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The probability estimate of the defects of the asynchronous motors based on the complex method of diagnostics

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Abstract. This article is devoted to the development of a method for probability estimate of failure of an asynchronous motor as a part of electric drive with a frequency converter. The proposed method is based on a comprehensive method of diagnostics of vibration and electrical characteristics that take into account the quality of the supply network and the operating conditions. The developed diagnostic system allows to increase the accuracy and quality of diagnoses by determining the probability of failure-free operation of the electromechanical equipment, when the parameters deviate from the norm. This system uses an artificial neural networks (ANNs). The results of the system for estimator the technical condition are probability diagrams of the technical state and quantitative evaluation of the defects of the asynchronous motor and its components.

1. Introduction

At heavy industry enterprises, in particular the mining industry, more than 75% of failures are failures of electromechanical equipment, that is why the level of their reliability and safety is largely determined by their technical condition. The electromechanical equipment is subject to significant wear and tear, the risk of defects and malfunctions, due to technical complexity and increasing of the overall production [1, 2]. The efficiency of electromechanical equipment directly depends on the reliability of individual units, which are based on an asynchronous electric motor and associated mechanical equipment.

Feasibility of introduction of systems of technical diagnostics is caused by actual problems [3]:

- need to improve the accuracy of determining the technical state of electromechanical equipment in dynamics conditions of the operational impacts;
- transition to maintenance according to the actual state and the formation of maintenance and repair programs on the basis of predicting the failure time of equipment with a certain probability on the basis of statistical data;
- need to predict the development of the level of defects and their impact on the residual life of electromechanical equipment on the basis of modeling.

2. Complex method of diagnostics

Methods based on controlling vibration characteristics at various points in the machine and electrical parameters (current, voltage, power consumption) have become most widely used in diagnostics, since up to 90% of defects can be diagnosed with the help of them [5, 7, 8]. It is also necessary to use indirect diagnostic methods to clarify the diagnosis, because of the complexity or impossibility of determining a number of parameters characterizing the operating conditions.

The decision on the applicability and comprehensiveness of the diagnosis type is based on the feasibility study, which determines the economic feasibility of using a diagnostic system using a minimum set of diagnostic parameters. That allows us to reliably and simply assess the technical condition [9]. The proposed approach to solving problems of increasing the accuracy and quality of the assessment of the state and residual life of electromechanical equipment is based on the analysis of data of systems for recording the quality of electrical energy, operative condition, vibration and electrical characteristics of the unit using an artificial neural network.

3. The acquiring information for the probability estimate of failure

Automation systems of technological processes using different types of sensors allow without stopping and without mounting to monitor the parameters of the unit, on which it is possible to estimate the actual state of the AC motor (Figure 1).

The data acquisition system for diagnostics consists of several sets of sensors, that transmit signals to an automated process control system (APCS). The acquisition dynamic signals form the main database, which also receives a static data from additional database, that contains information about the technical state of the unit (for example, T – the average temperature of the surrounding air, ρ – humidity, ξ – insulating strength and etc.) and process automation system data (e.g., $v_r(t)$ – gear speed signal, $v_i(t)$ – actuator speed signal and etc.).

The signals are processed by a software filter and written to a read-only memory, after which they arrive at the ANN input, forming a retrospective database of the main and additional parameters for further estimation of no-failure operation parameters of the electric motor.

