Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 126 (2024) 645–650

www.elsevier.com/locate/procedia

17th CIRP Conference on Intelligent Computation in Manufacturing Engineering (CIRP ICME '23)

Surface quality prediction for FDM-printed parts using in-process material flow data

Jan Mayer*, Tra Bui Thi Thanh, Turgut Caglar, Hendrik Schulz, Omar Ben Lallahom, Dongxu Li, Max Niemella, Burak Toptas, Roland Jochem

Chair of Quality Science, Technical University of Berlin, Berlin, 10587, Berlin, Germany

* Corresponding author. Tel.: +49 (0) 30 314 23996; Fax: +49 (0) 30 314 79685. *E-mail address:* j.mayer@tu-berlin.de

Abstract

Efficient and sustainable manufacturing practices rely on the early detection and removal of faulty components in production processes. In the context of Fused Deposition Modeling, this means that identifying defective parts during the production cycle can help to minimize waste and optimize resource utilization. However, conventional quality control methods, which involve post-process inspection, can be time-consuming and inefficient, particularly if nonconforming parts are detected after the production cycle is complete. To address this issue, a real-time quality prediction system has been developed that utilizes in-process flow sensor data to detect and identify nonconforming parts as they are being produced. The system was tested on cuboid test specimens, which were deliberately modified to include defects on the surface of the part. By analyzing the sensor data in real-time, the system was able to identify the defective parts and provide corrective actions to minimize waste and optimize resource utilization. By implementing this approach, manufacturing processes can be streamlined and resource utilization can be optimized while minimizing the production cycle time. This approach represents a significant advance over traditional quality control methods, which rely on post-process inspection and human factors.

Keywords: Additive Manufacturing; Surface Quality; Failure Detection; Fused Deposition Modeling; Machine Learning

1. Introduction

Recent advances in additive manufacturing have led to the development of new 3D printing technologies and materials that offer improved performance and functionality. For example, metal 3D printing has emerged as a promising technique for fabricating complex and high-strength components used in aerospace, medical, and defense industries. However, these advanced 3D printing technologies and materials require precise control of the printing parameters, such as temperature, pressure, and flow rate, to achieve optimal results [1].

In particular, filament flow is a critical factor in achieving the desired quality of the printed surface, and its characterization is essential for understanding the 3D printing process [2]. The filament flow rate determines the amount of material extruded per unit time and affects the thickness and quality of the printed layer. It is influenced by various factors, such as the viscosity of the material, the extruder temperature, and the printing speed. Correspondingly, examined quality criteria of FDM-produced parts are (1) dimensional accuracy (2) surface quality (surface quality and dimension accuracy are generic quality criteria) and (3) tensile strength [3]. Whether quality can be reproducibly attained is often discussed in the literature [4], some authors state that FDM can reproduce reliably, whereas others deny this. Furthermore, studies about prediction of the occurrence of many process specific errors like warping, over- or under-extrusion are frequently published [5].

10.1016/j.procir.2024.08.281

Moreover, in practice, process control must assert the correct execution of machine instructions to yield reproducible results. During the FDM-process, the position of the print head, the amount to extrude and the attainment of specified temperatures of the hotend, the printbed and of the environment are to be controlled feedback values. Deviations from reference inputs can negatively affect a part's quality [6]. For instance, the amount to be extruded can be affected by non-uniform filament diameter or by filament slippage between the rollers of the feeder [7].

In this context, the present study aims to develop a predictive model for assessing the quality of the printed surface based on filament flow analysis. Specifically, the study will investigate the effect of filament flow on the occurrence of over- or under-extrusion and other defects that lead to material waste and delays in the printing process. The model will incorporate machine learning techniques to analyze the 3D printing data and predict the area of a specific failure based on the desired quality of the preliminary printed surface according to occurring anomalies.

The main objective of this study is to enhance the economic feasibility and efficiency of 3D printing by reducing material waste, improving the quality of the printed surface, and minimizing the need for human intervention. The results of this study will provide valuable insights into the fundamental understanding of the 3D printing process and pave the way for the development of advanced 3D printing technologies and materials.

