Journal of Machine Engineering, 2024, Vol. 24
ISSN 1895-7595 (Print) ISSN 2391-8071 (Online)

Received*: 13 February 2024* / Accepted: *23 April 2024* / Published online: *13 May 2024*

milling, machine learning,
inhomogeneous material

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IN-PROCESS MONITORING OF INHOMOGENEOUS MATERIAL CHARACTERISTICS BASED ON MACHINE LEARNING FOR FUTURE APPLICATION IN ADDITIVE MANUFACTURING

Additively manufactured components often show insufficient component quality due to the formation of different defects. Defects such as porosity result in material inhomogeneity and structural integrity issues. The integration of in-process monitoring in machining processes facilitates the identification of inhomogeneity characteristics in manufacturing, which is crucial for process adaptation. The incorporation of artificial defects in components has the potential to mimic and study the behaviour of real-world defects in a more controlled way. This study highlights the potential benefits of cutting force and vibration monitoring during machining operations with the goal of providing insights into the machining behaviours and the effects of the artificially introduced defects on the process. Detection of anomalies relies on identifying changes in force profiles or vibration patterns that might indicate the interaction between the tool and the defect. Machine learning algorithms were used to process and interpret the collected data. The algorithms are trained to recognize patterns, anomalies, or deviations from expected behaviours, which can aid in evaluating the effect of detected defects on the machining process and the resultant component quality. The main objective of this study is to contribute to enhancing quality control of machining processes for inhomogeneous materials.

1. INTRODUCTION

Metal Additive Manufacturing (MAM) has become a significant technological advancement over the last decade [1]. While this technology provides unprecedented freedom in design, a combination of different materials, and process flexibility, it still faces certain challenges that demand further investigation and resolution. The specimen manufactured using MAM may experience various defects. Some of these defects include pores caused by gas being trapped in the material, the keyhole effect, and a lack of fusion during the melting process. The specimen may also experience cracks, surface irregularities, and roughness, all of which may contribute to the degradation of mechanical properties [2–5]. Different types of defects may arise in various shapes, sizes, and distributions.

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https://doi.org/10.36897/jme/187872

Lack-of-fusion defects can occur due to insufficient energy density and improper process parameters [4]. Such irregular regions inside the material, sometimes filled with unmelted metallic powder particles, have elongated shapes ranging from 50 μm to several millimeters in size [5].

Porosity caused by entrapped gas is characterized by its spherical shape. These defects can be on the order of 5 to 20 μm in PBF, while parts produced with Directed Energy Deposition (DED) are characteristically larger (>50 μm) [5]. Gas-entrapped porosity in a Laser Metal Deposition (LMD) process depends on process parameters and melt pool dynamics [5]. Ng et al. indicate that the gas-entrapped porosities lead to the formation of bubbles of larger diameter than the largest particle present in the metallic powder during the LMD process [6]. The authors conclude that these porosities tend to agglomerate and coalesce in the melt pool.

One common porosity source in MAM is the keyhole effect. Gibson et al. define it as an effect that occurs when plasma is generated by the heat source, causing a deep penetration depth and the production of vapor that can then accumulate at the bottom of the melt pool, leading to porosity in the final product [4].

Subtractive manufacturing has been an active area of research with a focus on utilizing advanced artificial intelligence techniques and in-process monitoring methods for a variety of purposes. Among the most widely investigated objectives in this field are the prediction of cutting forces and the assessment of tool wear. Multiple authors investigate different tool condition monitoring techniques in milling operations combined with advanced Machine Learning (ML) models [7–13]. Cooper et al. have developed a technique to monitor the condition of milling tools using acoustic signals [10]. They use a generative adversarial neural network to identify anomalies in the time-frequency domain of the tools' acoustic spectrum during cutting operations. By training the network and inverting the generator, the algorithm can differentiate between normal and anomalous tool conditions with a classification accuracy of 90.56%. Madhusudana et al. have incorporated in-process monitoring techniques that employ acceleration measurements to detect faults in the multipoint cutting tool [11]. They have used vibration data in conjunction with several ML algorithms for this purpose with an end-classification accuracy of almost 97%. Li et al. employed a high-precision Hall sensor to measure spindle current in Computer Numerical Control (CNC) systems. They developed a new method known as CNN-AD for predicting tool breakage [12]. Peng et al. explore a hybrid approach combining both measurement data and numerical data with the goal of predicting a cutting force in orthogonal cutting [13]. The results have shown a significant enhancement in prediction accuracy when compared to the conventional linear regression model.