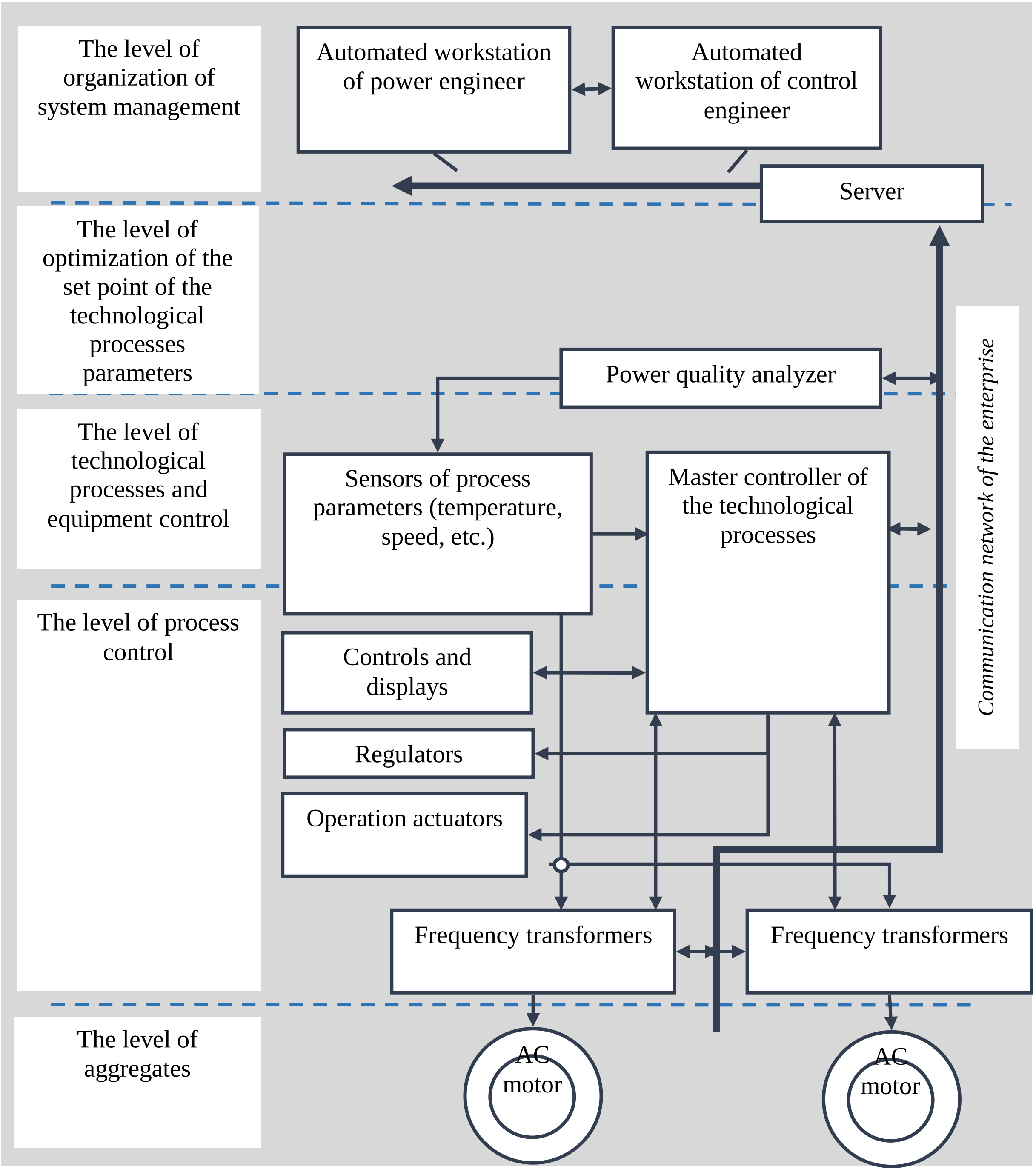

Figure 1. Structural diagram of the automatic process control system with an integrated system for diagnosing the technical condition and estimating the residual life of an electromechanical unit with an asynchronous motor.

4. The determination of the probability of no-failure operation of an induction motor using an artificial neural network

Determination of the probability of no-failure operation of the electric motor on the basis of a database of retrospective data with requirements for relative error, as the limit of the confidence interval for forecasting λ for p ≥ 95% - less than 5% can be represented as the function (1):

$$P = F(t, \Delta t, n, k, l, N_i, P_i(t), P(t-\Delta t), \ldots P_{im}(m_i), P_i(t-n\Delta t), \ldots\ldots P_{ih}(h_i), P_{ih}(t-n\Delta t)), \quad (1)$$

P_i – prediction probability; t – current time; Δt – time interval between measurements; λ – prediction interval; n – number of intervals in the past; k –number of intervals in the future; l – number of measured characteristics; $P_{im}(m_i)$, $P_{ih}(h_i)$ – values of probabilities by electric and vibration characteristics; Ni – indirect parameters that influence the compilation of the predict for the probability of no-failure operation (T – the average temperature of the surrounding air, ρ – humidity, ξ – insulating strength and etc.).

The structural diagram of the system for estimating the probability of no-failure operation based on the diagnosed electrical and vibration parameters of an AC motor and the artificial neural network is shown in Figure 2.

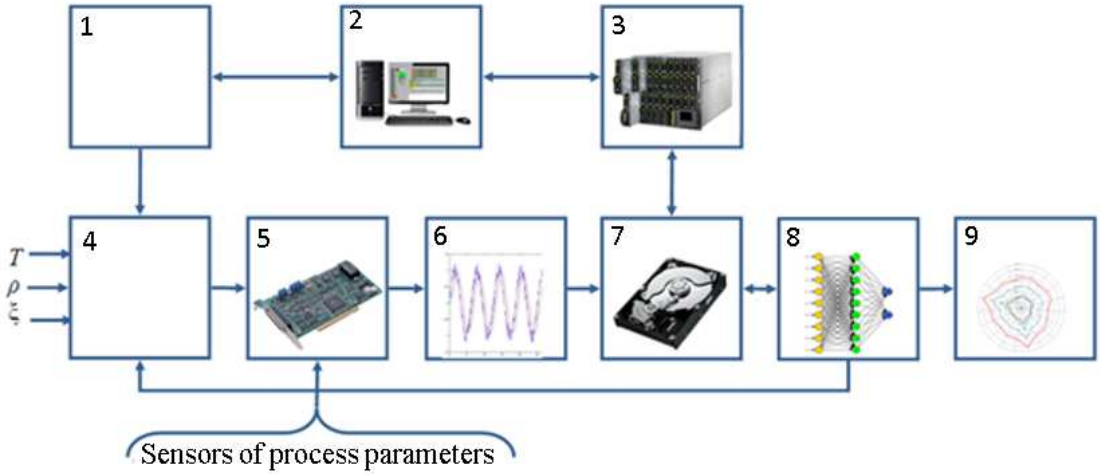

Figure 2. The structural diagram of the system for estimating the probability of no-failure operation based on the diagnosed electrical and vibration parameters of an AC motor and the artificial neural network: 1 - automated process control system (APCS), 2 - automated workstation of control engineer, 3 – server, 4 - data preprocessing block, 5 - data acquiring block, 6 – data filtering block, 7 - read-only memory, 8 - artificial neural network, 9 - visual representation

