Data Acquisition and Signal Analysis from Measured Motor Currents for Defect Detection in Electromechanical Drive Systems

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Abstract

This paper presents the development of a diagnostic method which uses the measurement of motor currents in order to detect defects in electromechanical systems. It focusses on two main topics: the acquisition of experimental data, and the development of the diagnostic method. The data acquisition was crucial for the successful development of a dedicated signal analysis method. For this purpose, a test rig for generating experimental training data was created. The rig provides the ability to simulate a wide range of defects experimentally. Different types of artificial defects, such as bearing damage or misalignments, were used; these are described in detail in the second section of the paper. The experimental data was obtained under varying operational conditions. Using all possible settings of operational parameters for data generation would mean excessive experimental time and effort. Therefore, a special approach using the theory of "Design of Experiments" was applied. By using a fractional factorial design based on orthogonal arrays, the number of experiments could be reduced significantly. Details of this approach are given in the third section. The main ideas of the classification algorithm, including some of the results, are summarized in the fourth section. A special method using a combination of Principal Component Analysis and Linear Discriminant Analysis was designed for the correct detection of damage or misalignments. With this method, a successful classification of the systems' health state could be obtained.

1. Introduction

Electric motors are usually inexpensive in comparison with the equipment of the powered process (e.g. a conveying system, a machine tool, or an assembly line). This is especially true for small engines with a power consumption below 1 kW. The use of additional sensors for such a motor increases the price of the component significantly. Therefore, such an approach to defect detection seems practically unfeasible in many cases. That is why monitoring the health conditions of electric motors is uncommon for industrial applications. However, in the case of a motor standstill, a stop of the entire process, for example a production line, may be required. In such a case, the monetary cost is usually significant. The problem may be prevented by collecting information about the motor condition and the dependent process from the motor's internal physical quantities. Much research has been done on the development of methods for condition monitoring using motor currents. Stack, Habetler, and Harley (2004), for example, focus on categorizing bearing faults as either single-point defects or generalized roughness; they describe the detection fault signatures by investigating machine vibration and shaft current. Widodo, Yang, Gu, and Choi (2009) apply discrete wavelet transform to transient current signals, followed by a component analysis as well as a support-vector-machine-based classification. Tran, AlThobiani, Ball, and Choi (2013) use a decomposition of current signals via a Fourier-Bessel expansion and classify the features with a special class of neural networks. Zhen, Wang, Gu, and Ball (2013) present the application of so-called "dynamic time warping", a special time-domain-based method, to motor current signals to detect common faults. In all these contributions, application-specific features are considered. However, in contrast to previous research, a generic approach to feature extraction using phasor description of motor current signals is pursued in the present paper (see Section 4).

For synchronous motors, the electric phase currents are measured to enable correct control of the motor operation. Hence, all currents are already known; they could thus be used to determine the current motor condition and its trend over time, offering the possibility of detecting defects with minimum resources by reusing these currents and without requiring additional sensors. The proposed method uses the motor's phase currents for the detection of faults and damaged components, such as e.g. rolling bearings in the electric motor itself or in the powered equipment.

To develop this diagnostic method, experimental data was required. The generation of suitable experimental data is a complex task, especially when the investigation focusses not on one specific type of damage, but rather on different types of defects in different components, as well as on combinations of such defects. The long-term aim is to integrate the proposed method into drive systems by using existing current measurements within frequency inverters in industrial applications. Therefore, systematically generated data of relevant damage and operational conditions must be available to develop the required diagnostic methods.

This paper will describe the necessary test setup, the design of experiments, and the development of the algorithms to detect defects in commonly used machine components, such as rolling bearings and gears. It will focus especially on the creation of a sophisticated database, which is essential for the development of the diagnostic method.

2. DEFECT SIMULATION VIA TEST SETUP

To generate experimental data, a specific test rig was developed and constructed. The test rig is a modular system to ensure flexible use of different artificial defects (or inaccuracies). A defect is a "non-fulfilment of a requirement related to an intended or specified use" (DIN EN ISO 9000, 2005). In this paper, defects are divided into two groups: damage and faults. Damage is constituted by defects which arise in a technical system after a period of time. They appear as a change in the shape of one or more components, e.g. fractures or pitting in gear wheels or bearings. The term fault is used for any defect that exists in a technical system from the start, such as assembly defects, as well as for any reversible defect which is forcibly introduced by the operational conditions, such as shaft deflection under high loads.

