Design Methodology of Modular-Ann Pattern Recognizer for Bivariate Quality Control

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***Abstract*— In quality control, monitoring unnatural variation (UV) in manufacturing process has become more challenging when dealing with two correlated variables (bivariate). The traditional multivariate statistical process control (MSPC) charts are only effective for triggering UV but unable to provide information towards diagnosis. In recent years, a branch of research has been focused on control chart pattern recognition (CCPR) technique. However, findings on the source of UV are still limited to sudden shifts patterns. In this study, a methodology to develop a CCPR scheme was proposed to identify various sources of UV based on shifts, trends, and cyclic patterns. The success factor for the scheme was outlined as a guideline for realizing accurate monitoring-diagnosis in bivariate quality control.**

***Index Terms*— Bivariate quality control; Control chart pattern recognition; Modular neural network; Unnatural variation.**

I. Introduction

Automated monitoring-diagnosis system in quality control is a part in advanced manufacturing system. When quality characteristics involve two correlated variables (bivariate), selection for an appropriate statistical process control (SPC) charting scheme for triggering and classifying the sources of unnatural variation has become more challenging. Challenge in monitoring involves the ability to rapidly identify quality condition whether in statistically in-control or out-of-control, with minimum false alarm. Challenge in diagnosis involves the ability to classify the sources of out-of-control.

The traditional SPC charts were designed based on monitoring approach to detect the presence of unnatural variation. Then, it was constantly being improved to be more sensitive for triggering small shifts. The control chart pattern recognition (CCPR) approach has been investigated as advanced SPC scheme for intelligence control of dynamic quality information towards improving capabilities in monitoring-diagnosis. CCPR has become an active area of research since 1980's. The applications of artificial neural network (ANN) for CCPR were among the earliest studies [1]. Since then, efficient progress has been made to enhance the performance of ANN-based CCPR schemes through various methodologies such as different input data representation and strategy, classifier design and training algorithms, among others. It is found that such methodologies aimed to achieve faster detection, accurate diagnosis, minimize false alarm and better capability. ANN is a massive parallel-distributed processor that is capable to learn, recall, and generate knowledge [2]. Several findings can be outlined as follows: (i) The properties of SPC chart patterns being recognized and classified are contaminated with noise, unknown distribution, and incomplete [3, 4]. (ii) The capability of ANN is a non-linearity, input and output mapping, adaptability, and fault tolerance. (iii) ANN is capable to control the noisy measurement and require the assumption of statistical distribution in monitored data [5]. Based on supervised learning approach, ANN shows the capability to recognize and classify patterns directly using identified series of process data streams.

In the related study, many reported researches focused on monitoring-diagnosis for multivariate process mean and/or variance using ANN [6, 7]. Numerous ANN-based models have been investigated, i.e., novelty detector, modular-ANN, ensemble-ANN and multi-module-ANN. Most of the ANN models have been successfully utilized as pattern recognizer in classifying abnormal patterns and in estimating the shifts magnitude of quality variables [8]. The training operations using ANN require for a sufficient or a large amount of data, which is quite difficult to obtain from real manufacturing process. Therefore, in many cases, synthetic SPC samples were mathematically generated [9]. ANN models that available in CCPR scheme can be used to identify abnormal patterns and detect deviations in the mean or the variance in the control chart [10].

The typical SPC chart patterns as illustrated in Figure 1 can be divided to several types according to the specific sources of variation such as normal, upward and downward shifts, increasing and decreasing trends, stratification and systematic [11]. In this study, investigation was focused on recognizing the shifts, trends, and cyclic patterns when dealing with bivariate SPC.

Based on its specific shapes and data properties, each SPC chart pattern can be discriminated mathematically. The upward and downward shifts show sudden change in the process mean such as raw materials or suppliers, changes in inspection methods, or changes in apparatus or machines. The upward and downward trends patterns are applicable for continuous movement toward either positive or negative side. Causes for trends are the gradual introduction of new raw materials, machine tools wear, loosening fixtures, equipment deterioration, and environmental change. Cyclic pattern behavior can be observed by a series of peaks and troughs occurred in the process. The typical reasons are rotation of different skill operators, systematic environmental changes or fluctuations in power supply.

