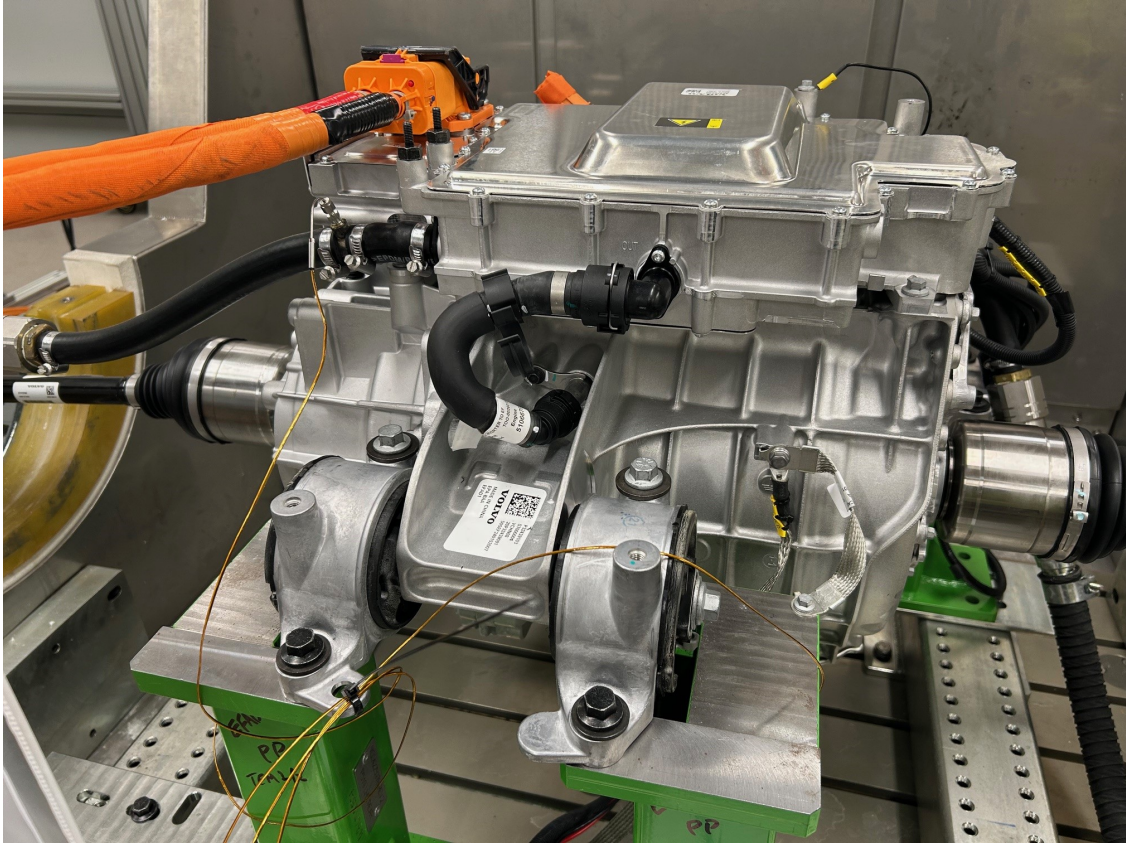




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Vibration Condition Monitoring of an Electric Drive Unit

Master's thesis in Mobility Engineering

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CHALMERS UNIVERSITY OF TECHNOLOGY
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Cover: Electric Drive Unit on which entire operations, measurements were performed.

Abstract

The increasing competition and rapid development in electromobility are driving accelerated product development, higher drivetrain performance, and consequently greater mechanical stress on components. Ensuring reliability and safety therefore requires effective condition monitoring during testing.

Vibration-based condition monitoring is widely used for this purpose; however, the effectiveness of such monitoring strongly depends on the measurement setup, particularly sensor placement. In practice, sensor positioning is often performed without a structured approach, which could lead to inconsistent and potentially unreliable results.

This study focuses on developing a standardized procedure for vibration measurement setup during drivetrain testing. Multiple real-time measurements were conducted and analysed using various evaluation metrics to assess the influence of sensor placement and operating conditions.

The results demonstrate that sensor placement must be carefully optimised for different machine configurations. In addition, the classification of load cases requires refinement to support a consistent and standardized testing methodology. The proposed approach contributes to improved reliability and comparability of condition monitoring results.

Key words: Electric Drive; Transmission; SKLT; Order Tracking; delta-Analyser; Reilhofer; Vibration; Endurance Testing; Condition Monitoring.

Sammanfattning

Den ökande konkurrensen och den snabba utvecklingen inom elektromobilitet driver på en snabbare produktutveckling, högre prestanda hos drivlinor och därmed större mekaniska belastningar på komponenter. För att säkerställa tillförlitlighet och säkerhet krävs därför effektiv tillståndsovervakning under provning.

Vibrationsbaserad tillståndsovervakning används i stor utsträckning för detta ändamål. Effektiviteten hos övervakningen är dock starkt beroende av mätuppställningen, särskilt sensorplaceringen. I praktiken utförs sensorplaceringen ofta utan ett strukturerat tillvägagångssätt, vilket kan leda till inkonsekventa och potentiellt otillförlitliga resultat.

Denna studie fokuserar på att utveckla en standardiserad procedur för uppställning av vibrationsmätningar vid provning av drivlinor. Flera realtidsmätningar genomfördes och analyserades med hjälp av olika utvärderingsmått för att bedöma påverkan av sensorplacering och driftförhållanden.

Resultaten visar att sensorplaceringen måste optimeras noggrant för olika maskinkonfigurationer. Dessutom behöver klassificeringen av lastfall förfinas för att stödja en konsekvent och standardiserad provningsmetodik. Den föreslagna metoden bidrar till förbättrad tillförlitlighet och jämförbarhet hos resultaten från tillståndsovervakningen.

Nyckelord: Elektrisk drivenhet; transmission; SKLT; orderanalys; delta-ANALYSER; Reilhofer; vibrationer; uthållighetsprovning; tillståndsovervakning.

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Preface

This master's thesis was carried out at Volvo Cars Corporation within the Electric Driveline Verification group as part of the MSc in Mobility Engineering at Chalmers University of Technology. The project was initially planned for one semester and was later extended to allow additional work on practical issues encountered during experimental testing. This provided a valuable opportunity to better understand the challenges involved in applying theoretical methods within a real testing environment.

The topic was of particular interest to me because it brought together knowledge from several areas covered during my studies, ranging from signal processing to fatigue and fracture. It allowed me to apply these subjects within one practical engineering project. My interest in vibration is also personal. I have previously worked with vibration analysis, and seeing my father develop strong expertise in this field has brought me closer to the subject and motivated me to contribute meaningfully to it.

I would like to express my sincere gratitude to Elvir Kendic, my supervisor at Volvo Cars Corporation, for his support throughout the project. I would also like to thank Håkan Johansson, my supervisor at Chalmers University of Technology, for his academic guidance and valuable feedback.

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Finally, I would like to thank my family for their constant belief in me, encouragement, and support throughout my studies and the completion of this thesis.

Göteborg, September 2026
Aditya Nalawade

Declaration of AI Use

Generative artificial intelligence tools were used during this thesis to support selected tasks, including Python scripting, code troubleshooting, language refinement, and improvement of textual clarity. These tools were not used as a substitute for technical analysis or engineering judgement. To the best of the author's knowledge, no information identified by Volvo Cars Corporation as confidential or proprietary was entered into generative artificial intelligence tools.

1

Introduction

1.1 Background

Volvo Cars is a Swedish passenger car manufacturer with its global headquarters in Gothenburg, Sweden (Volvo Car Corporation, 2026). A major part of Volvo Cars' operations is located in Torslanda, a few minutes north of Gothenburg, where both production and corporate functions are represented (Volvo Cars, 2026a). Volvo Cars offers multiple passenger car body types, including SUVs, estate cars, and sedans (Volvo Cars, 2026b). They are powered by electric drive units that vary widely in their specifications.

Volvo Cars' electric powertrain uses an electric drive unit (EDU) that integrates an electric machine, a gear transmission, and multiple rolling element bearings in a rigid aluminium housing. Since the EDU is expected to operate reliably for the entire vehicle lifetime across a wide range of loads and environmental conditions, verification testing is critical before the unit is released for series production. Insufficient validation can lead to field failures and, in the worst case, vehicle recalls, which are costly for both the company and the customer.

For durability verification, the EDU is mounted on a test bench and connected to two dynamometers (dynos), one on each output shaft, to represent the left and right wheels. The dynos operate in load control, applying controlled resisting torque and/or speed profiles that replicate road load, allowing the EDU to run under realistic operating conditions. One key verification activity is the System Key Life Test (SKLT), where the EDU is driven through a long, customer representative duty cycle intended to cover the targeted failure modes. During the full test duration, the unit is monitored using vibration based condition monitoring to track the development of deviations in the vibration response and identify emerging faults before failure becomes inevitable. To support this monitoring, Reilhofer delta-ANALYSER is used for both live supervision and post test evaluation.

The SKLT is designed to excite a broad set of operating conditions and failure mechanisms by running the EDU in a varied, customer like manner. In this work, the SKLT corresponds to approximately 12 weeks of effective rig operation, targeting the defined lifetime requirement (based on internal Volvo documentation, often linked to a high percentile customer usage profile, e.g., 350,000 km equivalent).

Condition monitoring tracks machine health by measuring vibration over time and detecting changes that indicate abnormal behaviour or damage. In many industries, this enables planned maintenance and reduced downtime. In EDU verification testing, the aim is not to prevent all damage, since tests may run until failure, but

to observe when and how degradation begins, which component is affected, and how the vibration response evolves under the applied duty cycle.

delta-ANALYSER is the monitoring and analysis software used during the tests. With vibration sensors connected to the measurement setup, operating windows/cycles (e.g., oil temperature, speed, torque) are defined and data is logged whenever the EDU operates within these conditions. The software enables inspection of spectra at specific operating points, trend/deviation views over time, and built in detection functions that compare the measured response to a defined reference to flag abnormal changes.

1.2 Purpose

The purpose of this thesis is to develop a standardised procedure for setting up accelerometers on different EDUs undergoing this type of verification testing. In addition, the thesis applies order tracking to follow key (fundamental) orders over time and evaluate how their behaviour changes during endurance tests. The aim is to relate these changes to different fault modes, supporting earlier fault identification before failure and limiting unnecessary secondary damage, while also supporting shorter testing time in development projects, with particular emphasis on the optimisation of the test setup.

1.3 Limitations

1.3.1 Limitations

The scope is constrained by the available time and resources. The main limitations are:

- **No fault injection.** Faults will not be artificially introduced. The study is limited to failure modes available in existing test data.

2

Frame of Reference

2.1 Electric Drive Unit (EDU) Overview

Modern electric vehicles often package their traction powertrain as a highly integrated module commonly referred to as an electric drive unit (EDU) or electric axle (e-axle). In integrated architectures, the EDU combines the traction motor with drivetrain elements that adapt motor speed to wheel speed and distribute torque to the left and right wheels. In the e-axle context, a frequently used definition is a fully integrated traction drive system combining the motor, inverter, and a gear stage (reducer and/or differential) within a compact assembly (Uemura, 2021).

From a functional standpoint, the EDU converts electrical energy from the high voltage battery into controlled wheel torque across a wide operating envelope. A practical consequence of electrification is that the absence of an internal combustion engine changes the overall noise environment, which can make drivetrain related noise and vibration phenomena more noticeable (Hua et al., 2021; Masri et al., 2024). This motivates careful attention to the EDU’s internal excitation mechanisms and structural transmission paths when studying NVH behavior and vibration based monitoring.

2.1.1 Main subsystems and their roles

Electric machine (traction motor). The traction motor provides propulsion torque and regenerative braking capability. Many EV traction machines operate at high rotational speeds to increase power density, which in turn drives the need for substantial reduction ratios and places stricter requirements on rotor dynamics, balance quality, and manufacturing tolerances (Stadtfeld, 2020; Uemura, 2021; De Gennaro et al., 2020). High speed operation can increase sensitivity to unbalance and electromagnetic force related vibration, making the motor a key contributor to the EDU vibration signature (Stadtfeld, 2020; Hua et al., 2021).

Power electronics (inverter) and control. The inverter converts battery DC to controlled AC for the motor and enables torque/speed control through modulation and feedback control loops. In many integrated concepts, the inverter is packaged within or directly adjacent to the EDU housing to improve packaging efficiency and overall power density (Uemura, 2021; De Gennaro et al., 2020; ElringKlinger). Integration also couples thermal and structural design decisions: inverter losses contribute to the EDU heat load, and inverter/motor integration can influence stiffness, damping, and the paths through which structure borne vibration reaches external measurement locations (De Gennaro et al., 2020; ElringKlinger; Masri et al.,

2024).

Reduction gearbox / transmission. A gearbox is used to match motor speed to wheel speed and to multiply torque at the wheels. Because EV motors can run efficiently over a wide speed range, many solutions use single speed reductions; however, the high motor operating speed means the overall ratio requirement can be large (Stadtfeld, 2020; Uemura, 2021). Gear design and manufacturing quality are strongly tied to NVH, particularly at high rotational speeds where tonal gear mesh content can become prominent (Stadtfeld, 2020).

