Planning offline inspection strategies in low-volume manufacturing processes

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Abstract

The design of appropriate and successful quality-inspection strategies plays an important role within manufacturing organizations. It is one of the leverage factors to ensure customers the expected quality level of products. In the case of low-volume or single-unit productions, such as those produced with emerging Additive Manufacturing (AM) technologies, the design of quality controls may be problematic due to the lack of historical data and the inadequacy of traditional statistical approaches. In literature some studies focused on the design and selection of in-process inspection strategies for low-volume productions. However, in some cases, such as AM productions, in-process inspections may not be adequate, easy to perform or cost-effective. To this end, the present work aims at identifying a general methodology for planning offline inspections for low-volume productions. The specific research question addressed concerns how to select the best compromise between effectiveness and affordability of alternative offline inspection strategies for such productions. The proposed method consists of formulating a probabilistic model for predicting defects and defining two performance indicators that outline the overall effectiveness and affordability of an offline inspection strategy. This approach is finally applied to a real low-volume AM production of parts manufactured by Selective Laser Melting (SLM) technique.

Keywords: quality control; offline inspection; inspection design; low-volume production; Additive Manufacturing

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1. Introduction

In a highly competitive context such as the global market, ensuring high product quality has become a key factor to withstand competition. In this regard, organizations are increasingly investing in the development and implementation of quality control systems (QCS) that can provide consumers with high quality products in line with their expectations (Azadeh et al. 2015; Mirdamadi et al. 2013). Moreover, QCS has always been the most cost-effective tool to reduce inefficiencies within the organizational supply chain (Mohammadi et al. 2015). In addition, due to the increasing complexity and customization of products, more and more sophisticated, flexible and therefore expensive quality control systems are required. Accordingly, designing effective and affordable inspection strategies represents an essential and challenging issue in quality control (Franceschini et al. 2018).

Inspection Process Planning (IPP) is the activity that defines which quality characteristics of a product should be inspected, where and when (Zhao, Xu, and Xie 2009; Pfeifer 2015; Mohammadi et al. 2015). Inspections may be designed using different strategies and following statistical or heuristic procedures (Montgomery 2012; Mandroli, Shrivastava, and Ding 2006; Tang and Tang 1994). Moreover, since products are increasingly customized and complex and therefore require highly changeable production processes, it is of increasing importance to develop appropriate control strategies, defining test procedures, cases and resources, in order to identify the most critical and vulnerable process characteristics (Colledani et al. 2014).

In the planning of inspections, a distinction between in-process and offline inspection strategies must also be considered. In in-process inspections, also called online inspections in the scientific literature, units are inspected during the manufacturing process (Tzimerman and Herer 2009; Tirkel et al. 2016; Azadeh et al. 2015; W. Wang 2009). On the other hand, in offline inspections the finished products are inspected after the manufacturing process is completed (Tzimerman and Herer 2009; Kang et al. 2018). Offline inspections consist in inspecting a random item from the batch and, based on the inspection result, a decision is taken on what to do next (Tzimerman and Herer 2009; Colledani and Tolio 2009; Raz, Herer, and Grosfeld-Nir 2000; C.-H. Wang 2007; Finkelshtein et al. 2005). In-process inspection regimes are considered more economical and effective than offline inspection ones (Tzimerman and Herer 2009). However, there are situations in which in-process inspections are not adequate, impossible to perform or not economically convenient; hence, offline inspections are required (Tzimerman and Herer 2009).

When designing an inspection strategy, not only effectiveness, but also cost-efficiency must be considered. According to Emmons and Rabinowitz (2002), implementing a quality system is expensive and requires valuable resources. As companies invest large amounts in products and production systems, implementing an efficient inspection strategy is of much importance to reduce quality related costs (Emmons and Rabinowitz 2002).

Several techniques such as cost-benefit models (Savio 2012), simulation (Neu et al. 2002; Neu et al. 2003; Münch et al. 2002), optimization models (Hanne and Nickel 2005; Shiau 2003) and mathematical programming models (Mohammadi et al. 2015) have been proposed to plan inspection processes. However, these techniques are highly applicable to massive production, but are not so suitable for small-sized productions. Indeed, the effectiveness of possible inspection strategies is strictly related to the production typology and volume (Genta, Galetto, and Franceschini 2018; Galetto et al. 2018). In the case of mass production, statistical process control (SPC) techniques are straightforwardly applied (Montgomery 2012); on the other hand, in low-volume productions, i.e., single-units or small-sized-lots, traditional statistical techniques may be not appropriate (Trovato et al. 2010; Celano et al. 2011; Marques et al. 2015; Del Castillo et al. 1996; Pillet 1996; Khoo and Quah 2002).

Previous works focused on designing in-process quality-inspection strategies in the case of low-volume productions, e.g. assembly processes, that are decomposable into a number of steps in which specific defects can occur (Franceschini et al. 2018; Genta, Galetto, and Franceschini 2018; Galetto et al. 2018; Trovato et al. 2010; Ho and Trindade 2009; Galetto, Verna, and Genta 2020). However, in literature a scant number of studies investigated the planning of offline inspection strategies in low-volume manufacturing productions, that is the typical case of Additive Manufacturing (AM) processes. To date, only few authors proposed analytical methods for in-process defect detection and control strategies to implement corrective or adaptive actions once a defect has been detected during the process (Tapia and Elwany 2014; Everton et al. 2016; Rao et al. 2015; Grasso and Colosimo 2017; Colosimo 2018; Tsung et al. 2018). As a result, quality inspections performed on AM products are mainly restricted to offline controls, i.e., carried out at the end of the production process.

The aim of this paper is to provide a powerful approach to assist inspection designers in early phases of inspection planning in selecting the most suitable offline quality-inspection strategy for low-volume manufacturing processes with specific application to AM. The work focuses the attention on a specific research question, concerning how to select the best compromise between effectiveness and affordability of alternative offline inspection strategies in a low-volume AM production. In order to answer this question, a probabilistic model for defect prediction is defined and two indicators for comparing alternative combinations of inspection strategies according to their effectiveness and cost are proposed.

The rest of this paper is organized into four sections. Section 2 illustrates the probabilistic model and the relevant characteristic parameters. Section 3 presents two inspection indicators related to the overall effectiveness and total cost of an inspection strategy. In Section 4, a case study concerning the practical application of the proposed method to the low-volume production of mechanical components produced using an AM technique, the Selective Laser Melting (SLM) process. Section 5 summarizes the original contributions of this research, focusing on its implications, limitations and possible future developments.

