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14. ABSTRACT

This paper compares in simulation six control approaches for an automated carrier landing design problem. The key requirements of this problem are that the aircraft must remain within tight bounds on a three dimensional flight path while approaching the ship, and then touchdown in a relatively small area with acceptable sink rate, angular attitudes and speed. Further, this must be accomplished with limited control authority for varying conditions of ship motion, air turbulence, radar tracking noise/data delays, and ship air wake. The control law approaches examined are: fuzzy logic, two neural network approaches, indirect adaptive and nonadaptive versions of dynamic inversion, and a hybrid approach that combines direct and indirect adaptive elements. In some of the cases, a genetic algorithm was used to optimize fixed parameters during design. The approaches were 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 statistics for landing with damage to both control and lifting surfaces in different environmental conditions.

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A COMPARISON OF NEURAL, FUZZY, EVOLUTIONARY, AND ADAPTIVE APPROACHES FOR CARRIER LANDING

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Abstract

This paper compares in simulation six control approaches for an automated carrier landing design problem. The key requirements of this problem are that the aircraft must remain within tight bounds on a three dimensional flight path while approaching the ship, and then touch down in a relatively small area with acceptable sink rate, angular attitudes and speed. Further, this must be accomplished with limited control authority for varying conditions of ship motion, air turbulence, radar tracking noise/data delays, and ship air wake. The control law approaches examined are: fuzzy logic, two neural network approaches, indirect adaptive and non-adaptive versions of dynamic inversion, and a hybrid approach that combines direct and indirect adaptive elements. In some of the cases, a genetic algorithm was used to optimize fixed parameters during design. The approaches were 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 statistics for landing with damage to both control and lifting surfaces in different environmental conditions.

Introduction

Adaptive and intelligent flight control approaches have arguably reached the level of maturity where it is feasible to consider using them for production aircraft. This is particularly true of approaches that can be implemented with limited authority to augment more conventional types of guidance and control laws. Examples of this on current Naval aircraft include the use of fuzzy logic in the orbit improvement system of the E-6A,[1] and the simple control law on the F-18E/F to deal with stabilator actuator failures. [2] A number of more advanced architectures have been successfully flight-demonstrated including the use of an adaptive neural network to compensate for modeling errors and failures on the X-36,[3] the use of a static neural network to store stability and control parameters for on-line control optimization on the ACTIVE F-15,[4] and the use of on-line parameter identification to compensate for simulated failures on the VISTA F-16.[5] While it

appears likely that these types of approaches will have an impact on future flight control design, it is not at all clear how much impact these approaches will have or how best to decide which approach to use for any given design problem. This is particularly true because these approaches may carry significant new challenges in design, analysis, testing, and validation. Further, even when well-designed, the use of one of these approaches in some circumstances may have a negative impact on performance or reliability impact relative to a more conventional control law.

There have been several common design problems that have provided some comparisons between different advanced flight control approaches. One early example is the AIAA design challenge.[6] While a few papers produced under that challenge were relevant to intelligent and adaptive control,[7] many of the papers dealt with linear multivariable approaches. Further, nonlinear approaches have advanced considerably since that time. Another important design problem is the GARTEUR robust control problem.[8] This work is notable in the extensive documentation of the methods applied and the fairly complex design criteria. The GARTEUR study focused on robust approaches and included several of the methods used in this paper, such as dynamic inversion and fuzzy logic.[9-10] A final design problem that is currently ongoing and particularly relevant is the NASA Guidance and Control Study for re-usable launch vehicles.[11] The NASA effort has a substantially different type of application, but includes several approaches relevant to the study described in this paper, such as a similar neural network based approach. [12]

This paper presents results from a broad study to compare different intelligent and adaptive flight control approaches. The approaches examined in this paper are fuzzy logic control, two different versions of neural network control, an indirect adaptive dynamic inversion control law, a hybrid approach that combines direct and indirect adaptive elements, and a scheduled dynamic inversion controller, which is used as a baseline. It should be emphasized that the point of this work is not

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to pick winners and losers, but only to provide empirical data to show potential strengths and weaknesses of each approach on problems 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. However, for these types of approaches to be useful for real production aircraft, control designers need to be able to adopt these approaches with a reasonable amount of effort to achieve better results than they get with whatever approach they are currently using. This paper demonstrates how well some of these approaches can work when developed with limited resources by flight control engineers who have experience with the techniques, but are by no means the leading experts with that approach.

Three different but closely related design problems have been examined during the course of this study. The reason for this is that the relative performance of highly nonlinear controllers can be very sensitive to a variety of factors in the design problem, such as the class of inputs or operating conditions. The initial design problem focused on tracking performance during simple maneuvers, such as pitch and roll doublets over a substantial part of the subsonic flight envelope and with a wide range of failure cases.[13] The second design problem looked at automated recovery over a more limited part of the flight envelope and with a smaller set of failure cases.[14] The final problem, which will be examined in this paper, is automatic carrier landing. The appeal of carrier landing as a demonstration problem is that it is one of the most difficult tasks routinely done by Naval aircraft.[15-16] A carrier landing system must precisely control three-dimensional flight path, speed, sink rate, and angular attitudes to allow a safe ship-board landing. The landing, itself, is essentially a precisely controlled crash onto a small moving target. The aircraft must stay within tightening error bounds as it approaches the carrier, and capture one of four closely spaced wires with a hook on the back of the aircraft. The aircraft must also make the landing with the proper speed and sink rate to avoid damage to the aircraft. The small landing area combined with significant carrier motion and disturbances makes this a very challenging problem. This is particularly true because most high performance aircraft have unforgiving dynamics at the speeds required for carrier approach. Further, an Automatic Carrier Landing System (ACLS) must operate with limited control authority and accommodate turbulence, the carrier's air wake, and significant sensor noise and delays.

