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Screwing process analysis using multivariate statistical process control

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Abstract

Screws are widely used for parts joining in industry. The definition of effective monitoring strategies for screwing processes can help to prevent or significantly reduce ineffective procedures, defective screwing and downtime. Monitoring several correlated variables simultaneously in order to detect relevant changes in manufacturing processes is an increasingly frequent practice furthered by advanced data acquisition systems. However, the monitoring approaches currently used do not consider the multivariate nature of the screwing processes. This paper presents the results of a study performed in an automotive electronics assembly line. Screwing process data concerning torque and rotation angle were analyzed using multivariate statistical process control based on principal component analysis (MSPC-PCA). The main purpose was to extract relevant information from a high number of correlated variables in order to early detect undesirable changes in the process performance. A PCA model was defined based on three principal components. The physical meaning of each component was identified, and underlying causes were inferred based on technical knowledge about the process. Monitoring tools, such as score plots and multivariate control charts allowed to detect the defective screwing cases included in the analyzed data set. Furthermore, eight periods of instability were identified. Considering that the out-of-control signals detected in these periods mainly correspond to delays at the beginning of the tightening operation, four potential causes to explain this behavior were ascertained and analyzed. This research allowed to acquire a deeper understanding on the screwing process behavior and about the causes with higher impact on its stability. Due to its flexibility and versatility, it is considered that this approach can be applied to effectively monitor screwing processes in the assembly of different product types either periodically or in real-time.

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1. Introduction

Screwing processes are typical in production of appliances and the most common way of joining parts by using automatic screwdrivers [1]. Standard threaded fasteners are capable of joining different materials in uniform and unusual joint configurations [2]. Fastener tightening consists of turning a lead screw (angular displacement) and torque (turning moment) in order to generate a tension. Torque-angle curves provide relevant information to properly qualify the capability of tightening tools [3].The required torque varies depending on the conditions of contact surfaces, thread types, material properties, etc. [4]. According to [3], the fastener torque-angle curve has the following distinct zones:

1. Rundown zone – occurs before the fastener head or nut contacts the bearing surface;
2. Snugging zone – wherein the fastener and joint mating surfaces are aligned to achieve a “snug” condition;
3. Elastic clamping zone – range in which the slope of the torque-angle curve is essentially constant;
4. Yield zone – wherein the destruction of the bolted joint begins.

The relevance of monitoring, analysing and controlling screwing operations parameters to detect deficiencies and ensure higher accuracy is reflected in different studies performed over the last years [5–8]. However, the monitoring and control methods in the literature are generally oriented to a specific purpose, such as controlling the conformance of individual tightening operations with respect to one quality characteristic (e.g., final torque, insertion depth, grip length, bolt preload). Moreover, the ability to monitor the overall screwing process behaviour over time is not addressed. In general, the tightening operations are monitored individually, and the emphasis is in error detection. Since several combinations of process variables may affect the same product property, monitoring the process helps to determine the underlying cause more easily [9].

Advanced automatic data acquisition has an extensive use in manufacturing industries and it is common to monitor several correlated quality variables simultaneously [10]. Monitoring one variable at a time is often ineffective and unfeasible [11]. Multivariate control charts have been widely used for monitoring multiple process variables [12]. Most of these charts are effective in detecting out-of-control signals in manufacturing processes based upon an overall statistics [10]. Out-of-control signals are evidences of special events with impact on the process performance and their causes (assignable causes) must be diagnosed using timely information. The identification of the process variables whose means have shifted is commonly used to determine assignable causes of variation [9].