2. Modelling manufacturing process and inspection strategy

Consider a manufacturing process in optimal settings condition in which there are m input variables that influence the final quality of each single product, which is evaluated through the measurement of n output variables. In this situation, each input variable may potentially affect each output variable with different levels of intensity. In order to check the conformity of the product, many different inspection strategies aimed at evaluating the output variables may be performed, such as dimensional verifications, visual checks, comparison with reference exemplars, mechanical tests, etc. (Savio et al. 2016; See 2012; Bress 2017). For each inspection activity, there is a risk of detecting a defect when it is not present (type I error), and a risk of not detecting it when it is actually present (type II error). Although these risks can be minimized by using sophisticated (manual and/or automatic) quality monitoring techniques, they can never be eliminated.

In the proposed model, schematized in Fig. 1, each input variable is denoted as X_i, where the index i is included between 1 and m. The output variables are denoted as Y_j, where j is included between 1 and n. Each output variable Y_j can be associated to three model parameters:

- p_{Y_j}: probability of occurrence of a defect related to output variable Y_j in nominal operating conditions;
- α_{Y_j}: probability of erroneously detecting a defect related to output variable Y_j (i.e., type-I inspection error);
- β_{Y_j}: probability of erroneously not detecting a defect related to output variable Y_j (i.e., type-II inspection error).

The estimation of the model parameters, which are supposed to be random variables, is not a trivial issue. The probabilities of occurrence of defects, p_{Y_j}, are strictly related to the intrinsic characteristics of the process. On the other hand, the inspection errors α_{Y_j} and β_{Y_j} depend on the quality of the inspection activity (including the inspection typology and procedure, the inspectors' technical skills and/or experience, the environmental conditions, etc.) (Duffuaa and Khan 2005; Kang et al. 2018; Tzimerman and Herer 2009; Tang and Schneider 1987). Both probabilities of occurrence of a defect (p_{Y_j}) and inspection errors (α_{Y_j} and β_{Y_j}), in practical applications, may be estimated by the implementation of probabilistic models and/or empirical methods (historical data, previous experience on similar processes, process knowledge, etc.) (Franceschini et al. 2018; Genta, Galetto, and Franceschini 2018; Galetto et al. 2018).

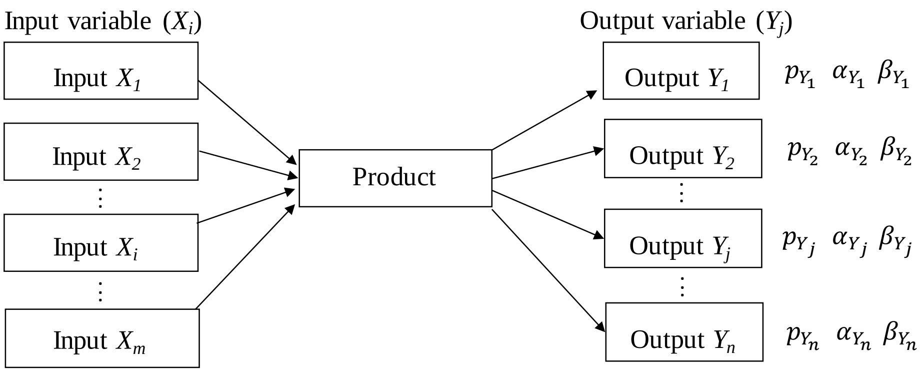

Fig. 1. Schematic of a production process with *m* input variables and *n* output variables and the related model parameters.

2.1. Estimation of defective-output variable probability

The basic assumption of the model is that there is a relationship among input and output variables. Consequently, if a defective-output variable occurs, it may be caused by some input variables. The probabilities of occurrence of defective-output variables may be therefore obtained using the mathematical function relating input and output variables (Montgomery 2017). In addition, the proposed methodology requires the knowledge of the input variables values that result in the best values of the responses. Finally, the specification limits of the output variables (upper specification limit, *USL*, and lower specification limit, *LSL*) are needed in order to determine whether the products meet the specifications imposed by regulations and/or company standards. Input variables can be discrete or continuous variables. In this paper only continuous variables are dealt with in detail.

Consider for example a case with only one output variable, denoted as Y, and one input variable, called X. The relationship between the two variables is given by the function $Y = f(X)$. However, in realistic cases, this function is not exactly defined, i.e., the coefficients of the mathematical model are affected by uncertainty. Furthermore, also the optimal value of the input variable (x^*), i.e. the value that optimizes the response output, is not exactly defined because of the uncertainty of the measurement device. For that reason, a variability range must be associated to it (by defining an upper *UL* and a lower *LL* variation limit, as illustrated in Fig. 2). The probability distribution associated to X depends on the characteristics of the input variable. For instance, if the values are all equiprobable in the interval, a uniform distribution should be considered. As shown in Fig. 2, the variance of the probability distribution of the output variable may be estimated by composing the uncertainties associated to both the input variable and the mathematical function, through the law of composition of variances (Ver Hoef 2012).

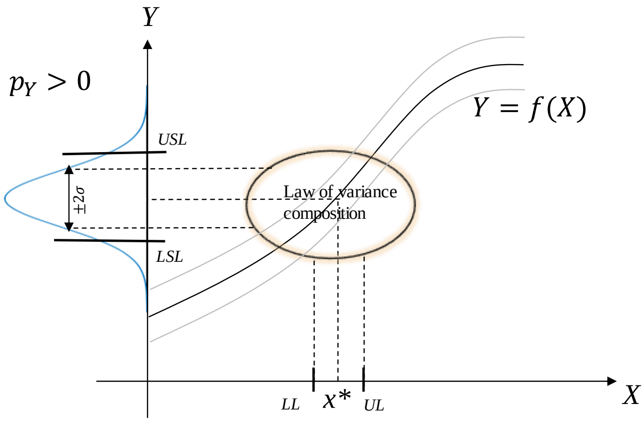

Fig. 2. Estimation of the probability of occurrence of defective-output variable (p_Y).

