DEVELOPMENT OF SYSTEM FOR DIAGNOSTICS OF BRUSHLESS DIRECT CURRENT MOTORS

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The paper describes the concept of improving the efficiency of the process of diagnostics and monitoring of the technical condition of the electric drive on the basis of brushless direct current (BLDC) motors of robots and vehicles on the basis of analysing diagnostic information of different physical nature, taking into account different types of diagnostic signals formed by individual elements of the drive and measured by electric current and rotor speed sensors. The project realisation provides increase of efficiency of control of technical condition of motors of robots and electric transport, allows to pass from planned maintenance of motors to maintenance on actual condition, to increase safety of movement, and also to introduce systems of automatic monitoring. Functional purpose of the system: monitoring of technical condition of actuator due to the use of digital twin and analysis of signals of mismatch between it and the real actuator. The imitation model of actuator diagnostics is developed.

KEYWORDS

monitoring, diagnostics, electric drive, brushless direct current motor, actuator

1 INTRODUCTION

The purpose of the study is to determine the influence of defects in the brushless direct current (BLDC) motor on the parameters in the state matrix and changes in output parameters such as electric currents flowing through the motor phases and its rotational speed. This research is necessary for the development of program and hardware for diagnostics and monitoring systems.

The methodology of the work is based on modern approaches in control theory, state-space representation of the motor and its digital twin, and simulation modelling.

One of the main problems associated with the construction of electric drive is its sensitivity to changes in parameters during operation. First of all, it refers to changes in active and inductive resistances of the stator winding due to defects. Hence the relevance of the problem of identification of induction motor parameters in the process of its operation.

A BLDC motor is a direct current motor that operates without brushes. Brushless motors are now more popular than DC collector motors because they have higher efficiency, can provide precise torque and speed control, and offer high durability and low electro-magnetic interference due to the absence of brushes.

2 LITERATURE REVIEW

With a significant number of scientific publications on identification of electric motor parameters [Turygin 2018, Nikitin 2018, 2020a & 2022a, Kuric 2021, Jancarik 2019, Hartansky 2017 & 2020, Peterka 2020, Bozek 2023] up to now there are no acceptable complex solutions that would allow to determine all the necessary values in real time during the operation of industrial plants. In addition, many solutions for parameter identification in modern electric drives constitute a trade secret. In general, identification means determination of the structure and parameters of the mathematical model of a dynamic object, which provide the best proximity of values of output quantities of the model and the object according to a given criterion of similarity at the same input influences [Lekomtsev 2021, Stepanov 2021].

Real time means that the rate of change of the current values of the quantities to be determined and the duration of the processes of their identification differ by the amount permissible for solving practical problems in the further use of the identification results (control, functional diagnostics or monitoring) [Bozek 2021a].

The most promising group of methods are passive methods based on registration and processing of easily available information about the motor in its operating mode [Chen 2020]. Under easily accessible information we will understand electric currents and rotor speed. A group of identification methods based on digital twin theory fulfils this requirement [Chen 2022].

The tuning mechanism may include various algorithms whose main goal is to find such a vector of parameters to minimise the mismatch between the outputs of the model and the control object. The quality index is often determined by a reference dynamic model of the control object [Chen 2019]. In the scientific literature, the theory of adaptive systems with a reference model is known as Model Reference Adaptive Control (MRAC) [Cheng 2021]. Alternatively, adaptive systems with a tunable model are considered, whose characteristics are first fitted to the dynamic characteristics of the object and then used to optimise the system [Ding 2019, Li 2022]. The process of fitting the model to the object is essentially an identification of the system, which results in the production of data for computing the optimal control in the next step [Lekomtsev 2020, Trefilov 2021]. The closeness of the model to the object is judged by the magnitude of the mismatch between the model output and the feedback signal of the real object. When the error becomes less than some specified value, the identification process ends and the process of tuning of the main loop controller for the purpose of optimisation starts automatically [Nikitin 2020b & 2022b,c, Zajac 2020, Bozek 2021b, Kuric 2022, Cheng 2023].

