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Quality monitoring of blind fasteners installation: An approach from the manufacturing chain and visual analytics

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Abstract:

Fastening is a recurrent assembly operation at the aerospace industry. Among the many different types of fasteners being used blind ones offer particular advantages but there is yet a lack of reliable installation monitoring methods for their massive adoption. The present paper proposes an installation evaluation solution for blind fasteners that integrates the effect of the previous drilling operation and allows the visualization of the relationships between hole quality parameters, installation variables and installation quality. The results show high precision values of 0.95 and accuracy of 0.9.

Keywords: Blind fasteners, riveting, manufacturing chain, quality monitoring, visual analytics

1. INTRODUCTION

Fastening is a recurrent operation in aircraft manufacturing being one of the most widely used option for the assembly of components (Dharmara, K. et al in 2018). Among the many different fasteners available in the market, blind ones are a specific type that can be installed by accessing just from the outer side of the assembly. This is a relevant advantage since it allows an easier automation of the operation. It is well known that automation is key for the aerospace industry not only to gain productivity and decrease costs but also to mitigate the leakage of skilled operators.

Unfortunately, the drawback of blind fasteners is that their mechanical performance is assessed by measuring the formed head at their back, on the non-accessible side of the assembly. This can be done today only for certain assembly configurations and by qualified operators using expensive equipment and time-consuming processes. As a result, the use of blind fasteners is limited despite their potential and when used, the number of installations is over calculated to compensate the lack of reliable inspection.

Research focused on the inspection of blind fasteners installation has consequently attracted attention. Martinsen et al. (2015) reaffirm this thought when stating that sensor-based process monitoring and control for an automated quality inspection represents one of the key challenges for improving sheet metal joining in aeronautics.

Quality inspection of the fasteners installation by using Non-destructive testing (NDT) techniques appears as an option. Being ultrasonics a recurrent technique for measuring gaps Zhang et al. (2017) developed a non-linear method based on vibroacoustic modulation for an early detection of the loosening of bolted fasteners in metallic joints of various types. However, NDT-based inspections involve cycle times which are hard to assume when having industrialization in mind. Some of the techniques and methods used in the theme are summarised in Table 1.

Table 1 Recent approaches to estimating quality in fastener installation

Author	Year	Methodology	Application
Xie et al.	2021	Visual inspection technique plus Region Classification Network	Rivet Flush Measurement Based on 3-D Point Cloud
Teixeira et al.	2021	Deep learning technique applied to image	An intelligent hexapod robot
Le et. al.	2018	B-scan ultrasonic testing	Method for inspection of rivets integrity
Van de Velde et al.	2020	Finite Element Modeling	Simulation of local plastic material properties of the blind rivet nut
Van de Velde et al.	2021	Numerical prediction of the torque	A 2D model that enables the prediction of stress and material flow with sufficient accuracy

Solutions based on the monitoring of the installation variables seem a more agile and affordable option for a 100% inspection rate. Granted patents by Wang (2008) and Weeks (2009) go in this direction by proposing riveting tools which

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integrate low cost transducers (load, displacement) and methods to identify fault installations from the evolution of the captured variables. Also relying on the installation variables Saygin et al. (2010) estimated the grip lengths, defined as the dimensions of an assembly thickness that a fastener is capable of joining, of installed fasteners and contrasted them against the expected values. Another interesting contribution comes from Palasciano et al. (2016) who developed a data-based model integrating machine variables with data collected by the operator during the operation. Camacho et al. (2016) and Urbikain et al. (2017) proposed a somehow hybrid method by combining in-process and post-installation measurements, namely the cycle time and the time of flight of an electronic pulse sent through the spindle of the installed fastener. In the work by Diez-Olivan (2017) pattern classification techniques are applied to understand and predict different installation scenarios while Ortego et al. (2020) presented a comparative of the performance of several shallow and deep learners on the evaluation of installations.

However, it is often dismissed that fasteners installation is preceded by drilling but Jinyang et al. (2019) remind the complexity of this operation which features tight dimensional tolerances. In recent years, with the increasing product quality requests the analysis of the whole manufacturing chain is gaining attention. Thus, Wuest et al. (2014) proposed the combination of cluster analysis and supervised learning techniques to monitor product quality along the chain and Filz et al. (2020) modelled a printed circuit board states throughout the assembly stages of components.

