National Aviation Academy

International Journal of Transportation Research and Technology
e-ISSN: 3079-6075
DOI: 10.71108/transporttech.vm01is01.04

Research Article

# Methodology for Assessment of the Technical Condition of Electric Motors and Descriptive Forms of Signals

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**Timescale of article**

Received: 26 August 2024
Accepted: 05 December 2024
Published: 24 December 2024

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**Keywords**

Electric motors, Technical condition, Fault types, Diagnostic monitoring, Complex fault, Fuzzy logic

**Cite this article as:**

Guliyev, H., Manafov, E. & Huseynov, F. (2024). Methodology for Assessment of the Technical Condition of Electric Motors and Descriptive Forms of Signals. *International Journal of Transportation Research and Technology*, 1(1), 42-54.
DOI: 10.71108/transporttech.vm01is01.04

**Abstract**

Although many different research papers have been conducted on the technical condition monitoring, detection and diagnosis of fast faults in stopping asynchronous motors widely used in transport, industry and household, the creation of a complex monitoring system for this purpose has not been fully resolved. For this purpose, the description and processing methods of various coordinate signals were considered for the construction of complex motor diagnostics and protection systems. It is possible to create an intelligent hybrid model of the fault diagnosis and motor protection system as a result of the grouping of failures of high powered asynchronous motors used in transport with the help of modern sensors. For this, the analog signals received from the sensors should be analyzed, various transformations should be performed on them and the evaluation of the technical condition should be considered based on the obtained final signal.

## 1. Introduction

The use of electric motors in almost all fields of activity has become the need of the hour: from the utility sector to the most complex industries, the transformation between electrical and mechanical energy is not possible and will not be possible without this type of electric machines. The interdependence between electric motors, the continuity of operation at the transportation, industrial or micro enterprise level, the maintenance of financial profitability and maintenance strategies of any organization, the development of more advanced methods for the detection and diagnostic monitoring of various faults that may occur in motors and this has opened the way for conducting numerous studies in this direction.

Despite numerous researches being conducted in current works on the identification of abnormal modes and protection and technical conditions of electric motors, especially traction motors, the principles, methods and algorithms of the complex approach to the mentioned issues, as well as the issues of realization on a real scale, have not been fully resolved (Merizalde et al., 2017; Stranneby & Walker, 2004).

The aim of the current research work is the real-time diagnosis of faults that may occur in electric motors and the complex grouping of faults and defects that may occur in them to prevent violations of technological activity processes in transport and industry. With the application of modern techniques and technology, the collection of data on the technical condition of electric motors and the monitoring of the condition of these data are of great importance in the correct assessment of the diagnostic condition. To determinei the technical condition of the motors, the informative signals received based on sensors should be processed correctly and certain decisions should be made by performing various analyses on these signals. Due to the processing and analysis of signals, it is possible to determine the technical situation in real-time. Different methods are used for signal analysis and processing, depending on the conditions and the amount of data obtained.

## 2. Descriptive forms of signals used in the diagnosis of asynchronous motors

Nowadays, a third of the total electricity generated is consumed by electric asynchronous motors, which are applied in various types of activities and industries. Undoubtedly, from the point of view of application, asynchronous motors are more preferable in the field of electric machines. Asynchronous motors, the main workforce of the industry, consume more than 60% of the total electricity produced in the world. Taking into account the variety and scope of application areas, in particular, improving the efficiency of production areas is an urgent issue from the point of view of the timely assessment of the technical condition of motor and their constant maintenance in working conditions to ensure.

Various signal representation forms are utilized in the diagnostics of asynchronous motors. These forms play a crucial role in the analysis and detection of faults within the motor. By analyzing signals in both the time and frequency domains, they provide accurate information regarding different types of faults.
The types of signal representation forms are listed below (Table 1):

- *Time-domain signals;*
- *Frequency-domain signals;*
- *Power spectrum;*
- *Wave packets and short-time fourier transform* (STFT);
- *Hilbert transform and phase analysis.*

***Time-Domain Signals.*** This analysis shows the variation of the signal over time. It is used to directly observe the operational state of the motor and the signs of faults. Signals such as voltage, current, vibration and speed are the primary indicators of this analysis. The key characteristics of time-domain signal analysis are defined by amplitude, mean and RMS values. This method can be employed to detect short-term anomalies and identify rapid changes. For example, during rotor imbalance, an instantaneous increase is observed in the vibration signal.

$$x(t) = \mathrm{A} \cdot sin(2\pi ft + \phi) \tag{1}$$

$A$ −Amplitude

$F$ −Frequency

$\varphi$ −Phase

***Frequency-domain signals.*** In this method, the signal is transformed from the time domain to the frequency domain and the spectral components of the harmonics are analyzed. Fourier Transform (FT) is widely used for this purpose. The key characteristic of frequency-domain signal analysis is the amplitude and phase of the signal at different frequencies. This method can be used to identify sideband frequency components during rotor bar breakage and imbalance. In cases of rotor faults, additional harmonics appear around the 50 Hz frequency.

