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Quality Control Analysis to Detect Defects in Drywall Fastener Screws

Análisis de control de calidad para detectar defectos en tornillos de sujeción en paneles de yeso

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Abstract

Screws are pieces designed to join two or more elements, they are composed of three parts that are thread, neck, and head. Depending onthe type of material they are made of their size and functionality can acquire different characteristics. This article describes the way in which a sample of 200 2-inch screws used for drywall were evaluated to detect potential failures in their manufacturing, through the application of quality tools, with which the main factors that intervene to achieve the best quality of these products were determined. In addition, the study of a real case allowed us to demonstrate feasible improvements that can be applied not only in a certain area, but in the whole industry, since the quality of a product also determines the potential growth of a company. The results obtained showed the degree of affectation of each defect, being advisable for the company to focus on bent screws, screws with deformed tips and screws with incorrect measurements, as these represent greater losses. In conclusion, in the industry it is necessary to use and manage tools to increase the productivity and quality of the processes, thus having a significant impact on all areas of production, achieving the best possible final product.

Keywords: Drywall screws, Screw defects, Screw manufacturing, Screw quality. **JEL classification:** D24, L15, L23, L25.

Resumen

Los tornillos son piezas diseñadas para unir dos o más elementos, compuestos por tres partes principales: cabeza, cuello y rosca. Dependiendo del material, funcionalidad y tamaño de ellos, estos pueden adquirir diferentes características. En este artículo se describe la forma en que se evaluó una muestra de 200 tornillos de 2 pulgadas utilizados para drywall con el fin de detectar posibles defectos en su proceso de fabricación, mediante la aplicación de herramientas de calidad, con lo cual se analizan los principales factores que intervienen para lograr la mejor calidad. de estos productos fueron determinados. Además, el estudio de un caso real nos permitió demostrar mejoras factibles que se pueden aplicar no solo en un área determinada, sino en toda la industria, ya que la calidad de un producto también determina el crecimiento potencial de una empresa. Los resultados obtenidos mostraron el grado de afectación de cada defecto, siendo recomendable que la empresa se enfoque en tornillos torcidos, tornillos con puntas deformadas y tornillos con medidas incorrectas, ya que estos representan mayores pérdidas. En conclusión, en la industria es necesario el uso y manejo de herramientas para incrementar la productividad y calidad de los procesos, logrando así un impacto significativo en todas las áreas de producción.

Palabras claves: Calidad en tornillos, Defectos en tornillos, Fabricación de tornillos, Tornillos para paneles de yeso.

1. Introduction

Screws are elements used in daily life or for the securing or adjustment of some object in industry, being so this metallic piece has the function of connecting two or more elements, and for its functional application the characteristics or properties of manufacture are important, when determining according to its material, the resistance, hardness, capacity and tenacity, An example of this is the case of a dialuminium alloy (aluminum-copper) that improves the resistance of aluminum, but decreases the tenacity capacities, due to the fact that hardening aluminum with silicon or metals increases the hardness, but also increases the fragility coefficient, these implications are also present in other cases, thus determining the use that can be applied to the screw. The manufacture of screws is rooted in different fields (metallic, wood, or others) implying that the processes, types and forms of manufacture vary according to what is required, this in turn leads to the existence of a growing problem in the process of manufacturing various factors that cause defects in the screws, thus impacting on their useful life, in contrast to what has been raised the problem becomes challenging, but essential to cover it because although the screws have variable shapes and designs, as they are essential in various mechanical components, they are essential in various mechanical components, In contrast to what has been stated, the problem becomes challenging, but it is essential to cover it because although the screws have variable shapes and designs, being essential in various mechanical components, it is necessary to cover their study so that they do not negatively affect the product in which they are used [1], highlighting this fact for this analysis it is necessary to use the tools of quality control, such as the Pareto diagram and Ishikawa diagram in conjunction with calculation of process capability and control charts to evaluate the causes of the problem and determine the variation of these finding an axis of action to repel this problem and increase the quality of the product in the company.

2. Literature review

Quality influences the service and the satisfaction of customer needs, it is in this way that quality is called as the generation of a product or service free of deficiencies, thus complying with the established requirements and that go according to the established regulations, equally in this is present in the attributes of the product, implying these characteristics or properties that influence its usefulness both in the short and long term [2]. But beyond this, quality does not simply imply improvement, but the learning of quality in which three stages prevail, the identification, analysis and understanding of the singular factors in the production process that can become a potential risk that the product has [3]. From this, quality control is important in the industry and should be a fundamental axis in every company, by increasing productivity and recording the factors that are causing deficiencies or declines in the production or quality of the process, it is in this way that this process is defined as a series of stages or mechanisms in which the current performance of the process is evaluated, a comparison with the standard criterion and the real one is estimated, thus acting in function of the performance improvement [2], all this is achieved by means of the implementation of quality control tools that allow the detection of the causes of the problem and estimates the variations that it could have with respect to the sample that is being analyzed. Thus, if defects are detected as far as possible before they generate a lower cost and reflects a palpable advantage if the procedure is well defined because it allows identifying the problem at a very early stage, this whole idea raised is the process management and efficiency to which companies are betting [4].