The basic components of the test rig are the drive motor, a torque-measuring shaft, the test modules, and a load motor (see Figure 1). Different types of faults and damage could be generated using the test modules. An implementation of several defects in combination was also possible. The detection of defects was carried out using measured motor current signals from the test data.

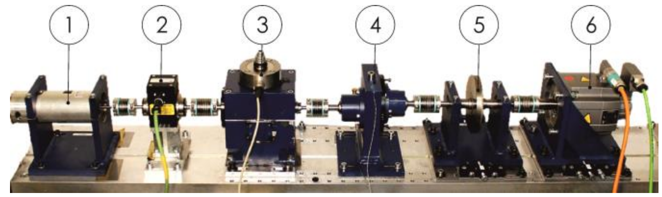


Figure 1. Modular test rig for generation of experimental data: drive motor (1), torque-measuring shaft (2), rolling bearing module (3), gear module (4), flywheel (5), load motor (6)

2.1. Test Rig

As described above, the test rig consists of different modules. The motor is a 425 W Permanent Magnet Synchronous Motor (PMSM) and is operated by an inverter with a switching frequency of 16 kHz. This inverter has a sensorless closed-loop structure. The motor phase currents were measured by a current transducer of the type MCTS 60/ IT60-S with a conversion ratio of 1:600. The signals are filtered by a 12.5 kHz low-pass filter and converted from an analogue to a digital signal with a sampling rate of 100 kHz. These devices were used for proof-of-concept instead of the inverter's internal ammeters because of their higher sampling rate and accuracy.

In industry, power inverters with pulse-width modulation are commonly used for driving synchronous motors. Therefore, all experiments described in this paper were performed using an industrial power inverter, even though the motor current signals show significant noise because of the disturbances from the pulse-width modulation. In previous experiments, better defect detection results were obtained with an alternatively used sine-wave generator (Lessmeier, Piantsop Mbo'o, Coenen, Zimmer, & Hameyer, 2012). Nevertheless, it was determined that it is possible to detect the defects despite noisy signals; thus, the noisy signals were chosen because of the prevalence of power inverters in industry. This practice-oriented selection ensures that an industrial application of the method developed here will be as easy as possible.

To record the operational conditions and to have the possibility of supplementing the diagnosis with additional information, the following parameters were measured: the radial force on the rolling bearings, load torque, rotational speed, surface acceleration of the housing, and the temperatures of both oil and housing.

The torque-measuring shaft has a nominal torque of 2 Nm and an accuracy of ±0.1 % of the nominal torque. It was used to measure and to record the torque synchronously to the motor currents.

The rolling bearing module provides the possibility of using a specifically prepared test bearing under continuously adjustable variable radial loads and shaft tilting. The assembly group consists of an outer and an inner housing. Only the inner housing with additional components is shown in Figure 2. The test bearing (1) is installed in a spherical bearing (2) to allow tilting of the outer ring in relation to the shaft. This tilting is forced by tilted discs (3) and pressure rings (4) on the outer ring of the test bearing. The self-aligning ball bearings (5) compensate force and deflection of the shaft by diverting it into the outer housing. The radial force on the test bearing is generated by tightening a screw between the outer housing and the thread (6). This force is measured and recorded by a load cell. The housing is sealed by radial shaft seals (7) and filled with oil through an inlet (8).

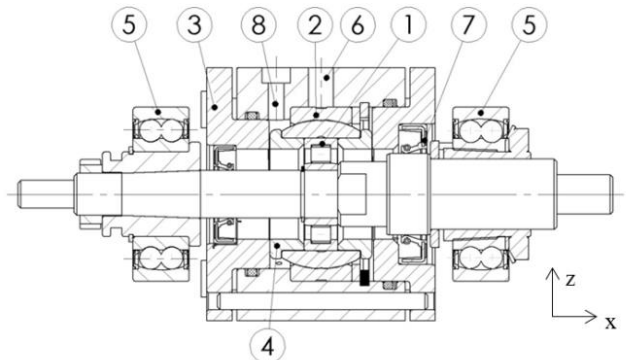


Figure 2. Shaft and inner housing of the rolling bearing module

In total, the following experimental conditions were implemented to generate faults in the rolling bearing test module under different conditions:

1. Tilting of the shafts (vertical or horizontal) to 0.1°, 0.2°, 0.3° or 0.5°;
2. Different types of mechanical damage in the rolling bearings;
3. Different rolling bearing types (6203 – ball bearing, N203 and NU203 – cylindrical roller bearings); and
4. Different lubricants and lubricant filling levels.