Differential and output interfaces (half shafts). The differential distributes torque between left and right wheels while allowing speed differences during cornering, and it interfaces with the half shafts and wheel end joints. In many EDUs the differential is integrated into the final drive to minimize packaging volume (Liu et al., 2026; ElringKlinger). This integration concentrates rotating elements, bearings, and gear meshes in a single housing, which is relevant for condition monitoring because multiple excitation sources can be transmitted through common structural paths (ElringKlinger).

Bearings, lubrication, thermal management, and housing. Rolling element bearings support rotating shafts and maintain alignment of the motor rotor and gear sets under torque and thermal loads. Lubrication reduces wear and influences vibration behavior through changes in contact conditions and system damping, while thermal management is critical in integrated EDUs because motor, inverter, and gearbox losses create coupled heat flows (Uemura, 2021; De Gennaro et al., 2020). The housing provides the structural reference for alignment and is also the dominant pathway by which internal excitations transmit to externally accessible measurement points used for vibration sensing (ElringKlinger).

2.1.2 Common EDU layouts

Two packaging concepts are frequently described: coaxial and offset/parallel axis arrangements. Coaxial EDUs are often associated with compact ratio realization using planetary gear sets, whereas offset EDUs commonly use spur/parallel axis gear stages, potentially in multiple stages, to route torque to the differential and half shafts (ElringKlinger). These layout choices affect bearing arrangements, gear mesh locations, housing stiffness distribution, and therefore the expected vibration transmission paths to the external surfaces where accelerometers are mounted.

2.1.3 Relevance to the remainder of this thesis

Because an EDU integrates multiple subsystems in one compact assembly, it concentrates multiple potential excitation sources (electromagnetic forces, gear meshing dynamics, bearing forces, and control related effects) into one structure. In EVs, where engine masking is absent, these phenomena can become more prominent and are therefore central to both NVH engineering and vibration based condition monitoring (Hua et al., 2021; Masri et al., 2024; Stadtfeld, 2020). This EDU overview therefore establishes the mechanical and functional context needed to interpret later sections on vibration measurement, sensor placement, and signal processing.

2.2 Vibration Fundamentals

In mechanical systems, *vibration* can be described as an oscillating motion about a reference position, and is commonly represented in terms of displacement, velocity, or acceleration relative to that reference (Brüel & Kjær, 1982; Gade et al., 1995). In practical machines and structures, vibration is difficult to avoid because it can arise from manufacturing tolerances, clearances, rolling/rubbing contact between parts, and out of balance forces in rotating or reciprocating components; moreover, even small excitations can be amplified when they excite structural resonances (Brüel & Kjær, 1982). Depending on operating conditions and excitation characteristics, vibration may include periodic components as well as random (noise like) behaviour (Brüel & Kjær, 1982; Gade et al., 1995).

A useful distinction in vibration theory and diagnostics is between vibration sustained by external excitation and the system response associated with “free” motion. In standard terminology, *forced vibration* refers to oscillation under the action of a forcing function (Gade et al., 1995), while *natural frequency* refers to the frequency at which a system vibrates when set into free vibration (in the idealised case, without damping) (Gade et al., 1995).

2.2.1 Vibration quantities and how they relate

Vibration amplitude is commonly expressed using three closely related kinematic quantities: displacement, velocity, and acceleration (Brüel & Kjær, 1982; Gade et al., 1995). These quantities are linked by time differentiation/integration, and the choice of which quantity to measure and report influences how different frequency ranges contribute to the measured level. In particular, displacement measurements weight low frequency components more strongly, while acceleration measurements weight high frequency components more strongly (Brüel & Kjær, 1982). Because piezoelectric accelerometers provide an acceleration proportional output that can be electronically integrated, acceleration measurements can be converted to velocity or displacement proportional signals when needed (Brüel & Kjær, 1982).

2.2.2 Time domain and frequency domain descriptions

A measured vibration signal may be analysed directly in the time domain as a waveform (amplitude versus time), or in the frequency domain as a spectrum (amplitude versus frequency) after Fourier analysis (Gade et al., 1995). Frequency analysis is widely used in diagnostic vibration measurements because it reveals prominent periodic components that can often be linked to fundamental machine motions and forcing functions (Brüel & Kjær, 1982). In modern instrumentation, spectra are typically computed using the Fast Fourier Transform (FFT), which efficiently computes the discrete Fourier transform of sampled time data and represents the signal in the frequency domain (Gade et al., 1995).

In structural dynamics, frequency response functions (FRFs) relate an applied input to a measured response as a function of frequency. A common example is *mobility*, defined as the frequency response function of velocity divided by force (i.e.,

velocity/force) (Gade et al., 1995). Practical measurement workflows often compute mobility from force and acceleration measurements and allow conversion between related FRF forms (e.g., accelerance, mobility, compliance) via integration (Gatzwiller and Herlufsen).

For broadband or noise like components, spectral representations are often expressed using the *power spectral density* (PSD), which is defined in terms of amplitude squared per hertz and is proportional to the power in a one hertz frequency band (Gade et al., 1995). This interpretation motivates band limited measures (e.g., RMS over selected frequency bands) used later for feature extraction.

2.2.3 Resonance and damping

Resonance refers to conditions of peak vibratory response where a small change in excitation frequency causes a decrease in system response, and the resonant frequency is the frequency of maximum amplification for a given damping ratio (Gade et al., 1995). The amplification factor (often denoted Q) characterises the mechanical gain at resonance and depends on damping: in the idealised limit of zero damping the amplification becomes unbounded, whereas at critical damping there is no amplification (Gade et al., 1995). In practice, this means the vibration observed at a sensor location depends not only on source strength but also on the dynamics of the transmission path (stiffness, damping, and resonant behaviour of the coupled structure).

2.2.4 Orders for rotating machinery

In rotating machinery, many vibration components scale with rotational speed. When speed varies during measurement, conventional fixed frequency spectra can suffer from smearing of discrete components. Order analysis addresses this by representing the spectrum as a function of harmonic order of the rotation frequency so that synchronous components remain aligned independent of speed variation (Gade et al., 1995). In standard vibration terminology, an *order* is a frequency normalised by turning speed (e.g., $\text{Order} = f/\text{TS}$), which is especially useful for comparing spectra across operating points or during run up/coast down events (Gade et al., 1995).

2.3 Vibration Sources and Transmission Paths in an EDU

Because an EDU integrates the electric machine, power electronics, and gearing within a compact assembly, vibration in operation is conveniently described using a *source–path–receiver* viewpoint: excitations are generated internally, transmitted through structural interfaces, and finally observed at accessible measurement points (e.g., on the housing). In battery electric vehicles, the absence of an internal combustion engine reduces masking, so noise and vibration contributions from the electric powertrain, particularly motor, gearbox, and inverter related phenomena,

can become more audible and more important to characterize (Hua et al., 2021).

2.3.1 Dominant excitation mechanisms (sources)

Electromagnetic excitation and torque ripple (electric machine + inverter). Traction machines can generate vibration through electromagnetic (EM) forces acting on the stator and surrounding structure. These forces include radial components that can excite structural modes and contribute to radiated noise, while tangential components are associated with torque ripple, which can modulate the drivetrain response (Dai and Lee, 2024). The inverter and its control strategy can further introduce harmonic order and switching related components that affect vibroacoustic behavior, motivating treatment of the motor–inverter system as a coupled excitation source within the EDU (Hua et al., 2021).

Gear meshing excitation (reduction stage and/or differential). In geared transmissions, a primary deterministic excitation is generated by tooth meshing, and the associated vibration is often concentrated around the tooth meshing frequency and its harmonics. In high power to weight gearboxes, meshing frequencies commonly extend into the kilohertz range, which is directly relevant for structure borne vibration measured on housings (Plöger et al., 2016). Gear design and manufacturing deviations (e.g., transmission error and micro-geometry) can increase tonal content, while damage mechanisms such as wear can introduce modulation and observable sidebands around meshing components in the vibration spectrum (Tuma, 2009; Zhang et al., 2017).

Rolling element bearing excitation (supports for shafts and rotor). Bearing defects are commonly associated with impulsive excitations at the source: as rolling elements pass a localized defect, repeated impacts excite resonances of the structure between the bearing and the sensor location (Randall and Antoni, 2011). This explains why resonance band selection and demodulation/envelope type approaches are widely used in bearing diagnostics, and why the measured signal depends strongly on the transmission path from the bearing to the accelerometer (Randall and Antoni, 2011).

Rotordynamic/mechanical faults (imbalance, misalignment). In addition to component specific excitations, classical rotating machinery faults such as imbalance and misalignment can contribute strong speed related components. Imbalance is frequently associated with dominant running speed (1X) behavior (Zhang et al., 2023), while misalignment can introduce higher harmonics and coupling dependent signatures (Patel and Darpe, 2009). These mechanisms are relevant when interpreting order content in EDU measurements, especially during run ups or operating point sweeps.

2.3.2 Transmission paths (how sources reach the measurement points)

The structural transmission path determines how strongly an internal source is observable at an external location. In an EDU, forces generated in the motor, gears, and bearings are transmitted through shafts and bearing seats into the housing, and further through mounts into the surrounding structure (vehicle body or test

bench). In EV applications, powertrain mounts are repeatedly identified as important transfer interfaces for structure borne noise, and operational transfer path methods have been used to quantify which connections dominate interior noise and vibration responses (Lu et al., 2019; de Klerk and Ossipov, 2010).

A practical consequence is that the measured vibration is not only a function of the source strength but also of the dynamic behaviour of the assembled structure. Transfer path formulations relate operational excitations at connection points to receiver responses through frequency domain transfer relationships, which can be expressed in forms equivalent to frequency response functions (FRFs) or transmissibility matrices (de Klerk and Ossipov, 2010). Operational Transfer Path Analysis (OTPA) estimates these path relationships directly from operational measurements, enabling contribution ranking with reduced additional testing effort (de Klerk and Ossipov, 2010; Lu et al., 2019).

For vibration based condition monitoring and sensor placement, this implies that accelerometer locations on the housing should be chosen to (i) provide high sensitivity to the targeted sources across the relevant frequency/order range and (ii) support consistent operational measurements under the boundary conditions of interest (mounting, load paths, and operating point) (Lu et al., 2019; Randall and Antoni, 2011).

2.4 Vibration Measurement in EDUs: Sensors, Mounting and Data Acquisition

After identifying the dominant vibration sources and transmission paths in an electric drive unit, the next question is how these responses are measured in practice. In rotating machinery, vibration based condition monitoring is commonly structured around four main stages: vibration measurement, signal preprocessing, feature extraction, and diagnosis (Tiboni et al., 2022). Because of its sensitivity to many common machine faults, vibration remains one of the most widely used monitored quantities for rotary systems (Tiboni et al., 2022).

2.4.1 Measurement objective and measurand

In an EDU, the quantities of primary interest are usually the structure borne vibrations transmitted to externally accessible parts of the assembly, such as the housing or bearing support regions. External vibration levels measured on machine frames and bearing housings can provide useful information about machine condition, balance, and alignment, but they are not direct measurements of the internal excitation forces themselves (Downham and Woods, 1971). Instead, the measured response is shaped by the dynamic characteristics of the source–path–receiver system, including local stiffness, damping, and impedance at the monitoring location (Downham and Woods, 1971). This is why sensor location and boundary conditions are important when interpreting housing vibration data.

2.4.2 Sensors for structure borne vibration

The most common sensors for vibration monitoring in machinery are accelerometers, especially piezoelectric accelerometers. In general, uniaxial accelerometers measure vibration along one axis, whereas triaxial accelerometers measure along three orthogonal axes (Hassan et al., 2024). This makes triaxial sensors attractive when the dominant vibration direction is not known in advance or when the directional distribution of vibration is itself of interest. Piezoelectric accelerometers are widely used because they are rugged, have broad bandwidth, and are well suited to dynamic vibration measurements (Hassan et al., 2024; PCB, 2021).

For industrial and laboratory vibration work, internally amplified IEPE/ICP type accelerometers are especially common. These sensors are powered by a constant current DC supply and provide a low impedance voltage output in which the dynamic vibration signal is superimposed on a DC bias (PCB, 2021; PCB Piezotronics). This arrangement simplifies cabling and signal conditioning compared with high impedance charge output sensors, especially when the acquisition system is some distance from the transducer (PCB Piezotronics).

Sensor selection is typically governed by three main considerations: amplitude range, frequency range, and environmental conditions (PCB, 2021). The upper end of the frequency response depends on the mechanical stiffness and seismic mass of the sensing element, while the lower end is influenced by the built in electronics and discharge time constant (PCB, 2021). For mounted accelerometers, the usable upper frequency range is limited by the mounted resonance and the manufacturer specified amplitude response under the intended mounting conditions.

2.4.3 Mounting and installation effects

Accelerometer mounting has a direct influence on measurement quality, particularly at higher frequencies. Common attachment methods include stud mounting, adhesive mounting, magnetic mounting, and probe tip/stinger mounting (PCB, 2021). Among these, stud mounting generally provides the widest frequency response and the most secure attachment, whereas less rigid mounting methods can reduce stiffness, add effective mass, and therefore compromise high frequency response (PCB, 2021; Robinson and Arlington). In practice, the mounting technique is often one of the most important and overlooked factors in vibration measurement quality (PCB Piezotronics).

