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Analysis of the correlation between vibrations and the number of shorted turns in the stator winding of a squirrel-cage induction machine

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Abstract: This paper presents a method of diagnosing a squirrel-cage induction motor based on the results of machine vibration analysis. The paper considers a fault involving an interturn short circuit in the winding of all phases of the stator. The waveforms of the diagnostic signals were recorded for selected configurations of winding shorts during steady state operation of the motor under constant torque load. In the next step of the study, wavelet packet decomposition was used to analyze the recorded waveforms of the vibration signals. The study focused on determining the correlation between the wavelet analysis results and the number of shorted turns. In addition, the effect of the wavelet used in the wavelet packet analysis on the correlation results was compared. As a result, a method was developed to detect shorted turns in the stator winding of an induction motor based on the results of wavelet packet analysis of the motor vibration.

Key words: correlation, diagnostic method, induction machine, shorted turns, vibrations, wavelet packet analysis

1. Introduction

The diminishing natural resources of the planet, which are vital for industrial processes, highlight the need for greater focus on extending the operational lifespan of machinery. Technological advancement plays a pivotal role in this endeavor, as it can markedly reduce production costs and enhance the efficiency of machinery. This is closely intertwined with the crucial aspect of equipment diagnostics.

Induction machines are one of the most commonly utilized devices in industry [18], employed in a multitude of sectors, including the production of belts, fans and compressors [1, 2]. As has been documented in numerous publications, some of the most common forms of damage observed in induction machines pertain to the stator winding area. The most common cause of stator damage in induction machines is the formation of coil short circuits [3, 6, 7]. In contrast to multiphase short circuits or ground faults, the impact of a short circuit in a single phase of the motor is often less perceptible. Furthermore, despite the occurrence of such a short circuit, the machine may continue to operate. A short circuit has a direct impact on the

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electromagnetic circuit of the machine, resulting in phenomena such as rotor misalignment or increased vibration. This can result in the destabilization of the entire system, which, in the long term, may result in permanent damage to the machine. Consequently, there is frequently an increase in mechanical and thermal loads, which further contribute to the deterioration of components. This can result in the premature failure of elements such as bearings, windings, and other critical components. Furthermore, the regular occurrence of short circuits can also result in a reduction of the lifespan of the machine, necessitating more frequent repairs and maintenance procedures, which in turn give rise to additional costs.

In the field of electrical machine diagnostics, a plethora of diagnostic methods exist, including thermal imaging analysis [8, 9], partial discharge analysis (PDA) [10, 11], electrical signature analysis (ESA) [12, 13], motor current signature analysis (MCSA) [5, 14–16], and vibro-acoustic analysis. Thermal imaging analysis employs the use of thermal cameras to identify any temperature anomalies, which may indicate the presence of an overload or damage to the object in question. Partial discharge analysis is of great importance in the assessment of insulation conditions, particularly in high-voltage motors, where it is able to identify potential points of insulation failure. Concurrently, the examination of electrical signals through techniques such as ESA or MCSA entails the assessment of parameters including voltage and current, with the objective of identifying both electrical irregularities such as short circuits or supply asymmetries, and mechanical faults. As previously stated, one of the numerous diagnostic techniques for induction machines is the vibration-acoustic method, which employs a vibration signal [4]. This method encompasses both vibration and acoustic analysis. Vibration analysis is a process that entails the measurement and assessment of the vibrations produced by a machine with the objective of identifying potential issues such as imbalance or bearing faults. In contrast, acoustic analysis entails the monitoring of the sounds generated by the machine, which can potentially reveal additional types of fault, such as those pertaining to gear system issues. Although the vibroacoustic method has been successfully employed to detect mechanical damage in the structural components of induction motors, this article proposes its utilization for the identification of damage in the electrical circuitry of the machine. The vibration-acoustic method is distinguished by its non-invasive nature, as it does not necessitate the cessation of machine operation during diagnosis. This quality renders it particularly advantageous for the continuous operation of essential machinery. Furthermore, the straightforwardness of the connection process facilitates straightforward implementation. The early detection of faults is beneficial in preventing unexpected breakdowns and costly periods of downtime. The high sensitivity of this method to changes in machine conditions renders it a reliable tool for predictive maintenance strategies, thereby enabling optimized maintenance and extended equipment life.

Nevertheless, the obtained time performance results are entirely illegible and necessitate sophisticated analysis to be accurately interpreted. In order to address this challenge, the authors of this paper employ the technique of Wavelet Packet Decomposition as a means of analyzing the vibration signal waveform. Wavelet Packet Decomposition is a modern technique that decomposes a signal into various frequency components, thereby significantly enhancing analytical capabilities for the detection and interpretation of subtle anomalies.

The results of the wavelet analysis were correlated with the number of shorted turns in induction machines, thus enabling a precise correlation between vibration data and the actual defects. This approach not only enhances the clarity and interpretability of the data but also facilitates the early detection of potential faults. By decomposing the signal into its constituent

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frequency components, this method permits the identification of anomalies that may be indicative of early-stage failure. As a result, this approach offers a comprehensive framework for diagnosing intricate issues in induction machines.

2. Experimental procedure for vibration data acquisition

A measurement system was designed and constructed for the purpose of recording machine vibration waveforms. A three-axis SVANTEK SV150 accelerometer, coupled with a 958A meter acting as a signal amplifier, was employed for the purpose of recording and archiving the vibration waveforms of the induction motor. The 3SIE100L4B squirrel-cage induction motor, manufactured by Celma Indukta, was selected for testing purposes. In order to facilitate the testing of inter-turn short circuits, the machine was prepared by leading selected turn wires outside the housing. A diagram of the measurement system is provided in Fig. 1 for reference.

