Obtained Value Through Quality Inspection

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Abstract

The design of quality-inspection procedures may be critical for short-run productions. In this paper, a probabilistic model representing the process propensity to produce defects is adopted, together with two indicators related to the effectiveness and cost of inspections. The combined use of the indicators allows to support in a practical way the selection of the more appropriate inspection procedures. A case study concerning the production of front fenders of a luxury car is extensively dealt with.

Keywords: quality inspection, short-run, inspection effectiveness, inspection cost, car fender

Introduction

The manufacturing of complex products is typically organized into several steps: acquisition of raw materials, processing, assembly, functional testing etc. Quality inspections are usually performed to check whether specifications and functional requirements are satisfied and to identify defects and/or anomalies. Inspection can be governed by strict or non-strict rules (e.g. periodic controls, fixed-percentage control etc.) and organized through well-defined or heuristic procedures.

The inspection strategies are significantly affected by the production volume. In the case of mass production, Statistical Process Control (SPC) techniques can be straightforwardly applied (Montgomery, 2013). On the other hand, in the case of productions of single units, small-sized lots (i.e. the so-called *short-runs*) or in the start-up of a process, most of the SPC techniques are

„The time will come when people will recognize that my paintings are worth more than the value of the paints used in the picture."
Vincent van Gogh

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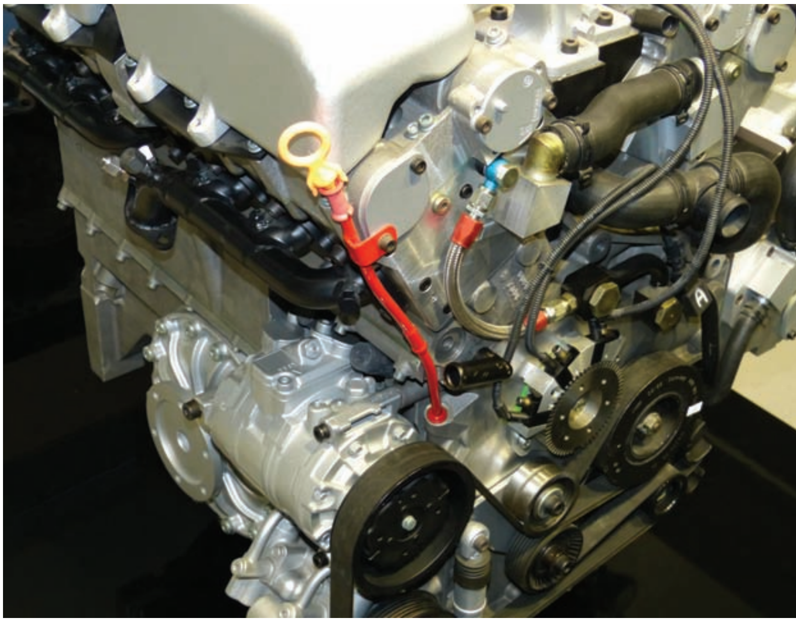
inappropriate (Del Castillo *et al.*, 1996; Marques *et al.*, 2015).

In many production environments (e.g. situations with low inspection costs, high salvage costs, high penalty costs or high defect probability) quality costs are significantly affected by inspection errors (Ballou and Pazer, 1982). The two types of errors associated with an inspection are taken into account, i.e. **(i)** the wrong rejection of a conforming unit, which is known as type-I error; and **(ii)** the erroneous acceptance of a nonconforming unit, which is known as type-II error (Mandroli, Shrivastava and Ding, 2006).

Currently, similar approaches are mostly implemented in the software engineering field (Rawat and Dubey, 2012). In particular, probabilistic models based on Bayesian networks were proposed for software defect prediction (Fenton, Neil and Marquez, 2008). Furthermore, inspection-oriented quality-assurance strategies are mainly aimed at identifying optimal formulations (Kelly *et al.*, 2016).

The present paper analyses the quality-inspection procedures for a short run manufacturing processes exploiting some results obtained in a previous work (Franceschini *et al.*, 2016). A case study in the automotive industry concerning the production of car fenders is extensively dealt with. The adopted probabilistic model for defect prediction enables to support the design and assessment of suitable inspection procedures. In detail, the problem of comparing several possible inspection procedures is dealt with.

