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Research article

METHODOLOGY FOR ASSESSING AND PREDICTING PERSONALIZED OCCUPATIONAL HEALTH RISKS BASED ON ADAPTIVE NEURAL FUZZY NETWORK FOR IMAGE RECOGNITION

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Health protection provided for industrial production workers is a national priority, which determines possibilities for preservation of occupational longevity. Given that, it is becoming especially vital to create and develop scientific grounds for analyzing occupational health risks associated with complex exposures to occupational and work-related risk factors with special emphasis placed on personalized estimates. In this study, we aimed to develop and test a methodology and software for assessing and predicting personalized occupational health risks based on an adaptive neural fuzzy network for image recognition.

The study design was based on an artificial intellect model as a mathematical structure trained to recognize regularities and establish whether an analyzed object belonged to a specific occupational health risk category per a system of indicators. Network training and validation were performed on an example sample made of workers employed at underground copper-nickel ore mining using data on their working conditions, exposure factors and individual biomedical indicators (175,000 parameters overall). The training sample equaled 80 % and the validating one 20 %. The network was tested on an independent sample of data about workers exemplified by blast-hole drillers as a basic occupation at the mine.

A methodology was developed and provided with relevant software; its theoretical ground was represented by an adaptive neural fuzzy network for image recognition. The network had a specific hybrid multilayer architecture, which ensured accuracy of predictive estimates and error minimization. Personalized occupational health risks for each worker in the validating sample were caused by vibrational disease associated with simultaneous exposure to occupational noise (10–40 dBA higher than MPL) and total vibration equal to 106–113 dB; these risks were ranked as 'high' and 'very high'. Health risks caused by sensorineural hearing loss (SHL) associated with combined exposure to noise (5–30 dBA higher than MPL) and adverse chemicals (2.0–2.5 times higher than single maximum MPC) were estimated as varying from medium to very high. Health prediction for workers of this occupation in the independent sample showed that vibration diseases accounted for 75 % of expected occupational and work-related diseases with risks varying from low to high; polyneuropathy, 48 %; SHL, 6 %; dorsopathy, 75 %; essential hypertension, 30 %. Profound medical examination of blast-hole drillers confirmed that these health risks were actually manifested as diseases in 87–89 % workers.

The developed and tested methodology is quite effective. The prediction accuracy is estimated to reach 89 ± 2 % and the prediction error trend comes to minimum. The methodology provides a considerably wider opportunity to obtain prompt

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and accurate personalized prediction of health risks for workers. The system is eligible for workers employed at variable productions and implements a transition from contact-based examinations to quantitative prediction without any information losses, which determines its scalability and possibility to replicate it.

Keywords: *occupational environment, work process, adverse and hazardous factors, exposure, occupational health risks, adaptive neural fuzzy network, image recognition.*

Protecting and promoting health of industrial workers is a national priority, which determines possibilities for preservation of occupational longevity in accordance with the pace of the socioeconomic development of the country and strengthening the national security [1–4]. Special attention is paid to achieving this goal among other priority trends of the state policy since it is a crucial factor for realization of strategic interests of the Russian Federation[1], which, among other things, include "…advanced growth of healthy life expectancy and a decrease in the total duration of temporary disability among employable population by 2030…"

Given prolonged occupational longevity [1, 4], issues of workers' health improvement, declining incidence of non-communicable diseases and losses of work activity associated with persistent or temporary disability are becoming especially vital [5–8]. The Federal State Statistics Service estimated the employed population to account for 62.0 % of the total RF population as of the beginning of 2025 (75.3 million people)[2]. Working conditions hold the most important place in the structure of factors determining occupational health risks as well as associated morbidity[3] [9–11]. Wide modernization and automation of major productions in leading brunches of the economy, implementation of energy-saving technologies etc. promote gradual changes in conventional work performed by workers with basic industrial occupations and make adverse occupational and work-related factors less pronounced [12]. At the same time, a considerably large proportion of workplaces cannot be considered conforming to the valid sanitary-hygienic requirements to working conditions[4]. This proportion reaches 55 % in ore mining and even 65 % in metal ore mining; it reaches 42 % in processing industry, 39 % in transport, 37 % in electric energy production and supply, and 30 % in oil production [13, 14]. Working conditions in these brunches are mostly assessed as hazardous (from medium to very high hazards, hazard classes 3.2–3.4) in conformity with the Federal State System of keeping data obtained by Special Assessment of Working Conditions (SAWC).

Hygienic studies have established that harmfulness and hazards of working conditions in leading industrial brunches are determined by a set of adverse factors, which affect approximately 47 % of the total employed population (as of the end of 2024)[5]. Of them, 30.4 % of workers are exposed to occupational noise and vibration; 11.8 %, chemicals in

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[1] O natsional'nykh tselyakh razvitiya Rossiiskoi Federatsii na period do 2030 goda i na perspektivu do 2036 goda: Ukaz Prezidenta Rossiiskoi Federatsii ot 07.05.2024 g. № 309 [On national goals and strategic tasks of the Russian Federation development for the period up to 2030 and the future prospect up to 2036: the RF President Order dated May 07, 2024. No. 309]. *Prezident Rossii: the RF President Official Web-site*. Available at: http://www.kremlin.ru/acts/bank/50542 (June 08, 2025) (in Russian).

[2] Skol'ko lyudei v Rossii rabotaet: statistika trudosposobnogo naseleniya [How many people work in Russia: data on the employable population]. *Skypro*. Available at: https://sky.pro/wiki/profession/skolko-lyudej-v-rossii-rabotaet-statistika-trudosposobnogo-naseleniya/ (June 10, 2025) (in Russian).

