Genetic Algorithms In Aerospace Design:
Substantial Progress, Tremendous Potential

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Executive Summary

This paper was written to provide an overview of the potential of using genetic algorithms (GA's) for aerospace design or to support aerospace design efforts. Genetic algorithms can design individual vehicle components, like the external aerodynamic shape, the internal supporting structure, the propulsion system, the autopilot, or just about any other system component that has requirements that can be mathematically represented and modeled. Genetic algorithms can also be used to support design studies through their ability to find optima for complicated multi-dimensional optimization topologies. This paper, which overviews multiple recent aerospace design efforts using genetic algorithms, was an invited paper presented at a joint NATO/Von-Karmen-Institute Workshop on Intelligent System held in Brussels, Belgium during May of 2002.

Abstract

Since the mid to late 1980's, Genetic Algorithms have been increasingly applied to aerospace problems, producing some exciting results. Almost every discipline in aerospace, from Guidance, Navigation, and Control to Propulsion and Structures, has yielded itself to the power of genetic algorithms. The shear volume of applications that GA's have been applied to has grown tremendously over the past decade. This growth can, to a large degree, be attributed to a growth in computer speed coupled with a growth in the understanding that advanced computing techniques can often produce designs vastly superior to those possible by trial and error or by experience alone. As the design and analysis space grows more non-linear for advanced systems, engineers and their managers are beginning to realize the potential of using a non-linear design and analysis tool to help produce better products.

Publications Analysis by Discipline

A quick survey of papers published in recent years that have used genetic algorithms as the key design/analysis tool is quite revealing. Figure 1 shows how the publication distribution has varied through the years for AIAA conference papers. It is interesting to note the categories that have received the most attention in recent years: multidisciplinary design optimization, aerodynamics, propulsion, and structures/structural-dynamics. Also interesting is the category called GA's. These publications have applied GA's to aerospace problems, plus they investigate different modes of GA behavior based on population sizing, crossover techniques, mutation levels, etc., to study how best to apply GA's to particular problems.

		Form Approved OMB No. 0704-0188

Report Documentation Page

1. REPORT DATE **01 JUN 2003**	2. REPORT TYPE **N/A**	3. DATES COVERED **-**

4. TITLE AND SUBTITLE **Genetic Algorithms In Aerospace Design: Substantial Progress, Tremendous Potential**	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Sverdrup Technology Inc./TEAS Group 308 West D. Avenue Building 260 Eglin Air Force Base, FL 32542, USA**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S)
	11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT **Approved for public release, distribution unlimited**

13. SUPPLEMENTARY NOTES **See also ADM001519. RTO-EN-022, The original document contains color images.**

14. ABSTRACT

15. SUBJECT TERMS

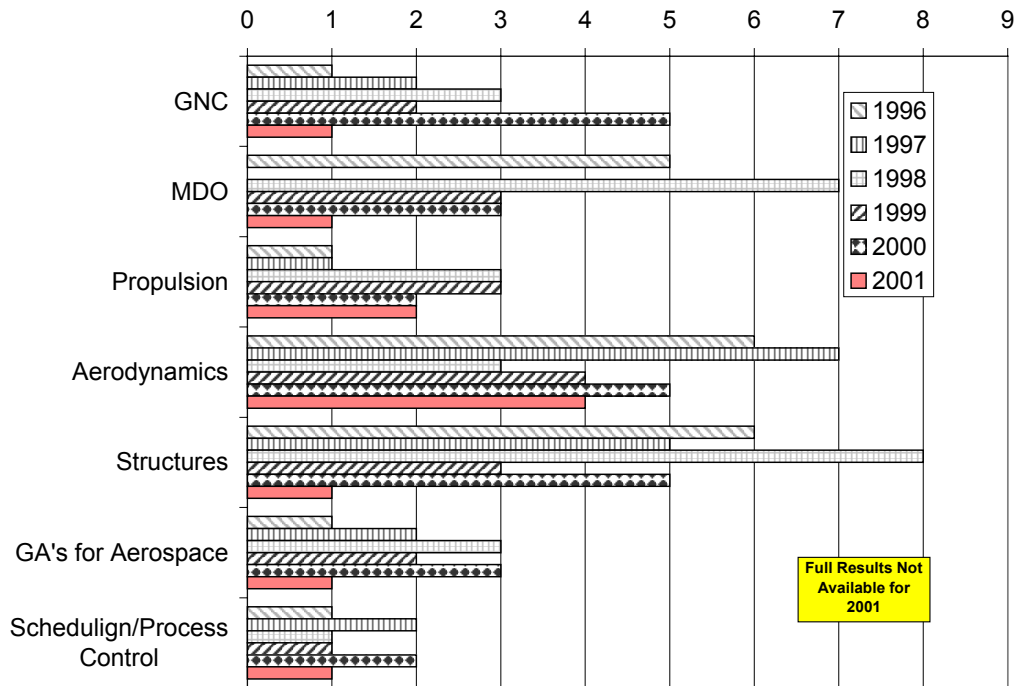| 16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**UU**	**20**	

