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Defect prediction models to improve assembly processes in low-volume productions

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A B S T R A C T

Assembly processes in low-volume productions, i.e., single-units or small-sized-lots, are often characterized by a high level of customization and complexity. As a consequence, the scarcity of historical data and the difficulty in applying standard statistical techniques make process control extremely challenging. Accordingly, identifying effective diagnostic tools plays a key role in such productions. This paper proposes an innovative method for identifying critical workstations in assembly processes based on defect prediction models. Starting from the level of complexity in terms of assembly process and design, the method allows identifying the workstations whose defectiveness deviates, at a certain confidence level, from the predicted average value. Once the causes leading to significant nonconformities have been detected, appropriate corrective actions may be promptly undertaken to improve the process. An example of implementation of the method in wrapping machines production is presented and discussed.

1. Introduction

Manufacturing companies are increasingly focusing on producing high-quality, fault-free products that meet customer needs. Defects in the final product, particularly those generated during the production processes, can have a dramatic impact on the product itself, both in terms of quality and cost. From this point of view, identifying appropriate process control and monitoring systems and adequate predictive maintenance techniques plays a vital role in the quality improvement process of manufacturing industries (Montgomery, 2012; Aivaliotis et al., 2017, 2019; Mourtzis et al., 2018). Statistical Process Control (SPC) consists of methods for understanding, monitoring, and improving process performance over time, with the aim to make the process stable or predictable, by distinguishing common variation from special or sporadic variation (Montgomery, 2012; Woodall, 2000). SPC techniques have been extensively used to monitor process performance and detect anomalous situations in multiple industrial contexts. However, traditional SPC approaches are usually not appropriate for single-unit or low-volume productions, and for situations where a wide variety of mixed products exist (Koons and Luner, 1991; Del Castillo et al., 1996; Does, 1997; Trovato et al., 2010; Marques et al., 2015).

The category of low-volume productions certainly includes low-volume assembly manufacturing processes, often characterized by a high level of customization and complexity, such as the case of wrapping machines for the packaging of palletized loads. The production of wrapping machines can be classified as a low-volume assembly process due to the high degree of customization, to the extent that each machine can be considered almost unique. Moreover, the total average number of such customized machines produced in a year reaches, typically, only a few tens of units. Therefore, due to the limited historical data available and the difficulty in applying the main SPC techniques, the process control represents a challenging issue in the industrial sector of wrapping machines.

In the past decades, different SPC methods specific for low-volume productions have been proposed in the literature, and each of these has its advantages, shortcoming, and is more suitable for certain production scenarios than for others (Koons and Luner, 1991; Del Castillo et al., 1996; Does, 1997; Trovato et al., 2010; Marques et al., 2015; Verna et al., 2020). This paper presents a novel and effective diagnostic tool for the assembly of low-volume productions that allows identifying the critical steps of the assembly process based on defect prediction models. Specifically, the Research Questions (RQ) addressed in this paper are as follows:

RQ1: *Can defects generated in assembly processes of low-volume productions be estimated using a defect prediction model?*

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RQ2: *How can the identified defect prediction model be exploited as a diagnostic tool to improve assembly processes?*

In order to answer these questions, the method involves the decomposition of the assembly process into several assembly steps (m), also called workstations, in which a specific operation is performed. According to previous studies in the electromechanical field, assembly defects caused by operators during assembly operations can be predicted modeling the level of complexity in terms of assembly design and process (Hinckley, 1993; Shibata, 2002; Su et al., 2010). Accordingly, for each workstation, two complexity factors are defined, namely the process-based and the design-based complexity factors (Hinckley, 1993; Shibata, 2002; Su et al., 2010). Then, basing on a combination of historical data and technical experience on the assembly of wrapping machines, a prediction model relating the observed defects per unit (*DPU*) in each workstation is developed. In accordance with previous studies (Hinckley, 1993; Shibata, 2002; Galetto et al., 2018; Galetto et al., 2020; Genta et al., 2018), the power-law behavior of the model is demonstrated. In detail, comparing the observed experimental values of *DPU* in each workstation with the expected average value obtained from the reference model, the method allows to easily identify critical workstations, i.e. those whose defectiveness deviates, at a certain confidence level, from the predicted *DPU*. Consequently, the appropriate corrective actions to improve the process can be promptly adopted once the causes leading to significant non-conformities are identified. The remainder of the paper is organized into four sections. Section 2 reviews the prediction models for operator-induced assembly defects based on assembly complexity factors developed for massive productions. In Section 3 the defect prediction model for low-volume productions is derived, using as a case study the assembly of wrapping machines. Section 4 presents how the defect prediction model can be used to identify critical workstations and to improve the assembly process; the relevance of the method is highlighted by examples referring to wrapping machines assembly. Section 5 summarizes the original contributions of this research, focusing on its implications, limitations and possible future developments.

