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Genetic Algorithms in Conceptual Design of a Light-Weight, Low-Noise, Tilt-Rotor Aircraft

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Abstract

This report outlines research accomplishments in the area of using genetic algorithms (GA) for the design and optimization of rotorcraft. It discusses the genetic algorithm as a search and optimization tool, outlines a procedure for using the GA in the conceptual design of helicopters, and applies the GA method to the acoustic design of rotors.

1 Introduction

Conceptual design of rotor systems often relies on partially qualitative decisions made by members of a design team to determine important design features. Selection of airfoil section(s) represents one example of this type of design decision-making. Such choices naturally reflect the bias, experience, and personal preferences of the designer and the design team. Other decisions made by designers are based on complicated analytical models for the aerodynamics, dynamics, weight, and performance of the rotor blades. Some optimization procedure, usually numerical or graphical, provides a basis for the final blade design. This design process can be characterized as complex, somewhat arbitrary, and very time-consuming.

These designers, who make the final decisions regarding the geometry and operating parameters of a rotor system, rarely have experience or training in the field of acoustics, nor is acoustic calculation, other than the observation of a few "rules of thumb," generally included in the analytical evaluation performed during the conceptual design process. Consequently, one of the more important attributes of a rotor system—its noise signature—tends to receive little or no attention during the phase of design which can affect it the most. It seems apparent, then, that a need exists for a tool which can not only provide a logical means for making design decisions, but which can also easily incorporate multi-objective and highly-complex goal functions (such as low-noise and low-weight). The genetic algorithm (GA) may provide a basis for the development of such a design tool.

Computer scientists developed genetic algorithms in the mid-1960's as a programming technique for constructing computer programs[1]. The methodology gradually found its way into other fields, particularly as an optimization tool. Applications of GA have only recently appeared in aerospace engineering problems[2]. Significant among the advantages of GA is the ability to combine discrete, integer, and continuous variables in a single optimization problem[3]. Thus, the selection of airfoil section (a discrete variable) or number of blades (an integer variable), can be handled by the GA-based optimization as easily as the choice of disk loading (a continuous variable). Because the genetic algorithm is not calculus-based, it can be used as a global optimizer of highly-non-smooth and discontinuous functions. The more widely-used numerical optimization procedures cannot readily handle non-continuous variables or functions because of their reliance on the computation of numerical derivatives.

2 Genetic Algorithms

Genetic algorithms mimic the patterns of natural selection and reproduction characteristic of biological populations. This concept of "survival of the fittest" as an optimization algorithm originated in work presented by Holland[4] and has since been expanded by Goldberg[5] and others. The methodology has developed into an accepted search and optimization technique. Design variables form the "genes" of a given design and are mapped into binary strings. These strings are then concatenated to form the "chromosome" for a combination of variables which represent an individual design point.

An initial generation is created by randomly placing "1"s and "0"s along the chromosome for a given number of individuals. The values of the design variables in each of these individuals is decoded from the binary string through a set of mapping relationships. From these values, a fitness is assigned to each individual. This fitness is analogous to the objective function value in a numerical optimization problem. Individual chromosomes with high fitness value are more likely to survive and be used as parents for subsequent generations. The search procedure used in GA follows a structured probabilistic information exchange among the members of the population of design points. The reproduction process includes crossover, where a "child" design inherits traits from both of its parent designs, and mutation, where a bit in the chromosome string is changed, thereby introducing a trait not seen in either parent.

Many current efforts in engineering design employ numerical optimization to improve upon the results of standard design processes. The genetic algorithm does not replace these numerical methods. Instead, it provides a tool for searching a larger and more difficult design space than is easily handled by the calculus-based procedures. GA can be used as a global optimizer of highly non-smooth and discontinuous functions because it does not require gradient evaluations and has no requirement for functional continuity. For a highly complex and multi-modal design space, GA provides a rapid search in the direction of the global optimum.

Because genetic algorithms do not compute gradients, they do not complete a search at a local optimum. In fact, the GA has no way of determining the optimality of a given design, and, therefore, a GA search cannot guarantee optimum fitness. In addition, GA can be prone to *premature convergence*[5] where the population has become uniform in character, but it lacks near-optimum individuals. Premature convergence can result when a problem statement is difficult for the genetic algorithm to approach (GA hard[5]) or from sampling error, especially in the initial randomly-generated population. Crossley[6] outlines methods for resolving these difficulties. As described above, however, a genetic algorithm can search a large region and will move the population in the direction of the global optimum. The technique, then, is appropriate in conceptual design where the design space is large and contains several types of variables. Once the search region is narrowed, a calculus-based method can usually select an optimal combination of the continuous design variables.

References [6], [7] and [8] describe the use of the genetic algorithm in conceptual design of helicopters and other rotorcraft along with results from the research into various means of improving the performance of the basic algorithm. The remainder of the report will focus on the approach to and results from using GA in designing rotors for low acoustic signature.

