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APPLICATION OF ARTIFICIAL NEURAL NETWORKS TO INCREASE THE EFFICIENCY OF WATER TREATMENT PROCESSES

Summary: The aim of the work is to evaluate the possibility of using neural networks to model ultrasound (US) effects on microorganism cells. A multilayer perceptron model with 5 input parameters, 12 neurons and 2 outputs, trained using the Levenberg-Markar algorithm, was proposed. The data of the correlation coefficients obtained from the simulation of the artificial neural network are within 99%, which demonstrates the high accuracy of the proposed model.

Keywords: biological water purification, artificial neural network, software package MATLAB, ultrasound, destruction of microorganisms

ZASTOSOWANIE SZTUCZNYCH SIECI NEURONOWYCH DO ZWIĘKSZENIA WYDAJNOŚCI PROCESÓW UZDATNIANIA WODY

Streszczenie: Celem pracy jest ocena możliwości wykorzystania sieci neuronowych do modelowania wpływu ultradźwięków (US) na komórki mikroorganizmów. Zaproponowano wielowarstwowy model perceptronu z 5 parametrami wejściowymi, 12 neuronami i 2 wyjściami, uczony przy użyciu algorytmu Levenberga-Markara. Dane współczynników korelacji uzyskane z symulacji sztucznej sieci neuronowej mieszczą się w 99%, co świadczy o dużej dokładności zaproponowanego modelu.

Słowa kluczowe: biologiczne oczyszczanie wody, sztuczna sieć neuronowa, pakiet oprogramowania MATLAB, ultradźwięki, niszczenie mikroorganizmów

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1. Introduction

In recent years, the scale of the formation and accumulation of various wastes has been catastrophically increasing, which leads to the alienation of new territories and pollution of the environment. One of the fastest growing in number, types of waste is the sediment of sewage [1].

The mud grounds are an extremely serious environmental problem because most of them are overcrowded, which has a negative impact on the environment. This testifies about the urgency and the need to solve the problem of treatment and disposal of sewage sludge [1].

Innovative technologies and developed water purification equipment must fully meet the requirements of energy and resource conservation, environmental safety, be competitive in the current conditions of a market economy. This is possible if they are based on progressive innovative ideas. One of these innovative directions is the effective use of cavitation phenomena. The quality of sewage treatment depends on the time of treatment of active sludge, and the treatment of sludge by ultrasound with its simultaneous contact with sewage increases its sorption properties and activity of microorganisms [1]. Ultrasonic treatment of the mud mixture in aerotanks also prevents the swelling of active sludge. Then the oxidizing power of the treatment facilities increases by 2.2-2.5 times, and at the same time the quality of the purified liquid is improved by the content of the compounds of nitrogen, phosphorus and suspended solids [1].

In last years, many highly effective, resource-saving and environmentally sound ultrasonic technologies have appeared.

The economic effect from the introduction of ultrasound to intensify the process of biological wastewater treatment is to reduce the volume and area under the treatment facilities, the specific air flow rates for aeration and operating costs for the wastewater treatment process [2].

1.1. Materials and methods

In order to study the process of ultrasonic destruction of microorganisms and water-soluble compounds of their destruction, we created model dispersions based on glucose and baking yeast of Saccharomyces cerevisiae. The UZDN-2T ultrasonic generator with a working frequency of 22 kHz and a power of 40 Vhv^{-1} was used. The change in the concentration of organic compounds in the dispersion was estimated by the chemical oxygen demand. The radius of agglomerates of yeast cells in the dispersion was determined using a sedimentation method.

We investigated the change in the value of the COD system during biological processes in the dispersion of yeast and under the influence of ultrasound. The results of the studies have shown that under the action of ultrasound, the concentration of cells in the system decreases and thus the index of COD due to biological processes is constantly falling and reaches a minimum value of 60 minutes. After 60 minutes, the influence of biological processes on the change of the COD practically disappears. At the same time, the change in the COD due to oxidation under the influence of ultrasound increases somewhat. This suggests that the destruction of vegetative microorganisms leads to an increase in the concentration of water-soluble organic substances and, as a result, increases the rate of oxidation of the substance.

