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Measurement of electric motor torque of powerful machines with the support of the finite element method

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Abstract:

The diagnostic method is used to measure the torque of an electric motor. When an electric motor develops defects, its electric current changes, resulting in a change in torque that is difficult and expensive to measure. An electric motor diagnostics system based on the model approach in the state space has been developed. A digital twin, which represents a model of electric motor and works in parallel with a real motor, is developed. The electric motor signals with electric current and angular velocity sensors and output signals of the digital twin are analyzed. The presence of defects of the real electric motor is determined by the magnitude of the misalignment. On detecting a defect, the system transfers the information about it to the control system, activates the indication on the defects appearance, then by methods of fuzzy logic or other methods defines the type of the defect, the system element where the defect occurred, forecasts the remaining life, the control system performs fail-safe operation. If the magnitude of the defect is insignificant, then appropriate maintenance actions are recommended. If the magnitude of the defect is significant, an emergency shutdown of the engine is necessary.

Keywords: torque, electric motor, heavy machinery, diagnostics, model approach, state space

1. Introduction

The relevance of electric motors of heavy machinery diagnosing and monitoring is very high, as engine failures at sea can lead to significant economic losses and even pose a threat to human life and health. A large number of scientific publications on this topic confirms this fact.

The aim of this work [1] is to measure and analyze the vibrations of electric motors of traction machines in order to reduce maintenance costs and implicitly contribute to making optimal decisions. In general, the faults that underlie electric motors are primarily due to mechanical and electrical efforts. Mechanical stresses occur as a result the overloads and rapid load variations. On the other hand, the overcurrent's and overvoltage's are usually in the close accordance with the power supplies. In this regard the mechanical faults cannot be analyzed by changing the parameters like voltage, current, power, frequency but in practice we can do analysis by used the high-performance testers with intelligent software for measuring the motor vibrations. The MarVib DC650 tester was used in this paper for analysis and measurement the vibrations of electric motors [1].

The reliability of the drive system is closely related to the safety of operation. A typical drive system has many advantages (mainly efficiency), but it is a source of high levels of vibration. Vibration can have a dangerous effect on the strength of the machinery and consequently on the safety of the machine's operation. Torsional vibrations of the power transmission drive system are usually most dangerous for the shaft guide and crankshaft. The power of propulsion system is quite often measured by commercial measuring device based on instantaneous angular speed (IAS). The angular speed measurements are performed using two optical sensors for reading the IAS, mounted at shaft line. The authors try to use existing apparatus for torsional vibrations' continuous monitoring. Designing monitoring methodology consists several analytical methods. Simplified method of torsional vibration calculation is a first one. Simplified calculation method gives us a determination possibility of torsional vibrations in typical and emergency working conditions. Natural frequency value (resonance location) as well as vibration amplitudes can be estimated on the base of the method. The presented calculation method was verified by comparison with the detailed finite element method calculation and measurements on real engines. The second part of the monitoring system contains methodology of monitoring of piston engine's crankshaft torsional vibrations by measurement of IAS at free and power output ends of the engine's crankshaft. It is assumed that calculation of differential value between both ends shall give the picture of torsion angle magnitudes and phases of the peak values. Analysis method of recorded signals (e.g., recalculation of angular distance sampling into constants time function and frequency base by FFT analysis) is also developed. The article describes measurements of torsional vibrations of the drive engine crankshaft with some simulated faults (fuel injection pump leakage and related to the installation of injection valve sets with different nozzle characteristics - spray nozzle angle). Presented results of experiment derive from test cycle carried out using laboratory stand of Gdynia Maritime University equipped with 3-cylinder self-ignition engine, powering electric generator. The planned monitoring system should have detected possibility of torsional vibration changes (propulsion system malfunction), the ability to assess the degree of danger of failure and eventually determination of the risk of damage and the causes of propulsion system's threat failure [2].

The article is devoted to the problem of creating a universal integrated monitoring system for traction diesel engines. A review of the existing systems for diagnosing the monitoring of engines is made, and their disadvantages are shown. The structure of diagnostic parameters and the selection method of measuring instruments are proposed. It is shown that the main objects to be monitored during the monitoring are the diesel engine workflow, the condition of the cylinder-piston group parts, the condition of the engine oil, vibration indicators of the engine, and systems serving the main engine. When creating monitoring systems, it is proposed to maximize the use of elements of the engine electronic control system and information obtained from the sensors of this system. The article outlines the steps for practical implementation of the developed system and shows that its implementation will reduce operating costs of mining companies and increase operational safety [3].