Figure 1. Trends in AIAA Conference Paper Publications

In terms of total numbers of publications within AIAA conferences, Figure 2 shows an interesting trend. Even number years have drawn considerably more publications than odd-number years. The reason for this trend is not clear. The year 1998 produced the most GA-Aerospace publications with 34. There is no clear growth trend in the total number of GA-related conference papers for AIAA alone during the 6-year time period shown in the figure. As the raw numbers show, there are not enough AIAA papers to support an independent GA Conference each year. Right now the GA applications are spread out among up to 5 or 6 different AIAA conferences each year, making it challenging to keep track of all the GA applications. By looking at the trends, there probably are enough papers to support a bi-annual AIAA GA conference similar to the International Conference on Genetic Algorithms, but such a conference would require significant coordination and might actually hinder the spread of GA's. By being presented as a "new" application at the individual discipline-specific conferences, GA's are given a good exposure across the breadth of the aerospace community.
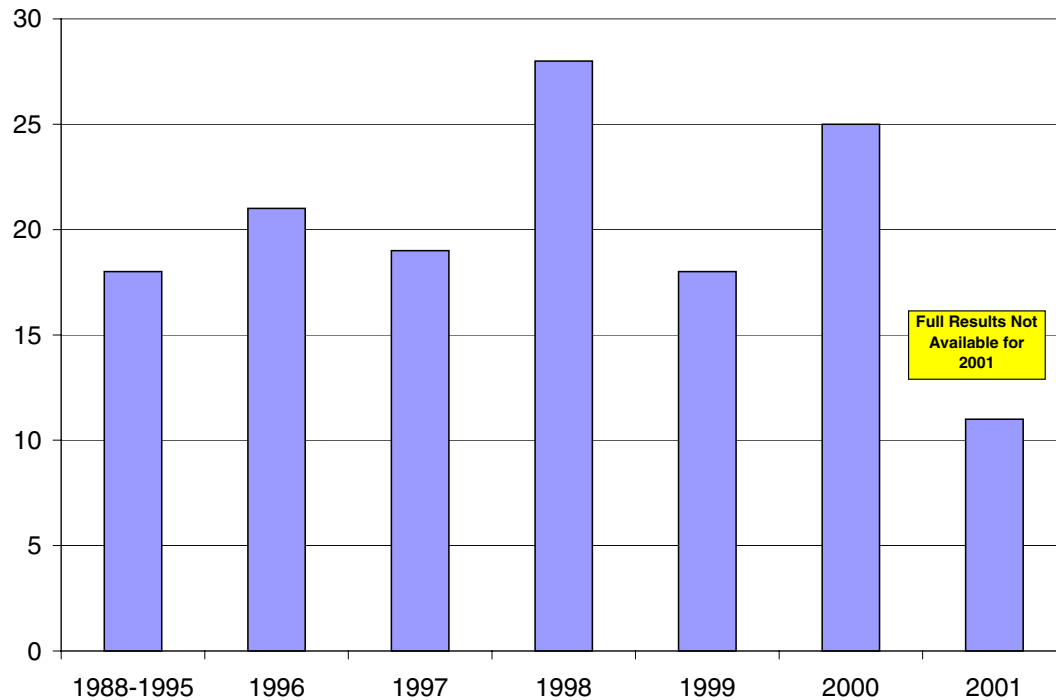
Figure 2. Total AIAA Conference Paper Publications

When a more broad inclusion of publications is considered, including aerospace-related GA publications in journals from ASME, AHS, or IEEE for example, it is interesting that GNC, aerodynamics, and structures/structural dynamics are still very dominant, but MDO is not (see Figure 3).   Scheduling/Process-Control emerges as a very important area for GA applications.   MEMS, communications, heat transfer, damage control, and acoustics all emerge during certain years, but do not have a steady publication record in general.
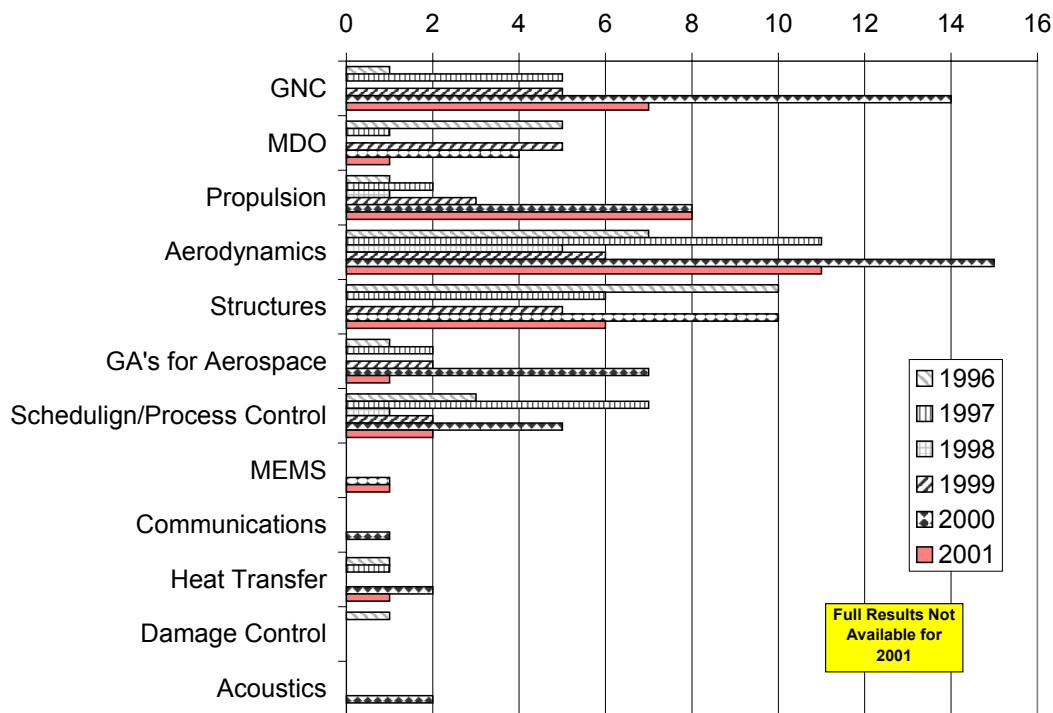
Figure 3. Non-AIAA Publications with Aerospace Applications

Figure 4 shows how AIAA contributes to the total number of GA-aerospace publications each year. In general, AIAA is generally a significant proportion of the total publications, but some years AIAA is less than ½ the total publications. This fact makes it difficult to stay abreast of all the GA publications that occur each year. There is no "one place" to look for GA-aerospace applications. The year 2000 was a significant year for GA-aerospace application publications, where the total number neared 100. If the year 2001 is omitted from consideration, there would seem to be a fairly consistent upward trend in the number of GA-aerospace publications. It is very likely that all of 2001's publications are not yet available on the internet, so the number of publications for 2001 could actually be higher than what is shown in the figure.
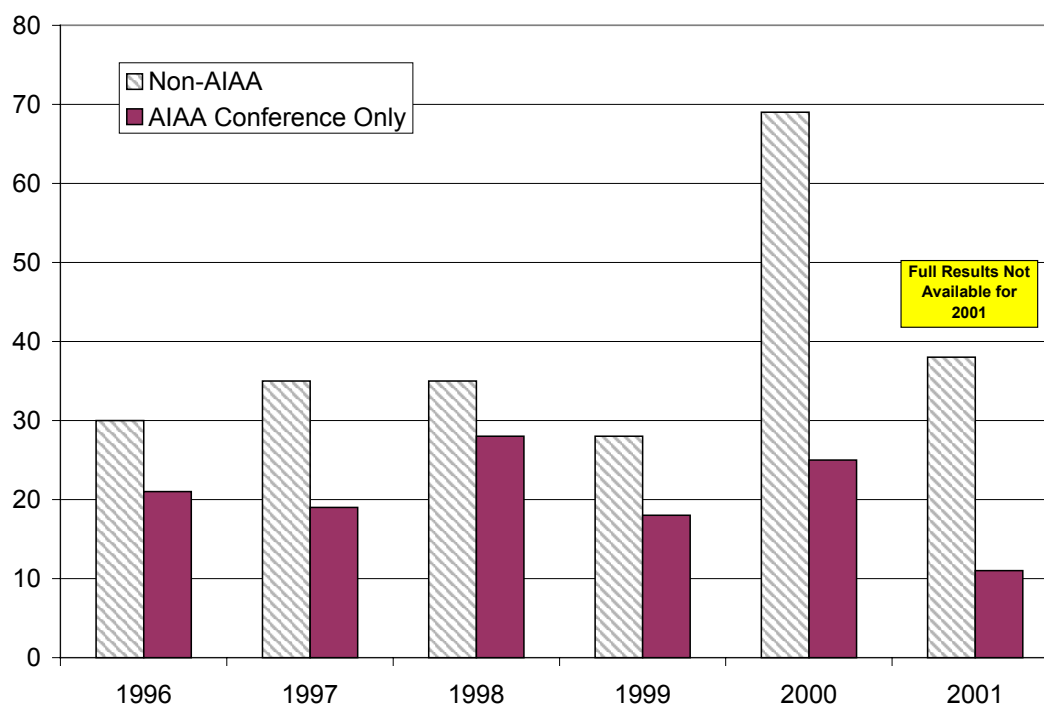
Figure 4. Comparison of Total AIAA and Non-AIAA Publications

