24th COBEM - 2017

24th ABCM International Congress of Mechanical Engineering
December 3-8, 2017, Curitiba, PR, Brazil

COBEM-2017-2905
STATISTICAL PROCESS CONTROL APPLICATION IN AUTOMOTIVE INDUSTRY

Evandro Leonardo Silva Teixeira
Universidade de Brasília, Faculdade UnB Gama, Engenharia Automotiva,
Área Especial de Indústria Projeção A, Gama - Setor Leste, Brasília, DF
CEP: 72.444-240
evandroleonardo@unb.br

Tatiana Silva Dias
Universidade de Brasília, Faculdade UnB Gama, Engenharia Automotiva,
Área Especial de Indústria Projeção A, Gama - Setor Leste, Brasília, DF
CEP: 72.444-240
tatiana-diass@hotmail.com

Mário de Oliveira Andrade
Universidade de Brasília, Faculdade UnB Gama, Engenharia Automotiva,
Área Especial de Indústria Projeção A, Gama - Setor Leste, Brasília, DF
CEP: 72.444-240
marioand@unb.br

Alessandro Borges Sousa Oliveira
Universidade de Brasília, Faculdade UnB Gama, Engenharia Automotiva,
Área Especial de Indústria Projeção A, Gama - Setor Leste, Brasília, DF
CEP: 72.444-240
abso@unb.br

Abstract. *Statistical Process Control (SPC) is a feasible and practical solution to monitor process capability. Based on statistical control charts, managers and industrial engineering can track possible performance deviation taking corrective action, in advance. Although, it seems to be a powerful method to implement quality control, there are few examples in current literature showing how to apply SPC in automotive industry. For this reason, this paper presents another contribution to perform statistical process inference for torque process control in automotive industry. Firstly, torque monitoring data was taken from automotive OEM to carry out normality test analysis. Afterwards, control chart were generated to perform screw tightening analysis and process capability estimation. Results highlight how statistical inference can significantly improve quality control guiding mangers and industrial engineering to better decision support.*

Keywords: *Statistical Process Control, Process Capability, Automotive Industry*

1. INTRODUCTION

Competitiveness is growing in automotive industry in last decades. As a consequence, automotive OEM and suppliers are looking for novel solutions to improve quality control, to reduce waste and rework, with ultimate goal to achieve better productivity. Customer perception about car mainly depends on brand image (Shende, 2014). As a result, it has required even more effort to reach quality product to retain customer satisfaction and preference. Indeed, automotive industry is constantly reshaping vision about quality for future.

Continuous improvement is a widely practiced by manufacturing firms to improve quality, to reduce lead time, and to improve deliverable availability (Singh & Singh, 2012). To guarantee quality of products, automotive OEMs maintain a dedicated team focusing on quality issues alone. The quality control (QC) team performs continuous monitoring executing regular observation routines, problems investigation, prioritising corrective and proactive actions. Generally, process control is recommended practice to implement in manufacturing (Slack *et al*, 2014).

In automotive industry, quality control is objective oriented and can be given by Statistical Process Control (SPC). In addition, SPC is based on statistic indicators to monitor and to control production process. Using SPC techniques, QC team can, in turn, monitor production performance enabling predictive action aiming to maximise productivity. By making possible mapping of production problems, SPC are at the top of quality control tools commonly applied.

Some researchers have regard SPC as an important solution to assist automotive manufacturing plant. For instance, Korenko *et al* (2013) used SPC to monitor production capability of ultrasonic welding machine employed on mounting components from door panel. In this research, control charts reveal process is stable following design specification. Prajapati (2012) studied defects in shocker seal of an automotive industry. With SPC, rejection percentage was reduced in four percentages leading to improve process capability. Godina *et al* (2016) also applied SPC to monitor dimensional patterns from automotive parts in many workstations. By using control charts, the researchers showed how to identify problems on each individual workstation avoiding potential error propagation. Ferrell (2017) investigated tool life of cutting tool inserts in machining. Guiding by control charts, labours could determine when machining inserts should be replaced in order to avoid dimensional non-conformity in automotive parts.

