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Для синтезу адаптивних систем керування асинхронним електроприводом, що містить двигун з дефектами або неякісностями, було запропоновано структуру та розроблено алгоритм навчання ПІД-нейрорегулятора на основі багатошарової нейронної мережі прямого поширення. Такий підхід дозволяє оперативно реагувати на зміну характеристик об'єкта керування, що виникають внаслідок появи і розвитку пошкоджень та неякісностей двигуна. Це дозволяє підвищити керованість двигуна, і, як наслідок, подовжити строк його експлуатації та підвищити енергоефективність роботи. Запропоновані рішення, на відміну від традиційних, не вимагають використання додаткового обладнання для реалізації. Необхідно лише змінити керуючу програму перетворювача частоти на основі розробленого алгоритму. Для практичної реалізації запропонованих рішень було синтезовано алгоритм навчання нейронної мережі ПІД-нейроконтролера з самоналаштуванням. Він дозволяє розраховувати вагові коефіцієнти нейронів, що в подальшому може бути покладено в основу програмного забезпечення фізичної системи керування з ПІД-нейроконтролером. Проведено математичне моделювання роботи АД з обривом стрижнів ротора та витковими замиканнями у обмотках статора при використанні запропонованого регулятора. Аналіз результатів моделювання засвідчив, що запропонований підхід керування електроприводом з пошкодженням АД дозволяє знизити амплітуду та кількість неосновних гармонік сигналів струму та потужності АД при збереженні заданих параметрів технологічного процесу. Показана ефективність застосування запропонованих рішень для задач підтримування заданих параметрів технологічного процесу для випадку стохастичної зміни характеристик об'єкта керування.

Ключові слова: ПІД-нейрорегулятор, нейронна мережа, асинхронний двигун, діагностика, система керування, перетворювач частоти, пошкодження.

DEVELOPMENT OF THE PID-NEUROCONTROLLER TO COMPENSATE FOR THE IMPACT OF DAMAGES AND DEGRADATION OF INDUCTION MOTOR ON OPERATION OF THE ELECTRIC DRIVE SYSTEM

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1. Introduction

Owing to the simplicity of design and relative reliability of operation, the induction motor (IM) is currently the most common converter of electrical energy into mechanical energy and is a key element of most controlling elements both in industry and in the national economy [1–3]. Given the massive introduction of controlled electric drive that has been observed over the last few decades, there are enhanced requirements to the controllability of IM. However, even the high quality adjusted control systems can exhibit, over time, degraded manageability indicators as a result of action of external factors, which cannot always be accounted for when designing the system. One of the most important factors in this regard is the emergence or development of damage or degradation in IM, leading to changes in the characteristics during operation. This leads in turn to the inefficiency of control systems tuned by standard methods using the law of PID-control. In such

cases, it is expedient to employ adaptive controllers that can maintain the specified parameters of technological process even at a change in the characteristics of IM. It is also necessary to consider the energy efficiency of utilizing such controllers. Execution of the tasks on maintaining the set parameters of the technological process for IM that is subject to damage or degradation can lead to the increased energy consumption and economic inefficiency of such a type of control.

Thus, there is an important task at present to develop methods to control the asynchronous electric drive, which includes motors with existing defects or degradation. Such methods, in addition to the implementation of actual support of the predefined parameters of the technological process, must make it possible to obtain improved energy performance indicators of the electric drive system.

It is possible to ensure the operation of motor with existing damage or degradation by using the method of frequency regulation using the adaptive control methods,

such as PID-control that employs artificial neural networks (NN) [4]. Typically, to obtain the coefficients of PID-controller, such methods are applied as the empirical method by Ziegler-Nichols, the Cohen-Coon method, the CHR method, or others. NNs possess a set of important properties that proved useful when creating control systems: the ability to adapt to a change in the properties of control object and external influence, the capability to learn by examples and the generalization of data.

Artificial NNs, in the general opinion of researchers, are the universal and effective means of modeling and identification of static non-linear objects [4]. At present, using NN successfully solves complex tasks on recognition, classification, and optimization. Equally promising is to use artificial NN, and above all the class of multilayered ones, for the synthesis of optimal (or rather, quasi-optimal) control algorithms over multi-connected nonlinear objects with complex dynamics. The combination of the two new concepts in the modern control theory, the synergy theory and the theory of artificial NN capable of learning, opens up broad prospects for the implementation of the task on synthesis of energy efficient controllers in the systems of electric drive.

From the standpoint of the modern theory of automatic control, the application of multilayered NNs, as objects controllers, is adequate for the tasks that emerge in the cases when an analytical synthesis of a control system becomes quite a time-consuming task because of the complexity or unreliability of the employed mathematical model of the object. Such a situation is inevitable if the object is a multiconnected system that includes nonlinearities while its operation is accompanied with uncontrollable changes in the dynamic properties over time, which is the case when IM is subject to damage or degradation.

NN can be used in various modifications of engagement in the structure of a control system, such as: control with a reference model of the control object, the method of hybrid control, the method of inverse control, the method of direct neuro-control, and others.

2. Literature review and problem statement

It is known that IM is typically designed for a 15–20-year-long service life without a major repair under condition of proper operation. In reality, however, there are situations when there is a deviation from the rated modes of operation in the case of the occurrence and development of damage, or due to a production defect, which could lead to an emergency mode [2, 3].

In order to prolong the life time of operation and to improve the manageability of IM that already has defects, they use methods for the compensation of the impact of certain types of defects or degradation on the operating modes of the system of an asynchronous electric drive.

Thus, one of the methods to compensate for the torque failure in the presence of the rotor asymmetry is the introduction of counter electromotive force to the circuit of the stator. The disadvantage of this method is that an error in the calculation of the full input impedance at a frequency different from the industrial one leads to the non-uniformity of the torque and a reduction in the maximum torque at the slip magnitudes that are lower than the critical [5].

Another method is the introduction of active resistances to the stator circuit [5]. The weakest point in a given method of compensation is a very low efficiency coefficient because of the large release of active power at rheostats.

The specified methods, as well as those similar to them, require the installation of additional equipment, and therefore are not promising given modern capabilities of automated control systems.

The most promising are those methods that do not require the installation of additional equipment, but instead require only a change in the operating algorithm within the existing control system. A significant number of modern systems of control over the asynchronous electric drive include frequency converters. That is why a change of the algorithm for operating this very device seems most convenient in order to adjust operational modes in case IM is subject to damage or degradation.

Thus, paper [6] reports analysis of operation of the electro-mechanical system under conditions of a power network degradation; studies [7, 8] proposed a method for compensating inactive components of instantaneous power when forming the compensation currents under conditions of low-quality parameters in a power supply network. The obtained theoretical results can be implemented in software for the frequency converter (FC) in order to adjust the operating mode of IM; they, however, require significant computational power to work in a real-time mode.

Paper [9] demonstrated a possibility to use FC to compensate for the asymmetry of IM under the scalar, and under vector, in [10], control technique. However, it is rather difficult at present to technically implement the proposed solutions and they require significant computing power.

To improve the performance of software for FC that implements the algorithm for the compensation of effect of defects and degradation in IM on operating parameters of the electric drive, it is advisable to use adaptive controllers based on neural networks (NN). The two most widely used methods to control the asynchronous electric drive with compensation for the impact of motor degradation are PID-control with self-tuning using a neural network (NN) and the phase asymmetry compensation using NN [11].