With all these publications, it is impossible to list or even discuss each one. But in order to give a sampling of the types of design studies encompassed in all these publications, a few papers in the most prominent technical areas are highlighted to show what is possible when a GA is used to help engineering design and analysis.

Genetic Algorithms in Guidance, Navigation, and Control

Guidance, Navigation, and Control (GNC) was one of the first technical areas in aerospace engineering exploited by GA's. For a time, David Goldberg[1], author of the most popular text on GA's, was at the University of Alabama in the Aerospace Engineering Department. K. Krishnakumar, the organizer of this NATO/VKI workshop was also a professor there at the same time.   Together, they published some of the first papers on using GA's for Aerospace applications. GNC was one of their first application areas. One 1990 conference paper, later a Journal of Guidance, Control, and Dynamics paper[2], showed how a GA can design a lateral autopilot and a windshear controller. In the words of the authors:

> *"The results show that a variety of aerospace control system optimization problems can be addressed using genetic algorithms with no special problem-dependent modifications."*

Certainly the authors were correct that a variety of control problems can be solved with GA's. But whether the authors could have forseen the growth of GA applications beyond control systems is unknown. Besides the autopilot/controller applications envisioned by the authors within the GNC field, GA's have also been used for mechanical control system component studies. For example, Rogers[3] has used a GA to help select the right actuator for a given problem.

Air data systems also play a significant roll in vehicle control. One of the earliest GA applications to air data systems was by Deshpande, Kumar, Seywald and Siemers[4] and later

by Anderson and Lawrence and Lopez[5]. In each of these papers a GA was used to design a working array of flush-orifice air data ports to provide accurate estimates of vehicle flight conditions.

Norris and Crossley[6] recently used a genetic algorithm to find gains to control a standard pedagogical two-disk torsional spring system. The approach used a very simple two-loop proportional-integral control system with velocity feedback. The two-loop controller had three gains that needed to be determined as a function of variable spring stiffness. The objective functions were defined such that good gain values produce little error between the commanded and achieved disk rotation angles. Since two separate disks were being commanded in twist, a pareto genetic algorithm was used to try to minimize the rotational errors in both disks simultaneously. At the conclusion of 80 generations, the resulting family (i.e. population of 80 members) of three controller gains were hybrid performers that would work reasonably well for both disks. Two points worth noting from this study was that the crossover probability was rather low (50 percent) and the population size was three times the number of bits required to represent the three gains (12 bits per gain, 36 bits total).

Aerospace control system publications have also led to GA's being applied in other fields. For example, another interesting genetic algorithm controller application was recently presented by McGookin[7] to control the steering of oil tankers to multiple waypoints in a narrow channel. In McGookin's work the control system consisted of a two-loop autopilot and a sliding mode controller (SMC). The four parameters being optimized consisted of the 1st and 2nd heading loop poles (frequency plane), a heading switch gain, and a so-called heading boundary layer thickness. The goal (e.g. objective function) of the study was to find values for these four parameters such that the oil tanker passed within an acceptable distance of each waypoint while minimizing rudder movement. Minimizing rudder movement saves fuel and time. The results shown indicate that the genetic algorithm found excellent values of the four "gains" in 100 generations. Rudder movement was minimal and each waypoint was reached with very little error. In terms of the genetic algorithm operation in this study, it is interesting that McGookin used a 5 percent mutation rate, which is at least an order of magnitude higher than conventional values of this parameter. Since there is no agreement among genetic algorithm researchers about value ranges for crossover and mutation, it is interesting to note what values other researchers use for their applications.

Another study by Martin[8] addressed the issue of autopilot gain scheduling by using genetic algorithms to replace the ad hoc design process typical in linear gain scheduling with a genetically-fit hyperplane-surface strategy. The genetic algorithm was basically used to optimally design the gain schedule. Of course a gain scheduling approach that might work for one scenario could be inadequate without adaptation. Adaptation strategies have been pursued by Karr and Harper[9] using genetic algorithms to augment fuzzy logic controllers. Coupling genetic algorithms with neural networks appears to offer improvement to adaptive control that neither approach has independently. The fuzzy controller (neural network) uses a "rule-of-thumb" strategy to control a chemical system, but the chemical system is periodically changed, thereby invalidating some of the rules-of-thumb. As the system changes, a learning algorithm (the genetic algorithm in this case) tests new rules-of-thumb so that the fuzzy controller can continue to control the chemical system. For autonomous systems[10] this type of approach has obvious advantages assuming the genetic algorithm can keep up with the rate of change of the system. Karr[11] later expanded this work to control the rendezvous of two spacecraft. Another excellent work in adaptive fuzzy logic controller design using genetic algorithms was done by Homaifar and McCormick[12] to control a simple electronic cart. The genetic algorithm designed both the rules-of-thumb and the membership functions for the system in an automated process that did not require human input. Other publications worth mentioning include Sweriduk, Menon, and Steinberg[13], Mondoloni[14], and Perhinschi[15].

