



27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017,
27-30 June 2017, Modena, Italy

Application of SPC and quality tools for process improvement

Sérgio Sousa^{a,*}, Nuno Rodrigues^b, Eusébio Nunes^a

^aALGORITMI Research Center, Campus de Gualtar, University of Minho - DPS, 4710-057 Braga, Portugal

^bProduction and Systems Department, University of Minho, Campus de Gualtar, 4710-057 Braga, Portugal

Abstract

This work presents a case study on the application of quality tools to improve product quality. One component was selected as object study because it presented higher percentage of nonconformities and was increasing over time. Before mass production, at pre-production, Statistical Process Control (SPC) was performed and it was concluded that the process was capable. No further SPC was done during production. After defective units were detected at increasing levels it was apparent that process variability had increased and the process was no longer capable. The study ends with the development of process improvement activities.

© 2017 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license

(<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Peer-review under responsibility of the scientific committee of the 27th International Conference on Flexible Automation and Intelligent Manufacturing

Keywords: Case Study; Measurement System Analysis (MSA); Process improvement; Quality tools, Statistical Process Control (SPC).

1. Introduction

The implementation of quality tools (QTs) and methodologies is necessary to reduce defective items, and thus reducing the overall quality costs. This can be achieved by reducing process variability, allowing further increase in organization's competitiveness and sustainability.

The quality function within a company ensures compliance with product specifications and implements process improvements [1], to produce with greater efficiency. However, the use of QTs is not generalized, particularly

* Corresponding author. Tel.: +351 253604762; fax: +351 253604761.

E-mail address: sergio.sousa@algoritmi.uminho.pt

amongst Small and Medium Enterprises (SMEs) [2]. This gap between expected benefits and practice may be reduced if further evidence and advantages of using quality tools is disseminated. Control charts are important tools used to monitor a process, to ensure that the process is in a state of statistical control and thus improving product quality.

This work was developed at a metal parts manufacturing company (classified as SME) with the objective of improving the company's production through the application of quality methodologies and tools [3]. From a large set of items produced by the company it was selected as object of study the one that presented higher percentage of nonconformities. Typically, SMEs do not have the resources to tackle all improvement opportunities and must prioritize areas or products for improvement [4]. These nonconformities were related with the non-compliance with the specification limits for one variable (dimension 51) of a given part produced. The problem is addressed using control chart for individual items with moving range, conventional \bar{x} -R control charts [5], Measurement System Analysis (MSA) and other QTs.

2. Methodology

The methodology used in this work is a longitudinal case study describing two years since the pre-production of a new part (Fig. 1). It describes the activities chronologically:

1. Data collection of the potential critical variable in the pre-production phase
 - a. Construction of control chart for individual items
 - b. Determine process capability indices
2. Definition of a process control procedure for the production phase
 - a. If $C_p < 1$ the manufacturing process should be redesigned
 - b. If C_p is around 1.33 the critical variable should be controlled
 - c. If $C_p > 1.6$ the variable is classified as non-critical and thus SPC is not applied
3. Re-assessment of process capability (after increased level of defective items are detected)
 - a. Construction of \bar{x} -R charts
 - b. Re-assessment of process capability index C_p
 - c. Analysis of control charts and comparison with historical data obtained during pre-production
4. Identification of assignable causes (of process variability). If necessary, perform Measurement System Analysis.
5. Development of improvement proposals, to reduce variability of the critical variable.

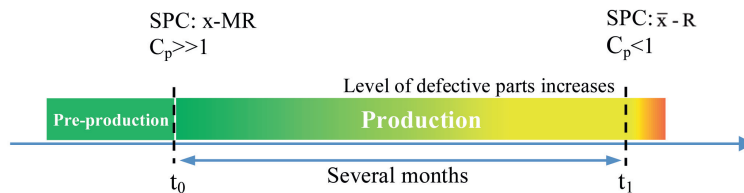


Fig. 1. Evolution of process capability over two years

3. SPC study

The product considered in this study is a metal part called *Epanouissements*, which is part of the vehicle induction braking system, also known as electrical or electromagnetic retarder (Fig. 2a). The product is obtained by cutting 15mm thick RAEX sheet metal undergoing various machining operations.

