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Neural Network Model for Control of Operating Modes of Crushing and Grinding Complex

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Abstract: This article investigates the application of neural network models to create automated control systems for industrial processes. We reviewed and analysed works on dispatch control and evaluation of equipment operating modes and the use of artificial neural networks to solve problems of this type. It is shown that the main requirements for identification models are the accuracy of estimation and ease of algorithm implementation. It is shown that artificial neural networks meet the requirements for accuracy of classification problems, ease of execution and speed. We considered the structures of neural networks that can be used to recognise the modes of operation of technological equipment. Application of the model and structure of networks with radial basis functions and multilayer perceptrons for identifying the mode of operation of equipment under given conditions is substantiated. The input conditions for constructing neural network models of two types with a given three-layer structure are offered. The results of training neural models on the model of a multilayer perceptron and a network with radial basis functions are presented. The estimation and comparative analysis of models depending on model parameters are made. It is shown that networks with radial basis functions offer greater accuracy in solving identification problems. The structural scheme of the automated process control system with mode identification based on artificial neural networks is offered.

Keywords: classification, modelling, neural network, networks with radial basis functions, RBF, multilayer perceptron, MLP

1. Introduction

Due to the development of digital technologies, more data is becoming available for control systems. The operation mode of the equipment is determined, as a rule, not by one parameter but by a set of parameters. However, the increase in the amount of information leads to an overload of the operator, which is most dangerous in critical situations: a stressful state of an operator, in combination with the growing flow of data about the plant, leads to incorrect decisions and even more significant losses. The advantage of operators in the control system is their experience in assessing operating modes, and the advantage of automated control systems is reliability and speed in decision-making. Therefore, there is a need to develop systems that could work in real-time to support or substitute the operator. Restoration of the normal operation of the equipment begins from the moment of identification of the event that caused the malfunction or violation of the mode.

2. Analysis of recent research and publications

The heuristic nature of human operator decision-making and the implicit functional relationship between the causes of equipment failures provide the precondition for creating systems based on artificial intelligence. Expert systems, fuzzy logic, neural networks and genetic algorithms are used with varying degrees of success to create support and management systems (Kalinchyk et al. 2021, Warwick et al. 1997).

The main advantage of Artificial Neural Networks (ANN) in diagnosing equipment failures is their flexibility with significant data flow and information interference. The main disadvantage is the duration of the training and the need for significant training samples that characterise the situation. Generalised regression neural networks (GRNN) with direct signal topology, probabilistic neural network (PNN), or adaptive (self-organised) fuzzy neural networks can be used to reduce learning time to acceptable results (Rolim et al. 2003).

Experience in the operation of electric motors shows many failures associated with emergencies (Ponomarev et al. 2011).

Failure of the engine causes significant damage, associated with both downtime of technological equipment and the need for repair work. Additional damage can occur due to reduced electrical and fire safety, which is associated with possible short circuits in the windings of the damaged motor. It is known that when the engine is running, there are short-term fluctuations in electrical quantities, such as current, power, and voltage. Therefore, while analysing the waveform of electrical quantities, it is possible to determine the possible damage and determine its type. For example, by constructing an approximation function on several points of the signal that characterises a particular type of damage, and in the process of diagnosis, to compare the current values with the values of this function with a certain error. Artificial neural networks are used to build mathematical models of various processes, pattern recognition and signal prediction. Examples of using ANN to solve problems related to automated control are: the estimation of the spectral composition of the information signal and classification of signals for decision-making (Malisuwan et al. 2016, Faek et al. 2009), classification of non-stationary data to create automatic control systems (Venkatesan et al. 2018), operational control of technological processes (Yang et al. 2021). Thus, neural networks make it possible to effectively determine the mode of operation of the complex and highlight the influence of individual factors on the target function, reflecting only the existence between the input and output values of the objective relationships.

3. The goal of this paper

This paper investigates the crushing and grinding complex's characteristics and modes of operation. The work aims to create a control system of a crushing and grinding complex to identify the mode of operation. The following objectives are addressed in the paper to achieve this goa:

- determining operating modes of the crushing and grinding complex,
- selecting the type and configuration of the artificial neural network to identify the mode of operation of the plant,
- modelling the operating modes of the plant and evaluating the quality of the neural network to identify the state,
- creating a structural scheme of the control system of the crushing and grinding complex.