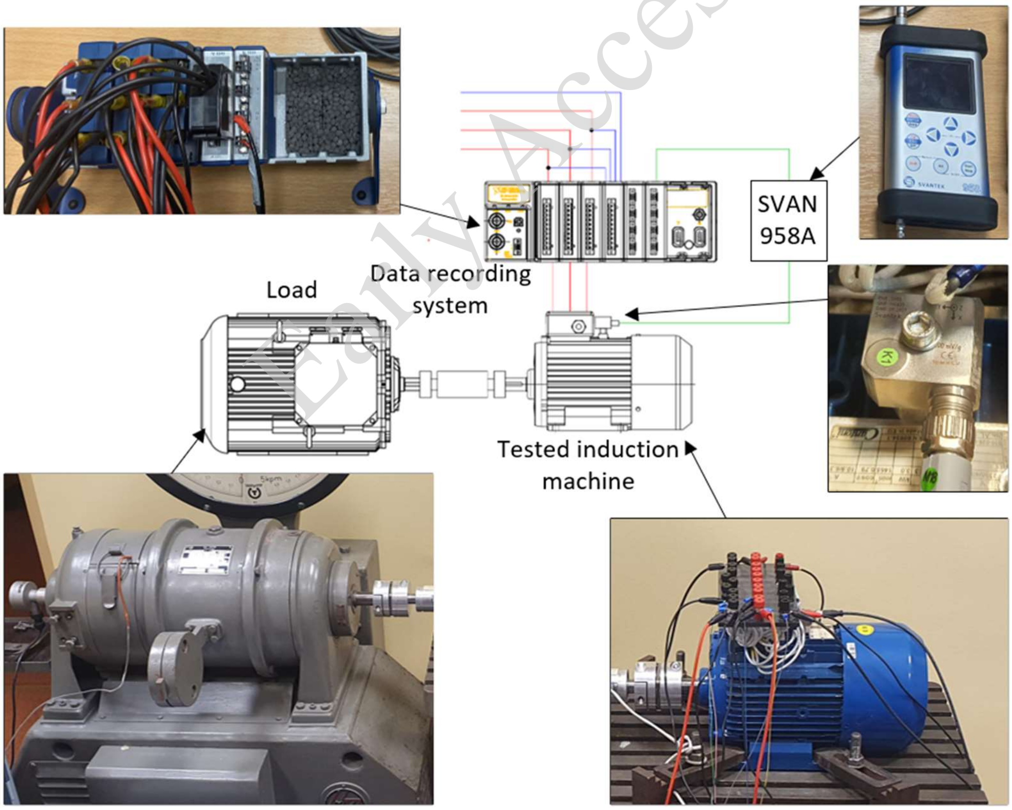

Fig. 1. The configuration of the measurement system

The National Instruments CompactDAQ housing, equipped with a set of measurement cards, was employed for the purpose of recording the waveforms. The measurement

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configuration was managed using the manufacturer's DAQ Express software, while MATLAB was employed for the archiving of measurements on disk and subsequent processing. The vibration transducer employed permitted the utilisation of the machine's vibration acceleration waveform for the subsequent test procedures. In order to facilitate the experimental research, software was developed using the MATLAB environment. The software automates the process of recording and archiving measurement data. Furthermore, the software enables communication with the measurement system, the reading of data from individual measurement card channels, the automatic saving of results to the computer's hard drive, and signal processing, including the scaling of measurement data, the calculation of signal parameters such as the root mean square (RMS) value, the performance of FFT analysis, and the simultaneous visualisation of waveforms for control purposes. Figure 2 presents a flow chart that illustrates the algorithm of the developed software.

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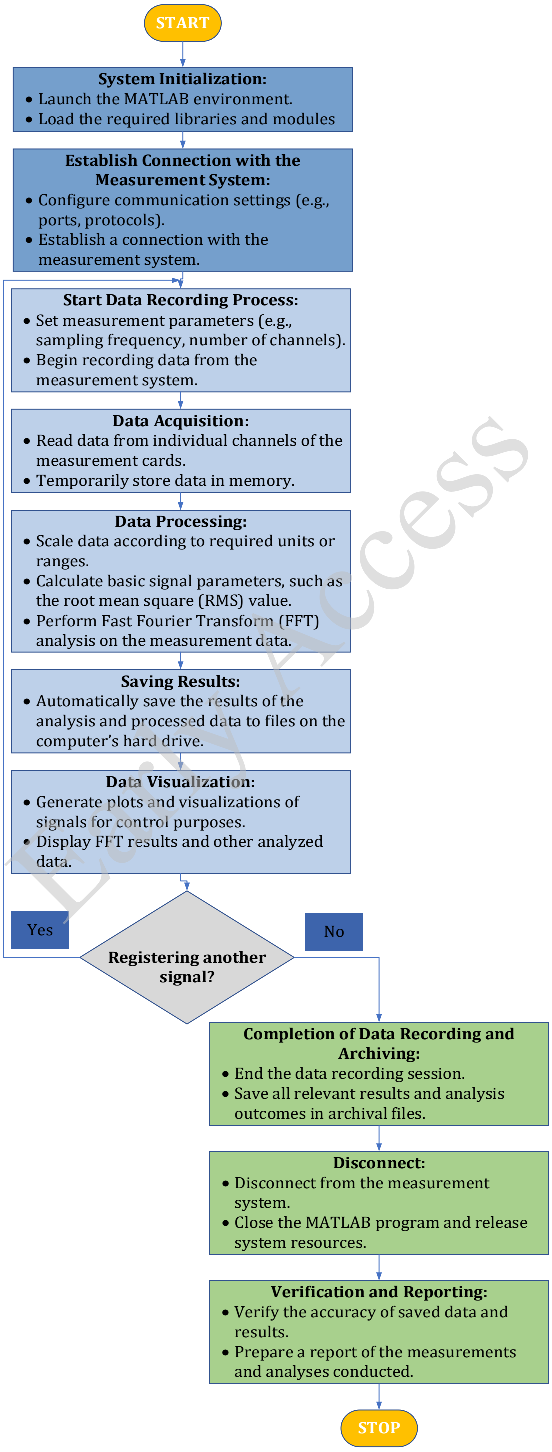

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Fig. 2. The algorithmic approach employed for the measurement

Measurements were performed for specified values of the number of shorted turns, as well as load torque. All possible combinations of parameters are illustrated in Fig. 3. It should be noted that the phases were not distinguished during the measurements, which may have introduced some degree of inconsistency.

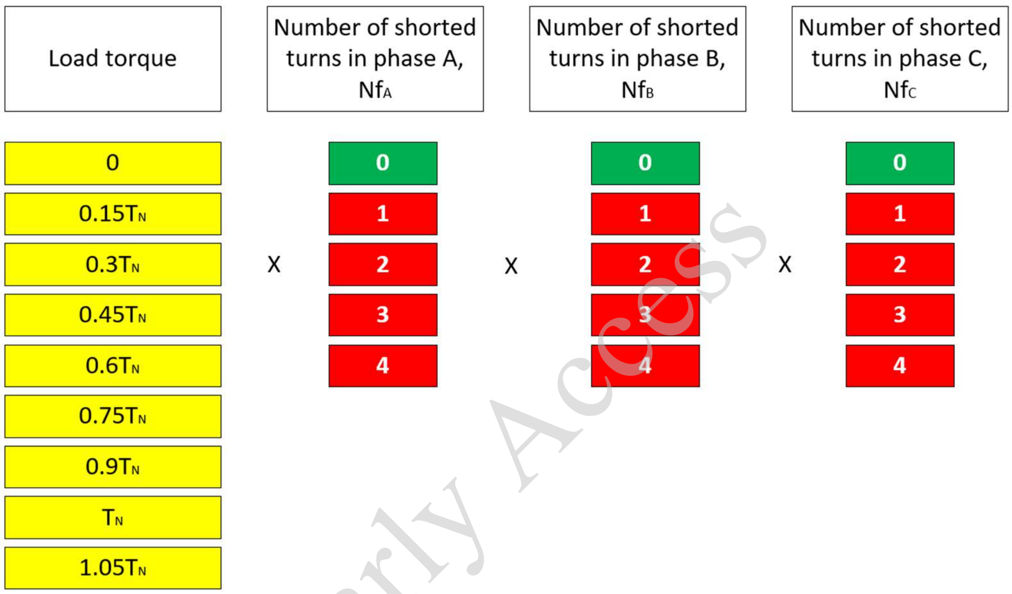

Fig. 3. The combination of measurements

In total, 315 distinct tests were conducted. The selected measurement results of the machine vibration signal waveforms are presented in Fig. 4. The figure illustrates the waveform of a healthy machine and a machine with four shorted turns in the stator winding. In both cases, the machine was operated at its rated torque.

