DIAGNOSTICS OF AN ELECTRIC MOTOR BASED ON A STATE-SPACE MODEL

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DOI: 10.17973/MMSJ.2022_10_2022085

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This paper develops a model for DC motor diagnostics based on a state-space model approach. Its digital twin works in parallel with the real motor. The output signals of the motor and the digital twin from the electric current and angular velocity sensors are analyzed. The motor defects are detected by the magnitude of the discrepancy. If a defect is detected, the diagnostic system transmits information about it to the control system, turns on the defect indication, then by fuzzy logic methods or other methods determines the type of defect, the system element in which the defect occurred, predicts the remaining life, the control system is 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 motor must be performed.

KEYWORDS

diagnostics, electric motor, model, defect

1 INTRODUCTION

Currently, electric motors are widely used in industry, digital manufacturing, CNC technologies [Vopat 2014, Jakubowski 2014], which achieve very precise products [Beno 2013, Peterka 2014], and transport due to their simple design and low cost. To improve the reliability, their diagnostics is required. The accuracy and reliability of electric motor diagnostics largely depend on the correct construction of diagnostic models. The mathematical apparatus based on vector-matrix models in the space of states in the time domain is chosen for diagnostics, since it has the following advantages:

- convenience of notation;
- compactness of records in vector-matrix form;
- simplicity of analysis;
- demonstrativeness, because behavior of drive is considered as behavior of point in Euclidean space.

The methods of analysis and synthesis of state-space models in vector matrix form have a significant advantage over operator methods in that they are relatively easy to extend to a wide class of technical systems.

Over the past two decades this method has been successfully implemented in many industries [Shaitor 2021, Mikova 2020]. A similar solution is also in the research work [Handrik 2017] with concrete results [Kopas 2017]. The diagnostics method using measured data from embedded sensors in real time is the most effective method and is becoming more and more common [Cacko 2014]. Measured data of drive operation parameters and state after identification can be used to develop an effective system of their control, diagnostics and prediction of residual life.

There are various methods of electric motor diagnostics, described in [Kuric 2021, Lei 2020, Yin 2020]. There are 2 main approaches: on the basis of data [Xue 2018, Fu 2017, Luo 2020, Bozek 2021] and on the basis of models [Ding 2013]. A special case of the data-based approach is a method based on fuzzy logic [Nikitin 2022a, Peterka 2020, Nikitin 2020a]. Model-based diagnostic methods are well studied and there are a large number of publications on this topic, for example, [Zhong 2018, Li 2017a, Li 2017b]. A special case of the model-based approach is the observer-based method [Yang 2015, Zhou 2018, Zhong 2017]. Another variant is the digital twin approach [Nikitin 2020b]. Its digital twin works in parallel with the real motor [Nikitin 2020c]. The output signals of the motor and the digital twin from the angular velocity (displacement), electric current and voltage sensors are analyzed. Then the presence of motor defects is determined by the magnitude of the discrepancy [Stepanov 2021].

The problem of synthesizing nonlinear state observers has been the subject of constant research over the past three decades. Observer synthesis methods for linear Kalman, Luenberger, H_∞-perturbation suppression, and high-gain systems have been extended to some specific classes of nonlinear deterministic systems. The proposed methods use a general framework for the estimation error dynamics of nonlinear systems and are based on asymptotic stability for the estimation error or on H_∞-suppression of the effect of perturbations on the estimation error. It should be noted that, just as in the case of linear systems, such an observer provides an optimal estimate of the state vector when $t \to \infty$. This distinguishes them from the original Kalman filter, which gives the optimal error for the stochastic system in terms of standard deviations at each time point, and which can be used at both infinite and finite time intervals. High-gain observer synthesis methods with no measurement distortion and small initial deviations of observer and system states can simultaneously suppress modeling uncertainty and quickly recover system states. To achieve the goals of reducing the influence of uncertainties and rapid state estimation, the gain of the observer is chosen large enough.

2 METHODS

The development of a mathematical model of a DC motor initially begins with differential equations that describe the electrical and mechanical parts of the motor. Then the motor model is written in discrete vector-matrix form in the state space.

The analysis and synthesis of technical systems is usually carried out by one of two basic methods. The first method is based on the Laplace transform, Z-transforms, and transient functions. This method is a frequency method. The second method is based on the space of states. It has the following advantages over the frequency method: the description in the space of states is convenient for solving problems on the computer; it allows unifying the description of one-dimensional and multidimensional systems; it can be applied to nonlinear and nonstationary systems.

