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Identification and quantification of concurrent control chart patterns using extreme-point symmetric mode decomposition and extreme learning machines

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ABSTRACT

Control chart pattern recognition (CCPR) is an important issue in statistical process control because unnatural control chart patterns (CCPs) exhibited on control charts can be associated with specific causes that adversely affect the manufacturing processes. In recent years, many machine learning techniques [e.g., artificial neural networks (ANNs) and support vector machines (SVMs)] have been successfully applied to CCPR. However, such existing research for CCPR has mostly been developed for identification of basic CCPs. Little attention has been given to the utilization of ANNs/SVMs for identification of concurrent CCPs (two or more basic CCPs occurring simultaneously) which are commonly encountered in practical manufacturing processes. In addition, these existing research for CCPR cannot provide more detailed CCP parameter information, such as shift magnitude, trend slope, cycle amplitude, etc., which is very useful for quality practitioners to search the assignable causes that give rise to the out-of-control situation. This study proposes a hybrid approach that integrates extreme-point symmetric mode decomposition (ESMD) with extreme learning machine (ELM) to identify typical concurrent CCPs and in addition to accurately quantify the major CCP parameter of the specific basic CCPs involved. The numerical results indicate that the proposed model can effectively identify not only concurrent CCPs but also basic CCPs. Meanwhile, the major CCP parameter of the identified concurrent CCP can also be accurately quantified.

1. Introduction

Control charts are the most widely applied statistical process control (SPC) tools used to identify assignable causes in manufacturing processes. Unnatural patterns exhibited on control charts can be associated with a specific set of assignable causes provided that appropriate process knowledge is available [1]. Since the traditional Shewhart control charts do not provide any pattern-related information, a series of supplementary rules (e.g., zone tests or run rules) has thus been developed to facilitate quality practitioners in detection of unnatural patterns [1–3]. However, utilization of all the available rules could result in excessive numbers of false alarms. Because of common-cause variation in the process, a run would still have a low probability of occurrence before a control limit breach signal the process as out-of-control [4]. As pointed out by Lucy-Bouler [5], run rules are often ineffective in recognizing control chart patterns (CCPs). In addition, expert systems (ESs) have also been tried for pattern recognition tasks [6]. Nevertheless, developing such application of ESs in CCP recognition (CCPR) still remains a very hard and time-consuming task.

Various machine learning techniques, e.g., artificial neural networks (ANNs), support vector machines (SVMs), and decision trees (DTs) have recently been utilized for detecting and recognizing typical unnatural CCPs. Wang and Chen [7] proposed a neural-fuzzy model for detecting mean shifts and classifying their magnitudes in a multivariate manufacturing process. Experimental results indicated that this model outperformed the Hotelling's T^2 control chart in terms of out-of-control average run length (ARL) (i.e., the average number of inspected samples required to signal a process shift after it has occurred) under fixed Type I error. Low et al. [8] developed a back-propagation neural network (BPN)-based model for detecting mean shifts in multivariate manufacturing processes. Experimental results indicated the superiority of the proposed neural system-based model in process control while multiple quality characteristics were simultaneously considered. Barghash and Santarisi [9] utilized ANN for pattern recognition of

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the most common CCPs. In their work, in order to identify the effect of the training parameters on the performance of the neural network, a resolution IV fractional factorial experiment was utilized to explore a portion of the range of selected parameters to obtain better performance of the neural network. The results showed that many parameters such as minimum shift, shift range, population size and shift percentage, have significant effect on the performance of the ANN, while others such as network size and window size do not have major significance on the performance of the ANN. Niaki and Abbasi [10] developed a hybrid model, in which Hotelling's T^2 control chart was used for detecting the out-of-control signals, while a BPN was used for identifying the source (s) of the out-of-control signals. Aparisi et al. [11] presented a similar research work. They evaluated the correct classification percentage, and showed that the neural network is better than traditional decomposition method. Wang and Kuo [12] proposed a hybrid framework composed of filtering module and clustering module to identify six typical types of CCPs. In particular, a multi-scale wavelet filter was utilized for denoising and three fuzzy clustering algorithms were employed to compare their performance of pattern classification. Experimental results demonstrated that the proposed method performed better than the ANN-based approaches in on-line CCPR. Guh and Shiue [13] proposed a straightforward and effective model to detect the mean shifts in multivariate control charts using DT learning techniques. Experimental results showed that the proposed model could not only efficiently detect the mean shifts but also accurately identify the variables that have deviated from their original means. Jiang et al. [14] proposed a neural network–numerical fitting (NN–NF) model to recognize different control chart patterns. Specifically, a BPN was first used to recognize CCPs preliminarily, and while numerical fitting method was then adopted to estimate the parameters and specific types of the patterns. Experiment results showed that the proposed NN–NF model can not only substantially improve the recognition rate but also significantly reduce the training time. El-Midany et al. [15] proposed a framework for multivariate process CCPR. The proposed methodology used the neural networks to recognize a set of subclasses of multivariate abnormal patterns, identify the responsible variable(s) on the occurrence of abnormal pattern and classify the abnormal pattern parameters. Salehi et al. [16] proposed a hybrid learning-based model consisting of two modules. In the first module using a SVM-classifier, type of unnatural pattern can be recognized. Then by using three ANNs for shift mean, trend and cycle it can be recognized magnitude of mean shift, slope of trend and cycle amplitude for each variable simultaneously in the second module. Du et al. [17] presented a SVM ensemble approach, in which several SVMs were jointly used for classifying the source(s) of process mean shifts in multivariate control charts. Experimental results indicated that the proposed approach can perform effectively for classifying the source(s) of process mean shifts. He et al. [18] proposed a DT-based model for bivariate process mean shift monitoring and fault identification. Specifically, two DT classifiers based on the C5.0 algorithm were built, one for process monitoring and the other for fault identification. Simulation results showed that the proposed model can not only detect the mean shifts but also give information on the variable or subset of variables that cause the out-of-control signals and its/their deviate directions.

