Data-Based Process Development and Control in Multi-Material Jetting Technology

Data-driven methods such as Data Mining (DM) and Machine Learning (ML) are contributing to the development and optimisation of new Additive Manufacturing (AM) technologies and associated materials beyond the limits of existing empirical knowledge [1, 2]. These methods enable an increase in manufacturing and development efficiency, accompanied by methods for condition monitoring and on-demand maintenance that increase asset availability [3].

Especially for the multi-stage ceramic process chain, the relationships between the process and material parameters as well as the component properties are highly complex and cannot be determined without these methods. The AM technology Multi-Material Jetting (CerAM MMJ; formerly CerAM T3DP) described in this publication offers the possibility to vary the process parameters for each of the deposited droplets or to use different materials, which increases the number of influencing parameters and interactions many times over.

Even though, many AM processes are more established and reliable today than they were a few years ago, there are still many challenges in the industrial application of this relatively young technology due to the high complexity of the individual AM technologies. In some cases, geometric deviations, lack of reproducibility, residual stresses and anisotropic mechanical properties limit the practicality of additively manufactured components [4, 5]. However, the use of production-relevant data from monitoring individual process states for process optimisation is often not exploited. Instead, users tend to rely on traditional methods and experiential knowledge during the commissioning process. They are often bound by deadlines and various restrictions.

Keywords
additive manufacturing, multi-material jetting, data-driven methods, droplet analyses, thermoplastic feedstock, statistical design of experiments methods

Consequently, due to a lack of real-time detection, process failures occur unnoticed during the manufacturing process and the quality and above all reproducibility of the products cannot be guaranteed. Especially in AM this is an important aspect, due to the ever-increasing demands for new, multifunctional and, at best, first-time-right manufacturing of components.

In the context of the in this article presented MMJ, process understanding is to be increased through the application of methods of quality management, to fully exploit the potential of CerAM MMJ. The acquisition of a thorough understanding of the process is addressed, which comprehensively describes the trilateral correlation between the device, material and process parameters.

Multi-Material Jetting (MMJ)

The AM technology MMJ developed at Fraunhofer IKTS (CerAM MMJ) is based on the selective deposition of thermoplastic feedstocks. These can be filled with particles to a high degree (~75–96 mass-% or 45–60 vol.-%), making it possible to produce dense components (>99 % of the theoretical density) from ceramics such as zirconia, alumina, aluminium nitride, silicon nitride, LTCC, stainless steels such as 316L or 17-4PH or cemented carbides and cermets. Alternatively, it is possible to process polymers or particle-reinforced polymers up to a melting temperature of approx 170 °C.

With CerAM MMJ, the material is applied drop by drop. Due to a high degree of parameterization, it is possible to adapt defined droplet parameters such as volume, diameter and height to the geometry, which is created. During the manufacturing process the drops are applied, overlapping one another, by using droplet fusion factors, thus forming a line structure on the substrate (Fig. 1) [6]. Depending on the degree of overlapping, the height and width can thus be influenced in addition to the dispensing parameters.

The dropwise material application and the thermoplastic properties of the feedstock make it possible to combine physically matched materials in a single manufactur-

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Fig. 1
Transition from single droplets to line structure using defined droplet fusion factors

ing step and thus produce multi-material components spanning different material classes. There are two core challenges in the manufacturing of multi-material components. The materials must be co-sintered and the differences regarding rheological properties of combined feedstocks must be considered. This leads to different process parameters and causes large variations in the droplet characteristics, such as volume, diameter and droplet height. In order to evaluate the droplet formation of the to be combined materials, appropriate experimental designs must be worked through and the feedstocks must be rheological characterised.