The tuning mechanism can include various algorithms, the main goal of which is to find such a vector of parameters to minimise the mismatch between the outputs of the model and the control object. The calculation of parameters by these algorithms is a rather complex mathematical problem. In addition, the information received in the system is often insufficient to immediately find new values of the required parameters. In this case, in order to solve the problem, it is necessary to accumulate information in the process of work.

One of the possible methods of parameter calculation is application of the extended Kalman filter. There are many modifications of such filters, and one can always choose an appropriate filter for a particular problem. The Kalman filter is a recursive linear optimal algorithm for processing measurement information and is used to obtain estimates of the parameters of a dynamic object under the influence of random noise. The algorithm allows efficient estimation of parameters and state variables of the object, including those that cannot be measured directly. The disadvantage of the filter is the need for preliminary adjustment, which consists in determining the covariance matrices of the object state noise and noise of the measurement

system, which may change with time, and their automatic correction during the operation of the motor may be difficult or impossible.
When attempting to add stator inductances to the state vector, the estimation process becomes unstable using the extended Kalman filter. This is explained by the fact that the extended Kalman filter is, in fact, a gradient method and gives a strict solution only for linear objects, and when applied to nonlinear objects, which include motors, it is possible not only to hit a local extremum with inaccurate estimates, but also the emergence of an unstable estimation process.
Another frequently used method of parameter estimation is the recurrent least squares method, which solves the problem of parameter estimation with minimisation of the mean-square error. The advantages of the method include the fact that the method does not require any a priori information. The disadvantages are that the object model should be described by algebraic equations with sufficient accuracy. There are known works that use a combination of Kalman filter and recurrent least squares method for simultaneous state identification and parameter adjustment.
Other algorithms for parameter search are also possible. There are works in which artificial neural networks, genetic algorithms, etc. are used.
As a rule, all these methods use the assumption that in the process of identification of one parameter, the others do not change. However, there are known works that show simultaneous identification of several parameters (e.g., simultaneous identification of stator resistances based on an adaptive observer).
Thus, the most promising at this point in time seems to be the approach to identification of motor parameters during operation on the basis of passive methods, since their application does not require any means other than software. It should be noted only that in this case simultaneous calculation of rotor active resistance and speed is impossible in static mode of operation - this is due to the degeneracy of the Jacobian of the corresponding system of algebraic equations for static mode of operation. At the same time, there is no such limitation for the dynamic mode.

3 RESEARCH METHODOLOGY

The purpose of the study is to determine the influence of defects in the BLDC motor on the parameters in the state matrix and changes in output parameters such as electric currents flowing through the motor phases and its rotational speed. This research is necessary for the development of program and hardware for diagnostics and monitoring systems.
The methodology of the work is based on modern approaches in control theory, state-space representation of the motor and its digital twin, and simulation modelling.
The BLDC motors is one of the most widely used types of electric motors due to its high efficiency, reliability and ability to accurately control the rotational speed. However, effective control of these motors requires the development of accurate mathematical models that account for the various nonlinear effects that occur during their operation.
1 Nonlinearity and discretisation
Various nonlinear effects occur during the operation of BLDC motors, such as saturation of the magnetic core, changes in inductance and winding resistance with temperature changes, and the influence of external factors such as load and ambient temperature. These factors make the task of creating an accurate model challenging and require nonlinearities to be taken into account.
In addition, modern motor control systems operate in digital mode, which requires the conversion of continuous models into discrete models. The discretisation process allows digital controllers to be used for motor control, providing high accuracy and stability.

3.1 Methods for building nonlinear discrete models

There are several methods of constructing nonlinear discrete models, each of which has its own peculiarities and area of application. Let us consider some of them.

3.1.1 Traditional methods

Finite difference method is used to approximate the derivatives of functions through difference relations. This method is simple to implement and can be applied to a wide range of problems. However, it has limited accuracy and sensitivity to noise.
Numerical methods for solving differential equations such as the Runge-Kutta method, allow the solution of complex differential equations describing engine performance. They provide high accuracy but can be computationally demanding.