[3] Professional'naya patologiya: natsional'noe rukovodstvo [Occupational pathology: national guide]. In: RAS Academician I.V. Bukhtiyarov ed. Moscow, GEOTAR-Media Publ., 2024, 904 p. (in Russian).

[4] Ob utverzhdenii sanitarnykh pravil SP 2.2.3670-20 «Sanitarno-epidemiologicheskie trebovaniya k usloviyam truda»: Postanovlenie Glavnogo gosudarstvennogo sanitarnogo vracha Rossiiskoi Federatsii ot 02.12.2020 g. № 40 [On Approval of sanitary Rules SP 2.2.3670-20 Sanitary-Epidemiological Requirements to Working Conditions: the Order by the RF Chief Sanitary Inspector dated December 02, 2020, No. 40]. *KODEKS: electronic fund for legal and reference documentation*. Available at: https://docs.cntd.ru/document/573230583 (June 10, 2025) (in Russian).

[5] Udel'nyi ves rabotnikov organizatsii, zanyatykh na rabotakh vrednymi i (ili) opasnymiusloviyam truda po vidam ekonomicheskoi deyatel'nosti na konets 2024 goda [Specific weight of workers employed at workplaces with harmful and (or) hazardous working conditions per kinds of economic activity as of the end of 2024]. Available at: https://docs.yandex.ru/docs/view?tm=1750065411&tld=ru&lang=ru&name=73631(5).pdf (June 10, 2025) (in Russian).

workplace air and aerosols with predominantly fibrogenic effects; 35.2 %, work hardness and intensity [8, 15, 16]. Harmful working conditions create considerable occupational health risks and risks of work ability losses and cause occupational and work-related diseases [12]; this has a substantial effect on human potential preservation and the demographic situation in the country as a whole. According to Rosstat, deaths of employable population accounted for 58 % of the total deaths due to all causes as of the beginning of 2024; of them, deaths due to diseases of the circulatory system accounted for 31 %[6]. The number of employed people is declining in Russia and the process is further accelerated by a downward demographic trend and accompanied with their ageing. This is confirmed by trends predicted by the Institute for Demography of the Higher School of Economics, which show that the number of people aged between 20 and 59 will go down by 2.6 million people in the Russian Federation between 2022 and 2030; the proportion of employed people aged younger than 40 years will go down by 6.6 million whereas the proportion of employed people aged between 40 and 59 will grow by 4.0 million. This can have a considerable effect on the country economy, the labor market included [17].

As human potential is declining in the country and simultaneously undergoing quantitative transformation, protection of employable population's health is becoming an especially urgent challenge [18]. Occupational risk assessment as an advanced analytical instrument for decision-making is conducted in occupational groups exposed to the same occupational factors; any personalized risk realization mostly covers sex, age, and work records [2, 12]. In addition, working conditions for workers with most common occupations in most leading industries are characterized, as a rule, by a complex interrelated system of risk factors that influence each other. Conventional occupational risk assessment methods employed in conformity with the valid Guide R 2.2.3969-23[7] do not consider this complexity to the full; this indicates the necessity to develop and update existing methodical approaches to occupational risk quantification and personalized prediction [19].

Analysis of management decisions as regards occupational and work-related diseases clearly reveals their specific restrictive essence. The existing practices on the matter do not contain all necessary elements of occupational risk management; do not meet actual demands in early detection of pre-nosologic states in workers with high likelihood of occupational and / or work-related diseases; do not involve subsequent development and implementation of personalized medical and preventive measures [20–22]. Most developed and implemented measures including those designed as corporate programs for workers' health protection are represented by general recommendations and are aimed at all workers employed by an enterprise as a whole [2, 4, 6, 12, 18]. Periodical medical examinations are conducted in strict conformity with the valid regulatory and legislative acts and are aimed at detecting already developed clinical forms of diseases, which are considered medical contraindications for beginning or continuing one's work activities.

Given that, it is necessary to develop and implement innovative methods and instruments in order to provide stable conditions for protecting and promoting workers' health at workplaces, to prevent occupational and general somatic pathologies associated with occupational factors, to decrease scopes of persistent or temporary disability [9, 10]. Assessment and prediction of occupational health

[6] Ivanova A.M., Moruga A.S., Nikitina S.Yu., Fatyanova L.N., Eumarina V.Zh., Elefterova M.P. Zhenshchiny i muzhchiny Rossii. 2024: Statisticheskii sbornik [Women and men in Russia. 2024: Statistical data collection]. Moscow, Rosstat, 2024, 176 p. (in Russian).