Modern information technologies facilitate control and adequate assessment of the performance of power plants, as they provide effective technical diagnostic services. The article proposes the structure and principles of construction of a monitoring and diagnostic system for monitoring elements of small power plants, which allows solving current problems faced by technical diagnostic systems [4].

2. Material and Methods

The implementation of a system for acquiring, transmitting and processing data necessary for the diagnostics of traction motors is the basis for standard maintenance. Determining the most influential operating parameters and performing monitoring, analysis and taking measures based on expert knowledge prevents downtime due to possible failures. Timely repairs and replacement of worn parts based on condition diagnostics allow for maintenance planning, which reduces the frequency of maintenance and the accumulation of unnecessary spare parts in warehouses. A system for remote data collection from electronically controlled traction motors was developed and applied for research purposes. The system was installed on a four-stroke high-speed drive engine, and the engine operating parameters were monitored during regular operation to detect irregularities and possible faults in time. The measurement system monitored the parameters obtained from the electronic engine control module via the J1939 protocol, and the following relevant engine parameters were analyzed in this work: engine speed, boost pressure, fuel consumption, and engine load at the current speed. The analysis included the creation of trend diagrams to present the distribution of the minimum, median and maximum values of each parameter of all the measurements performed. This study also investigated the failure simulation of a high-speed four-stroke engine model. Using sensor data from critical system components, this research explored various scenarios. The analysis aimed to elucidate the impact of these faults on engine performance. Based on the analyses of the relevant operating parameters of the engine, diagnostics were carried out [5].

Example: The conversion of marine current energy into electricity with marine current turbines (MCTs) promises renewable energy. However, the reliability and power quality of marine current turbines are degraded due to marine biological attachments on the blades. To benefit from all the information embedded in the three phases, we created a fault feature that was the derivative of the current vector modulus in a Concordia reference frame. Moreover, because of the varying marine current speed, fault features were non-stationary. A transformation based on new adaptive proportional sampling frequency (APSF) transformed them into stationary ones. The fault indicator was derived from the amplitude of the shaft rotating frequency, which was itself derived from its power spectrum. The method was validated with data collected from a test bed composed of a marine current turbine coupled to a 230 W permanent magnet synchronous generator. The results showed the efficiency of the method to detect an introduced imbalance fault with an additional mass of 80–220 g attached to blades. In comparison to methods that use a single piece of electrical information (phase current or voltage), the fault indicator based on the three currents was found to be, on average, 2.2 times greater. The results also showed that the fault indicator increased monotonically with the fault severity, with a 1.8 times-higher variation rate, as well as that the method is robust for the flow current speed that varies from 0.95 to 1.3 m/s [6].

The article is devoted to the development of an information system for monitoring and controlling a small power plant with the possibility of predicting technical condition parameters. A data flow diagram of the main processes in the information system for monitoring and controlling a small power plant it its own components has been developed and presented. For monitoring and controlling a mining power plant, an implementation of an information exchange scheme between the elements of a mining power plant is proposed. As an example, the implementation of an information model for monitoring diesel-electric equipment developed by the authors, which is part of a small power plant, is analyzed in detail. The article shows a variant of predicting technical condition parameters in dynamics with the possibility of detecting violations of the permissible limits of the values of the controlled parameters in the future in the corresponding time interval. The shown development will be useful for further research into the processes of monitoring and controlling the technical condition parameters of a small power plant, both for the corresponding forecast time and up to the obtained parameter values with the smallest forecast time value at which the set of permissible limits will be exceeded [7]. This article presents a condensed outline of how approaches to solving technical diagnostics tasks have changed over the last 50 years. It reviews different approaches to the modelling of wear and tear phenomena that are the subject of diagnosis, and draws attention to groundbreaking papers which are still of topical interest. Particular emphasis is placed on the development of vibroacoustic diagnostics methods, an area in which Polish scientists were among the world's Avangard. It is also shown how methodologies have changed with the progress of digital signal analysis. The example given in the second part of the article demonstrates that the well-known and technically important task of gear diagnostics can now be solved without searching for the classical state→symptom relationship through an exact dynamic description of the machine and comparing it with the results of the experiment, but instead by comparing observations at different points of n-dimensional space with an abstract pattern generated by a sequence of logical transformations. This formulation of the task opens up possibilities for the artificial intelligence method. It is noted that mining is one of the main areas of application of modern diagnostic methods, and it is shown that increasing the accuracy of vibroacoustic diagnostic techniques and the correctness of diagnostics allows the use of this methodology in other applications as well [8].