4. Presentation of the primary research material

When assessing the operational condition of the equipment, there are three provisions (Lukomski et al. 2003, Nguyen et al. 1995):

- normal or safe condition, where all indicators of the process are within normal limits,

- a warning or critical condition, where one or more indicators are approaching dangerous values,
- emergency or dangerous condition in which the normalised values are exceeded.

When approaching emergency conditions, the operator's load increases due to the flow of data that requires processing, which is called the "curse of dimensionality". However, the problem of exponential growth of information flow can be solved with the help of artificial neural networks.

Among the many types of ANN, it is worth noting that the multilayer perceptron, trained in the algorithm of backpropagation of error, capable of online learning. However, the main problem in the work of the perceptron is the selection of a training sequence of sufficient volume.

Multilayer perceptron (MLP) (Fig. 1) is described by the following equations (Kruglov et al. 2002).

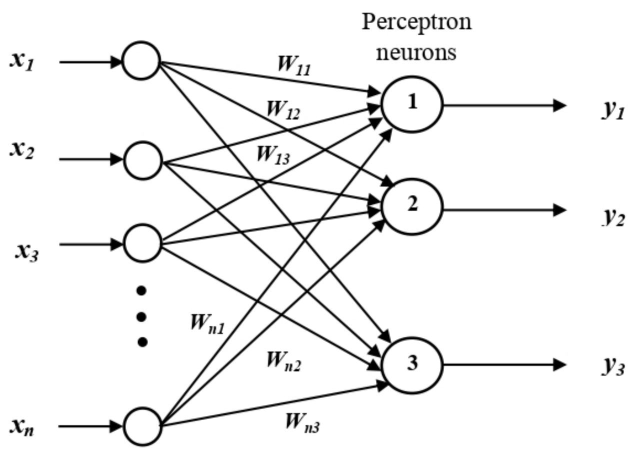

Fig. 1. Multilayer perceptron

At *n* inputs, input signals are fed, which then fall on the synapses of the three neurons that form the output layer of the network. At the outputs of the network, signals are generated:

$$y_i = f(\sum_{i-1}^{n} x_i \cdot w_{ij}) \tag{1}$$

The synapse weights of one layer of neurons can be represented as a matrix W, in which each element w_{ij} sets the value of the i-th synaptic connection of the j-th neuron. Thus, the processes occurring in the MLP neural network can be presented in matrix form:

$$Y = F(X \cdot W), \tag{2}$$

where:
X and Y – input and output vectors, respectively,
F – an activation function applied element by element to the parameters X, W.

Another type of network used to solve classification problems is the radial basis function (RBF) network. Networks with RBFs in the simplest form consist of three layers: the input layer that performs the distribution of sample data for the first layer of weights and the hidden and source layer (Callan 2000). The mapping from the input layer to the hidden layer is non-linear, while the mapping from the hidden layer to the output layer is linear.

Some hidden function φ is connected with each hidden element. Each of these functions accepts a combined input and generates an output activity value. The set of activity values of all hidden elements determines the vector on which the input vector is displayed.

$$\varphi(x) = \left[\varphi(x_1), \varphi(x_2) ... \varphi(x_M)\right], \tag{3}$$

where:
M – the number of hidden elements,
x – the input vector.

The connections of the elements of the hidden element determine the centre of the radial function for this hidden element. The input for each element is chosen equal to the Euclidean form:

$$net_j = \left\| x - w_j \right\| = \left[\sum_{i=1}^{n} (x_i - w_{ij})^2 \right]^{\frac{1}{2}}, \tag{4}$$

where:
n – the number of input elements.

Various functions are used for hidden elements, such as the Gaussian function:

$$\phi(r) = \exp(-r^2) \text{ or } \phi(r) = \sqrt{c^2 + r^2}\ . \tag{5}$$

Radial basis function (RBF) networks and multilayer perceptron (MLP) networks are examples of non-linear multilayer direct propagation networks (Haykin 2009). Both are universal approximators. However, these two types of networks differ in some essential aspects.