As the number of materials and the complexity of the component to be manufactured increases, so does the complexity of the process control. The diversity of the MMJ technology requires a systematic approach on the experimental design. In this case, one-factor-at-a-time methods are inappropriate, since correlations between several influencing factors are not recognized and experiments only provide optimal results by chance. Therefore, statistical Design of Experiments (DoE) methods were applied. DoE enables the many factors to be varied in order to map the effects and interactions. The identification of the main influences should allow the optimisation of the droplet quality according to defined target properties by using a multifactorial experimental design. Data-driven methods are used to increase process understanding and to optimise technology to achieve an industry-ready manufacturing process.

Based on the computer-aided evaluation of sensor data from the technological process chain for the manufacture of a component with CerAM MMJ, a data management plan was developed using an engineering workflow.

Process data management

CerAM MMJ can be divided into five sequential process steps: CAD generation, feedstock preparation, shaping (green part manufacturing), thermal post-treatment (debinding and sintering) and finally quality control (Fig. 2). To determine the interaction between the processing steps, intermediate results in the form of parameters (shape, dimension, radii of curvature, etc.) must exist on the green part, which allow conclusions to be drawn about correlations or shrinkage. An understanding of the interactions between the individual steps of the process chain can only be generated using data-driven methods. This requires holistic, technology-specific data acquisition, integrative data management and suitable algorithms for data analysis. The basis for both technology-oriented data acquisition and the design of experiments, and finally, the data analysis is a graphical process model.

Fig. 3 shows a simplified representation of a graphical process model of this kind. It visualizes the dependencies of individual process steps on others. The material flow chart identifies the preparation of the thermoplastic feedstock, MMJ, debinding, sintering, and finishing as key process steps. This article focuses on the preparation of the particle-filled thermoplastic feedstock and the AM of the green part using MMJ technology.

In order to achieve an effective scope of experiments, a statistical DoE was carried out. The focus was on the development of a data management system to be able to record, process and store the data belonging to the predefined influencing parameters. An essential aspect of data management is the definition of an identification system that makes it possible to track the material flow or the manufactured components and to assign them uniquely to the data. Each component requires a unique identifier, which must also be recorded as a parameter.

Based on the technological process chain (Fig. 2), an engineering workflow (Fig. 4) can be derived, which contains steps to be executed and ensures that the necessary process knowledge is available [7]. The activities "Design of Experiments", "Fab-

