Development of intellectual complex for adaptive control of microclimate parameters of flour storage processes

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Abstract. In the modern socio-economic and geopolitical development of Russia, the development of agriculture and food industry comes to the fore. As a result, the requirements to the quality and safety of the finished product increase many times, which significantly affects its competitiveness. Storage of flour is one of the most important stages of the technological process of flour production. Bulk storage of flour in silos is a complex technological process, which is largely affected by the environment (temperature, pressure, humidity, etc.). Today, neural networks can solve a wide range of data processing and analysis tasks − pattern recognition and classification, prediction and management. This article presents the development of an intelligent complex for adaptive control of microclimate parameters of flour storage processes and improving the efficiency of management of technological processes of flour storage through the use of intelligent technologies. A mathematical model of the control object was developed taking into account the inherent internal relationships between the parameters of the technological regime and external perturbing factors. Processing of research results was carried out using the software "MatLab".

1. Introduction
In order to store flour, it is necessary that the parameters of the microclimate are observed inside the industrial premises. Microclimate in production rooms is determined by air temperature, relative humidity, air speed, barometric pressure and intensity of thermal radiation from heated surfaces.

In order to maintain the stability of the storage process, it is advisable to control the parameters of the microclimate in the silo. Based on numerous studies, a neural network has been developed, which is used to regulate the main parameters of the microclimate: air temperature in the process room, air humidity, carbon dioxide concentration in the air.

Inside the process room, the temperature must be maintained between 5 and 15 ºC, the carbon dioxide content is approximately 500 -700 ppm and the humidity is 60-70%.

The silting process is an exclusively biological method of preserving feed plants.

The process of storing flour is carried out with the help of an operator, who monitors the parameters of the microclimate with the help of sensors, and on the basis of this data controls the microclimate. Standard PID regulators cannot solve this problem because they cannot take into account the non-linearity and mutual influence of microclimate parameters on each other.

Today, the use of neural network regulators to control microclimate parameters is the most promising. The creation of such a system will allow to improve the adaptability of the regulator, improve the quality of control and, therefore, the quality of the technological process [1].
2. Neural network development
It is necessary to develop an artificial neural network (ANN) to control the parameters of the microclimate in the process room for storing flour [2].

The development of ANN was carried out in Matlab R2015b environment. The Matlab Neural Network Toolbox package was used to solve the task.

The process of building a neural network model can be conditionally divided into 5 main stages.

The first step in building a neural network model is to carefully select the input data.

In the second step, the source data is converted and the information presentation methods are selected.

The third step is to design the ANN.

The fourth stage involves network learning, which can be conducted in a constructive or destructive manner.

At the fifth stage the obtained ANN model is tested on independent sample of examples.

3. Main process patterns and definition of input and output data
For the solution of a task by means of neural network it is necessary to collect data for training [3].

Output parameter extent of opening of valve $F$ is influenced by input parameters on the dependences given below. The output data calculated by formulas:

$$F_1 = 100 - \frac{T_1}{5} \ast \frac{T_2}{5}$$

where $F_1$ – degree of valve opening for heat supply;

$T_{1,2}$ – indoor and outdoor temperature 1 and 2.

$$F_2 = 100 - \frac{M}{2}$$

where $F_2$ - degree of valve opening for steam supply;

$M$ - indoor air humidity.

$$F_3 = 100 - \frac{CO_2(1)}{250} \ast \frac{CO_2(2)}{250}$$

where $F_3$ - degree of valve opening for live steam supply;

$CO_2 (1), (2)$ - is the carbon dioxide content inside the process room 1 and outside 2.

Next, we will prepare data for neural network training.

5 values will be supplied to the neural network input:

- Indoor air temperature.
- Air temperature outside.
- Indoor humidity.
- Indoor carbon dioxide content.
- Carbon dioxide content outside.

At the output, the neural network shall calculate:

- $F_1$ - % of valve opening for heat supply.
- $F_2$ - % of valve opening for steam supply.
- $F_3$ - % of valve opening for fresh air supply.

4. Data processing and preparation
Using the above formulas, create a table with a learning data set. It consists of 1000 examples [4].
Table 1. Training dataset.

