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Aerospace Science and Technology 9 (2005) 73–80

Aerospace Science and Technology

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Flight control system design and optimisation with a genetic algorithm

Ottimizzazione di un sistema di controllo di volo con algoritmo genetico

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Received 12 December 2003; received in revised form 31 August 2004; accepted 1 September 2004

Available online 26 October 2004

Abstract

A design procedure for a flight control system is here presented. An optimisation process, based on a genetic algorithm, is used to meet the frequency domain handling qualities requirements for the longitudinal plane. The parameters are implemented as fitness functions related to the expected magnitude of bandwidth and delay. The impact of the parametric shaping of the fitness functions on the search and optimisation process is also evaluated. The dynamic response of the augmented aircraft is obtained for a realistic simulation case, validated after comparison with reference test data. The bandwidth and the delay of the longitudinal short term attitude response are estimated before and after the inclusion of the flight control system in the simulation model, and the parameters are compared with the expected handling qualities levels. The feasibility of the design process is demonstrated and the overall performance of the generation process is analyzed.

Resumi

Nel presente articolo viene discussa una metodologia per il progetto di un sistema di controllo per un'applicazione aeronautica. In particolare, viene utilizzato un algoritmo di ottimizzazione di tipo genetico al fine di garantire il soddisfacimento dei requisiti normativi in termini di qualitá di volo. I parametri di riferimento nel dominio della frequenza sono implementati con diverse modalitá cosí da influenzare il comportamento della funzione obbiettivo. Dopo aver validato il modello di simulazione, il comportamento dinamico del sistema controllato viene confrontato con i dati disponibili per il velivolo reale. Vengono infine discusse le caratteristiche del processo evolutivo per la generazione della soluzione.

Keywords: Aircraft dynamics; Handling qualities; Control system design; Optimal design; Genetic algorithm

Keywords: Dinamica del volo; Qualitá di volo; Sistemi di controllo; Ottimizzazione; Algoritmi genetici

1. Introduction

Desired pole placement and eigenstructure assignment are conventional goals of the control design procedure. Furthermore, the performance of the controller may also be defined in terms of regions of interest instead of desired states. This is the case of aircraft handling qualities requirements. Stability, robustness, good command following, noise rejection and low sensitivity to model uncertainties are also significant concerns for the designer and their inclusion in the design process may be required to ensure adequate control performances.

Within this area of investigation, the search of optimal solutions, that should meet the above mentioned prerequisites, becomes a primary interest in the design of controllers.

The main types of search methods are considered in Ref. [5]: calculus-based, enumerative and random. Calculus-based methods are local i.e. the optimal conditions they search are the best in a neighborhood of the current point.

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1270-9638/$ – see front matter
doi:10.1016/j.ast.2004.09.003

Nomenclature

a	Coefficient (fitness function)
A	Amplitude
$[A]$	State matrix
b	Coefficient (fitness function)
$[B]$	State matrix
c	Coefficient (fitness function)
CG	Nondimensional longitudinal coordinate of the center of gravity
d	Coefficient (fitness function)
e	Coefficient (fitness function)
f	Fitness function
$G()$	Generic transfer function
GA	Genetic Algorithm
h	Altitude
i	Imaginary operator
k_{i}	Feedback gain ($\mathrm{i} = \mathrm{u}, \mathrm{w}, \mathrm{q}, \theta$)
$[K_{\mathrm{P}}]$	Feedback matrix (proportional)
$[K_{\mathrm{I}}]$	Feedback matrix (integral)
$[K_{\mathrm{D}}]$	Feedback matrix (derivative)
n	Number of parameters (fitness function)
p, q, r	Angular velocity components (body axes)
p_1	Coefficient (fitness function)
p_2	Coefficient (fitness function)
p_3	Coefficient (fitness function)
s	Complex variable (Laplace transform)
S	Wing area
T	Thrust
T_1	Time constant (lead-lag compensator)
T_2	Time constant (lead-lag compensator)
u, v, w	Velocity components (body axes)
$\bar{u}$	Control vector
x	Parameter (fitness function)
$\bar{x}$	State vector
W	Aircraft weight

Greek symbols

α	Angle of attack
δ_{a}	Aileron stick control
δ_{e}	Elevator stick control
δ_{r}	Rudder pedal control
$\Delta\phi$	Phase lag
φ, θ, ψ	Angles of roll, pitch and yaw (Euler angles)
ζ	Damping ratio
ω	Frequency
τ	Throttle control
τ_{P}	Phase delay

Subscripts

180	Neutral stability point ($\Delta\phi = -180^{\circ}$)
avg	Average
BW	Bandwidth
Gain	Gain limited
k	Index
low	Low frequency range
L	Lower axis range
max	Maximum
Phase	Phase limited
R	Reference
U	Upper axis range

They depend upon both the existence of derivatives and the continuity of the function to be maximized. This last point is a severe limitation in terms of robustness for several engineering applications. Enumerative methods seek the optimal solution by computing the objective function in every point of the search space. This makes the enumerative algorithms substantially inefficient and time consuming when applied to large domains of possible solutions. Random search is an alternative strategy that can bypass the limitations of the previous methods. The genetic algorithms belong to this last family of solvers, as the random choice of the possible solutions is combined with criteria for the direction of search which derive from natural evolution of species. This technique is considered global and robust in terms of search over the space of solutions (see Ref. [5] for a complete review of the subject).

