ELECTRICAL ENGINEERING, ELECTROMECHANICS AND ELECTROTECHNICAL MATERIALS

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EVALUATING THE POSSIBILITIES OF APPLYING AN ARTIFICIAL NEURAL NETWORK FOR CONTROL AND DIAGNOSTICS OF THE ELECTRIC DRIVE SYSTEMS

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The paper investigates and evaluates the possibilities of using an artificial neural network. Attention is paid to the structural and operational features of the artificial neural networks, the learning processes used in them and their capabilities. The methods of application of artificial neural network for the purpose of control and diagnostics of dynamic systems of the electric drives are considered. A comparative analysis of the electric drive systems with PID regulators and neuroregulators was conducted. The expediency and necessity of improving the abilities of training artificial neural networks for adaptive control and diagnostics of the electric drives with incomplete description have been revealed, including the drives operating under random influences and dynamically changing modes. The main circumstances preventing the use of artificial neural networks, the laws of the choice of types and methods of optimization in the process of artificial neural networks (ANN) training and the lack of criteria for choosing the number of the neurons in the network are given.

A review of well-known works devoted to the use of ANN in the electric drive systems, as well as a comparative analysis of the feasibility of using gradient and genetic methods of their training are carried out. The comparative analysis was carried out by summarizing the conclusions in various published works. Analysis shows that, in most cases, networks trained by genetic algorithms provide more accurate results, easier learning, and shorter duration. At the same time, in some cases, the use of the back propagation algorithm in the certain problems leads to better results. Thus, it can be stated that the use of the preferred algorithm depends on the formulation of the task.

Keywords: control, electric drive, artificial neural network, adaptive, neuroregulator.

Introduction. In the modern conditions of the development of science, new technological solutions are being developed, which quickly find their application in the design and improvement of various systems. The Electromechanical systems have complex structures, and the effectiveness of their research, control and diagnostics is mainly due to the study of the heterogeneous data obtained. For this reason, in the tasks of control and diagnostics of the electric drive systems, there is a need to use the most effective methods that enable the analysis of numerous data. This paper discusses the possibilities of using the artificial neural network in the electric drive systems. The very concept of an artificial neural network is clarified below.

An artificial neural network is a mathematical model that is based on the principles of functioning and connections between nerve cells of a living organism [1]. After the development of learning algorithms, the artificial neural network began to be used for practical purposes, in particular, for the control and solution of other tasks.

An artificial neural network is represented as a connected and interacting system of processes (artificial neurons). Each processor of such a system acts only on the basis of periodically received signals that are periodically sent to other processors [1, 2]. During the use of neural networks, it is possible to implement parallel information processing in all nodes, which significantly speeds up the information processing process [1]. The neural networks have the ability to learn and generalize the information received. A network trained on the basis of a limited amount of data can summarize the information received and develop such data that were not used during its preliminary training [2-4].

The neural networks are not programmed by the methods known to us, they are trained, which eliminates a possible programming error [1-4].

During the learning process, the neural network is able to identify complex relationships between input and output signals.

At present, the ANN is successfully used for the synthesis of the control systems of dynamic objects [5-10].

The use of INS in the electric drive systems. The neural networks are used in systems operating under conditions of external influence, for which the use of traditional control methods is not productive. With the use of neural networks, the control of the electric drive systems is advisable in the case when the dynamic parameters of the object vary widely.

The neural network is capable of performing various actions, such as control of the dynamic objects [4, 6, 10-13], equipment diagnostics [8,14-16], forecasting of the production situations, monitoring of the technological processes.

The general principles of building control systems based on the neural networks are shown in [4]. Traditional and modern, non-traditional methods of control systems are considered here, their advantages and disadvantages are presented. There are much more requirements for the modern control systems:

- precise speed control;
- providing high torque at low speeds;
- low dissipation currents and high efficiency;

- high dynamic characteristics.

Classical systems with a linear control principle have low quality indicators when controlling nonlinear and complex systems, as well as in the case of insufficient information about the control object. In these cases, the characteristics of regulators can be improved through fuzzy logic methods, neural networks and genetic algorithms.

The use of a fuzzy control method is usually recommended in the case of extremely complex processes (when there is no simple mathematical model to describe these processes), for high-order nonlinear processes.

Thus, if the object under consideration is nonlinear, complex, and it is impossible to identify it, but there are heuretic laws or experience of manual control of such an object, the control problem can be solved using the neural network regulator.

