ASCC 2022

ASCC 2022 (Hybrid Conference)
The 13th Asian Control Conference
May 4-7, 2022 (Wed~Sat), Booyoung Jeju Hotel, Jeju Island, Korea

ASIAN CONTROL ASSOCIATION
LEADING IN CONTROL, AUTOMATION AND SYSTEMS

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The 13th Asian Control Conference (ASCC 2022) will be held with a hybrid style in Jeju Island, Korea. ASCC emphasizes friendship as well as technical aspects. As a central event of the **Asian Control Association (ACA)**, ASCC provides researchers, engineers, and professionals worldwide with excellent opportunities to get together, exchange new findings and views, and discuss state-of-the-art technologies. The past ASCCs include Tokyo (1994, the 1st), Seoul (1997), Shanghai (2000), Singapore (2002), Melbourne (2004), Bali (2006), Hong Kong (2009), Kaohsiung (2011), Istanbul (2013), Kota Kinabalu (2015), Gold Coast (2017), and Kitakyushu (2019).

Submission Guidelines: When preparing the manuscript, the authors should adhere to the IEEE style for conference paper. All submitted papers must be written in English. Accepted papers are limited to 6 pages (regular paper) and 2 pages (position paper) at no extra charge. All publication material for presentation must be original.

Important Dates

Regular paper submission	~~December 31, 2021~~ January 20, 2022
Organized session/position papers	~~January 31, 2022~~

	February 14, 2022 (final)
Decision notification	~~February 18, 2022~~ ~~March 4, 2022~~ March 7, 2022
Final camera-ready paper submission	~~March 18, 2022~~ March 20, 2022
Early-bird registration close	April 8, 2022

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2022-03-14

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Revisiting the F-8 Aircraft Control Problem with Dynamic Programming

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***Abstract*—This paper presents empirical research on the implementation of dynamic programming to a classic and established nonlinear dynamical model of an F-8 aircraft's longitudinal motion. The model has been frequently used as a case study in academic environments for nonlinear dynamics and optimal controls topics. On the other hand, dynamic programming gives an exact solution to an optimal control problem. Hence, it can be used to benchmark other optimization methods. Before implementing dynamic programming, we first investigated the primary behavior of an F-8 aircraft's dynamical model. The existing dynamical model is inherently stable in the presence of a non-zero initial attack angle as long as its value is less or equal to 31.6°. However, the stall angle of an F-8 aircraft is reported as 23.5°, which is lower than 31.6°. Therefore, in this paper, an initial attack angle that is larger than 31.6° becomes one of our concerns. Our results show that dynamic programming can be used to regulate the states of an F-8 aircraft's dynamical model even when the applied initial attack angle is larger than 31.6°. We also compare our dynamic programming implementation to the MATLAB pattern search method and sequential quadratic programming. While the first gives results that are very similar to dynamic programming, the latter fails to provide satisfactory results.**

***Index Terms*—Optimal control, aerospace, nonlinear control systems, reinforcement learning**

I. INTRODUCTION

In 1977, Garrard and Jordan [1] designed a nonlinear control technique for an F-8 aircraft's longitudinal motion. The controller's goal is to stabilize the attack angle, pitch angle, and pitch rate of an F-8 Crusader aircraft in the presence of a non-zero initial attack angle. The work was started with the derivation of a nonlinear dynamical model of the longitudinal motion of an F-8 aircraft and followed by a control design based on the derived model.

In 1984, Desrochers and Al-Jaar [2] presented the reduced order of Garrard's model and designed an optimal controller based on this simplified model. In 1992, Banks and Mhana [3] also applied an optimal controller to Garrard's model, which had been linearized by using the standard Riccati's method. In 1993, Kaya and Noakes [4], [5] applied a time-optimal control to Garrard's model. Their method is a computer algorithm that works for both linear and nonlinear systems.

More recent and advanced works, as in [6]–[8], applied bifurcation theory to the nonlinear dynamical model of an F-8 aircraft's longitudinal motion. In both works, the dynamical model was re-derived. A profound analytic exploration of the nonlinear dynamical model of an F-8 aircraft's longitudinal motion can be found in these two works.

