Iranian Journal of Management Studies (IJMS) *http://ijms.ut.ac.ir/*
Vol. 14, No. 1, Winter 2021 *Print ISSN: 2008-7055*
pp. 1-37 *Online ISSN: 2345-3745*
Document Type: Research Paper *DOI: 10.22059/ijms.2020.222198.672415*

Process Capability Studies in an Automated Flexible Assembly Process: A Case Study in an Automotive Industry

Bakhtiar Ostadi[1*], Mohammadreza Taghizadeh-Yazdi[2], Abdolkarim Mohammadi-Balani[3]

1. Faculty of Industrial and Systems Engineering, Tarbiat Modares University, Tehran, Iran
2. Department of Industrial Management, Faculty of Management, University of Tehran, Iran
3. Department of Industrial Management, Faculty of Management and Economics, Tarbiat Modares University, Tehran, Iran

(Received: December 8, 2016; Revised: June 15, 2020; Accepted: June 16, 2020)

Abstract

Statistical Process Control (SPC) methods can significantly increase organizational efficiency if appropriately used. The primary goal of process capability studies is to obtain critical information about processes to render them even more effective. This paper proposes a comprehensive framework for proper implementation of SPC studies, including the design of the sampling procedure and intervals as well as process capability indices. Some of the most essential process capability indices in the literature were reviewed to develop a methodology to utilize process capability indices within the SPC framework. The current study presents an efficiency-oriented criterion designed for measuring SPC implementation productivity. The framework is applied to the windshield installation process of an Iranian automobile assembly line. The process was sampled in various sessions. Results verify that the implemented SPC framework could successfully improve the process and that the proposed framework could significantly address bottleneck in the process and enhance the quality level of the process from satisfactory to excellent according to the reference values of process capability indices. Managerial insights are also drawn from results.

Keywords

Statistical Process Control, Process capability indices, Automobile assembly facility, Windshield installation process.

* **Corresponding Author, Email:** bostadi@modares.ac.ir

Introduction

The ever-intensifying pace of market competition urges firms to improve processes to cut costs and increase process efficiency (He & Wang, 2018). Contemporary firms have less or no control over the increase of input material costs and the pressure of the market to decrease the prices of the final products while increasing the quality. Therefore, they have to optimize their process costs and increase process quality to alleviate the pressure and make value for consumers and the stakeholders (Senvar & Akburak, 2019).

SPC is a methodology that helps firms continuously improve processes by using control charts to evaluate the process capability and specification standards (Guarnieri *et al*., 2019). Many firms that have successfully implemented SPC have reported significant improvements in efficiency and other performance measures. Managers consider SPC as a continuous job, not a one-time project. SPC is capable of aiming for quality improvements at any timescales, ranging from daily schedules to comprehensive annual programs (Hesamian & Akbari, 2018). It is reported in the literature that management engagement, attitude toward teamwork, staff training at any organizational level, success recognition mechanisms, and emphasis on continuous improvements are the key contributing factors to a successful SPC (Cohen *et al*., 2016).

Process capability indices can provide management with valuable information about the processes if used properly. Such information, which is crucial to the functional improvement of the system, can be used to boost processes and make them more efficient and capable, and cut production costs while increasing customer satisfaction (Selmi *et al*., 2018). It is known that the quality of the final products obtained from processes is subject to variations. Process capability indices are designed to scrutinize processes and differentiate between the process capability studies and machine capability indices. Both of these approaches are intended to identify and evaluate random and systematic process variability (Nikzad *et al*., 2018).

Process capability study has been the topic of many studies. de-Felipe and Benedito (2017) reviewed the literature on univariate and multivariate process capability indices and identified three clusters with which univariate and multivariate process capability indices can be categorized. Yum and Kim (2011) provided a bibliographical study on process capability studies. Wu et al. (2009) reviewed the literature pertaining to the theoretical backgrounds and the applications of process capability indices with a focus on the area of quality assurance.

Dalalah and Hani (2016) studied the difference between real process capability values and the ones calculated using the signal to noise ratio approach. Besseris (2019) studied the characteristics of three robust scale estimators for process capability indices that follow a modified Weibull distribution. He explored different scenarios in terms of standard error estimators, bootstrap methods, and sample sizes. Dianda et al. (2016) used simulation experiments to scrutinize the characteristics of two multivariate process capability indices for both normal and non-normal distributions. Abbasi Ganji and Sadeghpour Gildeh (2016) proposed a new class of PCIs for processes with asymmetric tolerances, named $C_p'''(u, v)$. They also explored the relationship between the proposed process capability index and the departure ratio for process centering. Sharma et al. (2020) used a hybrid approach that combines PCI and multi-response optimization to study the stability of an industrial 3D printing process. Roberto Jose et al. (2018) proposed the use of distance measures other than the classic Euclidean distance, such as Canberra’s distance function, which can better fit the requirements for robust process capability indices. Salazar-Alvarez et al. (2016) proposed a maximum-likelihood-based methodology to enhance the fitting process for the calculation of PCIs in the presence of extreme values. Piña-Monarrez et al. (2016) derived PCIs for Weibull and lognormal distributions based on the characteristics of the mean and the variance of Weibull, Gumbel, and lognormal distributions which can be used instead of the normally distributed indices of C_p, C_{pu}, C_{pl}, and C_{pk}.

George and Sasi (2017) performed a comparative study between the parametric asymptotic lower confidence limits of PCIs under Esscher-Transformed Laplace Distribution. Rezaye Abbasi Charkhi et al. (2016) proposed two methods for the calculation of processes whose quality follows a logistic regression profile. Yen et al. (2018) proposed a variable sampling procedure using multiple dependent states and repetitive group sampling. Their proposed methodology is designed for one-sided process capability indices for current lots and preceding lots.

SPC projects involving process capability studies must be carefully planned and organized. The literature consists of numerous process capability indices, sampling procedures, key process characteristic selection methods, etc. A beneficial process capability study should carefully select proper methods that best fit the process characteristics and managerial requirements. With that in mind, this paper proposes a comprehensive framework for implementing SPC. First, the paper reviews the proposed indices in the literature and explores their managerial implications. Relevant process capability indices are discussed, and the proposed steps toward a comprehensive procedure for implementing the SPC are presented. The procedure is then applied to a real-world case, where the windshield installation process in an automobile assembly is investigated and improved. To measure the impact of the SPC, an appropriate criterion is proposed. Indices were able to show how much the process is improved after the implementation of the SPC.

Section 2 provides the related literature, while section 3 discusses the implemented methodology. Section 4 provides the numerical results of applying the procedure to the real-world case of automobile assembly. Section 5 is dedicated to the discussion of the results. The conclusions and suggestions for future studies are presented in section 6.

Theoretical Foundations

This section discusses the literature related to process capability analysis, process capability indices, process performance indices, and the general steps involved in a process capability study.