Surface preparation is also important. Recommended practice is to ensure that the mounting surface is as flat, clean, and debris free as possible, and for rigid mounting methods a thin lubricant layer can improve transmissibility of higher frequency content (PCB, 2021). Poor mounting can noticeably alter the mounted resonance frequency and therefore the usable bandwidth of the transducer (Brüel & Kjær, c). For triaxial accelerometers, manufacturer guidance commonly recommends mounting through the intended base surface using adhesive or a stud in order to preserve the specified multi axis frequency response (Brüel & Kjær, c).

The installation is not limited to the transducer body alone. Connectors and cables must also be suitable for the environment, and inadequate cable routing or strain relief can compromise an otherwise good sensor installation (PCB, 2021). In IEPE

systems, cable length, peak output voltage, and maximum frequency of interest all influence the current required to drive the signal properly, so sensor cabling should be considered part of the measurement chain rather than an afterthought (PCB Piezotronics).

2.4.4 Data acquisition and signal conditioning

Accurate vibration measurement requires not only a suitable sensor but also appropriate signal conditioning and data acquisition (DAQ). For IEPE accelerometers, the acquisition front end must provide constant current excitation and properly handle the sensor's DC bias and AC vibration output (PCB, 2021; PCB Piezotronics). In addition, because aliasing is a major concern in sound and vibration measurements, the acquisition system should include anti-alias filtering with sufficiently steep roll-off (National Instruments). Frequencies above the Nyquist frequency can otherwise fold back into the usable band and distort the measured spectrum (National Instruments).

Sampling frequency should therefore be selected in relation to the highest frequency content of interest, and the effective analog bandwidth of the front end should be consistent with that choice (National Instruments). High resolution ADCs and adequate dynamic range are also important because vibration signals often contain both strong and weak components simultaneously (National Instruments). When several channels are used, synchronized acquisition is valuable, especially when phase relationships, transmissibility, or multi axis comparisons are relevant.

2.4.5 Speed reference for rotating systems

For rotating machinery, measurements are often interpreted not only in the frequency domain but also in the order domain. Order analysis represents spectral content as multiples of rotational speed, which avoids the smearing that occurs in fixed frequency spectra when speed varies (Gade et al., 1995). In classical order tracking, a tachometer or equivalent speed reference is used so that the signal can be tracked and resampled with respect to shaft rotation (Gade et al., 1995; Brüel & Kjær, a). Brüel & Kjær documentation describes the tachometer signal as the tracking reference used by the order analyzer, while also noting that in some cases an autotracker can derive a reference indirectly from the measured vibration or acoustic signal if a direct tacho signal is unavailable (Brüel & Kjær, a,b).

This is especially relevant for EDU testing because many diagnostic features are synchronous with rotational speed or with specific shaft, gear, or electrical orders. As a result, the availability and quality of the speed reference strongly influence the quality of subsequent order based analysis (Gade et al., 1995; Brüel & Kjær, a).

2.4.6 Calibration and practical measurement quality

Calibration and verification are essential parts of a trustworthy vibration measurement chain. PCB's operating guide recommends verifying accelerometer performance before and after measurements, and notes that applications requiring higher accuracy or formal traceability need fuller calibration results (PCB Piezotronics). At the

standards level, ISO 16063-11 provides a reference framework for primary calibration of rectilinear accelerometers using laser interferometry (International Organization for Standardization, 1999). For routine working calibration, back-to-back comparison against a reference standard is commonly used to determine the sensitivity of piezoelectric accelerometers over frequency (PCB Piezotronics).

Beyond formal calibration, practical data quality depends on repeatable mounting, stable operating conditions, controlled cable installation, and consistent boundary conditions at the test object and its supports. Because housing vibration is a transmitted response rather than a direct source measurement, repeatability in these conditions is necessary if changes in measured vibration are to be interpreted as changes in machine condition rather than changes in the measurement setup itself (Downham and Woods, 1971; PCB, 2021).

3

Methods

3.1 Simulation based preselection of candidate accelerometer locations

To reduce the number of possible sensor mounting locations before physical testing, a simulation based preselection procedure was carried out using harmonic finite element results. The purpose of this stage was not to finalize the sensor layout from simulation alone, but to identify a smaller set of physically promising accelerometer positions for subsequent validation on the real EDU.

The harmonic simulations were performed in ABAQUS using an existing simplified finite element model of the housing and stationary structure of the electric drive unit. The model was provided by Volvo Cars and was used in this work as a basis for preselecting candidate accelerometer locations before physical testing. Four bearing locations were considered as excitation sources. For each bearing, harmonic force excitation of 1 N was applied separately in the three orthogonal directions X , Y , and Z . The resulting responses were extracted at the predefined accelerometer positions on the housing, again in three orthogonal response directions, denoted $U1$, $U2$, and $U3$. In this way, the simulation results were used as relative transfer functions from each bearing excitation point to each candidate accelerometer location.

For each excitation case, the FE export provides a complex displacement response at every candidate accelerometer position and frequency. Let the complex response be written as

$$X(f) = \Re\{X(f)\} + j \Im\{X(f)\}. \quad (3.1)$$

The displacement magnitude is then obtained as

$$|X(f)| = \sqrt{\Re\{X(f)\}^2 + \Im\{X(f)\}^2}. \quad (3.2)$$

Since the final measurements are performed using accelerometers, the simulation results were evaluated not only in terms of displacement, but also in quantities more directly related to accelerometer output. The response quantity used for ranking was obtained from

$$|H(f)| = |X(f)|(2\pi f)^p, \quad (3.3)$$

where $p = 0$ gives displacement, $p = 1$ gives velocity, and $p = 2$ gives acceleration. In the present work, acceleration based quantities were preferred for the ranking process, since they are most consistent with the intended measurement hardware.

A key point in the ranking methodology is that the final sensor is triaxial. Therefore, the three response directions at a given mounting position should not be treated as

three separate sensor locations. Instead, the directional responses were combined into a single triaxial response magnitude,

$$|H|_{3D}(f) = \sqrt{|H_{U1}(f)|^2 + |H_{U2}(f)|^2 + |H_{U3}(f)|^2}, \quad (3.4)$$

so that each candidate accelerometer position is represented by one three dimensional response curve for each excitation case.

Based on this common processing framework, three complementary ranking criteria were used.

Response strength ranking

The first criterion prioritizes positions with high overall response level across the selected frequency range. For each candidate accelerometer position and excitation case, a band averaged RMS value was calculated as

$$\text{BandRMS} = \sqrt{\frac{1}{\Delta f} \int_{f_{\min}}^{f_{\max}} |H|_{3D}(f)^2 df}, \quad \Delta f = f_{\max} - f_{\min}, \quad (3.5)$$

with the integral evaluated numerically by trapezoidal integration. This metric reflects the overall response energy in the band rather than the value at a single resonance peak.

For each bearing, the three excitation directions were then combined into one score for each accelerometer position using a weighted root-sum-square formulation,

$$R_{\text{strength}} = \sqrt{w_X R_X^2 + w_Y R_Y^2 + w_Z R_Z^2}, \quad (3.6)$$

where R_X , R_Y , and R_Z are the directional BandRMS values and $w_X + w_Y + w_Z = 1$. If one direction was unavailable, the weights were renormalized over the available components. Positions with higher values of R_{strength} were interpreted as more sensitive sensor locations.

Smoothness ranking

A high response level alone is not always desirable if it arises mainly from one or two very sharp resonances. A second criterion was therefore introduced to favour locations with a broader and more stable frequency response.

For each triaxial response curve, the logarithmic magnitude was defined as

$$L(f) = \log(|H|_{3D}(f) + \epsilon), \quad (3.7)$$

where ϵ is a small positive constant introduced to avoid numerical problems near zero magnitude. The smoothness metric was based on the mean absolute curvature of this curve,

$$S = \text{mean} \left(\left| \frac{d^2 L}{df^2} \right| \right). \quad (3.8)$$

Low values of S correspond to smooth, broadband responses, while high values indicate a response dominated by sharp resonance peaks.

Because the transformation from displacement to velocity or acceleration introduces a deterministic frequency trend in logarithmic form, this trend may be removed before differentiation so that the smoothness metric reflects resonance behaviour rather than the chosen response quantity. The three excitation directions for each bearing were then combined into one final smoothness score per accelerometer position using a weighted mean,

$$S_{\text{final}} = w_X S_X + w_Y S_Y + w_Z S_Z, \quad (3.9)$$

and positions were ranked in ascending order of S_{final} .

Separability based ranking

The third criterion addressed source discrimination. The aim here was to identify accelerometer positions that not only respond strongly, but also preserve information about which bearing excitation produced the response.

For each bearing and candidate accelerometer position, the frequency range was divided into a set of bands. Within each band, a band energy feature was computed from the triaxial response:

$$\text{BandFeat} = \sqrt{\frac{1}{\Delta f} \int_{\text{band}} |H|_{3D}(f)^2 df}. \quad (3.10)$$

This produced a feature vector describing how the response energy was distributed across frequency. The directional signatures for a given bearing were then combined using the same weighted RSS principle as in Eq. (3.6), giving one signature vector per bearing and accelerometer position.

Stacking these signature vectors as columns forms a signature matrix,

$$M = \begin{bmatrix} s_{B01} & s_{B02} & s_{B03} & s_{B04} \end{bmatrix}, \quad (3.11)$$

where each column represents the response signature of one bearing excitation at that location.

To quantify how distinguishable the bearing signatures were, cosine similarity was evaluated between the different signature vectors. The heatmaps used in this work show the raw cosine similarity values, for which values closer to 1 indicate more similar signatures and therefore poorer discrimination. For ranking purposes, however, similarity was converted into a separability measure:

$$\text{sep}_{\text{mean}} = 1 - \text{mean}(\text{off-diagonal cosine similarities}), \quad (3.12)$$

$$\text{sep}_{\text{worst}} = 1 - \max(\text{off-diagonal cosine similarities}), \quad (3.13)$$

so that larger values correspond to better discrimination between excitation sources. A sensitivity study was also performed in which one bearing case was excluded from the separability analysis. This improved the discrimination metrics, indicating that some bearing excitations produced highly redundant signatures in the simplified transfer path sense of the model. This observation is useful because it shows that the ranking reflects not only response magnitude, but also the ability of a candidate location to preserve source specific information.

Use of the simulation results

The three ranking strategies were used together to evaluate the predefined accelerometer positions from complementary perspectives. The ranking metrics were not built in functions in ABAQUS. Instead, ABAQUS was used to calculate the harmonic response data, after which the ranking metrics were implemented separately as post processing in this work. The response strength and smoothness metrics were based on suggestions from the Volvo Cars colleague who provided the existing FE model, while the separability metric was developed and evaluated as part of this thesis.

The response strength ranking highlighted sensitive locations, the smoothness ranking penalized positions dominated by narrow resonances, and the separability ranking favoured positions that better preserved information about the excitation source. Rather than relying on a single metric, the simulation results were used to reduce the candidate set to a smaller number of practically promising accelerometer locations. These simulation based results were then used as the basis for the experimental phase. A subset of favourable positions was selected from the FE study, after which real triaxial accelerometers were mounted on the physical EDU and evaluated using measured vibration data to further refine the sensor location selection.

3.2 Experimental Setup and Data Acquisition

3.2.1 Instrumentation and Sensor Installation

The vibration measurements were carried out using multiple triaxial accelerometers mounted on the electric drive unit (EDU) housing at selected candidate sensor locations. Before the measurements, a calibration check of the accelerometers was performed in order to verify correct sensor functionality. The data acquisition system used for the measurements was the PAK MK2 system.

Prior to sensor installation, both the sensor mounting surfaces on the EDU housing and the sensor bases were carefully cleaned in order to ensure proper attachment. The triaxial accelerometers were mounted using a metal to metal Loctite adhesive. The mounting procedure followed the general accelerometer installation guidelines, with particular attention paid to applying only the necessary amount of adhesive so as to avoid introducing undesirable mounting effects.

Care was also taken in cable management during the measurements. The sensor cables were not left unsupported or hanging freely, since this may introduce unwanted vibration contributions and affect the recorded signals. Instead, all cables were properly secured to minimize cable induced disturbances. After installation, a dry run was performed to confirm that the measurement chain, sensor mounting, and data acquisition system were functioning as intended before the actual test measurements were started.

3.2.2 Selection of Representative Operating Points

In order to select representative operating points for the sensor comparison study, an additional software tool was used to analyse the operating conditions that occur most

frequently during an SKLT cycle. In this work, SKLT refers to the endurance test sequence used to represent customer relevant operating conditions for the electric drive unit. This was done by processing all cycles and load steps that appear during a complete SKLT sequence and generating a combined histogram of rotational speed and torque occurrence. The purpose of this analysis was to identify operating points that are representative of the actual duty conditions experienced during the endurance test.

Based on this histogram evaluation, one dominant operating point was identified at approximately 430 rpm at the output and 40 Nm at the electric machine. In addition to this most frequently occurring condition, four further operating points were selected at different rotational speeds in order to cover a broader range of representative operating conditions. The selected operating points were:

- 200 rpm, 50 Nm,
- 600 rpm, 200 Nm,
- 800 rpm, 210 Nm,
- 1000 rpm, 35 Nm.

These operating points were used as the basis for the steady state vibration measurements used in the sensor location comparison.

3.2.3 Measurement Procedure and Data Export

For each selected operating point, the machine was operated at the prescribed speed and torque condition and vibration data were recorded from all mounted accelerometers simultaneously. The purpose of these measurements was to obtain comparable steady state vibration datasets for all candidate sensor locations under the same operating conditions.

