of clustering, from which it can be seen that five clusters were formed and include the following number of risk factors: Cluster 0 has 7 factors, cluster 1 has 2 factors, cluster 2 has 10 factors, cluster 3 has 4 factors, and cluster 4 has 14 factors.

Table 4. Risks and risk factors of VIMMCs distributed by cluster

Item No.	Cluster number	Risk (N)	x	Value (W)
1	0	N3	x10	0.22
2	0	N4	x15	0.26
3	0	N6	x18	0.22
4	0	N7	x21	0.22
5	0	N8	x23	0.26
6	0	N10	x29	0.22
7	0	N10	x30	0.24

Item No.	Cluster number	Risk (N)	x	Value (W)
8	1	N9	x25	0.27
9	1	N11	x34	0.28
10	2	N1	x1	0.59
11	2	N1	x3	0.69
12	2	N2	x4	0.78
13	2	N2	x5	0.68
14	2	N2	x6	0.39
15	2	N2	x7	0.78
16	2	N2	x8	0.87
17	2	N4	x14	0.52
18	2	N6	x17	0.39
19	2	N9	x26	0.39
20	3	N1	x2	0.36
21	3	N4	x13	0.33
22	3	N6	x19	0.33
23	3	N8	x24	0.34
24	4	N3	x9	0.13
25	4	N3	x11	0.13
26	4	N3	x12	0.07
27	4	N5	x16	0.13
28	4	N7	x20	0.17
29	4	N7	x22	0.14
30	4	N9	x27	0.07
31	4	N9	x28	0.07
32	4	N10	x31	0.10
33	4	N11	x32	0.05
34	4	N11	x33	0.14
35	4	N11	x35	0.17
36	4	N12	x36	0.11
37	4	N12	x37	0.10

Based on the clusters obtained and the analysis performed, it was possible to determine the scale for assessing the factors' significance (Table 5) and highlight those factors that should be paid special attention when management decisions are made.

Table 5. Scale of risk factor significance assessment

Cluster	Level	Range	Description of impact
4	Low	0.05-0.17	Risk factors that have the lowest impact on decision-making
0	Below average	0.22-0.26	Risk factors with a below-average impact on decision-making
1	Average	0.27-0.28	Risk factors that have no significant impact on decision-making
3	Above average	0.33-0.36	Risk factors that have to be considered in management decisions
2	High	0.39-0.87	Risk factors that have to be paid a lot of attention when management decisions are made

Thus, the results of the neural network modelling of cluster groups of risk factors have practical applications. According to the obtained clusters, the following conclusions can be made:

1. When making management decisions for VIMMCs, first, attention should be paid to the risk factors included in the second cluster, in particular to the following ones: (1) any imbalance of supply and demand on metal markets; (2) stricter requirements for environmental, social, and corporate governance and product quality on the part of the consumer and the market; (3) competition from other manufacturers of metal products selling metals at a lower price; (4) limitation of product exports due to an increasing intensity of decarbonization programs; and (5) introduction of foreign trade restrictions by foreign regulators.

2. The analysis perimeters exclude risk factors that are included in clusters 0, 1, and 4 because they do not have any direct or significant impact on managerial decision-making.

Thus, the use of this algorithm makes it possible to quickly identify the most significant risks for large vertically integrated companies with a complex organizational structure, a separate method of organizing technological processes, and a wide list of risks affecting their activities.

We also propose using the capabilities of artificial neural networks not only for clustering issues but also for identifying implicit patterns when processing a large data sample. This study emphasizes grouping the risk factors to exclude minor factors from the perimeters of a detailed risk analysis when management decisions are made. It is important to note that as the number and significance of factors change, the ranges of the factors will shift, which will result in a subsequent revision of the list of risk factors for detailed analysis.

5. Conclusion

Today, the problem of risk management in VIMMCs is attractive in light of the risks inherent not only in these enterprises but also in their turbulent external environment. By clustering the risk factors, one can quickly reduce the list of factors to be analysed and concentrate on the most significant factors when making management decisions. The research methodology is suitable for obtaining data that clearly indicate that the methods are effective and can be successfully applied in risk management processes.

In addition, the literature review indicates that although each of the scientific fields necessary for achieving the goal of the current study is covered at the national and international levels, the ties between all these disciplines must be investigated further. This research study is of practical importance, and the results obtained indicate that it is possible to combine various areas of research and draw interdisciplinary conclusions.

This study relied on the method of self-organizing Kohonen maps built with the DataBase Deductor Studio Academic 5.3 software to cluster the risk factors of mining and metallurgical companies.

The study proved to be effective for (1) identifying the major risks and risk factors inherent in the VIMMCs based on annual company reports; (2) assessing the impact and probability of the risk factors using an expert computational method; (3) graphically presenting a two-layer neural network for further simulation; (4) forming five groups using neural simulation based on Kohonen networks; and (5) interpreting the simulation results, identifying the most significant risks in management decision-making and putting forth brief recommendations on using artificial neural networks for risk analysis and assessment.

Overall, artificial neural networks can be applied not only for solving clustering problems but also for assessing specific risks or identifying dependencies between the analysed independent factors. The direction of the further research is to analyse the potential of neural networks in identifying risks using the capabilities of big data analytics.

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