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METHODOLOGY FOR DESIGNING A CONTROL CHART PATTERN RECOGNIZER IN MONITORING METAL STAMPING OPERATION

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ABSTRACT

Statistical process control (SPC) chart for variable is a powerful tool, which has been widely implemented for quality control in precision parts manufacturing. It is known to be effective in analyzing whether a manufacturing process lies within a stable or an unstable condition. In current practice, the conventional SPC chart will only detect an unstable process based on one point out-of-control. Unfortunately, this situation is too late for avoiding defective parts and leading to increase waste of materials. To overcome this issue, various studies have been focused on designing the SPC schemes based on control chart pattern recognition (CCPR) method. This advanced SPC scheme has improved the speed for detecting an unstable condition. Nevertheless, a broad of set studies in this area revealed that synthetic SPC samples have been utilized in analyzing the control chart patterns, which is limited to common causable patterns. In this research, a methodology to design a CCPR scheme using an original SPC data has been studied. Based on a case study in metal-stamping operation, the study involves (i) an identification of the unnatural variation for the critical-to-quality variables and (ii) an identification of the design elements for CCPR scheme. The sources of unnatural variation are investigated based on man, method, material, and machine. The CCPR scheme is designed using an artificial neural network (ANN) recognizer model. This methodology will be useful for industrial practitioners in identifying the root cause error in stamping-based operations based on its specific SPC chart pattern.

Keywords: artificial neural network, control chart pattern recognition, metal stamping, statistical process control.

INTRODUCTION

In quality control of precision parts, selection for an appropriate statistical process control (SPC) scheme for variables is critical in identifying the sources of unnatural variation in manufacturing process. Proper selection for an effective scheme will lead to avoid defective parts and waste of materials. Generally, the sources of unnatural variation are influenced by 4M, namely material, manpower, machine and method. Based on one point out-of-control method, the traditional SPC chart is known to be effective in detecting the existence of unnatural variation but it is too late to avoid defective parts.

In line with the development in computer sciences and information technology, research in designing SPC scheme to identify the control chart patterns (CCP) have been extensively investigated (Zorriassatine and Tannock, 1998). Pattern recognition technology that focuses on the recognition patterns and regularities data was applied in SPC for automatically recognizing CCP towards improving capability in monitoring and diagnosis. Identification of these pattern coupled with engineering knowledge of the process would lead to more specific diagnosis information. Control chart pattern recognition (CCPR) with artificial neural-network (ANN) have been widely proposed in most researches (Ebrahimzadeh *et.al*., 2013; Wang *et al*., 1998; Masood and Hassan, 2010).

ANN is a massively parallel-distributed processor that has the processor that has the ability to learn, recall and generalize knowledge (Haykin, 1999). The advantage of ANN is that it is capable of handling noisy measurements requiring no assumption about the statistical distribution of the monitored data (Bag and Gauri, 2012). It learns to recognize pattern directly through typical example pattern during a training phase. In CCPR, the ANNs were trained in order to learn specific patterns using a training set. ANN have been successfully applied to the pattern recognition task for identification of the abnormal pattern and estimation of key parameter (Guh and Tannock, 1999). Cheng (1997) noted that the ANN model can be used (i) for detecting deviation in mean or variance, and (ii) for identifying abnormal patterns on control charts. In such cases, the ANN were trained to recognize several types of out-of-control patterns such as trends, shifts, cyclic, and others. Therefore, an ANN training requires a sufficient data to be more efficient for detecting any shifts pattern. Ideally, the observation samples of SPC chart should be tapped from real manufacturing process environment. However, since a large amount of samples are required for training an ANN recognizer, synthetic SPC samples are commonly generated using Monte-Carlo simulation approach, which has been widely adopted in most researches (Masood and Hassan, 2010).

Nevertheless, a broad of set studies in this area revealed that synthetic SPC samples have been utilized in analyzing the CCP, which is limited to common causable patterns as shown in Figure-1. In this research, a design methodology to establish a CCPR scheme using an original SPC samples has been proposed.

SYNTHETIC SPC CHART PATTERNS

Automatically recognizing the CCP is an essential issue for identifying the process fluctuation effectively (Ebrahimzadeh *et.al*. 2013). The common SPC

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chart patterns can be described using descriptive words such as cyclic, normal, stratification, systematic, increasing trend, decreasing trend, upward shift and downward shift (Gauri and Chakraborty, 2008). It is also defined in terms of a run of points and limits on a SPC chart. Only the normal pattern is indicative that the process is operating under random chance causes (Bag and Gauri, 2012), all other patterns indicate that the process being monitored is not functioning correctly and requires adjustment. Figure-1 shows the eight types of common CCP (Gauri and Chakraborty, 2006; 2008).

