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Neuroprotection and Timely Troubleshooting of Electric Drive Equipment

Viktor M. Buyankin

Bauman Moscow State Technical University, Moscow, Russian Federation

E-mail: Viktor12Buyankin@yandex.ru

Abstract:. The article discusses the neurodiagnostics drives with the prediction of the future fault is a relevant task to avoid failure of electric motors and actuators. Such systems neurodiagnostics increase the reliability and safety of operation, anticipating contingencies. An important aspect in the management of complex dynamic objects designed to operate in harsh operating conditions, such as aggressive, explosive and dusty environments, extreme temperatures, increased vibration, is the use of real sensors. The use of state observers in such facilities will improve the operational reliability of the electric drive, avoid shock currents, reduce weight and size characteristics, etc. In recent years, there are high requirements for modern control systems of electric drives, namely: accurate speed control, maintaining high torque at low control speeds, limiting the starting and shock currents, high dynamic characteristics, high signal processing accuracy, improved coordinate accuracy.

Keywords: neural network, extended Kalman filter, fuzzy logic, genetic algorithm, induction motor, asynchronous electric drive.

1.INTRODUCTION

Today there are various methods of identification of parameters and variables of the state of the asynchronous electric drive which include the extended Kalman filter; the observer created on the basis of a neural network and using fuzzy logic; genetic algorithms [12-16]. Most well-known observers do not provide for maintaining the necessary accuracy of identification of parameters and variables of the state in the entire range of speed control at different modes of operation of the electric drive and non-sinusoidal forms of stator currents [9-11]. The last remark is typical when driving an asynchronous motor from a thyristor voltage regulator and an Autonomous voltage inverter [2-5]. The purpose of the study presented in this paper is a comparative analysis of the most common in practice, the observer of the state of the asynchronous electric drive on the simplicity of their implementation (in terms of mathematical description) and reliability. On the basis of this analysis, practical recommendations on their application in this type of electric drive in terms of their efficiency are developed [1].

Today, the use of real sensors in complex dynamic systems, and in particular, drives operating under severe operating conditions, is undesirable for a number of reasons, including a significant increase in installation, increase in weight and size characteristics, decrease in operational reliability, etc. [17-20] methods of identification of parameters and state variables attracted both domestic and foreign scientists [6-8]. To determine the parameters and state variables used by the observers based on extended Kalman filter, fuzzy logic, neural networks and genetic algorithms.

2. LITERATURE REVIEW

The ANN used to identify the parameters and state variables of complex dynamic objects is composed of three main layers: input, hidden and output. More than one hidden layers are possible.

To date, the most commonly used activation functions of the neuron include threshold, linear, sigmoidal, tangential, radial-basis activation functions. In practice, a linear function is used as the activation function of neurons in the output layer. The first layer of the neural network is a relay.

The activation function of the neurons of the hidden layer is mainly non-linear. According to the work [15], the most suitable activation function for neurons of the hidden layer is the tangential activation function.

To identify the parameters and state variables of complex dynamic objects it is necessary to use a dynamic neural network, which includes a dynamic neural network with delay at the input [16], a Jordan network [17], an Elman network [18], the combination of a dynamic neural network [19, 20]. The peculiarity of these neural networks is the presence of signal delays at the input, output and both input and output, which allows to provide the best learning and filter out strong pulse interference.

Before training a neural network, the developer must decide on the array of data needed for its training, and the choice of training algorithm.

An excessively large array of data from each of the input signals can lead to a retrain effect, as a result of which, within the training sample, the neural network gives a minimum evaluation error, and when working with a test sample (different from the training sample), the evaluation error is very large.

To date, there are a large number of training algorithms, the main of which are the gradient descent algorithm, gradient descent algorithm with perturbation, Moller's learning algorithm and Levenberg–Markvardt learning algorithm. The presented first three methods of training require small computing power of the computer, but are not able to find a global minimum learning errors. The Levenberg-Markvardt learning algorithm requires significant computing abilities of the computer, but is able to get out of the local minimum and find a global one.

