Dynamic Simulations for Lift Health Diagnosis

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Abstract. System simulations introduce new opportunities in lift health diagnosis, due to their quasi-real time computation and cross disciplines coverage.

The approach is based on an object-oriented model, where controller, machinery, hoisting and building layout are interconnected for computing the lift dynamics for its entire ride.

While most of the components impacting the dynamics of lifts are described by blocks with certain physical parameters, others are described more in detail, including local flexibility and eigenfrequencies expression. The created model is structured, modularized, and parametrized.

Several simulation outputs can be used for diagnosis: car position, velocity and vibrations, guide shoes forces, machinery current and torque, however in this paper the focus is on using spectrums of car vibrations for this purpose.

Healthy and several malfunction behaviors are computed and validated using system simulation, proving that this approach can be used for identifying the faults and providing solutions for mitigating them.

1 INTRODUCTION

KONE has a long history, where mechanic, electro-magnetic, thermal, acoustic and many other simulations have been used for virtual prototyping. The target being the optimization of component design, performance, or fulfilling the code requirements.

System simulations came later in KONE, as well as in other industries, because they require cross-discipline computation, cross-functional cooperation, and extensive validation.

However, the front-loaded effort is worth it. Due to real time or quasi-real time computations, the applications of the simulations can be extended beyond the development phase of the components, towards the entire lifetime of the equipment. System simulation can provide a better understanding of the lift or escalator reliability, lifetime performance, health monitoring, diagnosis, remote maintenance, and software testing.

The benefits of integrating synthetic data – the results of simulations - with measured data, collected from the systems, for a better diagnosis of the health of equipment, using machine learning algorithms, are discussed in several articles [1, 2].

The focus of this paper is to answer the research question: can simulation provide consistent, robust synthetic data that can be used for training machine learning algorithms in diagnosing lift health?

Studies for answering this question have been discussed in several master theses conducted in KONE [3, 4, 5, 6]. The conclusion is that by using adequate computational strategy, modularized and parametrized simulation models, a big step can be made toward better lift monitoring and health diagnosis.

2 SELECTION OF THE COMPUTATIONAL STRATEGY

The main requirements of using simulations during the operational phase of the equipment are the real or quasi-real computational time and the model possibility for parametrization. The challenge of using a fast computation method is the ability to capture the simulated physical phenomena, with acceptable accuracy.

High fidelity methods, such as finite element, are not effective for computing a fleet of complex equipment with large variations in dimensional and running parameters. Especially if results for computing the performance of new equipment are needed fast in the development phase.

A fast computational method, for example, an object-oriented method, can provide real time results; however, not all the phenomena, for example, local eigenfrequencies, can be described. For this reason, several methods have been combined. Ranking of several methods based on their computational time and fidelity of the results is presented in Figure 1.