2. Review of defect prediction models for mass productions

Starting from the prediction model that Hinckley (1993) derived by analyzing long term defect data provided by automobile, hard disk drive, and semiconductor companies involving tens of millions of parts and assembly operations, Shibata (Shibata, 2002) adapted it to the assembly of Sony's home audio products. Specifically, in order to derive a defect prediction model, Shibata analyzed several thousands of data related to four different models of audio equipment produced over months. In Shibata's study, the product assembly process was decomposed into a series of "operation standards" (Shibata, 2002), also called "workstations" in other studies (Su et al., 2010), in which a certain number of "job elements", i.e. elementary operations, are performed. In order to predict the defects per unit occurring in each i th workstation (DPU_i), a process-based complexity factor for each workstation, $Cf_{P,i}$, was considered as a predictor, defined as follows:

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

where $N_{a,i}$ is the number of job elements in the workstation i, SST_{ij} is the Sony Standard Time spent on the job element j in the workstation i, TAT_i is the total assembly time related to the workstation i, and t_0 is the threshold assembly time, i.e. the time required to perform the simplest assembly operation (Shibata, 2002). The correlation relationship between $Cf_{P,i}$ and DPU_i derived from experimental data (Shibata, 2002) was as follows:

$$DPU_i = \frac{(Cf_{P,i})^K}{C} \tag{2}$$

where C and K are two regression coefficients obtained by the linearization of the function, in the form:

$$\log DPU_i = K \cdot \log Cf_{P,i} - \log C \tag{3}$$

A further novelty introduced in the work of Shibata (2002) is the definition of an additional complexity factor, the design-based complexity factor $Cf_{D,i}$, defined as:

$$Cf_{D,i} = \frac{K_D}{D_i} \tag{4}$$

where K_D is an arbitrary coefficient for calibration with process-based complexity; D_i refers to the ease of assembly (EOA) of the i th workstation, which is evaluated by means of the design method for assembly/disassembly cost-effectiveness (DAC) developed by Sony Corporation (Yamagiwa, 1988). The correlation relationship between $Cf_{D,i}$ and the *DPU* can be expressed as follows:

$$DPU_i = a \cdot Cf_{D,i}^b \tag{5}$$

where a and b are again regression coefficients obtained by the linearization of the function, in the form:

$$\log DPU_i = b \cdot \log Cf_{D,i} + \log a \tag{6}$$

By combining Eqs. (2) and (5), Shibata derived a bivariate prediction model, which can be written as:

$$DPU_i = c \cdot (Cf_{P,i})^d \cdot (Cf_{D,i})^e \tag{7}$$

where *c, d, e* are again regression coefficients obtained by the linearization of the function, in the form:

$$\log DPU_i = d \cdot \log Cf_{P,i} + e \cdot \log Cf_{D,i} + \log c \tag{8}$$

In a later study, Su et al. (2010) modified the method proposed by Shibata to fit the assembly of copiers. Instead of using SST, a new process-based assembly complexity factor was formulated based on Fuji Xerox Standard Time, which was considered by the authors more suitable for copier production (Su et al., 2010).