[7] R 2.2.3969-23. Rukovodstvo po otsenke professional'nogo riska dlya zdorov'ya rabotnikov. Organizatsionno-metodicheskie osnovy, printsipy i kriterii otsenki; utv. Glavnym gosudarstvennym sanitarnym vrachom RF 07.09.2023 [Assessment of Occupational Health Risk for Workers. Organization and Methodical Essentials, Principles and Assessment Criteria; approved by the RF Chief Sanitary Inspector on September 07, 2023]. Moscow, 2023, 77 p. (in Russian).

risks based on a personalized approach is the key aspect of measures aimed at morbidity prevention since it determines their ultimate effectiveness. It is objectively necessary to use up-to-date technologies for profound examination of individual health, opportunities offered by the neural network artificial intelligence, which makes it possible to simulate complex relationships between effects produced by adverse occupational factors, individual indicators of workers' health and risks of occupational diseases. Scientific developments in the sphere such as conceptual foundations and creation of predictive digital neural network models trained on retrospective or actual data about working conditions, health, socioeconomic conditions and lifestyle factors provide information and analytical grounds for calculating and assessing evolution of personal and group (considering an occupation, age, and work records) occupational health risks for workers [21]. This approach has provided much wider possibilities offered by an instrumental base for assessment of personalized occupational health risks. At the same time, adverse exposures are multicomponent and negative health outcomes are multiple; they are described by qualitative and quantitative characteristics and this determines fuzziness and uncertainty of a simulated process (fuzzy input data). This requires using additional solution methods able to overcome limitations and to ensure accurate simulation of relationships, scenario analysis for image recognition, and minimization of errors[8] [23–26].

All the foregoing indicates the necessity to further develop scientific and methodical grounds for personalized prediction of likelihood of direct and indirect signs of health states pathogenetically associated with exposure to harmful and hazardous occupational and work-related factors. This development should be consistent with previously gained experience. Greater accuracy of personalized assessments will allow creating and implementing relevant algorithms and optimizing occupational health risk management as well as raising effectiveness of preventive activities aimed at prolonging occupational longevity.

The aim of this study was to develop and test a methodology and software for assessing and predicting personalized occupational health risks based on an adaptive neural fuzzy network for image recognition.

Materials and methods. The study design was based on an artificial intellect model as a mathematical structure trained to recognize regularities and establish whether an analyzed object belonged to a specific occupational health risk category per a system of indicators. Software necessary for the model functioning was developed in Python using Scikit-fuzzy library for creating and calculating membership functions for input data. A neural network that accepted input data was developed using TensorFlow, a library with high productivity and scalability for training and optimizing weights and parameters of membership functions [27–29]. Defuzzification was accomplished by the Centroid method in Python. At the output, a fuzzy result becomes quite an accurate value of a personalized occupational health risk.

When creating an input data sample, we have used a term-set (T), which describes levels of each indicator (for example, noise, vibration, chemical contents, physical loads, work records, etc.) as follows: T = {Negligible (N); Low (L); Medium (M); High (H); Very High (VH)}. A term-set for each indicator ($x_1…x_n$) is given as: N, L, M, H, VH. Occupational health risks for workers were assessed based on an obtained quantitative result (y_p). Occupational health risks for workers were assigned into various categories in conformity with the conventional scale based on establishing their membership within a specific range of scale values given in Table 1.

Matching a risk level with a specific scale range makes it possible to more accurately define this membership due to using sets with bounds, which are ± 20 % fuzzy. As a result,

[8] Jang J.-S.R. ANFIS: adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, 1993, vol. 23, no. 3, pp. 665–685. DOI: 10.1109/21.256541

values in neighboring scale ranges may overlap. If a risk level belongs simultaneously to two scale ranges, a more hazardous category is selected. If a personalized health risk falls into 'Low' category or higher, relevant measures should be taken to mitigate or eliminate it.

Table 1

Scale with ranges and categories of personalized occupational health risks for workers

Risk level range	Risk category *(R)* and respective color	
$R_1 \in [0; 0.25]$	Negligible	
$R_2 \in (0.15; 0.45]$	Low	
$R_3 \in (0.35; 0.65]$	Medium	
$R_4 \in (0.55; 0.85]$	High	
$R_5 \in [0.75; 1]$	Very high	

The obtained results were graphically visualized using a fuzzy inference surface representing a 3D-graph, where X and Y axis corresponded to input data (for example, risk factors) whereas Z axis corresponded to an output risk level after defuzzification.

Training and validation of the adaptive neural fuzzy network was accomplished on an example sample made of underground miners employed at a copper and nickel ore mine. The process relied on a detailed data array containing information about working conditions, exposure factors, exposure levels, age, and individual health indicators including those obtained by profound examinations (biochemical, immunologic, hematological, general clinical, chemical-analytical, functional and instrumental studies etc., and diagnosed diseases). Overall, 175,000 qualitative and quantitative parameters were covered. The training sample volume was 80 % and the validating sample volume was 20 %. The model was trained for 100 epochs. Accuracy of personalized health risk prediction was estimated by creating an Accuracy graph where the number of training epochs was shown on the horizontal axis and the vertical axis showed the level of accuracy varying between 0 and 1 (or between 0 and 100 % where 1 means 100 % accuracy). Conventionally, two lines are shown in such a graph; the first one to estimate accuracy for a training sample and the other one for a validating (test) sample. If both lines grow gradually and reach 100 %, this means a model is being trained with high quality. Losses within training were estimated by the model by creating a Loss graph where the horizontal axis shows the number of training epochs and the vertical axis shows the value of the loss function. Similarly, two lines are shown in this graph corresponding to losses in training and validating data sets. The lower is the value of the loss function the higher is quality of an estimated model.

Results and discussion. A methodology has been developed for assessing and predicting personalized occupational health risks for workers; its theoretical grounds are represented by an adaptive neural fuzzy network for image recognition, generalization of knowledge and a resulting inference. The network has a specific hybrid multilayer (5 layers overall) architecture. The prediction principles are formulated based on the network capabilities combining advantages of fuzzy systems with neural network training and structure. This ensures prediction accuracy and minimization of errors. Key aspects of these advantages include ability to learn and adapt to new data, which makes predictions more accurate; fuzzy logic, which makes it possible to analyze fuzzy and variable data; a neural component, which ensures non-linear approximation of complex relationships between risk factors and predicted indicators (for example, likelihood of a disease) as a basis for recognition of complex patterns (image-drafts); a combination encompassing fuzzy data analysis and capability to approximate neural networks, training with the use of data, which reflect complex cause-effect relations; interpretability of a resulting output, which makes it possible to get an insight into factors with the greatest impact on risk assessment; the latter is necessary for taking adequate regulatory actions.