Genetic Algorithms in Aerodynamics

In recent years researchers have applied gradient-based optimization schemes to aerodynamic design[16,17,18,19], but these methods are subject to several undesirable restrictions. First, these methods require knowledge of the aerodynamic derivatives for each parameter, or combination of parameters for higher order coupling. These derivatives may not be easily determined and must be continually recalculated as the design moves through the design space since few aerodynamic design problems have linear derivatives, especially in multiple dimensions. Second, gradient-based optimizers must start with a specified set of initial parameters, which can bias future solutions toward a local optimum in the viscinity of the starting point. Third, gradient-based methods cannot be applied to problems where there are discontinuities in the design space because the derivatives in these regions are not defined. Discontinuities are common in aircraft design. As Gage[20] points out, there are no partial engines or partial seats on an aircraft. Finally, gradient search procedures work efficiently when there are a small number of design variables and when the variables are essentially independent of each other. As the number of design variables increases and coupling of the variables occurs (most often the case for complex aerodynamic designs), gradient-based algorithms lose much of their efficiency. Only recently have attempts been made to couple artificial intelligence (i.e. learning) techniques to aerodynamic design. The research of Gage and Kroo[20] was focused on applying genetic algorithms to the topological design of nonplanar wings. In their work the wing was broken into several segments which were allowed to vary in incidence and dihedral angles. The goal of the optimization was to minimize induced drag given a fixed lift. Their approach used both a penalty and repair approach to deal with solutions not achieving the fixed lift value. Bramlette and Cusic[21] have also applied genetic methods to the parametric design of aircraft and Tong[22] has used genetic algorithms to conduct preliminary design of turbine engine airfoils after gradient methods had stalled in a local optimum. More recently Anderson[23] has applied genetic algorithms to subsonic wing design with the goal of producing good aerodynamic shapes, but also given the additional constraint that the structure must not break. Anderson used penalty weights to combine Lift, L/D ratio, and structural design margins into one global objective function. Anderson, like Gage[20], pointed out that the achieved solution is strongly dependent upon the values of the penalty weights, a very unappealing result. Later, Anderson[24] removed the weighting procedure and instead used a pareto genetic algorithm on the same problem. The results of this later work showed that pareto genetic algorithms are ideally suited for complex optimization problems with diverse goals. Such an approach does mean, however, that the designer must scan the resulting solutions in the pareto-optimal set to determine which solution or solutions are most desirable. Unlike single objective problems where there is a clear winner, multi-objective problems require judgement about which solutions are preferable. For cases where there are both aerodynamic and structural goals in the design, there is usually a willingness to trade-off some aerodynamic performance to ensure that structural integrity goals are met. Some very recent work by Sharatchandra, Sen, and Gad-el-Hak[25] shows that a genetic algorithm can be used to design micro-devices also. In this work a viscous micropump is designed to maximize the flow rate between two parallel plates encasing a rotating cylinder. The basic problem was to let the genetic algorithm determine the optimum plate spacing, the correct upper plate shape (only the lower plate was flat), and the optimal vertical location of the rotating cylinder in order to maximize the mass flow of the device at the exit plane of the two plates. The computational approach used to calculate the mass flow rate in the device was the Navier-Stokes equations. Since the Navier-Stokes equations can be rather time consuming to solve, what should be called a micro-genetic algorithm, in combination with a multi-point crossover (parameter-based) scheme and a high mutation rate, was employed in an attempt to reduce the total number of Navier-Stokes solutions attempted. The results indicated that the micro genetic algorithm with relatively few Navier-Stokes solutions (551 total) achieved good pump designs when compared to standard large population genetic

algorithms. Gregg and Misegades[26] used a "parameter evolution" strategy coupled with Jamesons' FLO-22 code (full potential method) to design transonic wings in a parallel mode. By distributing individual cases to multiple processors significant turn-around time reductions were achieved. The authors noted that taking advantage of the inherent parallelization capability of population based search techniques was a strength of the approach. The "parameter evolution" strategy is similar to simulated annealing and relies more heavily on random parameter variations than does the survival-of-the-fittest strategy embedded in a genetic algorithm. Both Sharatchandra[25] and Gregg[26] used procedures with essentially high mutation rates when compared to the standard genetic algorithm. For small populations, however, there continues to be emerging evidence that higher than normal mutation rates are justified. Other papers using GA's for aerodynamic optimization worth referencing are by Oyama, Obayashi, and Nakashi[27,28] of Tohoku University in Japan.

Another emerging trend in optimization using genetic algorithms is to couple the genetic algorithm with more traditional design techniques to speed convergence. The goal of these hybrid methods is to use the global search strength of the genetic algorithm to provide useful information (starting point) for gradient ascent/descent methods. Anderson, Lawrence, and Lopez[29] successfully coupled a genetic algorithm with a differential corrections method to find flight condition estimates (Mach, angle of attack, aerodynamic roll angle, freestream pressure) from static pressures measured around a missile forebody. The genetic algorithm provided the initial "guess" to the gradient descent method. Fast and accurate flight condition estimates were consistently obtained with this method. Selig and Coverstone-Carroll[30] used a genetic algorithm coupled with an inverse design method to design wind turbines (wind mills) which maximize power output at varying wing speeds. The design variables included blade pitch, blade chord, and blade twist distributions with span. In this case the genetic algorithm executed the design search and the inverse procedure enforced certain constraints while giving the designer flexibility in choosing which variables to iterate and which to send to the genetic algorithm. Another hybrid approach by Cao and Blom[31] coupled a genetic algorithm with a standard gradient approach to maximize lift coefficient for a multi-element airfoil. The design variables included flap angle, gap, overlap, and flap surface geometry. At some prescribed threshold lift coefficient, the genetic algorithm was halted and the gradient method was begun. This approach is very similar to the method of Anderson[29], however, it should be noted that both of these works found that selecting the proper threshold for switching algorithms is critical to the final result. GA's have recently been growing in popularity for aerodynamic design studies using Euler equations. Jang, and Lee[32] recently presented a study of transonic airfoil design using GA's coupled to Euler equations.

Genetic Algorithms in Multidisciplinary Design Optimization

MDO studies have varied significantly over the past few years. Jones, Crossley, and Anastasios[33] have included both aerodynamic and acoustic optimization together. Other authors are trying to expand the use of GA's to complete systems. For example, Perez[34], et. al. has recently used a GA to conduct conceptual design studies for aircraft. Anderson, Burkhalter, and Jenkins[35,36] have performed the same type of conceptual design studies for missiles, both ground-launched and air-launched, to defeat high speed re-entry vehicles and highly maneuverable targets. Ewing and Downs[37] have included a feature in their MDO study not commonly found so far in these types of studies, namely, financial return on investment. The financial area will probably be a growth area for these types of conceptual studies, and a defense contractor that could master providing the most cost-effective solutions to a given threat would never hurt for business. Mastering cost estimating during the design process would likely lead to higher profit margins during manufacturing, so the motivation should be there in industry to begin pursuing these types of studies.

