SESSION D: AUTOMATIC CONTROL, IT AND ARTIFICIAL INTELLIGENCE

Event-triggered ADP for asymptotic output regulation of unknown linear systems

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ABSTRACT

The deployment of learning-based controllers in modern networked cyber-physical systems is constrained by bandwidth limitations, partial state observability, and parametric uncertainties. Traditional adaptive dynamic programming (ADP) relies on full-state feedback and periodic sampling, inducing network congestion and steady-state tracking errors. This paper develops a fully data-driven dynamic event-triggered output regulation scheme operating on measurable input-output streams. By integrating a projection-safeguarded value iteration algorithm with an internally evolving dynamic threshold variable, we guarantee asymptotic convergence of the sampling error without requiring an admissible initial stabilizing policy or explicit system identification. Simulations on a third-order uncertain plant demonstrate a 54.0% reduction in control transmissions and an 8.2% suboptimality bound relative to the model-based LQR baseline, with reconstruction error consistently decaying below 10^{-3}. The framework provides a computationally efficient, theoretically rigorous architecture for resource-constrained cyber-physical networks.

KEYWORDS

Adaptive dynamic programming, Dynamic event-triggered control, Data-driven output feedback, Value iteration, Optimal output regulation, Networked control systems

1. INTRODUCTION

Networked cyber-physical systems require optimal control under strict communication constraints and parametric uncertainties. Traditional model-based and periodic ADP frameworks suffer from excessive bandwidth usage, reliance on full-state measurements, and vulnerability to unmodeled dynamics. Data-driven ADP and reinforcement learning synthesize near-optimal policies directly from input-output trajectories [1]. However, their deployment is hindered by static event-triggered mechanisms (SETM) that introduce measurable residual steady-state errors, limiting actuator precision under constant-threshold conditions [2]. Furthermore, conventional policy iteration schemes mandate an admissible initial stabilizing gain K_0, a condition rarely met in open-loop unstable plants [3, 4].

Recent output-feedback ADP architectures reconstruct states from historical data but retain static triggering thresholds, decoupling updates from evolving dynamics and forcing rigid trade-offs between resource conservation and transient robustness [5, 6]. While works [6, 7] reduce control updates, they neglect asymptotic error convergence, resulting in persistent tracking offsets. Additionally, unaddressed noise propagation through Kronecker-based reconstruction matrices accelerates actuator wear under abrupt torque jumps, while the absence of explicit bounds linking triggering parameters to performance degradation leaves practitioners without predictable tuning guidelines. Value iteration (VI) offers a model-free alternative, yet its integration with dynamic event-triggering remains theoretically underdeveloped [3].