1. An RBF network has one hidden layer, and a multilayer perceptron can have many hidden layers.
2. Typically, computational nodes of a multilayer perceptron, which are located in the hidden and source layers, use the same neuron model. Hidden network computing nodes with radial basis functions may differ from the source layer and serve different purposes.
3. The hidden layer of an RBF network is non-linear, while the source layer is linear. In a multilayer perceptron (MLP), the latent and source layers used as a classifier are non-linear. If an MLP is used to solve non-linear regression problems, linear neurons are usually chosen as the nodes of the source layer.
4. The argument of the activation function of each hidden node of the RBF network is the Euclidean norm between the input vector and the centre of the radial function. The argument of the activation function of each hidden node is the scalar product of the input vector and the vector of synaptic weights of this neuron.

In order to build a control system without any plant operator, it is necessary to solve the problem of error-free recognition of emergency modes and distinguish them from short-term modes allowed for this plant. This task is to identify the signs (properties) of the controlled plant and characteristics of the predominant class of modes and then develop the principle of operation of the protection and control system. The peculiarity of statistical image recognition is that the mode studied and described by n-parameters can be represented as an n-dimensional space of observations. If one gets a training statistical sample of situations with established affiliation to a class of modes, one can build in the space of boundary modes boundary surfaces that separate situations of different classes. The recognition procedure is a decision to establish belonging to a particular class of a new situation by comparing its parameters.

The paper evaluates and classifies the modes of operation of the crushing and grinding complex based on data on specific power consumption (W), performance (Q), the load of the mill (M) and grinding tone (T), which characterises the quality of the original product. The total sample of observations consists of 113 observations, which is provided in the form of a table (Table 1) and a graph of the distribution in the coordinates of specific power consumption (W) and performance (Q) (Fig. 2). Modes are divided into three classes: a – mode of optimal performance and electricity consumption, b – mode of low performance, c – mode of inflated specific electricity consumption. The classification will be based on 80 observations, and the last day's data will serve as a control sequence to verify the model's accuracy. The model's accuracy will be assessed by the average value of the relative error in the control sequence and the value of the relative error in classification.

Table 1. Indicators of operating modes of the complex

№	Q	M	W	T	Class	№	Q	M	W	T	Class
	x1	x2	y	z			x1	x2	y	z	
1	8.65	0.98	30.630	14.00	b	27	9.90	0.68	27.820	14.00	a
2	9.90	0.96	25.413	17.75	a	28	10.10	0.64	28.000	15.25	a
3	8.80	0.91	29.043	14.00	b	29	10.60	0.61	24.350	14.80	a
4	10.2	0.86	39.707	17.00	b	30	10.40	0.59	27.080	13.50	a
5	9.40	0.84	40.446	16.00	b	31	10.40	0.57	26.880	14.00	a
6	10.40	0.82	27.872	18.00	a	32	10.00	0.54	27.940	14.25	a
7	11.00	0.78	24.402	19.00	a	33	10.20	0.51	26.360	14.00	a
8	9.90	0.76	27.723	12.50	a	34	9.95	0.49	26.950	12.75	a
9	10.60	0.73	28.136	18.50	a	35	9.90	0.94	26.390	16.75	a
10	10.00	0.71	24.315	16.50	a	36	10.80	0.90	29.310	13.90	a
11	9.60	0.70	25.760	14.50	a	37	10.50	0.87	30.390	11.75	a
12	9.30	0.66	28.110	16.75	b	38	10.80	0.83	30.340	13.50	a
13	9.50	0.63	27.903	13.75	b	39	10.80	0.80	26.980	15.25	a
14	9.60	0.59	28.797	16.00	a	40	10.80	0.77	30.110	12.75	a
15	9.20	0.57	27.627	16.00	b	41	10.80	0.73	29.120	13.70	a
16	9.10	0.55	28.951	14.15	b	42	10.50	0.71	31.410	13.00	a
17	9.50	0.98	32.845	14.75	b	43	9.90	0.69	33.590	14.75	b
18	10.00	0.96	33.319	13.50	a	44	8.40	0.65	42.200	17.00	b
19	10.40	0.92	29.870	14.00	a	45	10.30	0.64	29.710	18.25	a
20	11.20	0.88	26.102	16.50	a	46	11.90	1.06	35.770	19.75	a
21	10.80	0.84	27.543	16.50	a	47	10.20	1.05	31.580	21.00	a
22	9.80	0.82	27.884	14.75	a	48	9.40	1.03	31.730	24.50	b
23	10.10	0.78	29.882	13.75	a	49	11.00	1.01	31.500	18.50	a
24	11.00	0.74	26.494	20.50	a	50	11.20	0.98	29.470	17.50	a
25	10.20	0.72	30.420	11.20	a	51	11.60	0.95	30.860	20.80	a
26	10.20	0.70	26.620	12.50	a	52	10.90	0.92	28.860	18.50	a

Table 1. cont.