It should be noted that the above-mentioned approaches are developed for identification of basic CCPs Therefore, they are incapable for identification of concurrent CCPs (i.e., two or more basic CCPs occurring simultaneously), which may be associated with different assignable causes. Such concurrent CCPs are commonly encountered in practical manufacturing processes. For example, in the turning process, the tool may wear (resulting in a trend pattern) and this pattern may be concurrent with a cycle pattern (resulting from other assignable causes that come and go on a regular basis, e.g., unstable material). In order to identify effectively each assignable cause that is present, it is essential to identify each "target" basic CCP separately. Due to the pattern interaction and resultant complexity, concurrent CCPs are more difficult to recognize than basic CCPs. Guh and Tannock [19] proposed a sequential neural network-based approach to detect and discriminate typical unnatural CCPs. Experimental results indicated that the proposed approach is capable of recognizing single and concurrent abnormal control chart patterns and also identifying key parameters of the specific CCP(s) involved. Chen et al. [20] proposed a hybrid approach that integrates wavelet transform and BPN to identification of concurrent CCPs. In their hybrid system, concurrent CCPs are first decomposed into different levels of basic CCPs by a wavelet transform. Then, the corresponding features are presented into BPN-based classifiers for CCPR. The same idea of using wavelet filtering for pattern decomposition and reconstruction was also investigated by Wang et al. [21] and Du et al. [22]. There are several problems with these wavelet-based methods including the determination of the proper level for decomposition, heavy computation burden involved in calculating wavelet basis, the selection of threshold for the wavelet coefficients, etc. Recently, independent component analysis (ICA) methods, which have been widely used in fields such as mobile communication [23,24], have been demonstrated as effective methods for identification of concurrent CCPs. Wang et al. [25] developed a hybrid approach based on ICA and DT to identify concurrent CCPs. Experimental results showed that the proposed approach was very successful to handle most of the concurrent CCPs. However, the developed method had two limitations in real-world applications: it needs at least two concurrent CCPs to reconstruct their constituent basic CCPs and it may be incapable to identify the concurrent CCP incurred by two correlated process ("upward shift" and "upward trend" as well as "downward shift" and "downward trend"). Lu et al. [26] proposed an ICA–SVM scheme where the FastICA algorithm [27] was first applied to decompose the concurrent CCPs. Then, a trained SVM was employed to recognize the basic CCP type for each component. However, there are several shortcomings. FastICA cannot provide a unique solution as different initial conditions will result in different solutions. Moreover, these ICA-based methods require the number of observed manufacturing process data equal to or greater than the number of independent components (ICs). Inherent permutation and scaling ambiguities are also common issues for those approaches [28], which result in the incorrectly estimated sign of recovered ICs. For the concurrent CCPs, a typical example is that the upward trend patterns will be incorrectly identified as the downward trend patterns. Therefore, these ICA-based methods may be inefficient in dealing with the concurrent CCPs. More recently, singular spectrum analysis (SSA) [29] has also been reported in the literature as another effective method for identification of concurrent CCPs. Gu et al. [30] proposed a novel approach based on SSA and learning vector quantization network (LVQ) to identify concurrent CCPs. However, the parameter selection of the SSA has not been discussed in detail. Moreover, it will be time consuming and costly to accumulate enough samples to train a LVQ in practice. Further tests indicate that the solution of LVQ is not stable in that different results will be derived even with same training parameters. These shortcomings stimulated Xie et al. [31] to investigate a new method based on SVM for this problem. Xie et al. [31] proposed a novel hybrid SSA–SVM scheme integrating SSA and SVM. The SSA allows decomposition of a mixed signal given only one observation, thus it is suitable for univariate manufacturing process. Compared with the traditional ICA-based methods, The SSA does not cause any inherent permutation and scaling ambiguity in the ICs. Therefore it has the