In order to provide greater precision in the observation of the characteristics, Fig. 5 depicts the same graph for a more concise period of time.

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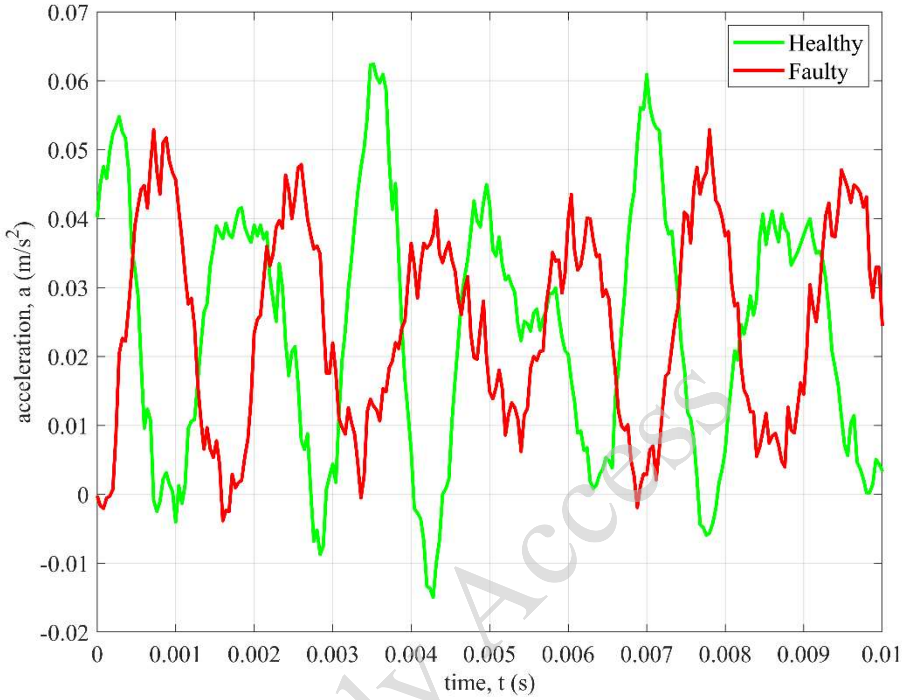

Fig. 4. The waveforms of vibration acceleration for a healthy and a damaged machine, with a time scale from 0 to 0.01 seconds

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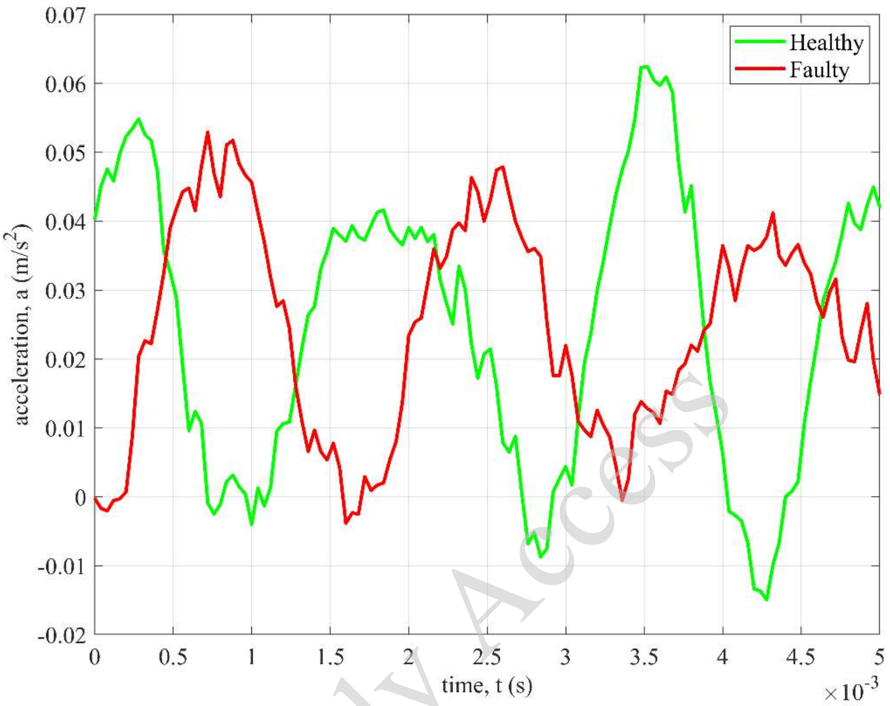

Fig. 5. The waveform of vibration acceleration for a healthy and damaged machine, with a temporal duration of 0 to 0.005 seconds

It can be observed that the vibration patterns of a healthy and damaged machine exhibit distinct frequency characteristics. Concurrently, these waveforms are characterised by high non-stationarity. Accordingly, an appropriate analytical methodology must be employed for the examination of such signals. One such method is wavelet packet analysis.

3. Wavelet packet decomposition for vibration signal analysis

A wavelet transform is employed for the analysis of a signal through the utilisation of Packet Wavelet Analysis. Wavelet analysis is a mathematical method that enables the decomposition of signals into components at various scales, thereby facilitating the simultaneous analysis of local features in both the time and frequency domains. The wavelet transform is a more flexible tool than the Fourier transform, making it particularly effective for examining nonlinear, discontinuous, and dynamically changing signals.

Wavelet analysis significantly enhances the ability to detect short circuits in the stator winding at an early stage of fault development. By enabling the simultaneous examination of local signal features in both the time and frequency domains, this method allows for the

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identification of subtle changes in signal structure that are undetectable using traditional techniques. The application of wavelet transformation in vibration studies enables the precise detection of discontinuities and transient events characteristic of the initial stages of faults.

The point at which short circuits become visible in the vibration signal depends on the severity of the fault and the sensitivity of the analytical tools employed. Wavelet transformation, combined with statistical methods and artificial intelligence techniques, facilitates earlier detection of signal changes. This approach ensures more effective diagnosis, even in cases where signal differences are minimal, providing critical insights for machine condition monitoring and failure prevention.

From a mathematical perspective, wavelet analysis employs the use of functions designated as wavelets, which possess a finite duration and can be scaled and shifted to accurately represent the various components of a signal. This process entails the utilisation of the discrete wavelet transform (DWT), which decomposes the signal into details (high-frequency components) and approximations (low-frequency components). This is accomplished through the utilisation of low-pass and high-pass filters. The low-pass filter permits the passage of low frequencies, thereby generating the approximation signal, whereas the high-pass filter allows high frequencies to pass through, thus creating the detail signal. This technique enables the efficient analysis and interpretation of complex vibration patterns, the detection of transient events, and the reduction of noise, which is of great importance in engineering monitoring and diagnostics. More information on wavelet analysis can be found in the paper [17].