A personalized digital model is built relying on a theoretical concept for calculating occupational health risks; the concept is implemented by using an adaptive neural fuzzy

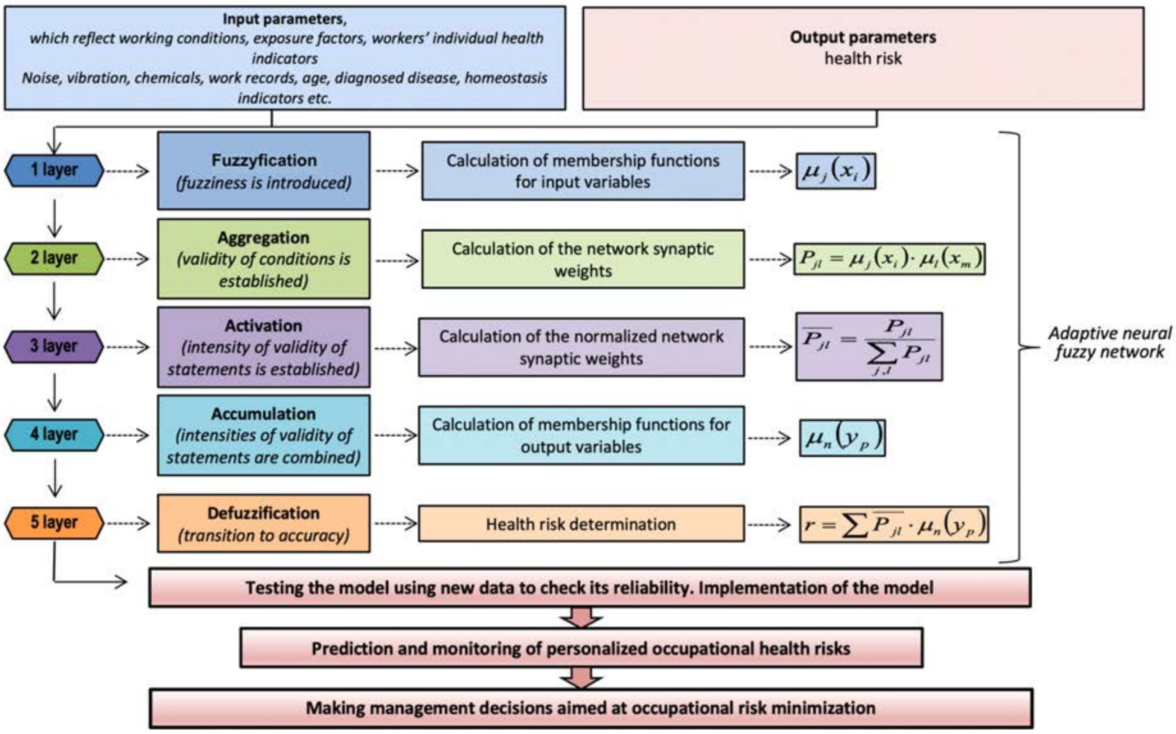

Figure 1. Multilayer hybrid architecture (5 layers) and operation stages of the adaptive neural fuzzy network for image recognition necessary for predicting personalized occupational health risks for workers

network for image recognition. Figure 1 provides basic components of the adaptive neural fuzzy network architecture.

The adaptive neural fuzzy network for image recognition includes the following subsequently linked operation stages:

– collecting and preparing analytical database about actual working conditions and exposure factors at workplaces combined with workers' personalized health indicators;

– selecting a set of input parameters (for example, noise, vibration, chemical levels in workplace air; work hardness and intensity; work records; age; individual levels of chemical in biological media; biochemical, hematological, and immunological indicator of homeostasis; functional indicators of organs and systems; a diagnosed diseases with ICD-10 code etc.) and an output resulting parameters (for example, a level of a personalized occupational health risk for a worker);

– fuzzyfication (introduction of fuzziness) using the membership functions for input variables: the first layer of network neurons (layer 1) is adaptive; it contains neurons that calculate values of membership functions for input variables: $\mu_j(x_i)$, where $x_i, i = \overline{1,n}$ are input variables. The layer ability to adapt is ensured by selecting a type of a membership function for input data, which determines level of membership of an element to a certain set. In this created system, three membership functions are employed simultaneously; they supplement each other considering their advantages, and this allows a substantial increase in prediction accuracy. They are the Gaussian function (ensures smooth transitions and accurate approximation), sigma function (implements smooth S-shaped transition of stated and a variable membership changes constantly), and trapezoid functions (represent values with complete membership at a certain interval of the membership function);

– aggregation (establishing intensity of validity of conditions) by analyzing a database of fuzzy linguistic rules: the second layer of network neurons (layer 2) is fixed; it contains neurons, which calculate the products of the membership function values established at the first layer:

$$P_{jl} = \mu_j(x_i) \cdot \mu_l(x_m), \qquad (1)$$

where P_{jl} are synaptic network weights, $\mu_j(x_i)$, $\mu_l(x_m)$ are values of the membership function;

