Virtual sensing based on executable digital twins in rotary machinery

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Abstract

The increased market demand on the transparency of the health status of electric motors drives the digitalization of the condition monitoring services. This paper presents the application of Executable Digital Twins to create virtual sensors and monitor critical positions where placing a physical sensor is not possible. To ensure the transferability and scalability of the created solution to different machinery sizes a highly parametrized simulation model was developed. This model was calibrated and validated based on both experimental and field data. Moreover, the approach was applied for a fleet of low voltage motors. Here, the assumptions, challenges, and limitations of scaling parameterized models were investigated. Conclusively, the provided solution was integrated in a productive condition monitoring system for low voltage motor fleets.

1 Introduction

The availability of electric motors plays a crucial role in industry and production. They drive critical assets, from pumps, fans or compressors to cranes, conveyor belts of packaging machines or even entire fleets of machines. The unexpected fault of a motor component leads to unplanned downtimes including repairs and motor replacements impacting production heavily. To monitor the health status of the motor component, physical sensors are used to measure the vibration or temperatures. However, the installation of physical sensors, especially for brownfield applications, is not always possible on the location of interest due to costs, limited space, moving parts or environmental conditions.

Executable Digital Twins (xDTs) provide the means to create virtual sensors and monitor critical positions where placing a physical sensor is not possible or feasible. The developed xDTs are fed with operation parameters from the machinery's controller and vibration data, which is used to estimate the defect size in the motor's bearing. The defect size is then used to calculate the stresses on the defect locations in bearings and the remaining lifetime.

To create the Executable Digital Twin of low voltage motors, a highly parametrized simulation model was developed. This parameterization allows the model to be easily scaled to different machinery sizes, hence enabling condition monitoring of various fleet assets. To use the model in parallel to the operation, it was packaged to FMU, deployed on an edge device communicating with the motor's frequency converter to retrieve live operation parameters.

In this presentation, we introduce the theoretical background behind the developed system model followed by a demonstration of the general approach of virtual sensors' creation using digital twin technology. The calibration and validation of the model based on both experimental and field data is detailed afterwards. Moreover, the application of the approach for a fleet of low voltage motors is be presented. Here, the assumptions, challenges, and limitations of scaling parameterized models are discussed. Finally, the integration of the provided solution into a productive condition monitoring system for low-voltage motor fleets is shown.

2 Executable Digital Twin & motor's condition monitoring

Executable Digital Twins (xDTs) were applied in industry across the entire product life cycle [1]. xDTs are used to generate new services - especially in operation and service [3], as described for the exemplary lemonade production [2]. An example for monitoring in operation would be the application for virtual measurements of stress hotspot locations of the anchorage of a truck axle to prevent its early failure [4]. With predictive services the future state of critical components can be estimated and the unpleasant behavior avoided through optimized decision planning.

xDTs can be used as virtual sensors to calculate the physical quantities on locations on which the physical sensors are not feasible. Such virtual sensors are based on simulation models and use available measurement data as input. Virtual sensors can be used for mechatronic drivetrains for load torque estimation [5]. Model-based virtual sensors can be applied for predictive maintenance for minimizing downtimes for low voltage electric motors [6]. The calculation can be performed in parallel to operation on edge devices [7].

Unplanned downtimes are expensive and scale with every minute they last and can affect the entire plant. Monitoring of the health status of electric motors allows the observation of the degradation of motor components and can be used in planning shutdowns and maintenance [8]. The recent developments of Siemens Industrial Edge devices enable the realization of virtual sensors for predictive maintenance of motors as an easy to install and use application. Moreover, the services can be deployed to a cloud platform. The measurement data from the drivetrain are provided with connectivity solutions.

3 Methodology

Monitoring the vibration of every critical internal component in the motor is rather costly and could be impossible for rotary components. Alternatively, a more cost-effective approach is *virtual sensing*; an approach through which vibration levels at unmeasured locations in the motor can be estimated using a simulation model. A reliable virtual sensing approach requires

1. Description of the dynamic and geometric characteristics of the electric motor
2. Representation of the lateral and rotary loads applied to the motor through the driven components
3. Parametric definition of the possible operation anomalies and faults of the drivetrain

3.1 Modelling

A 2D dynamics model is used to describe the rotary and stationary components of the drivetrain. In the scope of this work, the drivetrain consists of a low-voltage 3 kW motor, a jaw-coupling, and a centrifugal pump. The model is developed in Simcenter Amesim and is shown in Figure 1.