With respect to the above, in this article these tools were used to carry out a diagnosis and analysis of the causes that lead to the problem of defects in screws, taking as a starting point a sample of 200 screws, it is observed that most of these defects can result in the manufacturing stage, In order to reduce them and increase the efficiency of the process, a reliable method of inspection is deep learning, which implies a faster detection of defects, this methodology involves the classification of defective or non-defective in relation to the types of defects recorded [5]. According to this case there are several applications in the industry regarding the problem or how to minimize its impact, among these is the application of an intelligent manufacturing process that records defects through automated visual inspection, in this these faults or variations in the standard model are easily detected, and human costs are reduced thus reflecting sustainable growth, this model is also designed under real-time validation using open sources [6]. In general, this is known as machine learning by processing images that identify unknown parts on a visual basis requiring less hardware time [7]. Also, to this extent, the development of a study with 500 samples of non-defective bolts and 20 samples of defective bolts provided by a bolt factory directly targeted the detecting flaws in the industrial area in southern and central Taiwan using Artificial Intelligence, using image recognition technology checking nut damage during design or manufacturing, which instantly determines whether the inspected bolt passes inspection or not [8].

It can be said that this fusion between artificial intelligence and the internet of things offers as research shows that the potential for improvement in the manufacturing industry or other fields is more significant, generating better profits and new possibilities in terms of products or services, in other words, this manufacturing through Artificial Intelligence is innovative and can build a diagnosis and prognosis of failures, thus exploiting the analysis of big data in its maximum functionality, in conclusion this new form of quality control plays a critical role in production optimizing and product traceability [9]. In company to this study is the design of an automated optical inspection (AOI) system, which presents the same visual tool approach that records through photographs a product during its inspection, but here results in the fusion of a chain of visual geometry groups, Inception V3, a neural network that helps in the analysis of images and Exception algorithms, having the possibility of finding defective patterns that decrease the anomalies in the screws, but it should be clarified that in the state of transformation of things and the new methodologies that aim to innovation this research went further and implemented the message queue telemetry transport protocol better known by the acronym MQTT, in link with API (Application Programming Interface) and web programming methods, building panels in the cloud, instant notifications (automatic) and data communication systems, which detect the defect immediately by viewing the information on the platform interconnected with the whole process [10].

Particularly these studies detect and classify defects into scratches, structural defects, dents and missing parts, having in their record attention maps that locate anomalies, but as a variety of defects are present in this whole process that can detract the analysis and make it inefficient, these are focused on flaws that may arise in real-world circumstances [11]. Specifically, if these different defects are considered in their entirety, it represents the need to use several models or redesign them to detect defects with a high degree of accuracy, considering all part attributes, parameters, detection capability, system stability and accuracy [12]. Based on this automatic approach, manual detection is referred to as a not very viable path as it has a high cost that requires a greater investment of time, representing in turn an inefficient alternative, not all bolts can be inspected because it has a high error rate, since the human resource could not cover the entire production in real time [13]. In addition, manual inspection based on the variation of the screw size implies wear and tear on the operator, affecting the level of energy and experience of the person, thus reducing work efficiency due to long working days where, despite working all the time, it is not possible to control and inspect all the products in their entirety [14]. Another relevant fact about the manufacture of fasteners that can lead to failures due to defects is that the desired stability and the durability of their structure will depend of installation fastener, that is, if them are used, this would lead to the wear of the structure and its low resistance, It must be taken into account that drywall is the most used mechanical fastening in the world because it provides a strong union between the pieces. [15].

Another relevant methodology for the study of this problem is that proposed in the study by Hiroyuki Ukida, when designing a model for detecting defects in screws based on images of screw heads, a more accurate description is that the angle of rotation of the heads was estimated with the application of the open space method, the processing is also taken with the reference images, thus eliminating the edge points in disuse, allowing to discriminate whether a defect is possible or not by the number of remaining edge points. This study, although it requires more processing, it was found that, for defect recognition, the time involved is almost practical, being beneficial for the evaluation of the problem [16]. It should be noted that among these various studies many are involved with other areas of expertise or seek to apply new tools or methodologies, thus using MATLAB programming from the matrix form, delimiting the availability, repair rates and failures in fastener plants, this development being effective because it facilitates the measurement of complex structures with tabular and graphical representation as a function of time, this in order to show the trend in the failure rate of defects in fasteners [17]. Others build models that reflect the inspection findings are then combined into a Python interface with simple execution that instructs operators to identify potential quality concerns or check the quality of the product exiting the facility. [18].

However, despite many previous studies such as the ones mentioned above, a number of challenges still prevail, including proprietary information on the subject that in some cases is very precise and in others does not cover all the research questions or factors in depth, as well as the various communication standards, automation systems, low data quality, or a lack of built-in support for industrial equipment, making it difficult to manufacturing firms using effective data tools and techniques that allow them to find the flaws in their processes and manage better decisions or to know what is the focus of action on which they should start [19]. And it is important in this whole process to consider the environmental impact of fastener manufacturing, as many of the new technologies for quality inspection and in other areas have an eco-friendly approach, there are studies that analyze material selection in the production process, proving that using the information supplied by tools such as SolidWorks, it is possible to know that the use of aluminum alloy in the forging stage reduces the environmental impact of this industry and that the use of titanium alloy for the manufacture of screws is not favorable [20].