Summarizing the above, it can be stated that the advantages of fuzzy control methods related to the class of intelligent control systems include:

- implementation of the required nonlinear control algorithm for the process;
- the presence of a partial or incomplete description of the object, and in the case of a neural network there is no need for a description;
- creation of a controlled system that ensures the operation of the electric motor in dynamically changing modes.

A multilevel neural network in the dynamic control systems performs the function of an adaptive regulator. In this case, the neural system generates a control signal during the learning process at the input of the executive device of the system. The goals of network training and object control are identical, which means that a common target function is being formed. It is possible that the network operation consists of two stages:

- the learning phase of optimal control laws, which are previously known on the basis of any theory;

- the stage of developing an optimal control function at the output or input of the executive device.

Here, the target functions of network training and object control may differ from each other. Due to a number of advantages, the option of using a multi-level neural network for control purposes is widely used [4].

The multilevel neural networks are also used as devices for identifying the state of nonlinear dynamic objects, successfully competing with traditional linear and nonlinear identification devices. It should be noted that the neural networks are also used for optimal selection of the adjustment coefficients of traditional adaptive regulators.

The neural networks allow to create a model of an object that accurately characterizes its dynamic changes, while not requiring additional knowledge about the structure of the object and its parameters. The required data are only the input and output values of the signals, therefore, the object is presented as a box [4].

Currently, proportional-integral-differential PID or proportional-integral regulators are widely used in automatic control systems of the electric drive systems, which are used, in particular, in frequency converters. Consider the use of the neural networks in PID regulators. The neural networks can not only replace the PID controllers, but can also be used to adapt its settings to the current operating conditions [5-7]. The neural network, having the ability to learn, allows to use the expert's experience to train the ANN to form an algorithm for selecting the coefficients of the PID controller. Fig. 1 shows the structure of the neural network in the automation block [2].

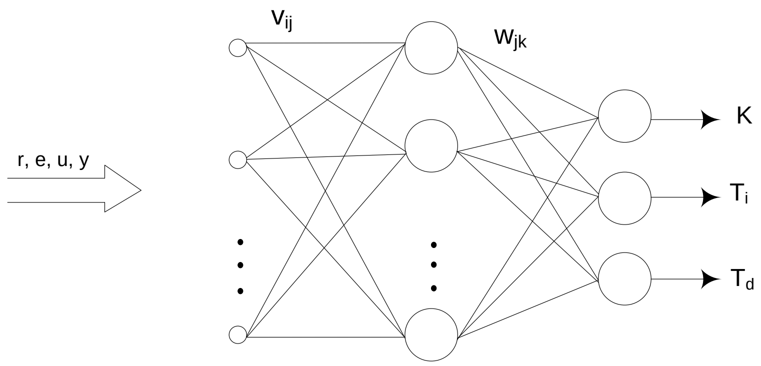

Fig. 1. The structure of the neural network in the automation block

Unlike conventional regulators, where the expert independently develops the laws of regulation of variables, using a neural network, the expert does not need to form the laws of regulation. Here it is necessary that during the training of the neural network, the expert independently adjust the regulator several times.

An artificial neuron is presented as a functional unit having one y output and n inputs $x_1, x_2, ..., x_n$, which generally implements a nonlinear transformation:

$$y = F(\sum_{i=1}^{n} W_i X_i + b),$$

where Wi is the weighting factor of the input variables, b - the constant shift, $F(\cdot)$ - the activation function of the neuron. For example, in the case of a sigmoidal function we have:

$$F(z) = \frac{1}{1 + e^{-az}}.$$

Fig. 2 shows a typical structure of an automated control system with a PID regulator and a neural network:

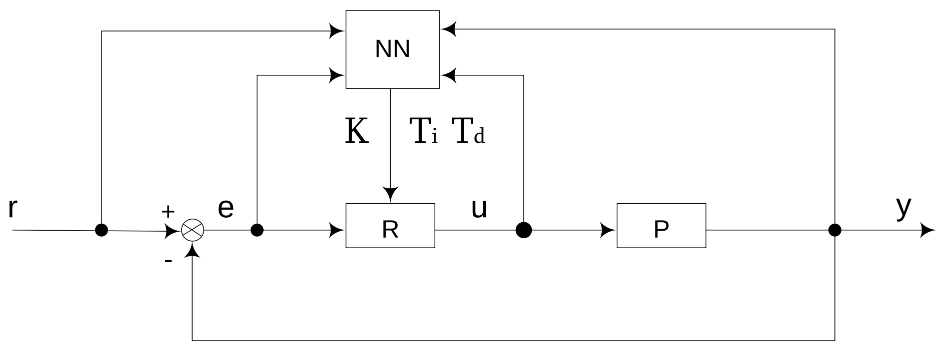

Fig.2. The structure of the PID regulator with an auto-tuning unit based on the neural network NN

