The Use of a Neurocontroller in a Multi-Mode Air Supply Control System at Agricultural and Industrial Facilities

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Abstract. The possibility of using a neurocontroller to control the aeration mode in the air supply circuit with a compressor unit has been investigated. The control algorithm is implemented using a multi-layer feedforward neural network. The control object model in the study included a frequency converter, motor and compressor. The analysis of the properties of the system was carried out by evaluating the obtained transients using MATLAB. The results showed that the system has high quality indicators in stabilization and programmed control modes.

1. Introduction

When regulating the air supply to industrial units using compressors, under certain conditions, self-oscillating mode is possible, which leads to increased air consumption and excessive energy consumption. Therefore, increasing the efficiency of compressor units for supplying air to industrial technical systems for various purposes (microclimate support systems in agricultural premises, at treatment facilities, mine compressors, boiler blowers, fermentation aggregates, etc.) is an urgent task. Conventional controllers with traditional controls are ineffective because they do not provide smooth start-up and do not prevent large DC overshoot when switched to steady state. The reason is that their adaptation to different operating modes of the system requires the complexity of the control algorithm, the adaptation of linear models to multimode and complex nonlinear systems, the presence of an accurate mathematical model of the control object, which in many cases is difficult and time-consuming. To solve this problem, this article explores a neurocontrol algorithm [1]. Unlike the traditional implementation of neural control algorithms, a mathematical model of the control object is not required [2]. However, neurocontrolled systems require training before using them for control [3]. The ability of neural networks (NN) to learn predetermined the effectiveness of neurocontrol of many objects. The results of a systemic study show the effectiveness of the algorithm in the control system of a two-mode electric drive of an asynchronous motor of an air supply compressor, based on the principle of a predictive control method [4]. This mode provides a smooth start of the compressor and a transition without overshoot to the stabilization mode. This mode of operation of the air control system is unattainable using traditional methods of positional and linear control. One of the reasons is the use of simplified models of control objects that do not allow sufficient consideration of uncertainty factors. As a result, over time, the models used do not reflect the real properties of real industrial facilities.
2. Method for solving the problem of developing a neural network air supply controller

Neural control algorithms are currently an alternative to the traditional methods of synthesis of control systems in conditions of uncertainty of the model of a controlled object [5]. A neural network (NN) is able to predict the behavior of a control object, which is determined not only by the choice of its architecture and the transformation function of individual neurons, but also by the number of neurons in the hidden layer $N_c$. However, the value of $N_c$ is in a wide range, which creates uncertainty when setting the NN. Therefore, to make a final decision on the choice of $N_c$, the system is simulated and the learning error of varying $N_c$ is estimated. As a result of training neural networks with different sizes of neurons in the hidden layer, it is possible even with a short-term forecast for the control period to achieve a decrease in overshoot and transient time, i.e. to improve the quality of control in the multi-mode air supply control system [6, 7].

The scheme of operative determining the number of hidden layer neurons can be represented as the following algorithm:

1. Form a neural network of input and output layers.
2. Add a hidden layer with one neuron.
3. Calculate the neural network learning error.
4. Adjust the link weights between the output and hidden layers, between the hidden and input layers.
5. Calculate the quality functional.
6. Add a neuron to the hidden layer.
7. Train the neural network.
8. Repeat steps 3–5.
9. The quality has degraded. Adjust the link weights between the output and hidden layers, and between the hidden and input layers.
10. The quality is achieved, save the structure of the neural network and the number of neurons in the hidden layer.

The developed algorithm made it possible to determine the number of neurons in the hidden layer of the neural network, which is optimal in the sense of the minimum learning error of the neural network. Figure 1 shows the simulation results. For the problem in question, the optimal number of $N_c$ is in the range from 7 to 15, the average learning error is $0.85 \cdot 10^{-8}$, and the instantaneous error is from $0.54 \cdot 10^{-8}$ to $0.11 \cdot 10^{-7}$.

![Figure 1](image-url)  
Figure 1. Dependence of the learning error on the number of neurons in the hidden layer.
The hyperbolic tangential function is used as the activation function of the hidden network layer [8]. The output layer activation function of the network is chosen to be linear in the entire range of changes of the input argument, since this excludes possible limitations of the output signals. The parameters of the forward propagation multi-layer neural network were adjusted by the method of backward error propagation [9].

Figure 2 shows graphs of the learning error change obtained for two quasi-Newtonian algorithms.

![Figure 2](https://example.com/figure2.png)

**Figure 2.** Convergence graphs of quasi-Newtonian neural network learning algorithms: 1 – algorithm proposed by Broyden, Fletcher, Goldfarb and Shanno; 2 – Levenberg-Marquardt algorithm.

The Levenberg-Marquardt algorithm provides higher accuracy with fewer training cycles. Experiments have shown that the learning error for the Levenberg-Marquardt learning algorithm was $4.1 \times 10^{-8}$ for 90 cycles and a time of 120.6 s.

