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MODEL PREDICTIVE CONTROL WITH ADAPTIVE PREDICTION HORIZON FOR LOAD ALLEVIATION IN VERY FLEXIBLE AIRCRAFT

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1 INTRODUCTION

Flight efficiency and the reduction of fuel burn have been pursued in commercial aviation since its inception. As a consequence, aircraft designs have increasingly shifted towards higher aspect ratio wings, resulting in more flexible structures and higher internal loads [1]. At the same time, the need to satisfy stringent airworthiness and safety requirements has motivated the development of novel control schemes, such as maneuver/gust load alleviation (MLA/GLA), in order to alleviate the internal loads [2]. The very flexible aircraft (VFA) at the extreme end of the range of aircraft flexibility exhibits strong elastic-flight-dynamics coupling, large deflections, and dozens of degrees of freedom [1]. Model Predictive Control (MPC) has been proposed to address load alleviation in VFA in [3]; its implementation by solving a quadratic programming (QP) problem with active set methods incurs a significant computational overhead.

MPC possesses several tunable parameters, including the prediction horizon, control horizon, constraint horizon, weights in the cost functional, and constraint tightening parameters [4, 5]. These parameters are typically set offline and maintained constant throughout the flight. Among these parameters, the prediction horizon directly dictates the size of the QP problem to be solved, also impacting the problem computational cost and, consequently, its tractability.

This paper proposes an approach to adjusting the MPC prediction horizon during constraint-active phases, without compromising recursive feasibility and closed-loop stability, aiming to decrease the MPC computational cost. More specifically, whenever a neighborhood of the feasible set is reached, the prediction horizon is modified in order to improve the computational tractability of the MPC. Simulation case studies are reported, including for a VFA model, showing that the prediction horizon may be intermittently reduced with terminal penalty adjustment without significant performance degradation while lowering the computational cost.

This abstract is organized as follows. Section 2 introduces the methodology for in-flight prediction horizon adjustment. Section 3 reports preliminary numerical results for a proof-of-concept mass-spring-damper model. Finally, Section 4 highlights what will be incorporated into the final paper.

2 METHODOLOGY

A typical MPC formulation based on QP is considered which employs a quadratic cost functional under a feasible set formed by a discrete-time linear time-invariant dynamic model for prediction and affine, along with states and control constraints.

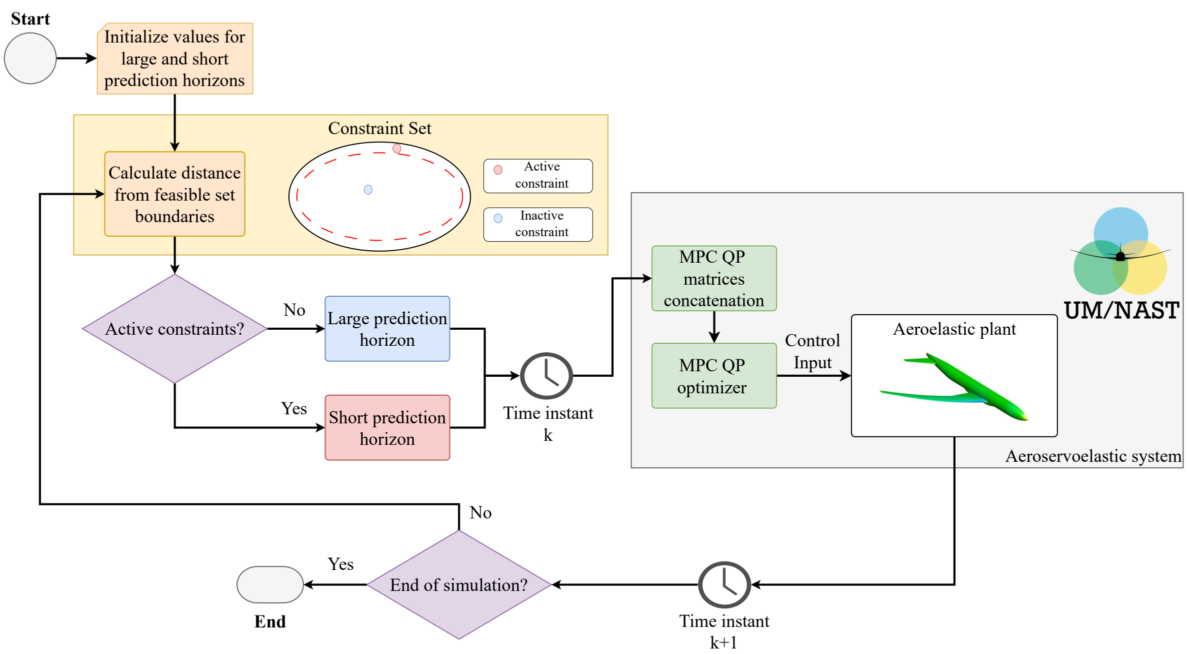

Figure 1: In-flight prediction horizon adjustment methodology.

