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ORIGINAL ARTICLE

A structured comparison of decentralized additive manufacturing centers based on quality and sustainability

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Abstract
Companies are increasingly adopting decentralized manufacturing strategies to manage multiple, geographically scattered manufacturing centers that are characterized not only by similar types of equipment, working methods, and productions, but also by variable mixes and volumes. This trend also applies to additive manufacturing, a well-established technology that allows the flexibility and customization of production to be increased, without significantly increasing the per unit cost. Thus, the need arises to monitor the performance of individual centers in a structured way, and to make practical comparisons of such centers. However, achieving this task is not so straightforward, given the inevitable differences in the characteristics of manufacturing centers and their productions. This paper presents a methodology that can be used to analyze and compare the production performance of a plurality of manufacturing centers from two different viewpoints: (*i*) quality, through a multivariate statistical analysis of product data concerning conformity with geometrical specifications, and (*ii*) process sustainability, with the aim of achieving a reduction in energy consumption, carbon dioxide emissions, and manufacturing time, through regression models pertaining to the selected metrics. The proposed methodology can be adopted during regular production operations, without requiring any ad hoc experimental tests. The description of the method is supported by an industrial case study.

Keywords Decentralized manufacturing · Additive manufacturing · Sustainable manufacturing · Quality · Product specifications · Energy consumption

1 Introduction

In today's highly competitive global marketplace, more and more companies of all sizes are adopting decentralized manufacturing solutions [1–3]. The main advantages of such solutions are flexibility, proximity with the customers, more accurate/timely information, highly customized products, and a greater both quantitative and qualitative adaptability to fluctuations in demand [4, 5]. On the other hand, decentralized manufacturing suffers from some weaknesses, such as the need of larger capital investments to set up multiple production facilities, reduced exploitation of economies of scale, higher per unit costs, and greater complexity of the coordination and management of production processes than traditional centralized manufacturing. Nevertheless, the ongoing technological growth contributes to making the arguments in favor of decentralized manufacturing prevail over those against it [6]. One of the most important emerging technologies in the last few decades is additive manufacturing (AM), a process which makes it possible to achieve high levels of customization, and which marks the epochal transition from the so-called "mass production" to "job production", also defined as "mass customization" [7].

The present research considers AM processes from the realistic perspective of companies that have to manage/coordinate a plurality of similar, though not identical, decentralized AM centers. Such centers may include, for example, similar types of equipment although with (*i*) different technological solutions (e.g., heated/cooled chambers/plates, deposition technology), (*ii*) different work parameters (e.g., layer thickness, infill patterns/densities, deposition rates), and/or (*iii*) different materials (for either the parts or the

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support bases) and different feedstock suppliers [8, 9]. Additionally, AM centers manufacture product units with similar (geometrical and structural) characteristics, even though they may often be of different quantities and/or production mixes, depending on the local demand [6, 10, 11]. In such a scenario, a company may need to monitor and compare the production performance of its individual AM centers from multiple perspectives, including (*i*) the quality of the manufactured products, in terms of conformity with specifications, and (*ii*) the sustainability of both the products and processes. The former aspect refers to the ability of individual AM centers to manufacture products with the required characteristics. As for the latter aspect, the three (environmental, economic, and social) pillars of sustainable development should be considered and balanced simultaneously [12]. Among others, the energy efficiency of the unit processes, the cumulative energy demand, and the related carbon dioxide emissions, as well as the productivity and the financial costs, are all factors of influence that are important for comparative analyses concerning industrial manufacturing approaches [13].

Analyzing the quality and sustainability of the production of decentralized AM centers may be useful for (at least) three practical reasons: (*i*) to assess the "state of health" of individual AM centers, (*ii*) to facilitate comparisons (in relative terms) between different AM centers, in order to show their strengths and/or weaknesses, and (*iii*) to stimulate the improvement of each AM center by identifying and sharing the most successful solutions. However, conducting the above evaluations in a structured and rigorous way is not so straightforward, because of the inevitable differences that exist among decentralized AM centers, not only in terms of manufacturing equipment but also in terms of the quantitative characteristics (i.e., production quantity, geometric/functional characteristics) and of the qualitative ones (i.e., production mix) of the production output.

1.1 Research gaps and the aim of the paper

Additive manufacturing technologies have received increasing attention from both academic and industrial communities in the last few decades. AM processes offer the particular features of being able to produce components in an additive way by depositing material layer by layer, together with their digital nature. Hence, customized and complexity-for-free parts can be produced within a new production paradigm that is characterized by decentralized manufacturing, with different impacts on time and energy consumption from those of conventional industrial contexts. The technological, environmental, and economic outcomes resulting from the employment of AM processes are still fields of investigation.

On the one hand, the importance of monitoring the quality of AM processes has grown, as evidenced by the numerous papers and extensive reviews on the subject [14, 15]. Apart from the research on the development of in situ monitoring systems for defect identification, numerous assessments were aimed at analyzing the quality of AM production using statistical process control techniques and process capability analyses. For example, Günay et al. [16] focused on the reproducibility issue of a polymer-based AM technology, identified the optimal process parameters, and analyzed the capability of the process to achieve repeatable minimum deviations from the target dimensions. Udroiu and Braga [17] proposed a methodology for the analysis of system and process capabilities in a polymer-based AM technology, using statistical quality tools for production management (i.e., the Gage R&R methodology and process capability analysis).

Many other studies have instead focused on the sustainability of AM processes, approaching this subject from different viewpoints, i.e., from the environmental, economic, and/or social perspectives. Among the many studies on this topic, the one by Taddese et al. [18] proposed a literature review of AM sustainability performance indicators based on product life cycle assessments. Kadir et al. [19] focused on the economic sustainability of AM production by proposing a classification review of cost estimation models. Niaki et al. [20] explored the key determinants for the adoption of additive manufacturing, while considering the economic, environmental, and social motive roles in the decision-making field. AM processes have also been assessed from a sustainability perspective within comparative frameworks involving traditional manufacturing processes. For example, Priarone et al. [21] compared wire arc additive manufacturing (WAAM)-based integrated additive/subtractive manufacturing approaches with conventional machining, considering such metrics as the cumulative energy demand, CO_2 emissions, the manufacturing time, and product cost, as well as the mechanical performance of the materials. Jiang et al. [22] focused on a comparison between laser-based additive manufacturing and CNC machining through an energy-based life cycle assessment methodology.

Therefore, although several studies have investigated either (*i*) the quality of the components made by means of AM or (*ii*) the process sustainability, a methodology that combines both these aspects is still lacking in the literature. In fact, only a few studies have assessed quality, efficiency, and sustainability in AM production in a combined way. Camposeco-Negrete [23] and Galetto et al. [24] carried out the optimization of quality and sustainability outputs of products made by means of the fused deposition modeling (FDM) technology, employing design of experiments (DoE) and statistical analyses for this purpose. A structured methodology which not only combines quality- and sustainability-related aspects pertaining to a single AM center but which also enables the performance evaluation and a comprehensive comparison of different decentralized AM centers is needed. The present paper aims to contribute to filling this research gap. Quality is here assessed through a multivariate statistical analysis on the conformity of different types of products, considering multiple quality characteristics to estimate the nonconforming fraction of the production output of individual production centers. As far as process sustainability is concerned, the environmental impact of AM centers is evaluated considering their energy demand and the related equivalent carbon dioxide emissions (CO_2) [25]. The latter indicator could affect both the decision-making and marketing strategies, considering the growing attention to global warming and resource depletion [26, 27]. A particular feature of the proposed analysis is that it does not require any ad hoc experimental tests, but is based solely on information collected directly during regular production processes. Furthermore, apart from the metrics assumed here for practical and explanatory purposes, the methodology presented in this paper can easily be extended to consider other economic and environmental impact categories. The remainder of this paper is organized in five sections. Section 2 presents a real-life case study of a company specialized in the design and manufacturing of automotive tooling components, which are produced in several decentralized AM centers. The description of the proposed methodology focuses on the case study to exemplify its application. Section 3 contains a quality analysis, which is based on a multivariate statistical approach to estimate the conformity of the products in each AM center. Section 4 details the analyses on the energy requirements, carbon dioxide emissions, and manufacturing times. A practical tool to synthesize quality and sustainability, and which results in a holistic and structured framework, is proposed in Sect. 5. The conclusions are summarized in Sect. 6, where the practical implications and limitations of the approach are specified, as well as insights for future research. The Appendix section provides further information on the achieved results to deepen the discussion.

2 Case study

A company specialized in the design and manufacturing of a variety of tooling solutions for the automotive industry, such as inspection fixtures, and production and assembly jigs, was considered. These kinds of products can be used as support tools, both for design/prototyping and in the production/assembly phases [28]. Figure 1 shows three fixtures with different geometries (labeled “Part A”, “Part B”, and “Part C” hereafter) that were assumed as the case study for the purposes of this research.

These components, which are used to facilitate the correct positioning of bent-sheet metal automotive components during various in-line tests and assembly operations, have overall dimensions of a few centimeters. The nominal volumes of the three fixtures are of the same order of magnitude (as detailed hereafter), although their precise geometries are not disclosed for confidentiality reasons. Each part type is characterized, among others, by three quality characteristics – i.e., features that are critical for functionality of the product [29] – with

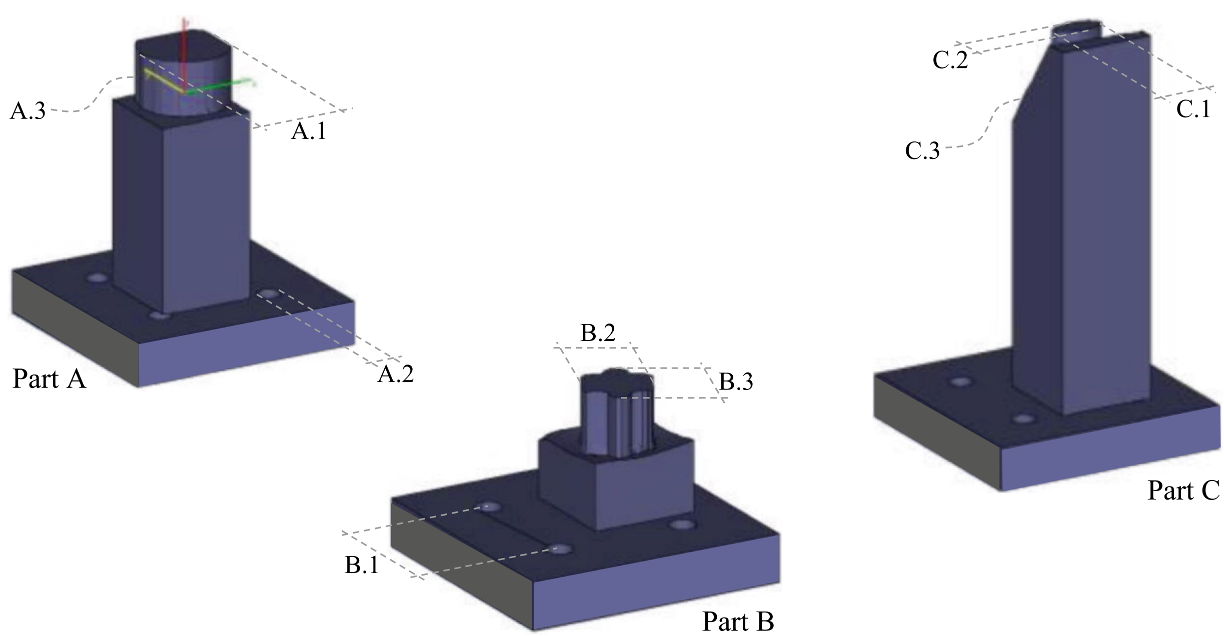

Fig. 1 Three fixtures used in the automotive industry as support structures during assembly and/or dimensional inspection, with their related quality characteristics

