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A COMPARISON OF INTELLIGENT, ADAPTIVE, AND NONLINEAR FLIGHT CONTROL LAWS

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Abstract

This paper compares in simulation six different nonlinear control laws for multi-axis control of a high performance aircraft. The control law approaches are fuzzy logic control, backstepping adaptive control, neural network augmented control, variable structure control, and indirect adaptive versions of Model Predictive Control and Dynamic Inversion. In addition, a more conventional scheduled dynamic inversion control law is used as a baseline. In some of the cases, a stochastic genetic algorithm was used to optimize fixed parameters during design. The control laws are demonstrated on a 6 Degree-of-Freedom simulation with nonlinear aerodynamic and engine models, actuator models with position and rate saturations, and turbulence. Simulation results include a variety of single and multiple axis maneuvers in normal operation and with failures or damage. The specific failure and damage cases that are examined include single and multiple lost surfaces, actuator hardovers, and an oscillating stabilator case. There are also substantial differences between the control law design and simulation models, which are used to demonstrate some robustness aspects of the different control laws.

Introduction

The last decade has seen substantial advances in nonlinear control due to both theoretical achievements,[1] and the availability of powerful computer hardware and user-friendly nonlinear simulation software. While nonlinear control approaches other than gain-scheduling have not been commonly used on aircraft,[2] there have been many research efforts that have produced simulation results. In a few noteworthy cases, nonlinear control algorithms have been flown on test aircraft[3-6] or used in limited ways on production aircraft.[34] Despite all of this work, it can be difficult to judge the relative value of different nonlinear control approaches for any specific flight control problem. Even for a single vehicle, nonlinear flight control laws may have widely varying performance depending on the class of inputs and the desired flight envelope. Nonlinear controllers have been known to demonstrate spectacular results on simplified aircraft models, but then display pathological responses when applied to higher fidelity simulation models. Actuator nonlinearities have been a significant problem, as many nonlinear control approaches tend to generate large effector commands or rates, and have poor performance when effectors become saturated. Even without actuator saturations, the issue of control power requirements is of importance for the acceptance of nonlinear flight control. Given the penalties involved with increasing control power or rate requirements on new aircraft designs, there is some reluctance to use any control law where it is not reasonably clear that every bit of effector command serves a useful and well-understood purpose. Other key areas of concern with nonlinear control laws include the ease with which designs can be tuned to incorporate pilot feedback, configuration changes, etc., and the ease with which designs can be analyzed and validated for safety of flight.

The purpose of the work described in this paper is to compare seven different nonlinear control approaches on an aircraft problem with some of the complexities of a real flight control law design. The author's background has included flight control applications of Fuzzy Logic Control,[7-8] Neural Network Control,[9] Backstepping Adaptive Control,[10-12] Indirect Adaptive Control,[13] Nonlinear

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Predictive Control,[14] Variable Structure Control,[15] and the use of Genetic Algorithms to optimize control laws.[10,16-17] The approaches developed under these efforts made adequate starting points for this study, although considerable alteration of previously developed designs was necessary to take into account more recent advances, and to deal with aircraft complexities not addressed in the earlier work. In addition to the above six approaches, a scheduled Dynamic Inversion (DI)[18-21] controller was used as a baseline, since it is a relatively mature technique. DI also is very closely related to most of the other controllers in this paper.

The basic concept behind Dynamic Inversion is to cancel out the aircraft's natural dynamics so it will follow desired dynamics inserted by a designer. A DI control law is shown in Fig. 1. The command generator outputs desired values of the controlled variables. The outputs of the command generator are combined with the sensed values of the controlled variables to create desired dynamics for the aircraft to follow. The desired dynamics take into account tracking error and integrated error in order to give the control law some robustness to uncertainty. The next step is the dynamic inversion block, which inverts a state-space model of the aircraft to choose actuator commands that will make the aircraft follow the desired dynamics. The state-space model has parameters that vary across the envelope, and need to be updated based on flight condition. Ideally, this control law should make the aircraft behave like an ideal integrator so that it tracks the desired dynamics precisely. In reality, control power limitations and modeling error prevent this from happening perfectly, so control allocation and an integrator anti-wind-up approach have to be used to determine acceptable actuator commands, and keep integrated error from unrestrained growth when the aircraft cannot achieve the desired performance.