– activation (establishing intensity of validity of statements) by normalizing levels of fuzzy rule activation, which shows, how relevant a rule is for a specific actual set of input data values, and is given by a number between 0 and 1 where 0 means complete irrelevance and 1 complete relevance. This intensity is necessary for weighing influence of each rule when creating a resulting system inference: the third layer of the network neurons (layer 3) is fixed; it contains neurons for calculating normalized synaptic network weights:

$$\overline{P_{jl}} = \frac{P_{jl}}{P_{11} + P_{12} \ldots + P_{55}}, \qquad (2)$$

where $\overline{P_{jl}}$ are normalized synaptic network weights, P_{jl} are synaptic network weights;

– accumulation (combining intensities of validity of statements) using the membership functions for output variables: the fourth layer of the network neurons (layer four 4) is adaptive; it contains neurons responsible for calculating values of the membership function for output variables and the product of values of the normalized synaptic network weights and the membership functions of output variables:

$$\overline{P_{jl}} \cdot \mu_n(y_p), \qquad (3)$$

where $\overline{P_{jl}}$ are normalized synaptic network weights, $\mu_n(y_p)$ are values of the membership functions for output variables;

– defuzzification (transition to accuracy) involving determination of the accurate value of the output variable (y_p): the fifth layer of the network neurons (layer 5) is fixed; it contains the neuron that calculates a personalized occupational health risk based on the sum of products of values of the membership function for output variables and normalized network weights:

$$R = \sum\left(\overline{P_{jl}} \cdot \mu_n(y_p)\right), \qquad (4)$$

where R is the value of a personalized occupational health risk;

– testing (validation and verification) the model using an independent set of new input data; this ensures proper tests of the model reliability, ability to generalize within image recognition and to adequately work with data not used in training;

– implementation of the model for personalized prediction, control and monitoring of occupational health risks involves use of the trained model in an actual system for health risk assessment and subsequent monitoring of changes in these risks over time.

Up to 96 % of the examined workers are simultaneously exposed to occupational noise, total vibration, chemicals (copper-nickel ore components, nitrogen oxides, carbon oxides, crystal silicon dioxide with its contents in dusts varying between 2 and 10 %, prop-2-en-1-al, ammonia, aliphatic saturated hydrocarbons C1-10 and other substances) in workplace air, work hardness and intensity. Duration of exposure varies between 2 and 22 years; the workers' age, between 43 and 63 years.

The results obtained by training the adaptive neural fuzzy network are given as the Accuracy and Loss graphs (Figure 2).

According to the Accuracy graph, the model is shown to remember training input data and to make personalized predictions of occupational health risks for the training sample (the blue line) with accuracy reaching 55 %; for the validating sample, (orange line), with accuracy reaching 72 %.

The Loss graph shows that the model error value tends to decline steadily over time for the training sample; the descending time-dependent trend is even more pronounced for the validating sample and its subsequent fluctuations are at the minimum, which means the model has been trained successfully and is quite stable.

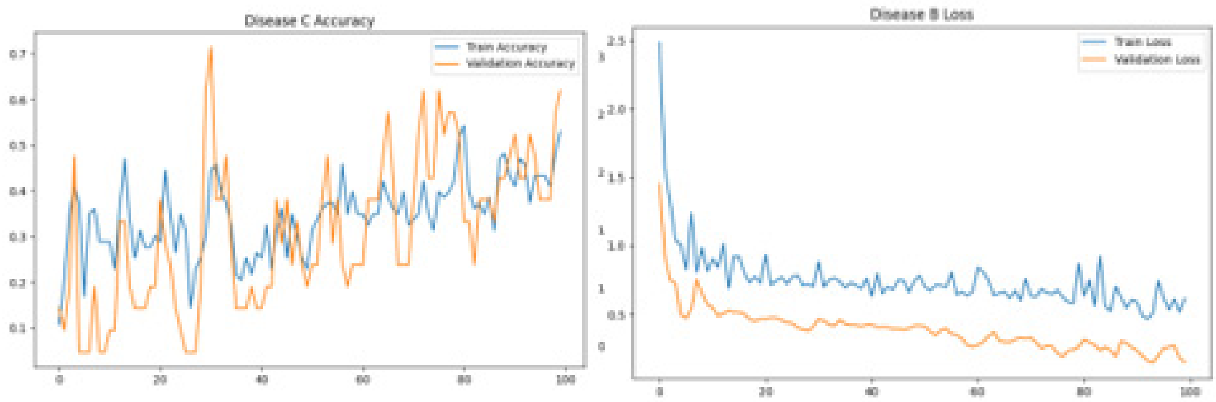

Figure 2. Accuracy and Loss graphs to describe the results obtained by training the adaptive neural fuzzy network

Table 2

Assessment and prediction of the group occupational health risk for all workers in thee validating sample

Disease	Predicted group occupational health risk for workers upon exposure to various combinations of occupational factors, work process, work records, etc.				
	Chemicals, work records	Noise, work records	Vibration, work records	Chemicals, vibration	Vibration, noise
Vibration disease	0.09	0.23	0.54	0.72	0.80
Sensorineural hearing loss	0.31	0.26	0.03	0.35	-
Dorsopathy	0.03	0.17	0.37	0.41	0.67

Our tests of the network involved assessing and predicting the group occupational health risks accomplished for the whole validating sample (Table 2). For example, simultaneous exposure to vibration and occupational noise was established to create the highest health risks caused by vibration disease (R = 0.80) and dorsopathy (R = 0.67). Combined exposure to occupational vibration and chemicals in workplace air created a group occupational risk (R = 0.35) caused by sensorineural hearing loss (SHL); it was assessed as ‘medium’.