A motor is always affected by perturbations caused by external factors such as load torque, measurement errors, parameter errors and additive defects, the motor model in discrete vector-matrix form in state space is extended as follows [Trefilov 2021, Nikitin 2022b]:

$$\mathbf{x}_{k+1} = A\mathbf{x}_k + Bu_k + E_d d_k + \xi_k + E_f f_k \qquad (1)$$

$$y_k = C\mathbf{x}_k + Du_k + F_d d_k + v_k + F_f f_k \qquad (2)$$

where **x** is state vector, *y* is measurement vector, *u* is control vector, *A* is status matrix, *B* is control matrix, *C* is measurement matrix, *D* is forward link matrix, *k* is discrete time, *E* and *F* are noise matrices of appropriate dimensions; *d* is a deterministic unknown input vector; ξ is a random variable depending on the system operation, considered to be normally distributed; v is a random noise measurement variable, considered to be normally distributed; $\boldsymbol{f}$ is an additive defect vector, independent of $\boldsymbol{u}$ and $\mathbf{x}$, $\boldsymbol{E}$ and $\boldsymbol{F}$ are defect distribution matrices of appropriate dimensions.

The matrices $\boldsymbol{E}$ and $\boldsymbol{F}$ can represent different defects in the engine. In the case of a defect vector $\boldsymbol{f}$, which is a function of motor state and input variables, the above representation can also describe multiplicative defects and the stability of motor control can be compromised [Trefilov 2018].
For example, for motors, such defects can be considered as inter-turn faults, which lead to a decrease in stator winding resistance and inductance.
As originally proposed in [Turygin 2018], the defect 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:

$$\mathbf{x}_{k+1} = A\mathbf{x}_k + Bu_k + L(y_k - \hat{y}_k)\,, \quad (3)$$

$$\hat{y}_k = C\mathbf{x}_k + Du_k\,, \quad (4)$$

$$r_k = y_k - \hat{y}_k\,, \quad (5)$$

where L is observer matrix, $\hat{y}$ is parameter estimate vector, r is residual vector.

In the case of normal functioning of the motor the value of the residual is equal to zero, the transfer function of the technical system can be implemented as a defect detection filter.
In the case of normal functioning of the motor the following equality is true

$$\lim r_k \to 0\,. \quad (6)$$

When a defect occurs, the inequality $r_k \neq 0$, which can be used as an indicator of a defect in the engine. In practice, however, perturbations are unavoidable, so the inequality $r_k \neq 0$ cannot be used unambiguously to make any decision. To cope with this problem, the non-convexity must be extended to the following formula, by introducing a so-called output filter V, which can be designed to increase the sensitivity to defects and reduce the sensitivity to residual.

$$r_k = V(y_k - \hat{y}_k) \quad (7)$$

where V is output filter.
The authors propose to use the motor armature current residual to diagnose a DC motor. When a defect such as an armature winding short circuit occurs, the resistance and inductance of the motor armature winding decreases compared to the reference model, which leads to an increase in the motor current discrepancy. A computational experiment was carried out to analyze the effect of inter-turn shorting in the DC motor armature winding.

3 RESULTS

The results of DC motor simulation at insignificant defects are obtained. Figure 1 shows a model of DC motor with digital twin with the following parameters: ke1=1.21, km1=0.95, J1=0.0031, R1=14.6, L1=0.248. U=220 V, I=2.17 A, T=1.91 N·m (t_{on}=0.1 sec), ω=155.6 rad·sec^{-1}. A voltage step is applied to the input. The load torque is applied after 0.1 sec. As a result of inter-turn short circuit, the armature winding resistance and inductance decreased by 10%: delta=0.9, J2=J1, R2=R1*delta, L2=L1*delta, ke2=ke1, km2=km1. The magnitude of the change in the electric current residual is shown in Figure 2. The magnitude of the change in the angular velocity residual is shown in Figure 3.

The peak value of the electric current residual is 41.5% for armature winding resistance and inductance when reducing by 10%.
The peak value of angular velocity residual is 6.4% for armature winding resistance and inductance when reducing by 10%.
As a result of inter-turn short circuit, the armature winding resistance and inductance decreased by 30%: delta=0.7, J2=J1, R2=R1*delta, L2=L1*delta, ke2=ke1, km2=km1.
The magnitude of the change in the angular velocity residual is shown in Figure 4. The magnitude of the change in the angular velocity residual is shown in Figure 5.