In this neural network scheme, NN acts as a functional converter that calculates the PID coefficients K, T_i, T_d of the regulator for each set of signals r, e, u, y and strives to reduce the error of the output signal, relative to a given value, to a minimum value.The complexity of the neural regulator design task lies in the definition of the ”learning” process. The learning process consists of identifying unknown parameters of neurons *wi, b* and *a*. To learn a neural network, electric drive control systems usually use gradient methods for finding the minimum of the standard function $\varepsilon = (u^* - u)^2$, which depend on the parameters of neurons. The search process is iterative, during any iteration all coefficients of the network are determined. At the beginning, the output layer of neurons, and then the previous one and so on until the first layer.

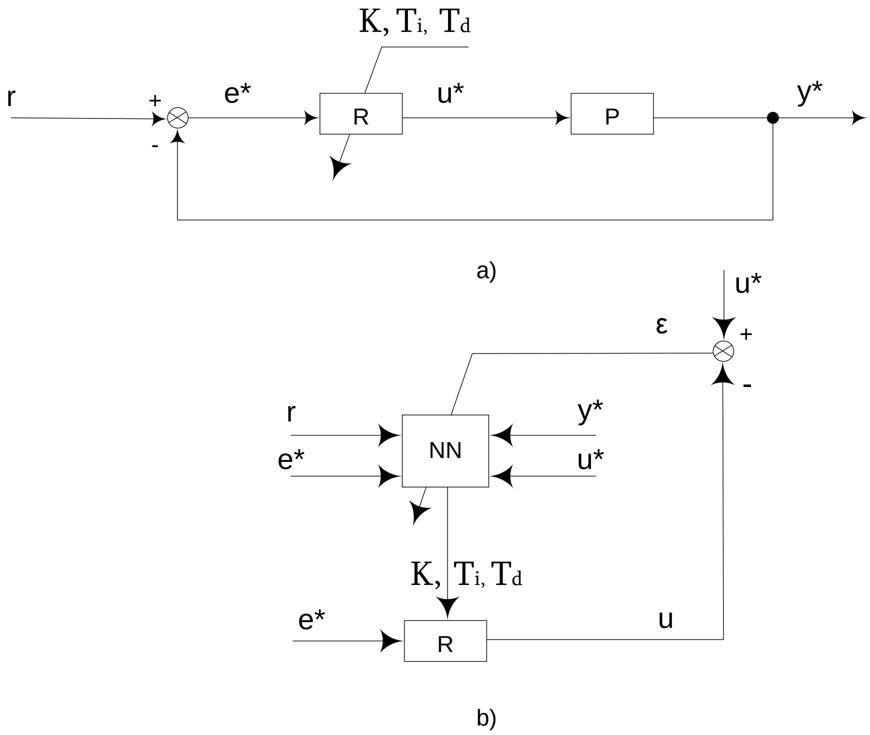

Fig.3. The scheme of learning the neural network in the auto setting unit

The learning process of a neural network is shown in Fig. 3 a [2]. The expert is given the opportunity to determine the K, T_i, T_d parameters of the regulator in a closed-loop automatic control system at various r(t) input influences. The time diagrams of the variables r, e*,u*,y* are recorded in the archive, and then transmitted to the PID controller connected to the neural network, Fig.3b.

The neural network is built in such a way as to minimize the error ε between the signals *u** and *u*. After the training process is completed, the parameters of the neural network are recorded in the automatic control node, Fig. 3b. The operational capability of the neural network is tested by applying new data that was not included in the training program. If the received error does not exceed the allowable threshold, then the neural network is considered trained [2].

The duration of the learning process and its quality are the main obstacles to the widespread use of the neural network method in the PID controller. At the same time, creating a neural network and checking for errors in it is often much faster and easier than creating a model of an electric motor and a controlled object and designing a PID controller based on this.

Analytical review of the use of a neural network in the problems of research, control and diagnostics of the electromechanical systems. The possibilities of using an artificial neural network in the electromechanical systems have been discussed in various scientific papers, which are presented below.

The method of monitoring the state of the DC motor winding is considered in [17]. The use of this method significantly reduces the cost of repairing the electric motor, since the problem is detected at an early stage. To protect the motor from overheating, a real-time temperature monitoring method has been developed in the rotor winding using a neural network. To collect the information necessary for learning, a special stand has been developed, on which a P-12 electric motor is installed operating in various dynamic modes. The motor parameters measured at the stand were entered into the computer. After that, the accumulated 30,000 samples of information were used to learn the neural network. The number of learning cycles was 100...1000. After completing the learning, the neural network, which is a reference model of a serviceable DC motor, was connected to the tested DC motor. The tests have shown that in the case of a serviceable motor, the output signal of the predictor almost coincides with the actual measured current value, and in the event of malfunctions and their further deterioration, signal inconsistencies appear. Depending on the value and sign of the discrepancy, as well as the rate of change of this value, the DC motor is tested during its operation.

