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Product complexity and design of inspection strategies for assembly manufacturing processes

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In the manufacturing field, the assembly process heavily affects product final quality and cost. Specific studies, concerning the causes of the assembly defects, showed that operator errors account for high percentage of the total defects. Also, models linking the assembly complexity with the operator-induced defect rate were developed. Basing on these models, the present paper proposes a new paradigm for designing inspection strategies in case of short-run productions, for which traditional approaches may not be carried out. Specifically, defect generation models are developed to get a priori predictions of the probability of occurrence of defects, which are useful for designing effective inspection procedures. The proposed methodology is applied to a case study concerning the assembly of mechanical components in the manufacturing of hardness testing machines.

Keywords: quality inspection; assembly process; product complexity; defect generation; inspection design; short-run production

1. Introduction

The manufacturing of complex products is typically organised into several activities: acquisition of raw materials, processing, assembly, functional testing, and so on. (Vandebroek, Lan, and Knapen 2016). In particular, the assembly process heavily affects product final quality and cost (Xiaoqing, Bo, and Shuchun 2010). Specific studies classify assembly defects into four categories: improper design, defective part, variance in assembly system (induced, e.g., by the changes of plan/schedule/arrangement of machine, fixture, tooling) and operator mistake (Su, Liu, and Whitney 2010). Previous research, focusing mainly on the first three categories, developed some useful assembly quality control technologies and management approaches (Zhang and Luk 2007; Pawar and Mukhopadhyay 2015). In terms of the fourth category, many investigations disclose that human errors have a significant influence on assembly system performance, sometimes more than the technological ones (Shin, Wysk, and Rothrock 2006). Therefore, reducing the number of operator mistakes is an important must for assembly manufacturing processes. Hinckley's research showed that many assembly defects can be avoided by reducing the 'complexity' of the product design or production activities (Hinckley 1993; Hinckley and Barkan 1995). From the conceptual point of view, the innovative idea of Hinckley was to connect, by a preliminary mathematical model, the product complexity with the likelihood of generating assembly defects. Accordingly, differences in defect reduction through the simplification of the product versus the improvement of the quality control may be highlighted. Hinckley assessed product complexity by means of Design for Assembly (DFA) methodologies (Boothroyd 1987; Hinckley 1993; Boothroyd 1996). Using these methods, estimates of the nominal times needed to perform most of the assembly operations (e.g. part handling, insertion, securing) can be readily obtained. Basing on the groundbreaking Hinckley's research, Shibata further explored the correlation between individual assembly operations and corresponding defect rates (Shibata 2002). He proposed to obtain the estimates of the assembly times relevant to the elementary operations by means of 'time standards' (Aft 2000). In detail, Shibata proposed a novel model enabling to predict the number of defects per unit only by means of the number of elementary operations of the assembly process and the time spent on each elementary operation. He also refined this model by considering the design complexity, i.e. the weights and the difficulties associated to design parameters. At this point, the first research question of the paper comes up: *how the knowledge of the potential number of defects per unit can influence the design of inspection strategies?* In the case of mass production, the design of process inspection methods is usually based on Statistical Process Control (SPC) (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 during the start-up of a process, most of the SPC techniques are unsuitable (Marques et al.

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2015). Moreover, the knowledge of possible occurring defects is required to evaluate the effectiveness of the inspection procedure. Therefore, the second research question arises: *how to organise the inspection procedure when the production volume is small and there is not an a priori knowledge about the number of assembly defects?*

In general, the manufacturing of complex products may be decomposed into a series of process steps with corresponding inspection activities (Lee and Unnikrishnan 1998; Carcano and Portioli-Staudacher 2006; Franceschini et al. 2016). This paper attempts to design effective inspection strategies by means of an a priori prediction of probabilities of occurrence of defects relevant to each process step. Above-mentioned Hinckley and Shibata models allow obtaining the 'a priori knowledge' from similar assembly manufacturing processes. Specifically, Hinckley and Shibata models have been inserted in the authors' model of inspection strategies for manufacturing processes (Franceschini et al. 2016). Once the elementary operations constituting the assembly process and the design parameters are known, the 'a priori knowledge' enables to predict, without any supplementary experimental test, the number of defects which can be generated. Hence, the probabilities of occurrence of defects in each process step may be derived. In the research phase, these predictions are useful to the producers for identifying the more effective inspection procedure. The block diagram in Figure 1 summarises the proposed methodology.