One simple adaptive modification to a DI controller is to replace the parameter scheduling block of Fig. 1 with on-line parameter estimation. The Indirect Adaptive Controller (IAC) uses the Modified Sequential Least Squares approach to identify the major stability and control parameters. MSLS has been successfully flight tested,[3] and demonstrated in simulation on an advanced tail-less configuration. While this indirect adaptive approach has many practical benefits, proving stability and convergence of the total system is very challenging. An approach more focused on theoretical proofs of total system stability and convergence is the Backstepping Adaptive Controller (BAC). The BAC also performs on-line estimation of parameters in a DI framework, but does so using parameter update laws chosen with a Lyapunov approach to ensure the nominal system's stability and convergence to zero tracking error. Another potential benefit of the backstepping approach is that actuator saturations can be dealt with to some extent without violating the stability proof. However, like many stability oriented approaches, achieving acceptable transient properties can be difficult. Currently, there have been only a fairly limited number of flight control simulation applications of this approach.[10-12,22]

Another modification of a DI controller that can be proven to be stable with a Lyapunov approach is to include a nonlinear adaptive term in the desired dynamics block of Fig. 1. This approach attempts to compensate for uncertainty without explicitly identifying changes in the aircraft model. The Neural Network Controller (NNC) and the Variable Structure Controller (VSC) both adopt this approach. The NNC uses a type of adaptive nonlinearity very loosely related to the parallel, distributed way the brain processes and stores information.[7-8] This approach has been flight tested and applied to several different aircraft simulation models.[23-24] Alternatively, the VSC uses an approximation of a discontinuous nonlinearity that has been proven to have considerable robustness properties in theory. This approach has been demonstrated for flight control on numerous simulation models.[15,25-26]

A sixth controller, the Model Predictive Controller (MPC) is related to Dynamic Inversion, but provides lead action by calculating a sequence of commands that optimizes a quadratic cost function over a short time interval. By solving the optimization problem using Sequential Quadratic Programming, it is also possible to directly incorporate a variety of useful constraints. The MPC controller used in this paper is also another indirect adaptive controller that uses MSLS parameter estimation for adaptation. Model Predictive Control is an approach that has been very successful in the process control industry, and has been demonstrated for flight control in numerous simulation studies.[14,27-29]

The final controller is the only one that does not explicitly use a model of the plant, and is quite different from DI. Fuzzy Logic is a machine intelligence approach in which desired behavior can be specified in rules, such as "if roll error is large and roll rate is medium then aileron position is large." This allows incorporation of complex nonlinear strategies based on pilot or engineer "intelligence" within the control law. While the fuzzy logic controller is a non-adaptive controller, the use of "pilot" strategies can allow considerable ability to respond to failures. Fuzzy Logic is currently used on production aircraft in a limited way[34] and has been demonstrated for flight control in a number of simulation studies.[7-8]

It should be stressed that this paper is not meant to pick winners and losers, but only to provide empirical data to show some potential strengths and weaknesses of each approach on a problem with some aspects of the complexity of a real aircraft design. All of the control laws examined in this paper display features that might make them a good choice for certain types of design problems. There are also numerous variations of each approach that could not be tried within the scope of this effort that might yield better results. Further, changes in the design problem or rating criteria could certainly yield different answers in the relative performance of each controller. For example, the use of a linear desired performance model may penalize the fuzzy logic or model predictive controllers, which have been demonstrated elsewhere to be particularly good with certain types of nonlinear performance criteria. Alternatively, the fixed controllers may have a disadvantage compared to the adaptive controllers due to the lack of any supervisory control like a pilot (though it is also possible a pilot might interact more unpredictably given the potential for pilot-vehicle coupling with some of these approaches).

II. Design Problem

The design problem examined in this paper includes the following elements:

1) Track a desired performance model for different types of single and multiple-axis maneuvers over the subsonic flight envelope. The controlled variables are roll angle, angle-of-attack, and sideslip angle.
2) Achieve this performance despite fairly restrictive actuator position and rate saturations. The control allocation technique was a simple ganging of ailerons, rudders, and stabilators into 3 pseudo-effectors. As a result, the controllers have to deal with much less control power than would be available with a more sophisticated control allocation approach. An additional complexity is that the saturation rates are substantially different for the different actuators. Ailerons, for example, are more than twice as fast as stabilators. Note that some initial results in combining some of these algorithms with other control allocation techniques can be found in ref 30.
3) Minimize control effector usage. It is typical in many research papers to use the maximum capability of an existing aircraft. However, for a new aircraft design, reduced control power requirements translate into lower penalties in areas such as weight and drag.
4) Demonstrate robustness to uncertainty in stability and control parameters, and in the structure of the aircraft model. Those approaches that use models used a simplifed nonlinear model that assumes among other things, constant velocity and no lift and drag effects of surface deflections. This model can be seen in refs. 10-12 and 30. Approaches that use a priori values of stability and control parameters also had to deal with substantial parametric error, even in unfailed cases.
5) Maintain stability and restore maximum tracking capability following single actuator hardover failures. For this paper, it is assumed that the flight control redundancy management system knows it can no longer command the failed actuator. However, the system does not know if the actuator failed in a neutral or in a hardover position.
6) Maintain stability and limited navigational capability following an oscillating stabilator failure. This failure is similar to one caused by a detached LVDT. In this case, due to the multiple correlated failure of the actuator sensors, it is assumed that there is no awareness of the actuator failure.
7) Restore maximum tracking capability following damage to the stabilator, aileron, and rudder surfaces singly and in combination. These cases were simulated by negating the effect of the control surface on the force and moment build-ups in the model. This approximates failures caused by battle or mid-air collision damage. It is assumed that there is no explicit identification of this failure.