3. Methodology

In accordance with the problem, a sample of 200 units of drywall screws was chosen, in which an investigative analysis was carried out with the implementation of basic tools of total quality control to seek continuous improvement of products, processes and services. With the help of statistical software (Minitab), firstly, a histogram was made where the different measures found in the screws were shown, then two diagrams were carried out, one of cause-effect and another of Pareto, in which the problems and defects found in them were studied, also the graphs of process capacity were executed looking for the percentages of defective products from specifications such as the Cpi (index of capacity for the lower specification), Cps (capability index for the higher specification) and Cpk (real process capability index), and finally, control charts were made to analyses the behavior of the quality in the chosen sample, thus exposing the assertiveness and effectiveness of these for the study of information. This is shown in the following diagram figure 1.

Fig. 1 Methodological process diagram

4. Development.

For the present study, a sample of screws was taken (n = 200), and under the meter measurement, the data were recorded in groups of 10, with a data oscillation between 4.6 to 4.9, these measurements were recorded in a data table in centimeters (cm). From these data, to carry out the histogram and its subsequent analysis, a frequency table was constructed, first determining the number of classes or intervals that would contain the data, given that the range of data is greater than 100 ($n \geq 100$), this involved the application of the Sturgess rule, resulting in 9 classes, based on this the width of the interval was determined with a maximum: 4.994 cm and minimum: 4.605 cm. see figure 2

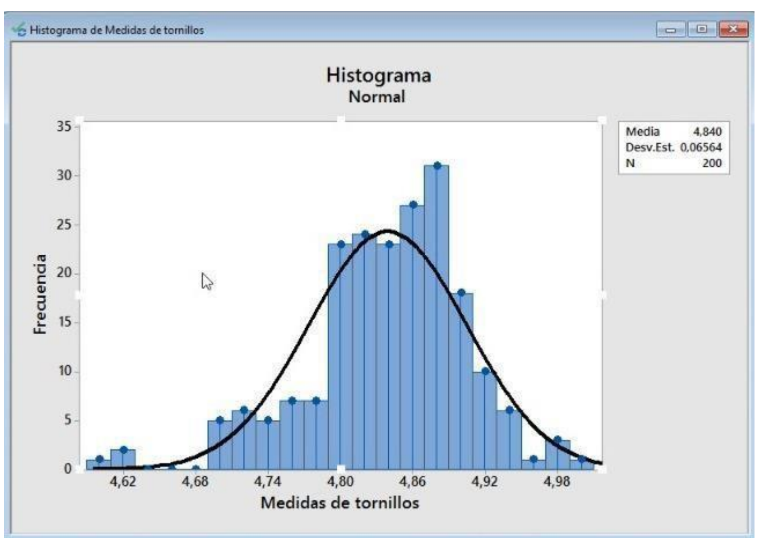

Fig. 2 Sample normal condition

Interpreting this graph it is determined that the screw manufacturing company found that in its production system the machine does not manufacture the same size in all its screws, registering in the 200 samples different sizes and the highest frequency obtained is 32, therefore, it can be said that the data's central tendency is as follows: The findings to have a lot of variability, off-center, fall outside the allowed limits and are skewed to the right, thus concluding that they are outliers. After this, a table of causes and frequencies was constructed for the Pareto diagram. Among the causes, defects such as bent screws, screws with deformed tips, screws with incorrect measurements, screws with incomplete threading and screws with a high degree of rust were recorded.

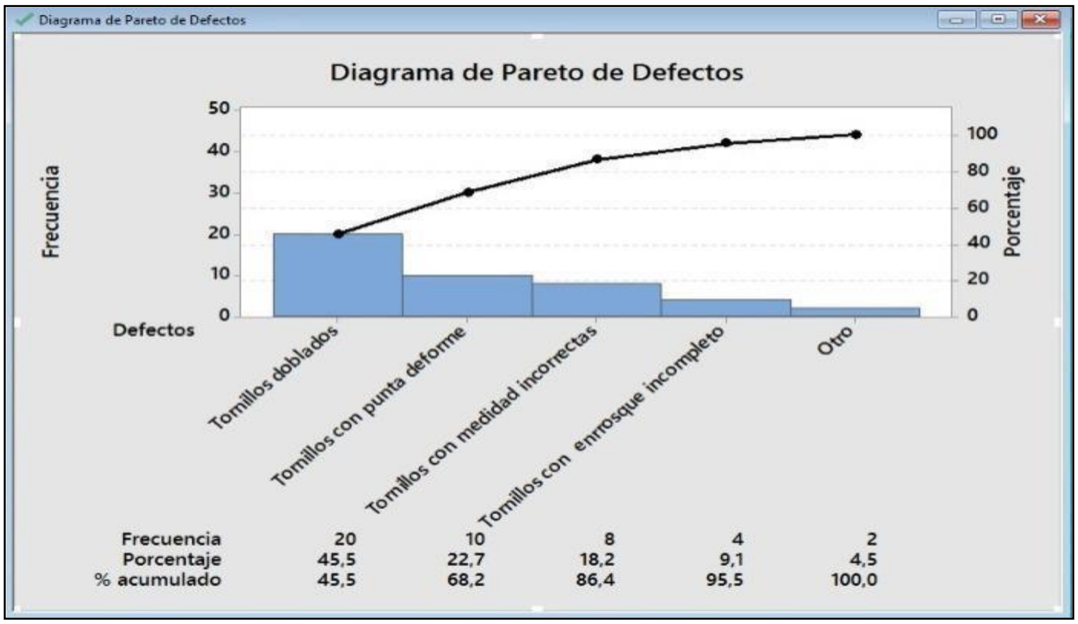

Fig. 3 Pareto diagram (Labs CUC - Minitab).