There are a number of differences between the design problem of this paper and the other two design problems examined earlier in this study. First of all, the ACLS problem is particularly difficult because it combines requirements for tight tracking as in the first design problem with the demands of achieving an acceptable terminal state under constraints as in the second problem. Plus, the ACLS problem has much more demanding tracking requirements due to the disturbance environment and the need to deal with ship motion. The ACLS design problem uses only a very limited part of the flight envelope compared to the earlier ones. However, this is a particularly challenging part of the envelope where actuator rate saturations can be extremely important. Finally, there is a unique disturbance environment with normal turbulence, the ship air wake, and substantial noise in aircraft position measurements. The noise is due to a combination of errors in radar tracking position and digital sampling issues between the shipboard computer and the aircraft mission and flight control computers. The noise in the command signal suggests some changes from past designs to avoid amplifying this noise through the use of lead information.

Design Problem

The design problem examined in this paper includes the following elements:
1) Start from level flight at a 10,000 ft range from the carrier with up to 500 ft. lineup error and 20 ft./sec velocity errors. Correct lineup and speed errors and intercept and track a 3.5 deg. stabilized glideslope. At about 13 sec. before touchdown, take into account ship motion. At 1.5 sec., freeze all outer loop commands.
2) Avoid waveoffs or aborted landings. Waveoffs are considered to have occurred when the altitude or lineup errors exceed specified bounds, which tighten as a piecewise linear function of distance to carrier. The bounds for altitude error are not symmetric and start at +450 ft. and −180 ft. at the beginning of the approach and decrease to +8 ft. and -5 ft. by 5 sec. before touchdown. The bounds for lineup are symmetrical and start at 20 ft. at 13 sec. before touchdown and decrease to 12.5 ft. by 5 sec. before touchdown.
3) Avoid rampstrikes. Rampstrikes are considered to have occurred when the aircraft's combined altitude and pitch attitude would cause a collision when it flies over the carrier ramp.
4) Avoid bolters. Bolters or unarrested landings are considered to have occurred when the aircraft hook touches down beyond the fourth and final wire.
5) Avoid hard landings. Hard landings are defined as landing with over 18 ft./sec. sink rate or over 260 ft./sec total velocity.
6) Minimize the standard deviation of touchdown position and of altitude over the ramp.

7) Stay within limits in roll angle, roll rate, and pitch angle. The limits are 30 deg. of roll angle, 11 deg./sec. of roll rate, and 3 deg./sec. of pitch rate. The reason for these fairly restrictive limits is the need to preserve safety despite the use of some non-redundant sensors.

8) Successfully perform the above with ship motion up to 1.5 deg. of pitch and 8 ft. of heave. The ship motion model had no roll or yaw motion.

9) Successfully perform the above with lost stabilator, aileron, rudder, lost combined aileron and rudder, lost combined stabilator and aileron, and lost trailing edge flap. The first 3 cases were simulated by negating the effect of the control surface on the force and moment build-ups in the model. The lost flap was simulated by adding increments to the force and moment build-ups based on wind tunnel testing of this damage case in power approach conditions. It is assumed that there is no explicit identification of these failures.

The aircraft simulation 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

$$\dot{u} = \frac{F_{X_A} + F_{X_T}}{m} - g\sin\Theta + rv - qw$$

$$\dot{v} = \frac{F_{Y_A} + F_{Y_T}}{m} + g\cos\Theta\sin\Phi + pw - ru$$

$$\dot{w} = \frac{F_{Z_A} + F_{Z_T}}{m} + g\cos\Theta\cos\Phi + qu - pv$$

$$\dot{p}\left(I_{xx}I_{zz} - I_{xz}^2\right) = I_{zz}\left(l_A + l_T - qr(I_{zz} - I_{YY}) + qpI_{xz}\right)$$
$$+ I_{xz}\left(n_a + n_T + qp(I_{xx} - I_{YY}) - qrI_{xz}\right)$$

$$\dot{q}(I_{YY}) = m_A + m_T + \left(r^2 - p^2\right)(I_{xz}) + pr(I_{ZZ} - I_{xx})$$

$$\dot{r}\left(I_{xx}I_{zz} - I_{xz}^2\right) = I_{xx}\left(n_A + n_T + qp(I_{xx} - I_{YY}) - qrI_{xz}\right)$$
$$+ I_{xz}\left(l_a + l_T - qr(I_{zz} - I_{YY}) + qpI_{xz}\right)$$

$$P = \dot{\Phi} - \dot{\Psi}\sin\Theta$$

$$Q = \dot{\Theta}\cos\Phi + \dot{\Psi}\cos\Theta\sin\Phi$$

$$R = \dot{\Psi}\cos\Theta\cos\Phi - \dot{\Theta}\sin\Phi$$

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. The turbulence model is the standard Dryden Gust model from MIL-STD-1797A[17] combined with a carrier air wake model close in to the ship. The air wake model contains both a random component and a deterministic component that increases as ship pitching motion increases. This ship motion model is a sum of 6 sine waves. Radar tracking error for aircraft position sensing is white noise passed through a first order shaping filter. There is a 100 ms. delay for all information sent from the ship. Note that this is actually somewhat benign since the actual case has a variable delay that ranges from 80 to 200 ms. due to the use of asynchronous processors.[18]

