

# Decision support tool for diagnosing the source of variation

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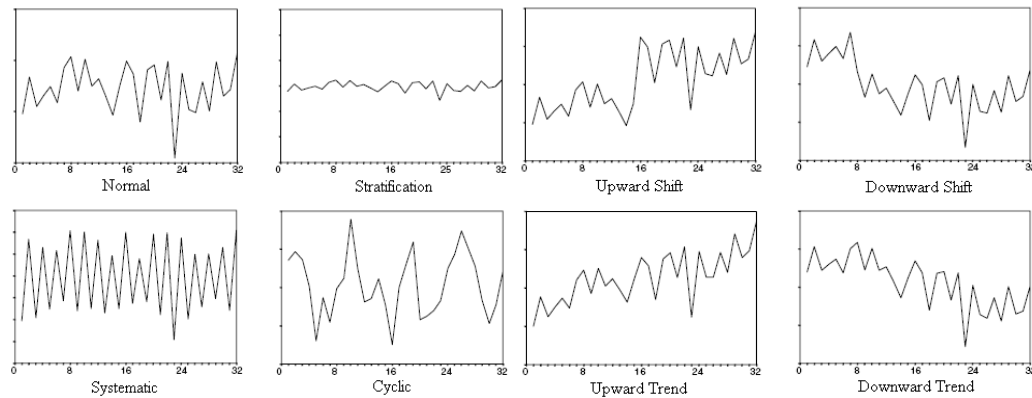
**Abstract.** Identifying the source of unnatural variation (SOV) in manufacturing process is essential for quality control. The *Shewhart* control chart patterns (CCPs) are commonly used to monitor the SOV. However, a proper interpretation of CCPs associated to its SOV requires a high skill industrial practitioner. Lack of knowledge in process engineering will lead to erroneous corrective action. The objective of this study is to design the operating procedures of computerized decision support tool (DST) for process diagnosis. The DST is an embedded tool in CCPs recognition scheme. Design methodology involves analysis of relationship between geometrical features, manufacturing process and CCPs. The DST contents information about CCPs and its possible root cause error and description on SOV phenomenon such as process deterioration in tool bluntness, offsetting tool, loading error, and changes in materials hardness. The DST will be useful for an industrial practitioner in making effective troubleshooting.

## 1. Introduction

In quality control, statistical process control chart or control chart has been widely used for monitoring out-of-control condition in manufacturing process. This condition is also known as unnatural variation. An early research in finding the sources of unnatural variation (SOV) using *Shewhart* control chart patterns (CCPs) has been reported by Nelson [1]. He found that the SOV can be represented by specific CCPs such as shifts, trends, cyclic, systematic, and stratification as shown in Figure 1. Nevertheless, there is no analysis about the relationship between CCPs and manufacturing process or geometrical features of parts being manufactured.

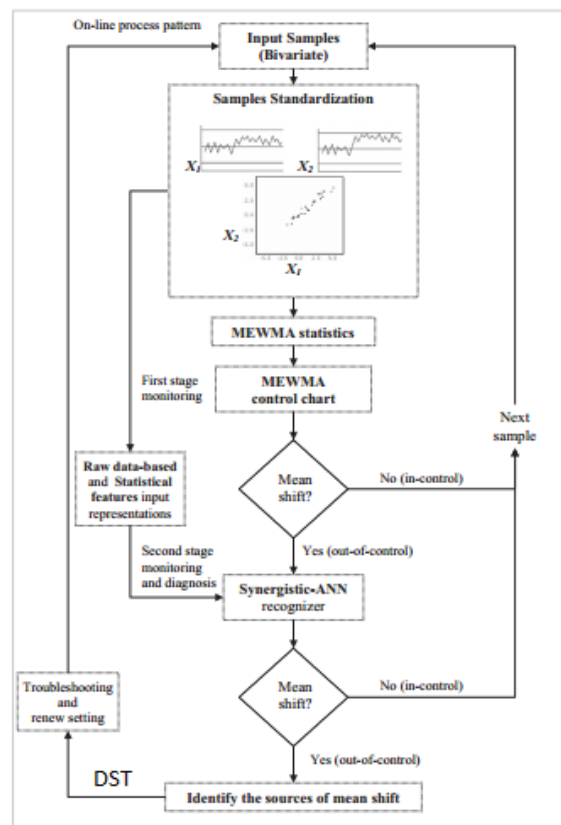
Since late 1980s, a branch of research has been focused on automated CCPs recognition using artificial intelligence theories such as expert systems, fuzzy logic, and artificial neural network (ANN) [2]. Based on the commonly known CCPs as reported by Nelson, various schemes have been proposed to improve the recognition accuracy and to enhance the recognition capability using features-based input representation [3], modular or ensemble recogniser model [4, 5], online recognition using dynamic data streams [6], and integration between traditional control chart and artificial intelligence technique [7].