We established personalized occupational health risks for each worker from the validating sample; individual risks caused by vibration disease were assessed as ‘high’, for example, upon exposure to occupational noise 10–40 dBA higher than MPL over a work shift and total vibration at the level of 106–113 dB considering the whole set of biological and medical health measures and other affecting factors (Figure 3). Using one specific worker from this sample as an example, we showed that a personalized health risk caused by SHL was equal to 0.85 and assessed as ‘very high’ (Figure 3) upon simultaneous exposure to total occupational vibration at the level of 109 dB and occupational noise (11 dBA higher than MPL) considering his individual health indicators and against all other affecting factors.

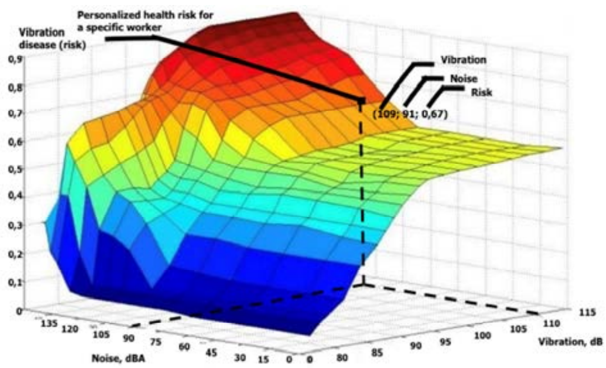

Figure 3. Graph which visualizes the surface of the fuzzy inference to assess personalized occupational health risk caused by vibration disease depending on exposure to occupational noise and work records against other affecting factors (a point at the surface denotes a specific worker with a personalized occupational health risk)

In another example, individual health risks are caused by SHL and are assessed as varying from medium to very high (Figure 4) upon combined exposure to occupational noise (5–30 dBA above MPL) and several chemicals (2.0–2.5 times higher than single maximum MPC) against other affecting factors. Using one specific worker from this sample as an example, an individual health risk caused by SHL was shown to equal 0.85 and assessed as 'very high' (Figure 4) upon simultaneous exposure to occupational noise 29 dB higher than MPL and chemicals in workplace air at the level 2.2 times higher than single maximum MPC considering his individual health indicators and against other affecting factors.

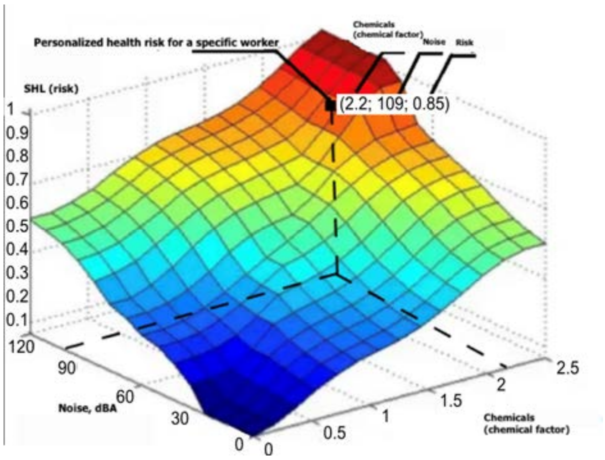

Figure 4. Graph which visualizes the surface of the fuzzy inference to assess personalized occupational health risk caused by SHL depending on combined exposure to physical (occupational noise) and chemical factors against other affecting factors (a point at the surface denotes a specific worker with a personalized occupational health risk)

We predicted personalized occupational health risks for workers from an independent sample (the model was tested using blast-hole drillers) using the adaptive neural fuzzy network. Our prediction showed that risks of expected occupational diseases and work-related diseases varied between low and high; of them, 75 % were caused by vibration disease; 48 %, polyneuropathy; 6 %, SHL; 75 % dorsopathy; 30 %, essential hypertension. Profound medical examinations of blast-hole drillers gave evidence that predicted health risks were actually realized in 87–89 % of the examined workers. The examinations established occupational diseases associated with simultaneous exposure to total vibration, occupational noise, work hardness and intensity including vibration disease, stage I, II and I-II (ICD-10 code T75.2), polyneuropathy (G62.8), and SHL (H90.6). Work-related diseases included neck and lumbar spine dorsopathy (M53.8) and essential hypertension (I11). Those workers were provided with individual recommendations to take medical and preventive measures aimed at reducing manifestations of negative health outcomes associated with working conditions. Rospotrebnadzor's territorial bodies were informed about predicted individual occupational health risks for workers employed at underground copper and nickel ore mining.

Therefore, this developed and software-supported methodology for assessing and predicting personalized occupational health risk is based on using the adaptive neural fuzzy network for image recognition. The methodology is quite effective, which is confirmed by the results of its testing on an independent dataset. The prediction accuracy is estimated to reach 89 ± 2 % and the prediction error trend comes to minimum ('flat bottom'). The system based on the suggested methodology has shown more accurate predictions, the results were easier to interpret; the system was more resistant to incomplete and variable data and errors in them and was able to optimize parameters on its own more effectively as compared to simplified statistical methods. The suggested scientific and methodical instruments based on image recognition provide a considerably wider opportunity to obtain prompt and accurate personalized prediction of occupational health risks for workers. This ensures making adequate decisions given multiple and uncertain cause-effect relations; allows developing more targeted, personalized and pathogenetically oriented preventive measures regulated by the valid legislation covering sanitary-epidemiological requirements to working conditions. The system is eligible for workers employed at variable productions and implements a transition from contact-based examinations to quantitative prediction without any information losses, which determines its scalability and possibility to replicate it.