3.1.2 State-of-the-art methods

Neural networks are a powerful tool for modelling nonlinear processes. They are capable of learning from experimental data and adapting to changes in operating conditions. The application of neural networks allows the creation of highly accurate models that can account for even the most complex nonlinear dependencies.
Genetic algorithms are used to find the optimal set of model parameters by simulating the process of natural selection. This allows finding the best model parameters without the need for a large number of experiments.

3.1.3 Parameter identification

Identification of model parameters is an important stage of its development. Various methods such as least squares method, maximum likelihood method and others are used for this purpose. Experimental data play a key role in this process, as they allow you to check the accuracy of the model and adjust its parameters.
Let us consider several examples of successful implementation of nonlinear discrete models for controlling the BLDC motors. For example, one project developed a model that uses neural networks to predict the behaviour of the motor under different loads. This model has significantly improved control quality and reduced power consumption.
However, it is worth noting that the development of such models involves certain difficulties, such as the complexity of parameter tuning and the high demand on computational resources.
When developing BLDC motors mathematical models, it is necessary to take into account such phenomena as the saturation of the magnetic core and nonlinear effects arising from the peculiarities of the motor design and its mode of operation. Let us take a closer look at how these factors are taken into account in BLDC motors models.
The saturation of the magnetic core occurs when the increase in magnetic flux in the core ceases to depend linearly on the applied field current. This phenomenon is related to the physical properties of the materials used in the magnetic core and manifests itself as a decrease in the inductance of the motor windings as the current increases.
To account for the saturation effect in the BLDC model, the following approaches are used:

1. Using piecewise linear functions: The motor inductance is represented as a piecewise function depending on the current.

For example, at low currents, the inductance is assumed to be constant, but when a certain threshold is reached, it starts decreasing as the current increases.

2. Modelling using magnetisation curves: To account for saturation more accurately, an experimentally obtained magnetisation curve of the magnetic core material is used.

3. Numerical modelling methods: In some cases, especially when spatial effects and magnetic field distribution need to be taken into account, the finite element method (FEM) is used. This method allows detailed modelling of the magnetic field distribution in the motor and accurate determination of the saturation moments.

Nonlinear effects in BLDC motors arise due to many factors such as:

- Rotor position dependence of inductance: The inductance of the windings varies with the angular position of the rotor relative to the stator. This is because the air gap between rotor and stator changes during rotation.
- Hysteresis and eddy current losses: Hysteresis in magnetic materials causes additional power losses and distorts the shape of the magnetic field. Eddy current losses also contribute to the nonlinearity of the model.
- Temperature variations: Temperature affects the winding resistance and magnetic properties of the materials, which also leads to changes in the motor parameters.

The following methods are used to account for these nonlinear effects:

1. Parametric identification: Model parameters such as inductance and resistance are determined by experimentation and then selecting values that provide the best fit to the real data.

2. Least Squares Method: It is used to minimise the difference between the calculated and measured parameters. This method allows adaptive modification of the model parameters depending on the current engine operating conditions.

3. Neural Networks and Machine Learning: Modern machine learning techniques such as artificial neural networks can be used to build non-linear models that can account for complex relationships between different factors.

4. Fuzzing and robust control: In case of parameter uncertainty or varying operating conditions, fuzzing and robust control methods are used to develop change-resistant motor control systems.

A variety of state-of-the-art methods are used to model BLDC motors, each with its own advantages and features. Let us consider some of them:

1. Finite Element Method (FEM)

It is one of the most powerful tools for modelling electromagnetic fields in complex geometries. The FEM method breaks the motor into many small elements and solves Maxwell's equations for each element, which gives an accurate representation of the magnetic field distribution, current density and other parameters.

Advantages:
- High modelling accuracy.
- Ability to account for complex geometry and inhomogeneous materials.
- Suitable for analysing saturation and nonlinear effects.

Disadvantages:
- High demands on computational resources.
- Difficulty in setting up and analysing results.