**Figure 1:** *Shewhart* control chart patterns

Figure 2 shows a CCPs recognition scheme that was developed in the previous study. In order to perform two stages monitoring and diagnosis, a control chart and an artificial intelligence technique were combined into an integrated framework. The traditional control chart, namely, multivariate exponentially weighted moving average (MEWMA) was applied to monitor the CCPs in the first stage. In the second stage, an ANN recogniser model was applied to confirm and classify the type of CCPs. Details discussion on the operation procedures, MEWMA statistics, synergistic-ANN model, input representation, and training-testing operations can be found in reference [8]. Function of this scheme was limited to pattern identification and classification, whereby focus is given on improved performance recognition.



**Figure 2:** CCPs recognition scheme with an embedded DST

In this study, focus is given on operating procedures design of the decision support tool (DST) as an embedded tool for the CCPs recognition scheme. The DST roles to identify the SOV, i.e., to find details information towards manufacturing process troubleshooting. This paper is organised as follows: Section 2 describes the design methodology of DST. Identification of SOV associated to its CCPs is presented in Section 2.1. Then, the FPC analysis and DST operating procedures are discussed in Sections 2.2 and 2.3 respectively. Finally, the conclusions are outlined in Section 3.

## 2. Design Methodology

The DST design has underlying three main phases. Phase 1 involves the SOV and CCPs identification, Phase 2 focuses on Geometrical feature-Manufacturing process-Control chart pattern (FPC) analysis, and Phase 3 dealing with the computerized DST operating procedures.

### 2.1 Phase 1: Identification of the source of variation and control chart patterns

Based on *Shewhart* (X-bar) control chart, the CCPs can be categorised to natural and unnatural patterns as shown in Figure 1. The natural pattern (normal) indicates that the manufacturing process condition is in statistically in-control, whereas the unnatural patterns (upward and downward shifts, upwards and downward trends, cyclic, stratification and systematic) indicate that the manufacturing process condition is in statistically out-of-control. The DST will be applied once the manufacturing process indicates an unnatural pattern. In this study, investigation was focused on normal, shifts and trends CCPs.

### 2.2 FPC analysis

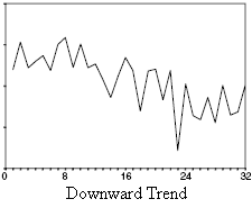
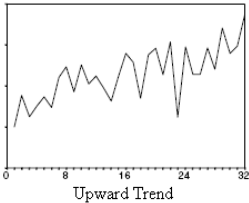
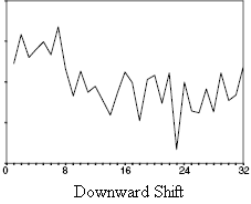
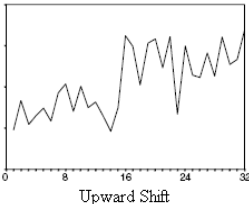
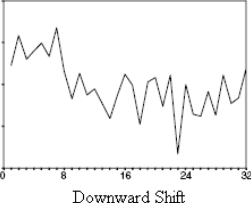
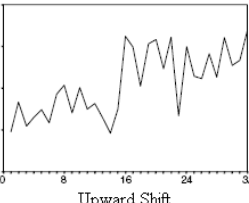
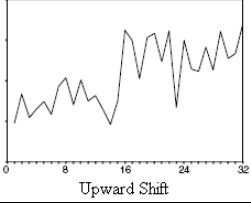
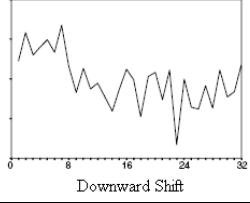
The FPC analysis was performed to find the relationship between geometrical features of part being manufactured (F), manufacturing process (P) and CCPs (C). The part geometrical features can be classified to the basic rectangular shape and rotational shape. Based on machining as the material removal process, the rectangular part will be machined using milling process, whereas the rotational part will be machined using turning (lathe) process. Milling process, for example, can be classified to (i) internal edge cutting such as bore, slot and other internal features, and (ii) external edge cutting such as length and width of parts. In practice, the existence of process disturbance and its SOV can be indicated by the specific unnatural CCPs. Table 1 shows several findings on the relationship between CCPs and its SOV such as tool bluntness, loading error, offsetting tool, and changes in material hardness.