Principal component analysis (PCA) is frequently used to enable the application of multivariate statistical process control (MSPC). PCA allows to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set [13]. It allows to identify a new set of variables that reflect underlying characteristics which explain the behaviour of a process [14]. The new variables are uncorrelated and represent linear combinations of the original variables. These variables are the principal components and their values for the individual observations are named scores. Principal components are ordered so that the first few retain most of the variation present in all of the original variables [13]. A PCA model is defined based on a reference data set which represents the Normal Operating Conditions (NOC) of the process. According to [9], an appropriate reference set is chosen using data collected from several periods when performance was good. However, the NOC observations should ideally contain all variation which leads to an acceptable performance in order to reduce the number of false warnings [15].

Multivariate control charts can be designed for the Hotelling’s T^2 and Squared Prediction Error (SPE) statistics such that their violation indicates irregular operating conditions [14]. Disturbances that cause deviations of the observation vectors from the vector that represents the PCA model mean are detected in the principal component subspace by T^2. Whereas disturbances that result in violations of the correlations structure of variables are detected by SPE. Thus, process instability can be identified using multivariate control charts.

This paper describes the results of a study performed in an assembly line of Bosch Car Multimedia Portugal. It was intended to detect disturbances in the screwing process behaviour and identify the main causes of instability. PCA was used to extract relevant information from data collected by the controller of a manual screwdriver concerning the torque and rotation angle. Afterwards, time series score plots and multivariate control charts were applied to monitor the process stability. The paper is organized as follows. Section 2 describes the results of the application of MSPC-PCA using real data from the screwing process. The main results are subsequently discussed in section 3. Finally, section 4 presents the conclusions of the study and provides guidelines for future research.

2. Screwing process analysis

After studying the distinctive zones of a typical torque-angle curve, a set of steps was defined to monitor the screwing process of an automotive electronics assembly line. The application of the defined approach using data from a manual screwdriver is described in this section.

Sample definition: A data set composed of 20194 screwing cases performed in the same workplace for a unique product type was considered. In the product assembly seven screws are placed following a predefined sequence. The aggregate data consist of thirteen samples collected in different days, between February 12, 2018 and March 3, 2018, and contain only 14 defective observations ("bad"). The data were collected in interleaved periods, since other product types were assembled in the analyzed workplace during the overall interval. A preliminary analysis of subsets of overlapping torque-angle curves using Unscrambler® software allowed to identify eight periods of higher instability. Each period corresponds to a different day and instability is mostly associated with delays at the beginning of the tightening operation (inefficient screwing). The delays include the screwing cases with an absolute angle higher than 2100 degrees (nearly 1.5 turns above the mean). Table 1 provides a description of the samples considered in the analysis.

Table 1. Description of the screwing process data samples.

Date	Number of product types	Total number of cases performed	Number of analysed cases	Production interval	Interval of higher instability	% Delays
12/02/2018	2	2893	1963	1-1963	1001-1500	12,8%
13/02/2018	2	3845	1387	2459-3845	3160-3845	6,3%
14/02/2018	3	3788	1611	1-1611	-	1,9%
16/02/2018	7	3422	2136	361-1972, 2008-2531	1082-1281	5,2%
19/02/2018	4	3079	1665	477-2141	499-929	17,4%
21/02/2018	4	3065	836	646-1841	646-870	10,0%
23/02/2018	4	4029	2119	188-2306	689-1609	2,5%
26/02/2018	2	2924	1073	1852-2924	2343-2750	6,3%
27/02/2018	4	3766	1434	1-1434	-	0,6%
28/02/2018	3	3488	35	3454-3488	-	0,0%
01/03/2018	2	4422	3807	1-3807	-	1,6%
02/03/2018	3	3637	460	3168-3637	-	13,0%
03/03/2018	1	1668	1668	1-1668	1-175	0,7%
Total		**59560**	**20194**			

Data pre-processing: During the tightening operation, the screwing machine controller usually records torque values at regular and very short periods of time. However, the corresponding rotation angle cannot be obtained at regular intervals because the angular displacement of the screw is not constant. Therefore, to obtain torque values for angles at intervals of 10 degrees between 0 and 2300, a linear interpolation was performed by applying an algorithm in R code defined for this purpose. Since the torque associated with a specific rotation angle represents a variable, a data set composed of 231 variables was obtained. Finally, to avoid missing values in the torque-angle curves data it was decided that whenever the final torque is achieved between 0 and 2300 degrees the subsequent variables should assume the value 0 until the end of the scale.