The proposed methodology is applied to a case study concerning the assembly of mechanical components in the manufacturing of hardness testing machines.

2. Defect modelling

While many works dealt with the reduction of cycle-time in assembly processes (Boothroyd and Alting 1992), Hinckley's research provided a new way to look at a product's assemblability through the complexity of the entire product (Hinckley 1993; Hinckley and Barkan 1995). Based on defect data of semiconductor products, Hinckley found empirically that defects per unit (*DPU*) were positively correlated with total assembly time and negatively correlated with number of assembly operations. He defined the assembly complexity factor (*Cf*) as:

$$Cf = TAT - t_0 \cdot TOP \tag{1}$$

where *TAT* is the total assembly time for the entire product, *TOP* is the total number of assembly operations and t_0 is the threshold assembly time. In order to calibrate the correlations between these parameters, Hinckley incorporated the threshold assembly time (t_0), which was defined as the time required for performing the least complex assembly operation. This operation requires a finite time for execution. Below a threshold of assembly time, neither assembly operations nor assembly defects are supposed to exist. Hence, the defect rate is related to assembly time exceeding the threshold value, and the assembly errors approach zero at the threshold of the minimum possible assembly time. Using the complexity index *Cf* (shown in Equation (1)), Hinckley found that the complexity and the corresponding defect rate show a positive correlation, as indicated by the following equations:

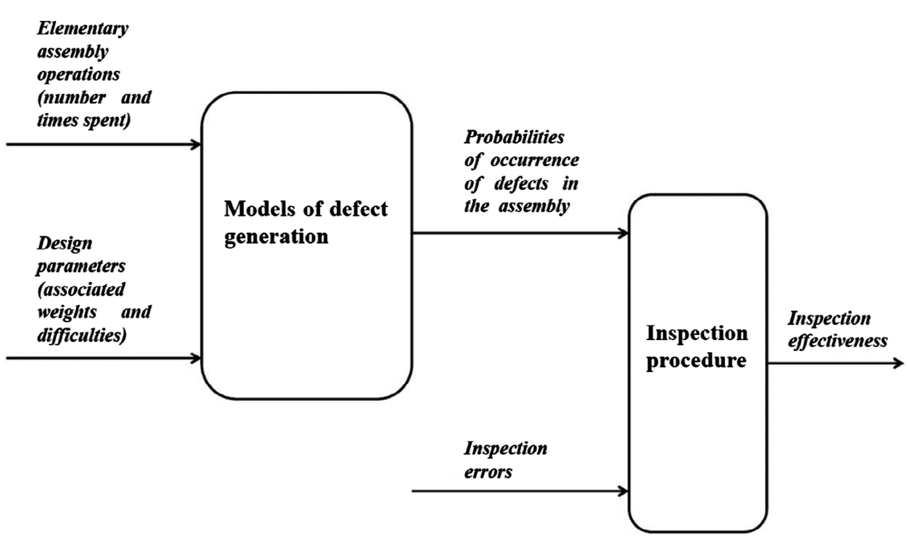

Figure 1. Block diagram of the proposed methodology.

$$\log DPU = K \cdot \log Cf - \log C \tag{2}$$

$$DPU = \frac{Cf^K}{C} \tag{3}$$

where C and K are the coefficients obtained by a power-law linear regression (Hinckley 1993).

Shibata, in a successive study, detailed the Hinckley model by subdividing the product assembly process into a series of 'workstations', defined through sheets of operation standards (Shibata 2002; Su, Liu, and Whitney 2010). In each workstation, a certain number of 'job elements' (Aft 2000), i.e. elementary operations, is performed, as shown in Figure 2. The job elements are the minimum components of a specific task. These should have easily identifiable starting and stopping points, and be repeatable on a regular basis throughout the work day.