The change of the concentration of aggregates of cells in the system was calculated by the formula:

$$N = N_0 - (N_1 - N_0)\cdot e^{k_1 t}, \qquad (1)$$

where N_0 – initial number of cells aglomerates;
N_1 – the number of single cells in the system, calculated from microscopy data;
k_1 – the constant of disaggregation.
The concentration of vegetative bacteria was calculated by the formula:

$$N_{\text{вег}} = N\cdot e^{-k_2 t}, \qquad (2)$$

where k_2 – the rate constant of the process of destruction of yeast cells during the ultrasonic treatment.
The value of the COD of the fermentation process without ultrasound by the action of oxygen is taken from the experimental data [3].
The value of the COD of the fermentation process in the presence of ultrasound was calculated by the formula:

$$\mathrm{COD} = \mathrm{COD}_0 /(1 + ((k_3/N_0)\cdot \mathrm{COD}_0 \cdot N_{veg})), \qquad (3)$$

where k_3 – the constant of reduction of the COD.
The change of the value of the COD of the oxidation process without fermentation was calculated according to the formula:

$$\mathrm{COD} = \mathrm{COD}_{eks} + (\mathrm{COD}_{0brod.\ us} - \mathrm{COD}_{brod.\ us}) \qquad (4)$$

The rate of radical chain oxidation of organic compounds in the system was calculated by the difference between the change in total COD in time, and the change of the COD due to biochemical oxidation.
The topology of the neural network depends on the number of layers in it, the number of nodes in each layer, and the nature of the transfer functions [4, 5]. Optimization of the topology of ANN [6, 7] is the most important factor in creating a network. In this paper, we used a three-layer neural network of back propagation error. The input parameters for simulation of the neural network to predict the change in the concentration of pollutants in water are the value of the number of agglomerates of yeast cells, the number of individual microorganisms, the value of COD $_{brod.}$, COD $_{brod.\ us}$, COD $_{ok.\ bez\ brod}$, shown in the Table 1. The change of the concentration of water-soluble organic matter and the amount of COD $_{okisl.\ us}$ were selected as the source parameters of the neural network model.

Table 1. The change of the number of agglomerates of the cells and the amount of chemical oxygen demand of the dispersion of microorganisms under the influence of ultrasound

Time	The number of agglomerates	The number of single cells	$COD_{brod.}$	$COD_{brod.\ us}$	$COD_{okisl.\ us}$	$COD_{okisl.\ bez\ brod.}$	The concentration of water-soluble organic matter
0	8000	8000	1,90E+02	1,90E+02	1,90E+02	1,90E+02	10
0,25	11229,43	11177,89	1,90E+02	1,90E+02	1,90E+02	1,90E+02	10
0,5	13415,94	13293,08	1,90E+02	1,90E+02	1,90E+02	1,90E+02	10,10622
1	15898,64	15608,78	1,90E+02	1,90E+02	1,90E+02	1,90E+02	10,21245
2	17558,43	16924,02	1,90E+02	1,90E+02	1,90E+02	1,90E+02	10,31867
3	17907,21	16945,52	1,90E+02	1,90E+02	1,89E+02	1,90E+02	10,53111
4	17980,5	16704,66	1,90E+02	1,89E+02	1,89E+02	1,90E+02	10,956
5	17995,9	16414,16	1,90E+02	1,89E+02	1,89E+02	1,89E+02	12,55843
10	18000	14974,84	1,89E+02	1,89E+02	1,88E+02	1,89E+02	15,64429
15	18000	13658,63	1,89E+02	1,88E+02	1,86E+02	1,88E+02	30,93306
20	18000	12458,11	1,89E+02	1,88E+02	1,85E+02	1,87E+02	44,91421
25	18000	11363,11	1,88E+02	1,88E+02	1,84E+02	1,87E+02	57,66651
30	18000	10364,35	1,88E+02	1,87E+02	1,83E+02	1,86E+02	69,29794
35	18000	9453,374	1,88E+02	1,87E+02	1,82E+02	1,85E+02	79,90703
40	18000	8622,471	1,87E+02	1,87E+02	1,81E+02	1,84E+02	89,58364
45	18000	7864,601	1,87E+02	1,87E+02	1,80E+02	1,83E+02	98,40972
50	18000	7173,343	1,87E+02	1,87E+02	1,79E+02	1,82E+02	106,46
55	18000	6542,843	1,86E+02	1,87E+02	1,77E+02	1,81E+02	113,8028
60	18000	5967,761	1,86E+02	1,87E+02	1,76E+02	1,79E+02	120,5001

Data are randomly divided into 70% of the training, 15% testing and 15% validation. These studies are used to determine the weighting of the network [8]. The training of the neural network is carried out with the help of the Levenberg-Markar algorithm. The number of nodes in the network layer was determined based on the maximum value of the correlation coefficient [9, 10].