This piece has to fulfill a set of dimensional and surface finish requirements, among others. Fig. 2b shows the technical drawing of the part with the dimensional variables. To approve product production, the client requires a study in the pre-production phase that allows evaluating if the process has the capacity to produce it continuously without great variations with regard to several critical dimensions. In this paper, the variable "dimension 51" is considered a potential critical variable, whose specifications are $51 \text{ mm} \pm 0.15$ and thus was subject to a capability study.

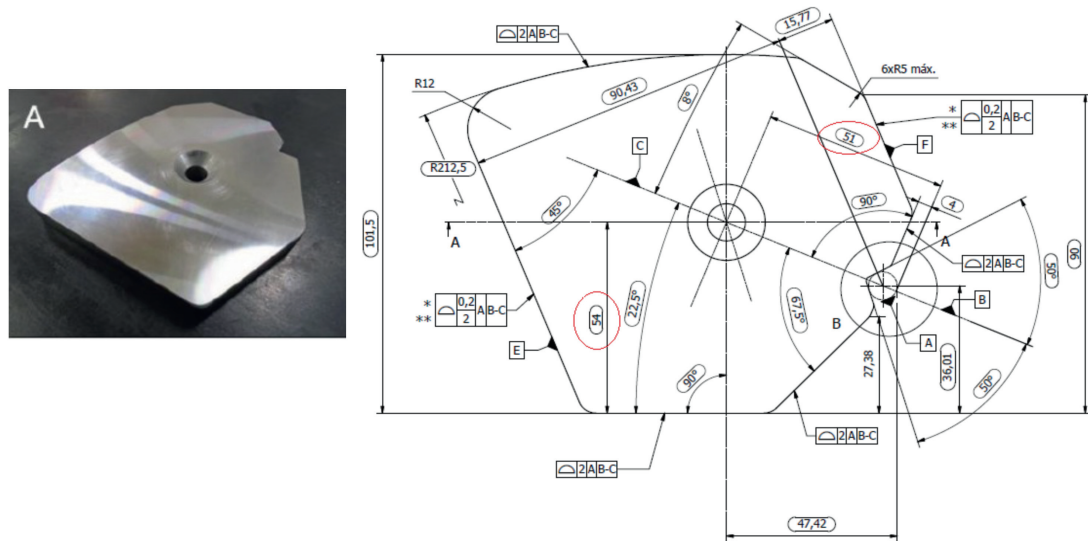


Fig. 2. (a) Epanouissements; (b) Critical dimensional variables of the part.

When dealing with a quality characteristic that is a measured variable it is necessary to monitor the average value of the quality characteristic and its variability. Usually, the mean quality level is assessed with the control chart for means or the \bar{x} control chart. Process variability can be monitored with either a control chart for the standard deviation (s control chart) or a control chart for the range (R control chart). The R control chart is more widely used and suited for small samples ($n < 10$).

3.1 Pre-production phase

At this stage, it was decided to use charts for individual measurements and moving range of span two, due to the reduced availability of resources. The study was based on 32 individual samples taken continuously from the process. During the sampling period the process was not stopped or adjusted. The visual analysis of the 32 pieces suggested the absence of defects and these followed for dimensional control. The individual values obtained for the “dimension 51” are shown in Table 1.

Table 1 – Data sample for “dimension 51”

Sample Number	X_i (mm)	MR	Sample Number	X_i (mm)	MR	Sample Number	X_i (mm)	MR	Sample Number	X_i (mm)	MR
1	50,981	-	9	51,030	0.009	17	50,992	0.052	25	50,974	0.073
2	51,020	0.039	10	51,028	0.002	18	51,046	0.054	26	51,030	0.056
3	51,029	0.009	11	51,033	0.005	19	50,990	0.056	27	51,014	0.016
4	50,982	0.047	12	51,023	0.010	20	51,039	0.049	28	51,018	0.004
5	50,985	0.003	13	51,007	0.016	21	51,030	0.009	29	51,044	0.026
6	50,948	0.037	14	51,053	0.046	22	50,962	0.068	30	51,029	0.015
7	51,036	0.088	15	51,019	0.034	23	50,972	0.010	31	51,021	0.008
8	51,021	0.015	16	51,044	0.025	24	51,047	0.075	32	51,002	0.019

3.1.1 Normality of data

When using the control chart for individuals it is important to check the normality assumption. A simple way to do this is with the normal probability plot. Probability plot obtained by Minitab 16 shows that there are no problems with the normality of the data.