The gear module (Figure 3) consists primarily of a set of gear wheels (1) with a gear transmission ratio i = 1, each of them on a shaft (3) in a housing (4). The gear wheels can be changed for damaged ones, and can be tilted by changing the spacer ring (2) to an angled one. With different spacer rings, the housing of the second shaft can be tilted horizontally or vertically.

The shaft offset because of gear and tilting is compensated by moving the subsequent modules of the powertrain. The positions are held by fixing and adjusting elements. So a change between different testing setups is easily possible without losing the alignment of the powertrain.

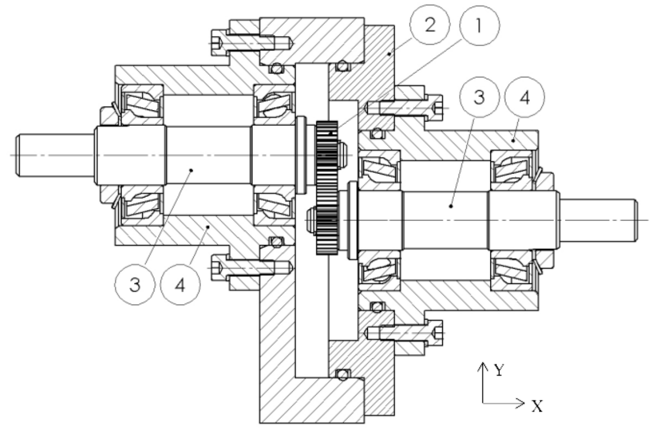


Figure 3. Sectional drawing of the gear module

The following experimental conditions were implemented to generate faults in the gear module:

1. Tilting of the shafts and gear wheels due to loads by external forces as well as manufacturing inaccuracies (vertical [y-axis] or horizontal [z-axis]) to 0.5°.
2. Different mechanical damage (e.g. wear, pitting, fracture).
3. Different lubricants and lubricant filling levels.

The flywheel and the load machine simulate the inertia and the load of the driven equipment, respectively. The load motor is a PMSM with a nominal torque of 6 Nm (Power of 1.7 kW).

Moreover, there are further test modules available for the test rig, such as a gearbox with planetary gears or an electromagnetic brake. These modules allow for follow-up investigations, which are, however, not in the focus of the present paper.

2.2. Defects: Faults and Damage

Before designing the test rig, the relevant defects were identified by a failure mode and effects analysis (FMEA) of a real system. Such a system may, for example, consist of a drum motor (Enge-Rosenblatt, Bayer, & Schnüttgen, 2012), and a conveyor belt. The failures identified as most relevant, which were therefore used for the experiments, are types of damage to bearings and gear wheels, as well as misalignments of the shafts due to loads or manufacturing inaccuracies.

To reduce the number of experiments, the defects were selected based on the resulting values from the FMEA. These values indicate the defect importance in combination with a factor related to the chance of detection. The following defects were selected:

Rolling bearing module:

- Tilting around the horizontal axis (y-axis)
- Damage in cylindrical roller bearing N203

Gear module:

- Tilting around the horizontal and vertical axis

Based on these evaluations, three levels were defined for each tilt defect (see Table 1).

Table 1. Tilt levels of bearings and gear wheels

Tilting of bearing		Tilting of gear wheel [tilting axis]	
Name	Angle	Name	Angle
AN0	0	WF0	0
AN2	0.2°	WF1 [z-axis]	0.5°
AN5	0.5°	WF2 [y-axis]	0.5°

Special artificial damage preparation is particularly necessary for the bearings in order to obtain reproducible test conditions. The types of damage were selected based on the completed FMEA while respecting the technical possibilities of their manufacturing.

For the experiments, four cylindrical roller bearings with different levels of damage, which represent pitting, were selected (Figure 4). The damage was limited to the cylindrical roller bearings, with severe damage at the outer ring. These simplifications were chosen, because a better possibility of detection and therefore an easier development of the classification method was expected. One bearing without damage was used as a reference (numbered LS0). The damage type denoted by LS1 was manufactured manually using an electric engraver and is 2 mm long in the rolling direction over the entire width of the outer raceway. The damage types denoted by LS2 and LS3 were manufactured using a wire-cutting electrical discharge machine. LS2 is a cylindrical groove (radius = 8 mm) and a depth of 0.2 mm at the centre. The last type of damage is a repetition of LS2 at irregular intervals, covering 120° degrees of the outer ring. These damaged bearings were used in the rolling bearing module in the high-load zone of the outer ring.