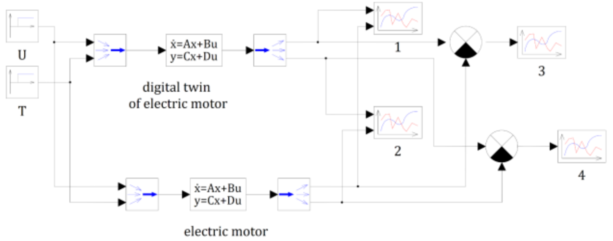

Figure 1. DC motor model with digital twin

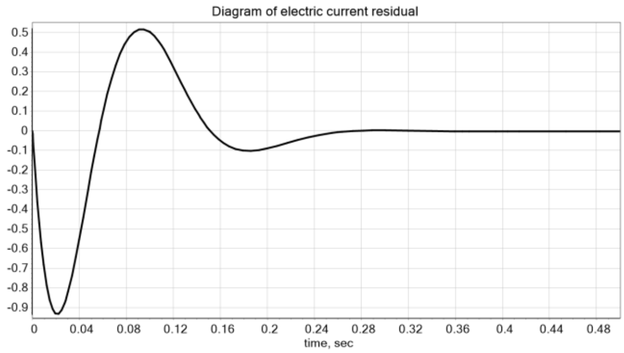

Figure 2. Change of electric current for armature winding resistance and inductance when reducing by 10%

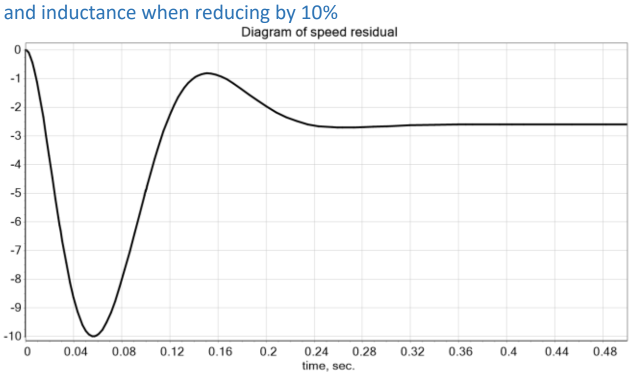

Figure 3. Change of angular velocity for armature winding resistance and inductance when reducing by 10%

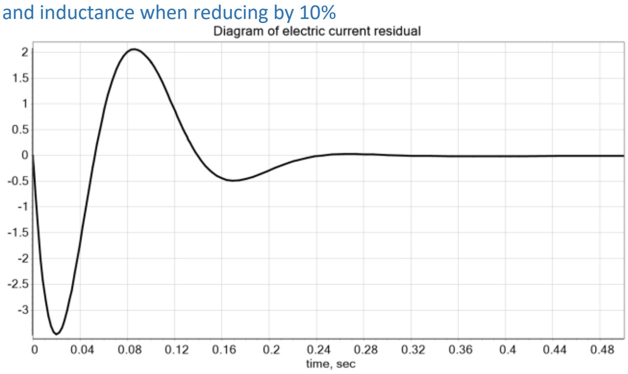

Figure 4. Change of electric current for armature winding resistance and inductance when reducing by 30%

The peak value of electric current residual is 157% for armature winding resistance and inductance when reducing by 30%.

The peak value of angular velocity residual is 22% for armature winding resistance and inductance when reducing by 30%.

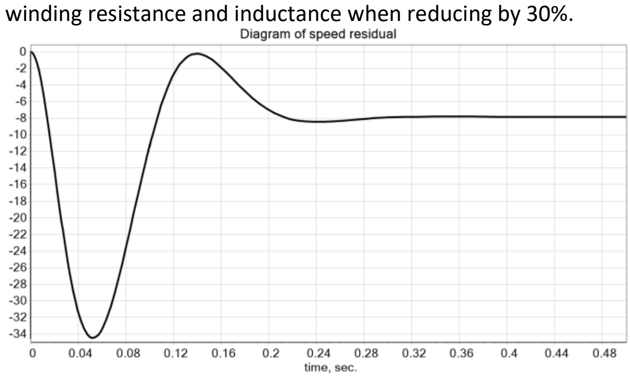

Figure 5. Change of angular velocity for armature winding resistance and inductance when reducing by 30%

Analyzing the results of DC motor simulation, we can conclude that when the defect - of inter-turn short circuit increased from 10% to 30%, the peak value of the electric current residual increased from - 0.92 A to -3.44 A, the peak value of the angular velocity residual increased from -9.8 rad·sec^{-1} to -34.4 rad·sec^{-1}.

Analysis of the results of the computational experiment shows that the electric current is more sensitive to motor defects. Therefore, the following experiments were carried out with measuring the electric current residual only.

Figure 6 shows models of DC motor with various reducing armature winding resistance, inductance and digital twin for a rectangular voltage input signal. The magnitude of the change in the electric current residual is shown in Figure 7.

