Smart sensorless prediction diagnosis of electric drives

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Abstract. In this paper, the discuss diagnostic method and prediction of the technical condition of an electrical motor using artificial intelligent method, based on the combination of fuzzy logic and neural networks, are discussed. The fuzzy sub-model determines the degree of development of each fault. The neural network determines the state of the object as a whole and the number of serviceable work periods for motors actuator. The combination of advanced techniques reduces the learning time and increases the forecasting accuracy. The experimental implementation of the method for electric drive diagnosis and associated equipment is carried out at different speeds. As a result, it was found that this method allows troubleshooting the drive at any given speed.

1. Introduction

The reliability and performance of electric drive are an important part of the electromechanical and technology process. Operation in poor technical condition of motors leads to financial losses related to unpredictable failure of equipment and a consequent violation of the technological process. Therefore, the actual problem is to ensure reliable and efficient operation of electrical drives. One way to solve this topic is to monitor the technical condition of the application of methods and means of predictive diagnosis. The main problem of the development of such methods is the large amount of non-formalized qualitative information that cannot be used with conventional modelling methods. However, the same information process is possible using artificial intelligent methods.

2. Materials and methods

Time consuming operational activity of the electrical motors at the large reversed loads can generate faults. Therefore, it is necessary to monitor the electrical equipment by means of a systematic predictive diagnosis. One of the most simple and accessible methods of diagnosing is the method of the spectral analysis of stator current signals, as it does not require additional material and time expenses and can be made directly on the working equipment. This method allows diagnosing the electric drive and related mechanical modules by registering the drive current values according to fixed temporal intervals.

The received data are converted into frequency domain using the Fourier transformation [1]. Characteristic frequency peaks reflect the electric drives faults and can be extracted from spectral analysis of the stator current. 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 on the characteristic frequencies [2, 3]. The search of faults is carried out by comparison of a currently acquired spectrum with the basic reference spectrum using computational intelligence. Midrange current signal (re-
fer to Eq. 1), which can be considered as a bias arising from process noise is obtained from all amplitudes of a current spectrum without characteristic frequencies:
\[ a_{mid} = \frac{\sum_{i=1}^{g} a_i - \sum_{j=1}^{h} a_j}{g-h}, \]
where \( a_i \) - current signal amplitude; \( i,j \) - frequency indices; \( g \) - frequencies of a spectrum interval; \( h \) - characteristic frequencies of diagnosing.

The spectrum analysts is restricted to the normalized characteristic frequencies under consideration (refer to Eq. 2).
\[ k_i = \frac{A_i - A_i^0 + \Delta a_{mid}}{a_{mid} 0 + A_i^0} \]
where \( A_i \) - amplitude of the analyzed spectrum on the \( i \)-th characteristic frequency; \( A_i^0 \) - amplitude of a reference spectrum on the \( i \)-th characteristic frequency; \( a_{mid 0} \) - midrange current signal of the reference spectrum; \( \Delta a_{mid} = a_{mid i} - a_{mid 0} \) - absolute deviation of the midrange current signal; \( a_{mid i} \) - midrange current signal of the analyzed spectrum.

If the analyzed spectrum is equal to the reference one, then the normalized factor is \( k_i = 0 \). If a fault occurred, then the change of the midrange current signal and the amplitude on characteristic frequencies lead to a change of normalized factor [4, 5].

If all normalizing factors are «nearby 0», the object is serviceable. If all normalizing factors are «nearby 1», then the object is corrupt. These data are written down in the form of predicate rules:

\[ IF \; k_i \; is \; B_1 \; and \; .... \; k_m \; is \; B_1, \; then \; x_i = f_1; \]
\[ IF \; k_i \; is \; B_2 \; and \; .... \; k_m \; is \; B_2, \; then \; x_i = f_2; \]

where \( k_i \) .... \( k_m \) - current amplitude on characteristic frequencies; \( B_1, B_2 \) - S and Z shaped functions of sigmoid type; \( x_i \) - predicted output fault; \( f_1 \) - conclusion «object is operational»; \( f_2 \) - conclusion «object is not operational».

The output is defined by means of fuzzy logic algorithm Takagi-Sugeno [6-8]. Similar sub-models are involved for making decision against each fault, having received a set of current factors of faults progress \( X = \{ x_i \}, i \in [1, n] \).

While faults lead to the object refusal, an approximating minimum function is chosen. The approximation is carried out by a radial basic network with Gauss activation functions [9-15], with the displayed target layer linear neuron.

Output of the radial neuron is computed using equation 3:
\[ F(x_i) = \sum_{i=1}^{N} \rho \left\| x_i - c_i \right\|, \]
where \( N \) - the number of neurons in the hidden layer; \( c_i \) - the center vector for neuron \( i \); \( \rho \) - Gaussian; \( \| \| \) - the Euclidean distance.