Fewer papers are involved in the investigation of utilizing ML methods for detecting defects on the workpiece in real time [14]. The study by Schlagenhauf et al. presents a novel method for detecting anomalies in workpieces during milling processes [14]. The authors created artificial anomalies in the form of boreholes ranging from 2 mm to 10 mm in diameter. These anomalies were larger than those observed in the current work. The authors utilized a convolutional-based encoder-decoder model to detect these anomalies in the milling of 16MnCr5 material. The paper seeks to showcase the effectiveness of this approach in identifying anomalies in workpieces and to explore the impact of domain shift, particularly concerning variations in tool diameter and material, on the model's performance. Gauder et al. have presented a new method for detecting pores in cast parts during the machining process [15]. The method uses an acoustic sensor to detect deviations in the acoustic signal, which are then analysed using a Convolutional Neural Network (CNN). The authors have used a non-destructive testing method of acoustic emission measurement with a sampling frequency of 1526 kHz. The proposed method uses only the raw data measured during the tests. To develop a pore detection algorithm, the authors produced samples with repeatable pores. Since it is not feasible to generate specific pores during the casting process, the authors used selective laser melting as an analogy method for controlled porosity implementation. The cylindrical pores with a diameter of 0.7–1.2 mm were manufactured using an SLM process in AlSi10Mg aluminum cubes. The Short-Time Fourier Transform (STFT) of the acoustic emission signals has been analyzed using the spectrograms as grayscale images and a CNN network was trained using these images. The accuracy of the model was tested, and it was found to be 90%.

Pfirrmann et al. conducted a study on detecting material defects during the micro-milling process using force and acoustic emission measurements [16]. The study aimed to identify defects in the workpiece that were not caused by the machining process and provide information about the quality of the raw part. The type I hard alpha defects investigated were local segregations that caused an increase in hardness in that area. To create representative material samples, Ti6246 specimens were heat-treated using a TIG torch, resulting in specific defects that served as representative material properties for the tests. After synthesizing the material defects, the sample was ground to ensure a defined, flat surface for further processing.

Axinte et al. conducted a study to examine the relationship between the quality of the machined surface in the broaching process and the output signals obtained from various measurements during the process [17]. These measurements include cutting force, acoustic emission and vibration measurements. The researchers found that the measurement signals could differ depending on the type of surface anomalies present.

This study presents a non-destructive process monitoring technique aimed at detecting material defects during the post-processing phase. To investigate different scenarios, artificially created defects were introduced to represent different processing scenarios with and without pores. The dataset is accurately labelled to differentiate between normal and anomalous conditions. Artificial defects with a diameter of 0.5 mm were introduced into samples, which represent relatively small defects when compared to [14]. These artificially introduced pores mimic the porosities that could typically occur in additively manufactured parts. The main goal of the artificial defect addition is to develop and validate non-destructive testing methods and machine learning models that could be helpful in anomaly detection directly during the manufacturing process. This would aid in benchmarking the detection capabilities of such systems. Intelligent anomaly detection algorithms have the potential to identify even smaller defects occurring in manufacturing processes. However, this primarily depends on the quality and resolution of the data. Higher resolution makes it possible for the algorithm to detect smaller defects. Furthermore, it depends on the complexity and training of the algorithm. To achieve high accuracy in detecting small defects, advanced algorithms require a large and varied training dataset. Combining high-resolution measurements with advanced algorithms and high-resolution sensors would make it possible to detect even the smallest anomalies and defects. The detection and control of anomalies in additively manufactured parts is a complex and critical task. In this regard, the model developed in this paper, holds significant potential for anomaly detection, particularly in the context of additively manufactured parts using transfer learning. Transfer learning is a method used to improve understanding of a particular task by relating it to other related tasks that have already been learned [18]. Such a learning method can be utilized in identifying anomalies in the post-processing of additively manufactured parts using the model pre-trained on the dataset collected on the probes with artificially introduced defects.

