Statistical characteristics of electric drives on end-of-line test benches

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Introduction

The emerging relevance of emission-free vehicles around the globe promotes fast increases in production volumes of electric drives. The quality standards must not be sacrificed during a such a ramp-up. Thus, each unit has to be tested on an end-of-line test bench. This typically involves a structure-borne noise measurement after final assembly. To reach the same depth of understanding of faults like present with internal combustion engines, a comparable knowledge about the internal kinematics and the corresponding acoustic behavior has to be generated for the next generation of electric drives. During the partial absence of complete knowledge, the quality has to be ensured already by automated identifiers. The identification of a present fault allows for a detailed inspection of said unit and therefore increase its understanding.

Typical examples of automated classifiers range from hard limits over statistical limits to machine learning methods for anomaly detection. Hard limits are only available for strongly detailed knowledge about the test bench and the units to be tested. Thus, new electric drive units that are not fully understood as there is still ongoing research on the fundamental excitations [1, 2] make fully developed testing methods unfeasible at the time. With increasing knowledge about the drive units partially introducing hard limits may become reasonable as an alternative. Machine learning (ML) techniques are able to reach high accuracies in the assertion of an anomaly in condition monitoring scenarios like [3, 4]. The expected scatter in an end-of-line testing scenario exceeds the measurement accuracy by factors as the complete chain of tolerances leads to different excitation strengths. In the case of condition monitoring, the measurement accuracy describes the scatter from which an algorithm has to filter out anomalies. Together with the reason of non-explainability of ML algorithms, the ML approach is not only expected to perform worse than in condition monitoring, it also prohibits the necessary build-up of explicit knowledge in order to enhance firstly the detection of faults in the future and improve assembly steps after identifying the corresponding source of a fault. Thus, we set the scope of this contribution on statistically testing electric drives in a high scatter environment like series production. Besides the definition of limits, the construction of a complete picture of excitations is needed to generate knowledge about the units passing through the end-of-line test bench.

The paper is structured as follows. First, the expected statistical characteristics of electric drives are presented, depending on the measurement scale. The best limit available to identify anomalies is then proposed by transforming the distribution towards normality. Then, a brief overview of the test bench and electric drive is given. Finally, the extractable knowledge about the units, by assessing parametrical information about the necessary transformation towards normality, is presented.

Statistical characteristics

The statistical characteristics of an ensemble can be described by the moments μ_n. The first moment represents the mean value of all values inside the ensemble. Typically, all higher moments are defined as centralized moments by the first moment. Thus, the second moment denotes the standard deviation of the ensemble. A normal gaussian distribution is defined by vanishing moments beyond the second moment. In the case of structure-borne noise measurements, the resulting amplitudes are always positive. Due this fact alone, it is impossible for the distribution of amplitudes to be fully described by a gaussian distribution. As a second step one has to decide whether the measurement values are evaluated on a linear (e.g. $\mathrm{m/s^2}$) or logarithmic (e.g. decibel) scale. The linear scale exhibits a strong tendency towards values at different orders of magnitude, which is also the initial reason that logarithmic scales were introduced. In the case of electrical engines, most of the engines resides near the normal excitation strength and a few engines show measurement values with said increase in amplitude. This inevitably results in a right-skewed distribution for the linear scale. The contrary of an engine being quieter by orders of magnitude seems unreasonable as the emitted noise consists of the main parametrical excitation and additional excitations based on tolerance deviations inside the production process. Therefore, the lower bound of the linear scale is sharply defined by the main parametrical excitation mechanisms resulting of normal movements during usage. The logarithmic scale tries to correct for the different orders of magnitude by enhancing differences in amplitude at low levels and compressing higher values into a higher density of distribution. While the logarithmic scale is mostly used for correlation towards human hearing, it typically overcompensates the skewness from the linear scale and thus results in an opposite skew to the left. This may represent the impression of hearing best, but conflicts emerge if statistical testing by lean means is aimed for.