3. MATERIALS AND METHODS

Rapidly expanding the range of functional requirements for automated systems the Electromechanical energy conversion in industry, transport, special equipment, stringent requirements for the dynamic characteristics of such systems and their energy efficiency would require the construction of control algorithms, which for some features can be called "intelligent". It is generally recognized that the synthesis of such algorithms is currently the Central problem of the modern theory of automatic control of electric drives. The conflict between obviously insufficient methodical basis of construction of "intellectual" algorithms of management of EP and growing opportunities of hardware becomes more and more acute as the modern condition of means of power and information electronics already allows to realize elements of "intelligence" (Intelligent Control) even in rather inexpensive serial SAU. According to the author, the sign of "intelligence" of the controlled electric energy Converter for electric drive systems is not the use of "exotic" methods (fuzzy logic, neural networks, genetic algorithms, etc.), as it is often presented, but functional completeness in solving the main problems of modern control theory in the Appendix to such complex objects as General industrial electric drive. "Intelligence" in this sense – is to provide a comfortable interface between a person and a microprocessor control system, a minimum of manually adjustable parameters of the EP, but in any case not the ability to independently set and solve new non-standard problems.

Particularly important tasks of identification and adaptive control become in the construction of common industrial frequency-controlled electric drives, one of the main requirements for which is the rejection of the use of external in relation to the controlled source of electrical energy (PM) sensors, including sensors directly controlled coordinates of mechanical motion.

4. RESULTS AND DISCUSSIONS

Electric drives are used in many branches of production such as machine-tool building, mechanical engineering, in the mining and oil-extracting industry. The motors work with a variety of loads in various modes: long lasting, intermittent, short-term modes. During operation, the drive equipment wears out over time, which leads to deterioration of static and dynamic characteristics, and sometimes to emergency situations. Therefore, the prediction and timely detection of faults of electric equipment is an urgent task.

However, predicting the malfunctions of the electric drive equipment is quite difficult and time-consuming task. A large number of diagnostic systems have been developed for fault detection, but it is not possible to determine the whole range of faults of the electric drive equipment by one hundred percent.

To improve the quality of diagnostics, we propose systems with neural networks that have proven themselves quite well in pattern recognition and approximation of complex nonlinear dependencies [1]. Fault diagnosis by many criteria coincides with pattern recognition and therefore, using neural networks, it is possible to achieve higher results of fault detection of electric drive equipment compared to other diagnostic systems.

There is a wide variety of neural networks that differ from each other in their advantages and disadvantages. When designing a system neurodiagnostics stop your choice on neural networks like: NEWFF and ANFIS [2].

That is, we will develop a combined neuroprotection system with an expert neural network approach. For initial identification of faulty components of the electric drive is advisable to use neuroprogenitor on the basis of neural networks like: NEWFF and ANFIS, and for a more detailed examination of the health elements of the drive it is advisable to use the system neuroprogenitor with expert neural network approach Fig. 1

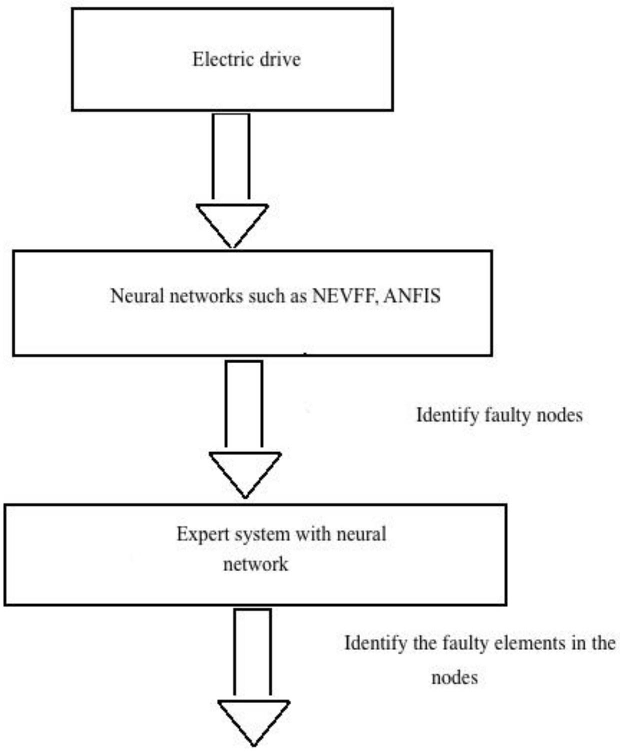

Fig. 1. System neuroprogenitor

The purpose of building a neural network expert system is the initial prediction of faulty electric drive units, which consists of a neuroregulator, a power Converter, an electric motor, a load mechanism Fig. .2