1. Process Capability Analysis

Process capability can be defined as the aptitude of a process's aptitude to fulfill the expectations of the consumer (Hadian & Rahimifard, 2019; Peruchi *et al*., 2018). Measuring process capability and the quality expectations in terms of quantitative values could pave the way for determining whether the process meets consumer expectations more accurately. Consumer expectations are usually introduced as the specification limits (SLs), which are comprised of lower specification limit (LSL) and upper specification limit (USL) (Geramian et al., 2020). The measured capability of a process can take any value. There is an active debate on the precise values of SLs;

however, there is a broad consensus that if it is too small, the process is considered incapable and does not fulfill the consumer's expected quality and if it is excessively large, the process has been performed too carefully, hence it has relatively high quality costs (Cakmakci & Demirel-Ortabas, 2019). In addition to the two-sided specification limits mentioned, there also exist one-sided specification limits (Chakraborty & Chatterjee, 2016).

A process characteristic may fall into one of the three following categories based on the specification limits. If the process is composed only of USL, smaller values of the capability indices are more favorable. If the process is comprised of only LSL, larger values of capability indices would be more desirable. Finally, if the process possesses both LSL and USL, a nominal value of the process capability is desired, and deviations from those nominal values are unfavorable (Cano *et al*., 2015).

Process capability analysis or process capability study generally involves defining process specification limits, defining process capability indices, measuring process capability indices, and determining how much the process is capable. One of the crucial steps in such studies is the selection of process capability indices to measure the process capability. In fact, this selection is of paramount importance since it can be considered as the heart of the analysis.

The literature on process capability includes a variety of process capability indices. The most important indices will be discussed in the following subsections.

2. Process Capability Indices (PCI)

The process capability index is an indicator to assay the actual performance of a process against the specifications needed for the quality of the final product. Numerous process capability indices have been proposed, but they chiefly are modifications and improvements of four base indices of C_p, C_{pk}, C_{pm}, and C_{pmk} (Kumar *et al*., 2019). This subsection introduces some of the most important process capability indices, their estimators, and their characteristics.

2.1. C_p index

C_p index can be calculated according to Equation 1 (Chao & Lin, 2006; Chen *et al*., 2010; Kotz & Johnson, 2002).

$$C_p = \frac{(USL - LSL)}{6\sigma} \tag{1}$$

where USL, LSL, and σ are the upper specification limit, lower specification limit, and standard deviation of the process, respectively. There has been a debate in the literature on the minimum acceptable value for C_p for a capable process.

Various studies assert that the value of 1.33 can be used as the minimum acceptable value for C_p (Ahmad *et al*., 2014; Balamurali and Usha, 2014). Kaya and Kahraman (2011) and Tsai and Chen (2006) proposed a comprehensive tool for interpreting C_p, which is reported in Table 1.

Table 1. Quality Conditions and C_p Values

C_p value	Quality condition
$2.00 \le C_p$	Super Excellent
$1.67 \le C_p < 2.00$	Excellent
$1.33 \le C_p < 1.67$	Satisfactory
$1.00 \le C_p < 1.33$	Capable
$0.67 \le C_p < 1.00$	Inadequate
$C_p < 0.67$	Poor

The standard deviation is calculated via the specific formula for samples, where n is the number of samples. The formula for calculating C_p is presented in Equation 2.

$$\widehat{C_p} = \frac{(USL - LSL)}{6\hat{\sigma}} \tag{2}$$

$\hat{\sigma}$ and $\bar{x}$ are calculated via Equations (3) and (4).

$$\hat{\sigma} = \sqrt{\left[\frac{1}{n-1} \cdot \sum_{i=1}^{n} (X_i - \bar{X})^2\right]} \tag{3}$$

$$\bar{X} = \frac{1}{n} \cdot \sum_{i=1}^{n} X_i \tag{4}$$

Given a process with its mean value equal to the target value and a high C_p value, one can obtain the proportion of the items outside the specification limits by shifting the process mean toward the specification limits. Figure 1 displays different distributions that have similar C_p values. This is chiefly due to their equal standard deviations and different means. The distribution on the left is ideal, and others involve deviations. Although far from the target value, the second and third distributions are acceptable because their distributions fall within USL and LSL. The fourth and the fifth distributions are not acceptable because they are extended beyond the acceptable region between USL and LSL.

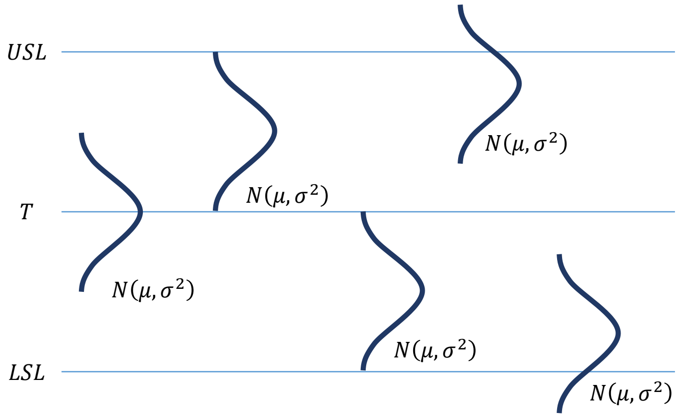

Fig. 1. Distribution of Five Example Processes

The main drawback of C_p is that it only checks whether the process range is within the specification limits but fails to take into account the deviations from the centerline of the process (Aslam, 2018; Cui *et al*., 2018; Kotz & Johnson, 2002). Other indices that pay specific attention to the mean also exist in the literature, and are discussed next.

2. 2. *CPL* and *CPU* Indices

When there are restrictions on the acceptable mean of the process, CPL and CPU indices are used, which can be calculated via Equations 5 and 6, respectively (Kotz & Johnson, 2002; Palmer & Tsui, 1999; Shi *et al*., 2016).

$$CPL = \frac{\mu - LSL}{3\sigma} \tag{5}$$

$$CPU = \frac{(USL - \mu)}{3\sigma} \tag{6}$$

Estimates of CPL and CPU can be calculated via Equations 7 and 8 (Kotz & Johnson, 2002; Palmer & Tsui, 1999; Shi *et al*., 2016).

$$\widehat{CPL} = \frac{(\bar{x} - LSL)}{3S} \tag{7}$$

$$\widehat{CPU} = \frac{(USL - \bar{x})}{3S} \tag{8}$$

C_p can be calculated via CPL and CPU (Equation 9). The same rule holds for their estimators (Equation 10).

$$C_p = \frac{CPL + CPU}{2} \tag{9}$$

$$\hat{C}_p = \frac{\widehat{CPL} + \widehat{CPU}}{2} \tag{10}$$

2. 3. C_{pk} Index

C_{pk} takes into account the mean value of the process in addition to the range. It is defined as the minimum CPL and CPU values (Equation 11) (Kahraman *et al*., 2017; Kotz & Johnson, 2002; Palmer & Tsui, 1999; Shi *et al*., 2016).

$$C_{pk} = \min\{CPL, CPU\} \tag{11}$$

It can also be calculated via Equation 12 (Kahraman *et al*., 2017; Kotz and Johnson, 2002; Shi *et al*., 2016).

