



Identifying Unnatural Variation in Precision Rotational Part Manufacturing

A. Kasmin^{1*}, I. Masood¹, N. Abdul Rahman¹, A.L. Fadzillah¹, M.N. Abdol Rahman¹

¹Faculty of Mechanical and Manufacturing Engineering,
Universiti Tun Hussein Onn Malaysia, 86400, Parit Raja, Batu Pahat, Johor, MALAYSIA

*Corresponding Author

DOI: <https://doi.org/10.30880/ijie.2021.13.02.021>

Received 1 January 2020; Accepted 3 December 2020; Available online 28 February 2021

Abstract: In the manufacturing industry, it is well known that in-process variation is a major contributor to poor quality products. In order to fabricate a precise part, the source of unnatural variation (UV) needed to be properly identified, monitored and controlled while the process is running. In relation to this issue, this study aims to identify the error root causes of UV in bivariate process associated with statistical process control (SPC) chart patterns. In research methodology, in-process variation in manufacturing roller head component was discussed systematically based on real product of roller head, computer aided design (CAD) and statistical process control (SPC) chart patterns. Initially, the CAD software was used to model a precise rotational part, and to analyse the cause of UV. Then, the programming software was used to generate the artificial SPC data streams based on an established mathematical model. Data generation also involved linear correlation between two dependent variables (bivariate). The outcome of this study would be helpful for industrial practitioners as a database when applying SPC for monitoring bivariate process.

Keywords: Statistical process control, unnatural variation, rotational parts

1. Introduction

Variation is a non-uniform process in the operational system that creates a difference in the quality of the output generated. Variation refers to the width of the specification besides process capability and process performance. There are two types of variation: (i) natural variation and (ii) unnatural variation. Poor quality due to unnatural in-process variation is known as a major issue in precision manufacturing. Failure to properly identify the causes of variation leads to poor quality product. Hence, monitoring and diagnosing unnatural variation is important to improve the level of quality (Hassan et al., 2003).

For in-process quality control, statistical process control (SPC) is a common industrial tool applied for monitoring data stream patterns of quality variables. The SPC data are taken based on quantitative inspection method of in-progress parts (El-Midany et al., 2010; Yu & Xi, 2009). SPC is also one of the tools used to support quality improvement circle as shown in Figure 1.

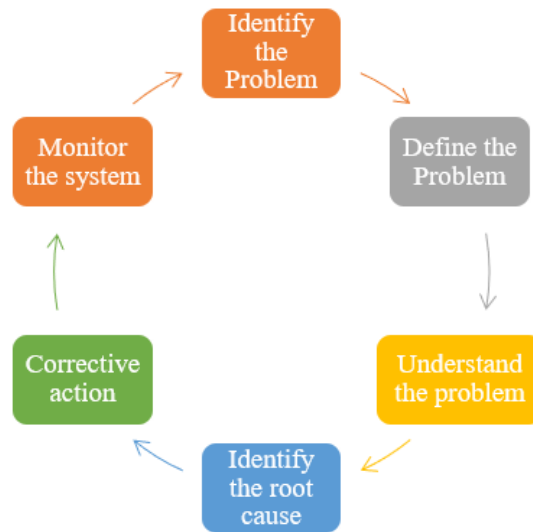


Fig. 1 - Quality improvement circle

In SPC, the Shewhart control chart patterns can be interpreted to its specific cause of variation or root cause error (Hachicha & Ghorbel, 2012). Root cause analysis (RCA) is a tool intended to help recognize what and how an event happens, and additionally why it occurs. Identifying root causes is the way to counteract similar repetition. Furthermore, RCA is a method used to address a problem or non-conformance in order to get to the root cause of the problem. However, identification of the root cause requires a high skilled industrial practitioner. Lack of knowledge in process engineering will lead to erroneous corrective action.

2. Methodology

In this study, the unnatural variation in machining precision rotational part, for example, Roller Head, was investigated based on knowledge in process engineering, graphical simulation and data modelling.

The methodology flow chart of research work is presented in Figure 2(a). The size of critical to quality (CTQ) variables was determined based on quantitative inspection using vertical profile projector and coordinate measuring machine. The measurement taken resembled the actual size of Roller Head. Then, 3D model of roller head was drafted using computer aided design (CAD) software to simulate how the unnatural variation occurred while the machining process was running. Each cause of unnatural variation indicated a specific SPC chart pattern, which is known based on knowledge and experience in process engineering and quality control. Artificial SPC data can be generated using the established mathematical model.