Since the F-8 aircraft's dynamical model is nonlinear, we can conclude that the general approach is typically linearizing the model around its equilibrium point and then using the linearized model for control design purposes. However, this linear control may have limited performance. Garrard and Jordan [1] reported that such a linear controller performed well when the initial attack angle was less than 29.3°. Further, Garrard and Jordan also proposed an optimization technique to design a quadratic and a cubic controller. These controllers were nonlinear and were reported to perform well for wider initial attack angles, which were 30.7° and 34.7°, respectively.

Even though the longitudinal motion of an F-8 aircraft has been very well studied, to the best of the author's knowledge, no work presents dynamic programming implementation on an F-8 aircraft's longitudinal motion. The closest work that we can find is in [3], where the analytic solution to the optimal control problem is found through solving Riccati's equation. Therefore, we decided to apply dynamic programming to Garrard's model. Dynamic programming has been well recommended as a benchmark controller since it visits all possible state combinations and provides an exact solution to an optimal control problem [9].

In this paper, we use the YADPF function package to implement dynamic programming into the dynamical model expressed in (1). The YADPF function package is an in-house software package created with MATLAB for deterministic dynamic programming. Further details on the YADPF function package can be found in [10].

This paper is divided into three major sections. In the first

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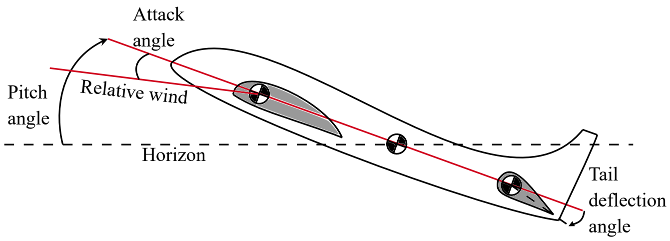

Fig. 1. Attack angle (x_1) pitch angle (x_2) and tail deflection angle (u) of an aircraft.

section, we re-state the dynamical model of an F-8 aircraft's longitudinal motion that has been derived in [1]. Here, we add several numerical analysis to some inherent properties of the selected dynamical model. In second section, we apply dynamic programming to generate optimal control policies to stabilize the aircraft in the presence of a non-zero initial attack angle. Finally, we present the conclusion and the future plan of our work in the last section of the paper.

II. Dynamical Model

As previously mentioned, Garrard and Jordan [1] proposed a nonlinear dynamical model to govern the longitudinal motion of an F-8 aircraft system. The dynamical model has three state variables ($\boldsymbol{x} = [x_1\, x_2\, x_3]$) and one input variable (u). It is written as follows.

$$\begin{aligned}\dot{x}_1(t) =& -0.877x_1(t) + x_3(t) - 0.088x_1(t)x_3(t)\\ &+ 0.47x_1(t)^2 - 0.019x_2(t)^2 - x_1(t)^2x_3(t)\\ &+ 3.846x_1(t)^3 - 0.215u(t) + 0.28x_1(t)^2u(t)\\ &+ 0.47x_1(t)u(t)^2 + 0.63u(t)^3\\ \dot{x}_2(t) =& x_3(t)\\ \dot{x}_3(t) =& -4.208x_1(t) - 0.396x_3(t) - 0.47x_1(t)^2\\ &- 3.564x_1(t)^3 - 20.967u(t) + 6.265x_1(t)^2u(t)\\ &+ 46x_1(t)u(t)^2 + 61.4u(t)^3\end{aligned} \tag{1}$$

Here, x_1 is the angle of attack, x_2 is the pitch angle, x_3 is the pitch rate and u is the tail deflection angle that acts as the control input (see Fig. 1). All unit are in degrees or radians. The dynamical model in (1) has cubic non-linearity. When no input is applied ($u = 0$), it has one real equilibrium point which is located at the origin: $\boldsymbol{x} = [0\,0\,0]$.