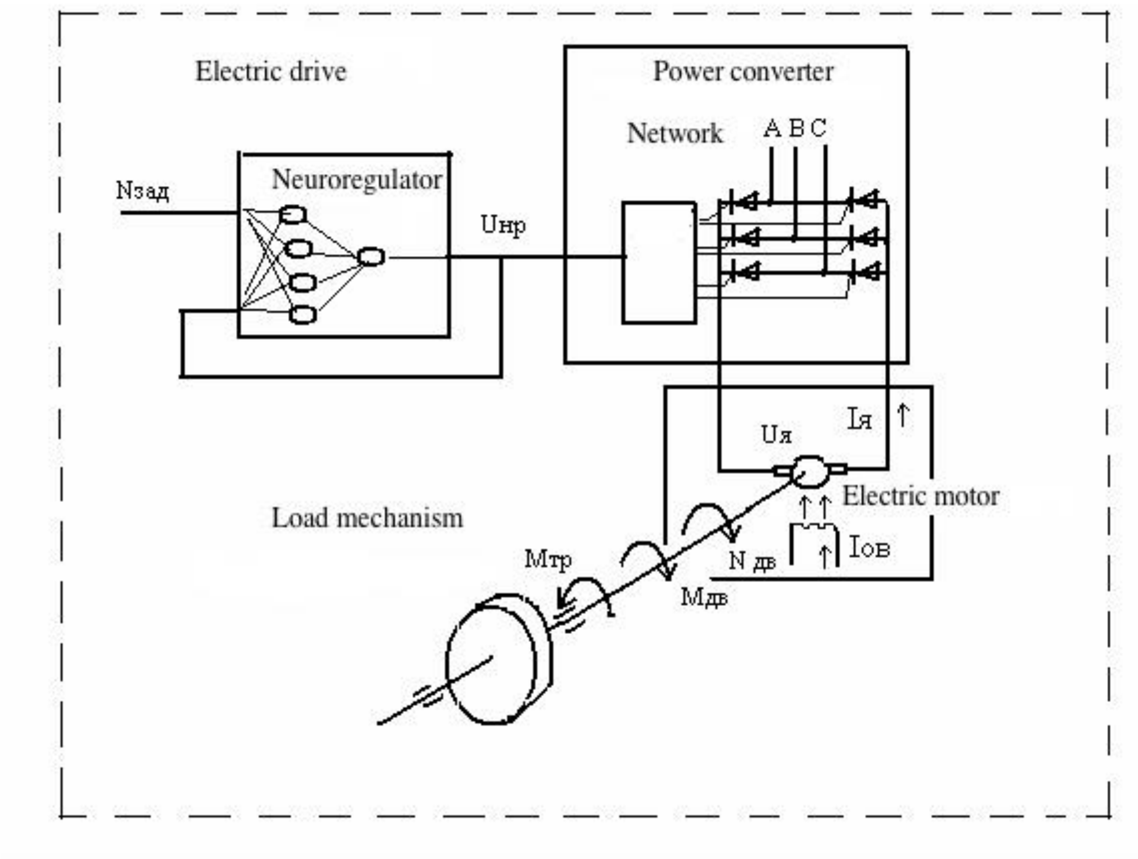

Fig. 2. Block diagram of electric drive

The operation of the actuator must comply with the rated static and dynamic characteristics. At rated load, the actuator must have a nominal armature voltage, rated current, nominal speed, which is displayed on the family of mechanical characteristics Fig. 3 Deviation from the nominal parameters leads to malfunctions, and sometimes to emergency situations of the electric drive equipment.