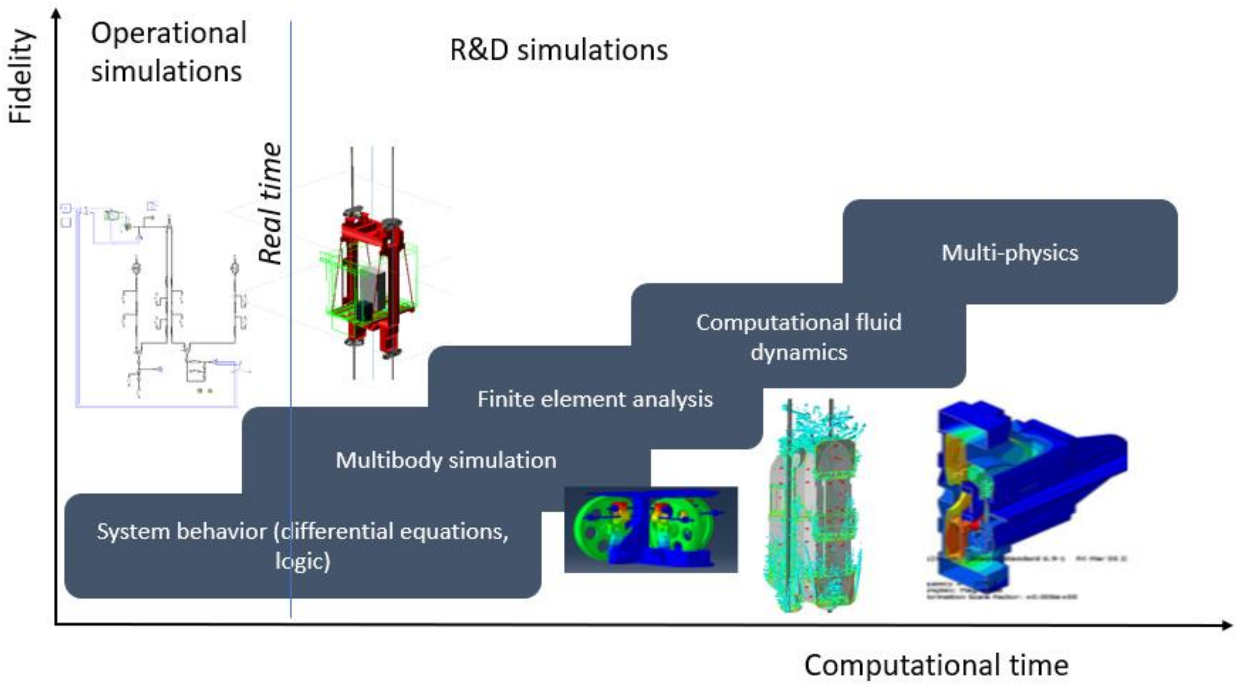

Figure 1 Ranking of different computational methods

Another challenge was the identification and selection of the components contributing to the lift dynamics and the method to describe their behaviour.

For creating the lift model, SimulationX software [7] has been selected. The software is based on the object-oriented description language Modelica [8]. The model contains blocks representing critical components with impact on lift dynamics. Each block is defined individually with mechanical, electrical, or logical inputs. These blocks represent machinery including its mechanical, electrical inputs, the motion control algorithm; the hoisting, including ropes and pulleys; car-sling-doors subsystem including their guide shoes and guide rails; lift safety features: safety gears, buffers, sensors; and building layout details, for example distances between floors, pit depth, and others (Fig. 2). The blocks are linked through specific connections.

