Machine Learning-Based Distributed Model Predictive Control of Nonlinear Processes

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Abstract

This work addresses the design of distributed model predictive control (DMPC) systems for nonlinear processes using machine learning models to predict nonlinear dynamic behavior. Specifically, sequential and iterative distributed model predictive control systems are designed and analyzed with respect to closed-loop stability and performance properties. Extensive open-loop data within a desired operating region are used to develop Long Short-Term Memory (LSTM) recurrent neural network models with a sufficiently small modeling error from the actual nonlinear process model. Subsequently, these LSTM models are utilized in Lyapunov- based DMPC to achieve efficient real-time computation time while ensuring closed-loop state boundedness and convergence to the origin. Using a nonlinear chemical process network exam- ple, the simulation results demonstrate the improved computational efficiency when the process is operated under sequential and iterative DMPCs while the closed-loop performance is very close to the one of a centralized MPC system.

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