Progress in Additive Manufacturing
https://doi.org/10.1007/s40964-021-00192-4

REVIEW ARTICLE

Process monitoring for material extrusion additive manufacturing: a state-of-the-art review

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Received: 22 February 2021 / Accepted: 30 April 2021
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Abstract
Qualitative uncertainties are a key challenge for the further industrialization of additive manufacturing. To solve this challenge, methods for measuring the process states and properties of parts during additive manufacturing are essential. The subject of this review is in-situ process monitoring for material extrusion additive manufacturing. The objectives are, first, to quantify the research activity on this topic, second, to analyze the utilized technologies, and finally, to identify research gaps. Various databases were systematically searched for relevant publications and a total of 221 publications were analyzed in detail. The study demonstrated that the research activity in this field has been gaining importance. Numerous sensor technologies and analysis algorithms have been identified. Nonetheless, research gaps exist in topics such as optimized monitoring systems for industrial material extrusion facilities, inspection capabilities for additional quality characteristics, and standardization aspects. This literature review is the first to address process monitoring for material extrusion using a systematic and comprehensive approach.

Keywords Material extrusion · Fused deposition modeling · Process monitoring · Quality assurance · Sensor technology · Research gaps

1 Introduction

Additive manufacturing is already an accepted technology for special applications and prototype production. However, it has considerable potential for further expansion in the future [1]. Examples of future applications are small-batch productions in the automotive [2] and aerospace [3] sectors as well as the production of customized medical devices [4]. Additive manufacturing can further be used in the jewelry [5] and construction industries [6]. Niche applications include mouthpieces for musical instruments [7] or textiles for clothing [8].

Solving the challenge of qualitative uncertainties in terms of materials, processes, and products, as well as process knowledge deficits, is vital to further incorporate additive manufacturing in the industry [9, 10]. Therefore, providing tools for comprehensive quality management is essential [11, 12]. Means of measuring process states and part properties during additive manufacturing are particularly relevant to achieving this aim [9, 13–15].

Process monitoring enables the assessment of whether a product satisfies certain requirements. In-situ inspection techniques fundamentally increase customer confidence in a product and reduce costs due to rejection, because process anomalies are detected immediately after they occur. Furthermore, information from process monitoring is the basis for implementing a closed-loop quality control [16]. A significant challenge for testing technologies in the field of additive manufacturing is the complex geometries of parts that contain infill structures and process-specific defects [17, 18]. This review aims to identify and analyze the existing literature on in-situ process monitoring for material extrusion (MEX), as it is one of the most widely used additive process categories [1, 19].

Former reviews, specifically on the additive manufacturing of metal parts, have already been published [17, 20, 21]. Their focus lies on monitoring techniques for powder bed [22] fusion and directed energy deposition [16, 23–27]. The

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Published online: 19 May 2021

results of these studies are not directly transferable to MEX because additive process categories are significantly different due to dissimilar processing principles being applied [9]. However, a number of reviews which comprise a wider range of additive process categories have been published: Vora and Sanyal [28] investigated the usability of different conventional inspection techniques for process monitoring in additive manufacturing. Their focus was the analysis of general functional principles. Process monitoring in MEX was merely minimally addressed. Charalampous et al. [29] discussed the research on sensor-based quality monitoring before, during, and after the additive manufacturing process. They presented nine different projects on MEX in-situ process monitoring. Controlling the additive processes using sensor technologies was the focus of a study [30] that listed commercially available solutions in addition to research work. It included eleven references regarding MEX. Lu and Wong [14] presented fundamental challenges and developed principles for monitoring with thermography, and acoustic emissions. However, MEX was only considered to a very limited extent. A review on ultrasonic testing by Honarvar and Varvani-Farahani [31] discussed two MEX projects. Furthermore, applications of machine learning have already been discussed in various publications [32–34]. One of their topics was process monitoring, but the presentation of MEX projects was marginal.

In summary, the studies on hand provide only a rather limited insight into the subject matter of MEX in-situ process monitoring. A comprehensive and systematic analysis of the state of knowledge has yet to be conducted. Therefore, the aim of this study is to compile and structure the current state of research using an approach that is as objective and comprehensive as possible. The following three central questions will be answered:

- How much activity is involved in the field of process monitoring?
- What methods and technologies are used for the process monitoring of which quality characteristics?
- What are the research gaps?

After an overview of the fundamentals of MEX in Sect. 2, the methodology for the literature search and analysis is introduced in Sect. 3. Subsequently, in Sects. 4, 5, and 6 the results are presented and discussed, structured according to the abovementioned questions. Finally, Sect. 7 summarizes the main conclusions of the study.

2 Material extrusion

In MEX, a feedstock is extruded and deposited in beads by the relative movement between a nozzle and a substrate. During extrusion, the material is in a semi-solid state and solidifies when it reaches its final position and shape [19, 35]. Various sub-categories are grouped under the MEX process category. They differ in the type of extruder (plunger, gear, or screw), form of feedstock (filaments, rods, or pellets) [36], and kinematic design (Cartesian, polar, delta, or robot arm) [37].

The advantages of MEX are the simplicity of the process, relatively low costs [9] and a large variety of feedstock materials [38]. In addition to standard plastics, fiber-reinforced polymers can also be processed [39]. Furthermore, it is possible to produce parts from concrete [6], metals, ceramics, and multiple materials [36]. Because of the high material deposition rates that can be achieved [40], special MEX systems can be used for large-format additive manufacturing (build volumes of over 1 m^3) [41]. MEX can compete with conventional manufacturing processes in terms of cost per unit for small and medium batch sizes [42]. An example of an application in this batch size range is polymer components for the aircraft industry [43].

Numerous influencing variables (e.g., process parameters and material properties) affect the mechanical and geometric properties as well as the surface characteristics of the parts produced by MEX [39, 44, 45]. Depending on the application, the requirements for the parts differ. Therefore, only certain quality characteristics related to the respective requirements are the target of process monitoring. Examples of quality characteristics are the geometric dimensions and density of parts [46]. Owing to the complex interactions among different influencing variables, various process faults that can negatively affect the quality of parts may occur. A selection of typical part defects is listed in Table 1.

3 Materials and methods

This study can be considered as a state-of-the-art review based on the classification of different review types by Grant and Booth [56]. The focus is on the presentation of the current status as well as the identification of research gaps. During the literature search step, as many thematically congruent publications as possible are identified using a systematic and reproducible search methodology. There is no evaluation and selection of publications based on the relevance of the study results and the quality of the study design. An aggregative approach is used to synthesize the identified sources by collecting and interpreting empirical

Table 1 Typical part defects in material extrusion

Defect	Cause	Outcome	References
Bubbles and bulges	Moisture bound in the material evaporates explosively during processing	Compromised mechanical properties, impaired surface quality	[47, 48]
Incorrect bead deposition position	Faults in the kinematic structure, printing of unsupported overhangs	Geometric deviations	[49–51]
Overfill	Incorrect process parameters, errors in motion control	Increased bead width, bump formation	[50, 52, 53]
Scars	Nozzle grinds over the previously printed layer	Impaired surface quality	[50]
Stringing	Printing temperature too high, incorrect filament retraction settings	Material oozes out of the nozzle of the moving extruder, even though no extrusion is intended	[50, 54]
Underfill	Faults in the kinematic structure, clogged nozzle, incorrect process parameters	Voids, reduced bead width, stopped material extrusion, compromised mechanical properties	[50, 52, 53, 55]
Warpage and shrinkage	Temperature gradients in the part	Delamination, cracking, part deformation	[50, 51]