Classic PID-controllers demonstrate poor quality indicators when controlling non-linear and complex objects, as well as at insufficient information on the control object, which occurs in the presence of an acquired damage or in the development of defect in IM. Characteristics of controllers in these cases can be improved by using the methods of fuzzy logic, NN, and genetic algorithms [12, 13]. The methods specified are referred to in the scientific literature as «soft-computing», emphasizing the difference from «hard-computing», which implies the ability to operate with incomplete and inaccurate data. A single controller can employ a combination of the above methods (fuzzy+PID, neural+PID, neural+fuzzy+PID, controllers with genetic algorithms). The main disadvantage of fuzzy and neural-network controllers is the complexity of their tuning (compiling a rules base and training NN).

NN are used in PID-controllers in two ways: to build the controller itself and to build the unit for setting its coefficients. The peculiarity of NN is the ability to «learn», which makes it possible to pass experience of an expert to the network. In contrast to methods of compensation, considered in [6, 7, 9, 10], the implementation of PID-controller with a properly trained NN has no essential effect on a decrease

in the performance of FC operation, therefore, it is a quite promising and relevant task for today.

The most difficult part in designing controllers with NN is the procedure of training a network. The training implies the identification of unknown parameters of the neurons. To train NN, typically used are the methods of gradient search for a minimum of the criterial function that depends on neurons' parameters. The search process is iterative, all coefficients of the network are derived at each iteration, first for the output layer of neurons, then the preceding one, and in the same way to the first layer (error back propagation method) [14]. Other search methods for a minimum are also applied, including genetic algorithms, the method of simulated annealing, the method of least squares [11, 12, 14]. To solve a problem on the compensation for the influence of IM degradation and defects on operating parameters of the electric drive system, it is advisable to previously train NN on mathematical models that simulate the work of IM with the most common defects.

Thus, at present, still unresolved at the appropriate level is the task on the development of methods and means of control over asynchronous electric drive with damaged or defective IM aimed at better manageability under conditions of a stochastic change in the control object parameters. This task can be solved by developing a structure of PID-controller and by training NN on the basis of mathematical models in order to examine operation of IM subject to degradation and defects.

3. The aim and objectives of the study

The aim of this study is to create control system using artificial NNs to control asynchronous electric drive with the possibility to compensate for the impact of motor damage or degradation.

To accomplish the aim, the following tasks have been set:

- to choose a mathematical apparatus for the development of NN as part of PID-controller;
- to devise the structure and operating algorithm of NN for the tasks on control over dynamic nonlinear objects;
- to implement and execute the process of training NN;
- to perform mathematical modeling of the operating modes of IM with a control system based on the developed PID-neurocontroller.

4. Analysis of operation of adaptive control system over asynchronous electric drive with a PID-neurocontroller

In this work, the main structure in the control system is NN. To implement adaptive control, we chose a network of the multilayered perceptron type, which is a supporting structure of neural-PID-control. The object of control is a model of IM subject to damage or degradation, built in the phase coordinate

system. The designed model is capable of simulating the operation in the presence of such defects as the short-circuited turns in stator windings, break of rotor bars, stator windings asymmetry, imbalance of the rotor, poor IM attachment to supports.

4. 1. Development of the structure and operating algorithm of a PID-controller

Fig. 1 shows the architectural graph of a multilayer perceptron with two hidden layers and one output layer. The network shown in the Figure is fully-connected, which is typical for a multilayer perceptron in the general form. This means that each neuron at any layer of the network is connected to all of the neurons (nodes) of the preceding one. Network signal is transmitted only in the forward direction, from left to right, from layer to layer.

To train the NN employed in the control system considered in this paper, we used the modified back-propagation algorithm (BP), namely, the algorithm of resilient back-propagation.

In contrast to a standard BP algorithm, the method of resilient back-propagation applies only the signs of partial derivatives in order to adjust weight coefficients [15].

The algorithm uses the so-called «learning by the epochs», when the adjustment of weights occurs after the network has been presented with all examples from the training sample.

Based on a chosen algorithm of NN functioning, we constructed a control scheme to train PID-controller with self-tuning (Fig. 2).

NN is used here instead of a human operator, which ensures the minimization of an error by adjusting the PID-coefficients.

The procedure for designing the structure of a PID-neurocontroller is described in [4].

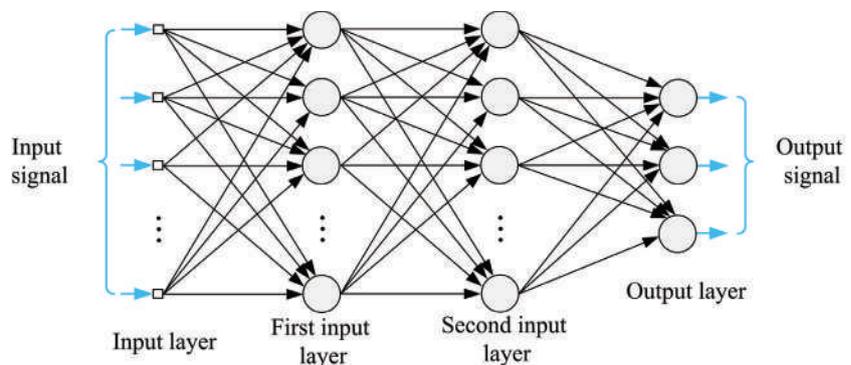


Fig. 1. Architectural graph of a multilayer perceptron with two hidden layers

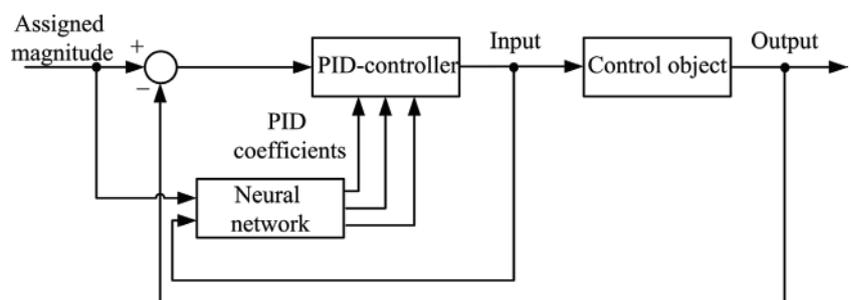


Fig. 2. Scheme of training a PID-controller with self-tuning

It is known that PID-controller with a discrete time is described by the following equations:

$$\begin{aligned} u(t) &= u(t-1) + K_p(e(t) - e(t-1)) + \\ &+ K_I e(t) + K_D(e(t) - 2e(t-1) + e(t-2)), \\ e(t) &= r(t) - y(t), \end{aligned} \quad (1)$$

where K_p , K_I and K_D are the PID coefficients, $r(t)$ is the assigned (desired) magnitude of the output signal from control object. To derive the algorithm for self-tuning a PID-controller, it is necessary to assign a cost function E , which is subject to the minimization:

$$E = \frac{1}{2} e^2(t+1). \quad (2)$$

The use of a three-layer NN implements a learning rule to search for suitable values for PID coefficients. Thus, the output signals of the output layer are K_p , K_I and K_D , denoted $O(1)$, $O(2)$ and $O(3)$, respectively. Based on the algorithm of the fastest descent, we derived expressions to calculate the weight coefficients of the output layer:

$$\Delta w_{kj}(t+1) = -\eta \frac{\partial E}{\partial w_{kj}} + \alpha \Delta w_{kj}(t), \quad (3)$$

and for the input layer:

$$\Delta w_{ji}(t+1) = -\eta \frac{\partial E}{\partial w_{ji}} + \alpha \Delta w_{ji}(t). \quad (4)$$