2. Equivalent Circuit Modelling

This method is based on representing the motor as an electrical circuit consisting of resistors, inductors and voltage sources. Equivalent circuits allow the dynamic behaviour of the motor to be simulated quickly and efficiently without the need for detailed electromagnetic fields.

Advantages:
- Easy to implement and understand.
- Low computational complexity.
- Good for rapid transient analyses.

Disadvantages:
- Lower accuracy compared to the FEM method.
- Difficulties in accounting for nonlinear effects and spatial inhomogeneity.

3. Multiscale Modelling

This approach combines different levels of detail for different parts of the model. For example, you can use the FEM method to model the magnetic circuit and then go to equivalent circuits to describe the electrical part of the motor.

Advantages:
- Optimal combination of accuracy and computational complexity.
- Allows focus on critical aspects of the model.

Disadvantages:
- Requires coordination between different modelling methods.
- Can be difficult to set up and interpret results.

4. Machine Learning and Neural Networks (Machine Learning and Neural Networks)

Modern machine learning techniques such as deep neural networks can be used to create models that can predict motor behaviour based on measured data. Neural networks are trained on large amounts of data and can capture complex non-linear dependencies.

Advantages:
- Ability to capture complex nonlinear interactions.
- High speed of performance after training.
- Flexibility to adapt to new environments.

Disadvantages:
- Need for large amount of data for training.
- Possible need for regular calibration and updating of the model.
- Limited understanding of the internal workings of the model.

5. Robust Modelling

This method takes into account uncertainties in the model parameters and seeks to minimise the impact of these uncertainties on the result. Robust modelling is often used in combination with other methods to produce robust and robust models.

Benefits:
- Robustness to parameter variations.
- Reliability of results under uncertainty.

Disadvantages:
- More difficult to set up and analyse.
- Possible decrease in accuracy compared to deterministic models.

6. Methods based on Chaos Theory and Fractal Geometry (Chaos Theory and Fractal Geometry)

These methods can be used to analyse complex dynamic systems such as engines with variable load or operating under extreme conditions. Chaos Theory and Fractal Geometry help to reveal hidden patterns and structures in the behaviour of the system.

Benefits:
- ability to identify hidden patterns;
- useful for analysing unstable and irregular processes.

Disadvantages:
- complexity of the theoretical framework.

The mathematical basis of vector control of the drive is differential equations that describe the drive equally correctly both in dynamics and statics. Due to the adequacy of control in dynamics, vector control, unlike scalar control, makes it possible to build highly dynamic and precision AC drives that provide the highest accuracy and speed of regulation. In addition, vector control uses the representation of three-phase quantities in the form of generalised vectors and control systems are built in rotating coordinates.

To solve the identification problem, a dynamic model of the BLDC motor in a rotating coordinate system (*d, q*) oriented along the magnetic axis of the rotor is often used. On the basis of Kirchhoff's 2nd law, an equation describing the electrical part of the BLDC motor in the coordinate system *d*, *q*, rotating with rotor speed ω:

$$\overline{u_s} = \overline{\imath_s}R_s + L_s\frac{d\overline{\imath_s}}{dt} + j\omega L_s\overline{\imath_s} + j\omega\overline{\Phi_0}, \quad (1)$$

where $\overline{u_s}$ is resultant voltage vector on the stator winding;

R_s, L_s are active resistance and total inductance of the stator phase;

$\overline{\Phi_0}$ is flow vector of the BLDC motor.

$$\frac{d}{dt}i_d = \frac{1}{L_d}V_d - \frac{R}{L_d}i_d - \frac{L_q}{L_d}p\omega i_q, \quad (2)$$

$$\frac{d}{dt}i_q = \frac{1}{L_q}V_q - \frac{R}{L_q}i_q + \frac{L_d}{L_q}p\omega i_d - \frac{\psi}{L_q}p\omega, \quad (3)$$

$$T_e = p\psi i_q + (L_d - L_q)pi_d i_q, \quad (4)$$

where L_q, L_d are stator inductances along the axes *q* and *d*;

R is stator winding active resistance;

i_q, i_d are stator current axial projections *q* and *d*;

V_q, V_d are stator voltage projections on the axes *q* and *d*;

ω is rotor angular speed;

ψ is magnetic flux induced by permanent magnets in the stator winding;

p is number of pole pairs;

T_e is electromagnetic torque of the BLDC motor.