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References

1. Bukhtiyarov I.V. Current state and main directions of maintaining and strengthening the health of the working population of Russia. *Meditsina truda i promyshlennaya ekologiya*, 2019, vol. 59, no. 9, pp. 527–532. DOI: 10.31089/1026-9428-2019-59-9-527-532 (in Russian).

2. Panova T.V. Zdorov'e rabotayushchego naseleniya – vazhneishee uslovie kachestva proizvoditel'nosti truda [Health of the working population is the most important condition for quality and labor productivity]. *Ekonomicheskie nauki*, 2018, no. 4 (161), pp. 39–41 (in Russian).

3. Chebotarev A.G., Pfaf V.F., Gibadulina I.Yu. Current State of Labour Conditions, Occupational Morbidity and Improvement of Medical and Preventive Care for Employees of Mining Operations. *Gornaya promyshlennost'*, 2021, no. 3, pp. 139–143. DOI: 10.30686/1609-9192-2021-3-139-143 (in Russian).

4. Meltser A.V., Erastova N.V., Volochkova A.I. Hygienic aspects of preserving and strengthening the health of employees in corporate programs (scientific review). *Profilakticheskaya i klinicheskaya meditsina*, 2024, no. 4 (93), pp. 4–12 (in Russian).

5. Gurvich V.B., Gazimova V.G., Shastin A.S., Fedoruk A.A., Ruzakov V.O., Plotko E.G. The basic organizational problems of preventing morbidity of working population in modern conditions. *Meditsina truda i promyshlennaya ekologiya*, 2018, no. 11, pp. 32–35. DOI: 10.31089/1026-9428-2018-11-32-35 (in Russian).

6. Ustinova O.Yu., Zaitseva N.V., Vlasova E.M., Kostarev V.G. Corporate programs for preventing health disorders among workers employed at adverse productions as a tool for occupational risk management. *Health Risk Analysis*, 2020, no. 2, pp. 72–82. DOI: 10.21668/health.risk/2020.2.08.eng

7. Zheglova A.V., Yatsyna I.V., Gavrilchenko D.S. Corporate health preservation programs are the main element of the health-saving system of the working population. *Zdravookhranenie Rossiiskoi Federatsii*, 2022, vol. 66, no. 5, pp. 385–389. DOI: 10.47470/0044-197X-2022-66-5-385-389 (in Russian).

8. Nikanov A.N., Vinnikov D.V., Syurin S.A., Shitikova E.D. Occupational diseases in pyrometallurgical nickel refining workers of various specialties. *ZNiSO*, 2024, vol. 32, no. 5, pp. 66–75. DOI: 10.35627/2219-5238/2024-32-5-66-75 (in Russian).

9. Panev N.I., Korotenko O.Yu., Filimonov S.N., Semenova E.A., Panev R.N. Prevalence of cardiovascular pathology in workers of the aluminum industry. *Gigiena i sanitariya*, 2019, vol. 98, no. 3, pp. 276–279. DOI: 10.18821/0016-9900-2019-98-3-276-279 (in Russian).

10. Syurin S.A., Kovshov A.A. Working conditions and work-related pathologies at enterprises located in Chukotka autonomous area. *Health Risk Analysis*, 2020, no. 4, pp. 98–105. DOI: 10.21668/health.risk/2020.4.11.eng

11. Chebotarev A.G., Sementsova D.D. Comprehensive assessment of working conditions and occupational disease rates at mining and metallurgical enterprises. *Gornaya promyshlennost'*, 2021, no. 1, pp. 114–119. DOI: 10.30686/1609-9192-2021-1-114-119 (in Russian).

12. Bukhtiyarov I.V., Chebotarev A.G., Courierov N.N., Sokur O.V. Topical issues of improving working conditions and preserving the health of employees of mining enterprises. *Meditsina truda i promyshlennaya ekologiya*, 2019, vol. 59, no. 7, pp. 424–429. DOI: 10.31089/1026-9428-2019-59-7-424-429 (in Russian).

13. Shur P.Z., Goryaev D.V. Sovremennye korporativnye programmy snizheniya professional'nogo riska zdorov'yu kak sredstva sokhraneniya trudovykh resursov [Modern corporate programs for reducing occupational health risks as a means of preserving human resources]. *Gumanizatsiya ekonomiki: blagopoluchie cheloveka i kreativnyi kapital: IX Permskii ekonomicheskii kongress [Humanization of the economy: human well-being and creative capital: IX Perm Economic Congress]*. Perm, 2025. Available at: https://economcongress.ru/wp-content/uploads/2024/02/5-Shur-Goryaev.pdf (May 23, 2025) (in Russian).

14. Titova E.Ya., Golub' S.A. Contemporary problems of health protection for workers employed at a large industrial enterprise and working under occupational hazards. *Health Risk Analysis*, 2017, no. 4, pp. 83–90. DOI: 10.21668/health.risk/2017.4.09.eng

15. Shaikhlislamova E.R., Karimova L.K., Volgareva A.D., Muldasheva N.A. Occupational health of workers in underground occupations producing polymetalliccopperzinc ores. *Sanitarnyi vrach*, 2020, no. 5, pp. 9–22. DOI: 10.33920/med-08-2005-01 (in Russian).