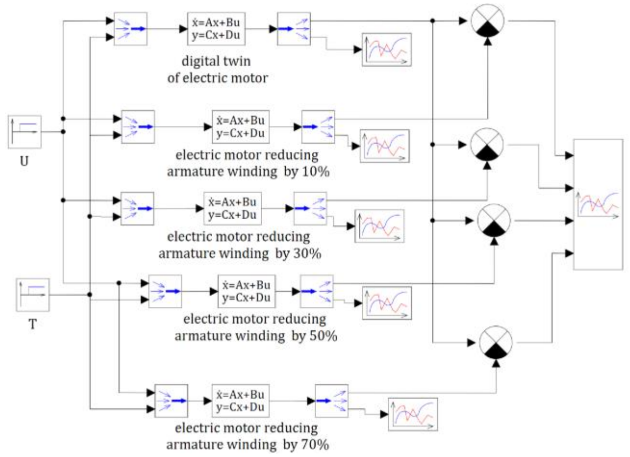

Figure 6. DC motors models with various reducing armature winding resistance, inductance and digital twin for a rectangular voltage input signal

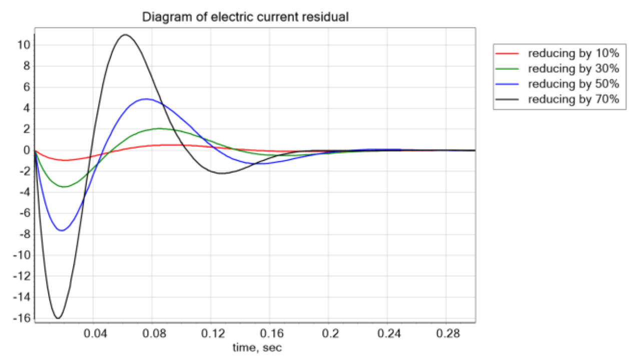

Figure 7. Change of electric current residual for armature winding resistance and inductance when various reducing by 10%, 30%, 50%, 70%

Figure 7 shows that when the armature winding resistance and inductance decreases, the peak armature current discrepancy increases. If the peak residual is zero, this indicates that the motor parameters are nominal and there are no defects.

Figure 8 shows models of DC motor with various reducing armature winding resistance, inductance and digital twin for a linear voltage input signal. The magnitude of the change in the electric current residual is shown in Figure 9.

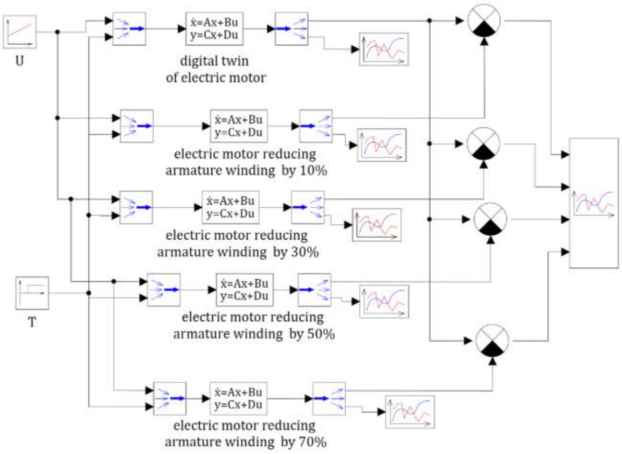

Figure 8. DC motors models with various reducing armature winding resistance, inductance and digital twin for a linear voltage input signal

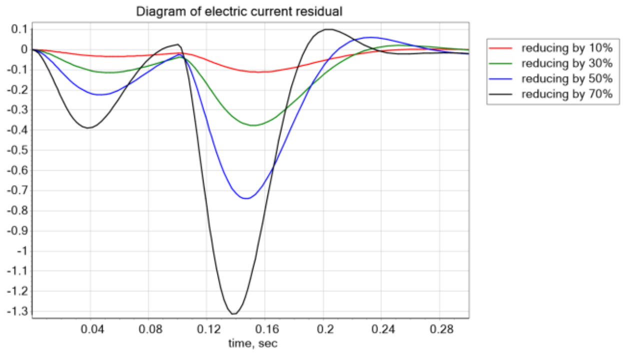

Figure 9. Change of electric current residual for armature winding resistance and inductance when various reducing by 10%, 30%, 50%, 70%

By comparing the value of the peak current residual, we can conclude that for a linear voltage input signal, the peak residual is 12.3 times less than for a rectangular voltage input signal. The smaller electric current residual for a linear voltage input signal is explained by the fact that the motor rotor together with the load have a certain moment of inertia. The sum of moments (electromagnetic torque with sign '+', load torque with sign '–') is equal to the product of the moment of inertia by the angular acceleration. For a rectangular voltage input signal, the angular acceleration tends to infinity at the time of the jump, with a linear change in angular velocity, the angular acceleration will be a constant. To provide infinite angular acceleration requires infinite motor torque and therefore infinite electric current.