After the completion of the measurements, the raw recorded vibration data were exported and stored in MATLAB `.mat` format for subsequent processing and analysis. These exported datasets formed the input to the signal processing and sensor ranking methodology described in the following section.

3.3 Methodology for Sensor Location Selection

The purpose of this methodology was to select the most suitable accelerometer location for vibration based monitoring of the electric drive unit (EDU) using measured steady state vibration data from multiple candidate triaxial sensor positions. The comparison was designed to identify a location that is not only sensitive to vibration response, but also stable over time and capable of providing clearly detectable machine synchronous content. The final retained methodology was based on steady state measurements at a set of discrete rotational speeds and combined both location level and axis level evaluation.

3.3.0.1 Objective of the comparison

The sensor selection problem was treated as a monitoring oriented ranking problem rather than a fault classification problem. The aim was therefore not to identify one

specific defect signature, but to compare candidate sensor positions in terms of:

1. sensitivity to relevant vibration content,
2. repeatability of the measured response over time,
3. detectability of rotationally synchronous behaviour.

The final selected location was intended to represent the most robust overall monitoring point across the investigated operating range, rather than the point giving the strongest response at only one isolated speed.

3.3.0.2 Measured data and candidate sensor locations

The vibration data were available in MATLAB `.mat` format as multichannel acceleration time histories measured on the EDU housing. Each candidate mounting position was instrumented using a triaxial accelerometer, such that every sensor location produced three orthogonal acceleration channels. In the final dataset, the comparison was performed across all candidate triaxial sensor locations available in the test setup.

3.3.0.3 Operating points considered

The selection procedure was based on steady state measurements at multiple fixed rotational speeds. The analysed operating points were:

$$200, 430, 600, 800, 1000 \text{ rpm.} \quad (3.14)$$

Each speed point was processed independently first, and the resulting rankings were then aggregated across all speeds to produce one final overall recommendation.

The use of discrete steady state operating points was chosen deliberately in order to obtain a transparent and repeatable comparison framework. At this stage, the methodology focused on fixed speed data rather than speed sweeps, so that all extracted features referred to measurements taken under approximately stationary conditions.

3.3.0.4 Segmentation of the time records

Each steady state measurement record was assumed to represent approximately 60 s of operation at the corresponding nominal speed. In order to quantify both the typical response level and the temporal stability of the response, each record was divided into six equal time blocks of 10 s each.

For a time record containing N samples over a duration $T = 60$ s, the sampling frequency was estimated as

$$f_s = \frac{N}{T}. \quad (3.15)$$

The number of blocks was fixed as

$$N_b = \frac{T}{T_b} = \frac{60}{10} = 6, \quad (3.16)$$

where $T_b = 10$ s is the block duration. The number of samples per block was then computed as

$$N_{\text{block}} = \left\lfloor \frac{N}{N_b} \right\rfloor. \quad (3.17)$$

If the total number of samples was not exactly divisible by six, the few remaining samples at the end of the record were discarded so that all six blocks had equal length. This ensured that the block wise feature values were directly comparable within each operating point.

3.3.0.5 Preprocessing

Feature extraction was first carried out independently for each acceleration axis. Prior to feature calculation, each signal was detrended by removing its mean value, so that any DC offset did not influence the band limited RMS or the spectral estimates. Two frequency bands were retained in the final methodology:

- a low frequency band of 10 to 2000 Hz,
- a high frequency band of 2000 to 6400 Hz.

These bands were selected in order to separate broader low frequency machine and structural response from higher frequency vibration content that may contain more localized dynamic information.

3.3.0.6 Axis wise feature extraction

The final retained feature set consisted of five quantities:

1. median low band BRMS,
2. coefficient of variation of low band BRMS,
3. median high band BRMS,
4. coefficient of variation of high band BRMS,
5. local $1 \times$ signal-to-noise ratio.

These features were extracted per axis first, then summarized at sensor level as described later.

3.3.0.6.1 Band limited RMS features For each 10 s block and for each axis, the signal was band-pass filtered in the chosen frequency band and its RMS value was computed. For a filtered discrete time signal $x_{\text{band}}[n]$ containing N_{block} samples, the band limited RMS was calculated as

$$\text{BRMS} = \sqrt{\frac{1}{N_{\text{block}}} \sum_{n=1}^{N_{\text{block}}} x_{\text{band}}^2[n]}. \quad (3.18)$$

This was done separately for the two retained bands:

$$\text{BRMS}_{\text{low}} : 10\text{--}2000 \text{ Hz}, \quad (3.19)$$

$$\text{BRMS}_{\text{high}} : 2000\text{--}6400 \text{ Hz}. \quad (3.20)$$

The low band BRMS was used as a measure of sensitivity to lower frequency machine and structural response, whereas the high band BRMS was used as a measure of sensitivity to higher frequency vibration content.

3.3.0.6.2 Median across blocks For each operating point and each axis, six block wise values were obtained for BRMS_{low} and $\text{BRMS}_{\text{high}}$. The typical level of each feature was represented by the median across the six blocks:

$$\tilde{F} = \text{median}(F_1, F_2, \dots, F_6), \quad (3.21)$$

where F_i denotes the feature value from block i .

The median was chosen instead of the mean in order to reduce sensitivity to occasional transient deviations or local outliers in a single block.

3.3.0.6.3 Coefficient of variation across blocks To quantify repeatability or stability over time at a fixed operating point, the coefficient of variation (CV) was calculated across the six block values:

$$\text{CV}(\%) = 100 \cdot \frac{\sigma_F}{\mu_F}, \quad (3.22)$$

where μ_F is the mean of the six block values and σ_F is their standard deviation. A lower CV indicates that the feature remains more stable across the 60 s record and therefore suggests better repeatability of the sensor response. The final retained repeatability measures were:

$$\text{CV}_{\text{BRMS,low}}(\%), \quad (3.23)$$

$$\text{CV}_{\text{BRMS,high}}(\%). \quad (3.24)$$

3.3.0.6.4 Local $1\times$ signal-to-noise ratio In addition to the band limited RMS features, the detectability of rotationally synchronous content was assessed through a local signal-to-noise ratio around the $1\times$ order.

For each axis, the full 60 s record was used to compute an amplitude spectrum after detrending and application of a Hann window. The nominal rotational frequency was defined as

$$f_{1\times} = \frac{\text{RPM}}{60}. \quad (3.25)$$

The frequency axis was converted to order by dividing by $f_{1\times}$. The amplitude of the $1\times$ component was taken as the maximum spectral amplitude in the interval 0.95–1.05 order. The nearby spectral floor was estimated from the median amplitude in the neighbouring order bands 0.80–0.94 and 1.06–1.20, excluding the peak region itself.

The local $1\times$ signal-to-noise ratio was then defined as

$$\text{SNR}_{1\times} = 20 \log_{10} \left(\frac{A_{1\times}}{A_{\text{floor}}} \right), \quad (3.26)$$

where $A_{1\times}$ is the peak amplitude near the $1\times$ order and A_{floor} is the estimated local noise floor.

This metric was retained because it quantifies how clearly the rotationally synchronous component can be distinguished from nearby spectral clutter, which is important for monitoring.

3.3.0.7 Retention of the final feature set

Only the five features listed above were retained in the final methodology. Additional exploratory descriptors such as raw $1\times$ amplitude, raw $2\times$ amplitude, and their block wise coefficients of variation were not retained in the final ranking framework. These quantities were judged to add unnecessary complexity relative to the core objective of sensor selection.

The final retained feature set was therefore chosen because it directly represented:

- vibration sensitivity in a lower frequency band,
- vibration sensitivity in a higher frequency band,
- temporal repeatability in each of those bands,
- detectability of machine synchronous content.

3.3.0.8 Axis level and sensor level evaluation

A key part of the final methodology was to distinguish between axis level performance and location level performance.

3.3.0.8.1 Axis level evaluation The primary feature extraction was carried out on each individual axis separately. This preserved the physically measured channel information and allowed the direct ranking of the actual channels that would be available in practice from a triaxial sensor.

3.3.0.8.2 Sensor level combined evaluation In addition to the axis wise analysis, a sensor level combined value was computed for each feature using a feature level root-sum-square (RSS) combination of the three orthogonal axes:

$$F_{\text{comb}} = \sqrt{F_x^2 + F_y^2 + F_z^2}. \quad (3.27)$$

This combination was applied at the feature level only, not to the raw time signals. Thus, the BRMS and $1\times$ SNR features were first calculated per axis and only then combined.

The purpose of the combined sensor level analysis was to compare the overall monitoring potential of a mounting location in an orientation robust manner. However, since a real triaxial sensor still produces independent axis signals, the final recommendation was not based solely on this combined score. Instead, the combined ranking was used as a location level screening tool and was cross checked against the axis wise rankings to ensure that the final location was also supported by practically useful individual channels.

3.3.0.9 Per speed ranking procedure

For each operating point, the candidate locations were ranked in two parallel ways:

1. axis level ranking, in which each axis was treated as an individual candidate,
2. combined sensor level ranking, in which the three axes of each triaxial location were represented by feature level combined values.

3.3.0.9.1 Criterion wise ranking Each candidate was ranked separately for each retained feature. For features where a higher value is desirable:

$$\widetilde{\text{BRMS}}_{\text{low}}, \quad \widetilde{\text{BRMS}}_{\text{high}}, \quad \text{SNR}_{1\times}, \quad (3.28)$$

the ranking was performed in descending order. For repeatability metrics where a lower value is desirable:

$$\text{CV}_{\text{BRMS,low}}, \quad \text{CV}_{\text{BRMS,high}}, \quad (3.29)$$

the ranking was performed in ascending order.

This criterion wise ranking preserved interpretability and allowed the identification of candidates that were strong in some respects but weaker in others.

3.3.0.9.2 Composite score at each operating point In addition to the criterion wise ranks, a composite score was calculated for each candidate at each operating point in order to produce an overall speed specific ranking.

Each retained feature was normalized across the candidates at that operating point using min-max normalization. For features where higher values were desirable, the normalized score was used directly. For CV features, the normalized scale was inverted so that higher normalized values always indicated better performance. The final retained weighting scheme was:

$$\begin{aligned} \text{Score} = & 0.20 S_{\text{med,low}} + 0.25 S_{\text{cv,low}} + 0.25 S_{\text{med,high}} \\ & + 0.20 S_{\text{cv,high}} + 0.10 S_{\text{snr,1}\times}, \end{aligned} \quad (3.30)$$

where:

- $S_{\text{med,low}}$ is the normalized median low band BRMS score,
- $S_{\text{cv,low}}$ is the normalized low band CV score,
- $S_{\text{med,high}}$ is the normalized median high band BRMS score,
- $S_{\text{cv,high}}$ is the normalized high band CV score,
- $S_{\text{snr,1}\times}$ is the normalized $1\times$ SNR score.

This weighting scheme intentionally gave strongest emphasis to low band repeatability and to the detectability of the $1\times$ component, while still retaining contributions from low band sensitivity, high band sensitivity, and high band repeatability.

3.3.0.10 Aggregation across operating points

Because the top ranked candidate changed with speed, the final overall recommendation was not based on a single operating point. Instead, the rankings from all steady state speed points were aggregated to identify the most robust overall candidate across the tested operating range.

This aggregation was carried out separately for:

1. combined sensor level candidates,
2. individual axis level candidates.

For each candidate, the following summary quantities were computed from the per speed composite ranks:

- composite rank at each speed,

- median composite rank across speeds,
- mean composite rank across speeds,
- worst composite rank across speeds,
- standard deviation of composite rank across speeds,
- number of first place finishes,
- number of top three finishes.

In addition, the average criterion rank across speeds was also calculated from the criterion wise ranks:

$$\bar{R}_{\text{criterion}} = \frac{1}{5} \left(\bar{R}_{\text{med,low}} + \bar{R}_{\text{cv,low}} + \bar{R}_{\text{med,high}} + \bar{R}_{\text{cv,high}} + \bar{R}_{\text{snr,1x}} \right), \quad (3.31)$$

where each $\bar{R}$ denotes the mean rank of that criterion across the investigated speed points.

3.3.0.11 Overall robustness score

To select the most robust candidate across the full speed range, an overall robustness score was constructed from the across speed summary quantities. The following five components were retained:

- median composite rank across speeds,
- worst composite rank across speeds,
- number of top three finishes,
- number of first place finishes,
- mean criterion rank across speeds.

After normalization, the overall robustness score was defined as

$$\begin{aligned} \text{Score}_{\text{overall}} = & 0.35 S_{\text{median rank}} + 0.20 S_{\text{worst rank}} \\ & + 0.20 S_{\text{top3}} + 0.10 S_{\text{first}} + 0.15 S_{\text{mean criterion}}, \end{aligned} \quad (3.32)$$

where:

- $S_{\text{median rank}}$ rewards a good median composite rank,
- $S_{\text{worst rank}}$ rewards a good worst case composite rank,
- S_{top3} rewards frequent top three performance,
- S_{first} rewards first place finishes,
- $S_{\text{mean criterion}}$ rewards consistently good criterion wise ranking.

This overall score was designed to favour robust all round performance across the operating range, rather than selecting a candidate that performs extremely well at only a single speed.

3.3.0.12 Final decision rule

The final recommendation was based on both combined sensor level and axis level evidence.

First, the combined sensor level ranking was used to identify the most promising mounting locations from a location screening perspective. Second, the axis level ranking was used as a practical validation to verify that the selected location also contained one or more strong individual measurement channels.

