Automated Quality Inspection in Additive Manufacturing for Lightweight Construction: A new Approach Based on Virtual Sonic Data and Machine Learning (ML-S-LeAF)

Ömer Faruk Yildiz[1], Alexander Fritz[2], Julian Storch[3], András Kátai[4], Sebastian Ribecky[4], Peter Hofmann[4], Anitha Bhat Talagini Ashoka[4], Rene Fassbender[2], Hannes Marckmann[1], Sascha Grollmisch[4], Stefan Jansen[5], Christian Adams[6], Irina Kroh[2], Olgierd Zaleski[1], Aswin Manohar[2], Sören Keuchel[1], Holger Merschroth[3], Thorben Schröder[1], Peter Gross[3], Yaxiong Ren[6], Cristiano De Boni[2], Italo Balestra[2], Raphael Ferretti[2], Johannes Schötz[2], Joachim Bös[4,7], and Matthias Weigold[3]

[1] *Novicos GmbH, 21079 Hamburg, Deutschland, Email: yildiz@novicos.de*

[2] *OmegaLambdaTec GmbH, 85748 Garching, Deutschland, Email: alexander.fritz@olt-dss.com*

[3] *TU Darmstadt, Fachgebiet PTW, 64287 Darmstadt, Deutschland, Email: p.gross@ptw.tu-darmstadt.de*

[4] *Fraunhofer IDMT, 98693 Ilmenau, Deutschland, Email: peter.hofmann@idmt.fraunhofer.de*

[5] *C.F.K. CNC-Fertigungstechnik Kriftel GmbH, 65830 Kriftel, Deutschland, Email: s.jansen@cfk-online.de*

[6] *TU Darmstadt, Fachgebiet SAM, 64287 Darmstadt, Deutschland, Email: christian.adams@sam.tu-darmstadt.de*

[7] *TU Ilmenau, Industrielle Anwendungen von Medientechnologien, 98693 Ilmenau, Deutschland, Email: joachim.boes@tu-ilmenau.de*

Introduction

Powder Bed Fusion (PBF) with a laser beam on metal is a popular additive manufacturing technique that allows for the creation of complex 3D shapes. The typically low weight of commonly used powders and possible load optimization when designing components make PBF an attractive choice for lightweight design. However, the current melting and solidification processes are prone to introduce defects, thus making quality inspection mandatory. These defects are expected to produce a characteristic sound that can be used to identify them as deviations from regular system noise. Thus, developing an automated process monitoring is highly desirable. PBF should benefit from a fully automated process that identifies and rejects defects during manufaction, which in turn saves time and leads to a higher product quality.

We therefore propose to utilize machine learning algorithms with training data obtained directly from in situ measurements of both airborne and structure-borne sound as well as numerically from supplementary acoustics simulations. In this work, we outline this project, Machine Learning Algorithms Using Virtual Sonic Data in Lightweight Construction for Quality Assurance in Additive Manufacturing (ML-S-LeAF), and give the strategic roadmap for developing reliable methods that are capable of recognizing deviations from common system operations in the printing process due to defects and other artifacts. The monitoring consists of three parts: First, acoustic signals are continuously collected during printing. Second, the machine learning models are applied using both measured and supplementary virtual data. Third, the acoustic signals are evaluated in order to asses a possible termination of the process if necessary. In the following sections, the measurement and simulation setup is briefly described, the training of machine learning models is discussed, and a preview of intermediate results from first machine learning experiments together with an early comparison of measurement and simulation data is given.

Measurements

Our measurement setup must meet the following criteria: Measurement campaigns must be reproducible to give similar results when using similar sensor types and positions within the printing chamber. In addition, a wide variety of different sensors capable of capturing both air- and structure-borne emissions should also be provided. Figure 1 shows our measurement setup, which includes two measurement microphones of type MM 302 [5] with a frequency range of 5 Hz to 100 kHz. The microphones located approximately 25 cm to 40 cm away from the center of the building plate. Two different types of accelerometers are used: A triaxial, piezoelectric accelerometer of type 4524-B [4] with a frequency range of 0.25 Hz to 3000 Hz is attached to the top of the building plate. A more in-depth and thorough account of our data acquisition process can be found in [2].