$$C_{pk} = (1 - |k|) \cdot C_p \tag{12}$$

Where

$$k = 2 \cdot \frac{|m - \mu|}{(USL - LSL)} \tag{13}$$

C_{pk} can be considered as the reduction of C_p by the factor of $1 - |k|$. It is worth mentioning that $|k| \leq 1$. It is also trivial when

$\mu = m$ then $C_{pk} = C_p$. Estimates of k and C_{pk} ($\hat{k}$ and $\hat{C}_{pk}$) can be calculated using Equations 14 and 15.

$$\hat{k} = \frac{2 \cdot |m - \bar{X}|}{(USL - LSL)} \tag{14}$$

$$\hat{C}_{pk} = \min\{\widehat{CPL}, \widehat{CPU}\} = \left(1 - \hat{k}\right) \cdot \hat{C}_p \tag{15}$$

$CPL\,(\widehat{CPL})$ and $CPU\,(\widehat{CPU})$ measure the proximity of the actual process mean and the lower and upper bounds of specification limits, respectively. k denotes the proximity of the process mean to the centerline. C_{pk} $(\hat{C}_{pk})$, which is defined as the minimum $CPL\,(\widehat{CPL})$ and $CPU\,(\widehat{CPU})$ values, and can take a maximum value equal to C_p $(\hat{C}_p)$ when $\mu = m$. When the process mean drifts away from the target mean (μ) beyond the smaller semi-tolerance, C_{pk} ($\hat{C}_{pk}$) would be equal to zero. C_{pk} ($\hat{C}_{pk}$) is equal to zero when the process mean is within or outside the specification limits (Wang *et al.*, 2016).

3. Process Performance Indices (PPI)

Process performance indices measure the degree to which the process performance can fulfill product specifications and standards (Geng *et al.*, 2016). Process capability indices are also known as short-term capability indices, indicating that they are suitable for short periods. On the other hand, process performance indices are sometimes called long-term process capability indices since they are more useful for the analysis of data relevant to more extended periods (Zhang *et al.*, 2020). The following subsections discuss the process performance indices used in this study.

3.1. P_p Index

C_p calculates the standard deviation via $\frac{\bar{R}}{d_2}$, which is an estimate of the true standard deviation. $\bar{R}$ is the average of the range of samples and just calculates changes within samples; thus, it can also be named the short-term standard deviation ($\hat{\sigma}_{ST}$) or an estimator of the standard deviation within samples $\hat{\sigma}_{\text{within}}$ (Flaig, 1999, 2002; Ile, 2014).

C_p denies deviations between different samples and only reflects the short-term standard deviation of the process capability. P_p is introduced to correct C_p flaws. It calculates the long-term process capability standard deviation ($\hat{\sigma}_{LT}$) or the overall standard deviation ($\hat{\sigma}_{\text{overall}}$) estimates based on each pair of deviations. The standard deviation is calculated for all m samples, where m is the total number of subgroups, and n is the subgroup sample size. The long-term standard deviation is calculated via Equation 16 (Flaig, 1999, 2002; Ile, 2014).

$$\hat{\sigma}_{LT} = S_{\text{overall}} = \sqrt{\hat{\sigma}^2_{\text{within}} + \hat{\sigma}^2_{\text{between}}} \tag{16}$$

$\hat{\sigma}_{LT}$ (S_{overall}) is the estimated sample standard deviation.

$$S_{\text{overall}} = \sqrt{\frac{\sum_{i=1}^{mn} \left(X_i - \bar{\bar{X}}\right)^2}{mn - 1}} \tag{17}$$

Thus P_p can be calculated via Equation 18.

$$P_p = \frac{USL - LSL}{6\hat{\sigma}_{LT}} \tag{18}$$

3.2. P_{pk} index

P_{pk} is calculated similar to C_{pk} except for the point that it uses long-term standard deviation as in Equation 19 (Crowder, 1992; Flaig, 1999, 2002).

$$P_{pk} = \min\left\{\frac{\mu - LSL}{3\hat{\sigma}_{LT}}, \frac{USL - \mu}{3\hat{\sigma}_{LT}}\right\} \tag{19}$$

4. General Steps of Process Capability Studies

Process capability studies are conducted mainly for the purpose of process capability supervision, where taking samples from the process is necessary. An accurate sampling scheme would involve collecting samples in continuous periods of time. The four main steps of process capability studies are shown in Figure 2 (Dovich, 1991).

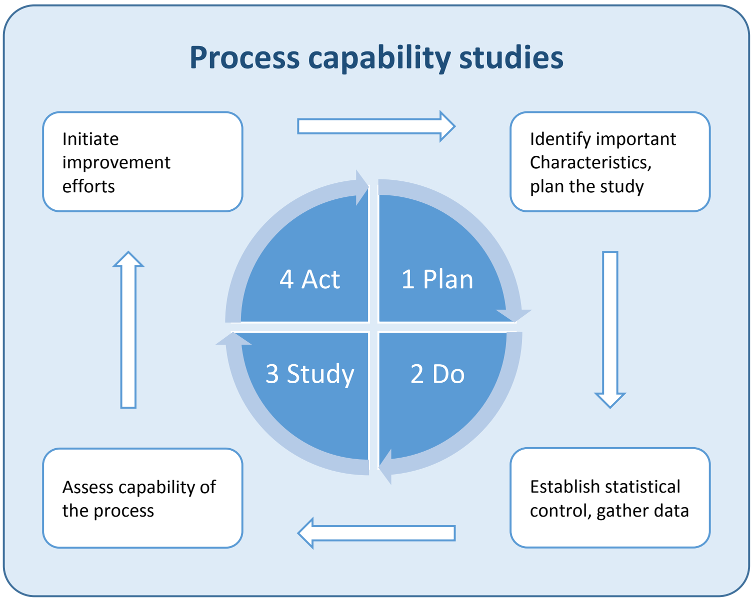

Fig. 2. Main Steps of Process Capability Studies

The cycle consists of four steps:

Identifying important characteristics and planning the study. Generally, only the most essential characteristics of a process need to be studied because it is almost impossible to monitor all aspects. Process capability studies need to be carefully planned in terms of the characteristics to be studied.

Establishing the statistical control and gathering data. An important topic to consider prior to conducting capability studies is to monitor the current status of process stability. Applying process capability studies on an unstable process would lead to results that lack the ability to be generalized to the future and are valid only within the study period. Statistical sampling procedures are used to collect data about the process.

Assessing the capability of the process. Process capability indices are specially organized to summarize the capability (performance) of a process numerically. If used correctly, they provide valuable information about a process. The information obtained from these indices would be used in process improvement projects.

Initiating improvement efforts. Finally, steps are made toward making the process more capable. Process capability studies provide more information about the current status of the process and pave the way for future improvements (Flaig, 2002).

Research Methodology (Implementing the SPC and Studying the Process Capability Indices)

The proposed methodology of this study is presented in this section. An overview is presented in Figure 3, and the details are discussed in the following subsections.