More in general, if there are m input variables, $\boldsymbol{X} = [x_1, \ldots, x_m]^{\mathrm{T}}$, the uncertainty of each one contributes to the variance of the related Y_j output variable, together with the contribution of the mathematical function coefficients, $\boldsymbol{A} = [a_0, a_1, \ldots, a_m]^{\mathrm{T}}$, as shown in Eq. (1), which is expressed in matrix form:

$$VAR(Y_j) \approx \left[\frac{\partial Y_j}{\partial \boldsymbol{K}}\right]^{\mathrm{T}} \cdot \mathrm{cov}(\boldsymbol{K}) \cdot \left[\frac{\partial Y_j}{\partial \boldsymbol{K}}\right] \quad (j = 1, \ldots, n) \tag{1}$$

where $\boldsymbol{K}$ is the vector of size $2m+1$ of the input variables and the coefficients of the mathematical function, defined as $\boldsymbol{K} = [\boldsymbol{X}, \boldsymbol{A}]^{\mathrm{T}}$, $cov(\boldsymbol{K})$ is the variance-covariance matrix and $\left[\frac{\partial Y_j}{\partial \boldsymbol{K}}\right]$ is the vector of the partial derivatives of Y_j with respect to each component of $\boldsymbol{K}$. In $cov(\boldsymbol{K})$, the element in the l, q position is the covariance between K_l and K_q, defined as:

$$cov(K_l, K_q) = \rho_{l,q} \cdot \sqrt{VAR(K_l)} \cdot \sqrt{VAR(K_q)} \tag{2}$$

where $\rho_{l,q}$ is the Pearson correlation coefficients between the parameters K_l and K_q (Devore 2011).

Given that the distribution of output variable Y_j originates by many different random contributions, according to the central limit theorem (Montgomery 2012), it can be approximated to a Normal distribution (see Section 4.3). Hence, the probability of occurrence of the defective-output variable p_{Y_j}, which represents the probability that Y_j falls outside the specification limits (*LSL* and *USL*), may be estimated by computing the area of the normal distribution outside the two specification limits by Eq. (3):

$$p_{Y_j} = 1 - P(LSL \leq Y_j \leq USL) \tag{3}$$

3. Indicators of inspection effectiveness and cost

According to authors' previous studies and re-elaborating the proposed probabilistic model for in-process inspections, the following probabilities can be calculated for each *j*-th output variable (Franceschini et al. 2018; Genta, Galetto, and Franceschini 2018):

$$P(\text{signalling the output variable } Y_j \text{ as defective}) = p_{Y_j} \cdot (1-\beta_{Y_j}) + (1-p_{Y_j}) \cdot \alpha_{Y_j} \tag{4}$$

$$P(\text{signalling the output variable } Y_j \text{ as not defective}) = p_{Y_j} \cdot \beta_{Y_j} + (1-p_{Y_j}) \cdot (1-\alpha_{Y_j}) \tag{5}$$

where $j = 1, \ldots, n$, i.e. the total number of output variables.

It is worth noting that Eqs. (4) and (5) are obtained under the hypothesis that the probabilities of occurrence of each defective output variable, p_{Y_j}, and the relevant inspection errors, α_{Y_j} and β_{Y_j}, are independent. The above probabilities represent the "elementary bricks" for the construction of two indicators depicting the performance of inspection strategies in terms of effectiveness and cost (Franceschini et al. 2018; Genta, Galetto, and Franceschini 2018).

Let us now define *n* Bernoulli random variables (W_j) as follows:

- W_j =0, when either (i) the truly defective output variable Y_j is detected as such or (ii) the output variable Y_j is not defective;
- W_j =1, the truly defective output variable Y_j is not detected as such.

According to Eq. (4) and (5), the following two relationships are obtained:

$$P(W_j = 0) = p_{Y_j} \cdot (1-\beta_{Y_j}) + (1-p_{Y_j}) \tag{6}$$

$$P(W_j = 1) = p_{Y_j} \cdot \beta_{Y_j} \tag{7}$$

where j is included between 1 and n.

Therefore, the mean number of real defective-output undetected for the j-th output-variable is:

$$D_{Y_j} = E(W_j) = p_{Y_j} \cdot \beta_{Y_j} \tag{8}$$

Considering the overall inspection strategy, the mean total number of defective-outputs which are erroneously not detected can be defined as:

$$D_{tot} = \sum_{j=1}^{n} E(W_j) = \sum_{j=1}^{n} p_{Y_j} \cdot \beta_{Y_j} \tag{9}$$

The variable D_{tot} is assumed as a first approximation of inspection effectiveness, since it provides an indication of the overall effectiveness of the inspection strategy performed on the product. It should be pointed out that Eq. (9) is obtained under the hypothesis of no statistical correlation between random variables, i.e. between the model parameters (inspection errors and defect probabilities) of different output variables. This correlation will be investigated in future research.

Regarding each output variable Y_j, the total cost for inspection and defects removal can be expressed as (Genta, Galetto, and Franceschini 2018):

$$C_{Y_j} = FC_j + c_j + NRC_j \cdot p_{Y_j} \cdot (1-\beta_{Y_j}) + URC_j \cdot (1-p_{Y_j}) \cdot \alpha_{Y_j} + NDC_j \cdot p_{Y_j} \cdot \beta_{Y_j} \tag{10}$$

where:

- FC_j is the fixed cost for controlling and keeping the input variables at the values which result in the best values of the response, and within their variability range;
- c_j is the cost of the j-th inspection activity (e.g., manual or automatic inspection activities);
- NRC_j is the necessary-repair cost, i.e., the necessary cost for removing defects of the j-th output variable;
- URC_j is the unnecessary-repair cost, i.e., the cost incurred when identifying false defective-

output variables; e.g., despite there is no cost required for defective-output variables removal, the overall process can be slowed down, with a consequent extra cost;

- NDC_j is the cost of undetected defective-output variables, i.e., the cost related to the missing detection of defective-output variables.

Eq. (10) requires, in addition to the estimates of the probabilities p_{Y_j}, α_{Y_j} and β_{Y_j}, the evaluation of the costs FC_j, c_j, NRC_j, URC_j, NDC_j , which are considered fixed parameters as a preliminary approximation. Typically, FC_j, c_j and NRC_j are known costs. URC_j is usually relatively easy to estimate, while NDC_j is usually hard to estimate since it may depend on difficult-to-quantify factors, such as external failure costs including legal fees related to customer lawsuits, loss of future sales from dissatisfied customers, product recalls, product return costs, after-sales repair costs, etc. (Galetto et al. 2018).

The total cost for inspection and defective-output variables removal related to the overall inspection strategy (n output variables) can be expressed as:

$$C_{tot} = \sum_{j=1}^{n} C_{Y_j} = \sum_{j=1}^{n} \left[FC_j + c_j + NRC_j \cdot p_{Y_j} \cdot (1-\beta_{Y_j}) + URC_j \cdot (1-p_{Y_j}) \cdot \alpha_{Y_j} + NDC_j \cdot p_{Y_j} \cdot \beta_{Y_j} \right] \tag{11}$$

Eq. (11) may be considered a preliminary approximation of the total cost of the inspection strategy. However, even for this indicator, it is assumed that no statistical correlation between inspection errors and defect probabilities of different output variables occurs. In some circumstances, e.g. cost sharing between the output variables, C_{tot} might overestimate the costs related to the inspection strategies when correlation between variables occurs.

