Electrical drive efficiency improving using an adaptive neural network controller

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Electrical drive efficiency improving using an adaptive neural network controller

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Abstract. This article discusses the possibilities of improving the energy efficiency, quality and reliability of electric drive control using an adaptive neural network controller. Asynchronous motors, working in modern conditions, are under constant random effects of various kinds, and are non-linear technical objects. The use of classical methods of regulation of electric drives based on PID controllers leads to difficulties and uncertainties in the process of control, while intelligent methods based on adaptive neural controllers provide efficient energy saving in control. The efficiency of using an adaptive neural network controller in circuits with direct torque control of an asynchronous motor is considered. Described and justified the useful effect of the use of neural network controller in comparison with the control based on the PID controller. A tuned adaptive neural network controller provides an increase in the efficiency and energy saving of electric drives in industrial enterprises solving the actual problem of modern electric power industry.

1. Introduction.
The general theory of proportional optimized regulation, used to work with various kinds of objects, has numerous difficulties in its application, due to the complexity of the designed tasks. It includes the design of a mathematical model of the control object, which describes the dynamic structure and applied analytical methods to variations of the control algorithms.

The mathematical model, being complex, will lead to absence of the possibility of satisfying processing speed conditions of various data of the technological process in real time by electronic computer existing methods. Continuous change of the system over time and the availability of data that can’t be represented as a model, which experts can actually describe, also leads to the absence of this possibility. Consequently, it is necessary to adjust the methods of automation of the technological process and methods of regulation based on classical algorithms.

The use of artificial neural networks (ANN) in the field of control is an integral part of technological progress. Ability to password computing, non-linear organization and self-learning of these networks are the main reasons for the use of control systems based on neural network controllers.

2. Artificial neural networks.
Artificial neural networks are similar to the structure of the neuron of the human brain. The components of the ANN are connected directly to each other, comprehensive links form networks of
elementary adaptive components in accordance with their structural system organization, oriented to interaction with elements of the real world, exactly the same way as the brain thinking process.

The signal received at the output of link when a single impulse is fed to its input is called the weight (impulse) function of the link. Thus, the weight function is the system's response to a pulse effect at zero initial conditions, and is used when summing, integrating, or averaging is performed in order to give some elements more weight in the resulting value compared to other elements.

The main purpose of training neural networks is the choice of ratios (weights) of this network through its training so that there is a correlation between the required input and output signals [1].

In the electric drives control structure, the most widely used are proportional-integral differential (PID) or proportional-integral (PI) regulators on which the control of frequency converters is based. Neural network controllers can both replace these regulators and be used in adapting their parameters to the current working conditions. A neural network, having the possibility of self-learning, allows you to use the experience of an expert to teach a neural network the chronology of adjusting the parameters of regulators.

The duration of the training procedure and its quality are the main difficulties that prevent the wide use of the neural network method in PID controllers. At the same time, setting up a neural network and checking it for errors is often much faster and easier than creating a simple model of the drive and control object and setting up a PID controller based on it. Moreover, the adjustment of the regulator based on the theory of automatic control systems may not always be optimal.

Other disadvantages of neural networks include the inability to predict the control error for input actions included in the set of training signals; the absence of criteria for choosing the number of neurons in the network, the duration of training, the range and number of training effects [2].

3. **Direct torque control of the asynchronous motor.**

Direct torque control of asynchronous motor is based on determining the most appropriate mode of operation of the inverter at each stage of the calculation, which changes the torque and stator flux linkage in the required direction.

There is a diversification of channels to control the magnetic flow and torque of the asynchronous motor. This method is based on torque control through a current and a magnetic field proportional to voltage. One of the advantages is the use of speed sensors only in the process of its control. Also, there is no need to convert coordinates; the presence of a simple control scheme; good dynamics; no position sensor required.

The presence of feedback is a major advantage, whereas in the modular control uses the open system control principle.

Direct torque control systems provide astatic moment control at low speeds without using a speed sensor [3].

The system operation algorithm begins with the determination of the electromagnetic moment of the electric motor and the stator flux vector. Then the module of the vector and the moment are compared with the given values, by means of regulators the logical error signals are formed. Possessing information about the operated signals and the interpretation of the stator flux vector, the optimal combination of conditions of the inverter keys is determined, in which the generated voltage vector is able to minimize the discrepancy of the specified values.

Due to the fact that the asynchronous motor is a non-linear system, it is difficult to achieve high control quality using hysteresis controllers [4].

The main disadvantage of this type of electric motor regulation is an increase in switching losses in the frequency converter and an increase in the pulsation torque of an asynchronous motor. The use of an adaptive neural network controller will minimize these disadvantages.

