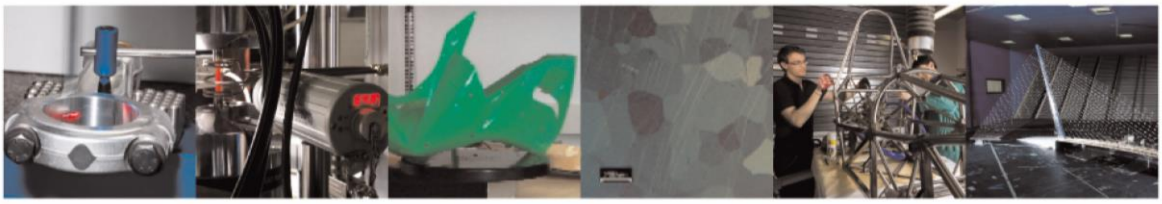

Opportunities and challenges of quality engineering for additive manufacturing

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This is an Accepted Manuscript of an article published by Taylor & Francis in JOURNAL OF QUALITY TECHNOLOGY on 18 Sep 2018, available online:
http://dx.doi.org/10.1080/00224065.2018.1487726

Opportunities and Challenges of Quality Engineering for Additive Manufacturing

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Abstract

Additive Manufacturing (AM), commonly known as three-dimensional printing, is widely recognized as a disruptive technology, and has the potential to fundamentally change the nature of future manufacturing. Building products layer-by-layer, AM represents a paradigm shift in manufacturing with many industrial applications. It enables production of huge varieties of customized products with considerable geometric complexity, and the same time, with extended capabilities and functional performances.

Despite tremendous enthusiasm, AM faces major research challenges for widespread adoption of this innovative technology. Specifically, addressing the unique challenges associated with quality engineering of AM processes is crucial to the eventual success of AM. This paper presents an overview of quality-related issues for AM processes and products, focusing on opportunities and challenges in quality inspection, monitoring, control, optimization, transfer learning and building quality into the product through design.

Introduction

Additive manufacturing (AM), also known as three-dimensional (3D) printing, refers to a new class of technologies associated with the direct fabrication of physical products from Computer-Aided Design (CAD) models using a layered manufacturing process. In contrast to traditional molding or material removal processes, AM products are produced by adding material layer by layer without part-specific tooling and fixturing. It holds the promise of direct digital manufacturing, that is, products with complex shapes or geometries are digitally described in 3D model files and then sliced into successive cross sections to initiate AM production.

In the past, the manufacturing paradigm experienced a revolutionary shift from craft production to mass production. A novel paradigm shift from mass production to mass customization has been emerging due to the introduction of AM. Unlike mass production, AM reduces tooling and intermediate steps for direct digital manufacturing. Complexity-free fabrication through layer-by-layer techniques enables individualized, customized manufacturing of low-volume products in huge varieties and of considerable geometric complexity.

Furthermore, advanced functional materials and novel design methods significantly expand the degrees of freedom in AM design and manufacturing (Bourell et al., 2009; Gibson et al., 2009; Hilton and Jacobs, 2000; Melchels et al., 2010; Campbell et al., 2011; Pan et al., 2014; Beyer, 2014). It is therefore widely recognized as a disruptive technology, having the potential to fundamentally change the nature of future manufacturing. Indeed, the changes can amount to a new *industrial revolution*, according to *The Economist* (Economist, 2012) and *Harvard Business Review* (d'Aveni, 2015) magazines.

AM market, though small comparing to traditional manufacturing, has grown rapidly (Figure 1). According to the latest Wohlers Report, *"overall the 3D printing industry grew by* 21% *in the* $2017-18$ *reporting period. This figure is an increase on the* 17.4% *in worldwide revenues from 2016, and is edging closer to the* 25.9% *growth reported in 2015"* (Huff and Wohlers, 2018). In the high-value added metal AM, *"system installations accompanies improved process monitoring and quality assurance measures in metal AM, although more work is ahead"* (Wohlers, 2018). Apparently quality is a key element to foster the industrial breakthrough of AM technologies in the manufacturing scenario.

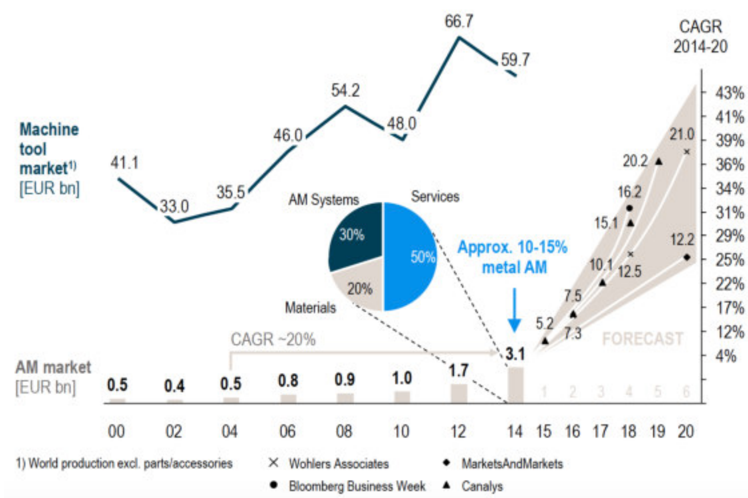

Figure 1: *World machine tool production (Langefeld, 2016)*

AM: product features and industrial sectors

One of the claimed advantages of AM is its natural capability to achieve *complexity-free fabrication*, i.e., complex geometries can be printed without dramatic increase in production costs. A manifestation of such capability is to design and build **lightweight** components, where product weight is reduced by exploring complex shapes and maintaining functionality at the same time (Figure 2). The application to aerospace and automotive sectors is crucial, where lightness directly translates into reduced fuel consumption (i.e., reduced buy-to-fly ratio) and limited CO2 emissions for green mobility.

One such testimonial is the GE fuel nozzle illustrated in Figure 2, a component of the Leap jet Engine (Kellner, 2017). Application of AM made this nozzle 25% lighter (with 15% of fuel savings) by reducing the number of components from twenty to one and increasing its durability five fold in comparison to the conventional design. This nozzle has an expected demand of about tens of thousands pieces per year and may eventually need more metal AM machines than the current annual worldwide demand (Kellner, 2017). In niche automotive (mainly racing), an electric motorbike achieves a weight reduction of about 30% (Figure 2) (Markham, 2016).

Figure 2: *Examples of lightweight designs (GE fuel nozzle, AIRbus A380 bracket, APWorks moptorbike)*

Another major area of exploiting complexity-free fabrication lies in **biomimetic and medical applications**. Personalization is particularly important when products have to adapt to individual patients' biometric features such as the shapes and sizes of teeth or hips and joints. Even the microscale features such as surface texture and porosity can be designed and built. AM built implant can replicate the surface of the bones and their inner structure, which is not fully dense but characterized by controlled density (as per hip implant shown in Figure 3, where surface undercuts facilitate osteointegration).