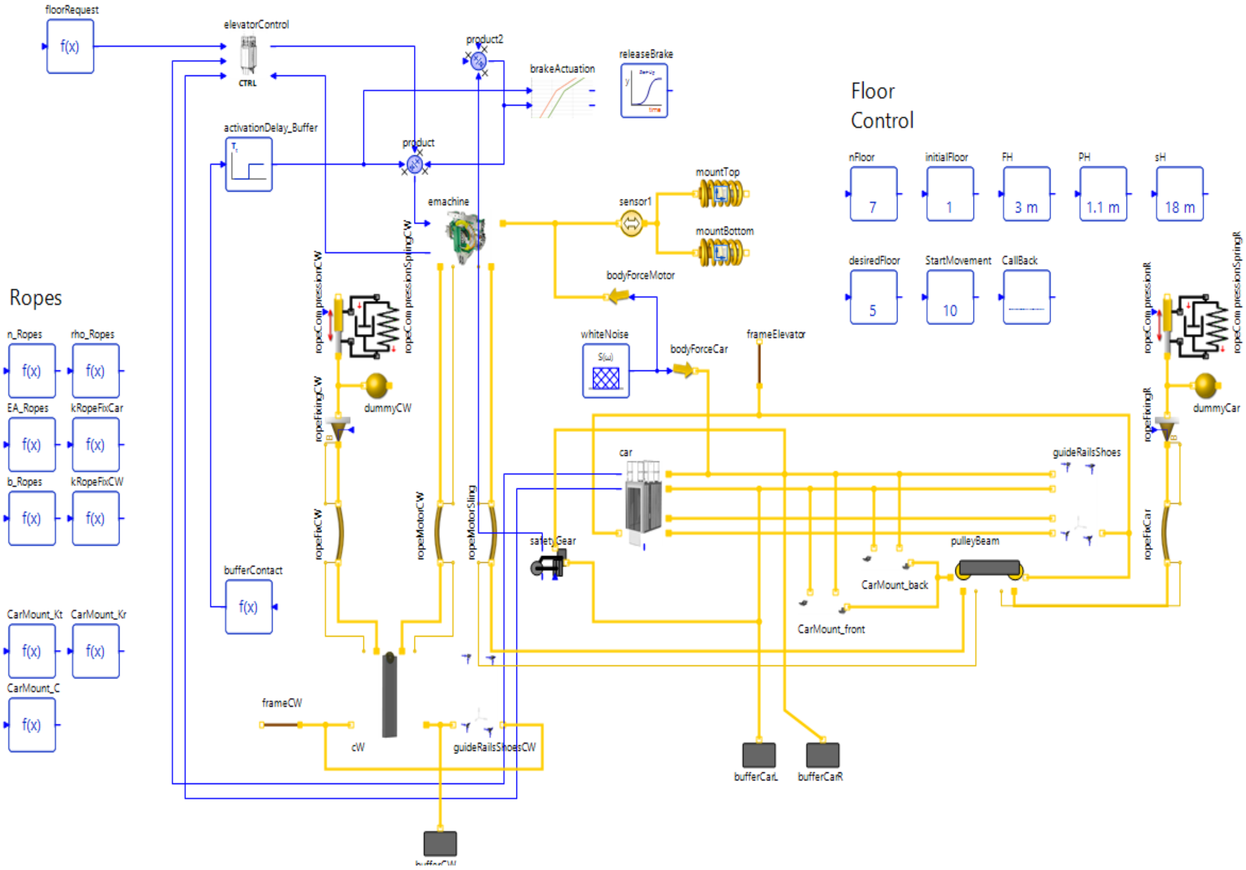

Figure 2 The architecture of lift model

The outputs of the simulation depend on the application, for further integration with measured data, the selected output of this model had to be easily collected from sites. For this reason, the three-dimensional car vibrations, velocity, and position in the shaft have been selected.

3 INPUTS

Each block in the model is described by inputs collected from different sources: product documentation, laboratory results, geometrical models, results of other simulation methods, or software code.

3.1 Mechanical inputs

The behaviour of each block is described with differential algebraic equations, constant or variable in time during simulation. However, the inputs describe the entire block – as an entity, therefore if the structure contains high space variations in the behaviour, for example, one component is very stiff while another is very flexible, the structure is divided into multiple blocks with similar behaviour.

In the machinery case, the structure has been divided into three blocks with similar properties: the frame, including the traction sheave, the top mount, and the bottom mount (Fig.3).

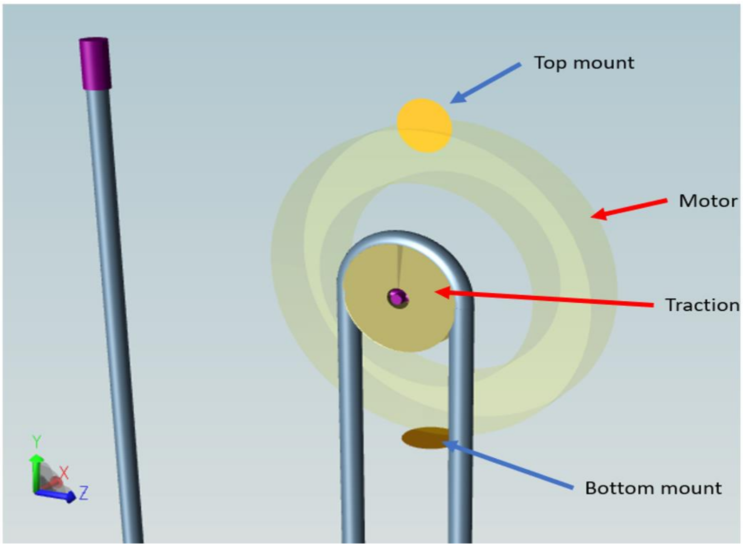

Figure 3 The machinery blocks

For each block, mass, centre of gravity and inertia tensor around centre of gravity are selected from documentation or 3D geometrical models.

The stiffness tensor of the blocks can be estimated as rigid, measured in the laboratory, or computed using an analytical or numerical method, for example, finite element method (Fig.4) calculated in this paper with the software Ansys [9]. The damping tensor can be estimated based on the stiffness tensor or measured in the laboratory, if possible.

