Received 14 July 2021
Revised 2 November 2021
Accepted 22 November 2021

QUALITY PAPER

A benchmark analysis of the quality of distributed additive manufacturing centers

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Abstract

Purpose – Nowadays, companies are increasingly adopting additive manufacturing (AM) technologies due to their flexibility and product customization, combined with non-dramatic increases in per unit cost. Moreover, many companies deploy a plurality of distributed AM centers to enhance flexibility and customer proximity. Although AM centers are characterized by similar equipment and working methods, their production mix and volumes may be variable. The purpose of this paper is to propose a novel methodology to (1) monitor the quality of the production of individual AM centers and (2) perform a benchmarking of different AM centers.
Design/methodology/approach – This paper analyzes the quality of the production output of AM centers in terms of compliance with specifications. Quality is assessed through a multivariate statistical analysis of measurement data concerning several geometric quality characteristics. A novel operational methodology is suggested to estimate the fraction nonconforming of each AM center at three different levels: (1) overall production, (2) individual product typologies in the production mix and (3) individual quality characteristics.
Findings – The proposed methodology allows performing a benchmark analysis on the quality performance of distributed AM centers during regular production, without requiring any *ad hoc* experimental test.
Originality/value – This research assesses the capability of distributed AM centers to meet crucial quality requirements. The results can guide production managers toward improving the quality of the production of AM centers, in order to meet customer expectations and enhance business performance.

Keywords Quality, Additive manufacturing, Distributed manufacturing, Capability analysis

Paper type Research paper

1. Introduction

In today's highly competitive global market, a growing number of companies of all sizes adopt distributed manufacturing solutions, focusing on high product customization (Maisano *et al.*, 2020; Matt *et al.*, 2015; Srai *et al.*, 2016). Some important advantages of distributed manufacturing are flexibility, proximity to customers, more accurate and timely information and greater adaptability to demand fluctuations (Rauch *et al.*, 2017, 2018; Roca *et al.*, 2019). Nevertheless, distributed manufacturing has some weaknesses compared to traditional centralized manufacturing, such as higher capital investment to create more production facilities, less exploitation of economies of scale, higher costs per unit and higher complexity in coordinating and managing distributed manufacturing processes. However, as technology continues to grow, the arguments in favor of distributed manufacturing tend to outweigh the arguments against it (Srai *et al.*, 2016).

This research was partially supported by the award "TESUN-83486178370409 finanziamento dipartimenti di eccellenza CAP. 1694 TIT. 232 ART. 6," which was conferred by "Ministero dell'Istruzione, dell'Università e della Ricerca."

One of the outstanding emerging technologies of the last decades is additive manufacturing (AM), which has enabled high customization and complexity levels. AM technologies have led to the epochal shift from the so-called "mass production" to "job production," also referred to as "mass customization" (Galetto *et al.*, 2020; Pine, 1993; Verna *et al.*, 2020). In this paper, the research focus will be on AM processes, from the practical perspective of companies having to manage and coordinate a plurality of similar, albeit not identical, distributed AM centers. Such centers may be characterized by similar technology equipment, but may differ in terms of (1) technology solutions, (2) work parameters and/or (3) materials (Gibson *et al.*, 2010; Huang *et al.*, 2017). In addition, the production quantities and/or production mixes of different AM centers may vary depending on their specific demand (Durão *et al.*, 2017; Rauch *et al.*, 2018; Zijm *et al.*, 2019).

In this scenario, the need arises for companies to monitor, evaluate and compare the quality performance of their AM centers, so as to (1) take a general picture of the entire production, (2) identify possible local criticalities and (3) guide possible improvement actions. In particular, the quality of the production output of AM centers is intended as its compliance with the relevant specifications, which are imposed by customers (Montgomery, 2019).

Monitoring and evaluating the quality of production is worth threefold in practice, as it enables:

(1) to evaluate the performance of single AM centers,

(2) a benchmark analysis between different AM centers, highlighting their strengths and weaknesses and

(3) to drive improvement in each AM center by identifying the most profitable solutions implemented in "competing" centers.

The inherent diversity among AM centers – not only in terms of production equipment but also in terms of quantitative (i.e. total production quantity, geometric/functional characteristics of individual product units) and qualitative (i.e. production mix) characteristics of the related productions – makes performing structured and rigorous quality assessments not straightforward.

The purpose of this paper is to propose a methodology for a structured comparison of a plurality of AM centers from the perspective of their quality performance. Quality is assessed through a multivariate statistical analysis of the compliance of different typologies of products, based on multiple quality characteristics, leading to an estimate of the overall defectiveness (or fraction nonconforming) of individual AM centers. A key distinguishing feature of the proposed analysis is not to require any *ad hoc* experimental testing, being based entirely on the information collected during regular production.

The remainder of this paper is organized into five sections. Section 2 presents the novel methodology to assess the quality performance of each AM center; this methodology is based on a multivariate statistical approach for estimating the conformity of the products in each AM center. Section 3 presents a real-world case study of a company dedicated to designing and manufacturing automotive tool components, which are produced in several distributed AM centers. The case study will exemplify the methodology proposed in Section 2. Section 4 summarizes the findings of the present study, specifying practical implications, limitations and insights for future research.

2. Research method

Consistently with the general definition of quality, that is, the "*degree to which a set of inherent characteristics of an object fulfils requirements*" (ISO 9001:2015, 2015), the quality of a generic manufacturing process can be defined as the "*ability to produce products that meet the relevant specifications*." In this paper, multiple AM centers are assumed to produce the same typologies of products, though in different quantities and mixes. A combination of three factors characterizes each AM center: (1) production equipment/machines and corresponding work/process parameters, (2) materials with specific characteristics and (3) operators and related work practices.