Fig. 3. Flowchart of the proposed methodology

1. Forming the Executive Team

To prepare the executive and management structure of the project, an executive team is formed. This team usually consists of top managers and operational supervisors.

2. Process Selection

Selecting an appropriate process among the numerous processes of manufacturing a particular product is one of the most critical steps in process capability studies. The executive team is responsible for studying the process. The following items are considered when selecting a process for statistical control (Pearn & Chen, 1997):

- The selected process must be associated with several symptoms, including customer sensitivity, high inspection costs, rework, and wastes.
- The selected process must be the cause of poor performance.

3. Studying the Selected Process

The process capability study must help the management gather useful information about different aspects of the process.

4. Determining Key Characteristics

The key characteristics to be studied should be selected from the process that is owned and controlled by the firm, not from the raw input or processed material. Processes to be studied by SPC should take place at a location governed by the firm (Burr, 2018). Various approaches for process identification exist in the literature. Zhao et al. (2017) proposed a data-driven approach to process identification based on the Markov Chain Modeling. Onggo et al. (2018) proposed an extension to the BPMN[1] for scrutinizing various aspects of the system, including processes, for discrete-event simulation. Bazhenova et al. (2019) explored new ways to identify the process by a hybrid methodology consisting of DMN[2] and BPMN. Mezouar et al. (2016) presented a meta-model-based design for process identification using BPMN and KPIs. Kodamana et al. (2018) reviewed the literature on probabilistic methods for robust process identification.

5. Defining the Productivity Measurement Index

Defining a suitable measurement index contributes significantly to improved interpretation of the results and their better implementation by the management. It can also help determine the system’s status at the beginning of the project. Such indices can be used to determine the exact amount of reduced waste, rework, and production volume as well as for increased production (Avinadav *et al.*, 2016).

1. Business Process Model and Notation
2. Decision Model and Notation

6. Preparing the Basic Control Chart

A basic control chart has two characteristics. It should only include variables that are under the control of the firm and should also have the proper features for the production process. General steps for the preparation of the control charts are as follows (Littig & Lam, 1993):

- Selecting the type of the control chart and indices for the process capability study.
- Selecting the number of subgroups and samples: In this study, 2×30 subgroups of size eight were used to draw basic control charts.
- Determining the measurement tool.
- Determining the measurement method.
- Planning for initial improvements: The executive team should investigate the process thoroughly and provide some improvements before sampling to correct some deviations that are not necessarily related to the characteristics to be studied but are fundamental to the process (Price, 2017).
- Sampling.
- Drawing control charts.
- Analyzing the control charts: Analyzing the obtained control points after drawing them is of great importance. If one or more points are located inside the area between the lower and upper limits, the process is under control, and the executive team can move on to the next steps. However, if the considered points are outside the control range, the executive team offers suggestions for improvement to stabilize the process, i.e., to improve the process so that all the control points lie within the control range. In case of the instability of the process, this procedure is repeated until the process is stabilized.
- Calculating the process capability indices and analyzing them: Process capability indices are compared with the reference values. If the indices are larger than the reference value, the obtained control charts could be used as basic control charts.

7. Implementation of SPC

The basic charts should be shared with the operators working in the production line for better recognition of the deviations. Basic control charts should be installed in appropriate places throughout the production line so that they are visible to operators. The executive team and operators provide feedback and suggestions for improving the process capability indices. Suggestions and modifications to the production line and subsequent changes in the process capability indices should be carefully documented. Out-of-control points are then investigated to devise plans for further corrective actions.

If the process capability indices are less than their target value, it is concluded that the process produces too much waste, meaning that the output should be controlled. In this study, sample sizes are equal to subgroups; therefore, there is no need to keep the time intervals between the samplings constant. A large process capability index indicates low waste (Daniels et al., 2004).

The sampling procedure used in this study consisted of two phases. In Phase I, there were two sampling sessions every day, where in phase II, there were two sampling sessions every other day. A total of four samples were taken during each sampling session. Process capability indices C_p, C_{pk}, P_p, and P_{pk} were calculated at the end of each day. Phase I was performed for 30 days, and if no significant deviations from the centerline were observed, the sampling procedure entered Phase II. Figure 4 presents a schematic view of the sampling procedure.

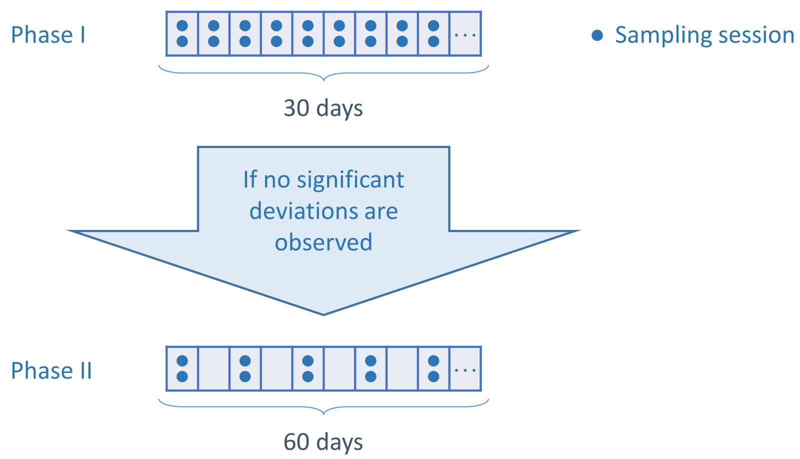

Fig. 4. The Sampling Procedure Used in This Study

Case Study and Findings

This section discusses the implemented SPC and the analyses performed on the obtained process capability indices for the flexible automatic assembling process of an automobile manufacturer.

The automotive industry is a collection of a wide variety of organizations that perform different tasks of supplying, manufacturing, and distributing cars to consumers (Sturgeon *et al*., 2008). It is considered as one of the most prominent industries in the world due to its large turnover. The automotive industry can also represent the general industrial status of countries (Townsend & Calantone, 2014). Ford Company was the first to establish a car assembly line, and car assembly processes have improved dramatically since then. Modern assembly lines comprise of major processes that are shown in Figure 5.

Fig. 5. Major Processes of a Car Assembly Line

The windshield is one of the vital parts of a car. Together with windows and mirrors, it provides drivers with comprehensive visibility and protects them from outer elements. During the windshield assembly process, a special glue is applied to the perimeter of the windshield, and the windshield is then installed in the position. This process belongs to the fourth step of the car assembly line, during which the interior parts of the car are installed (Figure 6). The amount of glue application process has certain specification limits, the satisfaction of which significantly affects the quality of the installed windshield. The case study of this paper focuses on the windshield installation process in one of the largest car manufacturers in Iran.