In addition, since DAC method was developed for evaluating the EOA of Sony electronic products, they remarked that it might not be directly suitable for different products, such as copiers. Accordingly, the evaluation method of the design-based complexity factor, reported in Eq. (3), was revised. First, in accordance with the method developed by Ben-Arieh for evaluating the degree of difficulty of the assembly operations (Ben-Arieh, 1994), l parameters (11 in the specific case of copier assembly) are selected as criteria for evaluating the design-based assembly complexity. Then, the weights of the l criteria are allocated using the analytic hierarchy process (AHP) approach (Wei et al., 2005; Saaty, 1980). In detail, e evaluators (6 assembly engineers in the specific study) are asked to compare the relative importance of each parameter in determining the difficulty of inserting a part into a product. From such evaluations, the weight w_q of the l parameters and the corresponding degrees of difficulty are obtained. The degree of difficulty, denoted as A_{kqi}, i.e. the evaluation of the parameter q in the workstation i estimated by the evaluator k, is rated by scores between 0 and 10. In light of this, the new design-based complexity factor was redefined as follows:

$$Cf_{D,i} = \sum_{q=1}^{l} \left(w_q \cdot \frac{1}{e} \cdot \sum_{k=1}^{e} A_{kqi} \right) \tag{9}$$

Su et al. (2010) tested the correlation between each redesigned assembly complexity factor and the *DPU*, showing that the best regression function, in both cases, was a cubic polynomial model. In

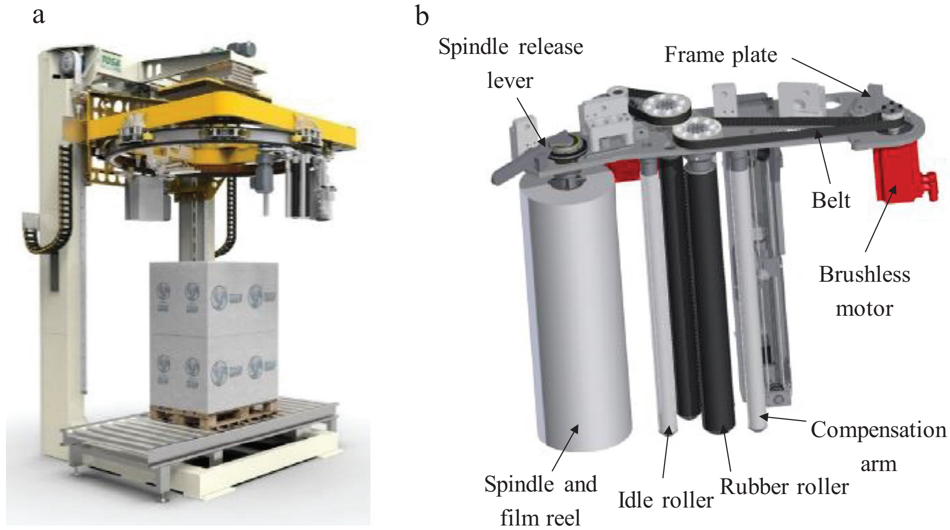

Fig. 1. (a) Rotating ring wrapping machine of Tosa Group S.p.A (Italy); (b) front view of the 3D CAD model of a pre-stretch device with indication of the main components.

addition, the redesigned process- and design-based complexity factors were also integrated into a new bivariate prediction model, whose behavior was confirmed to be again cubic Su et al., 2010). However, in a recent study Galetto et al. (2020) proved that the cubic models resulted from the logarithmic transformation bias that occurred when predicting defects, thus confirming the adequacy of the power-law behavior of Eqs. (2), ((5) and (7).

3. Defect prediction model for low-volume productions: the case of wrapping machines

In order to identify a defect prediction model for low-volume productions, the assembly of wrapping machines for the packaging of palletized loads is analyzed. Specifically, among the several typologies of products produced by the company Tosa Group S.p.A. (Italy), the rotating ring wrapping machine is considered, see Fig. 1(a). The production of these machines can be considered a low-volume production process as the total number of machines produced each year is of about 50 units. Moreover, due to the high level of product customization, each rotating ring wrapping machine can be considered a unique piece. This study focuses on the assembly of a single part of the rotating ring wrapping machine, namely the pre-stretch device, see Fig. 1(b). The main reason of this choice is that, although each machine differs from the others in some details, this device is common to all rotating ring wrapping machines. The pre-stretch device is an electromechanical device that performs the following functions: (i) pulling/unwinding, (ii) pre-stretch and positioning of the plastic film, (iii) performing the necessary number of windings. From the manufacturing point of view, the assembly process of the pre-stretch device may be subdivided into 29 workstations, as described in Table 1. Each of the subassemblies of the pre-stretch device is first assembled on the bench by the operator and then assembled on the frame plate. This double process is the criterion used to define the workstations listed in Table 1.