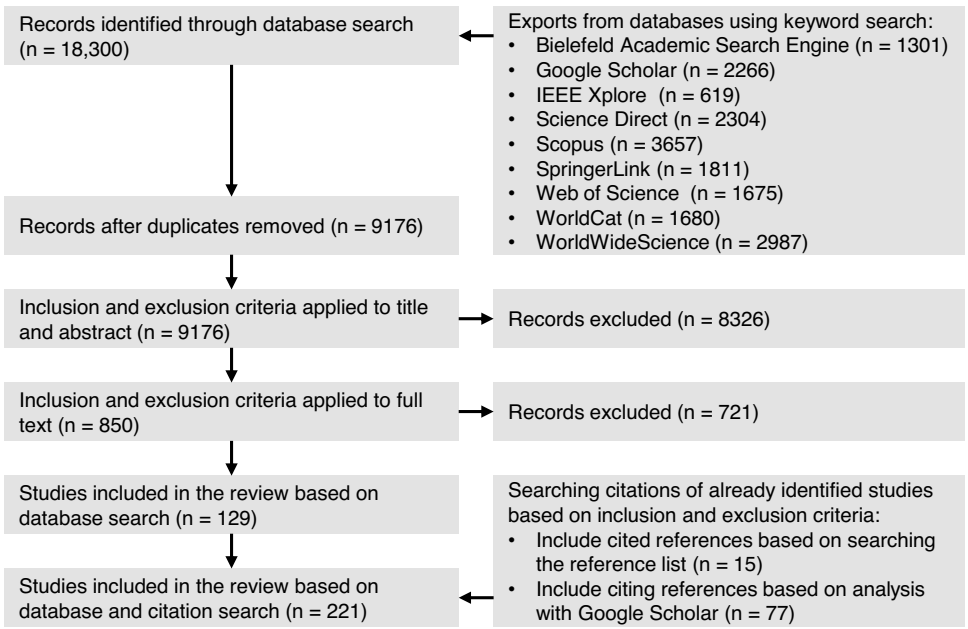

Fig. 1 Process of systematic search and criteria-based filtering with the specification of the number of considered records (n) in each step

data. In addition, a primary purpose is to provide an understanding of relevant research directions and topics [57].

The process of literature search shown in Fig. 1 included, as a first step, a literature search of nine different popular databases in February 2020. Each database was searched multiple times. The searches corresponded to the keyword ("fused deposition modeling" OR "fused deposition modelling" OR "fused filament fabrication" OR "material extrusion" OR "fused layer modeling" OR "filament freeform fabrication") AND ("process" OR "quality" OR "defect" OR "error" OR "fault" OR "condition") AND ("assurance" OR "control" OR "detection" OR "inspection" OR "measurement" OR "metrology" OR "monitoring" OR "sensor"). Single search operations contained only one term for naming the additive manufacturing process (first operand for the Boolean AND operators). Therefore, six individual searches were performed to query the keyword completely. In each database, the entire record was searched, but the number of exported hits was limited to 500 per single search operation. If the database supported a limitation of the search to titles, abstracts, and keywords of the publications, an additional search in these categories was performed without limitation on the number of exported hits.

After removing the duplicates with the aid of the literature management software Citavi (Swiss Academic Software GmbH), the dataset contained 9176 entries. To analyze relevant sources only, inclusion and exclusion criteria were

defined and applied to the dataset. The inclusion criteria were:

- one of the sub-categories of MEX is treated;
- central aim is in-situ process monitoring for quality assurance (assessing the status of 3D printer components or parts in production);
- contribution is original research (peer-reviewed), dissertation or active patent.

The exclusion criteria were:

- process monitoring is included but not for the purpose of quality assurance (e.g., sensor system to validate a simulation of the MEX process);
- not in English or German;
- older than 2013.

A total of 221 elements comprise the dataset for the review. The approach to analyze the identified publications, as well as the paper's corresponding sections, is presented in Fig. 2.

4 How much activity is involved in the field of process monitoring?

The analysis of the publication dates of the contributions in Fig. 3 shows that publication activity is growing steadily, and the research activity in the field of process monitoring has been gaining importance. Growth rates since 2013 have at least been in the same range as those found by Vyavahare

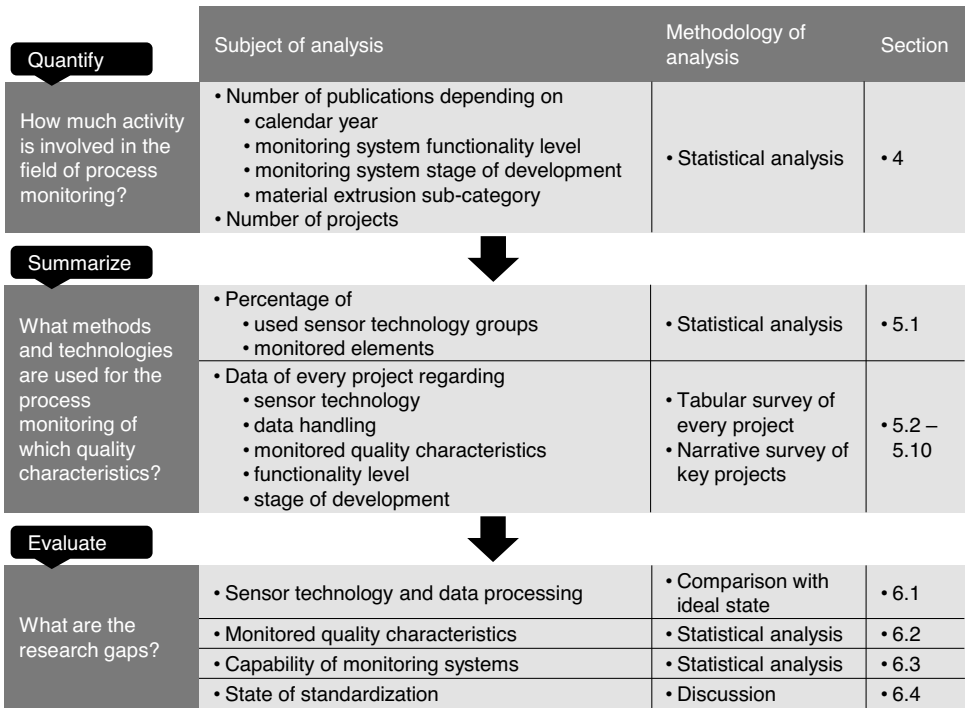

Fig. 2 Approach to analyze the identified publications

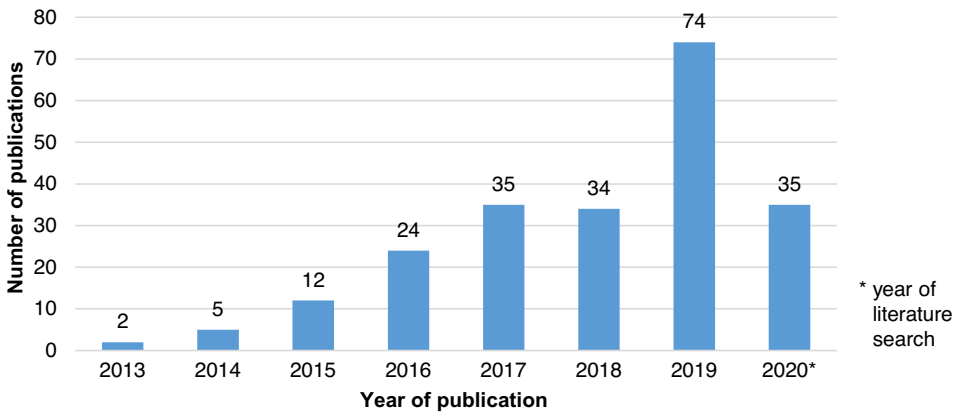

Fig. 3 Publication activity by calendar year

et al. [15] for the MEX research area in general. It should be noted that the value for the year 2020 cannot be interpreted directly because the process of searching the literature had been completed midyear.

The publication activity varies in the different sub-categories of MEX. The majority of the identified studies can be assigned to the field of monitoring techniques for fused deposition modeling [35]. The other sub-categories addressed are large-format MEX [58–63], bioprinting [64], and direct ink writing [65–68]. In addition to the processing of conventional filaments, some studies have examined manufacturing processes for continuous fibers [69, 70], pastes [71], and pellets [60, 62, 63, 72, 73]. Publications addressing MEX machines with delta [74–88] and robot arm [58, 72, 73, 89–92] kinematics are exceptions to the considered Cartesian systems.

Some monitoring systems have been published several times and sometimes, several systems have been described in one publication. The grouping of sources according to project affiliation indicated that the dataset involved 145 different MEX monitoring systems. The criteria for grouping the sources according to project affiliation were research group membership and sensor technology.

For further characterization of the dataset, Fig. 4 illustrates which levels of functionalities of a process monitoring system have been addressed by the publications and in which development stage they are. The sensor system (F1) is a pure hardware setup. In the level that builds on it, data are processed and extracted (F2), e.g., for visualization. The third functionality level describes the automated data evaluation (F3) for the detection of anomalies. A closed-loop control (F4) represents the maximum possible functionality level of a monitoring system. Note that these categories progress in a typical order (F1→F2→F3→F4), where the latter categories necessitate accomplishment of the prior categories. Publications are placed in the highest category that their content represents. The stage of development is described with the following classifications: patent (P), preliminary studies (D1), and realized solution (D2).