Genetic Algorithms in Propulsion

Airbreathing propulsion seems to dominate the current applications of GA's. Chernyavsky et.al[38] recently used GA's to design a 3-D hypersonic inlet. Torella and Blasi[39] recently published work on using GA's to design complete gas turbine engines. Uelschen and Lawerenz[40] were recently focused on the design of axial compressor airfoils using a combination of artificial neural networks and GA's. Schoonover, Crossley and Heister[41] recently used GA's to design hybrid rocket motors. Given the growing interest in hybrids, this type of application is expected to grow. On the solid rocket motor front, finding the optimal design of a solid rocket motor to meet certain criterion has been the subject of some limited research since the 1960's, although the 1970's saw some developments in capability with the advent of very capable mainframe computers. In 1980, Sforzini[42] commented in his own early solid rocket optimization paper that despite the tractable mathematics involved in designing a solid rocket motor, "limited treatment of this subject appears in the literature". Twenty-two years later, Sforzini's statement is still true to a great extent. The preferred optimization technique still relies heavily on experience and manual "hunt and peck" techniques to yield desirable rocket motor designs. Rigorous computer based optimization techniques have still not been able to penetrate the solid rocket design process in any more than just a few limited studies and publications. But given the vast increases in computing power over the past five years, it is worthwhile to apply computer-based optimization algorithms to preliminary design of solid rocket motor grains.

One of the first attempts at using an automated procedure to design a solid rocket motor was by Billheimer[43] in 1968. Although the physical modeling used in this study was limited by the computational resources available at the time, this paper really acknowledged the importance of automating the design process for solid rocket motors, and demonstrated through sensitivity parameters that automation can aide in the preliminary design environment. Another early attempt at using a computer to find an optimal solid grain geometry was by Woltosz[44] in 1977. Woltosz used a pattern search technique developed by Hook and Jeeves[45] and Whitney[46] to determine five critical design dimensions which maximizes the total impulse-to-motor weight ratio while meeting a specified minimum achieved velocity for a specific vehicle. This same pattern search technique was also used by Foster and Sforzini[47] to minimize the differences between computed and desired solid rocket motor ignition characteristics based upon five primary igniter design parameters. The pattern search technique was an early precursor to the type of GA work that would come much later. GA's also work on a pattern search basis, but are of course radically different.

One early study that was not based on sensitivity derivatives or any calculus-based methodology was done by Swaminathan and Madhavan[48]. A direct random search technique, similar to simulated annealing, was the method that was used to determine the "optimum" composition of propellant ingredients (such as binder, oxidizer, and additives) to generate the highest possible specific impulse.

Other gradient-based techniques have been used as recently as 1992 by Peretz[49] to look at extending the range of air-to-air missiles through a two-pulse thrust profile. A quasi-Newton algorithm was used to define thrust profiles that would allow the missile to enter a glide phase of flight to extend range prior to re-acceleration of the missile for intercept. One interesting conclusion of this study was that zero lift drag and minimum glide velocity had a much larger impact on eventual range than did conventional rocket motor design parameters such as specific impulse and mass fraction.

Two of the more modern approaches that have demonstrated applicability to solid rocket motor design were done by Clergen[50] and McCain[51]. The systems developed in these studies can be classified as soft-computing techniques. Clergen developed a computerized expert system with a hypertext user interface to aid designers in selecting preliminary designs based

on past experience (i.e. the experts). With this system the designer can select, with a user-friendly interface, design criteria such as minimum motor mass and obtain preliminary design parameters that might be suitable for the mission being planned. This system is build around a data base of known systems. McCain's system is also an expert system in the sense that it is heuristic. The heuristic performs an independent design variable selection, and these design variables are then passed to an existing pattern search optimization package to develop rocket performance characteristics. The heuristic then analyzes the effect of altering each independent SRM design variable and selects, based on sensitivity/partial derivatives, the variables to alter for the next design attempt. This technique is an advancement on the pattern search technique of Sforzini, but still has some of the inherent weakness of any sensitivity derivative approach.

Based on the literature review, the design of solid rocket motor is mostly based upon experience (experts and hunt-and-peck methods) or gradient/calculus-based techniques. In either case, historical knowledge and gradient methods tend to focus on, or end up with, designs that are not too dissimilar from known designs. GA's by the nature of the way they operate, can jump beyond this local knowledge (or optima) base. One recent GA application to solid rocket motor design was by Anderson, Burkhalter, and Jenkins[52,53]. The links to the genetic algorithm are all straightforward. The GA is the controlling routine which calls the rocket performance code as needed. The GA passes down the design parameters through the subroutine call statement and the rocket code passes back a measure of how well the design performed compared to a specified thrust profile. The fitness measurement is basically a root mean square error between the achieved thrust history and the specified history. Several cases are presented in the reference, but summary results for two cases are shown below. For the first case the desire was to design a large rocket motor capable of producing 30,000 lbf of thrust for 50 seconds. Figure 5 shows how well the genetic algorithm met this goal.
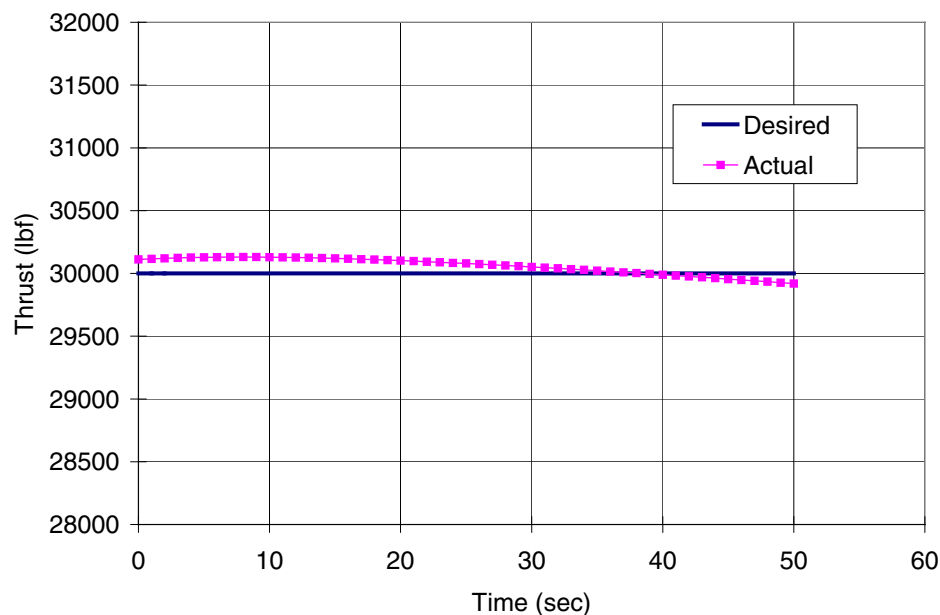