The internal components of the motor as well as the motor housing are represented by point masses in a 2D space. The masses are connected to one another using spring-damper elements, described by two radial and one rotary stiffnesses as well as damping coefficients.

The linear and rotary stiffnesses are obtained by assuming a beam behavior, where the radial stiffnesses would represent the bending stiffness of the beam k_b, and the rotary stiffness would represent its rotational stiffness, k_r, given by

$$k_b = \frac{EA}{L}, \tag{1}$$

$$k_r = \frac{GA}{L}. \tag{2}$$

The coupling's linear and rotary stiffnesses are provided by the manufacturer. On the other hand, the damping coefficients were identified by fitting simulated signals to experimental measurements.

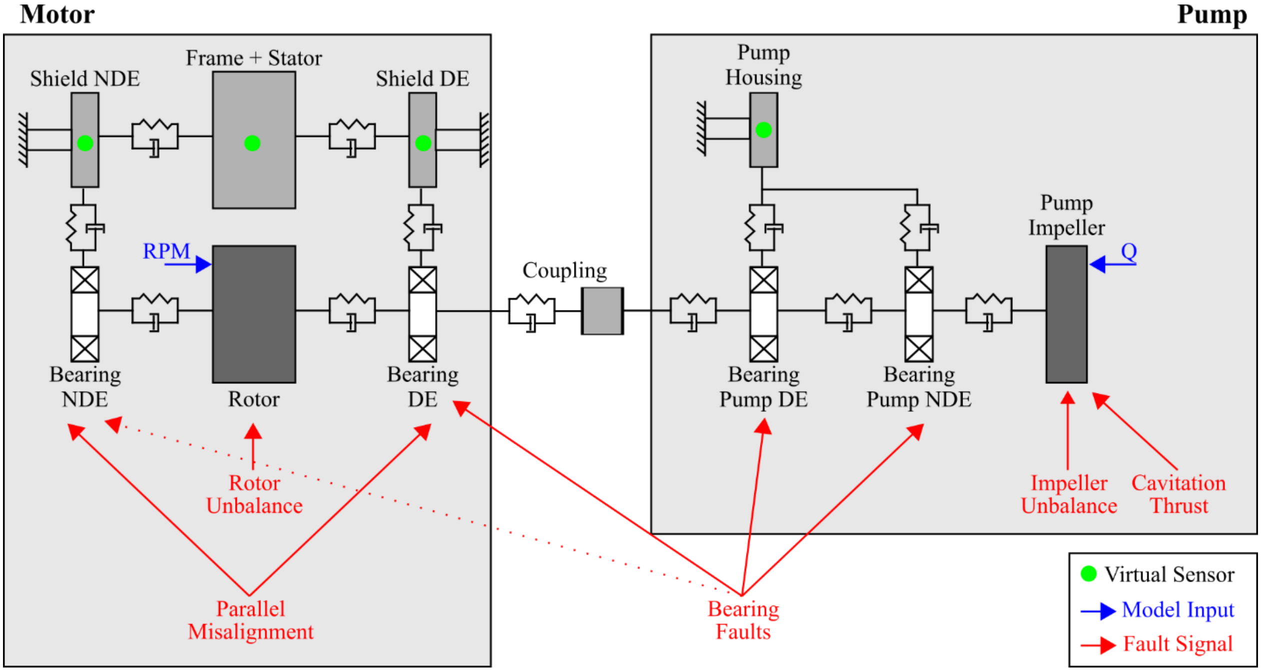


Figure 1: 2D model of the drivetrain

As mentioned, the motor considered in this work is used to drive a centrifugal pump. The pump performance is modeled by defining its characteristic curves. Depending on the flowrate, the pump's head and efficiency can be estimated, and hence the torque induced on the motor.

Operation anomalies such as motor and pump shaft misalignment, impeller abrasion, rotor unbalance, and bearing faults are parametrically defined in the model as functions of the motor's rotational speed. The bearing faults are described by radial harmonic forces applied at the bearing bodies at the respective ball-pass-frequencies of the outer race, inner race, rolling elements and cage. The unbalance and the impeller abrasion are described by a radial harmonic force with the running frequency of the motor applied at the rotor and the impeller bodies, respectively. Misalignments on the motor and pump shafts are described by a radial offset at the shaft ends.