3 Genetic Algorithms in the Design of Low-Noise Rotor Systems

The design process involves both a means for analyzing a candidate design and a method for choosing the best of those candidates. In the case presented here, the analysis component consists of a prediction of the noise level of a rotor system based on the known design variables. The genetic algorithm, on the other hand, performs the crossover and mutation operations and selects the individuals (or rotor systems) which will serve as parents to the next generation with no actual knowledge of the design variables themselves. For the most part, the procedures operate in isolation, with the GA routine requiring only knowledge of the fitness of each individual in a generation, and the fitness evaluation knowing only the selected values for the design variables.

3.1 Acoustic Fitness

In the conceptual design phase, the analysis tools used must provide realistic values for the performance of a given system. On the other hand, because many potential design points must be considered, the level of detail used in evaluating performance cannot be too high simply because of time considerations. Consequently, a compromise is made in determining the fitness of a given individual in the design point population.

Predicting the thickness noise requires knowledge of the rotor blade planform (including twist), airfoil section, and tip Mach number. Loading noise prediction, including that derived from BVI, demands a description of the complete, time-dependent loading distribution on the rotor blades. Modern practice in rotor noise prediction includes a wake analysis followed by an aerodynamics calculation, usually with the aid of a CFD tool. Results from the aerodynamic loading prediction are used as input to a noise prediction code. Several authors have shown fairly good results using this method, including Gallman[9] and Spiegel, *et. al.*[10].

Though the quality of the data resulting from the above methodology may be quite good, that benefit occurs only at the expense of time. A prediction method which is useful for conceptual design applications cannot take hours of computer time to run since thousands of design points must be analyzed within a reasonable time span. Thus, a compromise philosophy was followed in developing the fitness evaluation procedure for the low-noise rotor blade. The analysis utilizes a combination of "exact" and approximate techniques in an attempt to obtain reasonable, though not completely accurate, noise and performance levels. The reduced level of accuracy is tolerable at the initial stages of the design as long as the relative noise levels among various rotor designs are correctly predicted.

Reference [11] describes the prediction methodology used in preparing the acoustic fitness function for use with the genetic algorithm. The thickness and harmonic loading noise are computed exactly, with the aerodynamic pressures calculated using a blade element/panel method combination. Blade-vortex interaction (BVI) noise is estimated using a formula introduced by Hardin[12].

3.2 Fitness Function

The actual fitness of an individual is determined through the value of an objective function which can be described by

$$f = A_1 N_s + A_2 N_{BVI} + \sum_i C_i(\max[0, g_i(x)])$$

In the above equation, N_s and N_{BVI} represent the measures of noise produced by the steady thickness and loading, and by the blade–vortex interactions, respectively. A_1 and A_2 are coefficients chosen to weight the noise sources appropriately. The third term represents a penalty function which is used to ensure, for example, that the rotor is not stalled or that it meets any imposed constraints.

3.3 Genetic Algorithm Methodology

The genetic algorithm-based design code utilizes the three basic operators—selection, crossover and mutation. The code is customized for the current application with variations on these operators and with "higher order" operators which alter the performance of the basic genetic algorithm and help to avoid premature convergence (as described above).

A tournament selection method chooses individuals which will contribute to succeeding generations. In this approach, two individuals are selected without replacement from the current population. These individuals are evaluated for fitness, and that with the better fitness of the two survives for the crossover step. A second pair is evaluated in the same manner, and the superior individual from that pair is "mated" with the better of the original two. The process continues until the new generation is filled. Unlike more traditional roulette-wheel or rank-order selection methods[5], tournament selection compares two individuals at a time rather than comparing the relative fitness of one individual against the entire population. This avoids problems with fitness scaling which can lead to premature convergence. As an additional hedge against premature convergence, the code can use an "elitist" tournament selection in which the best individual from the current generation is retained and it replaces the least fit member of the next generation.

The design code can employ a further scheme to stall the onset of premature convergence. When no improvement in the best individual is noted after five generations, a G-bit improvement[5] method, a gradient-like bitwise improvement approach, is used. For the current best individual in the population, the G-bit improvement routine varies one bit at a time in the string. The single bit change producing the best fitness string is entered into the population, replacing the worst member of the current generation. The G-bit improvement, in effect, forces a mutation on the best individual in order to introduce new string patterns into the population.

Generation	Airfoil	# Blades	Solidity	Twist (degrees)	Tip Speed (ft/sec)	DL (lb/ft^2)	Taper	Power (HP)
1	0012	4	.115	-11	700	3.0	.4	2126
2	0012	5	.110	-11	700	3.0	.4	2074
5	0012	5	.120	-13	665	3.0	.8	2061
10	0012	5	.120	-15	680	3.0	.8	2146
15	0012	5	.120	-15	670	3.0	.8	2096

Table 1: Evolution of Low-Total-Noise Rotor System

To use the genetic algorithm, the seven design variables are coded into binary strings. The variable list contains one discrete variable—the airfoil section—and one integer variable—the number of blades. The other variables, blade twist, blade taper, solidity, rotor tip speed, and disk loading, are continuous, with the resolution of the binary string determining the level of continuity in these quantities. Better resolution of the continuous variables could be obtained by increasing the string length for each variable. However, even with the current total string length of 27 bits, a total design space of 2^{27}, or 134,000,000 different individuals are represented.

