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Expectation constrained stochastic nonlinear model predictive control of a batch bioreactor

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Model predictive control (MPC) refers to a class of control methods which explicitly employ a model to solve an open-loop optimal control problem (OCP) over a finite sequence of control actions at each sampling instance. Its main advantages are its ability to deal with constraints and strongly coupled, multi variable plants (Maciejowski, 2002). MPC based on linear models is relatively mature and well-established. Many systems, however, display strong nonlinear behaviour and have stringent performance demands, which necessitate the use of nonlinear model predictive control (NMPC) (Findeisen et al., 2003). In particular, batch processes require NMPC approaches because of unsteady state operation. NMPC further allows the direct optimization of economic criteria, which has attracted significant attention in recent years (Rawlings and Amrit, 2009). Nominal NMPC however is prone to errors due to unaccounted uncertainties. Consequently, there have been significant developments in robust NMPC (RNMPC) to handle uncertainties explicitly. RNMPC assumes uncertainties are deterministic and bounded. The main methods for RNMPC are min-max NMPC and tube-based NMPC. An alternative to RNMPC is stochastic NMPC (SNMPC) in which the uncertainties are given by known probability distributions. In this framework constraints are addressed in a probabilistic sense. Unlike RNMPC, in SNMPC the control of the objectives can be systematically traded-off with an admissible level of constraint violation (Mesbah, 2016). Important methods for SNMPC include polynomial chaos (Mesbah et al., 2014) and an approach based on Markov Chain Monte Carlo (MCMC) (Visintini et al., 2006). In this paper a tractable approximation to SNMPC is proposed based on Monte Carlo (MC) simulations, known as "sample-average approximation (SAA)" in stochastic programming (Homem-de Mello and Bayraksan, 2014). Variance reduction (VR) techniques are compared and applied to reduce the sample size required. The performance of the MC SNMPC is illustrated on a semi-batch bioreactor case study and compared to the performance of a nominal NMPC.

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