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Adaptive Control of Flight: Theory, Applications, and Open Problems

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Abstract—**This paper discusses the application of direct adaptive model reference control as it relates to the control of aircraft and weapon systems. Recent extensions in the approach, primarily driven by practical considerations, have led to very successful flight testing. The flight control architectures considered incorporate direct adaptive increments to augment a baseline control signal designed using nonlinear and/or linear robust control methods. Recently applied to a modified guided weapon, this adaptive flight control system was designed and flight tested without wind tunnel measurement of any aerodynamic changes to the modified weapon. This paper discusses the design methodology, practical considerations, extensions incorporated, as well as open problems that remain in making this approach acceptable in the aerospace community.**

Index Terms—**Adaptive control, flight control, aircraft control, weapon control.**

I. Introduction

In October 2004, and again in January 2005, the United States Air Force and The Boeing Company flight tested a modified MK-82 weapon at Eglin Air Force Base which was controlled with a new direct adaptive flight control system augmenting the production (baseline) flight control laws. Figure 1 shows the test weapon and the F-16 launch aircraft. This adaptive flight control system was designed to retrofit onto the existing autopilot. The algorithms use a reference model of the baseline control, and then adapt to make the modified variant fly as close as possible to the reference model. The hardware modifications to the weapon included the addition of a sensor nose-kit (the sensor fit into the existing nose), wire harnesses, straps with barrel-nuts, and symmetric tail-kit dog-ears where the sensor wire harness enters into the tail-kit.

Traditionally, a wind tunnel test would have been conducted to measure the aerodynamic changes introduced by these modifications, and a redesign of the flight control system would have been performed if the baseline autopilot could not handle the changes. This standard process would have been expensive in terms of schedule and budget. Instead, adaptive control was retrofitted onto the existing production flight control system, significantly reducing schedule and costs. This capability exists today due to the significant progress that has been made in maturing reconfigurable/damage adaptive flight control systems for manned and unmanned aircraft.

Since the early 1990's, the Air Force, Navy, and NASA working with industry and academia have made significant progress maturing reconfigurable/damage adaptive flight control for aircraft and weapons [1-16]. Several different approaches have been successfully flown on manned aircraft [2-4] and unmanned aircraft [5], and also on guided munitions [6]. Steinberg [1] has documented much of this progress in a recent paper on R&D of reconfigurable flight control systems.

The Self-Repairing Flight Control System [2] (SRFCS) achieved failure and damage tolerance through an indirect adaptive reconfigurable flight control architecture, which performed on-line damage isolation and estimation using hypothesis-testing techniques in conjunction with a bank of Kalman filters. The Self Designing Controller [3] (SDC) program successfully flight tested an indirect adaptive scheme on the VISTA/F-16 aircraft which used least squares system identification, with spatial and temporal constraints, to estimate the stability and control derivatives required for the solution of a receding horizon optimal control problem. The Intelligent Flight Control System [4] (IFCS) program (called Generation I) focused on an indirect adaptive scheme in which neural networks were used to learn and generate controller design matrices (A, B) containing the aircraft's aerodynamics coefficients, which were then used in a real-time Riccati equation solver to compute optimal control feedback gains. Parts of the IFCS-Gen I system were flown on NASA's F-15 research aircraft at Edwards.

The above mentioned SRFCS, SDC, and IFCS-Gen I adaptive control architectures were all based on indirect adaptive control, requiring identification of aerodynamic stability derivatives and redesign or re-allocation in the control laws based upon the aero parameter estimates. In contrast to these approaches, Kim and Calise [7] presented a direct adaptive approach based on neural network on-line learning for a feedback linearization control architecture and demonstrated the approach via simulation studies with an F/A-18 aircraft. This approach was later modified and used in the Reconfigurable Control for Tailless Fighters (RESTORE) program [5,8-10], which also incorporated a dynamic inversion control law in an explicit model following framework. The successful application of this technology under the RESTORE program led to the flight testing of the approach on the Boeing/NASA X-36 Agility Research Test Aircraft [10].