Many types of engineering and aerospace related optimisation problems in the area of controls can be solved using the genetic algorithm approach: linear and nonlinear control systems design, adaptive gain tuning, gain scheduling selection and, generally, multiple objective optimisation.

The review of references on the subject [6–12,15] suggests that the design of control systems with the support of optimal search by means of a genetic algorithm is feasible.

In any case, the majority of the above mentioned applications are devoted to design system dynamics by means of pole placement and shaping of time domain response, taking the stability and the robustness of the control system as a primary problem.

Differently, handling qualities are substantially related to the frequency domain response [13]. Furthermore, it can be observed that the implementation of handling qualities requirements in the design process is not straightforward and classical optimal control design tools may generally be inadequate for this purpose, as they may lead to a stable robust controller with unsatisfactory handling qualities. Note that the performance of the controlled system is evaluated in terms of regions of interest, as bandwidth and delay of the controlled system combined with other nonhomogeneous requisites which make gradient based search method harder to apply for the given case.

Within this area of interest, a research activity was started at Politecnico di Torino. The design methodology is based on the implementation in the search algorithm of the aircraft handling qualities requirements for small amplitude short term response.

2. Present work

The objectives of this paper are: to include the frequency domain handling qualities requirements in the design procedure of a flight control system, in a form suitable for search and optimisation by means of a genetic algorithm, to evaluate the feasibility of the design method and the impact of the fitness function on the algorithm performances, and to verify the dynamic response of the augmented aircraft by implementing the flight control system in a realistic simulation model.

3. Mathematical model

The mathematical model developed is a nonlinear representation of a single engine aircraft with rigid fuselage. No small angle assumption is invoked for aerodynamic angles of the vehicle and the aerodynamics of fuselage and stabilizers is modeled using static coefficients and damping derivatives obtained with wind tunnel experiments for different angles of attack and sideslip. The effects of controls (elevator, aileron and rudder) are superimposed in terms of increments. The rigid body motion of the aircraft is modeled using six nonlinear force and moment equations and three kinematic relations (Euler equations). The most important feature of this set of equations of motion is that the states need not to be small quantities; thus, all the kinematic nonlinearities associated with the motion of the rigid body are retained.

The order of the complete system is 9 and the state vector can be represented as $\bar{x} = [u\ v\ w\ p\ q\ r\ \theta\ \phi\ \psi]^{\mathrm{T}}$ while the control vector is defined as $\bar{u} = [\delta_{\mathrm{e}}\ \delta_{\mathrm{a}}\ \delta_{\mathrm{r}}\ \tau]^{\mathrm{T}}$.

Static thrust and throttle setting τ are computed from a parametric model for engine power output which accounts, in the dynamic case, for first order delays after throttle inputs. The primary control actuators are also included in the mathematical model and their dynamic response is represented by a second order transfer function where actuator's natural frequency and damping ratio were selected as $\omega = 52$ rad/s and $\zeta = 0.7$. The effects of atmospheric turbulence are optionally included in the present model [2].

Initial values of altitude, airspeed, turn rate, sideslip and climb angles are given as inputs of the trim procedure, which is based on residual minimization. The algebraic equations enforcing force and moment equilibrium (9 eqns.) are combined with the additional kinematic equations (2 eqns.) that must be satisfied in steady flight or in a turn, and the combined system (11 eqns.) is solved simultaneously. The solution yields control and throttle settings, trim attitudes and rates of the entire aircraft.

The response to pilot inputs is obtained from direct numerical integration of the equations of motion, starting from trim conditions. The time domain responses are obtained with a 4th order Runge Kutta explicit integrator.

A linearized set of small perturbation equations can be extracted from the nonlinear model ($\dot{\bar{x}} = [A] \cdot \bar{x} + [B] \cdot \bar{u}$). The coefficients of the state matrices $[A]$ and $[B]$ are derived numerically about the trim condition, using finite difference approximations. The linearization of the dynamic equations is carried out in the body fixed coordinate system. The state-space representation is also used for estimating the frequency response of the system.