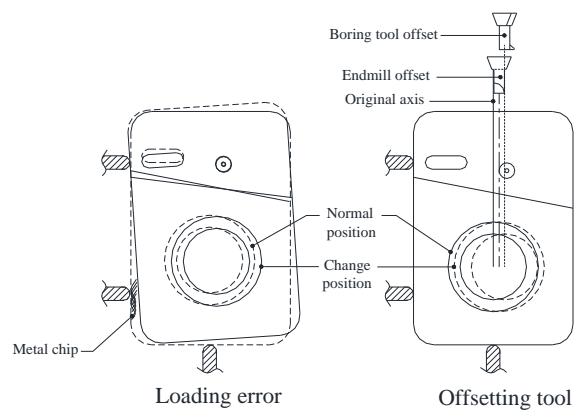
Details description for the rectangular part features are as follows: Tool bluntness can be identified by trend patterns, whereby an external edge cutting and an internal edge cutting show different effects. At an external edge cutting, tool bluntness would cause gradual increment (upward trend pattern) for the external features such as width or length of part. Inversely, the internal features such as bore diameter and slot width would be gradually decreased (downward trend pattern) at internal edge cutting.

Sudden change in material hardness of parts can be found when there is change or mixture in raw materials batch with out of specification. It can be identified by shift patterns, whereby over hardness materials and under hardness materials show an opposite effect. At external edge cutting, over hardness materials would cause sudden increment (upward shift pattern) for the external features due to reduction in material removal rate. Inversely, under hardness materials would cause sudden decrement (downward shift pattern) for the external features due to addition in material removal rate.

On the other hand, at internal edge cutting, under hardness materials would cause sudden increment (upward shift pattern) for the internal features due to increment in material removal rate. Inversely, over hardness materials would cause sudden decrement (downward shift pattern) for the internal features due to reduction in material removal rate.