Statistical limits for anomaly detection

In this section we want to describe the up- and downsides of the two scales in the environment of statistically testing. Consequently, a corrected scale is presented that eliminates the downsides of the logarithmic scale.

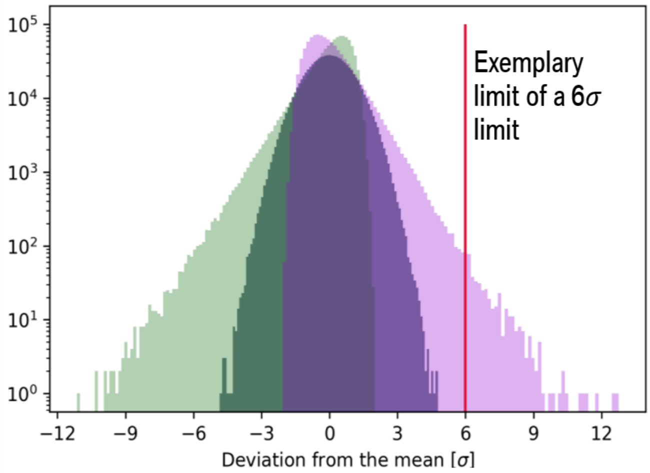

Figure 1: Examples of three different distributions. Grey represents a normal distribution, purple shows a typical linear scale distribution and green a logarithmic scale. An exemplary limit of 6σ is shown to assess whether engines would be rejected solely based on the choice of the measurement scale.

A lean approach of setting statistical limits is defined as:

$$\text{Limit} = \mu + n \times \sigma, \quad (1)$$

The mean value of the distribution of good engines is denoted by μ and σ is the corresponding standard deviation. Both parameters are estimated by a historical ensemble. The apparent skewness can lead to increased reject rates of good engines or blind spots that allow bad engines to pass the test. The limit is often assigned to represent the 6σ-criterion of production quality and efficiency. Thus, n is set to six for this example. The different distribution shapes and a corresponding limit are shown in Fig. 1. In the case of a linear scale (shown as purple in Fig. 1), the skewness towards the right side allows some engines to surpass the 6σ limit although they are located inside the continuous scatter and should not be classified as an anomaly. The opposite occurs using the logarithmic scale (shown as green in Fig. 1). Here, the fast descend in distribution density leaves a huge spacing between the upper bound of the distribution and the limit assessing anomalies. Thus, an engine can depart from normal behavior, but its logarithmic value is too low for the corresponding limit. In other words, the resulting limit in a logarithmic scale is often set too high and could be sharpened. The quickest way to correct for this deficiency is to reduce n until a more appropriate limit is found. This increases the complexity of setting up for limits in an automated testing environment drastically as a person has to define an appropriate number of standard deviations n for each measurement. In the case of testing structure-borne noise, the number of measurements is set by the number of engine orders tracked times the number of revolution speeds which are viewed. Thus, an automated identification of a true 6σ-equivalent is needed.

As each parameter (also the mean and standard deviation) is evaluated by a statistical ensemble of historic data, they exhibit a remaining uncertainty. Thus, the automated identification should require as few parametrical variables as possible to keep the accompanied uncertainty as low as possible. The proposed method consists of transforming the skewed distribution from the logarithmic scale towards a normalized distribution. The Box-Cox-transformation (2) offers a possibility to optimize the normalization by a single parameter λ to decrease higher moments of the initial distribution function [5].

$$\tilde{x} = \frac{x^{\lambda} - 1}{\lambda}. \quad (2)$$

If the initial distribution of x was already a gaussian distribution, λ equals one. If λ-values above 1 were required to reduce higher moments in the distribution, the initial skewness was left-sided. The expression of (2) converges towards a natural logarithm for $\lambda \longrightarrow 0$. A λ-value below 1 represents a needed correction of right-sided skewness. The transformation essentially maps both colored distributions from Fig. 1 towards the grey-colored gaussian distribution.