№	Q	M	W	T	Class	№	Q	M	W	T	Class
	x1	x2	y	z			x1	x2	y	z	
53	10.60	0.89	32.320	18.50	a	84	9.75	0.4	21.65	15.75	a
54	9.40	0.86	28.660	16.00	b	85	9.7	0.38	25.36	18.25	a
55	8.40	0.84	30.860	12.00	b	86	10.6	0.36	23.85	19.25	a
56	9.80	0.82	30.720	13.50	a	87	10.3	0.83	27.07	22.00	a
57	10.60	0.79	28.200	14.00	a	88	9.5	0.79	31.97	18.00	b
58	9.5	0.77	28.84	26.00	b	89	10.0	0.77	32.21	15.90	a
59	8.9	0.73	35.39	19.00	b	90	10.4	0.73	32.92	17.25	a
60	10.5	0.72	31.07	23.00	a	91	9.6	0.69	28.28	19.25	a
61	10.3	0.69	29.57	20.00	a	92	10.6	0.66	29.56	19.65	a
62	10.7	0.65	25.25	18.75	a	93	10.6	0.62	24.34	21.90	a
63	11.6	0.62	26.67	23.00	a	94	10.1	0.59	31.86	19.33	a
64	11.1	0.61	23.61	23.00	a	95	10.3	0.56	30.83	16.50	a
65	10.2	0.59	28.87	16.25	a	96	10.3	0.53	31.97	18.50	a
66	9.97	0.56	28.78	24.33	a	97	10.3	0.52	24.34	21.70	a
67	12.0	0.53	35.83	23.50	a	98	10.3	0.5	28.14	20.00	a
68	11.8	0.53	32.81	21.00	a	99	10.3	0.49	24.06	21.00	a
69	11.6	0.93	29.74	18.75	a	100	10.3	0.48	28.14	20.00	a
70	11.6	0.88	30.97	18.50	a	101	10.0	0.93	31.13	19.85	a
71	11.6	0.84	29.45	19.50	a	102	9.8	0.88	32.65	20.00	a
72	11.4	0.82	30.07	21.50	a	103	9.7	0.81	32.49	20.00	a
73	11.3	0.76	30.59	17.50	a	104	10.1	0.79	30.56	18.50	a
74	11.8	0.71	28.55	20.00	a	105	9.97	0.75	31.24	18.33	a
75	10.8	0.67	28.94	18.25	a	106	10.1	0.72	32.38	24.40	a
76	11.2	0.63	25.72	22.50	a	107	9.3	0.69	32.48	24.00	b
77	10.6	0.59	24.06	21.50	a	108	10.0	0.68	37.49	15.50	b
78	10.3	0.56	27.66	17.00	a	109	9.5	0.66	30.17	13.00	b
79	10.2	0.54	24.65	17.25	a	110	9.33	0.64	29.70	14.17	a
80	10.4	0.51	25.55	19.60	a	111	9.6	0.62	35.25	14.50	b
81	10.4	0.48	24.48	18.85	a	112	9.2	0.6	31.09	13.50	b
82	10.2	0.44	22.65	18.75	a	113	9.1	0.59	29.45	18.00	b
83	10.2	0.42	24.54	19.00	a						