Aiming to improve actual knowledge about SPC application in automotive industry, this paper presents another SPC application for automotive industry. In particular, this paper highlights practical approach to monitor process capability from automotive assembly lines. Using sampling data collected during pre-production inspections, the researchers showed how to obtain tightening process variability of screws using control charts and also process capability indexes. Experimental results highlights control charts as a potential tool to achieve better quality control.

This paper is organized as following. Second section presents a brief literature review about research domain. Third section highlights research methodology. Fourth section depicts industrial case study showing practical SPC application. Last section presents concluding remark and future work.

2. LITERATURE REVIEW

2.1 Statistical process control charts

Statistical process control (SPC) has played a major role in many companies and industries to achieve competitiveness of their products and services (Oakland, 2003). In particular, SPC provides an effective way to check whether process capability can reach desired product requirement. Based on statistical procedures, SPC can be viewed as a technique with predetermined goal offering greater importance to the facts rather than abstract concepts. SPC techniques usually require continuous process variability monitoring through data collection. One of the most common ways to implement SPC is through control charts. Indeed, control charts are considered as a powerful tool to assist decision making through better knowledge about process variability.

Control charts are essential to implement continuous quality control (Singh & Singh, 2012). It can also be defined as a graphical tool to display process behaviours using data collection over time. Control charts, also known as Shewhart chart, are certain kind of SPC tool to determine if a manufacture process is in a state of control. In turn, control chart provides some alarms for production plant highlighting unexpected or undesired process capability variability. Montgomery (2008) points out five reasons to implement control charts: (1) enhances productivity; (2) effective to prevent product defects; (3) avoid unnecessary process adjustments; (4) continuous diagnostic information; and (5) current information about process capability. Figure 01 shows an example of control chart.

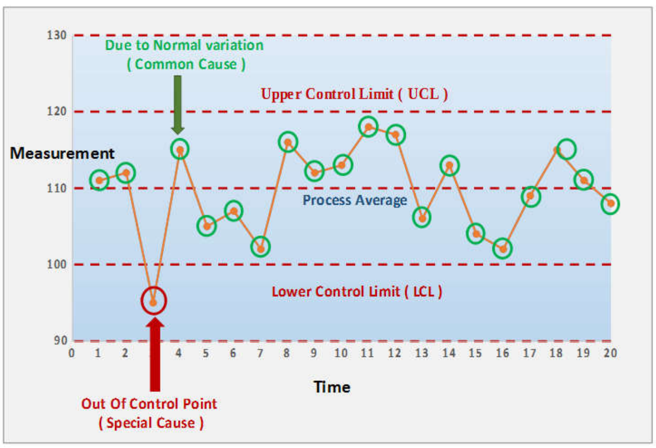


Figure 01: Statistical process control – control chart

Control chart is made up by: (1) process average; (2) lower control limit; and (3) upper control limit. Process Average (PAV) line indicates mean value of in-control process. It can be obtained from simple arithmetic mean calculation. Furthermore, upper control limits (UCL) and lower control limit (LCL) is also included on the chart. These control limits are selected to that almost all of the sampling points range with these limits as long as monitored process remains under control. Generally, these control lines ranges within design engineering limits.

Very often, control limits are given by symmetric distance from PAV line. For manufacturing process under control, these lines value is equivalent to three times sampling standard deviation (Montgomery, 2008). It is expected that 99.73 % of sampling will fall under control limits. Whenever a sample data falls outside the control limits, monitored process can be considered out of control requiring further investigation to find and eliminate root cause. For this reason, manufacturing companies usually expects control limit within design specification limits.