The available collection of wavelets is both comprehensive and extensive, comprising a vast array of diverse and sophisticated forms. Wavelets are classified according to a principle known as the "mother wavelet," which is employed to ascertain the fundamental structure of the group. The most commonly utilised wavelets can be categorised into the following groups: the Daubechies, Coiflet, Symlet, biorthogonal, and other wavelets. In this article, the authors present the results for three distinct Daubechies wavelets: Daubechies 3, 5, and 7 (db3, db5, and db7, respectively). Daubechies wavelets were selected for this study due to their exceptional properties that make them highly suitable for signal processing and analysis. Specifically, Daubechies wavelets are known for their compact support and orthogonality, which enable efficient computation and precise localization in both time and frequency domains. Their ability to represent signals with sharp discontinuities and to capture intricate details makes them ideal for analyzing complex datasets. Additionally, the different orders of Daubechies wavelets (db3, db5, db7) offer varying degrees of smoothness and vanishing moments, providing flexibility in balancing signal approximation and detail preservation. This selection allows for a comprehensive analysis by leveraging the strengths of each wavelet order to capture a wide range of signal characteristics. The waveforms for all the applied wavelets are presented in Fig. 6, while the parameters are shown in Fig. 7.

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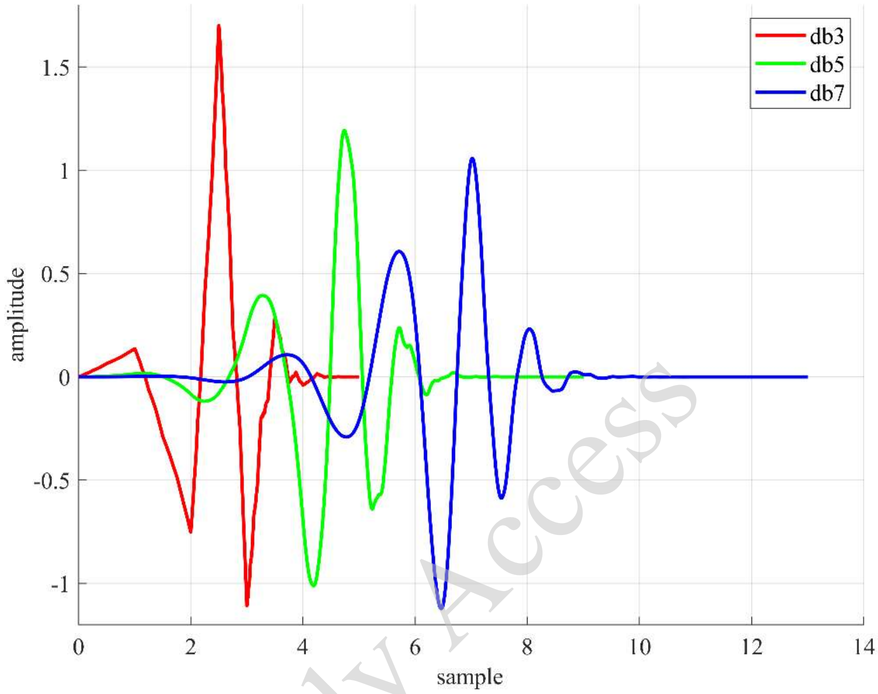

Fig. 6. The Daubechies wavelet waveforms are presented in red (db3), green (db5), and blue (db7)

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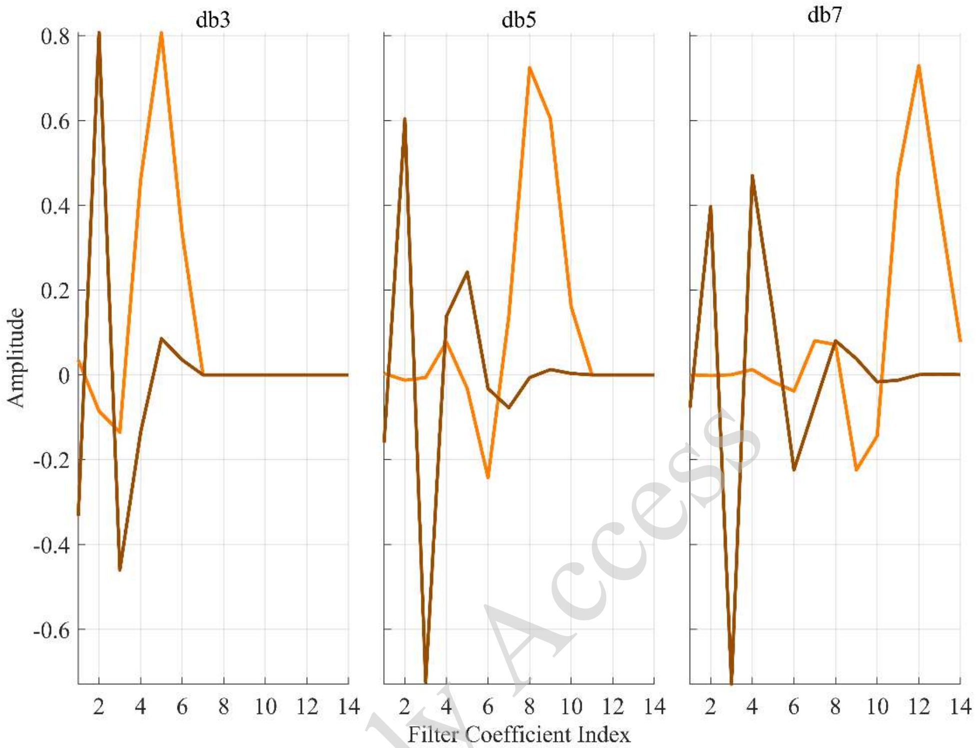

Fig. 7. The parameters of the high-pass filter (brown) and low-pass filter (orange) for db3, db5, and db7

The filter coefficients for the wavelet db3, db5 and db7 are provided in Table 1.

Table 1. Values of wavelet coefficient

Coefficient	db3	db5	db7
h0	0.3326706	0.0033357	0.0003537
h1	0.8068915	–0.0125808	–0.0018016
h2	0.4598775	–0.0062415	0.0004296
h3	–0.1350110	0.0775715	0.0125510
h4	–0.0854413	–0.0322449	–0.0165745
h5	0.0352263	–0.2422949	–0.0380299
h6		0.1384281	0.0806126
h7		0.7243085	0.0713092
h8		0.6038293	–0.2240362

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h9		0.1601024	–0.1439060
h10			0.4697823
h11			0.7291321
h12			0.3965393
h13			0.0778521

In this study, the Daubechies wavelets db3, db5, and db7 were selected for the analysis of vibration signals from induction machines due to their excellent time-frequency localisation properties, which are essential for the detection of transient and non-stationary faults. The db3 wavelet is effective in capturing subtle changes and transient events within the signal, thereby providing a clear and detailed analysis of the machine's operational conditions. The combination of simplicity and effectiveness makes it an appropriate selection for both computational efficiency and accurate fault detection. Furthermore, the established history of success in machine diagnostics guarantees dependability and resilience in the analysis. This selection enhances the diagnostic procedure, facilitating more expedient identification of faults and enabling more precise maintenance planning.

