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Development of Neuroxellar Algorithms for Adaptive Pi Adjustable Speed Control Parameters in Mining

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ANNOTATION: This article discusses the adaptive Pi regulator based on the basic function of a neural network (RBF) and it is used to control the velocity of a vector directional asynchronous motor. The structure of the control circuit consists of the RBF identifier of the standard Pi controller. The RBF Identifier is used to identify the Jacobian meaning of the asynchronous motor online. The "online" change of neural network parameters is performed by the gradient access method without prior training. Pi controller training is performed by using the "online" identification RBF model. It is advisable to test this controller under different conditions to finally make sure the reliability of the management technology we offer. Research has shown that the proposed controller provides good steadiness and stability of the steering system compared to what a conventional Pi controller provides.

KEYWORDS: RBF neural network Pi regulator, Pi control algorithm, Pi controller, inverted neural control, Pi regulator, RBF neuro-based Pi regulator, asynchronous motor. Nowadays, applied technologies of artificial neural networks are developing with special dynamism in the theory of intellectual computing. The following advantages of neurocellular approaches can be noted:

- Acceleration obtained as a result of parallel processing of information;
- Resilience to changes in management facility and environmental parameters;
- Reliability due to the abundance of system elements;
- Ability to use information hidden in the management object.

Multilevel network models have been developed in this direction, the prototypes of which are the functioning of the structures and mechanisms of biological nervous systems. They are used as a basic methodology to increase the management speed of various technical devices, which ultimately allows us to create super-fast control systems. Practice has shown that relying entirely on the application of a homogeneous neural network theory in the process of creating complex object management systems cannot lead to the desired results; that is, before creating a neural system of management that is close to or exceeds the results achieved using classical management systems. Modeling such networks requires large volumes of computing resources. To do this, it is advisable to use neuro-cellular devices, one of the components of the control system, or to use the decision-making modules that transmit the output signal, not directly related to the artificial neuro-network. Now let us analyze the use of artificial neuroxel, in the role of a neuroxell observer in the ventilation process with asynchronous electric motors of coal shafts.

The vector model of this process can be given the following form. Fig.1

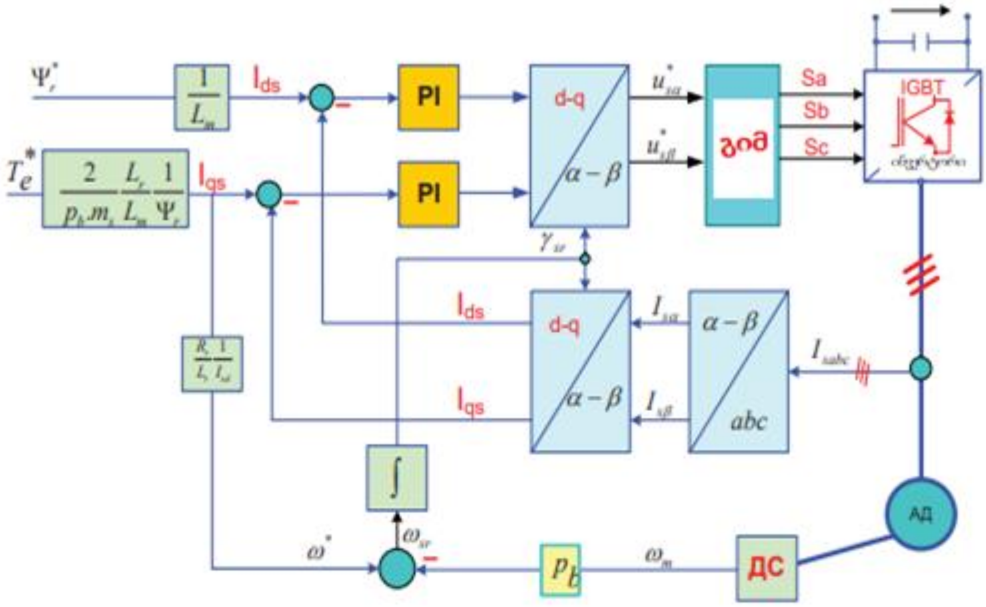

Fig. 1. Indirect field management block diagram

Transverse pulse modulation S_a, S_b, S_c inverter voltage source switch states:

Where P_p is the number of poles motor

γ_{Sr} - The vector angle of rotational flow

ω_{Sr} - Angular velocity of the rotor flow vector;

R_r - Rotor resistance during short circuit;

L_r - Rotor scattering inductance;

L_m - Main inductor of the rotor;

ψ_s – The vector of stator flow;

ψ_r - The vector of the rotor flow

T_e - Electromagnetic moment

M_c - static loading moment;

ω_m - Angular rotational frequency of the rotor;

J - moment of inertia of the electric motor.