Studies aimed at developing a system for identifying DC motor data using a neural network were carried out in [5]. In particular, an electric drive system consisting of a thyristor converter and a DC motor was investigated. Using methods of solving classical differential equations, a theoretical analysis was carried out, as a result of which the static and dynamic parameters of the motor were determined. To identify the motor data, a multilayer neural network NEWFF was used with direct signal transmission and error return. The input layer of the neural network consists of a sigmoid activation function of 20 neurons and a linear activation function of 1 output neuron. The neural network was learnt as a result of 500 cycles and the root-mean-square error was approximately 2.22875. Tests have shown that the characteristics modeled by means of a neural network and the characteristics of a real electric drive system are quite close to each other.

The results obtained in [5] make it possible, using a neural network, to obtain and study the characteristics of the motor and create its model, which can be used to solve the problems of adaptive control of neuroregulators.

In paper [7] a method for identifying the mechanical parameters of an asynchronous motor with a short-circuited rotor is proposed. A special neural network was used as an identification model, the adaptation of which was implemented on the basis of the gradient descent method. The parameters of the mechanical subsystem are obtained from the values of the synaptic weights of the neural identification model. Comparative analysis has shown that the reliability of the obtained parameters is high.

The stator currents and magnetic flux are used as input data, and angular velocity as an output parameter, the identification model adapts the weights of neurons. The output of the neural model is compared with the measured and desired angular velocities, and the resulting displacement serves to adapt the weights of the neurons.

In work [18], the possibility of using a neural network in various structural nodes of an electric drive system is considered. The author describes the basic principles of building a neural network. The author's approach to the development of a neural network of a dynamic system, which includes signal processing, evaluation of the reverse signal of an asynchronous motor and other processes providing control, is presented.

In work [19], the possibilities of using linear neural networks in power electronics are presented. In particular, the issues of identification of electric machines, the quality of electricity, sensorless electric drive system are considered. The effectiveness of the use of linear neural networks to ensure the required quality of electricity is substantiated.

The task of stabilizing a multi-rotor unmanned aerial vehicle under conditions of random external influences is considered in [20]. The classical proportional-integral-differential PID regulator is considered, its disadvantages are presented - the inability to respond to random influences and the need for manual adjustment of coefficients. A method for correcting the coefficients of the PID regulator based on the neural networks is proposed. To create an adaptive stabilization system for a multi-rotor unmanned aerial vehicle three-layer neural networks learned by the method of error back propagation were used. At different stages of network learning, graphs of transients are given, including taking into account random external influences. It is shown that with a sufficient number of learning iterations, the system meets the requirements of device stabilization. The above method of forming coefficients can be used to control unmanned aerial vehicles operating in a changing environment. The following requirements are imposed on the stabilization system:

- the duration of the transient process should not exceed 1 second;
- the system overcontrol should not exceed 10% of the maximum displacement angle.

In this work, the angle 90^o is taken as the maximum angle of displacement of unmanned aerial vehicles.

For each of the neurons, the coefficients are regulated by the method of error back propagation. For each weight, the relationship between its change and the change in the output value are calculated. The target E function is selected, the error of which must be reduced after k number of iterations [20]:

$$E(y) = \frac{1}{t_k - t_0} \int_{tk}^{t0} e(t,y)^2 dt,$$

where e(t,y) is the error between the real and the given angles, t is the number of iterations.

To regulate the weights, the learning factor is taken into account [20]:

$$\omega_{icorrected} = \omega_i + \gamma \frac{\delta E}{\delta \omega_i},$$

where γ is the learning coefficient.

Fig. 4 and 5 show the stages of regulation the coefficients of this network after various numbers of iterations for the roll angle of an unmanned aerial vehicle. As an object of regulation, a stand with one degree of freedom was used, on which an unmanned aerial vehicle with an initial shift of 30^0 with respect to the abscissa axis was installed.

Since the neural network learning algorithm is the same for all three angles, only one of these angles is shown in the Figure. During learning, the neural network regulates the values of the coefficients, changing the dynamics of stabilization. The graph shows the dependence of the angle on the stabilization step.