The aircraft simulation that was used to generate all results in this paper is a high performance aircraft with 2 engines, 2 stabilators, 2 ailerons, 2 rudders, 2 leading edge flaps, and 2 trailing edge flaps. The simulation uses the standard equations of motion and kinematic relations found in a variety of standard references on flight dynamics[31]

$$\dot{u} = \frac{F_{X_A} + F_{X_T}}{m} - g\sin\Theta + rv - qw$$
$$\dot{v} = \frac{F_{Y_A} + F_{Y_T}}{m} + g\cos\Theta\sin\Phi + pw - ru$$
$$\dot{w} = \frac{F_{Z_A} + F_{Z_T}}{m} + g\cos\Theta\cos\Phi + qu - pv$$
$$\dot{p}\left(I_{XX}I_{ZZ} - I_{XZ}^2\right) = I_{ZZ}\left(l_A + l_T - qr\left(I_{ZZ} - I_{YY}\right) + qpI_{XZ}\right) + I_{XZ}\left(n_a + n_T + qp\left(I_{XX} - I_{YY}\right) - qrI_{XZ}\right)$$
$$\dot{q}\left(I_{YY}\right) = m_A + m_T + \left(r^2 - p^2\right)\left(I_{XZ}\right) + pr\left(I_{ZZ} - I_{XX}\right)$$
$$\dot{r}\left(I_{XX}I_{ZZ} - I_{XZ}^2\right) = I_{XX}\left(n_A + n_T + qp\left(I_{XX} - I_{YY}\right) - qrI_{XZ}\right) + I_{XZ}\left(l_a + l_T - qr\left(I_{ZZ} - I_{YY}\right) + qpI_{XZ}\right)$$
$$P = \dot{\Phi} - \dot{\Psi}\sin\Theta$$
$$Q = \dot{\Theta}\cos\Phi + \dot{\Psi}\cos\Theta\sin\Phi$$
$$R = \dot{\Psi}\cos\Theta\cos\Phi - \dot{\Theta}\sin\Phi$$

The components of the aerodynamic forces (F_{XA},F_{YA},F_{ZA}) and moments (l_A,m_A,n_A) are calculated from table look-ups. Gross thrust, T, is calculated from the following equation:

$$T = \left[1 + a_1\alpha + a_2\alpha^2\right]F_T(h, M, P_{LT})\left[kP_{LT} + c\right]$$

where a_1, a_2, c, and k are constants, F_T is calculated from a table look-up, and P_{LT} is lagged throttle position. The throttle model is a first order linear system with a variable time constant and variable rate limit based on the value of P_{LT}. The actuator models are 2nd order linear systems (except for stabilators, which are fourth order) with rate and position limits as shown in Table 1. The turbulence model is the standard Dryden Gust model from MIL-STD-1797A.[32]

III. Controller Descriptions

For the following controller designs, the aircraft equations of motion were assumed to be of the form

$$\dot{y} = \Phi_0(x_1) + \Phi(x_1)w_1 + B(x_1)\omega$$
$$\dot{\omega} = \psi_0(x) + \psi_1(x)w_2 + D(w_u)u$$
$$\dot{\eta} = q_0(x) + q_1(x)w + q_2(w_u)u$$

where y is a vector of the outputs that will be controlled, w_1, w_2, and w_u are vectors of parameters that vary over the flight envelope, x is the state vector, x_1 is a subset of the state vector, u is the vector of control effector commands, and

$$y = (\phi, \alpha, \beta)^T$$
$$\omega = (p, q, r)^T$$
$$\eta = \theta$$
$$x = (p, q, r, \alpha, \beta, \phi, \theta)$$
$$x_1 = (\alpha, \beta, \phi, \theta)$$
$$w_1 = (z_\alpha, y_\beta)^T$$
$$w_2 = (l_\beta, l_p, l_q, l_r, l_{\beta\alpha}, l_{r\alpha}, \overline{m}_\alpha, \overline{m}_q, m_{\dot{\alpha}}, n_\beta, n_r, n_p, n_{p\alpha}, n_q)^T$$
$$w_u = (l_{\delta a}, l_{\delta e}, l_{\delta r}, \overline{m}_{\delta e}, n_{\delta a}, n_{\delta e}, n_{\delta r})^T$$

Note that this form is used only for design purposes. The full equations of motion of the proceeding section will be used for simulation. An error will be defined as

$$e = y - y_c$$

where y_c is the output of a command generator that is a linear, stable 3rd order system. Finally, all of the controllers were designed assuming an update rate of 100 Hz.