2. Related Work

In recent years, 3D printing technology has gained widespread popularity due to its ability to produce complex geometries and customized products with relative ease. However, one of the challenges associated with 3D printing is maintaining the surface quality of the printed objects. To address this issue, several studies have been conducted to investigate the impact of process parameters on the surface quality of 3D-printed components.

One study, documented in [8], examined the effect of overhanging structures on the surface quality of 3D-printed components. The researchers printed different samples with varying overhang angles and analyzed the surface quality to establish a relationship between process parameters, overhang angle and surface quality. Another study, described in [9], focused on evaluating the surface quality of 3D-printed Acrylonitrile Butadiene Styrene (ABS) parts by varying the parameters of infill height and infill density. The study aimed to determine the optimal combination of these parameters that would yield the highest surface quality for 3D-printed ABS parts. The impact of anisotropic resolution on the surface smoothness of 3D-printed objects was investigated in [10]. This study analyzed the effect of printing speed, inclination and orientation of the object, and position on the print bed on surface quality. The results highlighted the importance of considering these factors in optimizing 3D printing processes to achieve optimal surface quality. In [11], a promising approach was presented for assessing the quality of 3D-printed parts based on an entropy analysis of their 3D scans. The method allows for automatic and objective evaluation of surface quality during printing and enables corrective actions to be taken in case of suboptimal print quality. Other studies, such as those described in [12], [13], [14], [15] and [16] utilized sensors, cameras, and profilometers to monitor and detect quality issues in 3D printing. These tools enable real-time data collection and analysis, aiding in the identification and correction of printing failures.

In addition, there have been multiple case studies, showing the necessity of research in the combination of surface quality and anomaly detection during FDM processes.

Table 1. Case studies in the field of FDM and surface quality prediction.

Case Study	Input Data	Algorithm	Quality criterion
[14]	Point cloud (top-down in-situ laser profilometer), target G-Code	DT, Random Forest, Artificial Neural Network	Surface and infill quality
[17]	Thermal data from thermocouples, infrared temperature sensors, accelerometers	Ensemble learning	Surface roughness
[18]	layer thickness, print speed, acceleration	Linear Regression	Tensile strength
[19]	Layer height, extrusion temperature, print speed, print acceleration, flow rate	DT, Random Forest	Surface roughness (profile)
[20]	Layer height, build orientation	Polynomial to fit the outer perimeter	Surface roughness (profile)

The aforementioned studies underscore the importance of monitoring and detecting quality issues in 3D printing to improve the reliability and quality of the printed objects. By carefully considering process parameters and utilizing monitoring tools, 3D printing technology can be optimized to produce high-quality products. Since generic anomaly detection algorithms and filament flow has been neglected in current research, the objective of this study enables to fill this research gap.

3. Experimental Design

The experimental procedure consists of two main steps: 3D printing on an Ultimaker and subsequent scanning of the printed objects. The G-code was created and transferred to the Ultimaker via USB stick. It is important to note that the first layer of the print should be printed at approximately 40% of the speed of the remaining layers in order to ensure good adhesion to the print bed. A modification was made to the print bed using crepe tape to improve adhesion of the first layer and the underside of the walls. A specific enclosure was used for the printer to stabilize the temperature during printing, as temperature fluctuations can have an impact on the quality of the print.

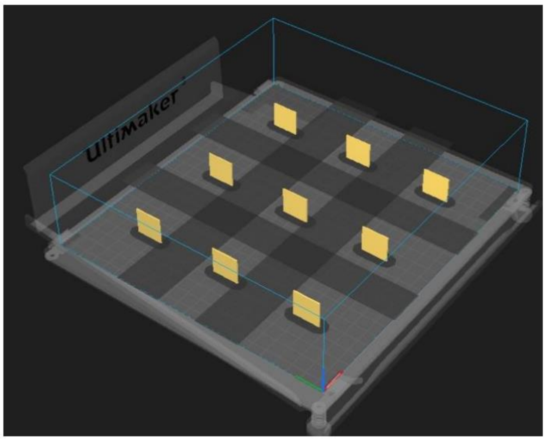

Fig. 1. 3D-printing bed with printed walls.