From this quality tool, it was observed that the main defect or fault is bent screws, which leads to a problem in production, this allows us to see that a considerable part of the company's focus should be directed towards solving this situation, as this, despite being a minimal problem, generates large losses and can affect the company's image and reliability. Furthermore, as can be seen in the picture, the y-axis (left) reflects the frequency with which the problems (defects) occur, the least frequent problem is the bolts with a high degree of oxidation and represents a trivial problem because it generates many problems, but these result in few losses. The y-axis (right) shows the percentages that accumulate according to the occurrences, and finally the x-axis at the bottom shows the categories of the chosen problems. Based on this graph, it can be concluded that the best decision is to focus on bent screws, screws with deformed tips and screws with incorrect measurements, as they represent just over 80% of the problems in the production and use of screws, while the other defects represent less than 20% of the total problem. An Ishikawa (Cause-Effect)

Diagram was then used to evaluate the context of the problem and its effect, recording six main causes and three sub-causes derived from each one, which constitute the root of the problem.

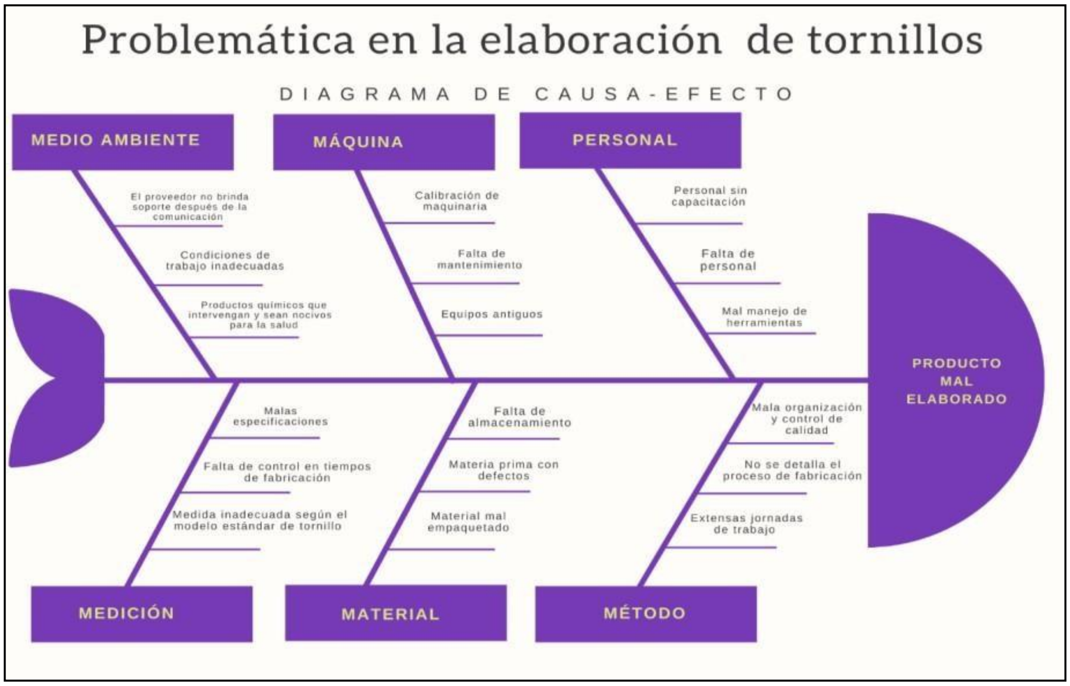

Fig. 4 Ishikawa diagram

This allowed proposals to be put forward to improve the quality of the screws, which are specified below.

a) *Reinforce staff training through lectures.*
b) *Establish measurement system according to the type of screw.*
c) *Carry out preventive and recurrent maintenance of the necessary machines and replace old machines with new ones.*
d) *Carry out more rigorous inspections on both incoming material and final product.*
e) *Provide employees who use chemicals with professional equipment to counteract their harmful effects.*
f) *Increase managers' communication with their work teams.*
g) *Change unsuitable locations to effective and usable locations for the production and/or storage process.*
h) *Establish working policies to improve external working hours, and if required, recruit new staff.*

Continuing with this analysis process, the capacity of the process was evaluated, taking as a requirement that the data be converted from decimals to whole numbers (4.6 = 46), as these allow for a better understanding of the data. After this, it can be plotted correctly. The required specification or measurement was 47, with a deviation of 1.6. From the calculations, it was found that the LSE = 48.6 and the LIE = 45.4. Similarly, using the Excel tool, the results obtained showed a mean of $\overline{X}$ = 47.97, a standard deviation of 0.617256, and a PCI (Capability Index) equal to Cp = 0.8640391. These results will be compared with the globally accepted patterns that are shown in figures 5 and 6.