After verifying the normality of the sample data, the mean and standard deviation of the 32 individual samples were calculated, and the following values were obtained.

$$\bar{x} = \sum_{i=1}^{32} \frac{x_i}{32} = 51.014 \text{ mm} \quad s = \sqrt{\frac{\sum_{i=1}^{32} (x_i - \bar{x})^2}{32 - 1}} = 0.027 \text{ mm}$$

3.1.2 Control chart for individuals and moving range (x_i, MR)

Many applications of individuals controls chart use the average of individual values as the estimation of average level of the process and the moving range of two successive observations as the basis of estimating process variability. The moving range is defined as:

$$MR_i = |x_i - x_{i-1}|, \quad i = 2, 3, \dots, m \quad (1)$$

Table 1 also shows the MR_i values obtained for the data under study. The average of the moving ranges of two observations can be written as:

$$\overline{MR} = \frac{\sum_{i=2}^m MR_i}{(m-1)} \quad (2)$$

The most common estimator of the sample standard deviation is based on the average moving range of span two:

$$\hat{\sigma} = \overline{MR} / d_2 \quad (3)$$

d_2 is tabulated and depends on sample size, in this case $n=2$.

This estimator is unbiased, assuming that no assignable causes are present in the sequence of m individual observations.

For the control charts for individual measurements and moving range of span two, the parameters are presented in Table 2. As a moving range of $n = 2$ observations is used, then $d_2 = 1.128$.

Table 2: Parameters for control chart for individuals and moving range

Individual value chart	Moving range chart
$UCL = \bar{x} + 3 \frac{\overline{MR}}{d_2}$	$UCL = D4 \overline{MR}$
$CL = \bar{x}$	$CL = \overline{MR}$
$LCL = \bar{x} - 3 \frac{\overline{MR}}{d_2}$	$LCL = D3 \overline{MR}$

Applying this procedure to the case under study results in $CL = 51.014$, $LCL = 50.930$ and $UCL = 51.098$. Similarly, for the moving range chart the parameters are: $CL = 0.0315$, $LCL = 0$ and $UCL = 0.1029$.

The individual control chart and the moving range chart are shown in Fig. 3. No points are out of control limits and, therefore, it is considered that at this stage of pre-production the process is under statistical control.

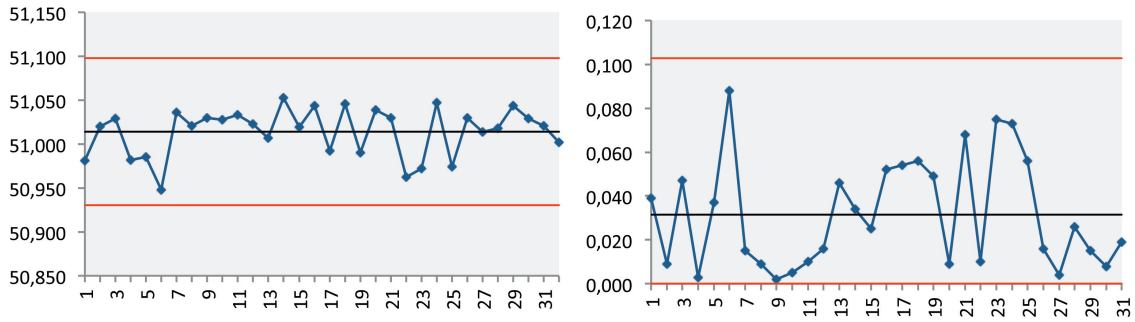


Fig. 3. (a) Individuals control chart; (b) Moving range control chart

3.1.3 Process Performance Indices

The Automotive Industry Action Group (AIAG) [6] recommends using the process capability indices C_p and C_{pk} when the process is in control, with the process standard deviation estimated by $\hat{\sigma} = \bar{R}/d_2$. If the process is not in control, the AIAG recommends using process performance indices P_p and P_{pk} , where,

$$\hat{P}_p = \frac{USL - LSL}{6s} \quad (4)$$

$$\hat{P}_{pk} = \text{MIN} \left(\frac{USL - \bar{x}}{3s}; \frac{\bar{x} - LSL}{3s} \right) \quad (5)$$

and s is the usual sample standard deviation given by

$$s = \sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 / (n-1)} \quad (6)$$