Dynamic Inversion (DI) – The DI controller had separate inner and outer loop control laws. The outer loop used desired values of ω as virtual effectors to track the commanded values of the outputs. The virtual effector commands were calculated by inverting the design model

$$\omega_d = B^{-1}(\dot{y}_d - (\Phi_0(x_1) + \Phi(x_1)w_1))$$

Since it is possible that a commanded ω_d will far exceed the capabilities of the aircraft, limits were set on ω_d that vary with flight condition. When the commanded values of ω_d did not exceed the limits, the desired dynamics were

$$\dot{y}_d = \dot{y}_c + K_{DI_P}e + K_{DI_I}\int e$$

where K_{DIp} and K_{DIi} were positive diagonal gain matrices. When the ω_d limits were exceeded, a control allocation approach was used to calculate the output of the control law, and integrator wind-up protection modified the above desired dynamics equation following the approach of ref. 19. The inner loop DI control law works similarly to the outer loop to track ω_d with control limits based on actuator position and rate saturations.

The control parameter vector w_u was scheduled during maneuvering using a coarse linear interpolation based on Mach number, angle-of-attack, and dynamic pressure. Scheduling of the stability parameter vectors w_1 and w_2 was done only for the trim condition at the beginning of a maneuver, and was then kept fixed. As a result, the DI control law was required to have considerable robustness to parametric errors, since the flight condition could change substantially during some maneuvers. Following detection of actuator hardover failures, the relevant control effectiveness parameters were updated, and the ω_d limits were set at a lower degraded setting. For other failure cases, the DI control law was not modified, since it was assumed the system has no knowledge of the failure.

Overall, the DI controller was relatively easy to design. The primary fixed parameters all had a relatively clear relationship to the aircraft's performance. The integrator anti-wind-up protection required some trial-and-error tuning, but this was not prohibitive.

Indirect Adaptive Controller (IAC) – An indirect adaptive version of the above DI controller was created by replacing the parameter scheduling block of fig. 1 with on-line parameter estimation. Parameter estimation was only used as part of the inner loop DI controller to identify the 21 parameters in the vectors w_2 and w_u. Parameter estimation was not used with the outer loop because the most important varying parameters have limited effect and are very hard to estimate. The parameter identification approach used was Modified Sequential Least Squares (MSLS). MSLS attempts to optimize a cost function that includes both the more conventional predicted squared error of the estimate over a weighted window of data, and a term that penalizes the estimate for deviations from a constraint of the form

$$k = M\theta$$

where θ is a vector of parameter estimates, M is a positive weighting matrix, and k is a matrix of constraints. The constraints penalize the estimate for large deviations from a weighted blending of previous and a priori estimates of the parameters. Finding good values for the weighting of these constraints along with the forgetting factor required considerable trial and error experimentation. For that reason, a stochastic genetic algorithm[33] was used for initial determination of these fixed parameters.

Backstepping Adaptive Control (BAC) - The Backstepping Adaptive controller is essentially another adaptive variant of the DI control law that attempts to estimate parameters on-line. However, unlike the above IAC, the parameter update laws were not chosen to minimize the predicted error of the estimate. Instead, the parameter update laws were chosen using a Lyapunov approach to ensure system stability and convergence to zero tracking error. The BAC was based on the design of ref. 10 and had the following parameter update laws:

$$\dot{\hat{w}}_1 = f_c L_1^{-1}(\Phi^T s + \psi_{1a}^T \tilde{\omega})$$

$$\dot{\hat{w}}_2 = f_c L_2^{-1}\psi_{2a}^T \tilde{\omega}$$

$$\dot{\hat{w}}_u = f_c L_3^{-1}\Psi_u^T \tilde{\omega}$$

where L_1, L_2, and L_3 were all positive definite diagonal matrices, $\tilde{\omega}$ was the difference between the desired and actual values of ω, and the ψ_{ia}'s and Ψ_u matrices were functions of the states and effector positions. f_c was a positive scalar function with bounded derivatives that normally equals 1, but can be decreased to reduce the growth of integrated error and rate of change of parameters when the actuators are approaching saturation. As described in refs. 10-11, f_c was made up of 2 components. The first was a fuzzy logic component and the second was a 3rd order linear stable system, chosen such that the derivative of f_c meets requirements for system stability.

The connection between fixed parameters and aircraft response in this control law is very complex, although understandable with effort. As a result, the fixed parameters in the control law were initially chosen using a stochastic genetic algorithm.