| №  | entrance | | exit |
|----|----------|---|------|
|    | T₁, °C   | M,%| CO₂(1), ppm | CO₂(2), ppm | 1 valve, % | 2 valve, % | 3 valve, % |
| 1  | 42       | 46 | 773      | 846         | 32         | 77         | 83         |
| 2  | 45       | 45 | 782      | 977         | 43         | 77         | 80         |
| 3  | 50       | 46 | 822      | 916         | 48         | 77         | 80         |
| 4  | 29       | 48 | 755      | 952         | 60         | 76         | 81         |
| 5  | 33       | 41 | 763      | 907         | 66         | 80         | 82         |
| 6  | 30       | 41 | 736      | 952         | 46         | 80         | 81         |
| 7  | 31       | 50 | 805      | 972         | 64         | 75         | 79         |
| 8  | 38       | 48 | 755      | 945         | 50         | 76         | 81         |
| 9  | 34       | 45 | 744      | 924         | 61         | 77         | 82         |
|    | ...      |    | ...      | ...         |   ...      |   ...      |   ...      |
| 990| 31       | 41 | 804      | 967         | 67         | 79         | 79         |
| 991| 30       | 42 | 730      | 977         | 48         | 79         | 81         |
| 992| 43       | 46 | 798      | 984         | 37         | 77         | 79         |
| 993| 29       | 42 | 835      | 912         | 46         | 79         | 80         |
| 994| 38       | 41 | 733      | 955         | 37         | 79         | 81         |
| 995| 44       | 46 | 728      | 982         | 20         | 77         | 81         |
| 996| 43       | 45 | 744      | 909         | 23         | 78         | 82         |
| 997| 47       | 46 | 780      | 985         | 45         | 77         | 80         |
| 998| 36       | 46 | 742      | 968         | 39         | 77         | 81         |
| 999| 45       | 46 | 709      | 916         | 52         | 80         | 79         |
| 1000|32      | 40 | 747      | 907         | 68         | 80         | 82         |

5. Selecting the type and architecture of a neural network

Our network will consist of 2 layers - hidden layer and output [5].

The first step is to choose the structure of the neural network. A two-layer unidirectional network with sigmoidal function will be used: (net = fitnet (hidden Layer Size, train Fcn)).

Next, select the number of neurons in the hidden layer. In this case, the required number of neurons in the hidden layer is experimentally established to be equal to 48.

The network will be trained according to the modified error reverse propagation algorithm: trainFcn = 'trainbr'.

Then we choose parameters of training of network, such as, the maximum quantity of eras, amount of eras between displays and the parameter of achievement of the goal. These parameters must be selected experimentally based on the completion criteria [6].

We set the maximum number of epochs of learning, which determines the number of epochs (time interval) after which learning will be terminated:

- net.trainParam.epochs = 1000.
- We choose the number of epochs between the shows equal to five:
- net.trainParam.show = 5.

We specify the target or hit achievement parameter - the deviation value at which the training will be considered completed:
net.trainParam.goal = 0.0001.

Next, divide the data into a training set (Training), test set (Validation) and test set (Testing):

- net.divideParam.trainRatio = 60/100;
- net.divideParam.valRatio = 35/100;
- net.divideParam.testRatio = 5/100.

6. Building and learning a neural network in matlab

Next we implement and train the neural network in Matlab. To do this, use the uiopen command.
The nnstart command will be used to enter the Neural Network Learning tab [7].

Figure 1 shows the selected structure of the artificial neural network. The input of the neural network receives signal x, in our case, it is indoor air temperature, outdoor air temperature, indoor air humidity, indoor carbon dioxide content, outdoor carbon dioxide content. The adder "multiplies each input bi by the weight wi and sums the weighted inputs. Then the value passes through the function of activation of the corresponding layer and the output is calculated: opening of the valve for steam supply, opening of the valve for heat supply, opening of the valve for fresh air supply.

In the network training process window, by clicking on the Performance button, you can see the network training schedule showing the behavior of the training error figure 2.

From the schedule in figure 3 it is visible that the training set decreases and reaches the minimum mistake, and the test set continues to grow, for 1000 eras a total mean square error, reached value 1,1476 \cdot 10^{-9} and is small, it indicates to us ideal training of our network of management of microclimate parameters.

Another tool for evaluating the training result of a neural network may be to construct results regression functions figure 3.

The correlation coefficient R is 0.9162 and 1, suggesting a strong bond between variables, indicating high accuracy of the built neural network [8].
Let's go to the training status charts shown in figure 4. The first graph shows that the closer the gradient coefficient is to zero, the more accurate the training and testing of the neural network will be carried out. The "valfail" graph shows the error change on the control set. The magnitude of this error indicates the accuracy of the model setting on the training set. The "mu" graph shows the change in the training parameter μ by Bayesian regularization, and the higher the given value μ, the more accurate the network will be trained.

To test the neural network, we will input 5 values using the command sim (net, [T1; T2; M; CO2(1); CO2(2)]).

After execution of the command, we received 3 values (52,0152; 80,1235; 79,2584). Proximity of the obtained values to the given result (52; 80; 79) indicates the applicability of the network. It can then be used to control microclimate parameters.

7. Conclusion
During the study, the following main results were obtained: the expediency of developing an intelligent complex for controlling parameters of the microclimate of the process of bulk storage of flour implemented on the basis of a neural network was justified. A model for controlling microclimate parameters in silos is presented, taking into account multiple relationships between process parameters and control signals.

The expediency of using systems of automatic control of microclimate parameters considering mutual influence of parameters of the control object is shown.
Technical solutions have been developed for introduction of intelligent complex of adaptive control of microclimate parameters on the basis of neural network into automated control system of process of bulk storage of flour.

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