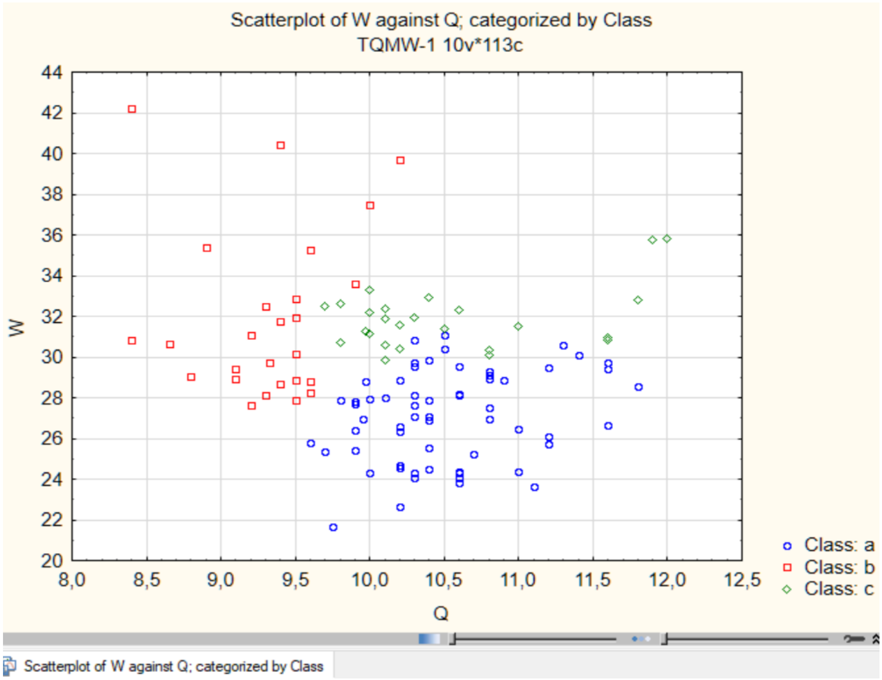

Fig. 2. Graphic representation of operating modes of the complex

Multilayer perceptron and networks with radial basis functions are accepted as models for the classification of modes. The number of inputs (2-3) of the network is determined by the number of parameters that determine the operating mode. In order to obtain a value that describes the target categorised function, three source elements are used, which correspond to a given number of classes. The number of neurons in the hidden layer of the perceptron is set at 3 to 25, and at 10 to 50 for networks with radial basis functions and will be adjusted depending on the accuracy of the model, which will be determined by performance on training and test sequences (70, 15 and 15% of the total sample respectively and selected at random). Threshold activation functions may take linear, logistic, hyperbolic, and exponential values. The error function is determined by the method of least squares and cross-entropy. We considered 2000 networks with randomly formed initial weights, from which the 50 best results are automatically selected based on which conclusions will be made about the suitability of networks to solve this type of problem. Network learning algorithms are BFGS (Broyden - Fletcher - Goldfarb - Shanno algorithm) for perceptron and RBFT (Redundant Byzantine Fault. Tolerance). The outcomes of neural network learning are presented in Table 2. Table 2 uses the following notation: Training perf. – network performance on input data; Test perf. – network performance on the test sequence: Validation perf. – network performance on the control sequence. Productivity refers to the percentage of correct classification in the data sample. The sum of squares of deviations (SOS) and cross-entropy (Entropy) are used as the Error function. The Hidden activation functions in the networks with the best performance are linear (Identity), logistic or sigmoidal (Logistic), hyperbolic tangent (Tanh), exponential (Exponentia) and Gaussian (Gaussian) functions.

Table 3 presents the matrix of errors for each of the constructed networks, which contains the percentage of correctly or incorrectly classified data for each class and the total number for all classes. All trained networks have no errors in the training sequences. In the test and control sequences, the learning error for all classes does not exceed 6.25% for individual networks. These results indicate sufficient accuracy of networks.

Table 2. Neural Networks Learning Outcomes (Q, W, M)

