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Increase the operational reliability of the electric drive of the weaving machine

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ABSTRACT

The main purpose of this research work is to analyze malfunctions, power consumption, engine overheating and vibrations based on the loadings of electrical circuits through artificial neural networks. The reliability of artificial intelligence systems was proven on the basis of a model-based system depending on the task, and the obtained values were experimentally compared in the electrical operation of existing equipment in general industrial enterprises. An imitation model of the real object was developed. A concept of increasing productivity was set up to identify malfunctions, in contrast to the existing annular method. The article developed an algorithm for increasing the operational reliability of the electrical operation of the weaving machine on the basis of integrated indicators of excitation to determine the probability of failure of electrical operation. The article proposes the possibility of directly processing the diagnostic energy parameters through artificial neural networks. An experimental combination of signals resulted in a model based on input power and torque, and was based on an asynchronous motorized electrical circuit. It has been proven that intellectual reliability can be increased by 3-5% compared to operational reliability in traditional methods.

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1. INTRODUCTION

The main purpose of this research work is to ensure the reliability and energy consumption of the electrical system using artificial intelligence and optimization algorithms. In addition, the proposed work is aimed at focusing on several existing gaps in terms of electrical performance reliability, power quality, and system efficiency. Currently, asynchronous motor power units are widely used in all industrial equipment. This, in turn, accounts for about 29% of consumption and 69% of industrial electricity [1]. In the course of the study, it was observed that there were many failures in electrical operations, which negatively affected the economic efficiency of production enterprises. Among the most common defects in electric motors are stator (37%), rotor (10%), and mechanical (41%) damage. As a result of the experiment, mechanical damage is known to occur more often with an increase in the nominal power of electric motors [2]. Depending on the speed of the engine, the weight of steel required for the stator is reduced from 13% to 33%, copper from 5% to 64%, and the insulation mass from 12% to 57% [3]. Based on the above values, we will use the model to create a percentage discrete representation of the input signals of artificial neural networks. On the same basis, it is possible to increase the reliability of the operation of electrical drives. The efficient operation of the power steering system plays an important role in reducing energy consumption and the high performance of the system. However, there are a number of problems that affect the efficiency of the electrical drive system:

- Low reliability of electrical drives: to increase the reliability of the electrical drive system, fault detection and diagnostics for asynchronous motors are carried out in various available works. However, accounting for fewer signals to detect anomalies leads to lower reliability. On the other hand, traditional algorithms such as artificial neural networks (ANN), radio frequency (RF), and intermediate frequency (IF) have been considered, which pose a number of problems in terms of low (early) convergence rate, low accuracy, and high complexity.
- Power quality is low: to improve power quality and reduce power losses, power factor improvement is carried out taking into account current or voltage in existing work. In addition, the reason for the low power factor was not taken into account. Thus, the power will lose and the power quality will be poor.
- Low system efficiency: several existing works performed fault diagnostics for less class failures and specific types of faults. In this way, it helps industrialists less to prevent failures in time. Thus, these failures reduce the reliability of the system.

An integral motto of this proposed work is to ensure the optimized operation of the electrical drive system by saving energy and implementing reliability. To do this, we introduced the rich advantages of artificial intelligence. The tool used in this work is a three-phase asynchronous motor, which is highly efficient and requires the least maintenance due to its simple and robust construction. The electrical drive system is a set of sources, power converter, three-phase asynchronous motor, intelligent control unit, and loadings. These are the components involved. In addition, capacitors are included. The motto of the moving work is achieved through the presented processes: i) increase the power coefficient; ii) diagnosis of asynchronous engine failure; iii) anomaly/fault detection; and iv) classification of malfunctions.