An optional feedback control loop is implemented in the mathematical model adopted for the present study. A lead-lag compensator is included in order to tune aircraft transient dynamic response

$$G(s) = \frac{1 + T_1 s}{1 + T_2 s}$$

and proportional-integral-derivative feedback gains can be specified for each component of the state vector

$$\Delta u(s) = [K_{\mathrm{P}}] \cdot x(s) + [K_{\mathrm{I}}] \cdot \frac{x(s)}{s} + [K_{\mathrm{D}}] \cdot s \cdot x(s)$$

that for the current analysis is reduced to the following proportional form

$$\Delta\delta_{\mathrm{e}}(s) = k_{\mathrm{u}} \cdot u(s) + k_{\mathrm{q}} \cdot q(s) + k_{\theta} \cdot \theta(s).$$

The gains of the feedback loop ($k_{\mathrm{u}}, k_{\mathrm{q}}, k_{\theta}$) and the parameters of the lead compensator (T_1, T_2) were determined with a search strategy based on a genetic algorithm.

The genetic solver adopted for the design of the control system (i.e. to obtain the feedback matrices) is a Fortran version of the driver described by D. Carroll in Refs. [3,4]. The code initializes a random sample of individuals with different parameters to be optimized using the genetic algorithm approach. The selection scheme used is tournament selection[4] with a shuffling technique for choosing random pairs for mating. The routine includes binary coding for the individuals, jump mutation,[5] creep mutation,[6] and the option

[4] Random pairs are selected from the population and the stronger of each pair is allowed to mate.

[5] One or more chromosomes of the child will be mutated in the range acceptable for the relative parameter, so that the altered chromosomes do not belong to either parents.

[6] One or more of the parameters in the child are mutated by a single increment.

for single-point[7] or uniform crossover.[8] Niching,[9] elitism[10] and an option for the number of children per pair of parents are available. Finally, the solution using a micro genetic algorithm is also possible. This last switch significantly reduced the number of function evaluations and demonstrated faster convergence to the near-optimal region. Very briefly, a micro-GA starts with a random, very small population. The population evolves in normal GA fashion and converges in a few generations. Then, a new random population is chosen while keeping the best individual from the previously converged generation and the evolution process restarts. Note that average population fitness values are not meaningful with a micro-GA because of the start-restart nature of the micro-GA evolution process.

Many numerical experiments were performed in Refs. [3,4] in order to tune the search algorithm adopted and, as a result, the suggested set-up is extended for the present application. The micro-GA operating mode was adopted combined with uniform crossover (the probability for a crossover occurring at each chromosome position was fixed to 0.5). The code was set for a maximum micro population size of 5 individuals, 60 bits per individual and 5 parameters (i.e. 12 binary bits per parameter and 2^{12} possible solutions per parameter). Niching and elitism were activated, creep mutation was disabled and two children per pair of parents were considered.

The fitness function to be optimized is supplied by means of an external subroutine called by the solver. In this case, a fitness function was designed in order to meet the handling qualities requirements for the longitudinal plane.

A complete analysis of aircraft handling qualities criteria is presented in Refs. [1,2,13,14]. The attention is here focused on the small amplitude short term criteria which relate to the aircraft's ability to perform small amplitude tasks such as closed loop compensatory tracking. The requirements are given in terms of bandwidth ω_{BW} and phase delay τ_{P} which are obtained from the frequency response (Bode plot) of the attitude response to pilot input, that is expected to match a reference level for gain margin and phase margin. The bandwidth parameter is a measure of the maximum closed loop frequency that the pilot can achieve with gain control without compromising the stability of the system. Phase delay is a measure of how quickly the phase lag increases beyond the neutral stability point ω_{180}. Aircraft with large phase delays are prone to pilot induced oscillations, i.e. small changes in pilot gain result in large loss of phase margin. A key aspect of bandwidth criteria is that they do not assume a characteristic response shape. Furthermore, no lower order model based on approximations was considered as a reference for the design of the requirements in Ref. [2]. Therefore, they are applicable to any response type (conventional, rate command attitude hold or attitude command attitude hold). The parameters are estimated with a numerical algorithm: the bandwidth ω_{BW} is the lesser of $\omega_{\mathrm{BW\,Gain}}$ and $\omega_{\mathrm{BW\,Phase}}$ while the phase delay is $\tau_{\mathrm{P}} = \Delta\Phi_{2\omega180}/2\omega_{180}$.

The handling qualities requirements are implemented in the fitness function used by the genetic search algorithm as parameters x_k: the bandwidth ω_{BW}, the phase delay τ_{P}, the average low frequency amplitude A_{low} of the frequency response, the peak gain value $A_{\max}$ and the average gain over the bandwidth A_{avg}. Hence, for the present analysis the number of parameters is $n = 5$.