Determine a local gradient:

$$\delta_k = \frac{\partial E}{\partial net_k}, \quad (5)$$

where

$$net_k = \sum_j w_{kj} O_j + \Theta_k.$$

Denote the output of the k -th neuron in the output layer through $O(k)$, then:

$$O(k) = f(net_k). \quad (6)$$

However, the values of PID coefficients are not limited to the range from 0 to 1. Therefore, after the output of network $O(k)$ one can use a certain transmission coefficient c , so that:

$$O(k) = c \cdot f(net_k), \quad c > 0. \quad (7)$$

Parameter c can also be determined by training, increasing the number of neurons in the hidden layer. For simplicity, it is possible to accept $c = 1$. Applying the chain rule, we obtain:

$$\frac{\partial E}{\partial w_{kj}} = \frac{\partial E}{\partial w_{kj}} \frac{\partial net_k}{\partial w_{kj}} = \frac{\partial E}{\partial net_k} O_j, \quad (8)$$

and

$$\delta_k = -\frac{\partial E}{\partial net_k} = -\frac{\partial E}{\partial y(t+1)} \frac{\partial y(t+1)}{\partial u(t)} \frac{\partial u(t)}{\partial O(k)} \frac{\partial O(k)}{\partial net_k}. \quad (9)$$

However,

$$\begin{aligned} \frac{\partial E}{\partial y(t+1)} &= \frac{\partial E}{\partial e(t+1)} \frac{\partial e(t+1)}{\partial y(t+1)} = \\ &= -(r(t+1) - y(t+1)) = -e(t+1), \end{aligned}$$

$$\frac{\partial u(t)}{\partial O(k)} = f'(net_k) = O(k)(1 - O(k)),$$

$$\frac{\partial u(t)}{\partial O(k)} = \begin{cases} e(t) - e(t-1); & k=1; \\ e(t); & k=2; \\ e(t) - 2e(t-1) + e(t+2); & k=3. \end{cases} \quad (10)$$

The last ratio was derived from (7) taking into account that $O(1) = K_p O(2) = K_I$ and $O(3) = K_D$. Thus, we come to:

$$\Delta w_{kj}(t+1) = -\eta \delta_k O_j + \alpha \Delta w_{kj}(t), \quad (11)$$

where

$$\delta_k = e(t+1) \frac{\partial y(t+1)}{\partial u(t)} O(k)(1 - O(k)) \frac{\partial u(t)}{\partial O(k)}. \quad (12)$$

We obtain for the hidden layer:

$$\begin{aligned} \frac{\partial E}{\partial net_j} &= \sum_k \frac{\partial E}{\partial net_k} \frac{\partial net_k}{\partial O_j} \frac{\partial O_j}{\partial net_j} = \\ &= -\sum_k \delta_k w_{kj} f'(net_j) = -\sum_k \delta_k w_{kj} O_j (1 - O_j). \end{aligned}$$

Thus,

$$\Delta w_{ji}(t+1) = \eta \delta_j O_i + \alpha \Delta w_{ji}(t), \quad (13)$$

$$\delta_j = -\frac{\partial E}{\partial net_j} = \sum_k \delta_k w_{kj} O_j (1 - O_j). \quad (14)$$

To determine coefficients δ_k using expression (12), it is necessary to know the Jacobian of system $\partial y(t+1)/\partial u(t)$; to obtain its estimate, we employ an emulator. Principal scheme of the emulator is shown in Fig. 3.

Thus, the learning algorithm for self-tuning a PID-neuro-controller can be represented in the following form:

- set the initial values for w_{kj} , w_{ij} , O_k , O_i , η , α . Assign $t = 0$.
- compute values for $e(t+1)$ and δ_k :

$$e(t+1) = r(t+1) - y(t+1),$$

$$\delta_k = e(t+1) \frac{\partial y(t+1)}{\partial u(t)} O(k)(1 - O(k)) \frac{\partial u(t)}{\partial O(k)}, \quad k=1, 2, 3,$$

where

$$\frac{\partial u(t)}{\partial O(k)} = \begin{cases} e(t) - e(t-1); & k=1; \\ e(t); & k=2; \\ e(t) - 2e(t-1) + e(t+2); & k=3, \end{cases}$$

- compute weight coefficients of the output layer:

$$\Delta w_{kj}(t+1) = -\eta \delta_k O_j + \alpha \Delta w_{kj}(t);$$

– compute a local gradient:

$$\delta_j = -\frac{\partial E}{\partial net_j} = \sum_k \delta_k w_{kj} O_j (1 - O_j);$$

– compute weight coefficients of each following layer:

$$\Delta w_{ji}(t+1) = \eta \delta_j O_i + \alpha \Delta w_{ji}(t);$$

– pass over to computing the values for the next time interval $t \rightarrow t+1$.

Based on a given algorithm, during a learning process, we determine weight coefficients of neurons from all layers of NN. The trained NN is ready to be used as an element of an actual adaptive PID-neurocontroller.

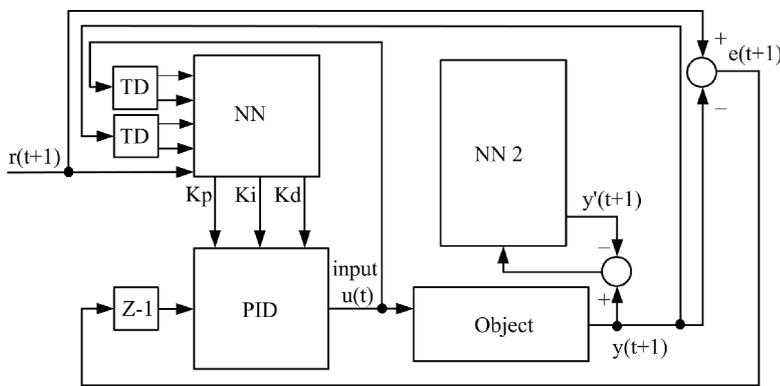


Fig. 3. Principal scheme of a PID neurocontroller with self-tuning, where neural network NN1 is used to determine PID coefficients, NN2 – to derive a Jacobian of the system

4. 2. Direct adaptive PID control

The application of artificial NN in control systems can be used for systems whose dynamics is not explicitly defined. Fig. 4 shows two typical schemes of employing NN in conjunction with PID-controller.

The first scheme is used when NN is applied as a direct control structure; in this case, the generation of PID-controller coefficients. In other cases, the network produces direct controlling influences for the control object. In the second case, NN produces a control error in order to ensure a more precise work of PID-controller; this is the case of indirect control.

PID coefficients are laid down into neural structures as weights, that is, they can be adjusted in the learning process. A learning rule is based on the error between an actual and estimated value. To tune PID-controller, it is possible to employ both the networks of direct propagation (perceptron) and the more complex types, such as the networks based on radial-basis functions or networks with wave functions. The basis is the method of direct adaptive PID neural control, except that NN receives not only the value for the signal of misalignment, but also the value of the set point. In the future, it is possible to implement an algorithm, in which a network additionally receives values for the current control signal from a PID-controller, in order to obtain more information to improve the accuracy in the selection of the values for coefficients. In a given system, the trained neural network receives the value for the signal of misalignment from a sensor, as well as a set point value, and generates values for the coefficients, which arrive to the controller, which also receives values over a feedback circuit.