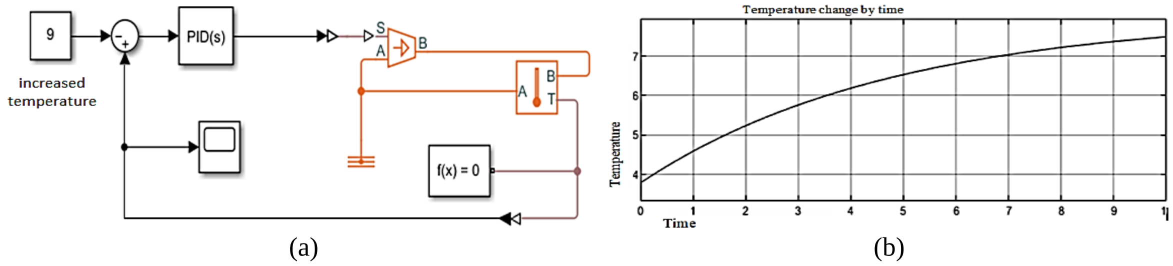
2. METHOD

2.1. Determining the level of factors affecting the operational reliability of the loom electric drive

The insulation of electric motors of long-running looms greatly affects the reliability of the system. The decisive factor in this is thermal wear, and the increase in load on them requires additional calculations. Insulation wear, loom body temperature, load increase, thread breakage effect, and electrical parameters were taken as the main parameters affecting operational reliability. Therefore, methods for calculating the rate of thermal wear of insulation for the analysis of different operating modes have become of special importance [4]. The initial works in this direction are of an experimental nature and are mainly related to heat resistance class - "A" insulation. An artificial neural network model was developed, which connects formula (1) the temperature and insulation service life and takes into account the main parameters of the electric drive based on the electric motor.

$$Tr = Tr0 \cdot e - \beta\theta \tag{1}$$

Temperature increase Δth is described as the first factor that causes the service life of electrical circuits to decrease. The expression of the temperature increase through an artificial neural network was implemented in the MATLAB program show in Figure 1. Figure 1 is a model representing the ease of checking and controlling the heat resistance of the electric drive system of the weaving machine Figure 1(a) weaving machine thermal wear process model of insulation, and Figure 1(b) characteristics of a model.



(a) (b)

Figure 1. A model representing the ease of checking and controlling the heat resistance of the electric drive system of the weaving machine (a) weaving machine thermal wear process model of insulation and (b) characteristics of a model (a) (x-time. [hour] and [y- temp. [°C])

A test mode was developed for electric motors with heat resistance class "E" and according to it, an artificial neural network model was developed based on Table 1, taking into account thermal changes when calculating the average time between failures of electric motors of looms. The main mathematical expressions that cause electrical circuit failure are cited in Table 2. It is based mainly on the development of the imitative model MATLAB program. Over time, an experimental pathway has been found to have a 70% chance of an electric motor with an exponential distribution failing.

Table 1. Calculation of thermal changes in time averaging

No.	Test mode for electric motors with heat resistance class	Average downtime (hours)	$\Delta\theta$
1	In bootloader mode, thermal aging at t=160 °C	1430	10.01
2	Aging at a temperature of t=160 °C, in reverse mode at A=0.5 g	320	8.90
3	Aging at a temperature of t=160 °C, A=1.5 g vibrational acceleration	499	8.37
4	Aging at a temperature of t=160 °C, A=1.5 g vibration	49.0	7.78

Table 2. Expressions in the mathematical model

Malfunctions	Failure %	Expressions in a mathematical model
Motor circuit damage (short circuit)	85...95%	$\frac{di_{1\alpha}}{dt}=\frac{1}{\sigma\cdot L_1}\cdot U_{1\alpha}-\frac{R_э}{\sigma\cdot L_1}\cdot i_{1\alpha}+\frac{R_2'\cdot L_m}{\sigma\cdot L_1\cdot L_2^2}\cdot\Psi_{2\alpha}+\frac{L_m}{\sigma\cdot L_1\cdot L_2}\cdot z_p\cdot w\cdot\Psi_{2\beta}$
Damage to bearings	5...8%	$M_м=\frac{3}{2}\cdot\frac{L_m}{L_2}\cdot z_p\cdot(\Psi_{2\alpha}\cdot i_{1\beta}-\Psi_{2\beta}\cdot i_{1\alpha})$; $\frac{dw}{dt}=\frac{1}{J}\cdot(M_м-M_c)$
Insulation heating	3%	$T_{r\,izolyat}=T_{r0}\cdot e^{-\beta\theta}$ T_r − insulation service life; T_{r0} − 0^0C the service life of the insulation; β − coefficient 0,0625...0,0808; θ − insulation temperature value
Body heating	1%	$T_{r\,korp}=T_{r01}\cdot e^{-ln2*\frac{\theta}{\Delta\theta}}$
In operational condition	70%	Probability of failure of an electric motor with an exponential distribution over time $P(t)=1-F(t)=1-Q(t)=e^{-\alpha_0 t}=e^{-\sum_{i=1}^{n}\alpha_i t}$ $P(t)=\prod_{i=1}^{n}P_n(t_n)=\prod_{i=1}^{n}[1-Q_i(t_i)]$

The artificial neural network intelligent diagnostic model presented in Figure 2 was used for fault detection. In this case, the input voltage represents the neutral state based on the signal. An asynchronous motor electric drive model was created using mathematical equations to express the constant values of electric drive in the neural system.