After printing was complete, the walls were scanned using a template and placed on a platform for scanning. The optimal number of walls that can be scanned simultaneously is nine, which fits on the scanning surface. The scanner was controlled using the Colins 3D software installed on an edge computing device. Reference data was collected to train the model and improve the reliability of the results. Standardized procedures were developed to minimize errors and ensure consistency in the printing and scanning process.

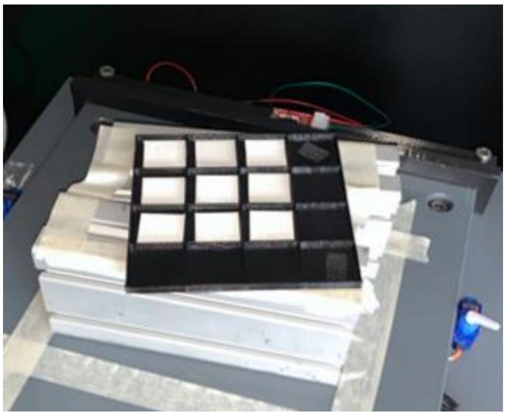

Fig. 2. Arrangement of walls in fixture during scan.

In order to generate a large amount of data, around 130 walls were printed with varying levels of correctness, including over- and under-extrusion. The final print speeds for the walls were approximately 6 minutes for a wall with a layer thickness of 0.3 mm, 7 minutes for 0.2 mm, and 9 minutes for 0.1 mm per wall. The overall advantage of this printing method was the ability to print multiple walls without manual intervention, which saved time.

3.1. Time series data processing

After dividing the data into individual printing cycles, the next step is to process the data to detect printing errors based on the curve pattern. Firstly, the sum of filament flow per fixed time interval of 200 milliseconds is determined. This time interval was chosen based on a trade-off between program run time and the minimum size of detectable errors. Objects to be printed have a track length of approximately 40mm per layer and require the printer approximately 6 seconds per layer at an average printing speed of 6.67mm/s. To ensure that at least one summing window falls within the error, the time interval must be chosen half as small as the time required by the printer to cover the distance. With the chosen parameters, detection of errors with a size of approximately 2.67mm length can be ensured, which is deemed sufficient for this project.

Next, a low-pass filter is applied to the summed data to reduce sensor noise. This filter smooths the signal and prevents unwanted fluctuations from being considered. Outliers at the beginning and end of each data set are removed. At the end of each data set, there is a filament retraction to prevent unwanted filament leakage after printing. At the start of each print, the desired pressure within the hotend must be rebuilt due to this retraction, which is done by a strong feed of material. Both processes are irrelevant to the relevant area of analysis and can be removed.

The summed data is then standardized to make it comparable. This involves normalizing the data to the mean and dividing by the standard deviation. To further reduce the amount of data to be considered, the standardized data is divided into equal-sized segments and the means and standard deviations are calculated for each segment. Each printed wall is divided into 100 segments, which has been found to be sufficient for proper analysis empirically.

A Savitzky-Golay filter is applied to smooth the means and standard deviations. This filter fits a quadratic approximation to each window of the signal. Multiplying the smoothed means and standard deviations has been found to be the easiest way to detect printing errors. The result is shown in the following figure, where the printed wall errors (peaks) are clearly visible (Fig. 3).

Fig. 3. Processed flow data with visual failure occurrence

In the last step, the printing data recorded in a logbook is read in the form of a CSV file. The relevant information for training the models, such as the relative position of the error, the magnitude of the error in percentage, the type of error (over- or under-extrusion) and the layer thickness of the printed wall.