On the other hand, Filz et al. (2020) again, as well as Soban et al. (2016), have pointed out visualization techniques as enablers for decision making when analysing manufacturing processes using data.

This paper proposes an evaluation method for the installation of blind fasteners that includes the analysis the of the previous drilling operation and the visualization of the evaluation outcomes.")

This paper proposes an evaluation method for blind fasteners installation that includes the analysis of the previous drilling operation. To carry out the visualisation of results, first, a Principal Component Analysis (PCA) is applied for the ease of the subsequent installation analysis. The PCA also provides a first insight to the significance of the hole quality parameters and the fastening variables selected. Then, a response surface, built up on the previous PCA results, provides predicting and visualization capabilities on the evolution of the installation quality against hole quality parameters.

2. EXPERIMENTAL PROCEDURE

2.1 Use case definition

For the experimental campaign a blind fastener of designation MONOGRAM CL-II specific for automated assemblies was selected. Figure 1 shows a non-installed fastener as well as the front and back (blind) sides of an assembly probe with several fasteners installed. For the installation, the riveting tool engages the disposable cylindrical nut making the inner screwed pin rotate and advance towards the back side of the assembly. Jointly with the pin the sleeve approximates and contacts the back side. Then, it deforms into the formed head until the pin breaks off and the installation is completed.

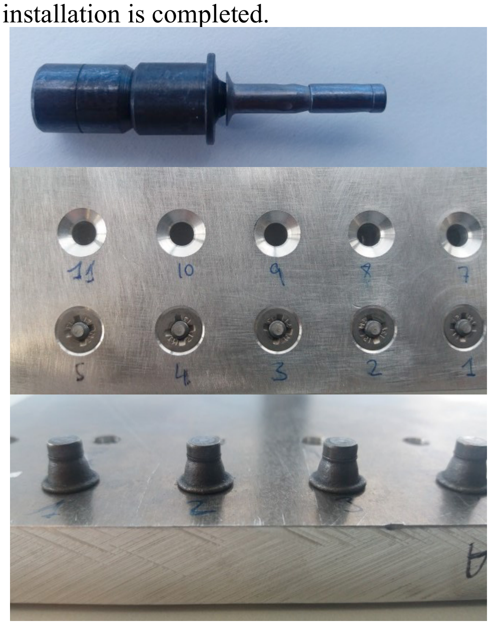
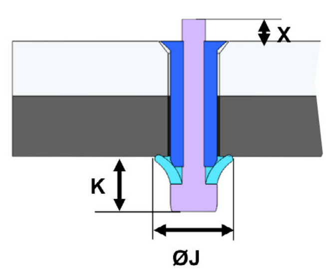


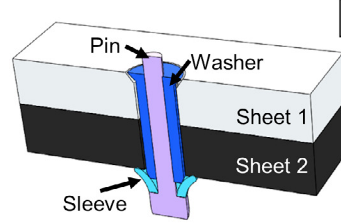
Figure 1 MONOGRAM CL-II blind fastener (top), probe front (middle) and back (bottom) with fasteners installed

The quality of the installation is assessed by verifying the dimensions of the diameter (J) and height (K) of the formed head together with the height of the pin over the front side, as illustrates Figure 2. The reference values vary with the diameter of the fastener.

Also, the dimensions of the hole and the countersink where the fastener is installed must be controlled according to the criteria shown in Figure 3 for a correct installation.

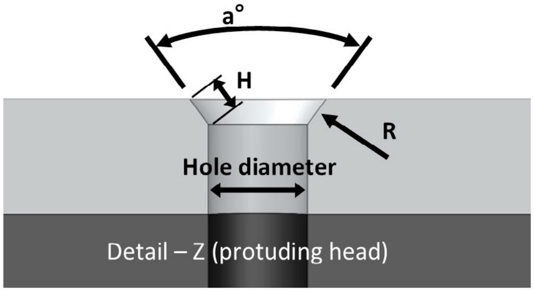


Diam. Nominal Fastener		Diam. "J" (mm)	"K" (mm)
code	mm	min.	max.
-5	4.17	6.35	7.62
-6	5.04	7.62	8.89
-7	5.77	8.89	10.16
-8	6.59	10.16	11.43
-9	7.35	11.43	12.70