Proofing the stability of the dynamical model in (1) is difficult since finding the Lyapunov function that can conclude its stability is not straightforward. Therefore, to proof that (1) has a stable equilibrium at the origin, we calculate the Jacobian matrix around the equilibrium point (the origin) numerically by using a perturbation method (see matrix A in (2)). After that, we can get the eigenvalues of this Jacobian matrix, which are $\lambda_1 = -0.6365 + 2.0372i$, $\lambda_2 = -0.6365 - 2.0372i$, and $\lambda_3 = 0$. Since the real parts of all eigenvalues are negative, this equilibrium point is a stable equilibrium point.

$$A = \begin{pmatrix} -0.877 & 0 & 1\\ 0 & 0 & 1\\ -4.208 & 0 & -0.396\end{pmatrix} \tag{2}$$

Since our main interest is the response of the aircraft for non-zero initial attack angle ($x_1(0)$), we simulated the dynamical model in (1) numerically for several different initial attack angles. Simply put, we performed brute-force sweeps from $x_1(0) = 10°$ to $x_1(0) = 40°$ with a step of $0.1°$. As a result, we found that the dynamical model started to diverge when $x_1(0) > 31.6°$. In practice, this describes the region of attraction of the dynamical model expressed in (1). However, a complete region of attraction must include all state variables.

III. Dynamic Programming Implementation

This section is divided into two sections. In the first section, we formulate the optimal control problem that we want to solve. In the second section, we provide the simulation results.

A. Optimal Control Problem Formulation

Dynamic programming implementation requires state and input discretization. Thus, it may suffer from the curse of dimensionality. For each experiment, we must find boundaries and resolutions for the discretization such that they fit into the available memory of the computer that we use for this research, which is a Xeon-E5-2699-v3 computer with 256 GB of memory.

We formulate the discrete optimal control problem as follows.

$$\min_{u_k \in U_k} \frac{1}{N+1}\sum_{k=0}^{N}\left\{\left[\frac{x_{1,k}}{\bar{x}}\right]^{2r} + \left[\frac{x_{2,k}}{\bar{x}}\right]^{2r} + \left[\frac{x_{3,k}}{\bar{x}}\right]^{2r}\right\} \tag{3}$$

such that

$$\begin{aligned}x_{1,k+1} =& \big[-0.877x_{1,k} + x_{3,k} - 0.088x_{1,k}x_{3,k}\\ &+ 0.47x_{1,k}^2 - 0.019x_{2,k}^2 - x_{1,k}^2x_{3,k}\\ &+ 3.846x_{1,k}^3 - 0.215u_k + 0.28x_{1,k}^2u_k\\ &+ 0.47x_{1,k}u_k^2 + 0.63u_k^3\big]\Delta t + x_{1,k}\\ x_{2,k+1} =& x_{3,k}\Delta t + x_{2,k}\\ x_{3,k+1} =& \big[-4.208x_{1,k} - 0.396x_{3,k} - 0.47x_{1,k}^2\\ &- 3.564x_{1,k}^3 - 20.967u_k + 6.265x_{1,k}^2u_k\\ &+ 46x_{1,k}u_k^2 + 61.4u_k^3\big]\Delta t + x_{3,k}\\ x_{1,k} \in& X_{1,k} = \{a, a+\Delta x, \ldots, b\}\\ x_{2,k} \in& X_{2,k} = \{c, c+\Delta x, \ldots, d\}\\ x_{3,k} \in& X_{3,k} = \{e, e+\Delta x, \ldots, f\}\\ u_k \in& U_k = \{-3°, (-3+\Delta u)°, \ldots 3°\}\\ k =& 0, 1, \ldots, N+1\end{aligned} \tag{4}$$

In (3), we want to minimize an objective function whose constraints are defined in (4). This objective function is based on [11] where it is used to minimize water-level deviation of open-channel flows. The similar objective function is also used in [12], [13] where it is used to minimize pressure fluctuation during water-hammer problems. In principal, this objective function minimizes the temporal fluctuations of state variables x_1, x_2, and x_3. Minimizing input variable u in not necessary. Moreover, this objective function is actually similar to the work of Garrard and Jordan [1]. However, in their work, they also applied minimization to the input variable as well.