If the control chart used during one pre-production setup, the process capability should not be determined but instead it should be calculated Process Performance indices: P_p and P_{pk} . However, if the data is normally distributed and within control limits, $\hat{P}_p \cong \hat{C}_p$ and $\hat{P}_{pk} \cong \hat{C}_{pk}$.

For the specification limits of the characteristic under study ($USL = 50.850$ and $LSL = 51.150$), we obtain $\hat{P}_p = 1.828$ and $\hat{P}_{pk} = 1.657$. Given that the process is normally distributed and in control, $\hat{P}_p \cong \hat{C}_p$ and $\hat{P}_{pk} \cong \hat{C}_{pk}$. Thus, it can be concluded that the process has the capacity to fulfil the specifications even presenting a significant gap ($\hat{P}_p > 1.33$). The value of $\hat{P}_{pk} = 1.657$, implies that very few nonconforming units are being produced.

3.2 Production phase

After pre-production phase, the product entered the production phase without introducing any change in the process. Since it was stable and with a reasonable capacity gap, SPC was not performed for several months, with process stability and variability being assessed by the level of nonconformities it produced. However, at a given time, an increasing number of customer complaints due to products supplied outside the specifications drew the attention of the Quality Engineer to the need for process control. It was then decided to use \bar{x} -R control charts.

As [5] states, the use of a control chart requires the engineer to select a sample size, a sampling frequency or interval between samples, and the control limits for the chart (design of the control chart). The design of a control chart has economic consequences, therefore, it is logical to consider the design of a control chart from an economic

viewpoint. Taking these aspects into consideration, the \bar{x} -R control charts for this phase of the study was constructed from 20 samples taken from the process with regular spacing between samples. Each sample is made up of 3 parts taken consecutively. The data obtained for "dimension 51" are presented in Table 3.

Table 3. Measurements (mm) for dimension 51

Sample Number	Observations			\bar{x}_i	R_i	Sample Number	Observations			\bar{x}_i	R_i
	1	2	3				1	2	3		
1	50.972	50.785	50.767	50.841	0.205	11	51.004	51.187	50.768	50.986	0.419
2	50.956	50.970	50.914	50.947	0.056	12	50.975	50.942	51.068	50.995	0.126
3	51.066	50.933	51.086	51.028	0.153	13	51.043	51.086	50.848	50.992	0.238
4	51.081	51.092	50.917	51.030	0.175	14	51.135	51.174	50.823	51.044	0.351
5	50.948	50.828	51.054	50.943	0.226	15	50.967	51.070	50.829	50.955	0.241
6	50.859	51.083	50.789	50.910	0.294	16	50.992	51.070	50.837	50.966	0.233
7	50.984	50.961	50.943	50.963	0.041	17	50.966	50.990	51.075	51.010	0.109
8	51.013	51.020	50.734	50.922	0.286	18	50.929	50.969	50.928	50.942	0.041
9	50.898	50.956	50.885	50.913	0.071	19	51.09	51.014	50.973	51.026	0.117
10	51.004	50.984	50.839	50.942	0.165	20	50.87	51.114	50.971	50.985	0.244

It was decided to construct \bar{x} -R control charts, assuming that the process maintained the average and standard deviation of the pre-production phase ($\bar{x} = 51.014$ mm and $s = 0.027$ mm). The control charts obtained showed several points outside the control limits. Thus, it was concluded that the average and /or standard deviation has changed (from pre-production values), suggesting that exists assignable causes in the production process.

With the values in Table 3, new control limits were calculated (Table 4) and because they show all the samples within control limits (Fig. 5) a new average ($\bar{\bar{x}} = 50.967$) and a new standard deviation $\sigma_{\bar{x}} = 0.19$ were estimated.

