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IDENTIFICATION OF UNNATURAL VARIATION IN MANUFACTURING OF HARD DISC DRIVE COMPONENT

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ABSTRACT

Hard disc drive (HDD) is known as a main device in a computer. In order to produce a high quality HDD, the source of unnatural variation need to be identified and controlled during manufacturing operation. In this research, simulation and modeling approach was utilized for analyzing the statistical process control (SPC) chart patterns of unnatural variation associated to its root cause error. Initially, the computer aided design (CAD) software was used to model a HDD component and to analyze the source of unnatural variation in manufacturing operation. Then, the artificial data streams for SPC were generated mathematically using MATLAB programming. The process started with normal (in-control) condition and can be followed by sudden shifts when there is a disruption of unnatural variation such as loading error, offsetting in cutting tool, and inconsistency in pneumatic pressure. The design parameters of artificial data streams can be manipulated in terms of window size (WS, length of data streams), magnitude of shifts (Sigma, size of unnatural variation), initial point of shifts (IS), and cross correlation (ρ) for bivariate data. The results indicated that the generation of artificial data streams can be adapted effectively to various condition of unnatural variation. Generally, this research has provided useful methodology for a quality practitioner in identifying the source of unnatural variation based on the SPC chart patterns.

Keywords: base casting, control chart pattern, critical to quality, hard disc drive, statistical process control.

INTRODUCTION

In quality control, the statistical process control (SPC) chart patterns should represent the relationship between process variation and its specific causes. In practice, the shift patterns indicate there are changes in material, operator or machine (Montgomery, 2009), the trend patterns indicate tool wear, whereas the cyclic patterns indicate voltage fluctuation in power supply (Chen, Lu and Lam, 2007). Nelson (1985) noted that stratification pattern represent the stratification of two subgroups data with different averages, whereas mixture pattern occur when two different populations of data are mixed from either one (not both populations) and made up the data average.

In preventive aspect, knowledge in process engineering associated with the SPC chart patterns can be applied in analyzing the source of unnatural variation that will affect the desired quality specification. Based on modeling and simulation approach, the computer aided design (CAD) software can be utilized to simulate the phenomena of unnatural variation, whereas the MATLAB software can be utilized to model the SPC chart patterns using mathematical model (Masood and Hassan, 2013). For examples, a natural process variation is represented by normal (in-control) pattern, while unnatural process variations are represented by abnormal (out-of-control) patterns such as upward and downward shifts, upward and downward trends, cyclic, systematic, stratification, or mixture. Based on a case study in manufacturing of hard disc drive (HDD) component, namely base casting, this paper presents a simulation and modeling approach for analyzing the SPC chart patterns, associated to the specific cause of unnatural variation in manufacturing operation.

METHODOLOGY

The simulation and modeling approach for analyzing the SPC chart patterns involves two phases. Phase I focuses on identification for the critical-to-quality (QTQ) features in Base Casting manufacturing operation. In this stage, knowledge or skill in process engineering is required. Phase 2 focuses on the simulation and modeling of unnatural variation. In this stage, the computer aided design (CAD) software was initially used to model a HDD component and to analyze the source of unnatural variation in manufacturing operation. Then, the artificial data streams for SPC were modeled mathematically using MATLAB programming. The process started with normal (in-control) condition and can be followed by sudden shifts when there is a disruption of unnatural variation such as loading error, offsetting in cutting tool, and inconsistency in pneumatic pressure.

CASE STUDY

In a HDD as shown in Figure-1, spindle motor roles in hard drive operation by turning the platters to provide consistent turning power for long hours use. The base casting, which is commonly made up of aluminum is used to place all the drive mechanics assemblies such as head-disk and spindle motor.

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Figure-1. Components in a HDD (CDE, 1997).

Phase-1. Identification for the CTQ features

a) Understand the manufacturing process plan

The process plan for manufacturing the base casting can be illustrated in Figure-2. Initially, die-casting process is used to form an aluminium to the basic shape with good surface quality. The casted part is then painted (in black colour) in order to avoid or to minimize oxidation. Then, the thread holes and the CTQ features are machined to form functional features such as spindle motor as shown in Figure-1.

b) Identify the CTQ features

The CTQ features were identified as positioning (P) and concentricity (C) between the counterbore head and counterbore hole as illustrated in Figure-3. These CTQ features need to be monitored and controlled simultaneously in order to maintain a proper assembly between the spindle motor and the base casting.

