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Simulation-based optimization of a single-stage failure-prone manufacturing system with transportation delay

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Abstract

This paper addresses the optimization of the continuous-flow model of a single-stage single-product manufacturing system with constant demand and transportation delay from the machine to the inventory. The machine is subject to either time-dependent or operation-dependent failures. The production is controlled by a hedging point policy. The goal is to determine the optimal hedging point, which minimizes the long-run average inventory holding and backlogging cost. Sample path analysis shows that the cost function is convex and sample gradient estimators are derived. A bi-section search algorithm based on simulation and sample gradients is proposed to determine the optimal hedging point.

Keywords: Manufacturing systems; Transportation delay; Continuous-flow model; Optimization; Simulation

1. Introduction

Continuous-flow models have been widely used for optimal control and design of manufacturing systems. From the point of view of optimization, continuous parameter optimization is often simpler than discrete parameter optimization. Kimemia and Gershwin (1983) were the first to use continuous-flow model to address the production control of a failure-prone manufacturing system. They showed that the optimal production policy has a special structure called hedging point policy in which a nonnegative production surplus should be maintained at times of excess capacity in order to hedge against future capacity shortages caused by machine failures. This pioneer work has triggered many interests and a very rich literature is now available for flow control of failure-prone manufacturing systems. In this paper, we focus on simulated-based techniques.

In a pioneer work, motivated by buffer allocation optimization problem in a production line, Ho et al. (1979) developed an efficient technique called perturbation analysis (PA). It enables one to compute the sensitivity of a performance measure with respect to some system parameters by a single simulation run. Ho and Cao (1991) developed an infinitesimal perturbation analysis (IPA) technique for the efficient computation of n-dimensional gradient vector of performance measure, $J(\theta)$, of a discrete event dynamic system (DEDS) with respect to its parameter vector θ (such as buffer size, inflow

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rate, service rate, etc.) using only one statistical experiment of the system. This is opposed to the traditional method of estimating sensitivity information such as $\mathrm{d}J(\theta)/\mathrm{d}\theta$. IPA calculates directly the sample derivative $\mathrm{d}L(\theta,\xi)/\mathrm{d}\theta$ using information on the nominal trajectory (θ,ξ) alone, where L denotes the sample performance measure and ξ, represents a vector of random variables. The basic idea is the following: if the perturbations introduced into the trajectory (θ,ξ) are sufficiently small, then the event sequence of the perturbed trajectory $(\theta+\Delta\theta,\xi)$ remains unchanged from the nominal, i.e., the two trajectories are deterministically similar in the order of their event sequence. In this case, the derivative $\mathrm{d}L(\theta,\xi)/\mathrm{d}\theta$ can be calculated easily (see also Glasserman, 1990).

Yan (1995) investigated a manufacturing system with a failure-prone machine. He illustrated how to devise gradient estimators based on the observations in a single simulation run and then designed an iterative algorithm, a constant step-size stochastic approximation (SA) procedure for finding the optimal number of circulating kanbans that minimizes the long-run average cost. Caramanis and Liberopoulos (1992) applied IPA to calculate the gradient estimates for the single unreliable machine-multiple product system. Haurie et al. (1994) proposed an IPA-based SA algorithm for the parameter optimization problem of continuous-flow model of a failure-prone manufacturing system with multiple part types. Sufficient conditions for convergence of SA are given for single-machine system and they observed that it is difficult to extend the results to two-machine problem.

For failure-prone tandem manufacturing systems, Yan et al. (1994) applied PA to obtain consistent gradient estimates. They estimated the optimal threshold values by using SA algorithm and proved its convergence to the optimal threshold values. Kushner and Vázequez-Abad (1996) generalized these results by weakening the conditions. Yan et al. (1999) studied the two-machine case of failure-prone tandem systems and derived an optimal buffer-control policy to minimize a long-run average cost function.

Xie (2002a) considered continuous-flow transfer lines composed of two machines subject to time-dependent failures and separated by a buffer of finite capacity. He established a set of evolution equations that determines the continuous state variables, i.e., cumulative productions and the buffer level, at epochs of discrete events. Based on these evolution equations, he proved the concavity of the throughput rates of the machines and derived gradient estimators and proposed a single sample path optimization algorithm. Xie (2002b) extended this approach to the performance evaluation and optimization of failure-prone discrete-event system by using a fluid-stochastic-event graph model, which is a decision-free Petri net.

Fu and Xie (2002) estimated the derivatives of the throughput rate with respect to buffer capacity for continuous-flow models of a transfer line comprising two machines separated by a buffer of finite capacity and subject to operation-dependant failures. They showed that IPA leads to biased gradient estimators and proposed smoothed PA estimators.

Stochastic fluid models (SFMs) have recently been considered as an alternative paradigm to *queuing networks* for modeling and simulation of telecommunication networks (see Cassandras et al., 2002; Panayiotou and Cassandras, 2004; Wardi et al., 2002; Wardi and Melamed, 2001; Wardi and Riley, 2002; Yu and Cassandras, 2004). SFM networks offer two advantages over their queuing-networks: (i) they can be faster to simulate, (ii) they give unbiased IPA gradient estimators for a large number of networks configurations, queuing disciplines and performance functions. Cassandras et al. (2003) used SFMs for control and optimization (rather than performance analysis) of communication network nodes processing two classes of traffic with one being uncontrolled and the other subject to threshold-based buffer control. All these works to date have been limited to a single node SFM. Only one exception is that of Sun et al. (2003), which considered a SFM consisting of several single-class nodes in tandem and performed PA for the node queue contents and associated event times with respect to a threshold parameter at the first node.

Continuous-flow models are natural models for process industry. They are also widely used for discrete manufacturing systems in the case of high production volume or in the investigation of the impact and strategies to cope with infrequent but important random events such as machine failures and demand changes. In such situations, it is cumbersome to track individual parts part by part either in performance evaluation or real-time flow control as it needed in a pure discrete flow model. The number of possible states is huge and is usually beyond reasonable limits, the number of events to consider in a simulation study is very large as