STU FCHPT

Experimental Application of Stochastic Approximated MPC

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Abstract

This paper experimentally validates the stochastic approximated model predictive control (MPC). Specifically, the random shooting (RS)-based approximated MPC is designed to offer an exploitable and solver-free alternative to standard MPC. However, the original RS-based MPC lacks guarantees for recursive feasibility and closed-loop stability. To address this, a recursive RS-based method with a dual-mode control strategy and a support controller was implemented, ensuring feasibility and stability. A case study demonstrates successful offset-free reference tracking on a fast-dynamics system, proving the methods effective under strict computational constraints and offering a fast, solver-free alternative without compromising stability or feasibility.

Random Shooting Approximated MPC

To reduce the computational burden of traditional MPC, an RS-based approximated MPC was proposed. It generates multiple random control sequences $u_1, \dots, u_N$ and evaluates their feasibility under constraints $\mathcal{X}, \mathcal{U}, \mathcal{T}$, and evaluates their performance via the MPC cost function:

$$J = x_N^\top P x_N + \sum_{k=0}^{N-1} x_k^\top Q x_k + u_k^\top R u_k.$$

Out of $N_{\max}$ iterations, the feasible sequence with the lowest cost is selected. Suboptimality of this method decreases as $N_{\max}$ increases.

Recursive Random Shooting Approximated MPC

This method integrates RS with the recursive structure of MPC to guarantee recursive feasibility and closed-loop stability. A dual-mode control strategy improves computational efficiency: when the measured state x_0 lies within a terminal set $\mathcal{T}$, a Linear Quadratic controller with gain K_{LQ} ensures stability and performance; otherwise, the random shooting method is applied. To further guarantee recursive feasibility and stability, a support controller is designed, feasible inside the set $\mathcal{X}$, with control inputs U_{sup} and cost function J_{sup}.

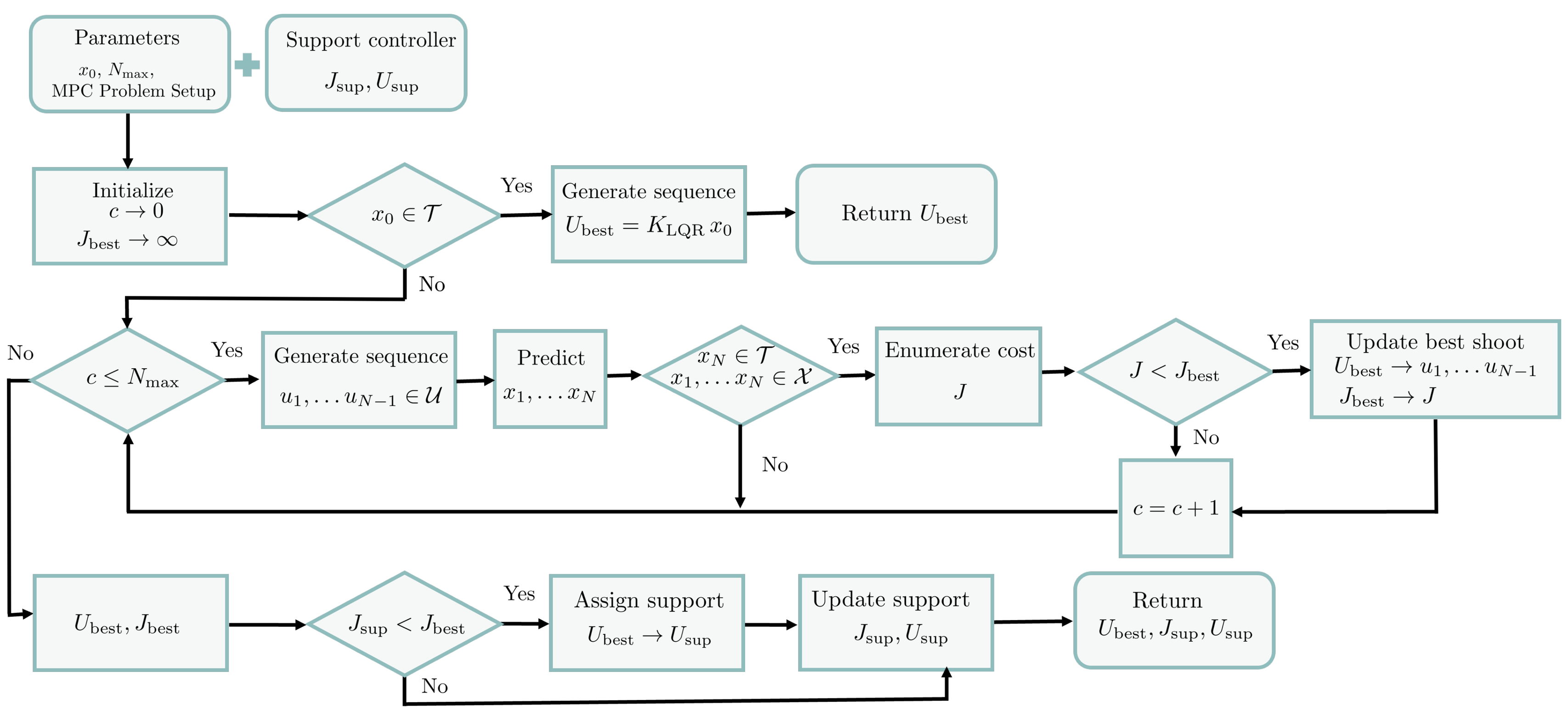

Figure 1. Flowchart of the recursive random shooting-based approximated MPC.