Neural Network Controller (NNC) – The Neural Network Controller is another modification of a dynamic inversion controller based on the approach of ref. 23. The neural network is placed in the desired dynamics block of Fig. 1 so that

$$\dot{y}_d = \dot{y}_c + K_{DI_P} e + w_{NN} \varsigma$$

where w_{NN} is a matrix of neural network weights and ς is a vector of the neural network basis functions. The neural network had 172 basis functions and its inputs were aircraft states and the past output of the desired dynamics block. Adaptation of weights in the neural network was done using a slightly modified form of

$$\dot{w}_{NN} = -\gamma(e\varsigma + \eta|e|w_{NN})$$

Where γ and η are positive constants less than one. The first term is derived from a Lyapunov stability approach, and the second term ensures the boundedness of the neural network weights. Choosing acceptable values for the fixed parameters in the neural network required considerable trial-and-error experimentation across the flight envelope as the parameters can effect the aircraft's behavior in complicated ways.

Variable Structure Controller (VSC) – Basic Variable Structure Control uses a discontinuous control law to compensate for uncertainty. In theory, this approach has impressive robustness properties. In reality, the discontinuity can create oscillations due to imperfect sensors and actuators. As a result, practical VSC designs often use a continuous approximation of the discontinuity around a boundary region, such as

$$sat(e) = \langle \begin{matrix} e/\varepsilon & if\ \varepsilon \geq abs(e) \\ sign(e) & if\ \varepsilon \prec abs(e) \end{matrix}$$

where ε is a positive scalar value. This term was added to the desired dynamics block in Fig. 1 so that the desired dynamics were

$$\dot{y}_d = \dot{y}_c + K_{DI_P}e + K_{VSC}sat(s)$$

where K_{VSC} is an adaptive gain. An adaptive gain is used since choosing values of K_{VSC} and ε to assure stability despite the worst-case uncertainty can lead to a very high gain controller. Adaptation of K_{VSC} was done using a supervisory set of fuzzy logic rules that includes actuator usage similar to the approach of refs. 10-11. The choice of fixed parameters in this control law was fairly challenging as the parameters can effect the system response in unpredictable ways for different inputs and flight conditions.

Model Predictive Controller (MPC) - The basic concept behind Model Predictive Control is to choose a sequence of control commands that optimize a quadratic cost function over a finite period of time. At each time step, only the first control value of the sequence is used. On the next time step, a new optimal sequence is computed. By solving this optimization problem using Sequential Quadratic Programming (SQP), it is possible to directly incorporate a variety of constraints, such as actuator position and rate limits. Unfortunately, there were some convergence problems with the basic MPC controller in some parts of the envelope, so a fast stable inner loop control law was used similar to the approach of ref. 27. There are a variety of adaptive approaches that can be used with MPC. Due to time constraints, it was decided to create an indirect adaptive version using the previously described MSLS parameter estimation approach. The fixed parameters in this control law all have a fairly easily understood effect on system performance individually. However, the effect of modifying multiple parameters was not always clear, particularly for cases of constrained optimization due to actuator saturations. As a result, the stochastic genetic algorithm was used to determine initial parameter values.

Fuzzy Logic Controller (FLC) – Fuzzy Logic Control is a machine intelligence approach that can be used to incorporate aspects of pilot "intelligence" with more conventional control approaches. This can, to a limited extent, duplicate some of the ways a pilot might respond to an aircraft that was not behaving as expected due to damage or failures. The FLC used in this paper was based on the Automatic Carrier Landing System of refs. 7-8. There were 3 rule bases that control roll, angle-of-attack, and sideslip. Separate rule bases were necessary because fuzzy logic controllers can become very unmanageable if there are more than a few important inputs. The main inputs were error, derivative of error, and integrated error of the controlled variable. The rules that use these inputs make up the majority of the rules, and are used essentially to create a nonlinear response with low damping for large errors and high damping for small errors. In addition, a small number of rules used some aircraft states and past commands. These rules were designed to deal with extreme damage or failure cases, and are of the form "if the aircraft is doing something substantially different from what was commanded, then perform this compensation". The membership functions were gaussian to allow smooth transition between rules. Initial values of the membership functions were determined using the stochastic genetic algorithm, although much further tuning was required. Each rule base had between 40-55 rules and outputted commands of decoupled pseudocontrols. The outputs were multiplied by the inverse of the control matrix to distribute commands among the three control pseudo-effectors. Further scheduling was done by scaling the inputs to the rule bases using the control effectiveness at each point of the envelope. For hardover failures, a pseudo-inverse is used to re-allocate the commands following loss of the actuator. For other failures, no changes are made.

IV Results

Given the large number of controllers, and the literally thousands of maneuvers that were done with each controller, it was extremely difficult to reduce the data into a meaningful form that could fit into a short paper. The following tables show average absolute error over a 15-second time window for a set of maneuvers at 4 flight conditions. The flight conditions are .9M, 10,000 ft. altitude, .8M 20,000ft, .7M 30,000ft., and .6M, 40,000 ft. The maneuvers are 4 second single and multiple axis pulses and triangular doublets from a trim condition. The tables are divided between small, medium, and large maneuvers whose magnitudes are shown in Table 2 for low dynamic pressure. The three sizes of roll maneuvers were 5, 60, and 180 degrees across the envelope. The three sizes of angle-of-attack maneuvers varied throughout the envelope and included small and medium negative maneuvers as well. At low dynamic pressure they were –15, -5, 5, 15, and 30 degrees from trim. At high dynamic pressure, the alpha maneuvers were –2, -1, 1, 2, and 5 degrees from trim. This adds up to a total of 26 maneuvers per flight condition.