Fig. 6. ***Windshield Installation Process***

An executive team was formed at the beginning of the project with the aim of managing the other affiliated teams. The executive team that was tasked with assessing the windshield installation process consisted of representatives from quality engineering, production engineering, quality control, engineering services, and maintenance and repair departments. In the next step, the process to study was selected. In order to enhance the quality of the windshields, the glazing process was selected for studying because its output widely affects the quality of the manufactured windshields. The next step mainly comprises studying the windshield installation (glazing) according to what was discussed in the previous section.

The next step consisted of analyzing two key characteristics of the glue that is used to join the two layers of glass to form a single windshield: the thickness and height of the glue. The key characteristics were measured in the assembly line of two models: Car A and Car B. This paper only focuses on the results for the height of glue for Car A. Next, a productivity measurement index had to be determined. The executive team, in collaboration with the top managers and operational staff, decided to define the productivity measurement index as the percentage of cars into which water could penetrate.

After defining the index, it was time for the basic control charts. Given the fact that the glue height is a quantitative variable that is hard and expensive to sample, and the sample sizes were subsequently small, $\bar{X}$ and R charts were used to analyze the process. Also, the target values for C_p, C_{pk}, P_p, and P_{pk} were defined to be equal to 1.33. As mentioned earlier, two subgroups of size 30 were studied, each with sample sizes of eight. A digital caliper was used as the primary measurement tool. The digital caliper measures the glue height after the windshield is installed.

In the next step, control charts were drawn by sampling from the studied process. Thirty samples, each of size eight, were collected from one working week and two shifts per day. $\bar{X}$ and R control charts were prepared using Minitab software, as shown in Figure 7.

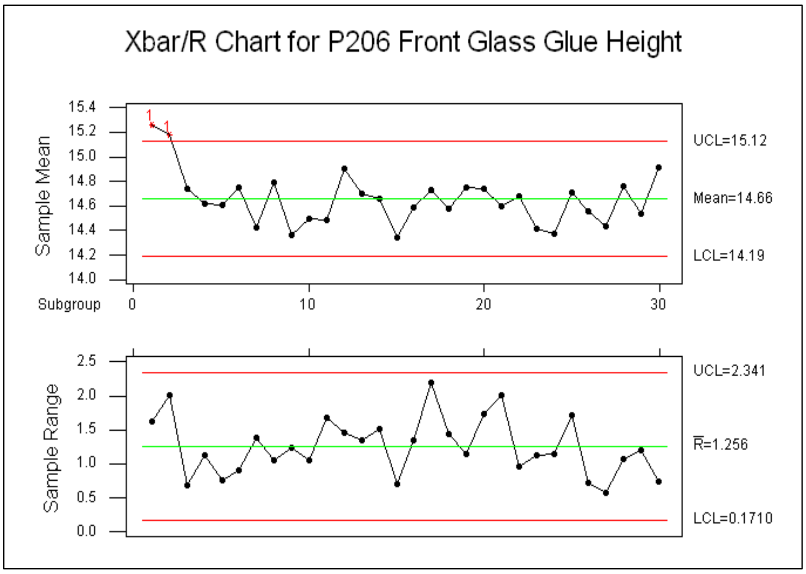

Fig. 7. $\bar{X}$ and *R* Control Charts for Front Glass Glue Height (Created With Minitab Software)

As it can be seen in Figure 7, two initial samples were outside the control limits. After investigations, the executive team concluded that they were caused due to operator carelessness; thus, the points were removed. Figure 8 displays $\bar{X}$ and R charts after the removal, where all the points are under control.

After selecting samples from the process, process capability indices could be calculated, as illustrated in Figure 9. It can be seen that C_p and P_p are larger than the target value of 1.33, indicating that the deviations from the centerline were negligible, and the process was in good status. However, C_{pk} and P_{pk} are less than 1.33, which means that the process was not a capable production process within technical specifications limits.

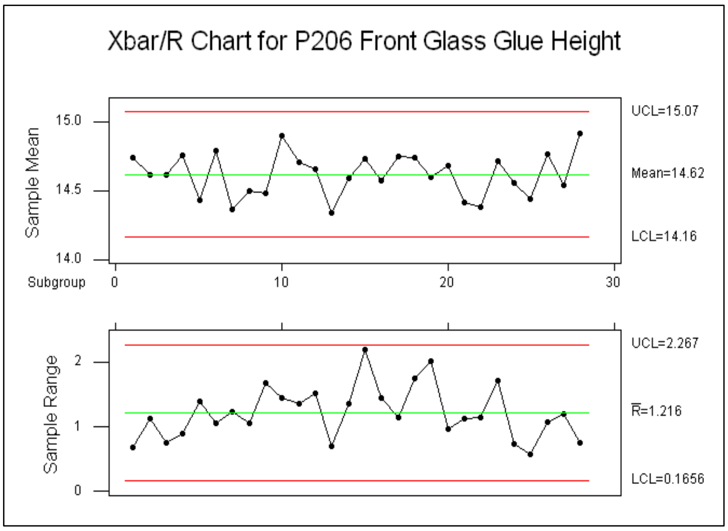

Fig. 8. $\overline{X}$ and *R* Control Charts After Removing the Outliers (Created With Minitab Software)

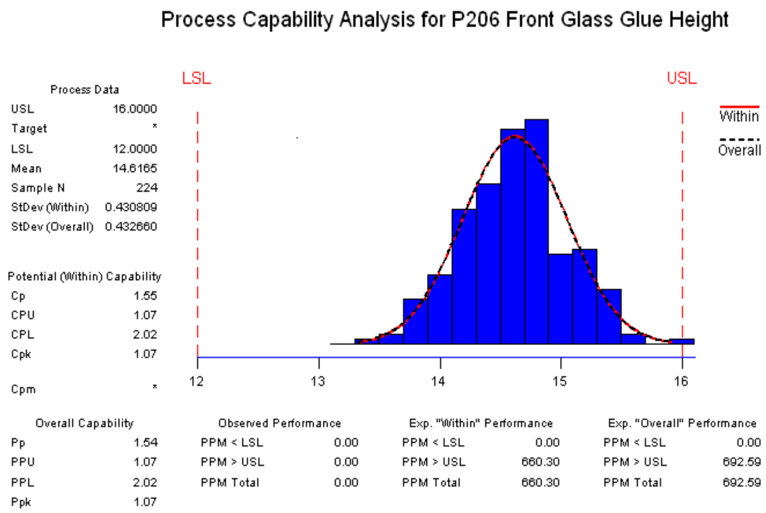

Fig. 9. Process Capability Analysis (Created With Minitab Software)

It is seen in Figure 9 that the process mean is larger than the target nominal (mean) value. The C_p value of the process is acceptable, according to the classification presented in Table 1. The process mean was corrected to match the target value through calibration, and another 30 samples in groups of eight were taken. Figure 10 displays $\bar{X}$ and R charts after the calibration, which indicates that the process was then under control.