The general methodology is organized according to the following steps:

1. identification of input and output variables;
2. designing experimental plans in order to obtain the mathematical functions (regression models) relating each output variable with input variables;
3. responses optimization (searching for the best values of the regression models);
4. identification of all the sources of uncertainty, including the uncertainty of the mathematical function variables and the resolution interval of input variables;
5. estimation of probabilities of occurrence of defective-output variables;

6. estimation of variables related to inspections, such as inspection errors and inspection costs;
7. comparison of alternative inspection strategies. An inspection strategy is defined as the combination of inspection methods used to perform quality controls on output variables. Each inspection strategy is evaluated by two indicators of (i) inspection effectiveness and (ii) inspection costs. The combination of these indicators allows the manufacturer to choose the most suitable one.

The proposed methodology will be described in detail through the case study in the next Section 4.

4. Case study: low-volume Additive Manufacturing production

4.1. SLM Process

Consider the low-volume production of components by Additive Manufacturing process based on Selective Laser Melting (SLM) technique, also called Direct Metal Laser Sintering (DMLS). In this process, a high-density object is built up layer by layer through the consolidation of metal powder particles with a focused laser beam that selectively scans the surface of the powder bed (Gibson, Rosen, and Stucker 2014). The aluminium samples, produced using the AlSi10Mg alloy, were prepared by SLM with an EOS M290 machine. In this machine, a powerful ytterbium (Yb) fiber laser system in an argon atmosphere is used to melt powders with a continuous power up to 400 W, a scanning rate up to 7 m/s, and a spot size of 100 μm. During the production process, three areas can be identified in the parts: up-skin, down-skin and in-skin, as shown in Fig. 3 (a). The up-skin is the region on the part layer above which there is no area to be exposed. The bottom region which is in contact with the building platform below it and laser exposed areas above it is called down-skin. The third area, the in-skin, is the region where there are above and below exposed areas. For each layer, a contour of the layer structure is exposed with the contour speed and the laser power. After that, the inner area is solidified by means of the laser beam which moves line after line several times. The distance between the lines is called hatching distance. Once the inner area is solidified, a second exposure of the exterior part contour is carried out in order to increase the accuracy of the building process (Calignano et al. 2013). Several studies (Krishnan et al. 2014; Tian et al. 2017; Trevisan et al. 2017) have shown that this region-wise differentiated parameter setting can achieve control of material properties, such as surface finishing and mechanical properties. In fact, according to Fig. 3 (a), up- and down-skin parameters are related to surface properties, while in-skin parameters to the core average properties of the component.

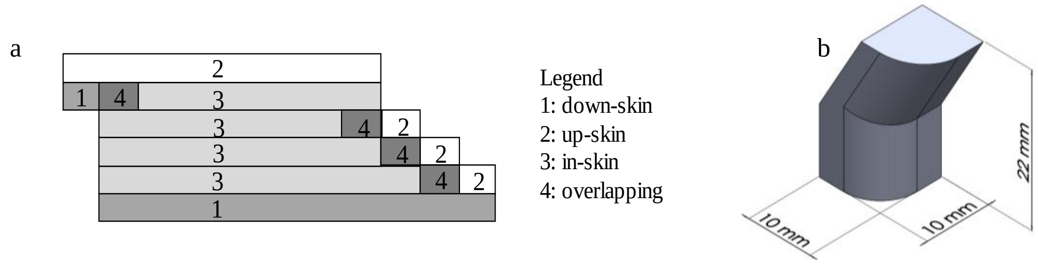

Fig. 3. (a) Schematic of up-skin, in-skin and down-skin areas; (b) Geometry of specimen.

4.2. Output variables optimization

In this case study, the output variables measured on the specimens were macro-hardness and up-skin roughness. It is evident from the literature that controlling and changing process variables may result in different quality outputs of the parts. Specifically, the most influencing process variables on the hardness of the parts are laser power, scan speed and hatching distance of the in-skin (Krishnan et al. 2014). For the surface roughness, process parameters chosen were laser power, scan speed and hatching distance of the up-skin (Calignano et al. 2013). The specimens, whose dimensions are 22x10x10 mm, were designed, according to Fig. 3 (b), in order to measure both surface roughness and hardness. The different inclinations of the sample will allow to evaluate how the roughness changes with the variation of the surface considered. In this study, the roughness of the upper surface is analysed in detail.

In order to obtain optimal process parameters that result in the best values of hardness and roughness, two experimental plans were designed. Specifically, two 3^3 full factorial design were performed in order to investigate possible quadratic effects of input variables. For the first response, the hardness, the three input variables relevant to the in-skin, laser power (PI), scan speed (vI) and hatching distance (h_dI), were kept at three levels. Similarly, three levels were chosen for the three input variables for up-skin, laser power (PU), scan speed (vU) and hatching distance (h_dU) (see Table 1). In this experiment, the down-skin roughness was not specifically investigated.

Variable values used were the same of those of the up-skin. Consequently, the results achieved for the up-skin can also be reasonably exploited for the assessment of the down-skin. The choice of the levels of the process variables set in both the experimental plans allowed to get a wide range of energy density function, ψ, which is calculated as follows:

$$\psi = \frac{P}{h_d \cdot v \cdot t}\left[\frac{\mathrm{J}}{\mathrm{mm}^3}\right] \tag{12}$$

where P and v are respectively the laser power and scan speed, h_d is hatching distance and t is layer thickness. Specifically, in the first experiment ψ varied from 35.09 to 124.58 J/mm^3 and in the second from 44.97 to 134.47 J/mm^3. Energy density is strictly related to the degree of consolidation of the powder particles and may cause defects by creating turbulences in the melt pool (Read et al. 2015). Consequently, it is often adopted in literature as reference parameter for the setup of a planned experimentation (Trevisan et al. 2017). The experiments were not randomized because the high repeatability of the machine allowed building the samples in a single job, by varying process parameters for each sample (Calignano et al. 2013; Read et al. 2015). This approach, as a first approximation, is the one adopted in the computer experiment field (Sacks et al. 1989).

Table 1. Process parameters values used in the two planned experimentations.