The damage introduced is based on investigations of damaged bearings from industrial applications. In particular, damage types LS1 and LS2 have a similar shape and size as the ordinary pitting of investigated bearings. Damage type LS3 is a severe damage type similar to the advanced damage caused by high numbers of cycles after the start of pitting. Because of this geometric similarity between the artificial defects and real bearing defects, it is assumed that a sufficient equivalence has been achieved in emulating real damage.

Name	Picture
LS0	
LS1	
LS2	
LS3	

Figure 4. Outer rings of the prepared cylindrical roller bearings

For future experiments, more damage types in bearings have been generated, including bearings from an accelerated lifetime test. These damage types are equivalent to damaged bearings from industrial applications. However, the artificial damage types were used for developing the diagnostic methods because they could be generated easily and quickly. In future experiments, the corresponding impact on the physical quantities of artificial and real damage has to be proven.

2.3. Operational Parameters

The test rig can be operated under different operational conditions (described by corresponding parameters of the test rig e.g. speed or load torque). To develop a detection method which is robust in the face of different operational conditions, it is also necessary to vary these parameters.

The main operational parameters are the rotational speed of the drive system, the load torque, and the radial force on the test roller bearing. To ensure constant boundary conditions and comparability of the experiments, three fixed levels were defined for each parameter (Table 2). All three parameters were kept constant for the measurement time of each data set.

Table 2. Levels of operational parameters

Rotational speed		Load torque		Radial force	
Name	[rpm]	Name	[Nm]	Name	[N]
N04	400	M01	0.1	F04	400
N09	900	M04	0.4	F10	1000
N15	1500	M07	0.7	F20	2000

Another parameter is the temperature, which was kept constant at roughly 45°C during all experiments after warming the test rig before every measurement.

3. DESIGN OF EXPERIMENTS

The test rig was used to generate data experimentally for the purpose of distinguishing several defect phenomena from healthy system behaviour. For this purpose, an algorithm was developed and tested as described in Section 4. This algorithm must be robust and able to decide correctly under different operational situations. Hence, such an algorithm must be developed based on a broad data set, considering all defect phenomena in question as well as a variety of operational situations.

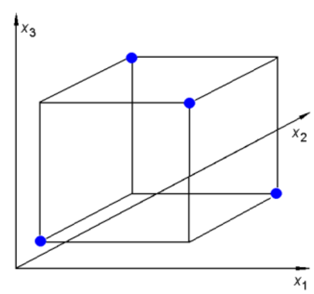
In a real system, each of the defect phenomena (see Section 2.2) and each of the operational parameters (see Section 2.3) can change any number of times. Each defect phenomenon would have to be investigated under different operational conditions in order to determine whether such a situation could be detected using only signals from electric phase currents. To consider the problem to its full extent, multiple measurements would have to be performed for all defect phenomena, in combination with all possibly occurring operational conditions. This would lead to an enormous number of experiments. A way around this dilemma is described in this section. It is based on completing a comparatively small number of experiments while still gathering all relevant information.

From the mathematical point of view, two groups of input parameters must be distinguished when simulating different situations using a test setup. First, there is the group of defects. The main attribute of this group is that there is exactly one level of every input parameter which corresponds to a functioning system, while all other levels of the input parameters belong to a damaged system. This group of input parameters describes the health conditions of a system. Secondly, there are the operational parameters. These parameters can vary between different levels during the operation of a system without impacting the health conditions of the system.

In Section 2.2, the most important levels of defect phenomena are described. This leads to a minimum of 4 levels of pitting in bearings, at least 3 levels of shaft misalignment, and 3 levels of gear wheel misalignment. Taking only these levels into account for investigation, it results in 36 possible combinations. In Section 2.3, some carefully selected levels of operational parameters are defined, leading to 3 different levels for each of the parameters revolution speed, load torque, and radial force on the main bearing. This gives additional 27 combinations. In total, 36 * 27 = 972 different experiments would have to be performed to examine all possible combinations. Hence, despite taking into account only the most important levels of input parameters, the number of possible combinations is still too high.