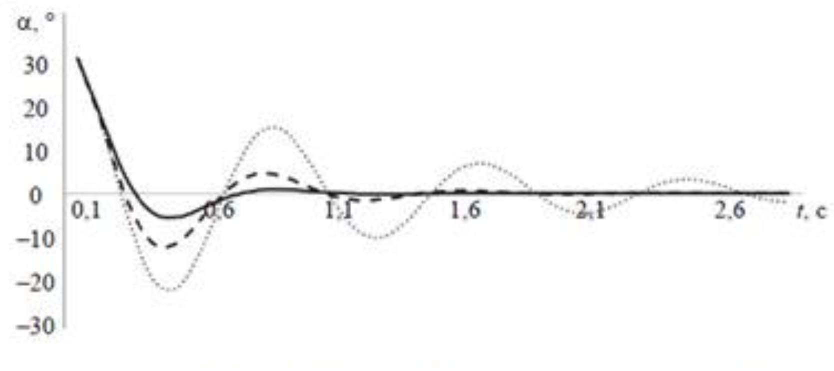

Fig.4. Graphs of transient processes for the angle of roll during stabilization at different stages of neural network learning

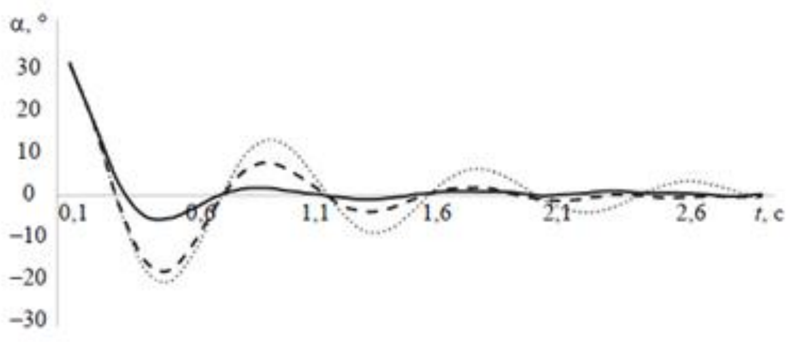

Fig.5. Graphs of transient processes for the angle of heel during stabilization, taking into account external disturbing influences

During the learning period, three configurations of coefficients are presented, which are set by the unmanned aerial vehicle. As can be seen from Graph 1, the configuration of the coefficients has a large oscillation amplitude and an overcontrol of more than 20^0, the duration of transients exceeds 2 seconds. On configuration 3, the control issues are solved better, the duration of transients does not exceed 1 second, and the angle regulation does not exceed 10^0, which is considered acceptable.

Fig.3 shows the behavior of an unmanned aerial vehicle in the presence of random factors. It is obvious that even a small increase in additional effects on the angle increases the required stabilization time of the model. At least 1000 iterations are required to bring the model to a stable state. The results obtained in [20] show that an unmanned aerial vehicle can optimize the PID coefficients of the regulator after a certain period of learning. The developed system can adapt to changing flight conditions in a short time without requiring large computing capabilities. The results obtained can be improved, for example, by reducing the required time to achieve optimal values of the PID coefficients of the regulator. At the same time, it becomes obvious that it is necessary to comprehensively investigate the influence of random factors on the behavior of an unmanned aerial vehicle.

Another adaptive DC motor control system is presented in work [6]. The control system consists of 2 neural networks. The first neural network is used to estimate the speed of the motor, and the second to regulate it. Since the system includes an DC motor and its control circuit, it is considered a complex model. As it is known, the use of a neural network makes it possible, in the presence of limited information about the object, to bring the quality of control to a high level [2], therefore, the author suggests to build a regulator based on a neural network. The results of modeling the control system using the ANN are compared with the PID regulator to show the advantages of the proposed method. The ANN was learnt on the basis of the error back propagation method.

In order to demonstrate the advantages of the proposed method, the tests were carried out in two ways: with a PID regulator and with the use of an ANN regulator (Fig. 6).

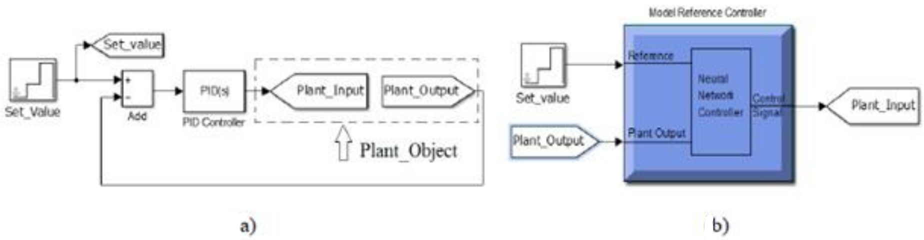

Fig. 6. The control schems: a - in the case of PDF controller; b - in the case of neural network controller

The simulation results show that despite the fact that in the case of the PID regulator, the system showed satisfactory results, nevertheless, the quality of control is not so high, in particular, the duration of transients and the response speed are longer. In the case of an ANN-based regulator, the quality of the control system is much higher and, consequently, the duration of transients and the response speed are shorter.