One important thing that we would like to emphasize is that the optimal control problem defined in (3) to (4) is not a trivial task since the objective function itself is an implicit function of the decision variables. Thus, finding the gradient of such an objective function requires solving the system dynamics first. As a result, it is challenging to derive the analytical equation of the gradient of the objective function.

There are two control parameters introduced in (3). The first one is $\bar{x}$, which is the tolerable deviation from the origin. The second parameter is r, which is any positive integer (unitless). We selected $\bar{x} = 0.01$ radians and $r = 2$ for faster response. Larger r or smaller $\bar{x}$ gives insignificant effects to the improvements to the response time.

Further, the state discretization interval is given by Δx, and the time discretization interval is given by Δt. We applied $\Delta t = 0.5$ seconds. The horizon length is given by $N + 1$, where $N = 20$. This is because the simulation was run for 10 seconds. As for the input boundaries, they were set similar to the work by Kaya and Noakes [5]. Since a time-optimal control was not our goal, we did not apply switching actions of two extreme values for the input.

Moreover, to avoid insufficient memory problems, the state boundaries (a to f) are set as tight as possible. This is done heuristically. For the upper boundaries, they were selected such that their locations were slightly above the maximum state values. For the lower boundaries, they were selected such that their locations were slightly below the minimum state values.

B. Simulation Results

For this paper, we simulated four different initial attack angles: $x(1) = 20.0°$, $x(1) = 22.9°$, $x(1) = 26.7°$, and $x(1) = 32.0°$ by using dynamic programming, MATLAB pattern search, and MATLAB sequential quadratic programming (SQP). The reason we selected MATLAB pattern search is because it is a global optimization method and it does not require the derivative of the objective function [14], [15]. As for the SQP, we supplied MATLAB with the derivative of the objective function which was calculated numerically by using the Complex-Step Derivative Approximation (CSDA) method [16]. We have made our MATLAB implementations for pattern search and SQP available online in [17].

During the simulations with dynamic programming, we had to readjust the state and input variable intervals according to Table I since we encountered insufficient memory space problem. The results are shown in Fig. 2 to Fig. 5. Both dynamic programming and MATLAB pattern search successfully generate input variable that can regulate the state variables.

As we can see from Fig. 5, since the input is constrained ($|u| < 3°$), the pitch angle reaches about $-80°$ when the initial attack angle is $32.0°$. Thus, we did not test for larger initial attack angles. In Table II and Table III, we present the absolute terminal distance of each state variable to its origin, for dynamic programming and pattern search, respectively. We do not include the result from the SQP since we expect smooth