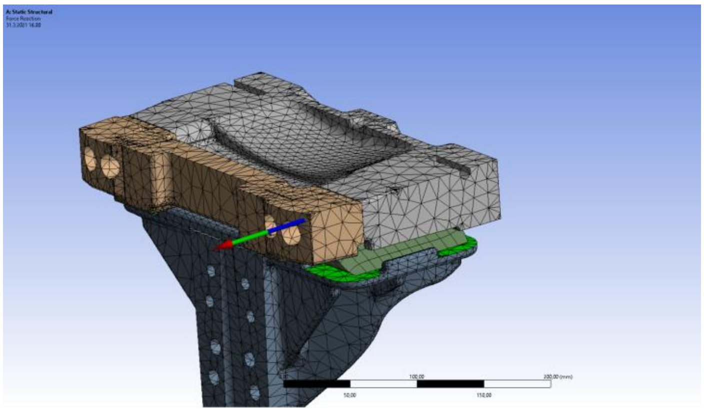

Figure 4 The bottom mount stiffness calculation

The computational time requirements create limitations in the number of blocks that can be created in the model. In addition, for certain components, the local eigenfrequencies, which are the frequencies at which the component tends to vibrate in absence of any driving force [10], may have a significant contribution to the in-car vibrations.

In this case, two different computational methods have been selected: finite element and meshless method [4]. The selection of the computational method depends on the complexity of the structure. For machinery bedplate, the recommended method for eigenfrequency extraction is finite element, for which Ansys software [9] has been used.

For sling-car-door subsystem, due to its complexity, the recommended method is the meshless one, computed in this paper with the software Simsolid [11]. The main difference between these methods is that for FEM, the structure must be divided into smaller substructures called elements, whereas meshless solutions remove the need for structure discretization and instead describe the structure only by the set of nodes used for approximation functions (Fig. 5). Therefore, instead of having strict pre-defined element-based shape functions, the meshless method has shape functions based on nodes in a local support domain. Otherwise, the same variational approach is used for both methods.

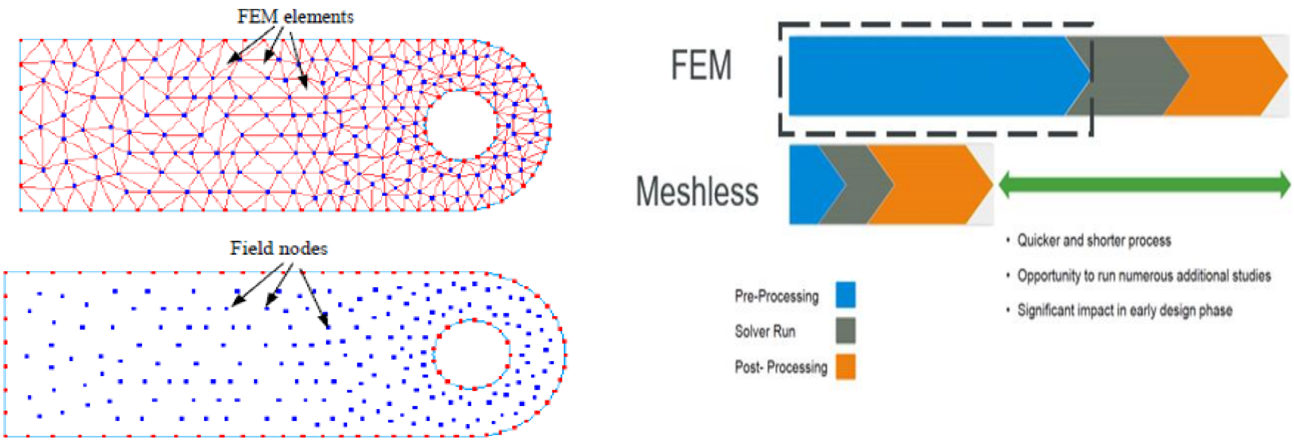

Figure 5 Comparison between finite element and meshless method

The meshless method is faster because it does not require geometry simplification, however, the FEM is more accurate, if the geometry simplification is minimum, which is rarely the case.