Montgomery (2008) classifies control charts according to the process features. If sampling can take values from continuous scale, control chart should be devoted as type variable. On the other hand, qualitative variables requires type attribute control chart. In addition, type variable control chart can also be classified as:

- **X-bar and R chart:** Average and amplitude control charts. First graph shows average level from monitored process. On the other hand, R chart presents amplitude variability indicating possible sampling dispersion due to special case. Those graphs are complementary and should be used together.
- **X-bar and S chart:** Average and standard deviation control charts. Show similar information about process variability. Nonetheless, they are recommended for large subgrouping data cluster.
- **X-bar$_{med}$ and R chart:** Median and amplitude control charts. X-bar$_{med}$ is considered more robust rather than X-bar. Yet, those graphs are complementary and should be used together.
- **X_i and R chart:** Individual and amplitude control charts. X_i is recommended when there is no sufficient data available or long time interval between samples. Again, those graphs are complementary and should be used together.

2.1.1 Process capabiltiy

Process capability monitoring is a practice way to compare output of an in-control process to the specification limits (NIST/SEMATECH, 2017). This evaluation is fundamental to guide quality control inspection rate and routines. Most often, process capability indices compares the output of a stable process to the design specification limits. Process capability indices state about how well the process meets desired limits comparing natural variability with the specification limits. Process variability indices can be estimated as follow (Kane, 1986):

$$\hat{C}_p = \frac{USL - LSL}{6s} \tag{1}$$

$$\hat{C}_{pk} = \min\left[\frac{USL - LSL}{3s}, \frac{USL - LSL}{3s}\right] \tag{2}$$

where:

USL is the upper specification limit;
LSL is the lower specification limit;
s is the standard deviation from sampling.

2.1.2 Shapiro-Wilk normality test

Control chart plotting requires data collected are normally distributed[1]. It is also necessary to guarantee statistical independence (i.e., no correlation) among individual data collected (Oakland, 2003). In fact, non-normally distributed data can increase likelihood of false alarms. For this reason, it is essential to test data for normality (i.e., adherence to an ideal normal distribution). Indeed, assessing the assumption of normality is required by most statistical procedures.

Shapiro-Wilk test has been viewed as the most powerful test for all type of distribution and sample sizes (Razali & Wah, 2011). This test aims to check out if particular sample came from predefined distribution population. In order to run Shapiro-Wilk normality test, some hypotheses should be tested:

- **Null hypothesis (H_0):** samples came from normally distributed population;
- **Alternative hypothesis (H_1):** samples do not follow a particular distribution.

The null hypothesis (H_0) states data came from normal distribution population. Pass on this hypothesis is fundamental to plot control chart without any data transformation. Nonetheless, sometimes H_0 hypothesis fails remaining alternate (H_1) hypothesis test for further analysis. Yet, H_1 plays an important role showing possible statistical

[1] Individual control charts can, in turn, be used to represent non-normally distribution; however, it requires specific data transformation in order to guarantee robustness.

inference application about sample data. Given an random sample (i.e., x_1, x_2, …, x_n), Shapiro Wilk normality test is defined as (Shapiro, 1965):

$$W = \frac{\sum_{i=1}^{n} a_i x_i}{\sum_{i=1}^{n} \left(x_i - \bar{x}\right)^2} \tag{3}$$

where:

x_i is the i^{th} order statistic
$\bar{x}$ is the sample mean

$$a_i = (a_1, \ldots, a_n) = \frac{m^T V^{-1}}{\left(m^T V^{-1} V^{-1} m\right)^{1/2}} \tag{4}$$

where:

$m = \left(m_1, \ldots, m_n\right)^T$ are the expected values of the order statistics of independent and identically distributed random variables sampled from the standard normal distribution, and V is the covariance matrix of those order statistics.

Significance index (W), also known as p-value, ranges from zero to one. Large W leads non reject H_0 hypothesis. As a consequence, random sample came from normal distribution. Nonetheless, small W value leads to refuse H_0 assumption, and H_1 statement can, indeed, be tested. In fact, p-value should be viewed as a measure of agreement between data sample and null-hypothesis corresponding to normal distribution (Razali & Wah, 2011).

2.1.3 Rational subgrouping

Subgrouping plays an important role for control chart (Montgomery, 2008). In particular, subgrouping can be viewed as a procedure where data is organised into group of items that were produced under similar conditions in order to measure the variability between the subgroup instead of between individual data points (Sefik, 1998). With subgrouping classification reduces search space of potential influences diminishing effort involved into statistical data analysis.