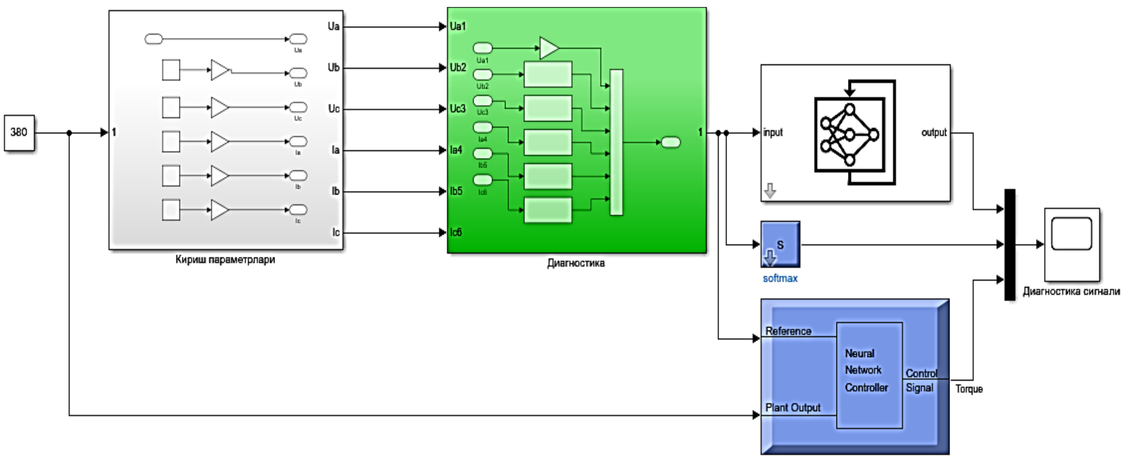


Figure 2. Artificial neural network intelligent diagnosis model

Here, the voltage change does not affect the speed of the motor, therefore, creating a mathematical model in the MATLAB environment, shown in Figures 3 and 4, the variables are placed as input signals. As an important parameter, sudden changes in angular frequency were considered as a factor causing failure. An increase in the load leading to a change in speed was analyzed with the help of the model. That is, when the change is in the range of 1.2-12%, the results of the effect on the parameters of operation in the load mode and exceeding it are reflected in the model.

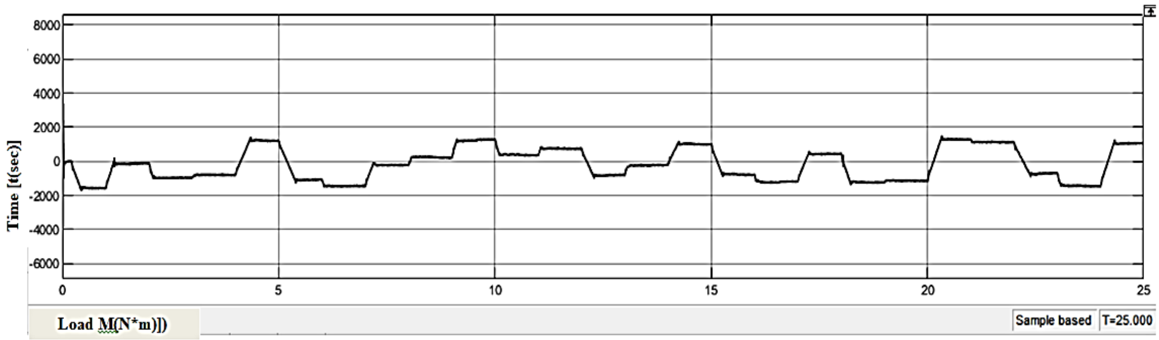


Figure 3. Changing the speed of the electrical circuit based on the load (x-time [t(sec)]; [y-load M(N*m)])

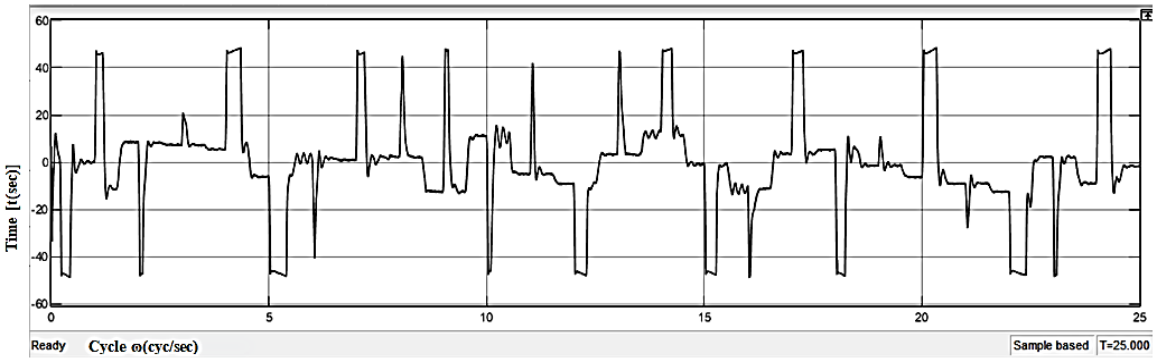


Figure 4. The degree of impact of speed change on reliability (x-time [t(sec)]; [y-cycle ω(cyc/sec)])

In order to determine the state of failure of electric motors, it is necessary to develop an express way to effectively assess the impact of working conditions. In order to increase the efficiency of the research work carried out and accelerate the introduction of the results obtained into scientific and practical activities, the concept of studying methods and means of increasing the operational reliability of electrical operations of weaving machines was developed, as shown in Figure 5.