This RESTORE direct adaptive approach for dynamic inversion based architectures was also applied to agile missiles in McFarland [11,12]. The motivation for this work was to cancel inversion errors (during high angle-of-attack maneuvers where the aero is uncertain) in real-time through a stable on-line learning algorithm derived using Lyapunov stability theory and implemented using neural networks. This work eliminated the need for complicated gain-scheduling dependent upon accurate aerodynamic models, (used by Wise [13] for the same problem).

These successes in the RESTORE dynamic inversion based neural-network control approach to aircraft and missiles offered the potential to develop flight control systems without knowledge of the aerodynamics (a radical idea that really could only be tested on a munition). Sharma, Calise, and Corban [14-16] in collaboration with Boeing applied the RESTORE approach to the control of a MK-84 munition, in which the production MK-84 LQR based flight control system was replaced with a dynamic inversion based scheme augmented with a direct adaptive neural-network control. This adaptive autopilot was designed at a single point in the flight envelope using aerodynamic data from missile DATCOM, and the on-line learning neural network was used to provide the stability and command following throughout the envelope. Prior to flight testing the adaptive design, this control architecture was tested in simulation environment using the production MK-84 6DOF flight simulation software with accurate aerodynamic models (truth model). The goal was to show that the adaptive system could provide the same degree of control and command following as the production autopilot. The testing was done both in the off-line 6DOF and in the hardware-in-the-loop facility. Simulations and flight testing of this adaptive autopilot were very successful.

The adaptive flight control work reported in this paper differs from the MK-84 work in that the production flight control system for the MK-82, which is LQR based, was ***augmented*** (rather than replaced) with an adaptive increment derived from an on-line learning algorithm (similar to the RESTORE approach). Thus if the missile aerodynamics were "close" to the production MK-82 then the baseline LQR control would be in command.

II. Baseline Control

In the control of aircraft and weapon systems it is important to have a baseline control that provides both performance and robustness for nominal flight conditions. In aircraft flight control problems, obtaining clearances for flight requires validation and verification (V&V) of the software, proving that the system satisfies structural mode interaction requirements, and progressing through low, medium and high speed taxi to demonstrate stability and control as the vehicle becomes aerodynamic. Following first flight, a build-up approach is undertaken to demonstrate adequate stability, control, and performance throughout the envelope. Typical control laws rely heavily on gain scheduling to satisfy design goals. Industry is yet to learn how to V&V and clear for flight a pure adaptive control law.

As an integral part of a flight envelope expansion testing, it is typical to compute real-time stability margins (RTSMs) for the aircraft during flight in the pitch, roll, and yaw axes. This process uses chirp signals to excite the aircraft in which the response to the chirp, through telemetry, is used to produce Bode plots to assess stability margins. If the test point clears, the pilot and flight test team quickly moves to the next test point. This process can significantly reduce the cost and schedule for flight envelope expansion. In adaptive flight control systems, as was flown during RESTORE [5,10], the process of assessing the stability and flying qualities becomes more complicated. This topic will be discussed further in the section on open problems.

The baseline MK-82 flight control system is a gain scheduled design, based on a state feedback LQR control, that is projected into an output feedback implementation. The state feedback design is formed using the robust servomechanism design model [17]. In the design process, integral control is appended to the plant dynamics and an optimal state feedback gain matrix is designed. Next, the dominant eigenstructure of the state feedback design is selected and used to form a static projection matrix [18] to create the output feedback implementation.