In order to significantly reduce the amount of work necessary for the experiments, the theory of Design of Experiments (DoE) was applied. This theory offers a broad range of approaches for carrying out experiments in a scientifically well-founded way (Box, Hunter, & Hunter, 2005), (Dean & Voss, 2008), (Wu & Hamada, 2009). In this context, several assumptions are made concerning particular linear and non-linear relationships between the input variables and the (usually just one) output variable. Using such assumptions, it is possible to deduce the complete results logically from a few – well-chosen – experiments, with a very high degree of confidence. Often, a so-called fractional factorial design based on orthogonal arrays is used for this purpose.

An example of such an approach is shown in Figure 5. It is assumed that there are 3 input parameters (x_1, x_2, x_3). Each parameter can take 2 different values, one lower value (denoted by –1) and one higher value (denoted by +1). The 3D representation on the left side of Figure 5 shows $2^3 = 8$ different combinations, represented by the 8 corners of the cube. All of these combinations have to be investigated to generate a complete statement about the parameter's influence on an output variable. But using an orthogonal array OA $(4,2^3)$ as shown on the right side of Figure 5, the effort can be reduced to 4 experiments. These experiments are represented by the 4 rows of the matrix. The disposition in 3D space can be seen on the left side, shown by the 4 dots at the cube's corners.



x_1	x_2	x_3
−1	−1	−1
+1	+1	−1
−1	+1	+1
+1	−1	+1

Figure 5. Fractional factorial experiment schema for 3 parameters: representation in 3D space (left), orthogonal array OA $(4,2^3)$ of parameter values (right)

In the context of generating an appropriate experimental data set using the test rig, the DoE approach is used to select a well-suited set of combinations of defect phenomena and operational parameters. This procedure was applied in two separate steps. First, an orthogonal array for all possible combinations of defect phenomena was determined. Because the levels to be investigated were assumed to be 4 by 3 by 3, the OA $(12,4^1 3^2)$ was found to be suitable, resulting in 12 combinations of defect phenomena. The OA $(12,4^1 3^2)$ is shown in Figure 6. It consists of the lines 1 to 12 of the left array.

In a second step, an orthogonal array for all possible combinations of operational parameters was determined. In this case, each parameter was assumed to have 3 different levels. Hence, the OA $(9,3^3)$ was found to be suitable, resulting in 9 combinations of operational parameters. The OA $(9,3^3)$ is shown in Figure 6. It consists of the lines 1 to 9 of the right array. These two steps lead initially to a total of 108 necessary experiments.

	Defect phenomena		
Number	Pitting	Shaft tilting	Gear wheel tilting
1	0	0	0
2	0	1	1
3	0	2	2
4	1	0	2
5	1	1	0
6	1	2	1
7	2	0	1
8	2	1	0
9	2	2	2
10	3	0	2
11	3	1	1
12	3	2	0
13	3	0	0
14	0	2	0
15	0	0	2

	Operational param.		
Number	Radial load	Load torque	Rotational speed
1	0	0	0
2	0	1	1
3	0	2	2
4	1	0	1
5	1	1	2
6	1	2	0
7	2	0	2
8	2	1	0
9	2	2	1
10	2	0	0
11	0	2	0
12	0	0	2

Figure 6. Results of Design of Experiments application: orthogonal array OA $(12,4^1 3^2)$ for defect phenomena (left), orthogonal array OA $(9,3^3)$ for operational conditions (right)

The possibility of using only one DoE design for all 6 input parameters was also considered, but quickly rejected. Using the same numbers of levels introduced above, this would have led to an orthogonal array OA $(12,4^1 3^5)$. A number of 12 experiments did not seem to be an appropriate investigation for such complex physical interrelations as those in the present case.

From the mathematical point of view, the two DoE designs shown in Figure 6 were found to be suitable. However, for a good understanding of the physical interrelations, there are some slight disadvantages to these two designs. All phenomena appear solely in combination; thus, there is no phenomenon for which its influence can be investigated singly. Hence, for a better understanding of the influence of varying a single phenomenon, the idea of including 3 additional experiments for the 3 defects and 3 additional experiments for the 3 operational parameters arose. Such additional experiments have no influence on the results of the two suitable DoE designs, as DoE theory was only used for decision support while planning the experiments.

As additional experiments, the edges of the parameter space were used, meaning the maximum parameter level in each case. The 3 additional experiments for defect phenomena are shown in the last 3 rows (numbers 13 to 15) of the left table in Figure 6. The last 3 rows of the right table in Figure 6 (numbers 10 to 12) show the additional experiments for operational parameters. Thus, $15 * 12 = 180$ experiments were finally found to be necessary in total as a result of a DoE-based selection.