Rational subgrouping can be considered as essential step for sampling manufacturing process. Basically, it performs sampling with appropriate representation leading data to information conversion. Based on collected data, SPC analysis targets to estimate population parameter (such as average, standard deviation, correlation among random variables, probability distribution, etc.). Therefore, rational subgrouping becomes a fundamental procedure to retrieve information from sample data. The proper selection of samples requires careful consideration of the process, with the objective of obtaining as much useful information as possible from the control chart analysis (Montgomery, 2008).

Rational subgroups are given by subset of the entire population with particular homogeneous condition. Very often, subgroup basis is the order of production. For instance, similar assembly procedure following regular sample time or specification limit can, in turn, become a strong candidate for subgroup foundation. Generally, subgroups are chosen to keep the change for difference within the group to a minimal and maximise the chance for a change to occur among subgroups (Oakland, 2003).

3. METHODOLOGY

The methodology adopted in this paper is based on quantitative and qualitative analysis. Investigations, interviews, reports, and dataset were also included on research scheme. Figure 02 highlights research phases from this project.

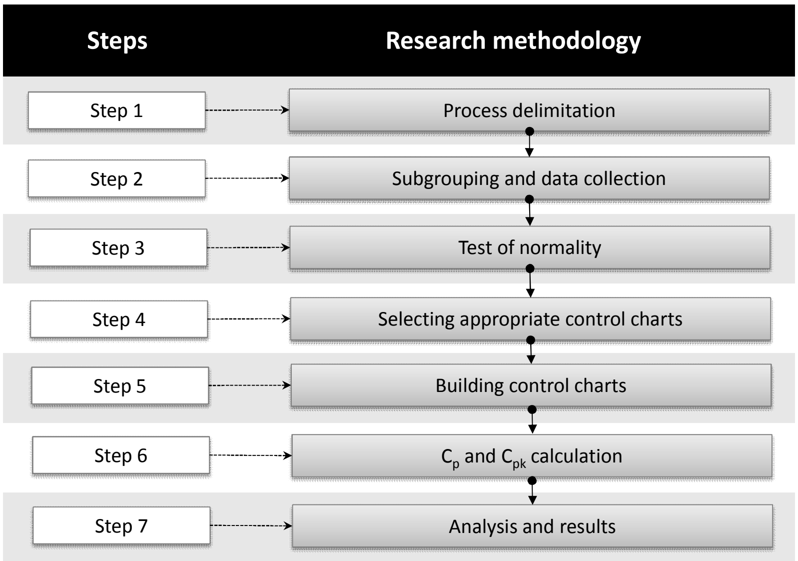


Figure 2. Research methodology.

Process delimitation is the first step from research methodology. Very often, automotive manufacturing lines involve numerous procedures and operations. As a consequence, production dataset entails massive amount of data from vehicle production. Thus, process delimitation bounds what type of assembly routine should be investigate over period of time. Subgrouping and data collection is another important procedure for data analysis. In this phase, those assembly routines selected on previous stage are scrutinized carefully to determine rational subgroups and sampling internal. Yet, whether next stages fail, rational subgrouping formulation should be reviewed.

The test of normality will guide next analysis direction. Generally, sampling data with normal distribution do not need additional transformation or procedure to ensure control chart robustness. Taking into account which assembly process is researchers will choose what kind of control chart is more appropriate to evaluate the selected assembly routine. Once previous steps have been accomplished, researchers can build control charts and calculate process capability indices. Using these information, quality control team can analyses results indicating what possible solution are.

4. INDUSTRIAL CASE STUDY

This case study analyses torque inspection data collected from an automobile manufacturing company. Statistical inferences and control charts are related with the assembly of two distinct parts from monitored assembly line. A Non-Disclosure Agreement (NDA) term protects company proprietary information. For this reason, some details about assembly process will be omitted from this paper. From now on, those processes will be devoted as process A and process B.

4.1 Assembly line and process description

In automobile assembly lines, verification procedures involve checking of screw torques. Once a torque specification is determined, the joint should be audited to verify if the screw has been fastened to the specified torque. Among three assembly lines, torque inspection occurs in the last two alone covering whole produced cars. Those lines contain assembly and inspection workstation executing process routine in a predefined period of time.