Data segmentation: The NOC was defined based on 252 screwing cases from a sequence of 36 products. Only cases classified as "good" were included. Furthermore, all the cases were taken from the sample of 01/03/2018 and correspond to a period in which no adjustments were made in the process. Fig. 1a shows the NOC torque-angle curves and Fig. 1b presents a typical torque angle-curve. Numbers 1, 2 and 3 are used to represent the rundown zone, snugging zone and elastic clamping zone, respectively.

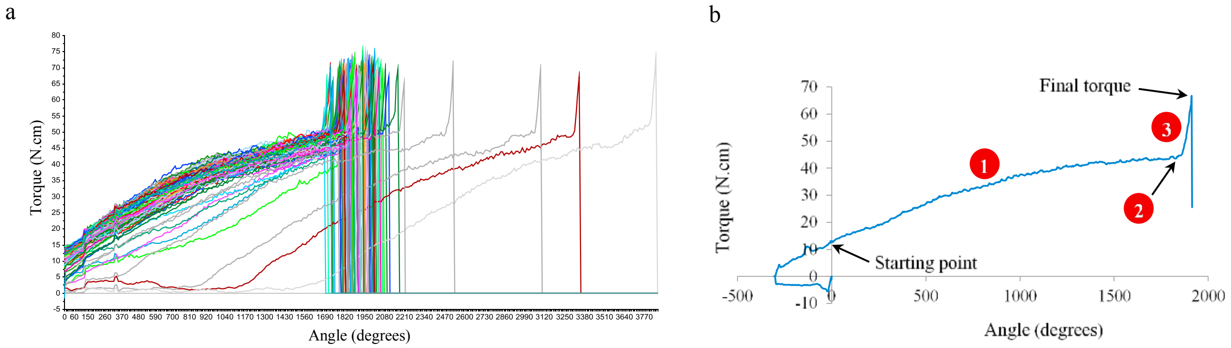

Fig. 1. (a) Torque-angle curves of the NOC observations; (b) typical torque-angle curve.

Principal components identification: PCA was applied to the NOC data using ProSensus MultiVariate software. The results showed that the first three principal components represent 83.62% of the total variation and the variation predicted is 77.44%. The variation explained by the ordered components is 72.98%, 6.71% and 3.93%. Whereas the variation predicted is 67.54%, 6.14%, 3.76%, respectively. The fourth principal component has substantially lower relevance since it only explains 2.37% and predicts 1.36% of the total variation. Therefore, only three principal components were considered in the analysis.

Principal components interpretation: The principal components interpretation was performed by a work team which includes process and statistic experts considering the variables' loadings and technical knowledge about the process. Loadings are the coefficients of the linear combinations which perform the PCA rotation and are the key to determine the scores. The combination of technical knowledge with information provided by the PCA model allowed to obtain a deeper understanding about the process. Afterwards, the meaning of the principal components was used to analyse the monitoring tools. The loading plot of the first principal component (Fig. 2a) shows high loadings over the angles that correspond to the rundown zone and a significant decrease as the snugging zone is reached. The negative loadings exhibited at the end of the scale are due to the decision of extending the tightening curves up to 0 after the final torque is achieved. Accordingly, this principal component refers to the whole torque variation. It allows to distinguish screws that exhibit relatively high torques at the rundown zone. This behaviour can be caused by differences between screws or tighter threads. In the second principal component loading plot (Fig. 2b), the loadings start to be negative and a growing trend is manifested as the rotation angle increases until most tightening operations are completed. Thus, the second principal component enables to differentiate screws that have low torques at the rundown zone and a relatively high final torque. This behaviour can be due to more open threads, which are mainly found in products that were subject to rework. Furthermore, this principal component also represents delays in engagement. The loading plot obtained for the third principal component (Fig. 2c) reveals several fluctuations over the entire scale of rotation angles. Nevertheless, the loadings' value remains close to 0 along the angles that correspond to the rundown zone. Afterwards, the loadings become negative over the snugging zone. At the end of the scale, loadings are positive and significantly higher. Thereby, the third principal component allows to distinguish screws that exhibit a moderate growth of torque with slight oscillations at the beginning of the rundown zone, followed by a large interval that reaches the snugging zone in which the torque increase ceases. The interruption of the torque increase contributes to delay the conclusion of the tightening operation. This can be related to differences between threads. Thread crests often exhibit irregularities or slightly different formats which result in unexpected variations in the torque evolution during the tightening operation.