Understanding the key success factor is essential to achieve efficient recognition performance. Several factors have been suggested in the reported researches such as the design of ANN structure, selection of training algorithms, training strategy and design of input data representation, among others [6 − 11].

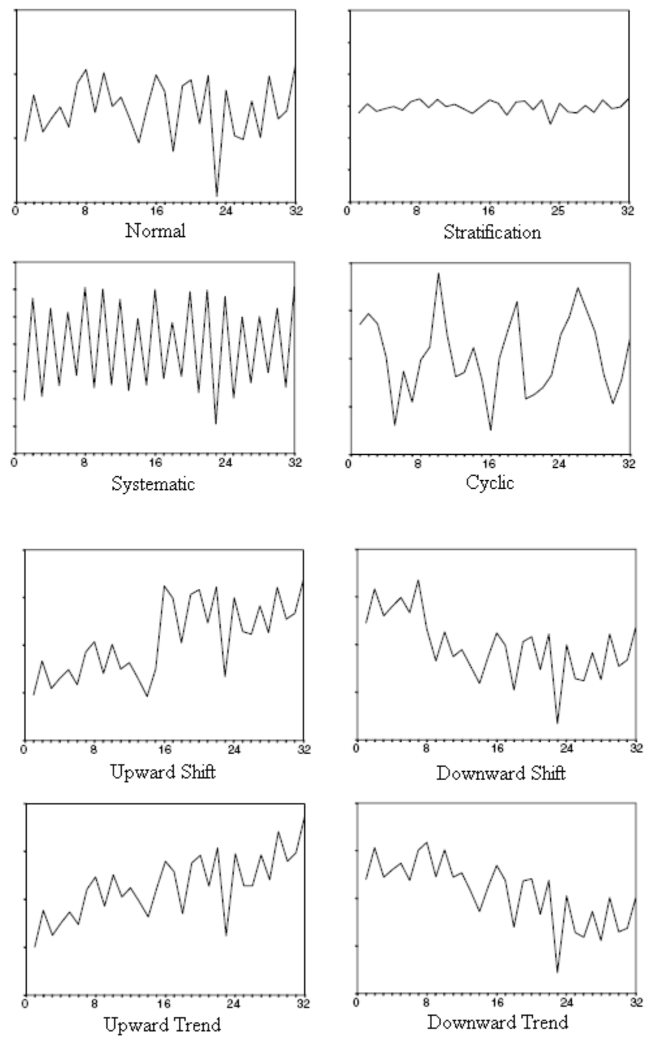

Figure 1: Typical type of SPC chart patterns

II. RESEARCH METHODOLOGY

Figure 2 shows the general phases to develop the CCPR scheme in this study. Then, the details methodology flow chart and framework of the CCPR scheme are presented in Figures 3 and 4.

Process monitoring refers to identification of process status either in a statistically in-control or out-of-control state, whereas process diagnosis refers to the identification of the source variable(s) of out-of-control state. This scheme was designed to achieve rapid detection with minimum false alarm and high accuracy in classifying the sources of unnatural variation.

A. Phase I - Problem Identification

In analysis and classification of bivariate patterns, the sources of unnatural variation are represented by shifts, trends and cyclic patterns. Shifts and trends are divided to eight (8) pattern categories, whereas cyclic are divided to three (3) pattern categories. Shifts patterns are: US10, US01, US11, DS10, DS01, DS11, USDS, and DSUS. Trends patterns are: UT10, UT01, UT11, DT10, DT01, DT11, UTDT, and DTUT. Cyclic patterns are C10, C01, and C11.

Symbols U and D represent upward and downward respectively. For example, US10 or UT10 means there is upward shifts or upward trends in the first quality variable (V1), while the second quality variable (V2) remain in a stable condition. Inversely, US01 or UT01 means there is upward shifts or upward trends in the V2, while V1 remain in a stable condition. For US11 or UT11, there are upward shifts or upward trends in both quality variables (V1, V2). In other case such as USDS and DSUS, V1 and V2 are shifted in the opposite directions.