The flowchart in Fig. 1 illustrates the adaptive horizon selection mechanism within an MPC framework for an aeroservoelastic system, implemented using the University of Michigan's Nonlinear Aeroelastic Simulation Toolbox (UM/NAST) as the simulation environment. The process begins with the initialization of parameters defining both the large and short prediction horizons. Subsequently, the algorithm evaluates the distance between the current system state and the feasible constraint boundaries within the constraint set. This analysis determines whether any constraints are nearly active, visually represented by red (active) and blue (inactive) circles. Based on this assessment, the control algorithm dynamically selects either a large prediction horizon, when constraints are inactive to enhance long-term performance, or a short prediction horizon with corrected terminal penalty, when constraints are active to reduce computational load and maintain feasibility. When transitioning from a large prediction horizon to a short prediction horizon, the previous solution is truncated during the warm-starting process. On the other hand, as the prediction horizon extends from short to long, the warm-start guess comprises the previous short prediction horizon solution supplemented by zeros. At time instant k, the selected horizon is used to formulate and concatenate the QP matrices. The resulting optimal control input is then applied to the aeroelastic plant, representing the physical aircraft structure, which evolves according to its aeroservoelastic dynamics. The system response is fed back into the controller, advancing the process to the next time instant $k{+}1$. The loop continues until the end-of-simulation condition is satisfied, ensuring that the control strategy adapts in real time to changes in constraint activity throughout the simulation. The final paper will contain a mathematical demonstration of recursive feasibility and stability for the proposed methodology in Fig. 1.

3 PRELIMINARY NUMERICAL RESULTS

3.1 Proof-of-Concept Model

For the final paper, simulation results based on a VFA model will be reported. However, to demonstrate an application of the methodology of the in-flight prediction horizon adjustment introduced in Section 2, a proof-of-concept (PoC) model is employed, which is a mass-spring-damper system. Aiming to resemble geometrically nonlinear VFA wings, the mass-spring-damper system incorporates cubic polynomial nonlinear springs. The mathematical representation of the proof-of-concept system is

$$\begin{bmatrix} m_1 & 0 \\ 0 & m_2 \end{bmatrix} \begin{Bmatrix} \ddot{x}_1 \\ \ddot{x}_2 \end{Bmatrix} + \begin{bmatrix} c_1 + c_2 & -c_2 \\ -c_2 & c_2 \end{bmatrix} \begin{Bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{Bmatrix} + \begin{bmatrix} k_1 + k_2 & -k_2 \\ -k_2 & k_2 \end{bmatrix} \begin{Bmatrix} x_1 \\ x_2 \end{Bmatrix} = \begin{Bmatrix} u_1 \\ 0 \end{Bmatrix}, \tag{1}$$

where $m_1 = m_2 = 1$ kg, $c_1 = c_2 = 1$ kg $\cdot$ s, $k_1 = (4 + x_1^3)$ N/m, and $k_2 = [9 + (x_2 - x_1)^3]$ N/m. The system operates under the control input u_1, tracking a sinusoidal reference signal for x_1, $r = 0.5 \sin(0.4\pi t)$ m, subject to $x_2 < 0.24$ m and $u_1 \in [-3, 3]$ N.

3.2 Proof-of-Concept Results

For this abstract, three scenarios were considered: Scenario 1 employs a longer prediction horizon ($N_p = 30$), scenario 2 adopts a shorter prediction horizon ($N_p = 20$), and scenario 3 implements the proposed adaptive scheme, in which the prediction horizon alternates between 30 and 20 depending on constraint activation. In all scenarios, the control horizon is $N_c = 20$, and the constraint horizon is the same as the prediction horizon.