3.2. Scan data processing

The process of component recognition begins in the lower left corner of the scan. Starting from this point, a fixed-size square is considered, and the number of recognized points within the square is counted. If the number of points corresponds to the expected number based on the scanner resolution for the examined area, it can be assumed that the square under consideration is part of a component. Connected points are then localized starting from the identified component point. The minimum and maximum points of the connected structure represent the limits of the identified component. The found component is saved and removed from the entire scan file. If the considered square does not contain sufficient points, the next adjacent square is examined. This process iterates over the entire scan until all components have been identified, as can be seen in Fig 4.

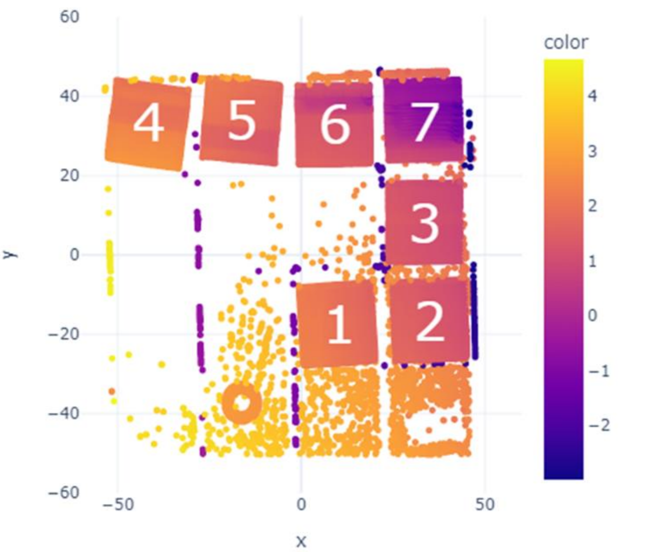

Fig. 4. Identified scan objects

Part of the data selection is already fulfilled by the localization of the scans. However, it is possible that isolated points around the actual scan are stored as well. These points are identified based on their distance from other points and removed from the scan.

The uniform format for processing component scans is a Numpy Array with three columns for X, Y, and Z coordinates. Numpy Arrays have the advantage of supporting a wide range of functionality through the Numpy library and beyond. In addition, many of these methods are optimized for run time, making them suitable for applications with large data volumes such as 3D point clouds.

Since the scanner has a fixed resolution, all measurement values are located within a defined grid, making it easy to identify measurement gaps. Points that are missing from the defined grid are filled with the mean value of all directly adjacent points. This ensures a continuous transition across all points in the scan, and gaps are not falsely identified as errors later.

To standardize and compare scans, an even orientation must first be established. If the measurement tray or the components in the measurement tray are unevenly oriented, the components may be rotated. To correct for this, a linear regression is performed on the points at the top and bottom ends of the component. The mean slope of the regression line is used to calculate the rotation of the component, which is then corrected using the Open3D library. In the second step, the edges of the component are flattened. The outermost rows or columns with a 99% point density relative to the scanner resolution are selected to remove any protruding points. Finally, the component is normalized to a size of one in the X and Y directions and saved.