$$f_s \pm n \cdot f_r \tag{2}$$

$f_s$ –Network frequency

$f_r$ –Rotor slip frequency

$n$ –Harmonic number

***Power Spectral Density (PSD).*** PSD shows the distribution of a signal's power across different frequencies. This method is more suitable for long-term analyses. One of the key features of this method is that the energy value of the signal varies at each frequency. The analysis of the power spectrum is applied in the vibration and noise analysis of motors.

$$PSD(f) = \lim_{T \to \infty} \frac{1}{T} E[|X(f)^2|] \tag{3}$$

$X(f)$ –Fourier transform of the signal

***Wave packets and STFT.*** Wave packets and Short-Time Fourier Transform (STFT) provide time-frequency analysis of the signal. These methods are effective in detecting short-term faults. *Wave packets* are used to localize changes such as vibration and overheating. STFT provides the frequency spectrum of the signal within each time interval. These methods are applied in cases of rotor locking and eccentricity.

***Hilbert transform and phase analysis.*** The Hilbert transform is used to determine the signal's envelope and instantaneous phase. Phase analysis helps detect asynchronous vibration and speed variations. The key feature of this method is the detection of instantaneous amplitude and phase changes. It can be applied to monitor vibration and speed variations.

$$H\{x(t)\} = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau} d\tau \tag{4}$$

$H\{x(t)\}$ –Hilbert transform of the signal

**Table 1.** Comparison of various signal representation forms

| Descriptive form | Purpose of use | Method | Field of application |
|---|---|---|---|
| Time Domain | Tracking Instantaneous Changes | Current and Vibration Analysis | Mechanical Coupling, Imbalance |
| Frequency Domain | Determination of Harmonics | FFT and MCSA | Rotor Bar Breakage |
| Power Spectral Density (PSD) | Distribution of Power Across Frequency | PSD Analysis | Vibration and Noise Analysis |
| Time Domain | Tracking Instantaneous Changes | Current and Vibration Analysis | Mechanical Coupling, Imbalance |

The use of various signal representation forms in motor diagnostics enables comprehensive analysis. While time-domain analysis is useful for tracking instantaneous changes, frequency-domain analysis accurately identifies the source of faults. Power spectrum, Short-Time Fourier Transform (STFT) and Hilbert Transform play an invaluable role in detecting more complex faults. The combined application of these methods ensures the precise and early detection of motor faults.

Currently, diagnostic monitoring of the technical condition of the motors are carried out by analyzing signals. For this reason, we can start this section mentioned by James Maxwell from a historical point of view and a theoretical basis (Merizalde et al., 2017; Stranneby & Walker, 2004). In his work "Dynamic Theory of the Electromagnetic Field", published in 1864, Maxwell presented a mathematical formula that combines electrical, magnetic and light wave-like behaviour and the energy of wave theories. The subsequent work of other researchers, such as Oliver

Heaviside, made it possible to summarize Maxwell's theory in four equations that demonstrated it more practically. From Maxwell's equations, we can write the equation that expresses the wave nature of the magnetic flux in the air gap, the voltage and current in terms of time and position. The main wave of these periodic sinusoidal signals and their components can be represented by a convergent series of trigonometric functions, i.e.:

$$f(t) = \frac{a_0}{2} + \sum_{n=1}^{\infty} a_n \cos n\,\omega t + \sum_{i=1}^{\infty} b_n \sin n\,\omega t \tag{5}$$

where $\omega = 2\pi \cdot T^{-1}$ and

$$a_0 = \frac{2}{T}\int_0^T f(t)dt;\;\; a_n = \frac{2}{T}\int_0^T f(t)\cos n\,\omega t dt;\;\; b_n = \frac{2}{T}\int_0^T f(t)\sin n\,\omega t dt \tag{6}$$

$f$ –Frequency

$T$ –Period of the signal

In real conditions, the analytical form of the function *f(t)* is unknown. *f(t)* is specified by a discrete set of equally spaced values (nodal points).

According to the sampling theorem, the number of nodal points of the function *f(t)* with a limited spectrum (N) must be no less than twice the number of the highest harmonic (nm).

