Forecasting of the electrical actuators condition using stator's current signals

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Abstract. This article describes a forecasting method for electrical actuators realized through the combination of Fourier transformation and neural network techniques. The method allows finding the value of diagnostic functions in the iterating operating cycle and the number of operational cycles in time before the BLDC actuator fails. For forecasting of the condition of the actuator, we propose a hierarchical structure of the neural network aiming to reduce the training time of the neural network and improve estimation accuracy.

1. Introduction
Modern development of automation and robotics require the increased accuracy and reliability of the actuator operation. In this context, the BLDC motors are widely useful as actuator systems. A typical BLDC based actuator is an electromechanical system including an electrical motor and a reducer connected by a coupler. Long operation activity of the BLDC based actuator [1] under the large reversed loads can produce failures. Therefore, it is necessary to monitor periodically the BLDC actuator. It is equally important to determine the time and the cause of equipment failure. This problem can be solved using the forecasting technical condition method for BLDC actuators.

The main problem of the development of the condition estimation methods is the large amount of non-formalized qualitative information that cannot be used with conventional modelling methods in contrast to artificial intelligence methods, where these data can be managed.

2. Materials and methods
One of the simplest and the most accessible methods of diagnosing is the spectral analysis of stator’s current signals, as it does not require additional setups and it is not time consuming. It can be performed directly on the working equipment.

This method allows estimating the technical condition of the electric motor and the mechanical devices connected with it. During the set time interval, the steady-state currents consumed by the motor are converted into the frequency domain using the Fourier transformation [2]. For the analysis, the current signal of a new serviceable motor, which is accepted to be the basic reference standard, is measured once before the long-time exploitation. When faults occur, there is a change in the common
level and single amplitudes at the characteristic frequencies. The investigation of failures is carried out by comparison of the current spectrum with the basic reference spectrum done by means of computational intelligence. Failure search is performed by comparing the amplitudes of the current spectrum and a new serviceable the actuator.

Midrange current signal (1), which can be considered as a bias arising from the process noise, is obtained from all amplitudes of a current spectrum without characteristic frequencies, is computed as follows:

$$a_{mid} = \frac{\sum_{i=g}^{h} a_i - \sum_{j=g}^{h} a_j}{g-h},$$  \hspace{1cm} (1)

where $a_i$ – current signal amplitude; $i, j$ – frequency indices; $g$ – frequencies of a spectrum interval; $h$ – characteristic frequencies of diagnosing.

The following equation describing the spectrum analysis is restricted to the normalized characteristic frequencies under consideration:

$$k_i = \frac{A_i - A^0_i + \Delta a_{mid}}{a_{mid 0} + A^0_i},$$  \hspace{1cm} (2)

where $A_i$ – the amplitude of the analyzed spectrum on the $i$-th characteristic frequency; $A^0_i$ – the amplitude of a reference spectrum on the $i$-th characteristic frequency; $a_{mid 0}$ – the midrange current signal of the reference spectrum; $\Delta a_{mid}$ = $a_{mid i} - a_{mid 0}$ – absolute deviation of the midrange current signal; $a_{mid i}$ – the midrange current signal of the analyzed spectrum.

If the analyzed spectrum is equal to the referential one, then normalized factor $k_i = 0$. If a fault occurred, then the change of the midrange current signal and amplitude at characteristic frequencies lead to a change of the normalized factor. These data are fed into the neuro-fuzzy troubleshooting model [3]. The received model output allows estimating a current condition of the object, having attributed it to one of the following classes: $F(x^*) = 1$ – serviceable; $0 < F(x^*) < 1$ – operative; $-1 \ll F(x^*) \ll 0$ – corrupted.

If the BLDC actuator is operative, it is possible to forecast its technical condition. Forecasting is carried out at two stages. The first stage consists in predicting the next time values of the function. At the second stage, the outputs of the first phase are approximated and are determined by the state of the BLDC actuator at the next iteration.

For forecasting of faults, a simulation model based on the neural network such as perceptrons with three inputs and one output is used. The network consists of three layers. The first and second layers have a sigmoid activation function. The third output layer has a linear activation function [4].

Initial data for the prediction values are defining functions in different time intervals $F_i(x^*_i)$, $i \in [1, n]$.