Three different fitness functions can be selected for the optimal search (see Fig. 1 and Table 1). The first function is a parabola characterized by a progressive decrease of performance index as long as the parameter x_k moves away from the reference value $x_{k_{\mathrm{R}}}$. Differently, the second function is tailored to provide an abrupt drop when the distance of the parameter x_k from the desired solution $x_{k_{\mathrm{R}}}$ exceeds a given tolerance. This property of the function should give a nominal improvement of the convergence process of the search algorithm, as the penalty in terms of fitness function should force the solution to remain close to the reference value of the parameter. The last case is a n-dimensional function (elliptic paraboloid) defined over the search space, while the other functions are obtained by additive superposition of operators depending on the single parameter x_k. The functions are maximized when the distance from the desired value $x_{k_{\mathrm{R}}}$ for the parameters x_k (given as an input of the search process) is minimized.

The shaping of the fitness functions is obtained by selecting the axis range for each single parameter x_k i.e. by defining an adequate performance of the fitness function in the symmetric interval $[x_{k_{\mathrm{L}}}, x_{k_{\mathrm{U}}}]$ where the maximum is found for $x_{k_{\mathrm{R}}} = (x_{k_{\mathrm{L}}} + x_{k_{\mathrm{U}}})/2$.

A deficiency function is also optionally added to the fitness function computed for the parameters x_k to include the effect of system stability in terms of penalty for the individuals which exhibit undamped poles. This solution does not interfere with the search process as the pole placement required to design the controlled system is not influenced within the area delimited by an acceptable damping ratio.

In order to compare the effect of the shaping of the fitness functions on the search process, the peak values of the functions are scaled to obtain the same maxima in the center of the acceptable range of variation for each parameter x_k.

The genetic algorithm iterates generation after generation the gains of the control system in order to fit the frequency response to the parameters x_k specified by the user. Convergence is verified by tracking the performance (i.e. the fitness function f) for the best individual of each generation.

[7] The chromosome set of the first parent is mapped in the child. Then, a crossover point is randomly selected where the chromosome set of the second parent overwrites the chromosome set of the first parent.

[8] Any combination of the two parents chromosomes is possible. This makes difficult for the child to retain the entire chromosomes of either parents.

[9] This is a method for avoiding premature convergence to a single solution trying to keep diversity within the population by restricting the generation of very similar individuals.

[10] This option ensures that the best set of chromosomes (best individual) is propagated in the next generation.

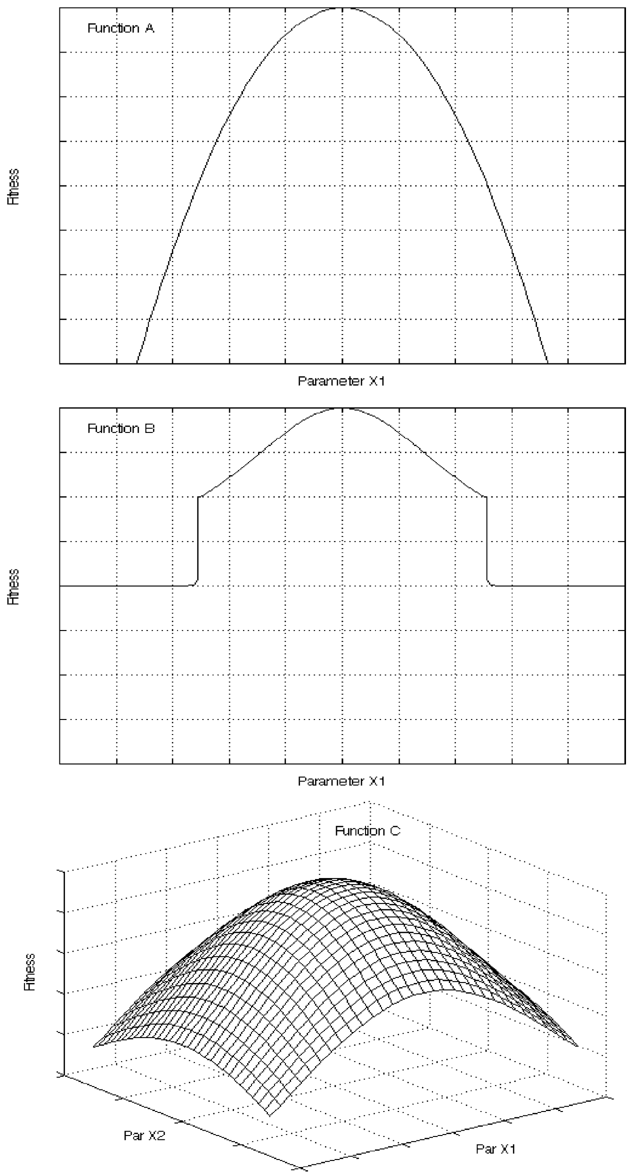

Fig. 1. The fitness functions adopted in the search process.

