Abstract - In this paper an evolutionary algorithm (EA) is shown to be a feasible approach to solving the problem of determining the characteristics of wind gusts that result in critical loading of aircraft structures. The EA outperforms a traditional method suitable for solving linear problems, then is extended to nonlinear problems for which there is no effective solution methodology.

I. INTRODUCTION

As most anyone who has flown regularly well knows, atmospheric turbulence can be quite unsettling, even dangerous for aircraft passengers. In addition, pilots are faced with having to maintain control of their aircraft during encounters with turbulence that can be extremely violent. Perhaps not quite as apparent is the fact that aircraft designers are also very concerned with atmospheric turbulence because they are faced with the problem of ensuring that the aircraft they design are capable of withstanding the severe dynamic loads that can be associated with turbulent wind gusts. Digital flight records of turbulence encounters during scheduled airline flights have been found to contain cases of severe atmospheric turbulence occurring near mountains and thunderstorms. These instances of turbulence typically appear as sharp changes both in the loads on the aircraft and to the corresponding response of the aircraft to these dynamic loads. Other cases of severe turbulence are found in strong updrafts above thunderstorm buildups that may be undetected by on-board weather radar [1].

Pilots must be sufficiently trained to deal with such instances of turbulence. Further, they must spend a substantial amount of time in flight simulators to ensure that they are prepared to react appropriately to such turbulence encounters. Even with ample training, turbulence presents pilots with perhaps their most challenging endeavor.

Aircraft designers are just as important as pilots are when it comes to dealing with turbulence. Designers must ensure that aircraft structures can adequately support the loading that results from these natural occurrences. Aircraft designs must be strong enough structurally to survive extreme cases of turbulence. To assist designers in their efforts, and to ensure that all aircraft testing is consistent, the Federal Aviation Administration (FAA) is interested in identifying several worst-case gust loads that can serve as a standard test suite for the aircraft industry.

Unfortunately, the problem of identifying a worst-case gust for an aircraft (let alone for a variety of aircraft) is a very difficult problem. First, the computational models of atmospheric turbulence are complex and not as accurate as one might like. Etkin [2] argues that turbulent models should “accommodate those events that are perceived as discrete, and described as gusts, as well as the phenomenon described as continuous turbulence.” Most of the computer models use mathematical and statistical methods, but are not able to adequately represent extreme gusts in the usual Gaussian probability models of continuous random turbulence.

Despite the complex nature of computer models of turbulent gusts, the problem of determining worst-case gust loads for linear aircraft models has been addressed with a certain degree of success. Jones and his co-workers [3]-[4] developed a method based on wavelet analysis that has been proven effective for linear cases. This wavelet analysis approach employs the statistical discrete gust (SDG) method [5] as a gust-loads analysis tool. It then allows for the calculation of the gust response by convolving the linear aircraft impulse response function with single ramp inputs of varying length and a modified von Karman gust pre-filter to determine the wavelet surface from which the worst-case input pattern is calculated. It is a time-domain approach and yields time-correlated gust loads. But, like other tools in this area, the method for determining the worst-case gust is applicable only to linear aircraft models.

This paper describes a new approach to determining worst-case gust loads – one that is applicable both to linear and nonlinear situations. The basic idea of this approach is to use an evolutionary algorithm (EA) for determining the worst-case gust for a particular aircraft by using the SDG method to model turbulent gusts and a nonlinear aircraft model to realistically represent the characteristics of real-world aircraft. The EA proposes gust parameters that are fed to the SDG method that yields a time-varying turbulent gust profile. The gust profile is then used as a forcing function in a nonlinear aircraft model that computes the loads associated with the proposed wind gust. A fitness function is defined that uses the values of the computed loads to evaluate the severity of the turbulent wind gust proposed by the EA. The EA continues proposing turbulent gusts until a worst-case gust is determined.
II. PROBLEM STATEMENT AND MOTIVATION

The primary structure of an aircraft must be designed to withstand all of the static and dynamic loads it is expected to encounter during the life of the aircraft. In general, the dynamic loads are more difficult to determine. The dynamic loads that must be accounted for include landing and taxi loads, maneuver loads, and gust loads. Of these, gust loads are by far the most difficult to account for due to the stochastic nature of gust loads as compared to other dynamic loads that at least tend to be deterministic.