When $N=2n_m$, formulas (5)-(6) respectively have the form, where the index (*) determines the estimate:

$$f^*(t) = \sum_{n=1}^{n_m-1}(a_n \cos n\,\omega t + b_n \sin n\,\omega t) + \frac{a_{n_m}}{2}\cos n\,\omega t \tag{7}$$

where

$$a_n^* = \frac{1}{n_m}\sum_{k=1}^{N-1} f(t_k)\cos n\,\omega t_k;\;\; b_n^* = \frac{1}{n_m}\sum_{k=1}^{N-1} f(t_k)\sin n\,\omega t_k \tag{8}$$

If $N>2n_m$ (let's take $N=2(n_m+1)$).

$$f^*(t) = \sum_{n=1}^{n_m}(a_n \cos n\,\omega t + b_n \sin n\,\omega t) \tag{9}$$

where

$$a_n^* = \frac{1}{n_m+1}\sum_{k=1}^{2n_i+1} f(t_k)\cos n\omega t_k;\;\; b_n^* = \frac{1}{n_m+1}\sum_{k=1}^{2n_i+1} f(t_k)\sin n\,\omega t_k \tag{10}$$

The formula is more clear from the point of view of harmonic analysis

$$f^*(t) = \sum_{n=1}^{n_m} A_n \sin(n\omega t + \psi_n) \tag{11}$$

where $A_n$ is the amplitude of the nth harmonic

$$A_n = \sqrt{a_n^2 + b_n^2} \tag{12}$$

$\psi_n$ – n-th harmonic offset angle

$$\psi_n = arctg(a_n/b_n) \tag{13}$$

Note that if we take the standard deviation δ as a criterion for assessing accuracy, i.e.

$$\delta^2 = \frac{1}{2\pi}\int_0^{2\pi}[f(t) - f^*(t)]^2\, dt \tag{14}$$

Then the greatest accuracy of approximation f(t) occurs if the coefficients $a_n$ and $b_n$ are calculated using formula (6).

Representation of the signal on a time scale allows to know some parameters such as amplitude, frequency, phase and conduct modulation. Nevertheless, when it is necessary to know the origin or causes of any abnormality that has arisen, it is preferred to study the frequency domain (Fig. 1) and this is done with the help of Fourier analysis (Merizalde et al., 2017; Boukra & Lebaroud, 2010; Zhang et al., 2011).

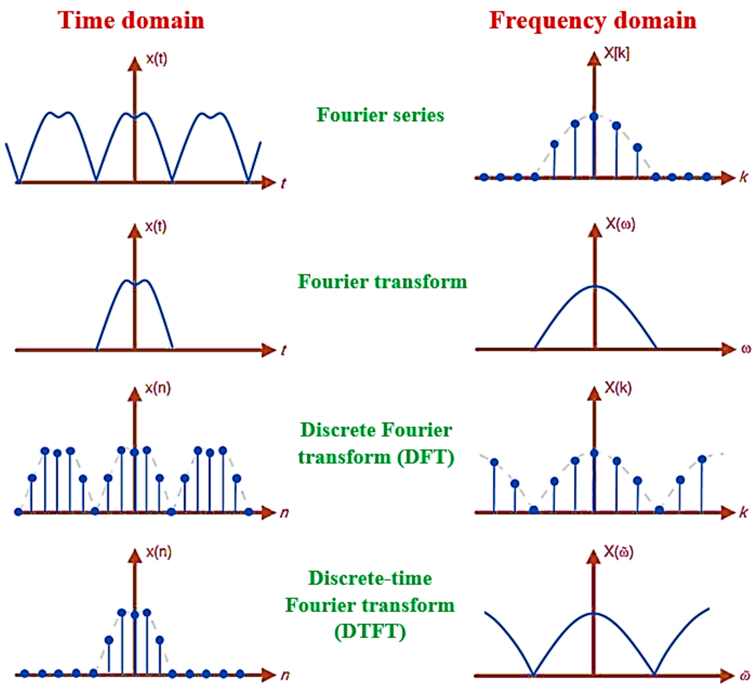



**Fig. 1.** Signal representations at different scales: time, amplitude, frequency space

According to Hansen, a periodic and continuous signal can be transformed into an aperiodic and discrete signal based on Discrete Fourier Transform (DFT). After exchanging the time and frequency domains, this signal can be converted back into a continuous signal based on the Discrete Time Fourier Transform (DTFT), making the first discrete and the second continuous (Fig. 2).

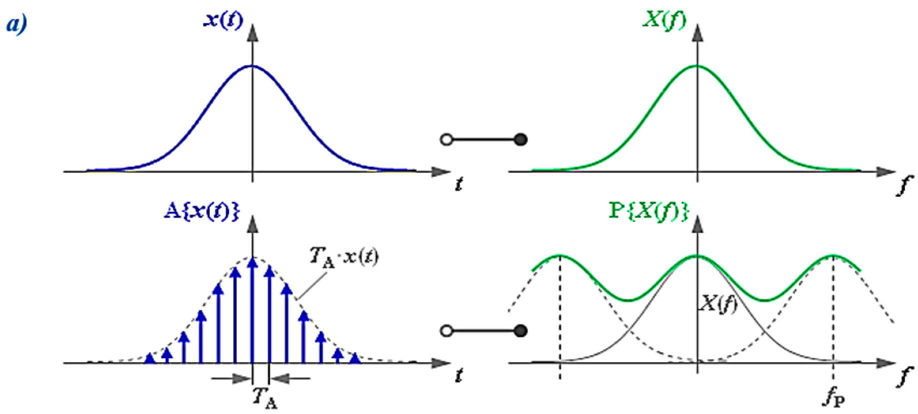
In its simplest form, the DFT can be written according to. The complex computations performed are proportional to $N^2$ and $Nlog_2N$ (where N is the number of signal samples) representing the significant quantity. For this reason, in the algorithms used to obtain the DFT, the repetition of operations, the symmetry of the functions with respect to the abscissa axis and the periodicity are significantly used to facilitate and simplify the calculation. This methodology is known as Fast Fourier Transform (FFT). The energy and spectral density are respectively given by:

$$X_N k \frac{\omega_s}{N} = \sum_{n=0}^{N-1} x_N(n) \cdot e^{-j2\pi(\frac{kn}{N})} = \sum_{n=0}^{N-1} x_N(n) \cdot W_N^{kn} \quad (15)$$

$$X_N k \frac{\omega_s}{N} = \sum_{n=0}^{N-1} x_N(n) \cdot W_N^{kn} = \sum_{n=0}^{(\frac{N}{2})-1} x_N(2n) \cdot W_{\frac{N}{2}}^{kn} + W_N^{kn} \sum_{n=0}^{(\frac{N}{2})-1} x_N(2n+1) \cdot W_{\frac{N}{2}}^{kn} \quad (16)$$

$$\sum_{n=-\propto}^{\propto} |x(n)|^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} |x(n)|^2 \, d\omega = \frac{1}{2\pi} \int_{-\pi}^{\pi} S_{xx} \, d\omega \quad (17)$$

$$\varphi_{xx}(\omega) = \sum_{k=-\propto}^{\propto} R_{xx}(K) \cdot e^{-j2\pi(\frac{\omega}{\omega})k} \quad (18)$$



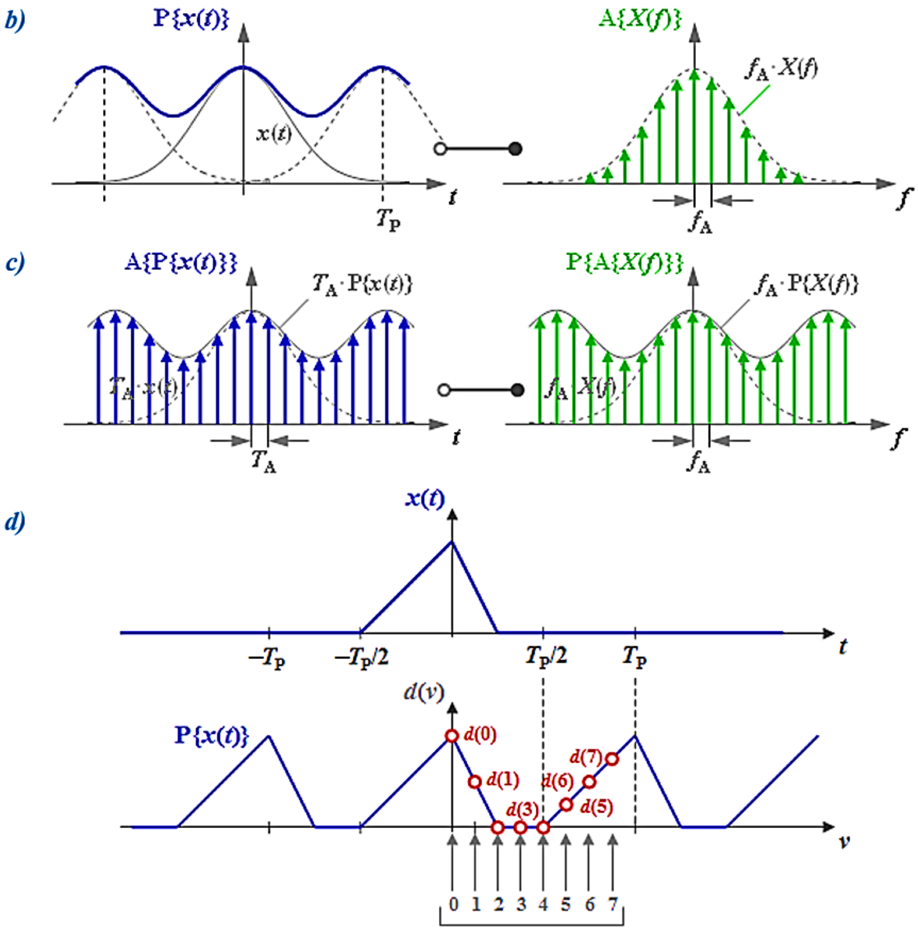



**Fig. 2.** Signal transformation based on Discrete Time Fourier Transform (DTFT) (A{x(t)}: Signal x(t) after "sampling" → A{...}; P{X(f)}: Spectrum X(f) after "periodification" →P{...}) *a) Time discretization – Periodification in the frequency domain; b) Frequency discretization – Periodization in the time domain; c) Finite signals of the Discrete Fourier Transform (DFT); d) On assigning of the DFT coefficients*