The selected type of neural control implies training NN in an off-line mode based on the pre-recorded behavior trajectories of control object, that is, the model of IM with defects.

A significant advantage of the chosen method is the application of NN with a relatively small complexity compared to the on-line training mode, which is an advantage in the further implementation of the chosen solutions in the form of lower-level software.

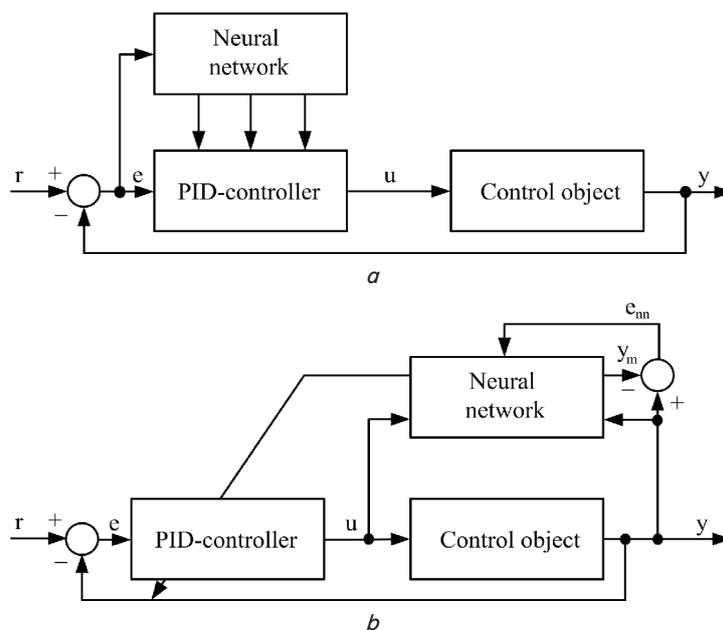


Fig. 4. Combining neural networks and PID-control: a – direct adaptive PID neural control; b – indirect control

4. 3. Mathematical model of the motor in the presence of stator and rotor windings defects

One of the most common types of IM degradation is the stator and rotor windings faults, specifically a parametrical asymmetry of the stator windings, break of the rotor bars, and the stator winding short-circuited turns [2, 3]. In order to build the mathematical model of IM, we applied a method of construction in the phase coordinate system [1].

Among the structural IM imperfections, the most common is the asymmetry of the stator windings. That emerges as a result of poor fabrication or repair (re-winding of windings) of IM, which results in a different number of turns of the winding in different phases.

The asymmetry of the stator phase windings is accounted for by using a coefficient ϵ , which equals 1 at full symmetry of the winding, 0 – at a complete asymmetry.

The presence of asymmetry affects parameters of the stator phase in the following way:

$$R_1 = \epsilon R_1; \quad L_{\mu} = \epsilon L_{\mu}; \quad L_1 = \epsilon^2 L_1.$$

Given this, the equation of current linkage for phase «A» of the stator takes the form:

$$\psi_A(t) = L_1 i_A(t) \epsilon^2 + L_{\mu} \epsilon \left(\begin{array}{l} i_a(t) \cos(\gamma) + i_b(t) \cos\left(\gamma + \frac{\pi}{3}\right) + \\ + i_c(t) \cos\left(\gamma - \frac{\pi}{3}\right) - 0,5(i_b(t) + i_c(t)) \end{array} \right)$$

Structural scheme of forming the current of phase «A» in the stator is shown in Fig. 5.

Thus, the mathematical model account for the impact of the presence of asymmetry in the stator windings on electric parameters of the model in general.

To test the adequacy of the model, we derived model data for IM of the type AO90S-4 (1.1 kW, 1,410 rpm; 2.8 A) with the following parameters (Fig. 6):

- $L_{\mu} = 0.166$ Gn – maximal magnitude of intra-inductance;
- $R_s = 7.62$ Ohm – active resistance of the stator;
- $R_r = 7.8$ Ohm – reduced active resistance of the rotor;
- $L_{\delta s} = L_s - L_{\mu} = 0.0221$ Gn – reduced inductance of the stator winding scattering;
- $L_{\delta r} = L_r - L_{\mu} = 0.0214$ Gn – reduced inductance of the rotor winding scattering;
- $J = 0.0017$ kg m² – motor inertia moment.

Fig. 6 shows that current grows in the phase with a reduced number of turns (phase «A»); in this case, it decreases in one of the other phases. This leads to the overheating of the winding, and its premature failure, since, although the active voltage of phase R_A decreases, the losses in copper, which are equal to $\Delta P_{m1} = i_A^2(t) R_A$, increase relative to the other phases. In addition, a substantial variable component emerges in the signals of speed and torque, indicating the occurrence of vibrations.

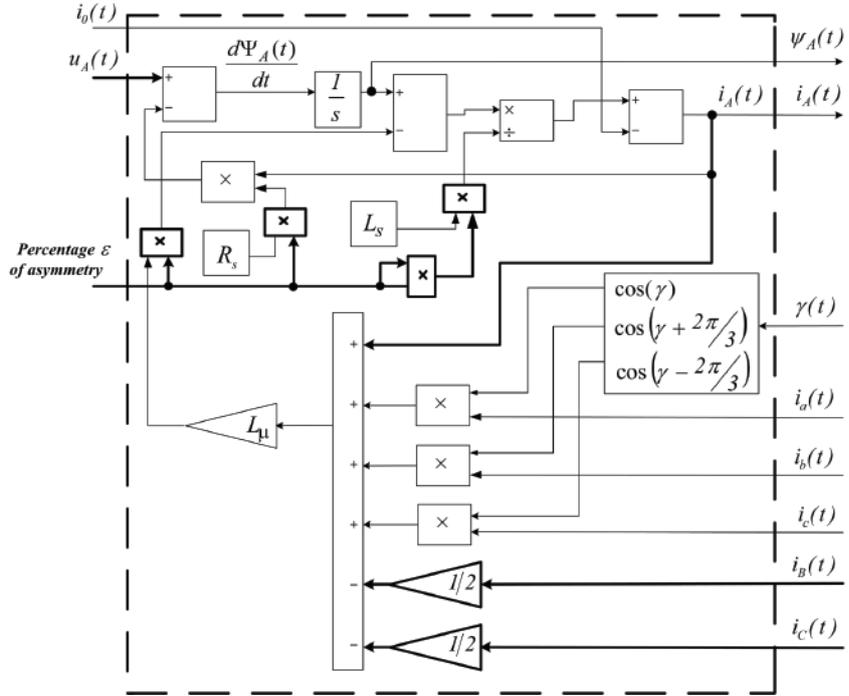


Fig. 5. Structural scheme of the mathematical model for phase «A» of the IM stator in the presence of asymmetry