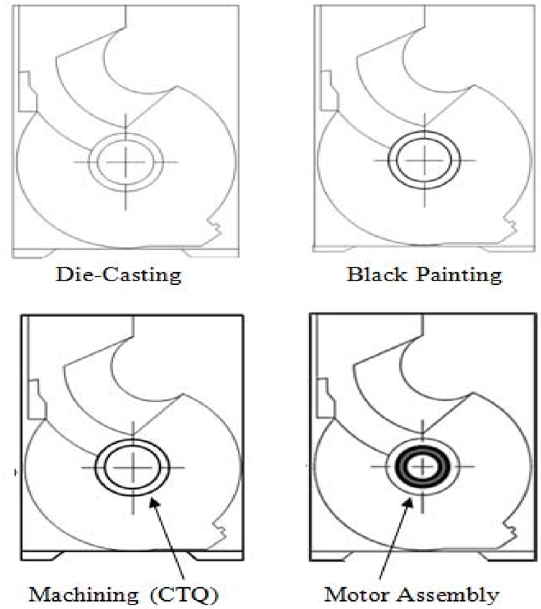

Figure-2. Manufacturing process plan for base casting.

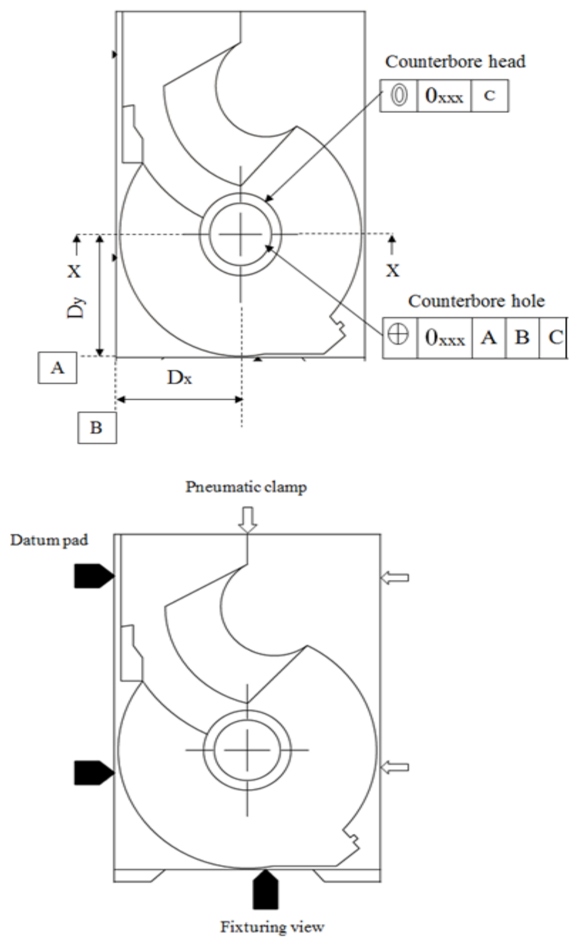

Figure-3. CTQ features.

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Phase-2. Simulation and modeling of unnatural variation

a) Analyzing unnatural variation using CAD

For machining the CTQ features, the work piece of base casting is automatically loaded into pneumatic fixture using a robotic system. The counterbore head and counterbore holes are machined using endmill and boring tool respectively. The root cause errors for unnatural variation can be simulated as loading error, offsetting tool, and inconsistent pressure as illustrated in Figure-4. These types of process disturbances can be represented as sudden shifts patterns (upward or downward shifts) in SPC data streams as shown in Table-1.