Guidance Law and Auto-Throttle
The controllers all use a modified version of the guidance law for the current F-18 Automatic Carrier Landing System, which is described in ref. 18. The shipboard part of the system uses radar information about the aircraft's position to calculate desired sink rate and roll angle commands. These commands are calculated using a combination of estimated error, integrated error, error rate, and error acceleration with gains that vary as a function of distance to the ship. Up to 13 sec. before touchdown, the altitude errors are calculated relative to a stabilized glideslope. After 13 sec., ship motion is taken into account as well with lead compensation. On the aircraft, there is an auto-throttle that attempts to maintain a constant angle-of-attack. The auto-throttle is fairly complex and uses proportional and integral angle of attack feedback combined with load factor to provide damping. In addition, pitch rate, roll angle, and stabilator command signals are used to provide some feedforward commands and reduce angle-of-attack changes due to maneuvers.

Controller Descriptions
Dynamic Inversion (DI) – The baseline control law is a Dynamic Inversion (DI) approach shown in Fig. 1, which was chosen because it is a fairly mature technique. This control law is partly based on the F-18 HARV control law design of refs. 19-20. 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. The input pre-processing consisted of limiters that vary as a function of velocity, and a first order lag at 10 rad/sec. It was not helpful to use lead on the command path due to the noise that results from radar tracking position error and data delays.

The outputs of the input pre-processing are next combined with the sensed values of the controlled variables to create desired dynamics for the aircraft to follow. The controlled variables of the inner loop controller were

$$y = \begin{Bmatrix} p \\ q + K_\alpha \Delta\alpha - pv/u + g/V(\cos\phi\cos\theta - \cos\theta_0) \\ r - K_\beta\beta - g/V(\cos\theta\sin\phi) \end{Bmatrix}$$

where K_i are fixed gains. This choice of variables is used to provide some axis decoupling and to minimize angle-of-attack and sideslip variations during pitch and roll maneuvers. The desired dynamics use proportional-integral feedback since dynamic inversion cannot make the aircraft behave as an ideal integrator in the presence of model error and actuator limitations. A significant difference from past designs is that the derivative of the command in the desired dynamics was not used. As a result, the following desired dynamics were used

$$\dot{y}_d = K_c y_c - K_p y + K_I \int e$$

where y is the sensed values of the controlled variables, y_c is the commanded values of the controlled variables, and

$$e = y_c - y$$

For the roll and yaw axis, it was found that values of the gains used in previous studies provided reasonably good performance. The values were a proportional feedback gain of 5, an integral gain of 6.25, and a proportional command gain of .5. Assuming perfect inversion, this will make the aircraft behave as a first order system through a stable pole-zero cancellation. The proportional feedback gain provides adequate bandwidth, and the substantial integrator gain provides sufficient robustness to model uncertainty and damage cases. The pitch axis required different gains and much more tuning effort due to the difficulties inherent in controlling sink rate with pitch rate. The most significant change was an increase in the proportional command gain to maintain a flat low frequency response while increasing the gain magnitude at higher frequencies to improve tracking of sink rate.

The next step is the dynamic inversion block, which inverts a state-space model of the aircraft to choose desired moment commands that will make the aircraft follow the desired dynamics. For the purposes of doing inversion, the aircraft model was assumed to be

$$\begin{pmatrix} \dot{p} \\ \dot{q} \\ \dot{r} \\ \dot{\alpha} \\ \dot{\beta} \\ \dot{\phi} \\ \dot{\theta} \end{pmatrix} = \begin{pmatrix} l_\beta\beta + l_q q + l_r r + (l_{pa}\beta + l_{ra}r)\Delta\alpha + l_p p - i_1 qr \\ m_\alpha\Delta\alpha + m_q q + i_2 pr - m_a p\beta + m_\alpha(g_0/V)(\cos\theta\cos\phi - \cos\theta_0) \\ n_\beta\beta + n_r r + n_p p + n_{pa}p\Delta\alpha - i_3 pq + n_q q \\ q - p\beta + z_\alpha\Delta\alpha + (g_0/V)(\cos\theta\cos\phi - \cos\theta_0) \\ y_\beta\beta + p(\sin\alpha_0 + \Delta\alpha) - r\cos\alpha_0 + (g_0/V)\cos\theta\sin\phi \\ p + q\tan\theta\sin\phi + r\tan\theta\cos\phi \\ q\cos\phi - r\sin\theta \end{pmatrix}$$