Figure 4 shows that the current focus of research is in F3 since the maximum number of D1 and D2 occurs on this level of functionality. However, the conspicuously high number of patents in F4 indicates that an economic benefit is seen particularly for this level of functionality. In the long term, therefore, further research activity can be expected in this area.

5 What methods and technologies are used for the process monitoring of which quality characteristics?

5.1 Sensor technology groups and inspected elements

Various sensor technologies are used for process monitoring. Figure 5 displays the percentage shares of sensor technology groups in the total number of sensors used. The grouping is based on the measured physical quantities. The respective share of each sensor technology that is used simultaneously with another is represented by the "sensor fusion" section of the bar. Furthermore, all sensor technologies that have a share of less than 2% in the "one sensor technology" section and cannot be assigned to the other groups are collected under "other."

Figure 6 depicts a statistical analysis of which elements of the additive manufacturing process are directly monitored by which sensor technology groups. On one hand, it is possible to monitor the components of the MEX machine that have an influence on the part quality. According to the main functional components of the MEX machine [19, 35, 45], the following are distinguished:

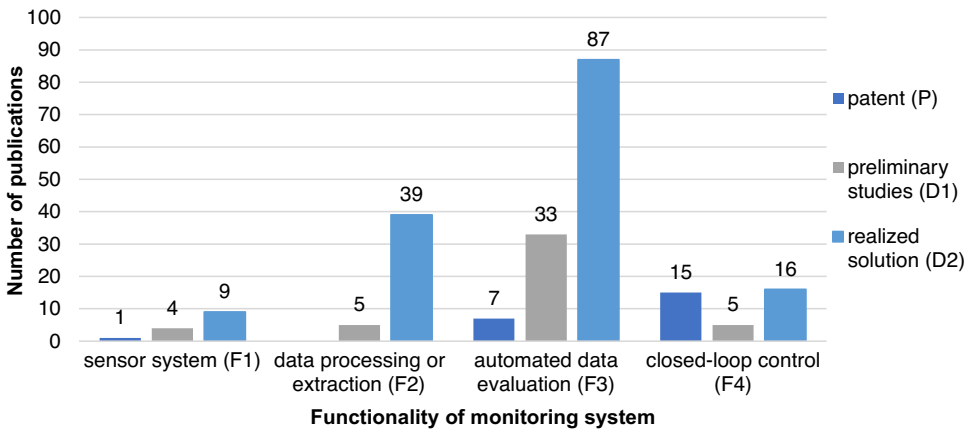

Fig. 4 Functionality of the examined monitoring systems depending on the stage of development

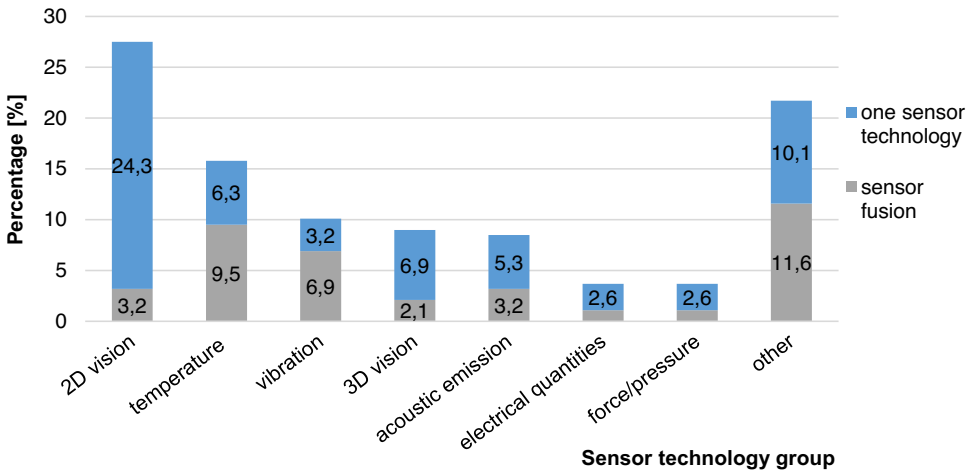

Fig. 5 Percentage of sensor technologies in the total number of sensors

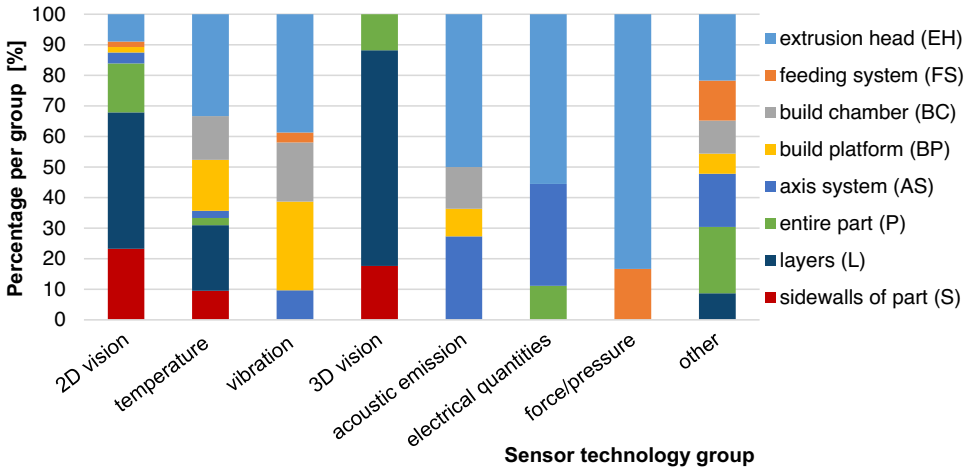

Fig. 6 Sensor technology groups and inspected elements

- extrusion head (EH), including the extrusion nozzle and feedstock delivery mechanism;
- feeding system (FS), for feedstock transport to the extrusion head;
- build chamber (BC), including the housing and frame;
- build platform (BP); and
- axis system (AS), including the motors.

On the other hand, the part can be directly monitored. The following are distinguished depending on the area of monitoring:

- entire part (P);
- layers (L), equivalent to the build surfaces in the majority of cases; and
- sidewalls of part (S).

Figure 6 shows that the measurement of vibration, acoustic and electrical signals, as well as force and pressure, is primarily used to monitor the components of the MEX machine. The part is inspected primarily using vision technologies. The focus is on monitoring the extrusion head and individual layers.

The following subsections describe the identified publications sorted by sensor technology groups and project affiliations. The general functional principles are introduced, and selected monitoring systems are explained precisely. For detailed descriptions of the treated sensor types and their general advantages and disadvantages, the reader can refer to Vora and Sanyal [28].

5.2 2D vision

In Table 2, the projects identified within the field of 2D vision are listed, along with their associated references. The projects were sorted based on the following priority: (1) used sensors (column "Sensors"), (2) inspected elements (column "Ele"), (3) project level of functionality (column "Fun"), and (4) stage of development (column "Dev"). The column "Data handling" provides a brief description of the methods