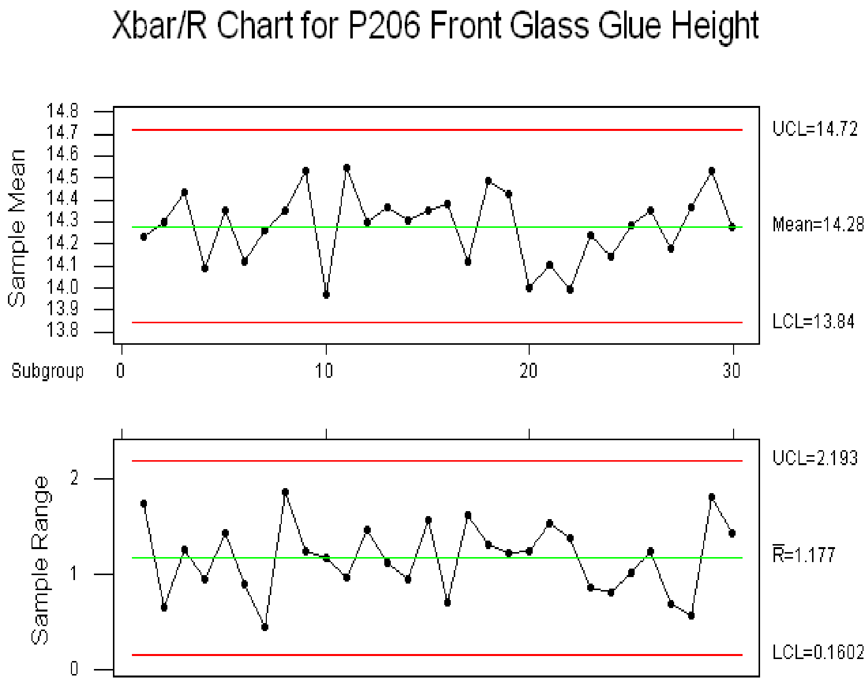

Fig. 10. $\bar{X}$ and R Control Charts After the Calibration (Made With Minitab Software)

Figure 11 displays the process capability indices after the calibration. It is observed that C_p is equal to 1.65, implying that it falls in the satisfactory category of Table 1. In fact, it is very close to perfect.

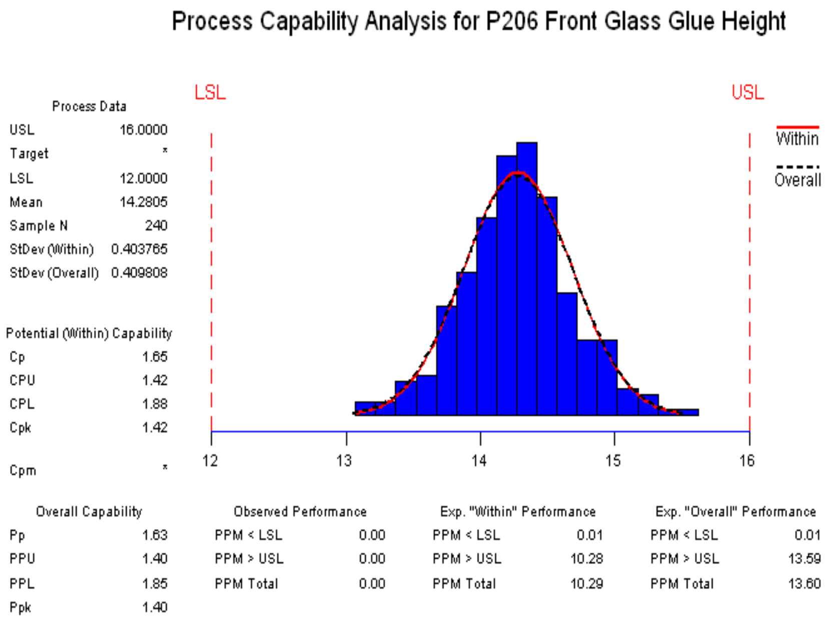

Fig. 11. Process Capability Indices After the Calibration (Created With Minitab Software)

The specification limits of Figure 8 and Figure 10 can be used to evaluate future operations. In other words, they can be used as the basic control chart. The charts were installed on the wall at the place where the process was implemented. The executive team conducted sampling sessions for another 30 days to assure that the process was within the specification limits, and the obtained process capability indices were reliable. Two samples of size eight were taken each day; thus, the team had 60 samples at the end of this step. Figure 12 and Figure 13 display the mean and range of these samples.

It can be seen in Figure 12 that the samples related to the 17th day (samples 33 and 34) were out of control. Further investigations were launched, and it was revealed that the two cases were due to overheating; thus, these samples (33 and 34) can be eliminated. Process capability indices for the new 60 samples were calculated as shown in Figure 14.

