Technological process automation of drinking water deodoration using the methods of machine learning

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Abstract. The study presents an analysis and the possibility of applying machine learning methods to automate the technological process of drinking water deodorization. One of the most actual and popular machine learning methods today is the use of artificial neural networks. Possible neural network structures, activation functions and the number of neural connections were described. The relevance of the introduction of these methods into the system of water management is described.

Obtaining and use of drinking water has been an urgent problem for mankind at all times [1-3]. There are many effective technological processes for obtaining drinking water that would meet all sanitary standards [2, 3]. However, in this area, the question of technological processes automation for the preparation of drinking water is open. In particular, the article discusses the possibility and results of using the automation of the deodorization technological process of drinking water [4, 5]. The basis, thanks to which it will be possible to carry out the automation process, is the use of modern machine learning methods. In particular, the application of methods based on the training of artificial neural networks was considered.

Investigating the issue of automation of the technological process of drinking water deodorization, first of all, one should consider the advantages and disadvantages of this innovation. The advantages are [6]:

- cost reduction for conducting experimental studies to select the optimal amount of sorbent and its dosage;
- the ability to predict the technological process;
- the ability to identify hidden, previously unknown for a given technological process of the enterprise general patterns;
- to identify the optimal parameters of the technological process without experimental research.

The following defects of automation process can be identified:

- the probability of system failure, or erroneous determination of the deodorization process parameters. In this case, an additional drinking water quality control system should be developed, which would additionally control the automation process.
- limited application within one technological scheme, one enterprise, one water source, i.e. in other words, the developed system may not lead to the desired results of water quality if there are changes in the water source or if changes are made to the technological scheme (for example, if a new technological process is introduced).

Today, the use of machine learning methods (in particular, based on training artificial neural networks) is one of the best practices for developing automated systems, managing information flows, etc. The application of machine learning methods is of great interest both for scientific research and for production processes [7, 8].

To use an artificial neural network in the automation system of the technological process of water deodorization, one should first of all determine its structure, the number of connections between neurons, the number of incoming and outgoing signals, and the neuron activation function.

First of all, consider the propagation of artificial neural network signals. One of the basic formulas that should be considered here is the propagation of incoming signals (1) [9]:

$$X = WI$$  

where:

$I$ - matrix for the values of the input signals of the artificial neural network;
$W$ is a set of signal weights, which are transformed into a matrix;
$X$ - matrix of neurons of the considered hidden layer of the artificial neural network.

For a neural network with one hidden layer, the matrix form will look like (2) [10]:

$$
\begin{pmatrix}
I_1 \\
I_2 \\
I_3
\end{pmatrix}
\begin{pmatrix}
w_{11} & w_{21} & w_{31} \\
w_{12} & w_{22} & w_{32} \\
w_{13} & w_{23} & w_{33}
\end{pmatrix}
= 
\begin{pmatrix}
x_1 \\
x_2 \\
x_3
\end{pmatrix}
$$

where $w$ are the weights of the connections of the artificial neural network, $I_1, I_2, I_3$, are the incoming signals, $x$ are the signals that go to each neuron.

The back propagation of an error using the example of an artificial neural network with two neurons in a hidden layer can be expressed as the formula (3)

$$E = \begin{pmatrix}
e_1 \\
e_2
\end{pmatrix} \begin{pmatrix}
\frac{w_{11}}{w_{11} + w_{21}} & \frac{w_{12}}{w_{12} + w_{22}} \\
\frac{w_{21} + w_{11}}{w_{22} + w_{12}}
\end{pmatrix}$$

where, $e$ is the error of each neuron in the hidden layer, $E$ is the total error of the artificial neural network layer.

In addition, it is necessary to take into account the updating of the weight coefficients of connections between neurons of an artificial neural network, depending on the error, outgoing signals in comparison with the test sample (4) [11]:

$$\frac{dE}{dw_{jk}} = -(t_k - o_k) \frac{1}{1 + e^{\sum_j w_{jk} o_j}} \left(1 - \frac{1}{1 + e^{\sum_j w_{jk} o_j}}\right) o_j$$

where $o_j$ is the output value of the hidden layer signal $o_k$ is the output value of the signal (output) of the neural network, $t_k$ is the actual value, $w_{jk}$ are the weights of the neural network connections.
Next, let's look at the structure of an artificial neural network. Figure 1. An example of the transmission of signals in an artificial neural network is presented.

![Figure 1](image1.png)

**Figure 1.** An example of signal transmission in an artificial neural network in graphical form.

If we consider the activation functions for each neuron of an artificial neural network, then there are quite a few of them - the most popular are the functions of hysteresis, logistic function, unit jump, and hyperbolic tangent (figure 2).

![Figure 2](image2.png)

**Figure 2.** Activation functions that are most often used for neurons.

As for the neuron activation function, here most often (and our case is not an exception) the sigmoidal activation function is used. (S-shaped function) activation (5).

\[
f(s) = \frac{1}{1 + e^{-x}}
\]  

(5)

The use of the sigmoidal activation function is due to the fact that it primarily provides a gradual learning of each neuron. This function is smoothed in the transition region, i.e. the function is continuous and, therefore, differentiable [12].

In addition, the number of neurons, the number of hidden layers and the number of connections should be justified. A fairly large number of techniques can be applied here, there are no universal
methods for determining the optimal number of neurons and the number of hidden layers, the selection method is very often used. However, in some cases, you can use the formula (6, 7)

$$\frac{mN}{1 + \log_2 N} \leq L_w \leq m \left( \frac{N}{m} + 1 \right) \left( n + m + 1 \right) + m$$

(6)

$$L = \frac{L_w}{n + m}$$

(7)

where $n$ is the dimension of the input signal of the artificial neural network; $m$ is the dimension of the output signal of the artificial neural network; $N$ is the training sample; $L_w$ is the number of synaptic weights.

The use of a trained artificial neural network as the basis of the automation process will help to more accurately calculate the most appropriate parameters for the deodorization process. In addition, this will reduce the resource consumption of the enterprise employees for the process of deodorization of drinking water [13].

As proof, consider an example. In the studied enterprise, in a ten-year period, the annual amount of the sorbent residue on average is 10.282 tons, while the amount of the remainder obtained on the basis of the trained artificial neural network data is only 15 kilograms.

The developed system will allow, first of all, to reduce the resource consumption of the enterprise for the preparation of drinking water, in addition, it will allow to reduce the sorbent residue after seasonal deodorization.

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