Table 2 Summary of publications on 2D vision

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[93]	Camera	EH	Convolutional neural network	Offset nozzle height	F3	D2
[94]	Camera	AS	Comparison with G-code	Area of layer	F3	D2
[95]	Camera	AS	Comparison with ideal process	Voids	F3	D2
[96]	Camera	P	Cascade classifiers, comparison with simulated reference image	Geometric deviations	F3	D1
[97]	Camera	P	Principal component analysis and support vector machine, convolutional neural network	Defective part	F3	D2
[98]	Camera	P	Deep learning	Defective process	F3	D2
[99]	Camera	L	Image visualization	Layer surface	F2	D1
[100]	Camera	L	Contour detection	Geometric deviations	F2	D2
[101]	Camera	L	Visualizing in mixed reality	Not applicable (n.a.)	F2	D2
[102, 103]	Camera	L	Comparison with reference	Infill structure, part position	F3	D1
[89]	Camera	L	Comparison with reference	Geometric deviations	F3	D1
[104–106]	Camera	L	Naive Bayes classifier, decision trees, random forest, k-nearest neighbors, anomaly detection, cyber-physical alert correlation	Infill structure voids	F3	D2
[107]	Camera	L	Comparison with STL file	Geometric deviations	F3	D2
[108]	Camera	L	Random forest	Infill structure voids	F3	D2
[58]	Camera	L	Data fusion, measurements	Bead thickness/intersections/ alignment, geometry	F3	D2
[65]	Camera	L	Comparison with G-code	Voids, bead shape	F3	D2
[109, 110]	Camera	L	Statistical process control	Layer contour, overfill, underfill	F3	D2
[111]	Camera	L	Comparison with tolerance range	Geometric deviations	F4	P
[112]	Camera	L	Convolutional neural network	Overfill, underfill	F4	D2
[113]	Camera	S	Differential imaging, blob detection	Detachment, geometric deviations, stopped material flow	F3	D2
[114, 115]	Camera	S	Image mining	Part quality	F3	D2
[88, 116]	Camera	S	Neural network	Blobs, voids, thick beads, crack, misalignment	F3	D2
[92]	Camera	S	Comparison with ideal, deep reinforcement learning	Geometric deviations	F4	D2
[117]	1/multiple cameras	S	Comparison with ideal	Geometric deviations	F4	P
[118]	1/multiple cameras	L, S	Comparison with CAD model	Parts geometry/position	F3	P
[119–126]	5 cameras	S	Comparison with reference	Extrusion stop, material color	F3	D2
[127]	Camera, illumination	P	Comparison with CAD model	Geometric deviations	F3	D2
[128]	Camera, illumination	P	Comparison with reference	Warping, detachment, extrusion stop	F3	D2
[129]	Camera, illumination	L	Comparison with STL file	Geometric deviations	F3	D1
[130]	Camera, illumination	L	Texture analysis	Layer surface irregularities, geometric deviations	F3	D1
[131–133]	Camera, illumination	L	Statistical process control	Layer contour	F3	D2
[134]	Camera, illumination	L	Comparison with ideal part, support vector machine	Defective parts	F3	D2
[59]	Camera, illumination	S	Fourier analysis	Layer height	F3	D1
[75]	Camera, illumination	S	Comparison with STL file	Geometric deviations	F3	D2
[135]	Camera, illumination	S	Comparison with reference	Layer shifting	F3	D2
[90, 91]	Camera, illumination	S	Measurements, comparison with theoretical model	Voids, shape contour	F3	D2
[136]	1/multiple cameras, illumination	P	Comparison with G-code	Detachment, extrusion stop, geometric deviations	F3	P
[66, 67]	2/3 cameras, illumination	EH, L	Various measurements	Bead structures, deposition area characteristics	F3	D2

Table 2 (continued)

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[137]	Multiple cameras, illumination	P	Comparison with CAD model, hidden Markov models, Bayesian inference, neural network	Outer surface of part	F4	P
[138]	Line scan camera, illumination	L	n.a	Defective process	F3	P
[139–155]	Camera, flatbed scanner	S	Texture analysis for feature extraction	Surface quality	F3	D1
[156]	Flatbed scanner	L	Distortion adjustment	Layer contour	F1	D1
[157, 158]	Digital microscope	EH	Measurements, filament feed speed control	Feeding gear slippage, material flow rate	F4	D2
[159]	Digital microscope	L	Image visualization	Voids, bead shape	F1	D2
[160–162]	2 digital microscopes, illumination	L	Texture analysis, k-nearest neighbors, naive Bayes classifier, linear discriminant analysis, support vector machine, PID controller	Overfill, underfill	F4	D2
[163]	Optical sensor	FS	n.a	Material flow rate	F4	P

used for sensor data processing. "Quality characteristics" are the features checked by the monitoring system. If the publications on a project do not contain certain information, this is indicated in the corresponding cell with the phrase "not applicable" ("n.a.").

The generic term 2D vision is used in this paper to describe all sensor technologies that acquire two-dimensional images of an object in the visible wavelength range. Seven of the 23 patents identified in this work exclusively addressed 2D vision [111, 117, 136–138, 163]. Therefore, the potential of the sensor technology for MEX process monitoring is considered high by the industry.

The 2D vision technology is often used for the sequential inspection of layers. One technical variant includes mounting the sensor on the extrusion head [58, 65–67, 89, 104–106, 111, 112, 159–162]. For example, Liu et al. [160, 161] investigated overfill and underfill defects using two digital microscopes, which were attached to the extrusion head to continuously analyze the layer surface in a small area next to the nozzle (Fig. 7). For the extraction of features, a texture analysis method in which the layer surface was described with a gray-level co-occurrence matrix was used. Subsequently, the layer surface was divided into five classes using the k-nearest neighbors algorithm. The material flow rate and speed of the cooling fan on the extrusion head were adjusted using a proportional-integral-derivative (PID) controller according to the classification to increase the layer quality.

In addition to projects that include mounting vision sensors on the extrusion head, another relevant approach is the stationary mounting of the camera with a view on the build platform. In this scenario, the entire layer is captured in one image acquisition [100, 101, 104–110, 129–134]. In one of the projects [131–133], statistical process control is used to evaluate the quality of the layer contours. Significant changes in the process caused by the exceedance of tolerance limits were displayed on quality control charts. In contrast, Delli et al. [134] compared images of a defect-free part with the actual manufactured part and used both a simple threshold method and a support vector machine to classify the part into one of two categories: good or bad.

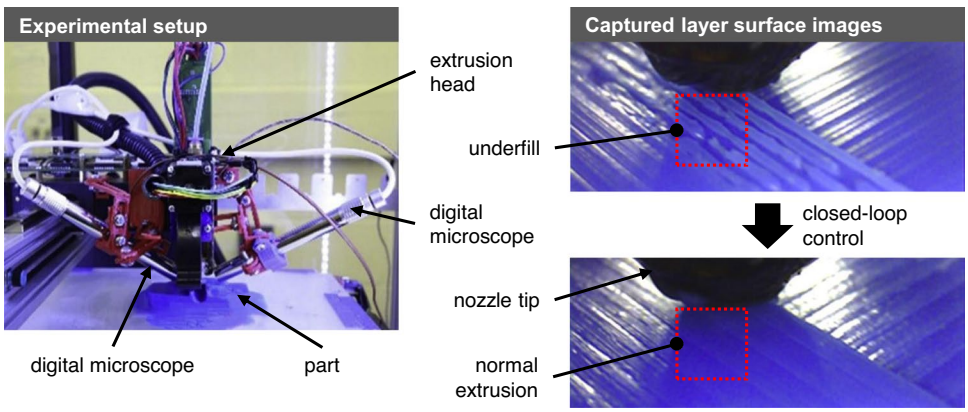

Fig. 7 Investigation of layer surface quality using two digital microscopes. Adapted from [160], copyright 2019, with permission from The Society of Manufacturing Engineers

Aside from process monitoring of individual layers, 2D vision sensors may also be used for the exclusive inspection of the sidewalls of parts. In this technical variant, the camera axis is often perpendicular to the normal vector of the build platform. Baumann et al. [113] used this approach to detect deformations on printed objects, detachments from the build platform, and lack of material flow. Because the 3D printer is a desktop device with an open housing, the camera can be placed in front of the 3D printer to capture images of one side of the part.

The use of a camera to inspect sidewalls in large-format additive manufacturing was investigated by MacDonald et al. [59]. Fourier analysis was used to determine the variation in layer heights from the image data. Due to the large size of the beads, they can be easily distinguished from one another with an algorithm. Especially in large-format MEX with pellet feedstock, the extrusion process is highly sensitive to parameter variations. The authors demonstrated that the resulting slumping of beads or small irregularities protruding from the sidewalls could be detected with the monitoring system.

In a series of publications, Straub [119–126] presented a sensor system consisting of five cameras arranged around the build platform. For data acquisition, the printing process is stopped, and the build platform is moved to a predefined position. Besides the use of multiple cameras, mobile solutions to move the camera around the object to be printed have been proposed in further studies [88, 90, 117]; thus, the sidewalls of the part can be fully captured. Figure 8 shows this as an example with a camera attached to the extrusion head of a robot MEX system using a special mount.

In addition to the inspection of manufactured parts, some systems also use 2D vision to monitor the mechanical components of a 3D printer. Greeff et al. [157, 158] utilized a digital microscope to inspect the filament delivery mechanism in an extrusion head. The speed and width of the filament were measured to calculate the volume flow. Moreover, the speed of the feeding gear was determined and compared with that of the filament to calculate slippage effects.

5.3 Temperature monitoring

Since materials are melted because of heat during MEX, the acquisition of temperature data is a practical method for evaluating the condition of the manufacturing process. Table 3 summarizes the corresponding publications. Temperature sensors for measuring and controlling the temperature of the build platform, extruder, and ambient air in the build chamber are conventionally installed in many MEX systems [178]. However, aside from sensors that are in contact with the measured surface, a large portion of the identified publications involve temperature determination via thermography. Thermography is an imaging technique used to display the surface temperature of objects. The intensity of the infrared radiation serves as a measure of the temperature.