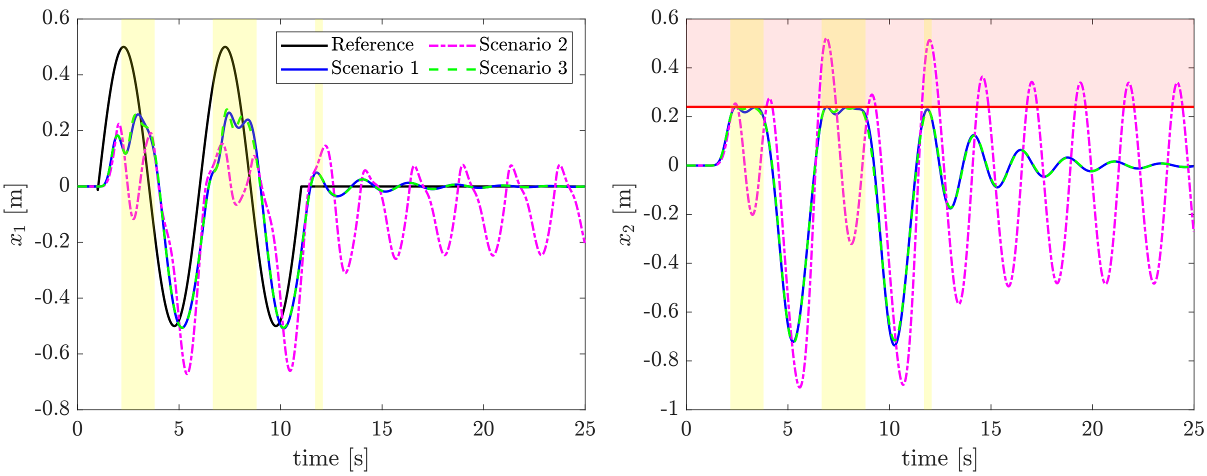

Figure 2: Displacements versus time. Yellow shaded areas represent time intervals while the prediction horizon is adaptively reduced. The red shaded area stands for the infeasible region.

The time-domain responses are shown in Fig. 2 and 3. As can be observed, the short-horizon configuration (scenario 2) exhibits moments of constraint infeasibility, manifested as saturations in the actuator signal, deviations from reference tracking, and constraint violations. This occurs because the reduced prediction horizon compromises the controller's ability to anticipate constraint intersections, leading to infeasible optimization problems when both displacement and input bounds are simultaneously active. Conversely, the adaptive-horizon strategy (scenario 3) successfully maintains feasibility throughout the maneuver by dynamically decreasing the prediction horizon, with a compensation on the terminal penalty, whenever constraint activation increases the computational burden. Also, Fig. 3 shows that, during the period of prediction horizon modification (yellow shaded areas), the CPU time achieves the lowest values for scenario 3, indicating an enhancement in the computational burden.

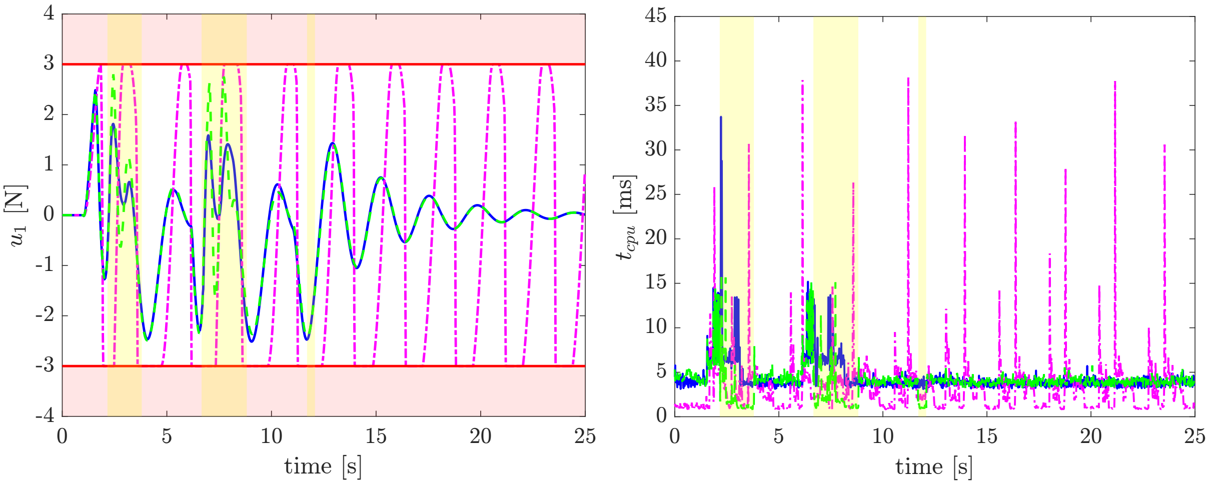

Figure 3: Input force on block 1 (left) and CPU time during the MPC optimization (right) versus time. Yellow shaded areas represent moments when the prediction horizon is adaptively reduced. Red shaded areas stand for the infeasible regions.

4 FINAL PAPER

The results on PoC model highlight the potential of this new methodology for in-flight adaptive modification of the prediction horizon with terminal penalty correction. For the final paper, the application of the methodology will be based on a VFA model while executing an oscillatory maneuver. Furthermore, the analysis of recursive feasibility and closed-loop stability will be included for the proposed methodology. Based on the results, the potential impact and benefits of the adaptive prediction horizon in MPC for MLA systems will be quantified.

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