Provided L_q=L_d

$$\frac{d}{dt}i_q = \frac{1}{L_q}V_q - \frac{R}{L_q}i_q + p\omega i_d - \frac{\psi}{L_q}p\omega, \quad (5)$$

$$T_e = p\psi i_q. \quad (6)$$

The mechanical part of the BLDC motor model is described by the system of equations:

$$\frac{d}{dt}\omega = \frac{1}{J}(T_e - F\omega - T_L). \quad (7)$$

This model has the disadvantage that the stator winding is considered as a whole, while in practice defects in the form of inter-turn faults can occur in any of the three phases of the BDPT stator winding. Therefore, it is reasonable to consider a model with separate equations for each phase. Fig. 1 shows a BLDC motor with one pair of poles.

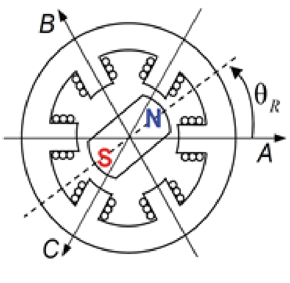

Figure 1. Single pole pair BLDC motor in cross section

Three windings (A,B,C) are wound on the motor stator, offset in space by 120°. Each winding consists of two sections switched on counterclockwise. Thus, when current flows in the winding, it creates two poles (positive and negative) inside the motor to which the magnetic rotor is attracted. This winding design is called a centred winding. It is usually characterised by a trapezoidal EMF shape.

In the further consideration we will consider as zero the angular position of the rotor (θ_R), at which the rotor flux vector coincides in direction with the phase A axis (axis of winding A). The equations of equilibrium of stator windings of BLDC motor at its inclusion in "star" in fixed phase coordinates ABC have the following form:

$$U_A = \frac{d\psi_A}{dt} + I_A R_A, \quad (8)$$

$$U_B = \frac{d\psi_B}{dt} + I_B R_B, \quad (9)$$

$$U_C = \frac{d\psi_C}{dt} + I_C R_C, \quad (10)$$

where U_A, U_B, U_C are phase voltages, ψ_A, ψ_B, ψ_C are flux in the winding, I_A, I_B, I_C are phase currents, R_A, R_B, R_C are the active resistance of the phase winding.

The flux in the winding of each phase is formed from the following components:

- flux induced by the own current of the phase;
- flux induced by magnetic fields of other phase windings;
- flux induced in the winding by the rotor magnets.

As shown by the system of equations:

$$\psi_A = L_A I_A + L_{AB} I_B + L_{AC} I_C + \psi_{fA}, \quad (11)$$

$$\psi_B = L_B I_B + L_{BC} I_C + L_{AB} I_A + \psi_{fB}, \quad (12)$$

$$\psi_C = L_C I_C + L_{AC} I_A + L_{BC} I_B + \psi_{fC}, \quad (13)$$

where L_A, L_B, L_C are phase winding inductance, L_{AB}, L_{BC}, L_{AC} are phase winding inductance phase winding inductance, ψ_A, ψ_B, ψ_C are currents induced in the windings by the rotor magnet.

The BLDC motor model is represented in the well-known state-space form as a system of equations. The presented a BLDC motor model is significantly nonlinear due to the presence of variable load torque. Therefore, the solution will be sought in the form of a discrete equation with a varying state matrix in the form of a vector-matrix equation in the state space.