Tracking Problem

Incorporating reference tracking into the approach allows the system to track reference effectively. To ensure offset-free tracking, an integral action is added to the system by augmenting the states:

$$\hat{x}(k) = \left[x(k),\ \sum_{j=0}^{k} (y_{\mathsf{ref}}(j) - y(j)) \right]^\top.$$

Controlled Plant

The Flexy device is a fast SISO system with a 0.1 s sampling time, the control input is a fan-actuated airflow and a sensor-based bending as the control output, modeled using the Strejc method and discretized with integral action for offset-free tracking.

Figure 2. Controlled Plant – Flexy device

Results

Three control strategies were verified on the Flexy device: RS-based approximated MPC, its recursive variant, and conventional MPC. All achieved offset-free tracking within constraints, with the recursive RS method offering the best trade-off between complexity and performance.

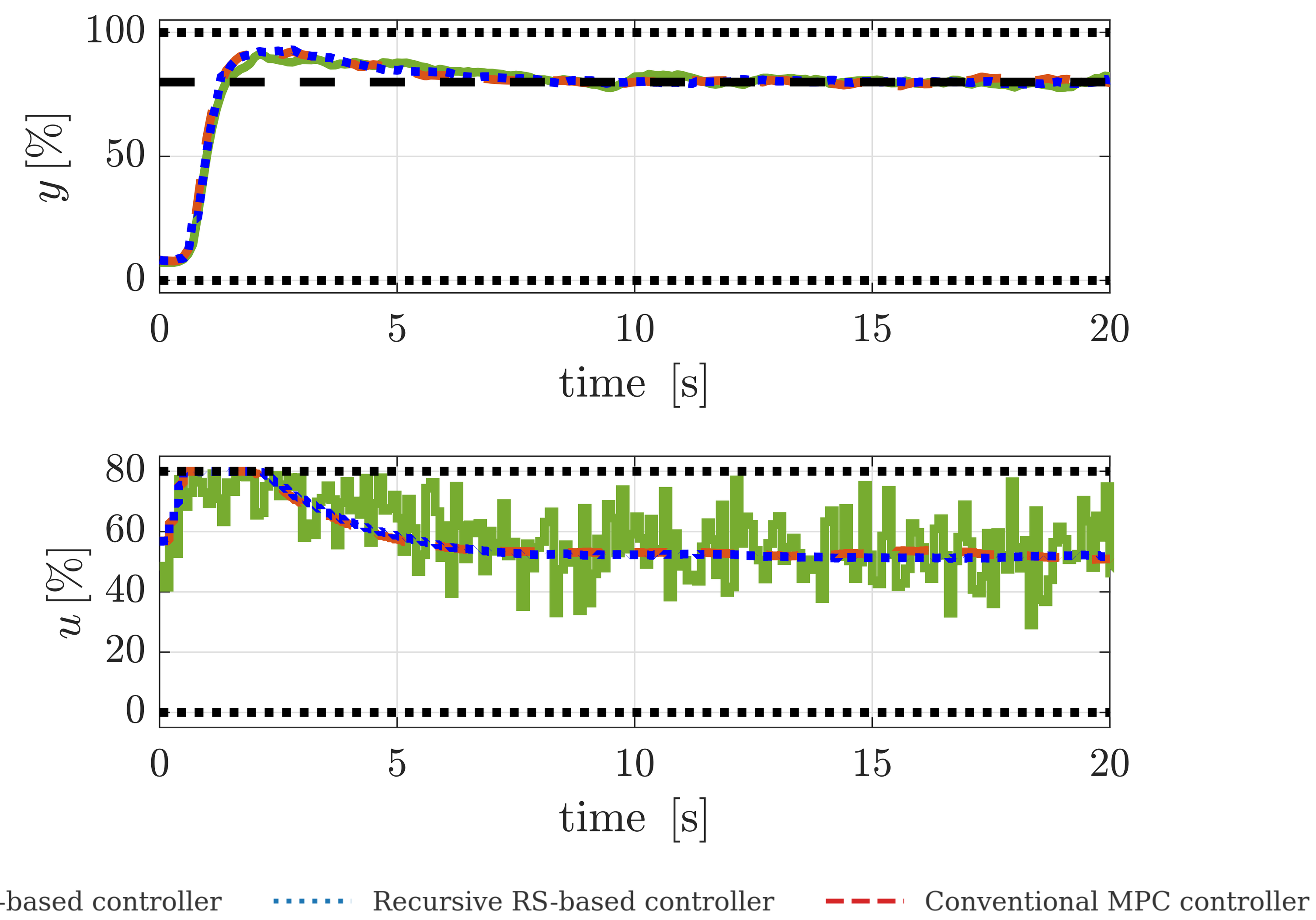

Figure 3. The control performance of reference tracking for the Flexy device.

While conventional MPC is optimal, it exceeds the 0.1 s sampling time of the Flexy device, limiting real-time use. In contrast, RS and recursive RS methods cut computation time by 51% and 84%, respectively. The recursive RS method achieved decisions in just 5.9 ms, well within the sampling limit. Control performance was also strong: the recursive RS method stayed within 0.4% of the optimal cost, versus 5% for standard RS. This suboptimality is tunable increasing the number of random-shoots. Although explicit MPC matched computational time, it required up to 96% more memory, demonstrating the efficiency of RS-based methods in constrained environments. These findings show RS-based control is ideal for fast, resource-limited systems.

Metric	MPC	EMPC	RS	Recursive RS
Time [ms]	36	2.5	18	**5.9**
Cost [$\times 10^7$]	†	2.36	2.45	**2.37**
Memory [kB]	0.30	7.06	0.31	**0.42**

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