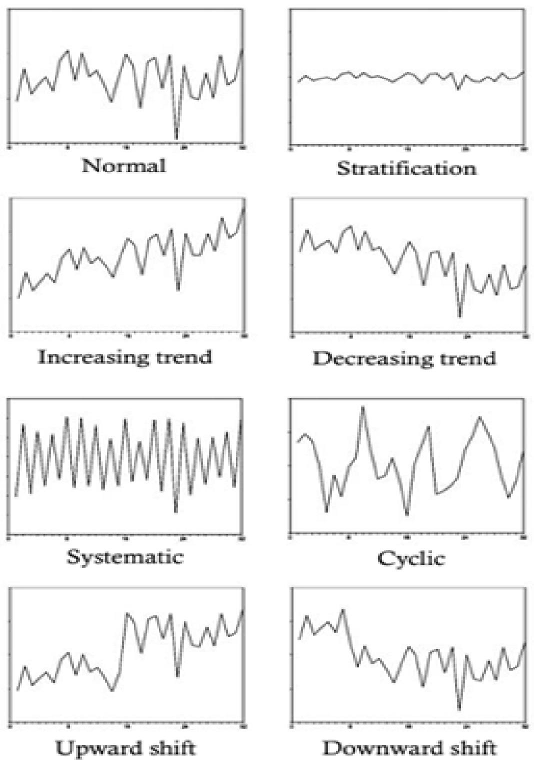

Figure-1. Common causable patterns.

In practice, shift patterns indicate there are changes in material, operator or machine. Trend patterns indicate tool wear. Cyclic patterns indicate voltage fluctuation in power supply (Chen *et al*., 2007). Whereas, stratification patterns represent the stratification of two subgroups data with different averages (Nelson, 1985) and mixture pattern occur when two different populations of data are mixed from either one (not both population) and made up the data average (Guh and Hsieh, 1999).

DESIGN METHODOLOGY

The methodology for establishing a CCPR scheme can be illustrated in Figure-2, which involves two phases. Phase 1 focuses on identification of the sources of unnatural variation (defects) in stamping operation. In this stage, fishbone diagram can be applied for analyzing the cause of defects based on 4M, namely manpower, method, materials and machine. The main causes will be identified and the CCPR scheme will be developed based on these causes. Phase 2 focuses on the training and evaluation of the CCPR scheme. In this stage, actual observation samples from SPC will be used for analysis. Figure-3 presents the details methodology flow chart for Phase 2.

Phase-1: Problem identification

i. Identification for Critical-to-Quality (CTQ) characteristics. The study is focused on stamping process of stamped parts in JP Metal Sdn Bhd.
ii. Analysis for the sources of defects. The analysis involves the In-process Quality Assurance (IPQA) data and Tooling Servicing Record (TSR). The analysis aims (i) to identify the SPC chart pattern for the unnatural (defect) process variations and (ii) to finds its respective root causes.

Phase-2: Design and evaluation

i. Design of pattern recognizer model. Investigation is focused on machine learning-based model particularly an artificial neural network (ANN) since it has been reported to be efficient for SPC pattern recognition (Pham and Wani, 1997; Hassan *et al.*, 2003; Niaki and Abbassi, 2005).
ii. Design of input representation. SPC samples for CTQ from IPQA will be transformed into input data series for pattern recognizer model. Various techniques could be applied for representing input data such as: (i) raw data-based - original samples data streams from SPC chart (Zorriassatine *et al*., 2003; Niaki and Abbassi, 2005), (ii) Features-based - original samples data is extracted to summary statistics or shape features (Pham and Wani, 1997; Gauri and Chakraborty, 2006; 2008) and (iii) combined raw-data with features-based (Masood and Hassan, 2014).
iii. Training and pre-testing. It involves 80% of the SPC samples, whereby 95% recognition accuracy (RA) to be set as performance target. Proper study in Steps (i – ii) will determine the effectiveness of the proposed scheme.
iv. Validation test. The overall performance of the scheme can be evaluated based on detection speed, reduction in false alarm rate, and diagnosis accuracy. Three performance measures can be used: (i) Average Run Length 0 (ARL_0) - this value measures the capability to avoid false alarm, (ii) Average Run Length 1 (ARL_1) – this value measures how fast the scheme able to detect unnatural variation, and (iii) Recognition Accuracy (RA) – this value measures the accuracy to classify the patterns of unnatural variation.

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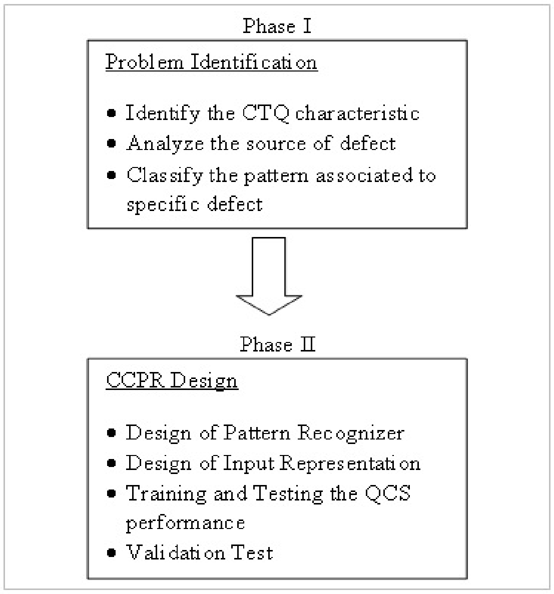

Figure-2. Phases in the design methodology.

CONCLUSIONS

This research proposed a methodology for designing and developing a CCPR scheme for QC application in metal-stamping operation. Using the original samples from the traditional SPC chart, the CCPR scheme can be established based on an identification of the unnatural variation for the CTQ variables. This will provide a major benefit for the metal stamping industry in order to reduce the defective parts and waste of materials. Thus, it will improve the productivity of the company.

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