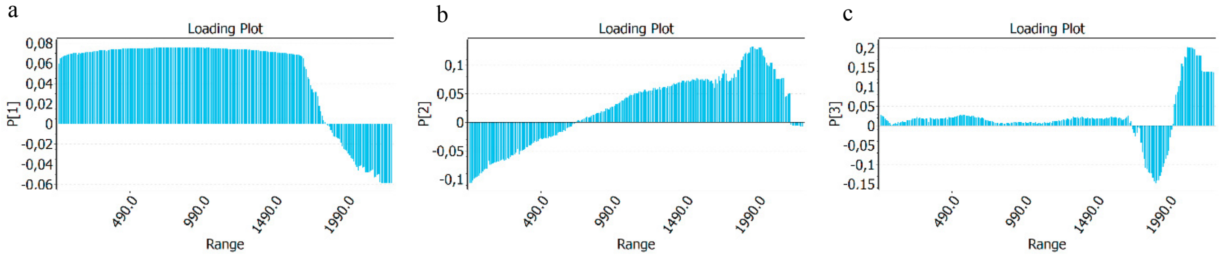

Fig. 2. Loading plots: (a) first principal component; (b) second principal component; (c) third principal component.

Control limits definition: Screwing process observations were analysed using score plots and multivariate control charts for the Hotelling's T^2 and SPE statistics. The control limits plotted in the monitoring tools were automatically determined in ProSensus MultiVariate software. It was considered that the limits defined by the 99% and 99.73% confidence intervals were appropriate warning limits both to detect defective screwing cases and identify inefficient tightening operations.

Behaviour identification: The NOC observations were analysed considering their location in the scatter score plot formed by the first two principal components (Fig. 3), which comprise 79.69% of the variation existing in the data. This analysis allowed identifying and characterizing observations which exhibit unusual behaviours, namely the screwing cases that are further away from the centre of the distribution (plot origin). The plot presents 7 observations outside the limit defined by the confidence interval of 99.73%. An individual analysis showed that observations 1, 2 and 3 correspond to cases that exhibit low torques at the first half of the rundown zone and were concluded with a slight delay comparing to the mean (less than 3 turns); observation 4 represents a case that shows very low torques over the rundown zone; and observations 5, 6 and 7 manifest significant delays at the beginning of the tightening operation (more than 3 turns).

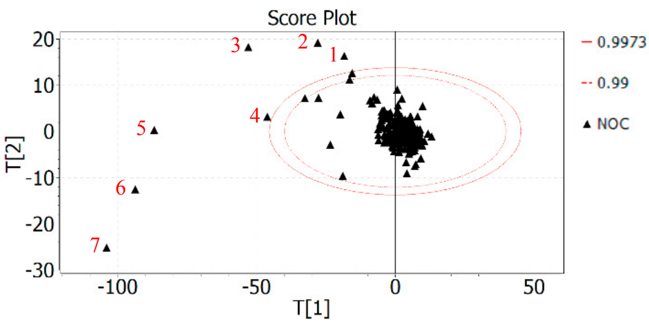

Fig. 3. Score plot.