The open-loop linear plant (missile) dynamics can be generalized and written in the form:

$$\begin{cases} \dot{x}_p = A_p\, x_p + B_p\, u \\ y = C_p\, x_p + D_p\, u \\ z_p = F\, y \end{cases} \tag{1}$$

where x_p is the plant state dynamics, u is the vector of fin deflection commands, y represents the sensor measurements, and z_p is the subset of plant outputs that are to be controlled (i.e. track the commands from guidance). The dynamics of the robust servomechanism controller can be generalized and written in the form:

$$\begin{cases} \dot{x}_c = A_c\, x_c + B_{1c}^z\, z_c + B_{2c}^z\, z_p \\ u = C_c\, x_c + D_{1c}^z\, z_c + D_{2c}^z\, z_p \end{cases} \tag{2}$$

where x_c is the controller state vector, z_c is the vector of outer-loop commands from guidance, z_p is the system controlled output, and u is defined in (1). Substituting (1) into (2), yields:

$$\begin{cases} \dot{x}_c = A_c\, x_c + B_{1c}^z\, z_c + B_{2c}^z\, F\left(C_p\, x_p + D_p\, u\right) \\ u = C_c\, x_c + D_{1c}^z\, z_c + D_{2c}^z\, F\left(C_p\, x_p + D_p\, u\right) \end{cases} \tag{3}$$

Consequently, the control input u in (3) becomes:

$$u = C_c\, x_c + D_{1c}^z\, z_c + D_{2c}^z\, F\, C_p\, x_p + D_{2c}^z\, F\, D_p\, u \tag{4}$$

Solving (4) explicitly for u one gets the ***nominal controller***:

$$\begin{aligned} u &= \left(I - D_{2c}^z\, F\, D_p\right)^{-1}\left(C_c\, x_c + D_{1c}^z\, z_c + D_{2c}^z\, F\, C_p\, x_p\right) \\ &= \underbrace{\left(I - D_{2c}^z\, F\, D_p\right)^{-1}\left(D_{2c}^z\, F\, C_p \quad C_c\right)}_{K_x^T}\underbrace{\begin{pmatrix} x_p \\ x_c \end{pmatrix}}_{x} + \underbrace{\left(I - D_{2c}^z\, F\, D_p\right)^{-1} D_{1c}^z}_{K_z^T}\, z_c \\ &= K_x^T\, x + K_z^T\, z_c \end{aligned} \tag{5}$$

Using (5), the extended system dynamics are

$$\begin{cases} \underbrace{\begin{pmatrix} \dot{x}_p \\ \dot{x}_c \end{pmatrix}}_{\dot{x}} = \underbrace{\begin{pmatrix} A_p & 0 \\ B_{2c}^z\, F\, C_p & A_c \end{pmatrix}}_{A} \underbrace{\begin{pmatrix} x_p \\ x_c \end{pmatrix}}_{x} + \underbrace{\begin{pmatrix} B_p \\ B_{2c}^z\, F\, D_p \end{pmatrix}}_{B_1} u + \underbrace{\begin{pmatrix} 0 \\ B_{1c}^z \end{pmatrix}}_{B_2} z_c \\ y = \underbrace{\begin{pmatrix} C_p & 0 \end{pmatrix}}_{C} x + D_p\, u \\ u = K_x^T\, x + K_z^T\, z_c \end{cases} \quad (6)$$

Based on (6), the closed-loop dynamics takes the form:

$$\begin{cases} \dot{x} = A\, x + B_1 \left(K_x^T\, x + K_z^T\, z_c \right) + B_2\, z_c \\ \quad = \underbrace{\left(A + B_1\, K_x^T \right)}_{A_{ref}} x + \underbrace{\left(B_1\, K_z^T + B_2 \right)}_{B_{ref}} z_c \\ y = C\, x + D_p \left(K_x^T\, x + K_z^T\, z_c \right) \\ \quad = \underbrace{\left(C + D_p\, K_x^T \right)}_{C_{ref}} x + \underbrace{D_p\, K_z^T}_{D_{ref}} z_c \end{cases} \quad (7)$$

Assuming known aerodynamics, the A_{ref} matrix in (7) is designed to be Hurwitz and it provides adequate tracking of the guidance commands. The feedback/feedforward gains in (5) are scheduled with flight conditions. Later on, the closed loop system (7) will serve as the reference model in the direct adaptive model following tracking design architecture.