Table 1
The fitness functions adopted in the search process

Function type	Equation
A	$f=\sum_{k=1}^{n} d_k \cdot (a_k x_k^2 + b_k x_k + c_k)$
B	$f=\sum_{k=1}^{n} e_k \cdot \frac{p_1}{(x_k-x_{k_L})^2+(x_k-x_{k_U})^2}$
C	$f=\left(p_2+p_3\cdot\sum_{k=1}^{n}\frac{(x_k-x_{k_R})^2}{x_{k_U}-x_{k_L}}\right)^{-1}$

4. Analysis of the results

The aircraft configuration selected for this study is representative of a single engine tactical jet fighter.

Trim states obtained from simulations are compared in Table 2 with available reference data for different flight conditions.

Table 2
Validation of the simulation model (trim states)

	Reference	Simulation	Reference	Simulation
α	3.59°	3.48°	4.16°	4.12°
δ_e	−1.11°	−0.87°	−1.43°	−1.1°
T	12537 N	12372 N	9581 N	9428 N
	$h=305$ m − $V=170$ m/s $W=108590$ N − $CG=0.043$		$h=3048$ m − $V=164$ m/s $W=90430$ N − $CG=0.113$	
α	6.16°	6.18°	9.54°	9.62°
δ_e	−2.5°	−1.87°	−4.23°	−3.0°
T	8477 N	8513 N	9021 N	9961 N
	$h=6096$ m − $V=158$ m/s $W=88890$ N − $CG=0.119$		$h=9144$m − $V=151$m/s $W=87690$ N − $CG=0.124$	
α	4.73°	4.73°	3.29°	3.2°
δ_e	−1.74°	−1.31°	−0.94°	−0.76°
T	8493 N	8507 N	10406 N	10480 N
	$h=4572$ m − $V=161$ m/s $W=84290$ N − $CG=0.137$		$h=1524$ m − $V=167$ m/s $W=86600$ N − $CG=0.128$	

Simulations were also performed and compared with a set of reference data for the unaugmented aircraft. An example is presented in Figs. 2 and 3 obtained for a longitudinal checked stick input. The response of the simulator reproduces accurately the reference time history demonstrating that the longitudinal dynamics of the aircraft is correctly represented by the mathematical model. Additional validation was also performed for different flight conditions (see Table 2) including both longitudinal and lateral-directional stick inputs. The analysis of this set of results shows that the aircraft exhibits, in the range of considered test conditions, a low level of coupling in terms of time response to separate longitudinal and lateral-directional commands.

A set of numerical experiments was performed to design a flight control system able to reshape the longitudinal aircraft response (pitch angle due to elevator input) i.e. obtaining an attitude command attitude hold response type. Another requirement was to increase the aircraft bandwidth and to decrease the time delay according to handling qualities requirements specifications.

Frequency responses from flight tests were only available for the following flight states: $h=1524$ m, $V=167$ m/s, $W=86600$ N and wing loading $W/S=4120$ N/m^2. Hence, these initial conditions were used for the design of the controller.

As a matter of fact, the unaugmented aircraft exhibits unsatisfactory parameters in terms of frequency domain response as ω_{BW} and τ_{P} fall in the Level 3 region for Category A flight phases.

The three previously described fitness functions (see Fig. 1) were designed to provide the same maximum ($f=1000$) for a set of given reference parameters x_{k_R}. The following desired handling qualities requirements were implemented in the search process: $\omega_{\mathrm{BW}}=8.75$ rad/s and $\tau_{\mathrm{P}}=0.050$ s. The frequency response was also expected to be limited in terms of average low frequency gain ($A_{\mathrm{low}}=20$ dB), peak value ($A_{\max}=25$ dB) and overall average

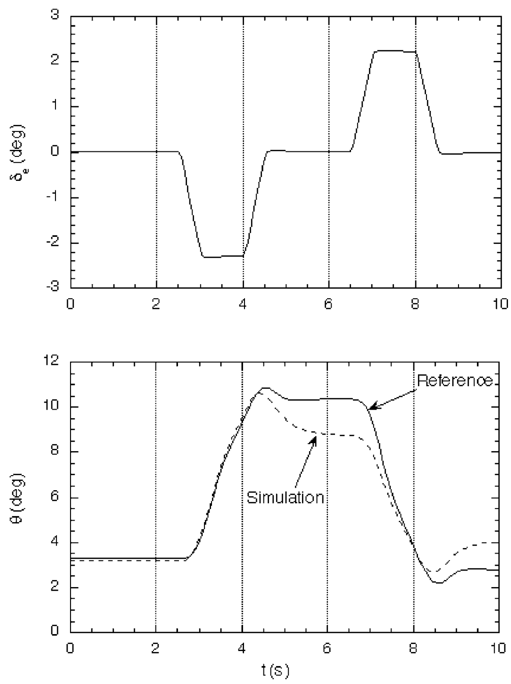

Fig. 2. Validation of the simulation model (time domain response to control input).