Shibata evaluated the defect rate for a generic workstation by considering the standard times in which the operators should complete each job element. Time standards allow to get accurate estimates, but a thorough understanding of the system and a significant practical experience are required (Aft 2000). He utilised home audio products as assembly case. In particular, Shibata defined the process-based complexity factor of a generic workstation i as:

$$Cf_{P,i} = \sum_{j=1}^{Na,i} SST_{ij} - t_0 \cdot N_{a,i} = TAT_i - t_0 \cdot N_{a,i} \tag{4}$$

where $N_{a,i}$ is the number of job elements in the workstation i, SST_{ij} is the time spent on job element j in the workstation i, TAT_i is the total assembly time relevant to the workstation i and t_0 is again the threshold assembly time. It is worth noting that, in Shibata's study, the assembly times SST_{ij} are determined by Sony Standard Time (SST), a commonly used time estimation tool for electronic products. SST is used to set the standard process time and estimate the required labour cost.

To clarify these last concepts, a pedagogical example is proposed. Let us consider an assembly process made up by a single workstation in which a screw is tightened by a screwdriver. Table 1 shows the performed job elements with corresponding times spent and defects which may be introduced.

Therefore, the number of job elements is $N_a = 5$, the total assembly time is $TAT = 90$ s and the threshold assembly time is $t_0 = 10$ s. Then, according to Equation (4), the process-based complexity factor is $Cf_p = 40$ s = 0.67 min.

Similarly to Equations (2) and (3), Shibata derived correlation relationships between the process-based assembly complexity factor and DPU for each workstation i, i.e.:

$$\log DPU_i = K \cdot \log Cf_{P,i} - \log C \tag{5}$$

$$DPU_i = \frac{Cf_{P,i}^K}{C} \tag{6}$$

where C and K are again the coefficients obtained by a power-law linear regression (Shibata 2002).

In addition, Shibata remarked that the time related measures may not capture all the sources of defects. For this reason, he defined also a design-based assembly complexity factor as follows:

$$Cf_{D,i} = \frac{K_D}{D_i} \tag{7}$$

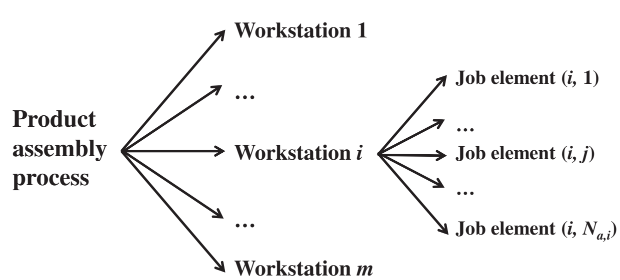

Figure 2. Scheme of Shibata's modelling of product assembly process.

Table 1. Subdivision of a workstation, i.e. the tightening of a screw by a screwdriver, into job elements with indication of times spent and possible defects.

Job element no.	Job element description	Time spent [s]	Possible defect
1	Grab the screw with the left (or right) hand	10	Fall of the screw
2	Position the screw on the screwing point	25	Screw positioned out of the screwing point
3	Grab the screwdriver with the right (or left) hand	10	Fall of the screwdriver
4	Position the screwdriver on the screw	15	Screwdriver wrongly positioned on the screw
5	Turn the screwdriver to tighten the screw	30	Damage to the screw

where K_D is an arbitrary coefficient for calibration with process-based complexity; D_i is called the ease of assembly (EOA) of workstation i, evaluated by the method of design for assembly/disassembly cost-effectiveness (DAC) developed in Sony Corporation (Yamagiwa 1988). Shibata found that the correlation relationships between the design-based complexity and DPU can be expressed as follows:

$$DPU_i = a \cdot Cf_{D,i}^{b} \tag{8}$$

$$\log DPU_i = b \cdot \log Cf_{D,i} + \log a \tag{9}$$

where a and b are still coefficients obtained by a power-law linear regression (Shibata 2002).