Due to the wide variety of joint, screws, and torques, fine tuning stations (FTS1, FTS2) and inspection workstation (IW1, IW2) are included in the end of body shop assembly line. The former must finalise assembly routine adjusting and verifying tightening of screws. The latter perform audit torques checking whether tightening does not fall within the expected design specification limits. Precise torque wrenches are used for inspection purpose alone.

Aside those verification and validation procedures, there is also a pre-production inspection (PPI) running over entire body shop assembly line. This mobile workstation runs some periodic audit in order to check applied torque. Indeed, PPI is an on-site production inspection procedure to monitor the conformity of part to your specification. It is also plays an important role to monitor production capability. Whenever inspected item does not meet design specification, tightening procedure should be run again before to send the vehicle to the next workstation. PPI data collected are stored within production database for further analysis. Figure 3 highlights body shop assembly workstations, with fine tuning, inspection workstations, and PPI.

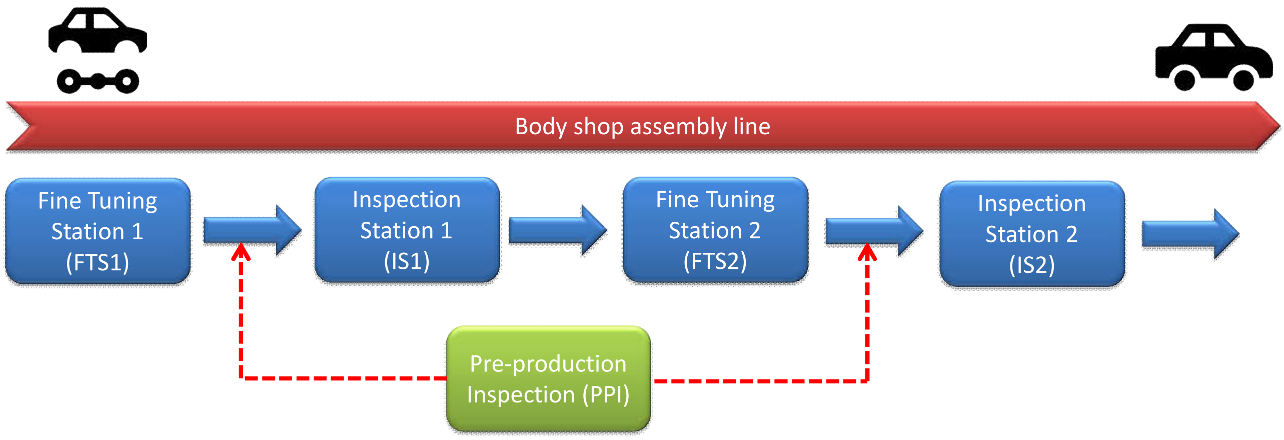


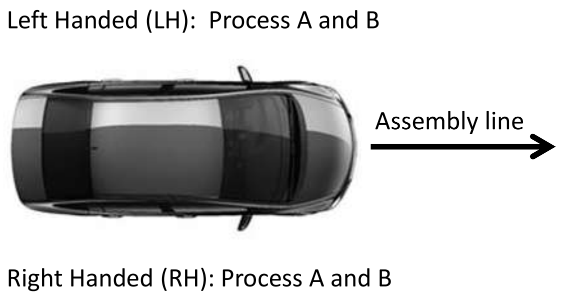
Figure 3. Simplified scheme of body shop assembly line.

4.2 Data collection

The case study is based on PPI torque inspection data obtained during three semesters. Those data were retrieved and analysed using statistical inference, control charts, with ultimate goal to calculate process capability. Process capability compares the output of an in-control process to the specification limits by using capability indices (NIST/SEMATECH, 2017). Using SPC techniques, data collected can provide process monitoring and indirect quality control starting proactive action reducing rework and also improving vehicle reliability.