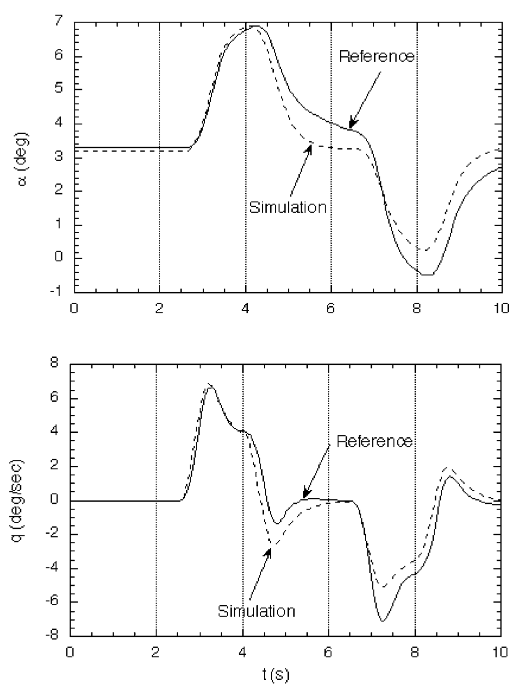

Fig. 3. Validation of the simulation model (time domain response to control input).

gain ($A_{avg} = -6$ dB). Note that all the targets for the search process are defined without a correlation between handling qualities requirements (ω_{BW}, τ_P) and frequency response shaping (A_{low}, A_{max} and A_{avg}). The consequence is that, possibly, these conditions cannot be simultaneously satisfied, i.e. the absolute maximum for the fitness function cannot be obtained. Hence, the solution will be an "optimal"

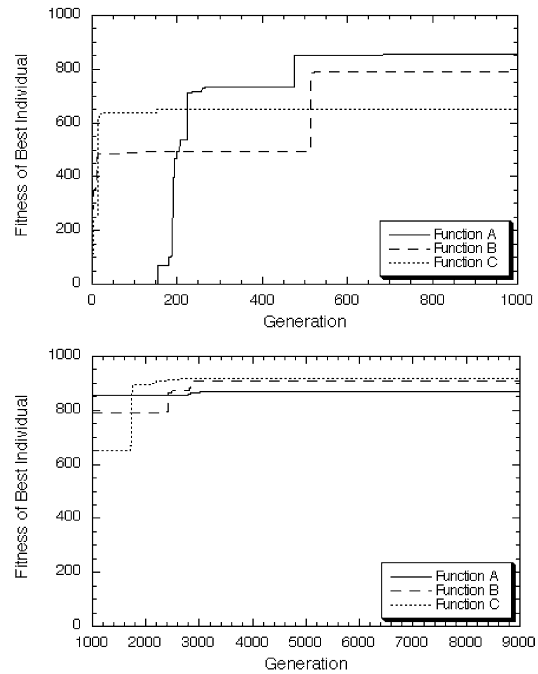

Fig. 4. The search and optimisation process (performance in terms of evolution).

compromise found after convergence of the genetic search process. This is a typical situation in control design where several requisites exist and none of them can be completely fulfilled in terms of solution.

A deficiency function was also added to the fitness functions computed for the parameters x_k to penalize the evolution of the individuals which exhibit poorly damped poles ($\zeta \leqslant 0.1$). Some tests demonstrated that, occasionally, the evolution process was substantially altered when this penalty function was omitted as the solver promoted a fast convergence to gain-limited controlled systems in the vicinity of the desired bandwidth and delay parameters.

A set of preliminary experiments was used to define the length of the generation process as a compromise between computational time and adequate evolution of performance. Hence, the present application of the genetic search process was initially propagated over 9000 generations. The test took 3.3 hours on a standard PC i.e. 1.4 seconds to complete a generation. The range was found to be always higher than the minimum propagation of generations required to obtain a substantial convergence with a wide range of initial conditions. Note that the performance of the genetic algorithm was analyzed by tracking the fitness of the best individual of each generation.

These numerical experiments also confirmed that starting the population with a different random seed number introduced a limited change of the time to convergence but the relative performance of the different fitness functions at the end of the search process was not altered.