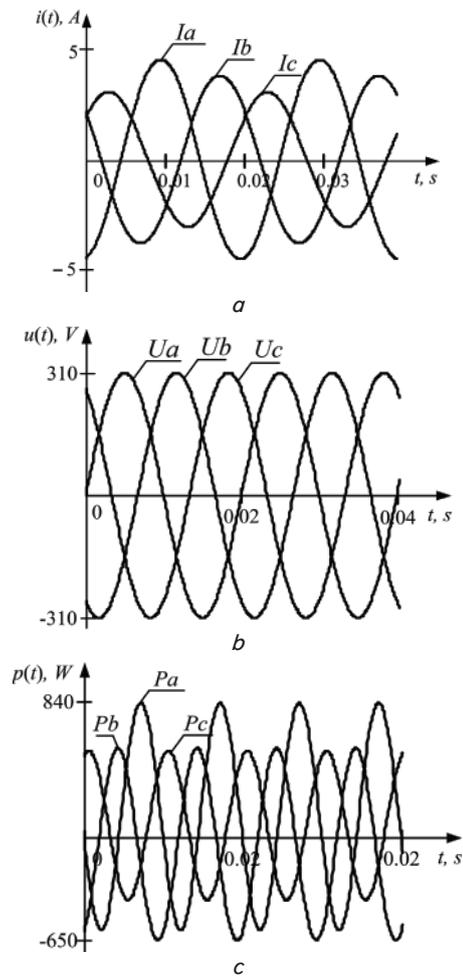


Fig. 6. Time dependences of electric signals of IM phases in the presence of the stator windings asymmetry (10 %) in the mode of idling: a – current; b – voltage; c – power

Damages of the rotor most often include a break of the bars, which, in turn, significantly affects operating conditions of IM. Therefore, we shall consider construction of a mathematical model for IM in a three-phase coordinate system in the presence of a break of bars of the rotor.

To study the impact of defects of the rotor windings, we extended the IM base model in a three-phase coordinate system. In particular, for better visibility and credibility of the obtained results, the model includes 12 bars on the rotor. This fact is taken into consideration in building complete equations of electrical equilibrium for the rotor circuits. Even though this complicates the mathematical notation, constructing such a model is necessary to enhance the reliability of the modelling results.

The system of equations for electrical equilibrium of the rotor circuits takes the form:

$$\begin{cases} 0 = i_a R_r + \frac{d\Psi_a}{dt}; \\ 0 = i_b R_r + \frac{d\Psi_b}{dt}; \\ 0 = i_c R_r + \frac{d\Psi_c}{dt}; \\ 0 = i_a' R_r + \frac{d\Psi_{a'}}{dt}; \\ 0 = i_b' R_r + \frac{d\Psi_{b'}}{dt}; \\ 0 = i_c' R_r + \frac{d\Psi_{c'}}{dt}; \end{cases} \quad (15)$$

$$\begin{cases} 0 = i_a'' R_r + \frac{d\Psi_{a''}}{dt}; \\ 0 = i_b'' R_r + \frac{d\Psi_{b''}}{dt}; \\ 0 = i_c'' R_r + \frac{d\Psi_{c''}}{dt}; \\ 0 = i_a''' R_r + \frac{d\Psi_{a'''} }{dt}; \\ 0 = i_b''' R_r + \frac{d\Psi_{b'''}}{dt}; \\ 0 = i_c''' R_r + \frac{d\Psi_{c'''}}{dt}. \end{cases} \quad (16)$$

The current linkage of each IM phase is defined by the magnitude of natural inductance of the winding and by intra-inductance with all other windings.

For example, for phase «A» of the stator:

$$\begin{aligned} \Psi_A(t) = & L_A i_A(t) + M_{AB} i_B(t) + M_{AC} i_C(t) + M_{Aa} i_a(t) + \\ & + M_{Ab} i_b(t) + M_{Ac} i_c(t) + M_{Aa'} i_{a'}(t) + M_{Ab'} i_{b'}(t) + \\ & + M_{Ac'} i_{c'}(t) + M_{Aa''} i_{a''}(t) + M_{Ab''} i_{b''}(t) + M_{Ac''} i_{c''}(t) + \\ & + M_{Aa'''} i_{a'''}(t) + M_{Ab'''} i_{b'''}(t) + M_{Ac'''} i_{c'''}(t), \end{aligned} \quad (17)$$

where L_A – phase inductance; M_{xy} – intra-inductance between windings x and y .

It is worth noting that at conditional division of the rotor winding into 4 groups (each group is a regular three-phase winding), there is a rotation angle φ relative to the main group of windings for each of the three additional groups.

Structural scheme for the stator phase «A» is shown in Fig. 7. The simulation is carried out similarly for the remaining phases of the stator and rotor.

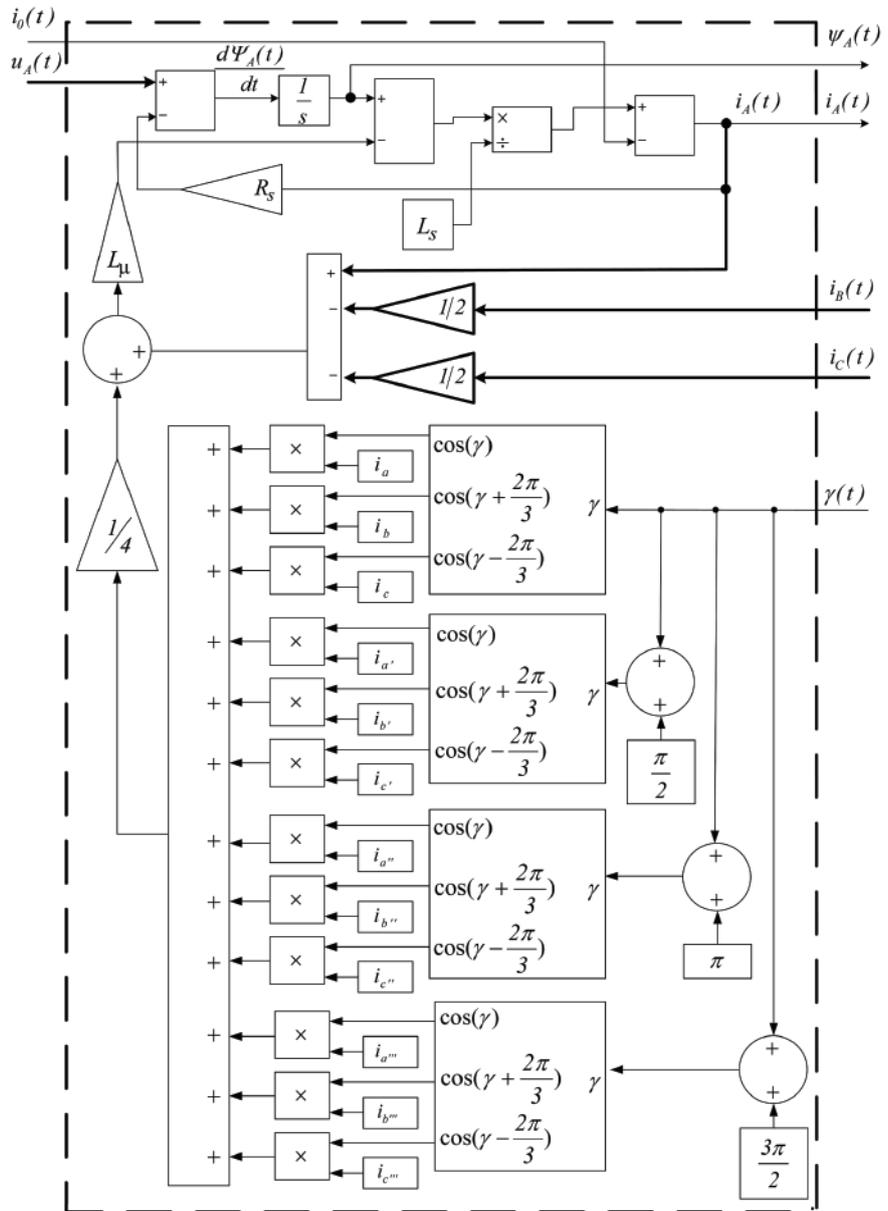


Fig. 7. Structural scheme of the stator phase «A»

When the modified model operates without a break of the bars, the obtained instantaneous values of signals completely coincide with the signals of the base model, which attests to the correctness of the construction.