Table 1 Geometric quality characteristics of the components (labeled as “Part A”, “Part B”, and “Part C” in Fig. 1)

	Code	Type	Description	NV	LSL	USL
Part A	A.1	Dimensional	External diameter of the pin (mm)	10.00	9.85	10.15
	A.2	Dimensional	Internal diameter of a reference hole (mm)	5.00	4.90	5.10
	A.3	Form	Cylindricity of the pin (mm)	-	-	0.15
Part B	B.1	Dimensional	Spacing between two reference holes (mm)	25.00	24.85	25.15
	B.2	Dimensional	Pin thickness considering the two opposite flat surfaces (mm)	18.50	18.35	18.65
	B.3	Dimensional	Pin width considering the two opposite rounded surfaces (mm)	15.00	14.88	15.12
Part C	C.1	Dimensional	Width of the major axis of the elliptical pin (mm)	10.00	9.88	10.12
	C.2	Dimensional	Width of the minor axis of the elliptical pin (mm)	5.00	4.88	5.12
	C.3	Orientation	Flatness of the inclined surface (mm)	-	-	0.16

the relevant specifications. The quality characteristics for part A are A.1, A.2, and A.3, while those for part B are B.1, B.2, and B.3, and those for part C are C.1, C.2, and C.3. Table 1 collects the nominal values (NV), as well as the lower and upper specification limits (LSL and USL) for each quality characteristic. In general, the specification ranges are not very stringent since they are of the order of a few tenths of a millimeter.

Some other technical requirements that characterize the production of the fixtures are as follows:

- The parts must be produced with a variable production mix that changes according to the customers’ demands. For instance, a production order characterized by a few dozen total product units could be placed every 48 h with a variable mix (e.g., four type A parts, three type B parts, three type C parts).
- The parts do not have any particular structural property, as they are mainly used as baselines for the correct positioning of specific automotive components during assembly/inspection operations.
- The parts, being in contact with metallic automotive components, should be made of a softer material to prevent scratching the components themselves.

In line with the above requirements, the company decides to produce the fixtures by means of dedicated AM processes, using acrylonitrile butadiene styrene (ABS) polymeric material. The production of the parts takes place in three different decentralized centers, using three different AM machines, the details of which are not disclosed for confidentiality reasons and which are here referred to as “Machine X”, “Machine Y”, and “Machine Z”. The three AM centers adopt the same technology, i.e., fused deposition modeling (FDM), although there are some equipment-related differences (e.g., concerning the dimension of the plate surfaces and build volumes, the cold/heated plates, the cold/heated chambers, the extrusion-head purge operations). However, to ensure a certain uniformity of the manufactured products, all the machines are fed with filaments of (namely) the same material. Moreover, two variants of the material are used to facilitate the manual separation of the support bases from the parts (after production). Similar process parameters are set on the three machines: e.g., the layer thickness is within the 180 to 200 μm range, the infill density is from 40 to 45%, and a “sparse” infill pattern was chosen. The corresponding mass of each part (i.e., net mass), and the additional mass of the support bases, may differ slightly from AM center to center, due to the inevitable differences between the machines and their operating parameters [30]. Conventionally, the gross mass is here defined as the sum of the net mass (of the component) and the mass of the support bases. The nominal mass values were estimated using a dedicated software application for each of the three machines, according to the geometries of the parts being manufactured. The production of each AM center was monitored and sampled for a certain period to collect a certain number of product units, i.e., about twenty for each part type. Table 2 contains some synthetic data related to the sampled productions. Experienced technicians supervised the production processes during the data collection to verify their regular functioning and the absence of accidents/malfunctions or any systematic faults [29]. Table 2 highlights that the production of each AM center is organized into several jobs, each of which contains a certain mix of parts A, B, and C; this aspect is explained in more detail in Sect. 3. Furthermore, the number of units produced in each job may vary from machine to machine, as the number is related to the dimensions of the plate surface. For example, Machine X can produce up to twelve fixtures per job, about twice as many as Machine Z, while Machine Y has an intermediate capacity. Data concerning (*i*) conformity with the specifications (listed in Table 1) and (*ii*) energy and time consumption were collected during the job-by-job production. These data are used for the quality and process sustainability analyses in the following two sections.

Table 2 Job-by-job sampled production of each AM center. The mix of parts produced (type and number) is reported for each job

Job	Machine X				Machine Y				Machine Z			
	A	B	C	Row tot	A	B	C	Row tot	A	B	C	Row tot
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
Col. total	21	19	19	59	21	21	20	62	19	20	21	60

3 Quality analysis

In line with the general definition of quality — i.e., the "degree to which a set of inherent characteristics of an object fulfils the requirements" [31] — the quality of a generic manufacturing process is here understood as the "ability to produce products that meet the relevant specifications". The case study of interest considers distinct AM centers that produce the same types of products, albeit in different quantities and mixes. In general, each AM center represents a unique combination of three factors:

- Production machines/equipment and corresponding process parameters.
- Feedstock materials with specific characteristics.
- Operators and relevant working practices.

These factors contribute to generating variability in the production output, here meant as the "inability to produce identical production units" [29]. Variability is classified as "natural" when referring to a manufacturing process that operates regularly, that is, without anomalies that can be systematically ascribed to at least one of the above three factors (e.g., machine failures, imperfect materials, or human errors). In the presence of accidents or anomalies, this variability tends to increase as does the propensity to produce products that do not comply with the specifications [29]. However, this does not mean that processes governed exclusively by natural variability cannot generate nonconforming products. In fact, this depends on how stringent the specifications are with respect to the corresponding natural variability. This section proposes a methodology to qualitatively assess the degree of "compatibility" of different decentralized manufacturing processes with their corresponding productions. Scientific literature has dealt with this problem in a very extensive and in-depth manner, within the so-called process capability analysis [32, 33]. The proposed methodology is inspired by some popular approaches, although it has been ad hoc built with reference to the problem of interest. In detail:

1. The production of each manufacturing center is divided into jobs, in which product units of various types (parts A, B, and C) are produced simultaneously. A job can be defined as "an elementary production run that generates a 'macro-product,' that is given by the composition of product units of various types, according to the customers' demands" [34].
2. Each part type has a plurality of quality characteristics, with their relevant specifications. In the case study, each part type has three geometric quality characteristics, with their respective specifications (Table 1).
3. The jobs may vary, according to the current demand, in terms of (*i*) the total number of parts and (*ii*) the corresponding assortment (subdivided into various part types).
4. The capacity of each AM center should be saturated as much as possible, job by job, to reduce the production times and costs. However, the number of products that have to be manufactured in a certain job naturally depends on the geometric characteristics of the machine (e.g., on the dimension of the plate surface) and of the parts.

In short, the proposed methodology includes two macro-phases, which are detailed in the following two subsections: (*i*) collection of the production data and (*ii*) determination of the quality-related data.

3.1 Collection of the production data

For convenience and economic reasons, the data collection can be carried out during regular production operations, without requiring any ad hoc experimental tests. A

Table 3 Mean values and covariance matrices related to the data reported in Tables 9, 10, and 11 (in Appendix 1).

Machine X												
Geometric quality characteristic		Part A				Part B				Part C		
		A.1	A.2	A.3		B.1	B.2	B.3		C.1	C.2	C.3
Mean values		9.978	5.012	0.054		25.033	18.469	14.929		9.976	5.012	0.083
		A.1	A.2	A.3		B.1	B.2	B.3		C.1	C.2	C.3
Covariance matrix	A.1	0.0032	0.0002	0.0005	B.1	0.0012	0.0005	0.0002	C.1	0.0013	0.0005	0.0000
	A.2	0.0002	0.0023	0.0003	B.2	0.0005	0.0012	0.0003	C.2	0.0005	0.0008	0.0000
	A.3	0.0005	0.0003	0.0004	B.3	0.0002	0.0003	0.0004	C.3	0.0000	0.0000	0.0008
Machine Y												
Geometric quality characteristic		Part A				Part B				Part C		
		A.1	A.2	A.3		B.1	B.2	B.3		C.1	C.2	C.3
Mean values		10.044	5.001	0.086		24.951	18.540	15.048		10.030	4.993	0.093
		A.1	A.2	A.3		B.1	B.2	B.3		C.1	C.2	C.3
Covariance matrix	A.1	0.0020	-0.0001	0.0012	B.1	0.0028	-0.0005	-0.0007	C.1	0.0013	0.0010	-0.0003
	A.2	-0.0001	0.0027	-0.0002	B.2	-0.0005	0.0017	0.0011	C.2	0.0010	0.0017	-0.0002
	A.3	0.0012	-0.0002	0.0013	B.3	-0.0007	0.0011	0.0015	C.3	-0.0003	-0.0002	0.0012
Machine Z												
Geometric quality characteristic		Part A				Part B				Part C		
		A.1	A.2	A.3		B.1	B.2	B.3		C.1	C.2	C.3
Mean values		10.000	5.027	0.076		25.043	18.470	14.975		10.032	4.971	0.048
		A.1	A.2	A.3		B.1	B.2	B.3		C.1	C.2	C.3
Covariance matrix	A.1	0.0021	0.0010	0.0008	B.1	0.0029	0.0002	0.0001	C.1	0.0016	0.0008	0.0007
	A.2	0.0010	0.0021	0.0004	B.2	0.0002	0.0009	0.0005	C.2	0.0008	0.0012	0.0003
	A.3	0.0008	0.0004	0.0006	B.3	0.0001	0.0005	0.0007	C.3	0.0007	0.0003	0.0014

fundamental requirement is to ensure that production takes place in the absence of any kind of accident/anomaly; otherwise, the whole analysis will be distorted. To this aim, it is appropriate that technicians and operators with in-depth experience carefully monitor the manufacturing process during the data collection. A job-by-job production of each AM center can then be carried out. Sampling continues until an adequate quantity of production units has been collected, indicatively at least fifteen/twenty units are necessary for each part type. This amount of data is considered acceptable for the proposed statistical analysis. Of course, increasing the number of collected units would increase the accuracy of the statistical analysis, but also the corresponding cost [29]. Table 2 shows details about the job-by-job configurations related to the production carried out in the three AM centers considered in the case study. Machine X, which has the widest plate, can produce about a dozen units per job. On the other hand, Machine Z is in the smallest AM center since, having a roughly halved capacity, it requires about twice as many jobs to produce a similar overall output. Subsequently, parts of the same type are aggregated independently of the jobs in which they were produced at each AM center. This aggregation is reasonable under the assumption (which should be verified) that the job factor has no systematic effects.