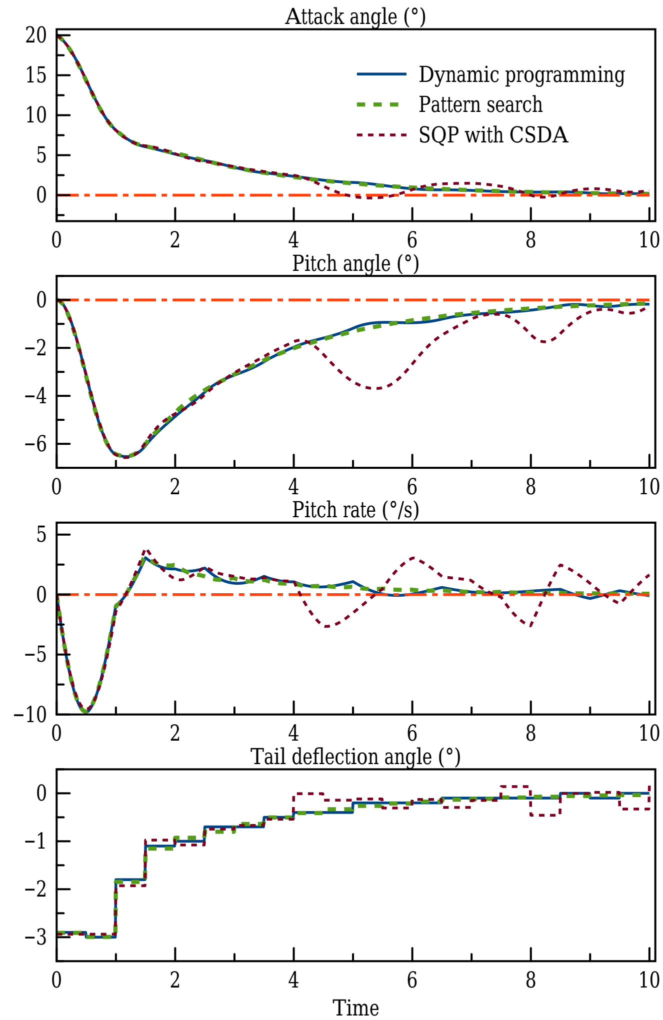

Fig. 2. The aircraft's stabilizing action when $x_1(0) = 20.0°$.

TABLE I
DISCRETIZED STATE AND INPUT RESOLUTIONS

$x_1(0)$	Δx	Δu	Δt
20.0°	0.002 radians	0.1°	0.5 seconds
22.9°	0.002 radians	0.1°	0.5 seconds
26.7°	0.002 radians	0.5°	0.5 seconds
32.0°	0.004 radians	0.5°	0.5 seconds

state trajectories considering the selected objective function. The maximum absolute terminal distance after the ten-second simulations is less than seven degrees.

Moreover, the generated state trajectories are relatively smooth because of the selected objective function. From the state trajectories generated by the MATLAB pattern search, we can see that zero-crossing only occurs at most once. More fluctuations appear in the state trajectories generated by dynamic programming, which is caused by the discretization process. The resolution for input variables needs to be higher. However, this requires more memory space beyond our computing system's specification.

We cannot compare our results with the work of Garrard

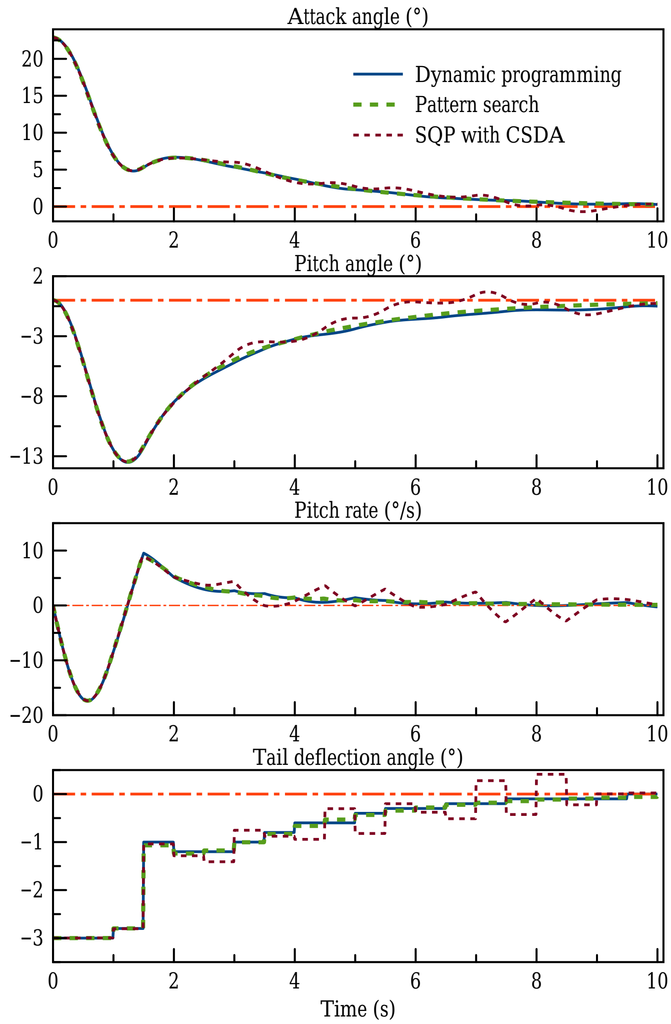

Fig. 3. The aircraft's stabilizing action when $x_1(0) = 22.9°$.