Tables 3 through 5 show average absolute error for small, medium, and large single and multi-axis maneuvers with no failures. The controllers all have somewhat comparable performance for small and medium maneuvers, except for the FLC that does noticeably worse. The larger error by the FLC is due to a large extent to its slower convergence to zero steady state error. This was necessary to provide the robustness to deal with failure cases. To a lesser extent, the VSC and the BAC also have more error. For large maneuvers, FLC does relatively better, and only the VSC has substantially higher error than the rest. The best result for large maneuvers is the MPC. The MPC did particularly well on large multi-axis maneuvers. Tables 6 and 7 show average absolute actuator position and rate for the above set of maneuvers. There were some substantial increases in actuator usage over the DI controller by some of the nonlinear controllers, particularly the FLC, MPC, BAC, and VSC.

Tables 7 through 8 show average absolute error for damaged control surfaces on the same set of small and medium maneuvers. The specific failure cases are 100% lost stabilator, rudder, aileron, and a combination of rudder and stab (that might reasonably be lost together since they are located in close physical proximity). The main direct and indirect adaptive approaches MPC, IAC, NNC, and BAC do the best with the other approaches having substantially larger error. The NN approach has the lowest error followed closely by the MPC. The DI control law does the worst. This is due primarily to a few cases with much worse error, rather than having consistently poorer performance on all maneuvers and failure cases.

Tables 10 and 11 show average absolute error for small and medium maneuvers with aileron, rudder, and stabilator hardover failures. For small maneuvers, the MPC leads, followed fairly closely by the BAC and the IAC. The NNC does poorly in roll error with stabilator and rudder failures, but does as well in the other axes and cases. The DI controller has the largest error, with the other approaches falling somewhere in between. For medium maneuvers, the MPC again does the best followed by the FLC and the VSC that both demonstrate admirable ability not to depart. The other approaches other than DI fall closely behind. Again poor performance by DI is due to some specific cases more than generally poor results. Table 12 shows the number of maneuvers where average absolute roll error was greater than 20 deg. or average absolute alpha or beta was greater than 10 degrees for just medium pulse maneuvers at high medium, and low dynamic pressure. DI has the largest number maneuvers with these large errors. Most of the other control laws have problems with stab and rudder failures at low dynamic pressure. The VSC does best at this condition, but has more problems at other flight conditions.

Tables 13 and 14 show the average absolute error for small and medium maneuvers with an oscillating stab failure. In this case, the least adaptive controllers FLC and VSC do the best, followed closely by the direct adaptive NN and BAC. The Indirect adaptive approaches do less well since they have convergence difficulties in this case. Table 15 shows the number of large error cases for medium sized pulse maneuvers with this failure.

In addition, to the general robustness demonstrated in the full simulation, some results were generated for robustness to specific types of uncertainty. For these tests, a perfect model of the aircraft was used as a starting point. The first test was for robustness to parameter variations using Monte Carlo analyses. For this test, 200 runs were done at each of the 4 flight conditions. Parameter variations were determined using a zero mean normally distributed random number generator with a standard deviation of 50% of the value of the stability and control parameters. Table 16 shows the mean and standard deviation for 10-90% rise time, settling time to 5% and percent overshoot of 180 degree roll steps. The desired model has values of 2 sec., 3 sec., and 0% respectively. Note that it may not seem to make much sense to test adaptive control laws this way, but all of the control laws used some knowledge of parameters in the design process and most used a priori values of parameters explicitly in the control law. As can be seen, all of the controllers did fairly well. The largest variations were for the DI controller followed by the VSC controller. Table 17 shows the worst values of the time domain criteria in all 800 maneuvers. Significantly, there were no cases where any of the controllers did not settle within 10 sec. or had overshoot greater than 50%.

The next robustness test was to check something approximating phase margin. Given the diversity of nonlinear approaches, there was no obvious elegant way to check phase margins that would have meaningful results among all approaches for comparitive purposes. Thus, the brute force approach of adding a lag to the control loop either at the actuators or at the sensors was used. Table 18 shows the value of the slowest first order lag that could be inserted in the input and output paths before the system produced oscillations that were not damping out within 50 seconds following a small oscillatory command. As can be seen the FLC and the VSC were the most sensitive to this test.