III. Adaptive Augmentation Design

In this section, a direct model following adaptive augmentation of the baseline controller is performed. Actuator dynamics are removed and system *matched* uncertainties are introduced. The open-loop system has the form as in (6):

$$\underbrace{\begin{pmatrix} \dot{x}_p \\ \dot{x}_c \end{pmatrix}}_{\dot{x}} = \underbrace{\begin{pmatrix} A_p & 0 \\ B_{2c}^z\, F\, C_p & A_c \end{pmatrix}}_{A} \underbrace{\begin{pmatrix} x_p \\ x_c \end{pmatrix}}_{x} + \underbrace{\begin{pmatrix} B_p \\ B_{2c}^z\, F\, D_p \end{pmatrix}}_{B_1} \Lambda \left(u + K_0\left(x_p \right) \right) + \underbrace{\begin{pmatrix} 0 \\ B_{1c}^z \end{pmatrix}}_{B_2} z_c \quad (8)$$

or equivalently:

$$\dot{x} = A\, x + B_1\, \Lambda \left(u + K_0\left(x_p \right) \right) + B_2\, z_c \quad (9)$$

Baseline inner-loop feedback / feedforward gains $\left(K_x,\, K_z \right)$ are calculated without accounting for system uncertainties. The uncertainties are represented by the diagonal matrix Λ, (control effectiveness uncertainty), and by the matched possibly nonlinear function $K_0\left(x_p \right)$, (aerodynamic moment uncertainty).

Substituting control signal from (6) into the open-loop dynamics (9) yields the following closed-loop system:

$$\dot{x} = \left(A + B_1\, \Lambda\, K_x^T \right) x + B_1\, \Lambda\, K_0\left(x_p \right) + \left(B_2 + B_1\, \Lambda\, K_z^T \right) z_c \quad (10)$$

Without the uncertainties, that is when $\Lambda = 1,\ K_0\left(x_p \right) = 0$, the dynamics in (10) coincides with the reference model:

$$\dot{x} = \underbrace{\left(A + B_1\, K_x^T \right)}_{A_{ref}} x + \underbrace{\left(B_2 + B_1\, K_z^T \right)}_{B_{ref}} z_c \quad (11)$$

By designing the nominal controller to yield stability and command following, the reference model is chosen using:

$$\dot{x}_{ref} = A_{ref}\, x_{ref} + B_{ref}\, z_c \quad (12)$$

A model reference direct adaptive *incremental* control signal u_{ad} is introduced to cope with the system uncertainties and to provide graceful degradation of the closed-loop system tracking performance in the face of modeling inaccuracies, environmental disturbances, and control power uncertainty. Towards this end, the total control input becomes:

$$u = u_{bl} + u_{ad} = \underbrace{K_x^T\, x + K_z^T\, z_c}_{u_{bl}} + \underbrace{\hat{k}_x^T\, x + \hat{k}_z^T\, z_c - \hat{K}_0\left(x_p \right)}_{u_{ad}} \quad (13)$$

In (13), $\left(\hat{k}_x,\, \hat{k}_z \right)$ are the incremental adaptive feedback / feedforward gains and $\hat{K}_0\left(x_p \right)$ is the on-line approximator of the matched system uncertainty $K_0\left(x_p \right)$. A feedforward neural network (NN) with N_0 *fixed* radial basis functions (RBF) in its hidden inner-layer is employed as the function approximation device:

$$K\left(x_p \right) = \Theta^T\, \Phi\left(x_p \right) + \varepsilon_0\left(x_p \right) \quad (14)$$

It is well known [19] that for a sufficiently large number of RBF neurons N_0, there exists an ideal outer-layer RBF NN weights matrix Θ, which provides function approximation on a compact n_p – dimensional x_p – domain $X_p \subset R^{n_p}$, within the approximation tolerance ε_0^*:

$$\left\| \varepsilon_0\left(x_p \right) \right\| \le \varepsilon_0^*, \quad \forall\, x_p \in X_p \quad (15)$$