On the other hand, cavitation anomaly occurs due to insufficient pressure at the suction end of the pump, or insufficient Net Positive Suction Head available (NPSHa). This results in the formation of air bubbles in the flow at low pressure, which explode and introduce radial thrusts on the pump's impeller. The calculator described in [1] is employed to identify the magnitude of the net radial thrust as a function of volumetric flowrate in the pump, suction head, and the rotation speed.

3.2 Virtual sensing

Virtual sensing allows estimating the vibration levels at internal components without additional instrumentation. In the scope of this work, the components of interest are the motor's drive-end (DE) and non-drive-end (NDE) bearings, and the pump's DE bearing.

Since virtual sensors utilize simulation models to estimate the vibration levels, critical operation scenarios could be simulated with less effort compared to conducting experiments. Typically, condition monitoring instrumentation is attached to the fins on the motor's frame and is used to detect anomalies and faults. Therefore, the vibrations at the motor's frame are additionally recorded.

The implementation of the virtual sensors in the model is achieved by recording the raw acceleration signals at the components of interest in the model. A common practice in condition monitoring of rotary machinery is to examine the velocity spectra of the signals for anomalous behavior to detect faults. Therefore, the magnitudes of the characteristic fault harmonics in the velocity spectrum are extracted by applying a bandpass filter around the frequency of interest and estimating the output signal’s peak-to-peak value. Typical frequencies of interest include multiples of the motor’s rotation frequency, bearings’ pass frequencies, and vane-pass-frequency of the pump.

To utilize the virtual sensing model in condition monitoring contexts as well as data synthesis, the Amesim model is exported as a functional mock-up unit (FMU). The inputs to the FMU are the motor speed, percentage of the best efficiency point (BEP), magnitude of misalignment, and mass of impeller material abrasion. The outputs of the FMU are the raw acceleration signals at the motor’s frame, where the condition monitoring instrumentation (SIMOTICS CONNECT 400) is mounted, the RMS value of the velocity signal at the middle of the motor frame, actual rotation speed, actual torque, and consumed power during operation.

4 Results and validation

To validate the model, a test rig comprising a 3kW asynchronous drive and a centrifugal pump is used, shown in Figure 2. The test rig is equipped with accelerometers mounted on the motor’s drive end (DE) and non-drive end (NDE) bearing shields, motor frame, and pump DE shield. Additionally, flow and pressure sensors are mounted on the pump’s suction end.