Conclusions

Seven different nonlinear controllers were applied to a complex aircraft design problem. Each of the controllers demonstrated some ability to achieve the design criteria. The baseline Dynamic Inversion controller was fairly robust, and it was quite challenging to develop other approaches that could consistently improve on its performance. In damage/failure cases where excess control power was highly limited, the approaches that used explicit identification of parameters tended to do the best, particularly Model Predictive Control due to its ability to optimize with nonlinear constraints. MPC also demonstrated excellent performance for large multi-axis maneuvers without any failures or damage. For cases, where faster adaptation was needed or control power limits were less important, the Direct Adaptive Neural Network and Backstepping approaches did very well. The neural network approach also did extremely well in the nominal case since it had the least negative impact on the system when no large errors requiring adaptation were present. The fuzzy logic control system had remarkably stable performance across the envelope for a fixed controller, though it was rarely the best performer due to its slow convergence to zero steady-state error. The variable structure control law demonstrated some ability to remain stable in cases where other controllers had much more difficulty, but was the most likely to have problematic performance for a variety of different maneuvers across the envelope.

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	Upper Limit (deg.)	Lower Limit (deg.)	Rate Limit (deg./sec.)
Aileron	45	-25	100
Rudder	30	-30	82
Stabilator	10.5	-24	40

Table 1 – Actuator Rate and Position Limits

Size	Roll (deg.)	Alpha (deg.)
Small	5	0
Med.	60	0
Large	180	0
Small	0	5
Small	0	-5
Med.	0	15
Med.	0	-15
Large	0	30
Small	5	5
Small	5	-5
Med.	60	15
Med.	60	-15
Large	180	30

Table 2 – Size of Maneuvers for Low Dynamic Pressure Flight Condition in degrees

Control	Roll	Alpha	Sideslip
DI	.0139	.0227	.0145
NN	.00780	.0251	.00161
FL	.152	.0811	.0182
BAC	.0111	.101	.00240
IAC	.0128	.0204	.0146
MPC	.0148	.0247	.0198
VSC	.0292	.0269	.0152

Table 3 – Average Absolute Error for No Failures and Small Commands in Degrees

Control	Roll	Alpha	Sideslip
DI	.176	.117	.163
NN	.157	.116	.133
FL	.676	.212	.238
BAC	.182	.303	.0722
IAC	.179	.107	.129
MPC	.154	.123	.149
VSC	.650	.260	.178

Table 4 – Average Absolute Error for No Failures and Medium Commands in degrees

	Roll	Alpha	Sideslip
DI	3.12	.308	.201
NN	2.63	.268	.453
FL	2.92	.230	.421
BAC	3.62	.724	.337
IAC	3.23	.315	.207
MPC	2.97	.301	.198
VSC	4.47	.872	.658

Table 5 – Average Absolute Error for No Failures and Large Commands in degrees

Control	Aileron	Rudder	Stabilator
DI	2.67	3.33	2.70
NN	1.93	3.44	2.82
FL	3.58	2.98	3.46
BAC	3.38	5.14	3.09
IAC	1.71	2.96	3.28
MPC	3.38	3.81	3.47
VSC	3.29	4.16	2.78

Table 6 – Average Absolute Actuator Position for No Failure Cases in degrees

	Aileron	Rudder	Stabilator
DI	4.49	4.70	2.58
NN	4.21	6.53	2.45
FL	5.38	5.59	3.67
BAC	6.52	6.78	3.47
IAC	3.16	4.97	2.13
MPC	5.84	6.39	5.90
VSC	5.35	7.67	3.53

Table 7 – Average Absolute Actuator Rate for No Failure Cases in degrees

	Roll	Alpha	Sideslip
DI	2.93	0.642	0.518
NN	0.268	0.122	0.0073
FL	0.613	0.491	0.659
BAC	0.231	0.182	0.0140
IAC	0.0817	0.0578	0.0171
MPC	0.107	0.0630	0.0183
VSC	1.28	0.178	0.153

Table 8 – Average Absolute Error for Damaged Surfaces and Small Commands in degrees

	Roll	Alpha	Sideslip
DI	3.40	0.994	2.07
NN	0.863	0.278	0.0621
FL	1.80	0.811	0.480
BAC	0.950	0.454	0.290
IAC	1.04	0.294	0.370
MPC	0.859	0.303	0.273
VSC	1.54	0.429	0.162

Table 9 – Average Absolute Error for Damaged Surfaces and Medium Commands in degrees

	Roll	Alpha	Sideslip
DI	17.1	5.2	4.43
NN	11.6	0.52	0.77
FL	3.77	1.42	1.38
BAC	3.44	0.54	0.41
IAC	4.65	0.18	0.31
MPC	3.41	0.25	0.41
VSC	4.85	2.44	2.52

Table 10 – Average Absolute Error for Hardover Surfaces and Small Commands in degrees