Given the non-stationary nature of the machine's vibration waveforms, it was determined that Packet Wavelet Analysis would be the most appropriate analytical technique to employ. This analysis entails the filtering of the input signal into its approximation and detail. This is accomplished through the utilisation of low-pass and high-pass filters, respectively. The distinction between this and the discrete wavelet transform (DWT) lies in the subsequent step of the wavelet packet decomposition (WPD) analysis, wherein both the approximation and detail are subjected to filtration. As a result, the analysed signal is decomposed into a set of approximations and details. The complete process can be represented in the form of a decomposition tree, as illustrated in Fig. 8.

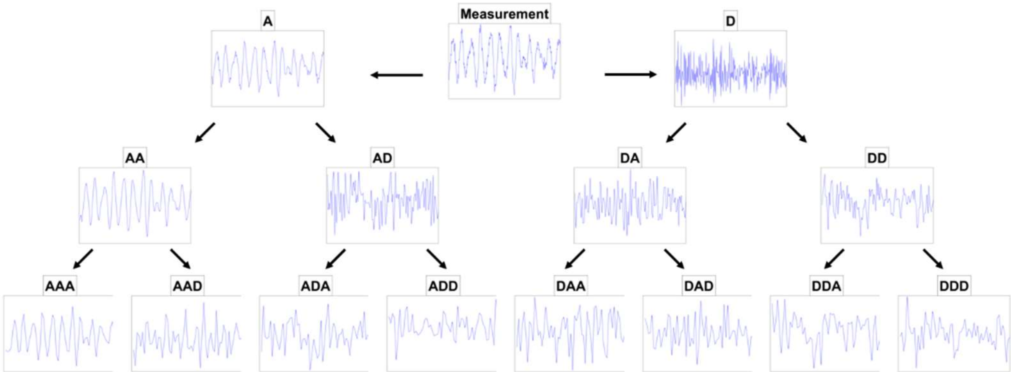

Fig. 8. The decomposition tree in wavelet packet analysis

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The subsequent stage of the analysis involved the calculation of the energy associated with the approximations and details present in the nodes of the decomposition tree at the lowest level. The calculation of the signal's energy in a wavelet decomposition tree necessitates an analysis of the energy distribution across the various frequency bands represented by the wavelet coefficients at different decomposition levels. By summing the squares of the wavelet coefficients at each level, the energy of the signal can be quantified, thereby providing insight into the signal's characteristics and the presence of anomalies. The aforementioned energy calculation is instrumental in identifying significant components and transient events, which are frequently indicative of faults or alterations in the machine's operational state. For each node n in the wavelet packet tree, calculate the energy E_n by summing the squares of its coefficients:

$$E_n = \sum_{i=1}^{N_n} {c_{n,i}}^2, \tag{1}$$

where $c_{n,i}$ are the coefficients for node n and N_n is the number of coefficients in node n.

4. Selected results of diagnostic signal analysis

The vibration waveforms of a healthy machine and a damaged machine were selected for Packet Wavelet Analysis for 9 load torque values, i.e., from no-load to a load of 105% of the rated torque. For the tests on the faulty machine, the waveforms of the vibrations were considered for the number of shorted turns ranging from 1 to 4 for all wavelets tested. Using the above formula, the energy for each node was calculated and the results are presented sequentially in Fig. 9 for db3, Fig. 10 for db5, and Fig. 11 for db7.

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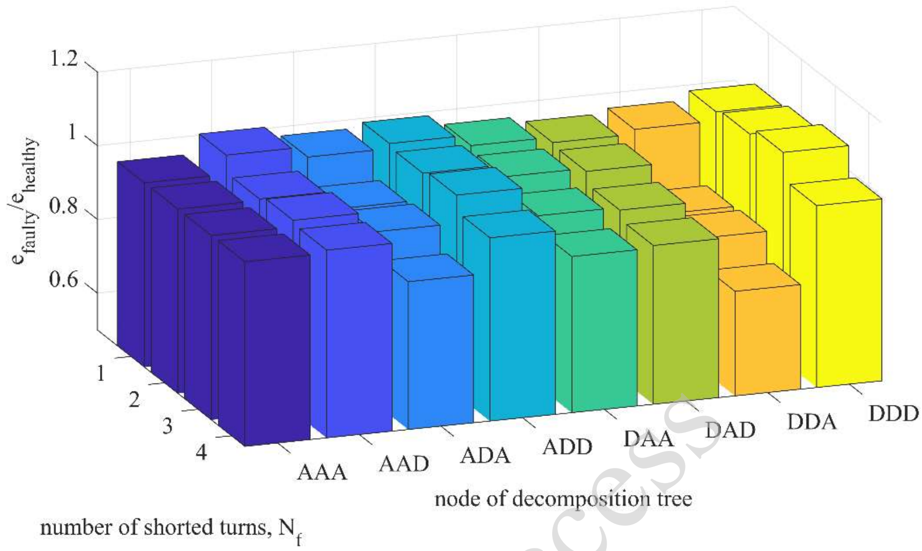

Fig. 9. Results of Packet Wavelet Analysis of the vibration signal using the db3 wavelet

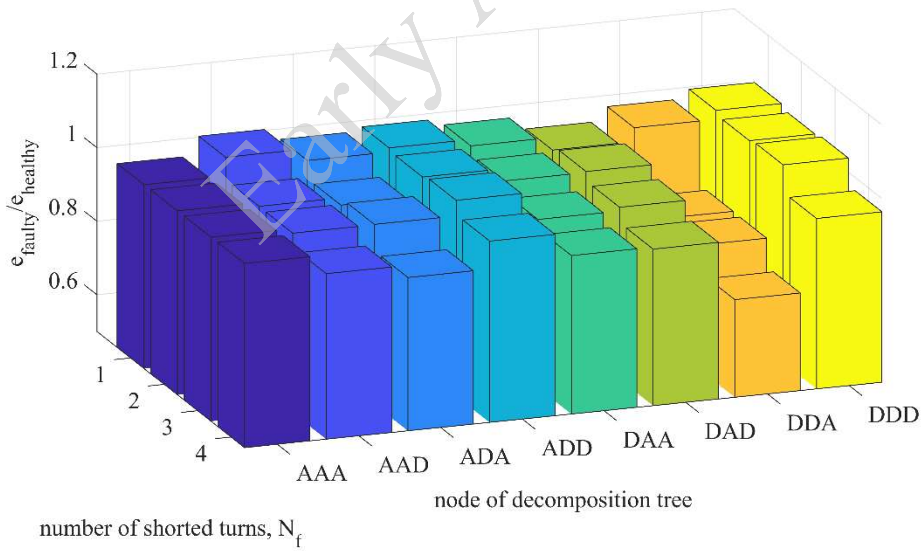

Fig. 10. Results of Packet Wavelet Analysis of the vibration signal using the db5 wavelet