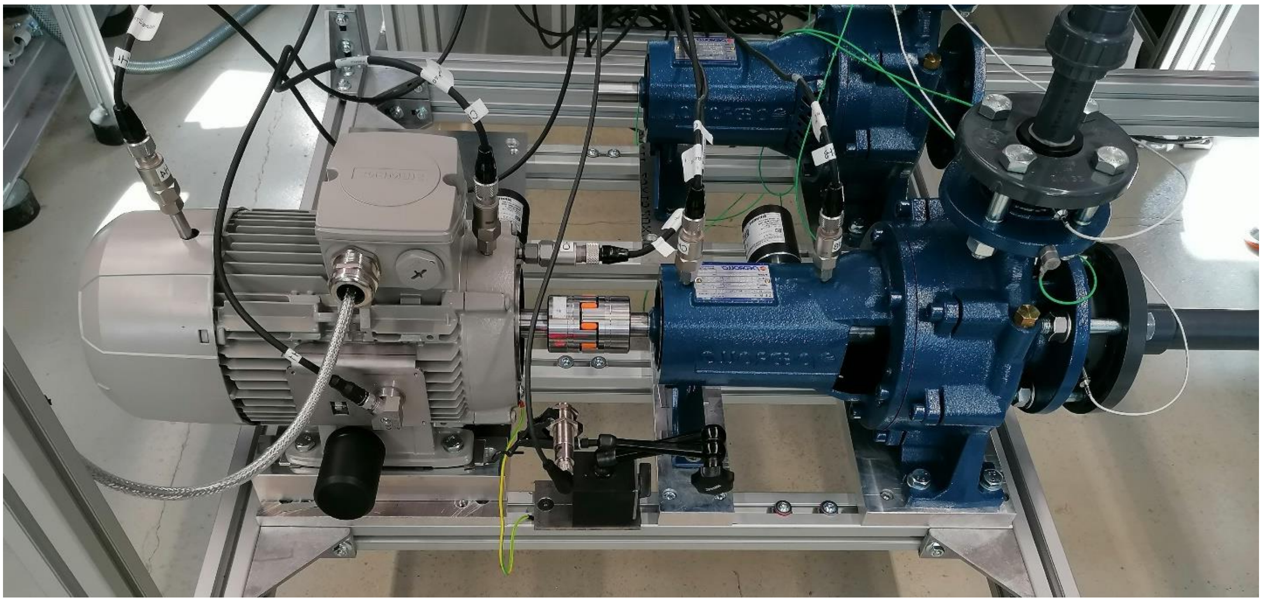
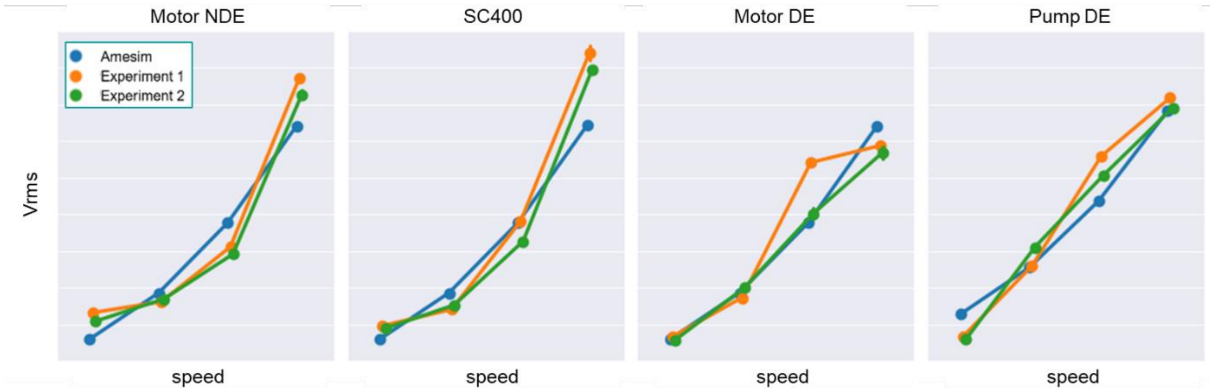


Figure 2: Validation test rig

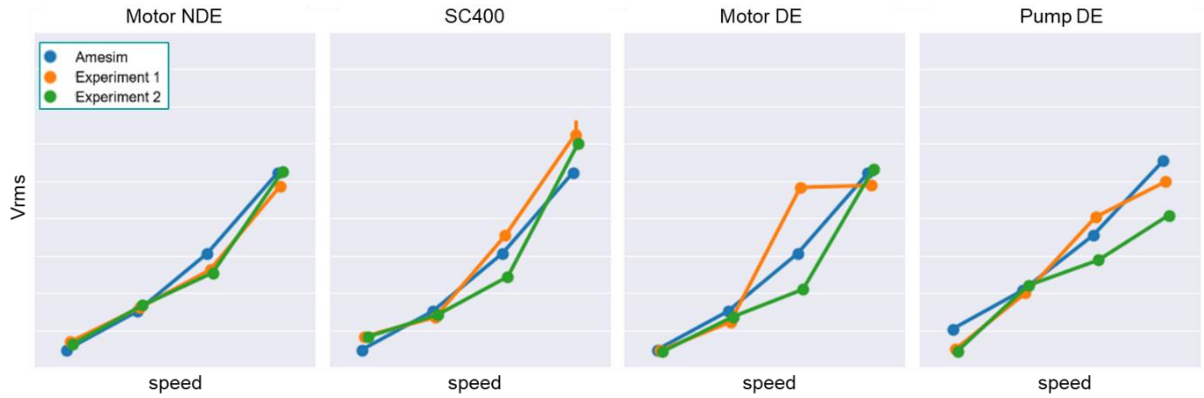
4.1 Validation healthy case

After identifying the damping coefficients of the spring-damper elements from experimental measurements, test runs with various operation conditions are conducted. The volume flowrates in the pump are varied from 0% to 100% of the flow rate at the BEP, and the rotation speeds of the motor is varied between 25% and 100% of the nominal speed (725 rpm and 2900 rpm, respectively). The entire test set was repeated twice. For both sets, the root-mean-square of the velocity signals (Vrms) measured at different positions sets were compared to their correspondents in the model.