All 180 experiments were carried out repeatedly, leading to at least 5 data sets of phase currents for each experiment. Based on these measurement results, a well-organized basis for development of an appropriate classification method could be established.

4. CLASSIFICATION ALGORITHM AND RESULTS

The goal of the research project was to find an algorithm which is able to distinguish between different defects (or health states) and operational conditions solely from measured electrical currents. For this purpose, two of the three phase currents of the synchronous motor were evaluated. For the classification approaches presented, all states and conditions found by DoE as well as the measurements from the test setup mentioned above were used.

Since the motor investigated was a synchronous machine, the phase currents are directly related to the angle of rotation of the device. Therefore, it is useful to relate the currents measured to this angle as well. Two of the currents behave as a rotating phasor with an elliptical shape of the amplitude trace, due to the 120° relative phase shift. Figure 7 shows the ideal trace as a dotted line. However, this trace will vary in real applications with the condition of the system and even with every cycle of rotation. During each experiment, a number of cycles were measured for each state and condition and each cycle was added to the phasor plot. Afterwards, the continuous angle of rotation α was divided into uniformly distributed sections in the range $[0,2\pi]$ leading to intervals $[\alpha_i, \alpha_{i+1}]$ with a certain number of measurement samples in each interval. These sample groups are suitable for statistical analysis. As a result, a modified phasor is obtained which has only one data point within each interval. A combination of statistical values can be used to obtain an artificial phasor, as shown in Figure 7 (solid line). This is simply derived using the mean value of all single phasors within one angular section. The amplitude of such a phasor with respect to the intervals can be used as a feature for classification purposes. This means n sections within $[0,2\pi]$ yield n features which characterize the phasor and its corresponding measurement.

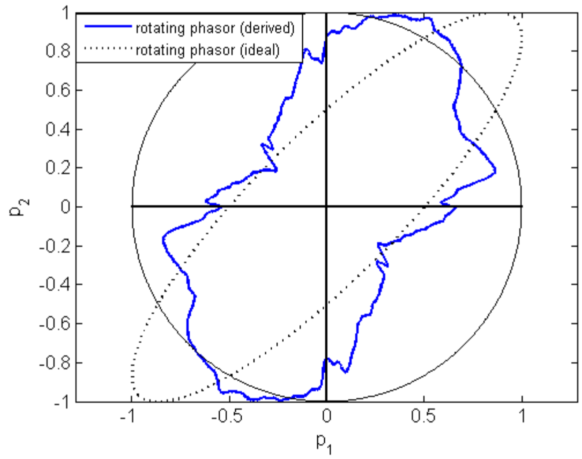


Figure 7. Ideal rotating phasor (dotted line) and artificial phasor determined using the mean value of original phasors within each section (solid line).

The complete experiment evaluates different health states and operational conditions where each state is measured multiple times. This leads to a large number of feature sets, as each measurement corresponds to one set of features. Each set can be arranged in a feature vector. The number of features, i.e. the length of such a vector, is typically too large for complete classification or visualisation and may contain redundant information. Therefore, two approaches were applied to reduce the number of features, which are described in detail by Bayer, Bator, Enge-Rosenblatt, Mönks, Dicks, and Lohweg (2013), or by Paschke, Bayer, Bator, Mönks, Dicks, Enge-Rosenblatt, and Lohweg (2013).

Principal Component Analysis (PCA), as discussed by Dunteman (1989) or Jolliffe (2002), and Linear Discriminant Analysis (LDA), as discussed by Mardia, Kent, & Bibby (1979) or Duda, Hart, & Stork (2000), were used to find structure in the data. Both methods lead to a reduced mathematical basis, which can be used to represent the original feature vectors by a linear combination. The related coefficients form a new and significantly reduced feature set, which can then be used for classification. The methods were examined separately to show different aspects of their usability. PCA turned out to be suitable for the recognition of unusual states throughout the entire test system.

The PCA may be used to find any similarities in the data. The idea is to represent each state, i.e. the respective feature vector, by a linear combination of typical states. These states are equivalent to the first few principal component vectors provided by performing a PCA of all available measurement data. The vectors then span a new sub-space, which the feature vectors are projected into. The coordinates of projected feature vectors form the final, reduced feature set.