The first input of the neural network is a vector of values defining function $F_1(x^*_i) ,..., F_{L-3}(x^*_i)$. The second input has the same parameters, but with a shift in one parameter to the right $- F_1(x^*_2) ,..., F_{L-2}(x^*_i)$. The third input has the parameters, which are shifted by one relative to the second entrance $- F_1(x^*_i) ,..., F_{L-1}(x^*_i)$. The data form the input vector of the neural network represented as follows:

$$P_i = [F_1(x^*_i) ,..., F_{L-3}(x^*_i); F_2(x^*_i) ,..., F_{L-2}(x^*_i); F_3(x^*_i) ,..., F_{L-1}(x^*_i)].$$

The purpose of vector $H$ is to determine the value of the function from the fourth to the $L$-th:

$$H_i = [F_4(x^*_i) ,..., F_L(x^*_i)].$$
Using input $P$, the neural network calculates the output value of defining function $Y$, which must comply with $H$. For the network learning algorithm, the back propagation approach is used [5,6]. To find the next value of the defining function, the input is represented as a column vector containing the last three values of the training sample:

$$C = \begin{bmatrix} F_{L-1}(x_i^*); F_{L-1}(x_i^*); F_L(x_i^*) \end{bmatrix}.$$ 

For the second phase of the forecasting process, a radial basis network (Figure 2) is simulated. The inputs of the network are fed to the output networks of the first stage. The mathematical minimum function is used for training the neural network.

If the network output of the second phase is positive, then the output networks of the first stage will be added to the training set, and the process repeats until the value of the output of the second phase becomes less than or equal to zero. The number of iterations equals the number of cumulative intervals up to the current time (Figure 1).

**Figure 1.** The neural network for the forecasting

### 3. Experimental results

The described method was used for BLDC motor condition estimation, where all the necessary readings were acquired from the coupling of the reducing gear connected to an actuation mechanism. Current measurement is carried out within a low level BLDC control, therefore, using a spectrum current, it is possible to determine only the technical condition of BLDC with the full load, which is directly connected with it. Reducing gear is a constant passive load hence there is no variable influence on a frequency spectrum of the current consumed by the motor. The given characteristic frequencies allow introducing the following classification illustrated in figure 2.
The investigations of changes in the technical condition of the BLDC actuator are performed with a long-term drive. At the frequency of 15 Hz, six measurements of current in a motor with constantly velocity of rotating and an interval of 30 minutes are conducted. The obtained data diagnostics are shown in Table 1.

**Table 1** Diagnostic results of the BLDC actuator condition in the continuous mode operation

| Time of exploitation of the BLDC actuator, min | 0  | 30  | 60  | 90  | 120 | 150  |
|-----------------------------------------------|----|-----|-----|-----|-----|------|
| Commutation faults                            | 0.877 | 0.705 | 0.96 | 0.9 | 0.21 | 0.998 |
| Rotor faults                                  | 1   | 1   | 1   | 1   | 1   | 1    |
| Voltage ripples                               | 0.768 | 1   | 0.95 | 0.9 | 1   | 0.965 |
| Coupling faults                               | -1  | -1  | -1  | -1  | -1  | -1   |
| Stator faults                                 | 1   | 1   | 1   | 0.7 | 1   | 1    |

From Table 1, it is evident that the dividing function, which characterizes the coupling state, reaches its minimal value. This indicates the coupling is failing. The changes in the coupling state can be estimated indirectly by the changes in the dividing function of others fault features. The changes in the coupling behavior impact the communication faults readings at overlapped characteristic frequencies. The forecasting of the time horizon, when the coupling damage appears, can be done by means of the evolution of dividing functions during the long-term actuator drive (Figure 3).

#### Figure 2. Classification of characteristic frequencies of diagnosing

| Characteristic frequencies of diagnosing | Harmonics of frequency of rotation | Harmonics of frequency of a power line |
|-----------------------------------------|-----------------------------------|--------------------------------------|
| Commutation faults                      | $2 \cdot k \cdot p \cdot f_r$     | $k \cdot f_r$                        |
| Rotor faults                            | $2 \cdot p \cdot f_r$, $k \cdot f_r \pm 2 \cdot p \cdot f_r$ | $k \cdot f_s$                        |
| Coupling faults                         | $k \cdot f_r$                     | $2 \cdot f_s$                        |

\(f_s\) - frequency of power supply for the rectifier, Hz;  
\(f_r\) - rotation frequency of the motor, Hz;  
\(k = 1,2,3\) - current harmonic number;  
p - number of poles.
From Figure 3, it is evident that the dividing functions progress periodically with a tendency approximated as linear. The coupling damage is possible at the time when one of the linear approximations cuts the time axis as first.

4. Conclusion
This paper proposed a forecasting method of the technical condition for the previous value of the current amplitude at specific frequencies to determine the time and cause of the drive fault based on the hierarchical neural network.

Using the trend line of previous current values, it is possible to perform short and long term condition estimation of the motor, the defects status and the forecasted time for equipment failure. The experimental research has confirmed the adequacy and accuracy of this method with reference to the theoretical findings and adopted technical solutions. The condition estimation reliability is 95%.

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