Figure 3 shows a comparison between the Vrms values between the experimental sets and the simulation, once for a full-load operation and once for a no-load operation. The comparison is carried out between measurements at the motor NDE shield, motor frame (referred to as SC400), motor DE shield, and pump DE side (side closer to the motor). The plots show that the model with the calibrated damping coefficients represents the dynamics of the model in health conditions precisely.



(a) Full load



(b) No load

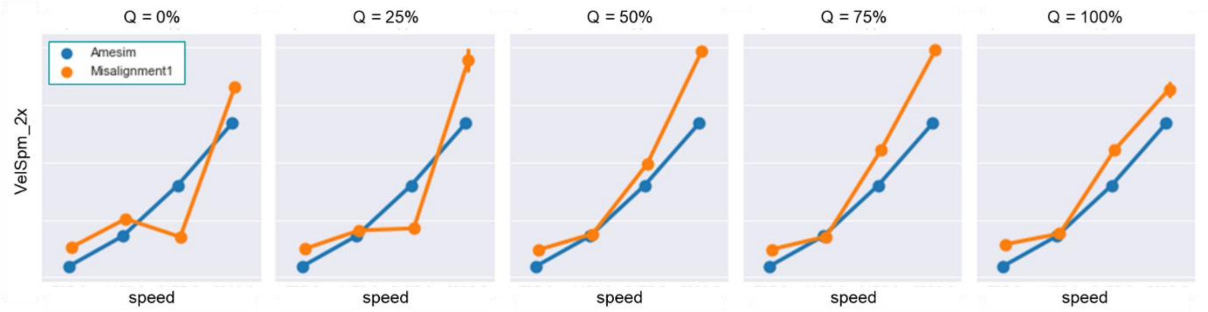
Figure 3: Comparison of Vrms from simulation and experiment at different positions on the drivetrain

4.2 Simulating misalignment

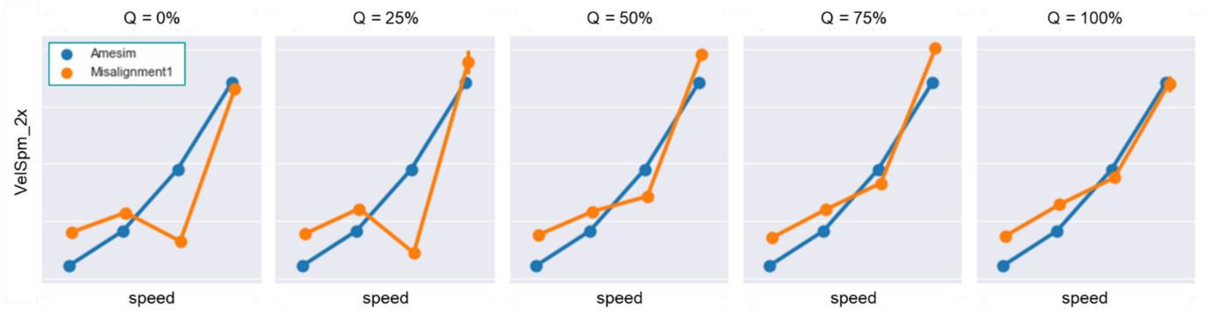
To compare the model's precision in simulating dynamics of a drivetrain with misalignment, a parallel misalignment of 0.5 mm between the motor and the pump is recorded on the setup and is accordingly introduced as spatial offset to the respective components in the model.

To examine the precision of modelling misalignment, the amplitude of the second harmonic of the velocity spectrum (velSpm_2x) is extracted from the virtual sensors' output. The values of velSpm_2x are compared at the motor DE as well as the pump DE for different motor speeds and different percentages of the BEP flowrate (percQ), as shown in Figure 4.

The model shows high precision at both sensor positions. Exceptionally, at 2175 rpm motor speed and low percent volumetric flowrate (<25%), the model shows a deviation from the sensor measurements. This could be attributed to a pump anomaly not considered in the model.