In Table 1, the nominal values of *DPU* occurring under stationary process conditions in each workstation are reported. Such experimental DPU_i values are obtained by drawing on the company historical data and on the experience of the Head of the Technical Department. They can, therefore, be considered as the reference values of the average defectiveness rate of the assembly process in optimal working conditions.

According to the studies of Shibata (2002) and Su et al. (2010), for each workstation, the process-based and the design-based complexity factors are obtained experimentally in order to define a predictive model correlating the *DPU*s with the complexity factors. Specifically, each workstation is subdivided into job elements, whose assembly time is measured three times and then the average value is considered. To derive the first predictor, $Cf_{P,i}$, Eq. (1) is applied by exploiting as the threshold assembly time, t_0, the time required to perform the least complex job element, equal to 0.04 min. The second predictor, $Cf_{D,i}$, is calculated according to Eq. (9) by deriving the weights w_q of 11 parameters, defined in Table 2, and the degrees of difficulty, A_{kqi}, from the evaluations of $e = 6$ evaluators (2 engineers and 4 assembly operators). The 11 parameters are selected by slightly modifying the parameters defined in the work of Ben-Arieh (1994) according to the assembly characteristics of the wrapping machines. The values of the obtained predictors, $Cf_{P,i}$ and $Cf_{D,i}$, are listed in Table 1.

Using the software *MATLAB*®, nominal DPU_i vs $Cf_{P,i}$ and $Cf_{D,i}$, reported in Table 1, are plotted, showing a power-law behavior, as evidenced in Fig. 2(a). Accordingly, the *DPU* values are analyzed using the power-law regression model developed by Shibata, see Eq. (7). Differently from Shibata, the regression coefficients are not obtained by linearizing the function, rather by using a nonlinear model, due to the well-known problem of retransformation bias (Galetto et al., 2020; Taylor, 1986; Perry, 2018). The prediction model derived is reported in Eq. (10) and illustrated in Fig. 2(a).

$$DPU_i = 5.04 \cdot 10^{-5} \cdot (Cf_{P,i})^{0.77} \cdot (Cf_{D,i})^{3.08} \tag{10}$$

As emerges from the analysis of the residuals between nominal *DPU* and predicted *DPU*, shown in Fig. 2(b) and (c), the power-law model describes well the trend of the *DPU* as a function of the assembly complexities not only when dealing with mass productions, but also for low-volume productions.

4. Use of the prediction model as a diagnostic tool

The defect generation model obtained for low-volume assembly processes, reported in Eq. (10), can be used as a reference model for the purposes of diagnostic analysis. Specifically, using the average values of the regression parameter estimates, the respective standard deviations and the correlation matrix for parameter estimates, obtained by applying the nonlinear regression model of Eq. (7) to data of Table 1, the variance associated with the predic-

Table 1
Pre-stretch device assembly of rotating ring wrapping machine: decomposition into workstations (WS), nominal DPU_i, $Cf_{P,i}$and $Cf_{D,i}$, predicted DPU_i, lower limit $LL_{PI}(DPU_i)$ and upper limit UL_{PI} (DPU_i) of the 95% prediction interval, and observed DPU_i detected in 6 months.