The model was developed using MATLAB version 2015 from MATHWoRkS using the Neural Fitting app. With this tool you can create, teach, visualize and simulate neural networks [11, 12].

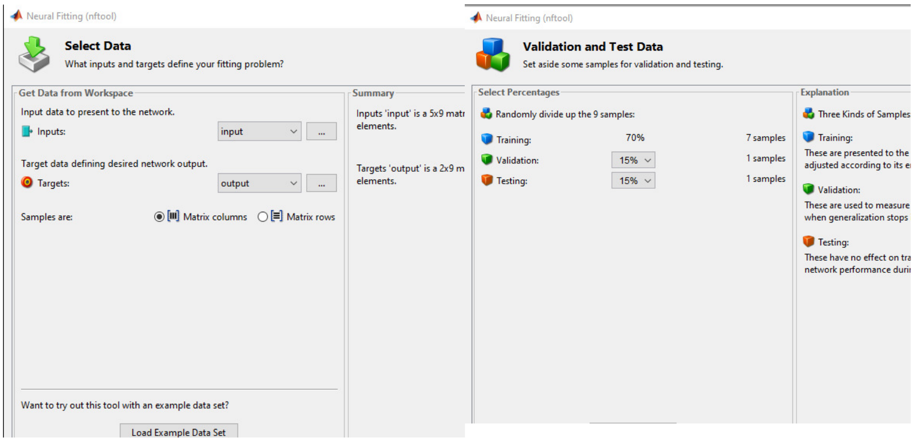


Figure 1. Creating an artificial neural network model in the MATLAB environment

Several statistical exercises for the investigated neural network are executed. These checks are used to generalize the network and stop learning when generalization ceases to improve [13, 14]. These tests do not affect the learning process of the network and provide an independent assessment of the effectiveness of the neural network during and after the completion of the training. The learning process stops when the synthesis stops improving because it indicates an increase in the mean square error of the data samples for verification. Learning several times generates different results due to different weighting factors and different initial conditions [15].

1.2. Results and discussion

In this work, for estimating the efficiency of the proposed model, we use the mean square error (MSE) and correlation coefficient (R). The value of MSE demonstrates the quality of the simulation through the relationship between the experimental and predicted values of the model parameters. The mean square error is the mean square difference between the normalized results and the target values, zero means no error, the value above 0,66667 shows a very large error.

$$MSE = \frac{1}{N} + \sum_{n-1}^{n} (q_{i,pre} - q_{i,\exp})^2, \quad (5)$$

Where: n – the number of data points, $q_{i,pre}$ – the network forecasting, $q_{i,exp}$ – the experimental feedback.

Various numbers of neurons from 5 to 19 in each layer were tested in this work. Each topology is repeated three times to avoid accidental correlation due to the random initialization of weight coefficients. Table 2 shows the relationship between the Mean Square Error, the Correlation Coefficient and the number of neurons in the layer.

Table 2. The dependence of mean square error and coefficient of correlation on the number of neurons in the layer of the neural network

The number of neurons	MSE, (%)	R^2, (%)
5	1.7311e^{-1}	8.52417e^{-1}
7	8.68312 e^{-1}	6.88710e^{-1}
10	1.41638e^{-1}	6.55134e^{-1}
12	7.57386e^{-1}	9.99954e^{-1}
15	2.69269e^{-0}	3.79391 e^{-1}
17	5.74090e^{-1}	8.62661e^{-1}
19	7.47591 e^{-2}	8.16147e^{-1}

As can be seen from Table 2, the minimum value of the Mean Square Error and the highest value of the Correlation Coefficient (7.57386e-1, R = 99%) is observed with the number of neurons 12. Therefore, the model of the neural network 5-12-2 is proposed (Fig. 2).