Sample data requires previous subgrouping classification. Rational Subgrouping (RS) is the name given to the way in which data are organised into subgroups for process control charts. In additional, RS involves the use of prior knowledge about production routines and manufacturing process. Furthermore, RS classification will always be required for short sample data collected over a predetermined period of time. Data collected from process A and B were split in six month in order to keep the same analysis period followed by automotive company.

Taking into account the sequence of assembly routines, process A and B were also break into distinct steps because similar items and procedures are constantly run in both sides of the car. Besides, both processes occur on left and right handed side tightening two screws. For this reason, each mounting process must be clustered on two rational subgrouping. Thus, tightening procedures should be assessed according to assembly item following the evaluation period. Figure 4 summaries subgrouping formation and data classification.



Sample period	Car side			
	LH		RH	
	Rational Subgrouping		Rational subgrouping	
Semester 1th, 2014	Upper	Lower	Upper	Lower
Semester 2th, 2014	Upper	Lower	Upper	Lower
Semester 1th, 2015	Upper	Lower	Upper	Lower

Figure 4. Sampling classification into rational subgroups.

4.3 Normality test

For control chart plotting, it is fundamental to guarantee that sample data are random variable with normal distribution (Montgomery, 2004). In practice, false alarms can occur whenever data collected are non-normally distributed showing that manufacturing process is out of control when, indeed, it is under control. For this reason, data without normal distribution should be avoided becoming useless for SPC without prior transformation.

Data obtained from process A and B were firstly checked by the normality test. Shapiro-Wilk was the test of normality used in this research. Using IBM-SPSS® software, torque inspection data collected were verified. Engineering confidence interval of 95% was chosen with significance level (α) of 0.05. Table 1 shows significance indices obtained from Shapiro-Wilk normality test.

Table 1. Significance indices - Shapiro-Wilk normality test.

Rational subgrouping	Significance index (Shapiro-Wilk)			
	Process A		Process B	
	Left Handed (LH)	Rear Handed (RH)	Left Handed (LH)	Rear Handed (RH)
Upper screw 1º 2014	0.535	0.058	0.253	0.253
Lower screw 1º 2014	0.727	0.184	0.314	0.314
Upper screw 2º 2014	0.509	0.985	0.495	0.757
Lower screw 2º 2014	0.335	0.971	0.270	0.179
Upper screw 1º 2015	0.343	0.828	0.549	0.126
Lower screw 1º 2015	0.666	0.883	0.482	0.150

Experimental results show that selected data came from a normal distribution population. From second until firth column contain significance indices for the process A and B from both car sides. Additionally, p-value obtained for each RS is greater than predefine significance level (i.e., 0.05). As a consequence, the null hypothesis (H_0) where data came from normally distributed population cannot be rejected suggesting that torque inspection data are normally distributed. Indeed, this analysis is mandatory to forward to the next stage of SPC analysis.

4.4 Plotting control chart

Once torque inspection data fits to the normal distribution, it can be used to plot graphs. Evaluating control charts, production and quality control team can quickly track undesired process variation executing proactive action, in advance. Before to plot control charts, it is fundamental to understand what feature or process variability should be assessed. This analysis plays a crucial role to select what type of control chart should be used.

Within manufacturing line, process A and B involves an automotive part assembly where torque screw should be somehow monitored statistically. Torque is a random variable which can take any value ranging within design specification limits. For this reason, type variable is the most recommended control chart. After selecting control chart, it is fundamental to check out data acquisition method.

Sample from process A and B were clustered following rational subgrouping method. It is requires because each assembly item entails upper and lower screws. Moreover, those components receive similar torque from the same torque wrenches regarding regular sample time. For example, samples from right side of the car are gathering on two rational subgrouping. Taking into account samples from continuous variable for two rational subgrouping, the most appropriate control char are the type X-bar and R. Figure 5 shows type X-bar and R control charts from left handed for the first sample period whilst table 2 shows control chart limits from acquired data.