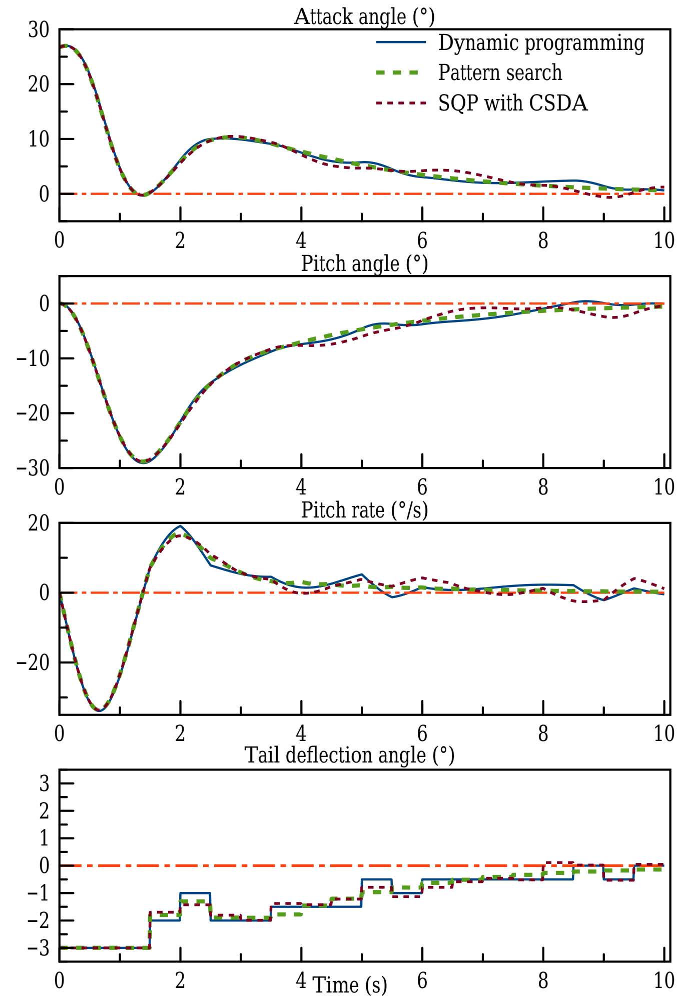

Fig. 4. The aircraft's stabilizing action when $x_1(0) = 26.7°$.

TABLE II
ABSOLUTE TERMINAL DISTANCE FROM THE ORIGIN WITH DYNAMIC PROGRAMMING

$x_1(0)$	$\lvert x_1(10)\rvert$	$\lvert x_2(10)\rvert$	$\lvert x_3(10)\rvert$
20.0°	0.1554°	0.1815°	0.0892°
22.9°	0.2809°	0.4917°	0.2693°
26.7°	0.6252°	0.0189°	0.4630°
32.0°	5.3055°	3.5105°	1.2110°

TABLE III
ABSOLUTE TERMINAL DISTANCE FROM THE ORIGIN WITH MATLAB PATTERN SEARCH

$x_1(0)$	$\lvert x_1(10)\rvert$	$\lvert x_2(10)\rvert$	$\lvert x_3(10)\rvert$
20.0°	0.1641°	0.1485°	0.0683°
22.9°	0.2669°	0.2424°	0.1089°
26.7°	0.6293°	0.5539°	0.2772°
32.0°	3.6255°	3.6920°	1.1044°

and Jordan since, in our work, the controller is an open-loop controller and the input is bounded differently. As with the work of Kaya and Noakes, they aimed for a time-optimal control. Implementing a time-optimal control with dynamic programming is not straightforward since dynamic programming requires a predefined time horizon.