Finally, the quality characteristics of each part type are measured. For this purpose, it is convenient to use a relatively accurate measuring instrument, whose measurement uncertainty is negligible with respect to the variability of the quality characteristics that have to be measured. If this is not possible, the measurement uncertainty should be estimated carefully, and thus could make the analysis more complicated. Since parts are produced through AM processes based on FDM technology, the intrinsic variability of the dimensional quality characteristics is of the order of one-tenth of a millimeter (Table 1). In the present case, the quality characteristics have been measured using a DEA Global Image coordinate measuring machine (CMM), which has a maximum permissible error (MPE) of 3 μm, i.e., about two orders of magnitude lower than the intrinsic variability of the measurands [35]. A measurement cycle is constructed for each part type and performed automatically. In order to obtain a more accurate estimate and to avoid possible measurement errors, three replicated measurements are made for each quality characteristic and then aggregated considering the arithmetic mean. The measurement results for each AM center are reported in Tables 9, 10, and 11 (in Appendix 1), respectively.

The box plot in Fig. 2 shows that the job factor does not seem to determine any systematic differences in quality characteristic A.1, with reference to the parts produced by Machine X: in fact, the four boxes related to the four jobs overlap each other [36]. The same result can be extended to all the quality characteristics of all the different types of parts produced by any AM center, thus justifying the previous assumption.

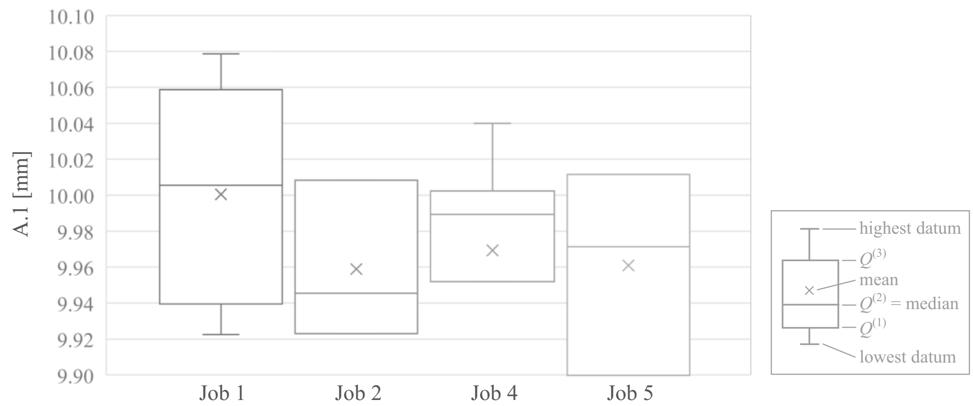

Fig. 2 Box plot of quality characteristic A.1 related to the type A parts produced by Machine X (see the data in Table 9 in Appendix 1)

3.2 Quality-related data

The proposed analysis is based on a hypothesis that is commonly adopted in multivariate process capability analysis, i.e., that the quality characteristics related to the same product can be modeled as correlated random variables, distributed according to a normal multivariate distribution [36–40]. Considering the case study, Anderson–Darling (AD) normality tests, related to the individual quality characteristics of each product type and AM center, do not contradict this hypothesis (see the data in Table 12 in Appendix 1). Using a sample of collected measurements, it is possible to estimate the parameters of the relevant normal multivariate distributions. Precisely, (*i*) the vector of the mean values and (*ii*) the covariance matrix of the quality characteristics can be estimated for each product type and AM center. Although the mean and covariance of the sample are unbiased estimators of the mean and covariance of the process, the sample variance is a biased estimator of the process variance, since it systematically underestimates it [36]. This bias can be corrected through the c_4 parameter — cf. Cochran's theorem [41] — which depends on the size (n) of the sample of measurements used to determine the sample variance and is available from the scientific literature [29, 42]. The unbiased estimates of the multivariate normal distribution parameters are defined in Eq. 1,

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

where n is the size of the sample selected to estimate the process parameters; "^" is the "hat" operator, which denotes the estimates of the process parameters; $\hat{\mu}_x$ is the estimate of the mean value of the generic quality characteristic x, through the sample mean; s_x is the standard deviation of the sample which, after being corrected using the c_4 parameter, provides an unbiased estimate of the process standard deviation of x (i.e., $\hat{\sigma}_x$); and $\widehat{cov}(x, y)$ is the sample covariance between two generic quality characteristics x and y.

Returning to the case study, Table 3 lists the estimated mean values and covariance matrices related to the quality characteristics of each part type for each manufacturing center. It is interesting to notice that the quality characteristics related to the same part type are often correlated. For example, with reference to Machine Y, quality characteristics B.1 and B.3 are negatively correlated — i.e., cov(B.1, B.3) = -0.0007, which corresponds to a Pearson correlation coefficient $\rho_{B.1,\ B.3} = -36.9\%$ [36] — while quality characteristics B.2 and B.3 are positively correlated, i.e., cov(B.2, B.3) = 0.0011, and correspond to a Pearson correlation coefficient $\rho_{B.2,\ B.3} = 69.2\%$. The above parameters make it possible to reconstruct the normal multivariate distributions, which describe the quality characteristics of each part type for each AM center. The next step is to estimate the fraction of nonconforming products (p) produced by the AM centers, comparing the normal multivariate distributions with the respective specifications. A preliminary estimate of the nonconforming fraction, from the one-and-only-one quality characteristic perspective, can be obtained by integrating the univariate normal distribution of the quality characteristic with the two "tails" beyond the relevant specification limits (LSL and USL[1]). Only the right tail was considered for quality characteristics A.3 and C.3, which have one-sided specifications that are only given by USL.

Next, the overall fraction of nonconforming products (i.e., the fraction of parts that do not meet at least one of the corresponding quality characteristics) can be estimated by integrating the normal multivariate distribution externally

[1] For example, the nonconforming fraction related to quality characteristic A.1 for type A parts manufactured by Machine X can be determined as $p_{A.1} = P(x_{A.1} < LSL_{A.1}) + P(x_{A.1} > USL_{A.1}) = 0.58\%$.

with respect to the hyper-rectangular region delimited by the specification limits of the respective quality characteristics. Considering the present case study, a Monte Carlo numerical integration has been carried out for each part type and each machine, thus generating 10,000 multivariate random realizations of some variables, which are compatible with the respective mean value vectors and covariance matrices. The "*Calc>Random Data>Multivariate Normal Distribution*" function of Minitab [43] was used for this purpose. The results of the integration are shown in Table 4 and Fig. 3. The overall nonconforming fractions of a certain AM center and a certain part type (e.g., A) are systematically lower than the sum of the nonconforming fractions related to the respective quality characteristics (e.g., $p_A < p_{A.1} + p_{A.2} + p_{A.3}$); this is not surprising, since the individual quality characteristics are not statistically independent of each other (see the covariance matrices in Table 3). With reference to the specific case study (see the data in Table 4), Machine X is in the AM center with the lowest nonconforming fraction values, while Machine Y is in the AM center with the highest ones. This result is even more evident when considering a synthetic indicator associated with the entire production of a certain AM center (Eq. 2),

$$p = \frac{\sum_{i \in \{A,B,\dots\}} p_i \cdot (w_i \cdot m_i)}{\sum_{i \in \{A,B,\dots\}} (w_i \cdot m_i)}, \tag{2}$$

where m_i is the mass of material of the i-th part type, manufactured by the AM center of interest. This mass can be classified as *net* as it does not include the additional material for the support bases or for the purge operation of the extrusion-head. This additional material is not taken into account since (*i*) it is not part of the finished product, (*ii*) it is destined to be scrapped, and (*iii*) its mass can vary significantly, depending on the construction strategy adopted by each AM center (e.g., infill pattern, infill density); w_i is an indicator of a portion of i-th type products for a given production mix (e.g., w_A=1/3, w_B=1/2, w_C=1/6).

Equation 2 can be interpreted as a weighted sum of the p_i values, with respect to the net masses of the products, related to each part type. This kind of weighting is necessary since the production mix may change from AM center to AM center. Additionally, p can be seen as the ratio between the estimated mass of the nonconforming products and the net total mass produced by a certain manufacturing center. A uniform production mix has here been considered for each manufacturing center: w_i=1/3 $\forall i \in \{A, B, C\}$; the m_i values are estimated as a function of the AM system and are reported in the last columns of Table 5. The resulting p values (which are shown in the last row of Table 4 and in the graph of Fig. 3) confirm that Machine X has the lowest p value, while Machine Y has the highest one. On the other hand, Machine Y has greater net masses (of around 10%), but lower masses for the support bases (around 25–30%).

The results of the quality analysis show relatively pronounced differences between the AM centers, in terms of dimensional accuracy. Since these centers manufacture similar parts using similar materials (Sect. 2), it is not trivial to justify these differences. They are likely attributable to the different characteristics of the machines/equipment and the slightly different process parameters [44]. Overall, it is worth noting that the results of the quality analysis refer to the specific types of analyzed products, with their respective specifications and production mix; these results do not necessarily have a general validity.