2. EXPERIMENTAL APPROACH

For the training of machine learning algorithms, extensive datasets are typically required, originating from the respective process. However, the generation of additive parts is often extremely time-consuming, in most cases this makes the collection of suitable datasets challenging. Against this backdrop, an analogy approach was chosen for representing inhomogeneities. Conventional approaches often involve printing parts that are subsequently analysed using measurement systems to identify those inhomogeneities. The chosen approach follows an inverse strategy. Instead of analysing positions and then linking them with the data, inhomogeneities are generated from predefined data. Specifically, randomized borehole positions are created through a MATLAB script and transmitted to the machine as NC code. These boreholes have a diameter of 0.5 mm, representing the sample preparation for the inhomogeneous specimens. For the homogeneous control specimens, sample bodies of the same geometry are used, which remain unaltered and thus exhibit no porosity/inhomogeneity. The two possible approaches are illustrated in (Fig. 1). Additionally, the choice of drilled specimens implies that the actual machining experiments are conducted in the same clamping. During these experiments, grooves with a width of 5 mm and a depth of 0.5 mm are milled. Performing sample preparation and machining experiments in a single clamping allows for the direct linkage of borehole position data with measurement data.

To capture various measurements on the workpiece side, the test specimen (specimen material: C45) is connected to different sensors. The sample body is directly mounted on the force measurement platform, a Kistler 9119AA. A 50g acceleration sensor (Kistler) is attached to this mounted specimen using wax. Acceleration and force data are recorded using an NI chassis with Type 9230 and 9223 measurement cards at a sampling rate of 10 kHz. QASS company's acoustic sensors are also attached to the specimen, recording data at a sampling rate of 1.6 MHz. Data acquisition is triggered by the NC code, allowing all systems to capture data within the same time window. This trigger also enables the precise calculation of the milling cutter's position at any given time. On the tool side, an Intendo² tool clamping system from Schunk is used. This hydro-deformable chuck is equipped with an acceleration sensor for recording raw data at a frequency of 15 kHz.

For the experiments, grooves are milled along the length of the specimen. The grooves are created using a Gühring KG Ratio Cutter RF 100 Sharp 5 mm. Different tools are used for the paths in the homogeneous test specimen and the paths in the inhomogeneous specimen. The tool is a 5 mm diameter end mill with four teeth.