It is worth noting that DAC method was developed for evaluating the EOA of Sony electronic products, therefore it may not be directly suitable for other types of products. In these situations, the evaluation method of the design-based complexity factor, reported in Equation (7), should be revised. Su et al. remarked that the DAC method is not suitable, as an example, for copier products (Su, Liu, and Whitney 2010) and proposed an alternative procedure for electromechanical products. First, the widely used method developed by Ben-Arieh for evaluating the degree of difficulty of the assembly operations (Ben-Arieh 1994) is considered. According to the characteristics of the products to be assembled, a certain number l of parameters is selected as criteria for evaluating the design-based assembly complexity. In particular, in Su's case study of copier assembly, $l = 11$ parameters were selected. To obtain an integrated index, the weights of the l criteria are allocated using the analytic hierarchy process (AHP) approach (Wei, Chien, and Wang 2005). In detail, a certain number e of evaluators is asked to compare the relative importance of each parameter in determining the difficulty of inserting a part into a product. In Su's case study, $e = 6$ assembly engineers were involved as evaluators. According to the evaluation by the e evaluators, the weight w_q of the l parameters and the corresponding degrees of difficulty are obtained. In particular, the degree of difficulty A_{kqi} is the evaluation of the parameter q in the workstation i estimated by the evaluator k. The values A_{kqi} are rated by scores between 0 and 10. In this way, the design-based complexity factors may be redefined as follows:

$$Cf_{D,i} = \sum_{q=1}^{l} \left(w_q \cdot \frac{1}{e} \cdot \sum_{k=1}^{e} A_{kqi} \right) \tag{10}$$

Therefore, this formula replaces Equation (7) in case of electromechanical products.

At this point, by combining Equations (5) and (9), Shibata derived the following bivariate prediction model:

$$\log DPU_i = k_1 \cdot \log Cf_{P,i} + k_2 \cdot \log Cf_{D,i} + \log k_3 \tag{11}$$

This model may also be written as:

$$DPU_i = k_3 \cdot Cf_{P,i}^{k_1} \cdot Cf_{D,i}^{k_2} \tag{12}$$

Unlike Shibata, authors propose to perform a power-law non-linear regression by referring to Equation (12). In fact, the logarithmic transformation may have a bias effect, mainly when applied to numbers between 0 and 1, such as DPU_i (Davidian and Giltinan 1995).

Now, in order to estimate the probabilities of occurrence of defects in each workstation i, two assumptions are made (Hinckley 1993). Firstly, suppose that each job element may introduce at most one defect. Secondly, assume that, for each workstation i, the probability of occurrence of the defect is the same for each job element and is denoted as d_i. In practical applications, these assumptions are reasonable when, for each workstation i, a refined segmentation of job elements is performed. Therefore, for each workstation i, the average number of defects per job element, i.e. the number of defects per unit (DPU_i) divided by the number of job elements ($N_{a,i}$), may be assumed as an estimate of d_i. Then, the yield Y_i of the workstation i (i.e. the fraction of non-defective outputs in the workstation i) can be predicted by the following binomial formula (Montgomery 2013):

$$Y_i = \binom{N_{a,i}}{0} \cdot d_i^0 \cdot (1 - d_i)^{N_{a,i}-0} = (1 - d_i)^{N_{a,i}} = \left(1 - \frac{DPU_i}{N_{a,i}}\right)^{N_{a,i}} \tag{13}$$

So, the probabilities of occurrence of at least one defect in each workstation i may be estimated as the fraction of defective outputs in the workstation i, i.e.:

$$p_i = 1 - Y_i = 1 - \left(1 - \frac{DPU_i}{N_{a,i}}\right)^{N_{a,i}} \tag{14}$$

3. Inspection procedures

Let us now subdivide the assembly manufacturing process into a number (m) of workstations (Shibata 2002; Su, Liu, and Whitney 2010) or process steps (Franceschini et al. 2016). Let us also assume that the parameters relative to different workstations are not correlated (Franceschini et al. 2016). In each workstation, different kinds of quality control activities may be performed, according to the specific types of defects, thus defining different inspection procedures.