As a key component of both the propulsion system and critical equipment, traction motors are undergoing a technological transition from traditional fault diagnosis to multi-physics collaborative modeling and integrated intelligent maintenance system. This paper provides a systematic review of the latest advances in fault monitoring of traction motors, focusing on key technical challenges in complex operating environments, and offers several innovative insights and analyses in the following aspects. First, regarding the fault development of electromagnetic-thermal-mechanical coupling, this study summarizes typical fault mechanisms such as bearing electrical erosion, rotor eccentricity, permanent magnet demagnetization, and insulation aging, and analyzes their modeling approaches and multi-physics coupling development paths. Second, in response to the problem of multi-source signal fusion, the applicability and limitations of feature extraction methods - including current analysis, vibration demodulation, infrared thermography, and Dempster-Shafer (D-S) evidence theory - are evaluated, providing a basis for designing subsequent signal fusion strategies. Regarding intelligent diagnostic models, this paper compares model-driven and data-driven approaches in terms of their suitability for different scenarios, highlighting their complementarity and integration potential in complex operating conditions, e.g. in traction engines. Finally, with regard to practical deployment needs, key aspects of implementing a monitoring platform in workplace edge computing environments are discussed. The study also identifies current research gaps and suggests future directions, such as digital twin-driven intelligent maintenance, fleet-level collaborative fuel management, and standardized condition data transmission. In summary, this paper offers a comprehensive analysis in the areas of failure mechanism modeling, feature extraction method evaluation, and system deployment frameworks to provide theoretical references and technical insights for the development of traction engine condition management technologies [9].

The relevance of electric motor diagnostics research is discussed in the following papers [10-20].

3. Results

The diagnostic method is used to measure the torque of an electric motor. When an electric motor develops defects, its electric current changes, resulting in a change in torque that is difficult and expensive to measure. An electric motor diagnostics system based on the model approach in the state space has been developed.

The development of a mathematical model of a DC electric motor initially begins with differential equations that describe the electrical and mechanical parts of the motor. The motor model is then written in discrete state-space vector-matrix form. The motor is always affected by disturbances caused by external factors, such as resistance torque, measurement errors, parameter uncertainties, and additive defects. The motor model in discrete state-space vector-matrix form is extended as follows:

$$\mathbf{x}_{\mathrm{k}+1} = \mathbf{A}\mathbf{x}_{\mathrm{k}} + \mathbf{B}\mathbf{u}_{\mathrm{k}} + \mathbf{E}_{\mathrm{d}}\mathbf{D}_{\mathrm{k}} + \boldsymbol{\xi}_{\mathrm{k}} + \mathbf{E}_{\mathrm{f}}\,\mathbf{f}_{\mathrm{k}}, \tag{1}$$

$$\boldsymbol{y}_{\mathrm{k}} = \mathbf{C}\mathbf{x}_{\mathrm{k}} + \mathbf{F}_{\mathrm{d}}\mathbf{D}_{\mathrm{k}} + \boldsymbol{v}_{\mathrm{k}} + \mathbf{F}_{\mathrm{f}}\,\mathbf{f}_{\mathrm{k}}, \tag{2}$$

where:
x_k - the state vector,
y_k - the measurement vector,
k - discrete time samples,
A - the state matrix,
B - the control matrix,
C - the measurement matrix,
u_k - the control vector;
E_d and F_d - interference matrices of the corresponding dimensions;
D_k - a deterministic unknown input vector;
ξ_k - a random variable depending on the system is considered to be normally distributed;
v_k - a random noise measurement value, considered to be normally distributed;
f_k - an additive vector of defects independent of u and x_k,
E_f and F_f - defect distribution matrices of the corresponding dimensions.