The DFT is a basic computational tool for analyzing the spectrum of a signal, but the output frequencies are modeled as sums of sinusoids that can be differentiated. Diagnosing the condition by independently analyzing the signal in the time or frequency domain can be improved by using Time-Frequency Representation (TFR). An even more sophisticated toolkit can be obtained by using directly classified TFR in the Doppler uncertainty plane to extract vectors associated with faults. Researchers propose a decision criterion based on "Mahalanobis distance" to safely diagnose broken rotor bars, pads and stator faults (Merizalde et al., 2017; Garcia-Perez et al., 2011; Batista et al., 2016).

Regardless of the methodology used, it is more convenient to use FFT as the main tool for signal analysis in monitoring, detecting and diagnosing faults in asynchronous motors.

The application of the latest wave "Artificial Intelligence" - AI (Artificial Intelligence) technique is preferred in the methodology for diagnosing faults of electric motors. Research should be deepened in the direction of creating such systems that allow making decisions as close as possible to the thinking of the human brain, so that each of the failure can be diagnosed separately and comprehensively evaluated when several failure occur at the same time (Manafov & Huseynov, 2023).

One such system is the theory of "Fuzzy Logic", which serves as an effective tool in the diagnostics and signal analysis of motors. This theory is widely applied to assess the technical condition of electric motors, detect faults and implement preventive measures, as it enables working with uncertainty and imprecise data.

In this context, data on motor vibrations, temperature, noise levels and current fluctuations are analyzed based on fuzzy logic rules. For instance, if vibration levels are high and the current deviates from the norm, it indicates a mechanical problem in the motor. Furthermore, fuzzy systems analyze current and vibration signals to *detect* *faults in the stator or rotor*, such as short circuits, insulation failures, or broken rotor bars. *Problems related to load* – such as instability during load conditions or abnormalities in operating modes – are also evaluated using fuzzy logic.

Fuzzy logic plays a crucial role in signal analysis. *In spectral analysis*, spectral components obtained through Fourier or wavelet transforms of vibration or noise signals are fed into the fuzzy logic system. Fuzzy rules then determine whether faults exist within specific frequency ranges. Additionally, “*signal filtering and noise reduction*” are achieved through fuzzy logic-based filtering to minimize external noise and isolate the useful components of the signal. Fuzzy systems accurately identify transition zones between "normal" and "abnormal" conditions in signals.

Fuzzy logic-based systems offer several advantages in determining the technical condition of motors. *Adaptation to uncertain systems* allows the detection of faults in early stages, even when signals are asymmetric or indicators are imprecise. *Real-time monitoring* becomes possible, enabling the tracking of motor performance during startup, loading and normal operation.

Thus, fuzzy logic provides significant benefits in motor diagnostics and signal analysis, as it enables the precise identification of instabilities and early detection of faults in motor operation. These systems not only mimic human expertise but also automate the decision-making process in real time.

In this direction, the diagnosis of faults of electric motors based on the use of Soft Computing paradigms has recently been given place. In this case, the use of fuzzy logic apparatus is more relevant. At the same time, in this case, it is not required to know the exact analytical relationship between the input and output quantities of the diagnostic system and it is enough to approximate this relationship in linguistic language ("if"-"then") (Manafov et al., 2022; Boukra & Lebaroud, 2010; Bellini et al., 2008; Zhang et al., 2011).

$$R_i: \text{if } \ e = A_i \text{ and } \dot{e} = B_i \text{ then } u = C_i \tag{19}$$

Where $A_i$, $B_i$ and $C_i$ - are fuzzy sets; $e, \dot{e}$ – is a signal about the technical condition of the motor and its derivative.

The output signal is determined by minimizing the fuzzy logic output and defuzzifying the center of gravity:

$$u(e, \dot{e}) = \frac{\sum_{i=1}^{n} \overline{C_i}\, min\left(\mu_{A_i}(e), \mu_{B_i}(\dot{e})\right)}{\sum_{i=1}^{n} min\left(\mu_{A_i}(e), \mu_{B_i}(\dot{e})\right)} \tag{20}$$

Where $\mu_i(\cdot)$ –denotes the membership functions of the signals.

When the quantity $\overline{C}_i$ reaches the maximum of $C$, it represents the quantity $u$. A triangular representation of the membership function in this model is given in Fig. 3.