"X" (mm)	
min.	max.
+0.000	+2.620

Figure 2 Formed head and screw dimensions defining the quality of a CL-II installation



Nominal fastener diam. (mm)	Hole diameter	
	min.	max.
4.14	4.192	4.267
5.03	5.055	5.130
5.77	5.792	5.867
6.59	6.604	6.680
7.35	7.366	7.442

Nominal fastener diam. (mm)	100°countersunk head		
	a°	H (mm)	R (mm)
<7.4	50°-60°	0.65 0.80	0.75 1.00
>8		0.85 1.05	1.00 1.25

Figure 3 Hole and countersink tolerances to install a CL-II fastener

2.2 Test bench and test program for fastening quality assessment

To carry out the installation of the fastener it is necessary to drill a hole in the preliminary phase. The drilling operations have been done in an IBARMIA 5 axis milling machine. The spindle is able to reach 18000rpm, thus ensuring typical values of drilling parameters (high revolutions) in the aluminium selected material. The fastening stage is implemented in an ANAYAK 3 axis milling machine. The pneumatic fastening head has been adapted to the machine head in order to control the position during the installation. The clamping system design provides easy alignment when moving the probe from the drilling station to the fastening one.

Fastening is monitored in-line via a dedicated measuring chain (sensors and acquisition systems). The monitoring signals being acquired are described in Figure 4.

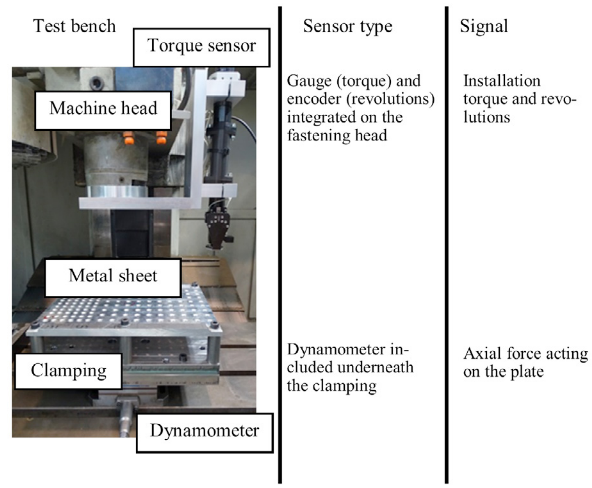


Figure 4 Test Bench for fastening installation with inline monitoring

The fasteners selected for the experimental tests are blind fasteners with designation Monogram CL-II. The fasteners have been selected as the benchmark so the same reference and dash will be used for all tests. Grips to be used will be 350 and the immediately upper and lower values (400, 300) and two different supply batches will be tested (A, B). Five thickness references (XS, S, M, L, XL) will be set around the mid-range value for grip 350 (8,26mm) which will be assigned as the medium (M) thickness. Graded values around these five references will be used to simulate a broad enough range of thicknesses. Tests using no plates at all will also be made as an extreme condition of "in-air" installations. The rest of installation variables (plate material, countersink dimensions, air pressure) will be kept fixed. At least 10 iterations per test are foreseen though modifications could be introduced in order to obtain the adequate amount of OK/NOK installation to build up the data driven classifier. A total of 400 blind fasteners have been installed. Table 2 shows a summary of the selected parameters.

Table 2 Test program table

Test N#	Plate thickness	GRIP Code	GRIP Installed	Installation conditions based on grip selected
1	0	0	300	In-air. no plate
2	0	0	350	In-air. no plate
3	0	0	350	In-air. no plate
4	2.3	100	300	In-air. extra-high grip
5	2.3	100	350	In-air. extra-high grip
6	2.3	100	400	In-air. extra-high grip
7	3.2	150	300	In-air. very high grip
8	3.2	150	350	In-air. very high grip
9	3.2	150	400	In-air. very high grip
10	8.89	350	350	Upper limit grip
11	8.89	350	400	Lower limit grip
12	8.26	350	300	Low grip
13	8.26	350	350	Middle grip
14	8.26	350	400	High grip
15	7.62	350	300	Upper limit grip
16	7.62	350	350	Lower limit grip
17	10.16	400	350	Very low grip
18	10.16	400	400	Upper limit grip
19	11.43	450	350	Extra-low grip
20	11.43	450	400	Very low grip
Batch:	A/B	Total fasteners installed:		400

3. BUILDING UP OF THE INSTALLATIONS CLASSIFIER

This section presents the steps taken for the classification of the correct installation of fasteners. This includes the previous hole measurement data, followed by a preliminary preparation and selection of the characteristic areas of the revolution-torque diagram, then a reduction of order and selection of variables through the PCA and then the modeling of the response surface.