Valor del índice C_p	Clase o categoría de proceso	Decisión (si el proceso está centrado)
$C_p \geq 2$	Clase mundial	Se tiene calidad Seis Sigma.
$C_p > 1.33$	1	Adecuado.
$1 < C_p \leq 1.33$	2	Parcialmente adecuado, requiere de un control estricto.
$0.67 < C_p \leq 1$	3	No adecuado para el trabajo. Un análisis del proceso es necesario. Requiere modificaciones serias para alcanzar una calidad satisfactoria.
$C_p \leq 0.67$	4	No adecuado para el trabajo. Requiere modificaciones muy serias.
Nota: Si el $C_{pk} < C_p$, entonces una vez que se centre el proceso se tendrá la clase de proceso que se indica.		

Fig. 5 Table 9.1 Cp values and their interpretation. From the book: *Total Quality and Productivity*.

Valor del índice (corto plazo)	Proceso con doble especificación (índice C_p)		Con referencia a una sola especificación (C_{pi}, C_{ps}, C_{pk})	
	% fuera de las dos especificaciones	Partes por millón fuera (PPM)	% fuera de una especificación	Partes por millón fuera (PPM)
0.2	54.8506	548506.130	27.4253	274253.065
0.3	36.8120	368120.183	18.4060	184060.092
0.4	23.0139	230139.463	11.5070	115069.732
0.5	13.3614	133614.458	6.6807	66807.229
0.6	7.1861	71860.531	3.5930	35930.266
0.7	3.5729	35728.715	1.7864	17864.357
0.8	1.6395	16395.058	0.8198	8197.529
0.9	0.6934	6934.046	0.3467	3467.023
1.0	0.2700	2699.934	0.1350	1349.967
1.1	0.0967	966.965	0.0483	483.483
1.2	0.0318	318.291	0.0159	159.146
1.3	0.0096	96.231	0.0048	48.116
1.4	0.0027	26.708	0.0013	13.354
1.5	0.0007	6.802	0.0003	3.401
1.6	0.0002	1.589	0.0001	0.794
1.7	0.0000	0.340	0.0000	0.170
1.8	0.0000	0.067	0.0000	0.033
1.9	0.0000	0.012	0.0000	0.006
2.0	0.0000	0.002	0.0000	0.001

Fig. 6 Table 9.2 Cp, Cp(i) and Cp(s) indices. Extracted from the book: *Total Quality and Productivity*.

According to the table extracted from the book Total Quality and Productivity, to measure the capability index and to interpret it, it corresponds that $0.67 < Cp \leq 1 = Se\ tiene\ que\ intervenir\ el\ proceso$, which means that given the results of Cp, the process must be improved to meet the customer's requests. Moreover, the upper Cpk is equal to $Cpk(s)$ = 0.3402154 and the capability index for the lower specification Cpk(i) is $Cppk(i)$ = 1.3878627, i.e., in the case of screws, the process is not suitable to comply with the LSE because the Cpk(s) is 0.34 being that the Cpk(s) is not greater than 1.25, also when evaluating the Cpk(i) by giving 1.38 reflects that the process is suitable to comply with the LSE, since it complies with the rule of 1.38 > 1.25. 1,25. Finally, when calculating the actual capability index of the process Cpk by giving 0.3402154, it does not comply with at least one specification, also as the Cpk is much smaller than the Cp = 0.8640391 it means that the mean of the process is far from the center of specifications. In the case of percentage using table 9.2 extracted from the book Total Quality and Productivity it turns out that since the $Cpk(i)$ = 1.3878627, then the percentage of product weighing less than $LIIE$ = 45.4 is 0.0048%. And in the upper specification the $Cpk(s)$ = 0.3402154, then the percentage of product weighing more than LSE = 48.6 is 18.40%. see figure 7.