WS no.	Workstation description	Nominal DPU_i	$Cf_{P,i}$[min]	$Cf_{D,i}$	Predicted DPU_i	LL_{PI} (DPU_i)	UL_{PI} (DPU_i)	Observed DPU_i
1	Motor no. 1 bench assembly	0.0364	7.1	4.4	0.0214	0.0000	0.0755	0.0357
2	Motor no. 2 bench assembly	0.0364	7.4	4.6	0.0250	0.0000	0.0788	0.0357
3	Support plate of motor no. 2 bench assembly	0.0182	5.8	5.1	0.0287	0.0000	0.0802	0.0000
4	Spindle bench assembly	0.0000	3.8	4.3	0.0126	0.0000	0.0639	0.0000
5	Rubber tyres bench assembly	0.1091	11.9	5.7	0.0715	0.0134	0.1295	0.1071
6	Idle rolls bench assembly	0.0545	7.7	4.9	0.0320	0.0000	0.0843	0.0714
7	Rubberized pads bench assembly	0.0000	3.5	2.8	0.0030	0.0000	0.0538	0.0000
8	Belt tensioner device bench assembly	0.0364	2.4	3.5	0.0045	0.0000	0.0551	0.0357
9	Driven wheels of transmission system bench assembly	0.0000	0.3	3.7	0.0012	0.0000	0.0512	0.0000
10	Pre-stretch frame plate preparation	0.0182	4.8	4.2	0.0142	0.0000	0.0663	**0.0714**
11	Rubber rollers on pre-stretch frame plate assembly	0.0182	5.2	5.3	0.0312	0.0000	0.0849	0.0357
12	Idle rollers on pre-stretch frame plate assembly	0.0182	5.7	5.1	0.0298	0.0000	0.0815	0.0000
13	Motor no. 1 on frame plate assembly	0.0000	3.7	5.1	0.0205	0.0000	0.0730	0.0000
14	Transmission system of motor no. 1 assembly	0.0000	0.9	5.4	0.0084	0.0000	0.0618	0.0000
15	Motor no. 2 on frame plate assembly	0.0182	8.5	4.9	0.0355	0.0000	0.0883	0.0357
16	Transmission system of motor no. 2 assembly	0.0364	0.8	4.9	0.0060	0.0000	0.0573	0.0357
17	Motor no. 1 bracket on pre-stretch frame plate assembly	0.0000	0.9	4.2	0.0041	0.0000	0.0544	0.0000
18	Belt tensioner on pre-stretch frame plate assembly	0.0364	1.7	4.3	0.0067	0.0000	0.0573	0.0357
19	Transmission system of motor no. 1 calibration	0.0364	5.7	5.2	0.0306	0.0000	0.0826	0.0357
20	Transmission system of motor no. 2 calibration	0.0364	6.3	5.2	0.0332	0.0000	0.0850	0.0357
21	Spindle preparation for assembly on pre-stretch frame plate	0.0000	2.2	5.2	0.0147	0.0000	0.0682	0.0000
22	Spindle group on pre-stretch frame plate assembly	0.0364	13.4	5.6	0.0738	0.0155	0.1322	0.0357
23	Rubber pads on pre-stretch frame plate assembly	0.0000	2.3	4.1	0.0075	0.0000	0.0581	0.0000
24	Motor assembly no. 1 final steps	0.0545	1.1	4.1	0.0041	0.0000	0.0544	0.0357
25	Motor assembly no. 2 final steps	0.0545	1.2	4.3	0.0049	0.0000	0.0553	0.0357
26	Spindle release lever bench assembly	0.0000	1.2	4.1	0.0042	0.0000	0.0545	**0.1786**
27	Spindle release lever on pre-stretch frame plate assembly	0.0000	7.9	4.7	0.0293	0.0000	0.0828	0.0000
28	Compensation arm bench assembly	0.0909	12.2	5.5	0.0672	0.0113	0.1230	0.1071
29	Compensation arm on pre-stretch frame plate assembly	0.0000	5.4	5.0	0.0257	0.0000	0.0771	0.0000

Table 2
Parameters exploited for the evaluation of the design-based complexity factor and their weights.

Parameter label	Parameter description	Weight
P1	Shape of mating objects	0.139
P2	Force required	0.120
P3	Alignment of components	0.150
P4	Mating direction	0.169
P5	Ratio of the mating component's weight to the mated one	0.094
P6	Ratio of length to width (diameter) of the mating component	0.091
P7	Reachability to the assembled component	0.056
P8	Mating component's length,	0.064
P9	Amount of support required for the assembly	0.037
P10	Stability of the resultant assembly	0.041
P11	Length of components intersection	0.038

tion of the *DPU* in each workstation, $VAR(DPU_i)$, can be estimated as follows:

$$VAR(DPU_i) \approx \left[\frac{\partial DPU_i}{\partial \boldsymbol{K}}\right]^T \cdot \mathrm{cov}(\boldsymbol{K}) \cdot \left[\frac{\partial DPU_i}{\partial \boldsymbol{K}}\right] \tag{11}$$

where $\boldsymbol{K} = [c, d, e]^{\mathrm{T}}$is the vector of regression parameters and $\mathrm{cov}(\boldsymbol{K})$is the variance-covariance matrix of regression parameters, both estimated by applying the Gauss-Newton method implemented in the software *MATLAB*® to the model of Eq. (7) (Bates and Watts, 1988).