Thermal cameras are often used to determine the temperature of the layers. Borish et al. [60] developed a method for calculating the average temperature of a layer in large-format MEX. They paused the printing process until the temperature decreases below a certain value. When this condition is attained, the next layer can be processed. The thermal camera is attached to a movable arm that is pneumatically driven. The study shows that temperature measurements are particularly relevant for large-format additive manufacturing since in rapid printing processes cooling times are sometimes insufficient and parts collapse under their own weight.

Monitoring the sidewall of a part with a thermal camera, Ferraris et al. [171] determined a correlation between the characteristic temperature curves and the size of the bonding surfaces between adjacent beads. Using a similar hardware setup, the tensile strength of samples was predicted in a work by Bartolai et al. [173, 174].

5.4 Vibration monitoring

Vibration can be measured at many of the mechanical components of the 3D printer (Table 4). A key issue is the monitoring of extrusion head vibrations. Tlegenov et al. [181, 182] attached an accelerometer to an extruder to determine

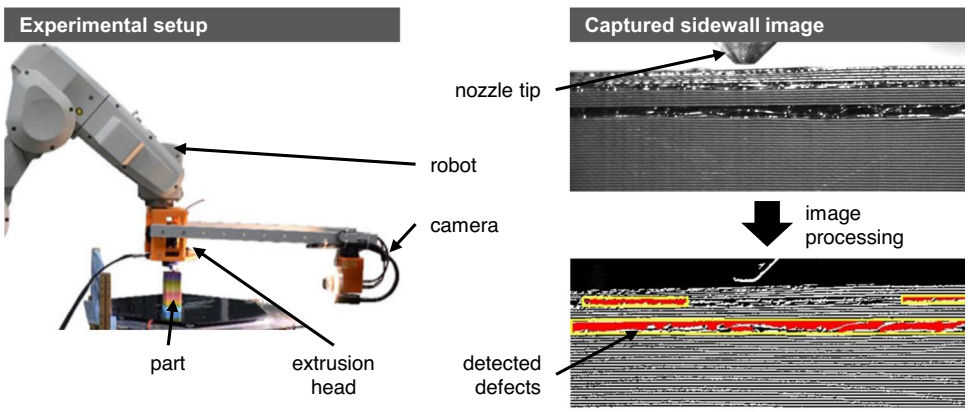

Fig. 8 Camera attached to the extrusion head of a robotic MEX system for continuous multi-view inspection of sidewalls. Adapted from [90], © Emerald Publishing Limited all rights reserved, with permission from Emerald Publishing Limited

Table 3 Summary of publications on temperature monitoring

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[164]	Thermal camera	EH	Temperature control methods	Polymer melt temperature	F4	D2
[165]	Thermal camera	L	Spatial and time-domain data processing	Layer temperature	F2	D2
[166–168]	Thermal camera	L	Sensing with limited sensor data	Layer temperature	F2	D2
[169, 170]	Thermal camera	L	Rules of knowledge, support vector machine	Nozzle clogging, warping, underfill, geometric deviations	F3	D2
[60]	Thermal camera	L	Process temperature data, control layer start time	Short layer build times	F4	D2
[171]	Thermal camera	S	Spatial and time domain data processing	Surface temperature, bond shape between beads	F2	D2
[61]	Thermal camera	S	Spatial domain data processing	Temperature profiles	F2	D2
[172]	Thermal camera	S	Correct temperature measurements	Surface temperature	F2	D2
[173, 174]	Thermal camera	S	Analytical prediction model	Temperature of weld interface, part tensile strength	F3	D2
[175]	Infrared	EH	n.a	Irregular material flow	F4	P
[176, 177]	2 thermistors	EH	Feed-forward control	Temperature of nozzle/heater block	F4	D2
[178]	3 thermistors	EH, BC, BP	PID controller	Local temperatures	F4	D1
[179]	3 thermocouples	L	Time domain data processing	Local layer temperature	F2	D2
[180]	Infrared, thermocouple, thermistor	EH, BP, L	Neural network, support vector machine, linear regression, PID controller	Distortion	F4	D2

Table 4 Summary of publications on vibration monitoring

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[181, 182]	Accelerometer	EH	Analytical model, frequency and time domain analysis	Nozzle clogging	F2	D2
[183]	Accelerometer	AS	Logistic regression, support vector machine, random forest	Warping, extrusion stop	F3	D2
[184]	Accelerometer	n.a	Frequency and time domain analysis, comparison with ideal working status	Various defects	F3	D1
[162]	2 accelerometers	EH, BP	Statistical process control	Voids	F3	D2
[185]	2 accelerometers	EH, BP	Support vector machine, neural network	Filament jam, warpage, material leakage	F3	D2
[87]	5 accelerometers	BC, AS	Neural network	Mechanical failure, axle failure	F3	D2

the effective nozzle diameter, which was used as a measure for nozzle clogging conditions. They observed that the amplitude of the vibration increased nonlinearly with decreasing effective nozzle diameter. The results of an analytical model for the theoretical determination of the amplitude exhibited good agreement with those of the experiments using both Bowden and direct extruders. In another research work [185] sensors were attached to both the extrusion head and build platform. This enabled the detection of part deformations and defective extruder conditions. The detection of defects in mechanical components of the MEX machine was solely investigated by Yen and Chuang [87].

5.5 3D vision

The advantage of 3D vision compared to 2D vision is that height information can be captured. Table 5 indicates that nearly all of the publications address the monitoring of individual layers, in which comparison with different types of digital reference information was used for error detection.

If structured light or stereoscopic imaging systems are used, the sensors are rigidly aligned to the build platform [75, 76, 100, 186–191, 193]. Holzmond and Li [193] for example, used two five-megapixel cameras to create a stereoscopic imaging system. The viewing axes of the cameras were aligned perpendicular to the layers. To capture images of the layers, the extrusion head was moved out of the viewing axis by making it print a waste part parallel to the target part. After each layer, the extrusion head moved to the waste

Table 5 Summary of publications on 3D vision

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[186]	Camera, structured light	L	Extracting sub-region features, comparison with CAD model	Holes, bumps, curling	F3	D2
[187]	2 cameras, structured light	L	Deep learning	Process shifts	F3	D2
[100, 188–191]	2 cameras, structured light	L	Comparison with G-code	Geometric deviations	F3	D2
[154, 155]	2 cameras, structured light	S	Texture analysis	Surface quality	F3	D1
[192]	Camera, illumination	L	Comparison with reference, artificial intelligence control	Various defects	F4	P
[193]	2 cameras, illumination	L	Comparison with G-code	Geometric deviations, holes, blobs	F3	D2
[75, 76]	3×2 cameras, illumination	S	Comparison with STL file	Geometric deviations	F3	D2
[194]	3D camera	P	Comparison with reference	Geometric deviations	F4	P
[195]	Laser triangulation	L	Comparison with CAD model, measurement of defects	Underfill, overfill	F3	D2
[196]	Laser triangulation	L	Visualizing sensor data	Bead shape	F4	D1
[62]	Laser triangulation	L	Comparison with G-code	Underfill, overfill	F4	D2
[72, 73]	Laser triangulation	L	Comparison with nominal layer height, re-slicing	Layer height, bead width	F4	D2
[64]	Laser triangulation	L	Comparison with reference, generating modified path	Spatial bead position	F4	D2
[197]	2 laser triangulation	L	2D comparison with G-code	Geometric deviations, voids	F3	D2
[198]	n.a	L	Comparison with reference	Geometric deviations	F3	P

part, creating a time window for image acquisition. A reference point cloud was generated from the G-code, which could be compared with the captured point cloud to detect defects. The approach was limited in that the system could only inspect materials with naturally textured surfaces.

In contrast, laser triangulation sensors record single height profiles. Therefore, a relative movement between the inspection object and sensor should be attained to generate a 3D point cloud from a large number of height profiles. Hence, the laser triangulation system is attached to the extrusion head of the MEX machine and can be moved over the layer surface [62, 64, 72, 73, 195–197].