Hardness HB [HB]				Roughness Ra [µm]			
Process Variable	Values	Fixed Parameter	Value	Process Variable	Values	Fixed Parameter	Value
PI [W]	340 – 355 - 370	Layer thickness [µm]	30	PU [W]	340-355-370	Layer thickness [µm]	30
vI [mm/s]	900 – 1300 - 1700	Spot size [mm]	0.1	vU [mm/s]	800-1000-1200	Spot size [mm]	0.1
h_dI [mm]	0.11 – 0.15 – 0.19	PU [W]	355	h_dU [mm]	0.11-0.16-0.21	PI [W]	355
		vU [mm/s]	100			vI [mm/s]	1300
		h_dU [mm]	0.16			h_dI [mm]	0.15

After the production, the 27 specimens for hardness measurements were polished. Then, the Brinell hardness test was performed according to the industrial standard ISO 6506-1:2014 (ISO 6506-1:2014). The test was carried out using a sphere with a diameter of 2.5 mm and applying a force of 62.5 kgf, thus evaluating Brinell hardness in the scale HBW 2.5/62.5. For simplicity of notation, the measurement unit of Brinell hardness will henceforth be indicated in this paper with the symbol HB. Three measures for each specimen were taken and the average value was examined. The coefficient of variation of the three hardness measurements ranges from a minimum of 1% to a maximum of 7% (see Appendix A).

The surface roughness on top surface of the other 27 samples was measured according to industrial standards ISO 4287 and ISO 4288, using a contact stylus, Veeco Dektak 150 Surface Profiler, with a 2 μm radius stylus tip (ISO 4287:2009; ISO 4288:2000). The roughness parameter calculated from the filtered roughness profile was Ra, defined as the average value of the ordinates from centreline. For surfaces having a periodic profile, such as the top surfaces of the samples, the prescribed sampling length is based on the mean width of profile elements (RSm). When RSm is included between 0.13 mm and 0.4 mm, it is recommended to use a sampling length for filtering of 0.8 mm and to perform measurements over five consecutive sampling lengths, resulting in an evaluation length of 4 mm (ISO 4288:2000). Three measurements, each 1 mm apart, in the direction perpendicular to the scan path were performed on each sample, and the average value was examined. The coefficient of variation of the three roughness measurements ranges from a minimum of 1% to a maximum of 18%, except for a single sample which reaches 48% (see Appendix B). Such high value may be attributed to the peculiarities of the measurement activity. Indeed, due the discrete nature of the measurements obtained using the contact stylus, each roughness measurement may be sensitive to localised defects. However, considering the mean value of three measurements, the roughness value obtained can be considered representative of the up-skin. The use of a non-contact device, such as a Point Autofocus Instrument (PAI), as will be illustrated in Section 4.4, could help to reduce measurements' uncertainty and the related inspection errors.

The arrangement of the two 3^3 full factorial designs with the indication of the three measurements, the resulting mean value, standard deviation and coefficient of variation for the hardness and the up-skin roughness are reported in Appendix A and B, respectively.

The Response Surface Methodology (RSM) was used to analyse the results and optimize the process for both the experimental designs (Montgomery 2017). The arrangement of the two full factorial design allowed the development of an appropriate empirical equation, a second order polynomial multiple regression equation. The standard stepwise regression was adopted to obtain a model containing exclusively significant factors. This method both adds and removes predictors at each step, according to selected Alpha-to-Enter and Alpha–to-Remove values (Devore 2011). These two values were set at 10% to allow entering terms very close to the significance level of 5%. The software Minitab®, which was used to perform the analysis, provided the coefficients of the significant regression terms with their relevant standard errors, reported in Table 2, and the regression equations showed in Eqs. (13) and (14). The analysis of residuals, i.e. the differences between the observed and the corresponding fitted value, for both hardness and roughness, showed a random pattern of residuals and the absence of systematic errors. Furthermore, the R^2 value, a measure of goodness model fit, shows that the variation in the response explained by the model is 92.32 % for HB and 72.50 % for Ra. Moreover, the *S* value, also known as the standard error of the regression or as the standard error of the estimate (Devore 2011), is 4.55 for HB and 4.13 for Ra. The 3D surface plots representing how the fitted responses are related to the process variables are reported in Fig. 4 and Fig. 5.

$$HB = a_0 + a_1 \cdot PI + a_2 \cdot vI + a_3 \cdot h_d I + a_4 \cdot vI \cdot vI + a_5 \cdot vI \cdot h_d I \tag{13}$$

$$Ra = b_0 + b_1 \cdot vU + b_2 \cdot h_d U + b_3 \cdot PU \cdot PU + b_4 \cdot PU \cdot vU + b_5 \cdot PU \cdot h_d U \tag{14}$$

In order to find the best values of laser power, scan speed and hatching distance, two response optimizations were performed. The objective functions were the maximization of hardness and the minimization of surface roughness. Parameters setups and the respective value of energy density ψ are summarized in Table 3, together with the predicted value of responses.

Table 2 Estimates of regression models' parameters (see Eqs. (13) and (14)), with their standard errors (SE), separately for the hardness HB [HB] and roughness Ra [µm]. The standard error of the estimate is 4.55 for HB and 4.13 for Ra.

Hardness HB [HB]				Roughness Ra [µm]			
Variable	Parameter	Parameter estimate	Parameter SE estimate	Variable	Parameter	Parameter estimate	Parameter SE estimate
constant	a_0 [HB]	$-5.12 \cdot 10^{1}$	$3.57 \cdot 10^{1}$	constant	b_0 [µm]	$8.71 \cdot 10^{1}$	$8.45 \cdot 10^{1}$
PI	a_1 [HB/W]	$-1.42 \cdot 10^{-1}$	$7.16 \cdot 10^{-2}$	vU	b_1 [µm/(mm/s)]	$-2.99 \cdot 10^{-1}$	$1.41 \cdot 10^{-1}$
vI	a_2 [HB/(mm/s)]	$2.19 \cdot 10^{-1}$	$3.28 \cdot 10^{-2}$	h_dU	b_2 [µm/mm]	$9.85 \cdot 10^{2}$	$5.64 \cdot 10^{2}$
h_dI	a_3 [HB/mm]	$4.85 \cdot 10^{2}$	$1.10 \cdot 10^{2}$	$PU \cdot PU$	b_3 [µm/W²]	$-5.85 \cdot 10^{-4}$	$6.68 \cdot 10^{-4}$
$vI \cdot vI$	a_4 [HB/(mm/s)²]	$-5.46 \cdot 10^{-5}$	$1.16 \cdot 10^{-5}$	$PU \cdot vU$	b_4 [µm/(W·mm/s)]	$8.76 \cdot 10^{-4}$	$3.96 \cdot 10^{-4}$
$vI \cdot h_dI$	a_5 [HB/(mm²/s)]	$-2.69 \cdot 10^{-1}$	$8.22 \cdot 10^{-2}$	$PU \cdot h_dU$	b_5 [µm/(W·mm)]	$-2.58 \cdot 10^{0}$	$1.59 \cdot 10^{0}$