2.2. Development of a fault detection algorithm based on electrical reliability

The lack of methods for increasing the operational reliability of electrical systems is related to the difficulty in creating a database for statistical testing of fault classification. The development of such a database is carried out based on the predicted number of failures. It is stated that it is necessary to describe the mathematical equations on the basis of the model to solve the problem without requiring a database for each part [5]–[8]. Accordingly, it takes a long time to develop a database containing predefined parameters for tracking defective and normal equipment and classifying errors. Also, reliability is improved by relying on special algorithms based on the business process of the enterprise in accordance with the field of database production [9], [10].

When organizing the algorithm through artificial neural networks, Uf is a feedback signal as an input signal, and the initial value of a (condition) is zero when the system adopts the discrete simulation mode with k steps. This process is characterized by fault representation and fault classification. The fact that the last value of α is equal to one every time the looping process is repeated means the effect on operational reliability, shown in Figure 6. In the algorithm, when a reach the value of the feedback signal, the zero value is conditionally expressed, which leads to an increase in system reliability. In the return case, the probability r (T_{zd}) of operating the looms without failure is triggered. This allows the time T_{zl} of the electric drive to be taken from the algorithm. It is also determined by the ratio of the number of electric looms that worked continuously until the time of T_{zl} to the total number of looms.

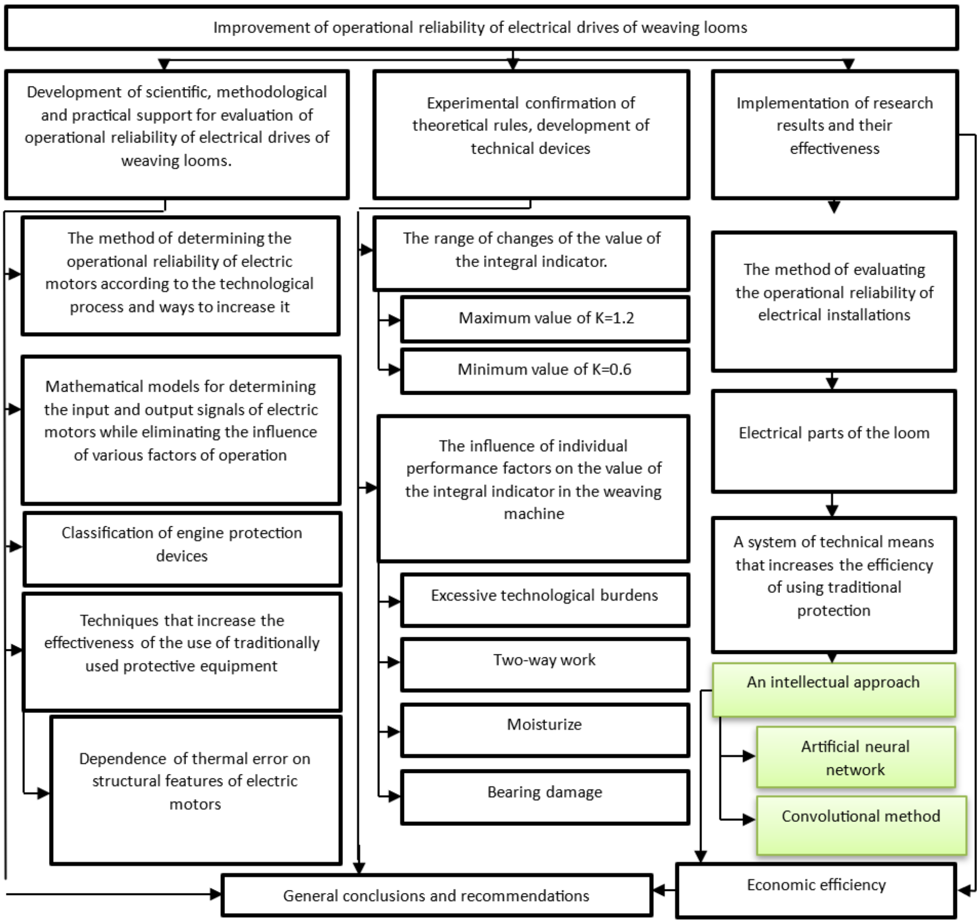


Figure 5. The structural scheme of increasing operational reliability of electric drives of weaving looms