Table 6 Summary of publications on acoustic emission monitoring

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[199]	Acoustic emission	EH	Feature-based time domain analysis	Filament breakage	F2	D2
[200]	Acoustic emission	EH	Frequency domain analysis	Extruder state	F2	D2
[201]	Acoustic emission	EH	Clustering by fast search and finding of density peaks	Extruder state	F3	D2
[202, 203]	Acoustic emission	EH	Hidden semi-Markov model, support vector machine	Extruder state	F3	D2
[74, 204]	Acoustic emission	BP	Hidden semi-Markov model, support vector machine, acoustic emission hits	Curling, detachment	F3	D2
[205, 206]	Acoustic emission	BP	k-means clustering, neural network	First layer defects	F3	D2
[207]	Audio recorder	EH, AS	Gradient boosting regression, logistic regression classifier	Geometric deviations	F3	D2
[208]	Microphone	EH, AS	Audio classifier for comparison with ideal process	Infill pattern, fill density	F3	D2
[209]	Microphone	EH, BC, AS	Neural network	Nozzle offset height, fan activity, 3D printer activity, door opening/closing, axes movements	F3	D2
[210]	Smartphone	EH, AS	Comparison with ideal process	Malicious modified G-code	F3	D2

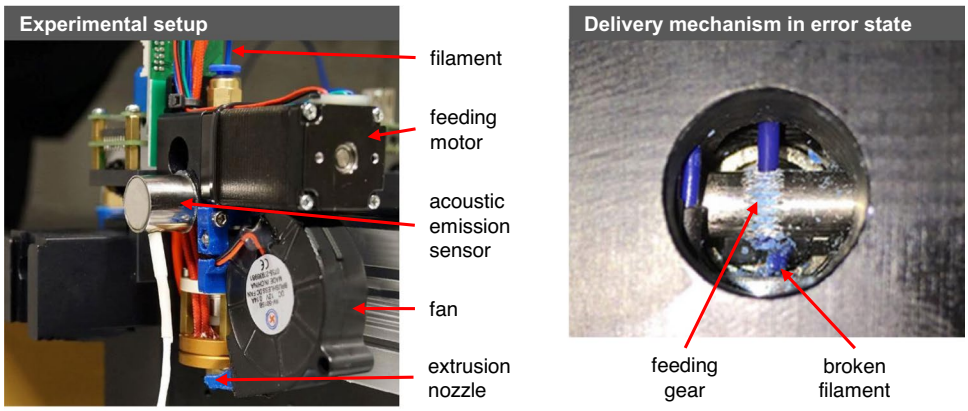

Fig. 9 Installation of an acoustic emission sensor attached to the extrusion head. Adapted by permission from Springer Nature: Springer Int. J. Adv. Manuf. Technol. [203], copyright 2016

5.6 Acoustic emission monitoring

Acoustic emission monitoring can be used because various actuators and mechanical components of the 3D printer generate noise (Table 6). If anomalies occur, they will cause changes in the acoustic emissions. Many studies have used this sensor technology to monitor extrusion heads. For example, Wu et al. [203] attached an acoustic emission sensor to an extruder with vacuum grease. The mounting arrangement is depicted in Fig. 9. The state of the extruder was classified into the following using a hidden semi-Markov model: extruding without material, material loading/unloading, idle, and normal extruding. In validation experiments, a classification accuracy of more than 90% was achieved.

In another study [205, 206], a sensor mounted on the build platform next to the part could detect detachment of the part from the build platform and deformations. The defective part came into contact with the nozzle, which resulted in altered acoustic emissions. Moreover, recording devices can be placed next to the 3D printer [207–210]. Using this setup, Chhetri et al. [207] reconstructed the geometry of layers based on the acoustic emissions of the axes and motors. By comparing the reconstructed geometry with the original G-code, they were able to identify cyberattacks. Evaluation experiments demonstrated that a modified geometry of a quadcopter baseplate was detectable.

5.7 Electrical quantities monitoring

Table 7 lists all identified sources in the field of monitoring electrical quantities. The sensors used are often for monitoring motor currents. For example, the currents of the motors to push the filament through the extrusion head or to move the axes are measured. Nozzle blockages or incorrect axis movement cause changes in the motor current and can be evaluated. Kim et al. [211–213] observed that the motor current of an extruder is correlated with the level of extrusion pressure. The extrusion pressure depends on the size of the nozzle outlet and the distance between the nozzle and substrate. If the part is deformed and the distance to the nozzle outlet is reduced, or if a foreign object prevents the material from exiting, the pressure will increase and changes in the motor current will occur.

5.8 Force and pressure monitoring

Hitherto publications on force and pressure measurements focused on investigations of extrusion head elements (Table 8). Klar et al. [71] showed that the extrusion force in a piston-based extrusion device for processing ceramic, silicone, and acrylic pastes can be measured using a load cell. Force variations were directly related to the flow characteristics of the material. Other than the extrusion forces,

Table 7 Summary of publications on electrical quantities monitoring

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[211–213]	Current	EH	Graphical frequency and time domain analysis	Extrusion pressure, foreign objects, deformation	F2	D2
[214]	Current	EH	Analytical model	Nozzle clogging conditions	F3	D2
[215]	Current	EH, AS	Similarity measure with defect-free reference	Sabotage attacks in G-code	F3	D2
[216, 217]	Capacitive	P	n.a	Number of layers, holes	F1	D1
[108]	Power	EH, AS	Random forest	Infill structure voids, extrusion temperature	F3	D2

Table 8 Summary of publications on force and pressure monitoring

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[71]	Load cell	EH	n.a	Piston force	F1	D2
[218]	Load cell	FS	Digital-twin, threshold for defect detection	Filament amount in storage	F3	D2
[219]	Force	EH	n.a	Contact force against the nozzle	F3	P
[69]	Force/torque	EH	Visualization, threshold for defect detection	Fiber pullout/shearing	F3	D2
[220]	Pressure	EH	n.a	Pressure in the liquefier, material flow rate	F4	P

Table 9 Summary of publications on other sensor technologies

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[221, 222]	Fiber Bragg grating	P	Analysis of wavelength changes	Strain	F2	D2
[223–225]	Fiber Bragg grating	P	Analysis of wavelength changes	Strain	F2	D2
[226]	Fiber Bragg grating	P	Analysis of wavelength changes	Strain	F2	D2
[227]	1/2 fiber Bragg grating	P	n.a	Strain, temperature	F1	D2
[228]	Optical backscatter reflectometry	P	Analysis of frequency shifts	Strain, voids	F2	D2
[229]	Ultrasonic	P	n.a	Infill structure	F1	D1
[230, 231]	1/2 ultrasonic	P	n.a	Fiber-scale print errors, bonding strength, orientation of beads	F1	D2
[232, 233]	4 ultrasonic	P	Comparison with ideal part, control feedback	Delamination, geometry	F4	D1
[234]	Ultrasonic, laser Doppler vibrometer	L	Data visualization	Foreign objects, holes	F1	D2
[235, 236]	Optical encoder	FS	Calculation of filament movement	Filament blockage/speed, lack of filament	F3	D2
[237]	Linear encoder	AS	Proportional-integral control	Position of axes	F4	D2
[238]	Laser displacement	L	Comparison with CAD model	Geometric deviations	F2	D2
[239]	Interferometry	BP	Calculation of surface curvature	Deformations	F2	D2
[240]	Vibroacoustic	BP	Discrete wavelet transform	First layer adhesion	F2	D2
[93]	2 strain gauges	BP	Threshold analysis	Warping	F3	D2
[208]	Gyroscopic	AS	Real-time visualization	Infill pattern, fill density	F2	D2
[241]	Coordinate measuring machine	P	Comparison with reference, adjust process	Geometric deviations	F4	P
[242]	Split ring resonator probe	P	Generate 3D map of part	Relative dielectric permittivity, dimensions	F2	D2
[243]	Velocimetry	EH, FS	Controller	Extrudate flow rate, filament feed rate	F4	P
[244]	Magnetic	FS, BC, AS	n.a	Door access, motor step losses, build platform level, material transport	F1	D2
[245]	n.a	L	Re-slicing	Various defects	F4	P

forces acting at the nozzle tip owing to the external effects of substrate defects can also be measured [219]. Furthermore, in the MEX of continuous fibers, fibers that are not fed at a sufficient rate by the delivery mechanism result in analyzable changes in forces. Exceedingly high forces, in turn, cause fiber pull-out and shearing [69].