3.1 *Parameter definition*

The outcome of each i-th workstation may be modelled by a Bernoulli distribution (Montgomery 2013). Hence, each i-th workstation can be described through three parameters:

- p_i: probability of occurrence of a defective-workstation-output (i.e. the parameter of the Bernoulli distribution);
- α_i: probability of erroneously signalling a defective-workstation-output (i.e. type-I inspection error);
- β_i: probability of erroneously not signalling a defective-workstation-output (i.e. type-II inspection error).

where $i = 1, \dots, m$, i.e. the total number of workstations. The first parameter (p_i) concerns the quality of the process relatively to the i-th workstation, while the other two parameters (α_i and β_i) concern the quality of the corresponding inspection(s).

The parameter p_i may be estimated, as a first approximation, using Equation (14) as model of defect generation in i-th workstation. These models are mainly useful in the case of short-run productions, for which most of the SPC techniques are unsuitable (Marques et al. 2015).

The parameters α_i and β_i, which strictly depend on the inspector activity and inspection procedure, are estimated basing on prior experience, i.e. using empirical values obtained by inspectors in similar processes.

3.2 *Model representation and performance indicators*

According to the adopted model (Franceschini et al. 2016), the following probabilities can be calculated for each (i-th) workstation:

$$P(\text{signalling a defective - workstation - output in the workstation } i) = p_i \cdot (1 - \beta_i) + (1 - p_i) \cdot \alpha_i \tag{15}$$

and

$$P(\text{not signalling a defective - workstation - output in the workstation } i) = p_i \cdot \beta_i + (1 - p_i) \cdot (1 - \alpha_i) \tag{16}$$

where $i = 1, \dots, m$, i.e. the total number of workstations.

In the case a defective-workstation-output is signalled, this will be true with a probability $p_i \cdot (1 - \beta_i)$ or false with a probability $(1 - p_i) \cdot \alpha_i$ (see Equation (15)). On the other hand, in the case no defect is signalled, this will be the result of an inspection error 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 Equation (16)). The above probabilities represent the 'elementary bricks' for the construction of indicators depicting the performance of inspection procedures (Franceschini et al. 2016).

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

- $X_i = 0$: when (i) a defective-workstation-output is correctly signalled or (ii) no defect is present in the i-th workstation.
- $X_i = 1$: when a defective-workstation-output is erroneously not signalled in the i-th workstation.

Therefore, the mean total number of defective-workstation-outputs which are erroneously not signalled in the overall inspection procedure can be defined as:

$$D = \sum_{i=1}^{m} E(X_i) = \sum_{i=1}^{m} p_i \cdot \beta_i \tag{17}$$

The variable D is assumed as indicator on inspection effectiveness, since it provides an indication of the overall effectiveness of the inspection procedure. To provide a general overview of the inspection design, this indicator is analysed together with inspection costs indicators. Some preliminary results of this analysis are reported in a recent work of the authors (Franceschini et al. 2016). A detailed study of the economic effects of inspection design will be object of future research (De Ruyter, Cardew-Hall, and Hodgson 2002; Avinadav and Perlman 2013; Savio et al. 2016).

Therefore, the block diagram schematising the proposed methodology (reported in Figure 1) may be detailed according to the notation adopted in case of assembly of electromechanical products, as shown in Figure 3.

4. Case study: assembly of hardness testing machines

Let us consider a manufacturing process aimed at producing hardness testing machines, specifically *AFFRI*® *LD* 3000 *AF* (Figure 4). The production of these machines can be considered a short-run production process. From the manufacturing point of view, this process may be subdivided into nine assembly phases, as shown in Table 2.