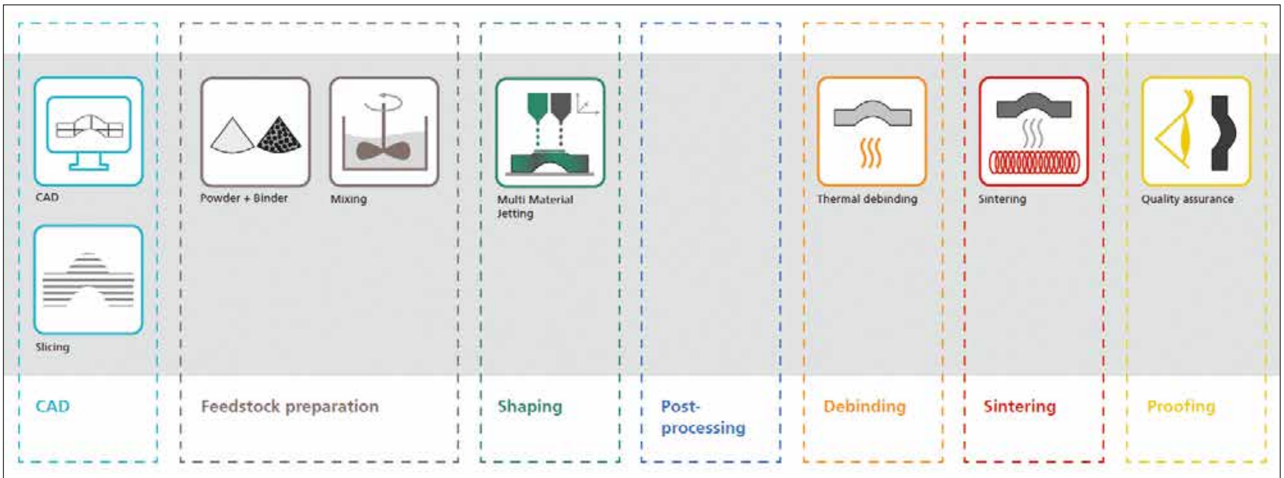

Fig. 2
MMJ-process chain

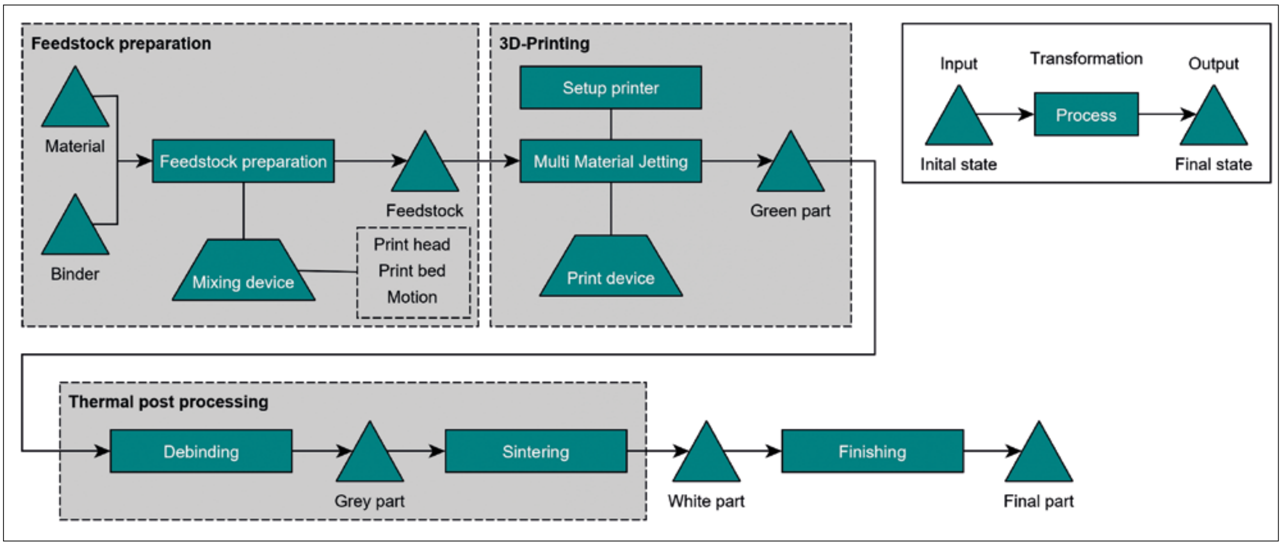

Fig. 3
Simplified graphical process model

rication of Components" and "Evaluation of Predefined Characteristics" in Fig. 4 are assigned to the processes. The data can be assigned to instruction design, experimental design, work instruction, process raw data (sensors), process raw data (machine), metadata template, evaluation instruction, process parameters, components properties, and cause-effect correlation.

During the acquisition of the relevant experimental data and the analysis and synthesis of the acquired data, the characteristics of the components instances and the state changes of the process and resource instances are logged and stored in the database. To ensure that the assignment of responsibilities and appropriate resource planning can be considered for the implementation of the data management plan, specifications such as ID, project, owner, contact, creation date, edit date, format, software, size and quantity must be defined for the metadata.

All knowledge gained from the modelling and analyses is stored systematically and in a structured manner to enable effective reusability and thus form a process knowledge database. Insights are identified process windows (as manufacturing parameters), material parameters (as a basis for simulation applications), models of cause-effect relationships (as a basis for process control) and process models (as a basis for process planning). The transfer of the demands on the required data management from a methodological and production-technological point of view achieved with the concept developed makes no claim to comprehensiveness, from which follows the need for the successive development of the data management plan [7].