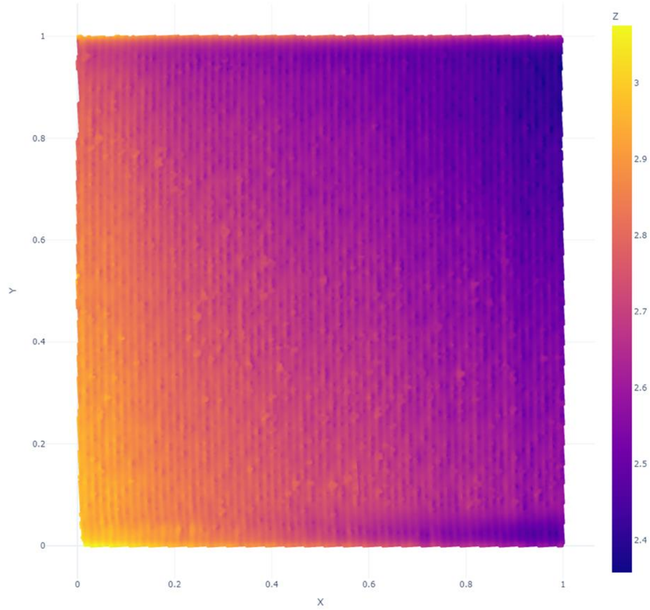

Fig. 5. Processed workpiece after cleaning procedure

The result of the previous steps should be a standardized component within dimensions of one by one. Any irregularities at the edges or measurement gaps within the scan should have been removed. Fig. 5 shows an example of a cleaned component. The point density over the component can be examined to verify its validity. If the point density corresponds to the scanner resolution and is evenly distributed over the component surface, the component is likely to be valid. An additional manual visual check can be performed by displaying the component scan as a scatterplot.

3.3. Anomaly detection

Errors resulting from over- or under-extrusion during 3D printing can be identified in the component scan by their altered Z-values relative to error-free areas. Due to the inertia of the test setup, errors typically extend across the entire width of the affected printing layers. The objective of error detection in the component is to identify the printing layers affected by the error and determine the error's dimension in the component.

A noticeable edge in the scan usually indicates the beginning or end of an error, and a large difference in Z-values between two printing layers can be used to detect these edges. Common methods for edge detection in image processing can be employed for error detection in the component.

The first step of the error detection process involves aggregating the component to a fixed resolution to ensure uniform point distribution for further processing. Aggregation is performed by averaging values in the aggregation area. An experimental resolution of 0.01 by 0.01 has been determined to strike a balance between accuracy and run time.

The second step of error detection involves edge highlighting. The aggregated scan is first filtered to differentiate between X and Y position. Two feature maps are generated with horizontal and vertical Sobel filters. MaxPool operations are then performed for each feature map to remove noise and emphasize critical points.

The third step of error detection involves dividing the processed component scan into columns or rows based on filter orientation. The values along these columns or rows are then summed. Rows and columns with the highest absolute sums are assumed to be the error boundaries. However, since the error extends across the entire width of the printing layers, only boundaries along the layers are retained. The sums along the printing layers are typically much higher and thus more easily detected (Fig. 6). Finally, the dimensions of the error are stored and can be utilized as a label during model training.

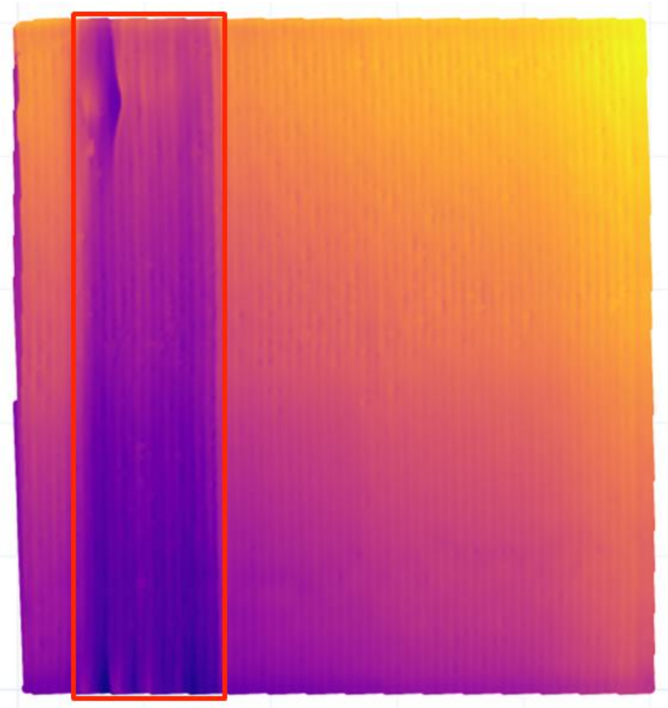

Fig. 6. Visualized anomaly detection

The aim of this investigation is to forecast the surface of a material utilizing filament flow data. The filament flow data serves as the input for this purpose. Furthermore, a comparison of three different machine learning models is examined. Particularly, linear regression, support vector regression (SVR) and long short term memory (LSTM) were chosen.