Simulations

Figure 2 shows the simulation setup for the creation of virtual data in a two-tiered process: First, a decision tree pertaining the most important parameters of the 3D model allows for the creation of Design of Experiments (DOE) that cover many different cases with unique combinations of environmental, critical, and minor non-critical parameters. Each element in the decision tree may be assigned a probability p a-priori depending on the prevalance of the respective parameter. Second, depending on the present parameters in each DOE, Polynomial Chaos Expansion (PCE) [3] of the system response is de-

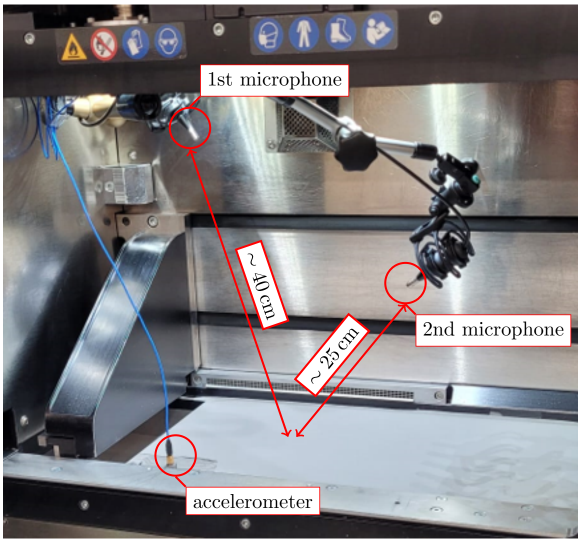


Figure 1: Measurement setup including two equal microphones and an accelerometer for capturing airborne and structure-borne sound, respectively.

rived. From the PCE a set of nodes and weights can be obtained using Gaussian quadrature. The set of nodes then serve as the actual simulation candidates [1]. In the early project phase the focus is on simulation in the frequency domain for structure-borne emissions in the ultrasonic frequency range. Once a high confidence in the model-to-hardware correlation has been established, the setup and simulation models can be extended.

Machine Learning Models

Induced defects during printing include balling and gaps and could be readily identified on the optical images after the printing process. Acoustic data was labelled via synchronisation of optical and acoustic signals that corresponded to identical defects. The measurement campaigns allowed for the collection of a sufficient amount of real measurement data with labelled defects that can be used as a training set for supervised Machine Learning (ML). The final training sample consists of 192 audio recordings of printed lines, half of which containing defects.

In order to identify the signatures of defects and their most important correlated features, the acoustic sensors data were analyzed using different signal-processing methods including Short Time Fourier Transform (STFT), mel, and wavelet spectrogram. Time and frequency slice cuts on the spectrograms have also been performed to understand which part of the printing process and what frequencies are more relevant for the defect identification.

Different combinations of input features and ML models including convolutional neural networks, gradient-boosting classifiers, and random forest classifiers were explored. The test set is composed of 96 additional audio recordings, 48 of which having defects. The results of ML classifiers on real data are encouraging, showing an accuracy above 90% in detecting defects. In a subsequent

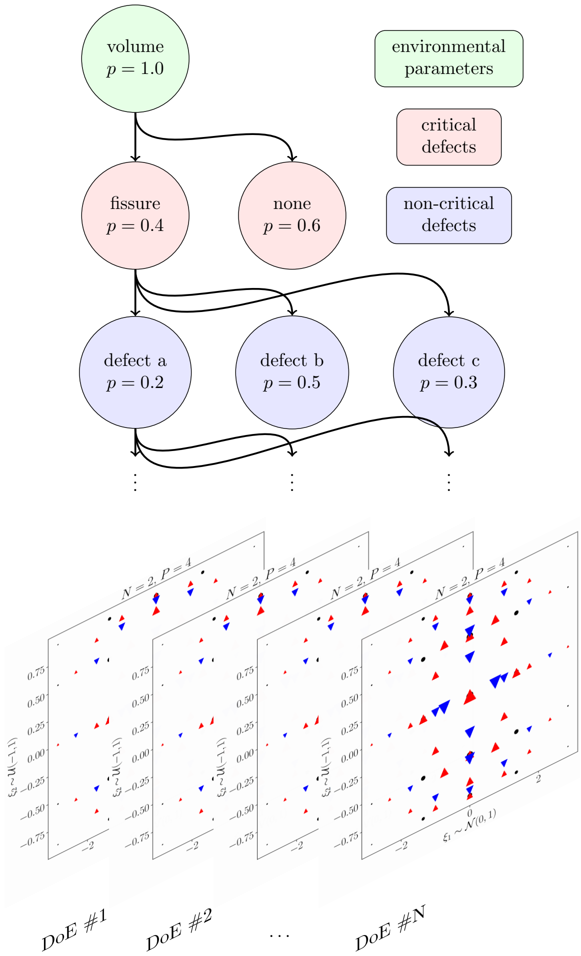


Figure 2: Simulation setup for creating DOE through combining decision trees and PCE.