The resulting mathematical model allows us to examine electromagnetic processes in IM maximally close to the actual pattern in the machine operating mode.

The mathematical model of IM in a three-phase coordinate system with the decomposition of the rotor windings was derived in the following way: simulation of a rotor winding bar break is executed by equating to zero the current

that flows through a given bar. Thus, a zero current value in one of the bars causes the asymmetry in the rotor windings and distorts the shape of currents in other bars.

A break of one of the rotor bars increases the fluctuations of starting torque of IM and currents; one also observes the asymmetry of rotor currents due to the damage.

Thus, we have constructed the IM mathematical models in the phase coordinate system, which make it possible to simulate the work of asynchronous machine in the presence of short-circuited turns in the stator winding and a break of the rotor bars. The models built are suitable to examine control systems based on artificial NN.

4. 4. The synthesis of a model for the automated control system over asynchronous electric motor based on a PID-neurocontroller

Based on the developed structure and the operating algorithm of PID neurocontroller, we proposed a model of the automated control system (ACS) over asynchronous electric drive whose structural scheme is shown in Fig. 8. This model employs the synthesized mathematical models of IM with the rotor bars breaks and short-circuited turns in the stator winding. A given model is based on the principle of applying the PID law of control and is supplemented with an artificial NN. The use of artificial NN ensures quantitative and qualitative indicators of control. Since an artificial NN can function under conditions of essential non-linearities, and is capable of data generalization, the ACS based on its application can be considered adaptive and robust.

NN receives three input signals at its input:

- signal of misalignment from the current sensor $e(t)$;
- value of the set point U ;
- controlling signal from PID-controller U_{PID}^{-1} with a time delay time (time delay is needed to prevent the formation of an algebraic loop).

Based on the data received, NN generates coefficients for a PID-controller, which in turn controls the operation of a frequency converter.

4. 5. Development and training a neural network

To implement the designed controller, we chose a feedforward network of the multi-layer perceptron type with three layers: two hidden and one output. The size of the first hidden layer is 50 neurons, second - 75, the activation function for both layers is hyperbolic tangent. The structure of NN is shown in Fig. 9, the first input layer the size of 3 neurons was disregarded because it performs the function of distributing information to the first hidden layer. The structure of the output layer is shown in Fig. 10. Parameters for the structure of NN were chosen empirically. Since the procedure for creating NN does not exist, the developer chooses parameters according to the task and the results obtained in the learning process.

We have chosen the resilient backpropagation algorithm *trainrp* as a training algorithm. This algorithm is selected for reasons of saving computational resources in a computer or controller. Alternatively, it is possible to employ a method of gradient descent with respect to moments and with adaptive learning.

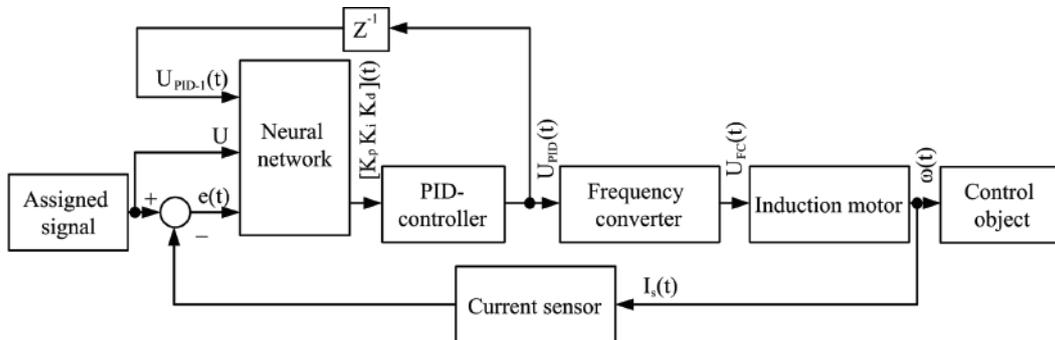


Fig. 8. Structural scheme of adaptive ACS to control an electric drive

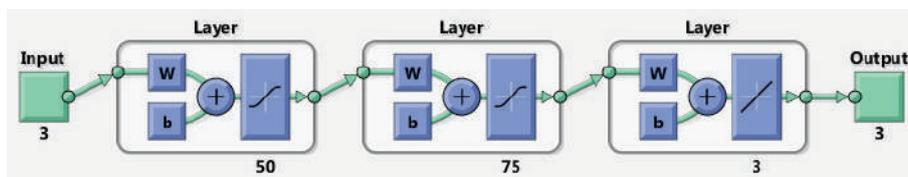


Fig. 9. The structure of NN underlying ACS

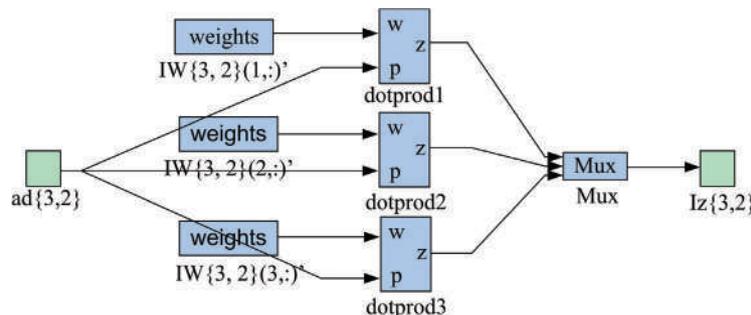


Fig. 10. Structure of the NN output layer

NN was trained over 2,500 cycles, the condition of stopping for a deviation from the standard is 0.001. The mean square error (MSE) was used as an option for estimating the functioning of the network (a network error).

Fig. 11 shows the process of modifying a network error in the learning process. A training error is an indicator of accuracy of tuning the model of NN on the training sample; it can be applied as a condition to terminate the training. However, this criterion does not make it possible to estimate the accuracy of model's performance with new data that were not included in the learning process, that is, the generalizing capacity of the network. When training NN, special attention was paid so that the NN would not enter the mode of relearning; in that case it would lose the capability to generalize data, that is, the function of adaptivity.

Fig. 12 shows the correlation field between the target-vector T and the output of neural network Y after the process of training. The high value of the correlation coefficient $R=0.99998$ testifies to the high quality of network learning.