**Table 1.** Unnatural patterns associated to SOV in milling process

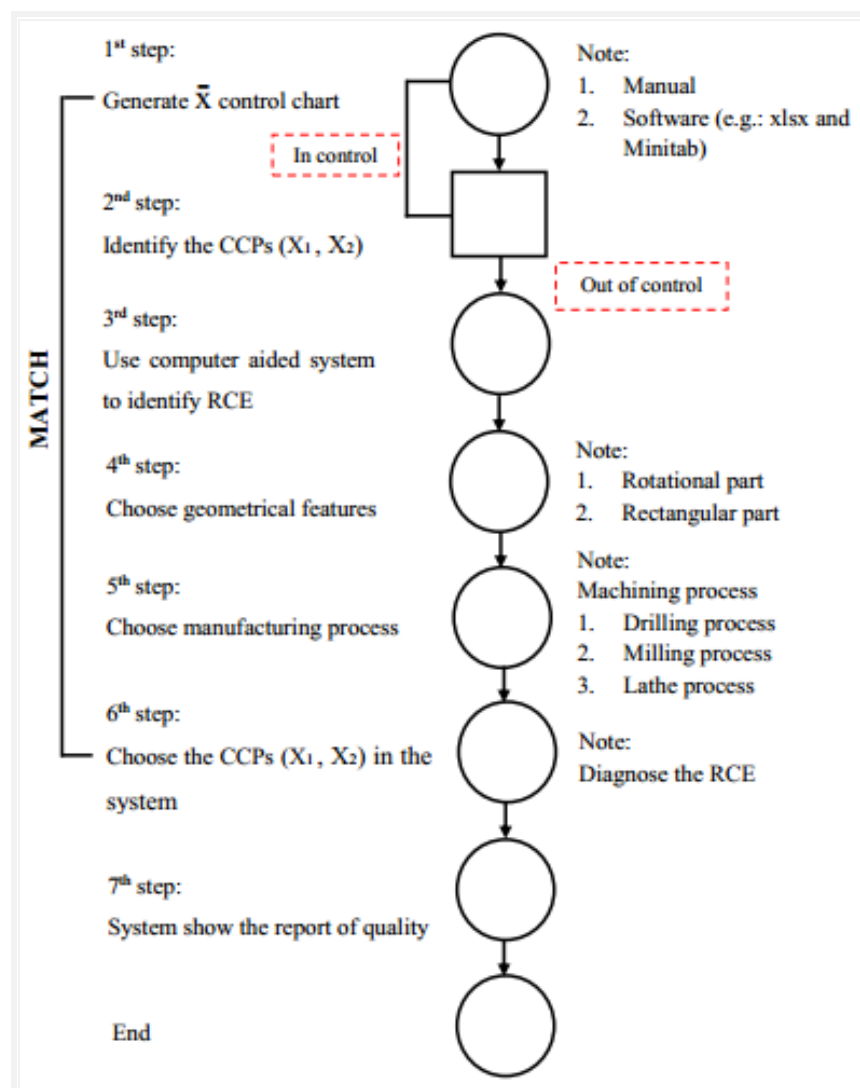
Source of Variation	Internal Edge Cutting	External Edge Cutting
Tool Bluntness	 Downward Trend	 Upward Trend
Loading Error	 Downward Shift	 Upward Shift
Offsetting Tool	Upward or Downward Shift depend on location of compensate	
Changes in Material Hardness	Over Hardness  Downward Shift	Over Hardness  Upward Shift
	Under Hardness  Upward Shift	Under Hardness  Downward Shift

**Figure 3:** Phenomenon of loading error and offsetting tool

Examples of loading error and offsetting tool can be illustrated in Figure 3. Loading error occurred when metal chips stick at the fixture datum, whereas offsetting tool occurred when metal chips stick between cutting tool and its gripper (collet). In both cases, the positioning of internal features would be suddenly increased (upward shift pattern). In general, loading error can be identified by shift patterns. In external edge cutting, loading error would cause sudden decrement (downward shift pattern) for an external feature. The positioning of internal features would also be suddenly increased (upward shift pattern) when dealing with internal edge cutting.

### 2.3 DST operating procedures

Figure 4 shows the DST operating procedure which is designed to provide information on the SOV as described in Section 2.2. The operation begins with a control chart analysis, whereby it can be done using the CCPs recognition scheme as shown in Figure 2 or other statistical process control tools. At this step, recognition accuracy of CCPs is critical. Once the CCP was recognised, the DST starts to find the root cause error (RCE) by manual or automatic selection of geometrical features of part and manufacturing process. At this step, FPC database is critical in determining the system efficiency.



**Figure 4:** DST operating procedures

### 3. Conclusion

The main focus of this study is to design a DST framework for diagnosing the SOV. The FPC analysis showed a clear relationship between geometrical features of part (F), manufacturing processes (P), and unnatural control chart patterns (C). Tool bluntness, loading error, offsetting tool, and changes in material hardness are several examples of SOV that can be found in part production. Based on such information, the computerized DST will be useful for industrial application. Since this study is limited to the machining process, further investigation can be extended to other manufacturing process such as stamping, casting, and injection moulding.

### Acknowledgement

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