step, the real measurements will be augmented using the synthetic data in the manner described above in order to have a more balanced and diverse training dataset.

Figure 3 summarizes the process of training ML models through the proposed hybrid solution of combining real and synthetic data. A combination of real and synthetic data will be used to train a number of different ML models in the future. Those ML models must also be tested, adjusted, and optimised in an iterative procedure in order to identify the best-performing model for the detection of each specific defect type. The final goal is to achieve a classification model that will be capable of detecting different defects with high accuracy.

Figure 4 shows two examples of training data for our machine learning classification of printed lines based on the acoustic signal: Spectrograms calculated through STFT in the lower panels and the corresponding image of the printed lines in the upper panels. Lines without defects are shown in Figure 4 (a) and lines with enforced defects are depicted in Figure 4 (b). Machine learning models are trained for classification of these two types of printing runs. Ultimately, a real time detection and classification of various defect types are planned.

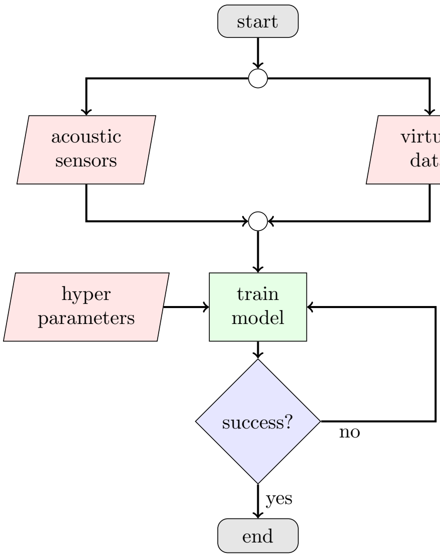


Figure 3: Summary of training machine learning models through the hybrid approach of using measured data together with virtual data from acoustics simulation.

Comparing Measured and Virtual Data

Before ML models can be trained with both measured and simulated data, the simulation results must be verified in terms of physical plausibility, accuracy, and reliability for both structure-borne and airborne sound. Only the latter case has been investigated as of writing of this paper. For this purpose, a 3D model of the argon-filled printing chamber has been generated with appropriate dimensions and boundary conditions for the walls and the powder bed.

Figure 5 shows the 3D pressure distribution in dB with $p_{ref} = 20\,\mu\text{Pa}$ within the chamber due to a unit excitation at the position of the printed lines at 10 Hz and 2 kHz using a commercial Finite Element Method (FEM) solver. It can be clearly seen, that as the frequency increases the position of the microphones will have a larger impact. This information may be useful when optimizing the microphone placement in upcoming measurement campaigns.

Figure 6 shows a direct comparison between measured and simulated pressure at the microphone positions shown in Figure 1: The comparisons have been conducted for different printed lines with and without defects. There is a consensus between measured and simulated frequency responses, as the amplitudes of the spectra generally decrease with the frequency in both cases. However, the agreement may be improved by updating the existing model and the approximative boundary conditions. Thus, the final simulation model may not only provide training data for various geometrically complex objects, defects, and shifting environmental conditions, but also data at positions different from the two microphones shown in Figure 1.

Outlook

The early results in the project ML-S-LeAF are promising. The measurement and simulation results agree sufficiently well. The ability to reliably detect defects from measured audio samples marks the first milestone of many in the project's roadmap. In the future, additional accelerometers for measuring structure-borne ultrasound will be attached to the bottom of the building plate. As in the case of airborne sound, the measured structure-borne sound will also be compared to simulations. Additionally, the Boundary Element Method (BEM) will be used as well in order to increase the frequency range of the simulations to the ultrasonic spectrum. Upcoming milestones in the near and immediate future include determining and specifying the final measurement setup, and improving as well as detailing the exact 3D models for computer simulation. The final milestones comprise the training of the final classification models based on abundant real and virtual data, and the testing or experimental verification of said model.