4 Process sustainability analysis

The concept of sustainability of a manufacturing process is broad and has several practical implications, ranging from the need to reduce the consumption of raw materials,

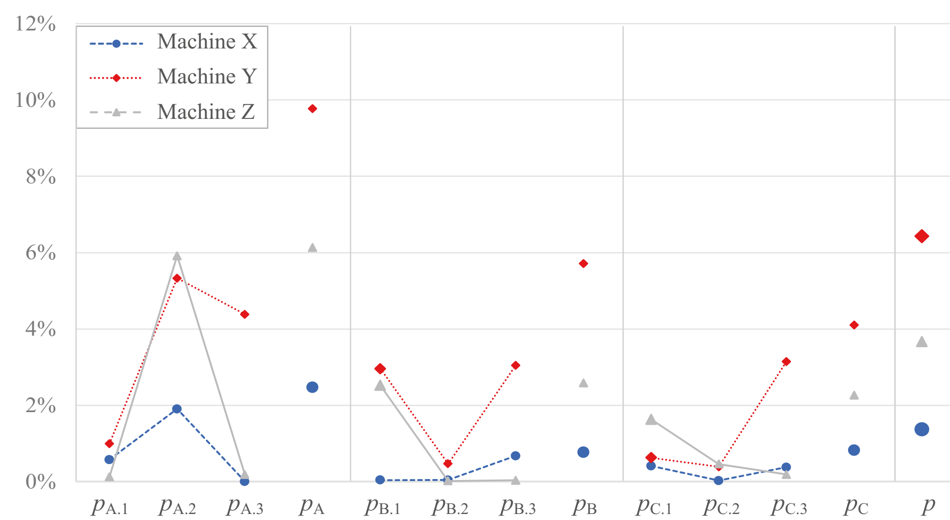

Fig. 3 Estimation of the nonconforming fraction of the production output related to the three AM centers at the level of (*i*) the individual quality characteristics (e.g., $p_{A.1}$, $p_{A.2}$), (*ii*) the single parts (e.g., p_A, p_B, p_C), and (*iii*) the overall production output (p)

energy, resources, and water, to the selection of convenient end-of-life strategies, with the maximization of the recycling/reuse of the products and/or components [45, 46]. As already introduced in Sect. 1, this study proposes a simplified sustainability analysis of the process, which focuses on the electric energy consumption and manufacturing time. The first metric that was chosen is the specific energy consumption, as it is one of the major concerns of AM processes [47]. The latter is closely related to process productivity. Moreover, in addition to the metrics that can be measured directly in the field, the equivalent carbon dioxide emissions related to the electricity consumption of the AM centers are also estimated by assuming an average value of 0.286 kg/kWh for EU28, according to indications of the European Environmental Agency [26]. The sustainability analysis of the process relies on the production of the samples already examined in the quality analysis (in Sect. 3). To implement the methodology, the following data have to be measured (or estimated), per each produced job (Table 2):

1. *Energy consumption*. The electric energy demand has to be monitored during the production phase, in which the layer-wise deposition of the material takes place, as well as during the preceding (i.e., setting-up/warm-up of the machine) and following operations (i.e., removal of the finished products and plate cleaning).
2. *Manufacturing time*. The total duration of each job has to be timed taking into account both the operational and stationary/idling modes (the manual operations should also be included).
3. *Feedstock material flow*. The material consumption has to be quantified by weighing the total mass of the production output, i.e., using a weight scale with a measurement uncertainty of the order of a tenth of a gram.

The total deposited mass (i.e., *gross* mass) is computed while accounting for both the *net* mass and the mass of the support structures (to be scrapped). The mass of the wasted material from the extrusion-head purge operation should also be included, although this contribution is generally negligible, compared to the previous two ones [25]. As already documented in Table 5, the different AM centers are characterized by a certain heterogeneity of the mass needed for the support bases, even when considering the same types of manufactured parts. In general, machines that minimize the input/output material ratios are preferable from the sustainability viewpoint. This aspect is taken into account in the following analysis (in Sect. 5). The data are summarized in Table 6. It is not surprising that the masses corresponding to the three total productions are close to each other, since the productions themselves are also similar (see the row labeled “Col. sums” in Table 6). On the other hand, relevant differences among the AM centers can be observed, in terms of both total energy consumption and manufacturing time (see the “Col. sums” row in Table 6).

Regardless of the AM center, some common aspects can be highlighted:

- Although the mix of manufactured products varies from job to job, the production capacity of each machine is almost saturated (Sect. 3).
- The different components (A, B, and C) have comparable volumes, support bases (Tables 1 and 5), and expected structural characteristics (e.g., material and infill pattern/density).
- Considering that the different components have z-dimensions (i.e., heights in the build direction) and geometrical features quite similar to each other, and the layer thickness for deposition is constant for each AM center, neither the total energy consumption (E_j) nor manufacturing time (t_j) change dramatically from job to job.

On the basis of the above considerations, it is reasonable to assume the following empirical relationships for each j-th job of a given AM center [25]:

1. A linear relationship between E_j and M_j (the energy consumption and gross mass deposited in the j-th job, respectively), in the $E_j = E_0 + E_1 \bullet M_j$ form. In parallel, a similar model is assumed for CO_2 emissions.
2. A linear relationship between t_j (the manufacturing time related to the j-th job) and M_j, in the $t_j = t_0 + t_1 \bullet M_j$ form. The predominant contribution is expected to be that of the deposition time, which in turn depends on the mass of the material being deposited and, ultimately, on the product size and the relevant structural characteristics (e.g., infill pattern/density).

Figure 4a graphically represents the E_j values as a function of the M_j values (i.e., the gross masses) for each j-th job by each machine, consistently with the proposed linear model. Moreover, the proportional CO_2 emission values can be simultaneously read on the secondary axis. Applying the least squares method [36], a regression of the available data is performed, using a first-order polynomial (i.e., linear) model. In order to improve the accuracy of the estimation of the regression line parameters for each AM center, an additional job (“Addit. job” in Table 6)—with a significantly lower M_j value than the other jobs—is considered. Specifically, this job involves the production of a single product unit of type A, for the first two AM centers (Machine X and Machine Y), and a single unit of type C for the third one (Machine Z). The resulting regression lines are plotted in Fig. 4a, together with the equations and R^2 values (i.e., the coefficients of determination). The fact that the E_0 (or $CO_{2\,0}$) values are negative suggests that only the contributions related to the material deposition phase (which are,

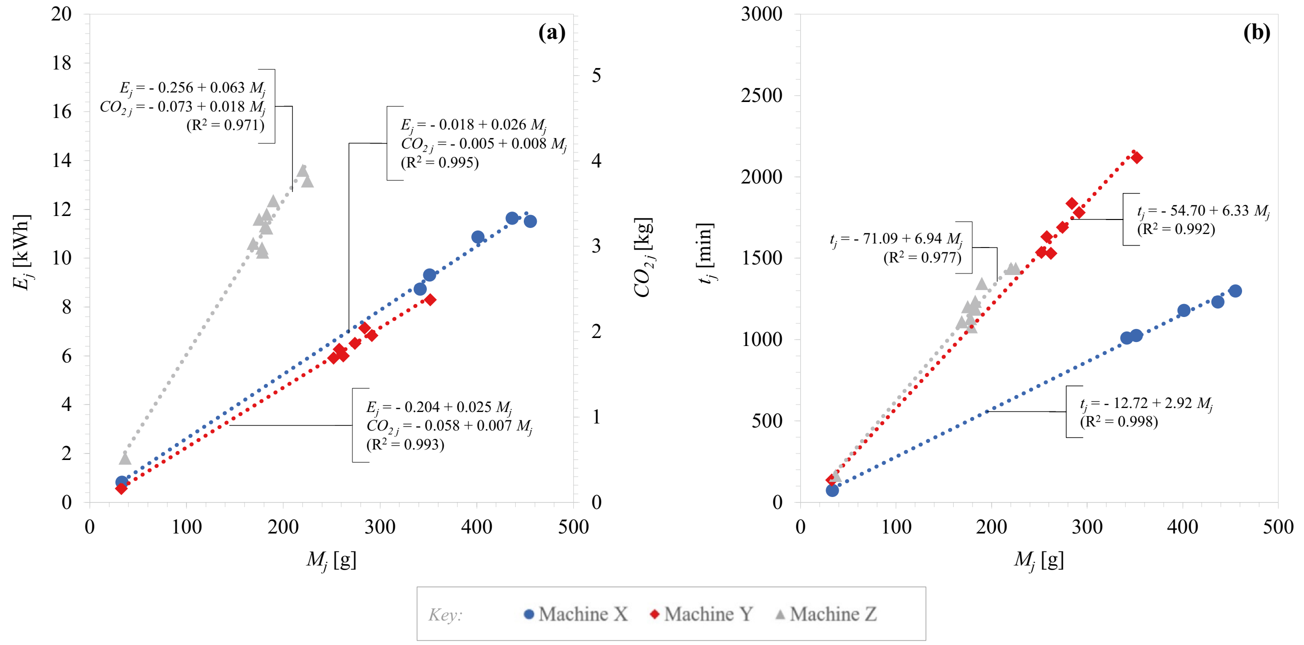

Fig. 4 Energy consumption, E_j, CO_2 emissions, $CO_{2\,j}$ (**a**), and time, t_j (**b**), as a function of the gross mass, M_j, deposited in each j-th job by each of the three AM centers

in turn, related to the amount of mass being deposited) are significant, as formally demonstrated hereafter. The R^2 values, which are all larger than 97%, denote a good fit of the regression lines with respect to the input data. The regression output is examined by means of ANOVA (analysis of variance). It can be deduced, through a t test with $p<0.05$, that the E_1 terms (slope) of the various relationships are significant, while the E_0 terms (intercept) are not. Figures 7 and 8 (in Appendix 2) report the regression results for all the three AM centers. The results indicate that the error made by considering E_j (or $CO_{2\,j}$) $\propto M_j$ (i.e., neglecting the intercept, E_0 or $CO_{2\,0}$) is statistically insignificant.

Figure 4b presents the t_j values as a function of the M_j values (i.e., the gross masses) for each job by each machine. A good fit of the proposed linear model ($t_j = t_0 + t_1 \cdot M_j$) can be observed and statistically verified. In particular, the machine with the lowest regression line is Machine X, which—for a given deposited mass—appears to be faster than Machine Y and Machine Z. The regression output is examined by means of ANOVA. Again, through a t test with $p<0.05$, it is deduced that the t_1 terms (slope) of the various relationships are significant, while the t_0 terms (intercept) are not. The results in Figs. 9 and 10 (in Appendix 2) confirm that the error made by considering $t_j \propto M_j$ (i.e., neglecting the intercept, t_0) is statistically insignificant. The regression models allow a quantitative comparison of the performances of the three machines to be made, with reference to specific productions. Additionally, these models can be useful to a priori estimate the energy consumption and production time required for future production jobs.