After the decrease in higher moments, the statistical limit is evaluated in the space of adequate statistics:

$$Y = \frac{\tilde{x} - \mu(\tilde{x})}{\sigma(\tilde{x})} \quad (3)$$

If the limit shall be evaluated in the space of decibel values, an equivalent limit of $Y = 6$ can be inversely transformed back from the adequate statistical space towards a limit for the distribution of x. This reduces the computational time for each successive measurement and can thus reduce the total time of testing at the test bench. A sharper overall quality goal can be achieved by lowering the limit value in the adequate statistics.

Test bench and electric drive

All measurements were performed on an end-of-line test bench. It consists of a stiff mount for the electric drive, two NVH sensors and two load machines. The load machines control the speed of the engine, while the unit itself controls the torque in order to simulate a real driving situation. The sampling frequency for both NVH-sensors is set to 100kHz and the time-domain signal is resampled towards an angular-domain. This allows minimal smearing effects between different engine orders during a ramp of revolution speeds. An engine order is defined by the measured frequency divided by the instantanous speed of a shaft. The order resolution is set to 1/16 and the rotor is defined as a reference shaft. The electric drive is constructed highly-integrated. Thus, all components can only be tested in complete assembly. The unit consists of an inverter, stator, rotor and a two-stage spur gear. The components are integrated near each other to reduce the total space required by the unit. This leads to strong coupling effects between neighbouring components regarding their movement during usage. The schematic overview of the electric drive is given in Fig. 2.

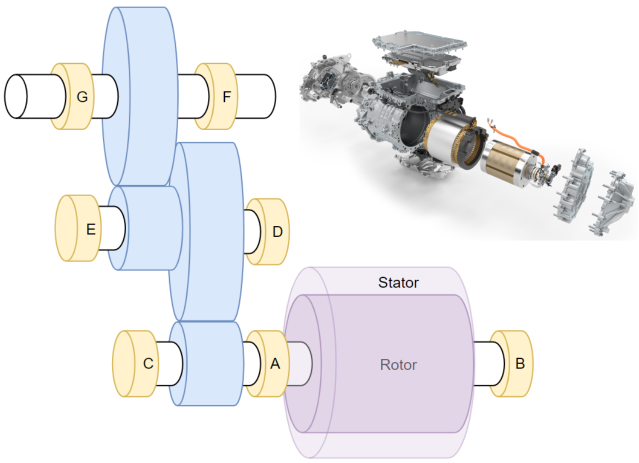

Figure 2: Schematic overview of the electric drive. Gears are colored blue, bearings are denoted yellow.

The helical teeth project a portion of their tangential stiffness fluctuations towards the axial direction. In contrast, the main excitation of the magnetic fields between the rotor and stator point out radially. Thus, the two NVH-sensors are positioned axially towards the gearbox and radially towards the stator. Therefore, the two main vibration directions are captured near their corresponding source.

Knowledge generation from parametrical normalization

The successive step of rejecting engines after failing to stay below the automated limits is to fully understand what kind of fault occurred during the corresponding assembly steps. As the interaction of many rotating parts results in a non-trivial picture of different excitations at different speeds, one has to present a complete picture of excitations that has to be understood. We propose to employ the λ-parameter of the Box-Cox transformation for an ensemble of good engines as it condenses the statistical shape of the distribution function for each engine order and speed. This presentaion is called lambdagram.

A speed and order combination which is excited randomly will exhibit λ-values near one as no further correction towards a normal distribution is necessary. For λ values being significantly above one, a parametrical excitation due to physical reasons can be assumed. The previous arguments of Section *Statistical characteristics* apply for the logarithmic scale. In the rare case of negative λ-values, the engineer should examine carefully if a bad engine was in the ensemble. Two lambdagrams for each sensor respectively are shown in Fig. 3. The harmonics of gear meshing are present in the signal of both sensors as the respective amplitude is high enough to excite the whole structure (e.g. 46th engine order or multiples of 6.93th order). On the radial sensor, one can observe sidebands near the number of stator teeth (54) equally spaced by one engine order. These are not visible in the signal of the sensor at the gear box. In contrast, the sensor at the gear box is able to capture structures