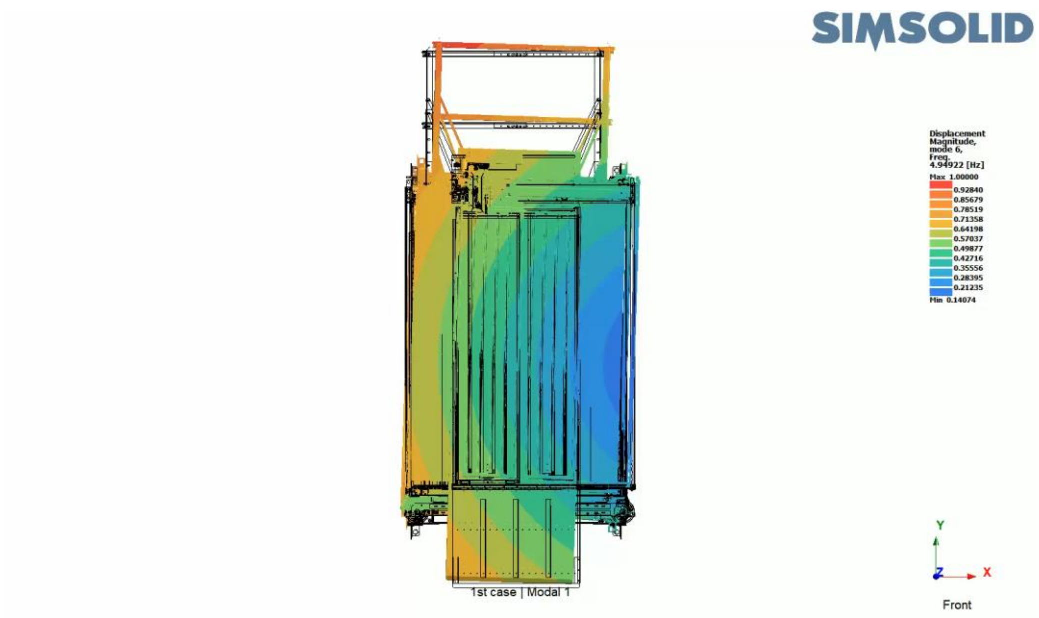

Figure 6 Eigenfrequency extraction for sling-car-doors subsystem with meshless method

Regardless of the chosen solution, a frequency response analysis is required in order to rank the vibrational modes, and include in the lift model just the significant ones in the frequency region of interest, between 0 and 100Hz (Fig.7).

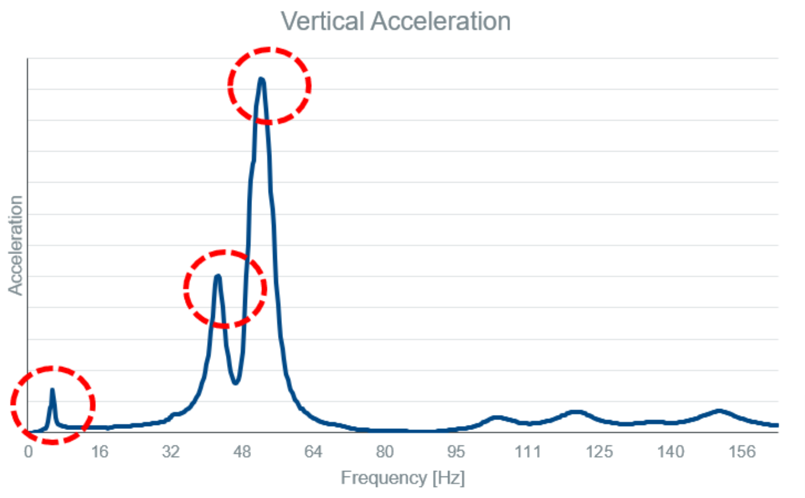

Figure 7 Frequency response of the sling-car-door susbsystem

3.2 Electrical inputs

The model of machinery has been done as an equivalent circuit with an ideal invertor (Fig.8), however, the model can be mode detailed based on the simulation targets.

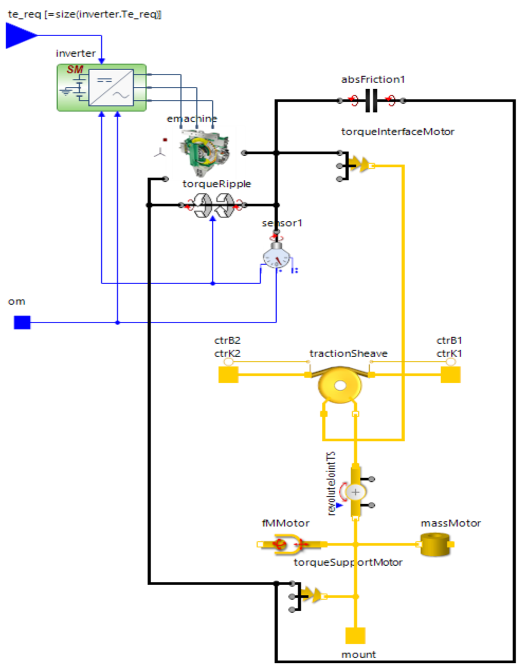

Figure 8 Machinery blocks including mechanical and electrical inputs

3.3 Controller structure

A motion controller, that calculates the desired car velocity has been modelled, using the real lift velocity profile algorithms packed in a mock-up function (Fig.9).