The control algorithm of a brushless DC motor based on ANN is presented in [21]. In high-performance media, proportional-integral or proportional-integral-differential regulators are mainly used. Such regulators require precise mathematical models for their design. For such a motor, it is difficult to develop an accurate mathematical model based on conventional methods. Moreover, the properties of the motor are usually unknown and change over time. Conventional regulators are not able to provide optimal control for changes in operating conditions such as load fluctuations, saturation, parameter changes or sound propagation. The paper proposes a control algorithm for a brushless DC motor using a standard adaptive model based on an ANN, the block diagram of which is shown in Fig. 7 [21].

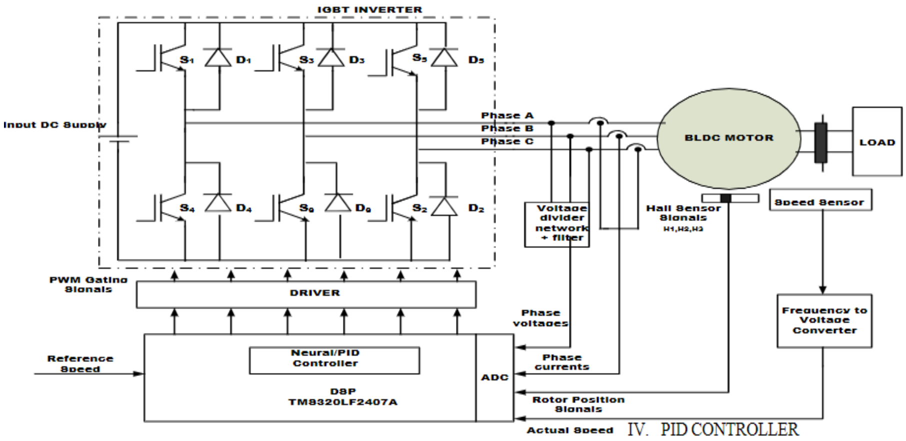

Fig.7. Speed control system of a brushless DC motor

It consists of an IGBT inverter, a brushless DC motor and a TMS320LF2407A microcontroller.

It should be noted that in the tasks of identification, control and diagnostics, the use of INS is still limited, due to the following reasons [13]:

- there are no exact laws for choosing the type of ANN;
- there is no reliability of the choice of the optimization method during the learning period of the ANN, which leads to large errors in the learning time and prediction;
- there are no criteria for choosing the number of neurons in the network.

The main functions of the ANN are:

- approximation;
- classification and recognition of regularities;
- prediction;
- identification and evaluation.

Comparative analysis of the neural network learning algorithms.

In most of the studies conducted, ANN learning is based on gradient methods, mainly based on the back error propagation algorithm [22-24]. However, some studies [25] show that the back error propagation algorithm and gradient algorithms do not show better results and are not the fastest in the learning process of neural networks. The research results of papers [26-29] show that the use of genetic algorithms can replace gradient methods and show better results. The widespread use of the back error propagation algorithm is mainly due to the simplicity of its implementation, since there are many software packages, such as Matlab Neural

Network Toolbox-n, Nueral Works Proffesional II/Plus, etc. This algorithm is ranked to the family of deterministic approximation, which performs a local search.

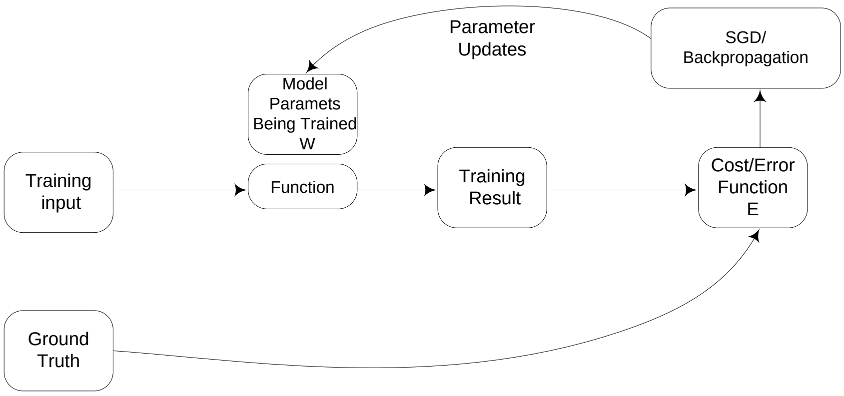

Fig. 8. The structure of the back error propagation algorithm

In general, the principle of the algorithm (Fig. 8) is as follows [30]: the error function compares the average quadratic displacement between the results obtained in the learning process and the real values. After that, this value is propagated back to optimize the weights of the neurons. The weights are refined along with the direction of propagation, which reduces the error of the output value.