Unlike direct vector management, indirect vector management is one of the most popular methods in the manufacturing field where required

$$\boldsymbol{U_{qs} = R_s i_{qs} + \frac{d}{dt}\Psi_{qs} + \omega_{sr}\psi_{qs}}$$

$$\boldsymbol{U_{ds} = R_s i_{ds} + \frac{d}{dt}\Psi_{ds} + \omega_{sr}\psi_{qs}}$$

$$\boldsymbol{U_{qr} = R_r i_{qr} + \frac{d}{dt}\Psi_{qr} + (\omega_{sr} - \omega_m)\psi_{dr}} \qquad \textbf{(1)}$$

$$\boldsymbol{U_{dr} = R_r i_{dr} + \frac{d}{dt}\Psi_{dr} + (\omega_{sr} - \omega_m)\psi_{qr}}$$

The main method of the Field Oriented Control (FOC) method is the transformation coordinate method. The power vector is measured by the real coordinate α-β.

Therefore the power components I_sα, I_sβ must be converted to a rotating d-q system. Similarly, the support voltage vectors U_ (sα), U_sβ must be converted from the d-q system to the α-β system. The Y_{sr} angle of the rotor flow is required for these transformations. According to the result of this angle (obtained by calculation), managing can be two types: Direct ThoseareDirect Field Oriented Control (DFOC) and Indirect Field Oriented Con¬trol (IFOC) methods. The Y_{sr} angle of the rotor flow is obtained by reference I_{ds}, I_{qs} currents. The angular velocity of the rotor flow vector is calculated by the following formula:

$$\boldsymbol{\omega_{rs} = \omega_{sl} + p_b\omega_m} \qquad (2)$$

$$\omega_{rs} = \omega_{sl} = \frac{1}{I_{sd}} \frac{R_r}{L_r} I_{sq} \qquad (3)$$

Developing algorithms for neurocellular adaptation of Pi regulator parameters for asynchronous motor speed control.

Pi controllers are widely used in the management of dynamic objects, particularly in the management of asynchronous motors. The use of classic Pi regulators still has some limitations. The article discusses the Pi regulator, which is based on the use of a neural RBF network when driving an asynchronous motor. The system management structure (for parameter management) using the neural RBF network is given in Fig.2. It is an intelligent Pi regulator that uses the operation of a neural RBF network.

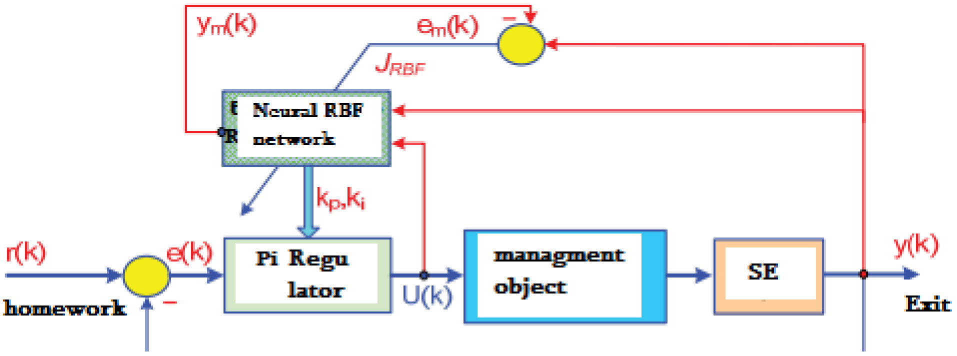

Fig. 2. RBF network dependent Pi regulator.

r (k) - assignment, e (k) - constraints, U (k) - signal management, y (k) - exit to the control object, y_m (k) - RBF identifier at the output.