We will consider as faulty the electric drive of deviation of parameters which exceed the maximum deviations.

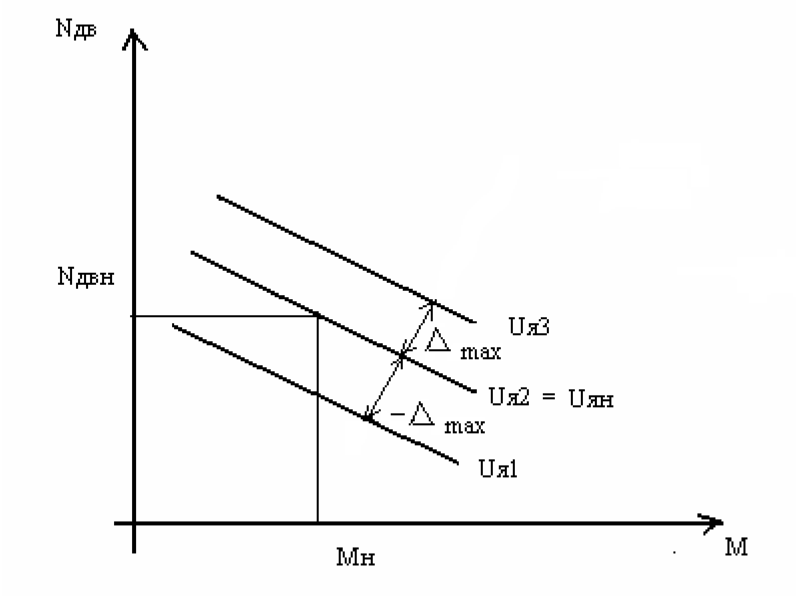

Fig. 3. Mechanical characteristics of the electric drive

Will develop a system of neurodiagnostics in the beat of a forward current in the excitation winding Iob(n+1) (and voltage in the armature of the motor (S) using a neural network NEWFF [3]. Suppose there is a database containing the current values of the Iov table 1, Fig. 4.

Table 1. Data structure

*I*ов(*n*-9)	*I*ов(*n*-8)	*I*ов(*n*-7)	*I*ов(*n*-6)	*I*ов(*n*-5)	*I*ов(*n*-4)	*I*ов(*n*-3)	*I*ов(*n*-2)	*I*ов(*n*-1)	*I*ов(n)	*I*ов(*n*+1)
203ма	192ма	203ма	230ма	200ма	198ма	205ма	199ма	190ма	206ма	?