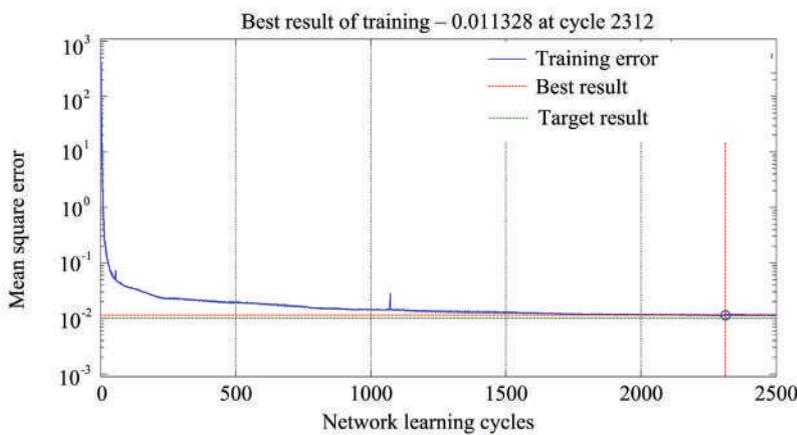


Fig. 11. The process of modifying a network error in the process of training

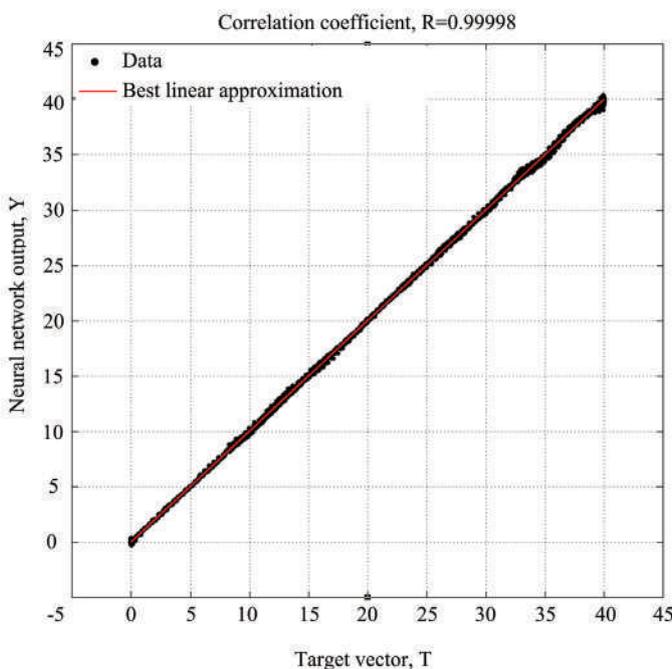


Fig. 12. Correlation field after the process of training

The result of training is the derived values for the weighting coefficients of the NN output layer.

Weights can be considered to be the end result of creating and training a network since the NN output signal forms mainly due to them.

Weighting coefficients can be considered to be a kind of NN memory.

4. 6. The synthesis and experimental testing of operation of the neural-PID control system over IM subject to defects or degradation

Based on the parameters of NN, obtained as a result of its training, we synthesized a mathematical model for the neural-PID control system over IM that has defects or degradation (Fig. 13).

Experimental study of the developed system was performed for the case of IM operation with short-circuited turns in the stator winding, breaks of the rotor bars, and for the presence of both above defects at the same time.

Based on this model, we analyzed performance of the proposed control system. A number of experiments were conducted that simulated varying degrees of IM damage development (Table 1). The analysis was carried out according to the procedures described in [2, 3, 16–20]. For our study, we chose IM operation with short-circuited turns in the stator windings, IM operation with broken rotor bars, and the operation of IM in the presence of both specified defects at the same time.

We shall analyze the obtained results of modeling using data from experiment No. 8 as an example (Table 1), conducted for the case of presence, at the same time, of the break of one of the rotor bars and the short-circuited turns for 2.52 % of phase C winding turns.

Using a PID-controller greatly reduces the amplitude of the variable component of the signals of speed and torque. In this case, the average speed for the case of using a controller corresponds to that set in the mode of idling (0–1.5 s). Speed signal contains a relatively small variable component under the mode of loaded operation (1.5–3 s). At the same time, for the case of the system operating without a controller, the average speed value is less than the desired one by almost twice. It is observed both at work under the mode of idling and under a load (Fig. 14).

In addition, the spectra of current and phase power, as well as the spectrum of total power of three phases, contain a significantly fewer quantity of harmonics compared with the corresponding spectra for operation without a controller. That indicates less energy consumption from the grid that is not spent for performing useful work, and, consequently, the improved energy efficiency in the operation of an electric drive system (Fig. 15).

Thus, the study that we conducted based on the mathematical models demonstrated the efficiency of applying the developed adaptive PID neurocontroller to compensate for the impact of defects and degradation of IM on power consumption of the electric drive system.

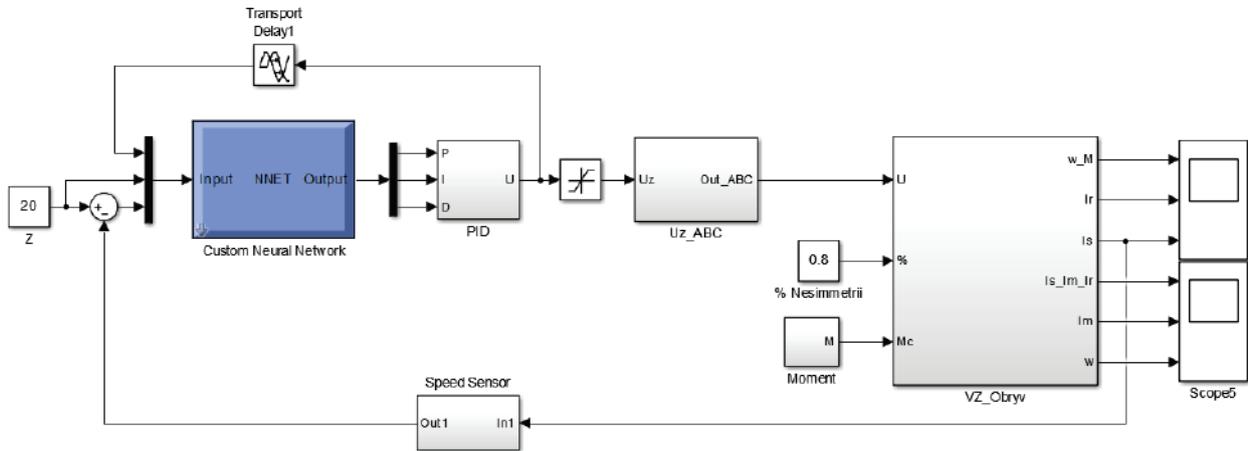


Fig. 13. Mathematical model of the IM control system with a PID-neurocontroller

Table 1

Investigating the operation of IM with defects

No.	Type of damage	Phase C winding short-circuit, %	Number of broken rotor bars
1	Motor without damage	–	–
2	Short-circuited turns in the stator windings	0.3	–
3		2.52	–
4		14	–
5	Breaks of the rotor bars	–	1
6		–	2
7		–	3
8	Short-circuited turns in the stator windings and breaks of the rotor bars	2.52	1
9		2.52	2
10		2.52	3