By exploiting the uncertainty associated with the DPU_i estimate, the 95% prediction interval of each DPU_i may be calculated, as shown in Eq. (12):

$$DPU_i \pm 2.055 \cdot \sqrt{VAR(DPU_i) + S^2} \tag{12}$$

where *S* is the standard error of the regression, also called the standard error of the estimate, derived from the sum of the squared residuals *RSS*, the number of observations *N* and the number of free parameters *P*, according to Eq. (13) (Bates and Watts, 1988):

$$S = \sqrt{\frac{RSS}{N - P}} \tag{13}$$

In this case, *S* is equal to 0.024. In Table 1 the defects per unit in each *i* th workstation (DPU_i) predicted using Eq. (10) and the corresponding 95% prediction interval, expressed as lower limit and upper limit, denoted respectively as LL_{PI} (DPU_i) and UL_{PI} (DPU_i), are reported. It should be noted that negative values of the lower limits of prediction intervals of *DPU* are set equal to zero in Table 1. Accordingly, for most workstations, the prediction interval is not symmetric with respect to the predicted DPU_i.

The prediction limits defined in Table 1 can be used to determine if the low-volume assembly process is in a state of control, i.e. stable, with variations coming only from sources common to the process. In other words, the prediction interval limits can be used to distinguish common causes of variation from special causes of variation (Montgomery, 2012). Specifically, the methodology requires that, once the prediction model has been developed, defects detected in each workstation, over a specific period of time, are divided by the number of units inspected in order to obtain the observed *DPU* values. Then, a diagnostic test is performed to verify whether such observed *DPU* values fall within the prediction interval. A special cause of variation occurring in any workstation of the assembly process can be detected if the observed DPU_i falls above the upper limit or below the lower limit of the corresponding 95% prediction interval. It should be noted that if the DPU_i is higher