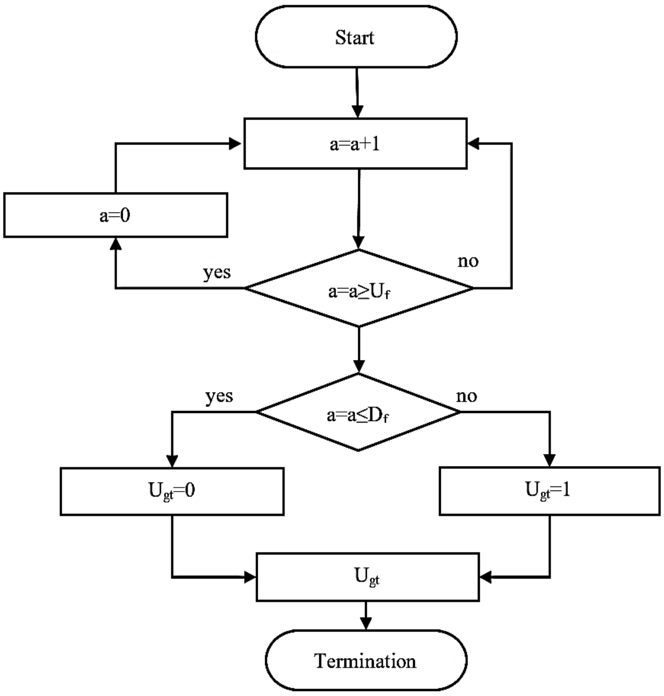


Figure 6. Fault detection and reliability improvement algorithm

The failure rate D X(t) is the number of circuit failures per unit time, where the change in time (t) is expressed in terms of the number of electrical circuits [11], [12]. Therefore, the amplitude adjustable feedback signal in loom electric currents is generated in the dot box during the simulation, and the slope of the electric current wave remains unchanged. According to formula (2), T_{cr} is the average time of failure, and formula (3) the mathematical expression of the first failure of the electrical circuit is calculated.

$$p(T_{зд}) = \exp\left[-\int_0^t \gamma(t)dt\right] \quad (2)$$

$$T_{cp} = \int_0^\infty R(t)dt \quad (3)$$

2.3. Increasing the reliability index of the electric drive of the loom on the basis of the model

Based on the studied process, dynamic systems are divided into discrete-time and continuous-time systems. In discrete-time systems, traditionally called cascades, the behavior of the system or equivalently, the trajectory of the system in phase space, is described by a sequence of states. In continuous-time dynamic systems, traditionally called flows, the state of the system is determined for each instant of time. Cascades and flows are the main part considered in symbolic and topological dynamics [13]–[15]. The description of the system using a discrete space can be expressed by (3) and (4), where the matrix A in the space form, shown in Table 3. Meanwhile, the output matrix in Table 4 relates the variable to the output.

Table 3. Spatial matrix fault detection results

Matrix1	Matrix2	Matrix3	Matrix4	Matrix5	Matrix6	Matrix7	Matrix8	Matrix9	Matrix10
0	0	0	0	0	0	0	0	-0.0010	93.3676
0	0	0	0	0	0	0	0	0.0000	0.00200
1.000	0	0	0	0	0	0	0	-0.1857	-260.29
0	1.000	0	0	0	0	0	0	-0.0001	-0.0920
0	0	1.000	0	0	0	0	0	0.0258	487.75
0	0	0	1.000	0	0	0	0	0.0001	1.0220
0	0	0	0	1.000	0	0	0	0.4119	-636.31
0	0	0	0	0	1.000	0	0	-0.0002	-2.7525
0	0	0	0	0	0	1.000	0	0.5182	315.42

Table 4. An output matrix that associates a variable with an output result

Matrix1	Matrix2	Matrix3	Matrix4	Matrix5	Matrix6	Matrix7	Matrix8	Matrix9	Matrix10
0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	1

In this case, artificial neural networks serve as the optimal solution for reducing the energy consumption of existing electrical systems in textile enterprises. The analysis of existing electric drives in the enterprise showed that in order to implement control with speed modes that shown in Figure 7, changing the speed affecting the product by adjusting the rotation speed of the drive, combining artificial neural networks based on a mathematical model and giving the effect of giving the desired speed based on the constant product size the necessity of formation was considered.