Designations of phase currents i_d , i_q changed to I_d, I_q.

$$\begin{bmatrix} I_d(k+1) \\ I_q(k+1) \\ \omega(k+1) \\ \theta(k+1) \end{bmatrix} =$$

$$= \begin{bmatrix} 1 - T\frac{R_s}{L_d} & Tp\omega(k) & 0 & 0 \\ -Tp\omega(k) & 1 - T\frac{R_s}{L_q} & T\frac{-p\psi}{L_q} & 0 \\ 0 & T\frac{p\psi}{J} & 1 - T\frac{F}{J} - T\frac{T(k)}{J\omega(k)} & 0 \\ 0 & 0 & T & 1 \end{bmatrix} \begin{bmatrix} I_d(k) \\ I_q(k) \\ \omega(k) \\ \theta(k) \end{bmatrix} +$$

$$+ \begin{bmatrix} T\frac{1}{\mathrm{L_d}} & 0 \\ 0 & T\frac{1}{\mathrm{L_q}} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} U_d(k) \\ U_q(k) \end{bmatrix}, \quad (14)$$

$$\begin{bmatrix} \widehat{I_d} \\ \widehat{I_q} \\ \widehat{\omega} \\ \widehat{\theta} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} I_d \\ I_q \\ \omega \\ \theta \end{bmatrix} + \begin{bmatrix} \xi_{I_d} \\ \xi_{I_q} \\ \xi_\omega \\ \xi_\theta \end{bmatrix}, \quad (15)$$

where $[\xi_{I_d}\xi_{I_q}\xi_\omega\xi_\theta]^T$ is measurement error vector;

$[\widehat{I_d}\widehat{I_q}\widehat{\omega}\ \widehat{\theta}]^{\boldsymbol{T}}$ is measured state vector.

$$T(k) = \varepsilon(k)J + T_L = \frac{\omega(k+1) - \widehat{\omega}(k)}{T}J + T_L, \quad (16)$$

$$\hat{\omega}(k) = \frac{\hat{\theta}(k)-\hat{\theta}(k-1)}{T}, \qquad (17)$$

where $T(k)$ is motor torque, T_L is load torque, $\varepsilon(k)$ is angular acceleration, ω is angular velocity, θ is angular displacement, J is equivalent moment of inertia.

Rotation frequency $\omega(k+1)$ denotes the target point on the trajectory, which allows us to calculate the required torque at each control step, which we substitute into the state matrix.

We investigate the determinant of the square matrix $(A_r^T)^{n-1}C_k^T$, at n=4, as having the greatest influence on the closeness of the moment of loss of identifiability. We will also investigate the technical feasibility of the control in terms of the maximum allowable currents and voltages of the BLDC motor, respectively we can determine the control current on k step:

$$|I_s| = I_q(k) = \frac{2M(k)}{3p\psi_f} = \frac{2\omega(k+1)-\hat{\omega}(k)}{3pT\psi_f}, \qquad (18)$$

$$U_s = U_q(k)e^{-j\alpha} = U_q(k)e^{-j\frac{L_s I_q \omega(k)}{-E+I_q R_s}} =$$

$$= (-\psi_f\omega(k) + I_q R_s)e^{-j\frac{L_s I_q \omega(k)}{-\psi_S\omega(k)+I_q R_s}}. \qquad (19)$$

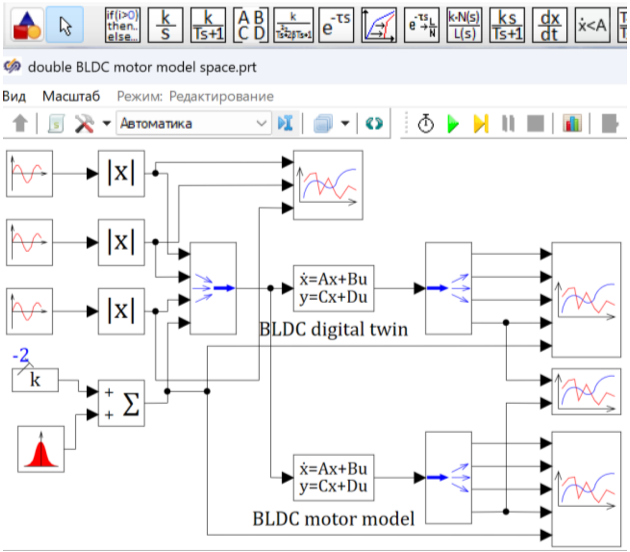

Figure 2. A schematic of the parallel operation of the BLDC motor and the digital twin

Modelling of the BLDC motor in SimInTech software has been carried out. The digital twin of the motor with frequency converter is represented as a model in the SimInTech dynamic modelling environment. Fig. 2 shows a schematic of the parallel operation of the BLDC motor and the digital twin to calculate the rotational velocity incoherence signal, the programme for calculating the elements of the state, control and measurement matrices of the BLDC motor parameters.