4. **Control of pump-compressor electrical equipment.**

Pressure and flow are the main characteristics of the pump.
The load of centrifugal and axial pumps, fans and other fan-type mechanisms are called fan load [5].

The asynchronous motor torque is in squared dependence with the rotational speed of the technological mechanism. To determine the dependence of the load torque on the motor shaft by its rotational speed, it is necessary to have mathematical expressions for the properties of the pump and pipeline.

In addition to changes in the flow of the operating fluid, its characteristics (temperature, pressure, etc.) are also subject to changes due to environmental changes. Also, there are effect of installed equipment in the pipeline circuit and other factors. The specific pressure loss of the pump increases with viscosity and density of the liquid increasing and with increased saturation of additives in it.

In this regard, the concentration of substances and the rheological properties of the transported liquid during the operation of centrifugal pumps can be characterized as controlled indicators.

These parameters in conjunction with the required fluid flow, can affect both the energy and hydraulic characteristics of the pump unit of the transport system and the preparation of working fluids systems [6].

Based on the chemical and rheological parameters of the operating fluid, the use of neural network controllers will lead to ability to avoid the occurrence of cavitation conditions.

In order to solve the problems of determining or approximating functions, multilevel networks of directional propagation are subjected to adjustment of weights. The adjustment is carried out on the basis of the created learning algorithms for neural networks, which are of three types [7-10]:

- Training with a teacher. Sets a set of training vectors - input parameters and the wishful outputs of the neural network. The weighting ratios in the learning procedure are chosen in order to get the outputs by acquired inputs as close as possible to the specified ones.
- Training with assessment. The required vector of output signals is not initially defined, but according to the results of the work, the neural network receives a positive or negative assessment.
- Training without a teacher. A set of input vectors is set, which are analyzed by self-organization methods, which allows the neural network to acquire the ability to solve these problems.

The neural network controller is developed on the basis of a neuro-emulator, which is trained on the basis of receiving back propagation of an error. For the development of a neuro-emulator, a multilevel network of direct distribution is established with independently determined weights and a training set consisting in network input systems — the wishful output, and the state of the system at the output. The task of development is to select weighting rations to minimize a certain objective function. The objective function is the sum of the squares of network errors on the models from the training set, and reducing this option is the least-squares solution method.

A neural network speed controller for an electric motor consists of a linearizer of feedback data received from a neural network controller, a neuro-emulator, in which training data sets are installed, a memory cell, which provides the procedure of determining the output error of the neural network output signal, the controlled organ, asynchronous motor, based on pulse width modulation and engine flow analyzer [11].

Adaptation of the neural network in the neuro-emulator occurs in relation to speed. In order to organize these parameters are used to determine the relationship of the weights of the network. After weights determining, the test data, other from the trainers, are entered into the neuro-emulator system to analyze the speed and control its generalizing capability.

5. Control simulation based on neural network controller and PID controller
To compare the regulation efficiency of both systems, it is necessary to make a clear calculation of measurements and model characteristics both of them. The basis of the comparative analysis is the frequency-controlled electric drive, the technical data of which are given in Table 1.
To begin, we determine the angular velocity of the pump, depending on its supply:

$$\omega = \omega_{\text{nom}} \cdot \left( \frac{H_c}{H_F} + (1 - \frac{H_c}{H_F}) \cdot \left( \frac{q_{\text{max,cons}}}{q_{\text{nom}}} \right)^2 \right)^{\frac{1}{2}} = 154.4 \cdot \left( \frac{1000}{1625} + (1 - \frac{1000}{1625}) \cdot \left( \frac{100}{140} \right)^2 \right)^{\frac{1}{2}} = 139.1 \text{ s}^{-1} \quad (1)$$

Pressure, reached with obtained velocity speed:

$$H = H_c + (H_{\text{nom}} - H_c) \cdot \frac{H_F \cdot \left( \frac{\omega}{\omega_{\text{nom}}} \right)^2 - H_c}{H_F - H_c} = 1000 + (1300 - 1000) \cdot \frac{1625 \cdot (\frac{139.1}{140})^2 - 1000}{1625 - 1000} = 1153 \text{ m} \quad (2)$$

Stable pressure:

$$(Z_2 - Z_1) + H_{3y} = \frac{H - H_{\text{nom}} \cdot \left( \frac{q_{\text{max,cons}}}{q_{\text{nom}}} \right)^2}{1 - \left( \frac{q_{\text{max,cons}}}{q_{\text{nom}}} \right)^2} = \frac{1153 - 1300 \cdot \left( \frac{100}{140} \right)^2}{1 - \left( \frac{100}{140} \right)^2} = 999 \text{ m} \quad (3)$$