4 Results

Reference [11] shows results for GA design of a low-thickness-noise rotor, a low-loading-noise rotor, a rotor system with low thickness and loading noise, and a low-total-noise rotor. Included here are results for the low-total-noise rotor system, which includes the thickness, loading and blade-vortex interaction noise components in the fitness function. The coefficients in the objective function were chosen to make the BVI and the steady loading terms approximately equal for a nominal case. Table 1 shows the evolution of the rotor design variables along with the power required to hover for several generations. (Note that "DL" refers to the disk loading.) The individual described in the table represents that with the lowest noise signature of the population. This case was terminated after 15 generations because of excess CPU time requirements, though the population continued to evolve.

According to the presented results, the GA suggests a higher tip speed than one would normally expect in an optimized design. This may be driven by the fact that the higher tip velocity allows the blade sections to operate at lower lift coefficient, thereby reducing the strength of the trailing tip vortex. However, the solution should be allowed to evolve further before any real conclusions can be drawn about the resulting rotor design.

5 Conclusions and Further Study

The research demonstrates the feasibility of utilizing a relatively new methodology for the design of a low-noise rotor system. The genetic algorithm method can incorporate discrete, integer, and continuous variables into one optimal design procedure, and it, therefore, seems particularly appropriate for use in the selection of rotor design and operational parameters. The paper presents solutions for the design of rotors with lowered acoustic signatures, and, examines the trade-offs required in order to achieve a low-noise design.

The results provide several low-noise rotor blade solutions. Though none of these is guaranteed to be optimal in the sense that it represents the very lowest-noise rotor in the design space, all of them are "good" solutions. In general, the lowest noise solution is not the lowest power solution, although the noise-lowering trends in some of the design variables decrease the power required to hover as well. If it is desired to design a low-noise and low-power rotor, the fitness function can be defined to include a power term with an appropriate coefficient. In this way, the genetic algorithm is well-suited to handle multi-objective design problems. The results presented here indicate that the method will easily incorporate low noise as part of a multi-objective fitness function in the design of rotor systems. To improve upon the speed of the GA method, work continues in the development of an improved acoustic fitness calculation, in particular for determining the harmonic loading noise and the BVI noise.

References [6], [7], [8], and [11] were prepared all or in part under the sponsorship of this grant.

References

[1] Holland, J. H., "Genetic algorithms," *Scientific American*, pp. 66–72, July 1992.

[2] KrishnaKumar, K., "Genetic algorithms–a robust optimization tool," *AIAA 93-0315*, January 1993.

[3] Lin, C.-Y. and Hajela, P., "Genetic algorithms in optimization problems with discrete and integer design variables," *Engineering Optimization*, vol. 19, pp. 309–327, 1992.

[4] Holland, J. H., *Adaptation in Natural and Artificial Systems.* MIT Press, 1992.

[5] Goldberg, D. E., *Genetic Algorithms in Search, Optimization and Machine Learning.* Addison Wesley, 1989.

[6] Crossley, W. A., *Using Genetic Algorithms as an Automated Methodology for Conceptual Design of Rotorcraft.* PhD thesis, Arizona State University, August 1995.

[7] Crossley, W. A., Wells, V. L., and Laananen, D. H., "The potential of genetic algorithms for conceptual design of rotor systems," *Engineering Optimization*, vol. 24, pp. 221–238, 1995.

[8] Crossley, W. A., Regulski, J., Wells, V. L., and Laananen, D. H., "Incorporating genetic algorithms and sizing codes for conceptual design of rotorcraft," in *AHS/NASA Vertical Lift Aircraft Design Conference*, (San Francisco), January 1995.

[9] Gallman, J. M., Tung, C., Yu, Y. H., and Low, S. L., "Prediction of blade-vortex interaction noise with applications to higher harmonic control," *AIAA-93-4331*, 1993.

[10] Spiegel, P. and Rahier, G., "Theoretical study and prediction of bvi noise including close interactions," in *Proceedings of the International Technical Specialists Meeting on Rotorcraft Acoustics and Rotor Fluid Dynamics*, American Helicopter Society and Royal Aeronautical Society, October 1991.

[11] Wells, V. L., Han, A. Y., and Crossley, W. A., "Acoustic design of rotor blades using a genetic algorithm," in *AGARD Symposium on Aerodynamics and Aeroacoustics of Rotorcraft*, pp. 35.1–35.10, October 1994.

[12] Hardin, J. C. and Lamkin, S. L., "Concepts for reduction of blade/vortex interaction noise," *Journal of Aircraft*, vol. 24, pp. 120–125, February 1987.