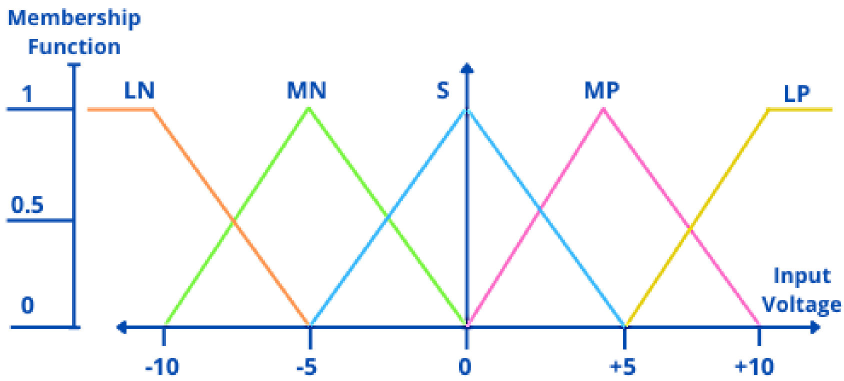



**Fig. 3.** Normalized triangular membership function

## 3. Types of failures of asynchronous motors and statistics of their occurrence

Many factors and failures cause the deterioration of the technical condition of the motor. Therefore, faults of electric motors can be classified from different perspectives as shown in table 2. Table 2 shows a preliminary grouping of the environmental factors to which the motor is exposed and which may cause failures. A factor can often belong to more than one group.

Various studies have been conducted in the direction of statistical grouping of faults. Table 3 shows several statistics sorted by source of studies. Although there is no coincidence with the prices, we can observe that the trend is very similar for the included cases. Thus, the failure rates are classified in the following form from the largest to the smallest: bearings, stator and rotor.

**Table 2.** Factors that cause failures in electric motors

| Environmental | Operations | Equipment | Human | Electric power |
|---|---|---|---|---|
| Temperature | Vibration | Aging | Bad selection of electric motor | Transients due to:<br>Short circuit<br>Fluctuations<br>Resonance<br>Transfers<br>Reconnections<br>Capacitors<br>Insulation<br>Drivers |
| Moisture | Overload | Quality | Bad use | Voltage drop |
| Rust | Excessive starts | Design defects | Lack of maintenance | Voltage low |
| Ventilation | Alignment | Manufacturing defects | Improper maintenance or repairs | Voltage unbalance |
| Pollution | Resonance of the System | | Inappropriate or poor quality parts | Harmonics |
| Strange Objects | Shaft currents<br>Stator-rotor<br>Friction<br>Partial Discharge(PD) | | Lubrication | Defective electrical installation |

**Table 3.** Average cost of faults according to parts of an electric motor

| Failure | % |
|---|---|
| **Bearing Related** | |
| Sleeve bearings | 16 |
| Antifriction bearings | 8 |
| Seals | 6 |
| Thrust bearing | 5 |
| Oil leakage | 3 |
| Other | 0.9 |
| Total | 41 |
| **Stator Related** | |
| Ground insulation | 23 |
| Turn insulation | 4 |
| Bracing | 3 |
| Wedges | 1 |
| Frame | 1 |
| Core | 1 |
| Other | 4 |
| Total | 37 |
| **Rotor Related** | |
| Cage | 5 |
| Shaft | 2 |
| Core | 1 |
| Other | 2 |
| Total | 10 |

Taking into account the factors and statistical data that cause the failure of the motors mentioned above, the development of the algorithm of the monitoring system of their technical condition based on the Soft Computing paradigm is relevant and will be considered in the next research works.

## 4. Determination of faults related to the main components of the motor based on signal analysis

**Determination of bearing-related motor faults based on signal analysis.** Bearing failures as statistics show, "bearing" failures in asynchronous motors can cause serious problems, because these failures both reduce the performance of the motor and lead to serious mechanical damage. Signal analysis methods are used to detect bearing failures at an early stage. Below is information about these methods and diagnostic methods.

*Types of bearing failures*. Wear of the bearing surface - wear caused by friction, causing increased vibrations. Damage to the inner or outer rings - caused by shocks and mechanical pressure. Broken rollers - caused by heavy work or lack of proper lubrication. Lubrication failures - lack of adequate oil increases friction and creates noise in the motor.

***Signal analysis methods for cushion fault analysis.*** Various signal analysis methods are used to determine bearing faults (Table 4).

*Vibration analysis*. Vibration analysis is one of the most widely used methods for determining bearing failures. Faulty bearings produce unusual vibration frequencies. Analysis in the time domain - increased vibration amplitude and unusual pulses are detected. Harmonic signals are observed at certain frequencies through analysis in the frequency domain - Fourier Transform (FFT). Analysis of defect frequencies - specific characteristic frequencies arise during bearing failures: inner ring defect frequency, outer ring defect frequency, roller transition frequency, rotation frequency.