5 Quality and process sustainability synthesis

A practical tool to synthesize the quality and sustainability analyses is proposed in this Section, although the authors are aware that any synthesis, useful and practical as it may be, inevitably results in the loss of a part of the initial information [48]. Focusing on process sustainability, the regression model that links the energy to the mass can be summarized through Eq. 3:

$$e_{s_j} = \frac{E_j}{M_j}, \tag{3}$$

where the denomination e_{s_j} stands for the specific energy per unit (gross) mass for the j-th job. The choice of accounting for the total energy consumption, E_j (and not the energy contribution related to only the material deposition), is justified by the fact that the other energy contributions (such as the setting-up, the heating phase, and the post-deposition part handling) have proved to be negligible. Therefore, no significant differences in the results due to different modeling choices are expected. An identical approach (which is here omitted for the sake of brevity) can be followed for CO_2 emissions. Moreover, the regression model that links time and mass can be summarized through a similar synthetic indicator (Eq. 4) that corresponds to the average manufacturing time per unit (gross) mass for a generic j-th job:

$$t_{s_j} = \frac{t_j}{M_j}. \tag{4}$$

The e_{s_j} and t_{s_j} indicators from the j-th job can be extended to the entire production (sampled for a certain machine), which results in the two more general indicators in Eq. 5:

$$e_s = \frac{\sum_{\forall j} E_j}{\sum_{\forall j} M_j} \quad \text{and} \quad t_s = \frac{\sum_{\forall j} t_j}{\sum_{\forall j} M_j}. \tag{5}$$

Table 7 lists the resulting indicators for each of the three AM centers. Figure 5 plots a 2D-map that represents the positioning of the AM centers on the basis of the proposed synthetic indicators, both at the level of a single job (e_{sj} – or CO_{2sj} - and t_{sj}, $\forall j$) and for the whole production (e_s – or CO_{2_s} – and t_s). Since all the indicators have a negative connotation, the most desirable region for AM centers within the 2D-map would be around the bottom-left vertex. This would imply two difficult-to-combine requirements for AM centers: the reduction of the overall energy consumption and the reduction of the manufacturing time by increasing the mass deposition rate.

The proposed 2D-map facilitates comparisons between different AM centers. The correlation between a single printer feature, such as the cold or heated chamber/plate, the build chamber enclosure, and the system for controlling the positioning of the filament extruders, or even a combination of these features, and the part quality, energy consumption and CO_2 emissions, is not trivial, and has here been excluded from the boundaries of the assessment. This study was aimed at developing a general methodology to compare different production centers (at the macro level) without focusing on the specific machine and its features (at the micro level). It is worth mentioning that the main differences could be due to the architecture/size of the machine, since Machine X and Z are commercial solutions that have already been adopted for an industrial production, while Machine Y is a desktop-oriented solution. In the case study exemplified here, the following considerations can be made:

- Machine X has the lowest overall defectiveness (p) and appears to be the best choice in terms of manufacturing time, likely due to the higher technological level than previous generations of FDM 3D printers, such as Machine Z. Moreover, the relatively high production capacity allows the number of jobs to be reduced. Therefore, the overall performance is relatively good.
- Machine Y has the highest overall defectiveness (p), but a slightly lower specific energy consumption than Machine X (albeit of the same order of magnitude). The manufacturing time is, instead, closer to that of Machine Z, which is the highest one.
- Machine Z appears to be the least sustainable center, with reference to the case study under consideration, and it is represented in the top-right region of the 2D-map. It exploits an energy-intensive heated chamber technology

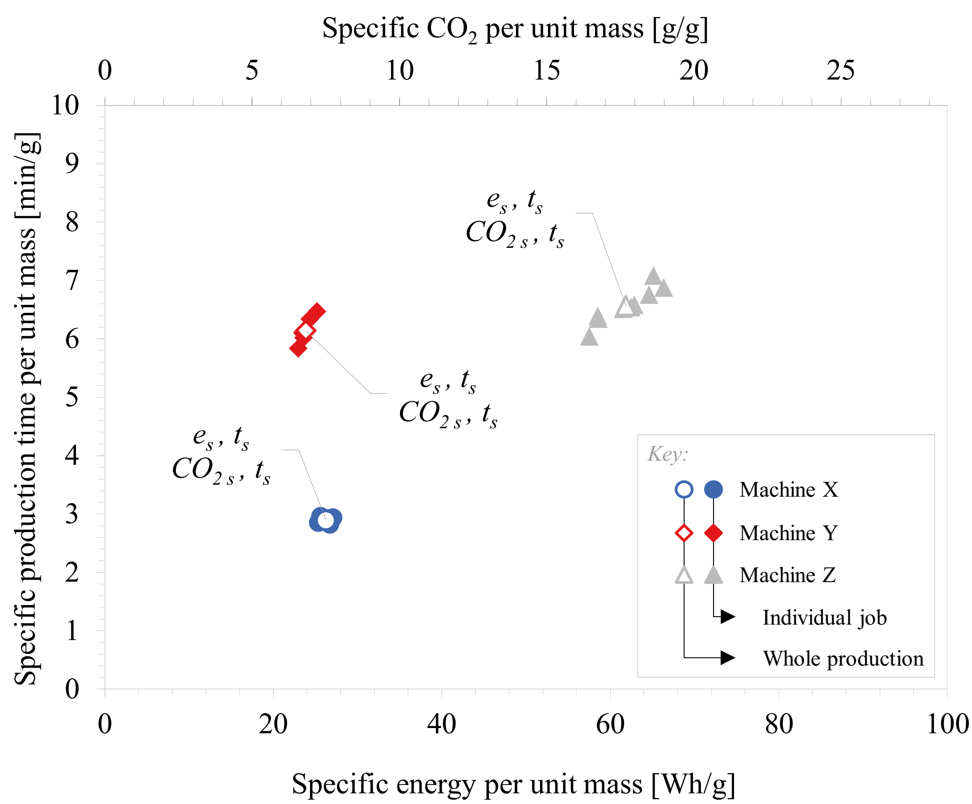

Fig. 5. 2D-map representing the specific indicators listed in Table 7 at both an individual job level and the whole production level for each AM center

during both preparation/setting-up and material extrusion/deposition. Moreover, being the machine with the lowest production capacity, it requires a relatively high number of jobs.

The two synthetic indicators in Eq. 5 can be corrected by no longer referring to the *gross* mass unit but to the *net* mass unit, thus excluding the contribution for support bases, according to Eq. 6:

$$e'_s = \frac{\sum_{\forall j} E_j}{\sum_{\forall j} M'_j} \quad \text{and} \quad t'_s = \frac{\sum_{\forall j} t_j}{\sum_{\forall j} M'_j}, \tag{6}$$

where the M_j' values represent the net masses of the parts produced in the various jobs (Table 6). The corrected indicators related to the three AM centers can be represented in the same 2D-map (Table 8 and Fig. 6). Next, the quality and sustainability dimensions can be further analyzed by making another correction, that is, by referring the energy/time consumption to the *conforming* mass unit (Eq. 7) instead of the generic *net* mass unit:

$$M''_j = (1-p) \cdot M'_j, \tag{7}$$

where M'_j is the net mass produced in the j-th job and p is the previously estimated nonconforming fraction for the production of the machine of interest. The new synthetic indicators are defined as in Eq. 8:

Table 4 Estimation of the nonconforming fraction related to (*i*) the individual quality characteristics (e.g., $p_{A.1}$, $p_{A.2}$), (*ii*) the single parts (e.g., p_A, p_B, p_C), and (*iii*) the overall production output of each AM center (p), based on 10,000 Monte Carlo simulations for each part type

Nonconforming fraction	Machine X	Machine Y	Machine Z
$p_{A.1}$	0.58%	1.00%	0.13%
$p_{A.2}$	1.91%	5.33%	5.92%
$p_{A.3}$	0.01%	4.39%	0.19%
p_A	2.47%	9.77%	6.13%
$p_{B.1}$	0.04%	2.96%	2.52%
$p_{B.2}$	0.05%	0.47%	0.02%
$p_{B.3}$	0.68%	3.05%	0.04%
p_B	0.77%	5.71%	2.58%
$p_{C.1}$	0.41%	0.63%	1.63%
$p_{C.2}$	0.03%	0.39%	0.46%
$p_{C.3}$	0.38%	3.15%	0.19%
p_C	0.82%	4.10%	2.26%
$\boldsymbol{p}$	**1.37%**	**6.42%**	**3.66%**

$$e''_s = \frac{\sum_{\forall j} E_j}{(1-p)\cdot\sum_{\forall j} M'_j} = \frac{\sum_{\forall j} E_j}{\sum_{\forall j} M''_j} \quad \text{and} \\ t''_s = \frac{\sum_{\forall j} t_j}{(1-p)\cdot\sum_{\forall j} M'_j} = \frac{\sum_{\forall j} t_j}{\sum_{\forall j} M''_j}. \tag{8}$$

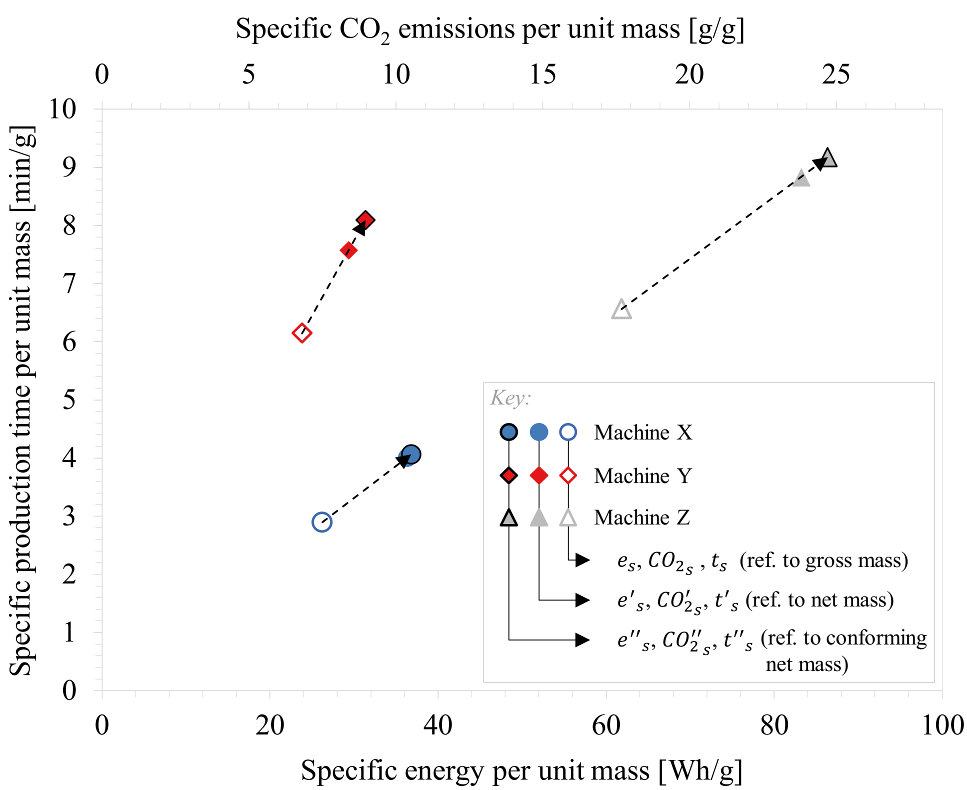

Fig. 6. 2D-map showing the average synthetic indicators referring to the *gross*, *net*, and *conforming net* mass unit for each AM center