Through the model developed in the MATLAB program above, intellectual failure diagnostics (IFD) employs machine learning theories such as artificial n1eural networks (ANN), vector support machine (SVM), and neural networks (DNN) to diagnose machine failures [16], [17]. Over the past few years, researchers have begun to take advantage of the capabilities of in-depth study and convolutional neural networks in error detection and diagnostics in order to reduce or eliminate the disadvantages of shallow ANN architecture [18], [19], but the results obtained in their uniformity of failure diagnostics considered through motors remain unclear. And the result obtained through the model means that there is a lack of diagnostics. Deep learning refers to a class of machine learning techniques typical of multiple layers of data processing steps in deep architecture, which are used for pattern classification and other tasks [20], [21]. However, the application of deep learning models presents new problems in the field of model hyperparameters tuning [22], [23]. Convolutional neural network models, which are now widely used, help solve these solutions. Deep learning is seen as a black box method in which the researcher is unable to manually adjust parameters because layers are hidden and there are many hyperparameters associated with network structure and training algorithms [24]. The choice of appropriate hyperparameter values is very important because they directly control the movement of training algorithms and have a significant impact on the performance of the model [25]. Bayesian optimization is a very efficient way to solve this type of optimization problem [26], and is superior to other global optimization algorithms. In this article, we will try to automatically optimize the hyperparameters and architecture of a multichannel deep convolutional neural network using Bayesian optimization.

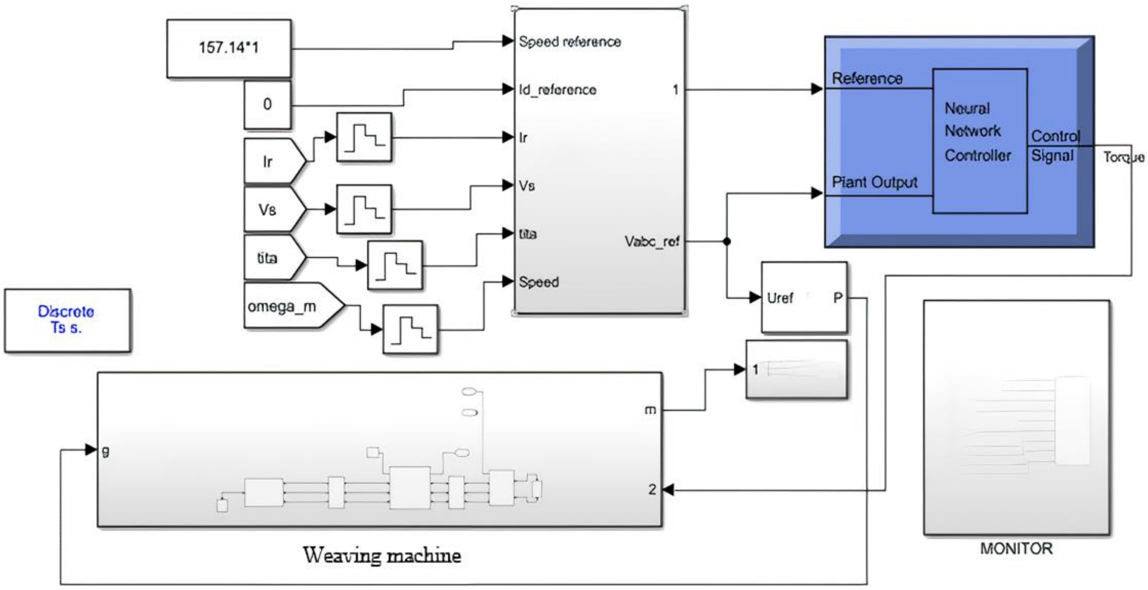


Figure 7. An overview of the model in MATLAB

3. RESULTS AND DISCUSSION

The application of reliability improvement method based on convolutional neural network in the loom was carried out in the assessment of the annual economic efficiency of the enterprise through some factors. They are: i) the ability to choose the optimal operation of the mechanism in the technological process (through the model), ii) probability of failure of mechanisms, iii) overload operation control and exclusion of direct starting of engines, which significantly reduces the cost of frequent repairs of electrical equipment; and iv) increase the reliability and durability of the loom. Start by using the expert planning department to estimate the redundancy of electrical drives within 0-600 hours, the parameters are listed in Table 5.