Such factors contribute to variability in production output, referred to as the "*inability to produce identical units of output*" (Montgomery, 2019). Variability is classified as natural if it refers to a production process that runs smoothly, without accidents/anomalies that can be systematically attributed to at least one of the three aforementioned factors (e.g. machine failure, imperfect materials or human error) (Swamidass, 2000; Woodall and Thomas, 1995). Anomalies/incidents are occurrences that may occasionally be present in a process, which result in an increased variability compared to the natural one, leading to an unacceptable level of process performance. When assignable causes of variations occur, these result in a shift to an out-of-control state where a larger proportion of the process output does not conform to requirements (Montgomery, 2019). With accidents/anomalies, variability tends to increase and, alongside it, the propensity to produce products that do not meet specifications (Montgomery, 2019). However, even in the absence of anomalies/accidents, a process can generate nonconforming products, since this may depend on how stringent the product specifications associated with quality characteristics are, compared to the corresponding natural variability.

The remainder of this section proposes a novel methodology to qualitatively assess the degree of suitability of different distributed AM processes, with respect to the production they are supposed to achieve. The existing scientific literature thoroughly addresses this issue within the so-called process capability analysis (de-Felipe and Benedito, 2017; González and Sánchez, 2009; ISO 22514-6:2013, 2013). Although the proposed methodology is inspired by some widespread approaches in this field, it is purposefully tailored with reference to the considered problem. In detail, the following four features define the problem of interest, which is characterized by the following four features:

(1) In each AM center, the production is divided into the so-called jobs, in which product units of various typologies are produced at the same time (e.g. part typologies α, β, γ). A job can be defined as "*an elementary production run that generates a "macro-product," given by the composition of product units of various typologies, according to the customer demand*" (Choudhari *et al.*, 2012).

(2) Several characteristics and related specifications distinguish each typology of product, for example, geometric quality characteristics.

(3) Depending on current demand, jobs may vary in terms of (1) total quantity of product units and (2) corresponding assortment (i.e. subdivision of products into various typologies).

(4) For shortening production time and costs, production capacity of each AM center should be saturated as much as possible, job by job. Clearly, the number of products to be manufactured in a given job depends on the geometric characteristics of the production equipment (e.g. the geometric characteristics of the plate of the AM machines) and the part units.

In summary, the proposed methodology includes two main phases: (1) the production data gathering and (2) the multivariate statistical approach to analyze these data.

2.1 Production data gathering

Data collection can be performed during regular production, without requiring expensive and time-consuming *ad hoc* experimental testing. In order not to distort the analysis, it is essential that production takes place in the absence of incidents/anomalies of any kind. To this end, it is recommended that technicians, operators and engineers follow the production process closely during data collection. A job-to-job production sampling is then performed in each AM center, until an adequate quantity of production units is collected (indicatively, at least 15–20 units for each product typology) (Montgomery, 2019). This amount of data is reasonably acceptable for the statistical analysis described in Section 2.2. Clearly, increasing the number of units collected will increase the accuracy of the statistical analysis, but it will also increase the associated costs (Montgomery, 2019).

Next, parts of the same typology are aggregated for each AM center, independently of the jobs in which they were produced. This aggregation is reasonable under the assumption – that will be verified – that the "job factor" has no systematic effect.

The last step entails the measurement of the quality characteristics related to each typology of part. To this aim, it is convenient to use a relatively accurate measuring instrument that allows neglecting the measurement uncertainty, with respect to the variability of the measured quality characteristics (Montgomery, 2019). Alternatively, the measurement uncertainty has to be included in the analysis, thereby complicating it.

2.2 Multivariate statistical approach for quality performance benchmarking

The proposed analysis is based on a common assumption in multivariate process capability analysis, namely that quality characteristics related to the same typology of product can be modeled as correlated random variables, which are distributed according to a multivariate normal distribution (Alevizakos and Koukouvinos, 2020; Chen *et al.*, 2003; Ross, 2009; Tano and Vännman, 2012; Wang, 2005). A normality test, such as the Anderson–Darling (AD) test, may be performed to verify the normality of the distribution of each individual quality characteristic, for each part typology and AM center (Montgomery, 2019).

Then, the relevant normal multivariate distribution parameters should be estimated using the sample of measurement data collected in the previous phase (see Section 2.1). In detail, for each product typology and AM center, the (1) vector of mean values and (2) covariance matrix of the corresponding quality characteristics can be estimated. Whereas the sample mean and covariance are unbiased estimators of the process mean and covariance, the sample variance is a biased estimator as it systematically underestimates the process variance (Ross, 2009). Such a bias may be corrected through the parameter c_4 (see Cochran's theorem) (Bapat, 2000), which depends on the sample size (n) of the data used to determine the sample variance and can be found in the scientific literature (Duncan, 1974; Montgomery, 2019). Accordingly, the unbiased estimates of the multivariate normal distribution parameters are:

$$\widehat{\mu}_x = \frac{\sum_{i=1}^{n} x_i}{n}, \quad \widehat{\sigma}_x = \frac{s_x}{c_4} = \frac{1}{c_4} \cdot \sqrt{\frac{\sum_{i=1}^{n} (x_i - \mu_x)^2}{n-1}}, \quad \widehat{\mathrm{cov}}(x, y) = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \mu_x) \cdot (y_i - \mu_y)}{n-1}}, \tag{1}$$

where:

(1) "n" is the size of the sample selected for estimating the process parameters,

(2) "^" is the hat operator, denoting estimated values,

(3) "$\widehat{\mu}_x$" is the estimation of the mean value of the generic quality characteristic x, through the sample mean,

(4) "s_x" is the sample standard deviation that, after being corrected using the parameter c_4, provides an unbiased estimate ($\widehat{\sigma}_x$) of the standard deviation of x and

(5) "$\widehat{\mathrm{cov}}(x, y)$" is the unbiased estimation of the covariance between two generic quality characteristics x and y through the sample covariance.