№	Net. name	Training perf.	Test perf.	Validation perf.	Training algorithm	Error function	Hidden activation
1	RBF 3-10-3	91.3580247	100	100	RBFT	SOS	Gaussian
2	RBF 3-50-3	98.7654321	93.75	100	RBFT	Entropy	Gaussian
3	RBF 3-10-3	82.7160494	93.75	100	RBFT	SOS	Gaussian
4	RBF 3-50-3	100	93.75	100	RBFT	Entropy	Gaussian
5	RBF 3-50-3	95.0617284	93.75	100	RBFT	Entropy	Gaussian
6	RBF 3-10-3	93.8271605	87.50	100	RBFT	Entropy	Gaussian
7	RBF 3-10-3	91.3580247	81.25	100	RBFT	Entropy	Gaussian
8	RBF 3-10-3	95.0617284	93.75	100	RBFT	Entropy	Gaussian
9	MLP 3-10-3	90.1234568	87.50	100	BFGS 8	Entropy	Identity
10	RBF 3-50-3	97.5308642	87.50	100	RBFT	Entropy	Gaussian
11	RBF 3-10-3	90.1234568	81.25	100	RBFT	SOS	Gaussian
12	RBF 3-10-3	91.3580247	81.25	100	RBFT	Entropy	Gaussian
13	RBF 3-50-3	100	93.75	100	RBFT	Entropy	Gaussian
14	MLP 3-8-3	86.4197531	93.75	93.75	BFGS 8	Entropy	Identity
15	RBF 3-10-3	97.5308642	93.75	100	RBFT	Entropy	Gaussian
16	RBF 3-10-3	95.0617284	93.75	100	RBFT	Entropy	Gaussian
17	RBF 3-10-3	95.0617284	93.75	100	RBFT	Entropy	Gaussian
18	RBF 3-10-3	81.4814815	93.75	93.75	RBFT	Entropy	Gaussian
19	RBF 3-10-3	91.3580247	87.50	93.75	RBFT	Entropy	Gaussian
20	RBF 3-50-3	100	100	93.75	RBFT	Entropy	Gaussian
21	MLP 3-9-3	96.2962963	93.75	93.75	BFGS 15	Entropy	Logistic
22	RBF 3-10-3	97.5308642	87.50	93.75	RBFT	Entropy	Gaussian
23	RBF 3-10-3	83.9506173	87.50	93.75	RBFT	Entropy	Gaussian
24	RBF 3-50-3	96.2962963	93.75	93.75	RBFT	Entropy	Gaussian
25	RBF 3-50-3	98.7654321	93.75	93.75	RBFT	Entropy	Gaussian

Table 2. cont.

№	Net. name	Training perf.	Test perf.	Validation perf.	Training algorithm	Error function	Hidden activation
26	RBF 3-10-3	91.3580247	93.75	93.75	RBFT	Entropy	Gaussian
27	RBF 3-10-3	86.4197531	87.50	93.75	RBFT	Entropy	Gaussian
28	MLP 3-4-3	97.5308642	87.50	93.75	BFGS 23	SOS	Identity
29	RBF 3-10-3	88.8888889	81.25	93.75	RBFT	SOS	Gaussian
30	RBF 3-10-3	87.654321	93.75	93.75	RBFT	SOS	Gaussian
31	RBF 3-10-3	86.4197531	81.25	93.75	RBFT	SOS	Gaussian
32	MLP 3-4-3	80.2469136	93.75	93.75	BFGS 20	SOS	Exponential
33	RBF 3-10-3	91.3580247	93.75	93.75	RBFT	Entropy	Gaussian
34	MLP 3-8-3	97.5308642	93.75	93.75	BFGS 18	Entropy	Tanh
35	RBF 3-10-3	91.3580247	93.75	93.75	RBFT	Entropy	Gaussian
36	RBF 3-10-3	80.2469136	81.25	93.75	RBFT	SOS	Gaussian
37	RBF 3-50-3	100	93.75	93.75	RBFT	Entropy	Gaussian
38	RBF 3-50-3	98.7654321	93.75	93.75	RBFT	SOS	Gaussian
39	RBF 3-50-3	93.8271605	93.75	93.75	RBFT	Entropy	Gaussian
40	RBF 3-10-3	85.1851852	87.50	100	RBFT	Entropy	Gaussian
41	RBF 3-10-3	91.3580247	93.75	93.75	RBFT	Entropy	Gaussian
42	MLP 3-9-3	90.1234568	93.75	93.75	BFGS 36	SOS	Identity
43	RBF 3-50-3	97.5308642	93.75	93.75	RBFT	Entropy	Gaussian
44	RBF 3-50-3	98.7654321	93.75	93.75	RBFT	SOS	Gaussian
45	RBF 3-10-3	96.2962963	93.75	93.75	RBFT	Entropy	Gaussian
46	RBF 3-10-3	90.1234568	81.25	93.75	RBFT	SOS	Gaussian
47	RBF 3-10-3	87.654321	87.50	93.75	RBFT	Entropy	Gaussian
48	RBF 3-50-3	100	93.75	93.75	RBFT	Entropy	Gaussian
49	RBF 3-10-3	88.8888889	93.75	100	RBFT	Entropy	Gaussian
50	RBF 3-10-3	88.8888889	93.75	93.75	RBFT	Entropy	Gaussian

Table 3. Network errors in the training, test and control sequences

Learning sequence					
		Class-a	Class-b	Class-c	Class-All
13.RBF 3-50-3	Total	45.0000	16.0000	20.0000	81.0000
	Correct	45.0000	16.0000	20.0000	81.0000
	Incorrect	0.0000	0.0000	0.0000	0.0000
	Correct (%)	100.0000	100.0000	100.0000	100.0000
	Incorrect (%)	0.0000	0.0000	0.0000	0.0000

Table 3. cont.