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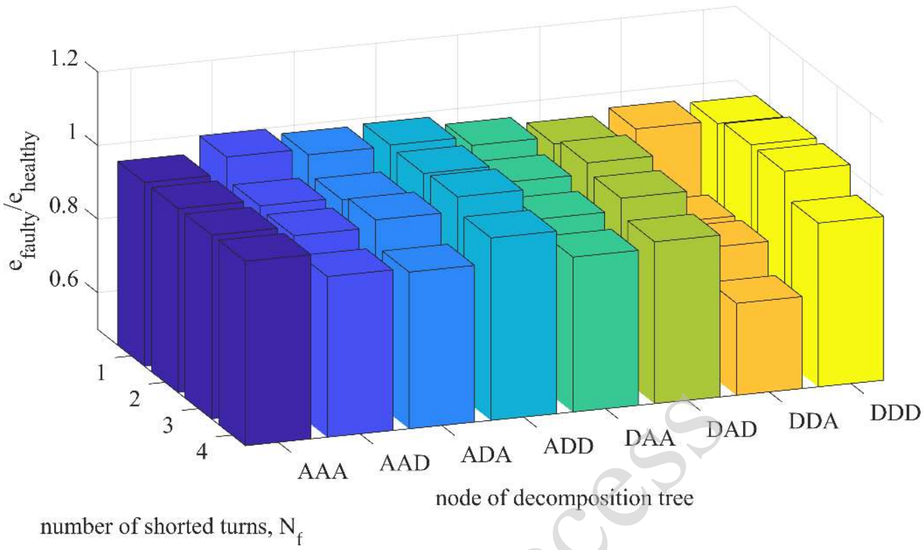

Fig. 11. Results of Packet Wavelet Analysis of the vibration signal using the db7 wavelet

The evaluation of the charts displayed above is rendered challenging by their substantial similarity. Accordingly, the decision was taken to calculate the mean of all the values and to determine the standard deviations. The results of these calculations are presented in Fig. 12.

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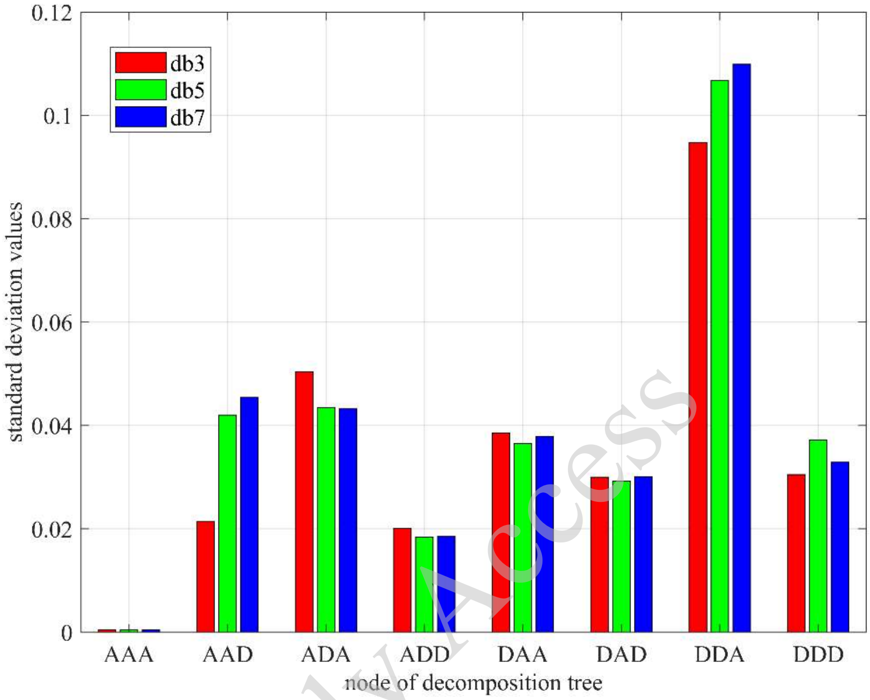

Fig. 12. The standard deviation values for the wavelets db3, db5, and db7

As can be observed, the greatest standard deviation is evident in the DDA node. The results demonstrate that the various wavelets under examination exhibit comparable outcomes. It is therefore evident that the deployment of a higher-order wavelet is not a viable proposition in this particular context.

The results of the Packet Wavelet Analysis are shown in Fig. 13. The healthy machine is coloured green, and the faulty machine is coloured red. The figure shows the tendency that as the number of shorted turns increases, the percentage of energy transferred for the obtained ADA and DDA increases. This phenomenon would be almost impossible to observe with a smaller number of cases.

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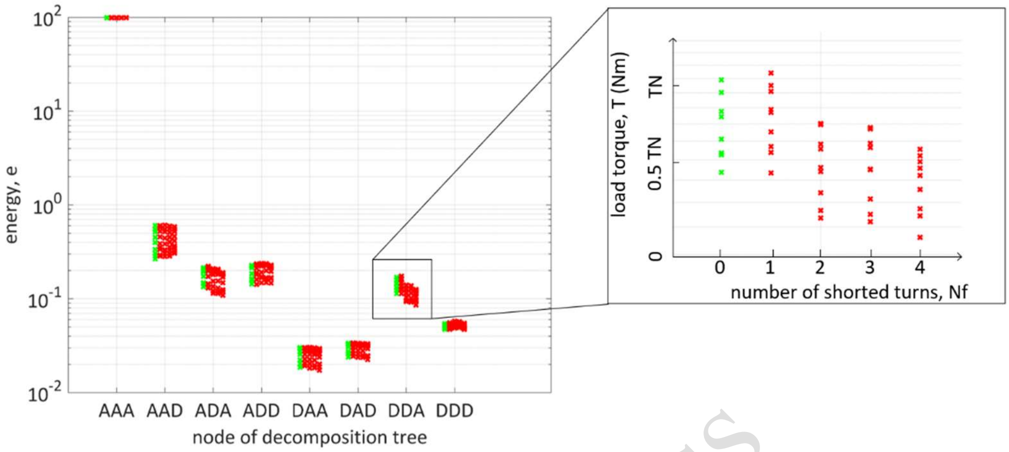

(a) (b)

Fig. 13. The waveforms of vibration acceleration for a healthy and faulty machine, presented at two different resolutions: (a) low resolution and (b) detail

Subsequent research was conducted with the objective of identifying the relationship between machine vibrations and the number of short-circuited turns in its stator winding. To achieve this, the correlation between the two aforementioned quantities was calculated using the following methodology. The Pearson correlation coefficient was selected for this purpose, as it is widely used in statistical analysis to measure the strength and direction of a linear relationship between two variables. Its application in this study allows for a clear evaluation of how changes in the number of short-circuited turns affect the vibration signal, providing valuable insights into the diagnostic potential of vibration analysis. The general form of the Pearson correlation coefficient is presented in Eq. (2)

$$\rho(A,B) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{A_i-\mu_A}{\sigma_A}\right)\left(\frac{B_i-\mu_B}{\sigma_B}\right). \quad (2)$$

In this context, μ_A and σ_A represent the mean and standard deviation of A, while μ_B and σ_B correspond to the mean and standard deviation of B.

The A value represents the energy values for the subsequent nodes of the decomposition tree for the reference signal, whereas the B values pertain to the correlated one. Table 2 illustrates the values of A and B, which are employed in the calculation of the correlation in a healthy machine between the signal measured at $T = 0$ and $T = T_N$.