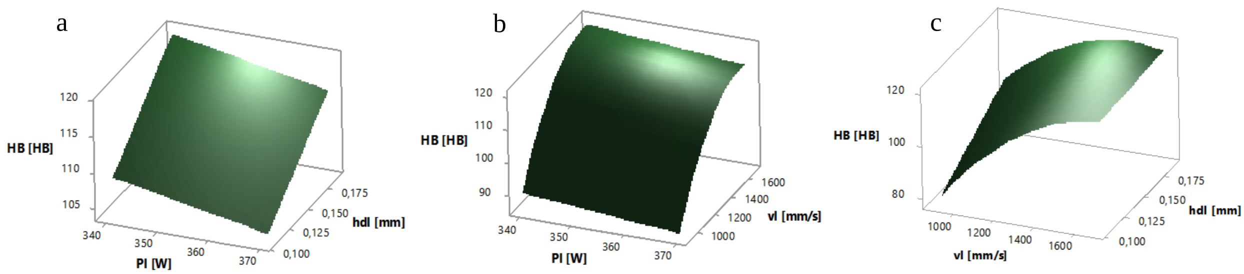

Fig. 4. Surface plot of HB [HB] versus: (a) h_dI [mm] and *PI* [W] (*vI* was set to 1300 mm/s); (b) *vI* [mm/s] and *PI* [W] (h_dI was set to 0.15 mm); (c) h_dI [mm] and *vI* [mm/s] (*PI* was set to 355 W).

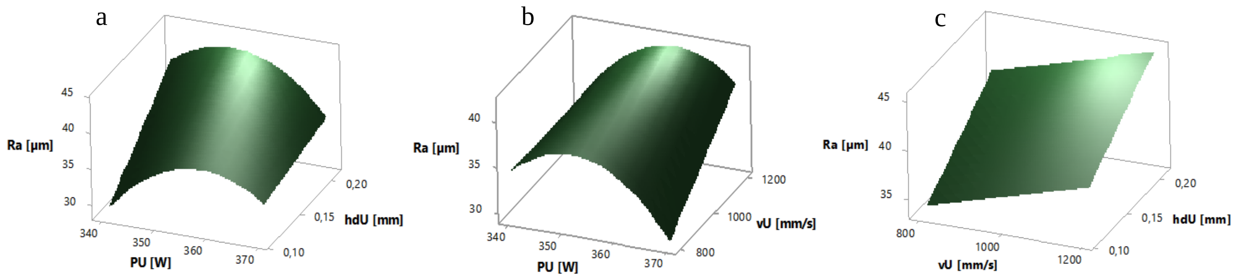

Fig. 5. Surface plot of Ra [µm] versus: (a) h_dU [mm] and *PU* [W] (*vU* was set to 1000 mm/s); b) *vU* [mm/s] and *PU* [W] (h_dU was set to 0.16 mm); c) h_dU [mm] and *vU* [mm/s] (*PU* was set to 355 W).

Table 3. Responses optimization (max. HB and min. Ra): process setups and predicted values.

Control factors				HB predicted value	Control factors				Ra predicted value
PI	*vI*	h_dI	ψ	Mean value	*PU*	*vU*	h_dU	ψ	Mean value
[W]	[mm/s]	[mm]	[J/mm^3]	[HB]	[W]	[mm/s]	[mm]	[J/mm^3]	[µm]
340	1538	0.19	38.78	122.45	340	1200	0.11	85.85	29.68

4.3. Estimation of the probabilities of occurrence of defective-output variables

Once the input parameters optimizing the responses were obtained, the variances of the output variables were derived, according to Eq. (1), by propagating the uncertainty of both the mathematical function parameters (see Table 2) and the input variables, evaluated as the resolution of the AM machine (see Table 4). The AM measuring device that displays the values of input variables is digital. In such case, the distribution of the resolution contribution is uniform, because the measurand can be assumed to have an equal probability of occurrence at any point in the range associated with the displayed value, i.e. the resolution interval (JCGM 100:2008 2008). Accordingly, the standard deviations of the input variables are calculated considering a uniform distribution and are reported in Table 4 (JCGM 100:2008 2008). The Pearson correlation coefficients between the parameters of the regression models used in the variance-covariance matrix (see Eq. (2)) were derived by the software Minitab®. The computations were performed using the software MATLAB® and the obtained variances of hardness and roughness are reported in Eqs. (15) and (16) respectively.

Table 4. Variability range (i.e., resolution interval) and standard deviation of input variables, under the assumption of uniform distributions. It is reminded that the variance of a uniform distribution is $\sigma^2=a^2/3$, where a is half of the variability range.

Up-skin and in-skin process variables	Resolution of AM machine	Process variable variability range	Process variable standard deviation
Laser power [W]	0.1	$(PI \pm 0.05)$ $(PU \pm 0.05)$	$\sqrt{0.05^2/3} = 2.89 \cdot 10^{-2}$
Scan speed [mm/s]	0.1	$(vI \pm 0.05)$ $(vU \pm 0.05)$	$\sqrt{0.05^2/3} = 2.89 \cdot 10^{-2}$
Hatching distance [mm]	0.01	$(h_dI \pm 0.005)$ $(h_dU \pm 0.005)$	$\sqrt{0.005^2/3} = 2.89 \cdot 10^{-3}$

$$VAR(\mathrm{HB}) \approx \left[\frac{\partial HB}{\partial \boldsymbol{K}_{HB}}\right]^{\mathrm{T}} \cdot \mathrm{cov}(\boldsymbol{K}_{HB}) \cdot \left[\frac{\partial HB}{\partial \boldsymbol{K}_{HB}}\right] = 4.62\,\mathrm{HB}^2 \tag{15}$$

where $\boldsymbol{K}_{HB} = [PI, vI, h_dI, vI \cdot vI, vI \cdot h_dI, a_0, a_1, a_2, a_3, a_4, a_5]^{\mathrm{T}}$.

$$VAR(\mathrm{Ra}) \approx \left[\frac{\partial Ra}{\partial \boldsymbol{K}_{Ra}}\right]^{\mathrm{T}} \cdot \mathrm{cov}(\boldsymbol{K}_{Ra}) \cdot \left[\frac{\partial Ra}{\partial \boldsymbol{K}_{Ra}}\right] = 6.55\,\mu\mathrm{m}^2 \tag{16}$$

where $\boldsymbol{K}_{Ra} = [PU, vU, h_dU, PU \cdot PU, PU \cdot vU, PU \cdot h_dU, b_0, b_1, b_2, b_3, b_4, b_5]^{\mathrm{T}}$.