*Noise analysis*. During the noise analysis, the sound waves generated as a result of micro cracks or abrasions in the bearing are analyzed. High-frequency sound signals are collected and analyzed through noise sensors. Noise analysis provides sensitive results even in the early stages of faults.

*Current signal analysis*. Bearing faults cause changes in motor current. Motor Current Signature Analysis (MCSA) - the effect of bearing faults is determined by analyzing the harmonics in the motor current signal. Also, vibration and mechanical pressures cause the appearance of new frequency components in the current spectrum.

*Temperature monitoring*. As a result of lack of lubrication or mechanical friction, the temperature of the bearing increases. With the help of temperature sensors, temperature changes are monitored and failures are detected at an early stage (Garcia-Perez et al., 2011; Soualhi et al., 2015; Aroui et al., 2007; Thomson & Fenger, 2001).

**Table 4.** Analysis of bearing failure signals

| Failure | Character of signals | Diagnostic method |
|---|---|---|
| Inner ring damage | High amplitude harmonics in the frequency spectrum (BPFI) | Vibration and current signal analysis |
| Outer ring wear | BPFO frequency peaks and high harmonics | FFT analysis |
| Damage to rollers | BSF peaks in the frequency spectrum | Noise and vibration analysis |
| Lack of lubrication | Alarms of increased temperature and vibration | Temperature and vibration monitoring |

Various measures can be taken to prevent bearing failures. Regular maintenance - regularly check the condition of the bearings and oils. Vibration monitoring system - using sensors to perform continuous vibration analysis. Proper lubrication - proper lubrication materials should be applied to reduce the friction of the bearings. Maintenance of mechanical balance - rotor imbalance can cause bearing failure, so balancing checks must be carried out.

Apparently, bearing failures in induction motors cause both mechanical problems and reduced motor performance. Signal analysis methods, especially vibration and noise analysis, are important for detecting these faults at an early stage.

**Determination of stator-related motor faults based on signal analysis.** Stator faults in asynchronous motors seriously affect the efficiency and durability of the motor. Problems with the stator windings and insulation can cause phase imbalance, overheating and even burns. Signal analysis methods play an important role in early detection of these faults.

*Types of stator faults.* Short-circuit in phase windings - short-circuit between windings of the same phase or between different phases. Insulation weakening - the occurrence of electrical leaks due to wear of the insulation material of the windings. Phase unbalance - current differences in different phases bring an uneven load to the motor. Damage from high temperatures - prolonged excessive heat causes melting and damage to bandages.

***Signal analysis methods for stator fault analysis.*** Various signal analysis methods are used to determine stator faults (Table 5).

*Motor Current Signal Analysis* (MCSA). When a fault occurs in the stator windings, unbalance and harmonic components occur in the phase current. Also, side frequencies appear in the current spectrum. For example, when a winding is short-circuited, additional harmonics appear around the fundamental frequency. The main advantage of such analysis methods is that they allow easy diagnosis without contact. The main components observed in the frequency spectrum during faults: fs - network frequency (for example, 50 Hz); $f_s \pm f_r$ - harmonics depending on the rotor frequency.

*Vibration analysis.* Failures in the stator windings lead to uneven distribution of the rotor magnetic field and increased vibrations in the motor. Harmonic components in the vibration spectrum are analyzed by FFT (Fourier Transform). Low-frequency vibrations in the motor can indicate winding problems.

*Impedance and phase measurement.* Impedance differences between phases occur when the phase windings are unbalanced. Based on this, imbalances are determined by analyzing current and voltage phases in different phases.

*Temperature monitoring.* When the insulation is weakened, the motor overheats. An excessive increase in winding temperature increases the risk of a short circuit in the motor. The wrap temperature is monitored with thermosensors or infrared cameras.

*Noise analysis.* Micro-short-circuits and faults in the windings produce noise emissions. Noise sensors are placed on the surface of the motor and analyze high-frequency signals.

**Table 5.** Analysis of stator fault signals

| Failure | Character of signals | Diagnostic method |
|---|---|---|
| Short circuit in phase winding | Additional harmonics in current spectrum | Unbalanced phases MCSA, Vibration Analysis |
| Insulation failure | Increased temperature and high frequency noise signals | Temperature and Noise Analysis |
| Phase unbalance | Current differences between phases | Vibration peaks Current and Vibration Analysis |
| Overheating of the winding | High temperature and weakening of insulation | Temperature Monitoring |

Various measures can be taken to prevent stator faults. *Regular maintenance* - regularly check the insulation condition of the windings. Temperature monitoring - prevent overheating by monitoring the winding temperature. *Phase balance* - ensuring balance between phases and avoiding unbalanced loads. *High-quality insulation materials* - to increase the insulation quality of the windings and use long-lasting materials.