The matrices E_f and F_f can represent various defects in the motor. In the case of a defect vector f_k that is a function of the motor's state and input variables, the above representation can also describe multiplicative defects and may cause instability in the motor's control. For example, in the case of motors, inter-winding faults can be considered as defects that lead to a decrease in the resistance and inductance of the stator winding. The fault detection filter is the first type of observer-based model generator (Fault Detection and Isolation, FDI). A full-order state observer can be implemented as follows:

$$\hat{\mathbf{x}}_{k+1} = \mathbf{A}\hat{\mathbf{x}}_k + \mathbf{B}\mathbf{u}_{k+1} + \mathbf{L}(\mathbf{y}_k - \hat{\mathbf{y}}_k), \tag{3}$$

$$\hat{\mathbf{y}}_k = \mathbf{C}\hat{\mathbf{x}}_k + \mathbf{D}\mathbf{u}_k, \tag{4}$$

$$\mathbf{r}_{\mathrm{k}} = \mathbf{y}_{\mathrm{k}} - \hat{\mathbf{y}}_{\mathrm{k}}, \tag{5}$$

where:
L - the observer matrix;
r_k - the residual value.

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In the case of normal engine operation, the residual value is equal to zero, and the transfer function of the technical system can be implemented as a defect detection filter. In the case of normal electric motor operation, the following equality holds:

$$\lim_{k\to\infty} \mathbf{r}_k = 0. \tag{6}$$

When a defect occurs, the inequality $r_k \neq 0$ can be used as an indicator of a defect in the engine. However, in practice, disturbances are inevitable, so the inequality $r_k \neq 0$ cannot be used unambiguously to make any decision.

4. Discussion

The simulation results were obtained in the SimInTech software package. Fig. 1 shows a model of an electric motors with a digital twin with the following parameters: back EMF coefficient ke_1=1.21, torque coefficient km_1=0.95, moment of inertia J_1=0.0031, armature winding resistance R_1=14.6, and armature winding inductance L_1=0.248. The input voltage is U=220 V, and the load resistance torque is M=1.91 N·m in the form of a step. As a result of the inter-turn short circuit, the resistance of the armature winding and its inductance decreased by 10%, 30%, 50%, 70%: delta=0.9, 0.7, 0.5, 0.3, $J_2=J_1$, $R_2=R_1$*delta, $L_2=L_1$*delta, $ke_2=ke_1$, $km_2=km_1$.