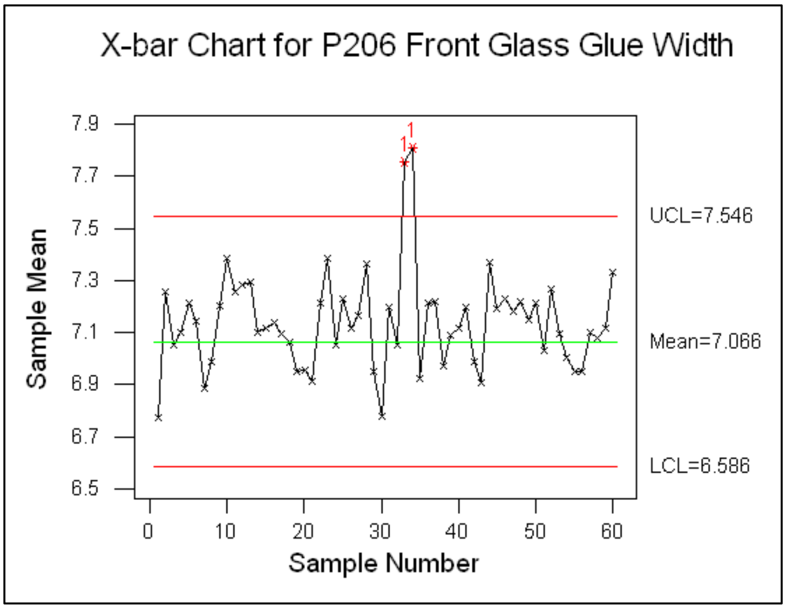

Fig. 12. $\overline{X}$ **Control Chart (Created With Minitab Software)**

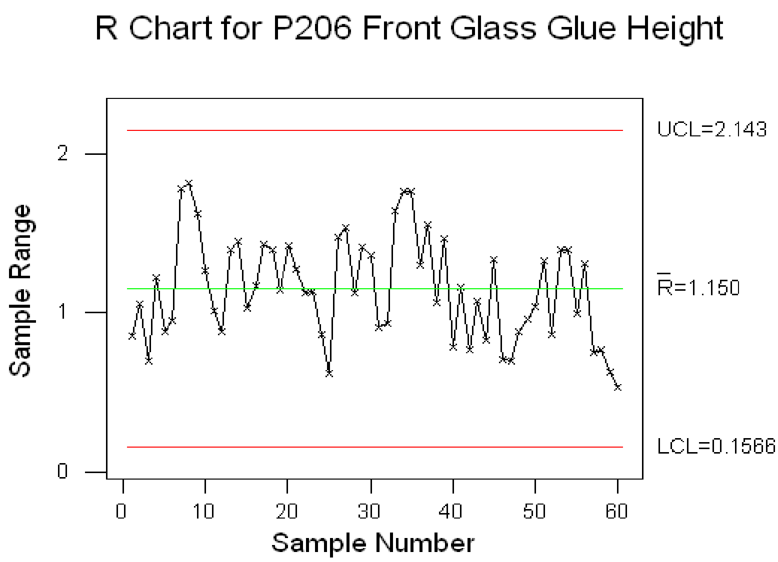

Fig. 13. ***R*** **Control Chart (Created With Minitab Software)**

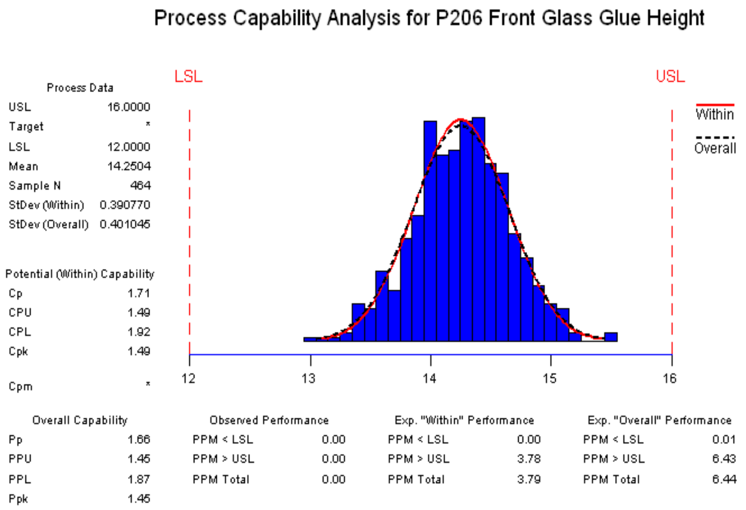

Fig. 14. Process Capability Indices for the 30-Day Samples (Created With Minitab Software)

It can be seen in Figure 14 that process capability indices are significantly above the target value of 1.33. This means that the process was under control within the technical specification limits. As a consequence, the time interval was increased to two months because the process was stable during the one-month period. $\bar{X}$ and R control charts related to this step are presented in Figure 15 and Figure 16.

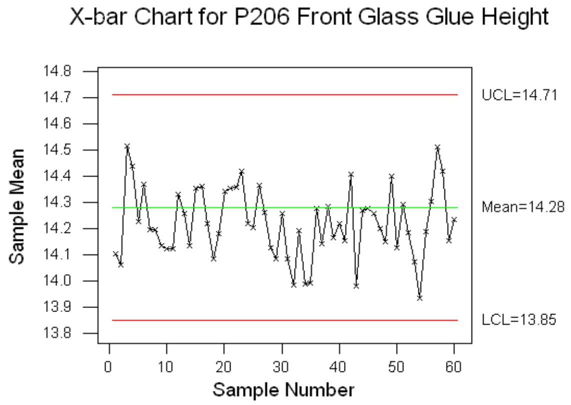

Fig. 15. $\bar{X}$ Control Chart (Created With Minitab Software)

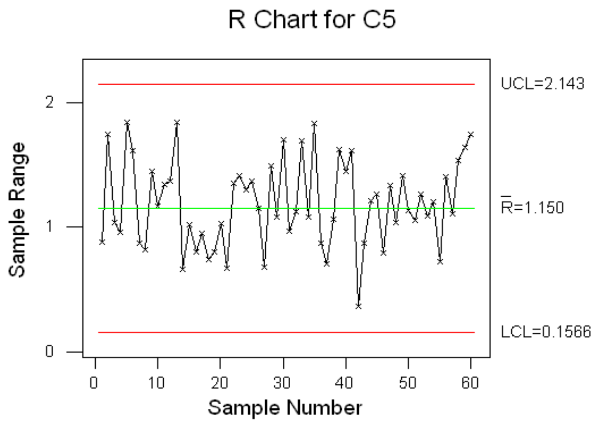

Fig. 16. *R* Control Chart (Created With Minitab Software)

Figure 15 and Figure 16 show that the process was under control. Capability indices for the two-month sampling are presented in Figure 17.

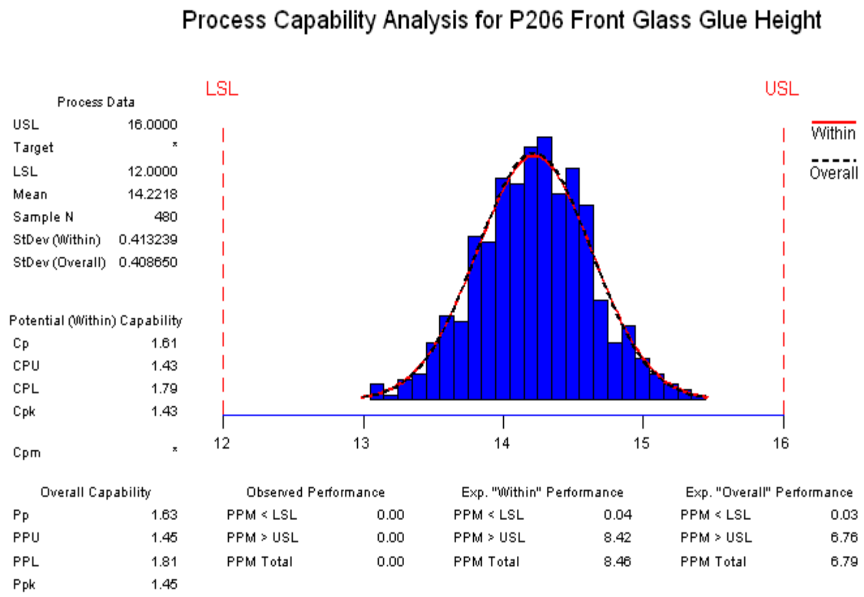

Fig. 17. Process Capability Indices (Created With Minitab Software)

It can be seen in Figure 17 that the process capability indices and process performance indices were in fine conditions. C_{pk} shows that the process capability was excellent, according to Table 1. The management took samples from the studied process after the project. The reports confirmed that the number of cars having the problem of windshield water penetration was noticeably decreased.

Discussion and Managerial Implications

1. Discussion

Process capability is defined as the ability of a process to consistently meet the specified customer requirements and is often reported in terms of process capability indices. Key findings of this study are listed as follows:

- Automated processes are usually in-control.
- Automated processes are usually capable and excellent, according to the classification presented in Table 1.

Processes that are reported to be in-control are only affected by common causes that affect the mean and variance of the productivity measures. This point is visible in the control charts. Processes that are not in-control are affected by special causes other than the common process deviation causes. An in-control process behaves consistently over time and can render consistent quality with low or no further optimization costs. For example, if the volume of the delivered milk in a milk bottle filling process is out of control, consumers might decline to buy milk bottles with lower amounts of milk. This causes them to go sour, and the company will incur a loss.