Outputs of the radial neuron are multiplied by weights vectors of the linear neuron. Weights vectors of the linear neuron are set on an interval [-1, 1] such that maximum \( F(x_i) \) corresponded the minimum weight. As a training function is the minimum, then the output of the linear neuron is:
\[ F(x_i) = min(a_i F(x_i^*)), \]
where \( a_i \) - are the weights of the linear output neuron.

The received output value allows one to estimate a current condition of the object, having carried it to one of the following classes: \( F(x^*) = 1 \) - serviceable; \( 0 < F(x^*) < 1 \) - operative; \( -1 \ll F(x^*) \ll 0 \) - corrupt.
If the drive is operative, it is possible to forecast its technical condition. Forecasting is carried out in two stages. At the first stage, the algorithm predicts the following values of the function. At the second stage, the outputs of the first phase are approximated and are determined by the state of the motor next time.

The forecasting of faults is modeled using a neural network consisting of perceptron with three inputs and one output. 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. Initial data for the prediction values are defining functions in different time intervals \[ F_i(x^i), \quad i \in [1, n]. \] The inputs of neural network \( P \) are the values of the training sample with offset by one, according to the window method [16]. The purpose of vector \( H \) is to determine the value of the function from the fourth to the \( L \)-th. From 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 is used [17]. To find the next value of the defining function, the input is represented by a column vector containing the last three values of the training sample.

For the second phase of forecasting, the radial basis network is simulated. The inputs of the network are fed to the output networks of the first stage. The training function is the minimum function. If the network output of the second phase is positive then the outputs networks of the first stage 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 past time intervals up to the recent time. The structure of the predictive drive diagnosis model is shown in Figure 1.

![Figure 1. The structure of the predictive drive diagnosis model](image)

### 3. Experimental results

The proposed method of forecasting has been evaluated on the BLDC motor and transferred through 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 for BLDC with the full load, which is directly connected with it. Reducing gear is a constant passive load and there is no variable influence on a frequency spectrum of the current consumed by the motor. In Fig. 2, the basic typical faults of the BLDC motor and their characteristic frequencies are summarized.
Figure 2. Classification of characteristic frequencies of diagnosing

Time series of the consumed current of the motor are recorded at frequency of rotation 15 Hz. Two types of equivalent measurement were performed, one — with a priori faultless coupling, and the other — with a damaged coupling that exhibits a side crack. The collected data are converted by fast Fourier transformation to the frequency domain and scanned by the aforementioned method. The result of diagnosis is shown in Figure 3.

![Figure 3. Result of BLDC motor diagnosis](image)

Figure shows that results of the diagnosing certifies the coupling fault.

Prediction of the technical condition of the BLDC actuator is performed with a long-term drive. At the frequency of 15 Hz, six measurements of current at a constantly rotating motor with an interval of 30 minutes are conducted. From the obtained data, diagnostics is shown in Table 1.
Table 1. Results of diagnostic BLDC actuator for continuous mode operation

| Time of exploitation of the BLDC actuator, min | 0   | 30  | 60  | 90  | 120 | 150 |
|---------------------------------------------|-----|-----|-----|-----|-----|-----|
| Commutation faults                          | 0.8765 | 0.70493 | 0.9575 | 0.868 | 0.213 | 0.9978 |
| Rotor faults                                | 1   | 1   | 1   | 1   | 1   | 1   |
| Voltage ripples                             | 0.7684 | 1   | 0.9499 | 0.855 | 1   | 0.9649 |
| Coupling faults                             | -1  | -1  | -1  | -1  | -1  | -1  |
| Stator faults                               | 1   | 1   | 1   | 0.71 | 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 fault. 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 provide a largest impact on the describing values representative for the commutation faults, since the latter offers the overlapped characteristic frequencies. The forecasting of the time horizon when the coupling damage appears can be done by dividing functions during the long-term actuator drive (Figure 4).

![Figure 4. Forecast of development of faults](image)

From Figure 4, it is evident that the dividing functions progress periodically with an approximated linear tendency. The coupling damage is possible at the time when one of the linear approximations cuts the time axis as first. The forecasting of the technical conditions of actuator allows predicting a nearby time horizon of the coupling damage.
4. Conclusion
The neuro-fuzzy method of predictive diagnosing of electric drive allows one to determine the technical drive condition, using the current spectrum of the steady-state drive, from which the normalized characteristic values are determined. In view of that, the proposed method allows forecasting the technical condition for the previous value of the current amplitude at specific frequencies and determining the time and cause of drive fault. Experimental results have confirmed the adequacy and accuracy of this method.

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