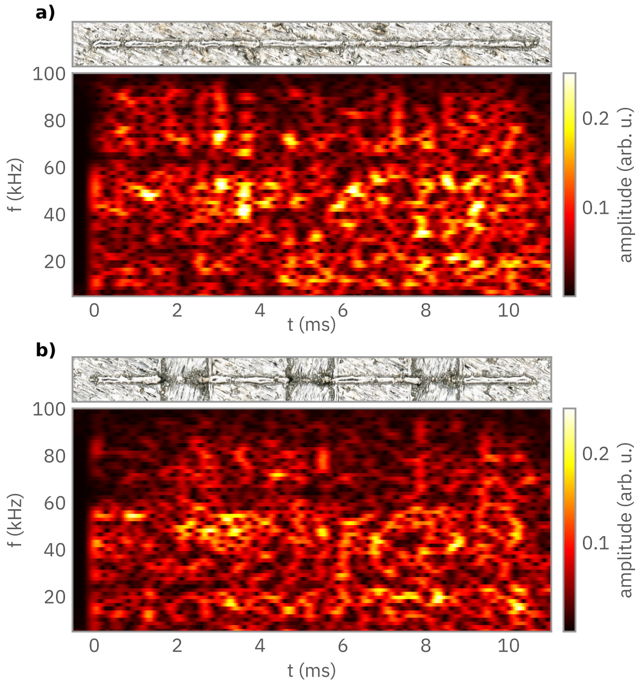


Figure 4: Examples of training data for machine learning classification consisting of spectrograms computed via STFT for printed lines (a) without defects and (b) with defects.

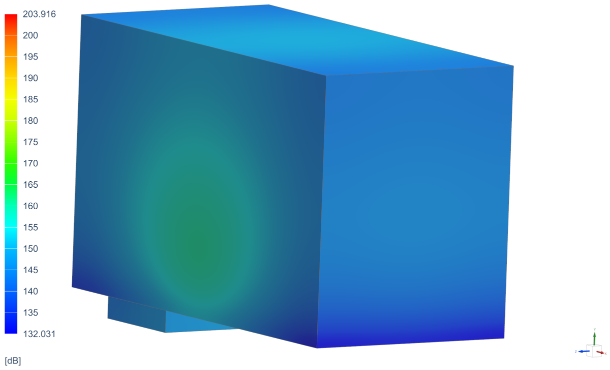
Acknowledgments

This work was funded by the Bundesministerium für Wirtschaft und Energie (BMWi).

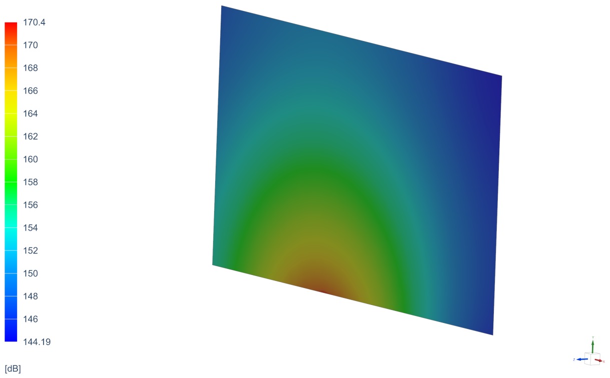
References

[1] Yildiz, Ö. et al.: Polynomial Chaos-Based Procedural Generation of Synthetic Training Data in Machine Learning for Automated Acoustic Monitoring. Internoise 2022 Proceedings, 2022

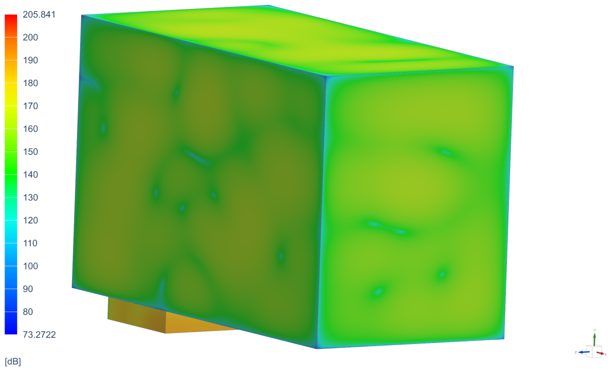
[2] Ren, Y. et al.: Acoustic data acquisition for quality monitoring during Powder Bed Fusion with Laser Beam (PBF-LB) DAGA 2023 Proceedings, 2023