The final selected location was therefore required to satisfy two conditions:

1. it should rank highly in the combined sensor level analysis across speeds,
2. it should also be supported by strong axis level performance, so that the recommendation remains representative of the actual independent channels available from a real triaxial sensor.

This two level decision rule was retained because it provides a more defensible basis for sensor selection than either combined axis ranking alone or axis level ranking alone.

3.3.1 Validation of Sensor Placement During Representative SKLT Operation

The ranking process described in the previous subsection indicated that sensor position has a clear influence on the measured vibration response. However, since the final monitoring during endurance testing is performed in *delta-ANALYSER* throughout the SKLT, it was necessary to assess whether the identified differences in sensor position remain practically relevant under actual SKLT operation.

To perform this validation, two knock sensors were installed simultaneously on the electric drive unit: one representing the best available candidate location from the earlier sensor position study and one representing a location chosen randomly. In contrast to the triaxial accelerometers used in the previous measurements, the knock sensors required bolted mounting and therefore could only be installed at locations with an available threaded hole. As a result, the final positions used in this validation step were selected as the closest practical compromises to the previously identified best candidate region.

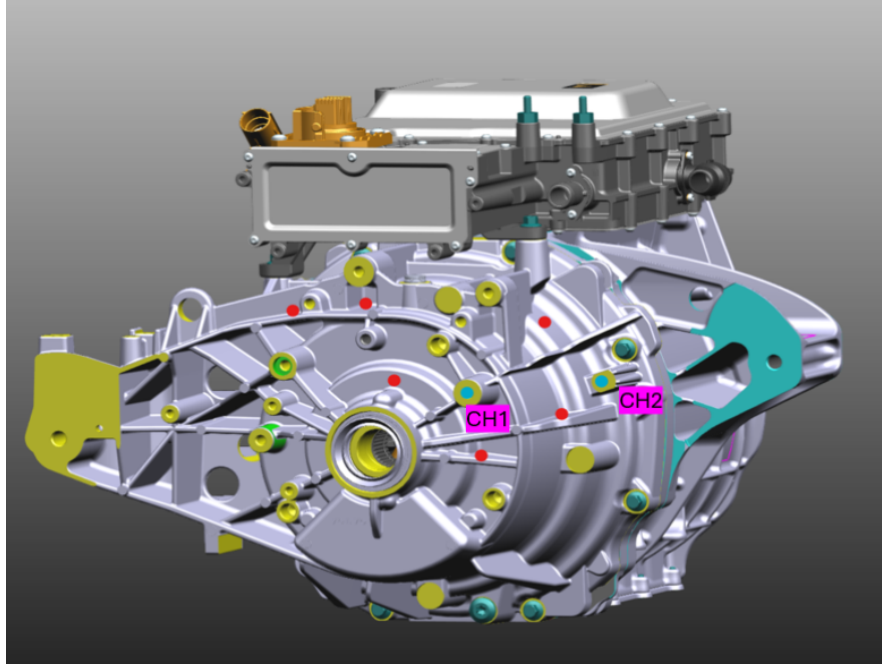
Following sensor installation, the testbed and load step configuration were prepared in the measurement software for execution of the SKLT. Due to project time constraints, the full SKLT duration was not repeated. Instead, a representative portion of the test consisting of several SKLT cycles was conducted. One SKLT cycle contains 48 different operating scenarios intended to represent a range of customer relevant driving conditions, from low speed rough road operation to higher speed highway type operation.

The objective of this validation step was to compare the responses from the two sensor locations under identical operating conditions and determine whether sensor placement has a meaningful influence on the visibility and usefulness of vibration features during endurance test monitoring. The comparison was therefore based on the measured responses from the best and randomly chosen practical sensor locations during the same SKLT segment.

The practical sensor locations used for the SKLT validation are shown in Fig. 3.1. Figure 3.1a shows the sensor positions on the EDU model, while Figs. 3.1b and 3.1c show the corresponding installations on the physical machine. The cross-sectional view in Fig. 3.1d illustrates the nearby internal structure.

3.3.1.1 Monitoring Principle in Reilhofer *delta-ANALYSER*

The SKLT endurance monitoring was performed using the Reilhofer *delta-ANALYSER* system. This software is used to monitor the vibration behaviour of the electric



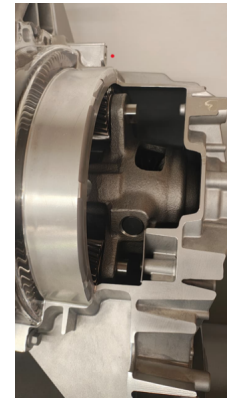
(a) Sensor locations indicated on the electric drive unit model.



(b) Sensor 1 mounted on the machine.



(c) Sensor 2 mounted on the machine.



(d) Cross-sectional view showing the internal regions corresponding to the sensor positions.

Figure 3.1: Practical knock sensor locations used for validation during representative SKLT operation. The sensor positions are shown on the electric drive unit model, on the physical machine, and in cross-section to indicate the nearby internal structure.

drive unit during the execution of the SKLT and to detect changes in the measured response over time. The monitoring principle is based on a learning phase, which is defined during the test setup before the actual evaluation phase is started.

During the learning phase, the machine is operated under the defined SKLT conditions while the software records a specified amount of vibration data. The learning phase can be defined either by a fixed time duration or by a fixed number of analysis instances. Once this learning criterion is reached, the vibration spectra measured during this phase are used to generate a reference spectrum. This reference spectrum represents the baseline behaviour, or vibration fingerprint, of the machine under the selected operating conditions.

After the learning phase is completed, each new analysis instance recorded during the SKLT is compared against the corresponding reference spectrum. If the deviation between the current measured spectrum and the reference exceeds the predefined alarm limits, the software flags the occurrence as a potential abnormal condition. In this way, the system does not only evaluate the absolute vibration level, but rather monitors how the current behaviour of the unit changes relative to its learned baseline.

An example of this comparison principle is shown in Fig. 3.2. In the *delta-ANALYSER* interface, the blue spectrum represents the reference spectrum generated during the learning phase, while the red spectrum represents the current measured occurrence or analysis instance. The difference between these two spectra forms the basis for detecting deviations during endurance test monitoring.

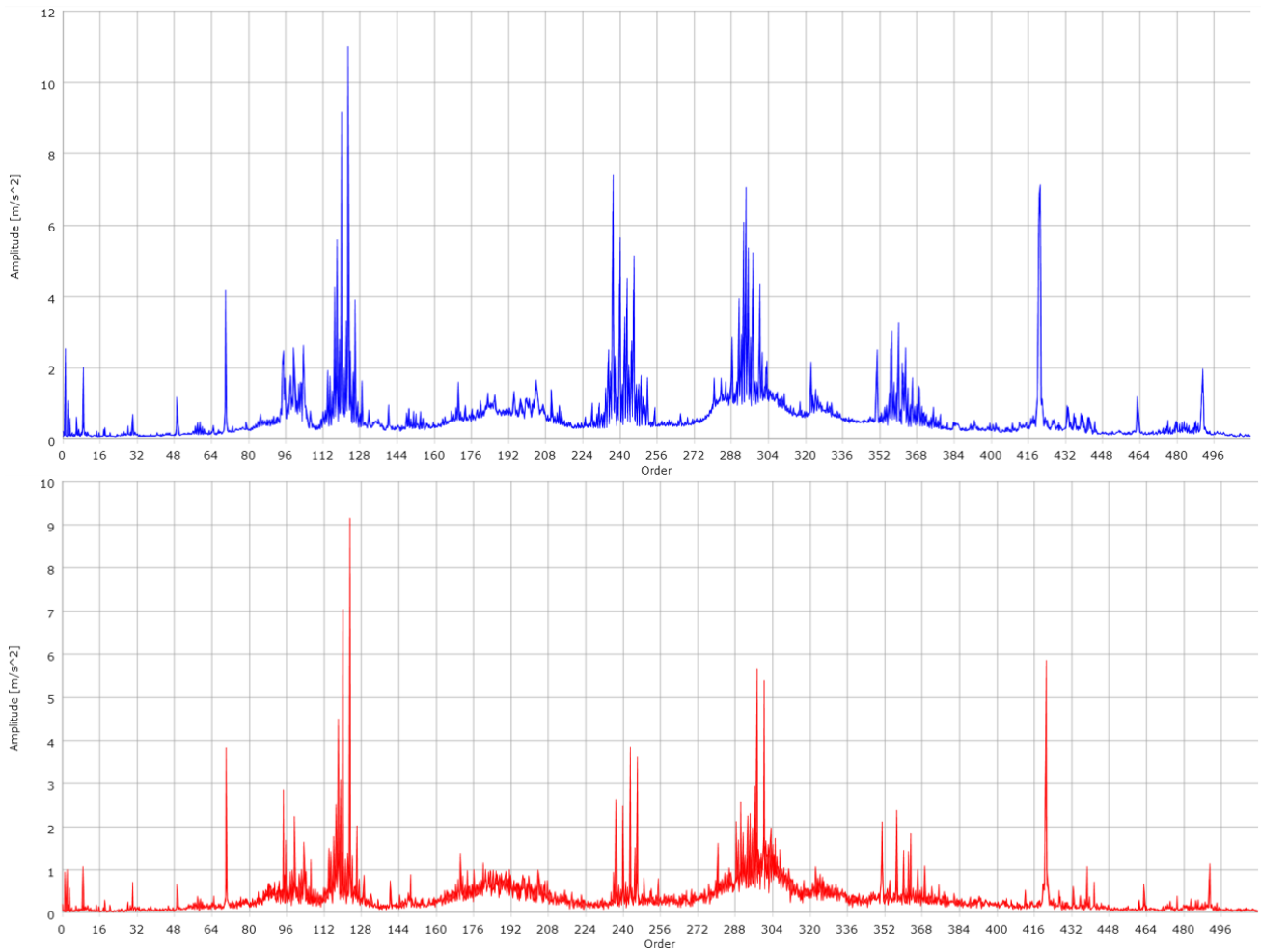


Figure 3.2: Example of reference and current spectrum comparison in Reilhofer *delta-ANALYSER*. The blue spectrum represents the learned reference spectrum, while the red spectrum represents the current measured analysis instance during SKLT operation.

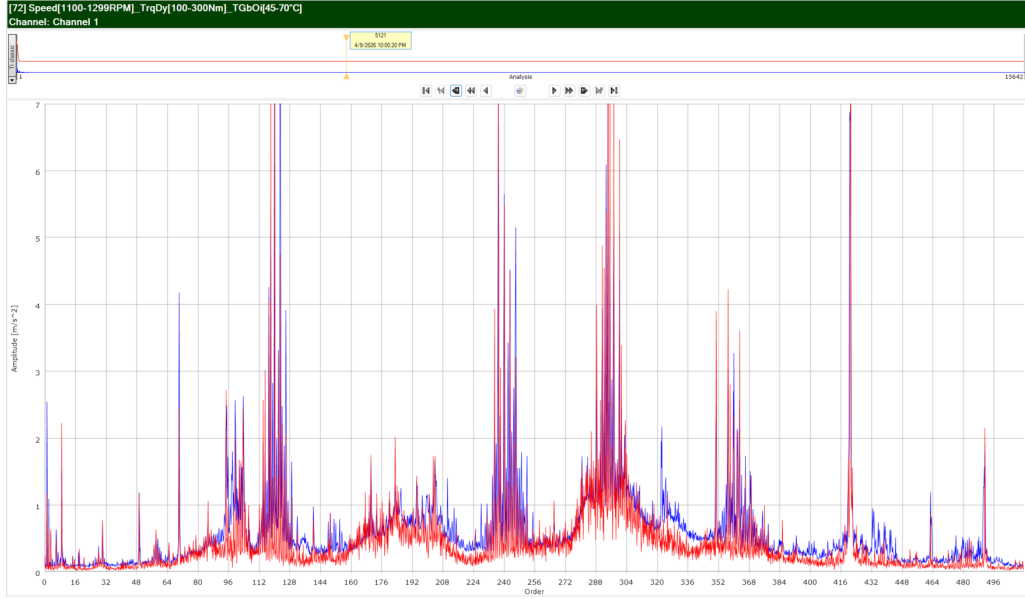
3.3.1.2 Comparison of Spectral Agreement for the Two Sensor Locations

To evaluate how the two practical knock sensor locations behaved during representative SKLT operation, the spectral response of each sensor was compared with its corresponding learned reference spectrum in the Reilhofer *delta-ANALYSER* system. In this comparison, Sensor 1 corresponds to Channel 1 and represents the location identified earlier as the best available position, subject to the mounting compromise required for the knock sensor installation. Sensor 2 corresponds to Channel 2 and represents the randomly chosen, less favourable location.