3.1 Signal Pre-processing and Feature Engineering

The installation torque signal measured at the pneumatic actuator and the rotation produced is recorded and analysed, as it can be seen in Figure 5. A pre-processing treatment has been applied to the signal prior to any analysis:

- Only positive angular increments are considered
- Resampling of data to have a constant angle period (increment)
- After applying different filtering methods (Hilbert transformation, Low-pass frequency filter and moving average) the moving average filter has shown to be the most suitable
- Three different alignment options (align signal to maximum value, align signal with truncate and align signal without truncate signal) have been tested being alignment via cross-correlation without further truncation the most suitable option.

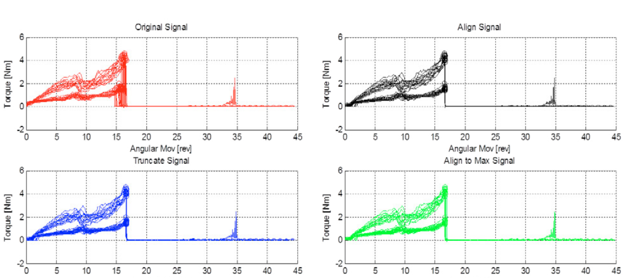


Figure 5 Different signal alignment options tested: no alignment (red), alignment (black), alignment and truncation (blue), alignment to peak values (green)

The torque-revolution installation diagrams have been used for a time domain study. By observing the obtained signal features, the areas under the revolution-torque diagram should reflect whether the installation is OK or NOK have been identified. Then a set of descriptors which characterize the patterns differences have been defined and estimated as it can be seen in Figure 6.

The estimation has been based on a previous identification of the critical points. These points defined the different stages of the installation:

1- Installation start (change on the slope).
2- Stop of sleeve rotation (calculated as the maximum of the detrend signal).
3- Sleeve contact (change on the slope positive values).
4- Sleeve formation (slope increasing).
5- Installation completed (maximum torque value).
6- Spindle turn off (torque value reaches almost zero).

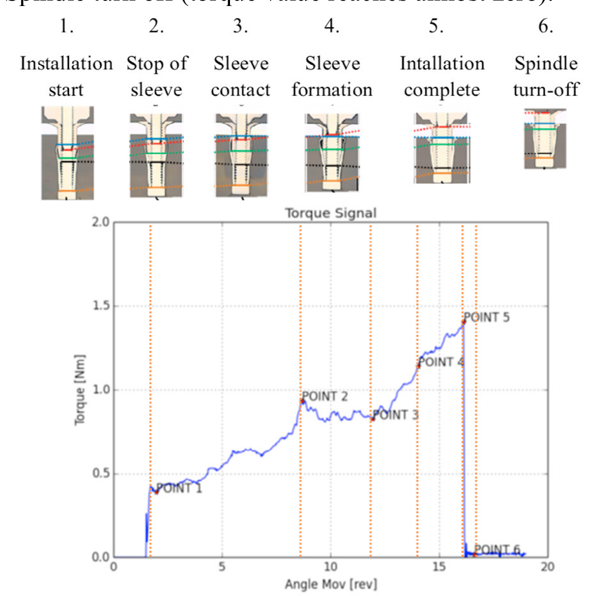


Figure 6 Torque-Angle Mov diagram for fasteners installation: relevant points determination

3.2 Order reduction and variables selection

The Principal Component Analysis (PCA) is a technique that groups a set of variables into a set of lineal and uncorrelated functions called Principal Components (PCs). Though the number of PCs equals that of the original variables, it is usual to find that a selection of the PCs accounts for the 80-95% of the variability of the process the variables are representing, Jackson (1991). Technically, PCA looks for the projection according to which the data are best represented in terms of least squares. It converts a set of observations of possibly correlated variables into a set of values of non-linearly correlated variables called principal components. Since the correlation matrix is symmetric, these eigenvalues are called the weights of each of the principal components.