Despite the relevance of the back error propagation algorithm, it has certain disadvantages. The gradient search method in some cases tends to unpredictable implementation of the optimal solution and, being in a local (closed) environment, the gradient search method does not work well when obtaining a general optimal solution [28]. During learning, the most important task is the ability to download learning data. This means that during a certain period of learning, the network does not improve the ability to solve its task. In this case, the learning stops at the point of the local minimum, which leads to inefficient results.

As an alternative, a genetic algorithm can be used to learn a neural network [31]. Unlike other algorithms, in the case of a genetic algorithm, the search is performed not by trajectory, but by population. This algorithm allows you to find a global solution from a very large and complex space. The weak side of the genetic algorithm is that global optimal convergence requires complex computational operations. The capabilities of the ANS using genetic and back-propagation algorithms were compared (Table).

Table

Comparative results of application of genetic and back error propagation algorithms

N	Author	Journal	Formulation of the problem	Conclusion
1	Gupta, J.N.D [27]	Omega	Prediction of chaotic time series.	GA surpasses BE in ease of use and efficiency.
2	H. Hasan [28]	*Expert systems with applications*	Classification of 10 databases.	GA provides more accurate results.
3	Ahmad F.N.A [29]	*Intelligent Systems Design and Applications*	Predetermination of malignant and diabetes mellitus diseases.	Rprop algorithm of BE propagation provides the best indicators Rprop>GA>BE
4	Requena-Pérez [31]	*Microwave Theory and Techniques*	Determination of multilayer structures, dielectric permittivity of layers.	The use of GA+BE algorithms provides higher performance than GA and BE taken separately.
5	Shifei Ding [32]	*Artificial intelligence review*	Classification of 4 databases.	GA and BE algorithms can be combined and get the best result.

The results obtained in the problems of solving chaotic time series [27] with the use of ANN show that GA surpasses the BE algorithm in efficiency, ease of use and productivity of network learning.

In paper [28], the problems of classification of 10 different databases using GA and BE algorithms of the neural networks are considered. The results obtained show that the use of GA provides more accurate results in solving classification problems.

The results obtained in the tasks of diagnosing tumor and diabetic diseases [29] show that the use of GA is generally superior to most of the applications of BE algorithms, but the back propagation Rprop algorithm shows the best results.

Conclusion

The analysis shows that, despite the fact that the use of the artificial neural networks to solve existing problems in the electric drive systems is effective, nevertheless, there are various problems associated with system identification, network regulation, and the use of neuroregulators that require appropriate solutions.

Based on the results of previous studies, it can be concluded that currently using the back error propagation algorithm is simpler, since there are a number of software packages based on this algorithm. However, the results of the study showed that in most cases, networks learnt on the basis of a genetic algorithm provide more accurate results and the duration of learning is shorter. It should also be noted that in some cases the application of the back error propagation algorithm leads to better results. Thus, we can conclude that the preference in using one or another algorithm depends on the formulation of a given task.

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ԷԼԵԿՏՐԱԲԱՆԵՑՄԱՆ ՀԱՄԱԿԱՐԳԵՐԻ ԿԱՌԱՎԱՐՄԱՆ ԵՎ ԱՐԱՏՈՐՈՇՄԱՆ ՀԱՄԱՐ ԱՐՀԵՍՏԱԿԱՆ ՆԵՅՐՈՆԱՅԻՆ ՑԱՆՑԻ ԿԻՐԱՌՄԱՆ ՀՆԱՐԱՎՈՐՈՒԹՅՈՒՆՆԵՐԻ ԳՆԱՀԱՏՈՒՄԸ