Frequency converter electromotive force:

$$E_{FC} = \frac{U_{\text{phase,nom}}}{V_{\text{cont,nom}}} = \frac{3464}{0.985 - 0.00375 \cdot p_n} = 3544 V \quad (4)$$

Static ratio of the frequency converter:

$$K_{FC} = \frac{E_{FC}}{V_{\text{cont,nom}}} = \frac{3544}{10} = 354.4 V \quad (5)$$

Frequency converter transfer function:

$$W_{FC}(p) = \frac{K_{FC}}{pT_{FC} + 1} = \frac{354.4}{0.01p + 1} \quad (6)$$

The transfer ratio of the internal feedback of the engine electromotive force:

$$K_{\omega} = \frac{i_{\mu,\text{nom}} \cdot (k_E + x_1)}{\omega_{\text{1nom}}} = \frac{27.286 \cdot (124 + 7.676)}{157} = 22,884 V \cdot s \quad (7)$$

Electromagnetic constant ratio frequency controlled drive:

$$T_E = \frac{K_E}{R_E} = \frac{0.0851}{2.966} = 0.0287 s \quad (8)$$

Torque transfer ratio:

$$K_M = \frac{M_{\text{nom}}}{K_{\omega} \cdot (\omega_{1\text{nom}} - \omega_{\text{nom}})} = \frac{3238.34}{22,884 \cdot (157 - 154.4)} = 54,427 \frac{N \cdot m}{V} \quad (9)$$

Electro drive transfer function:

$$W_{M}(p) = \frac{K_M}{pT_E + 1} = \frac{54,427}{0.0287p + 1} \quad (10)$$

Pump unit inertia torque:

$$J_E = 1.2 \cdot J_{ED} = 1.2 \cdot 11 = 13.2 \text{ kg} \cdot \text{m}^2 \quad (11)$$

Speed unit transfer function:
\[ W_s(p) = \frac{1}{pJ_2} = \frac{1}{13.2p} \]  

Pressure feedback transfer ratio:
\[ k_f = \frac{U_{\text{nom,control}}^{0.5}}{(Z_2-Z_1)+H_{SV}} = \frac{10+0.5}{999} = 0.012 \frac{V}{m} \]  

Pump pressure transfer ratio:
\[ k_{pr} = \frac{H_{\text{nom}}}{\omega_{\text{nom}}} = \frac{1300}{154.4} = 8.42 \text{ ms} \]  

PI controller constant ratio:
\[ T_p = \frac{2\times T_{FC}\times K_{FC}\times K_M\times k_f \times k_{pr}}{J_2} = \frac{2\times 0.01\times 354.4\times 54.427\times 0.012\times 8.42}{13.2} = 2.953 \text{ s} \]  

PI controller transfer function:
\[ W_{PI}(p) = \frac{T_{EP}+1}{T_{PP}+1} = \frac{0.0287p+1}{2.953p} \]  

Proportional unit ratio:
\[ P = \frac{T_E}{T_{PP}} = \frac{0.0287}{2.953} = 0.00972 \]  

Integral unit ratio:
\[ I = \frac{1}{T_p} = \frac{1}{2.953} = 0.338 \]  

Simulated systems based on a PID controller and on neural controller are shown in Figure 1.

**Figure 1.** Systems models based on a PID controller and neural controller in the MatLab Simulink.

As a result of the experiment, the output characteristics of the two control systems presented in Figures 2 and 3 were obtained.
Figure 2. Pressure output characteristic of PID controller system.

Figure 3. Pressure output characteristic of an adaptive neural network controller system.

6. Conclusion.
A neural network controller modeled as an observer showed high efficiency in estimating rotational speed, rotor current, and torque. When the motor is started, using the neural network controller, the current and torque are 12% and 25% less respectively, than when using the PID controller. When the engine is started with a neural controller in the control circuit at idle, the current and torque are 15% and 14% less respectively, than when using the PID controller. Starting the motor with a neural controller at full rated load showed a decrease in starting current and torque by 10% and 10% respectively, than when using the PID controller.

Artificial neural networks are considered as a modern type of mathematical model that controls dynamic objects, since they are based on the functioning methods of the brain biological nerve cells.

Learning by example, combining and simultaneously processing multiple flows of incoming data, a system based on a neural network controller leads to associativity and guarantees high reliability of the control system. The neural network of the neural emulator training is based on the back-propagation error algorithm, and the neural network controller itself works in prediction mode and error reduction. The use of a neural network controller in the control circuit of the electric drive, as well as a neural network controller in conjunction with the PID controller, can improve the mechanical and energy characteristics of the electric motor.

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