The remainder of the paper is organized into three sections. Section 2 illustrates the probabilistic model and its characteristic parameters and then it describes two practical indicators which depict the overall effectiveness and economic convenience of an inspection procedure. Section 3 presents a structured case study, concerning the application of the adopted model and indicators in the short-run production of front fenders of luxury cars. Section 4 summarizes the contributions of this research, including its possible limitations.



Model and Indicators

Model assumptions and parameters

The production process is decomposed into manufacturing steps or just steps, i.e., individual operations providing an added value to the final product. The adopted model (Franceschini *et al.*, 2016) is based on the following hypotheses:

- For each step, there can be one-and-only-one defect typology.
- Defects originated in the different steps are uncorrelated.
- The occurrence of defects and that of inspection errors are uncorrelated.

Each *i*-th step of the production process is modelled with a Bernoulli distribution (Montgomery, 2013). Then, each step can be described through three parameters:

- $\boldsymbol{p_i}$: probability of occurrence of the defect in the i-th step (i.e. the parameter of the Bernoulli distribution);
- $\boldsymbol{\alpha_i}$: probability of (erroneously) detecting the defect when it is not present in the inspection in the i-th step (*false defect* or *false positive*);
- $\boldsymbol{\beta_i}$: probability of not detecting the defect when it is present in the inspection in the i-th step (*false negative*).

The index i is included between 1 and m, i.e. the total number of manufacturing steps. The three parameters are usually difficult to estimate. The first parameter concerns the quality of the process, while the other two parameters (related to the type-I and type-II errors) concern the quality of the inspection (Tang and Schneider, 1987; Duffuaa and Khan, 2005).

Model representation

The graph in Figure 1 represents a generic production process with m steps in series. More complex processes can be represented using graphs with mixed structures (in series and in parallel). Consistently with what was described before, each (i-th) step can be associated with three parameters (p_i, α_i, β_i):

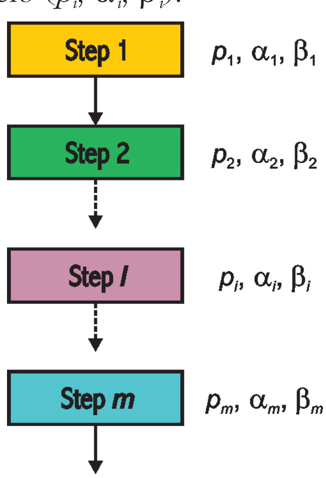


Figure 1 – *Representation of a production process with* ***m*** *steps in series*

The following probabilities can be calculated for each (i-th) step:

P(detecting the defect in the step i) –
– $p_i \cdot (1 - \beta_i) + (1 - p_i) \cdot \alpha_i$ **(1)**

and

P(not detecting the defect in the step i) – $p_i \cdot \beta_i + (1 - p_i) \cdot (1 - \alpha_i)$ **(2)**

where i is included between 1 and m, i.e. the total number of steps.

In the case the defect is detected, it will be *authentic* (i.e. actually present) with a probability $p_i \cdot (1 - \beta_i)$ or *false* with a probability $(1 - p_i) \cdot \alpha_i$ (see Eq. **(1)**). On the other hand, in the case no defect is detected, this will be the result of an inspection error (*false negative*) with a probability $p_i \cdot \beta_i$, or will be due to the real absence of any defect with a probability $(1 - p_i) \cdot (1 - \alpha_i)$ (see Eq. **(2)**). The above probabilities represent the „elementary bricks" for the construction of two indicators depicting the performance of the inspection procedures, which are further presented.

Indicator on inspection effectiveness

Let us consider m Bernoulli random variables (X_i), defined as follows:

- $X_i = 0$: when (i) an authentic defect is detected or (ii) no defect is present in the i-th inspection.;
- $X_i = 1$: when an authentic defect is not detected in the i-th inspection.