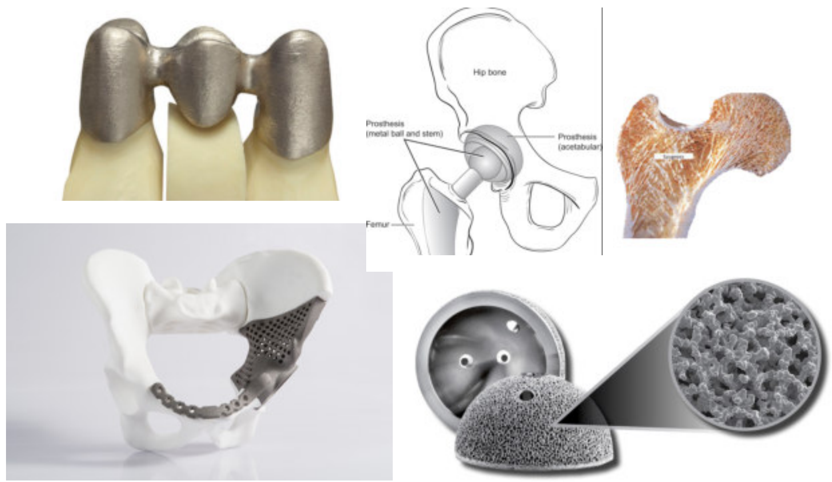

Figure 3: *Examples of Biomimetic and personalized products via AM (courtesy EOS, Arcam, Renishaw)*

Machinery and tooling industries take the advantage of the design freedom of AM to enhance cooling and heat exchange. Examples of AM built thermal exchangers, tooling and molds are shown in Figure 4 (top row). Conformal cooling in tools and molds (see Figure 4) is achieved with curvilinear channels, which follow the complex patterns of the external surfaces to dissipate heat close to heat sources. Increased heat transfer performance can result in 20% cycle time reduction and a 50% increase in the quality. It should be noted that complex curvilinear internal channels can hardly be realized with conventional processes.

Creative industries benefit from design freedom offered by AM. The bottom row of Figure 4 illustrate new designs for lighting, furniture, jewelry and textiles.

Figure 4: *Examples of AM built products in machinery (top) and creative industries (bottom) (courtesy EOS, Renishaw, pinterest)*

Quality challenges in AM

The paradigm shift to mass customization calls for a new quality control paradigm for AM. For this purpose, effects of various AM complexities on quality inspection, monitoring and process optimization have to be investigated:

- *Complexity of product geometry*: AM theoretically renders the fabrication process free of geometric complexity. This is only partially true, as complexity translates into increased processing times and defective rates. Moreover, quality measurement and inspectability are inversely related to product complexity. Internal surfaces, undercuts or hidden features can be easily printed but not measured or inspected.
- *Complexity of process optimization*: AM is most suitable for the extremely low volume or even personalized manufacturing of complex products with frequent change of geometries. This presents a unique challenge to calibrate AM processes for high dimensional and geometric accuracy. In mass production processes such as the injection molding process, weeks or even months can be afforded for fine-tuning process parameters and tooling setups because the same configuration

remains unchanged for a large batch of identical products. One possible way to speed up process optimization is by combining process simulation with experimental design. Unfortunately, process simulation is difficult per se, as typical AM processes generally involve material phase-changing, namely, liquid, paste or loose powder and solid have to be modeled at the same time. This phase-changing process is difficult to simulate and is usually not able to capture all the phenomena (porosity due to melt pool instability as well as distortion due to thermal stresses) which arise at different scales. Achieving accuracy and predicting defects is a daunting task.

- *Complexity of product data collection*: Statistical Quality Monitoring (SQM) or Statistical Process Control (SPC) methods have mainly been developed for mass production. SPC relies on sufficient sample data to support control chart design. In AM with frequent design changes and low volume production, it is often cost-prohibitive to collect sufficient sample data in order to establish credible statistical distributions for quality characterization. The existing SPC methodology therefore faces the short-run production challenge.

Although AM has evolved from rapid prototyping to product manufacturing in the past 30 years, the bulk of current AM research is devoted to new development of CAD and process planning methods, finite element modeling (FEM), novel materials, processes, and machines suitable for AM, innovative solutions for in-situ sensing (Bourell et al., 2009). Although process monitoring and control have been identified as critical issues, there is a dearth of research in improving the quality of AM products (Bourell et al., 2009; Huang et al., 2015). A review of the state of the art indicates that existing quality control methods are unable to serve the unique needs of AM. Due to multiple complex interacting physical and chemical phenomena, fabricating interchangeable parts using AM often relies on basic trial-and-error approaches to a certain degree. Post-processing with machine tools is then still required to meet design specifications, significantly negating the time and cost benefits of direct digital manufacturing. The challenges in accuracy control in AM call for new research to establish theoretical foundations that enable complexity-free quality control.

AM processes, typical defects and quality inspection

AM embraces many different processes and materials (polymers, metals, ceramics, composites - see Table 1). According to the standards ISO/ASTM 52900 (ISO, 2015), seven processes are possible, all sharing the same principle of manufacturing the product layerwise. The basic principle behind the seven AM processes is briefly described in Figure 5, thanks to the nice summary provided by Loughborough University on its website (Loughborough, 2017).

Table 1: *AM: process families and materials*

Materials	Process categories						
	Vat photopolymerization	Material Jetting	Binder Jetting	Powder Bed Fusion	Material Extrusion	Directed Energy Deposition	Sheet Lamination
Thermoset Polymers	X	X					
Thermoplastic Polymers		X	X	X	X		X
Wood							X
Metals			X	X	X	X	X
Industrial ceramic	X		X	X			X
Structural ceramic			X	X	X		
Note: Combinations of the above material classes, e.g. a composite, are possible							

Quality characteristics of AM-built products includes geometric and dimensional accuracy, surface finish, volumetric properties (e.g., grain structure and size) and volumetric errors (pores, cracks, etc.). Some of these elements eventually define the mechanical properties of the part (e.g., stress, tensile strength, fatigue resistance), which are very important for product functionality. According to the National Institute for Standards and Technology (NIST) (Mani et al., 2015): *"the variability in part quality due to inadequate dimensional tolerances, surface roughness, and defects, limits the*

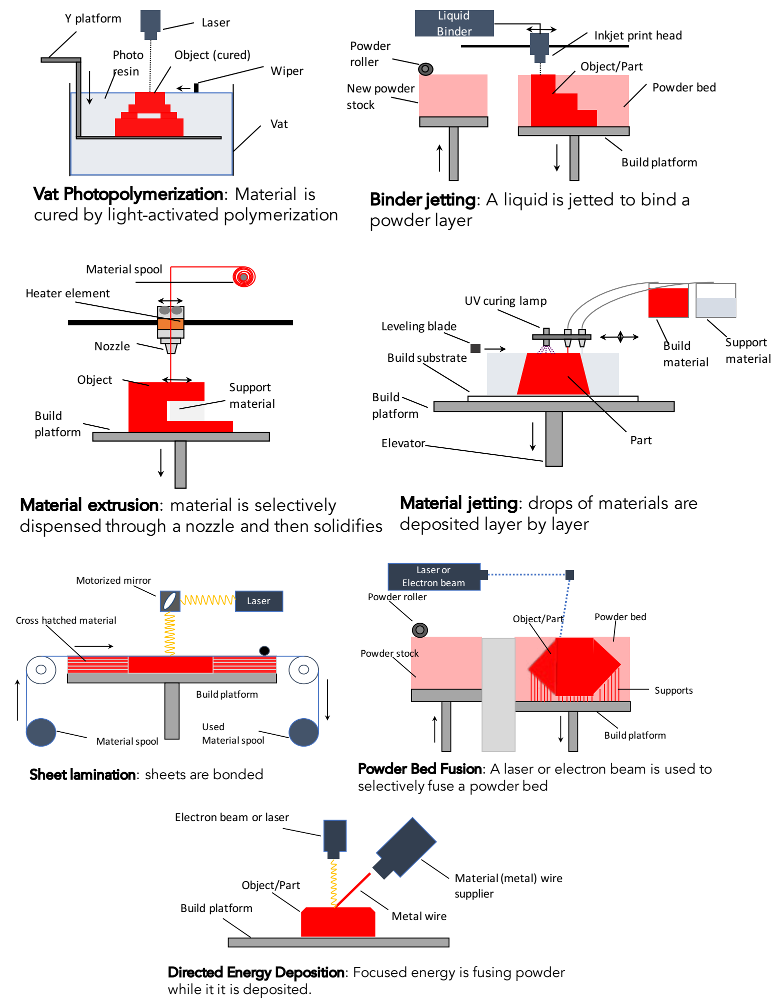

Figure 5: *AM processes - (Loughborough, 2017)*

metal AM broader acceptance for high-value or mission-critical applications".