Table 2. Example values for A and B

Node of decomposition tree	*A*	*B*
AAA	99.1590	98.8261

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AAD	0.3491	0.5534
ADA	0.1196	0.1869
ADD	0.1646	0.2252
DAA	0.0292	0.0188
DAD	0.0331	0.0243
DDA	0.0944	0.1158
DDD	0.0510	0.0471

A correlation matrix was obtained by calculating the correlation between all measured waveforms for a specific machine fault condition and a variable load torque. The matrix for a healthy machine and single-phase faults is depicted in Fig. 14 as a plane.

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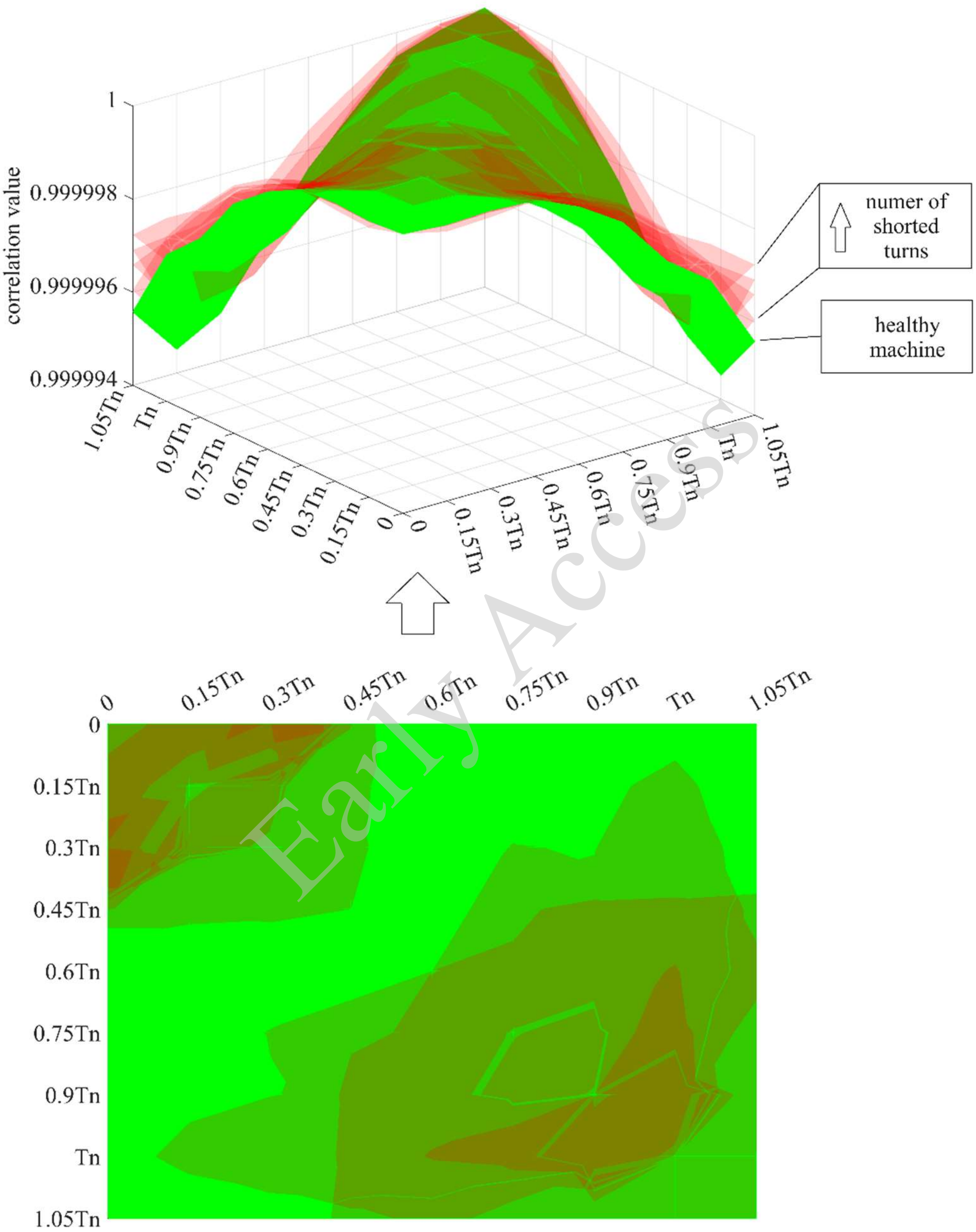

Fig. 14. Correlation plane, three-dimensional view, and bottom projection

The correlation results presented in Fig. 14 provide clear evidence of the distinctions between the degrees of damage caused by the machine. In the context of low load torque

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values, the correlation is most tenuous in the case of a healthy machine. Nevertheless, as the load torque increases, a notable correlation becomes evident.

The experiments were repeated, this time utilising the remaining wavelets (db5 and db7), and the results are presented in Fig. 15.

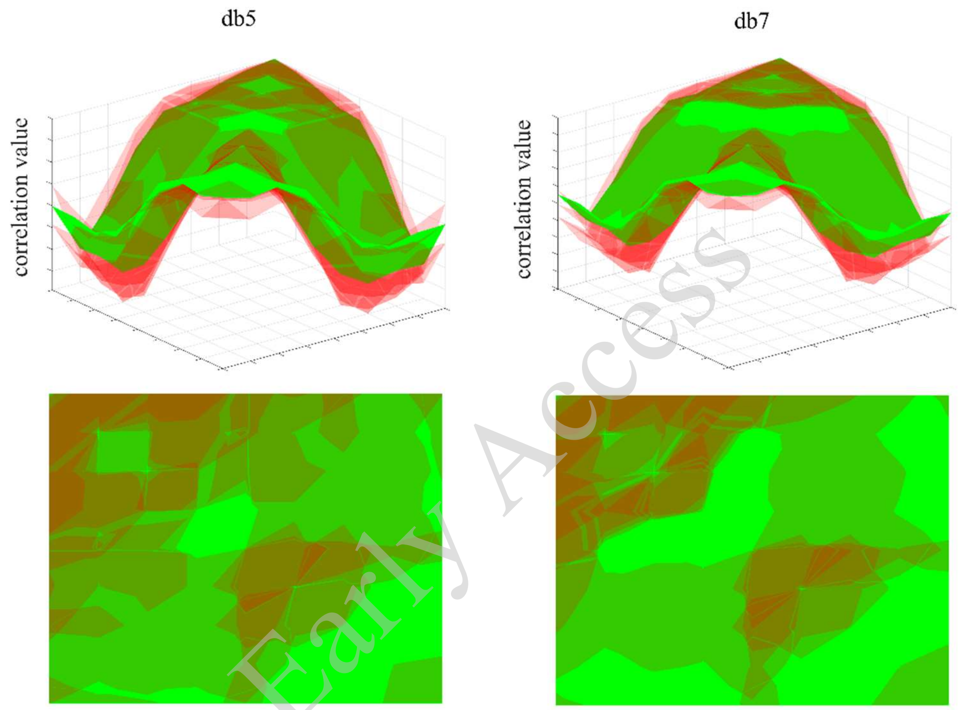

Fig. 15. Graphs for db5 (left) and db7 (right)

While patterns can still be discerned in the plots, the assessment of fault is now considerably more ambiguous. In both cases, for a machine in good working order, the correlations between the plots for high torque values are relatively low, while they are high for low torque values. To facilitate a more detailed analysis, green markers with varying degrees of fill were incorporated, and the results are presented in Fig. 16.