In this paper, for simplicity of representation, only the first four assembly phases (i.e. the overall assembly of machine head) are dealt with in detail. Each of this four assembly phases may then be subdivided into a certain number of operations, performed in different workstations, as detailed in Table 3 together with the specific types of performed controls.

With reference to Shibata and Su models (see Section 2), Table 4 provides, for each workstation i, the total assembly time TAT_i, the number of job elements $N_{a,i}$, the process-based complexity factor $Cf_{P,i}$, the design-based complexity factor $Cf_{D,i}$ and the defects per unit DPU_i. The process-based complexity factors are calculated by exploiting the threshold assembly time t_0, which is equal to 0.5 min. The latter represents the time required to perform the least complex job element. The design-based complexity factors are obtained using the parameters shown in Table 5 together with their weights. These parameters were selected according to the characteristics of the assembly of hardness testing machines, slightly modifying the parameters relevant to copiers chosen by Su, Liu, and Whitney (2010). Defects per unit are

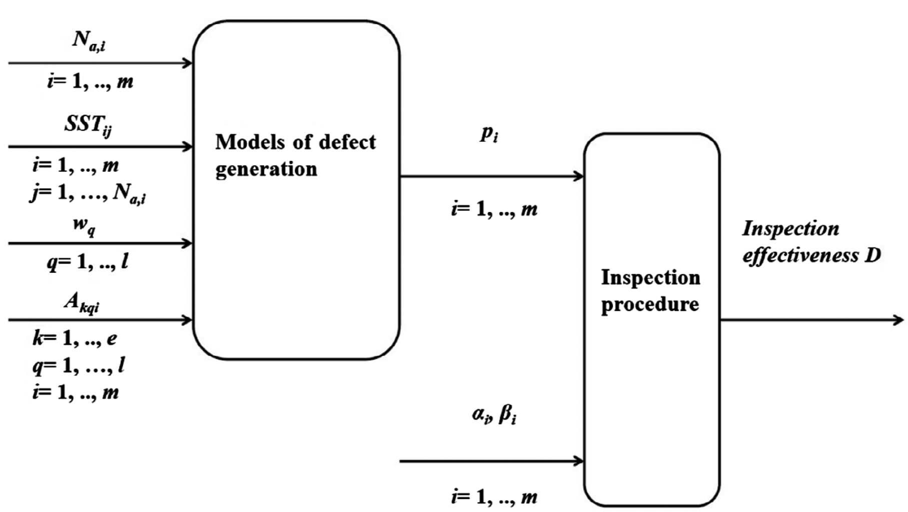

Figure 3. Scheme of the proposed methodology with the notation adopted in case of assembly of electromechanical products (see Equations (4), (10), (12), (14) and (17)).

Figure 4. *AFFRI®* *LD* 3000 *AF* hardness testing machine.

Table 2. Manufacturing process of hardness testing machines, subdivided into specific assembly phases.

Assembly phase no.	Assembly description
1	Threaded shaft
2	Machine working axis
3	Axis movement mechanism
4	Machine head
5	Reference plan movement device
6	Measurement device unit
7	Machine processing unit
8	Machine electrical system
9	Final assembly

calculated from the corresponding process-based and design-based complexity factors using Equation (12). In particular, by reprocessing Su's data with a power-law non-linear regression, the following equation is obtained:

$$DPU_i = 3.00 \cdot 10^{-5} \cdot Cf_{P,i}^{1.28} \cdot Cf_{D,i}^{1.49} \tag{18}$$

As a first approximation, this model, concerning a similar case study involving mechatronic devices, may be exploited.

Table 3. Subdivision into different workstations of the overall assembly of machine head with indication of the specific type of performed controls.