Results of the proposed methodology showed that the statistical process control can be successfully used for obviating the bottleneck of the studied process and further optimize them to maintain consistent quality over time. The proposed methodology allowed the manufacturer to thoroughly scrutinize the studied process and determine which aspects of the process are causing inconsistency. The special sampling scheme helped lowering the costs associated with sampling by assigning less frequent sampling sessions to the period where the process could be regarded as sufficiently stable.

2. Managerial Implications

As it is illustrated in the process management cycle in Figure 2, after the status of the process was obtained in terms of statistical measures, the management needed to launch appropriate corrective plans to optimize the key characteristics of the process. Such programs should be grounded on the results of process capability indices. The following managerial implications can be made according to the results of this study:

- The management could visually understand the capabilities of the processes and their quality characteristics reported in monthly reports.
- Measurements after the project by the firm confirm that the SPC project improved the quality criteria of the studied processes on the two cars.

SPC has never been meant to be implemented as a one-time project. Instead, it should be considered as an ongoing quest for better quality. This implies that each measurement made during the capability studies is valid for a particular - often short - period. This is mostly because the contributing factors to process deviations are not fixed over long periods of time. For example, in the context of the milk bottle filling process, the management of the quality control department should regularly take samples from the products at points when the risk of failure is high. If a process is in control now, it does not guarantee that it will continue to be in the future.

Conclusions

The accurate implementation of SPC could remarkably help organizations achieve favorable results in terms of efficiency and costs. This study mainly focused on gathering information about processes via process capability indices. The information obtained provides avenues for the improvement of the processes and making them even more profitable. The systematic use of process capability indices provides the management with valuable information about the ongoing processes and their possible future trend. Such information can specifically help organizations cut production costs and increase their production rate as well as boosting customer satisfaction.

Various process capability indices are proposed in the literature. Since C_p index neglects the deviation of the process from target values, this study used C_{pk}, which takes into account the deviations from the target values, besides C_p to achieve more credible results. CPL and CPU indices were used to determine how close the mean value of the process is to lower and upper technical specification limits. The combined analysis of C_p and C_{pk} gives a clearer picture of the process variability. Small C_{pk} values signify that the process should be double-checked for variability using C_p for stable decisions. C_p measures the process variability based on the distance between the technical specification limits. If $C_p > 1$, the centerline of the process is located within the lower and upper technical specification limits. However, C_{pk} measures how close the current process mean is to the intended target value and how it will change in the future.

This paper proposed a comprehensive framework for implementing SPC. First, a process capability index was defined based on a review of the literature. Then, the necessary steps towards a comprehensive methodology and the proper implementation of SPC were proposed. The methodology addressed the details of the statistical sampling procedures in different stages, adaptive sampling intervals, the indices used during the framework, and the interpretation of the results. Next, the proposed methodology was applied to a real-world case study of the windshield installation process in one of Iran's largest automotive firms to verify the capabilities of the proposed methodology. The obtained results showed that the proposed methodology could successfully improve the studied process.

1. The most important results and research advantages

$\bar{X}$ and R charts revealed that two of the samples fell outside the control limits. The two points were removed because their origins were of little importance; thus, the remaining points were located somewhere between the upper and lower control limits. Further investigations based on process capability indices revealed that the process is incapable according to process capability indices; therefore, the variation sources were identified and eliminated. After eliminating the range inconsistencies, the executive team focused on the centerline of the process to bring it closer to the target value to make the process more stable. Regulating the machinery brought the centerline of the process closer to the nominal value. Further samples during a six-month period following the study indicated that two of the samples were outside the control limits. Again, the source was identified to be stick overheating, and preventive measures were suggested to eliminate it. The results of a one-month sampling after the corrective measures revealed that the process was stabilized, and the executive team decided to increase the time interval between the samplings to two months as a result.

2. Findings of the previous related works in order to position of the findings of this study

This subsection compares the findings of this paper with related studies in the literature. Table 2 summarizes the findings of the related studies in the literature and compares them to the findings of the present study.

Table 2. Comparison of the Current Study with Related Works in the Literature

Reference	Objective	Methods	Finding
Bahria et al. (2019)	Developing an integrated production, SPC, and maintenance policy	Mathematical formulation	The integrated model could successfully improve the quality of the products, while lowering production costs.
Tsung et al. (2018)	Extending SPC to statistical transfer learning	Literature review and mathematical formulation	The concept of statistical transfer learning can be enriched with statistical process control.
Kulkarni et al. (2019)	Using SPC to improve the quality of torque wrenches used at workstations	SPC equations and charts	SPC can greatly enhance the consistency of the considered process.
Silva et al. (2017)	Improving the performance of a continuous tablet manufacturing line	Multivariate Statistical Process Control (MSPC) based on Principal Component Analysis (PCA)	MSPC could optimize the considered process.
Sousa et al. (2017)	Finding and eliminating the inefficiencies in the process	Statistical process control	SPC could successfully improve the robustness of the production process.
(Sousa et al., 2018)	Maintaining the consistency of a process over long periods	Statistical process control and process capability indices	SPC in conjunction with process capability indices was able to improve the process quality and eliminate the process quality degradation over long periods.
Luan et al. (2017)	Inferring specification bounds for products with additive manufacturing and low order sizes	Statistical process control and Exponentially Weighted Moving Average (EWMA)	The proposed extended approach was able to provide more robust specification limits for statistical shape deformation monitoring for stereolithography process.
Gaikwad et al. (2019)	Improving the operational performance of the spring support in medical devices	Statistical process control and Define, Measure, Analyze, Improve, and Control (DMAIC)	The proposed hybrid approach could increase process quality in short periods.
Fuentes-García et al. (2018)	Comparing univariate SPC with multi-variate SPC	Univaritate SPC, multi-variabte SPC (MSPC), Principal Component Analysis (PCA)	Univariate SPC performs more consistently than the multi-variate counterpart.
Jin et al. (2019)	Applying SPC for bearing fault detection	Statistical process control and Principal Component Analysis (PCA)	Statistical process control could successfully facilitate fault detection procedure.

3. Limitations and Restricting Assumptions

Control charts are based on the measurements gathered from the production line. The main measurement tool used in this study was the digital caliper. Although the caliper used in the assembly line was calibrated regularly, the error in data measurement might be one of the limitations of this study. Another limitation is that the statistical calculations were based on the assumption that the sample distribution was normal, especially in Equations 1 and 11. Although this did not necessarily wreck the calculations, using other indices and cross-checking might improve the robustness of the calculations.

4. Suggestion for Future Studies

Future studies are encouraged to tackle the limitations and restricting assumptions of this study, which is discussed in section 5.3, and make generalized approaches that can cover a broader range of studies and capability indices. Future research can also focus on a variety of final products or even the complete output of one firm or factory. Working on customers and stakeholders' needs and expectations and optimizing the process according to them are suggested for future studies.

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