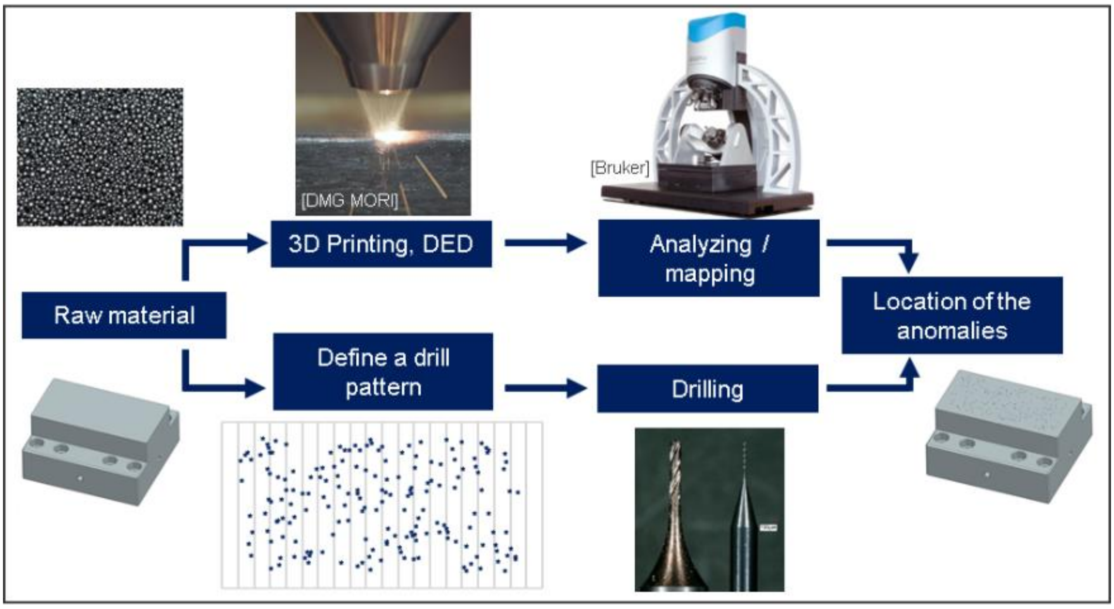

Fig. 1. Possible approaches to a milling surface with the knowledge of anomaly positions

The width (ae) during grooving is 5 mm, with an axial depth of cut (ap) of 0.5 mm. This involves face milling, and two teeth are always engaged. According to the manufacturer's specifications, the C45 probe is machined at a cutting speed of 180 m/min and a feed per tooth rate of 0.0264 mm/tooth.

Twenty grooves are milled and recorded per specimen. To reduce potential variations, a randomized experimental plan is followed, considering parameters such as homogeneous/ inhomogeneous probes and porosity levels of 0.5% and 1%.

3. DATA HANDLING AND TRAINING

The captured data undergo initial processing for training, wherein the idle and tool entry/exit regions are removed. Subsequently, the data is normalized and a mean-shifting transformation is applied to set the mean to a Y-axis intercept of zero. (Fig 2) illustrates this data processing using a defined borehole pattern, created solely for visualization purposes.

To verify the reliability of the algorithm, its reliability is determined as follows. The positions of the bores determined by the algorithm are compared with the positions of the actually introduced bores. This results in the number of correctly recognized inhomogeneities. The reliability is calculated by dividing this number by the total number of milled bores.

To account for material variations and influences from wear or other anomalies, these factors are varied in both the un-drilled homogeneous and inhomogeneous test specimens. Wear is measured by the cutting-edge radius, which is 7 µm for a new tool and 16 µm for a worn one. Algorithm training is performed using randomly compiled data from experiments on different test days and wear conditions. Randomized milling paths are also created and checked for the examined test specimens. In each case, 100 paths were used to verify the algorithm.