Therefore, one of these experiments was selected as a reference in order to compare the performance of the different implementations of the fitness functions (function A, B or C

Table 3
The evolution of the augmented system (control system)

Generation	k_u	k_q	k_θ	T_1	T_2
Function A					
1	−4.33E−01	−3.90E+00	−2.35E+00	7.48E+00	1.31E+01
3000	1.22E−03	−4.87E−01	−4.74E−01	5.82E+00	7.06E+00
6000	1.22E−03	−4.99E−01	−4.69E−01	1.39E+01	7.54E+00
9000	1.22E−03	−4.99E−01	−4.69E−01	8.58E+00	7.50E+00
Function B					
1	1.69E+00	−4.24E+00	−3.13E−01	7.07E+00	1.46E+01
3000	1.22E−03	−5.04E−01	−4.15E−01	1.49E+00	1.02E+01
6000	1.22E−03	−5.04E−01	−4.15E−01	1.95E+01	1.00E+01
9000	1.22E−03	−5.04E−01	−4.15E−01	1.81E+01	1.00E+01
Function C					
1	1.69E+00	−4.24E+00	−3.13E−01	7.07E+00	1.46E+01
3000	1.22E−03	−3.92E−01	−6.25E−01	5.40E+00	6.25E+00
6000	1.22E−03	−3.92E−01	−6.25E−01	1.61E+01	6.25E+00
9000	1.22E−03	−3.92E−01	−6.25E−01	1.68E+00	6.25E+00

Table 4
The evolution of the augmented system (performance)

Generation	ω_{BW}	τ_P	A_{max}	A_{avg}	A_{low}	Fitness
Function A						
1	4.0365	1.20E−02	86.847	55.114	76.221	−3.11E+03
3000	10.186	8.71E−02	22.048	−6.8828	17.029	8.66E+02
6000	10.186	8.66E−02	22.08	−6.9148	17.054	8.69E+02
9000	10.186	8.66E−02	22.083	−6.9143	17.055	8.69E+02
Function B						
1	0.8356	0.22621	51.897	20.62	16.398	2.57E+02
3000	10.186	8.66E−02	22.718	−6.8421	17.37	9.10E+02
6000	10.186	8.66E−02	22.728	−6.8406	17.372	9.10E+02
9000	10.186	8.66E−02	22.728	−6.8406	17.372	9.10E+02
Function C						
1	0.8356	0.22621	51.897	20.62	16.398	1.12E+02
3000	9.3756	9.05E−02	20.293	−6.8527	16.197	9.16E+02
6000	9.3756	9.05E−02	20.293	−6.8527	16.197	9.16E+02
9000	9.3756	9.05E−02	20.293	−6.8527	16.197	9.16E+02

in Fig. 1), where the three generation processes were initialized with the same random seed number.

The evolution of the best individual is presented in Fig. 4. The graph shows that the fitness function becomes substantially stable after a rapid growth phase completed in 3000 generations. The same evolution process is also presented in Tables 3 and 4. The results presented confirm that the last part of the convergence process introduces minimal changes in terms of control system design and performance and that after 9000 generations the functions B and C exhibit a performance which is 5% higher than the additive parabolic function A. The best result is obtained with the n-dimensional function (elliptic paraboloid) that shows a good ability to provide a greater fitness over the search space.

The handling qualities levels are presented in Fig. 5, before and after the inclusion of the optimized control system. Even if the target was in the Level 1 area, the augmented aircraft shows Level 2 handling qualities located in the area surrounding the expected ω_{BW} and τ_P. This is the effect of a compromise among tight loop closure, low frequency tracking, command anticipation and desired shaping of the

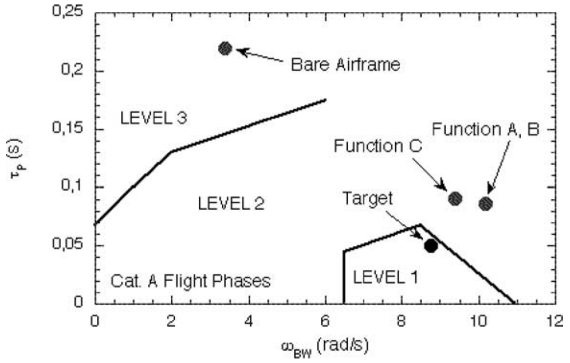

Fig. 5. The handling qualities levels before and after the inclusion of the control system in the simulation model.

frequency response. In any case, the final rate for the best individual obtained is ≈ 92% of the available range, i.e. in the close vicinity of the absolute maximum of the fitness function. The result also suggest that additional increase of performance should be provided by either relaxing the requisites on A_{low}, A_{max} and A_{avg} or changing the characteristics of the control system configuration.

The time domain response to light atmospheric turbulence was also reproduced for the controlled aircraft and the results show that the feedback loop is performing an effective short term attitude stabilization.

5. Concluding remarks

The frequency domain handling qualities requirements were included in the design procedure of a flight control system, in a form suitable for search and optimisation by means of a genetic algorithm. The dynamic response of the augmented aircraft was verified by implementing the flight control system in a realistic simulation model.