Process monitoring: The process observations (Table 1) were represented in time series score plots and multivariate control charts in order to detect periods of instability. Observations that correspond to delays are represented by orange points and the remaining observations are depicted by black points. Furthermore, the intervals that reveal higher instability were marked with numbers from 1 to 8. The first principal component time series score plot (Fig. 4a) shows that the observations which represent the most significant delays fall below the lower control limit of the plot. However, observations with an absolute angle close to 2100 degrees are between the control limits, since the NOC also includes delays. In the second and third principal components time series score plots (Fig. 4b and Fig. 4c), observations that correspond to significant delays are placed bellow the lower control limit, whereas observations that exhibit moderate delays and high end torque are above the upper control limit. Nevertheless, the second principal component is more effective in detecting delays. The percentage of observations which correspond to delays that fall outside the 99.73% control limit in the time series score plot of the ordered components is 38.9%, 90.5% and 66.9%, respectively. The highest points represented in the Hotelling's T^2 control chart (Fig. 4d) correspond to delays and screwing cases classified as “bad”. However, observations with low torques at the rundown zone (reworks) can also be found above the limits. In the SPE control chart (Fig. 4e), the points which are further away from the control limits refer to screwing cases that were concluded considerably earlier comparing to the mean. Although several observations that correspond to delays are also above the limits, they reveal much lower deviations from the principal components’ subspace. Therefore, the eight periods of instability are more easily identified in the Hotelling’s T^2 control chart. This chart shows 93.2% of the observations related to delays above the 99.73% control limit. The torque-angle curves of the observations from period of instability 1 are presented in Fig. 4f. It can be observed that in this period a high number of delays occurred.