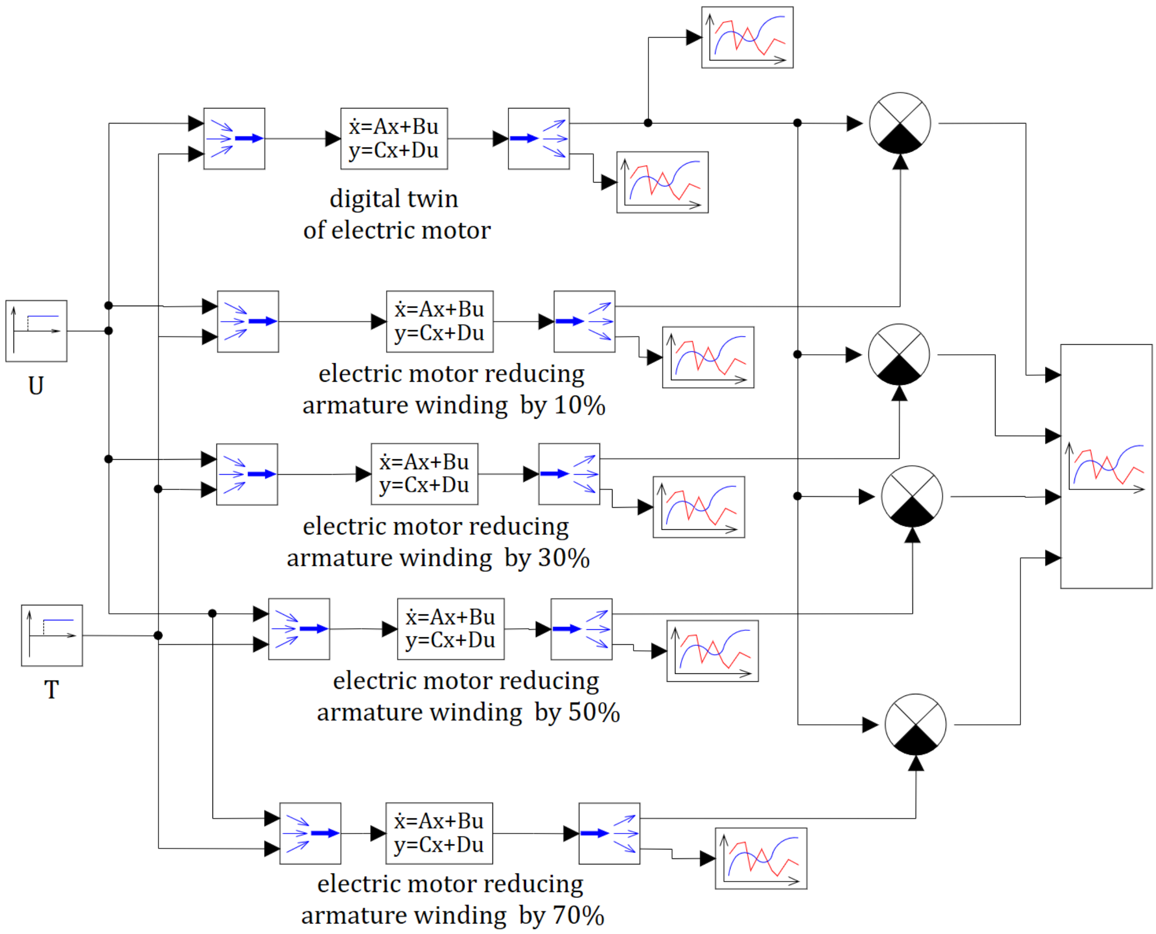

Fig. 1. Models of electric motors with different reductions of armature winding resistance, inductance, and digital twin for a rectangular voltage input signal

Fig. 2. shows the magnitude of the change in the electric current of digital twin. Fig. 3. shows the magnitude of the change in the electric current of motor reducing armature winding by 70%.