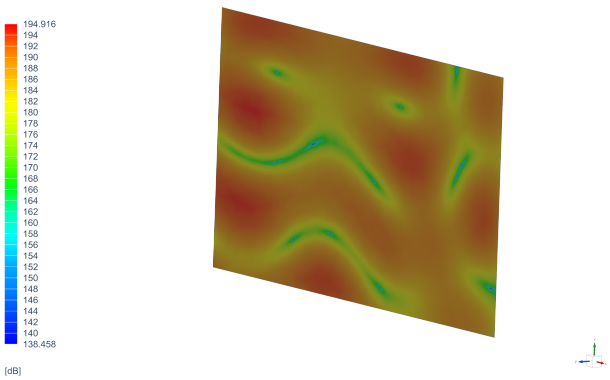
(a)



(b)

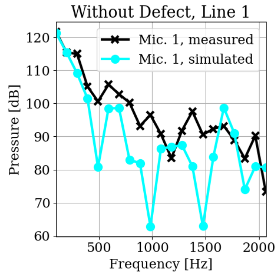


(c)

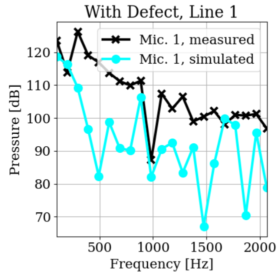


(d)

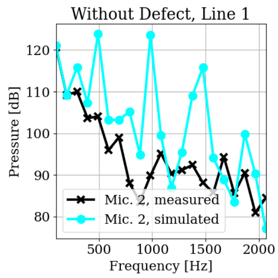
Figure 5: Pressure distribution in dB with $p_{ref} = 20\,\mu\text{Pa}$ within the printing chamber due to a unit excitation. (a) 3D view at 10 Hz. (b) Cross-section at 10 Hz. (c) 3D view at 2 kHz. (d) Cross-section at 2 kHz.



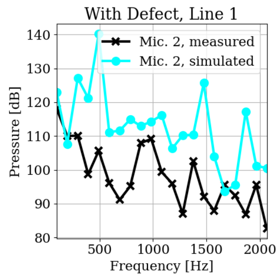
(a)



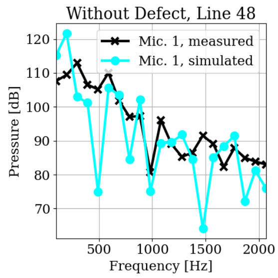
(b)



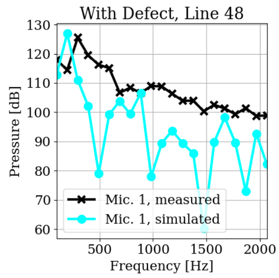
(c)



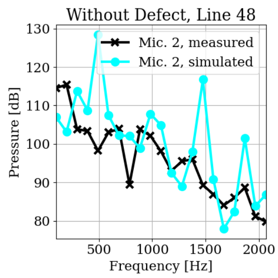
(d)



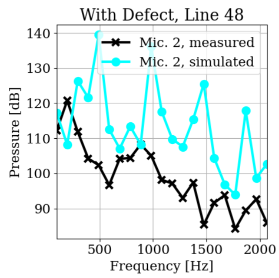
(e)



(f)



(g)



(h)

Figure 6: Comparison of measured data from an accelerometer attached to the bottom of the building plate and virtual data from simulation of an equivalent 3D model.

[3] Xiu, D.: Numerical Methods for Stochastic Computations: A Spectral Method Approach. Princeton University Press, 2010

[4] Triaxial, piezolectric accelerometer of type 4524-B, URL: `https://www.bksv.com/de/transducers/vibration/accelerometers/ccld-iepe/4524-b`

[5] Measurement microphone of type MM 302, URL: `https://www.microtechgefell.de/komplettmessmikrofon?wl=942-MM302`