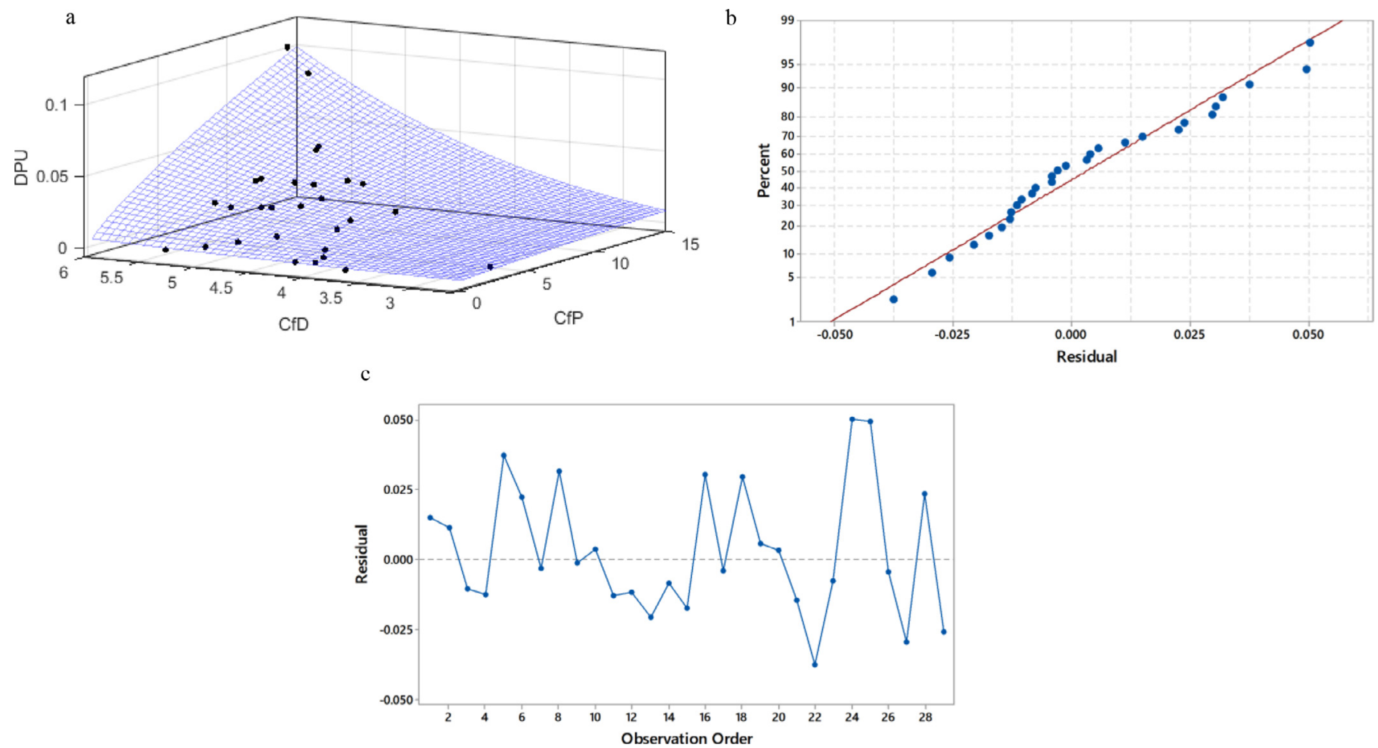

Fig. 2. (a) Surface plot of *DPU* against Cf_P and Cf_D: theoretical model and nominal *DPU*; (b) Normal Probability Plot and (c) Residuals vs Order Plot for residuals between nominal *DPU* and predicted $DPU.DPU_i \pm 2.055 \cdot \sqrt{VAR(DPU_i) + S^2}(12)$.

than the upper prediction limit, it means that an abnormal defectiveness is occurring in such workstation. In the same way, a DPU_i below the lower prediction limit should be signaled, as it could be due to an arbitrary reduction of the *DPU* detected by operators during quality inspections. The diagnostic method, therefore, aims at signaling abnormal workstations after having collected defects for a certain period of time. In this view, the tests carried out may be seen as in-progress controls, to be performed whenever *DPU* values are available on each workstation.

The proposed method was tested by collecting the defects occurring in each workstation over a period of 6 months (corresponding to 28 pre-stretch devices). Starting from the observed defects, the *DPU* in each workstation were derived and are reported in Table 1. As can be easily assessed, in workstations 10 and 26 the observed DPU_i values, written in bold, are higher than the upper limit of the prediction interval, whereas no DPU_i observed is lower than the corresponding lower limit. In order to investigate the causes leading to the anomalous defectiveness found in the two workstations, specific and accurate checks were carried out. As far as the workstation 10 is concerned, the critical assembly operation was found to be the finishing of the frame plate holes, performed by the operator with a manual grinding machine. The inadequate training of the operator was, therefore, the variation cause. On the other side, the root cause of the workstation 26 was a batch of an out-of-tolerance mechanical component purchased from an external supplier used for assembling the spindle release lever.

5. Conclusions

In low-volume assembly processes, the non-applicability of traditional statistical process control techniques and the scarcity of historical data available make process control and monitoring a remarkable issue. This paper proposes a new approach based on the formulation of a probabilistic model for defect prediction in low-volume assembly processes, which can be exploited as a diagnostic tool for the identification of critical workstations. The workstations whose defectiveness deviates, at a certain confidence level, from the predicted value can be easily identified, by verifying whether the observed *DPU* value does not fall within the prediction interval. By discerning the common causes of variation from the special causes of variation, the proposed approach represents a powerful tool for improving the assembly process. In fact, by identifying the causes leading to significant non-conformities, appropriate corrective actions to improve the process can be readily implemented. An application concerning the assembly of a real-life low-volume production of wrapping machines was presented.

The proposed approach may be exploited for low-volume assembly manufacturing processes in similar industrial fields of the present case study, where the occurrence of defects is of the same order of magnitude. In fact, the *DPU* values estimated through the prediction model derived using wrapping machines data can be considered a good approximation of the average defects per unit where historical data or expert estimates are not available.

A limitation of the proposed method has to be discussed. The obtained prediction model, and therefore the nominal *DPU* values and the related prediction intervals, are derived from historical data and estimates provided by the expert. Future research will be aimed at refining the model by including more accurate data that are being collected experimentally.

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