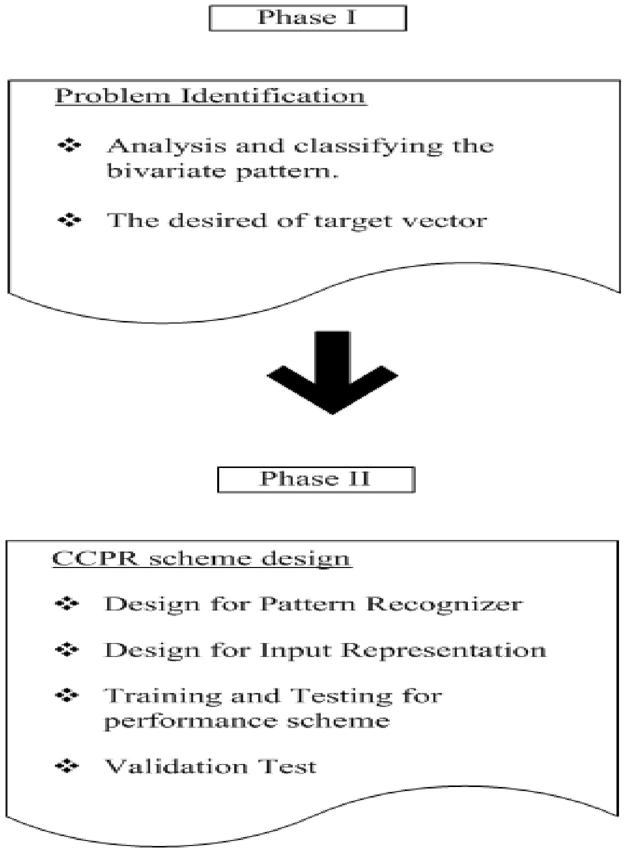

Figure 2: Phases in the design methodology

B. Phase II: Design, Training and Validation

The development of CCPR scheme involves four main steps: (i) design of pattern recognizer, (ii) design of input representation, (iii) training and pre-testing, and (iv)validation test.

In designing the pattern recognizer, modular-ANN model that consists of multi-layer perceptron's (MLP) in each isolated model was utilized. Attention was given to MLP since it has been widely used and proven effective for classification tasks [12].

In designing the input representation, various techniques can be used to represent input data for ANN such as: (i) raw data, i.e., original samples from SPC chart [13-14], (ii) features-based, i.e., original samples are extracted to shape features, summary statistics or statistical feature [15-16], and (iii) combination between raw data and features-based [17].

In training and testing, the target performance for the CCPR scheme was determined at normal (N)= $\geq$ 95%, trends (T)= $\geq$ 95%, shifts (S)= $\geq$ 95% and cyclic (C)= $\geq$ 95%. A proper study in a step of pattern recognizer and input representation designs will determine the effectiveness of the proposed scheme.

In validation test, overall performance of the CCPR scheme can be judged based on the detection speed, reduction in the rate of false alarms and the accuracy of diagnosis. Three performance measures were used: (i) Average Run Length 0 (ARL0) - measures the ability to prevent false alarms, (ii) Average Run Length 1 (ARL1) - measures the value of how fast scheme it can detect unnatural changes, and (iii) Recognition Accuracy (RA) – measures the accuracy for pattern classification.

Figure 5 shows the network architecture between feature-based ANN and raw data-based ANN in three-layer MLP model as being utilized in the new Modular-ANN recognizer. Sizes of the input representation determine the number of input neurons. Raw data input representation requires 48 neurons, whereas the statistical characteristics input representation requires only 14 neurons. Output contains seven layers of neurons, which are determined according to the number of pattern categories. One hidden layer with 26 neurons and 22 neurons is determined empirically for raw data-based ANN and features-based ANN, respectively.