$$+ \begin{pmatrix} l_{\delta_{lel}} & l_{\delta_{ler}} & l_{\delta_{ail}} & l_{\delta_{air}} & 0 & 0 & l_{\delta_{rud}} \\ m_{\delta_{lel}} & m_{\delta_{ler}} & m_{\delta_{ail}} & m_{\delta_{air}} & m_{\delta_{lcf}} & m_{\delta_{tcf}} & m_{\delta_{rud}} \\ n_{\delta_{lel}} & n_{\delta_{ler}} & n_{\delta_{ail}} & n_{\delta_{air}} & 0 & 0 & n_{\delta_{rud}} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0. & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \delta_{lel} \\ \delta_{ler} \\ \delta_{ail} \\ \delta_{air} \\ \delta_{lcf} \\ \delta_{tcf} \\ \delta_{rud} \end{pmatrix} \quad (1)$$

which can be put in a form of

$$\dot{y} = \Phi_0(x) + \Phi(x)w_1(x) + B(x)u$$

where w_1 is a vector of stability parameters that vary over the flight envelope, B is a matrix of control effectiveness parameters that vary over the flight envelope, and u is the vector of control effector commands.

The desired moment commands were then calculated using a standard form of

$$m_d = (\dot{y}_d - (\Phi_0(x) + \Phi(x)w_1))$$

Finally, because there are more controls than controlled variables, a direct allocation approach[21-22] is used to determine the commands to the actuators. When the control allocator cannot achieve the desired moments, an integrator anti-windup approach is used. The stability and control parameters used in the inversion and the allocation were scheduled with a linear interpolation based on Mach number, angle-of-attack, and dynamic pressure with angle-of-attack being most important. It was also necessary to schedule values of the trim angle of attack for the model used. Parameters were determined using central difference numerical perturbations of the full nonlinear simulation at 108 flight conditions and so have some error relative to the simulation model.

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 Identification was used for the stability terms

$$(l_\beta, l_p, l_q, l_r, \overline{m}_\alpha, \overline{m}_q, m_\alpha, n_\beta, n_r, n_p, n_q)$$

for 3 bias terms, and for the control effectiveness terms in the B matrix. This included a few cross-coupling parameters that are only significant following damage cases and are not used in the model for the baseline DI controller. This yields a total of 27 parameters that need to be identified.

The parameter identification approach used was Modified Sequential Least Squares (MSLS).[5,23] 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 constraints. A simplified form of the cost function is

$$J(\theta) = \frac{1}{2} \sum_{n=t_0}^{t} r(n)^T r(n) + q(n)^T W_0 q(n) + p(n)^T W_1 p(n)$$

$$r(n) = y(n) - \theta^T(n-1)\phi(n)$$

$$q(n) = \theta(n) - \theta(n-1)$$

$$p(n) = M\theta(n) - k$$

where y is the measurements, θ is a vector of parameter estimates, W_0 and W_1 are positive diagonal weighting matrices, and ϕ is a vector of system states and control inputs. The constraints q and p penalize the estimate for large deviations from a weighted blending of previous (temporal) and a priori (spatial) estimates of the parameters. The combination of these constraints provides fairly well-behaved parameter estimates with the proper choice of constraint weightings. However, finding good values for the weights along with a forgetting factor requires considerable trial and error experimentation. For that reason, a genetic algorithm was used for initial determination of these fixed parameters based on a closed-loop performance metric.[24] A genetic algorithm was very effective since it appeared mainly necessary to get the right order of magnitude of the parameters. It was found that a ratio of about 15 to 1 in spatial to temporal constraint weightings was effective for closed loop control in this problem, though it was not clear at all how optimal this was. It was easier to find reasonable values of the parameters for this problem than for the two earlier ones since an adaptation time of several seconds was acceptable, and there was considerable excitation.

An additional modification was made to this controller to freeze the values of the estimated parameters at approximately 15 sec. before touchdown. This avoids deviations in the parameter estimates caused by the effect of the ship air wake, which degraded the closed loop response in an important part of the approach. It was not possible under the scope of this effort to determine a better approach to dealing with the carrier air wake.

Neural Network Controller with Linear Parameterization (NNL) – The Neural Network Controller is another modification of a dynamic inversion controller based on the approach of ref. 25. The neural network is placed in the desired dynamics block of Fig. 1 so that

$$\dot{y}_d = \dot{y}_c + K_P e + \int K_I e + w_{NN}\varsigma$$

where w_{NN} is a matrix of neural network weights and ς is a vector of the neural network basis functions. Note that unlike in the baseline DI controller, the derivative of the command was used. This is necessary in order to provide a stability proof with a Lyapunov approach. The commands are passed through 2nd order filters, which are different for each axis. The use of an integrator with the neural network may seem redundant. However, this provided better robustness to damage cases and significantly improved tracking in the presence of the ship air wake and turbulence. The neural network had 172 basis functions and its inputs were aircraft states and the past output of the desired dynamics block passed through a squashing function. Adaptation of weights in the neural network was done using a slightly modified form of

$$\dot{w}_{NN} = -\gamma((K_1 e + K_2 \int e)\varsigma + \eta|e|w_{NN})$$

Where γ and η are positive constants and K_1 and K_2 are constants determined based on the values of the gains in the desired dynamics block. 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 since too large a value causes oscillations and other undesirable behavior while too small a value prevents rapid adaptation. In past work, the choice of learning rates was automated by running several hundred simulation cases at each flight condition with different inputs and failure cases, and then reducing the learning rate by 25% when a significant oscillation in the neural network was detected. This was not easy to do in this case since the guidance law can cause oscillatory behavior due to poor inner loop response. As a result, it was necessary to do much tuning by hand.