Table 5 Approximate volume and mass of the product unit (A, B, and C) and the relevant support bases

Part type	Nominal volume	Nominal mass			
		Machine	Product unit (*net* mass)	Support bases	Total (*gross* mass)
A	26.4 cm^3	X	23.9 g	9.2 g	33.1 g
		Y	26.5 g	6.1 g	32.6 g
		Z	23.7 g	7.9 g	31.6 g
B	19.3 cm^3	X	17.5 g	8.6 g	26.1 g
		Y	19.1 g	5.3 g	24.4 g
		Z	17.2 g	7.6 g	24.8 g
C	32.1 cm^3	X	28.8 g	10.4 g	39.2 g
		Y	32.3 g	6.6 g	38.9 g
		Z	28.4 g	8.8 g	37.2 g

Table 6 Job-by-job measurements of the time, energy, and (*gross* and *net*) mass for each of the three AM centers

Job	**Machine X**				**Machine Y**				**Machine Z**			
	t_j (min)	E_j (kWh)	M_j (g)	M_j' (g)	t_j (min)	E_j (kWh)	M_j (g)	M_j' (g)	t_j (min)	E_j (kWh)	M_j (g)	M_j' (g)
1	1180	10.87	401.2	289.6	1690	6.52	274.0	221.8	1439	13.17	225.1	174.0
2	1010	8.74	341.4	239.4	1633	6.27	257.7	207.4	1439	13.61	220.2	169.0
3	1300	11.52	455.3	333.0	1838	7.15	284.0	230.9	1129	10.42	177.9	131.1
4	1233	11.65	436.7	321.6	1782	6.84	291.6	236.4	1236	11.81	182.9	134.1
5	1026	9.32	351.3	250.9	1537	5.92	252.1	201.5	1188	11.34	181.5	132.4
6	-	-	-	-	1530	6.01	262.0	210.6	1203	11.60	174.9	128.8
7	-	-	-	-	2119	8.30	352.0	292.9	1079	10.26	178.5	132.9
8	-	-	-	-	-	-	-	-	1191	11.24	182.7	134.4
9	-	-	-	-	-	-	-	-	1111	10.61	168.8	121.7
10	-	-	-	-	-	-	-	-	1345	12.32	189.8	140.3
Col. sums	5749	52.10	1985.9	1434.5	12,129	47.01	1973.4	1601.5	12,360	116.38	1882.3	1398.7
Addit. job	73	0.83	33.2	23.8	138	0.57	32.7	26.8	167	1.82	36.5	27.8

Table 7 Average synthetic indicators with reference to the gross mass unit at both a job level and at a whole production level

Job	**Machine X**			**Machine Y**			**Machine Z**		
	e_{sj} (Wh/g)	CO_{2sj} (g/g)	t_{sj} (min/g)	e_{sj} (Wh/g)	CO_{2sj} (g/g)	t_{sj} (min/g)	e_{sj} (Wh/g)	CO_{2sj} (g/g)	t_{sj} (min/g)
1	27.09	7.75	2.94	23.80	6.81	6.17	58.51	16.73	6.39
2	25.60	7.32	2.96	24.33	6.96	6.34	61.81	17.68	6.53
3	25.30	7.24	2.86	25.18	7.20	6.47	58.57	16.75	6.35
4	26.68	7.63	2.82	23.46	6.71	6.11	64.57	18.47	6.76
5	26.53	7.59	2.92	23.48	6.72	6.10	62.48	17.87	6.55
6	-	-	-	22.94	6.56	5.84	66.32	18.97	6.88
7	-	-	-	23.58	6.74	6.02	57.48	16.44	6.04
8	-	-	-	-	-	-	61.52	17.60	6.52
9	-	-	-	-	-	-	62.86	17.98	6.58
10	-	-	-	-	-	-	64.91	18.56	7.09
Whole production	26.23	7.50	2.89	23.82	6.81	6.15	61.83	17.68	6.57

It can be noted that the same quantity (M_j'') appears as the denominator of both indicators in Eq. 8, which corresponds to the estimated mass of *conforming* product units, i.e., excluding the estimated portion of products that do not meet the

Table 8 Average synthetic indicators referring to the *gross* mass unit (e_s, CO_{2s}, and t_s), *net* mass unit (e_s', CO_{2s}', and t_s'), and *conforming* (net) mass unit (e_s'', CO_{2s}'', and t_s'') for each AM center

Machine	Specific energy demand (Wh/g)			Specific time (min/g)			Specific CO_2 emissions (g/g)		
	e_s	e_s'	e_s''	t_s	t_s'	t_s''	CO_{2s}	CO_{2s}'	CO_{2s}''
X	26.23	36.32	36.82	2.89	4.01	4.06	7.50	10.39	10.53
Y	23.82	29.35	31.37	6.15	7.57	8.09	6.81	8.40	8.97
Z	61.83	83.21	86.37	6.57	8.84	9.17	17.68	23.80	24.70

specifications. On the other hand, the complementary term $p \cdot \sum_{\forall j} M_j'$ corresponds to the estimated (net) mass of defective product units. Table 8 contains the e_s'', CO_{2s}'', and t_s'' indicators associated with each of the three AM centers. Obviously, $e_s'' > e_s' > e_s$, $CO_{2s}'' > CO_{2s}' > CO_{2s}$, and $t_s'' > t_s' > t_s$; however, the differences are relatively small, as typical p values are limited to a few units in percentage terms (Table 4). The same results can be represented graphically by means of the 2D-map in Fig. 6, which shows the transition from the (e_s, t_s) or (CO_{2s}, t_s) values to the (e_s', t_s') or (CO_{2s}', t_s') values, which reward the ability of an AM center to reduce materials for support bases, and the further transition to the (e_s'', t_s'') or (CO_{2s}'', t_s'') values, which reward the AM centers with the highest production quality.

In this case, the positioning of the AM centers is not unlike that of the map in Fig. 5. In particular, Machine Y– despite being the one with the highest p value, i.e., the highest "distance" between points (e_s', t_s') and (e_s'', t_s'') on the 2D map – continues to be by far the best in terms of energy consumption reduction.

6 Conclusions and outlooks

This paper proposes an operational methodology that can be used to compare decentralized AM centers that carry out similar job-by-job productions, in terms of the characteristics of the produced parts and of the production mix and quantities. The comparison is performed by analyzing the AM centers from the dual quality and process sustainability perspective. With reference to quality, the nonconforming fraction of each AM center is estimated at the levels of (*i*) the whole production, (*ii*) the individual product types, and (*iii*) the individual quality characteristics. The link between energy consumption (and the related equivalent carbon dioxide emissions), manufacturing time, and deposited mass is analyzed, with reference to process sustainability, through regression models and synthetic indicators. The concurrent assessment of quality and sustainability is synthesized and graphically represented by a 2D map, which is based on indicators of the specific energy consumption, CO_2 emissions, and time consumption per unit (conforming net) mass (i.e., excluding the material for nonconforming units and support bases and/or structures). By showing the strengths and weaknesses of the compared AM centers, the picture provided in the 2D-map can be used to guide possible improvement actions [3]. The construction of the synthetic indicators requires a preliminary data collection and sampling a part of the actual production of each AM center. It is recommended collecting at least fifteen/twenty units for each product type to ensure the results are statistically accurate. Increasing the quantity would improve the accuracy results, but also the times and involved costs [29]. Each machine production should be monitored—job by job—in terms of time and energy required during sampling. The critical quality characteristics of the sampled product units should then be measured. In the here presented case study, the dimensional quality characteristics have been measured using a CMM. However, the proposed methodology can be adapted to other typologies of quality characteristics (e.g., micro-hardness, surface roughness, residual stresses). It should also be mentioned that the suggested methodology suffers from some limitations, which are briefly summarized below:

- The production mix of each AM center is hypothesized to include products that have a similar geometry (i.e., volume, height) and similar constructional characteristics (i.e., type of material, infill pattern/density and deposition path).
- The quality characteristics of each product type are assumed to follow a multivariate normal distribution. Although this assumption is common in the scientific literature concerning process capability analysis, it should be verified case-by-case.
- The measurement uncertainty of the instruments (e.g., CMMs) used to measure the quality characteristics is neglected.
- Similar materials have been used in the here presented case study to manufacture both product units and support bases.
- The comparison of decentralized AM centers does not consider certain costs (e.g., the energy, material and labor costs).

Thus, the present research may be extended with the aim of overcoming at least some of the abovementioned limitations.

Appendix 1. Extra tables on quality analysis

This section contains some other tables related to the quality analysis conducted in Sect. 3.

See Tables 9, 10, 11, and 12.

Table 9 Dimensional measurements — expressed in mm — related to the quality characteristics of the types A, B, and C parts produced by Machine X; each value is the average of three replications performed using a 3D coordinate measuring machine (CMM) by DEA Global Image. The values in bold do not meet the relevant specification limits (Table 1)

Measurements of part A (mm)					Measurements of part B (mm)					Measurements of part C (mm)				
Job	Part No	A.1	A.2	A.3	Job	Part No	B.1	B.2	B.3	Job	Part No	C.1	C.2	C.3
1	1	9.994	5.013	0.064	1	1	25.046	18.473	14.941	1	1	9.934	4.997	0.136
1	2	10.018	4.945	0.041	1	2	25.061	18.510	14.951	3	2	9.952	5.017	0.101
1	3	10.079	5.049	0.061	1	3	24.995	18.431	14.921	3	3	10.000	5.024	0.116
1	4	9.967	5.075	0.072	2	4	25.006	18.492	14.929	3	4	10.038	5.027	0.100
1	5	9.922	5.013	0.046	2	5	25.001	18.476	14.915	3	5	9.999	5.005	0.093
1	6	10.023	4.956	0.058	2	6	25.059	18.488	14.969	3	6	9.948	5.022	0.078
1	7	9.930	5.031	0.036	2	7	24.986	18.393	14.888	3	7	10.021	5.032	0.081
1	8	10.071	5.050	0.089	2	8	25.019	18.479	14.920	3	8	9.935	4.978	0.049
2	9	9.945	5.054	0.069	2	9	25.028	18.460	14.919	3	9	9.964	5.024	0.037
2	10	10.008	5.021	0.086	2	10	25.048	18.444	14.946	3	10	9.981	5.033	0.099
2	11	9.923	5.068	0.049	2	11	25.004	18.451	14.958	3	11	9.918	5.013	0.126
4	12	**9.849**	5.009	0.047	2	12	25.069	18.443	14.930	4	12	9.981	4.993	0.099
4	13	9.989	5.008	0.071	3	13	25.090	18.543	14.942	4	13	9.966	4.982	0.086
4	14	9.998	5.049	0.060	3	14	25.111	18.455	14.912	4	14	9.959	5.014	0.061
4	15	10.040	5.036	0.047	5	15	25.025	18.511	14.922	4	15	9.986	5.023	0.068
4	16	9.952	5.052	0.035	5	16	25.002	18.451	14.935	4	16	10.030	5.058	0.047
4	17	10.002	4.984	0.072	5	17	25.007	18.472	14.930	5	17	10.012	5.069	0.081
4	18	9.954	4.904	0.019	5	18	25.030	18.487	14.922	5	18	9.996	4.965	0.084
5	19	9.971	5.034	0.014	5	19	25.038	18.449	14.901	5	19	9.931	4.960	0.037
5	20	9.900	4.942	0.043										
5	21	10.012	4.959	0.047										