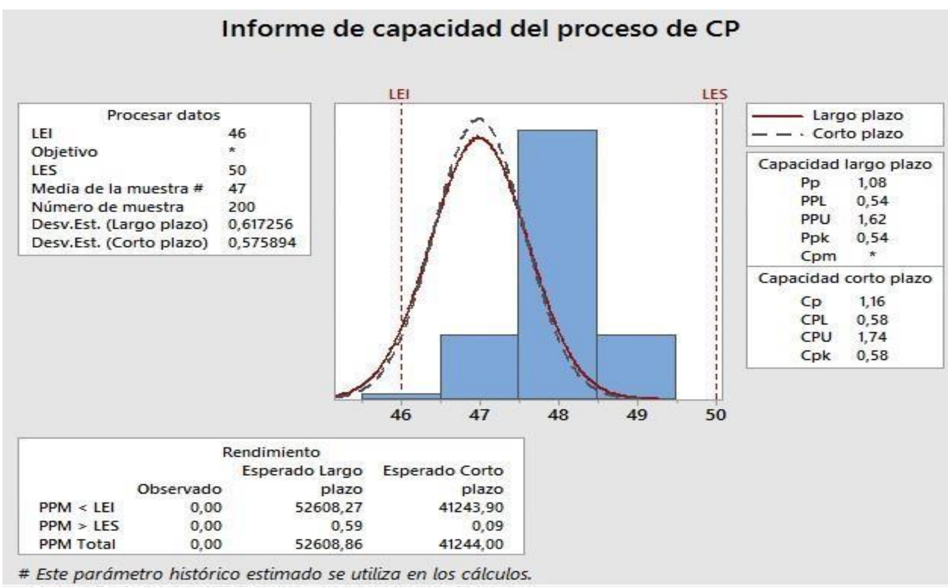

Fig. 7 Cp

At the end of the process capability analysis, X, R and S control charts were applied, for the construction of the table and subsequent construction of the graph, an overall average of 4.83954 was obtained, followed by the overall range, giving a result of 0.1916. It should be added that the plotting of a control chart is meaningless without a coherent interpretation, after having done the plotting, it is essential to observe whether the process that was analyzed is in statistical control both in the variability it has and in the range. The calculated control limits help us to find the causes that prevent us from achieving control. See figure 8,9,10, and 11.