Adaptation is halted when actuator saturation occurred. There was some experimentation done with the pseudo-control hedging method[12] to allow adaptation to continue during control adaptation. However, this did not yield any significant benefits for this design problem, and added some additional undesirable complexities to the control law.

Neural Network Controller with Nonlinear Parameterization (NNN) - This controller is similar to the above neural network except that it uses a

nonlinearly parameterized neural network as described in ref. 26. The output of this network can be written as

$$v = W^T \sigma(V^T \zeta_{NL})$$

where W and V are adaptive weights and σ is a sum of sigmoidal activation functions of the weighted inputs. There are less inputs required for this network than the linear one, and tuning of the parameters was a bit more difficult.

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. 27-28 There were 3 rule bases that control roll, pitch, and yaw. Separate rule bases were necessary because fuzzy logic controllers can become very unmanageable if there are more than a few important inputs. The use of somewhat decoupled controlled variables and an advanced control allocation approach to determine final actuator commands helps alleviate the need to do this. The main inputs were 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 lower damping for large errors and higher 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 desired moments. The fuzzy operators have max/min used for or/and, the product method is used for implication, and the centroid method is used for defuzzification. As with the earlier designs, direct allocation was used to determine the actuator commands. Some scheduling was done by scaling the inputs to the rule bases based on angle-of-attack. However, very little scheduling was required since this flight condition is relatively constant during the approach. This was a distinct advantage for this approach relative to the earlier design problems.

Hybrid Control Law (HYB) – This control law combines the nonlinearly parameterized neural network approach and MSLS parameter identification. The major change from the above designs was that it was necessary to modify some of the parameters to minimize adverse interactions between the parameter identification and the neural network adaptations.

Results

All results were computed in Matlab/Simulink 5.3. For each damage and failure case, a set of 5 starting conditions and 3 environmental conditions were used. The starting conditions were 10,000 ft. range from the carrier, lineup errors of 0, 50, 250, 500, and 1,000 ft., and initial velocity errors of 20 ft./sec. for the first 2 cases and -20 ft/sec for the last 3. The 3 environmental conditions were no ship motion or turbulence, ship motion of .75 deg. maximum pitch with 4 ft maximum heave and moderate turbulence, and ship motion of 1.5 deg. maximum pitch with 8 ft. maximum heave and severe turbulence. This added up to a total of 15 different scenarios. Further, each scenario was run 6 times to get more meaningful information about performance relative to non-deterministic disturbances and noise. This leads to a total of 90 runs for each damage case. The most significant variations were caused by the phase of the ship motion model.

Fig. 2 shows the boarding rate and percentage of excellent landings for the no damage case. Boarding rate is defined as landings that are not waveoffs (aborted landings), bolters (unarrested landings), or ramp strikes. Excellent landings are also not hard landings and touchdown between the number 3 and number 4 wire only. As can be seen, the results are fairly comparable for each of the controllers. The missed landings were split roughly evenly between waveoffs and bolters, and generally occurred only for severe environmental conditions. The fuzzy logic controller and the controllers that use on-line identification do slightly better. The neural network controllers have minimal differences from the baseline Dynamic Inversion (DI) controller. The standard deviation for the DI controller in touchdown position was 28.2 ft. in downrange (X axis) and 3.13 ft. in lineup (Y axis). The standard deviation of height over the ramp was 2.32 ft. Fig. 3 shows the percent reduction in these quantities for all of the controllers relative to the DI baseline. The FL controller did the best here due to its nonlinear response capabilities, followed by the indirect adaptive approaches. Fig. 4 shows the rms tracking error in sink rate over the course of the maneuver. The fuzzy logic and indirect adaptive controllers perform best.

Fig. 5 shows the boarding rate and percentage of excellent landings for a case with a lost aileron and rudder. There is not a severe drop in performance for any of the controllers as neither surface is really critical for this task. The 2 controllers that use parameter ID were the only ones to stay above 90% boarding rate and have very comparable results in this metric to the no failure case. The standard deviation for the DI controller in touchdown position was 28.5 ft. in downrange and 3.99 ft. in lineup. The standard deviation of height over the ramp was 2.30 ft. Fig. 6 shows the percent reduction in these quantities for all of the controllers relative to the DI baseline. As can be seen, each of the other controllers had some significant improvements over the baseline controller, particularly in the standard deviation of lineup error. Fig. 7 shows the rms error in tracking the sink rate command for each controller. Some of the adaptive controllers do not do as well here. However, this is at least partly due to the improved roll performance, which causes larger sink rate deviations early in the maneuver but does not really affect the final touchdown position.

Fig. 8 shows the boarding rate and percentage of excellent landings for a case with a lost aileron and stabilator. There is a much more significant drop in boarding rate, though all of the controllers except for the dynamic inversion controller are able to maintain about an 80% boarding rate. The standard deviation for the DI controller in touchdown position was 30.5 ft. in downrange and 2.80 ft. in lineup. The standard deviation of height over the ramp was 2.29 ft. Fig. 9 shows the percent reduction in these quantities for all of the controllers relative to the DI baseline. As can be seen, each of the other controllers had some significant improvements, particularly the hybrid approach. Finally, fig. 10 shows the rms error in tracking the sink rate command for each controller.