16. Bukhtiyarov I.V., Chebotarev A.G., Prokhorov V.A. Problems of the promotion of healthy working environment, prevention of occupational diseases of the personnel of a mining and smelting complex. *Gornaya promyshlennost'*, 2015, no. 6 (124), pp. 14–17 (in Russian).

17. Denisenko M.B., Mkrtchyan N.V. Demograficheskie izmeneniya i predlozhenie rabochei sily v regionakh Rossii [Demographic changes and labor supply in the regions of Russia]. *Nauchnyi daidzhest*, 2022, no. 5 (10), 10 p. (in Russian).

18. Kontsevaya A.V. Korporativnye programmy ukrepleniya zdorov'ya v ramkakh Natsional'nogo proekta «Prodolzhitel'naya i aktivnaya zhizn'» [Corporate health promotion programs within the framework of the National Project «Long and Active Life»]. *Meditsinskii komponent korporativnykh programm ukrepleniya zdorov'ya na rabochem meste: vozmozhnosti 2025»: simpozium v ramkakh XX Vserossiiskogo foruma «Zdorov'e natsii – osnova protsvetaniya Rossii»* [*Medical Component of Corporate Health Promotion Programs at the Workplace: Possibilities for 2025: symposium within the framework of the XX All-Russian Forum "Health of the Nation – the Basis for Russia's Prosperity»*]. Moscow, May 14–16, 2025. Available at: https://docs.yandex.ru/docs/view?tm=1750087297&tld (June 10, 2025) (in Russian).

19. Fokin V.A., Zaitseva N.V., Shur P.Z., Redko S.V., Khrusheva E.V. Assessing and predicting individual occupational risk and determining its exact categories using probabilistic methods. *Health Risk Analysis*, 2021, no. 4, pp. 92–99. DOI: 10.21668/health.risk/2021.4.10.eng

20. Ponomareva T.A., Vorobeva A.A., Vlasova E.M., Ustinova O.Yu. Rehabilitation of employees of titanium-magnesium production with the installed disease of the upper respiratory ways. *Meditsina truda i ekologiya cheloveka*, 2019, no. 4 (20), pp. 39–49. DOI: 10.24411/2411-3794-2019-10046 (in Russian).

21. Zaitseva N.V., Kiryanov D.A., Zemlyanova M.A., Goryaev D.V., Ustinova O.Yu., Shur P.Z. Conceptual foundations of a corporate intelligent risk-based system for analysis, prediction and prevention of occupational and work-related health disorders of workers. *Health Risk Analysis*, 2023, no. 4, pp. 19–32. DOI: 10.21668/health.risk/2023.4.02.eng

22. Bukhriayrov I.V., Kuzmina L.P., Izmerova N.I., Golovkova N.P., Nepershina O.P. Improvement of mechanisms of detecting early signs of health disorders for preservation labor longevity. *Meditsina truda i promyshlennaya ekologiya*, 2022, vol. 62, no. 6, pp. 377–387. DOI: 10.31089/1026-9428-2022-62-6-377-387 (in Russian).

23. Gridina N.V., Evdokimov I.A., Solodovnikov V.I. Construction of hybrid neural networks using fuzzy logic elements. *Iskusstvennyi intellekt i prinyatie reshenii*, 2019, no. 2, pp. 91–97. DOI: 10.14357/20718594190209 (in Russian).

24. Teslenko A. Neuro-fuzzy methods in the management of technical systems and objects. Yazyk v sfere professional'noi kommunikatsii: sbornik materialov mezhdunarodnoi nauchno-prakticheskoi konferentsii prepodavatelei, aspirantov i studentov [Language in the Sphere of Professional Communication: Collection of Materials of the International Scientific and Practical Conference of Teachers, Postgraduates, and Students]. Ekaterinburg, Azhur Publ., 2020, pp. 698–703 (in Russian).

25. Andrievskaya N.V., Reznikov A.S., Cheranev A.A. Features of application of neuro fuzzy systems in systems of automatic control. *Fundamental'nye issledovaniya*, 2014, no. 11–7, pp. 1445–1449 (in Russian).

26. Abushariah M.A.M., Alqudah A.A.M., Adwan O.Y., Yousef R.M.M. Automatic heart disease diagnosis system based on artificial neural network (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) approaches. *Journal of software engineering and applications*, 2014, vol. 7, no. 12, pp. 1055–1064. DOI: 10.4236/jsea.2014.712093

27. Glushenko S.A. An adaptive neuro-fuzzy inference system for assessment of risks to an organization's information security. *Business Informatics*, 2017, no. 1 (39), pp. 68–77. DOI: 10.17323/1998-0663.2017.1.68.77 (in Russian).

28. Alkhashedi A.A., Obadi A.A., Nuriev N.K., Pechenyy E.A. Development of a mathematical model for recognition task requests of communications services. *Fundamental'nye issledovaniya*, 2017, no. 6, pp. 9–14 (in Russian).
29. Yankovskaya A.E., Kitler S.V. Prinyatie reshenii na osnove parallel'nykh algoritmov testovogo raspoznavaniya obrazov [Decision-making based on parallel algorithms for test image recognition]. *Iskusstvennyi intellekt*, 2010, no. 3, pp. 151–152 (in Russian).

Zaitseva N.V., Savochkina A.A., Zemlyanova M.A., Goryaev D.V., Fadeev A.G. Methodology for assessing and predicting personalized occupational health risks based on adaptive neural fuzzy network for image recognition. Health Risk Analysis, 2025, no. 2, pp. 4–15. DOI: 10.21668/health.risk/2025.2.01.eng

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