	Roll	Alpha	Sideslip
DI	28.3	14.03	9.44
NN	15.6	1.97	1.47
FL	13.3	1.87	3.92
BAC	14.8	1.98	1.75
IAC	16.8	3.10	2.93
MPC	7.93	2.15	2.14
VSC	12.5	2.94	2.81

Table 11 – Average Absolute Error for Hardover Surfaces and Medium Commands in degrees

	Low	Medium	High
DI	15	3	3
NN	8	2	0
FL	9	0	1
BAC	8	0	1
IAC	8	2	2
MPC	8	2	2
VSC	6	3	4

Table 12 – Number of Large Error Cases for Medium Sized Maneuvers and Hardover Failures

	Roll	Alpha	Sideslip
DI	19.4	4.59	4.83
NN	4.15	2.85	1.12
FL	2.64	2.54	1.11
BAC	2.34	2.24	0.97
IAC	5.78	3.72	2.04
MPC	6.35	6.92	3.18
VSC	4.34	2.08	1.06

Table 13 – Average Absolute Error for Oscillating Stab Failure and Small Commands in degrees

	Roll	Alpha	Sideslip
DI	32.1	4.97	5.40
NN	8.86	2.40	1.31
FL	3.82	2.66	1.32
BAC	3.13	2.48	1.09
IAC	6.41	3.98	2.38
MPC	7.04	7.53	2.65
VSC	4.06	2.68	1.26

Table 14 – Average Absolute Error for Oscillating Stab Failure and Medium Commands in degrees

	Low	Medium	High
DI	1	3	4
NN	0	0	1
FL	0	0	0
BAC	0	0	0
IAC	0	0	2
MPC	0	0	3
VSC	0	0	1

Table 15 – Number of Large Error Cases for Medium Sized Maneuvers and Oscillating Stab Failure

	Rise Time (Sec)		Set. Time (Sec)		% Over	
	M.	Std.	M.	Std.	M.	Std.
DI	1.88	.148	6.24	3.41	9.18	12.1
NN	1.98	.026	3.07	.034	.035	.039
FL	1.97	.038	3.06	.065	1.23	1.29
BAC	1.95	.058	2.97	.050	.377	.452
IAC	1.96	.014	3.04	.017	.003	.007
MPC	1.98	.018	3.09	.022	.014	.016
VSC	1.95	.017	4.78	3.01	5.64	11.2

Table 16 – Time Domain Statistics for Monte Carlo Analysis

	Rise Time	Set. Time (sec.)	% Over.
DI	2.04	9.98	42.2
NN	2.06	3.16	.171
FL	2.13	3.38	3.65
BAC	2.02	3.04	1.33
IAC	2.02	3.06	.0575
MPC	1.98	3.04	.0467
VSC	2.02	4.89	4.01

Table 17 – Worst-Case Time Domain Criteria found in Monte Carlo Analysis

	Input	Output
DI	7.0	6.8
NN	6.2	5.9
FL	11.4	9.0
BAC	4.0	3.9
IAC	8.4	7.6
MPC	8.7	8.1
VSC	12.3	9.6

Table 18 – Slowest First Order Lag Acceptable

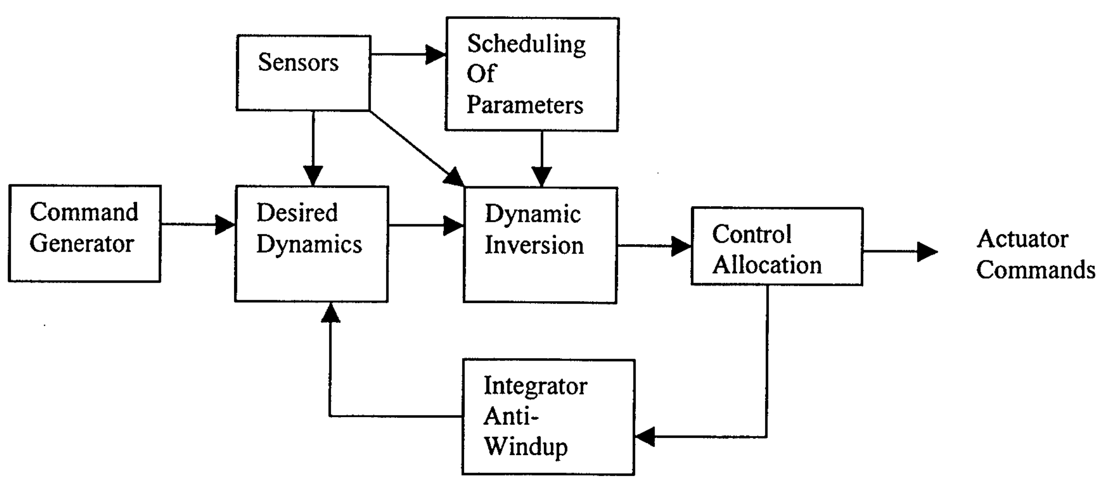

Figure 1 – Dynamic Inversion Controller