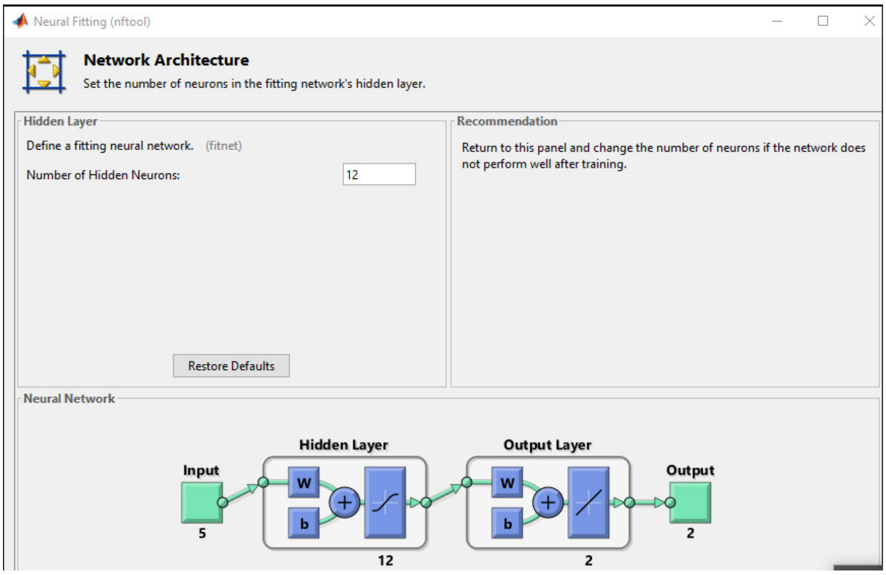


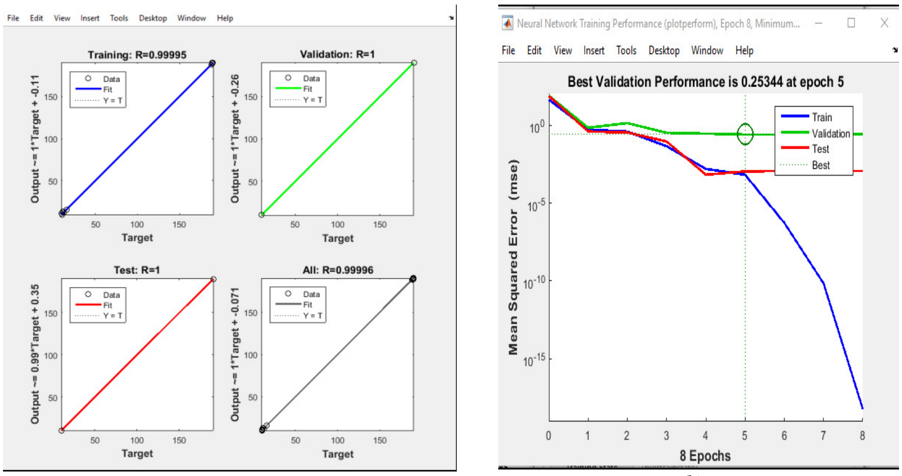
Figure 2. The structure of the proposed model of ANN

The process of training the neural network stops when the test error increases. In this case, the training was stopped in the epoch 8. In Figure 3b shows a graph of training errors, error checking and testing of the neural network. The best efficiency is obtained in the era of 5.

The benefits of our result are as follows:

- the final mean square error is small;
- a text set error and a verification check error have similar characteristics;

- there was no significant re-training on iteration 5 (where the best test was carried out).



a) *b)*

Figure 3. The diagrams of the efficiency of the selected neural network model: a) – the Correlation Coefficient; b) the Mean Square Error.

The Correlation Coefficient (R) determines the relationship between the results obtained experimentally and the predicted.

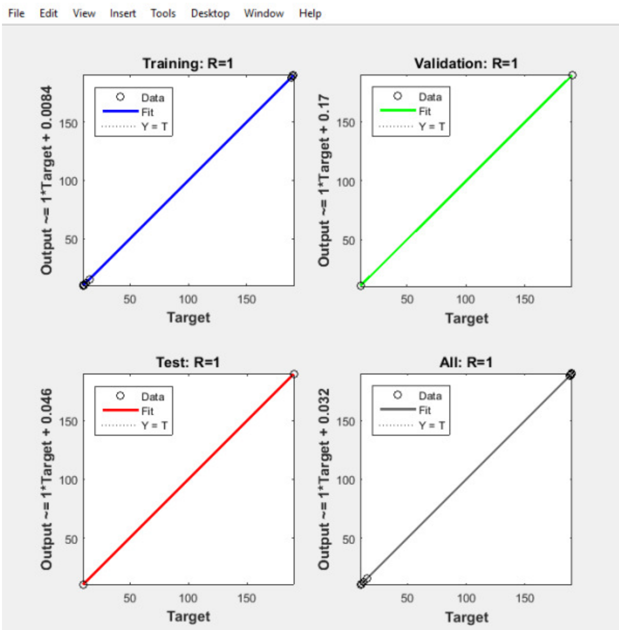


Figure 4. The network regression diagrams

Fig. 4 shows a linear regression between network outputs and the corresponding goal. The results of training, checking and testing are consistent with the target, showing an acceptable ratio between the results of all three sets of data.
In Fig. 5 shows a neural network performance histogram for three sets of data (training, testing, and testing).