Figure 5. Genetically Engineered Constant Thrust Profile

The evolution of the grain design producing this thrust is shown in Figure 6. A five pointed star, which has a nearly constant burn area as a function of time, was quickly found by the GA.
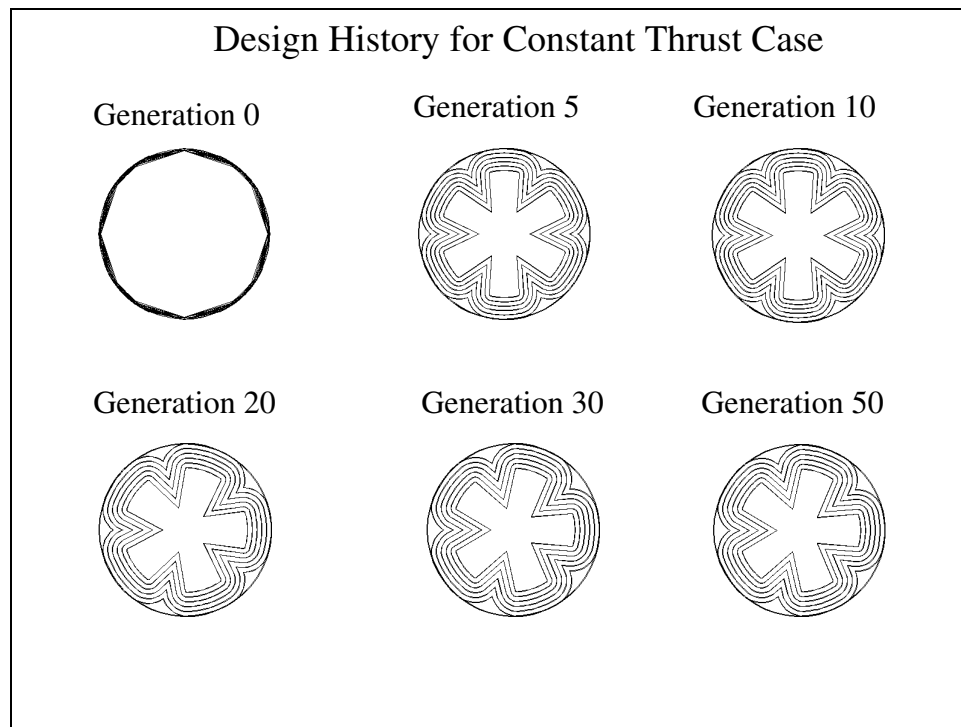
Figure 6. Evolution of Motor Design for Constant Thrust Case

Figure 7 shows an example of a regressive thrust profile for a much smaller rocket motor. As with the constant thrust case, the GA nearly perfectly matches the desired profile.
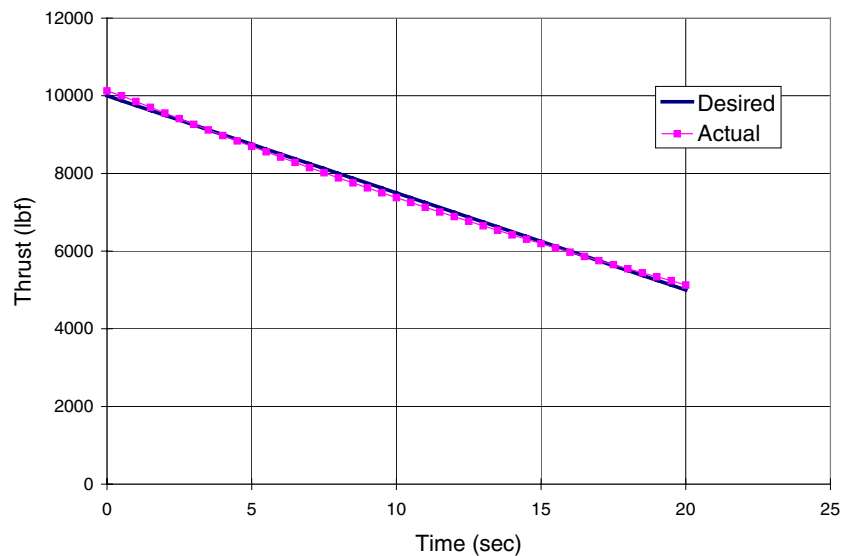

Figure 7. Genetically Engineered Regressive Thrust Profile

Figure 8 shows the evolution of the design for this case. Eight and nine pointed star grain designs were the "best" during the solution process, and the GA eventually settled on a nine-pointed star by generation 60.
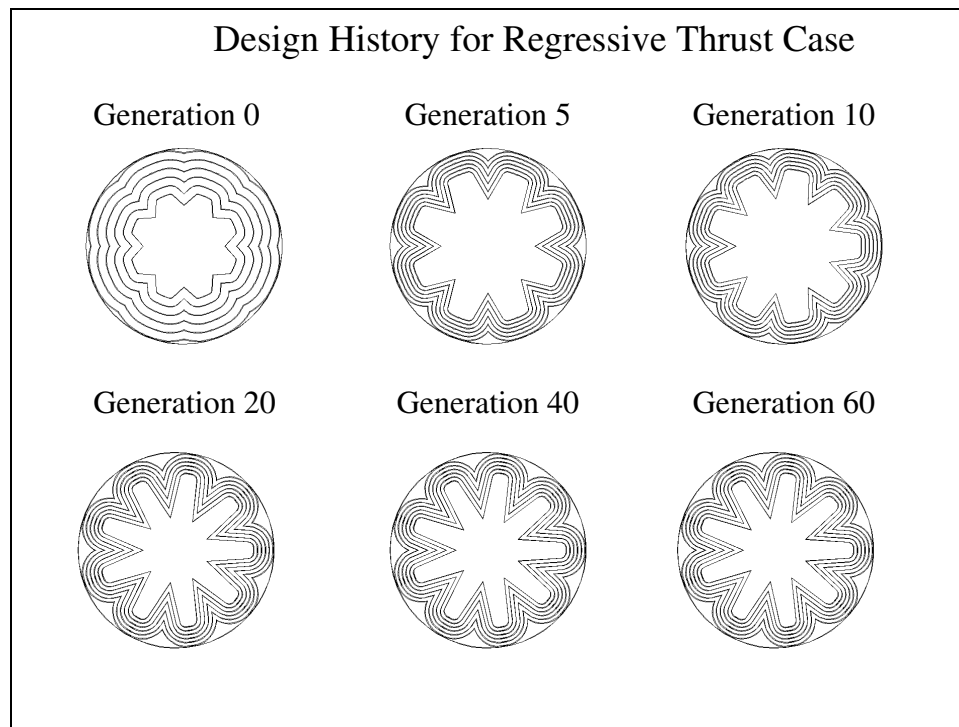
Figure 8. Evolution of Motor Design for Regressive Thrust Case

Genetic Algorithms in Structures

GA's applied to structures/structural-dynamics is one of the most popular GA applications. Composite laminate studies have been popular, and there are too many publications to mention each one, but there are some worth mentioning. Venter and Haftka[54] used a two species GA to design composite laminates subjected to uncertainty. Liu, Haftka, and Akgun also used GA's and response surface methods to design composite wing structures. Other researchers have also coupled GA's to other methods. Nair and Keane[55] coupled GA's with approximation techniques to design structures. Missoum[56] et. al have also developed a GA-based topology tool for designing continuum structures. Furuya and Lu[57] recently combined GA's and neural networks to produce optimal structural designs. On the space side, Bishop and Striz[58] used GA's to design vibration suppression systems in space structures.