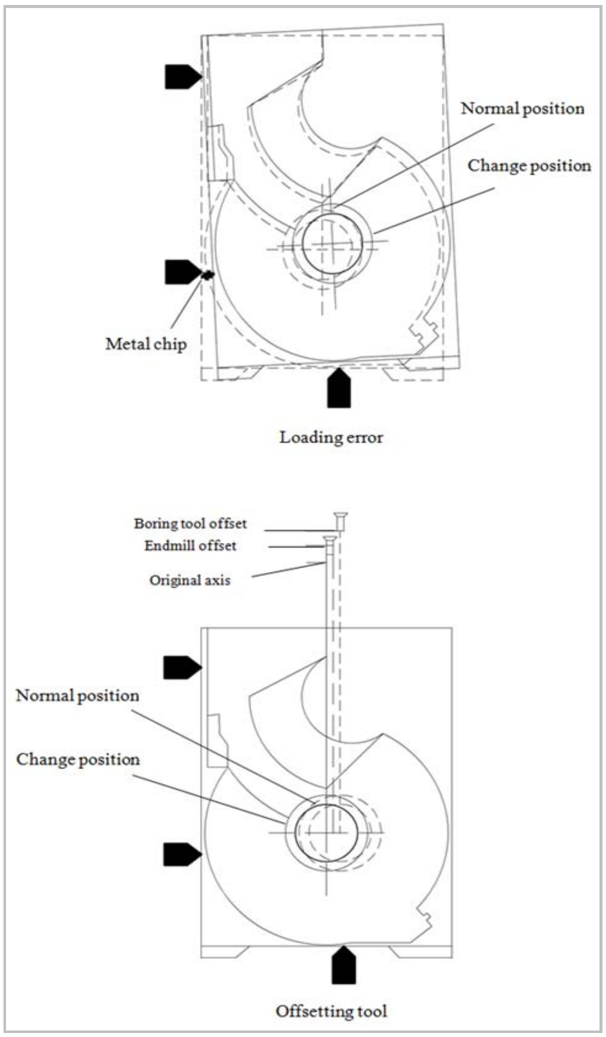
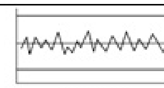
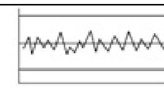
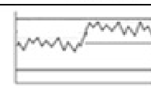
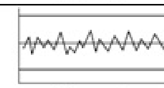
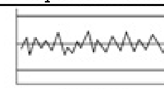
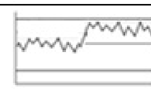
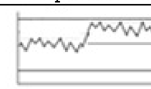


Figure-4. Unnatural variation in machining operation

Loading error due to metal chips or hard particle stuck at datum pad will cause upward shifts in P, while C remain in-control (normal pattern). On the other hand, offsetting tool due to metal chips or hard particle stuck at the tool holder will cause upward shifts in C, while P remain in-control (normal pattern). In both situations, the correlation between P and C is small ($\rho < 0.4$). In another situation, inconsistent pressure due to problem in pneumatic system will cause upward shifts in both CTQ features (P, C) at high correlation ($\rho > 0.4$).

Table-1. SPC patterns associated to unnatural variation.

	Positioning	Concentricity
In-control	 Normal	 Normal
Loading error	 Upward Shift	 Normal
Offsetting tool	 Normal	 Upward Shift
Inconsistent Pressure	 Upward Shift	 Upward Shift

b) SPC pattern modeling using MATLAB

Modeling program is utilize to generate the artificial observation samples for SPC chart associated with the unnatural variation in the manufacturing operation. It is assumed that the CTQ variables (P, C) represent a bivariate case, which is monitored jointly. Let $P_i = (P_1, \ldots, P_{24})$ and $C_i = (C_1, \ldots, C_{24})$ represent 24 observation samples for process variable 1 and process variable 2 respectively. Observation window for both variables start with samples $i = (1, \ldots, 24)$. It is dynamically followed by $(i + 1)$, $(i + 2)$, …., and so on. When a process is in-control (normal) condition, samples from both variables is assumed as identically and independently distributed (i.i.d.) with zero mean ($\mu_0 = 0$) and unity standard deviation ($\sigma_0 = 1$). Depending on process situation, the bivariate samples can be in low correlation ($\rho = 0.1 \sim 0.3$), moderate correlation ($\rho = 0.4 \sim 0.6$) or high correlation ($\rho = 0.7 \sim 0.9$).