Table 10 Dimensional measurements — expressed in mm — related to the quality characteristics of the types A, B, and C parts produced by Machine Y; each value is the average of three replications performed using a 3D coordinate measuring machine (CMM) by DEA Global Image. The values in bold do not meet the relevant specification limits (Table 1)

Measurements of part A (mm)					Measurements of part B (mm)					Measurements of part C (mm)				
Job	Part No	A.1	A.2	A.3	Job	Part No	B.1	B.2	B.3	Job	Part No	C.1	C.2	C.3
1	1	10.013	4.985	0.038	1	1	24.948	18.647	**15.130**	1	1	10.065	5.037	0.091
1	2	10.049	4.958	0.078	1	2	24.926	18.536	15.045	1	2	10.002	4.943	0.076
2	3	10.050	4.935	0.058	1	3	24.917	18.541	15.040	1	3	10.050	4.987	0.110
2	4	10.096	4.997	0.106	1	4	24.926	18.517	15.026	3	4	10.024	5.017	0.042
2	5	10.046	5.034	0.059	3	5	24.908	18.588	15.095	3	5	10.098	5.059	0.085
2	6	10.081	4.959	**0.163**	3	6	24.989	18.547	15.103	3	6	10.045	5.027	0.076
2	7	10.038	5.039	0.049	3	7	24.885	18.536	15.042	4	7	10.007	4.949	**0.160**
2	8	10.047	**4.899**	0.085	4	8	24.925	18.557	15.043	4	8	9.941	4.897	0.074
2	9	10.061	5.025	0.092	4	9	24.975	18.504	14.998	4	9	10.021	5.025	0.109
2	10	10.082	**5.100**	0.104	4	10	**24.847**	18.551	15.069	4	10	10.052	5.040	0.089
3	11	10.031	5.014	0.087	4	11	24.952	18.548	15.067	4	11	10.021	4.949	0.122
3	12	9.979	5.057	0.073	5	12	24.862	18.571	15.092	6	12	10.058	5.006	0.033
3	13	10.063	4.987	0.106	5	13	24.993	18.464	14.988	7	13	9.998	5.011	0.147
5	14	10.000	5.010	0.082	5	14	25.024	18.572	15.065	7	14	10.082	4.998	0.102
5	15	10.072	5.022	0.103	5	15	24.960	18.489	15.072	7	15	10.010	4.979	0.085
5	16	10.136	5.029	**0.156**	5	16	24.945	18.482	15.036	7	16	10.009	4.966	0.079
5	17	9.994	**4.898**	0.073	6	17	25.044	18.537	15.025	7	17	10.031	5.039	0.097
6	18	9.963	5.039	0.039	6	18	25.026	18.541	15.004	7	18	10.003	4.988	0.094
6	19	10.068	5.022	0.086	6	19	24.988	18.497	14.990	7	19	10.061	4.980	0.041
6	20	10.085	4.967	0.138	6	20	24.988	18.532	15.039	7	20	10.017	4.973	0.154
7	21	9.972	5.041	0.030	6	21	24.952	18.583	15.034					

Table 11 Dimensional measurements — expressed in mm — related to the quality characteristics of the types A, B, and C parts produced by Machine Z; each value is the average of three replications performed using a 3D coordinate measuring machine (CMM) by DEA Global Image. The values in bold do not meet the relevant specification limits (Table 1)

Measurements of part A (mm)					Measurements of part B (mm)					Measurements of part C (mm)				
Job	Part No	A.1	A.2	A.3	Job	Part No	B.1	B.2	B.3	Job	Part No	C.1	C.2	C.3
3	1	9.995	5.026	0.080	3	1	25.116	18.458	14.982	1	1	10.115	4.999	**0.160**
3	2	9.991	5.002	0.079	3	2	25.015	18.494	14.996	1	2	10.065	5.007	0.084
4	3	10.051	5.051	0.086	3	3	24.982	18.423	14.946	1	3	10.062	4.975	0.002
5	4	10.066	5.083	0.087	4	4	25.035	18.463	14.961	1	4	10.002	4.986	0.002
5	5	9.913	4.936	0.021	4	5	25.010	18.450	14.983	1	5	10.063	4.979	0.090
5	6	10.036	**5.114**	0.118	4	6	25.084	18.491	14.966	1	6	10.002	4.962	0.013
6	7	10.017	5.039	0.067	5	7	25.105	18.470	14.957	2	7	10.052	5.023	0.058
6	8	10.061	5.020	0.084	5	8	25.019	18.432	14.926	2	8	10.023	4.952	0.010
7	9	10.004	4.983	0.113	6	9	25.022	18.509	14.967	2	9	10.041	4.964	0.058
7	10	9.996	4.956	0.061	6	10	24.986	18.477	14.990	2	10	10.083	4.983	0.075
7	11	10.015	5.013	0.108	6	11	25.092	18.459	14.945	2	11	10.088	5.021	0.039
7	12	10.005	5.053	0.069	7	12	**25.153**	18.531	15.024	2	12	9.972	4.949	0.023
8	13	9.916	5.017	0.035	7	13	25.007	18.465	14.972	3	13	10.017	4.912	0.023
8	14	9.994	5.065	0.092	8	14	25.003	18.513	14.987	4	14	9.989	4.932	0.028
8	15	9.923	4.993	0.053	9	15	24.978	18.459	14.997	4	15	10.015	5.029	0.056
8	16	9.960	5.092	0.048	9	16	25.097	18.429	14.966	5	16	9.999	4.910	0.036
8	17	10.016	4.999	0.080	9	17	25.036	18.508	15.031	6	17	9.977	4.978	0.049
9	18	10.046	5.053	0.082	9	18	24.971	18.485	14.970	9	18	10.069	4.998	0.015
10	19	9.996	5.021	0.078	10	19	25.046	18.444	14.959	10	19	9.997	4.932	0.086
					10	20	25.102	18.449	14.971	10	20	10.036	4.958	0.053
										10	21	10.014	4.954	0.046

Table 12 Results of the application of the Anderson–Darling normality test, with reference to the quality characteristics of the types A, B, and C parts, produced by each of the considered AM systems. "AD" stands for the so-called Anderson–Darling goodness-of-fit statistic [49]. The relatively high p values show that the assumption of normality is not contradicted for any of the quality characteristics

	(a) Machine X					(b) Machine Y					(c) Machine Z				
	Mean	St. Dev	N	AD	p value	Mean	St. Dev	N	AD	p value	Mean	St. Dev	N	AD	p value
A.1	9.978	0.05614	21	0.161	0.937	10.044	0.04434	21	0.329	0.493	10.000	0.04548	19	0.623	0.089
A.2	5.012	0.04695	21	0.690	0.061	5.001	0.05080	21	0.477	0.213	5.027	0.04512	19	0.139	0.969
A.3	0.054	0.01963	21	0.258	0.684	0.086	0.03601	21	0.369	0.394	0.076	0.02489	19	0.360	0.411
B.1	25.033	0.03390	19	0.380	0.368	24.951	0.05209	21	0.189	0.889	25.043	0.05333	20	0.590	0.109
B.2	18.469	0.03346	19	0.258	0.678	18.540	0.04101	21	0.347	0.447	18.470	0.03003	20	0.256	0.687
B.3	14.929	0.01952	19	0.203	0.856	15.048	0.03777	21	0.289	0.580	14.975	0.02527	20	0.351	0.434
C.1	9.976	0.03532	19	0.192	0.883	10.030	0.03524	20	0.360	0.414	10.032	0.03934	21	0.317	0.515
C.2	5.012	0.02845	19	0.354	0.426	4.993	0.04041	20	0.210	0.838	4.971	0.03431	21	0.166	0.929
C.3	0.083	0.02829	19	0.252	0.698	0.093	0.03463	20	0.432	0.276	0.048	0.03737	21	0.502	0.184

Appendix 2. Additional data on the regression models

This section contains additional data related to the construction of the regression models shown in the sustainability analysis in Sect. 4. Figures 7 and 8 refer to the model linking of the (job-by-job) energy consumption with the deposited mass: $E_j = E_0 + E_1 \cdot M_j$. Despite the limited number of available data, which is equal to the number of production jobs in each AM system, the residual plots in Fig. 7 overall seem satisfactory. Each regression output is quantitatively examined by means of an analysis of variance (ANOVA),

Fig. 7 Minitab residual plots resulting from the regression analysis ($E_j = E_0 + E_1 \bullet M_j$) for each of the three considered AM centers