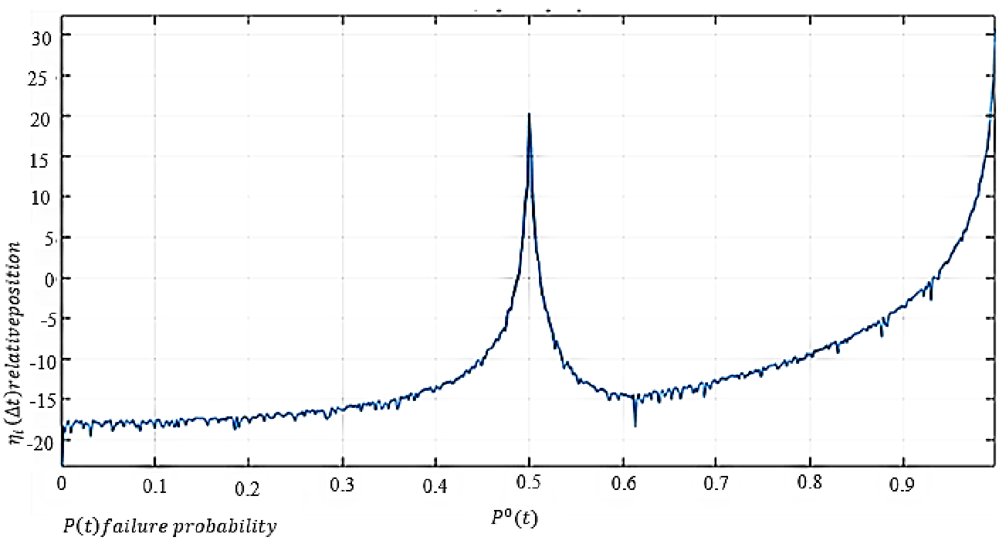
The fact that the highest figure is in the range of 150-400 hours was determined using the MATLAB program, on the basis of which the characteristics presented in Figure 8 were obtained. The reasons for the failure of electric drives 85% based on the fact that the electric motors are malfunctioning. For this reason, the load factor of electric motors is also considered important in determining operational reliability below in Tables 6-8. The load factor of electric motors is Kz = 0.1...31% at 0.6; Kz=0.6 at 41%...0.8; Kz=0.8 at 20%...1.0; and 8% had Kz=1.1. The reasons for the failure of electric motors were conditionally operational (50%), technological (35%), and constructive (15%). In operation, operational failures are caused by emergencies (70%) and failures associated with the wear of the insulation (30%), and emergency modes, in turn, accidental failures - 40...50%, parking of the working machine - 20...25%, 10 in long-term overloads...15%, violation of isolation due to humidity - 15...20%.

Table 5. Preliminary data on failures based on a model built in MATLAB

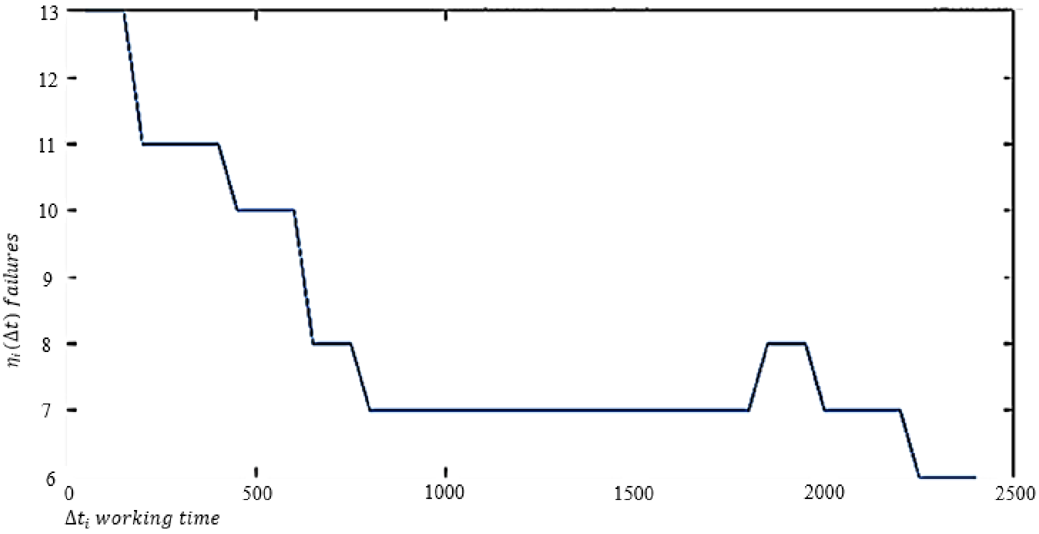
Δt_i	$n_i(\Delta t)$	Δt_i	$n_i(\Delta t)$	Δt_i	$n_i(\Delta t)$	Δt_i	$n_i(\Delta t)$
0-150	13	600-750	8	1200- 1300	7	1800- 1900	8
150-400	11	750-1000	7	1300- 1600		1900- 2200	7
400-600	10	1000-1200	7	1600- 1800		2200- 2400	6