The functioning of the neural network controller consists in the implementation of an iterative optimization algorithm [4], which minimizes the quality functional of the form:

$$ J = \sum_{j=N_1}^{N_2} (g[i+j] - \hat{y}[i+j])^2 + \rho \sum_{j=0}^{N_u} (\hat{u}[i+j-1] - \hat{u}[i+j-2])^2, $$

where $N_1$ – lower forecast horizon; $N_2$ – upper forecast horizon; $N_u$ – control horizon; $\rho$ – weighting coefficient, which determines the contribution made by the control power to the quality criterion; $g$, $\hat{y}$ – reference and true responses of the neural network model of the controlled object (the task signal is used directly as a reference response); $\hat{u}$ – control signal.

### 3. Experimental study of a neural network air supply control system
The air supply circuit consists of a neural network controller and a generalized control object, including frequency converter (FC), asynchronous electric engine (E) and compressor (C) (figure 3).

![Figure 3](https://example.com/figure3.png)

**Figure 3.** Scheme of a generalized research object.
In the course of research, the neural network model of the control object was taken as follows: number of neurons in the hidden layer – from 3 to 11; sampling cycle – 0.5 s; number of delay elements at the input – 2; number of delay elements at the output – 2.

The study of neurocontrol with this mathematical model was carried out in two modes: transient and stabilization. The model obtained in [10] was used as a simulation model of the controlled object. The transfer function of the frequency converter (FC) is a first order aperiodic link:

\[ W_{FC}(p) = \frac{k_{FC}}{T_{FC} p + 1}, \]

where \( k_{FC} \) – gain of the FC; \( T_{FC} \) – time constant of the FC.

With numerical values of the parameters, the transfer function of the FC is:

\[ W_{FC}(p) = \frac{5}{0.0005 p + 1}. \]

The transfer function of an asynchronous electric engine (E) is represented as:

\[ W_{E}(p) = \frac{k_{E}}{T_{M} T_{E} p^2 + T_{M} T_{E} p + 1}, \]

where \( k_{E} \) – transmission coefficient; \( T_{M} \) – mechanical time constant; \( T_{E} \) – electromagnetic time constant of the engine.

With numerical values of the parameters, the transfer function of the asynchronous electric engine (E) is:

\[ W_{E}(p) = \frac{1.05}{2.08 p^2 + 14.8 p + 1}. \]

The transfer function of the compressor (C) is adopted as follows:

\[ W_{C}(p) = \frac{k_{C}}{T_{C} p + 1}, \]

where \( k_{C} \) – compressor transfer coefficient; \( T_{C} \) – compressor time constant, \( T_{C} = 1 \) s.

With numerical values of the parameters, the transfer function of the compressor (C) is:

\[ W_{C}(p) = \frac{0.062}{p + 1}. \]

Taking into account the performed transformations, the mathematical model of the object is represented as a product of transfer functions (2), (4), (6).

The tuning coefficients of the quality functional are taken to be \( N_1 = 1, N_2 = 15, N_U = 2, \rho = 0.05 \). The scheme of the neural network control system is represented in Figure 4. The most effective for building a neural network system is the NN Predictive Controller. The controller uses a model of the controlled object in the form of a neural network to predict its future behavior. In addition, it calculates a control signal that optimizes the behavior of the object at a given time interval.
Figure 4. Scheme of the neural network control system: NN Predictive Controller – neuralcontroller; Frequency convertor – FC; Engine – E; Compressor – C.

Graphs of transient processes in the system at $N_c = 3; 5; 7; 9; 11$ are shown in figure 5. As can be seen from Figure 5, increasing the parameter $N_c$ from 5 to 9 does not significantly affect the positioning accuracy of the system, although at $N_c$ from 7 to 9 slightly increases the rise time. A decrease in the $N_c$ to 3 does not lead to a delay in the transient process, but causes a deterioration in its quality (overshoot appears up to 25 %). After selecting the optimal value of $N_c = 11$, transient processes were obtained with a stepwise change in the task of the neuralcontroller (figure 6).

Figure 5. Graphs of transient processes in the system at different values of $N_c$.

Analysis of transient processes showed that the air supply neurocontrol system has good characteristics in the stabilization mode and in the program control mode. Graphs of transient processes are monotonic and aperiodic. The maximum overshoot of the process is 0.28 %.
4. Results and discussion

The actual problem of synthesis of the system with neurocontrol that ensures the quality of air supply control with a wide range of changes in the controller tasks has been solved. Increasing control accuracy with neurocontrol allows to give less load on the compressor, and, therefore, use less electricity when supplying compressed air.

A feature of the developed neural network control for an asynchronous electric engine with a frequency converter is that it is very sensitive to the number of neurons in the hidden layer. Therefore, to improve the quality of control, the number of neurons in the hidden layer should be considered as an important parameter for configuring the neural network, taking into account the transient (starting) and steady-state modes of the system. Since there are no reliable algorithms to determine this parameter, the rational number of hidden layer neurons is selected experimentally.

5. Conclusion

The results of studies of the system with a neurocontroller show the possibility of providing the requirements for the control of air supply to technological units of agro-industrial complex in the stabilization and program control modes.

From the results of the experiments it can be seen that the use of the proposed system to control the air supply leads to a significant decrease in the control error and the elimination of the auto-oscillation mode. Therefore, excess supply air is eliminated and energy savings are achieved. This is confirmed by the results of modeling a neurocontrolled system with a small number of neurons in a hidden layer. The described neurocontrol algorithm, which includes the determination of a rational number in the hidden layer, should be used when setting up the neural network in air supply control systems at various industrial units and installations of the agro-industrial complex.
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