The above parameters allow reconstructing the multivariate normal distributions related to the quality characteristics of each part typology, with reference to a certain AM center.

The next step is to estimate the fraction of nonconforming products produced by the AM centers by comparing the multivariate normal distributions with the associated specifications. A preliminary estimate of the fraction nonconforming, from the perspective of a single quality characteristic, can be made by integrating the univariate normal distribution of the quality characteristic into the two "tails" beyond the relevant specification limits: lower specification limit (LSL) and upper specification limit (USL). For quality characteristics with unilateral specifications, only one tail (right or left, depending on the specific case) has to be considered.

The next step of the proposed methodology concerns the estimation of the overall fraction of nonconforming products – p_i, that is, the fraction of parts of i-th typology, which do not meet at least one of the related quality characteristics – by integrating the normal multivariate distribution externally with respect to the hyper-rectangular region, delimited by the specification limits of the respective quality characteristics (de-Felipe and Benedito, 2017). As exemplified in Section 3 referring to the case study, a Monte Carlo numerical integration can be performed for each part typology and each machine, generating a number of multivariate random realizations of some variables, which are compatible with the respective mean-value vectors and covariance matrix.

For a specific AM center, a synthetic indicator of the overall fraction nonconforming (p) of the total production output (i.e. considering the totality of part typologies) can be defined as:

$$p = \frac{\sum_{i \in \{\alpha,\beta,\ldots\}} p_i \cdot (w_i \cdot m_i)}{\sum_{i \in \{\alpha,\beta,\ldots\}} (w_i \cdot m_i)}, \tag{2}$$

where:

(1) m_i is the mass of material, including material for support bases and purging, related to the production of the i-th part typology,

(2) w_i is an indicator of the portion of parts of i-th typology, for a given production mix and

(3) $\alpha, \beta, \ldots$ are the product typologies.

Eq. (2) is a weighted sum of the p_i values with respect to the corresponding mass (m_i), for each i-th part typology. This form of weighing seems reasonable, considering that the different parts are produced according to different product mixes. Additionally, p can be seen as the ratio between the mass related to the fraction nonconforming of products and the total mass of products from a certain AM center. Such a synthetic indicator can represent a performance measure of the quality of each AM center. Indeed, the higher the value of p, the lower the ability of the AM center to meet the quality requirements imposed by the customers. The analysis of this indicator for a certain AM center and its comparison with the indicators related to other "competing" centers can support managers in selecting quality improvements actions.

Section 3 exemplifies the application of the proposed methodology to a real case study in the automotive sector, highlighting its practical utility.

3. Case study

3.1 AM centers and production data

In the proposed case study, three AM centers of a company specialized in designing and implementing tooling solutions for the automotive industry are considered. The company's name is not revealed for confidentiality reasons. The product units manufactured include inspection fixtures, production and assembly jigs that can be used as support tools, both in the design/prototyping and in the production/assembly phases. Figure 1 shows some sample fixtures of different geometry that allow the precise positioning of some pressed sheet-metal components of a car door during assembly or dimensional quality inspections.

Three specific typologies of fixtures (referred to as α, β and γ) with comparable overall dimensions are considered. These fixtures can be used to support the proper placement of specific automotive components during various in-line tests and are only a few centimeters in size. The precise geometry of the three fixtures is not disclosed for reasons of confidentiality. For each geometry, three quality characteristics that are crucial for the functionality of the fixture itself are identified (i.e. α.1, α.2, α.3, β.1, β.2, etc.); each of these quality characteristics is associated with corresponding specifications. Table 1 reports the nominal value (NV) and the LSL and USL for each quality characteristic. As shown, specifications are generally not very stringent since they are of the order of magnitude of a few tenths of a millimeter.

Further technical requirements characterizing the production of the fixtures of interest are summarized below:

(1) the parts are generally not produced in large quantities, albeit with a variable production mix, depending on current demand,

(2) the parts do not have particular structural properties, as they are mainly used as a support for the positioning of specific automotive components during assembly operations and

(3) being in contact with metal automotive components, parts are made of a softer material that can be worn without scratching metal components.

Fixtures are produced in three distributed AM centers, referred to as "Center I," "Center II" and "Center III." All AM centers use polymeric materials, although the three different machines in use are not disclosed for industrial secrecy reasons. Although these AM centers adopt the same technology, that is fused deposition modeling (FDM), the architecture and

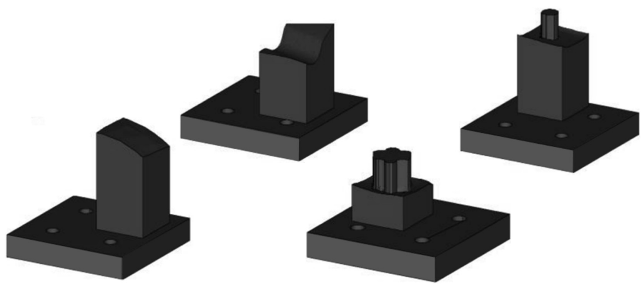

Figure 1. Sample fixtures used as supports for parts manufactured in bent-sheet metal during assembly and/or dimensional inspection in the automotive industry