In the droplet analysis example, rows of droplets are applied to the print bed according to the test plan and the raw data of the individual droplets is recorded using a profile laser (Keyence). These raw data consist of up to 15 000 height profiles, which can be assembled into a three-dimensional height profile at a defined scanning frequency and considering the traversing speed of the measuring head. Depending on the process parameters

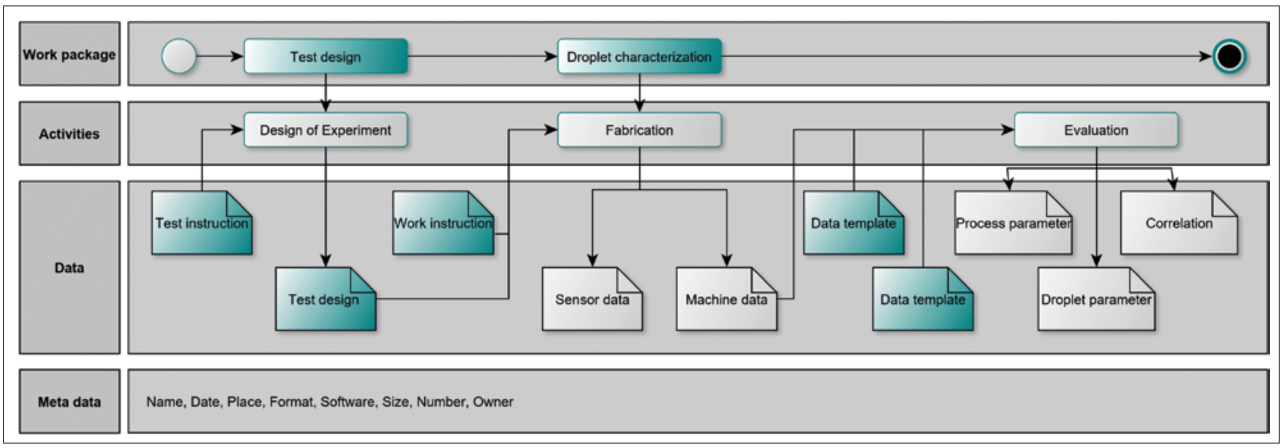

Fig. 4
Engineering workflow of the data collection for the process step 3D-printing – droplet analyses

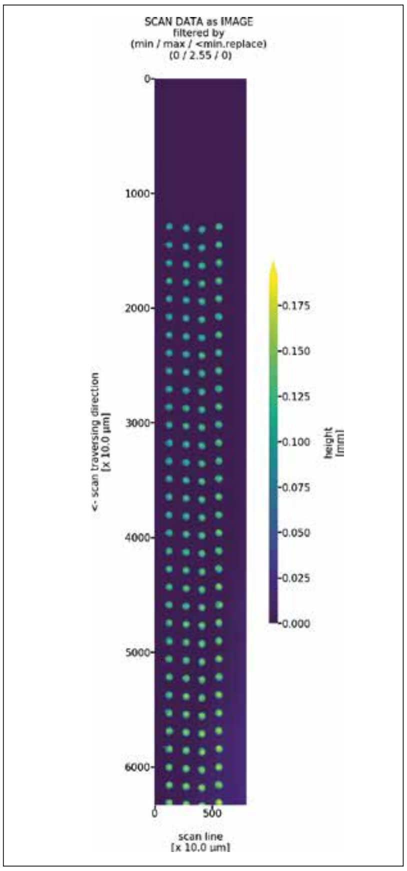

Fig. 5
Exemplary overview of scanned drop series

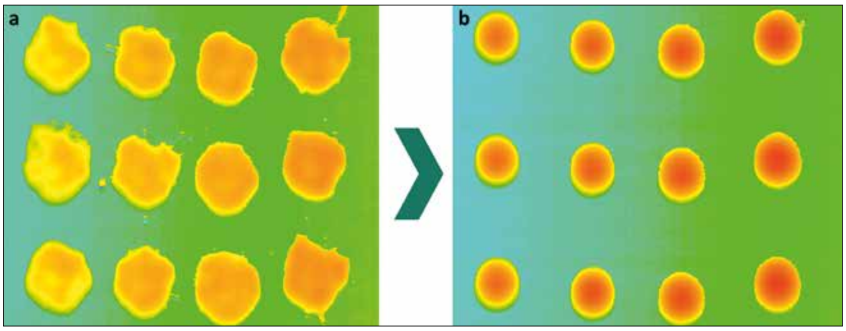

Fig. 6
Comparison of target parameters for the droplets produced: a) poor circularity and satellite particles, and b) good circularity and low amount of satellite particles