Fig. 11 shows the boarding rate and percentage of excellent landings for a case with a lost trailing edge flap. This is a very challenging case for a carrier landing as can be seen by the poor performance of the dynamic inversion controller. There is a much more significant drop in boarding rate, though the fuzzy logic and the controllers that use parameter identification are able to maintain about an 80% boarding rate. The standard deviation for the DI controller in touchdown position was 33.8 ft. in downrange and 6.01 ft. in lineup. The standard deviation of height over the ramp was 2.77 ft. Fig. 12 shows the percent reduction in these quantities for all of the controllers relative to the DI baseline. As can be seen, each of the other controllers had some significant improvements, but the indirect adaptive approach is particularly notable in its reduction of downrange dispersion. Finally, fig. 13 shows the rms error in tracking the sink rate command for each controller.

Study Results

This section will provide some discussion of relative results across all three design problems. For more information about the earlier problems, see refs. 13-14.

The baseline DI controller had fairly good robust stability, though it did depart following severe actuator failures like hardovers, and damage conditions that significantly impacted on the stability properties of the aircraft. Its robust performance following failures was not as good, as can be seen in this paper, where it maintains stability but has much poorer tracking performance in some cases than the other approaches. It sometimes had poor tracking performance even for modest model errors in the key stability derivatives. These results show that for a relatively stable aircraft with conventional effectors and a fairly accurate design model, a well-designed traditional robust control law may be capable of dealing with all but the most severe failure situations. Thus, there is a clear design trade-off between achieving that extra capability to react to failures, and paying the additional design costs involved with applying the current state of-the-art in adaptive and intelligent control laws. The Dynamic Inversion (DI) controller was by far the easiest approach to design and to re-design for each successive problem, as one can use many traditional analysis tools despite the fact that it was technically a nonlinear controller. For example, it was fairly easy to generate both multivariable and single-loop stability margins using linearized models and to use these to tune the design. The biggest open design issue seems to be how to most effectively schedule the stability and control parameters, and what degree of accuracy is required.

The Indirect Adaptive Controller (IAC) generally did well on problems where it had at least 1-3 sec. of time to adapt. On problems where faster adaptation was required, such as automated recovery from a low-altitude dive it did poorly compared to some of the other approaches. On problems where it had the time, though, it was perhaps the best approach at using the maximum remaining control resources as effectively as possible when used with either dynamic inversion or a model predictive control approach. It also had particularly good robust performance following the transient identification period, though its transient performance was sometimes a problem. From a design point of view, the experience was mixed. On the positive side, indirect adaptive control allows a great deal of flexibility to design the underlying control law as desired using traditional techniques. On the negative side, there are on the order of 100 parameters that need to be set (or many more if the off-diagonal terms are

used). There is little to help in doing this other than some guidelines from past designs that provide a range of several orders of magnitude that may or may not be the proper place to search. Another problem is that it was not clear whether to adjust these parameters to get the most accurate open-loop identification or the best closed-loop response or some combination thereof. There may also be a need to schedule some of these parameters as the ID generally did not do as well in some parts of the envelope and there was not sufficient time under this study to examine how to improve this. Another issue was the impact on parameter ID of disturbances like the ship air wake. This was avoided in this case by stopping adaptation, but may be a problem for unexpected unusual disturbances like wind shears.

The neural network approaches were by far the most capable of the Lyapunov-based approaches that were examined under this study. They did much better than either the sliding mode or backstepping controllers in terms of ease of design and robust performance and just not having occasional unpredictable highly erratic behavior. Though, the NN approaches were not always as good in terms of robust stability as other direct approaches. Compared with all the controllers, the NN approaches had particularly fast adaptation in less than one sec. and were quite good at dealing with situations where time was a factor. Both neural network approaches generally were quite effective at dealing with changes in control effectiveness, but the nonlinear neural network seemed to do significantly better at dealing with changes to the aircraft's stability properties, particularly in the lateral-directional axes. From a design point of view, this type of control law was reasonably easy to design. The NN has limited effect on the system when errors are small. When failures occurred, robust performance was generally satisfactory relative to a desired response model when the parameters were chosen correctly. This, though, is arguably both strength and a weakness. For example, in some extreme failure cases the NN did the best job of tracking the response model and took the aircraft into parts of the envelope it couldn't recover from, while other "less capable" controllers did not. Modifying the response model in different situations is likely to be an important and time-consuming part of the design of this type of controller. Flight control laws have typically had fairly complex qualitative and quantitative requirements, particularly given the need to be a "zero-weight" software fix to many problems on the aircraft. This creates difficulties when the response model does not take into account all of the criteria that might go into the design and tuning of a more conventional control law, but are not always explicitly and quantitatively provided. Another issue is the setting of

the adaptation rate to avoid oscillatory behavior. This is a particular problem with the network that uses a linear parameterization. The proper choice of the parameters seems to be linked to the size of the error, and so is dependent on having a good idea of the maximum error the system will encounter. It may be of value to have some type of variable adaptation rate to minimize problems with this, and gain-scheduling has been used in earlier design problems of this study.