The RBF network of the radial base function is a three-layer supply of artificial neurons that use the radial function as the activation function. The output signal from the network is a linear combination of the radial base function at the input and the neuron (as parameters). Radial basic functional networks also have multiple uses, approximation function, time series prediction, classification and system control. It has a quick self-learning ability as well as avoiding the problem of local minimums in the system management area. Therefore, the RBF - neural network is used in the development of control parameters in the Pi regulator settings. RBF - The neural network has three levels: input, covert, and output. Let's assume that our RBF neural network has 2 input levels, 5 hidden levels and 1 output level. The network structure is given in Fig. 3.

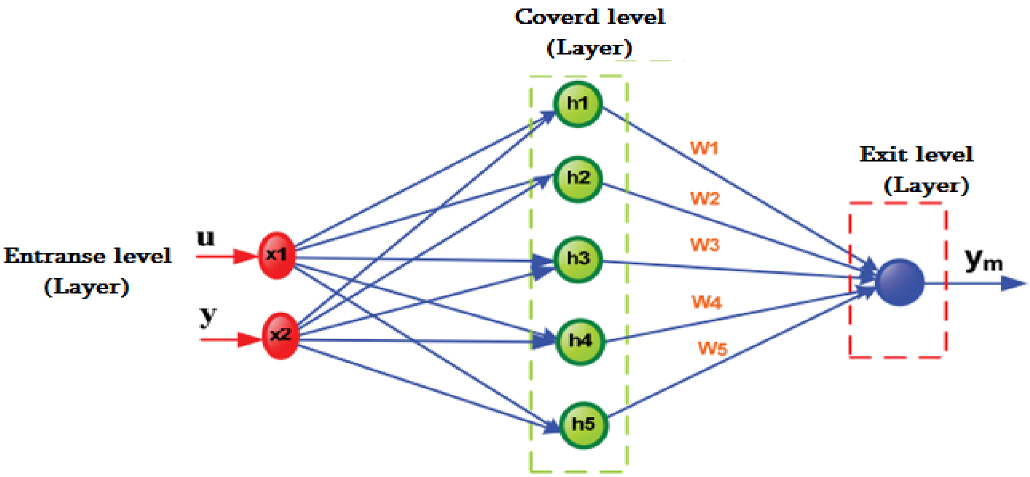

Fig.3. Neural Network RBF

In addition, the Jacobian matrix is used in the management strategy to adjust the parameters of the Pi regulator. The design network RBF, as already mentioned, consists of three levels (layers): entrance, covered and exit (see Fig. 2). We have two inputs in this grid so the input vector will look like this:

$$X = [x_1, x_2, \dots, x_i]^T = [u, y]^T; \qquad \{i = 1, 2\} \qquad (4)$$

The function of the activator in the RBF neural network is performed by the Gaussian function. Neurons covered by the Gaussian function are realized as basic functions and radial basal vectors $H = [\boldsymbol{h_1}, \boldsymbol{h_2}, \dots, \boldsymbol{h_j}, \dots, \boldsymbol{h_s}]^T$ can be expressed by the Gaussian function as follows:

$$\boldsymbol{h_j(x) = exp\left[\frac{-\|x - c_j\|}{2b_i^2}\right]; \quad \{i = 1, 2, \dots, 5\}} \qquad (5)$$

Where X - is the input vector of the neural network $C_j = [c_{j1}, c_{j2}]$- is the vector of the j-node on the coated layer, 〖b〗 _j is the width of the j-node of the coated layer a_j- is the number of neurons on the coated level (this Index variables are used in formula (17)).