Disturbance from assignable causes on the component variables (P only, C only, or both P and C) represent the source of unnatural variation. This occurrence could be identified by shift patterns with positive correlation ($\rho > 0$). Four possible categories of shift patterns can be considered as follows:

- N(0, 0) : both variables P_i and C_i remain in-control
- US(1,0): P_i shifted upwards, while C_i remains in-control
- US(0,1): P_i shifted upwards, while C_i remains in-control
- US(1,1): both variables P_i and C_i shifted upwards

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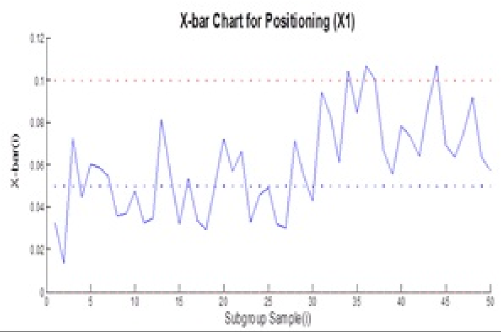
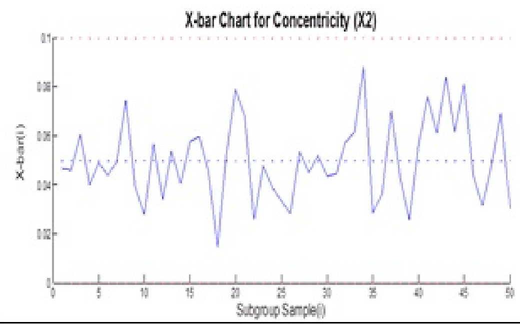
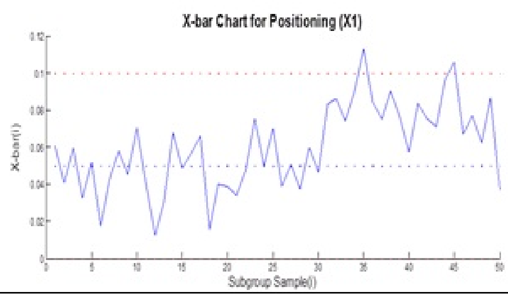
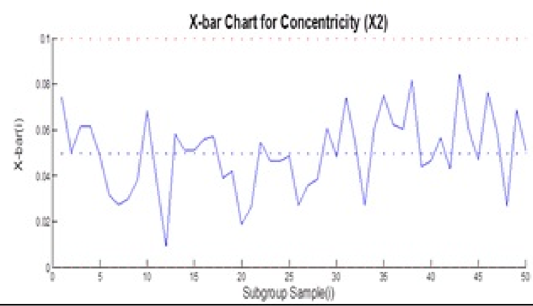
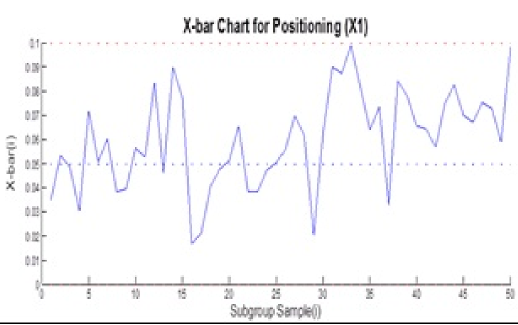
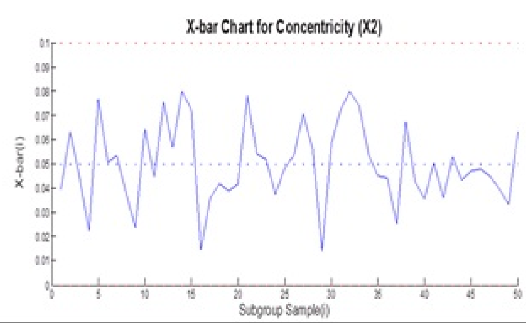
Table 2. Artificial observation sample for SPC chart.