The distributions of the two responses (*HB* and *Ra*) were also obtained through a computer simulation. In both cases, the normality of the distributions cannot be rejected by the Anderson-Darling test at a significance level of 5%. Thus, under the hypothesis of normal distribution, the probabilities of occurrence of the defective-output variables may be obtained. Given the mean values, reported in Table 3, the variances of Eqs. (15) and (16), and the specification limits, the probabilities of occurrence of defects, p_{HB} and p_{Ra}, were derived by applying Eq. (3). The specification limits were fixed according to technological requirements for the produced parts (for hardness a lower specification limit, *LSL*, was set to 114 HB and for roughness an upper specification limit, *USL*, was set to 36 µm). The two resulting probabilities are shown in Eqs. (17) and (18).

$$p_{HB} = P(HB \leq LSL) = 0.55\% \tag{17}$$

$$p_{Ra} = P(Ra \geq USL) = 0.67\% \tag{18}$$

4.4. Comparison of alternative inspection strategies

The AM production of these components may be inspected through different offline inspections concerning macro-hardness and roughness evaluations. In this section, four alternative inspection strategies are examined and compared. With respect to hardness, the Brinell Hardness (HB) and Rockwell Hardness (HRB) tests are examined. HB test is a widely used method for characterizing specimens by SLM. The main advantage is the simplicity of implementation, while the main defect is represented by the difficulty (and ambiguity) of the measure (Herrmann 2011). HRB test is much faster and cheaper than the Brinell test, making this a widely used method of measuring metal hardness in industrial context. However, the considerable practical advantages are accompanied by a loss of the metrological characteristics (Herrmann 2011). As far as roughness measurement is concerned, two instruments belonging to two different classes of methods for surface texture measurements, the Line Profiling and the Areal Topography, are considered (Leach 2011). Specifically, the first instrument is a Contact Stylus (CS) and the second one is a Point Autofocus Instrument (PAI). In CS, the stylus is loaded on the surface to be measured and then moved across the surface at a constant velocity to obtain surface height variation (Leach 2011). A PAI is a non-contact, optical measuring instrument that automatically focuses a laser beam to a single point on the surface and raster scans an area of interest (Maculotti et al. 2019). Each of the four different methods is characterized by the three probabilities p_{Y_j}, α_{Y_j} and β_{Y_j}, which are reported in Table 5.

Table 5. Estimates of defects probabilities, inspection errors, cost parameters and inspection indicators related to each inspection method (HB, HRB, CS and PAI).

Output variable	Inspection method	p_{Y_j} [%]	α_{Y_j} [%]	β_{Y_j} [%]	CF_j [€]	c_j [€]	NRC_j [€]	URC_j [€]	NDC_j [€]	D_{Y_j} [-]	C_{Y_j} [€]
Hardness	HB	0.55	2	1	15	12.5	50	50	100	$5.53 \cdot 10^{-5}$	28.77
	HRB	0.55	3	2	15	4.2	50	50	100	$11.05 \cdot 10^{-5}$	20.97
Roughness	CS	0.67	5	4	15	6.3	1.3	1.3	80	$26.79 \cdot 10^{-5}$	21.39
	PAI	0.67	2	1	15	125	1.3	1.3	80	$6.70 \cdot 10^{-5}$	140.04

In Table 5, hardness defect probabilities (p_{HB} and p_{HRB}) were considered identical and equal to the probability p_{HB} obtained in Eq. (17), as well as for roughness defect probabilities (p_{CS} and p_{PAI}), which were set equal to p_{Ra} derived in Eq. (18). In fact, as a preliminary approximation, the two different methods for inspecting both hardness and roughness are based on similar technologies with comparable performances in terms of detection of defects. In other words, although p_{HB} and p_{Ra} are strongly dependent on the instrument used, they can be considered good estimates of the actual defectiveness in terms of order of magnitude. In order to refine the estimates of p_{HRB} and p_{PAI}, future research will be aimed at designing a specific planned experimentation. The inspection errors α_{Y_j} and β_{Y_j} were estimated by the inspectors, for each inspection method, basing on empirical values obtained from similar parts produced with the adopted SLM technique and other manufacturing process such as casting processes. Table 5 also reports the estimates of the cost parameters for each inspection method (HB, HRB, CS and PAI). CF_j were estimated as the cost for calibrating the AM machine carried out by the supplier during the preventive maintenance. The estimates of c_j were calculated considering the time required for the inspection and the labour cost of operators/inspectors. NRC_j and URC_j were estimated starting from the time required for identifying and repairing possible defects (necessary or unnecessary), and the respective labour cost. Finally, NDC_j included external failure costs. According to Eqs. (8) and (10), the indicators D_{Y_j} and C_{Y_j} were calculated for each inspection method and were reported in Table 5.

By combining the four different inspection methods of Table 5, four inspection strategies may be performed (see Table 6). The first one, IS1, includes Brinell hardness test and roughness measurement with the contact stylus CS. The second, IS2, is performed with a Brinell hardness test and a roughness test using a PAI. IS3 requires hardness to be measured with a Rockwell test (HRB) and roughness with the contact stylus CS. Finally, IS4 involves measuring hardness with a Rockwell test (HRB) and roughness using a PAI. Table 6 shows the indicators D_{tot} and C_{tot} obtained for the inspection strategies IS1, IS2, IS3 and IS4, calculated using respectively Eqs. (9) and (11). The strategy with the lowest value of D_{tot} is IS2, but it is also the most expensive one. Conversely, IS3 has the lowest C_{tot}, but it is characterized by the highest mean total number of undetected defects. IS1 and IS4 are two intermediate strategies between IS2 and IS3. According to these results, the producer of SLM parts may easily select the best inspection strategy that adequately satisfies its needs. In fact, according to cost-benefit logic, if the producer is willing to accept a high mean number of undetected defective-output variables in order to have low total inspection costs, the best choice is IS3. On the contrary, if his objective is the minimization of defects, the producer will select IS2, while accepting a quadruple increase in costs with respect to IS3. The decision is strictly related to the producer requirements, which are in turn connected with the certification constraints imposed by the product application sectors. For instance, if the component is designed for medical or aerospace sectors, the producer may be more inclined to choose the strategy that minimizes D_{tot}, instead of choosing the most affordable one, because of the considerable consequences that residual defects could have. On the contrary, if the sector requirements are not so stringent, the producer is led to choose the most affordable strategy. However, it should be highlighted that the number of undetected defects in all the four strategies is very small, also considering that it refers to a low-volume production. Indeed, despite in IS3 the indicator D_{tot} is almost three times greater than in IS2, it means that given a production of 10^4 components, there are nearly 4 defective-output variables which are erroneously not signalled. Since the production of these components can reach a hundred parts per year, the number of defects which are erroneously not signalled is actually very low.