Therefore, the network output can be formally described as:

$$\boldsymbol{y_m(k) = \sum_{j=1}^{j} w_j h_j(x)} \qquad (6)$$

Where $\boldsymbol{w_j}$ - are the weights of the RBF neural network. The functionality of the productivity index can be given as follows:

$$\boldsymbol{E(t) = \frac{1}{2}[y(k) - y_m(k)]^2} \qquad (7)$$

Where y (k) - is the ideal output. If we use the gradient access method, the RBF neural network parameters will be updated as follows:

$$\boldsymbol{w_j(k+1) = w_j(k) + \eta[y(k) - y_m(k)]h_j + \alpha[w_j(k) + w_j(k-1)]}$$

$$\boldsymbol{c_{ij}(k+1) = c_{ij}(k) + \eta[y(k) - y_m(k)]h_j w_j \frac{(x_i - c_{ij})}{b_j^2} + \alpha[c_{ij}(k) + c_{ij}(k-1)]} \qquad (8)$$

$$\boldsymbol{b_j(k+1) = b_j(k) + \eta[y(k) - y_m(k)]h_j w_j \frac{\|x_i - c_{ij}\|^2}{b_j^3} + \alpha[b_j(k) + b_j(k-1)]}$$

$$\boldsymbol{\frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial y_m(k)}{\partial u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_{1j} - x_1}{b_j^2}}$$

Where $\boldsymbol{x_1 = u(k)}$, $\boldsymbol{\eta \in (0,1)}$ - is the network learning velocity, α∈ (0,1) - is the momentum coefficient. Jacob's matrix algorithm is given by the formulas [13,15]. The parameters of the Pi regulator are determined by the Jacob matrix of the control device, which is obtained by identifying the RBF neural network.

It is known that the output of the Pi regulator depends on the k_p and k_i parameters. Much depends on the correct selection of these parameters for the efficient operation of the Pi regulator. In the RBF neural network it is possible to select the k_p and k_i parameters in different situations using the Jacob matrix. Formulas [7, ..., 14]

First of all, the expected error function in the network is defined:

$$\boldsymbol{E(k) = \frac{1}{2}[r(k) - y(k)]^2} \qquad (9)$$

The $\boldsymbol{k_p\ and\ k_i}$ parameters are then selected using the iterative gradient assumption method as follows:

$$\Delta \boldsymbol{k_p = -\eta \frac{\partial E}{\partial k_p} = -\eta \frac{\partial E}{\partial y} . \frac{\partial y}{\partial u} . \frac{\partial u}{\partial k_p} = \eta e(k) \frac{\partial y}{\partial u} . xc_1(k)} \qquad (10)$$

$$\Delta \boldsymbol{k_i = -\eta \frac{\partial E}{\partial k_i} = -\eta \frac{\partial E}{\partial y} . \frac{\partial y}{\partial u} . \frac{\partial u}{\partial k_i} = \eta e(k) \frac{\partial y}{\partial u} . xc_2(k)} \qquad (11)$$

Where $\frac{\partial y}{\partial u}$ - is the Jacob matrix given by Equation (8). $\boldsymbol{xc_1(k)}$ and $\boldsymbol{xc_1(k)}$ - the values are the inputs of the Pi regulator. Their calculation formulas are given below.

Management Pi algorithm

In this algorithm, the error between the desired and actual values, as shown in Figure 2, is determined by formulas (12), (13) as follows:

$$\boldsymbol{e(k) = r(k) - y(k)} \qquad (12)$$

$$\boldsymbol{e_m(k) = y(k) - y_m(k)} \qquad (13)$$

Pi regulator inputs can be expressed as follows:

$$\boldsymbol{xc_1(k) = e(k) - e(k-1)} \qquad (14)$$

$$\boldsymbol{xc_2(k) = e(k)} \qquad (15)$$

The gradient assumption method is used to determine the proportions k_p and integral k_p.

$$k_p(k+1) = k_p + \Delta k_p = k_p + \eta e(k)\frac{\partial y}{\partial u}.xc_1(k) \qquad (16)$$

$$k_i(k+1) = k_i + \Delta k_i = k_i + \eta e(k)\frac{\partial y}{\partial u}.xc_2(k) \qquad (17)$$

The Pi regulation algorithm is given as follows:

$$u(k) = u(k-1) + k_p\{e(k) - e(k-1)\} + k_i e(k) \qquad (18)$$

Brief description of neural RBF network based (PID) regulation.

The zero-RBF network-based Pi regulation block diagram is shown in Figure 4. It can be divided into the following stages:

- At the selection stage, select each value (k);
- Calculate the network **m** outputs according to the selected values;
- To get the Jacob matrix by using equations,
- Pi regulator settings apply for Pi regulation;
- Send a command to an asynchronous motor;
- Multitude k=k+1.