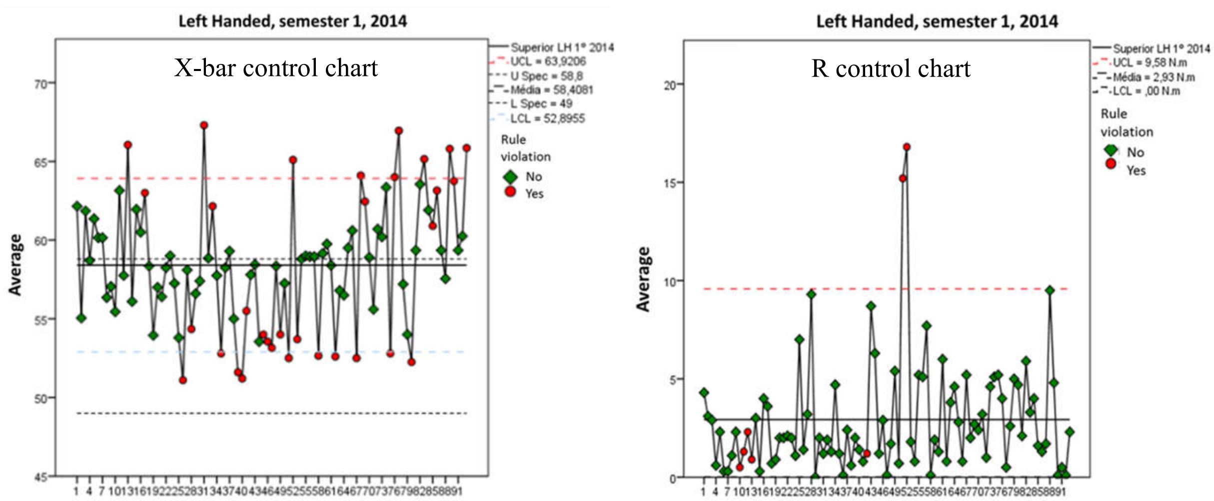


Figure 5: Control charts for first semester 2014 (process A).

Table 2. Charts control limits.

Sample period	Parameter	Process A		Process B	
		LH (Nm)	RH (Nm)	LH (Nm)	RH (Nm)
First semester 2014	UCL	63.92	64.09	37.88	36.15
	PAV	58.40	58.45	31.21	30.15
	LCL	52.89	52.81	24.54	24.16
Second semester 2014	UCL	63.21	62.63	35.85	35.14
	PAV	56.77	56.52	30.32	29.34
	LCL	50.32	50.41	24.80	23.54
First semester 2015	UCL	64.59	65.08	36.15	36.51
	PAV	59.00	58.93	29.81	30.31
	LCL	53.42	52.78	23.45	24.12

Legend: **UCL** – Upper Control Limit; **PAV** – Process AVerage; **LCL** – Lower Control Limit

Control chart data analysis for the first period shows a considerable data out of control limits. Moreover, PAV value (58.41 Nm) is close to the upper specification limit (58.8 Nm). It suggests a biased average deviation from design specification (58.41 Nm against 53.9 Nm). Similar to the other evaluated periods, control limits do not embraces design specification limits. A preliminary analysis reveals that a systematic influence is increasing average torque value. Besides, lower control limits, process average, and upper control limit are always above specification limits.

This observation raises some important questions about quality control procedure such as: (1) how PPI torque data are, in turn, collected? (2) Are quality control team running standard calibration and procedures? (3) What are consequences over process capability index?

After meeting quality control team, some answers revealed potential insights about PPI inspection process. Firstly, PPI data collection procedures must be reviewed. In particular, labours who audit screws should execute standard routine to reduce human influence over sampling. Additionally, PPI instrument calibration time should be strictly followed. Most often, rule violation has occurred when calibration time has expired. It requires more commitment from quality control team to maintain rigorous control over instrument calibration time. In the last, some inadequate corrections running over assembly workstation should also be avoided. Table 3 presents process capability indices.

Table 3. Process capability indices.