	Label	Type	Description	NV	LSL	USL
Part α	α.1	Dimensional	Two-plane distance [mm]	34.50	34.35	34.65
	α.2	Dimensional	Internal diameter [mm]	18.40	18.30	18.50
	α.3	Form	Cylindricity [mm]	–	–	0.20
Part β	β.1	Dimensional	Hole spacing [mm]	48.60	48.45	48.75
	β.2	Dimensional	Two-plane distance [mm]	24.30	24.15	24.45
	β.3	Form	Flatness [mm]	–	–	0.20
Part γ	γ.1	Dimensional	Two-plane distance [mm]	15.00	14.80	15.20
	γ.2	Dimensional	Two-plane distance [mm]	28.60	28.45	28.75
	γ.3	Orientation	Parallelism [mm]	–	–	0.15

Table 1. Geometric quality characteristics of the parts α, β and γ

equipment of the AM machines are different, leading to possible differences in terms of resulting quality of the parts (Galetto *et al.*, 2021). The AM machines used in each AM center have different production capacity: the machine of Center I has the largest surface of the plate, followed by that of Center II and Center III, respectively. To ensure a certain standardization of the manufactured products, all the machines are equipped with filaments of proprietary materials (both in reference to the parts and to the corresponding support bases), whose mechanical/functional properties and parameters of the deposition process are available in the technical sheets provided by the material supplier.

The effective production of each AM center was monitored and sampled for a variable period in order to collect an adequate amount of product units, that is, about 15–20 for each part typology (α, β and γ). To assure that the sampled data reflect the behavior of the production processes – in the absence of accidents/anomalies or any systematic source that could bias the natural variability (Montgomery, 2019) – the AM processes were supervised by skilled and experienced technicians. The production of each AM center is organized into jobs, characterized by a certain mix of the parts α, β and γ. Secondly, the number of units produced in each job may vary from machine to machine, being related to the plate surface. For example, the machine of Center I can produce a dozen units per job, that is, about twice as many as the machine of Center III; the machine of Center II has an intermediate capacity. Table 2 describes the job-to-job configurations related to the production carried out on the three AM centers.

A DEA Global Image coordinate measuring machine (CMM) with a maximum permissible error (MPE) of about 3 μm was used to measure the quality characteristics. The resolution of this instrument is about two orders of magnitude lower than the intrinsic variability of the measurands, which is of the order of magnitude of one-tenth of a millimeter; see Table A1 (Hexagon Manufacturing Intelligence, 2021). For each part type, a measurement cycle was constructed and automatically performed. In order to obtain a more accurate estimate and avoid possible measurement errors, three replicated measurements were carried out for each quality characteristic and then aggregated through the arithmetic mean. Measurement results related to the parts manufactured in each of the three AM centers are reported in Tables A1–A3, respectively.

The box-plot in Figure 2 shows that the "job factor" does not seem to determine systematic differences in the quality characteristic α.1, with reference to the parts produced in AM Center I; the four boxes relating to the four jobs are, in fact, all overlapping (Ross, 2009). To provide statistical evidence of the nonsignificance of the "job factor," a one-way ANOVA (Ross, 2009) is also performed, confirming that there is no systematic difference between the means of the jobs with respect to the quality characteristic α.1, with a p-value of 0.178. The same result can

Table 2.
Job-to-job sampled production of each AM center. For each job, the mix of parts produced, the relevant typology and number are given

	(a) AM Center I				(b) AM Center II				(c) AM Center III			
Job	α	β	γ	Job total	α	β	γ	Job total	α	β	γ	Job total
1	8	3	1	12	2	4	3	9	–	–	6	6
2	3	9	–	12	8	–	–	8	–	–	6	6
3	–	2	10	12	3	3	3	9	2	3	1	6
4	7	–	5	12	–	4	5	9	1	3	2	6
5	3	5	3	11	4	5	–	9	3	2	1	6
6	–	–	–	–	3	5	1	9	2	3	1	6
7	–	–	–	–	1	–	8	9	4	2	–	6
8	–	–	–	–	–	–	–		5	1	–	6
9	–	–	–	–	–	–	–		1	4	1	6
10	–	–	–	–	–	–	–		1	2	3	6
Column total	21	19	19	59	21	21	20	62	19	20	21	60

be extended to all quality characteristics of all typologies of parts produced in any AM center, allowing, therefore, to aggregate data related to the same part typology, which are produced in different jobs in the same AM center.

Next, the AD test was used to test the normality of the distribution of each individual quality characteristic for each product typology and AM center (Marsaglia and Marsaglia, 2004). The relatively high p-values of the AD test show that the assumption of normality is not contradicted for any quality characteristics (see Table A4).

Eq. (1) is then applied to estimate the mean values and covariance matrices related to the quality characteristics of each product typology and AM center. Such values are contained in Table 3. It is interesting to note that the quality characteristics related to the same product type are often correlated. For instance, referring to AM Center I, the quality characteristics $\alpha.2$ and $\alpha.3$ are positively correlated, that is, $\text{cov}(\alpha.2, \alpha.3) = 0.0014$, corresponding to a Pearson correlation coefficient $\rho_{\alpha.2,\ \alpha.3} = 77.4\%$, while the quality characteristics $\gamma.1$ and $\gamma.3$ are negatively correlated, that is, $\text{cov}(\gamma.1, \gamma.3) = -0.0008$, corresponding to a Pearson correlation coefficient $\rho_{\gamma.1,\ \gamma.3} = -52.8\%$ (Ross, 2009).

Next, a Monte Carlo numerical integration was carried out for each part typology and AM center, after generating 10,000 multivariate random realizations of some variables, compatible with the respective mean-value vectors and covariance matrix. For this purpose, the "Calc > Random Data > Multivariate Normal Distribution" function of Minitab was adopted (Minitab, 2021).