The Pi regulatory block diagram of the neural RBF network is given in Fig. 4

MODELING RESULTS

Computer modeling of a vector-asynchronous motor is performed using the MATLAB / Simulink package. IFOC and pulse were used for asynchronous motor ventilation. A comparison with the usual Pi regulation is given in Fig. 6.

We selected the standard parameters of the Pi regulator using the trial and error method, which we selected using the appropriate coefficients. For the speed controller these settings are $k_p = 110$, $k_i = 10$. The frequency of the selector inverter is 5 kg, the nominal voltage of the intermediate circuit is 100 V. The selection time interval for modeling is $T_S = 0,02$ ml.

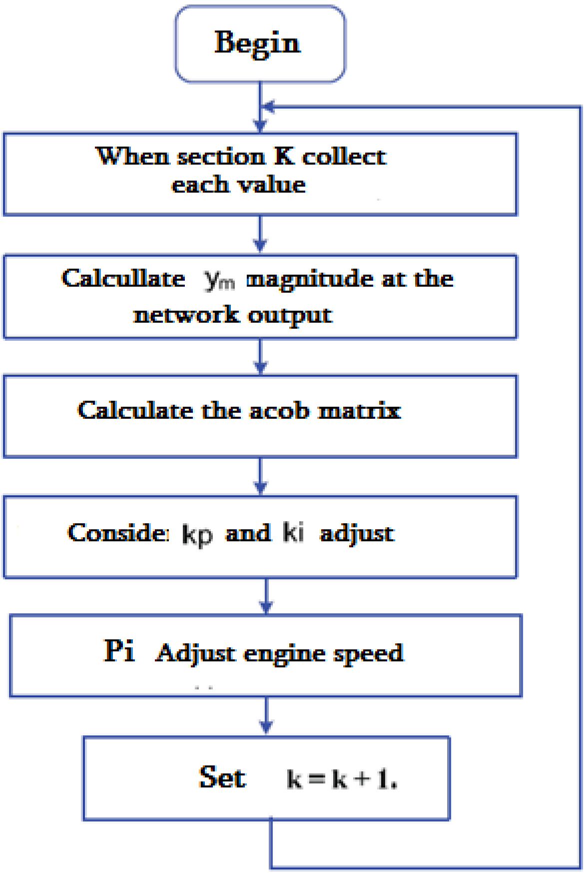

Fig.4. Block diagram of RBF neural network regulation

Figure 6 shows that the induction motor of a motor assembled on a neural network requires less adjustment and also contains less stationary error than conventional steering. When setting up a neural network, control options can be selected online.