The manufacturing process plan of roller head is illustrated in Figure 2(b). Initially, the aluminium extrusion round bar was turned into a fuzzy size. Later, it was turned to form functional features such as inner diameter, groove and flange. The machining of inner diameters was then carried into the process of sharpening to achieve tight tolerances for bearing assembly. The critical to quality (CTQ) or functional features can also be viewed in Figure 3.

3. Results and Discussion

Unnatural variation in bivariate process occurred in turning-to-size process due to tool bluntness and loading error (refer to Tables 1 and 2). These disturbances caused undesired changes to the SPC data streams. Based on Figure 3, the roller head work piece was loaded automatically into pneumatic chuck using a robotic arm. The front side inner diameter (ID2) and rear side inner diameter (ID1) are two correlation variables (bivariate) to be monitored and diagnosed simultaneously, as well as the flange thickness (T) and groove width (L). Loading error can occur when the metal chip or hard particle were stuck between the chuck and flange or small cylindrical portion of roller head as shown in cases 1, 2, 5, 6 and 7. On the other hand, tool bluntness can occur when the tool was exposed to the cutting edge for too long, resulting in wear and tear as shown in cases 3 and 4. Tables 1 and 2 also cover the Shewhart control chart patterns associated to the identified root cause.

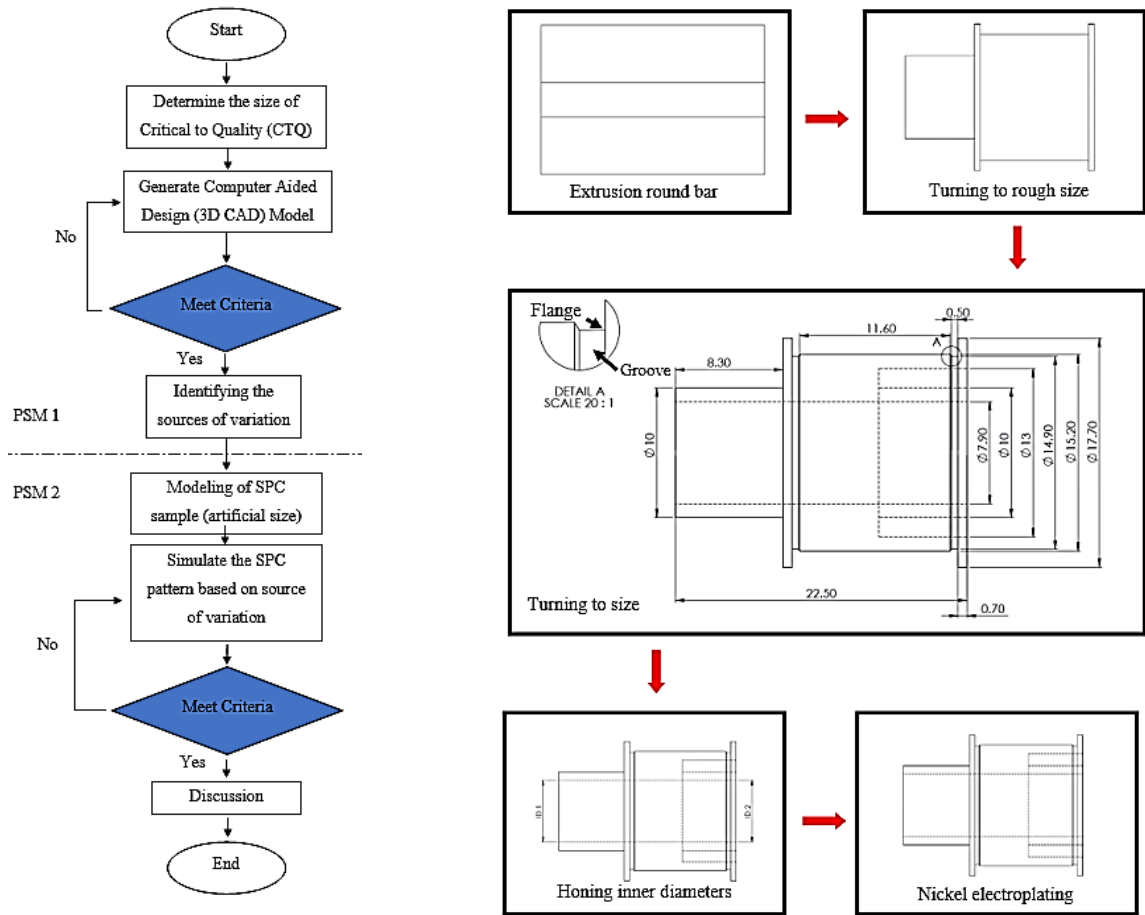


Fig. 2 - (a) Methodology flow chart; (b) Manufacturing process plan

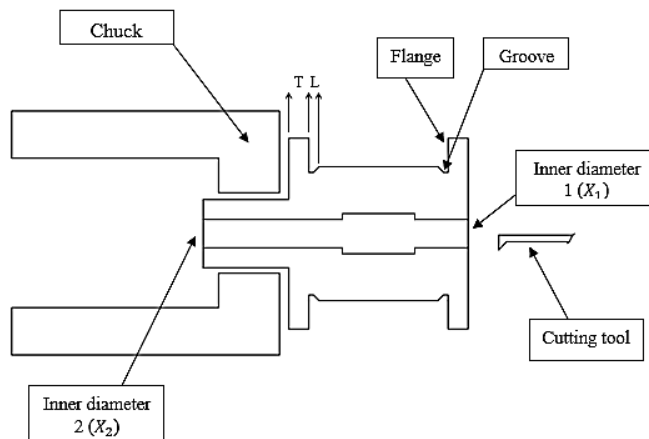


Fig. 3 - In-process inner diameters, flange and groove

Case 1: Loading error caused the work piece to be misaligned. Based on fixed cutting condition in terms of speed, feed rate and depth of cut, the ID1 became smaller (downward shift pattern) due to under-cut material, while ID2 became larger (upward shift pattern) due to over-cut material. The SPC pattern was denoted as DSUS, where symbols

DS and US represented downward shift for variable X_1 (ID1) and upward shift for variable X_2 (ID2), respectively. In this case, the variables (X_1 and X_2) were in unnatural or out-of-control condition.

Case 2: Loading error caused the work piece to be offset. Based on fixed cutting condition, both IDs became smaller (downward shift pattern) due to under-cut material. The SPC pattern was denoted as DS11, where symbols DS and 11 represented downward shift and out-of-control for both quality variables (X_1 and X_2).