3.2 Results and discussion

Results of the integration are shown in Table 4 and Figure 3. The fraction nonconforming related to a single quality characteristic of certain part typology is derived by integrating the univariate normal distribution of the quality characteristic into the two "tails" beyond the relevant specification limits, for example, for the quality characteristic $\alpha.1$, related to the typology-α parts manufactured in AM Center I, the fraction nonconforming can be determined as $p_{\alpha.1} = P(x_{\alpha.1} < LSL_{\alpha.1}) + P(x_{\alpha.1} > USL_{\alpha.1}) = 0.17\%$.

In addition, Table 4 shows that, for a given AM center and part typology, the overall fraction nonconforming is lower than the sum of the fractions nonconforming related to corresponding quality characteristics (e.g. $p_\alpha < p_{\alpha.1} + p_{\alpha.2} + p_{\alpha.3}$). This finding is not surprising as the individual quality characteristics are not statistically independent (see covariance matrices on Table 3).

Focusing on the fraction nonconforming related to the single parts (i.e. $p_\alpha, p_\beta, p_\gamma$, as shown in Table 4), AM Center I has the lowest fraction nonconforming, while AM Center III has the

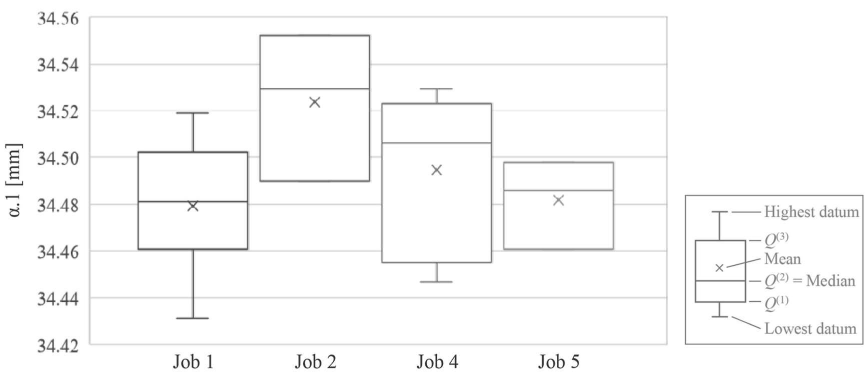

Figure 2. Box-plot of the quality characteristic $\alpha.1$, relating to the α part typologies, produced by AM Center I

Table 3. Mean values and covariance matrix related to the data reported in Tables A1–A3

		$\alpha.1$	$\alpha.2$	$\alpha.3$		$\beta.1$	$\beta.2$	$\beta.3$		$\gamma.1$	$\gamma.2$	$\gamma.3$
(a) AM Center I												
Mean values		34.491	18.390	0.093		48.615	24.267	0.068		14.980	28.627	0.095
Covariance matrix	$\alpha.1$	0.0010	−0.0001	0.0000	$\beta.1$	0.0014	0.0000	0.0002	$\gamma.1$	0.0012	−0.0002	−0.0008
	$\alpha.2$	−0.0001	0.0025	0.0014	$\beta.2$	0.0000	0.0029	0.0013	$\gamma.2$	−0.0002	0.0010	0.0007
	$\alpha.3$	0.0000	0.0014	0.0013	$\beta.3$	0.0002	0.0013	0.0013	$\gamma.3$	−0.0008	0.0007	0.0016
(b) AM Center II												
Mean values		34.472	18.376	0.064		48.612	24.257	0.071		15.010	28.568	0.104
Covariance matrix	$\alpha.1$	0.0011	0.0003	0.0002	$\beta.1$	0.0016	0.0001	−0.0004	$\gamma.1$	0.0018	−0.0006	−0.0003
	$\alpha.2$	0.0003	0.0017	0.0010	$\beta.2$	0.0001	0.0011	0.0003	$\gamma.2$	−0.0006	0.0021	0.0011
	$\alpha.3$	0.0002	0.0010	0.0010	$\beta.3$	−0.0004	0.0003	0.0017	$\gamma.3$	−0.0003	0.0011	0.0023
(c) AM Center III												
Mean values		34.483	18.433	0.082		48.563	24.333	0.073		14.998	28.570	0.100
Covariance matrix	$\alpha.1$	0.0013	0.0005	0.0006	$\beta.1$	0.0023	0.0012	0.0010	$\gamma.1$	0.0021	−0.0006	−0.0009
	$\alpha.2$	0.0005	0.0023	0.0021	$\beta.2$	0.0012	0.0035	0.0024	$\gamma.2$	−0.0006	0.0027	0.0013
	$\alpha.3$	0.0006	0.0021	0.0026	$\beta.3$	0.0010	0.0024	0.0025	$\gamma.3$	−0.0009	0.0013	0.0018

highest one. This result is even more evident when considering the synthetic indicator associated with the entire production of a certain AM center (see Eq. (2). A uniform production mix for each AM center was here considered: that is, $w_i = {}^1\!/_3 \ \forall i \in \{\alpha, \beta, \gamma\}$; the m_i values are estimated in the last column of Table 5. The resulting p values are shown in Figure 3, supporting the assumption that AM Center I has the lowest p-value, while AM Center III has the highest one.

The proposed fraction nonconforming indicators – at the level of (*1*) individual quality characteristics (e.g. $p_{\alpha.1}$, $p_{\alpha.2}$, etc.), (*2*) single parts (i.e. p_α, p_β, p_γ) and (*3*) overall production output of each AM center – (p) provide a snapshot of the current quality of each AM center, facilitating comparison with other AM centers.