Since the ideal weights matrix Θ is not known, its on-line estimated counterpart $\hat{\Theta}$ is used instead. The corresponding *function approximation error*

$$\Delta K\left(x_p \right) = \underbrace{\hat{K}\left(x_p \right)}_{\hat{\Theta}^T\, \Phi\left(x_p \right)} - K\left(x_p \right) \quad (16)$$

is directly related to the on-line *parameter estimation error*

$$\Delta\Theta = \hat{\Theta} - \Theta \quad (17)$$

Basically, the former depends linearly on the latter:

$$\Delta K\left(x_p \right) = \hat{K}\left(x_p \right) - K\left(x_p \right) = \underbrace{\left(\hat{\Theta} - \Theta \right)}_{\Delta\Theta}^T\, \Phi\left(x_p \right) - \varepsilon_0\left(x_p \right) \quad (18)$$

Using Lyapunov-based design approach coupled with the Barbalat's Lemma, bounded output tracking is achieved through on-line parameter adaptation process:

$$\begin{cases} \dot{\hat{k}}_x = \Gamma_x\, \mathrm{Proj}\left(\hat{k}_x,\, -x\, e^T\, P\, B_1 \right) \\ \dot{\hat{k}}_z = \Gamma_z\, \mathrm{Proj}\left(\hat{k}_z,\, -z_c\, e^T\, P\, B_1 \right) \\ \dot{\hat{\Theta}} = \Gamma_\Theta\, \mathrm{Proj}\left(\hat{\Theta},\, \Phi\left(x_p \right) e^T\, P\, B_1 \right) \end{cases} \quad (19)$$

In (19), symmetric positive-definite matrices $\left(\Gamma_x, \Gamma_z, \Gamma_\Theta \right)$ represent the adaptation rates, $e = x - x_{ref}$ is the model following state tracking error, and P is the unique symmetric positive-definite solution of the Lyapunov algebraic equation:

$$P\, A_{ref} + A_{ref}^T\, P = -Q \quad (20)$$

with a symmetric positive-definite matrix Q. In addition, $\text{Proj}(*,*)$ (Pomet, Praly [20]) denotes the *Projection Operator*, which is designed to keep the adaptive parameters bounded. Moreover, *dead-zone modification* of the adaptive laws must be used in order to provide robustness to noise and to prevent the adaptive process from improving the baseline closed-loop characteristics. Basically, the dead-zone logic freezes adaptation process when the norm of the tracking error falls below a pre-specified tolerance.

IV. Adaptive Control Design Modifications In The Presence Of Actuator Constraints

One of the major challenges that arise in control design and in flight control in particular is input saturation, which implies that either a control position or its rate limit has been exceeded. This challenge is even more acute in weapon systems where the flight control system is designed to achieve the highest bandwidth possible. A common ad-hoc approach for most adaptive systems involves slowing or completely stopping adaptation when control input saturates. In Lavretsky and Hovakimyan [16], a theoretically justified direct adaptive model reference control design modification was proposed that provided and maintained stable adaptation in the presence of control input constraints. The design approach was termed "Positive μ – modification". It requires modifications of the reference model (12) and of the total control command (13). The two adaptive design modifications account for control saturation phenomenon created by static actuator model:

$$u(t) = U_{\max}\,\text{sat}\left(U_{\max}^{-1}\,u_c(t)\right) = \begin{pmatrix} u_{\max}^{1}\,\text{sat}\left(\dfrac{u_c^1(t)}{u_{\max}^1}\right) \\ \vdots \\ u_{\max}^{m}\,\text{sat}\left(\dfrac{u_c^m(t)}{u_{\max}^m}\right) \end{pmatrix} \tag{21}$$

where $u_c \in R^m$ is the total commanded m–dimensional control input, $U_{\max} \in R^{m\times m}$ is a diagonal matrix with actuator position saturation limits on its main diagonal, and $u \in R^m$ is the actuator output which in its turn drives extended system (8).