Figure 7 shows the weights of each variable in the PCs for the 400 blind fasteners and the uncorrelated projections of the data cloud. Where *D* is the Hole diameter average (mm), *Th* is the thickness of the sheets (mm), *G* grip as thickness minus the countersink (mm), *A2, A3, A4* and *A5* as the Areas under the curve in the steps 2, 3, 4 and 5.

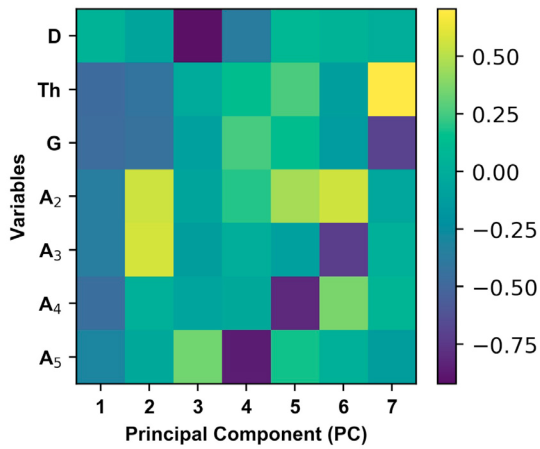


Figure 7 Heat map of variable weights of principal components

Based on the PCA results, the dimensionality can be reduced to four PCs which explain more than 85% percent of the variability as can be seen in Figure 8.

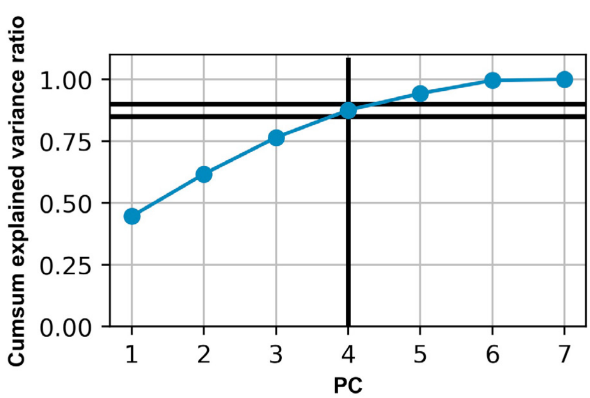


Figure 8 Cumsum explained variance ratio of principal components.

The PC equations are function of the geometrical and torque signal parameters,

$$\boldsymbol{PC_1} = 0.05 \cdot D - Th - 0.47 \cdot G - 0.35 \cdot A_2 - 0.36 \cdot A_3 - 0.5 \cdot A_4 - 0.30 \cdot A_5 \tag{1}$$

$$\boldsymbol{PC_2} = -0.06 \cdot D - 0.42 \cdot Th - 0.43 \cdot G + 0.55 \cdot A_2 + 0.57 \cdot A_3 + 0.02 \cdot A_4 - 0.034 \cdot A_5 \tag{2}$$

$$\boldsymbol{PC_3} = -0.92 \cdot D - 0.024 \cdot Th - 0.101 \cdot G - 0.06 \cdot A_2 - 0.11 \cdot A_3 - 0.06 \cdot A_4 + 0.34 \cdot A_5 \tag{3}$$

$$\boldsymbol{PC_4} = -0.37 \cdot D + 0.13 \cdot Th + 0.26 \cdot G + 0.20 \cdot A_2 + 0.01 \cdot A_3 - 0.03 \cdot A_4 - 0.86 \cdot A_5 \tag{4}$$

The first PC is dependent of all the torque areas and the two grip length, the second PC is function of two grip lengths and the first two areas, the third PC is dependent of hole diameter and the last PC is function of torque area 5.

Therefore, the statistical approach reduces the dimensionality to four PCs which explain more than 85% of the process variance. These are the inputs for the blind fastener classification.

3.3 Surface response-based classification

The approach developed classifies the blind fastener installation analysing the relationship between the independent variables and the desired response.
The independent variables are the four PCs, before studying, which explain more than the 85% of the process variance and are function of the initial geometrical and signal variables.
The desired responses are the formed head diameter J, the formed head height K and the spindle break off X. These quality responses define the blind fastener classification strategy.
Table 3 summarizes the main variables of the response surface method that classifies the installations.

Table 3. Results of response surface methodology for three outputs.