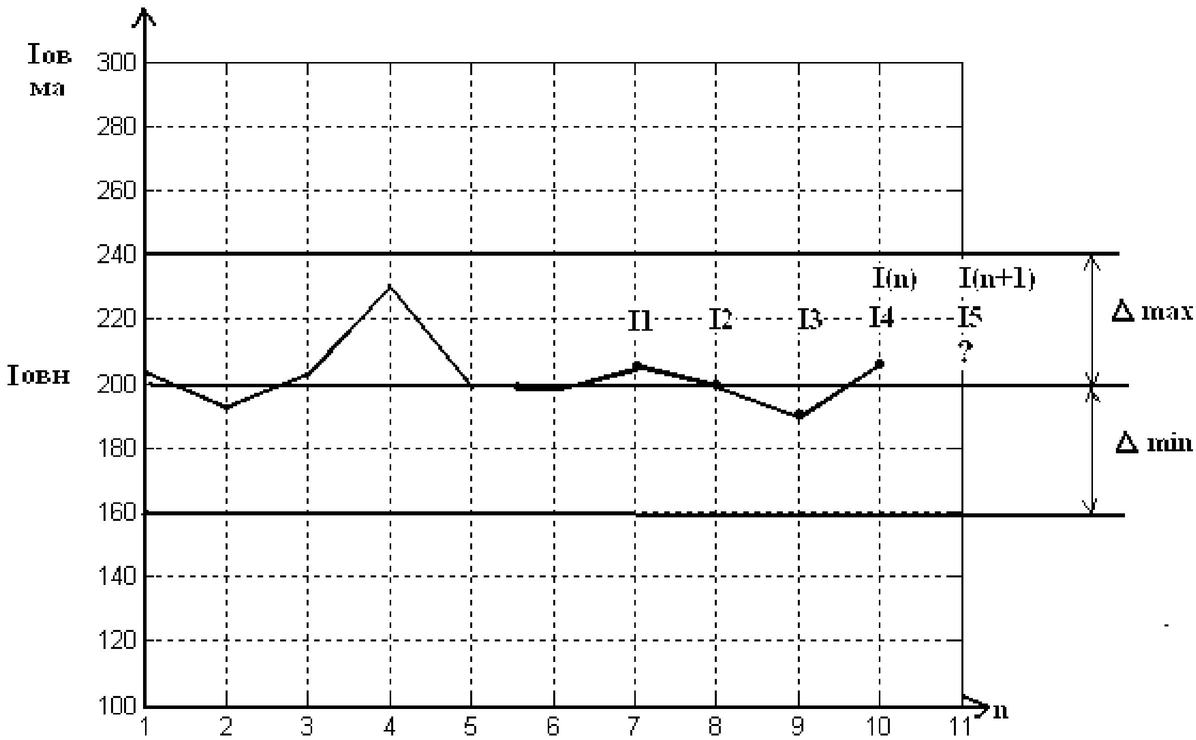

Fig. 4. Value of current *I*ов

Six lines of training samples for a neural network consists of four inputs I_1, I_2, I_3, I_4 data, and the desired output is the data of the subsequent clock I_5 (Table 2). The neural network training was carried out in the MATLAB environment.

Table 2. Matrix for training the neural network

I_1	I_2	I_3	I_4	I_5
203	192	203	230	200
192	203	230	200	198
203	230	200	198	205
230	200	198	205	199
200	198	205	199	190
198	205	199	190	200

The NEWFF predictive neural network has four inputs and one output (Fig. 5).

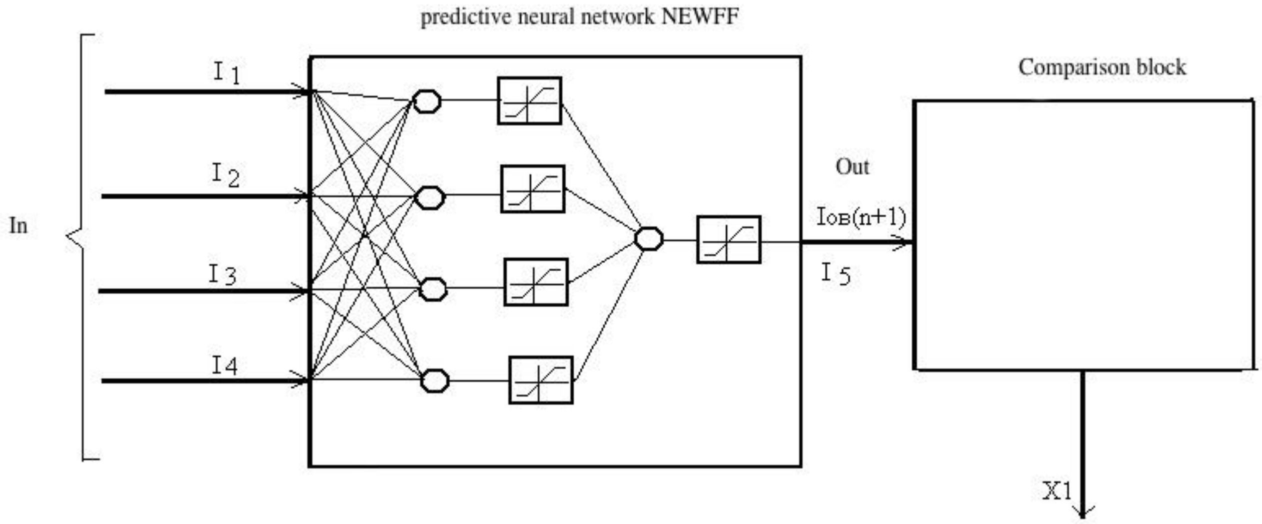

Fig. 5. NEWFF Predictive neural network

System neurodiagnostics in tact ahead of the current in the excitation winding I_5, $I_{ОВ}(n+1)$ described by the following system of neuromante [4].