Table 1 - Unnatural variation in machining inner diameters

Case	SOV diagram	ID1 (X_1)	ID2 (X_2)
Case 1: Loading error (Misaligned)		<p>Downward shift</p>	<p>Upward shift</p>
Case 2: Loading error (Offset)		<p>Downward shift</p>	<p>Downward shift</p>
Case 3: Tool bluntness		<p>Downward trend</p>	<p>Downward trend</p>

Case 3: Tool bluntness caused material removal rate at IDs to be decreasing from time to time. Based on fixed cutting condition, both IDs became smaller (downward trend pattern). The SPC pattern was denoted as DT11, where symbols DT and 11 represented downward trend and out-of-control, respectively. In this case, variables (X_1 and X_2) were deteriorating towards unnatural condition.

Case 4: Tool bluntness caused material removal rate at groove and flange to decrease from time to time. Based on fixed cutting condition, L became smaller (downward trend pattern), while T became larger (upward trend pattern). The SPC pattern was denoted as DTUT, where symbols DT and UT represented downward trend for X_1 (L) and upward trend for X_2 (T). In this case, both quality variables were deteriorating towards unnatural condition.

Case 5: Loading error caused a gap between chuck and flange. Based on fixed cutting condition, L remained in-control (normal pattern), while T became smaller (downward shift pattern). The SPC pattern was denoted as DS01, whereby symbols DS, 0 and 1 represented in-control for variable X_1 (L) and downward shift (out-of-control) for variable X_2 (T).

Case 6: This offset just affected the IDs but did not cause any changes to the groove width (L) and flange thickness (T). Based on fixed cutting condition, L and T remained in-control (normal pattern). The SPC pattern was denoted as N00, whereby symbols N and 00 represented in-control condition for X_1 (L) and X_2 (T). However,

there was another critical feature that changed, the outer diameter. This situation is known as multivariate process, whereby the third quality variable was needed for further simulation.

Table 2 - Unnatural variation in machining groove and flange

Case	SOV diagram	Width, L (X_1)	Thickness, T (X_2)
Case 4: Tool bluntness		<p>Downward trend</p>	<p>Upward trend</p>
Case 5: Loading error		<p>Normal pattern</p>	<p>Downward shift</p>
Case 6: Loading error		<p>Normal pattern</p>	<p>Normal pattern</p>
Case 7: Loading error		<p>Normal pattern</p>	<p>Downward shift</p>

Case 7: Loading error affected the groove and flange, and inner diameters simultaneously. For groove and flange, the effect was similar to Case 5. For inner diameter, the effect was similar to case 2.