Let $u_{LinP} = u_{bl} + u_{ad}$ denote linear in parameters total control signal from (13). Note that due to the presence of actuator model (21), the commanded signal and the actuator output may no longer be equal to each other. Towards this end, a *control deficiency* vector is introduced as follows:

$$\Delta u_{LinP} = u - u_{LinP} \tag{22}$$

Component wise, relation (22) can be written as:

$$\Delta u_{LinP}^{i} = u_{\max}^{i}\,\text{sat}\left(\frac{u_c^i(t)}{u_{\max}^i}\right) - u_{LinP}^{i} \tag{23}$$

Next, a vector of *conservative* actuator limits is defined:

$$u_{\max}^{\delta} = u_{\max} - \delta \tag{24}$$

where the m – components of the constant vector δ are chosen such that:

$$0 \le \delta_i \le u_{\max}^{i}, \quad (\forall 1 \le i \le m) \tag{25}$$

Based on (24), *conservative control deficiency* vector Δu_c is defined component wise as:

$$\Delta u_c^i = \left(u_{\max}^{\delta}\right)_i \text{sat}\left(\frac{u_c^i}{\left(u_{\max}^{\delta}\right)_i}\right) - u_c^i, \quad (\forall 1 \le i \le m) \tag{26}$$

Finally, total commanded control input u_c with μ – modification is formed:

$$u_c = u_{LinP} + \underbrace{\begin{pmatrix} \mu_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \mu_m \end{pmatrix}}_{\mu} \Delta u_c = u_{LinP} + \mu\,\Delta u_c \tag{27}$$

It is clear that the total command u_c in (27) is defined implicitly. Choosing $\mu_i \ge 0$, total control command can be derived in its explicit form:

$$u_c^i = \begin{cases} u_{LinP}^i, & \left|u_{LinP}^i\right| \le \left(u_{\max}^{\delta}\right)_i \\ \dfrac{1}{1+\mu_i}\left(u_{LinP}^i + \mu_i\left(u_{\max}^{\delta}\right)\right), & u_{LinP}^i > \left(u_{\max}^{\delta}\right)_i \\ \dfrac{1}{1+\mu_i}\left(u_{LinP}^i - \mu_i\left(u_{\max}^{\delta}\right)\right), & u_{LinP}^i < -\left(u_{\max}^{\delta}\right)_i \end{cases} \tag{28}$$

While relation (28) defines the modified total commanded control signal, the modified reference model dynamics is written based on (12).

$$\dot{x}_{ref} = A_{ref}\,x_{ref} + B_{ref}\left(z_c + \hat{K}_u^T\,\Delta u_{LinP}\right) \tag{29}$$

In (29), $\hat{K}_u$ is the adaptive gain for changing the reference model dynamics. The gain adaptation law is derived using Lyapunov approach:

$$\dot{\hat{K}}_u = \Gamma_u\,\text{Proj}\left(\hat{K}_u,\,\Delta u_{LinP}\,e^T\,P\,B_{ref}\right) \tag{30}$$

In order to gain further insight into the design modification, consider its simplification.

Set $\mu_i = \delta_i = 0$. Then the total command (28), the reference model (29), and the adaptive law (30) take the form

$$\begin{cases} u_c = u_{LinP} = \left(K_x + \hat{k}_x\right)^T x + \left(K_z + \hat{k}_z\right)^T z_c - \hat{\Theta}^T\,\Phi\left(x_p\right) \\ \dot{x}_{ref} = A_{ref}\,x_{ref} + B_{ref}\left(z_c + \hat{K}_u^T\left(u - u_{LinP}\right)\right) \\ \dot{\hat{K}}_u = \Gamma_u\,\text{Proj}\left(\hat{K}_u,\,\left(u - u_{LinP}\right)e^T\,P\,B_{ref}\right) \end{cases} \tag{31}$$

In other words, the adaptation will regulate the gain $\hat{K}_u$ such that the reference model state x_{ref}, driven by the modified commanded signal

$$z_c^{\text{mod}} = z_c + \hat{K}_u^T\left(u - u_{LinP}\right) \tag{32}$$

will not cause control saturation during tracking.