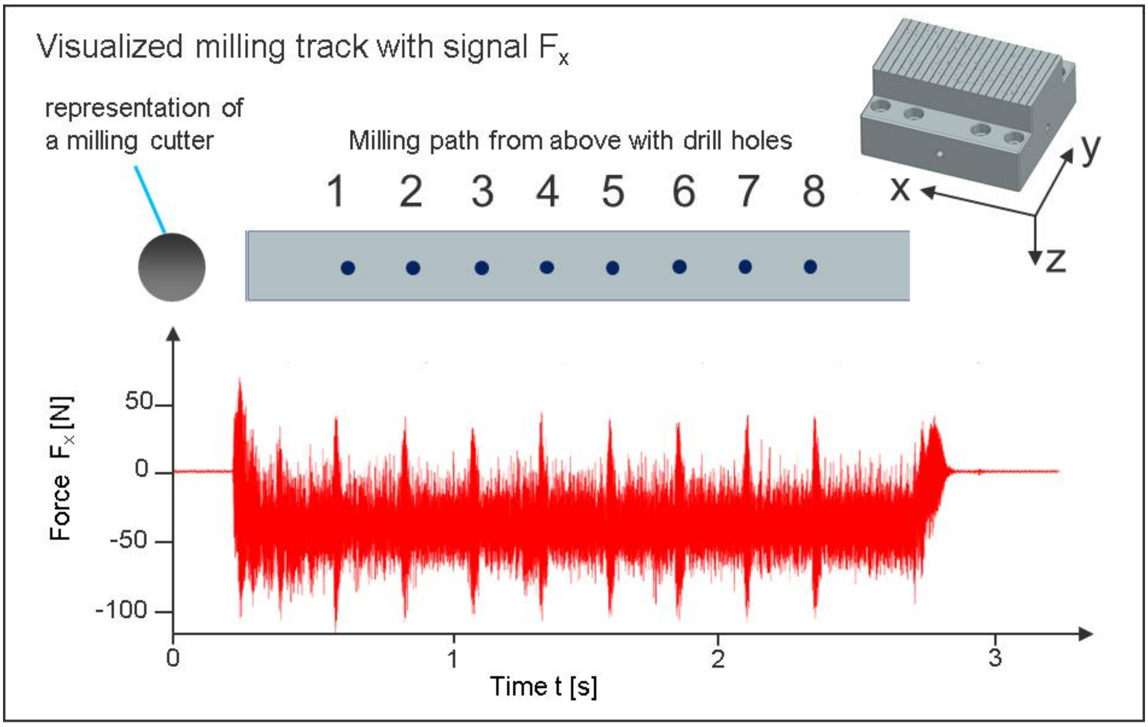

Fig. 2. Data handling

For anomaly detection, an autoencoder model has been used in this paper. Autoencoders are neural networks, consisting of an encoder and decoder, used for unsupervised learning to reduce dimensionality [19]. The aim of an autoencoder is to learn representation functions for data [20]. In this study, two different types of autoencoders are used for the task of anomaly detection. Dense autoencoders or fully connected autoencoders, have the layers in both the encoder and decoder densely connected meaning that each neuron in one layer is connected to every neuron in the next layer. A Long Short-Term Memory (LSTM) autoencoder is a type of autoencoder that uses LSTM cells in its architecture. LSTM cells are effective with sequential data, making this type of autoencoder suitable for real-time applications [21]. Ou et al. use Order Analysis (OA) and a Stacked Sparse Auto-Encoder (SSAE) to extract features and monitor tool wear state using the three-phase spindle current signals [22]. The method has been successfully implemented and the combination of OE with SSAE yielded a recognition accuracy of the tool of 95%. Schlagenhauf et al. also successfully employed a conventional encoder-decoder model for anomaly detection during milling [14].

4. RESULTS

The results of various sensor data and their analysis with both machine learning algorithms are presented below. The use of the Dense-Autoencoder with individual force measurement data, as shown in (Fig 3) for the *X*-direction, serves as an example for the detection of anomalies. For this purpose, the data of a trajectory is inserted into the model and the reconstruction loss is considered as the outcome. The reconstruction loss shows an increase in the values as soon as an anomaly is detected. These peaks can be marked automatically. Thus the line plot is overlaid by a scatterplot with the anomalous points. These points are also marked in the raw signal (image on the right)

If the position data of the individual holes are taken into account, the correctness of the detection can be evaluated. This can be seen not only in the force measurement data but also in other sensor data so that the Dense-Autoencoder can detect anomalies such as in this example the drilled holes.

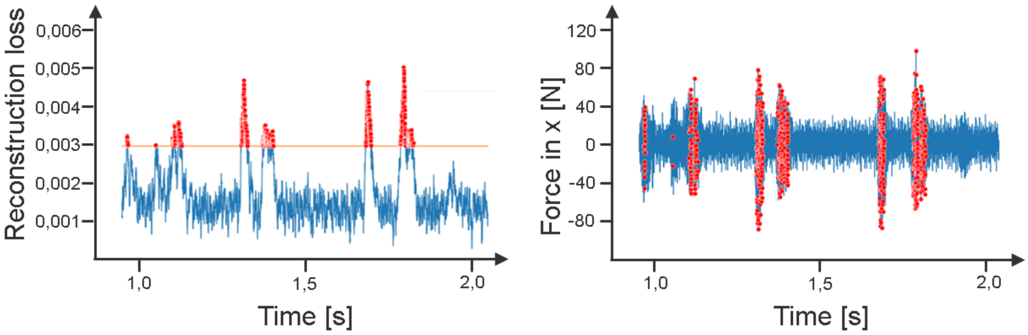

Fig. 3. Bore detection with Dense-Autoencoder for forces in X-direction

The same procedure was performed with the acceleration data in (Fig. 4). The reconstruction loss is illustrated on the left and the raw data with the anomalies marked in red on the right. Four holes were successfully detected in this example data set.