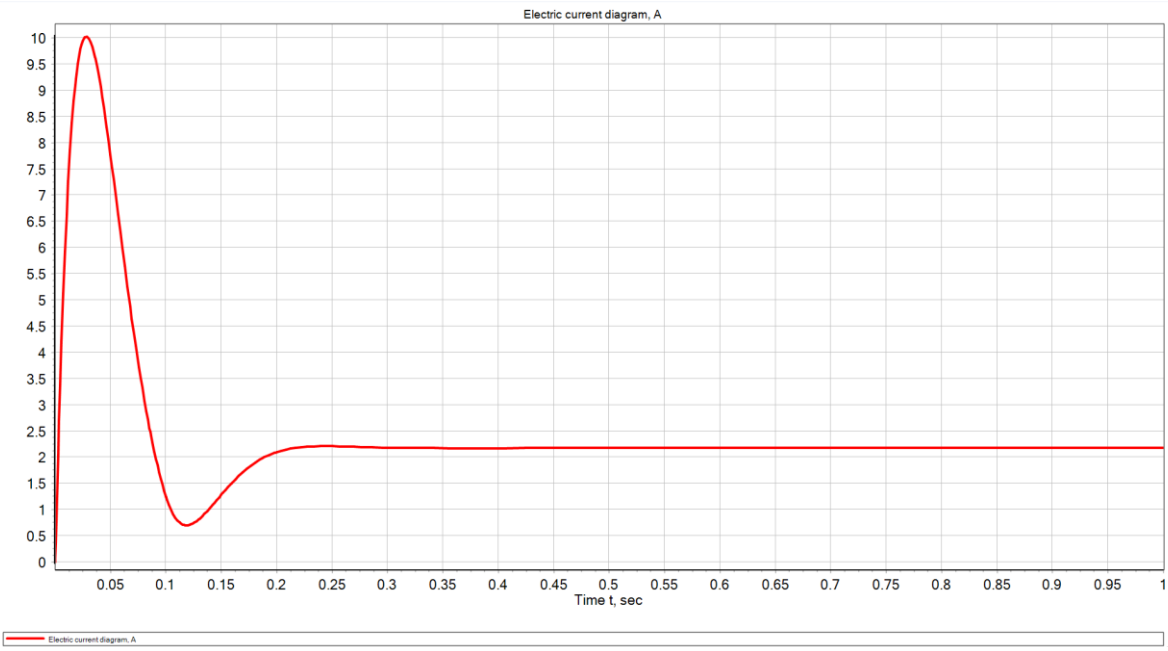

Fig. 2. The magnitude of the change in the electric current of digital twin

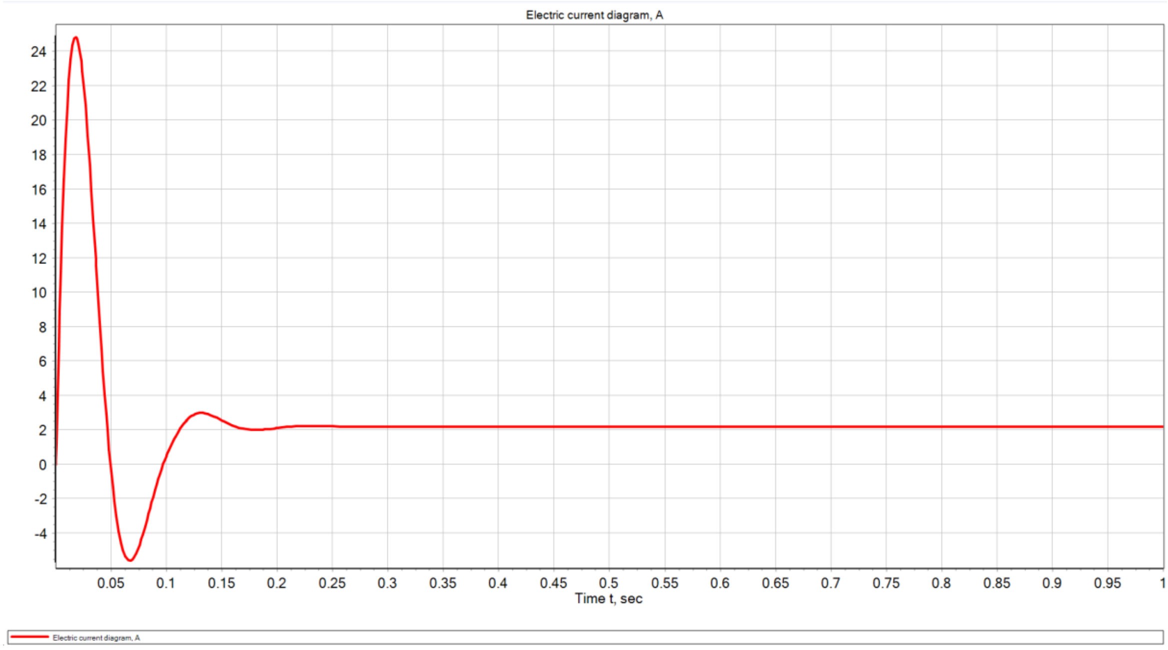

Fig. 3. The magnitude of the change in the electric current of electric motor reducing armature winding by 70%

Fig. 4. shows the magnitude of the change in the speed of digital twin. Fig. 5. shows the magnitude of the change in the speed of electric motor reducing armature winding by 70%.