4 DISCUSSION

A full-dimensional state observer serves as the core of the defect detection filter, whose online computational cost is much higher than that of a reduced-dimensional observer. In contrast, a reduced dimensional observer can provide similar estimation performance, but with much lower online computational cost. This is one reason for creating observers of minimal complexity, such as Luenberger observers.

The diagnostic observer scheme yields a reduced-order unconstraint with less computational complexity, which is desirable for online diagnostic implementations.

In scientific papers, depending on the type of system under consideration, two procedures for calculating the unrelatedness are considered. One is statistical testing, which is mainly applied to stochastic systems [Ding 2019]. The other is norm-based estimation, which is focused on systems containing deterministic perturbation or system uncertainty [Luo 2017]. Because of the lower computational online computation and the systematic calculation of the threshold, standard unconstraint is widely used.

L_2 and L_∞ are two standard normals used in diagnostics for estimating the unrelatedness and threshold value. The L_2 norm is one of the popular functions for estimating the unsteadiness. The L_2 norm measures the energy of the jitter signal. For a given signal of unsteadiness, the L_2 norm is defined as:

$$J_2 = \sum_{k=0}^{\infty} r_k^T r_k \tag{8}$$

Since it is not practical to estimate the unsteady signal on an infinite time interval, it is common to use an estimate on a time interval from k1 to k2.

$$J_{2[k1,k2]} = \sum_{k=k1}^{k2} r_k^T r_k \tag{9}$$

In practice, the mean square value is often used instead of the L_2 norm, which measures the average energy of the unconformity over the time interval [1; n]. The estimation function of the RMS value is defined as follows:

$$J_{2RMS[k,n]} = \frac{1}{n} \sum_{i=1}^{n} r_k^T r_k \tag{10}$$

The L_∞ norm (also known as peak norm, maximum norm) is defined as the maximum absolute values of its components. For diagnostic purposes, the following peak value estimation function is usually used:

$$J_{peak} = (r_{kpeak}^T r_{kpeak})^2 \tag{11}$$

The choice of the threshold for defect detection significantly affects the efficiency of the diagnostic system. It is found that the threshold value is a tolerance limit for model interferences and uncertainties under no-failure conditions. Setting a lower threshold typically results in the diagnostic system being subjected to more false alarms, and a higher threshold setting typically causes a higher probability of missing a defect. Therefore, based on the chosen evaluation function, the threshold can be generally defined:

$$J_{th} = \sup J_e \tag{12}$$

where J_e represents the sign of the unrelated signal, which can be L_2, L_2, $[k_1; k_2]$, $J_{RMS[k;n]}$ and J_{peak}.

The simplest logic for making a defect decision is to compare the function of the estimated difference value J_e with a given threshold J_{th} [Lekomtsev 2021]. Thus, the decision is made as follows: If $J_e \leq J_{th}$, there are no defects.

If $J_e > J_{th}$, then defects are detected and the diagnostic system determines the type of defect, the degree of its development and predicts the remaining service life.

If a defect is detected, the diagnostics system transmits information about this to the control system, turns on the indication of the occurrence of defects, then by methods of fuzzy logic or other methods determines the type of defect, the system element in which the defect occurred, predicts the remaining life, the control system is 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 is necessary.

5 CONCLUSIONS

Every company that wants to maintain its competitiveness in the market must permanently ensure a constant increase in efficiency and productivity. Only then can it be ensured that the prices of his products will not grow more than the market will accept. Continuous modernization of production processes is one way to achieve higher productivity [Karrach 2022]. Such a possibility is to increase the reliability of machines and equipment as stated by the authors [Kuric 2020, Zajacko 2018] especially electric motors thanks to their diagnostics.

A model for DC motor diagnostics based on a state-space model approach is developed. Its digital twin works in parallel with the real motor. The output signals of the motor and the digital twin from the electric current and angular velocity sensors are analyzed. The motor defects are detected by the magnitude of the residual. If a defect is detected, the diagnostic system transmits information about it to the control system, turns on the defect indication, then by fuzzy logic methods or other methods determines the type of defect, the system element in which the defect occurred, predicts the remaining life, the control system is 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 motor must be performed.

ACKNOWLEDGMENTS

This paper was prepared as part of project KEGA 006STU-4/2021: “Progressive form of interdisciplinary education and supporting the subject-specific study development at universities”.

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