$$\begin{aligned}
&E_1 = I_1W_{11} + I_2W_{11} + I_3W_{11} + I_4W_{11} + B_1,\\
&E_2 = I_1W_{21} + I_2W_{22} + I_3W_{23} + I_4W_{24} + B_2,\\
&E_3 = I_1W_{31} + I_{21}W_{32} + I_3W_{33} + I_4W_{34} + B_3,\\
&E_4 = I_1W_{41} + I_2W_{42} + I_3W_{43} + I_4W_{44} + B_4,\\
&R_1 = \tan sigE_1,\\
&R_2 = \tan sigE_2,\\
&R_3 = \tan sigE_3,\\
&R_4 = \tan sigE_4,\\
&Y_0^{'} = R_1W_1^{'} + R_2W_2^{'} + R_3W_3^{'} + R_4W_4^{'} + B_1^{'},\\
&I_5 = \tan sigY_0^{'},
\end{aligned} \tag{1}$$

where I_1, I_2, I_3, I_4 the input signals of the neural network; I_5 the output signal of the neural network; X_0 the input signal of the neural network; Y_0 the output signal of the neural network; Y_1, Y_2, Y_3 the output signals of the neural network were detained in 1,2,3 tact; $E_1 \ldots E_{10}$ output signals of the first layer of neurons; $W_1 \ldots W_{215}$ weight of the first layer of neurons; $B_1 \ldots B_{10}$ displacements of the first layer of neurons; $B_1 \ldots B_{10}$ signals at the output of blocks of activation of the first layer of neurons; Y_0` signal at the output of the second layer of neurons; $W_1$`…W_{10}` weight of the second layer of neurons; $B_1$` the offset of the second layer neurons, the signals output from the neural network were detained in 1,2,3 tact; displacements of the first layer of neurons; $R_1 \ldots R_{10}$ signals at the output of blocks of activation of the first layer of neurons; Y_0` signal at the output of the second layer of neurons; $W_1$`…W_{10}` weight of the second layer of neurons; $B_1$` displacement of the second layer of neurons.

After modeling and neural network learning algorithm Fig. 6 we obtain the required weights and biases [5].

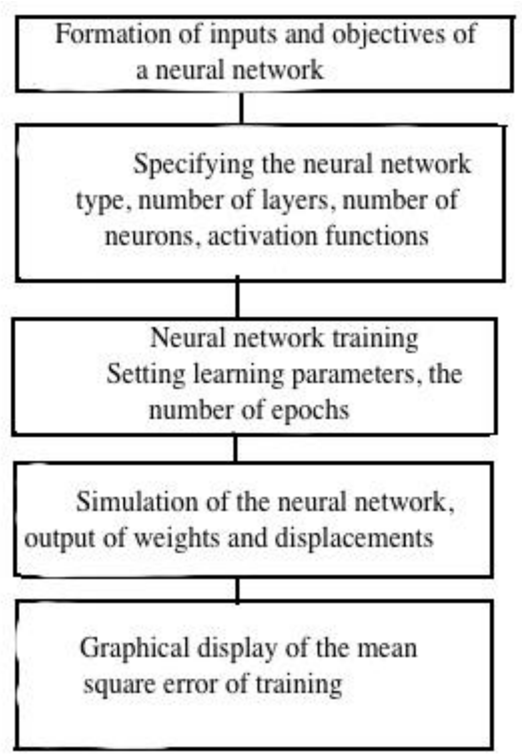

Fig. 6. Neural network modeling and learning algorithm

Weights of the first layer of neurons:
W11= 0.0218, W12= 0.0203, W13= 0.0186, W14= 0.0213,
W21=-0.0019, W22=0.0213, W23=0.0074, W24=0.0202,
W31=-0.0097, W32=-0.0171, W33= -0.0092, W34=-0.0329,
W41=0.0148, W42= -0.0029, W43=0.0252, W44=0.0145.