used and the resulting drop volumes, between 100–300 drops are recorded with one scan in less than 1 min and then evaluated (Fig. 5). The evaluation is performed in a self-programmed software tool.

Using a Deep Neural Network (DNN), an object recognition, in this case for the drops, is realised. Through training sets, it was possible to automate the drops based on image recognition algorithms using the DNN model. Each captured droplet is assigned its own ID and correspondingly defined target values for traceability.

The DMAIC methodology is used for the definition of the target condition. For the description of the intended condition, the target values droplet height, droplet circularity, the number of ambient satellite particles, and associated standard deviations of the produced droplets are introduced. These are assessed according to their significance for the quality, thus enable an evaluation of the structures produced, taking into account several target values. In Fig. 6 drops with poor circularity and satellite particles (a) and drops without satellite particles but good circularity (b) are shown as an example. After defining the starting or central points for the optimisation tests, the main effects of the test variables are described.

For this purpose, the correlation with the output variables (drop dimension in feed direction DDA, drop dimension perpendicular and droplet height DHE) are functionally described by including all factor levels of a test variable. That indicates the response of the output variables to the defined change of the test variables within the investigated range. By including the results of the hypothesis test, a unitless comparison can be made while assessing the significance of the effects. Null hypotheses are tested to assess the significance of the modelled main effects and to calculate sensitivity.

Only the outcome data of the starting points as well as those of the adjacent factor levels are included in the analysis, as these reflect the range of values to be tested within the optimisation experiments according to the Centrally Composed Design (CCD). Thus, three subsets with different sample sizes and standard deviations are analysed, necessitating the use of Welch's test [8, 9]. CCD as a representative of response surface designs is suitable for the realisation of contour plots. In this case, the experimental design should fulfil the properties of orthogonality and rotatability [10].

Since correlations occur as soon as more than two factors are mixed within an experimental design, it is necessary to set all not plotted parameters to zero when considering two factors separately.

Fig. 7 compares the effects and interactions of several test variables on the DHE. The number of isolines, each bounding a range of values of 5 µm, indicates the magnitude of the effects. Changing the Supply Pressure (ASP) and the Rising Time (RT) causes a maximum change in the DHE in the test range of about 15 µm. The influence of the Falling Time (FT) and the Needle Lift (NL) on the DHE in contrast is much stronger, with changes of more than 50 µm.

The distance between the lines provides further information about stronger or weaker effects. Simultaneous plotting of two influencing variables allows estimation of the most efficient modification of target properties using the shapest slope method. The shortest path to a maximum or minimum is given by a vector that intersects the isolines at right angles and points to the desired target (Fig. 7) [7, 10, 11].

Conclusion

To support an analysis of MMJ developed at Fraunhofer IKTS, a holistic approach to process data management was applied, whereby quality-describing target characteristics and suitable measurement tools for their acquisition were assigned to the steps of the manufacturing process.

Based on the technological process chain for manufacturing a component using MMJ and an engineering workflow reflecting the steps to be processed, a data management plan could be developed as a framework for a computational evaluation of mass sensor data. Focused on the green part manufacturing process step, droplet structures were geometrically described as intermediates of 3D-generation.