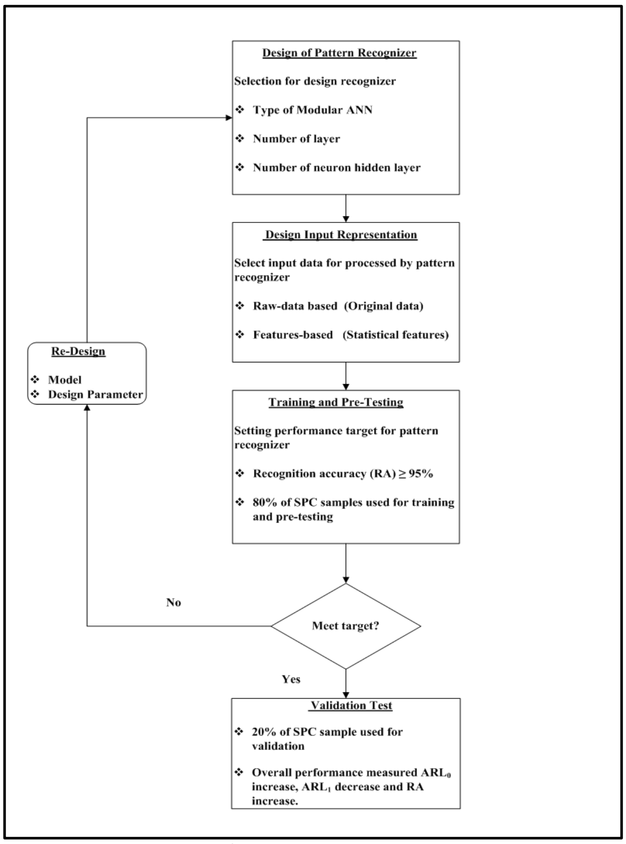

Figure 3: Process flow chart in designing CCPR scheme

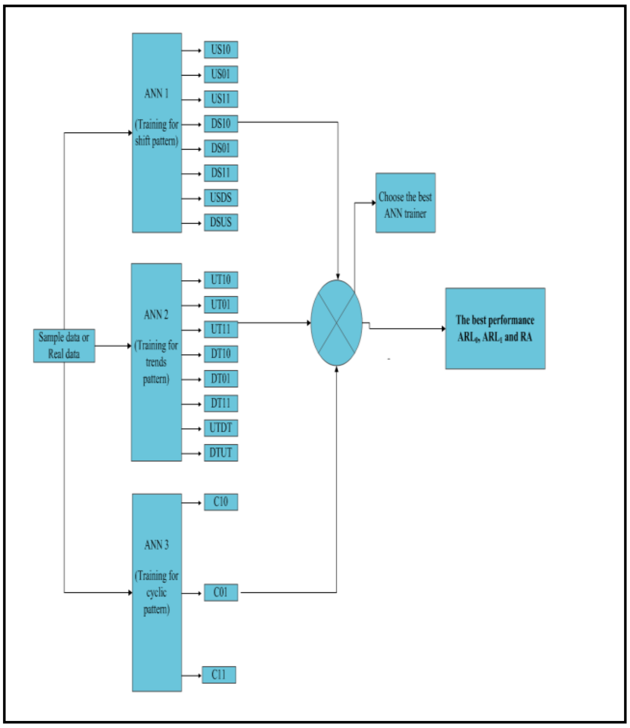

Figure 4: The CCPR scheme using modular neural network

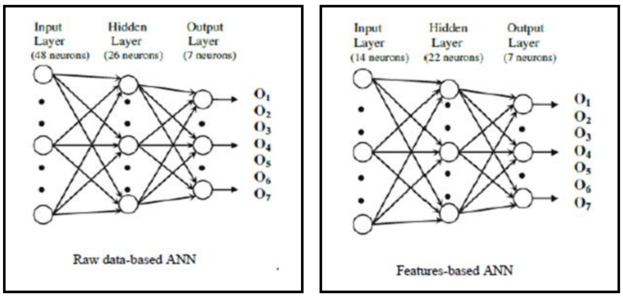

Figure 5: Network architectures

III. Conclusion

The purpose of this study is to develop a CCPR scheme in identifying various sources of unnatural variation based on shifts, trends and cyclic patterns. The scheme aims to realize accurate monitoring-diagnosis in bivariate quality control, which involves bivariate correlated quality variables. The sources of unnatural variation were represented by eight (8) categories of shifts and trends patterns, and three (3) categories of cyclic patterns. The key success factors for the scheme are strongly dependent on a proper design of input representation, recognizer model, and training and pre-testing algorithm.

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