5.9 Other sensor technologies

In this section, different sensor technologies with small numerical shares of publication in the literature are summarized (Table 9). In some publications, fiber Bragg grating sensors are presented as possible means of measuring strains. In such a system, the printing process is interrupted at a certain point and optical fibers are placed on the

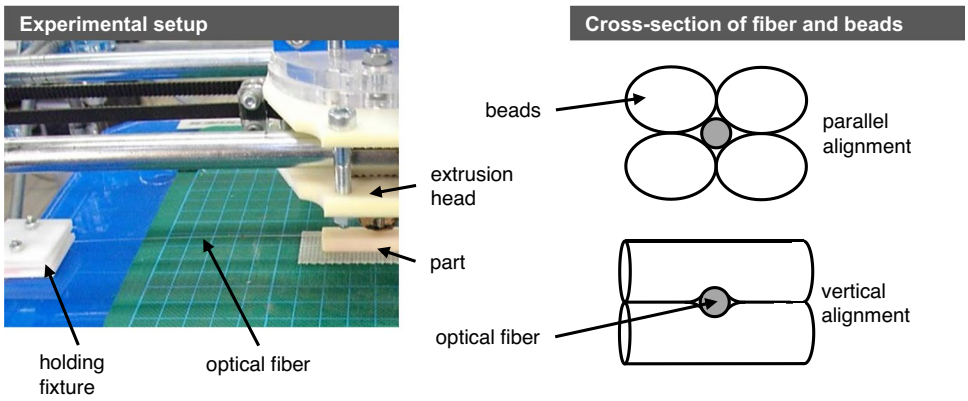

Fig. 10 Process monitoring with embedded optical fiber and schematic view of the cross-section. Left figure adapted from [224], copyright 2013, with permission from Elsevier. Right figures redrawn and adapted from [221], copyright 2016, with permission from Elsevier (Creative Commons license. https://creativecommons.org/licenses/by-nc-nd/4.0)

unfinished part. Subsequently, these are overprinted with additional material (Fig. 10). If deformations of the part and consequently of the optical fiber occur, they can be detected and analyzed [221–227]. Since the placement of the optical fibers as well as the properties of the surrounding material have an impact on the accuracy of the measurements, Falcetelli et al. [246] discussed and investigated different fiber embedding strategies.

Some research groups used ultrasonic sensors to analyze the part structures. Reflections of high-frequency pulses exerted onto the part were analyzed based on the duration until detection [229–233]. Another relevant approach is the use of encoders to determine the axis positions and to implement closed-loop control of the axis movement. This approach is considered state of the art within the NC machine industry [237]. It is also present in some MEX machines available for purchase [30].

The heterogeneity of monitoring systems prevented the further formation of clusters with similar functional principles. Therefore, the authors refer to individual publications for additional information.

5.10 Sensor fusion technologies

The fusion of data from multiple sensor technologies is a powerful method for monitoring a large number of features. Table 10 and Fig. 5 show that 2D vision and 3D vision are rarely used in combination with other sensor technologies. This is presumably due to the large information volume of the measurement data of the optical inspection systems. Additionally, optical measurement techniques are commonly used to inspect the quality characteristics of a part. In contrast, measurements that describe the condition of the 3D printer must be obtained via various routes to characterize the heterogeneous components of the machine.

An effective grouping of the identified monitoring systems is not possible. As an example, a monitoring system consisting of six thermocouples for temperature measurements at the extruder, at the build platform, and in ambient air is presented here. Furthermore, two sensors were used to measure the vibrations of the build platform and extrusion head. An infrared sensor measured the temperature of the build surface near the nozzle at the location at which the material was deposited. The authors explained that no additional benefit could be expected from using the thermocouples; therefore, only vibration and infrared sensors were used for process monitoring. The dimensional accuracy, surface roughness, and underfills could be determined [276–278]. The underfills were classified as "normal operation," "stringy extrusion," and "nozzle clogged." When producing a standard test artifact, the system achieved an accuracy of 97% for classifying into these three categories [276].

6 What are the research gaps?

6.1 Key topics for sensor technology and data processing

In a workshop of the National Institute of Standards and Technology, USA, the measurement science roadmap for polymer-based additive manufacturing was elaborated. Said roadmap specifies developments concerning measurement science required for the industrialization of additive manufacturing. For process monitoring, four prioritized roadmap topics (RT) were identified [13]:

- RT1: new in-situ imaging modalities
- RT2: real-time process measurement at required spatial and temporal resolution
- RT3: in-situ control and model integration
- RT4: big data analytics

A comparison of RT1 with the identified literary sources shows that the current research activity likewise focuses on the development of imaging modalities. From an industrial perspective, approaches that address the inspection of layers are particularly promising. Here, a single sensor module can

Table 10 Summary of publications on sensor fusion technologies

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[247]	Pressure, thermocouple	EH	Rheological modeling of polymer melt	Polymer melt pressure/temperature	F2	D2
[77–86]	Angle, gyroscopic, accelerometer, magnetic	EH	Machine learning approaches	Joint bearing abrasion, driving belt fault	F3	D2
[157, 158]	2 digital microscopes, strain gauge	EH	Analytical model, measurements, filament feed speed control	Feeding gear slippage, material flow, pressure drop over liquefier	F4	D2
[248]	Acoustic emission, strain	BC	Feature extraction, filtering	Driving belt fault	F2	D2
[179, 226, 249–251]	Fiber Bragg grating, thermocouples	P	Analysis of wavelength changes and temperature profiles	Strain, local layer temperature	F2	D2
[60, 62, 63]	Laser profilometer, thermal camera	L	Comparison with reference, control layer start time and layer height	Underfill, overfill, low layer times	F4	D2
[252]	3D printer data	EH, FS	Digital twin with formal logic	Extruder temperature, energy efficiency	F3	D2
[253]	Encoder, sensor module	EH, AS	Control module	Filament feed rate, axes position	F4	P
[68]	Touch probe, electrical touch plate	EH, L	Feedback loop architecture	Nozzle height, layer height	F4	D2
[254, 255]	4 microphones, 3 accelerometers, 3 magnetic, current	BC, AS	Regression model, classifiers, comparison with digital twin	Geometric deviations, flowrate	F3	D2
[256]	2D vision, 3D vision, other	BC, P	Comparison with reference	Anomalies in material, part, environment	F3	P
[257]	2D vision, 3D vision	L, S	Comparison with reference, change machine code	Various defects	F4	P
[235, 236, 258, 259]	Optical encoder, thermometer, thermistor, humidity, array of photodiodes	EH, FS, BC	Collection and storage of data streams	Nozzle/ambient temperature, humidity, filament diameter/speed	F2	D2
[260–262]	Load cell, 4 thermocouples, 3D printer data, encoder	EH, FS, BC	Analytical models	Polymer melt characteristics, filament flow rate, interlayer contact characteristics	F3	D2
[263]	2 accelerometers, 2 temperature	EH, BC, BP	k-nearest neighbors, decision tree, support vector machine, naive Bayes classifier, random forest, k-means clustering, expectation maximization	Interferences	F3	D2
[264]	Thermal camera, accelerometer, acoustic emission	EH, BC, AS	Bayesian networks	3D printer condition	F3	D1
[265]	Strain gauge, tension, 4 accelerometers	EH, BP, AS	Digital twin, comparison with predicted data	Not specified in detail	F3	D1
[266]	3 accelerometers, acoustic emission	EH, BP, AS	Support vector machine	Loosened bolt, shifting of layers	F3	D2
[267]	2 thermocouples, 2 accelerometers, infrared	EH, BP, L	Ensemble method with multiple machine learning algorithms	Surface roughness	F3	D2
[268]	2 cameras, encoders	EH, AS, P	Comparison with G-code and 3D model	Axes position, geometric deviations, extrusion stop	F3	D1
[269]	2 optical encoders, 4 thermocouples, camera	EH, AS, L	Fusion of sensor data	Axes position, filament flow, extruder temperature, layer defects	F2	D2
[270]	2 accelerometers, magnetic, camera, acoustic emission	EH, AS, S	Kalman filter, Canny filter, random forest	Infill geometry, printing speed, layer height, fan speed	F3	D2
[271, 272]	Infrared, thermocouple, accelerometer	BC, BP, L	Neural network	Tensile strength	F3	D2

Table 10 (continued)

References	Sensors	Ele	Data handling	Quality characteristics	Fun	Dev
[197, 273]	2 laser triangulation, accelerometers	BC, AS, L	Comparison with reference, predictive modeling with random forest, decision tree, and neural network	Overfill, underfill, detachments	F4	D1
[274]	Vibration, magnetic, temperature, dust, humidity	EH, FS, BC, BP	Low-pass filter with fast Fourier transform	Machine and part state	F4	D1
[275]	3 accelerometers, acoustic emission, 3 thermocouples, thermal camera	EH, BC, BP, L	Support vector machine	Bed leveling	F3	D2
[276–278]	6 thermocouples, 2 accelerometers, infrared	EH, BC, BP, L	Dirichlet process mixture model and evidence theory, sparse estimation, quantitative and qualitative models	Insufficient extrusion, dimensional accuracy, surface roughness	F3	D2
[279]	n.a	P	Comparison with reference	Build perimeter/height/volume	F3	P
[70]	n.a	P	Comparison with reference, adjust G-code	Bead characteristics	F4	P

be utilized to inspect both the outer walls and inner structures of parts. Geometries and surface characteristics can be effectively inspected using 2D vision and 3D vision. Optical temperature measurements can be used to verify the thermal material properties. In addition to imaging techniques, monitoring of extrusion head conditions should be prioritized in future research because it is a key element of MEX systems. Measurements of current, vibrations, and acoustic signals are advantageous because the sensors can be installed with minimal effort. In contrast, force and pressure measurements require modifying the mechanical extrusion head components. However, this enables precise determination of the polymer melt conditions.