Figure 6 shows some examples of defects in AM-built products. In particular, Figure 6 a) to c) show different types of geometric errors, ranging from dimensional and geometric accuracy (a), to incomplete printing (b), and warping (c). These defects can be due to many possible causes: wrong product design, problems with the powder deposition system, improper parameter selection or scanning strategy, incorrect air gas flow, etc. Shrinkage is a typical problem in thermal processes, due to volumetric changes during solidification and cooling. It can result in bending (Figure 6 c), or even cracking (Figure 6 e). We will specifically focus on possible approaches to prevent/correct shrinkage defects in the following sections dealing with part-to-part control. Figure 6 d) shows internal porosity, which is a very relevant defect, especially in metal products. Pores are small, hidden voids inside the printed workpiece that can strongly affect its mechanical performance (e.g., fatigue limit). Porosity can occur due to many different phenomena, such as gas intrapped in the powder or wrong selection of the process parameters (excessive or insufficient energy density delivered by the process during melting).

Metrological challenges in AM

With reference to measurement and inspection, different challenges have to be faced when the quality of AM parts is of interest. Indeed, shape complexity plays an important role, especially for internal cavities and channels, undercuts or porosity. Traditional measurement systems, such as Coordinate Measurement Machines (CMMs) or Optical scanners (e.g., laser scanners, structured light) allow one to inspect and acquire external, accessible surfaces. When internal geometries are of interest, X-Ray Computer Tomography (X-Ray CT) is emerging as the only viable solution (Hiller and Hornberger, 2016; Villarraga-Gómez et al., 2018) for AM product inspection. Borrowed from medical applications, X-Ray CT uses X-rays to reconstruct cross-sections

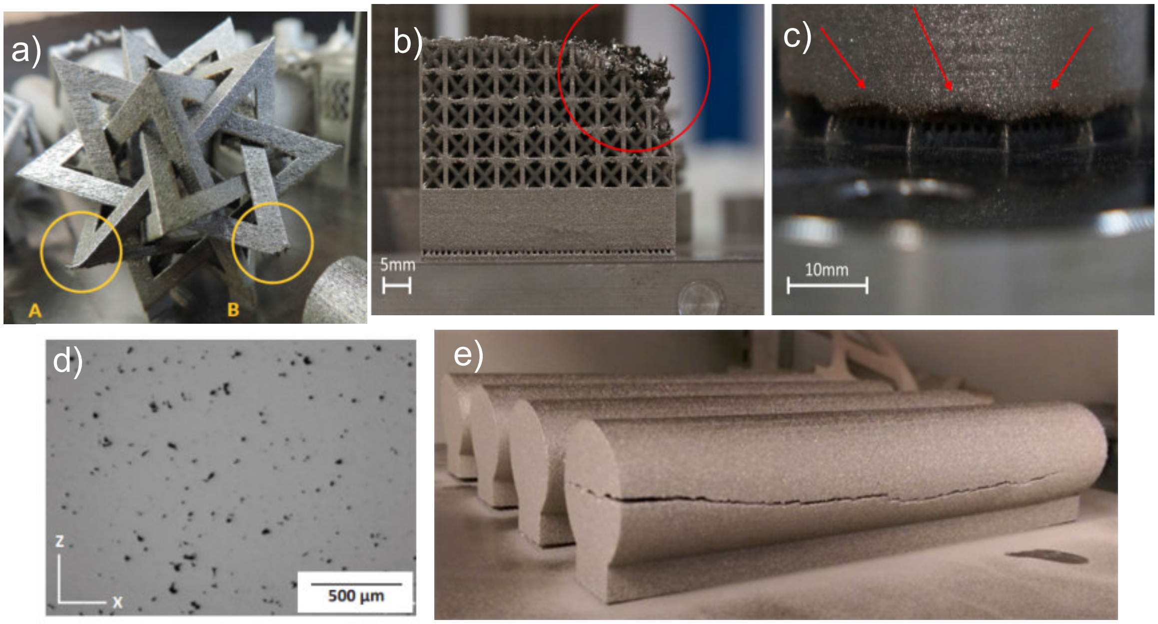

Figure 6: *Typical examples of defects in AM built products: a) to c) geometric and dimensional errors; d) internal porosity (courtesy LPW); e) cracking (courtesy Renishaw, AddMeLab - Politecnico di Milano).*

of a physical object, which are used to recreate the virtual 3D model of the inspected product without destroying it.

From a metrological viewpoint, different research directions are currently open to assess X-Ray CT as a reference instrument for the quality inspection of AM parts. Among these directions, uncertainty estimation and system calibration play a major role (Villarraga-Gómez et al., 2018; Hiller and Hornberger, 2016; Kruth et al., 2011).

One key feature of X-ray CT is that it produces voxel-based reconstructions. A voxel is a three-dimensional extension of a pixel. As pixel-based images can be modeled as a greyscale on a bi-dimensional grid, voxel-based data can be represented as a grey scale in a 3-dimensional or volume grid (Figure 7). Surface reconstruction and geometry modeling starting from voxel-based data is an interesting area where more research is needed. Existing literature on data modeling and monitoring in biomedical applications of X-Ray CT will possibly represent a starting point (Kalender, 2006). Furthermore, multisensory data fusion in dimensional and geometrical metrology will possibly be further exploited to combine data provided by different metrological systems to enhance surface reconstruction for AM applications (Weckenmann et al., 2009; Colosimo et al., 2015; Wang et al., 2015; Xia et al., 2011).

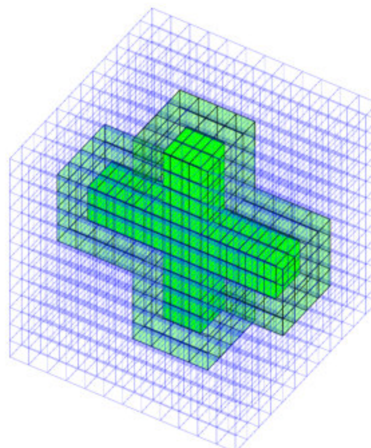

Figure 7: *A voxel-based reconstruction where greyscale is representing reconstruction uncertainty.*

Statistical Quality Monitoring (SQM) or Statistical Process Control (SPC) for AM

Product quality and process repeatability have been recognized as major barriers for wide adoption of AM technologies (Bourell et al., 2009; Tapia and Elwany, 2014; Gao et al., 2015; Huang et al., 2015). There is still a lack of consistency when building AM products across across machines, operators, and manufacturing facilities. Current AM technologies are insufficient to meet the stringent requirements of industrial sectors, which provide wide room for quality control methodolgoies.

With reference to process stability, SQM can be based on product or process data.

In the first case, quality features are measured on a sample of products to detect possible out-of-control states. In the second case, data gathered from the process (e.g., signals, images) are considered as drivers to detect the onset of process instability. In the following, both these two approaches are discussed with reference to AM processes.

SQM for product data

When product data are of interest, recent literature on profile and surface monitoring can be considered as a viable solution to perform SQM on 3D-printed objects (Woodall, 2007; Wang et al., 2014; Colosimo et al., 2014, 2008). In this case, a statistical model of the geometric profile or surface is firstly fitted. Then, all the estimated coefficients and the residual variance can be monitored via control charting.

Considering the high level of shape complexity characterizing AM products (Figure 2-4), profile or surface model fitting can turn out to be a cumbersome task. An alternative solution is computing simpler quality descriptors that have to be monitored with time. As examples, different statistics computed considering the actual deviation from the nominal shape (mean, standard deviation, min or max deviation) can possibly be considered as quality features in control charting.

