Setup Adjustment of Multiple Lots Using a Sequential Monte Carlo Method

Zilong LIAN

Department of Industrial and Manufacturing Engineering
The Pennsylvania State University
University Park, PA 16802

Bianca M. COLOSIMO

Dipartimento di Meccanica–Politecnico di Milano
Piazza Leonardo da Vinci 32
20133 Milano, Italy

Enrique DEL CASTILLO

Department of Industrial and Manufacturing Engineering
The Pennsylvania State University
University Park, PA 16802

A new sequential Monte Carlo (SMC) adjustment method is presented for solving the machine setup adjustment problem when process parameters are unknown. In setup adjustment problems, the mean of the distribution of the quality characteristic of parts can change from lot to lot due to an improper setup operation. It is shown how a first SMC approach has performance equivalent to a recently proposed Markov chain Monte Carlo method but at a small fraction of the computational cost, allowing for on-line control. A second, modified SMC rule that avoids unnecessary adjustments that can inflate the variance is also presented. A simulation approach is presented that allows tuning of the modified SMC rule to provide robust adjustment with respect to the unknown process parameters. Applications in short-run manufacturing processes are discussed.

KEY WORDS: Bayesian hierarchical models; Engineering process control; Random-effects model; Short-run manufacturing.

1. INTRODUCTION

In this article we consider the so-called "setup adjustment problem," first studied by Grubbs (1954). This problem refers to a machine that produces discrete parts in lots or batches, with the possibility of an improper setup operation resulting in an error or offset in the quality characteristic of interest. If there are considerable costs associated with producing off-target relative to the cost of adjusting a process, then adjusting is justified. This problem often arises in discrete machining processes that may experience large lot-to-lot variation. We discuss some instances within the range of applications of this problem in Section 3.

Grubbs proposed two solutions to this problem, depending on whether one considers a single lot of parts or multiple lots of parts with one setup operation before each lot is started. The objective in either case is to minimize the sum of squared deviations from target of the quality characteristic (i.e., the only relevant cost is a quadratic off-target cost). Grubbs's solutions to the setup adjustment problem were recently studied and extended by Trietsch (1998) and by Del Castillo, Pan, and Colosimo (2003a, b). In this article we focus on the second problem studied by Grubbs, the multiple-lot case, in which the initial offset can vary from lot to lot, and propose a Bayesian approach to its solution. One main difference from past efforts is that we make the more realistic assumption of unknown process parameters. The problem is then one of estimation and adjustment, not only of adjustment.

Recent work by Colosimo, Pan, and Del Castillo (2004) presents a Bayesian adjustment rule for the multiple-lot, unknown-parameters case, based on Markov chain Monte Carlo (MCMC) techniques (Gilks, Richardson, and Spiegelhalter 1996). Lian, Colosimo, and Del Castillo (2006) conducted a sensitivity analysis on the performance of this MCMC adjustment rule and modified it to obtain a rule that is more robust with respect to a wider set of process conditions.

Despite the good performance of the modified MCMC setup adjustment rule of Lian et al. (2006), this rule requires substantial computational time at each point in time, an obvious disadvantage if on-line control is needed for a process in which the time between parts is relatively short. This motivates the approach taken in the present article. As an alternative to MCMC methods, we consider sequential Monte Carlo (SMC) methods applied to the multiple-lot, unknown-parameters, setup-adjustment problem.

SMC methods also rely on Monte Carlo algorithms for the solution of Bayesian inference problems in which posterior distributions of the unknown parameters are created numerically from the generation of a large number of random variates or "particles." SMC techniques use the observation available at time $t + 1$ to update the previous posterior distributions at time t (the priors at time $t + 1$). The new posterior is then used to obtain updated inferences that are useful for adjustment purposes. In contrast to SMC techniques, MCMC methods do not use this sequential updating approach. Every time that a new observation is available, MCMC starts from the prior distributions available before observing data and passes through all data up to the current time to derive posterior distributions. Clearly, the computational efficiency of SMC techniques is relevant in production environments in which the time between consecutive parts is short and rapid on-line adjustments are required.