Regardless of the sensor technology, there is a fundamental necessity for research on integrating sensors into industrial MEX systems. New and improved sensor concepts that are designed for high ambient temperatures and large build volumes are required. Furthermore, efficient sensor modules, which can be realized in MEX machines despite restrictions due to moving machine parts and frame structures, must be developed.

The large number of patents on closed-loop control in Fig. 4 indicates that this topic is considered to be fundamentally important in the industry. High-performance measurement technology (RT2) is a prerequisite for these control loops (RT3). For the resolution of acquired data and speed of data processing, satisfactory results have already been achieved for some specific measurement tasks. This is demonstrated by the first controlled systems that adjust process parameters in sufficiently short periods and with adequate accuracy [63, 160, 180]. However, these systems require much improvement. For example, sensor technologies for detecting small voids or part contours in large-area, high-resolution layer images at high speeds are not yet available. Furthermore, classifying monitoring systems use only a few classes; therefore, they have low resolutions. Moreover, the current closed-loop control is based on simple causal relationships. Mathematical models that describe complex relationships between several process parameters, control variables, and part properties have not yet been sufficiently researched.

Large and complex datasets generated by different sensor technologies and assignable to the field of big data analytics (RT4) were not used in the identified publications. Therefore, datasets with heterogeneous sensor data from several varying print jobs must be generated in the future to train robust inspection algorithms. The analysis of the literature has confirmed the significance of this subject by demonstrating that, owing to the complexity of the inspection task, only multi-sensor approaches enable comprehensive monitoring of the MEX process.

6.2 Rarely examined quality characteristics

Aside from the specific wear-prone components of the 3D printer, all properties of the parts are, in principle, relevant to MEX monitoring. The requirements for a part can be divided into mechanical and geometrical requirements, surface requirements, and requirements for feedstock materials [280].

The focus of the current research is on part geometries and surface properties in terms of overfill and underfill. However, measurements of surface roughness were addressed by only two research projects [267, 276–278]. The measurement of mechanical properties is another important aspect that was investigated by merely two works as well: Bartolai et al. [173, 174] and Zhang et al. [271, 272] addressed the prediction of tensile strengths. Means of inspecting material characteristics were not considered in any publication. The monitoring of these quality characteristics, which the current research only addresses to a limited extent, represents a gap for future research.

6.3 Variety and complexity of monitored parts

A challenge with MEX monitoring is the required flexibility [14]. Varying and often complex part geometries are manufactured in very small batches. Furthermore, many different materials can be processed. Therefore, the extent to which the flexibility of the MEX is reflected in the reviewed monitoring systems was investigated. The properties of parts manufactured in projects with the aim of process monitoring for quality assessment were analyzed considering the aspects listed below:

- complexity of geometries (simple or complex),
- number of different geometries,
- materials used, and
- number of different materials used.

The analysis showed that 19.3% of the projects contained an investigation of complex part geometries, 55.9% monitored simple geometries, and 24.8% did not specify the geometry. Simple geometries include, among others, cuboids, cylinders, or single material beads. In contrast, the complex geometries describe a prosthesis or valve housing, for example. For the number of different geometries per project, the authors observed that 47.6% of the projects investigated one geometry, 12.4% two geometries, and 7.6% three geometries. More than three geometries were analyzed in only 8.3% of the projects, while 24.1% did not specify the geometry.

40.7% of works did not specify the material. Polylactide (PLA) and acrylonitrile butadiene styrene (ABS) were used in 34.5% and 26.9% of the projects, respectively. Composite materials were used in 6.2%, polycarbonate in 2.1%, and ceramic materials in 1.4% of the projects. Other materials had a proportion of $< 1\%$ each. In 74.4% of the projects that specify the material, only one type of material was investigated, while 19.8% of the projects used two, 4.7% three, and 1.2% four different materials. Projects that employed more than one material consistently produced different parts separately from just one material each. Only one publication [252] stated that the part was made from PLA and one additional support material.

The results show that projects with high complexity and variation in part geometries and materials are strongly underrepresented in the dataset. The analyzed monitoring systems tend to monitor manufacturing processes for simple geometries and small numbers of varying parts. Regarding the materials used, ABS and PLA dominate the research projects, the number of different materials per project is oftentimes low and multiple material parts are only considered to a minor extent. However, complex geometries and cost-intensive materials (e.g., metal-filled or fiber-reinforced plastics) are particularly suitable for process monitoring, because this is where the economic efficiency of the inspection system is most easily achieved. Therefore, there is considerable potential for further research regarding the monitoring of various complex parts.

6.4 Standardization

Owing to the novelty of the technology and the diversity of the topic, standardization in the field of additive manufacturing is still in its early stages. There are only a limited number of standards for the specification of part properties and non-destructive testing methods [14, 28]. Analysis of the identified publications has also shown that no consistent definitions are used for quality characteristic names, feature specifications, and tolerance limits.

As a first step towards standardization, ISO/ASTM 52901 [281] basically describes how part characteristics, tolerances, and test methods are to be defined between the customer and the supplier. With regard to process monitoring, the decision of whether a process variation represents a defect or not is particularly crucial [282]. Future projects can use the draft standard ISO/ASTM DIS 52924 [46] to specify these tolerance limits, as the document defines the quality levels of MEX plastic parts in terms of relative part density, dimensional accuracy, and mechanical properties for an entire part. However, to analyze small defects with high spatial resolution, MEX-specific characteristics must be considered. For example, unsupported bridging results in changes in geometric tolerances.

For the description of part characteristics, general standards such as the geometrical product specification matrix model [283] are applicable. Here, surface imperfections in the layer structure can be characterized according to the ISO 8785 standard, which specifies the nomenclature and characteristics of these irregularities [284]. Furthermore, standards for conventional non-destructive testing methods can be adapted to the process monitoring of MEX [14].

7 Conclusion

Monitoring of MEX during the manufacturing process is crucial for the industrial use of this technology. The publication activity in this field is increasing. This clearly indicates that the subject is significant. The wide range of sensor technologies used and quality characteristics monitored demonstrate that the existing monitoring systems have been researched at many functional levels. However, for the widespread utilization of monitoring systems, further optimization is required.

The strength of this review is in its systematic approach to the literature search and the large dataset used. The state of knowledge is presented comprehensively, and research gaps are identified. Limitations exist because of the possibility that the literature evaluation and identification of future priorities are affected by the individual perspectives of the authors. For a highly differentiated analysis of the publications, future reviews may also include more systematic and detailed assessments of the results and quality of studies.

Author contributions Alexander Oleff: Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Project administration, Funding acquisition Benjamin Küster: Writing - Review & Editing, Project administration, Funding acquisition Malte Stonis: Writing - Review & Editing, Project administration, Funding acquisition Ludger Overmeyer: Conceptualization, Methodology, Writing - Review & Editing, Supervision, Funding acquisition

Funding This work is part of the research project 20714 N of the Research Community for Quality (FQS), August-Schanz-Str. 21A, 60433 Frankfurt/Main and has been funded by the AiF within the program for sponsorship by Industrial Joint Research (IGF) of the German Federal Ministry of Economic Affairs and Energy based on an enactment of the German Parliament. Open Access funding enabled and organized by Projekt DEAL.

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