Table 6. Failure rate based on set times

$n_i(\Delta t)$	P*(t)	$n_i(\Delta t)$	P*(t)	$n_i(\Delta t)$	P*(t)	$n_i(\Delta t)$	P*(t)
200	0.92	750	0.71	1300	0.57	1900	0.44
400	0.85	1000	0.69	1600	0.56	2200	0.42
600	0.78	1200	0.65	1800	0.52	2400	0.38



(a)



(b)

Figure 8. Preliminary data on failures based on a model built in MATLAB: (a) preliminary information about failures y- $\eta_i(\Delta t)$ failures and x- Δt_i working time and (b) change in time y- $\eta_i(\Delta t)$ relative position, x- P(t) failure probability

Table 7. Reliability figures when the probability of failure is 0.35

Nº	K_i	$l_{1.исп}$	K_i	N_i	N_{i},, K_i	$\frac{(N_i \cdot K_i'')}{\sum N_i \cdot K_i''}$	$\tau_{вi}$	$\frac{N_i \cdot K_i''}{\sum_{i=1}^{n} N_i K_i''} \bar{\tau}_{вi}$
1	13	14	15	16	17	18	19	20
1	179.2	1	179.2	1	179.2	0.08	3.28	0.262
2	40	1	40	1	40	0.02	1.83	0.037
3	129.8	1	129.8	1	129.8	0.06	1.83	0.110
4	13.1	1	13.1	1	13.1	0.01	1.83	0.018
5	450	1	450	1	450	0.21	1.83	0.384
6	31.4	1	31.4	1	31.4	0.01	0.625	0.006
7	60	1	60	1	60	0.03	0.625	0.002
8	13.8	1	13.8	1	13.8	0.01	0.625	0.006
9	833	1	833	1	833	0.38	3.28	1.246
10	2.6	1	2.6	1	2.6	0.00	1.83	0.000
11	432	1	432	1	432	0.20	3.28	0.656
		Total			2190		20.9	2.727

Table 8. Economic efficiency of the proposed method

Loom equipment	The available method		The proposed method		Difference %
	Average downtime (hours)	Thermal wear Δth%	Average downtime (hours)	Thermal wear Δth%	
AD1 GF1-3 kWt	15779	5.85	23779	4,77	0.507003
AD 1 GF2-37 kWt	13245	4.91053	16879	3.38588	0.507003
AD 2 GF3-45 kWt	12135	4.499002	14523	2.913273	0.274368
AD 3 GF4-11 kWt	13988	5.185994	16999	3.409951	0.196786
AD 4 GF5-15 kWt	12321	4.567961	14879	2.984685	0.215256
AD 5 GF6-22 kWt	8403	3.115378	12365	2.480384	0.207613
AD 6 GF7-11 kWt	13988	5.185994	17825	3.575644	0.471498
Bearings	850	9.1	1250	7.78	0.470588
Isolation	23285	26.8	26285	20.01	0.128838
Corps fever	25345	4.34	29345	3.4	0.157822

4. CONCLUSION

As a result of research on increasing the operational reliability of the electric drive of the loom, the following conclusions were made: Faults occurring in industrial asynchronous motors were identified and diagnosed while increasing the reliability of the electric drive of the loom. The structural scheme of weaving loom to increase the operational reliability of the electric drive was developed. It was determined that 60% of the failures occurring in the looms are mechanical and 40% are electrical failures.

Based on an intellectual approach, a structural scheme for increasing the operational reliability of the integrated indicator values of the loom electric drive in the range of 0.6÷1.2, as well as an algorithm for increasing the reliability of the electric drive system was developed based on the diagnosis of asynchronous motor failures, the classification of anomalies and failures. The effect of the weaving machine electrical circuit on operational reliability as a result of the interruption of the technological process has been proven to manifest itself in a mathematical model through artificial neural networks. Based on the current state of the electrical circuits of the textile enterprise, it was found that the use of associative memory systems in the method of detecting an artificial neural network failure will give a significant result.

A mathematical model has been developed that describes the reliability of the exploitation of the dimensions of the electrical operation of the weaving machine based on differences in change. A classification of malfunctions has been developed, which allows you to determine the number of malfunctions in a weaving machine using artificial intelligence control modules. Combining the developed algorithms resulted in the development of a "model-based" system for detecting matrix failures in spatial representation and increasing reliability based on The Matrix connecting the variable to the output. As a result, an improvement in the operational reliability indicator of electrical operation was achieved by 3%. The development of a neural network method on the basis of an intellectual approach, in contrast to methods of increasing anemic reliability, leads to the development of electrical circuit sox in the future, as a result of which it is possible to determine in advance the reasons for the failure of electrical circuit. The service life of the weaving machine electrical operation can increase up to three years.

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