Remark 1 **-** As one might expect, for a nonzero vector δ, large values of $\mu \ge 0$ in (28) will result in large changes to the reference dynamics. At the same time, the control deficiency is reduced, thus potentially avoiding control saturation phenomenon completely. Thus, the design constants μ and δ can be viewed as tuning knobs that allow a trade-off between the adaptive changes to the reference model and a protection against saturating actuator position which is required for tracking the model.

Remark 2 **-** It is often possible to use a constant value of the gain $\hat{K}_u = K_u$ and thus eliminate its adaptive law from (31). Moreover, setting $\delta_i = 0$, using (22), (26), and (27) yields:

$$\Delta u_c = u - u_c = \underbrace{u - u_{LinP}}_{\Delta u_{LinP}} - \mu\,\Delta u_c = \Delta u_{LinP} - \mu\,\Delta u_c \qquad (33)$$

Consequently:

$$\Delta u_c = \left(I_m + \mu\right)^{-1}\ \Delta u_{LinP} \qquad (34)$$

and therefore:

$$\begin{aligned} u_c &= u_{LinP} + \mu\left(I_m + \mu\right)^{-1}\ \Delta u_{LinP} \\ &= \left(K_x + \hat{k}_x\right)^T x + \left(K_z + \hat{k}_z\right)^T z_c + \mu\left(I_m + \mu\right)^{-1}\ \Delta u_{LinP} - \hat{\Theta}^T\,\Phi\left(x_p\right) \end{aligned} \qquad (35)$$

To this end, choose matrix μ such that:

$$\left(K_z + \hat{k}_z\right)^T K_u^T = \mu\left(I_m + \mu\right)^{-1} \qquad (36)$$

Relation (36) implies that μ must be set to:

$$\mu = \left(I_m - \left(K_z + \hat{k}_z\right)^T K_u^T\right)^{-1}\left(K_z + \hat{k}_z\right)^T K_u^T \qquad (37)$$

Then the total control command in (35) can be written as:

$$u_c = \left(K_x + \hat{k}_x\right)^T x + \left(K_z + \hat{k}_z\right)^T \underbrace{\left(z_c + K_u^T\,\Delta u_{LinP}\right)}_{z_c^{\mathrm{mod}}} - \hat{\Theta}^T\,\Phi\left(x_p\right) \qquad (38)$$

or, equivalently:

$$u_c = \left(K_x + \hat{k}_x\right)^T x + \left(K_z + \hat{k}_z\right)^T z_c^{\mathrm{mod}} - \hat{\Theta}^T\,\Phi\left(x_p\right) \qquad (39)$$

As a result, both the total control input u_c and the reference model dynamics (29) will utilize the modified command z_c^{mod} instead of the original signal z_c. However, the former depends on the control deficiency Δu_{LinP}, which depends on the control signal u, which in turn depends on the commanded control signal u_c. Consequently, relation (39) gives *implicit* definition of the latter. Its implicit expression can be easily obtained by substituting matrix μ from (37) into relation (28) with $\delta_i = 0$.

V. Flight Test of the Adaptive Flight Control System

Two flight tests were conducted. They consisted of a canned and a guided flights. During the canned flight, the weapon flew a pre-programmed set of maneuvers. Following release, the weapon executes a rate capture sequence immediately followed by an angle-of-attack (AOA) and angle-of-sideslip (AOSS) capture and regulation to zero. This puts the weapon on a ballistic trajectory. After two seconds, AOA is ramped up to its maximum value, held there for 10 seconds, and then ramped back to zero. Two seconds later a +30 degree bank is commanded and the AOA is ramped back up to its maximum value. This is held for 10 seconds, at which time the weapon is commanded to bank to -30 degrees. Two seconds following the -30 degree bank, a positive AOSS step is commanded (converted into an equivalent lateral acceleration). The weapon is then commanded back to a zero bank angle, the AOA is ramped back to zero, and another AOSS step is commanded in the negative direction. Following this maneuver AOA is commanded to a large value (this was at the end of the trajectory) to represent a terminal guidance update at a high dynamic pressure flight condition. During the guided test, the performance of the weapon was tested against a stationary target. Both the canned and the guided flight testing was very successful, with all objectives met. Details of the flights can be found in [21].