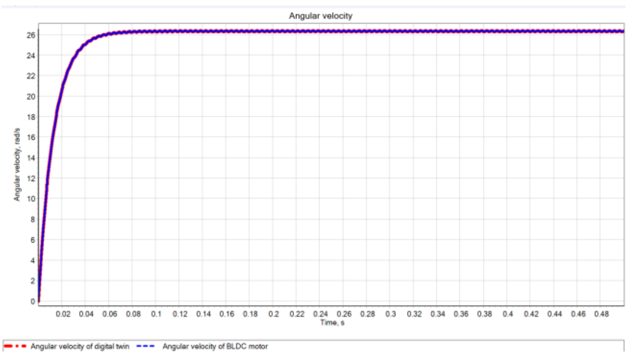

Figure 3. The angular velocities of the BLDC motor in the absence of defects and the digital twin

Fig. 3 shows the angular velocities of the BLDC motor in the absence of defects and the digital twin. It can be seen that they coincide completely. This fig. shows that when the BLDC motor is not defective, the angular velocity of the real BLDC motor is the same as that of the digital twin.

Fig. 4 presents the angular velocities of the BLDC motor when phase A are short-circuited (RA_2=0) and digital double. It can be seen that the BLDC motor cannot operate, its speed fluctuates around zero. This fig. shows that when phase A is short-circuited (RA_2=0), the rotor angular velocity fluctuates around 18 rad/s. The BLDC motor does not fulfil its function.

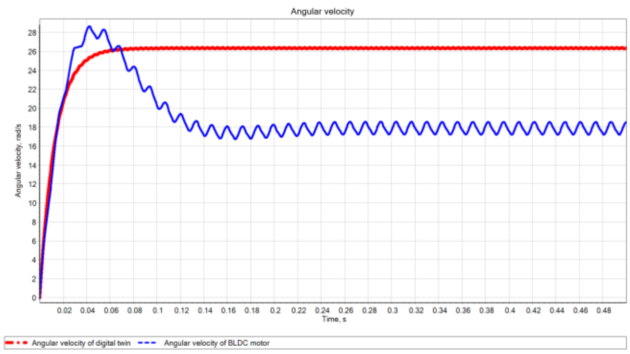

Figure 4. The angular velocities of the BLDC motor when phase A are short-circuited (RA_2=0) and digital double

Fig. 5 shows the angular velocities of the BLDC motor at phase A breakage and digital twin. The rotational speeds differ by a factor of 1.5. This fig. shows that when phase A breakage occurs, the rotor angular velocity of the BLDC motor and the digital twin have different angular velocities.

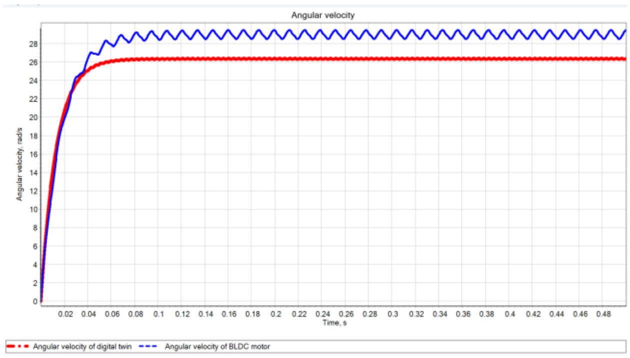

Figure 5. The angular velocities of the BLDC motor at phase A breakage and digital twin

Fig. 6 shows the angular velocities of the BLDC motor at demagnetisation of the permanent magnets and the digital double. The rotational speeds differ by a factor of 2. This fig. shows that when BLDC motor at demagnetisation of the permanent magnets, the rotor angular velocity of the BLDC motor and the digital twin have different angular velocities.