IV. Conclusion and Future Work

We have briefly explored the dynamical model of an F-8 aircraft's longitudinal motion in the presence of a non-zero initial attack angle. The dynamical model used in this paper is inherently stable around its equilibrium point. However, it has a finite region of attraction that requires further analysis to define its boundary of attraction. We have not yet done such analysis in this paper and it will be an interesting topic for us to investigate in the future.

As for dynamic programming implementation, the results demonstrate that dynamic programming can solve the stabilization problem of an F-8 aircraft's longitudinal motion. Additionally, the selected objective function that minimizes temporal fluctuation suits the real-world applications since it generates smooth state trajectories that are physically realizable.

Overall, the results from dynamic programming are very

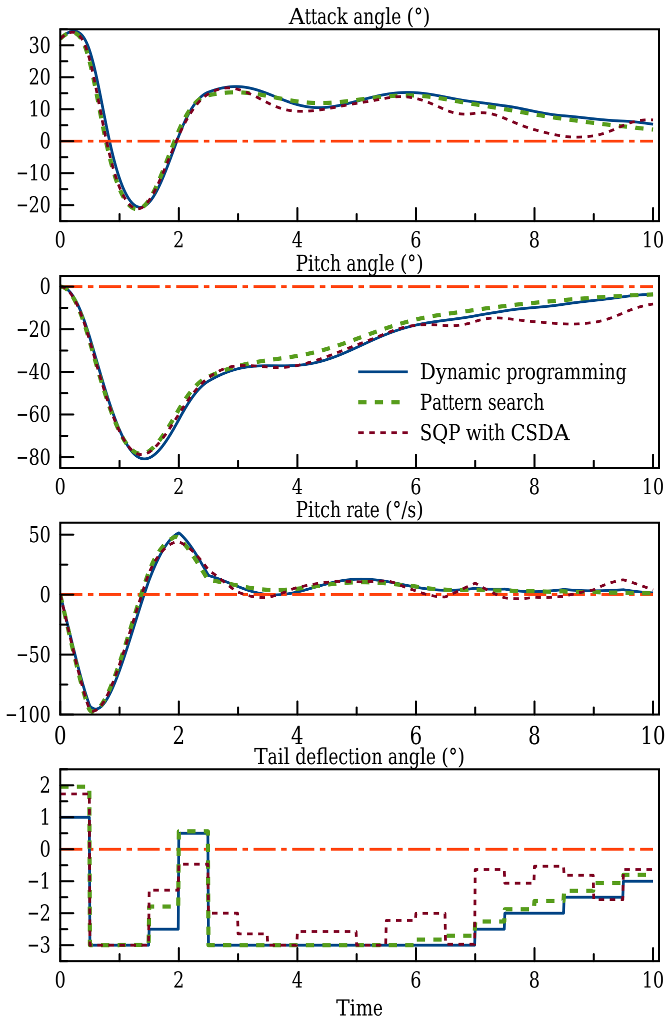

Fig. 5. The aircraft's stabilizing action when $x_1(0) = 32.0°$.

similar to the MATLAB pattern search method. Thus, we can ensure that the MATLAB pattern search method can also be used as a benchmark for optimal control design for the dynamical model stated in (1). Such an information is very beneficial since MATLAB pattern search is faster and requires less memory space when compared to dynamic programming. Yet, MATLAB pattern search successfully gives the exact solution that is similar to dynamic programming.

In this current work, the input variable, the tail deflection angle, is generated as a piecewise-constant function. This is because our in-house dynamic programming function package, the YADPF, applies zero-order-hold (ZOH) operations when discretizing the input variable. Additionally, the proposed dynamical does not include the tail's dynamic. Since a piecewise-constant function is not realizable in actual physical systems, a piecewise-linear function can be used in the future. This may require an additional state variable or modifications in the YADPF function package. Another interesting future work is to find the analytic derivative of the objective function for a successful SQP implementation.

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