The hybrid approach often did not do as well as the best of the indirect or direct approaches for any given problem. However, it also often did better than the worst of the indirect or direct adaptive approaches. As a result, it may be an effective approach for controllers that need some of the capabilities of both across a wide range of problems. However, this controller had all of the design complexities of both indirect and direct approaches combined with additional new problems caused by adverse interactions between the 2 adaptive elements.

The fuzzy logic controller had remarkably good robust stability for a fixed non-adaptive controller, and can be tailored to have excellent performance in narrow circumstances such as the ACLS problem. It is quite challenging, however, to create a fuzzy logic controller that has good performance against a wide range of flight conditions and requirements. This is particularly true due to the lack of analysis tools that are as effective as those that exist for the feedback linearization based approaches. There are many uncertain design issues dealt with through questionable rules of thumb such as membership function type and number, type of operators, implication, and defuzzification, stability and transient analysis, etc. As a result, fuzzy logic may be best if used only for specific tasks that require the use of heuristics or nonlinear responses, particularly for narrowly defined outer loop and guidance tasks. It is not an easy approach to design for inner loop control, though it is substantially easier to design for outer loop or guidance functions.

Conclusions
This paper examines six different intelligent and adaptive approaches on a carrier landing problem. The baseline Dynamic Inversion approach had good robust stability, but had significantly degraded tracking responses following some failures that lead to many aborted and missed landings. This was particularly true for lost stabilator and trailing edge flap cases in severe environmental conditions. The other approaches could all be designed to have somewhat comparable results on many of the failure cases. The Indirect Adaptive Control and Hybrid approaches arguably did the best at achieving the design criteria. Given the less severe

failures and the fact that all failures occur at a trim point when there is time to recover meant that the slower rate of adaptation was not an issue. Similarly, the advantage of knowing more accurate stability and control derivatives was quite significant given the nature of the problem, and there was ample excitation. However, there were some issues with the carrier air wake that required some fairly ad hoc fixes for all of the adaptive controllers. The Neural Network approaches did fairly well, particularly with the nonlinear adaptation law and generally improved the responses over the baseline. Fuzzy logic was quite good due to its very tailored response for tight tracking, though it did have more degradation following failures than the adaptive approaches.

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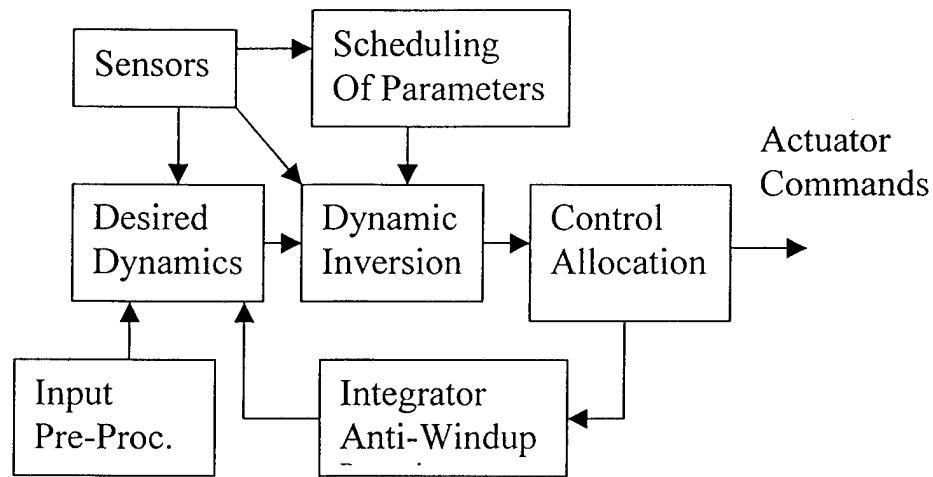
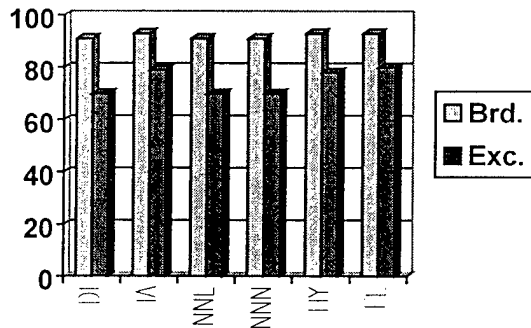Fig. 1 – Dynamic Inversion Controller
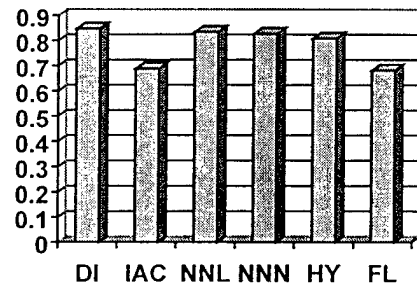

Fig. 2 Percent Landing
Rate (No Damage)

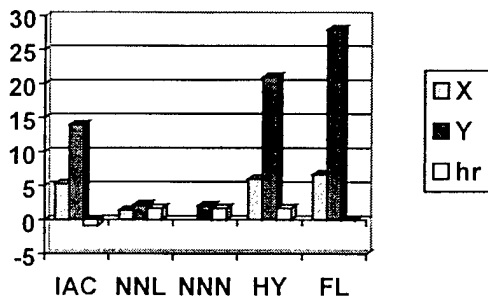Fig. 4 Sink Rate RMS error
(ft./sec.) (no damage)