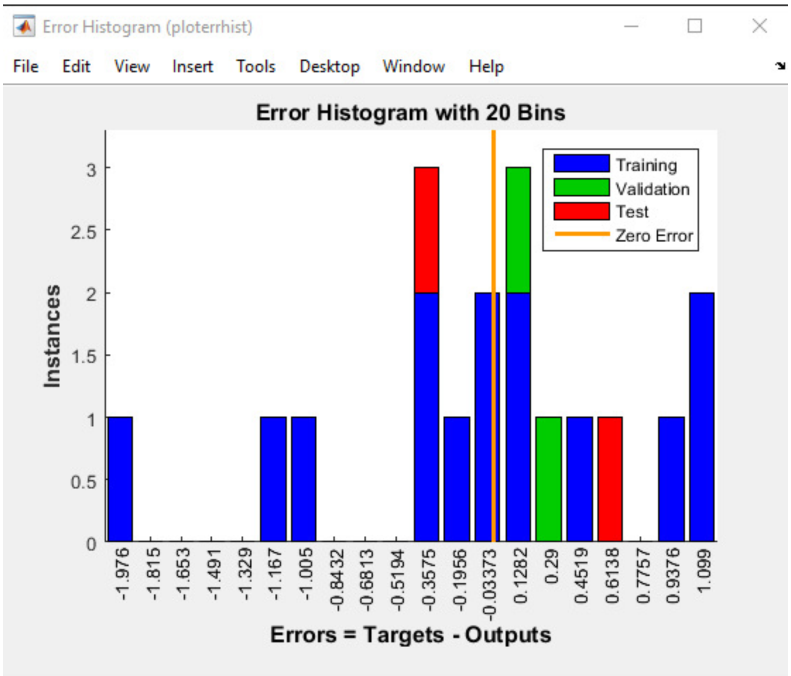


Figure 5. The histogram of the neural network performance

On Fig. 5 blue, green and red color indicate training data, test data and test data respectively.

The proposed model of the network demonstrated acceptable performance and errors on the training, control and test sets. This indicates the adequacy of the proposed model.

2. Conclusions

Today there are a great number of methods for assessing the quality of wastewater treatment, but they do not allow the timely response to this process, therefore, it is necessary to use an artificial neural network model based on the results of ultrasound efficiency in the process of treatment of waste water from biological and organic pollution.
Consequently, due to the use of these models, it is possible to predict the effectiveness of the parameters of the process of destruction of water pollution, which will allow the timely adoption of a managerial decision to increase the efficiency of the processes

of purification and disinfection of water and minimize the negative impact of insufficiently treated wastewater on the environment.
The MATLAB software package, as one of the most powerful data processing tools, provides the basic tools for creating the ANN models. The main benefits of using the program are the ability to create individual architectures and change the weight of the neurons.
An artificial neural network was created to predict changes in the number of microorganisms in the water. The optimal network structure is selected after multiple training with the change in the number of neurons in the intermediate layer from 5 to 19, based on the minimum value of the Mean Square Error and the maximum value of the Correlation Coefficient R = 99%. To construct the model, a multi-layer perceptron with 5 input parameters was used (indicators of the number of agglomerates of yeast cells, the number of individual microorganism cells, values of chemical oxygen demand (COD): $COD_{brod.}$, $COD_{brod.us}$, $COD_{ok.\ bez\ brod.}$), 12 neurons and 2 initial parameters - the concentration of water-soluble organic matter and the amount of $COD_{okisl.\ us}$, trained using the Levenberg-Markar algorithm.
The data of the correlation coefficients obtained from the simulation of the artificial neural network are within 99%, which demonstrates the high accuracy of the proposed model.
Consequently, a multilayered neural network with 5 input parameters, as well as 12 central neurons, well predicts the concentration of water-soluble compounds, confirming this is the minimum Mean Square Error and the maximum magnitude of the Correlation Coefficient. The proposed model can be used to predict changes in the concentration of pollutants in water.

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