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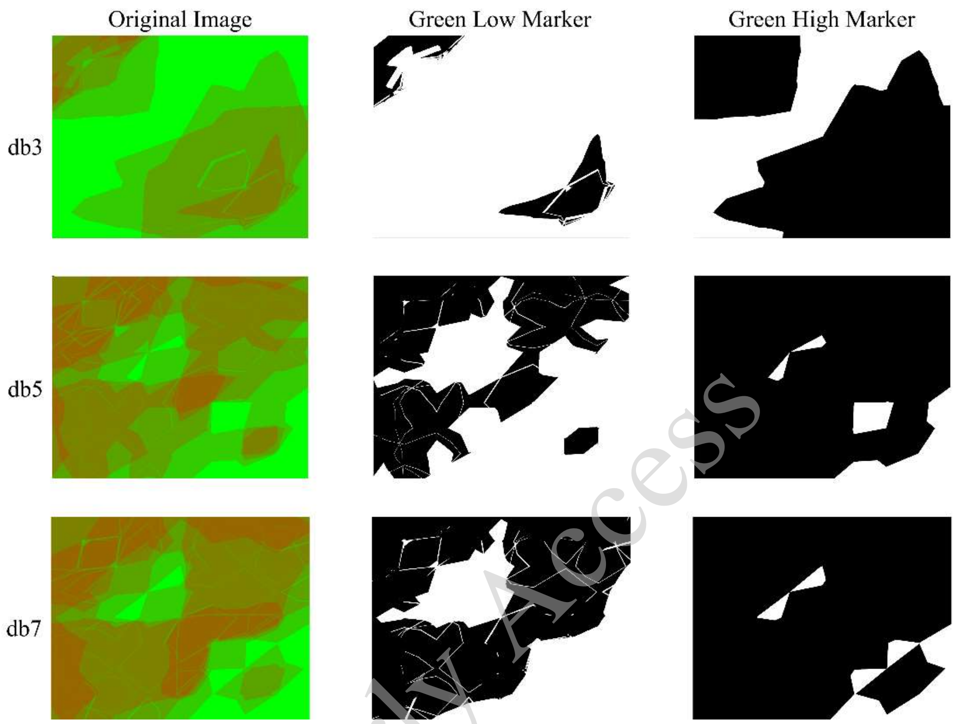

Fig. 16. Plot of markers: original plot (left), low green marker – 60% (centre), high green marker − 80% (right)

Figure 16 provides a more detailed illustration of the reduced correlation observed between the examined signals when the db3 wavelet is employed, particularly in the context of a healthy machine. Conversely, for the db5 and db7 wavelets, regions can be identified where these correlations are higher (for low torque values) and lower (for high torque values).

In the final step, the correlation values were compared by calculating the difference between the values obtained for the healthy machine and the faulty one. The db3 wavelet was employed for the requisite transformations, and the resulting data are presented in Fig. 17.

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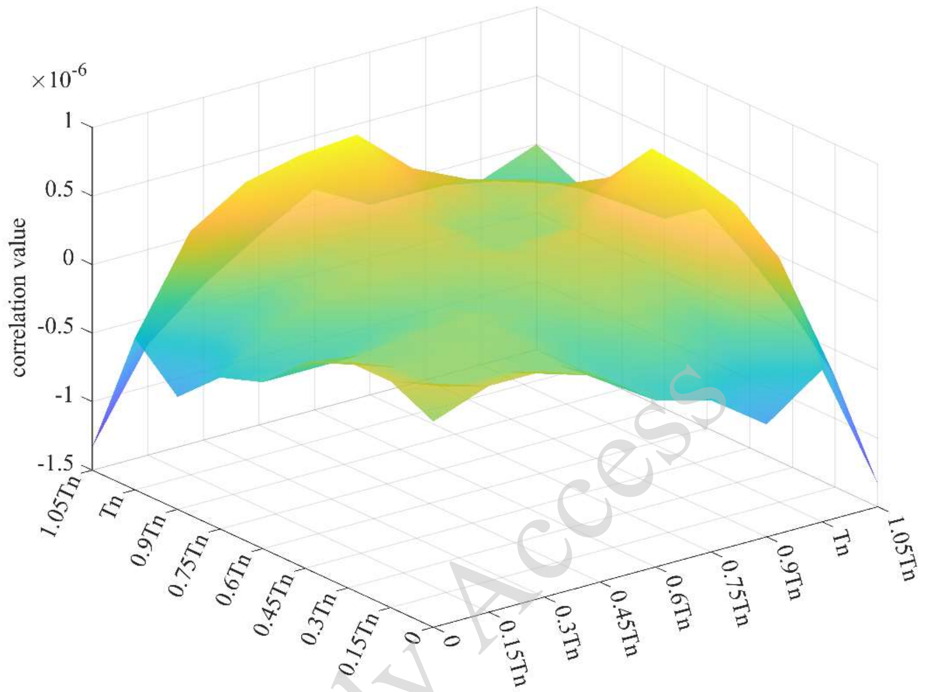

Fig. 17. The differentiation between machines that are in a state of good health and those that are not

The high level of correlation is particularly evident for the points calculated for cases exhibiting high load torques. As demonstrated in the chart above, these areas represent the optimal conditions for observing the correlation, which is essential for achieving optimal results.

5. Conclusions

This paper presents a method for diagnosing interturn short circuits in different phases of the stator winding of a squirrel-cage induction machine by analysing its vibrations. A dedicated measurement system was developed for the study, which allowed the simulation of faults in all phases of the machine and the adjustment of the torque. The resulting data from these simulations were subjected to Packet Wavelet Analysis using the third, fifth and seventh Daubechies wavelets. The results clearly show that this analysis is crucial for interpreting aperiodic waveforms, such as the vibration accelerations recorded.

The energy of the derived waveforms was then calculated. By comparing the energy values under different scenarios, clear trends emerged, indicating their potential application in diagnostic techniques. The next step was to calculate the correlation between the previously obtained energy characteristics under different load torques, with the results presented as a

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three-dimensional surface plot. By comparing the surfaces representing a healthy machine with those of a machine with varying degrees of failure, characteristic points were identified, revealing trends that help to assess the condition of the machine. To improve visualisation, two-dimensional projections of the graphs were also created, along with colour markers to highlight specific results. Analysis of these visualisations supports the effectiveness of the proposed diagnostic method in identifying faults in squirrel-cage induction machines.

The conclusions drawn in this article suggest the need for further research to extend these findings, in particular by analysing a wider range of cases. In particular, the development of a classification method based on machine learning that exploits the observed dependencies is recommended. The described method, which combines wavelet analysis and correlation, could also be applied to the diagnosis of other types of rotating machinery and different fault conditions. In conclusion, the vibration-based diagnostic approach for squirrel-cage induction machines proposed in this article shows promise but requires further research to fully validate its industrial application.

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