If the conditions of the system are similar, data points will accumulate in the projected feature space and build clusters. Different health states as well as operating states will form independent clusters. Figure 8 shows the clustering for a particular health state class under different operating conditions, such as rotational speed or load. There were 12 operating states in total, of which at least 8 can be seen in the figure. The remaining 4 states overlap with existing clusters, as only two axes of the feature space were used for visualisation. The results indicate that, in general, different states can be distinguished using the PCA approach. The variation within each cluster is sufficiently small, which is mandatory for reproducibility.

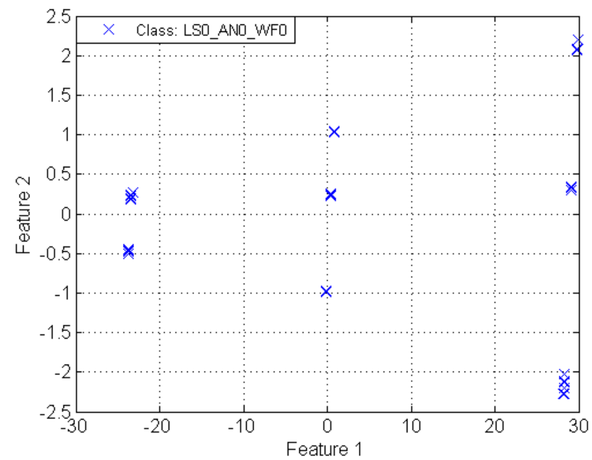


Figure 8. Clustering of operational condition states within a health state class after performing PCA: The features 1 and 2 are the first two of the reduced feature set. They already allow for the separation of at least 8 of 12 states measured in total.

However, the clustering of operational states prevents a good classification of actual health states. Each health state would consist of sub-clusters produced by different operating conditions; hence, a health state cannot be described by a single cluster function, e.g. multivariate normal distribution. In reality, only health states as actual "classes" to be distinguished from each other are relevant here. The LDA provides a method of producing coherent health state clusters in the feature space independently of operational conditions. However, sample measurements from each class are required for LDA, which is usually a problem in practical applications. Since the experimental setup used here allows for damage and fault emulation, different health states are known from the measurement procedure. LDA offers a reduced mathematical basis for data representation, which ideally separates known and pre-defined classes in the present application. For different health states, the results are shown in Figure 9.

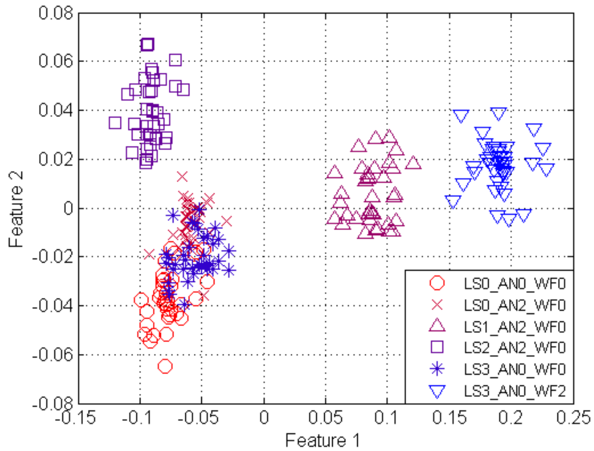


Figure 9. Separation of health state classes after LDA: The features 1 and 2 are the first two of the reduced feature set. The notations of the health states are declared in Table 1 and Figure 4.

Here, the clusters are independent of operation conditions. The separation of classes is not ideal for two reasons. First, at least 5 features are necessary to separate the 6 classes safely, but only two of the features, i.e. two axes, are used for visualisation. Second, some states may not be different enough for reliable classification. The LDA approach works quite well, but requires comprehensive knowledge about the system. In general, the results show that distinguishing health states would be possible. The classification itself is typically carried out using a fuzzy pattern approach. For example, the clusters may be described by particular multivariate normal distribution functions, which yield fuzzy membership values with respect to all known states. From this result, the most likely class membership can be determined for each measured state.