Sampling Period	Process A				Process B			
	Left Handed (LH)		Rear Handed (RH)		Left Handed (LH)		Rear Handed (RH)	
	C_p	C_{pk}	C_p	C_{pk}	C_p	C_{pk}	C_p	C_{pk}
First semester 2014	0.629	0.05	0.614	0.044	0.519	-0.192	0.578	-0.089
Second semester 2014	0.537	0.223	0.537	0.264	0.627	-0.118	0.598	0.007
First semester 2015	0.621	-0.026	0.564	-0.015	0.546	-0.045	0.560	-0.105

Process capability indexes emphasise those analysis mentioned before. In addition, process capability indices (C_p and C_{pk}) obtained from IBM-SPSS® software suggests that process A and B are statistically out of control. Researchers also regards that previous data collection can also influence SPC results. An inevitable consequence is the entire inspection over process A and B on IW1 and IW2 which are, indeed, occurring. Those results were compiled and presented to the automobile company with suggestion of improvements in the production and inspection routines.

5. CONCLUSION AND FUTURE WORK

Statistical Process Control is viable solution for continuous improvements in automotive manufacturing. With control charts, quality control team can constantly supervise in-control process running proactive actions and reducing waste and rework. In spite of the fact that SPC is a potential method to implement quality control, there are few examples illustrating SPC application in automotive companies. For this reason, this paper presents another contribution showing how perform SPC in process for torque audit in automotive assembly lines.

Research methodology shows each step required to implement SPC techniques. After to determine what process should be monitored, researchers took inspection data from automotive OEM. Those data cover three semester of pre-production inspection.

Results obtained from industrial case study analysis reveal that torque audit do not follow, strictly, desired specification limits. This observation was also confirmed by quality control manager requiring 100% of inspection in IW1 and IW2 workstations. Additionally, researchers also suggest some potential routine modification in order to improve process capability and inspection procedure. Further analysis is also required after to implement suggested modifications.

6. REFERENCES

Godina, R. Matias, J.C.O. and Azevedo, S.G., 2016. “Quality Improvement With Statistical Process Control in the Automotive Industry”. International Journal of Industrial Engineering and Management. Vol. 07, No 1, p. 01-08.

Kane, V.E., 1986 “Process capability indices". Journal of quality technology. Vol. 18 No.1 p. 41-52.

Korenko, M. Kaplík, P. Bujna, M. and Prístavka, M., 2013. “Statistical process control in automotive industry”. In *Acta Technologica Agriculturae*. Vol. 16, p. 39-42.

Montgomery , D. C., 2008. *Introduction to Statistical Quality Control*. Wiley, 6th edition.

NIST/SEMATECH, 2017. “e-Handbook of Statistical Methods”. 20 Sep. 2017 <http://www.itl.nist.gov/div898/handbook>.

Oakland, J. S., 2003. *Statistical Process Control*. Butterworth-Heinemann, Burlington, 5th edition.

Prajapati, D.R., 2012. “Implementation of SPC Techniques in Automotive Industry: A Case Study”. International Journal of Emerging Technology and Advanced Engineering. Vol. 02, p. 227-241.

Razali, N.M. and Wah,Y.B., 2011. “Power comparisons of shapiro-wilk, kolmogorov-smirnov, lilliefors and anderson-Farrel, E.R., 2017. *Analysis of tool wear and tool life of cutting inserts using statistical process control charts: a case study*. Master thesis. Morehead State University, Ann Harbor.

Sefik, M. 1998 “Importance of the rational subgroups in designing control charts. “ Computers & industrial engineering. Vol. 35 Nº 1-2 p. 205-208.

Shapiro, S. S., and Wilk, M. B., 1965 “An Analysis of Variance Test for Normality (Complete Samples).” Biometrika, Vol. 52, No. 3/4 p. 591–611.

Shende, V. 2014 “Analysis of research in consumer behavior of automobile passenger car customer.” International Journal of Scientific and Research Publications. Vol. 04. No. 02 p. 1-8.

Slack, N. Brandon-Jones, A. , R., 2014. *Operations Management*. Pearson, 7th edition.

Singh, J. and Singh, H., 2012. “Continuous improvement approach: state-of-art review and future implications.” International Journal of Lean Six Sigma. Vol. 3 No. 2 p. 88-111.

7. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.