Table 6. Indicators values calculated for IS1, IS2, IS3 and IS4.

Indicator	IS1	IS2	IS3	IS4
D_{tot} [-]	$3.23 \cdot 10^{-4}$	$1.22 \cdot 10^{-4}$	$3.78 \cdot 10^{-4}$	$1.78 \cdot 10^{-4}$
C_{tot} [€]	50.16	168.81	42.36	161.01

5. Conclusion

Designing effective and affordable inspection strategies plays an important and challenging role in manufacturing process. In literature, several techniques have been proposed to plan inspection strategies in massive productions. However, these techniques are often not suitable for low-volume productions. This paper proposes a powerful approach to assist inspection designers in the selection of the best compromise between effectiveness and affordability of alternative offline inspection strategies, when in-process controls are not adequate or impossible to be performed. A probabilistic model for defects prediction is formulated starting from some process parameters which influence product final quality and output variables inspected on the product. Two practical indicators to compare different inspection methods according to their effectiveness and cost are proposed. According to cost-benefit logic, the combined use of the inspection indicators allows the comparison of alternative inspection strategies, and the selection of the most appropriate according to the manufacturer requirements. This approach may represent a powerful approach to assist inspection designers in early design phases of inspection planning. In this work, a case study concerning the low-volume production of metal components by AM is discussed and the comparison of four different inspection strategies is presented. A first limitation of this study is that the probabilistic model and the two indicators do not consider possible correlations between parameters of different output variables. In addition, the estimation of various not-so-easily-quantifiable parameters is required. Nevertheless, a deep knowledge of the process and expert opinion can help to overcome this limit. Future research will aim at introducing correlations between variables and at developing specific models for predicting inspection errors using an approach similar to that adopted for defect generation models. Moreover, specific studies will focus on the uncertainty assessment of the two indicators of effectiveness and affordability.

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Appendices

Appendix A: Arrangement of the 3^3 full factorial design to evaluate the hardness HB [HB], with indication of the three measurements, the resulting mean value, standard deviation and coefficient of variation.

PI [W]	*vI* [mm/s]	h_dI [mm]	Measurement 1 [HB]	Measurement 2 [HB]	Measurement 3 [HB]	Mean value [HB]	Standard deviation [HB]	Coefficient of variation [%]
340	900	0.11	87	84	86	85.7	1.5	2
340	900	0.15	93	88	90	90.3	2.5	3
340	900	0.19	104	102	105	103.7	1.5	1
340	1300	0.11	101	89	100	96.7	6.7	7
340	1300	0.15	112	115	118	115.0	3.0	3
340	1300	0.19	119	120	124	121.0	2.6	2
340	1700	0.11	116	121	124	120.3	4.0	3
340	1700	0.15	118	120	118	118.7	1.2	1
340	1700	0.19	113	122	124	119.7	5.9	5
355	900	0.11	76	75	77	76.0	1.0	1
355	900	0.15	84	90	89	87.7	3.2	4
355	900	0.19	99	99	101	99.7	1.2	1
355	1300	0.11	107	109	108	108.0	1.0	1
355	1300	0.15	114	118	117	116.3	2.1	2
355	1300	0.19	117	118	124	119.7	3.8	3
355	1700	0.11	111	114	119	114.7	4.0	4
355	1700	0.15	115	121	120	118.7	3.2	3
355	1700	0.19	117	116	113	115.3	2.1	2
370	900	0.11	80	80	76	78.7	2.3	3
370	900	0.15	87	88	87	87.3	0.6	1
370	900	0.19	88	78	88	84.7	5.8	7
370	1300	0.11	103	100	98	100.3	2.5	3
370	1300	0.15	107	111	113	110.3	3.1	3
370	1300	0.19	119	116	120	118.3	2.1	2
370	1700	0.11	119	120	122	120.3	1.5	1
370	1700	0.15	114	117	118	116.3	2.1	2
370	1700	0.19	112	116	121	116.3	4.5	4

Appendix B: Arrangement of the 3^3 full factorial design to evaluate the up-skin roughness Ra [µm], with indication of the three measurements, the resulting mean value, standard deviation and coefficient of variation.

PU [W]	*vU* [mm/s]	h_dU [mm]	Measurement 1 [µm]	Measurement 2 [µm]	Measurement 3 [µm]	Mean value [µm]	Standard deviation [µm]	Coefficient of variation [%]
340	800	0.11	26.6	29.6	28.7	28.30	1.5	5
340	800	0.16	36.4	31.1	32.8	33.43	2.7	8
340	800	0.21	38.3	35.1	38.3	37.23	1.8	5
340	1000	0.11	28.2	37.4	28.5	31.37	5.2	17
340	1000	0.16	40.0	33.2	35.3	36.17	3.5	10
340	1000	0.21	40.3	40.5	47.6	42.80	4.2	10
340	1200	0.11	41.7	24.6	15.9	27.40	13.1	48
340	1200	0.16	30.4	32.8	30.4	31.21	1.4	4
340	1200	0.21	42.1	30.7	31.3	34.70	6.4	18
355	800	0.11	28.0	30.6	25.6	28.07	2.5	9
355	800	0.16	42.4	39.8	32.6	38.27	5.1	13
355	800	0.21	46.4	37.4	34.7	39.50	6.1	16
355	1000	0.11	33.0	33.2	31.9	32.70	0.7	2
355	1000	0.16	47.3	36.7	43.5	42.50	5.4	13
355	1000	0.21	44.3	39.3	44.9	42.83	3.1	7
355	1200	0.11	36.4	38.5	41.4	38.77	2.5	6
355	1200	0.16	46.3	42.2	42.9	43.80	2.2	5
355	1200	0.21	44.8	54.4	46.5	48.57	5.1	11
370	800	0.11	27.8	32.5	30.6	30.30	2.4	8
370	800	0.16	30.9	30.2	41.3	34.13	6.2	18
370	800	0.21	25.6	27.1	34.1	28.93	4.5	16
370	1000	0.11	31.3	42.4	35.2	36.30	5.6	16
370	1000	0.16	32.1	40.9	38.8	37.27	4.6	12
370	1000	0.21	39.3	29.3	30.9	33.17	5.4	16
370	1200	0.11	37.6	37.4	36.7	37.23	0.5	1
370	1200	0.16	39.5	31.2	33.5	34.73	4.3	12
370	1200	0.21	43.0	39.8	49.7	44.17	5.1	11