Table 4. Control limits for \bar{x} , R control charts

\bar{x} chart			R chart		
LCL	CL	UCL	LCL	CL	UCL
50.773	50.967	51.161	0	0.190	0.488

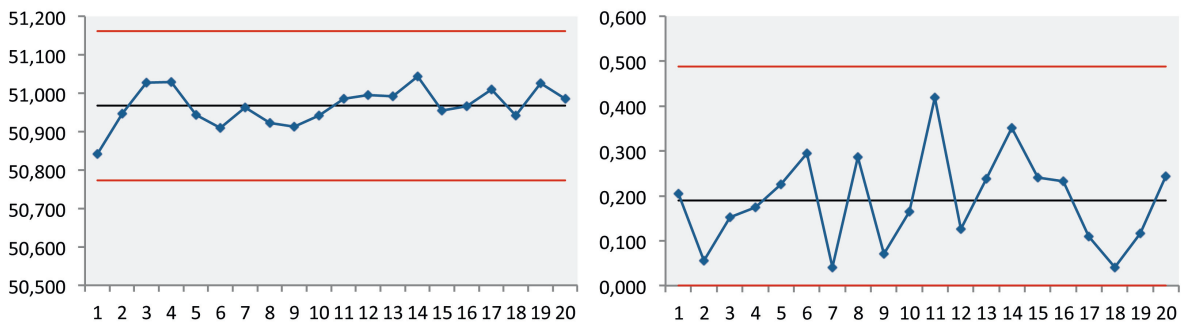


Fig. 5. (a) \bar{x} control chart production phase; (b) R control chart for production phase

From these charts it is concluded that the process is stable at the production phase. Thus, process capacity can be calculated by equation (7) and estimate the standard deviation of the process by $\sigma_x = \bar{R}/d_2$ with $d_2=1.693$.

$$C_p = \frac{USL - LSL}{6\sigma_x} \tag{7}$$

Although the process is under statistical control it does not have the capacity to produce the components because the value of C_p is less than 1 ($C_p=0.447$).

3.2.1 Root cause analysis and improvement plans

The causes of dimensional variation (critical defect) were discussed in brainstorming sessions with people involved in the manufacturing process of the product under study. From these sessions resulted one cause and effect diagram that highlighted two main causes (Measurement System and Machine) of dimensional variability.

Related to the cause Machine was considered the tool and the gauge as the most significant causes of dimensional variation. The tool refers to the drill bit used in the CNC machine for drilling the parts. This tool showed signs of wear after some time of use. To eliminate this potential cause, the drill was replaced with a new one but the problem persisted. An analysis was then made to the templet used for the placement of the pieces and it was found that it had slacks in the grip of the pieces. To solve this problem, changes were introduced in the templet for the placement of the parts (Fig. 6a), the placement and tightening of the parts to be done differently (Fig. 6b).

A R&R study was made to measurement system, consisting of a 150 mm vernier caliper and three employees of the Quality department. For the R&R study, 10 samples of the product were collected, representing a large part of the admissible range of variation of the characteristics to be controlled. With the result of this study, it was verified that, for “dimension 51” the precision to tolerance ratio (PTTR) was 30%, led to considering the measurement system acceptable. It was also verified that for other dimensional characteristics of the same component (“dimension 54”) the measuring system presented $PTTR > 30\%$, which is considered unacceptable, and actions were taken to improve the measurement system. Fig. 7 is intended to show the difficulty of measuring dimension 54 given the difficulty of placing the parallel caliper with the face of the part. A small movement of the caliper results in quite different read values.