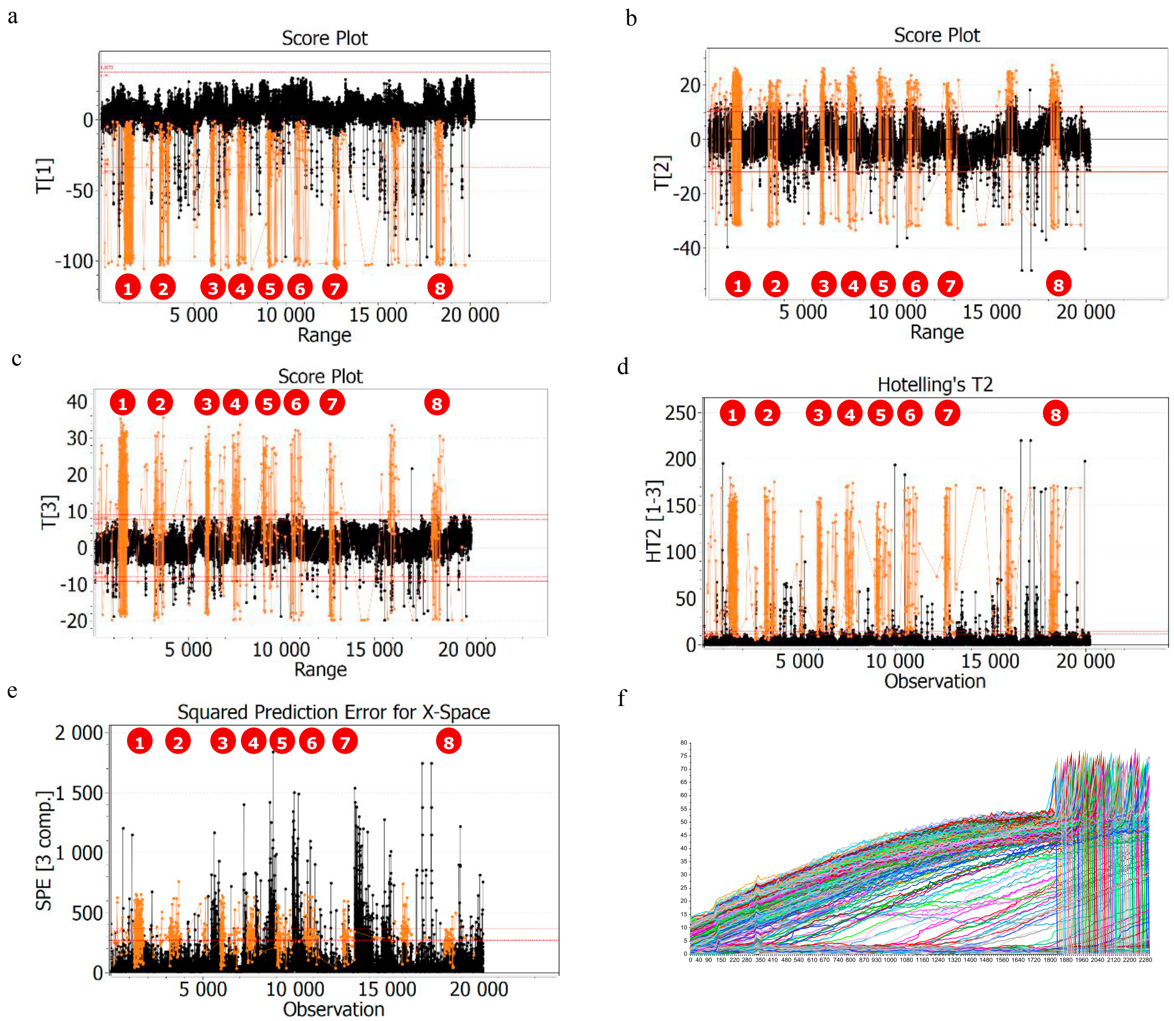

Fig. 4. (a) First principal component time series score plot; (b) second principal component time series score plot; (c) third principal component time series score plot; (d) Hotelling’s T^2 control chart; (e) SPE control chart; (f) torque-angle curves of period of instability 1.

3. Discussion of results

The analysis of maintenance records and operating mode of the screwing equipment, and the operators’ feedback allowed to establish four potential causes to explain the delays occurred in the eight periods of instability. Table 2 presents the description of the potential causes and their classification according to the occurrence probability. Causes 1 and 3 are related to the operating mode, cause 2 is associated with the equipment condition, and cause 4 corresponds both to the operating mode and equipment condition.

Table 2. Description and classification of the potential causes of delays.

Potential cause	Description	Number	Occurrence
Voluntary activation of the screwdriver by the operator before it contacts the joint	• Frequent behaviour adopted by the operators in manual workstations; • The positioning system does not control height and, therefore, the workstation tightens screws in different planes.	1	High
Dirtiness in the vacuum sleeve	• Hinders its normal compression at the beginning of the tightening operation;	2	High
Attempt of performing the screwing operation without screw	• It occurs when the operator performs the screw picking in the feeder of the screwdriver and does not detect that the screw was not pulled out; • Most of these cases result is “Bad”, however, the most experienced operators detect the symptom during the operation (sensorial feedback of the screwdriver) and rapidly perform a new screw picking (well succeeded).	3	Average
Misalignment of the vacuum sleeve with the screwing guide	• This misalignment promotes friction in the guide walls that consequently causes difficulty in achieving the joint; • It gives a false sensorial feedback to the operator so that he activates the screwdriver before it contacts the joint.	4	Low