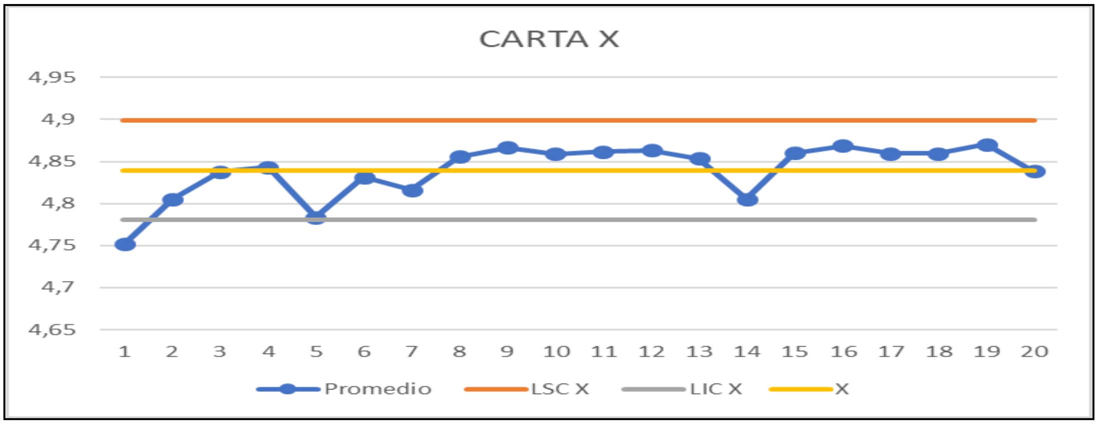

Fig. 8 Average chart

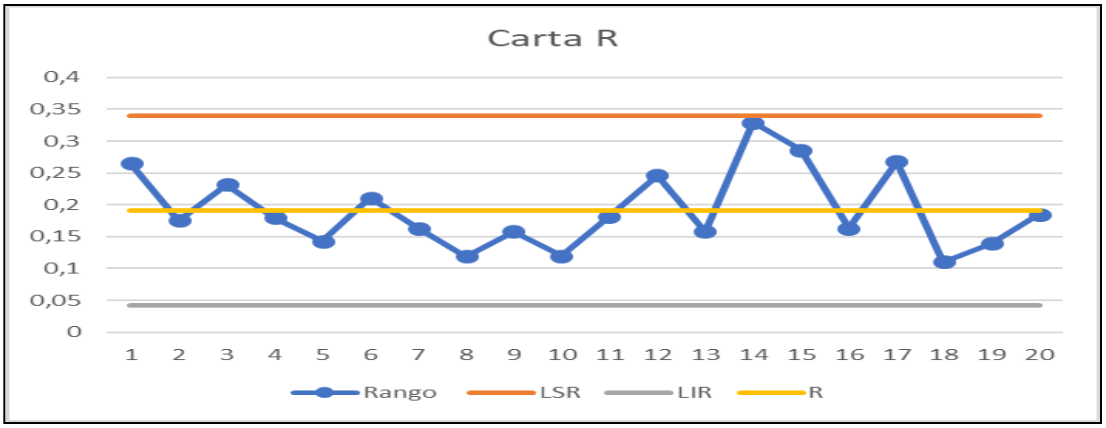

Fig. 9 Ranges chart

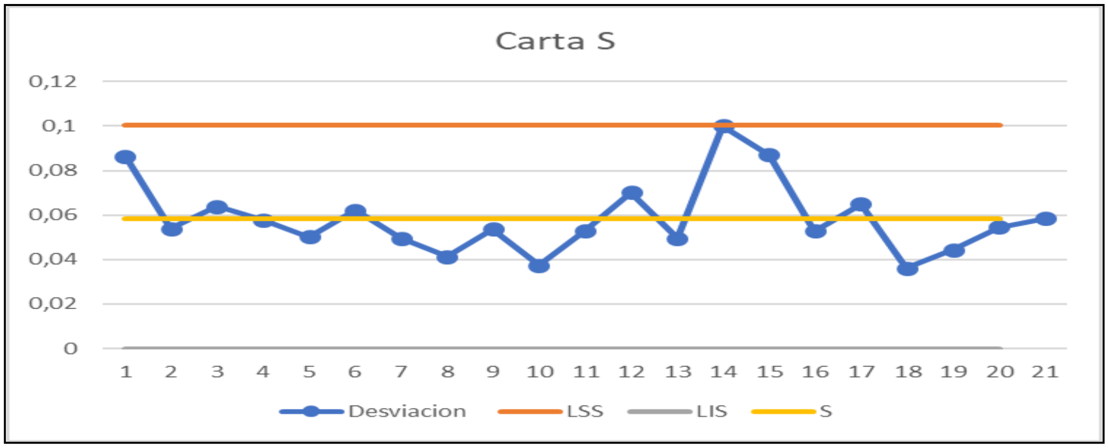

Fig. 10 Deviations chart

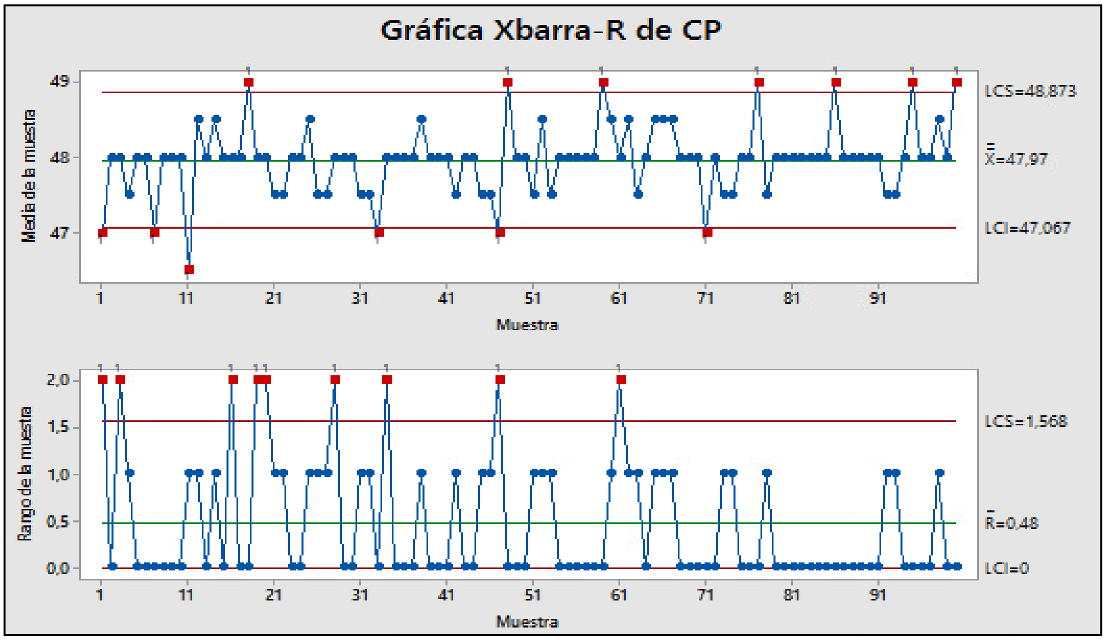

Fig. 11 Xbarr - R chart of Cp

In the X chart, the upper, lower and X control limit can be found, as shown in the graph, a point of the average overpasses the lower limit, this is because there was a displacement or change in the level of processes caused by a change in the process mean. And in the R and S chart, very similar patterns are found, which are called recurrent cycles, since in the process, consecutive points are detected that grow and decline in a similar way. It is said that if this pattern is reflected in the R chart, the possible causes are employee fatigue. In addition, these charts were validated, and the run graph was generated using the Minitab tool in Labs-CUC.

The test applied in the Minitab software of the Xbar - R graph of Cp produced some points that exceeded three times the deviation: 1; 7; 11; 18; 18; 33; 47; 48; 59; 71; 77; 86; 95; 100.

At this stage of the analysis and interpretation a run chart was constructed, here it was found that there is no presence of clusters or mixtures, since the P values exceed what is established for this to occur. And it can also be said that there is no presence of trends or oscillations since the P value for these two is higher than 0.05. see figure 12.