If the results of the two sensor signals are compared, differences can be seen. For the force measurement, the basic noise of the reconstruction loss is 0.002, whereas it is up to 0.006 for the acceleration. If the peak value that occurs with an anomaly is now considered, differences can be recognized here. The maximum values for force measurement are 0.005 and for acceleration up to 0.017. Therefore, an interesting difference in the values exists, but in particular the ratio between max and noise changes. The ratio is 2.5 for the force measurement and 3.4 for the acceleration. This larger ratio also spans a larger range for separating anomalous and normal data. Detection therefore appears to be easier.

With the combined acceleration data (Fig. 5), calculated using the quadratic mean, even better detection is possible. This is again discernible through the reconstruction loss. The base noise ranges between 0.001 and 0.006 for individual spatial direction data ((Fig. 4) shows the acceleration data in the X-direction), whereas for the quadratic mean, the reconstruction loss ranges between 0.001 and 0.002. Regarding peak values, no difference can be observed. For individual spatial directions and combined data, the maximum reconstruction loss is 0.017. However, due to the significantly larger difference between noise and peak in anomalies, the separation of anomalous data from normal data is easier.

When examining the results of the LSTM-Autoencoder (Long Short-Term Memory), differences in the noise are apparent. The noise is around two for the reconstruction loss. However, the peak values also increase, particularly with acoustic emission data, exceeding 20 (seen in (Fig. 6)). This disproportionate increase in peak values compared to the increase in noise allows for improved bore detection with the code used.