When SQM is applied to AM products, a second important challenge can be the small amount of Phase 1 or training data set available for control chart design. Indeed, AM is often used in high-value-added contexts (e.g., aerospace and biomedical products) where customized, short-run or even one-of-a-kind productions are considered. Short-run settings have been discussed in the SPC literature for a long time (Quesenberry, 1991; Crowder and Eshleman, 2001; Castillo et al., 1996) and the *nominal control chart* has been proposed as a possible solution to the lack of training data. In nominal control charts, the main idea is to "standardize" the quality characteristic. In the literature, the deviation from the target is often used as a "standardized" feature, assuming that this quantity does not depend on the specific product, and hence Phase

1 data can be collected across many different product types. Self-starting control charts (Hawkins, 1987; Sullivan and Jones, 2002) can be further used to start monitoring as soon as data become available.

For AM products, the percentage of shrinkage defined in Huang (2016) and Luan and Huang (2017b) can be a possible choice of "standardized" quantity. Suppose an ideal AM process builds a circle and square shape as shown in Figure 8. With the presence of only natural process variation, the built products in solid curves should be contained within narrow envelops. Quantities such as roundness or cylindricity are not appropriate here because these measures tend to be shape-dependent, which limits the ability to quantify a different shape.

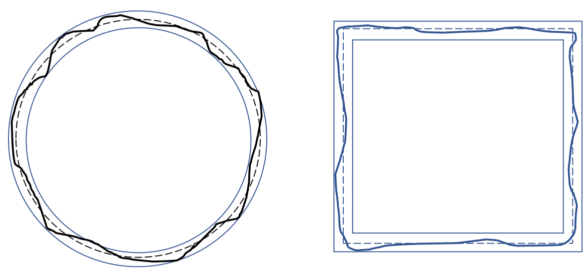

Figure 8: *Statistic for AM process monitoring Luan and Huang (2017b)*

One possible measure of shape deformation across different shapes is the percentage of shrinkage η, which can be defined as

$$\eta = \frac{|\Delta S|_{Actual}}{S_{Nominal}} \tag{1}$$

where $S_{Nominal}$ represents the nominal in-plane surface area of the product and $|\Delta S|_{Actual}$ is the measured, absolute change of surface area from the design. Extension to the 3D case naturally follows.

Under stable process condition and with the same materials, we may expect that products with various shapes will have similar percentages of shrinkage and consequently individual control charts such as EWMA can be applied for process monitoring.

SQM on process data: in-situ process monitoring

In a recent report, the National Institute of Standards and Technology (NIST) (Mani et al., 2015, 2017) outlined how in-situ process monitoring and control represent a significant opportunity to reduce process variation and ensure quality. As a matter of fact, many features of the process signature are observable in-line during the build and can be directly correlated to the final quality of AM products (Tapia and Elwany, 2014; Everton et al., 2016; Spears and Gold, 2016; Grasso and Colosimo, 2017).

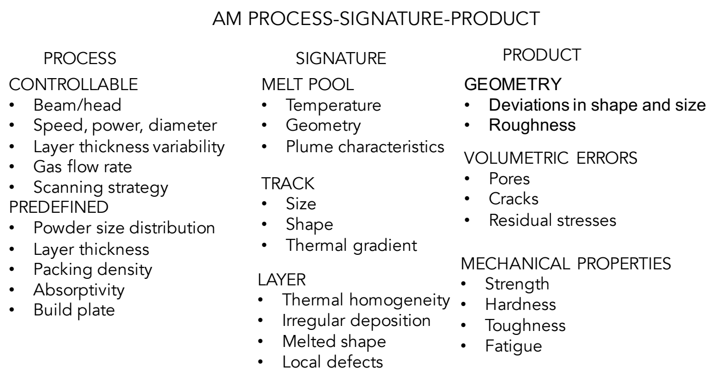

Figure 9: *AM from process parameters to product quality via process signature (adapted from (Mani et al., 2015))*

Figure 9 refers to powder bed AM and it summarizes the most important set of process parameters (first column) affecting the final quality of products (third column), which is characterized by geometric and volumetric errors and mechanical properties. In the second column, possible descriptors of the *process signature* are listed. The process signature can be acquired in-situ and in-line, and represents the link between the parameters and the final quality of 3D-printed products (first and third columns, respectively (Mani et al., 2015). With reference to laser powder-bed processes, Figure 10 describes different levels for in-situ data gathering, namely:

- *melt pool* level (where the laser melts the powder);
- *laser track* (the scanning path of the laser);
- *slice* (part of the layer where the powder has been melted);

- *powder bed*, which is where the powder has been delivered just before scanning.

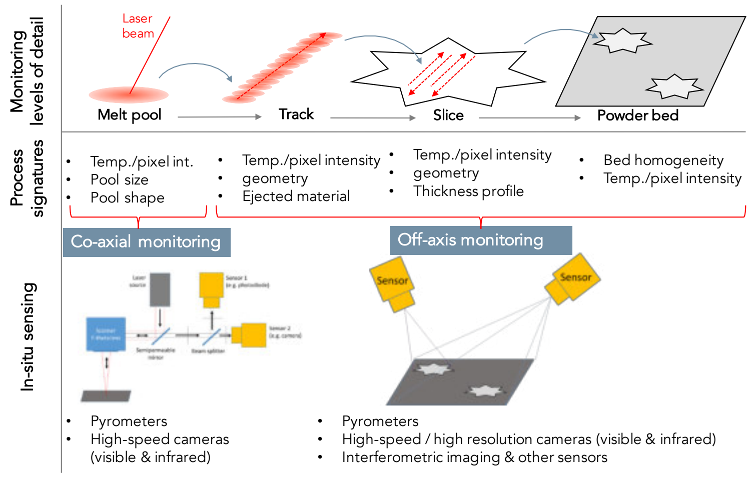

Figure 10: *Different scales and possibilities for in-situ monitoring of AM processes.*

All this information can be usefully monitored with time to detect onset of defects. All the information at the melt pool level can be linked to volumetric errors, i.e., detecting undermelting and overmelting conditions which can result in internal porosity. Instability of the melt pool can be also detected, as an indicator of possible volumetric erros in the final job. At the laser track level, the information on the spatial and temporal cooling rates can be gained. This information can be used to predict thermal stresses and cracks. It is worth noting that the actual monitoring systems can provide information on the last layer only, while no information can be gained on the heating/cooling phenomena underneath. As the spatio-temporal distribution of temperature among layers influences thermal stresses, defects originating in the underneath layers can be hardly detected using in-situ sensing. Eventually, data observed at the powder bed level can allow one to compute the geometric and dimensional deviations of the printed geometry with respect to the nominal one (using image analysis to detected the melted shape). A second important information at the powder bed level is detection of *hot spots*, i.e., locations where the cooling rate is too slow (and maybe a redesign of the part, including additional supports, is needed). Eventually, powder bed images can allow one to detect an improper distribution of the powder spread into the bed, before starting the selective melting step. This problem can result in porosity due to overmelting/undermelting or local geometric defects.

Data provided by the different sensing architectures can be mainly classified into three data types (Figure 11, 12,13):

- *Signal data*, which can be represented as a time series or profile, functional data, and which are associated with some quality features of interest (e.g., temperature or area of the melt pool) (Grasso et al., 2018);
- *Image data*, or high-resolution pictures of the build layer (before or after scanning) (Grasso and Colosimo, 2017);
- *Video-image data* recording of the process melting and cooling transient (Grasso et al., 2017; Colosimo and Grasso, 2018).