Learning sequence					
		Class-a	Class-b	Class-c	Class-All
20.RBF 3-50-3	Total	45.0000	16.0000	20.0000	81.0000
	Correct	45.0000	16.0000	20.0000	81.0000
	Incorrect	0.0000	0.0000	0.0000	0.0000
	Correct (%)	100.0000	100.0000	100.0000	100.0000
	Incorrect (%)	0.0000	0.0000	0.0000	0.0000
37.RBF 3-50-3	Total	45.0000	16.0000	20.0000	81.0000
	Correct	45.0000	16.0000	20.0000	81.0000
	Incorrect	0.0000	0.0000	0.0000	0.0000
	Correct (%)	100.0000	100.0000	100.0000	100.0000
	Incorrect (%)	0.0000	0.0000	0.0000	0.0000
48.RBF 3-50-3	Total	45.0000	16.0000	20.0000	81.0000
	Correct	45.0000	16.0000	20.0000	81.0000
	Incorrect	0.0000	0.0000	0.0000	0.0000
	Correct (%)	100.0000	100.0000	100.0000	100.0000
	Incorrect (%)	0.0000	0.0000	0.0000	0.0000
Test sequence					
		Class-a	Class-b	Class-c	Class-All
13.RBF 3-50-3	Total	10.0000	5.0000	1.0000	16.0000
	Correct	9.0000	5.0000	1.0000	15.0000
	Incorrect	1.0000	0.0000	0.0000	1.0000
	Correct (%)	90.0000	100.0000	100.0000	93.7500
	Incorrect (%)	10.0000	0.0000	0.0000	6.2500
20.RBF 3-50-3	Total	10.0000	5.0000	1.0000	16.0000
	Correct	10.0000	5.0000	1.0000	16.0000
	Incorrect	0.0000	0.0000	0.0000	0.0000
	Correct (%)	100.0000	100.0000	100.0000	100.0000
	Incorrect (%)	0.0000	0.0000	0.0000	0.0000
37.RBF 3-50-3	Total	10.0000	5.0000	1.0000	16.0000
	Correct	9.0000	5.0000	1.0000	15.0000
	Incorrect	1.0000	0.0000	0.0000	1.0000
	Correct (%)	90.0000	100.0000	100.0000	93.7500
	Incorrect (%)	10.0000	0.0000	0.0000	6.2500

Table 3. cont.

Test sequence					
		Class-a	Class-b	Class-c	Class-All
48.RBF 3-50-3	Total	10.0000	5.0000	1.0000	16.0000
	Correct	9.0000	5.0000	1.0000	15.0000
	Incorrect	1.0000	0.0000	0.0000	1.0000
	Correct (%)	90.0000	100.0000	100.0000	93.7500
	Incorrect (%)	10.0000	0.0000	0.0000	6.2500
Control sequence					
		Class-a	Class-b	Class-c	Class-All
13.RBF 3-50-3	Total	7.0000	5.0000	4.0000	16.0000
	Correct	7.0000	5.0000	4.0000	16.0000
	Incorrect	0.0000	0.0000	0.0000	0.0000
	Correct (%)	100.0000	100.0000	100.0000	100.0000
	Incorrect (%)	0.0000	0.0000	0.0000	0.0000
20.RBF 3-50-3	Total	7.0000	5.0000	4.0000	16.0000
	Correct	7.0000	5.0000	3.0000	15.0000
	Incorrect	0.0000	0.0000	1.0000	1.0000
	Correct (%)	100.0000	100.0000	75.0000	93.7500
	Incorrect (%)	0.0000	0.0000	25.0000	6.2500
37.RBF 3-50-3	Total	7.0000	5.0000	4.0000	16.0000
	Correct	6.0000	5.0000	4.0000	15.0000
	Incorrect	1.0000	0.0000	0.0000	1.0000
	Correct (%)	85.7143	100.0000	100.0000	93.7500
	Incorrect (%)	14.2857	0.0000	0.0000	6.2500
48.RBF 3-50-3	Total	7.0000	5.0000	4.0000	16.0000
	Correct	6.0000	5.0000	4.0000	15.0000
	Incorrect	1.0000	0.0000	0.0000	1.0000
	Correct (%)	85.7143	100.0000	100.0000	93.7500
	Incorrect (%)	14.2857	0.0000	0.0000	6.2500

Based on the selected network (RBF), we can create an automated control system for the crushing and grinding complex, considering the facility's performance and power consumption to maintain the optimal mode. The structure of the control system of the crushing and grinding complex is shown in Fig. 3.