Timely detection and elimination of stator faults of asynchronous motors ensures continuous and reliable operation of the motor. Current signal analysis, vibration analysis, temperature monitoring and noise analysis are effective tools for monitoring motor condition and early detection of potential problems.

**Determination of rotor-related motor faults based on signal analysis.** The rotor of asynchronous motors is one of the most important parts of the motor and its failures seriously reduce the efficiency of the motor. If rotor faults are not detected in time, they can cause severe mechanical damage or motor shutdown. Signal analysis is an important diagnostic method to detect rotor faults at an early stage and ensure uninterrupted operation of equipment (Table 6).

***Types of rotor faults.*** *Bar breakage in the rotor cage* - due to the breakage of the bars, the magnetic field becomes weak and uneven. *Locked rotor* - serious mechanical problems occur when the rotor is stuck or does not turn. *Eccentricity* - the location of the rotor outside the center of the stator causes uneven distribution of the magnetic field and vibration. *Rotor distortion and imbalance* - when the rotor is unbalanced, excessive vibration occurs in the motor.

**Signal analysis methods for rotor fault analysis.** Various signal analysis methods are used to determine rotor faults.

***Motor Current Signal Analysis (MCSA).*** Broken or damaged rotor bars create harmonic components in the motor current. Side frequencies $f_s \pm 2\times f_r$ (harmonics with rotor slip frequency added to mains frequency) are observed. Increased asymmetry and imbalances are determined in the current spectrum during a rotor fault. MCSA allows non-contact rotor fault detection and is particularly effective for cage bar breaks.

***Vibration analysis.*** As a result of rotor imbalance and eccentricity, vibrations in the motor increase. With FFT, harmonics are observed in the vibration spectrum of the rotor rotation frequency. In cases of eccentricity, low-frequency vibration peaks and unusual harmonics appear.

***Spectral analysis of rotor faults.*** Rotor faults produce characteristic harmonics corresponding to the rotation frequency. The main frequencies generated in the spectrum during rotor bar failure are:

$f_s \pm f_r$ - rotor slip frequency, $2\times f_r$ - frequency components corresponding to bar breaks.

**Temperature monitoring.** As a result of rotor imbalance and mechanical problems, the rotor begins to heat up. The temperature of the rotor is monitored with thermosensors and overheating is detected at an early stage.

**Noise analysis.** Rotor faults generate noise signals. High-frequency signals are collected and analyzed with the help of noise sensors.

**Table 6.** Analysis of rotor fault signals

| Failure | Character of signals | Diagnostic method |
|---|---|---|
| Rotor bar breakage | Harmonics at $f_s \pm 2\times f_r$ in the current spectrum | MCSA (Motor Current Signature Analysis) and vibration analysis |
| Eccentricity | Harmonics and vibration peaks at rotational frequency | Vibration analysis |
| Rotor imbalance | High-amplitude vibration and mechanical stress | FFT (Fast Fourier Transform) and temperature monitoring |
| Mechanical jamming (locking) | Excessive vibration and increased heating | Vibration and temperature analysis |

Various measures can be taken to prevent rotor faults: *Rotor balance inspections* - regularly checking the rotor to prevent unbalanced operation of the motor. *Regular vibration analysis* - monitoring vibration levels to detect potential issues at an early stage. *Temperature monitoring* - preventing excessive overheating of the rotor. *Periodic inspection of the rotor cage* - identifying bar breakages at an early stage.

Early detection of rotor faults in asynchronous motors plays a crucial role in enhancing motor reliability and reducing the risk of failures. The signal analysis methods mentioned above are essential tools for monitoring rotor condition and identifying potential problems.

## 5. Conclusions

Many techniques and methodologies developed for the diagnostic evaluation of electric motors allow for the modelling of potential faults under various motor technical conditions. However, there has been limited research on comprehensive solutions to the investigated faults, which is critical for the development of new motor designs and ensuring uninterrupted operation during their service life.

To enhance traditional diagnostic methods through "soft computing", it is necessary to determine and predict the motor's condition from its equivalent circuit and apply specialized approaches for different types of faults. The development of new modes of transportation further emphasizes the need for reliable operation of electric motors and the timely evaluation of their technical condition under current operating conditions.

The operational challenges of traction asynchronous motors, particularly those used in transportation, increase the probability of faults. Therefore, the methods explored in this study for fault detection through signal analysis can serve as key tools in achieving more precise results when applied comprehensively to traction motors. The research will play an important role in selecting informative parameters for future "intelligent diagnostic systems" for traction motors, contributing to the effective monitoring and maintenance of their performance.

## Abbreviations

DFT : Discrete Fourier Transform
DTFT : Discrete Time Fourier Transform
FFT : Fast Fourier Transform
TFR : Time-Frequency Representation
MCSA : Motor Current Signal Analysis
PSD : Power Spectral Density

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