Program simulation was generated to show the differences in the resulting data patterns. To run this simulation, the study applied MATLAB software to generate variation data stream generation in the roller head manufacturing process. The data generation was based on variation in Case 1.

Data generation can be modified according to some process conditions, and among the processes performed were the mean (μ), standard deviation (σ), window size (ws), correlation (ρ) and shift point (ϵ_0). Table 3 shows the patterns with different window size or number of plotted point, $ws = 50$ and $ws = 100$.

Table 3 - SPC data generation with different window Size

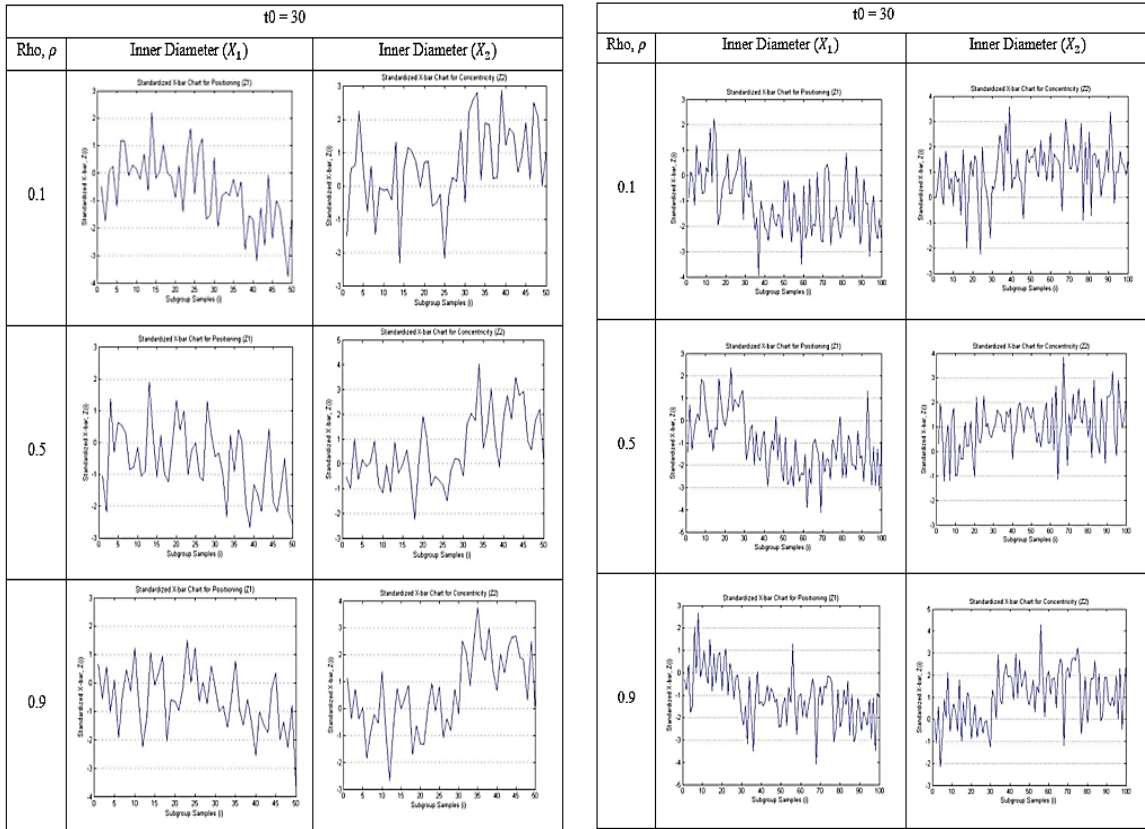


Table 4- SPC data generation with different change point (t0) and correlation (rho)