Formed head diameter J (mm)		Formed head height K (mm)		Spindle break off X (mm)	
R-squared: 0.77		R-squared: 0.83		R-squared: 0.77	
Prob(F-statistic): 8.68e-114		Prob(F-statistic): 1.67e-138		Prob(F-statistic): 1.47e-112	
Pcs	P>|t|	Pcs	P>|t|	Pcs	P>|t|
INT	0.002	INT	0.000	INT	0.000
PC_1	0.000	PC_1	0.000	PC_1	0.000
PC_2	0.000	PC_2	0.000	PC_2	0.000
PC_3	0.002	PC_3	0.004	PC_3	0.729
PC_4	0.362	PC_4	0.024	PC_4	0.002
PC_1^2	0.000	PC_1^2	0.000	PC_1^2	0.000
PC_2^2	0.000	PC_2^2	0.081	PC_2^2	0.000
PC_3^2	0.324	PC_3^2	0.457	PC_3^2	0.047
PC_4^2	0.163	PC_4^2	0.221	PC_4^2	0.004
$PC_1 \cdot PC_2$	0.000	$PC_1 \cdot PC_2$	0.001	$PC_1 \cdot PC_2$	0.000
$PC_1 \cdot PC_3$	0.520	$PC_1 \cdot PC_3$	0.487	$PC_1 \cdot PC_3$	0.383
$PC_1 \cdot PC_4$	0.000	$PC_1 \cdot PC_4$	0.000	$PC_1 \cdot PC_4$	0.004
$PC_2 \cdot PC_3$	0.633	$PC_2 \cdot PC_3$	0.83	$PC_2 \cdot PC_3$	0.941
$PC_2 \cdot PC_4$	0.000	$PC_2 \cdot PC_4$	0.015	$PC_2 \cdot PC_4$	0.088
$PC_3 \cdot PC_4$	0.096	$PC_3 \cdot PC_4$	0.049	$PC_3 \cdot PC_4$	0.443

To guarantee a good classification method, the surface response methodology requires the good values of fitted and the curvature. In this case, the R-squares of responses are reasonably good (0.77, 0.83 and 0.77), consequently the responses are well fitted. The curvature is studied with prob(F-statistic) to know the accuracy. In these cases, the values are low (8.68e-114, 1.67e-138 and 1.47e-112) ensuring the curvatures. In addition to this, when the value of P>|t| is close to zero, the variables and the interactions (i.e., $PC_1 \cdot PC_2$) are significant (great influence) and when this one is great, the variable and the interactions have not influence (i.e., $PC_1 \cdot PC_3$ and $PC_2 \cdot PC_3$) in the responses.
To visualize the surfaces, it is proposed the estimated response as a function of PC1 and PC2 keeping constant the rest of the PCs. Therefore, Figure 7 illustrates the formed head diameter J, the formed head height K and the spindle

break off X as a function of the first and the second principal components, respectively.