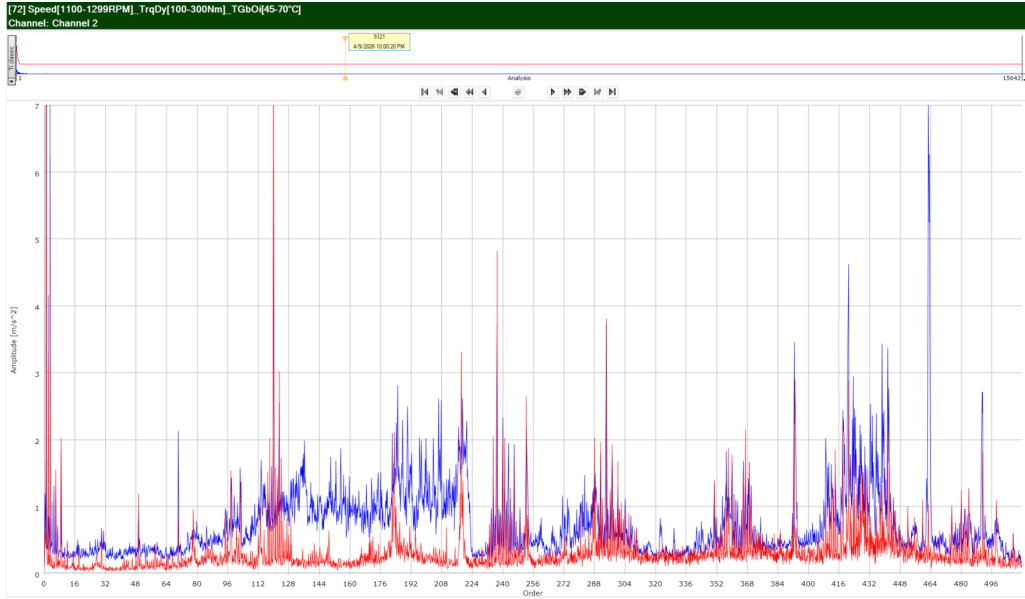
A qualitative assessment was first carried out by visually comparing the current measured spectra with the corresponding reference spectra at multiple analysis instances during the SKLT run. To make the comparison clearer, representative examples from three different analysis instances are shown in Figs. 3.3–3.5. Each figure shows Sensor 1 and Sensor 2 for the same analysis instance. For each example, the blue curve represents the learned reference spectrum, while the red curve represents

3. Methods

the currently measured spectrum.

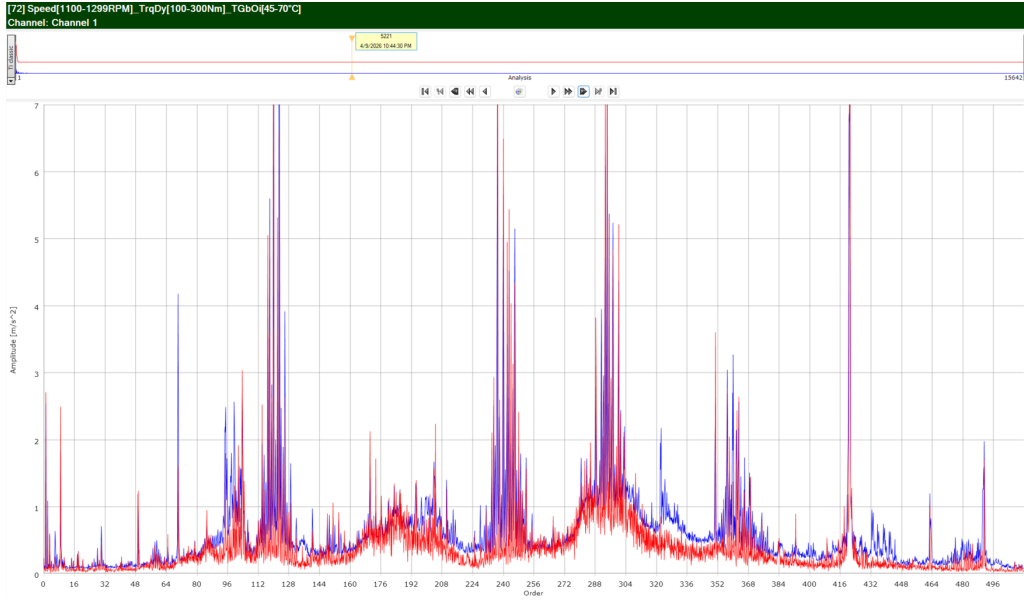


(a) Sensor 1.

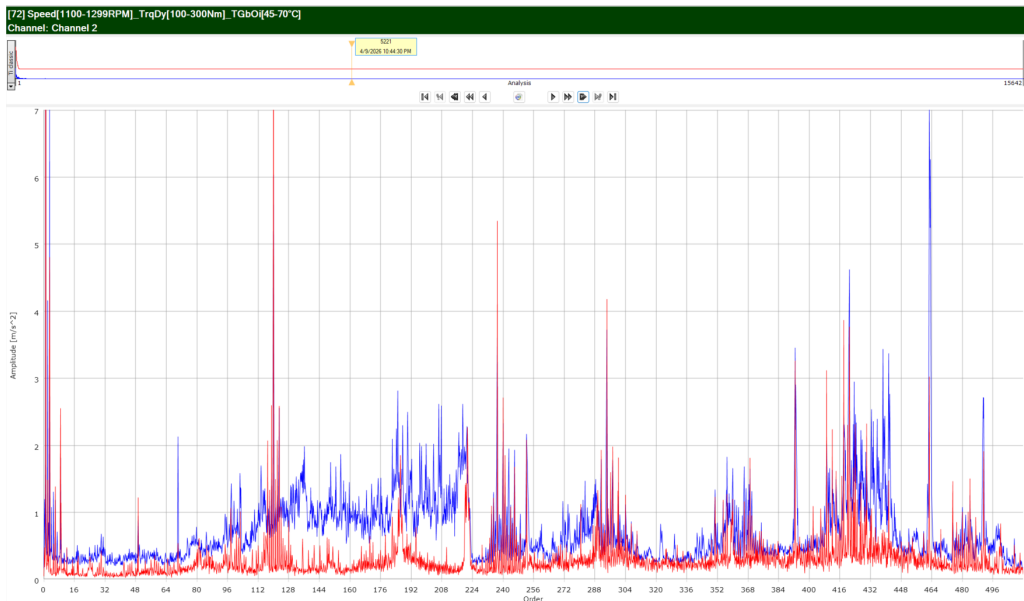


(b) Sensor 2.

Figure 3.3: Comparison of reference and current spectra during SKLT operation for example 1. The blue curve represents the reference spectrum generated during the learning phase and the red curve represents the current measured spectrum.



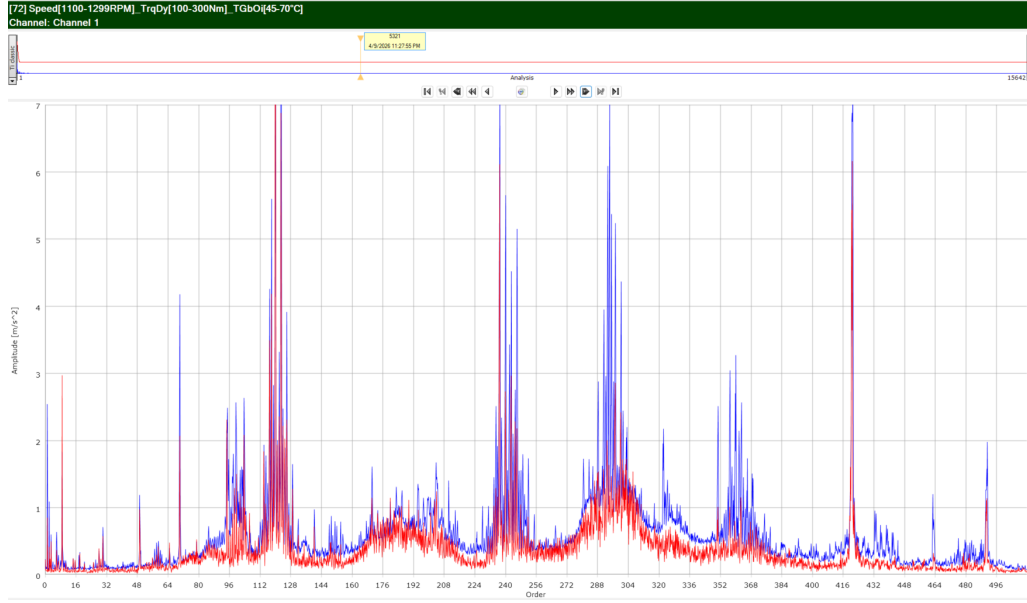
(a) Sensor 1.



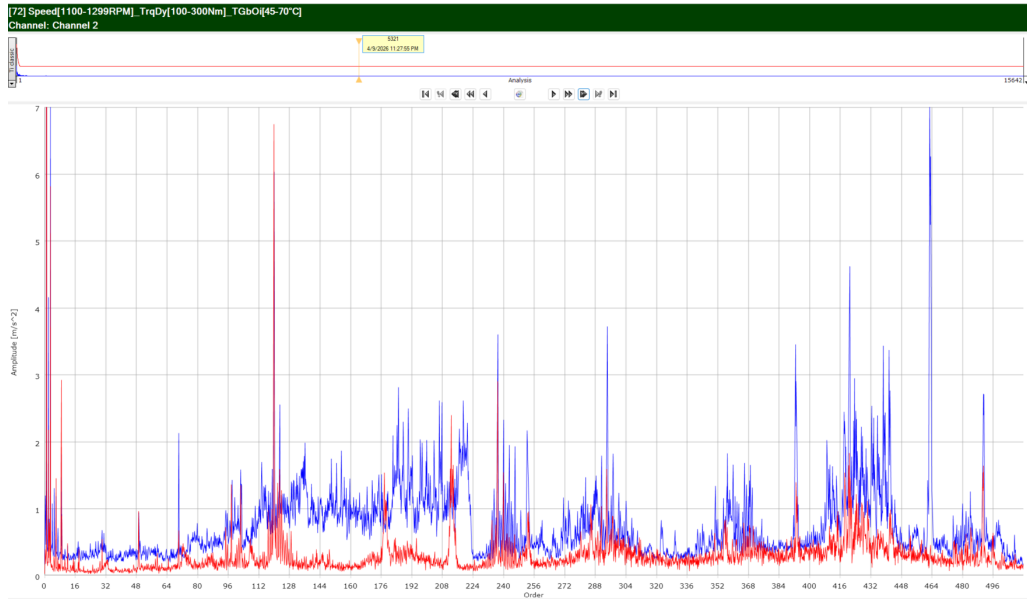
(b) Sensor 2.

Figure 3.4: Comparison of reference and current spectra during SKLT operation for example 2. The blue curve represents the reference spectrum generated during the learning phase and the red curve represents the current measured spectrum.

3. Methods



(a) Sensor 1.



(b) Sensor 2.

Figure 3.5: Comparison of reference and current spectra during SKLT operation for example 3. The blue curve represents the reference spectrum generated during the learning phase and the red curve represents the current measured spectrum.

From the visual comparison, Sensor 1 appears to show closer agreement with its corresponding reference spectrum than Sensor 2. In the selected examples, the current spectrum measured by Sensor 1 follows the reference more closely, whereas Sensor 2 exhibits more noticeable deviations from its learned baseline. This suggests that the vibration response obtained at Sensor 1 is more stable and more repeatable under the same operating conditions, which is desirable for monitoring applications based on spectral deviation from a learned reference.

3.3.1.3 Deviation Metric Around the Stage 2 Fundamental

To support the qualitative observations with a quantitative comparison, the deviation between the current spectrum and the learned reference spectrum was evaluated for one selected order case, namely the Stage 2 fundamental. For this purpose, a local order window of ± 6 orders around the Stage 2 fundamental was considered. Within this window, a normalized deviation metric was calculated as the average absolute difference between the current and reference amplitudes, divided by the average reference amplitude in the same window.

The deviation metric can be written as

$$D = \frac{\frac{1}{N} \sum_{i=1}^N |A_{\text{curr},i} - A_{\text{ref},i}|}{\frac{1}{N} \sum_{i=1}^N A_{\text{ref},i}}, \quad (3.33)$$

where $A_{\text{curr},i}$ is the amplitude of the current spectrum at order sample i , $A_{\text{ref},i}$ is the amplitude of the reference spectrum at the same order sample, and N is the number of samples within the considered order window. The window was centred around the Stage 2 fundamental and extended from $(o_{\text{S2}} - 6)$ to $(o_{\text{S2}} + 6)$, where o_{S2} denotes the Stage 2 fundamental order.

This metric provides a normalized measure of how strongly the current response deviates from the learned baseline in the vicinity of the selected order. A lower value indicates a closer agreement between the measured spectrum and the reference spectrum, whereas a higher value indicates a larger deviation.

The distribution of this deviation metric for the two sensors is shown in Fig. 3.6. The boxplot highlights the difference between the two sensor locations. Sensor 1 exhibits a lower deviation and a tighter distribution, indicating better repeatability and a closer correspondence to the learned reference. In contrast, Sensor 2 shows a higher deviation and a broader spread, suggesting a less stable response and a weaker match with its baseline spectrum.