	(a) AM Center I	(b) AM Center II	(c) AM Center III
$p_{\alpha.1}$	0.17%	1.80%	5.35%
$p_{\alpha.2}$	0.20%	0.10%	1.18%
$p_{\alpha.3}$	1.90%	0.12%	1.27%
p_α	2.23%	2.01%	7.15%
$p_{\beta.1}$	0.01%	0.05%	1.24%
$p_{\beta.2}$	1.49%	0.11%	0.98%
$p_{\beta.3}$	1.31%	3.14%	2.79%
p_β	2.78%	3.30%	4.54%
$p_{\gamma.1}$	1.17%	1.98%	4.41%
$p_{\gamma.2}$	0.01%	0.49%	0.95%
$p_{\gamma.3}$	5.62%	11.90%	12.27%
p_γ	6.31%	14.15%	17.04%
p	3.62%	6.02%	9.22%

Table 4. Estimation of the fraction nonconforming related to (*1*) individual quality characteristics (e.g. $p_{\alpha.1}$, $p_{\alpha.2}$, etc.), (*2*) single parts (i.e. p_α, p_β, p_γ) and (*3*) overall production output of each AM center (p)

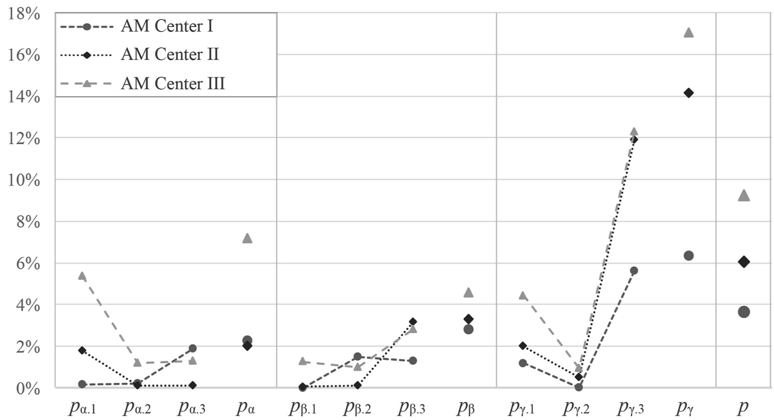

Figure 3. Estimation of the fraction nonconforming of the production output obtained through the three AM centers. Estimates are performed at the level of (1) individual quality characteristics (e.g. $p_{\alpha.1}$, $p_{\alpha.2}$, etc.), (2) single parts (i.e. p_α, p_β, p_γ) and (3) overall production output of each AM center (p)

Part typology	Approximate unitary volume and mass					
	Product unit		Support base		Total	
α	67.7 cm^3	48.6 g	2.6 cm^3	1.8 g	70.3 cm^3	m_A = 50.4 g
β	59.3 cm^3	42.5 g	2.2 cm^3	1.6 g	61.5 cm^3	m_B = 44.1 g
γ	52.4 cm^3	37.5 g	2.9 cm^3	2.1 g	55.3 cm^3	m_C = 39.6 g

Table 5. Approximate volume and mass of each typology of product unit (α, β and γ) and relevant support base

The results in Table 4 and Figure 3 show that Center III is the worst in terms of part quality for all three part typologies (α, β and γ). In particular, the gap between Center III and the first two centers is particularly evident for part α, the defectiveness being about 5 percentage points higher (i.e. 7.15% vs. 2.23% and 2.01%, respectively). Centers I and II perform similarly for parts α and β, while showing some difference for the part γ, as the fraction nonconforming of Center II is more than 1.5 times higher than that of Center I.

The AM center with lowest fraction nonconforming of overall production is Center I (3.62%), followed by Center II (6.02%) and then Center III (9.22%). Center I's supremacy is probably due to the use of a new-generation FDM system, with increased production capacity and quality of production output. In the light of these results, it would be appropriate for production managers to ensure that Centers II and III reach the quality levels of Center I, taking the latter as a benchmark.

4. Conclusions

This paper proposed an operational methodology to compare distributed AM centers, characterized by job-by-job productions with similarities in terms of parts produced, quantities produced and production mix. The comparison is conducted by analyzing the AM centers from the point of view of the quality of production, intended as capability to meet the product specifications imposed by costumers. In detail, the proposed methodology makes it possible to estimate the fraction nonconforming of each AM center, at the level of (1) individual quality characteristics, (2) individual product typologies and (3) overall production. Providing a synthetic picture of the quality performance of the AM centers being compared, it can also be useful to guide potential improvement actions (Maisano *et al.*, 2020). The operational methodology was then exemplified in a real-world case study of an industrial company producing automotive tool components in three distributed AM centers.

A distinctive feature of the proposed analysis is that it does not require any *ad hoc* experimental testing. Only a preliminary sampling of (part of) the actual production of each AM center is required. Afterward, relevant quality characteristics of the sampled parts have to be measured. In the case study, dimensional quality characteristics were measured using a CMM; however, the proposed methodology can be adapted to other types of quality characteristics (e.g. microhardness, surface roughness, residual stresses).

The proposed methodology is quite general as it can be applied to benchmark a plurality of AM centers, with different production volumes and mixes. The application to the specific case study exemplified a possible quality assessment and ranking of three "competing" AM centers. Since these results refer to the specific typologies of products analyzed, with their respective specifications and production mix, they do not necessarily have general validity. By changing the typology of parts and therefore their structural, geometric and constructional characteristics, the quality performance of AM centers can change.

This research has several practical implications. By applying the proposed methodology, companies with several distributed AM centers can make more structured evaluations and comparisons in terms of quality performance. The proposed methodology may also guide management in assigning rewards to leading centers and stimulate performance improvement in others. In addition, it can help implement ambitious plans such as zero waste, zero-defect manufacturing or the achievement of sustainable development goals (Psarommatis *et al.*, 2020; Verna *et al.*, 2021).

Some limitations to the proposed methodology are summarized below:

(1) The production mix of each AM center is assumed to include products with similar geometry (i.e. volume, height, etc.) and constructional characteristics (i.e. typology of material, infill strategy/density and deposition path).