In many practical cases, there is no reference data for pre-defined health states. Even the consideration of operating conditions might be too costly in terms of effort. Therefore, the classification was restricted to the recognition of a previously trained, "good" state, regardless of operating conditions. The proposed method uses self-learning techniques and is based on PCA. The goal is to automatically find system states that are unusual and may represent arbitrary failures or defects. The challenge is to avoid false alarms caused by varying operating conditions. It must be assumed that the system is in a healthy condition during the learning phase and that all relevant operating conditions have appeared in the past. From the data gathered, one can construct a reduced mathematical basis using PCA. This basis spans a subspace that contains approximately all the measured data from the past. Any data measured in the future that lies outside this subspace represents an unknown state. This new state is then generated either by new operating conditions or by some defect or failure of the system. The geometric distance of a measured state to the known subspace was regarded as an error indicator. In Figure 10, the result obtained from the experimental setup is shown. The reference state LS0_AN0_WF0 has no artificial defects, and represents the system in good condition. Regardless of the operating conditions, the state is identified correctly. All other states shown are characterized by introduced defects, whereas the set of operating conditions was the same as for the reference state. The dashed line is determined by the variance of the error indicator produced using the reference state. It separates healthy states from defective states. This classification method works quite well and is mostly suited as an additional indication for maintenance service. However, it may not expose the actual defect or source of deviation.

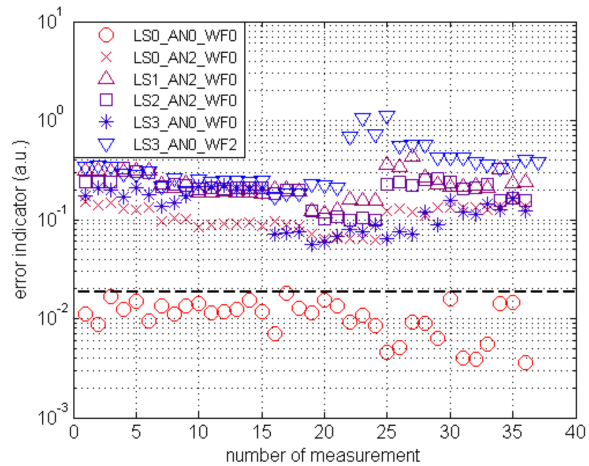


Figure 10. Indicator for unknown states of the system: LS0_AN0_WF0 is the reference health state, which also contains different operating conditions.

To verify the robustness of the algorithms developed here, signals gathered directly from the frequency inverter were also evaluated. Typically, these signals exhibit more noise and the sample rate is reduced. However, the data analysis approach also proved to be effective under these circumstances. This provides the basis for a possible integration of the algorithms into the motor control or the automation system.

5. CONCLUSION

The paper presents the main steps in the development of a diagnostic algorithm for defect detection in technical systems driven by electric motors. For this purpose, only measurement signals from the motor's electric currents are used. Additional sensors were applied to the system in order to obtain the process parameters, but were not used for detection of defects. Following this idea, the complete system of defect detection becomes a complex one in a mathematical sense. However, such a system can be realised at low expense because of the absence of additional sensors. Often, the mathematical algorithms can be executed on the existent control unit of the motor.

This paper focusses on three steps which are necessary for a successful preparation of such a complex algorithm for signal analysis. Firstly, a sufficient basis of measurement data is needed. This data was obtained using a test setup designed for this special purpose. The capabilities of this setup in mimicking particular defects are described in detail in the paper. Secondly, all possible operating conditions of such a motor have to be considered. This leads to enormous effort in order to measure all possible combinations of defects and operating conditions. Hence, specific methods for reducing this effort without risking loss of information have to be employed. Finally, a complex combination of different signal analysis methods has to be applied. Two of these primary methods are mentioned in the paper. Particular results of signal analysis and classification are shown. In doing so, the paper demonstrates that the method developed here works correctly under a broad range of circumstances.

The present work focuses on synchronous motors. An expansion to other types of electric motors is part of planned future research. Furthermore, a combination of sensor-based information about the industrial process and the method discussed here, which is based on measurement of electric currents, is also worth being investigated. Last but not least, improved methods of introducing artificial damage in bearings are in progress. The defects are expanded to the inner rings and to ball bearings. Moreover, real damage from accelerated lifetime tests will be used to examine the impact of artificial bearing damage on the physical quantities as compared to real damage. The creation of a database with experimental data for a wide range of different bearing defects is another goal for future work.

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NOMENCLATURE

DoE	Design of Experiments
FMEA	Failure mode and effects analysis
i	Gear transmission ratio
LDA	Linear discriminant analysis
OA	Orthogonal array
PCA	Principal component analysis
PMSM	Permanent magnet synchronous motor

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BIOGRAPHIES

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