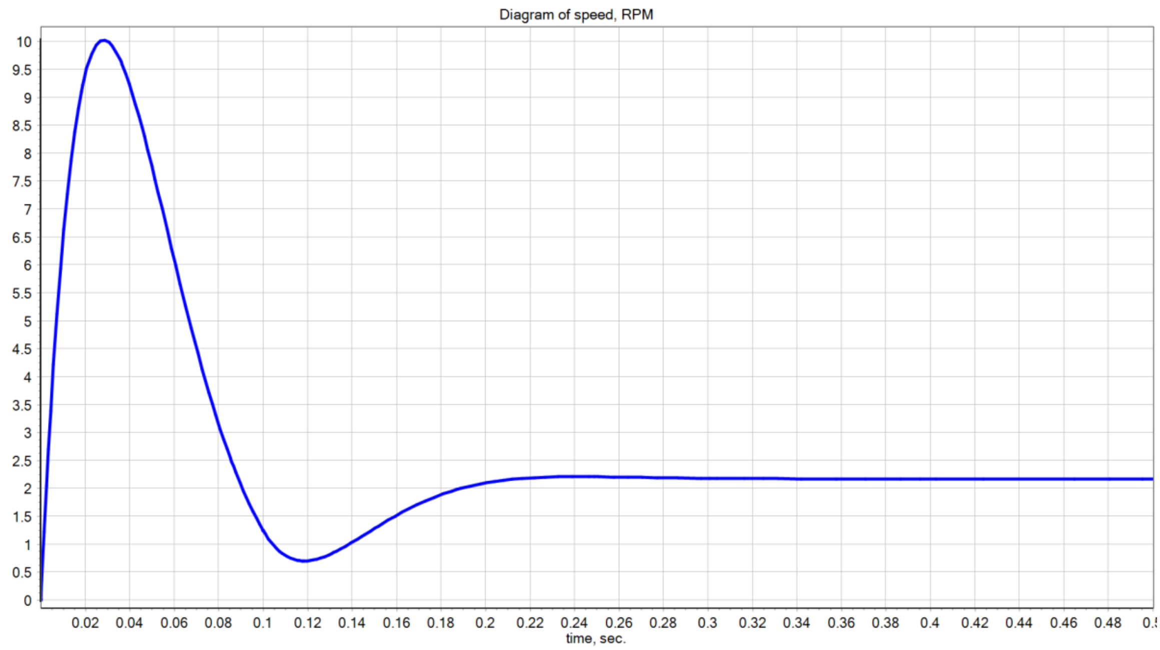

Fig. 4. The magnitude of the change in the speed of digital twin

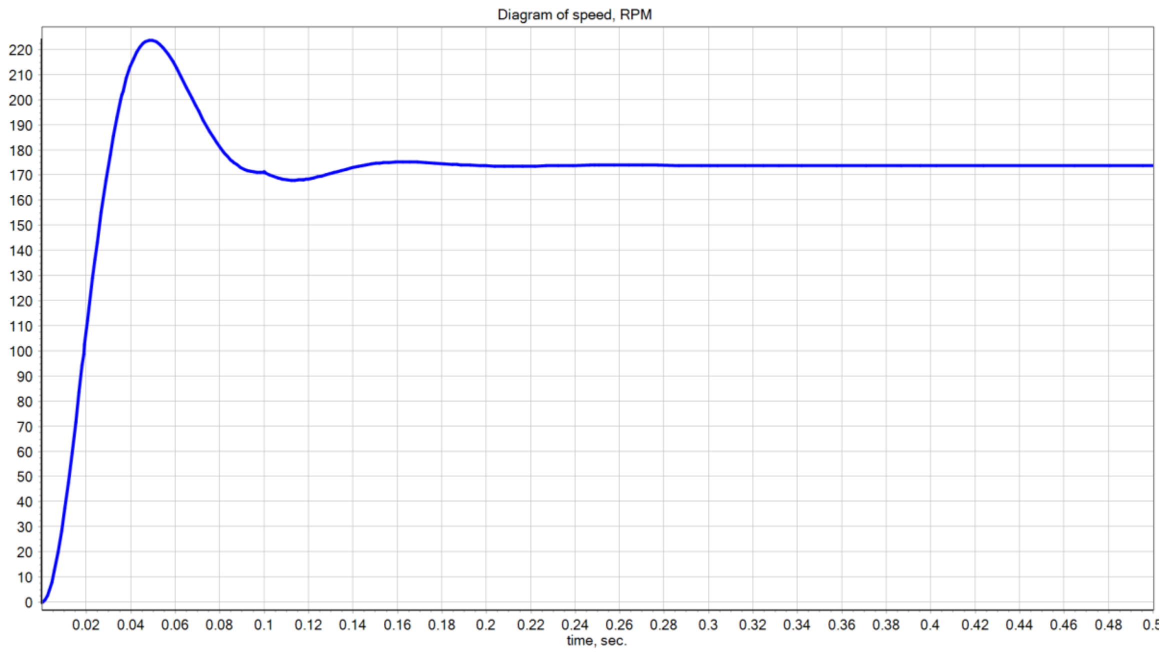

Fig. 5. The magnitude of the change in the speed of electric motor reducing armature winding by 70%

The change in the electric current residual is shown in Fig. 6.