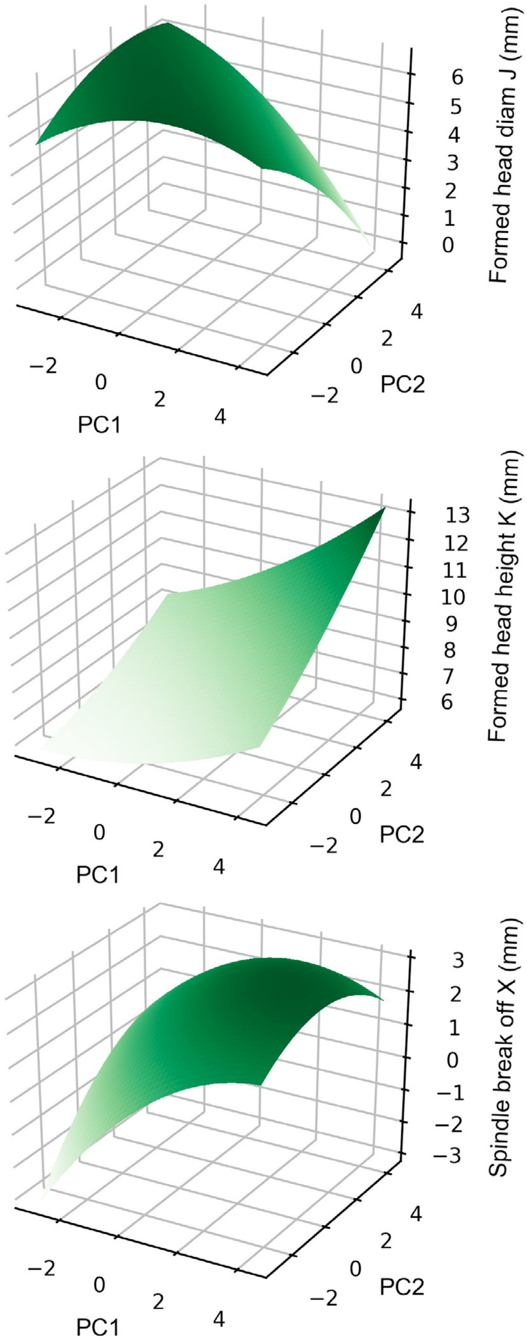


Figure 9 Formed head diameter J, the formed head height K and the spindle break off X as a function of PC1 and PC2.

Figure 8 illustrates the feasible space of OK and the NOK space for classifying the blind fasteners quality. The intersection of three responses (J, K and Z), depending of PC_1 and PC_2,provides the feasible OK space where all the True Positives (TP) are in this area and outsize of this region, in this case two zones as can be seen in Figure8, the NOK space where the Total Negative (TN) are in these areas.

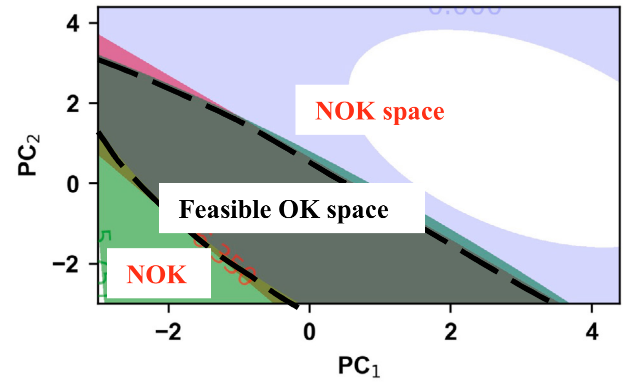


Figure 10 Contour plot of responses (J, K and X) as a function of PC_1 and PC_2.

The quality monitoring approach requires a study to know the number of TP, TN, False positive (FN) and False Negative (TN). Therefore, Table 5 illustrates the confusion matrix and the main variables to study the precision of the classification strategy. according to geometrical requirements of Figure 2 These variables being calculated according to Eqs. 5-6.

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

Table 4. Confusion matrix and main principles.

TP	TN	FP	FN	Precision	Accuracy
177	183	9	31	0.95	0.9

From the results high scores are observed in correctly detecting both NOK and OK installations (TP and TN respectively) being the weakest value that corresponding to NOK installations detected as OK (FN). Despite it would be desirable a lower FN score, it must be born in mind that a security coefficient is always applied to installations so that their number is overestimated from calculations. Globally, the results can be considered as good, pointing out both the precision in detecting NOK installations and the accuracy in differentiating NOK from OK cases (0,95 and 0,9 respectively) a robust and reliable classification.

4. CONCLUSIONS

A novel approach for evaluating the installation of blind fasteners has been presented. The solution proposed includes the drilling stage prior to fastening into the analysis. Also, uses the surface response method to predict and visualise the installation quality.

The main conclusions from the results obtained are

- The proposed classifier provides robust predictions featuring a high precision in the detection of OK installations (0,95) and slightly lower but yet high accuracy in terms of differentiating between OK and NOK cases (0,9).
- The hole and assembly measurements included as variables into the classifying system (diameter, plate thickness, grip length) have shown to be relevant.

Being all the holes within design tolerances, this means that prior drilling stage influences the quality of the installation. Since the fastener grip is selected based on the plate thickness, the dependency on this variable on the installation outcome is also an interesting finding.

- The use of the surface response method in combination with the previous order reduction by the PCA helps to understand the weight of the drilling and fastening variables into the installation outcome and provides at the same time a visualization of the space where OK installations should be expected.

This paper lays the foundation for a machine-based implementation of a blind fastener quality monitoring process that considers the entire fastener assembly chain: from drilling to final installation. In addition, variables specific to the drilling process such as torque signal, forces, vibrations, or acoustic emissions, among others, could be included. Also, the extension of the technique to other types of fasteners.

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