Genetic Algorithms in Scheduling/Control

GA's have been applied to the problem of Air Traffic Control several times over the years. Perhaps most recently, GA's have been used to help controllers get the information they need in an optimal way to help do their jobs better. Shaviv and Grunwald[59] were responsible for this work, which focused on air traffic control displays. Communications is certainly an area where GA's have merit. Frayssinhes[60] recently showed how GA's can produce good satellite constellation geometries, which has a variety of applications beyond just communications. A couple of "directly applicable" non-aerospace applications are worth mentioning also. In one case, U.S. West[61] found that laying fiber optic cable, which is usually done based on experience and intuition, can be more efficiently done using a genetic algorithm. During the genetic algorithm process, cable networks that require more cable die and ones that require less cable survive. The end result is that network design cycle times has been cut from two months to two days, saving U.S. West $1 million to $10 million per network. Texas instruments[61], also unleashed a genetic algorithm on a computer chip design

problem and the algorithm came up with a design that required 18 percent less space, using a cross connection strategy that no human had thought of. These two diverse examples show that GA's can be used to support the components that help overall aerospace systems function better and more efficiently.

Genetic Algorithms in Flight Test Data Extraction

Another growth area for GA's is extracting information from flight test data. Wollam, Kramer, and Campbell[62] recently showed that it is possible to do reverse engineering of foreign missiles given these kinds of data. Another significant growth area for GA's concerns simulation validation and verification. As test budgets shrink and the use of Modelling and Simulation grows, model verification becomes increasingly important. One example worth mentioning was recently done by Anderson[63]. In basic terms, verification of launch/jettison performance predictions requires implementation of accurate mathematical models of the weapon aerodynamics, the aircraft interference flowfield contributions, the ejector performance, the flight control system, and knowledge of the actual flight conditions at launch. The aerodynamic math models typically include coefficients or parameters whose numerical values must be determined or estimated for the various flight conditions of interest. Values for these parameters are obtained from wind tunnel tests, analytical or numerical methods, and flight test observations. Wind tunnel tests are usually conducted on scaled models of the actual vehicle of interest and in a simulated flight environment, characterized by non-dimensional parameters such as Mach number and Reynolds number for typical weapon delivery flight conditions. The extent of representation of the physical phenomena in the describing algebraic or differential equations limit analytical and numerical methods. Flight-testing provides the actual environment of interest, but aerodynamic loads are usually not measured directly but rather inferred or estimated based on measurements of the dynamic motion of the vehicle in response to either naturally or intentionally induced disturbances.

A number of parameter estimation methods, such as maximum likelihood, linear regression, and Kalman filter, among others, have been applied to flight data analyses[64,65,66]. The methods are based on the assumption that a correct math model of the aerodynamic loads acting on a vehicle will produce six degree-of-freedom (6-DOF) simulation results which closely match the observed data, with goodness of the model judged by the goodness of representation of the observed data. Consideration must be given to the fact that the observations usually contain measurement noise which cannot be exactly replicated in the simulation. The common approach is to seek to minimize in a least-squares sense the difference between the observed and predicted flight behavior at discrete times along the vehicle trajectory. Iterative procedures are usually invoked, beginning with initial estimates of the parameters, to modify the parameter estimates until convergence is achieved. Two sources of error need to be recognized in this approach; namely, (1) the modelling error in representing the fidelity of the dynamic equations governing the physical motion of the vehicle, and (2) the measurement errors associated with the observations of the vehicle motion itself. The quality of parameters extracted from any identification method can degrade in the presence of either of these error sources. In order to gain confidence in a simulation, however, it important for the simulation to be able to mimic the flight test data as closely as possible. Generally this comparison is done in the basic six degrees of freedom (yaw, pitch, roll, x, y and z). If a set of parameters cannot be found that causes the simulation to mimic the flight test data, this situation leads to an overall lack of confidence in the simulation.

For many flight vehicle configurations, a general form of the appropriate math model can be derived from knowledge of the vehicle shape and flight conditions, such as Mach number, altitude, and expected angle of attack range. The model may consist of explicit analytical

functions, implicit functions requiring the solution of differential equations, or look-up tables, but will, in general, contain a finite number of parameters, the values of which need to be deduced from the measured information. With noise included in the measurements, uniqueness of the parameter set is not guaranteed for a minimum error solution, since, in general, different combinations of parameters may produce solutions having equivalent, least-squares differences relative to the data. In fact, local minima may exist in the search space, making convergence to a true minimum difficult for many traditional, gradient-based methods if the initial parameter estimates are of poor quality. A genetic algorithm has shown that it can provide good parameter estimates[67].

To better gauge how well the new post-flight analysis approach works, it will be compared directly against a "hill climbing" gradient optimization approach. Gradient methods have been the standard way to perform optimization problems such as this one for many years. However, for highly non-linear optimization problems, the advantages of this new approach will become readily apparent.

Figure 9 shows the Euler pitch angle history for the hill climber and the genetic algorithm compared to flight test data. The hill climber obviously got stuck in a local optima and did not compare nearly as well with the flight test data than the genetic algorithm. Forgetting the genetic algorithm comparison for a moment, it could be said that the hill climber captured the right "trend". Engineers often talk about trend comparisons with the actual comparisons are not as good as they would like.

The yaw angle history plot, Figure 9, shows much better performance by the hill climber, however, it is still not as good as the genetic algorithm. Both methods provide very reasonable yaw behavior for the vehicle.

Figure 11 shows the roll angle comparison. The hill climber missed the initial roll to the right and lacked overall trend performance. The genetic algorithm mimicked the flight test data very well. Even the fairly complex roll motion (right-left-right) is captured nearly exactly.