The results show that the design method is characterized by straightforward inclusion in the search process of the design requisites and robustness of the algorithm with an adequate computational workload. The method also overcomes the limitations of other optimal control design methods which ask for a higher complexity to translate a set of handling qualities requirements in terms of implementation.

The impact of the fitness function on the algorithm performances was evaluated and the best results were obtained with the n-dimensional function (elliptic paraboloid) that shows a good ability to provide a greater fitness over the search space.

Nevertheless, the convergence of the search strategy is based on inspection of the fitness for the best individual at each generation, i.e. the solution is found after a number of generations that cannot be assessed in advance.

Furthermore, the requisites cannot be superimposed without considering their interactions, which may lead to a compromise in terms of performance of the solution. As a matter of fact, the user cannot predict the distance of the solution from the target and some kind of tuning of the reference parameters may be necessary. Additional constraints are required to lead the controlled system in the range for dynamic stability. Areas of penalty can be specified depending on the real and imaginary parts of system poles, the presence of non-minimum phase zeros and the magnitude of singular values. The relative weight of parameters combined in the fitness function may also be used to enhance the evolution towards the area of convergence (in the present case all parameters give their contribution with the same weight). Another promising alternative – not explored here – in order to promote the proximity of the best individual to the target region could be the use of real encoding of parameters with an adaptable range of variation.

Finally, the present work does not claim to draw general conclusions about the limitations and the advantages of this control design technique, as additional experiments should be performed in a wider range of flight conditions with available reference flight test data.

Acknowledgements

The authors wish to thank Alenia Aeronautica (Dipartimento LSIT) for providing the reference data of the single engine jet fighter adopted for the validation of the simulation model and David L. Carroll for the development of the genetic solver used for the present research.

References

[1] Anonymous, Military Specification – Flying Qualities of Piloted Airplanes, MIL-F-8785C, Department of Defense, USA, 1980.
[2] Anonymous, Flying Qualities of Piloted Aircraft, MIL-HDBK-1797, Department of Defense, USA, 1997.
[3] D.L. Carrol, Chemical laser modeling with genetic algorithms, AIAA J. 34 (2) (1996) 338–346.
[4] D.L. Carroll, Genetic algorithms and optimizing chemical oxygen-iodine lasers, in: Developments in Theoretical and Applied Mechanics, vol. 18, School of Engineering, The University of Alabama, 1996, pp. 411–424.
[5] D.E. Goldberg, Genetic Algorithm in Search, Optimisation and Machine Learning, Addison Wesley, Reading, MA, 1989.
[6] G.J. Gray, Y. Li, D.J. Murray-Smith, K.C. Sharman, Specification of a control system fitness function using constraints for genetic algorithm based design methods, in: 1st IEE/IEEE International Conference on Genetic Algorithms in Engineering Systems, Sheffield, United Kingdom, 1995.
[7] G.J. Gray, Y. Li, D.J. Murray-Smith, E. Romeo, K.C. Sharman, The application of genetic algorithms to gain-scheduling controller analysis and design, in: 2nd IEE/IEEE International Conference on Genetic Algorithms in Engineering Systems, Glasgow, United Kingdom, 1997.
[8] A. Homaifar, C.X. Qi, S.H. Lai, Constrained optimisation via genetic algorithms, Simulation 62 (4) (1994) 242–254.
[9] I. Kitsios, T. Pimenides, Structured-specified robust-multivariable-controller design for practical applications using genetic algorithms, Control Theory and Applications, IEEE Proceedings 150 (3) (2003) 317–323.
[10] S.C. Kramer, R.C. Martin, Direct optimisation of gain scheduled controllers via genetic algorithms, J. Guidance Control Dynam. 19 (3) (1996) 636–642.
[11] K. Krishnakumar, D.E. Goldberg, Control system optimisation using genetic algorithms, J. Guidance Control Dynam. 15 (3) (1992) 735–740.
[12] J.D.J. Mao, Robust flight controller design for helicopters based on genetic algorithm, in: 15th IFAC Congress, Barcelona, Spain, 2002.
[13] D.G. Mitchell, D.B. Doman, D.L. Key, D.H. Klyde, D.B. Leggett, D.J. Moorhouse, D.H. Mason, D.L. Raney, D.K. Schmidt, Evolution, revolution and challenges of handling qualities, J. Guidance Control Dynam. 27 (1) (2004) 12–27.
[14] D. Moorhouse, R. Woodcock, Background Information and User Guide for MIL-F-8785C, Military Specification – Flying Qualities of Piloted Airplanes, AFWAL-TR-81-3109, USA, 1982.
[15] J. Ouyang, W.D. Qu, Robust pole placement using genetic algorithms, in: IEEE International Conference on Machine Learning and Cybernetics, Beijing, PR China, 2002.