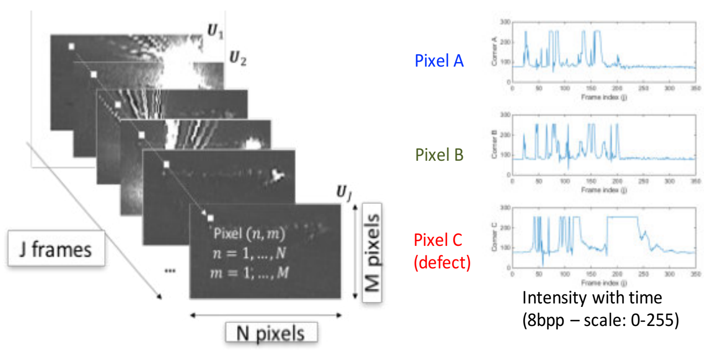

Figure 11: *Examples of signals taken from video-image data (Grasso et al., 2017).*

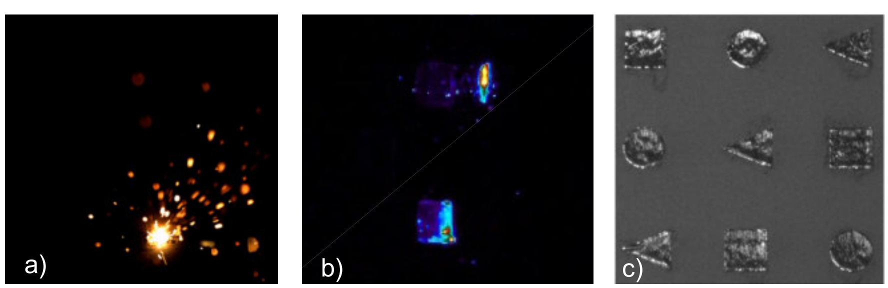

Figure 12: *Examples of AM images: a)frame from high-speed video; b) frame from infrared video; c) high spatial resolution image (20 m/pixel) of the powder bed after laser scan.*

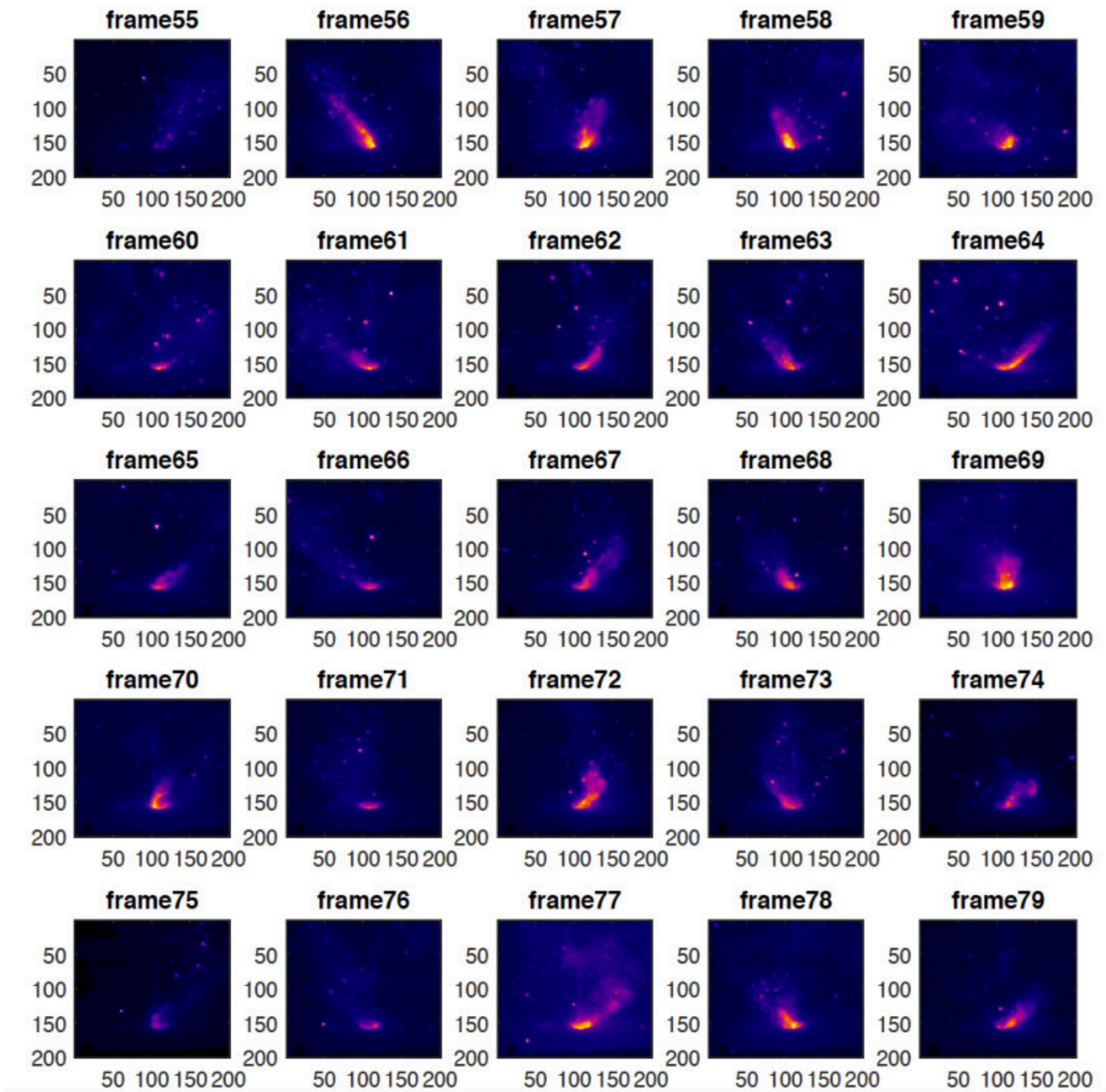

Figure 13: *Examples of video-image data: Frames sub-sampled by the video acquired while AM processing of zinc via Selective Laser Melting (Grasso et al., 2018)*

SQM can be applied to the context of in-situ data monitoring by following different approaches. At a first level, signals, images and videos can be pre-processed to select a set of quality indicators that have to be monitored with time. As an example, a multivariate control chart can be used for monitoring the dimension and the intensity of the laser plume (Grasso et al., 2018). Similar approaches can be used for the number and size of spatters (Repossini et al., 2017) acquired with high-speed video imaging. In these cases, effort is required to select the appropriate set of descriptors. Furthermore, approaches for autocorrelated data have to be considered, as data are usually acquired at high frequency (e.g., 1000 frames per second), setting the stage for *big data* SQM.

At a more general level, approaches for the statistical monitoring of images or video-image data have to be developed. Recent literature on SQM outlined how image-based SQM is going to play a relevant role in the near future (Megahed et al., 2011, 2012; Qiu, 2005, 2018; Colosimo, 2018). To this aim, approaches combining spatio-temporal models with control charting (Grasso et al., 2017; Colosimo and Grasso, 2018) or spatio-temporal modeling (Yan et al., 2017b,a) appear as promising solutions. The feasibility of these approaches in almost-real-time settings is an open issue, deserving further attention.

Part-to-part quality prediction and control

For low-volume AM production with potential frequent changes of product designs, materials, and processing conditions, part-to-part quality prediction and control is essential to make AM a viable manufacturing technique.

As previously mentioned, the quality of AM-built products includes shape accuracy, surface finish, mechanical properties (e.g., stress, tensile strength), and structure properties (e.g., grain size, pores, cracks, etc.). Since some quality characteristics such as surface finish are more invariant to part-to-part design changes than shape accuracy, our discussions focus more on the geometry of AM-built products.

The objectives of part-to-part quality prediction and control include, but are not limited to (i) representing of shape accuracy; (ii) establishing models for predicting shape accuracy through the learning of previously built products; (iii) enhancing prescriptive models by learning new data; (iiv) improving the shape accuracy of new builds through compensation.