This served to prepare the data for an experimental design for multifactorial detection of various interdependent influences

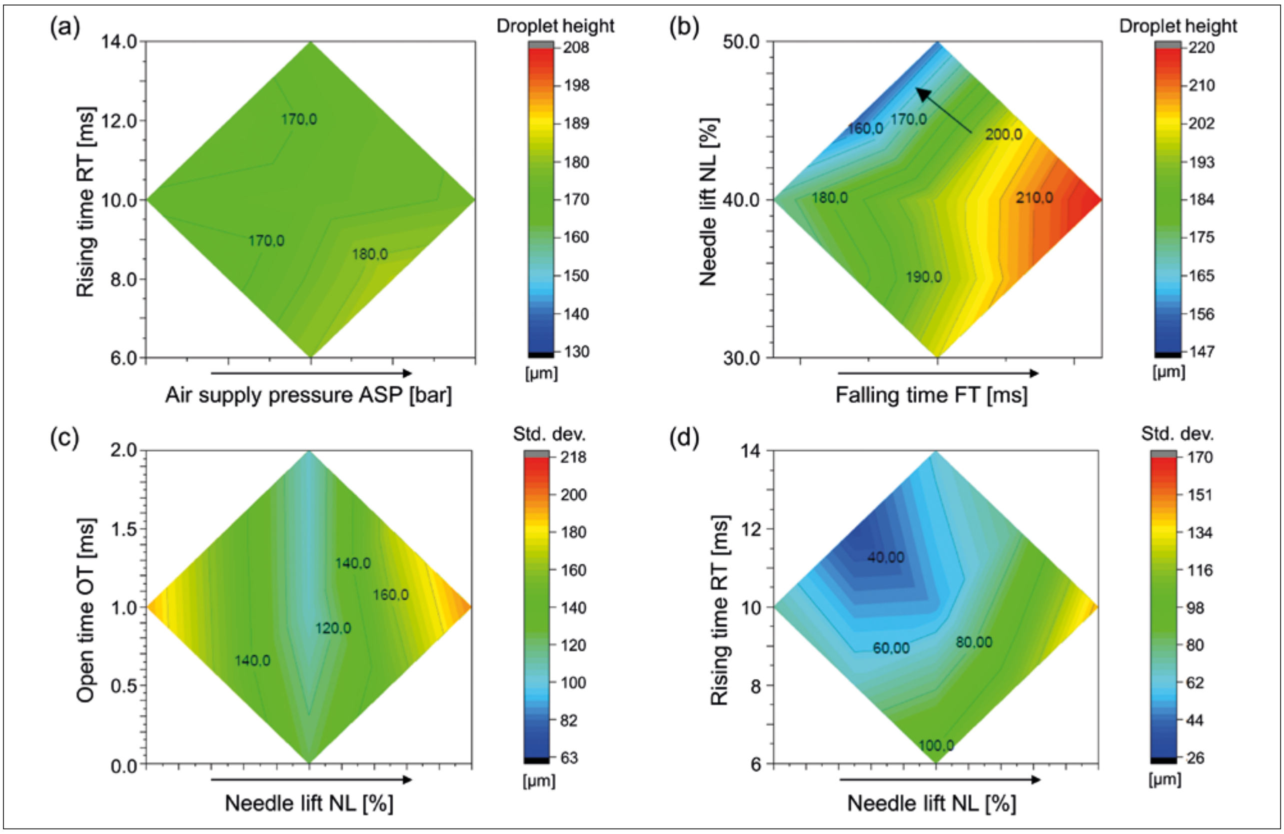

Fig. 7
Exemplary contour plots of the drop height and its standard deviation as a function of selected process parameters [7]

on the geometric properties of the deposition results. By means of single-factor pretests, a weighting of the influencing factors was determined in advance and a reduction of the factors to be considered in the statistical design of experiments was made possible. The identification of significant influences allowed an optimisation of the drop geometry according to the presented target properties by means of a multifactorial design of experiments. Taking into account the technological interrelationships in droplet generation, individual output variables, e.g. droplet height, can be adjusted as required, for example by changing the falling time. To get closer to the future goal of fully integrated automated process control, autarkic analysis methods, such as machine learning concepts, have to be implemented with an extended scope of sensor technology.

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