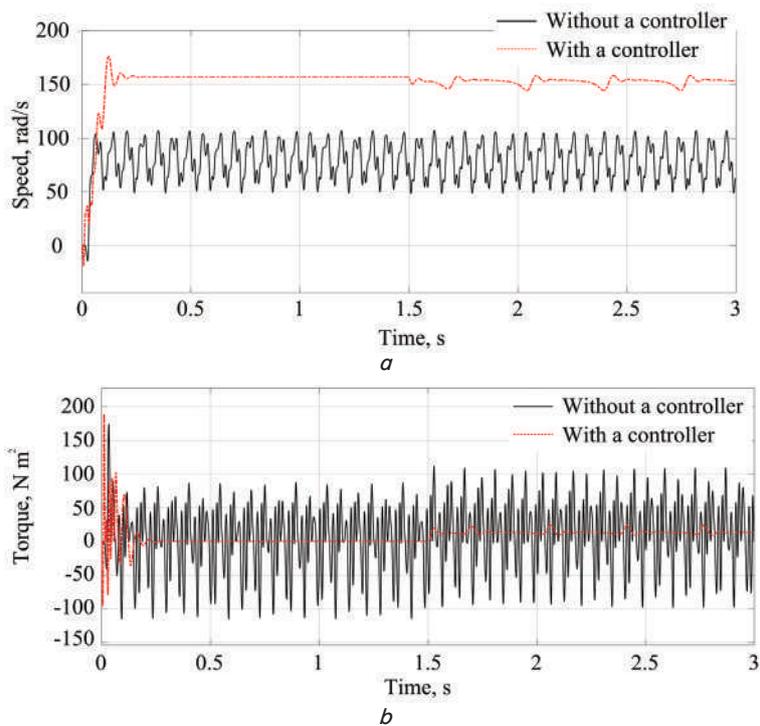


Fig. 14. Time diagrams of control systems with and without a PID-controller: *a* – speed; *b* – torque

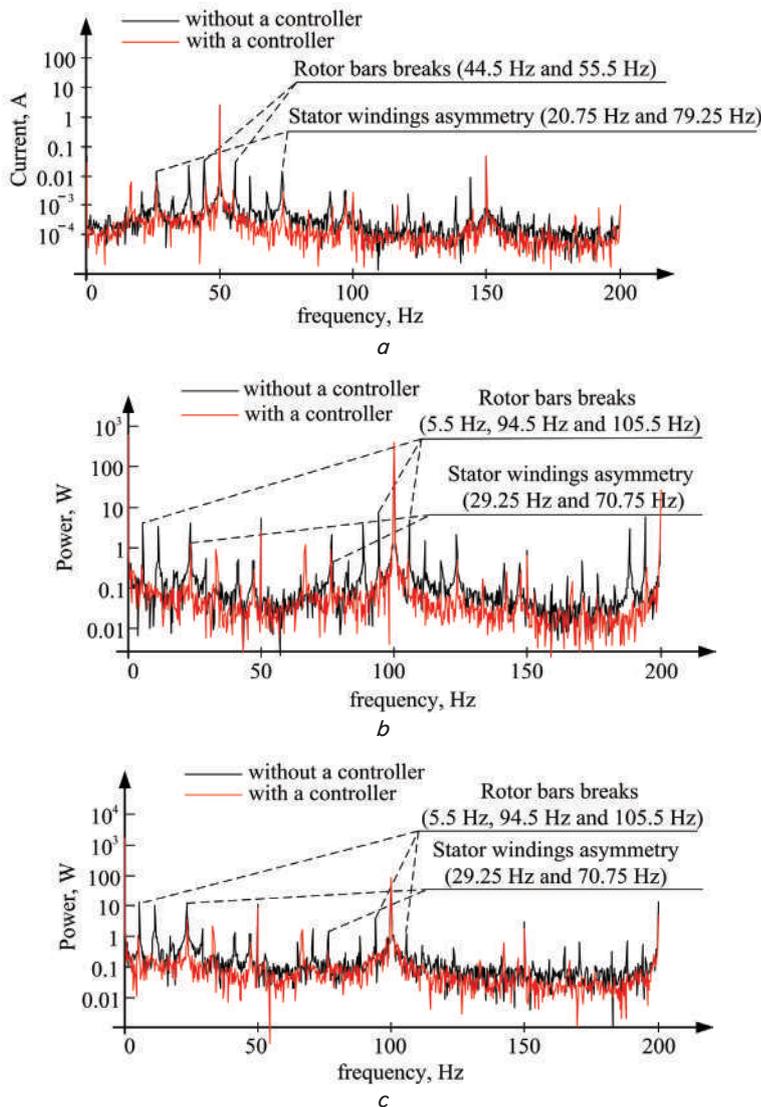


Fig. 15. Spectral composition of current and power of control system over IM with defects when operating with and without a controller: a – spectrum of phase B current; b – spectrum of phase A power; c – spectrum of the total power of three phases

5. Discussion of results of applying the developed adaptive control system based on a PID-neurocontroller

The obtained results regarding a reduction of the variable component of signals of speed and torque are explained by the parameters chosen to train NN. During training, the main criteria were to maintain the speed and torque of IM at the predefined level, even when a damage emerges and develops.

However, it should be noted that reaching the preset parameters of the controlled magnitude under operating conditions of the damaged motor will lead to increased losses and decreased efficiency in comparison with the operation of a regular IM. Therefore, such a correction technique should be uses for a certain time required to make a decision about replacing or repairing the damaged motor.

The proposed approach for adjusting the operating modes of asynchronous electric drive with a defective motor, in contrast to analogs, makes it possible to operatively, in a real-time mode, to determine coefficients of the PID-controller

in case of the emergence and development of the detected defect. It is only required that NN training should be properly managed.

Applying NN in order to calculate coefficients of PID-controller at the emergence and development of defects or degradation of IM ensures the operation of a control system without the need to recalculate and reset the controller. Training NN on the mathematical models for operating IM with other types of defects and degradation, which were not considered in this work, as well as the performance of an experimental sample under field conditions, would make it possible to improve the accuracy and quality of NN operation.

The study conducted suggests the possibility of using the proposed approach to create a PID-neurocontroller in the tasks on improvement of quality control over systems of induction electric drive that include a motor with existing damage or degradation. Such an approach allows not only maintaining the desired operating parameters of a technological process, but a reduction of the negative impact of increased energy use by motor with a damage and, therefore, it implements the objectives of energy efficiency. The developed structure of NN and the algorithm of its operation will in the future be used when creating a physical model of control system based on the adaptive PID-neurocontroller.

The disadvantage of the proposed approach is the necessity to preliminary train NN, which requires the construction of mathematical models that describe operation of the electric drive system in the presence of possible degradation and damage. Therefore, further work will imply building the models for the operation of IM with the most common types of damage and degradation, as well as constructing an experimental sample of the control system that implements the proposed solutions in the form of a frequency converter software.

6. Conclusions

1. Based on an analysis aimed at the implementation of adaptive control over the electric drive that includes IM with damages, we selected a PID neurocontroller based on NN of the multilayer perceptron type, which makes it possible to improve the response of the controller to the disturbances, which were not learnt by the perceptron.

2. We have developed a structure of the control system over an induction motor, based on the adaptive PID-neurocontroller, which uses a multilayered feedforward neural network to derive values for the coefficients of the controller in the process of operation. Such an approach makes it possible to operatively respond to a change in the characteristics of control object that can occur in case of the emergence and development of motor damage and degradation, which ensures the prolongation of its service life and the improvement of energy efficiency.

3. We have synthesized a NN learning algorithm for a PID-neurocontroller with self-tuning, which makes it possible to derive the weights of neurons, which in the future

could be used when implementing software for a physical control system with a PID-neurocontroller.

4. By employing mathematical modeling, we have proved the effectiveness of the proposed solutions, which make it possible to maintain the preset parameters of control ob-

ject in case of the emergence and development of damage and defects of IM and enable a decrease in the number and amplitude of variable components in the characteristics of a control object, which indicates the energy efficiency of the system in general.

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