Representation of shape accuracy

The shape accuracy of AM-built objects is often assessed by a Coordinate Measurement Machine (CMM) or a 3D scanner. The measurement data is normally in the form of a point cloud with point coordinates defined in a Cartesian coordinate system (CCS). Representation of geometric accuracy based on point cloud data can be a non-trivial matter because of the infinite possibilities of design shapes. A shape-dependent representation would likely lead to shape-dependent models, which would restrict learning and extrapolation from limited tested cases (Huang et al., 2015). Considering the nature of low-volume production, a unified representation of shape accuracy is desirable for quality control in AM. Such a representation will facilitate modeling and learning from limited sample data, and also facilitate the equally important task of drawing inferences on the prediction and compensation of untested shapes.

One solution is to transform or pre-process the point cloud data before modeling. Examples include transforming in-plane ($x - y$ plane) and out-of-plane (z direction) shape deviations from the CCS to the Polar Coordinates System (PCS) as deviation profiles (Huang et al., 2015; Jin et al., 2016), and representing 3D shape deviation in the Spherical Coordinate System (SCS) as deviation surfaces (Huang, 2016). The motivation of this transformation is to decouple the geometric shape complexity from the deviation modeling. Figure 14 shows examples of deviation profiles presented in PCS for simple disk shapes with varying diameters and a polygon shape.

Note that other data representation approaches should be explored depending on

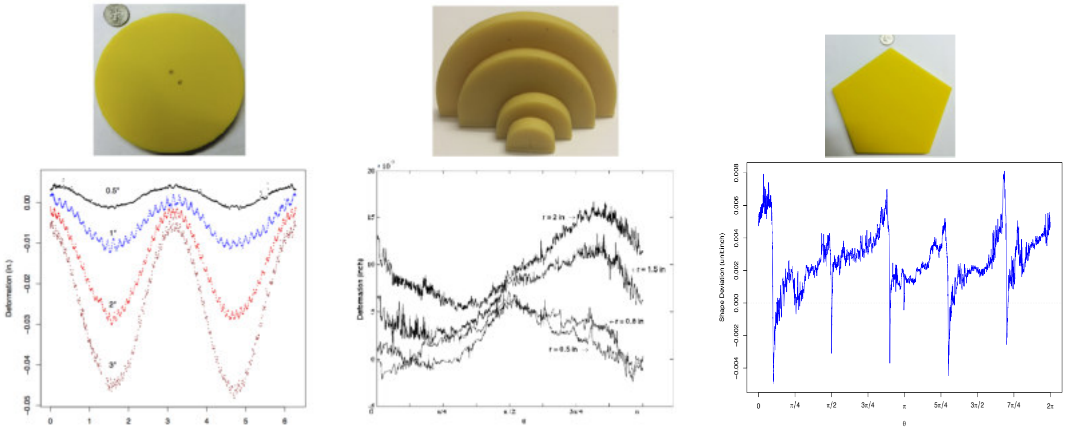

Figure 14: *(a) Deviation profiles of 4 disks printed horizontally (left panel) Huang et al. (2015); (b) Deviation profiles of 4 half-disks printed vertically (middle panel) Jin et al. (2016); (c) Deviation profile of a pentagon printed horizontally (right panel) Huang et al. (2014)*

the learning objectives.

Establishing models for predicting shape accuracy through learning

Quality prediction for AM aims to predict the quality of both built and untried products based on a limited number of test cases. For example, a limited number of test shapes and training data might be available in AM processes (Figure 15). The geometric accuracy of a new product with a completely different shape may have to be predicted for effective quality control. AM modeling for quality prediction can therefore be classified as predictive modeling and prescriptive modeling. While traditional predictive modeling tipically makes predictions within its experimental domains, e.g., a class or family of products, prescriptive modeling is able to predict quality of new and untried categories of shapes beyond the experimental scope.

As shown in Figure 14, four full disks printed horizontally manifest repeatable harmonic patterns which can be captured, for example, by the Fourier series. Adding shape size as an additional variable in the predictive model slightly increases the data collection and modeling efforts (Huang et al., 2015). When half-disks are printed

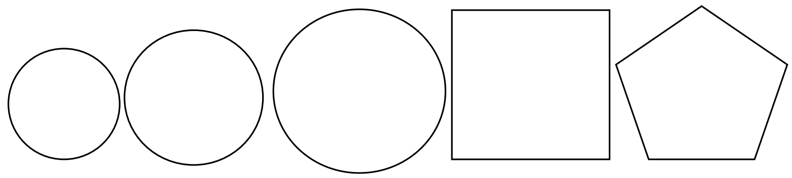

Figure 15: *Training data*

vertically, or when building truly 3D objects in general, however, the deviation patterns change dramatically. Furthermore, the patterns vary with sizes due to complicated inter-layer interaction along the vertical directions (Jin et al., 2016).

Even objects printed in the same direction, say, horizontally, incorporating shape as another learning variable, will significantly complicate the model building process owing to the fact that the dimension of shape space is infinite. Figure 14 illustrates a pentagon printed horizontally and its observed deviation profiles (Huang et al., 2014). Compared to the smooth profiles of the circular disks, the pentagon deviation profile exhibits sharp transitions at the corners, thereby ruling out the feasibility of simply applying Fourier series approximation because of the large number of terms needed. One attempt to add shape as a learning variable is through the so-called cookie-cutter modeling framework (Huang et al., 2014). Extension to 2D freeform shapes is presented in Luan and Huang (2017a). Little work has been done on exstending these ideas to 3D shapes (Jin et al., 2016).

Enhancing prescriptive models by systematic augmentation of new data

Predicting the shape accuracy of untried products involves larger uncertainties. Specifying the functional basis in prescriptive models can often be heuristic making prediction errors for new products inevitable. Thus, there is a need to systematically augment data from the newly printed products and extract new shape deviation features to enhance prediction performance.

In Sabbaghi et al. (2017), an adaptive Bayesian methodology is developed to improve prescriptive models by re-learning the updated training data after a new product is printed. A sequential and adaptive learning of in-plane deviation models is established. Figure 16 compares the improvement of model prediction before and after the Bayesian learning procedure.

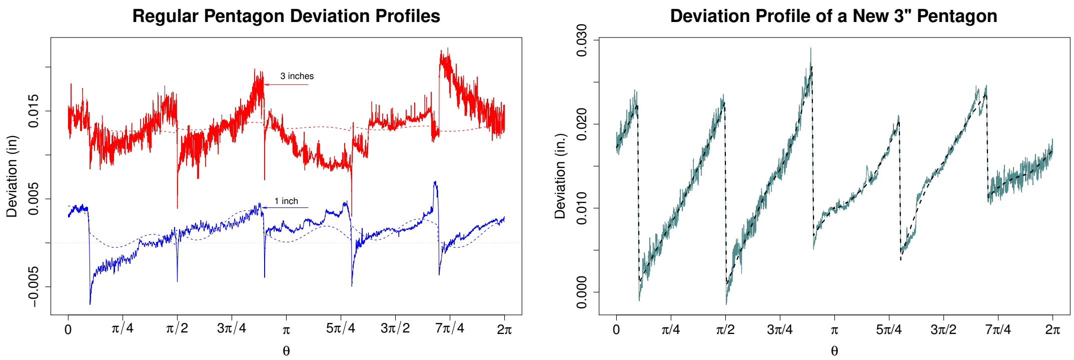

Figure 16: *(a) Predicted in-plane shape deviation (dashed lines) of two regular pentagons before Bayesian learning (solid lines) (Huang et al., 2014). (b) Predicted in-plane shape deviation of a new pentagon after Bayesian learning Sabbaghi et al. (2017)*

However, more research is required to develop sequential learning algorithms with the aim of better predicting deviation profiles of untested shapes. Research is also needed for more reliable quantification of uncertainty associated with such predictions.