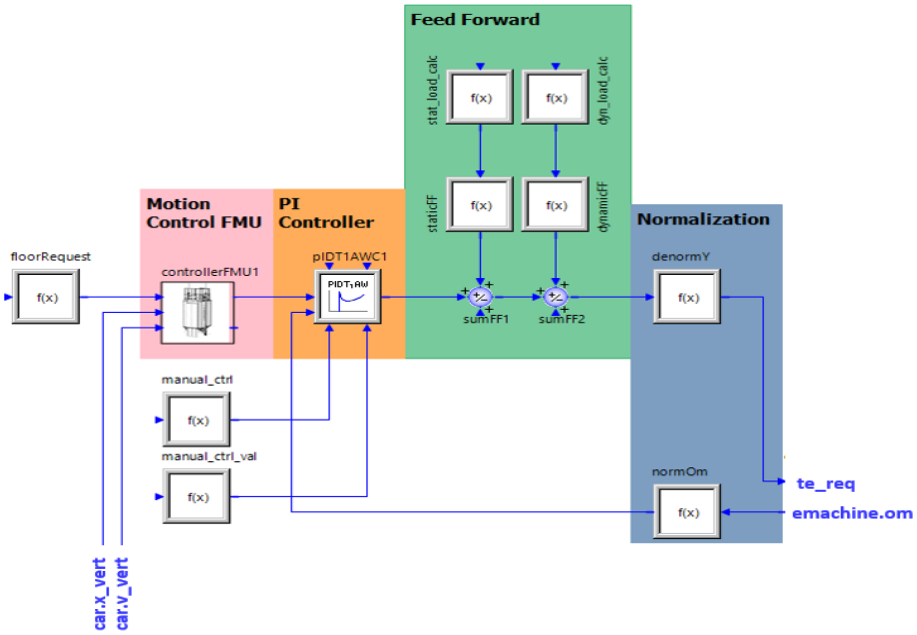

Figure 9 Motion controller

4 THE RESULTS OF THE SIMULATION

Several types of analysis can be done using the model described before: normal or faulty runs, car sag and bouncing, safety tests, etc. In this paper, the focus is on normal and faulty runs and the possibility of identifying the root cause of certain faults in the measured data.

The procedure for identifying the root cause of the malfunction was the utilization of the spectrum for in-car vibrations in three directions, for the time period when the car was running at a constant speed, between different floors.

By comparing the computed spectrum of an "ideal" lift with the median measured spectrum of a "real lift" (Fig.10) collected during 274 rides, we can conclude that in the real lift, there are more excited frequencies in the car. The sources of these excitations can be identified from known rotational frequencies or eigenfrequencies of the system. Each of these sources can be simulated separately or simultaneously in the system model (Fig. 11).

In the same manner, unknown variables in the system, such as guide rail misalignments and damping, can be calibrated in the simulation based on measured data. After model calibration, monitoring of the lift health can be performed with good confidence, relying on the fact that analysing a big volume of data will increase the accuracy of the diagnosis.

Machinery eccentricity due to manufacturing tolerances, machinery harmonics of supply frequency, harmonics of flat spots of rolling guide shoes and harmonics of the contact between ropes and pulleys due to the manufacturing or condition of the wires and strands of the ropes and other faults can be simulated.

These faults can be labelled and identified in the measured vibrations of the cars, by using trained machine learning algorithms. In addition, by knowing the frequency response of the car, based on the system simulation of the lift, these amplitudes can be monitored and a threshold can be used to flag potential changes and malfunctions before they become critical.