Assembly phase no.	Assembly description	Workstation no.	Workstation description	Control type
1	Threaded shaft	1	Bearings – support	Geometric and mechanical
		2	Bearings – threaded shaft	Geometric and mechanical
		3	Threaded shaft – bearing support	Geometric and mechanical
		4	Threaded shaft – pulley	Dimensional and mechanical
2	Machine working axis	5	Guide – carriage	Mechanical
		6	Carriage – block	Geometric
		7	Spring holder – carriage	Geometric and mechanical
		8	Nut screw – spring holder	Geometric
		9	Spring – spring holder	Mechanical
3	Axis movement mechanism	10	Threaded shaft – machine working axis	Mechanical
		11	Spring preloading device	Dimensional and mechanical
		12	Optical limit switch	Mechanical
		13	Mechanical limit switch	Geometric and mechanical
4	Machine head	14	Motor – lower flange	Geometric and mechanical
		15	Lower flange – reducer	Geometric and mechanical
		16	Reducer – upper flange	Geometric and mechanical
		17	Reducer – pulley	Dimensional and mechanical
		18	Motor – axis movement mechanism	Mechanical

Table 4. Application of Shibata and Su models to the overall assembly of machine head.

Assembly phase no.	Workstation no.	TAT_i [min]	$N_{a,i}$	$Cf_{P,i}$ [min]	$Cf_{D,i}$	DPU_i
1	1	17.0	6	14.0	3.5	0.0057
	2	15.5	7	12.0	3.7	0.0051
	3	9.0	5	6.5	2.4	0.0012
	4	9.5	6	6.5	3.3	0.0020
2	5	6.0	2	5.0	1.7	0.0005
	6	11.0	3	9.5	2.9	0.0027
	7	18.5	6	15.5	2.9	0.0051
	8	5.0	3	3.5	4.8	0.0016
	9	4.5	5	2.0	3.2	0.0004
3	10	13.5	7	10.0	4.0	0.0046
	11	8.5	5	6.0	4.4	0.0027
	12	4.5	3	3.0	3.2	0.0007
	13	7.0	3	5.5	3.3	0.0016
4	14	3.0	2	2.0	3.7	0.0005
	15	7.0	6	4.0	5.9	0.0025
	16	3.0	2	2.0	3.7	0.0005
	17	5.0	3	3.5	3.3	0.0009
	18	12.5	6	9.5	3.4	0.0034

Now, for each workstation i, the probability of occurrence of a defective-workstation-output p_i is obtained from the defects per unit DPU_i through Equation (14). For low values of DPU_i, the differences with the corresponding values of p_i (shown in Table 6) are negligible, i.e. p_i values may be approximated by the corresponding DPU_i values. This result may be proved by considering the first-order Maclaurin series expansion of p_i with respect to DPU_i obtained from Equation (14), i.e.:

Table 5. Parameters for evaluating the design-based assembly complexity in case of hardness testing machines with indication of weights. See also Su, Liu, and Whitney (2010).

Parameter no.	Parameter description	Weight
1	Components shape	0.095
2	Forces required	0.070
3	Coupling directions	0.104
4	Components alignment	0.167
5	Components size	0.118
6	Components geometry	0.119
7	Ratio between components size and geometry	0.081
8	Components play	0.130
9	Worktable stability	0.063
10	Equipment requirements	0.052
11	Electrical disturbances	0.000

Table 6. Estimates of probabilities p_i, α_i and β_i relevant to each workstation, in the overall assembly of machine head.

Assembly phase no.	Workstation no.	p_i [%]	α_i [%]	β_i [%]
1	1	0.57	2.0	0.5
	2	0.51	1.0	0.1
	3	0.12	3.0	1.0
	4	0.20	1.5	0.5
2	5	0.05	0.5	0.1
	6	0.27	3.5	1.0
	7	0.51	0.5	0.1
	8	0.16	1.0	0.2
	9	0.04	0.5	0.1
3	10	0.46	4.0	0.7
	11	0.27	0.5	0.1
	12	0.07	0.5	0.1
	13	0.16	1.0	0.2
4	14	0.05	0.5	0.1
	15	0.25	3.0	1.5
	16	0.05	0.5	0.1
	17	0.09	1.0	0.3
	18	0.34	0.5	0.1

$$p_i(DPU_i) \approx p_i(0) + \left.\frac{\mathrm{d}p_i}{\mathrm{d}DPU_i}\right|_{DPU_i=0} \cdot DPU_i \approx DPU_i \tag{19}$$

where

$$\left.\frac{\mathrm{d}p_i}{\mathrm{d}DPU_i}\right|_{DPU_i=0} = \left.\left(1 - \frac{DPU_i}{N_{a,i}}\right)^{N_{a,i}-1}\right|_{DPU_i=0} = 1 \tag{20}$$