Improving shape accuracy of new builds through compensation

While predicting shape deformation can be interpreted as the classical problem of prediction, minimizing shape deformation of AM-built products is an inverse problem, which is challenging due to geometric complexity, product varieties, material phase-changing and shrinkage, interlayer bonding, and limited sample data. Various methods and strategies have been developed to improve the geometric quality of AM processes, for example through simulation study based on the first principles (Storåkers et al., 1999; Secondi, 2002; Mori et al., 1996); offline optimization of process settings through experimentation (Wang et al., 1996; Zhou et al., 2000; Sood et al., 2009), calibration through building test parts (Wang et al., 1996; Wang, 1999; Zhou et al., 2000; Lynn-Charney and Rosen, 2000; Tong et al., 2003, 2008), part geometry calibration through extensive trial-build (Hilton and Jacobs, 2000), or adjustment of product design and process planning (Lynn-Charney and Rosen, 2000; Cho et al., 2003; Zhou et al., 2009; Tong et al., 2003, 2008; Huang et al., 2015, 2014; Sabbaghi et al., 2014; Moroni et al., 2014; Xu and Chen, 2015).

Once models of predicting quality are established, one viable and efficient approach to shape accuracy control is to compensate the product design to offset the geometric shape deviations. The key issue is therefore to determine the optimal amount of compensation based on measured or predicted shape deviation for both 2D and 3D cases.

The prevalent method of determining compensation in practice is the shrinkage compensation factor approach, which is rooted in the material shrinkage study in casting and injection molding processes. This approach applies a shrinkage compensation factor uniformly to the entire product or different factors to the CAD model for each section of a product (Hilton and Jacobs, 2000). This method implicitly assumes that the shape deviation is uniform in the section where the compensation factor is applied. Since products built via AM often have complex shapes, this assumption does not hold for general cases. The compensation factor approach is thus far from being optimal for AM.

An analytical and optimal compensation approach was developed in (Huang et al., 2015; Huang, 2016), where the minimum area deviation criterion and the minimum volume deviation criterion are proposed to derive a close-form solution for compensating 2D and 3D shape deviations, respectively. Experimental validation shows that the compensation method can improve accuracy by an order of magnitude for cylindrical products (Huang et al., 2015), by at least 75% for polyhedrons (Huang et al., 2014), and by at least 50% for freeform shapes (Luan and Huang, 2015, 2017a). New compensation criteria and algorithms can be developed to reduce both global and local shape deviations.

Note that a large body of AM work on surface quality, mechanical properties, structure defects such as porosity and lamination are not included in the discussion. A majority of the work are experimental in nature or process planning (Armillotta, 2006; Sun et al., 2008), with some exceptions of applying classical Design of Experiments to identify optimal process condition to reduce defects.

Statistical Transfer Learning for AM

Traditional machine learning methods assume that training and test data have the same feature space and follow the same distribution so that patterns extracted from historical data can be used to predict future outcomes. When this assumption does not hold, most predictive models will suffer degraded performance and have to be rebuilt using training data from the target domain(Pan and Yang, 2010). However, in many real applications, obtaining sufficient training data from a new domain can be expensive or infeasible. In such cases, statistical transfer learning would be desirable, which addresses the problem of how to achieve high predictive performances for a target domain by transferring knowledge from a related source domain with statistical models and methodologies.

In the past a few decades, a great deal of research has been undertaken on statistical transfer learning. The survey papers by Pan and Yang (2010) and Weiss et al. (2016) present an extensive overview of existing transfer learning methods and applications in the fields of machine learning and data mining. In addition, there are some successful statistical learning applications in the field of quality engineering, such as network modeling (Huang et al., 2012), the predictive modeling of degenerate biological systems (Zou et al., 2015) and surface shape prediction (Shao et al., 2017). A recent survey paper (Tsung et al., 2018) provides a review of transfer learning literature from a statistical perspective and discussed some extensions to SPC. Based on different forms of transferring information from a domain, current methods to statistical transfer learning mainly fall into three categories: instance transfer, feature transfer and parameter transfer (Pan and Yang, 2010). The instance transfer reuses certain parts of the source data in the target task based on the assumption that instances from the source and target are generated from two different but closely related distributions. The feature transfer aims to find a common feature representation that reduces the difference between source and target domains. The parameter transfer assumes that different domains should share some parameters or hyper-parameters of prior distributions.

Quality control for AM involves improving the geometric accuracy of fabricated products. In contrast to mass production, for one-of-a-kind manufacturing processes, an effective quality control strategy involves increasing the predictive performance of statistical shape deformation models for any new shape and deriving an effective compensation plan for any new and untried product. Due to the huge variety of product shapes and the low volume of production in AM processes, it is usually cost-prohibitive to collect sufficient sample data, which means only limited sample data for limited shapes are available. Thus, there is a great need to improve the predictive performance for new target shapes by transferring information from source shapes. There are, however, two major obstacles to achieving this. First, it is not feasible to build a single comprehensive model for a large variety of complex shapes based on data-driven methods due to insufficient data. Second, the connection between shape deformations of distinct shapes is unknown, which makes it difficult to infer a new target shape based on limited source shapes.

To tackle the above challenges, a novel in-plane shape deformation modeling scheme from a statistical transfer learning perspective has been proposed by Cheng et al. (2017), which uncovers the connection among the shape deformation of different products based on error decomposition and greatly improves the predictive performance for any new shape. In particular, the shape deformation of a product is decomposed into two parts: the shape-independent error, which is determined by the coordinates of product boundary points, and the shape-specific error, which is additionally induced due to specific shape features. The shape-independent error can be modeled in the CCS with measured deviations of a grid of marks designed inside a large plate, which are rarely affected by the shape boundary. The learnt model can be directly used to predict the shape-independent error component for any shape. Then the shape-specific error for each shape can be isolated from the shape-independent error and will only depend on shape features. This will make it much easier to investigate modeling of the shape-specific error instead of directly modeling the total shape deformation, especially when only sample data for limited shapes are available. Preliminary studies have shown that the shape-specific error for any new shape can also be well predicted from source shapes by choosing a reasonable shape feature representation such as the derivative of radius defined in the PCS. Extension of the in-plane shape deformation transfer learning framework to 3D cases should be studied further.

A major assumption for transfer learning among different shapes is that the manufacturing condition is unchanged. However, in reality, variations such as changes of AM machines, machine conditions and materials often exist and will make a systematic change to the manufacturing condition. The predictive performance of the models acquired from the old manufacturing condition will be degraded in the new condition. To avoid re-collecting the entire training data, there is a great need to develop statistical transfer learning approaches for AM quality control from one manufacturing condition to a new condition. This kind of transfer learning framework can have greater practical value in future cybermanufacturing systems, when data from heterogeneous sources are aggregated together. Efforts in this direction have been made in (Sabbaghi and Huang, 2018, 2016; Cheng et al., 2018). However, various approaches to these works are still limited to certain classes of shape. More transfer learning frameworks have to be developed.

Design of Experiments for AM

For more than the past five decades, design of experiments (DOE) has played a crucial role in quality engineering. However, DOE for improving the quality of AM processes involves a major paradigm shift due to the unique challenges associated with (a) the non-standard quality representation of AM-manufactured products leading to complex responses (typically profiles), (b) dissimilar experimental units making it difficult to replicate experiments, (c) the complex nature of input factors such as intended product geometry.

As explained in previous Sections, a convenient manner to obtain the 2D representation of AM-built product quality is to model the shape deformation as a function of the polar angle. Such deformation models have been effectively utilized in the compensation-based approach for quality control of AM-products, as previously described. However, the success of this approach depends on accurate modeling and predicting the quality of AM-built products, a task that can only be achieved through a careful experimental approach. Clearly, predicting the deformation of each individual shape by creating a test product is too expensive, and practically impossible. Prediction of deformation models must therefore involve a sequential strategy. Let $\{\psi_1, \ldots, \psi_K\}$ denote a class of shapes for which deformation models need to be predicted, where K is large, and suppose we have already obtained deformation models $\hat{f}_1(\psi_1), \ldots, \hat{f}_L(\psi_L)$ by manufacturing a small subset of shapes $\{\psi_1, \ldots, \psi_L\}$ where L is much smaller than K. The design question can be formulated as follows: suppose we have resources to make N test products. Which of the remaining $(K - L)$ shapes should be manufactured so that it is possible to predict deformation models for the untested shapes with the maximum possible efficiency?