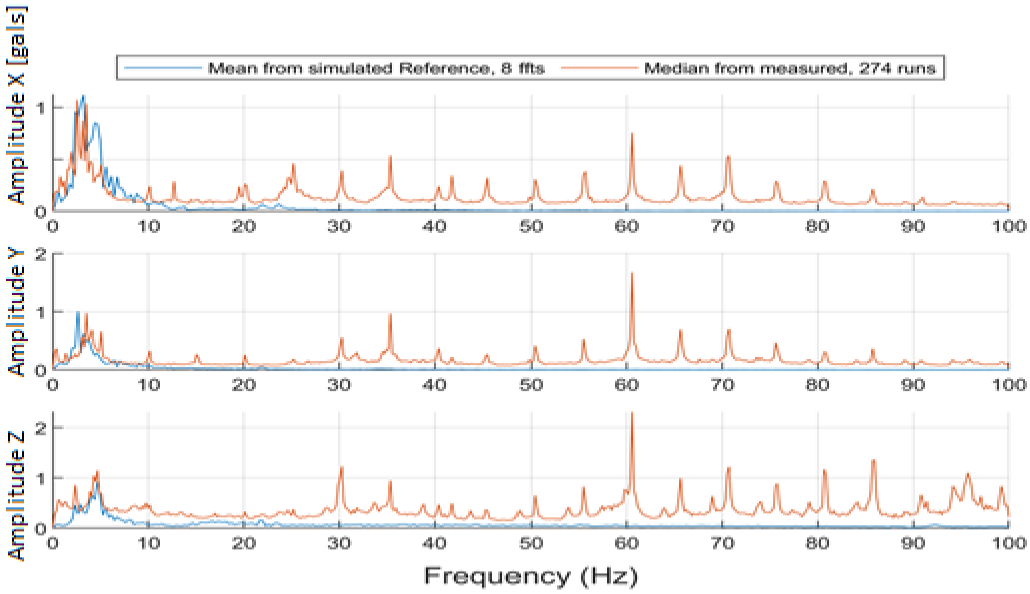

Figure 10 Spectrum of in-car vibrations for the constant speed period

Comparison between ideal lift and measured lift

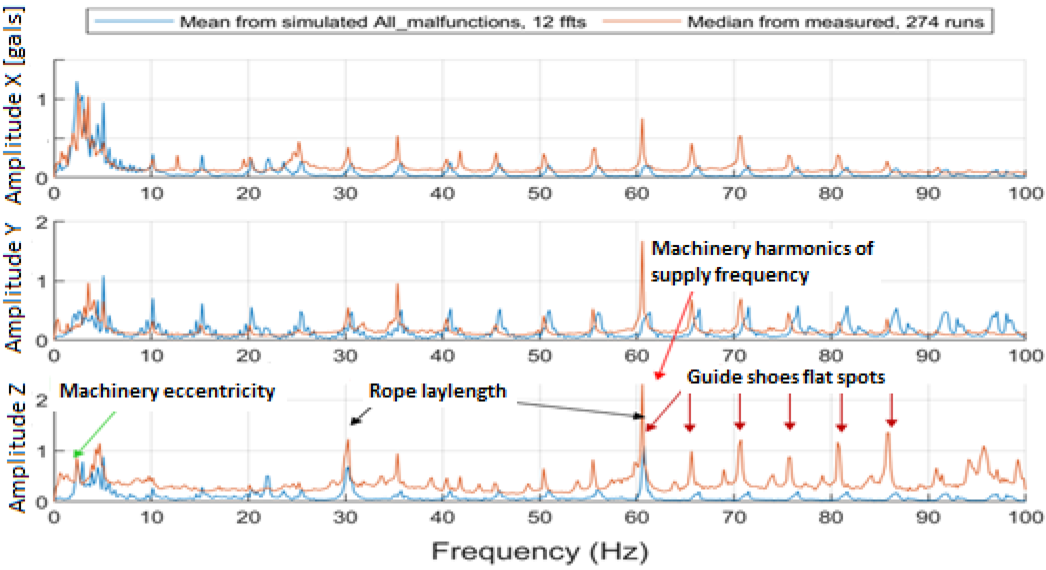

Figure 11 Spectrum of in-car vibrations for the constant speed period

Comparison between lift with certain malfunctions and measured lift

5 DISCUSSION

In this paper, a combination of object-oriented simulations with finite element and meshless method is presented for the normal run of an ideal lift and a lift with certain malfunctions.

After post-processing of the simulated and measured in-car vibrations, one can conclude that this procedure can be used for monitoring and identifying malfunctions of the lift using trained machine learning algorithms with synthetic data.

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BIOGRAPHICAL DETAILS

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Education

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Work Experience

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Work Experience

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