According to the general probabilistic model (Franceschini *et al.*, 2016), the mean total number of authentic defects which are not detected in the overall inspection procedure can be defined as:

$$D = \sum_{i=1}^{m} E(X_i) = \sum_{i=1}^{m} p_i \cdot \beta_i \qquad \textbf{(3)}$$

The variable D provides an indication of the overall effectiveness of the inspection procedure.

Indicator on inspection cost

The total cost for inspection and defect removal related to each (i-th) step may be expressed according to the following model (Franceschini *et al.*, 2016):

$$C_{tot,i} = c_i + NRC_i \cdot p_i \cdot (1 - \beta_i) + URC_i \cdot (1 - p_i) \cdot \alpha_i + NDC_i \cdot p_i \cdot \beta_i \quad \textbf{(4)}$$

where:

- c_i is the cost of the i-th inspection;
- NRC_i is the necessary-repair cost, i.e., the necessary cost for removing the defect;
- URC_i is the unnecessary-repair cost, i.e., the cost incurred when identifying false defects; e.g., despite there is no cost required for defect removal, the overall process can be slowed down, with a consequent extra cost.
- NDC_i is the cost of undetected defect, i.e., the cost related to the missing detection of defects.

Apart from the estimates of the probabilities p_i, α_i and β_i, the calculation of the total cost therefore requires the estimate of additional cost parameters. In general, c_i and NRC_i are known costs, URC_i is generally known or easy to estimate, while cost NDC_i is difficult to estimate, since it may depend on difficult-to-quantify factors, such as image loss, after-sales repair cost etc.

The total cost for inspection and defect removal related to the overall production process (m steps) can be expressed as:

$$C_{tot} = \sum_{i=1}^{m} C_{tot,i} \quad \textbf{(5)}$$

The indicator C_{tot} provides a preliminary indication of the total cost related to the inspection procedure in use. In this sense, it can be used as a proxy for economic convenience of an inspection procedure.

Practical case study

Process description and modelling

Let us now consider an automotive manufacturing process aimed at producing the front fender of a luxury car. Due to the relatively small number of parts produced over time, it can be considered a short-run production. The manufacturing process is organized into four main operations: three

welding operations in three different working locations (operations no. 10, 20 and 30) and a final activity of calibrating and assembly (operation 40). Figure 2 shows, as an example, one the welding operations (operation 30). Red circles show the corresponding weld areas.

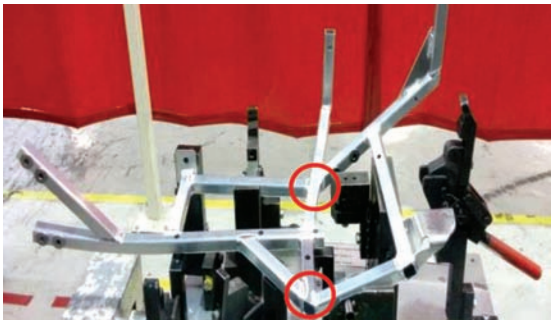


Figure 2 – *Welding operation 30*

Figure 3 shows the calibrating and assembly operation (operation 40):

Figure 3 – *Calibrating and assembly operation (operation 40)*

The two last operations involve the use of a calibrated artefact for dimensional verification of the frame geometry and then the assembly of brackets and bushings. Each of the three welding operations is preceded by a corresponding activity of set-up of welding parameters (operations 10, 20 and 30). Therefore, the process can be divided into seven total steps (three for set-up, three for welding and one of calibrating and assembly), as represented in Figure 4:

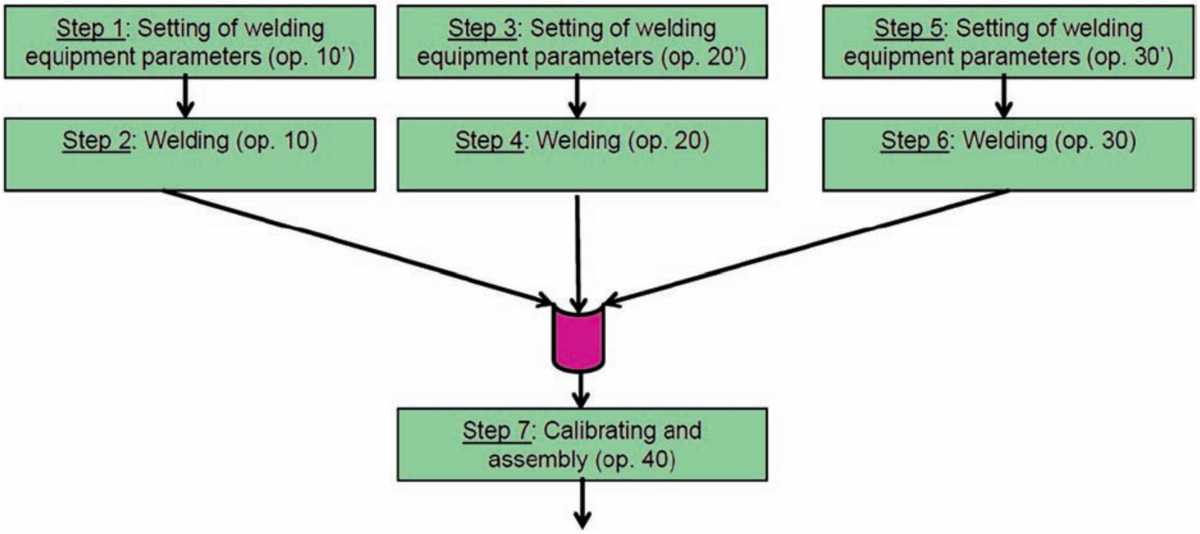


Figure 4 – *Flow chart representing the production process*

Set-up operations are in series with the relevant welding operations. The three pairs of set-up and welding operations are in parallel with each other and followed by the (unique) operation of calibrating and assembly (operation 40).

For the same process of interest, two alternative inspection procedures are compared. In the first procedure, self-inspections are performed after welding operations (operations 10, 20 and 30) and a final inspection is performed by an appointed staff after the calibrating and assembly operation (operation 40). Figure 5 represents the production process integrated with the first inspection procedure:

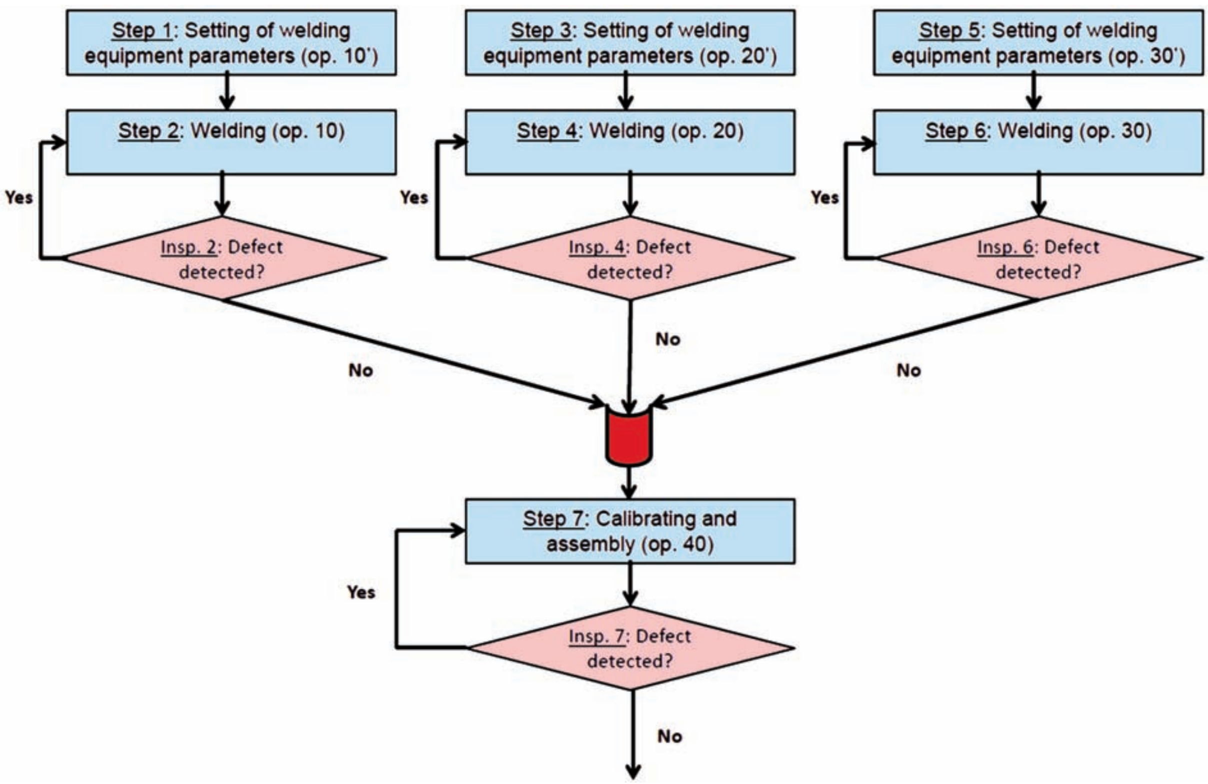


Figure 5 – *Integrated the first inspection procedure*

A self-inspection is performed after the steps 2, 4 and 6, while an inspection by an appointed staff is executed after the step 7. In the second inspection procedure, the individual self-inspections are performed after each of the seven steps (see figure 6).