Clearly, this problem can be solved only if the deformation of the K shapes $\psi_1, \ldots, \psi_K$ can be modeled using a suitable parametric or non-parametric function of the input variables $\boldsymbol{x}$. Consider a simple example: suppose our goal is to fit deformation models for circles with an arbitrary nominal radius r_0. Note that we can represent the in-plane deformation model of a cylinder by a function $f(x)$, where $x \equiv r_0$. Suppose we have manufactured three cylinders with radii 0.5, 1.0 and 1.5 inches, and used their deformation data to fit a model $\hat{f}(x)$. Then, K is infinite and $L = 3$. Now, the design question is, what should be the radius of the next cylindrical test product so that $f(x)$ can be predicted with the maximum possible efficiency?

Another example is a more general problem where the goal is to fit deformation models for regular polygons with an arbitrary number of vertices p and an arbitrary nominal circum-radius r_0. The argument $\boldsymbol{x}$ for such deformation functions $f(\boldsymbol{x})$ is a vector $\boldsymbol{x} = (p, r_0)$. Thus choosing the dimension of the next polygon to manufacture is a two-dimensional optimization problem.

When the class of shapes being considered is such that the dimension of $\boldsymbol{x}$ is fixed (such as one in our first example and two in the second), the problem of choosing subsequent input values (design points) $\boldsymbol{x}$ can be treated as a sequential optimal design problem. Solving such problems entails defining a criterion based on the information content about the unknown parameters of the model and choosing the subsequent design points by maximizing such criterion. Sequential Bayesian designs for solving such problems have been proposed and successfully implemented in other application areas in the recent past; see for example Zhu et al. (2014) and Lee et al. (2018). Such designs appear to be natural candidates for AM application, due to the non-linearity of the prescriptive models and the Bayesian approach adopted for model-fitting (Huang et al., 2015; Sabbaghi et al., 2018). However, the functional nature of the response adds a layer of complexity to this problem and requires new research.

What makes this design problem even more challenging is the need to adaptively and collectively improve the knowledge about an ensemble of shapes that include multiple primitive shapes as well as derived freeform shapes. Suppose we have two tentative deformation models, one for the circular shape and one for a regular polygon with p edges, that we want to fine-tune with a few additional test products. The problem now is to assign these new (to-be-manufactured) shapes to circles of different radii and polygons with a different number of edges and radii of their circum-circle so that the generated data maximize the collective information about the deformation models for circles and polygons. Such optimal design problems with varying dimensions of input variables may be of interest to researchers in experimental design.

Physical Models, Calibration and Uncertainty Quantification for AM

Even with smart algorithms for generating sequential designs, the need for a structured framework to develop simulation models for the deformation of AM-manufactured shapes is being increasingly felt for the following reasons. First, relying solely on physical experiments to predict deformation models is unlikely to be a successful approach in the long run due to the great diversity in shape and size of AM-built products. Thus, only a limited number of physical experiments can be conducted that may be grossly inadequate for building generic and flexible prediction models. Second, to make the prediction models more flexible, it is important to incorporate process physics into the models. Such integration of physical knowledge into empirical models can be done using the principles of calibration of computer models.

To illustrate the idea with the simplest case of manufacturing cylindrical products, assume that based on process physics, $\eta(x, \theta; \boldsymbol{\phi})$ is an interpretable and deterministic physical model that can be used to simulate the in-plane deformation of a cylinder of radius x at polar angle θ. Here $\boldsymbol{\phi}$ denotes a calibration parameter vector which needs to be set at a fixed value to generate a value of the function $\eta(x, \theta; \boldsymbol{\phi})$. Suppose three cylinders with radii 0.5, 1 and 3 inches have already been manufactured. We would like to calibrate the physical model based on the actual observations on deformation. For this purpose, as in Kennedy and O'Hagan (2001), we model the "true" output $\xi(\boldsymbol{x}, \theta)$

of a physical experiment as the sum of the deterministic simulation model $\eta(\cdot, \boldsymbol{\phi})$ and a discrepancy term $\delta(\cdot)$, that is,

$$\xi(\boldsymbol{x}, \theta) = \eta(\boldsymbol{x}, \theta, \boldsymbol{\phi}) + \delta(\boldsymbol{x}, \theta). \tag{2}$$

The observed output from the physical experiment is then expressed as the sum of the true output and a noise term:

$$y(\boldsymbol{x}, \theta) = \xi(\boldsymbol{x}, \theta) + \epsilon(\boldsymbol{x}, \theta). \tag{3}$$

Using the data obtained from the three cylindrical products, we would like to (a) estimate the discrepancy function $\delta(\cdot)$, (b) find an "optimal" value of the calibration parameter ϕ, and (c) determine the radius of the next cylinder to manufacture. Such analyses are discussed quite extensively in computer experiments literature on calibration (Kennedy and O'Hagan, 2001; Tuo and Wu, 2015) and statistical adjustment to engineering models Joseph and Melkote (2009) but the aspects of AM that pose new challenges are (i) the functional nature of the response and (ii) the focus on identification and estimation of the discrepancy function δ. Research conducted so far on calibration with functional responses (Bayarri et al., 2007; Higdon et al., 2008), makes strong assumptions about the discrepancy (such as its representation by the same basis function as the reality) that are unlikely to hold in the current scenario.

Conclusions

With the advancement of Industrial Internet of Things and its Cyber-physical Systems as a backbone, future product creation and manufacturing environments will be hyper-connected and globalized. One important trend of this manufacturing revolution is cyber-enabled AM, which has inspired the formation of entirely new Product-Service-Systems and cyber communities of additive manufacturers centered around the creative design and fabrication of innovative products. In this scenario, quality engineers and statisticians should combine their joint efforts to provide novel solutions that answer to the pressing industrial demand for a new generation of robust, reliable and high-quality AM systems. Automated Machine Learning of AM data, monitoring, control and optimization will play a major role in this transition.

The paper describes how AM is fostering the need of a novel generation of tools, revising quality inspection, monitoring, control and process optimization using "big" data streams, going from voxel-based 3D data (from X-ray CT), fast video-images, complex shapes point clouds and signals. In this scenario, companies are looking for novel tools to take proper advantage of this huge data stream and improve the overall AM process quality, which is quite poor at this time.

Considering the specific target of AM toward high-value, personalized production, a renewed attention to short-run approaches has been pointed out as mandatory. Different approaches for modeling part-to-part, machine-to-machine and process-to-process variability were mentioned as critical for AM applications at this time. To this aim, approaches for statistical transfer learning will be playing a relevant role in the near future.

This paper briefly indicated prospects of building statistical models from computer experiments, AM processes' simulation is still an ongoing field of research and no mature software products for industrial use exist at this time. On the other side, simulation of the AM product performances with respect to functional requirements and geometrical constraints is a flourishing area including topological optimization. Connection with metamodeling and process optimization via data fusion of computer and real experiments is of great interest in the near future.

In conclusion, this paper outlined new interesting directions for future research connecting the emerging challenges in advanced manufacturing with some current trends in statistical quality engineering. In this area, we really hope to encourage the development of novel tools to overcome existing barriers and challenges.

Acknowledgements

We thank David Steinberg for his helpful comments, which allowed us to clarify and improve the paper. Colosimo's work was partially funded by the AMATHO Project - Additive MAnufacturing for Tiltrotor HOusing - under H2020-CleanSky2 Programme. Huang's work is supported by US National Science Foundation with grant # CMMI-1544917.

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