Weights of the second layer of neurons

W’1=40.5136, W’2= 40.4765, W’3= -39.8220 W’4= 40.4293.

Displacements for the first layer of neurons

B1= -5.9110, B2=-0.1183, B3=1.4517, B4=-0.9472

Displacements for the second layer of neurons

B’1=38.7585

For Fig. 7 the dependence of learning errors depending on the number of epochs is given.

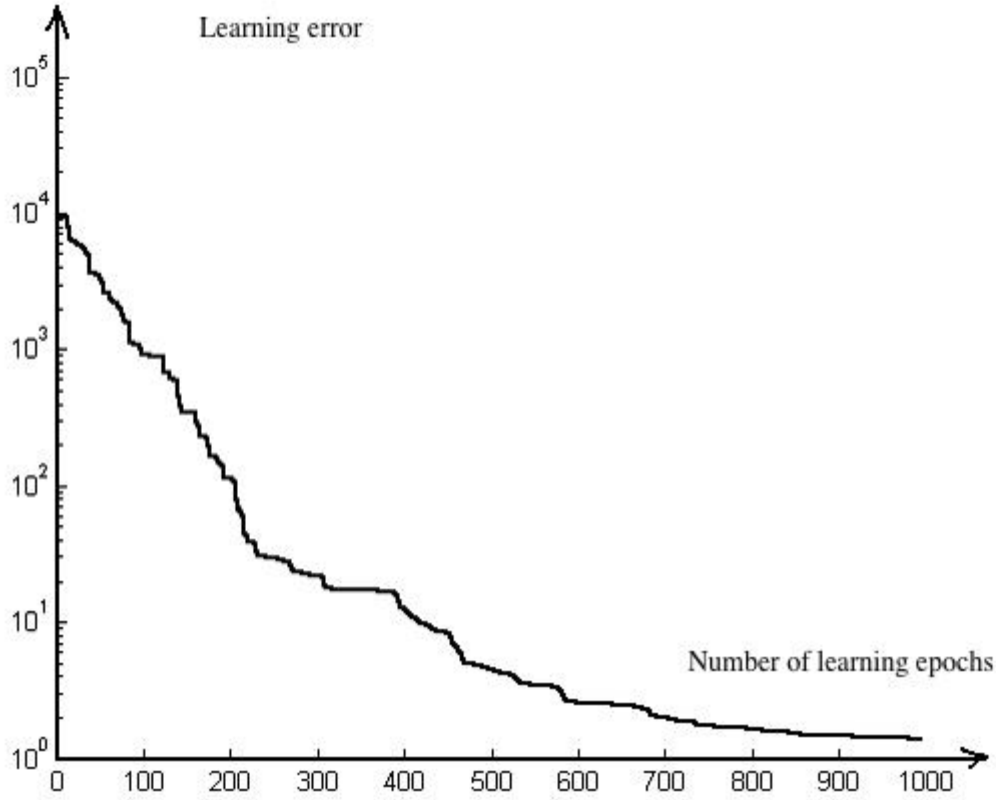

Fig. 7. The dependence of the training error depending on the number of epochs

When testing and predicting neural network, we get the future value I_5=200.0000 After predicting the future value Iов(n+1) compare it with Iовн. If the difference Iовн и Iов(n+1) greater than the maximum value allowed, the variable X_1 assigns 1 otherwise 0. A value of 1 indicates an emergency condition in the motor excitation winding.

5. CONCLUSION

Based on the data provided about the state observers, it can be concluded that it makes no sense to allocate a specific identifier. Each of them has its advantages and disadvantages. Everything will depend on the area in which the observer will be used and what performance criteria he or she should support.

Robustness have the majority of observers state. State observers, implemented on the basis of a mathematical model, require knowledge of the internal parameters of the object of identification.

For creation of observers of a state at the same computing abilities of the computer the observers constructed on the basis of the genetic algorithm and the extended Kalman filter are the most labor-consuming.

The work of such observers is possible for most identifiers, except for the genetic algorithm. The scope of application of state observers is quite wide – from social Sciences to technical Sciences (up to the construction of new computer architectures).

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