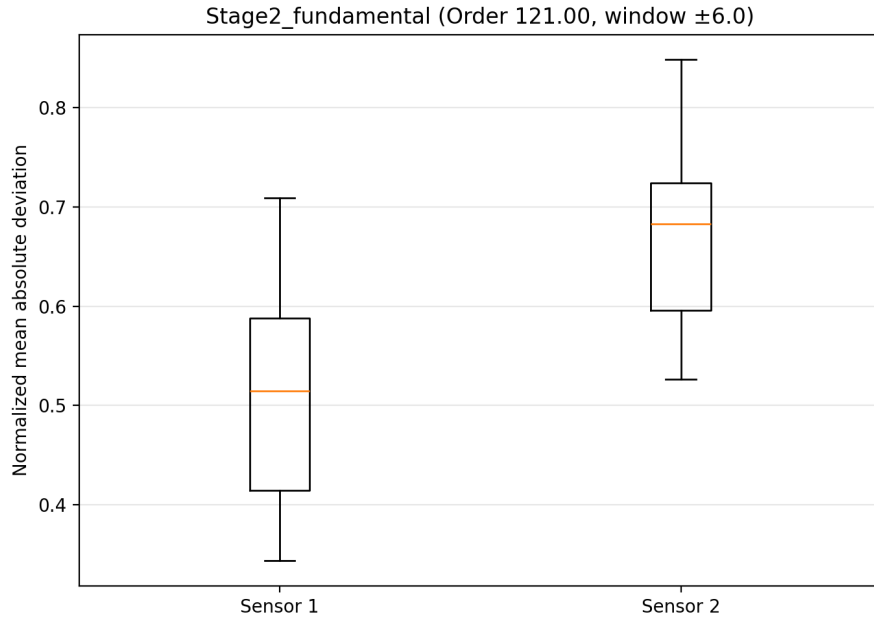


Figure 3.6: Boxplot comparison of the normalized spectral deviation metric around the Stage 2 fundamental for the two practical knock sensor locations during representative SKLT operation.

The results of both the visual spectral comparisons and the deviation based boxplot suggest that sensor position has a clear influence on the usefulness of the measured vibration data during SKLT monitoring. The better performing location, represented here by Sensor 1, appears to provide a response that is more consistent with the learned reference and may therefore be more suitable for deviation based condition monitoring. This supports the importance of studying sensor placement before using the location for endurance test monitoring.

Furthermore, once a suitable sensor location has been identified, maintaining the same position consistently across different tests is beneficial. A fixed and repeatable sensor placement improves the similarity of vibration measurements when comparing the same machine across multiple test campaigns and also supports more reliable comparisons between similar machines tested under comparable conditions. In this sense, careful sensor positioning contributes not only to improved local signal quality, but also to greater consistency in vibration based evaluation over time.

3.3.2 Refinement of Load Step Class Definition

In the Reilhofer *delta-ANALYSER* system, the measured analyses are not treated as one single population. Instead, they are grouped into operating condition classes, also referred to as load step classes. Each class represents a defined range of operating parameters, such as rotational speed, torque, and oil temperature. An example of the load step class structure is shown in Fig. 3.7, where the operating conditions are grouped into separate classes based on defined parameter ranges. This classification is necessary because the vibration behaviour of the electric drive unit changes with

operating condition. Consequently, spectra obtained under substantially different operating points should not be evaluated together, as this would mix responses originating from different machine states and reduce the meaningfulness of the comparison.

The purpose of the class structure is therefore to group analyses recorded under similar operating conditions, so that each occurrence can be compared against a more relevant learned reference. In this way, the monitoring process becomes more sensitive to actual deviations in machine behaviour rather than normal differences caused by changes in speed, load, or temperature.

Initially, the analysis relied on the default predefined classes supplied by the software manufacturer. However, after running multiple tests, it became evident that the predefined class structure was not well matched to the actual operating behaviour observed during the SKLT. Many predefined classes never occurred during the test, and several others contained very few analyses. As a result, the available analyses were concentrated in only a small number of classes, while a large portion of the theoretically possible classes remained unused.

The original class configuration consisted of 28 speed intervals, 6 torque intervals, and 9 oil temperature intervals, resulting in a total of

$$28 \times 6 \times 9 = 1512$$

possible classes. In practice, however, not all of these classes were populated during the representative test runs.

A summary of the class distribution before and after refinement is provided in Table 3.1. In the original configuration, 27.3% of all analyses belonged to only the single most populated class, while the five most populated classes together accounted for 67.8% of all analyses. Furthermore, 91.5% of all analyses were concentrated in only the 20 most populated classes. This indicates a highly uneven class distribution, where a small subset of classes dominated the dataset.

Table 3.1: Comparison of load step class distribution before and after class refinement.

Metric	Before	After
Top 1 class share	27.3%	20.4%
Top 5 classes share	67.8%	50.7%
Top 10 classes share	80.8%	70.8%
Top 20 classes share	91.5%	83.2%
Share of analyses in classes with fewer than 300 analyses	6.7%	13.7%

To improve the class distribution, the predefined classes with no occurrences and those with very low occurrences were not removed entirely, since rare operating conditions should still remain represented if they occur during future tests. Instead, these low populated or unused classes were merged appropriately, while the most frequently populated classes were further subdivided according to RPM. The objective of this refinement was to distribute the analyses more evenly across the available classes while still preserving coverage of less common operating regions.

After introducing the additional RPM based split, the class distribution became more balanced. The share of analyses in the five most populated classes decreased from 67.8% to 50.7%, while the share in the 20 most populated classes decreased from 91.5% to 83.2%. This indicates that the analyses were no longer concentrated as strongly in only a few classes, but instead were distributed more evenly across the class structure.

The refinement did, however, introduce a trade-off. In the original class definition, classes containing fewer than 300 analyses accounted for approximately 6.7% of the total dataset. After the RPM based split, this share increased to approximately 13.7%. Thus, while the refined class structure improved the overall balance of the distribution, it also created a larger number of low populated classes.

Figures 3.7a–3.7c illustrate the progression of the class refinement. Figure 3.7a shows the complete predefined class structure, Fig. 3.7b highlights the classes that did not occur during operation, and Fig. 3.7c shows the updated class configuration after refinement.

The reasoning behind this refinement was that a more balanced class distribution should reduce the variation within individual classes and thereby improve the agreement between the analyses assigned to a class and its learned reference spectrum. In principle, this should help the monitoring system compare each occurrence against a more representative baseline. However, within the scope of the present work, a direct validation of this effect was not completed. Therefore, the refinement should be interpreted primarily as a rational improvement of the class structure based on the observed operating point distribution, rather than as a fully validated optimization of monitoring performance.

TrqDynRight

Select Select

Active	From / To
☐	-2800Nm - -2700Nm
☐	-2700Nm - -2500Nm
☐	-2500Nm - -2300Nm
☐	-2300Nm - -2100Nm
☐	-2100Nm - -1900Nm
☐	-1900Nm - -1700Nm
☐	-1700Nm - -1500Nm
☐	-1500Nm - -1300Nm
☐	-1300Nm - -1100Nm
☐	-1100Nm - -900Nm
☐	-900Nm - -700Nm
☐	-700Nm - -500Nm
☐	-500Nm - -300Nm
☐	-300Nm - -100Nm
☐	100Nm - 300Nm
☐	300Nm - 500Nm
☐	500Nm - 700Nm
☐	700Nm - 900Nm
☐	900Nm - 1100Nm
☐	1100Nm - 1300Nm
☐	1300Nm - 1500Nm
☐	1500Nm - 1700Nm
☐	1700Nm - 1900Nm
☐	1900Nm - 2100Nm
☐	2100Nm - 2300Nm
☐	2300Nm - 2500Nm
☐	2500Nm - 2700Nm
☐	2700Nm - 2800Nm

TGbOil

Select Select

Active	From / To
☒	0°C - 20°C
☒	20°C - 45°C
☒	45°C - 70°C
☒	70°C - 90°C
☒	90°C - 120°C
☒	120°C - 140°C

Speed out

Select Select

Active	From / To
☒	0RPM - 99RPM
☒	100RPM - 299RPM
☒	300RPM - 499RPM
☒	500RPM - 699RPM
☒	700RPM - 899RPM
☒	900RPM - 1099RPM
☒	1100RPM - 1299RPM
☒	1300RPM - 1499RPM
☒	1500RPM - 1600RPM

(a) Original predefined load step classes.

TrqDynRight

Select Select

Active	From / To
☒	-2800Nm - -2700Nm
☒	-2700Nm - -2500Nm
☒	-2500Nm - -2300Nm
☒	-2300Nm - -2100Nm
☒	-2100Nm - -1900Nm
☒	-1900Nm - -1700Nm
☒	-1700Nm - -1500Nm
☒	-1500Nm - -1300Nm
☒	-1300Nm - -1100Nm
☒	-1100Nm - -900Nm
☒	-900Nm - -700Nm
☒	-700Nm - -500Nm
☒	-500Nm - -300Nm
☒	-300Nm - -100Nm
☒	100Nm - 300Nm
☒	300Nm - 500Nm
☒	500Nm - 700Nm
☒	700Nm - 900Nm
☒	900Nm - 1100Nm
☒	1100Nm - 1300Nm
☒	1300Nm - 1500Nm
☒	1500Nm - 1700Nm
☒	1700Nm - 1900Nm
☒	1900Nm - 2100Nm
☒	2100Nm - 2300Nm
☒	2300Nm - 2500Nm
☒	2500Nm - 2700Nm
☒	2700Nm - 2800Nm

TGbOil

Select Select

Active	From / To
☒	0°C - 20°C
☒	20°C - 45°C
☒	45°C - 70°C
☒	70°C - 90°C
☒	90°C - 120°C
☒	120°C - 140°C

Speed out

Select Select

Active	From / To
☒	0RPM - 99RPM
☒	100RPM - 299RPM
☒	300RPM - 499RPM
☒	500RPM - 699RPM
☒	700RPM - 899RPM
☒	900RPM - 1099RPM
☒	1100RPM - 1299RPM
☒	1300RPM - 1499RPM
☒	1500RPM - 1600RPM

(b) Classes with no occurrences during operation.

Speed out

Select All Select None

Active	From / To
☒	0RPM - 99RPM
☒	100RPM - 299RPM
☒	300RPM - 499RPM
☒	500RPM - 599RPM
☒	600RPM - 699RPM
☒	700RPM - 899RPM
☒	900RPM - 999RPM
☒	1000RPM - 1099RPM
☒	1100RPM - 1163RPM
☒	1164RPM - 1248RPM
☒	1249RPM - 1600RPM

TGbOil

Select All Select None

Active	From / To
☒	0°C - 45°C
☒	45°C - 70°C
☒	70°C - 140°C

TrqDynRight

Select All Select None

Active	From / To
☒	-2800Nm - -700Nm
☒	-700Nm - -500Nm
☒	-500Nm - -300Nm
☒	-300Nm - -100Nm
☒	100Nm - 300Nm
☒	300Nm - 500Nm
☒	500Nm - 700Nm
☒	700Nm - 900Nm
☒	900Nm - 2800Nm

(c) Updated class configuration after refinement.

Figure 3.7: Development of the load step class structure from the original predefined configuration to the refined class definition.

4

Experimental Challenges

During the thesis work, several practical challenges were encountered during the preparation and execution of the experimental measurements. These challenges affected the quality and usability of some recorded datasets and therefore had to be considered before selecting data for analysis. In a testbed environment, the measured vibration response is influenced not only by the electric drive unit itself, but also by the measurement chain, software configuration, operating parameter communication, and mechanical condition of the test setup. For this reason, the reliability of each dataset was evaluated before it was used for sensor position validation or SKLT monitoring analysis.

4.1 Data Acquisition Setup for Triaxial Accelerometers

One of the first challenges was related to setting up the data acquisition system for the triaxial accelerometers. Since the initial sensor position study required several accelerometer channels to be recorded simultaneously, the complete measurement chain had to be prepared and verified before the measurements could be performed. This included sensor installation, channel assignment, signal acquisition, and the communication of relevant operating parameters from the testbed.

Initially, some operating parameters required for the analysis, such as rotational speed, torque, and temperature, were not transmitted correctly to the measurement system while the machine was running. These parameters were important because the vibration response had to be related to the corresponding operating condition. Without reliable speed, torque, and temperature information, the recorded vibration data could not be interpreted correctly in relation to the test condition.

After troubleshooting, the parameter transmission was corrected and the measurement setup worked as intended. This made it possible to continue with the planned triaxial accelerometer measurements.

4.2 First Occurrence of Dynamometer Shaft Looseness

After the measurement setup was prepared, a significant mechanical issue was encountered during one of the early test runs. The output shaft connection between

the electric drive unit and the dynamometer was found to be loose at the dynamometer side end. In this work, this issue is referred to as dynamometer shaft looseness.

This issue was important because the dynamometer shaft connection is part of the mechanical load path between the test object and the testbed. Any looseness in this connection can introduce additional vibration and therefore influence the measured response. As a result, the recorded vibration data may no longer represent only the behaviour of the electric drive unit.

The problem was especially critical for the Reilhofer *delta-ANALYSER* monitoring approach, because the software creates a reference spectrum during the learning phase. If the shaft connection is already loose during the learning phase, the learned reference spectrum may include vibration behaviour caused by the testbed issue. In that case, the reference does not represent a clean baseline condition, and later comparisons against this reference become less reliable.

After this first occurrence was identified, the shaft connection was fixed and a new run was performed.

4.3 Incorrect RPM Scaling in the Measurement Software

After the first shaft looseness issue was corrected, a new run was carried out. However, another issue was then observed in the measurement software. The rotational speed recorded in the software was scaled incorrectly. The recorded RPM was approximately half of the actual machine speed. For example, when the machine was operating at 100 rpm, the software recorded approximately 50 rpm.

This caused two main problems. First, the load step classification became incorrect. Analyses recorded at true operating speeds of approximately 600–1000 rpm were assigned to lower speed classes, such as 300–500 rpm. Therefore, the class population no longer represented the real operating conditions of the machine.