Մ.Ք. Բաղդասարյան, Վ.Դ. Հովհաննիսյան, Տ.Է. Հակոբյան

Կատարվել են արհեստական նեյրոնային ցանցի կիրառման հնարավորությունների հետազոտություն և գնահատում: Անդրադարձ է կատարվել արհեստական նեյրոնային ցանցի (ԱՆՑ) կառուցվածքային և աշխատանքային առանձնահատկություններին, դրանում օգտագործվող ուսուցման գործընթացին ու վերջինիս հնարավորություններին: Դիտարկվել են դինամիկ էլեկտրաբանեցման համակարգերի կառավարման և արատորոշման նպատակով ԱՆՑ–ների կիրառման եղանակները: Կատարվել է PID կարգավորիչով և նեյրոկարգավորիչներով էլեկտրաբանեցման համակարգերի բնութագրերի համեմատական վերլուծություն: Բացահայտվել են պատահական ազդեցությունների պայմաններում, դինամիկ փոփոխվող ռեժիմով աշխատող, ինչպես նաև ոչ ամբողջական նկարագրով էլեկտրաբանեցման համակարգերի հարմարվողական կառավարման և արատորոշման համար ԱՆՑ-ների կիրառման նպատակահարմարությունն ու ուսուցման ունակությունների կատարելագործման անհրաժեշտությունը: Նշվել են ԱՆՑ-ների օգտագործմանը խոչընդոտող հիմնական հանգամանքները. ԱՆՑ-ի տեսակի՝ ուսուցման ընթացքում օպտիմալացման մեթոդների ընտրության օրենքները և ցանցում նեյրոնների քանակի ընտրության չափանիշների բացակայությունը:

Անդրադարձ է կատարվել էլեկտրաբանեցման համակարգերում նեյրոնային ցանցի կիրառմանը վերաբերող հայտնի աշխատություններին: Կատարվել է համեմատական վերլուծություն՝ բացահայտելու ԱՆՑ-ների ուսուցման գրադիենտային և ծագումնաբանական մեթոդների կիրառման նպատակահարմարությունը: Համեմատական վերլուծությունն իրականացվել է հրապարակված տարբեր աշխատություններում կատարված եզրակացությունների ամփոփման ճանապարհով: Վերլուծությունը ցույց է տալիս, որ գերակշիռ դեպքերում ծագումնաբանական ալգորիթմի միջոցով վարժեցված ցանցերն ապահովում են ավելի ճշգրիտ արդյունքեր, ուսուցման պարզություն և ավելի կարճ տևողություն: Միաժամանակ, առանձին դեպքերում հետադարձ տարածման ալգորիթմի կիրառումը որոշակի խնդիրներում հանգեցնում է ավելի լավ արդյունքների: Այսպիսով, կարելի է արձանագրել, որ նախընտրելի ալգորիթմի օգտագործումը կախված է առաջադրված խնդրի դրվածքից:

Առանցքային բառեր. կառավարում, էլեկտրաբանեցում, արհեստական նեյրոնային ցանց, հարմարվողական, նեյրոկարգավորիչ:

ОЦЕНКА ВОЗМОЖНОСТЕЙ ПРИМЕНЕНИЯ ИСКУССТВЕННОЙ НЕЙРОННОЙ СЕТИ ДЛЯ КОНТРОЛЯ И ДИАГНОСТИКИ СИСТЕМ ЭЛЕКТРОПРИВОДА

М.К. Багдасарян, В.Д. Ованнисян, Т.Э. Акопян

Проведено исследование и дана оценка возможностей применения искусственной нейронной сети (ИНС). Особое внимание уделено структурным и рабочим особенностям ИНС, используемым в них процессам обучения и их возможностям. Рассмотрены методы применения ИНС с целью управления и диагностики динамических систем электроприводов. Дан сравнительный анализ систем электроприводов с ПИД регуляторами и нейрорегуляторами. Выявлены целесообразность и необходимость совершенствования способностей к обучению ИНС для адаптивного управления и диагностики электроприводов с неполным описанием, включая приводы, работающие при случайных воздействиях и в динамически изменяющихся режимах. Отмечены основные факторы, препятствующие использованию ИНС, законы выбора видов и методов оптимизации в процессе обучения ИНС и отсутствия критериев выбора количества нейронов в сети.

Проведен обзор известных работ, посвященных применению ИНС в системах электроприводов, а также дан сравнительный анализ целесообразности использования градиентных и генетических методов их обучения путем обобщения заключений в различных опубликованных работах. Анализ показывает, что в большинстве случаев сети, обученные посредством генетического алгоритма, обеспечивают более точные результаты, простоту обучения и их малую длительность. В то же время в отдельных случаях применение алгоритма обратного распространения в определенных задачах приводит к более удовлетворительным результатам. Таким образом, можно заключить, что использование того или иного метода зависит от постановки заданной задачи.

Ключевые слова: управление, электропривод, искусственная нейронная сеть, адаптив, нейрорегулятор.