(a) Motor DE



(b) Pump DE

Figure 4: Comparison of the velocity spectrum 2nd harmonic's amplitude at the motor and pump

4.3 Simulating impeller abrasion

Abrasion is a common anomaly in pumps, especially if the pump experiences excessive cavitation. Due to the explosive thrusts introduced by the accumulating air bubbles in the flow, material could wear off the impeller blades. This introduces unbalance effects to the rotary components of the drivetrain. Similar to rotor unbalances, the impeller unbalance could be detected by monitoring the amplitude of the first harmonic of the velocity spectrum (velSpm_1x) and the root-mean-square of the velocity signal (Vrms).

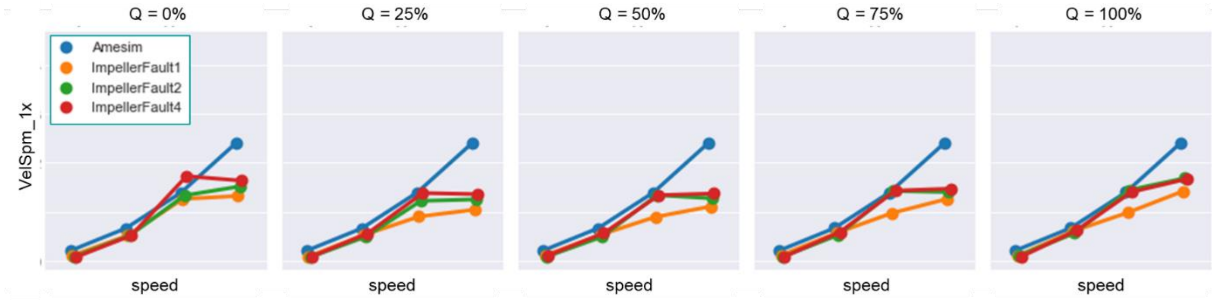
The healthy pump impeller is replaced with an abraded impeller where 120 g of the impeller's material was synthetically scraped off to emulate the random material abrasion that would occur during operation. In the simulation model, equivalent material loss was assumed uniformly distributed around the eye of the impeller.

Figure 5 shows both velSpm_1x and Vrms plotted for the simulation and three different experimental runs at different speeds and percentage volume flowrates. The model coincides significantly with the experimental results at all operation points, except for a slight deviation in velSpm_1x observed at full speed.

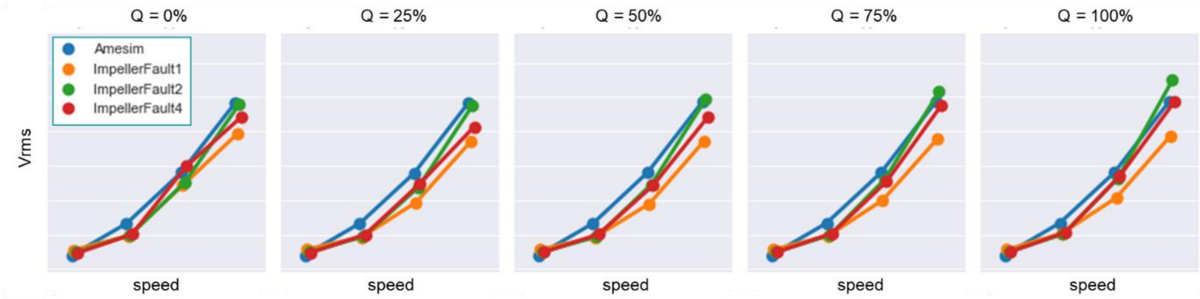
5 Conclusion

In this paper the methodology for the development of an Executable Digital Twin based on virtual sensors and the application of virtual sensors to monitor critical positions was presented. The established model is highly parametrized to ensure the transferability and scalability of the created solution to different machinery sizes. The calibration & validation using experimental data demonstrates high precision of the simulation.

The created virtual sensor can be used for the generation of the synthetic data for the failure scenarios for a drivetrain including motor, coupling, and pump. Moreover, the output vibration signals from the model can be applied as boundary conditions for a numeric model to calculate the stresses at critical locations, e.g. bearings. Such calculations can be used for remaining life estimation.



(a) Amplitude of the first harmonic of the velocity spectrum (velSpm_1x)



(b) Root mean square of the velocity signal (Vrms)

Figure 5: Velocity spectrum 1st harmonic and velocity RMS at the motor frame

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