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A Comparison Study of Distribution-Free Multivariate SPC Methods for Multimode Data

M. Grasso, B.M. Colosimo, Q. Semeraro, M. Pacella

Abstract

The data-rich environments of industrial applications lead to large amounts of correlated quality characteristics that are monitored using Multivariate Statistical Process Control (MSPC) tools. These variables usually represent heterogeneous quantities that originate from one or multiple sensors and are acquired with different sampling parameters. In this framework, any assumptions relative to the underlying statistical distribution may not be appropriate, and conventional MSPC methods may deliver unacceptable performances. In addition, in many practical applications, the process switches from one operating mode to a different one, leading to a stream of multimode data. Various nonparametric approaches have been proposed for the design of multivariate control charts, but the monitoring of multimode processes remains a challenge for most of them. In this study, we investigate the use of distribution-free MSPC methods based on statistical learning tools. In this work, we compared the kernel distance-based control chart (K -chart) based on a one-class-classi fi cation variant of support vector machines and a fuzzy neural network method based on the adaptive resonance theory. The performances of the two methods were evaluated using both Monte Carlo simulations and real industrial data. The simulated scenarios include different types of out-of-control conditions to highlight the advantages and disadvantages of the two methods. Real data acquired during a roll grinding process provide a framework for the assessment of the practical applicability of these methods in multimode industrial applications.

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