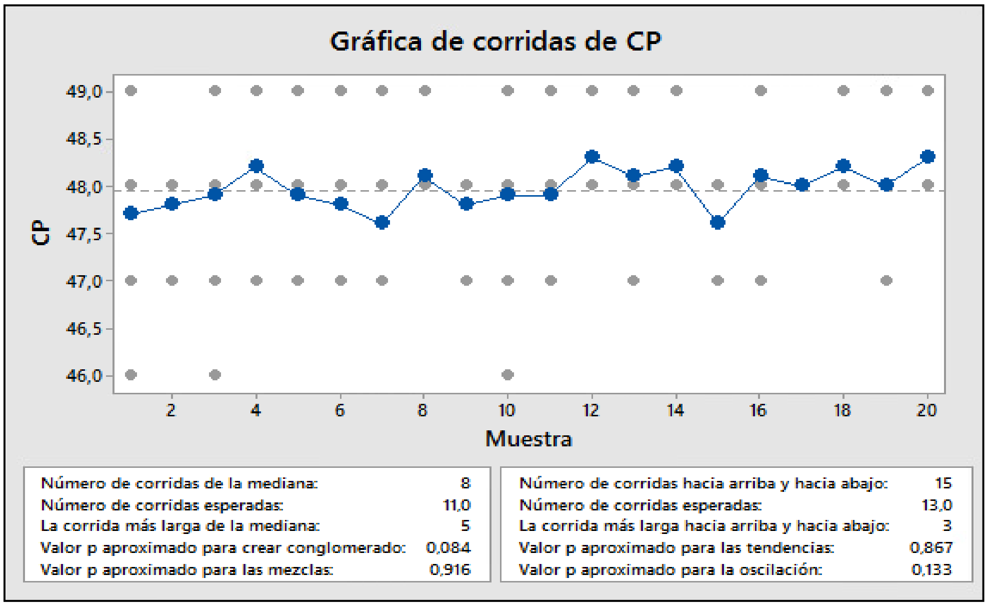

Fig. 12 Plot of CP runs.

Next, the C, U and P charts were plotted, observing that in the C chart graph, sample 1 is out of control, since it is above the upper limit. It is also observed that there is not much variation in the average number of defects, samples 8, 10 are around the lower limit and this means that there is a lot of variation between samples. In the U-chart graph, sample 1 indicates subgroups that do not pass tests for unusual or special reasons are not under statistical control. In these results the average is 0.18 and the process does not seem to be under control and two samples were found to be above the lower limit. And finally in the P- chart one can find values which are below the lower limit, also values which excessively exceed the upper limit, this means that certain values are out of control and the values within the limits show a random pattern. See figure 13, 14, and 15.

Fig. 13 Chart-C.

Fig. 14 Chart-U

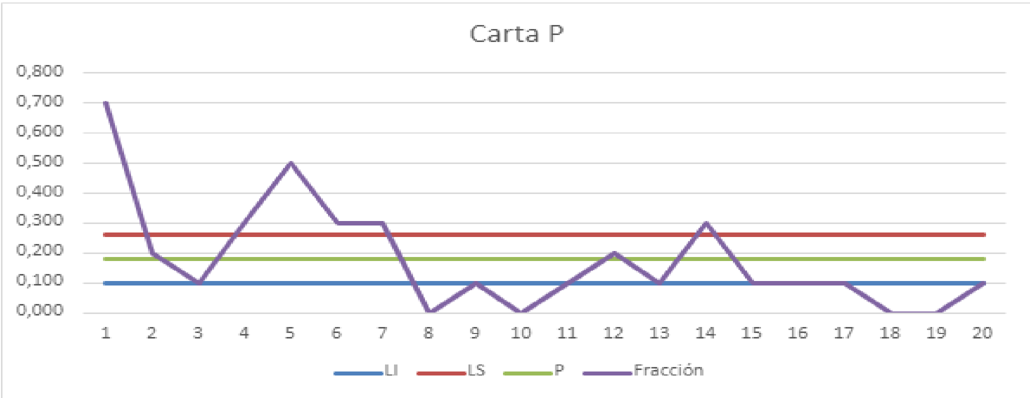

Fig. 15 Chart-P

Finally, for the analysis of the data with the quality control tools, a random sampling is performed, in order to have a batch acceptance plan where a specific confidence level is established, thus determining whether or not a batch is complying with the tolerable limits of conformity, determining whether the batch should be accepted or rejected. The lot size defined for the 200 units was 4 lots (2 of 40 units and 2 of 60 units), after which the list of random numbers chosen for each batch. For the batch of 40, the first sample size was N=7 and the second N=5, resulting after locating in the sample size code table extracted from the book Total Quality and Productivity with a batch size of 26 to 50 and general inspection level II, a result of code D, and when addressing to the quality level table extracted from the book Total Quality and Productivity with a percentage of 0.15, an Ac= 0 and Rc=1. From this and the defective units found in each of the samples (Sample1=2, Sample2=0), the decision on the lot is, the first one is rejected and the second one is accepted.

As for the batch of 60, the first sample size was N=9 and the second N=6, giving as a result after the location in the sample size code table extracted from the book Total Quality and Productivity with a batch size from 51 to 90 and general inspection level II , a result of code E, and when we go to the quality level table extracted from the book Total Quality and Productivity with a percentage of 0.15, an Ac= 0 and Rc=1. From this and the defective units found in each of the samples (Sample1=0, Sample2=0), the decision on the lots is, accepted.

As for the batch of 60, the first sample size was N=9 and the second N=6, giving as a result after the location in the sample size code table extracted from the book Total Quality and Productivity with a batch size from 51 to 90 and general inspection level II , a result of code E, and when we go to the quality level table extracted from the book Total Quality and Productivity with a percentage of 0.15, an Ac= 0 and Rc=1. From this and the defective units found in each of the samples (Sample1=0, Sample2=0), the decision on the lots is, accepted

5. Conclusions

In conclusion, through the quality tools used, the problem of defects in screws was studied and the usefulness of this methodology was observed, as it allows the identification of the causes that affect quality, the production process and in the future may represent a threat to the company, generating significant losses or the misuse of these resources. Also, through this study it was possible to establish improvements to significantly reduce the problems in the manufacture of screws by means of the results obtained.

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