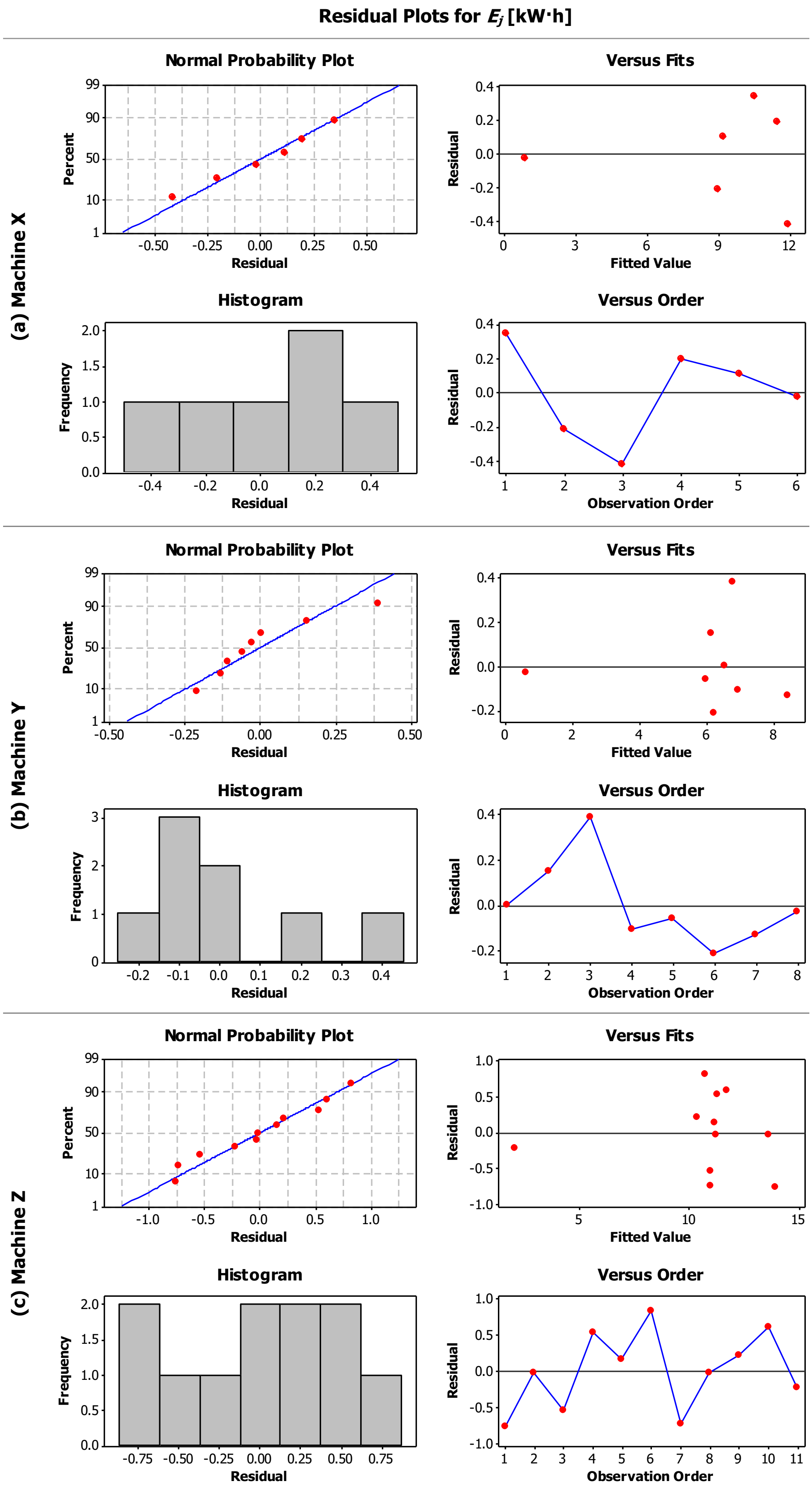

Fig. 8 Results of the regression analysis ($E_j = E_0 + E_1 \bullet M_j$) for each of the three considered AM centers

Regression Analysis: E_j [kW·h] versus M_j [g]

(a) Machine X

Regression Equation

$E_j = -0.018 + 0.0263 \cdot M_j$

Coefficients

Term	Coef	SE Coef	T	P
Constant	-0.0183	0.3306	-0.06	0.959
M_j	0.0262689	0.0009054	29.01	0.000

Summary of Model

S = 0.314401   R-Sq = 99.5%   R-Sq(adj) = 99.4%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	83.202	83.202	841.72	0.000
Residual Error	4	0.395	0.099		
Total	5	83.598			

(b) Machine Y

Regression Equation

$E_j = -0.204 + 0.0245 \cdot M_j$

Coefficients

Term	Coef	SE Coef	T	P
Constant	-0.2037	0.2199	-0.93	0.390
M_j	0.0245300	0.0008279	29.63	0.000

Summary of Model

S = 0.204963   R-Sq = 99.3%   R-Sq(adj) = 99.2%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	36.879	36.879	877.86	0.000
Residual Error	6	0.252	0.042		
Total	7	37.131			

(c) Machine Z

Regression Equation

$E_j = -0.256 + 0.0631 \cdot M_j$

Coefficients

Term	Coef	SE Coef	T	P
Constant	-0.2560	0.6586	-0.39	0.706
M_j	0.063069	0.003646	17.30	0.000

Summary of Model

S = 0.566911   R-Sq = 97.1%   R-Sq(adj) = 96.8%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	96.156	96.156	299.19	0.000
Residual Error	9	2.892	0.321		
Total	10	99.048			

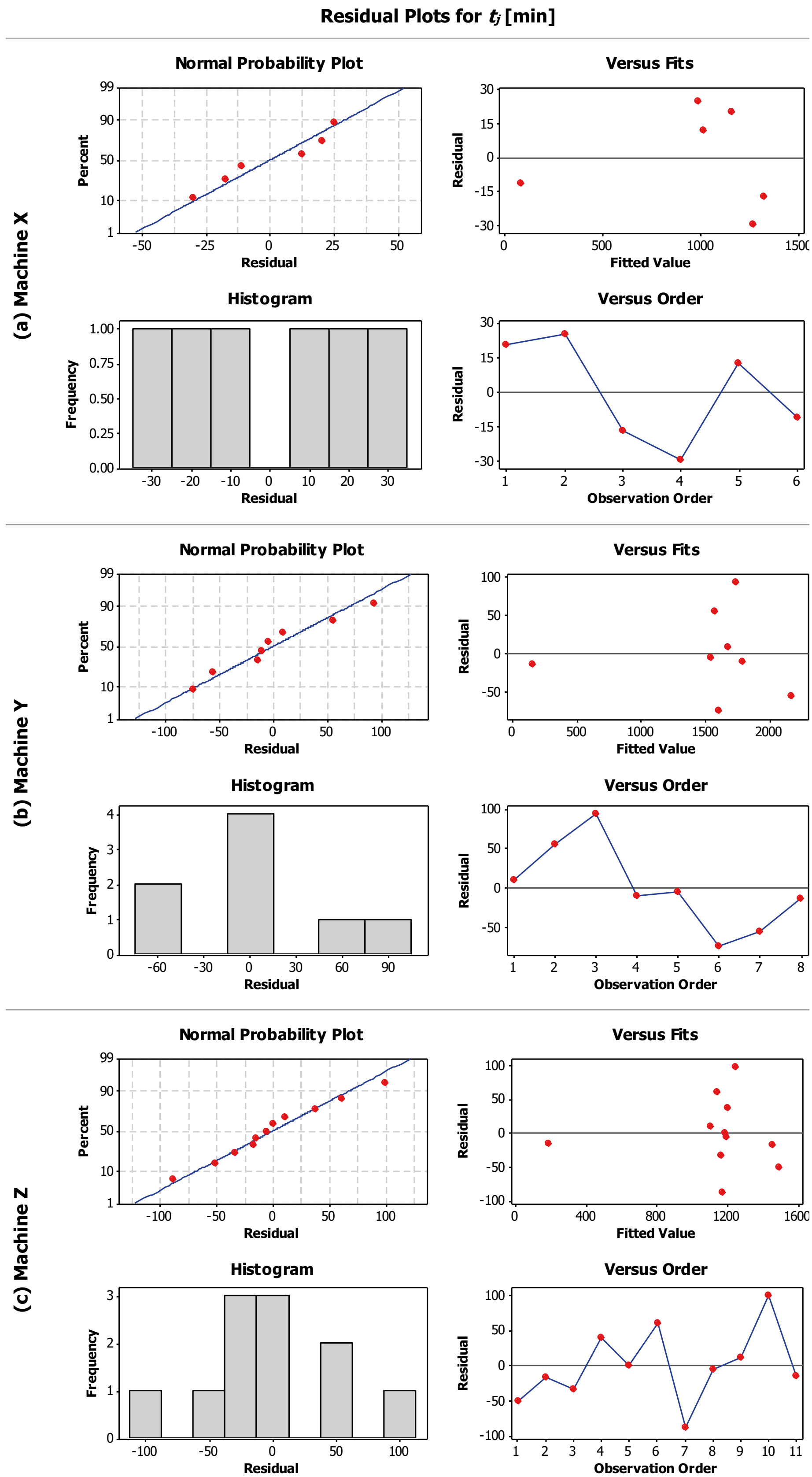

Fig. 9 Minitab residual plots resulting from the regression analysis ($t_j = t_0 + t_1 \cdot M_j$) for each of the three considered AM centers

Fig. 10 Results of the regression analysis ($t_j = t_0 + t_1 \bullet M_j$) for each of the three considered AM centers

Regression Analysis: t_j [min] versus M_j [g]

(a) Machine X

Regression Equation

$t_j = -12.7 + 2.92 \cdot M_j$

Coefficients

Term	Coef	SE Coef	T	P
Constant	-12.72	26.59	-0.48	0.657
t_j	2.92128	0.07281	40.12	0.000

Summary of Model

S = 25.2827 R-Sq = 99.8% R-Sq(adj) = 99.7%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	1028956	1028956	1609.72	0.000
Residual Error	4	2557	639		
Total	5	1031513			

(b) Machine Y

Regression Equation

$t_j = -54.7 + 6.33 \cdot M_j$

Coefficients

Term	Coef	SE Coef	T	P
Constant	-54.70	63.50	-0.86	0.422
t_j	6.3330	0.2391	26.49	0.000

Summary of Model

S = 59.1892 R-Sq = 99.2% R-Sq(adj) = 99.0%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	2458100	2458100	701.64	0.000
Residual Error	6	21020	3503		
Total	7	2479120			

(c) Machine Z

Regression Equation

$t_j = -71.1 + 6.94 \cdot M_j$

Coefficients

Term	Coef	SE Coef	T	P
Constant	-71.09	64.00	-1.11	0.295
t_j	6.9361	0.3543	19.58	0.000

Summary of Model

S = 55.0892 R-Sq = 97.7% R-Sq(adj) = 97.5%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	1	1163000	1163000	383.22	0.000
Residual Error	9	27313	3035		
Total	10	1190314			

which shows that the model fits the experimental data for each of the three AM centers (Fig. 8). Additionally, it can be deduced, on the basis of the t test at $p < 0.05$, that all the E_1 terms (slope) are significant, while the E_0 terms (constant/intercept) are not significant. Figures 9 and 10 refer to the model that links the production time to the deposited mass:

$t_j = t_0 + t_1 \bullet M_j$. The results are similar to those related to the previous model: although the residual plots (Fig. 9) overall seem satisfactory, the ANOVA table (Fig. 10) shows that the model fits the experimental data for all the AM systems. Additionally, it can be deduced, on the basis of the *t* test at $p < 0.05$, that all the t_1 terms (slope) are significant, while the t_0 terms (constant/intercept) are not significant.

Author contribution D.A. Maisano: conceptualization, methodology, formal analysis; E. Verna: formal analysis, investigation; P. Minetola: resources, investigation; V. Lunetto: data curation, investigation; A.R. Catalano: methodology, formal analysis; P.C. Priarone: supervision, funding acquisition.

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Availability of data and materials The manuscript has no associated data. Data will be made available upon request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent to publish Not applicable.

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