The trajectory of the vehicle (see reference) was captured very well by the genetic algorithm.
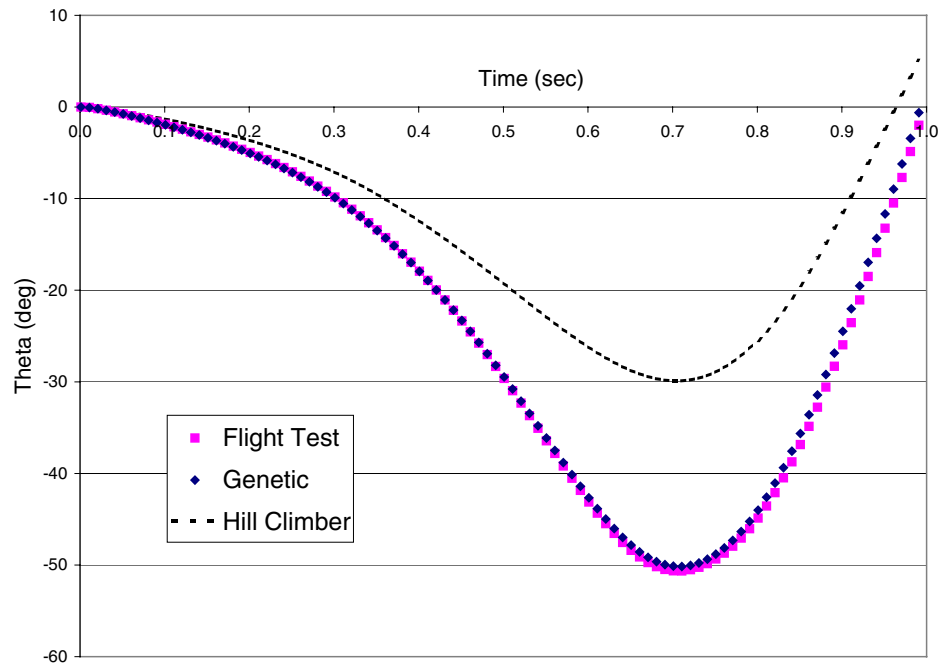
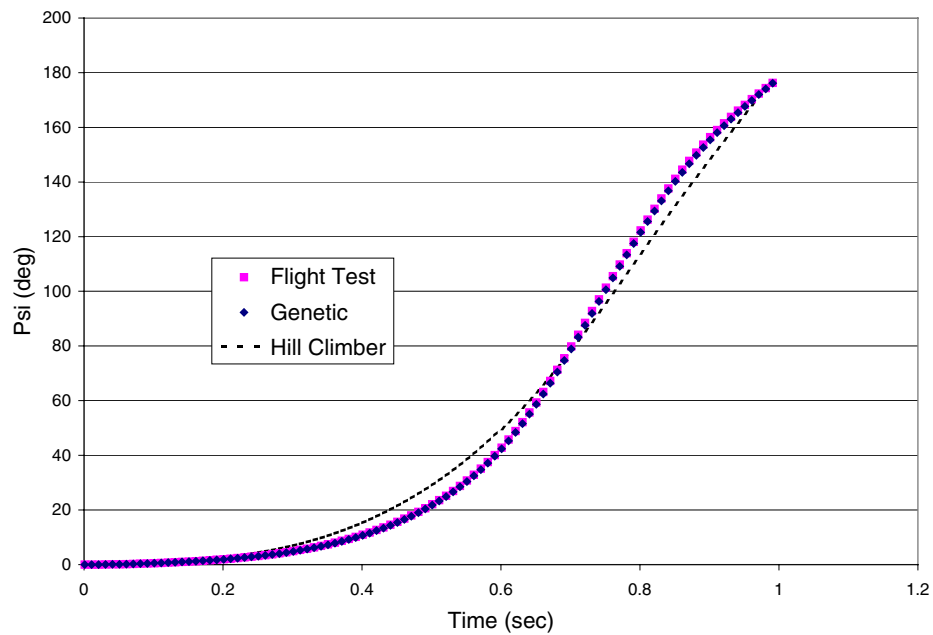Figure 9. Euler Pitch Angle Comparison

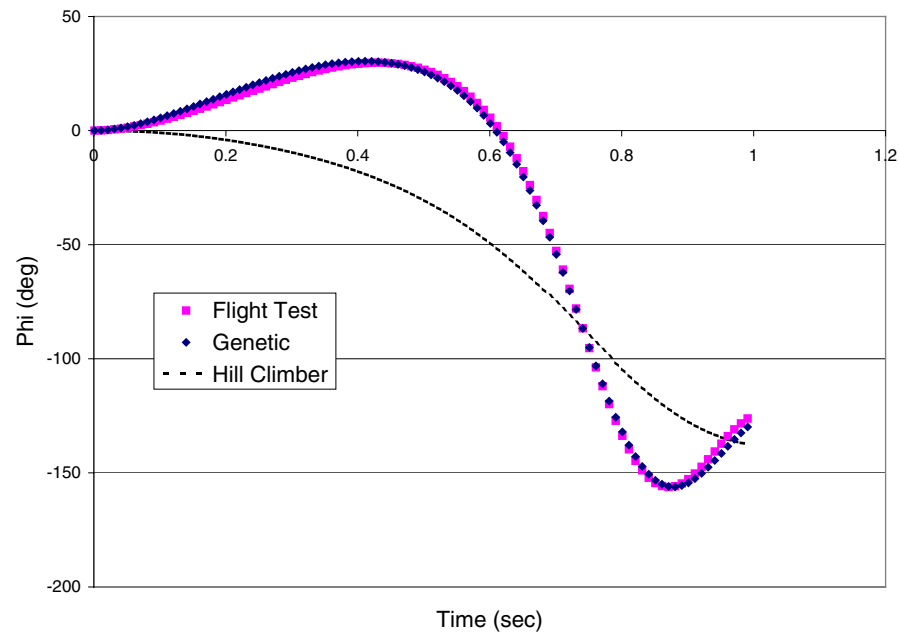Figure 10. Euler Yaw Angle Comparison

Figure 11. Roll Angle Comparison

The gains evidenced by the genetic algorithm are not, however, without cost. The hill climber found its answer in roughly 500 simulation runs (roughly 2 hours of CPU time). The genetic algorithm answer was generated in 50,000 simulation runs (500 generations with 100 members per generation).

Conclusions

As all these applications show, GA's have made significant contributions to the aerospace field. They have shown themselves to be superior to traditional design and analysis tools when complicated non-linear phenomena dominate the optimization space. The growth in the published applications of GA's shows that they are growing in popularity as design teams see their power. GA's have secured a significant role for themselves in future aerospace work. The conceptual design studies referenced in this paper show that they are capable of "system-level" optimization, and with the inclusion of additional considerations such as financial return or manufacturing suitability it is probable that GA's will become a tool for aerospace companies to use to gain a competitive edge.

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