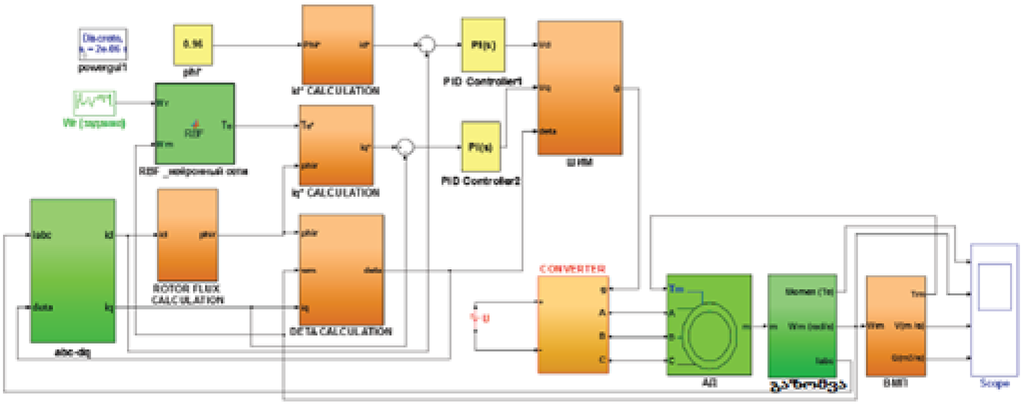

Fig.5. Simulink model of control vector asynchronous motor

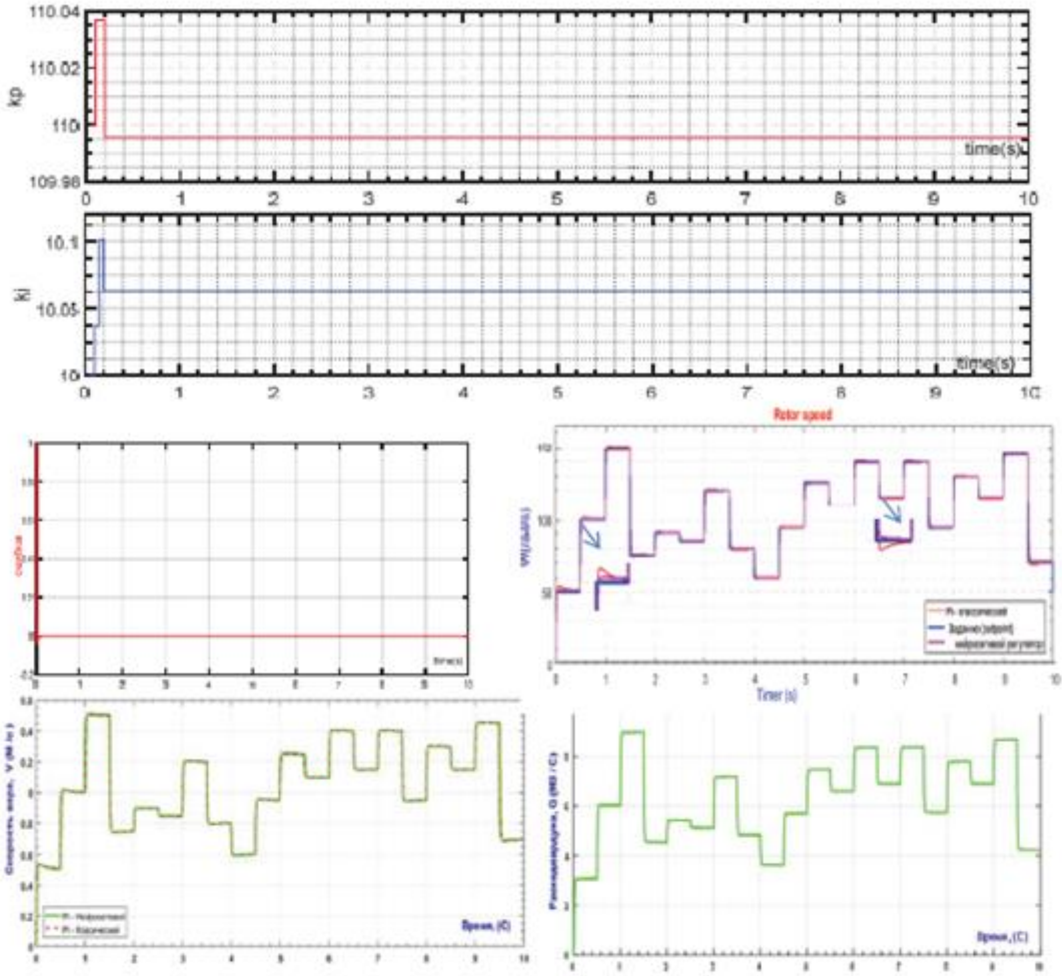

Fig.6. Neurocontroler modeling concepts

Parameter name and unit of measurement	**Meaning**
1	**2**
Power, quota	**25**
Tension in volts	**380/660**
Rotation speed, r / min	**3000**
Network frequency, Hz	**50-60**
cos ϕ	**0,88**
Multiplication of the initial check driving torque by the nominal	**1,9**
Minimum moment multiplication by the denominator	**1,3**
Multiplication of maximum moment with minimum	**2,5**
Moment of inertia (J), kg / m 2	**0,085**
Relative mass, kg / kW	**9,5**
Stator active phase resistance R_s, O_M	**0,455**
Active impedance of the rotor R_R, O_M	**0,413**
Inductor of stator and rotor scattering	**0,0048**
Mutual inductance L_μ	**0,698**
Fan diameter, m	**0,6**
Working area, m2	**12,1**

Managing the ventilation process of shafts in mining enterprises using neural networks ensures the creation of a normal production (working) climate in these enterprises and at the same time significantly reduces the economic costs of energy consumption.

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