WS = 50; IS = 30; Sigma = 1.5 standard deviation		
ρ	Positioning (P)	Concentricity (C)
0.1		
0.5		
0.9		

Based on Lehman (1977) mathematical model, the artificial observation samples of SPC chart can be generated using the following steps:

Step 1: Generate random normal variants for process variable-1 (n_1) and process variable-2 (n_2), which is identically and independently distributed (i.i.d.) within [−3, +3]:

$$n_1 = b \times r_1 \quad (1)$$

$$n_2 = b \times r_2 \quad (2)$$

Parameters (r_1, r_2) and b represent random normal variants (random data) and noise level respectively. Random normal variants are computerized generated data, whereby the noise level is used to rescale its variability. In this research, b = 1/3 is used to ensure that all random data are simulated within ± 3.00 standard deviations (does not exceed the control limits of Shewhart control chart).

Step 2: Transform random normal variants for process variable-1 (n_1) into random data series (Y_1):

$$Y_1 = \mu_1 + n_1\sigma_1 \quad (3)$$

Parameters μ_1 and σ_1 respectively represent the mean and the standard deviation for Y_1.

Step 3: Transform random normal variants for process variable-2 (n_2) into random data series (Y_2) dependent to (Y_1).

$$Y_2 = \mu_2 + [n_1\rho + n_2\sqrt{(1-\rho^2)}]\sigma_2 \quad (4)$$

Parameters μ_2 and σ_2 respectively represent the mean and the standard deviation for Y_2, whereas ρ represents the correlation coefficient between (Y_1, Y_2).

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Step 4: Compute mean and standard deviation from (Y_1, Y_2). These values represent in-control process mean (μ_{01}, μ_{02}) and standard deviation (σ_{01}, σ_{02}) for component variables.
Step 5: Transform random data series (Y_1, Y_2) into normal or shift (pattern) data streams to mimic real observation samples (X_1, X_2):

$$X_1 = h_1 (\sigma_{01} / \sigma_1) + Y_1 \quad (5)$$

$$X_2 = h_2 (\sigma_{01} / \sigma_2) + Y_2 \quad (6)$$

The magnitudes of mean shifts (h_1, h_2) are expressed in standard deviation of in-control process. A pair observation sample (X_1, X_2) represents a bivariate vector measured at time t (X_t) that follows the random normal bivariate distribution N (μ_0, Σ_0). The notations μ_0 and $\Sigma_0 = [(\sigma_1^2\ \sigma_{12})\ (\sigma_{12}\ \sigma_2^2)]$ represent mean vector and covariance matrix for bivariate in-control process with variances (σ_1^2, σ_2^2) and covariance ($\sigma_{12} = \sigma_{21}$).
Step 6: Rescale pattern data streams into a standardize range within [−3, +3]:

$$Z_1 = (X_1 - \mu_{01})/\sigma_{01} \quad (7)$$

$$Z_2 = (X_2 - \mu_{02})/\sigma_{02} \quad (8)$$

A pair standardized sample (Z_1, Z_2) represents a standardized bivariate vector measured at time t (Z_t) that follows the standardized normal bivariate distribution N (0, R). Zero value and $R = [(1\ \rho)\ (\rho\ 1)]$) represent mean vector and general correlation matrix for bivariate in-control process with unity variances ($\sigma_1^2 = \sigma_2^2 = 1$) and covariance equal to cross correlation ($\sigma_{12} = \sigma_{21} = \rho$).

The artificial patterns can be manipulated using the specific design parameters namely Window Size (WS) (length of data stream pattern), magnitude of shifts (Sigma)(size of unnatural variation), initial point of shifts (IS), and cross correlation (ρ) for bivariate data (P, C). Table-2 shows the simulation results using WS = 50, IS = 30, and Sigma = 1.5 standard deviation. The effect of cross correlation (ρ) cannot be identified graphically using X-bar control chart. However, it can be presented using scatter diagram.

CONCLUSIONS

This paper presents the simulation and modeling approach, which is useful in analyzing the SPC chart patterns of unnatural variation. Based on machining operation in manufacturing of the HDD component, process disturbance (assignable cause) such as loading error, offsetting tool, and inconsistent pressure can be simulated and modeled using CAD and SPC chart patterns respectively. The condition of shift patterns can be modeled mathematically according to the intensity or phenomena of disturbance. This approach showed that transferring knowledge in process engineering into mathematical model would be useful towards implementing preventive quality control.

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