(2) The quality characteristics of each part typology are assumed to follow a multivariate normal distribution. Although this assumption is relatively common in the scientific literature concerning process capability analysis, it has to be verified case-by-case.

(3) The measurement uncertainty of the instruments used to measure the quality characteristics was neglected.

(4) For the comparison between AM centers not to be far-fetched, it seems reasonable to assume that the centers themselves adopt the same production and quality control practices. This scenario is quite realistic, as companies often centralize quality assurance and planning activities, defining operational practices to be adopted uniformly in distributed manufacturing centers (Illés *et al.*, 2017).

(5) The comparison of distributed AM centers does not consider costs (e.g. cost of energy, material and labor).

Future research should take into account and overcome (at least some of) the limitations mentioned above. Additionally, the proposed quality analysis will also be extended to distributed AM productions of metal parts and will be complemented with a sustainability analysis.

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Appendix

This section contains further tables related to the quality benchmarking, concerning the real-world case study in Section 3

Measurements for part α [mm]					Measurements for part β [mm]					Measurements for part γ [mm]				
Job	Part No.	α.1	α.2	α.3	Job	Part No.	β.1	β.2	β.3	Job	Part No.	γ.1	γ.2	γ.3
1	1	34.477	18.328	0.110	1	1	48.600	24.227	0.054	1	1	14.938	28.684	0.125
1	2	34.485	18.438	0.116	1	2	48.626	24.321	0.140	3	2	15.002	28.584	0.077
1	3	34.519	18.405	0.101	1	3	48.597	24.215	0.038	3	3	14.984	28.657	0.068
1	4	34.495	18.370	0.082	2	4	48.604	24.294	0.076	3	4	14.999	28.669	0.131
1	5	34.461	18.441	0.141	2	5	48.609	24.324	0.117	3	5	14.948	28.568	0.051
1	6	34.505	18.438	0.103	2	6	48.589	24.307	0.070	3	6	14.997	28.627	0.136
1	7	34.431	18.478	0.144	2	7	48.650	24.269	0.107	3	7	14.985	28.650	0.104
1	8	34.461	18.392	0.117	2	8	48.629	24.341	0.134	3	8	14.957	28.647	0.092
2	9	34.529	18.307	0.029	2	9	48.645	24.204	0.014	3	9	14.953	28.636	0.147
2	10	34.490	18.388	0.068	2	10	48.658	24.256	0.081	3	10	14.954	28.662	**0.166**
2	11	34.552	18.440	0.119	2	11	48.577	24.244	0.032	3	11	14.950	28.617	0.095
4	12	34.494	18.475	0.157	2	12	48.538	24.313	0.044	4	12	14.989	28.590	0.052
4	13	34.447	18.379	0.080	3	13	48.647	24.206	0.046	4	13	15.014	28.607	0.070
4	14	34.523	18.409	0.118	3	14	48.698	24.304	0.049	4	14	15.017	28.640	0.086
4	15	34.529	18.351	0.120	5	15	48.578	24.286	0.076	4	15	14.957	28.614	0.085
4	16	34.508	18.363	0.058	5	16	48.626	24.221	0.041	4	16	15.028	28.614	0.092
4	17	34.455	18.314	0.039	5	17	48.622	24.286	0.075	5	17	14.914	28.609	0.144
4	18	34.506	18.393	0.081	5	18	48.605	24.320	0.070	5	18	15.051	28.592	0.002
5	19	34.486	18.377	0.058	5	19	48.582	**24.142**	0.036	5	19	14.986	28.652	0.083
5	20	34.498	18.378	0.085										
5	21	34.461	18.335	0.037										

Table A1.
Dimensional measurements related to the quality characteristics of the parts produced in AM Center I. The values highlighted in gray do not meet the corresponding specification limits (cf. Table 1)

Measurements for part α [mm]					Measurements for part β [mm]					Measurements for part γ [mm]				
Job	Part No.	α.1	α.2	α.3	Job	Part No.	β.1	β.2	β.3	Job	Part No.	γ.1	γ.2	γ.3
1	1	34.442	18.388	0.024	1	1	48.500	24.306	0.041	1	1	15.037	28.579	0.065
1	2	34.462	18.400	0.058	1	2	48.567	24.169	0.007	1	2	15.039	28.492	0.074
2	3	34.456	18.377	0.083	1	3	48.628	24.368	0.129	1	3	14.980	28.579	0.021
2	4	34.469	18.382	0.043	1	4	48.650	24.234	0.074	3	4	14.991	28.616	**0.163**
2	5	34.526	18.435	0.103	3	5	48.578	24.358	0.090	3	5	15.073	28.600	0.100
2	6	34.471	18.325	0.054	3	6	48.618	24.263	0.088	3	6	14.968	28.501	0.100
2	7	34.454	18.364	0.054	3	7	48.617	24.263	0.085	4	7	15.027	28.549	0.088
2	8	34.501	18.428	0.076	4	8	48.648	24.279	0.057	4	8	14.946	28.611	0.116
2	9	34.465	18.433	0.107	4	9	48.651	24.217	0.055	4	9	14.957	28.598	**0.182**
2	10	34.443	18.375	0.072	4	10	48.600	24.275	0.104	4	10	14.968	28.552	0.074
3	11	34.514	18.381	0.116	4	11	48.598	24.235	0.082	4	11	14.996	28.569	0.126
3	12	34.493	18.311	0.008	5	12	48.627	24.225	0.069	6	12	15.032	28.626	0.132
3	13	34.522	18.433	0.105	5	13	48.636	24.284	0.070	7	13	15.083	28.485	0.042
5	14	34.470	18.278	0.000	5	14	48.650	24.156	0.007	7	14	14.979	28.600	0.148
5	15	34.533	18.346	0.035	5	15	48.660	24.234	0.036	7	15	14.986	28.554	0.058
5	16	34.457	18.376	0.043	5	16	48.636	24.179	0.047	7	16	15.053	28.575	0.097
5	17	34.417	18.366	0.086	6	17	48.612	24.299	0.098	7	17	15.033	28.558	0.106
6	18	34.415	18.372	0.061	6	18	48.659	24.230	0.102	7	18	15.063	28.497	0.111
6	19	34.447	18.337	0.051	6	19	48.624	24.322	0.100	7	19	14.973	28.580	0.062
6	20	34.474	18.378	0.075	6	20	48.559	24.206	0.016	7	20	15.018	28.631	**0.207**
7	21	34.474	18.407	0.080	6	21	48.542	24.291	0.132					