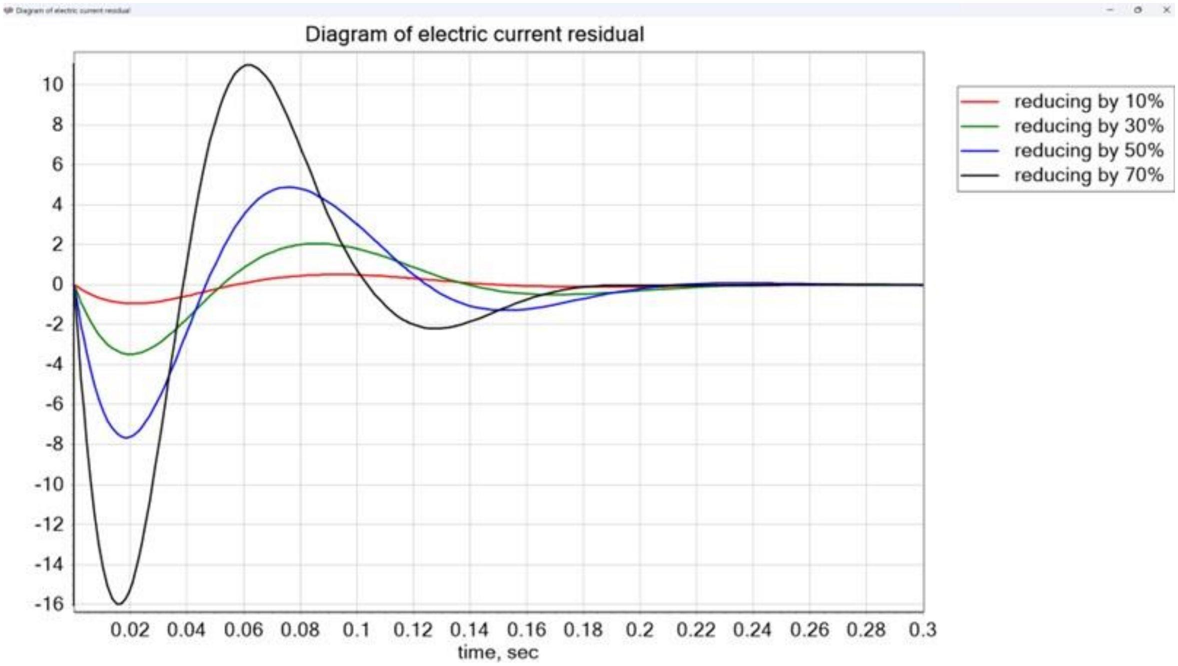

Fig. 6. Change in the electric current residual for electric motor models with reduced armature winding resistance and inductance by 10%, 30%, 50%, and 70%

5. Conclusions

Analyzing the results of the electric motor modeling, it can be concluded that when the defect - inter-turn short circuit increases from 10% to 70% (in relative values from the armature winding), the peak value of the electric current discrepancy increased from 10 A to 24.5 A, the peak value of the angular velocity discrepancy increased from 10 RPM to 220 RPM. The analysis of the results of the computational experiment showed that the electric current is more sensitive to the defects of the motor – the inter-turn short circuit. Therefore, the following computational experiments were carried out only with the measurement of the discrepancy in the electric current.

Fig. 6. shows that as the resistance and inductance of the armature winding decrease, the peak value of the armature current residual increases. If the peak error is zero, it indicates that the motor parameters are nominal and there are no defects. By comparing the peak current residual value, we can conclude that the peak residual value is 12.3 times smaller for a linear voltage input signal than for a rectangular voltage input signal. The lower residual electric current for a linear voltage input signal is due to the fact that the motor rotor, along with the load, has a certain moment of inertia.

A model of electric motor diagnostics is developed on the basis of the model approach in the state space. In parallel with the real motor, its digital twin works. The output signals of the motor and the digital twin from the electric current and angular velocity sensors are analyzed. The presence of defects in the motor is determined by the value of the discrepancy. When defects are detected, the diagnostic system transmits information about them to the control system, displays an indication of the occurrence of defects, and then uses fuzzy logic or other methods to determine the type of defect, the system component where the defect occurred, and predicts the remaining service life. The control system then ensures fault-tolerant operation. If the defect is minor, appropriate maintenance actions are recommended. However, if the defect is significant, the engine must be shut down immediately.

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NOTE

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