For training a machine learning model, the filament flow data is uniformly aggregated into a set of time series with the same duration. In such cases, the start and end points of the excursion in the filament flow are used as inputs instead. The excursion represents the deviation from the mean filament flow and larger excursions correspond to larger errors in the filament flow. To train the machine learning models, the largest contiguous area under the aggregated curve of the filament flow is identified, and the start and end values of the excursion are determined from this area. The error boundaries in the scan file, previously calculated, are used as the label for the input data.

The data is partitioned into training and testing datasets with a four-to-one ratio, and the machine learning models are trained with the k-fold method. The accuracy of the models is evaluated using the Root Mean Square Error (RMSE). The RMSE is a commonly used metric to measure the accuracy of predictions made by a machine learning model. It indicates the average distance between the predicted values and the actual values. In this case, the RMSE reflects the average deviation of the predicted boundaries of errors from the real boundaries of errors.

4. Results

The task at hand is to predict the position of errors on a component using machine learning models. To achieve this, a dataset was created consisting of 73 experiments, in which the filament flow and scanning could be clearly assigned. This data was used to train three different machine learning models: linear regression, SVR and a LSTM model.

The final models for predicting the position of errors on the component are stored in an app and the RMSE over the test data can be directly read from the app.

The RMSE over the test data can be improved by retraining the models. The models were trained on a subset of the dataset, and the remaining data was used to test the models. The results show that for linear regression and SVR, an RMSE of 0.1 was achieved over the test data. This means that the predicted boundaries of errors deviate from the real boundaries of errors by an average of 10%. For the LSTM model, the RMSE was slightly higher at 0.12.

It's worth noting that the component size is normalized to dimensions of one by one. This means that the component has been scaled to a standard size, which makes it easier to compare different components. It also means that the RMSE can be understood as the average deviation of the predicted boundaries of errors from the real boundaries of errors, relative to the size of the component.

5. Conclusion

The accurate prediction of surface quality is a critical factor for ensuring the performance and reliability of manufactured products. In this context, the task of predicting surface quality based on filament flow has received considerable attention as an efficient and cost-effective means of monitoring the additive manufacturing process.

The present study aimed to investigate the potential of predicting surface quality based on filament flow and to identify the key factors affecting the performance of the prediction model. To achieve this objective, a dataset consisting of 73 components with varying levels of surface quality was collected, and the filament flow and corresponding scans were processed for model training.

The prediction model was developed using a LSTM network, a type of artificial neural network commonly used for sequence prediction tasks. The model's performance was evaluated using a mean deviation accuracy metric, which measures the difference between the predicted and actual surface quality values. The achieved average deviation accuracy of 10% indicates that the model has significant potential for predicting surface quality based on filament flow.

However, the model's performance was influenced by several factors, including the inconsistent data quality of the filament flow sensor, the limited extrusion range observable in the filament flow, and the limited time for data acquisition and evaluation. These factors may affect the accuracy and reliability of the prediction model, and efforts were made to mitigate their impact through robust data cleaning and evaluation.

Despite the achieved accuracy, a certain degree of inaccuracy should be expected due to the many sources of interference in the additive manufacturing process. Therefore, further improvements to the prediction model are necessary to reduce the level of inaccuracy and increase the reliability of the prediction. The developed application provides a means to simplify the entire process of predicting surface quality based on filament flow, and further data can lead to significant improvements in the model's performance, particularly for the LSTM model.

Acknowledgements

This work was funded by the Bundesministerium für Wirtschaft und Klimaschutz (German Federal Ministry for Economic Affairs and Climate Action) and Forschungsgemeinschaft Qualität e.V. (Research Association Quality e.V.) within the project 21675 N/1 (FPQ). The authors would like to thank for the financial support.

References

[1] Gao, X., Yu, N., Li, J., 2020. Influence of printing parameters and filament quality on structure and properties of polymer composite components used in the fields of automotive, in Structure and Properties of Additive Manufactured Polymer Components, Elsevier, p. 303.