An ANN input consists of a training data generation unit and an ANN creation unit that determines the type of neural network, the number of intermediate layers, the number of neurons and the activation functions. In the training block, the parameters and the selected learning algorithm are specified. In the blocks of testing and estimating the quality of prediction, the probability of no-failure operation of AC motor by electric vibrational and indirect parameters is estimated in comparison with the reference electric motor values.

5. Algorithm of artificial neural network

For ANN, it is necessary to form a training and test sample of the diagnosed indicators from the database of retrospective data, that is, the data obtained from the sensors are required for the operation of the neural network. These data can be supplemented by indirect (additional) parameters, affected on the compilation of the prediction for assessing the importance of the correlation coefficients.

The prediction algorithm of the estimating the probability of no-failure operation of electric motor was based on the function (1) and on ANN with the multilayer perceptron, that was shown in [6].

The algorithm for constructing the ANN looks like this: the first, setting the initial conditions for the neural network (for example, weights, the number of training samples, the accuracy of the prediction); the second, acquiring the values of the measuring parameters; then converting the signals into relative values of Y_i, which are in the range $0 \le Y_i \le 1$.

The predicted output of the system is compared with the actual value of the parameter, and when the error exceeds the specified allowable level (more than 5%), the system is retrained on new data. If the condition is met, the learning process ends, otherwise the process repeats. Table 1 bases on values of predicting the probability of no-failure operation for electric motor by electrical, vibrational and indirect parameters.

Table 1. Matrix for the calculation of the probabilities of a defect in electric motor by electric and vibration parameters.

Type of defect	**Probability of appearance**				
	Normal state	**Pre-crisis state**	**Crisis state**	**According to the passport data**	**Actual state**
Damage to the insulation of the winding relative to the housing	0,12	0,2	0,28	0,1	0,18
Damage to interfacial insulation	0,12	0,2	0,28	0,1	0,16
turn-to-turn short circuit	0,1	0,18	0,26	0,09	0,3
Defect of stator winding	0,12	0,2	0,28	0,1	0,14
Short circuits in the stator winding	0,12	0,2	0,28	0,1	0,12
Defect of the rotor winding	0,08	0,16	0,24	0,08	0,14
Damage to the bearing	0,1	0,18	0,26	0,09	0,17
Damage to the rotor	0,12	0,2	0,28	0,1	0,16
Damage to the rotor magnetic circuit	0,12	0,2	0,28	0,1	0,14
Damage to the stator magnetic core	0,2	0,28	0,36	0,14	0,2
Dynamic eccentricity	0,12	0,2	0,28	0,1	0,3
Static eccentricity	0,12	0,2	0,28	0,1	0,3
Unbalance of the supply voltage of the zero sequence	0,1	0,18	0,26	0,09	0,14
Negligence of the negative sequence supply voltage	0,1	0,18	0,26	0,09	0,17
Nonsinusoidality of supply voltage	0,12	0,2	0,28	0,1	0,14
Contact defect	0,12	0,2	0,28	0,1	0,16
Unbalance of rotor masses	0,2	0,28	0,36	0,14	0,18
Mechanical weakening	0,12	0,2	0,28	0,1	0,22
Gearbox defect	0,12	0,2	0,28	0,1	0,15
Shaft alignment	0,1	0,18	0,26	0,09	0,14

After the completion of the training process, the ANN analyzes the quality of the prediction, based on the obtained probability, and calculates the probability of its location in the limits, taking into account the diagnosis of electrical and vibration parameters, and evaluation of the following characteristics of the neural network: learning performance, performance test, the average value of the target output variable, the target standard deviation of the output variable, average error of the output variable, the average absolute error ratio of the standard deviation to the standard deviation of the error data, Spearman rank correlation coefficient, calculated between the target vector and the real output vector.

As a result of the probability evaluation (Table 1), exceedance of critical values for three defects was detected, one parameter was in the pre-crisis state. The results of the ANN work can be used to assess the technical state of the electric motor and build systems for predicting the residual life.

6. Conclusions

The future of the mining industry is to increase efficiency and safety without increasing harmful emissions and costs associated with the operation of equipment. The creation of systems for diagnosis and evaluation of the residual life of electromechanical equipment will allow enterprises of the industry to remain competitive without increasing the cost of maintenance and repair. The proposed method for estimating and predicting the technical state of an electromechanical unit based on vibration and electrical diagnostic parameters will improve the accuracy of predicting the technical state. The use of an artificial neural network allows us to predict the reference values, for diagnostic patterns of technical state probabilities, taking into account indirect parameters and detected defects.

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