Fig. 3 Percent Reduction
in Standard Deviation
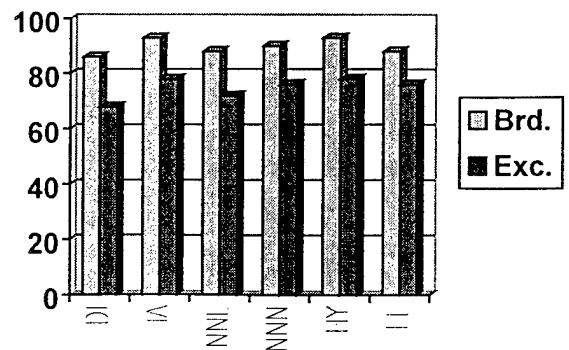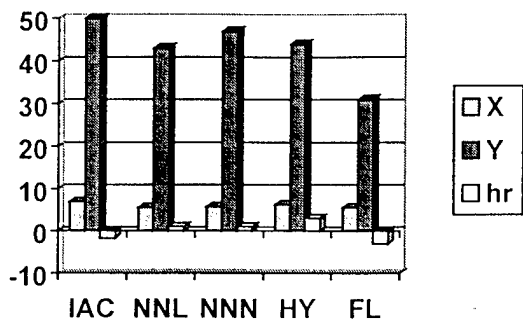

Fig. 5 Perc. Landing
Rate (Lost Ail. & Rud.)
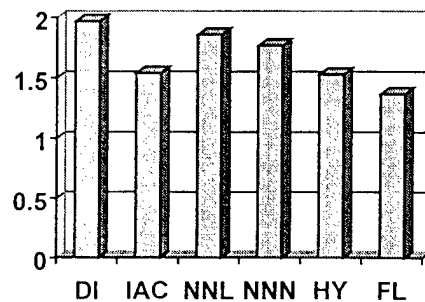
Fig. 6 Perc. Red. in error dev. (lost ail. & rud.)
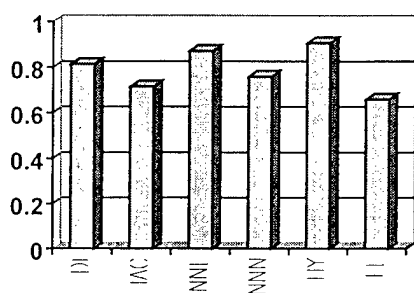
Fig. 7 Sink Rate RMS error (ft./sec.) (lost ail. & rud.)

Fig. 8 Percent Landing Rate (lost ail. & stab.)

Fig. 9 Perc. Reduction in Standard Deviation
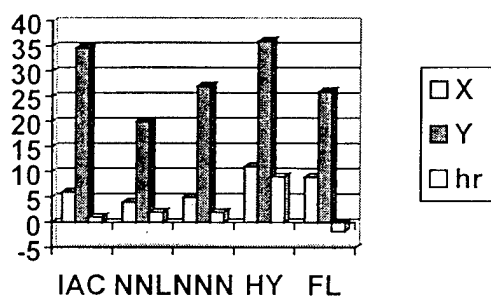
Fig. 10 Sink Rate RMS error (ft./sec.) (Lost stab. & ail.)
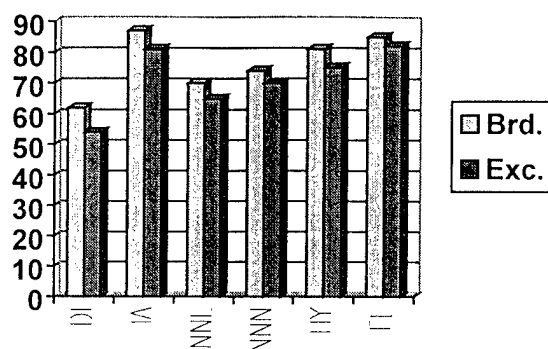
Fig. 11 Perc. Landing Rate (Lost TEF)
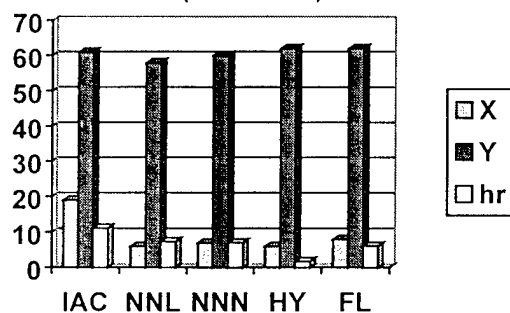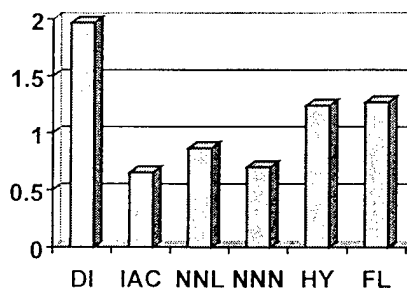
Fig. 12 Reduction in error dev. (ft.) (lost TEF)

Fig. 13 Sink Rate RMS error (ft./sec.) (lost TEF)