[2] Valerga, A.P., Batista, M., Salguero, J., Girot, F., 2018. Influence of PLA Filament Conditions on Characteristics of FDM Parts. Materials (Basel) 11.

[3] Dey, A., Yodo, N., 2019. A Systematic Survey of FDM Process Parameter Optimization and Their Influence on Part Characteristics 3, p. 64.

[4] Gebhardt, A., Hötter, J.-S., 2016. Additive Manufacturing: 3D printing for prototyping and manufacturing. Carl Hanser Fachbuchverlag, Munich, Cincinnati, OH.

[5] Hsiang Loh, G., Pei, E., Gonzalez-Gutierrez, J., Monzón, M., 2020. An Overview of Material Extrusion Troubleshooting 10, p. 4776.

[6] Fu, Y., Downey, A., Yuan, L., Pratt, A. et al., 2021. In situ monitoring for fused filament fabrication process: A review 38, p. 101749.

[7] Agarwala, M.K., Jamalabad, V.R., Langrana, N.A., Safari, A. et al., 1996. Structural quality of parts processed by fused deposition 2, p. 4.

[8] Fox, J.C., Moylan, S.P., Lane, B.M., 2016. Effect of Process Parameters on the Surface Roughness of Overhanging Structures in Laser Powder Bed Fusion Additive Manufacturing 45, p. 131.

[9] Sammaiah, P., Rushmamanisha, K., Praveenadevi, N., Rajasri Reddy, I., 2020. The Influence Of Process Parameters On The Surface Roughness Of The 3d Printed Part In FDM Process 981, p. 42021.

[10] Arnold, C., Monsees, D., Hey, J., Schweyen, R., 2019. Surface Quality of 3D-Printed Models as a Function of Various Printing Parameters. Materials (Basel) 12.

[11] Fastowicz, J., Grudziński, M., Tecław, M., Okarma, K., 2019. Objective 3D Printed Surface Quality Assessment Based on Entropy of Depth Maps. Entropy (Basel) 21.

[12] Soriano Heras, E., Blaya Haro, F., Del Agustín Burgo, J.M. de, Islán Marcos, M. et al., 2018. Filament Advance Detection Sensor for Fused Deposition Modelling 3D Printers. Sensors (Basel) 18.

[13] Del Burgo, J.M.d.A., D'Amato, R., Méndez, J.A.J., Ramírez, A.S. et al., 2019. Real time analysis of the filament for FDM 3D printers, in Proceedings of the Seventh International Conference on Technological Ecosystems for Enhancing Multiculturality, ACM, New York, NY, USA, p. 354.

[14] Wulfsberg, J.P., Hintze, W., Behrens, B.-A., 2020. Production at the Leading Edge of Technology: Proceedings of the 9th Congress of the German Academic Association for Production Technology (WGP), September 30th - October 2nd, Hamburg 2019. Springer Vieweg. in Springer Fachmedien Wiesbaden GmbH, Berlin, Heidelberg.

[15] Jin, Z., Zhang, Z., Gu, G.X., 2020. Automated Real‐Time Detection and Prediction of Interlayer Imperfections in Additive Manufacturing Processes Using Artificial Intelligence 2, p. 1900130.

[16] Jin, Z., Zhang, Z., Gu, G.X., 2019. Autonomous in-situ correction of fused deposition modeling printers using computer vision and deep learning 22, p. 11.

[17] Li, Z., Zhang, Z., Shi, J., Wu, D., 2019. Prediction of surface roughness in extrusion-based additive manufacturing with machine learning 57, p. 488.

[18] Böhme, M., Reifegerste, F., Wohlrabe, H., 2014. Optimierung der mechanischen Eigenschaften von mittels 3D-Druck erzeugten Objekten.

[19] Barrios, J.M., Romero, P.E., 2019. Decision Tree Methods for Predicting Surface Roughness in Fused Deposition Modeling Parts. Materials (Basel) 12.

[20] Taufik, M., Jain, P.K., 2016. A Study of Build Edge Profile for Prediction of Surface Roughness in Fused Deposition Modeling 138.