It has to be remarked that the empirical validation of the proposed methodology is a very delicate issue. Since a short-run production is considered, a real data collection cannot be easily completed in a short time. However, for some workstations, data relevant to productions of several types of hardness testing machines may be put together. Let us consider, e.g., the first four workstations relevant to the assembly of threaded shaft. For these workstations, empirical values of defects per units DPU_i consistent with those reported in Table 4 are obtained by considering other similar hardness testing machines assembly lines. Moreover, the corresponding empirical values of p_i are comparable with those reported in Table 6. This represents a preliminary validation of the proposed methodology. In the long term, the mathematical model proposed in Equation (18) may be refined by completing the real data collection for all the workstations of the assembly line.

The adopted inspection procedure requires the controls reported in Table 3. Each control is affected by inspection errors. Estimates of α_i and β_i (see Table 6) were obtained by the inspectors basing on empirical values obtained in similar assembly processes. In fact, most of the controls performed in case of hardness testing machines are common to other mechatronic devices.

Finally, the indicator on inspection effectiveness D may be calculated using Equation (17) and the estimates of the probabilities in Table 6. It results that the mean total number of defective-workstation-outputs which are erroneously not signalled in the overall inspection procedure is:

$$D = \sum_{i=1}^{18} p_i \cdot \beta_i = 1.8 \cdot 10^{-4} \tag{21}$$

In other words, given a production of 10^4 machine heads, there are, on average, about two defective-workstation-outputs which are erroneously not signalled. Since the production of the examined type of hardness testers is only of some tens per year, the number of defective-workstation-outputs which are erroneously not signalled is negligible. By extending the analysis to the other five process phases, the indicator D becomes $3.9 \cdot 10^{-4}$, which is still a small value. These results are, of course, considered reasonable by the producer of hardness testing machines and they are supported by the experience matured in the field.

Moreover, since D is a sum, it possible to separately analyse and compare its addends $p_i \cdot \beta_i$ in order to identify the most critical workstations. Working on the highest addends (corresponding, in this case study, to the workstations no. 10 and 15), more effective inspection procedures may be designed.

5. Conclusion

In the manufacturing field, the assembly process heavily affects product final quality and cost. Specific studies, concerning the causes of the assembly defects, showed that operator errors account for high percentage of the total defects. In this paper, models of Hinckley (1993), Shibata (2002) and Su, Liu, and Whitney (2010) are considered for predicting and evaluating the operator-induced defect rate. In the assembly processes of mechatronic devices, these models represent very powerful tools, since they enable to predict the defects per unit without any specific prior knowledge. In fact, given an assembly process, subdivided into a certain number of workstations, the defects per unit may be calculated only from the number of job elements in each workstation, the time spent on each job element in each workstation and the weights and the difficulties associated to design parameters. Basing on Shibata approach, defect generation models are defined in order to get reliable predictions of the probability of occurrence of defects in each manufacturing step. These models are mainly useful in the design of quality inspections for short-run productions for which traditional SPC approaches may not be performed. The proposed methodology is applied to a case study concerning the assembly of mechanical components in the manufacturing of hardness testing machines. A priori predictions of the probabilities of occurrence of defects are useful to the producer of hardness testing machines for designing effective inspection procedures. Future research will concern a comprehensive sensitivity analysis to test the robustness of the proposed defect-generation models and a detailed analysis of economic effects of the proposed inspection design. Finally, it is planned to develop specific models for the prediction of inspection errors using an approach similar to the one adopted for the defect-generation models.

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Disclosure statement

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