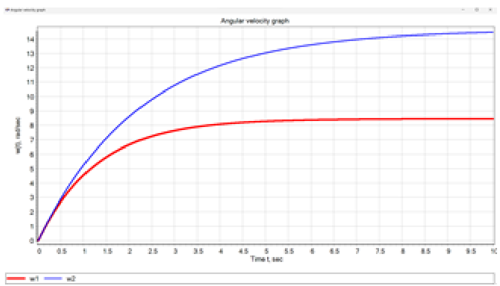

Figure 6. The angular velocities of the BLDC motor at demagnetisation of the permanent magnets and the digital twin (km1=0.95, km2=0.55)

Fig. 7 shows the electric current and angular velocity uncertainties of the BLDC motor when the load moment of inertia is increased by a factor of 2 and the digital twin. The rotational velocity inconsistencies have a maximum value of 2.14 rad/s at 1.55 sec. and decreases to zero at steady-state.

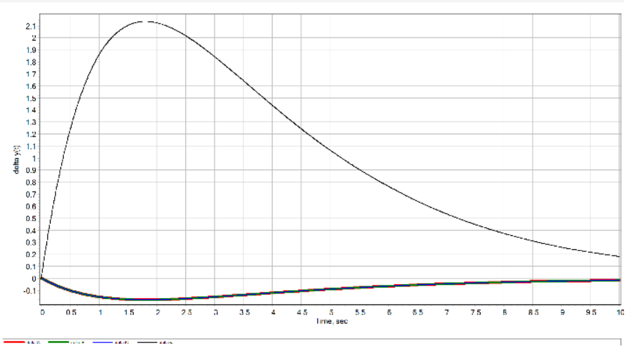

Figure 7. The electric current and angular velocity uncertainties of the BLDC motor when the load moment of inertia is increased by a factor of 2 and the digital twin

Fig. 8 shows the electric current and angular velocity incoherencies of the BLDC motor when the resistance of phase A is reduced by a factor of 2 and the digital double.

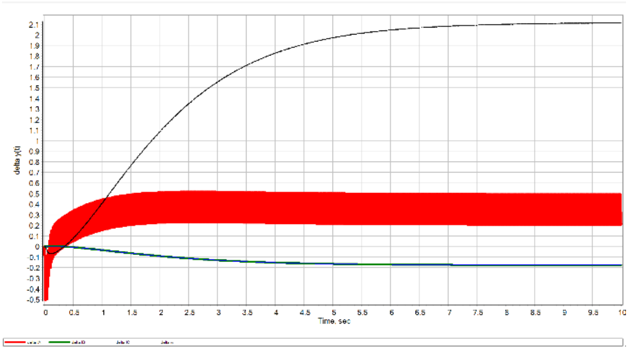

Figure 8. The electric current and angular velocity incoherencies of the BLDC motor when the resistance of phase A is reduced by a factor of 2 and the digital twin

4 DISCUSSION

The simulation results show that there are differences in the angular velocity of BLDC motor and digital twin when defects occur. When phase is short-circuited (R=0), the rotor angular velocity fluctuates around zero. The BLDC motor does not fulfil its function. When BLDC motor at demagnetisation of the permanent magnets, the rotor angular velocity of the BLDC motor and the digital twin have different angular velocities.

5 CONCLUSION

1. On the basis of theoretical and experimental studies, the actual task of creating a system of diagnostics and monitoring of BLDC motor, which differs from similar systems by joint analysis of mechanical and electrical parameters, is solved. Thus, the efficiency of technical condition monitoring is increased in the form of reliability index increase.
2. A simulation model of BLDC motor and its digital twin has been developed, on the basis of which it is possible to investigate the dependences between defects and changes in rotation speed and electric current. To determine the defect, by enumerating all parameters of the BLDC motor, as well as changing the load and moment of inertia, the angular velocity and electric current between the BLDC motor and the digital twin should be matched as closely as possible.

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