Second, the order calculation was affected. Order tracking depends directly on the rotational speed signal, and an incorrect RPM signal leads to incorrect order positions in the spectrum. Therefore, the resulting order spectra could not be used reliably for interpretation.

Due to this issue, the affected dataset was not suitable for the intended analysis. The RPM scaling in the software was later corrected, and another run was performed. In this corrected run, the order positions appeared at the expected locations and the load step classification represented the actual operating conditions more accurately.

4.4 Corrected RPM Run and Second Shaft Looseness Occurrence

After correcting the RPM scaling issue, a further run was performed. This dataset initially appeared suitable for analysis because the speed signal, order positions, and class assignments were correct. This was the dataset used for the sensor location

comparison discussed earlier, where Sensor 1 and Sensor 2 were compared during representative SKLT operation.

However, during later investigation it was found that the dynamometer shaft had again been loose at the start of this run. The shaft connection was fixed during the test, meaning that the dataset contained both affected and corrected operating periods.

Although the testbed condition was not ideal, the dataset was not fully discarded for the sensor location comparison. The reason is that both knock sensors were installed and measured simultaneously during the same run. Therefore, Sensor 1 and Sensor 2 were exposed to the same machine condition, same testbed condition, and same operating sequence. As a result, the comparison between the two sensors remained meaningful as a relative comparison of sensor position.

However, this limitation must be considered when interpreting the results. The dataset can support conclusions about the relative behaviour of the two sensor locations, but it should not be interpreted as a fully clean representation of the absolute vibration behaviour of the electric drive unit.

4.5 Updated Class Definition and Third Shaft Looseness Occurrence

After the load step class definition was refined, another run was performed using the updated class structure. The purpose of this run was to evaluate the improved class distribution and to obtain data under the revised classification setup.

During this run, the dynamometer shaft looseness occurred again. This was the third occurrence of the same mechanical issue during the experimental work. The repeated nature of this problem showed that the dynamometer shaft connection was a persistent practical challenge in the test setup.

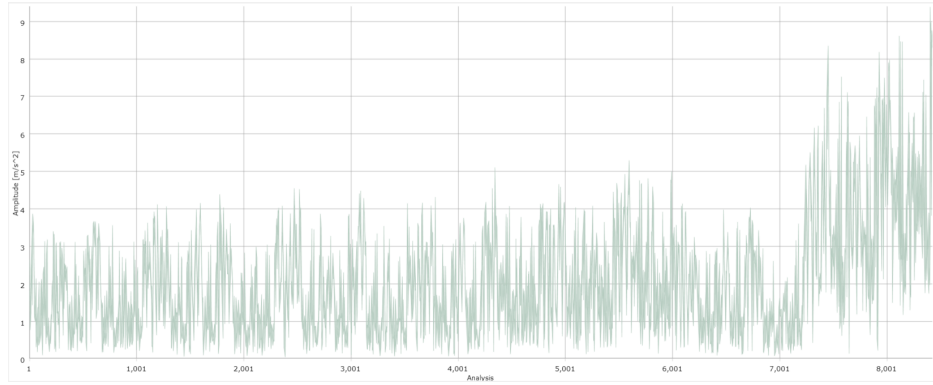
In particular, an increase in amplitude was observed around the output shaft order when the looseness was present. This indicated that the mechanical connection between the electric drive unit and the dynamometer had a measurable effect on the vibration response.

Representative examples from the three shaft looseness cases are shown in Fig. 4.1. These examples show how the issue appeared in the vibration data, especially around the output shaft order.

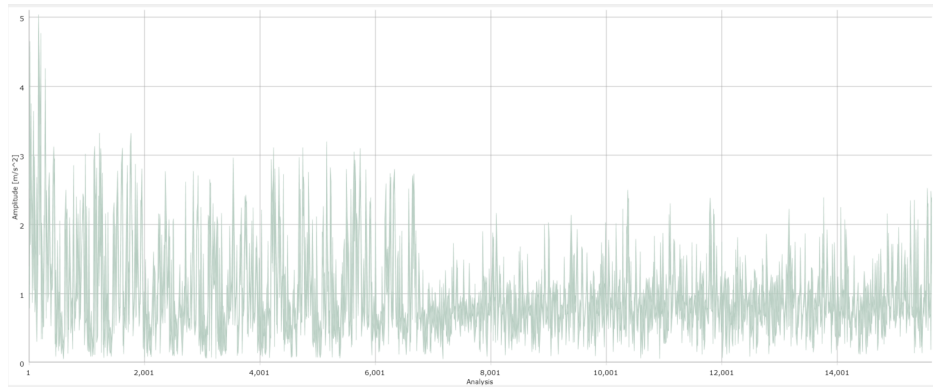
4.6 Summary of Data Quality Considerations

These challenges show that vibration based monitoring in a real endurance test environment depends strongly on the quality of the complete test setup. The recorded vibration response cannot always be interpreted as originating only from the electric drive unit, since external factors such as shaft connections, speed signal configuration, and data acquisition setup can also influence the measured data.

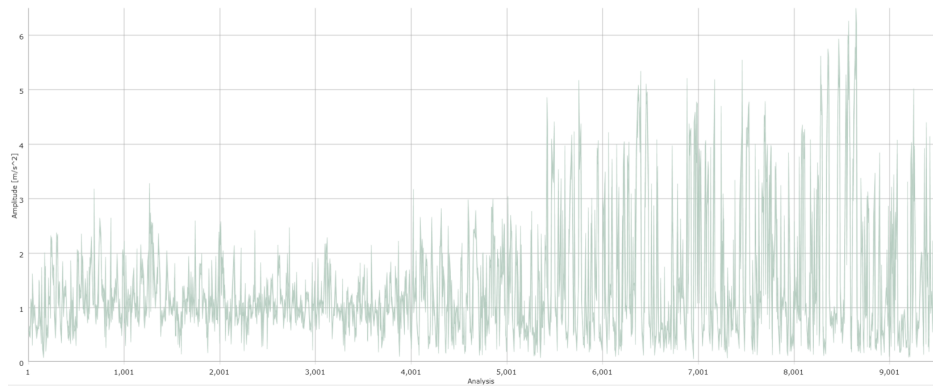
At the same time, these issues provided useful practical insight. Real experimental data is rarely ideal, and an important part of the thesis work was identifying which



(a) First occurrence during an early run.



(b) Second occurrence during the corrected RPM run.



(c) Third occurrence after class definition update.

Figure 4.1: Examples of the three observed occurrences of dynamometer shaft looseness. The issue was confirmed visually and was also reflected in the vibration data through increased amplitude around the output shaft order.

datasets were reliable, which were affected by setup issues, and which could still be used for limited or relative comparisons. This experience is relevant for applying vibration based condition monitoring in real endurance test environments, where the quality of the monitoring result depends not only on the analysis method, but also on the stability and correctness of the complete test setup.

5

Conclusions, Learnings and Future Work

This thesis investigated vibration based monitoring of an electric drive unit during endurance test operation, with focus on sensor placement, practical monitoring using Reilhofer *delta-ANALYSER*, and the influence of load step class definition. The work suggests that the quality of vibration based analysis depends on more than the selected signal processing method. It is also affected by sensor location, sensor mounting, speed signal accuracy, operating parameter communication, class definition, and the mechanical condition of the test rig.

The observations from the thesis indicate that vibration based monitoring in an endurance test environment should be treated as a complete measurement strategy. Reliable analysis depends on obtaining useful and consistent data during the test. This requires careful preparation of the test object, sensors, measurement system, software configuration, and rig condition before the actual test is started.

5.1 Main Conclusions and Learnings

One of the main learnings from the thesis work is that additional setup checks on both the test object and the test rig are important before starting a full endurance test. A basic sanity check of the machine and rig condition can help identify whether the system is operating under suitable baseline conditions before the monitoring reference is created. This is particularly relevant when using a learning based monitoring approach, since any abnormal behaviour present during the learning phase may become part of the reference spectrum.

The repeated occurrence of dynamometer shaft looseness during the experimental work highlighted the importance of the rig condition. The measured vibration response cannot always be assumed to originate only from the electric drive unit. Mechanical effects from the surrounding test setup, such as looseness in the shaft connection between the unit and the dynamometer, can also contribute to the recorded response. This suggests that rig verification should be considered an important part of vibration based test preparation.

The work also suggests that sensor placement has a clear influence on the usefulness of the measured vibration data. During the representative SKLT validation, Sensor 1, corresponding to the selected candidate location with the practical mounting compromise, showed better agreement with its learned reference spectrum than Sensor 2, which was located at a randomly selected less favourable position. The deviation

metric around the Stage 2 fundamental also indicated a difference between the two sensor locations. This suggests that the selected sensor position can influence the stability and repeatability of the measured response.

Based on these observations, sensor location should ideally be studied before running a full endurance test. Selecting a sensor position only based on convenience may lead to less useful data, especially when the aim is to compare vibration behaviour over time or across units. A more suitable sensor location may improve the quality of the measured signal and make the data more useful for deviation based monitoring.

Another important learning is the need for consistency in sensor placement. Once a suitable location has been identified, using the same location across similar tests and similar machine models may improve comparability. If the sensor location changes between tests, differences in the measured vibration response may be caused by the changed mounting position rather than by actual differences in machine behaviour. Therefore, consistent sensor placement can support more meaningful comparison across different units, test campaigns, and time periods.

The load step class refinement also provided useful insight. Since the vibration behaviour of the electric drive unit changes with speed, torque, and temperature, grouping analyses into suitable operating condition classes is important. In this work, the original class distribution was highly concentrated in a small number of classes, while many predefined classes were unused. The RPM based refinement helped distribute the analyses more evenly across the class structure. This suggests that class definition can influence how representative the learned reference spectrum is for each operating condition.

However, the effect of the refined class structure on actual monitoring performance was not fully validated within the scope of the thesis. Therefore, the class refinement should be interpreted as a practical improvement based on the observed operating point distribution, rather than as a fully validated optimization of the monitoring system.

5.2 Future Work and Suggestions

Future work should include further validation of the refined load step class definition. In the present work, the class refinement mainly focused on improving the distribution of analyses across the available classes. A useful next step would be to compare the deviation between current spectra and reference spectra before and after class refinement under similar test conditions. This would help determine whether the updated class structure reduces within class variation and improves the relevance of the learned reference.

Further refinement of the class structure could also consider torque in addition to RPM. In this thesis, the most frequently populated classes were split mainly based on RPM. However, torque is also expected to influence gear loading and vibration behaviour. A torque based split, or a combined RPM and torque refinement, may help capture gear related behaviour more accurately. Oil temperature may also be considered further if temperature dependent changes in vibration behaviour are observed.

It is also recommended that the class definition be kept consistent for tests performed

on the same machine model. If different tests use different class structures, comparison between test campaigns becomes more difficult. A standardized class definition for a given machine type could make it easier to compare vibration behaviour across units and over time.

Another important recommendation is to consider design for testing during the design phase of the machine. If vibration monitoring is expected to be used during endurance testing, suitable sensor mounting locations should ideally be included in the mechanical design. This could involve providing accessible surfaces, threaded holes, or defined mounting points close to regions where relevant vibration information is expected to be transmitted. Considering sensor access early in the design phase could reduce compromises during testing and improve measurement repeatability.

Detailed simulation could also be used to support sensor position selection. Structural or vibration simulations may help identify areas of the housing where vibration from relevant internal components is expected to be transmitted clearly. These simulation based candidate locations could then be checked experimentally using temporary sensors during steady state operating conditions. A combined simulation and test based approach may provide a stronger basis for selecting sensor locations.

Triaxial accelerometers can be useful for sensor position studies because they provide vibration information in three directions and can be mounted temporarily at several locations. This makes them suitable for comparing different candidate positions on the housing. However, their use during a full length SKLT requires further consideration. During removal after the project, the adhesively mounted triaxial sensors detached very easily. This observation raises the question of whether adhesive mounting would remain reliable throughout a long endurance test.

If triaxial accelerometers are to be used for longer test durations, the adhesive mounting method should be investigated further. The mounting should be strong enough to remain attached throughout the test, while also avoiding excessive adhesive thickness or inconsistency between mounting points. Too much adhesive, or inconsistent adhesive application, may affect vibration transmission and damping. Therefore, the mounting method would need to be standardized and validated before being used for long duration endurance monitoring.

Bolted sensors may offer better mechanical reliability for long tests, but their use depends on the availability of suitable threaded mounting points. These threaded holes may not always be located at the best vibration measurement positions. This again supports the need to consider sensor mounting requirements during the design phase of the electric drive unit.

5.3 Final Remarks

Overall, the thesis suggests that vibration based condition monitoring in an endurance test environment is strongly influenced by practical implementation. Sensor position, sensor mounting, class definition, RPM accuracy, operating parameter communication, and rig condition all affect the usefulness of the measured data. Therefore, reliable monitoring requires both suitable analysis methods and careful control of the experimental setup.

The work also showed that real experimental data is rarely ideal. Issues such as

missing operating parameters, incorrect RPM scaling, and repeated dynamometer shaft looseness affected the measurement process. However, these challenges provided important practical learning. They showed the importance of verifying the full measurement chain and testbed condition before interpreting vibration changes as changes in the unit under test.

The main practical recommendation from this thesis is that sensor placement, setup verification, and class definition should be treated as part of the monitoring strategy itself. A useful monitoring result does not begin only after the data has been recorded. It begins before the test, by ensuring that the machine, rig, sensors, and software are prepared in a consistent and reliable way.

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