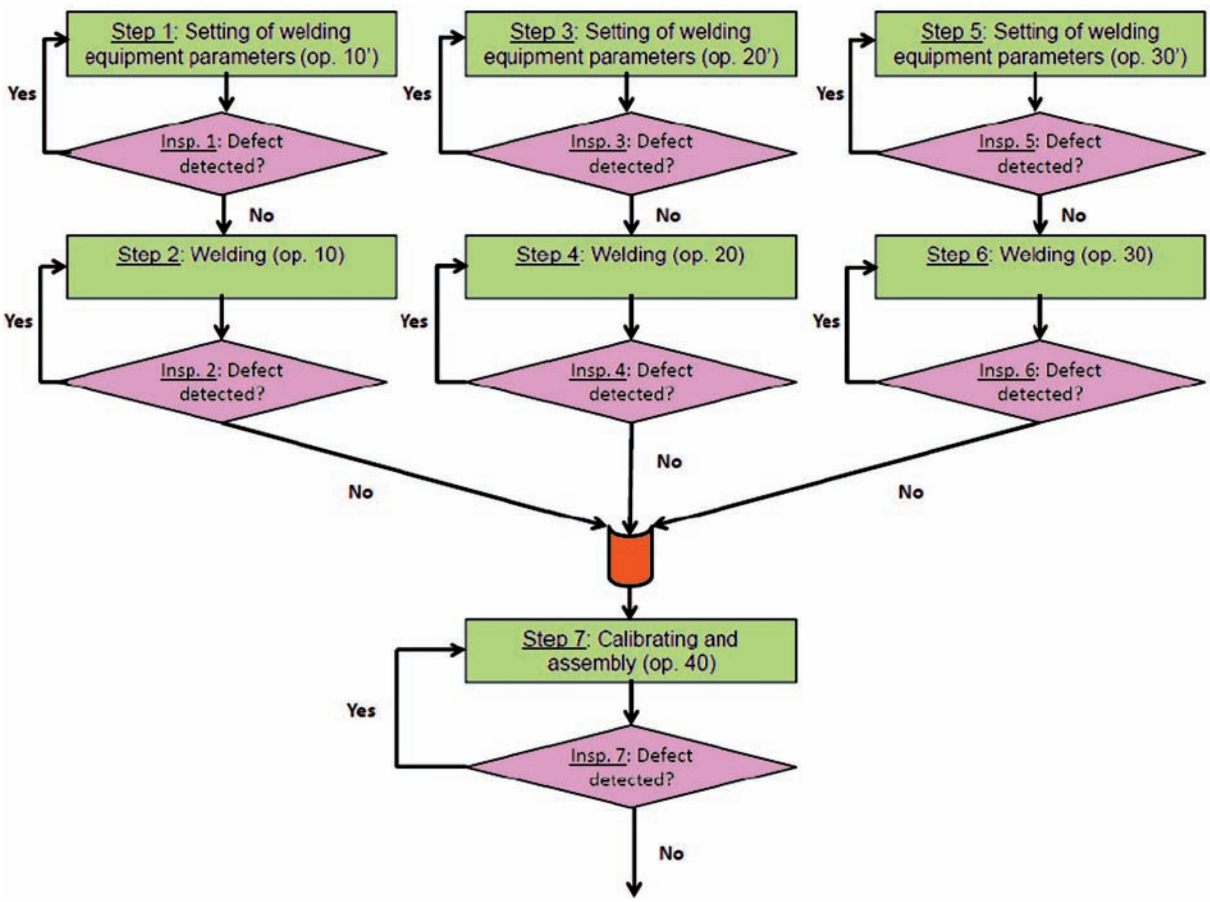


Figure 6 – *Integrated the second inspection procedure*

A self-inspection is performed after each of the seven steps. The adequacy of the inspection procedure is of paramount importance. Figure 7 shows an example of damage in a car fender due to a defect in a welding operation:

Figure 7 – *Damage in a car fender*

The frame indicates the damaged zone, while the arrow indicates the location of the defect.

Comparison of inspection procedures

The indicators previous described were applied to compare the two inspection procedures. Tables 1 and 2 report estimates based on prior experience of the indicators for each process step, considering the first and the second inspection procedure respectively. Estimates of cost parameters are just indicative because their actual values are confidential. The parameters that did not need to be estimated are italicized.

Table 1 – *Estimates of parameters related to the first inspection procedure*

Step no.	Operation type	p_i [%]	α_i [%]	β_i [%]	c_i [€]	URC_i [€]	NDC_i [€]
1, 3, 5	Set-up parameters	0.1	0.0	100.0	0	10	100
2, 4, 6	Welding	5.0	1.5	1.0	10	150	400
7	Calibrating and assembly	1.0	4.0	2.0	50	200	500

Table 2 – *Estimates of parameters related to the second inspection procedure*

Step no.	Operation type	p_i [%]	α_i [%]	β_i [%]	c_i [€]	URC_i [€]	NDC_i [€]
1, 3, 5	Set-up parameters	0.1	1.0	0.5	5	10	100
2, 4, 6	Welding	5.0	1.5	1.0	10	150	400
7	Calibrating and assembly	1.0	2.0	1.5	20	200	500

For both the inspection procedures, it is supposed that probabilities and cost parameters related to steps 1, 3, 5 and steps 2, 4, 6 are coincident, while those related to step 7 are independent. Table 3 reports the numerical values of D and C_{tot}, calculated for both the inspection procedures, using the parameters in Table 1 and Table 2 respectively. This result shows that the second inspection procedure is, on average, significantly better, as it has lower mean total number of undetected defects (D) and total inspection cost (C_{tot}).

Table 3 – *Indicators values calculated for the two inspection procedures*

Indicator	First procedure	Second procedure
D	0.0047	0.0017
C_{tot} [€]	111.7	92.7

Conclusions

In the manufacturing processes, the inspection strategy is strictly related to the production volume. SPC techniques are popular for mass productions, although difficult to manage for short-run and single-unit productions. This paper examined the latter ones, adopting an overall probabilistic model for defect prediction together with two indicators for estimating the expected inspection effectiveness and cost. According to a cost-benefit logic, the combined use of these indicators makes it possible to compare two or more inspection procedures in order to select the more effective and economically convenient for a process of interest.

An application example concerning a short-run production of front fenders of luxury cars exemplified the comparison of two different inspection procedures. The major limitation of the adopted probabilistic model and indicators is that they require the estimation of various not-so-easily-quantifiable parameters (i.e., p_i, α_i, β_i, c_i, URC_i, NDC_i). A thorough understanding of the process of interest and the expertise contributed to overcome this limitation.

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„He only profits from praise who values criticism."
Heinrich Heine