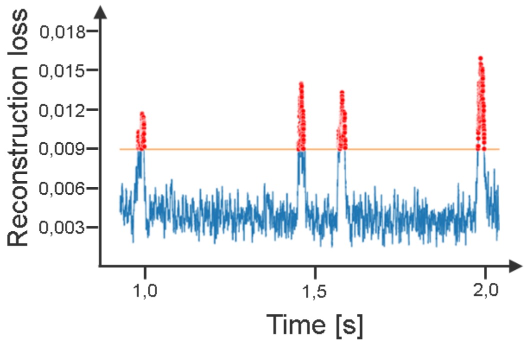

Fig. 4. Bore detection with Dense-Autoencoder for accelerations in X-direction

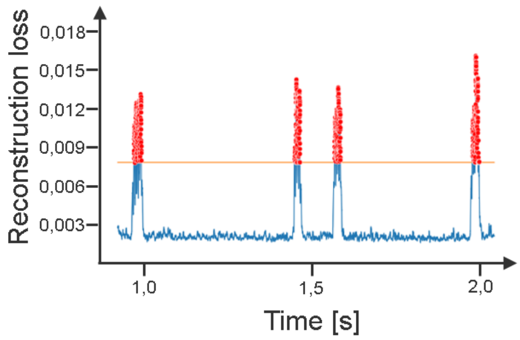

Fig. 5. Bore detection with Dense-Autoencoder for combined accelerations

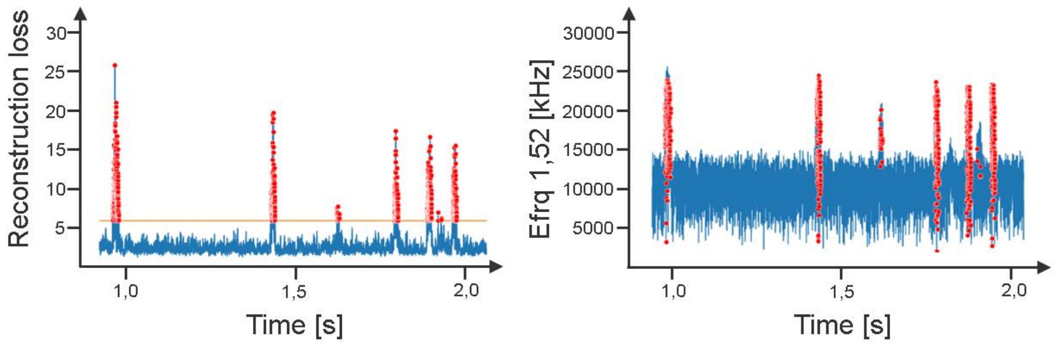

Fig. 6. Bore detection with LSTM-Autoencoder for acoustic emission data

This improvement is clearly evident in the reliability overview presented in Table 1, especially with a noticeable 12 increase in reliability for acoustic emission data. Evaluating other sensors and data reveals improvements in reliability across the board. The evaluation of the algorithm with the 100 test paths also highlighted that combined forces and accelerations achieve better results. Within the acceleration data, the use of the LSTM-Autoencoder leads to an increase in reliability from 94% to 98% in the X-direction. It is once again apparent that the reliability of force data is lower, reaching a maximum of 92% with LSTM, while this was already achieved with Dense using acceleration data.

In addition to the combined acceleration data, the iTENDO^2 data stands out in (Tab. 1). The training time per step is lower, but reliability is already high at 94% with Dense Autoencoder. Using the LSTM-Autoencoder, a reliability of 96% can be achieved, demonstrating successful detection of defects, whether on the spindle or tool side.

Table 1. Experimental literature data for WAAM manufacturing

	Trainingstime per Step - Dense	Reliability Dense	Trainingstime per Step - LSTM	Reliability LSTM
Acceleration in x	18.4 s	92 %	349.8 s	94 %
Acceleration in y	19.4 s	90 %	344.5 s	92 %
Acceleration in z	18 s	92 %	348.2 s	92 %
Acceleration combined	19.6 s	98 %	351.4 s	98 %
Force in x	16.3 s	88 %	330.9 s	88 %
Force in y	14.6 s	84 %	338.2 s	88 %
Force in z	16.2 s	84 %	320.6 s	86 %
Forces combined	22.8 s	88 %	346.7 s	92 %
iTENDO^2	9.3 s	94 %	96.05 s	96 %
QASS	14.2 s	84 %	315.4 s	98 %

5. SUMMARY AND OUTLOOK

In summary, the investigations have successfully demonstrated that both high-end and low-cost sensors, as well as both workpiece-side and tool-side measurement techniques, can effectively detect bores as small as 0.5 mm. Both the type of sensor and the algorithm used have an impact on the reliability of bore detection. To verify and compare reliability, 100 milling paths were examined, and the bore positions were compared with those identified by the algorithms. In particular, the LSTM-Autoencoder employed in these studies proved to be efficient, achieving a reliability of 98%. This was notable, especially in the case of acceleration, iTENDO^2 and acoustic emission data (QASS).

The results presented include training and validation using data collected in the same process. To ensure that the model can also be used in other milling processes and with other materials, further investigations will be carried out. For this purpose, additive manufactured parts, aluminum, gray cast iron and other materials as well as different cutting conditions are to be investigated. This includes the milling of real geometries, changes to ae and ap, as well as any necessary adaptation by means of transfer learning. In the context of the described investigations, transfer learning could be employed to adapt the pre-trained model of the shown anal to improve the detection of inhomogeneity in varying conditions. By applying transfer learning, the need to collect large amounts of training data for each new task can be reduced, as existing knowledge from previous training processes can be leveraged to enhance the model's performance. Depending on the available data, various methods such as inductive, transductive, or unsupervised transfer learning can be applied and optimized.

Inhomogeneities in additively manufactured parts, as well as in casted parts, have a size distribution. To get closer towards a realistic comparison this size distribution should be represented by the different bore diameters. Therefore, different bore sizes have already been tested. The results will be shown in another publication.

A further approach for detecting anomalies using feature-based learning methods will also be investigated.

ACKNOWLEDGEMENTS

The presented research results were elaborated within the research projects supported by the Federal Ministry of Economic Affairs and Climate Action through the German Federation of Industrial Research Associations (AiF) as part of the program for promoting industrial cooperative research (IGF) based on a decision by the German Bundestag and AISA (Artificial Intelligence Software Academy) with support from the Ministry of Science, Research and Arts Baden-Württemberg. The authors are sincerely grateful for the funding of these research initiatives.

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