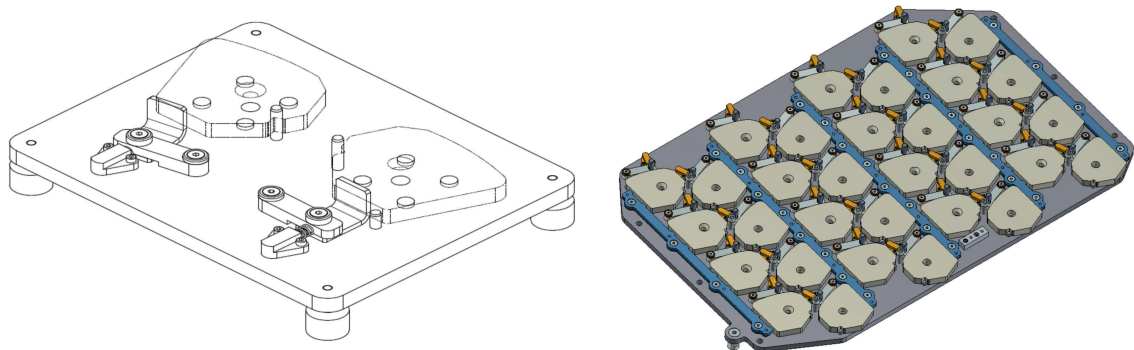


Fig. 6. (a) Templet used for the placement of the pieces; (b) New clamping device for measuring parts



Fig. 7. Measurement support tool

In a brainstorming session it was concluded that part of this problem would be solved with a new tool, which instead of having the cylindrical pin, has a flat plate that is pressed against the flat face of the part by a system of springs. In this way, when the vernier caliper is touched to measure “dimension 54”, it remains fixed, resulting in measurements with less variation.

4. Results and Discussion

Initially, one potential critical variable was studied, during the pre-production phase, using control chart for individual items. The production process showed capability to fulfill the specification limits ($C_p > 1.6$). It was concluded that this variable was not critical and it was expected that the level of defectives parts caused by this variable would be negligible. Consequently, no SPC procedure for the production phase was defined.

For several months of parts production, no defective parts were detected. However, approximately one year later, the number of defective parts increased, caused by variability of the studied variable. Consequently, an SPC study was conducted using \bar{x} -R charts.

The implementation of the SPC charts showed the process in statistical control but lacking the ability to produce within specification limits ($C_p < 1$). An analysis of SPC charts allowed to identify changes in the mean and the variability of the process, when compared with the data obtained in the pre-production. It would be necessary to improve the process to reduce variation, and ultimately reduce the number of defective parts.

For the analysis of the causes of process variability brainstorming sessions were held and cause-effect diagram was designed. Several potential root causes were identified, particularly related to the Measurement System and the Machine.

Changes were proposed in the templet and through the R&R study [1], [5] it was verified that the measuring system is acceptable for dimension 51 but unacceptable for one related dimensional variable and thus improvement suggestions were given.

5. Conclusions

This study allowed to identify the main causes of variability in the production process of a metal part, through the application of QTs, and to propose measures to improve process and reducing the percentage of defective parts.

Loss of process capability, from the pre-production phase to an advanced stage of production, can be seen as an indicator of process degradation (equipment, measurement system, etc.), suggesting that non critical quality variable, may, over time, become critical and thus the need to control it vary along time.

Acknowledgements

This work has been supported by COMPETE: POCI-01-0145-FEDER-007043 and FCT – Fundação para a Ciência e Tecnologia within the Project Scope: UID/CEC/00319/2013.

References

- [1] J. M. Juran, and A.B. Godfrey, "Juran's Quality Handbook", 5th ed., McGraw-Hill, 1999.
- [2] I. Lopes, E.P. Nunes, S.D. Sousa, D. Esteves, Quality improvement practices adopted by industrial companies in Portugal, Lecture Notes in Eng. and Computer Science: Proceedings of the World Congress on Engineering 2011, WCE 2011, 6-8 July, 2011, London, UK, 696-701.
- [3] N. Rodrigues, "Aplicação de ferramentas da Qualidade para melhoria da produção numa empresa de soluções industriais", MSc Thesis in Quality Eng. and Mgmt, University of Minho, 2016.
- [4] H. Teixeira, I. Lopes, S. Sousa, Prioritizing Quality Problems in SMEs: A Methodology, The TQM Journal, 27:1 (2015) 2 – 21.
- [5] D.C. Montgomery, "Introduction to Statistical Quality Control", Sixth Edition, Arizona State University, John Wiley & Sons, Inc., 2009.
- [6] AIAG Measure System Analysis (2010). Automotive Industry Action Group (4th ed.). Southfield, Mich.