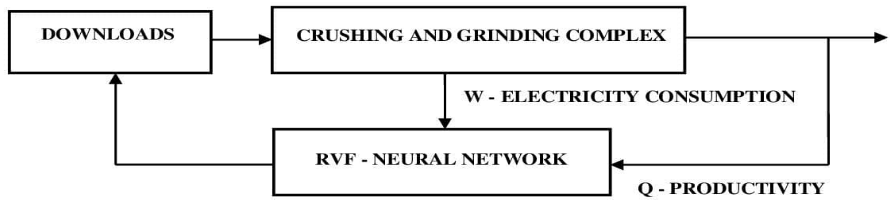

Fig. 3. Structural scheme of the control system of the crushing and grinding complex

The proposed structure of the control system envisages feedback on productivity and power consumption, which with the help of an artificial neural network, will assess the operating mode of the complex and form a control effect.

5. Conclusions

According to the research results, the following significant indicators were determined to assess the operation of the crushing and grinding complex, such as the performance of the complex, specific electricity consumption and the grinding load. Artificial neural networks such as MLP and RBF were trained based on the numerical values of significant indicators. The best indicators for solving the classification problem were shown by the RBF network, which indicates the advantages of such networks in their use to create automated control systems to identify the state of the complex. Increasing the number of parameters taken into account when determining the mode complicates the model and reduces its accuracy; therefore, when building control systems, it is advisable to use only the basic of the accepted parameters (performance and power consumption).

References

Callan, R. (2000). Neural networks. *Hotline – Telecom*, 280.

Faek, F.K. (2009). Digital Modulation Classification Using Wavelet Transform and Artificial Neural Network. *Journal of Zankoy Sulaimani*, *13*(1), 59-70.

Haykin, S. (2006). Neural networks: A Complete Course. *Williams Publishing House*, 1104.

Kalinchyk, V., Meita, O., Pobigaylo, V., Kalinchyk, V., Filyanin, D. (2021). Neuromodel of the “Crusher mill” Mechatronic Complex. *Rocznik Ochrona Środowiska*, *23*. 470-483.

Kruglov, V.V., Borisov, V.V. (2002). Artificial neural networks. Theory and practice. *Hotline – Telecom*, 382.

Lukomski, R., Willkosz, A. (2003). Power System Topology Verification Using Artificial Neural Network Utilization of Measurement Data. *IEEE Power Tech Conference*, 180-186.

Malisuwan, S., Malisuwan, S., Suriyakrai, N., Madan, N. (2016). Radio Spectrum Valuation by Applying the Artificial Neural Network Model. *Journal of Advances in Computer Networks*, *4*(1), 19-23.

Nguyen, T.T. (1995). Neural Network Load Flow. *IEEE Trans of Distribution, Generation and Transmission Conference*, 51-58.

Ponomaryov, V.A., Suvorov, I.F. (2011). Comprehensive approach of diagnostics of electric motors based on the use of artificial neural networks. *News of electrical engineering*, *5*(71).

Rolim, Zurn, G.J.G. (2021). Interpretation of Remote Backup Protection of Fault by Fuzzy Expert System. *IEEE Power Tech Conference*, 312-315.

Venkatesan, M., Gokul, S., Gandhi, D.R.I. (2018). Artificial Neural Network Based Automated Escalating Tools for Crises Navigation. *International Journal of Trend in Scientific Research and Development*, *2*(3), 350-354.

Warwick, K., Ekwure, A., Arragwal, R. (1997). Artificial Intelligence Techniques in Power System. *IEEE Power Ingeneering Series*, *22*, *Bookart Printed*, 17-19.

Yang, J.X., Li, L.D., Rasul, M.G. (2021). Conceptual Artificial Neural Network Model in Warehouse. *Receiving Management. International Journal of Machine Learning and Computing*, 11(2), 130-136.