Table A2. Dimensional measurements related to the quality characteristics of the parts produced in AM Center II. The values highlighted in gray do not meet the corresponding specification limits (cf. Table 1)

Measurements for part α [mm]					Measurements for part β [mm]					Measurements for part γ [mm]				
Job	Part No.	α.1	α.2	α.3	Job	Part No.	β.1	β.2	β.3	Job	Part No.	γ.1	γ.2	γ.3
3	1	34.504	18.406	0.034	3	1	48.551	24.305	0.028	1	1	14.979	28.591	0.107
3	2	34.483	18.389	0.040	3	2	48.555	24.256	0.004	1	2	15.002	28.625	0.121
4	3	34.509	18.39	0.074	3	3	48.487	24.307	0.056	1	3	14.935	28.539	0.098
5	4	34.455	18.424	0.079	4	4	48.585	24.372	0.131	1	4	15.051	28.456	0.092
5	5	34.463	18.481	0.068	4	5	48.608	24.234	0.032	1	5	14.986	28.486	0.046
5	6	34.413	18.376	0.010	4	6	48.547	24.380	0.114	1	6	14.934	28.653	0.158
6	7	34.482	18.462	0.113	5	7	**48.441**	24.275	0.029	2	7	15.011	28.601	0.087
6	8	34.566	18.467	0.129	5	8	48.545	24.332	0.047	2	8	15.010	28.593	0.094
7	9	34.453	18.421	0.077	6	9	48.594	24.411	**0.178**	2	9	14.938	28.612	**0.175**
7	10	34.464	18.409	0.070	6	10	48.613	24.425	0.111	2	10	15.048	28.591	0.075
7	11	34.530	18.549	**0.206**	6	11	48.583	24.376	0.072	2	11	15.022	28.570	0.111
7	12	34.508	18.415	0.036	7	12	48.502	24.308	0.074	2	12	15.070	28.582	0.106
8	13	34.457	18.433	0.091	7	13	48.578	24.298	0.054	3	13	15.086	28.508	0.024
8	14	34.507	18.357	0.002	8	14	48.521	24.288	0.000	4	14	15.038	28.526	0.010
8	15	34.471	18.493	0.154	9	15	48.591	24.293	0.037	4	15	14.959	28.533	0.106
8	16	34.486	18.431	0.099	9	16	48.568	24.372	0.079	5	16	15.009	28.569	0.132
8	17	34.502	18.429	0.060	9	17	48.574	24.255	0.035	6	17	14.978	28.611	0.120
9	18	34.428	18.408	0.086	9	18	48.598	24.426	0.130	9	18	14.948	28.532	0.077
10	19	34.493	18.491	0.136	10	19	48.628	24.383	0.104	10	19	14.982	28.592	**0.174**
					10	20	48.592	24.357	0.135	10	20	14.960	28.550	0.084
										10	21	15.017	28.648	0.110

Table A3.
Dimensional measurements related to the quality characteristics of the parts produced in AM Center III. The values highlighted in gray do not meet the corresponding specification limits (cf. Table 1)

Table A4. Results of applying the Anderson–Darling normality test to the data reported in Tables A1–A3, regarding the quality characteristics of the parts produced by each AM center

	(a) AM Center I					(b) AM Center II					(c) AM Center III				
	Mean	St.Dev.	N	AD	p-value	Mean	St.Dev.	N	AD	p-value	Mean	St.Dev.	N	AD	p-value
$\alpha.1$	34.49	0.031	21	0.188	0.891	34.47	0.033	21	0.443	0.259	34.48	0.036	19	0.228	0.783
$\alpha.2$	18.39	0.049	21	0.240	0.745	18.38	0.041	21	0.436	0.270	18.43	0.047	19	0.397	0.335
$\alpha.3$	0.093	0.036	21	0.295	0.563	0.064	0.032	21	0.180	0.903	0.082	0.050	19	0.259	0.676
$\beta.1$	48.61	0.036	19	0.203	0.856	48.61	0.042	21	0.736	0.046	48.56	0.046	20	0.607	0.099
$\beta.2$	24.27	0.053	19	0.462	0.230	24.26	0.057	21	0.178	0.908	24.33	0.059	20	0.410	0.312
$\beta.3$	0.068	0.035	19	0.547	0.138	0.071	0.036	21	0.251	0.707	0.073	0.049	20	0.390	0.349
$\gamma.1$	14.98	0.004	19	0.301	0.545	15.01	0.041	20	0.404	0.323	15.00	0.044	21	0.223	0.801
$\gamma.2$	28.63	0.032	19	0.187	0.891	28.57	0.045	20	0.564	0.125	28.57	0.051	21	0.263	0.665
$\gamma.3$	0.09505	0.040	19	0.298	0.551	0.104	0.047	20	0.201	0.863	0.100	0.042	21	0.440	0.264