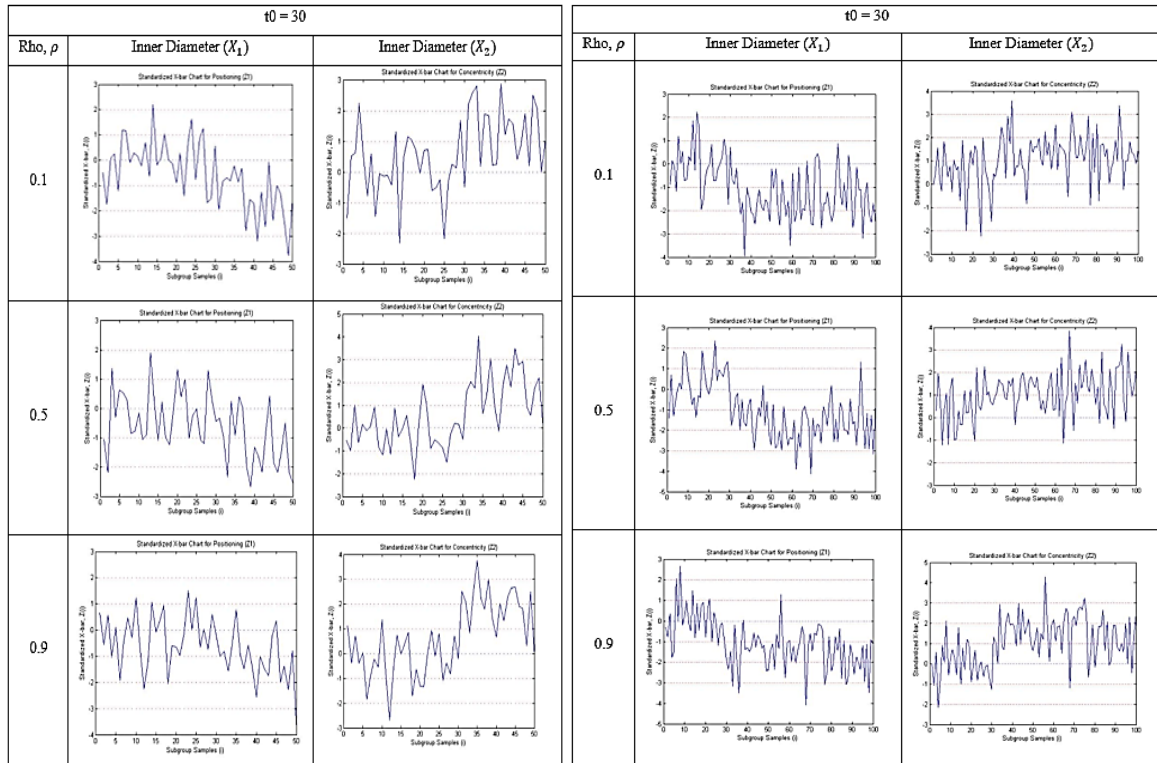


Table 4 shows the SPC patterns modified at various change points (t_0) and correlation (ρ). This process started with normal state and the shift only occurred when there was an unnatural variation such as tool bluntness and

loading error.

The SPC data generation also involved setting of correlation between bivariate process variables (X_1 , X_2), which can be presented graphically using scatter diagram. Correlation, $\rho = 0.1, 0.5$ and 0.9 showed a weak, medium and strong correlation condition between two variables (bivariate).

4. Conclusion

In conclusion, the objective of this study is achieved by showing the pattern of data for each cause of process variation. It can be shown using MATLAB software. This developed system is a system that leads to an analysis of the source of product defects. This study is proactive and reactive and at the same time achievable by comparing any changes to the product defects that have been analysed. The studies involve tool bluntness and loading error in machining operations, whereby the proposed scheme shows an effective monitoring capability in identifying the bivariate in-control process without any false alarm. Hence, this study aims to help new practitioners in the field of quality control.

Acknowledgement

The authors would like to thank Universiti Tun Hussein Onn Malaysia (UTHM) who sponsoring this work.

References

- [1] W. Hachicha and A. Ghorbel, "A survey of control-chart pattern-recognition literature (1991-2010) based on a new conceptual classification scheme," *Computers and Industrial Engineering*, vol. 63, no. 1, pp. 204–222, 2012
- [2] A. Hassan, M.S. Nabi Baksh, M.A. Shaharoun and H. Jamaludin, "Improved SPC chart pattern recognition using statistical features," *International Journal of Production Research*, vol. 41, no. 7, pp. 1587-1603, 2003
- [3] T.T. El-Midany, M.A. El-Baz and M.S. Abd-Elwahed, "A proposed framework for control chart pattern recognition in multivariate process using artificial neural networks," *Expert Systems with Applications*, vol. 37, pp. 1035-1042, 2010
- [4] J.B. Yu and L.F. Xi, "A neural network ensemble-based model for on-line monitoring and diagnosis of out-of-control signals in multivariate manufacturing processes," *Expert Systems with Applications*, vol. 36, pp. 909-921, 2009