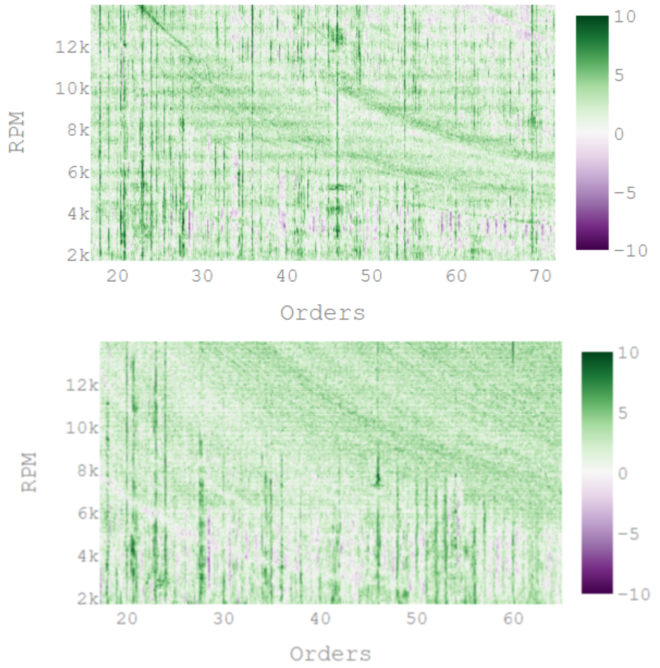

Figure 3: Lambdagrams for two different sensors measuring the structure-borne noise on the end-of-line. The upper figure shows an sensor pressed axially onto the housing of the gearbox. The lower figure shows the characteristics of radial vibrations at the housing of the stator. The underlying ensemble size is 367 engines tested on an end-of-line test bench.

of sidebands along the speed ramp of the 46th order at high speeds. The sidebands occur in the distance of the elementary engine orders corresponding to the A- and C-bearing as these modulate the stiffness of the surrounding structure for the gear meshing contact. These remain hidden for the radial sensor at the stator. It also has to be noted, that some negative λ-values occur at the gear sensor around the 60th to 70th order despite the logarithmic scaling of the underlying decibel axis. These can be attributed towards bearing harmonics inside the gearbox housing. If such features appear inside the lambdagram, a careful examination of the corresponding engine orders and possible excitation mechanisms has to be undertaken. In this case, the excitations are due to normal fluctuations inside the production process of the bearings and leave no concern for the units. As not all bearings show a small increase above the noise floor, one experiences the noisy fluctuations for most engines. A few are able to surpass the noise floor and shift the mean above the median, which creates a right handed distribution. If negative lambda values occur due to the noise floor effect, typically the emerging excitations are very weak (as they nearly surpass the noise). The signal is also too weak to be measured on the radial sensor as none of the harmonic features is present in the lambdagram. Negative λ values in the logarithmic scale and a typical excitation with a good signal-to-noise ratio often indicate faults, which are present in the underlying distribution of engines. Thus, a detailed inspection of the lambdagramm allows for an easy identification of all engine orders that have to be understood to fully comprehend the NVH-behavior of the electric drive at hand. Depending on the measurement position and direction different features will be enhanced or dampened.

Conclusion

New topologies of electric drives are in need of an even faster understanding of its accompanying NVH behavior. In order to maintain a sharp quality during the ramp-up and partial knowledge about faulty engines (as these were never produced yet) an automated identification of anomalous engines is presented. It is based on statistical limits in the adequate statistical space in contrast to statistics on skewed distributions, as these may lead to blind spots or increased reject rates. In addition to the automated generation of statistical limits, we also presented a complete picture about the NVH behavior of the electric drives at hand. It is able to differentiate between random excitations due to noise fluctuations and parametric excitations with a physical motivation. Thus, an NVH-engineer can monitor occurring excitations and easily check for his complete understanding of all significant movements inside the electric drive that he has comprehend. Future research will aim at the automated classification of identified faults and also check for the transferability of the presented results towards other electric drives with comparable topologies.

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