VI. Open Problems

This section contains a short discussion on several open problems in adaptive flight control of aircraft and weapon systems.

Reference Model Design - Central to the design of model reference adaptive controllers is the model used for the reference. For aircraft and weapon systems the choice of a suitable model remains an open problem. For aircraft, scheduling of these models for takeoff roll, rotation, climb-out, cruise, approach, and landing is in itself a challenging problem. Often the reference model desired for command tracking, depending upon the maneuver or task, is not the same reference model for gust rejection. For weapon systems, the large changes in flight envelope create scheduling problems in which the transients due to scheduling parameters can be significant, and introduce unwanted dynamics.

Parameter Tuning Guidelines - There are several parameters and matrices used in the design process that need tuning. Engineers in industry like to have rules of thumb for selecting/creating the design. It is clear that more insight and research is needed to improve the transient performance of adaptive systems if they are to become part of industry's design methods.

The Lyapunov matrix, Eq. (20), requires the selection of the Q matrix. The size of Q and how full the matrix is influences P, and $\dot{\hat{k}}_i$ through $e^T PB$ in Eq. (19). The learning rate matrices $\left(\Gamma_x, \Gamma_z, \Gamma_\Theta\right)$ also influence the adaptation dynamics. Trial and error methods are currently used to design these parameters. When the adaptation rate is too fast, undesirable oscillations occur. When the adaptation rate is too slow, the adaptive control is ineffective in coping with the fast nature of the tracking problem at hand.

To prevent high frequency oscillations, Cao and Hovakimyan [22,23] has developed a novel approach incorporating feedback and a low pass filter to remove undesirable high frequency dynamics from the control signal, while preserving the asymptotic convergence of the tracking error to zero.

Tracking error thresholds used to prevent parameter drift influence the transient and steady state behavior of the system. Sizing the dead-zones is critical step in the design process. It is imperative in flight control systems that noise does not cause the parameters to drift and escape.

Adaptive Dead-zone and Learning Rates - An interesting problem in designing adaptive control for aircraft and weapons is gust and turbulence rejection. For gust rejection, fast learning rates can aid in preventing departures. However, in other instances these high learning rates introduce unwanted high frequency oscillations and transients. Dead-zones can be adjusted to prevent the adaptive control from fighting (responding) to turbulence. However, widening the dead-zone negates many of the benefits the adaptive control provides.

Adaptive Structural Mode Suppression - Flight control engineers must compensate for structural mode interaction with the control system. Typically a gain stabilization approach is used in which there is enough frequency separation from the rigid body modes and the structural modes. To account for changes in mass properties and the flight envelope, the filters are often conservative and reduce stability margins more than necessary. Eliminating this conservatism would have benefits in many areas.

Gain and Phase Margins for Adaptive Systems – The notion of gain and phase margins for adaptive systems is quite appealing. Simulation analyses have shown that adaptive system with high learning rates are not robust to time delays in the feedbacks. This begs the question as to how much "margin" is present in the design, and how best to analyze such a nonlinear problem. In addition, how can adaptive systems be evaluated using RTSMs during flight envelope expansion testing.

VII. CONCLUSION

Direct adaptive model reference control has proven to be a valuable tool for aircraft and weapon flight control problems. Not only can the algorithms provide compensation for uncertain aerodynamic parameters, they can compensate for actuation failures, battle damage, and unknown unknowns, creating a system with reliable performance in the presence of what seems like large uncertainty. This paper has reported on recent successes and has identified areas for continued work based on application of the methods.

The applications and successes reported in this paper represent a major transition of technology from academia to industry. Through the excellent theoretical work of many researchers adaptive flight control designs are emerging from industry and finding their way into DoD products. Although they haven't been incorporated into manned aircraft, it will be through the maturation of these designs and architectures using weapon systems that the maturity and understanding required for manned aircraft will come.

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Figure 1 Test weapon on the launch aircraft.