The beginning and end time of each period of instability were associated with events related to the work scheduling, such as operator turnover and shift changes (Table 3). It was intended to identify whether the operator had relevant influence in the process performance. The collected information allows to verify that the tightening operations of period 1 were all performed by the same operator, because they belong to an interval which begins after the operator turnover and lasts until the end of the shift. Since no failures that could affect the screwdriver performance were detected, the tightening delays may have been originated by cause 1, 3 and 4. Nevertheless, cause 1 is more frequent than causes 3 and 4. Period 2 includes tightening operations performed by two operators, as the shift changes at 23:00 and this period ended at 23:59 of 13/02/2018. Maintenance records show that in 14/02/2018, between 00:04 and 00:42, a failure in the screwing equipment was detected and resolved. The vacuum sleeve got stuck due to dirtiness and, therefore, had to be cleaned. Thus, cause 2 is highlighted as the main reason that justifies instability. The same failure was identified in 16/02/2018 at 03:54 and it was corrected until 04:27. However, the period of higher instability detected on this day occurred between 06:08 and 06:58. Therefore, causes 1, 3 and 4, must be considered to justify instability in the process. These causes are also highlighted as the main reasons of the tightening delays in periods 5 and 7, because no failures with impact in the screwdriver performance were verified. Furthermore, all the tightening operations of each period were performed by a unique operator. Period 6 was identified in the observations of 23/02/2018, between 03:07 and 08:39. During this period, the problem in the vacuum sleeve detected in 14/02/2018 and 16/02/2018 occurred again. The failure detection was performed at 04:14 and the corresponding maintenance action was concluded at 05:09. Therefore, since the period ended at 08:39, it is considered that cause 2 is not the main reason of instability. Finally, period 8 is the shortest period. During the day to which the observations of this period belong, there were no failures that affected the screwing equipment. Although causes related with operating mode are the more plausible explanation to the tightening delays, differences verified in a small set of components lots could also have influenced the behaviour of the tightening curve.

Table 3. Events related to the work schedule.

Period number	Date	Beginning time (A)	End time (B)	Description	Maintenance action
1	12/02/2018	11:29	14:24	A – Operator turnover B – End of the shift	
2	13/02/2018	20:31	23:59	A – Operator turnover	From 00:04 to 00:42 of 14/02/2018.
3	16/02/2018	06:08	06:58	A – Beginning of the shift	From 03:54 to 04:27.
4	19/02/2018	09:01	11:23	B – Operator turnover	
5	21/02/2018	07:15	08:26	B – Operator turnover	
6	23/02/2018	03:07	08:39	B – Operator turnover	From 04:14 to 05:09.
7	26/02/2018	20:58	22:53	B – End of the shift	
8	03/03/2018	00:06	00:50		

4. Conclusion

In this paper, a sequence of 19942 tightening operations performed over different intervals of thirteen working days was monitored using the torque-angle curve data to identify disturbances in the screwing process of a specific product type. Eight periods of instability were identified applying monitoring tools, such as time series score plots and multivariate control charts. Considering that the out-of-control signals detected in these periods mainly correspond to delays at the beginning of the tightening operation, four potential causes to explain this behavior were identified. Two are related to the operating mode (influenced by the operator), one is associated with the equipment condition (vacuum sleeve of the screwdriver) and there is also one that is related both to the operating mode and the equipment condition (misalignment of the vacuum sleeve). Although the existence of dirtiness in the vacuum sleeve has been detected in two periods of instability, it was not possible to confirm that this cause originated the delays identified in these periods, since the same problem was detected in a period in which the process was stable. Therefore, the voluntary activation of the screwdriver by the operator before it contacts the joint is considered the most likely cause of the instability periods. Other possible causes, however less probable, are the attempt of performing the screwing operation without screw and the misalignment of the vacuum sleeve with the screwing guide. The misalignment of the vacuum sleeve is generally induced by the operator when he is trying to initiate the screwing operation.

This analysis allowed to confirm the effectiveness of the defined monitoring approach in detecting undesirable changes in the screwing process. The same approach will be applied in real time, in order to obtain information that can support the implementation of condition-based maintenance activities. Since human interaction proved to have a high influence on the process performance, it is expected that the analysis of data from a robotic machine will enable to examine more accurately the impact of equipment failure modes.

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