The process for computing the dynamic loads resulting on an aircraft from a turbulent gust is rather involved and mathematically intensive. In the current effort, this process is achieved in a five-step process:

1. waveform coefficients are proposed (either initially at random or by an EA);
2. the waveform coefficients are converted into an excitation waveform using the SDG model;
3. the excitation waveform is transformed into a gust profile using a modified von Karman pre-gust filter;
4. the excitation waveform is used as a forcing function to a nonlinear aircraft model which computes time-varying values of (a) wing bending moment, (b) wing torque, (c) engine lateral acceleration, and (d) normal acceleration at the center of gravity;
5. the four loads computed in step 4 are used in a fitness or objective function that provides an indication of the severity of the gust proposed in step 1.

A brief description of the three main components used in the process (the SDG model, the modified von Karman pre-gust filter, and the nonlinear aircraft model) are described below.

2.1 SDG Model

This study uses the SDG representation of atmospheric turbulence. This model of turbulence is preferred over the Power Spectral Density (PSD) model primarily because the PSD model assumes the phase components of the turbulence to be uncorrelated. Thus, the SDG model achieves the exponential tails on the distribution of loads through the composition of a succession of “Gaussian patches,” a mathematical model which bears no relation to physical reality. On the other hand, it has been argued by Jones [3] that the SDG representation of atmospheric turbulence does take account of the phase correlations in measured turbulence. According to Jones this is accomplished by explicitly modeling the associated ramp-shaped gust components, and expressing the statistical description of the atmosphere in the form of probability distributions of patterns comprising both single and multiple ramp components.

<table>
<thead>
<tr>
<th>TABLE 1</th>
<th>COEFFICIENTS FOR AN EXCITATION WAVEFORM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>Pulse 1</td>
</tr>
<tr>
<td>Amplitude (a)</td>
<td>1.0000</td>
</tr>
<tr>
<td>Start Time (b)</td>
<td>4.7278</td>
</tr>
<tr>
<td>Width (c)</td>
<td>4.7278</td>
</tr>
</tbody>
</table>

Figure 1: The excitation waveform shown above is generated by the SDG model using waveform coefficients.

The SDG model is provided with several parameters associated with ramp and pulse functions. The model uses these waveform parameters to define a time-varying gust that can in turn be used as the forcing function in an aircraft simulation program. An excitation waveform is generated, as a function of time, from the set of discrete coefficients known as waveform parameters. The current study uses what is known as a four-pulse excitation waveform. Basically, the SDG model requires values of twelve parameters to generate the requisite excitation waveform. Table 1 shows a sample of the input required for the SDG model, and Figure 1 shows the corresponding output of the model. Note that Figure 1 is not a depiction of a gust, rather it shows the information that serves as input to the modified von Karman pre-gust filter which will compute a gust representation.

2.2A. Modified von Karman Pre-Gust Filter

The modified von Karman pre-gust filter uses the excitation waveform generated using the SDG model to produce a gust profile. The pre-gust filter employs a computational model of the atmosphere in the form which has been previously used for the von Karman PSD model of turbulence [6]. It converts the excitation waveform into atmospheric turbulence using a “gust generation” function. Details of the von Karman pre-gust filter can be found in Mehrotra [7]. Figure 2 shows the gust profile generated using the modified von Karman pre-
gust filter when presented with the excitation waveform shown in Figure 1. Note that this gust profile is in a form suitable to use as a forcing function in a nonlinear aircraft model.

Figure 2: The time-varying gust profile shown above results from the modified von Karman gust pre-filter.

2.3 Nonlinear Aircraft Model

The nonlinear aircraft model used in this study simulates the time-varying loads on an aircraft excited using a gust profile like the one shown in Figure 2. The four loads computed using the nonlinear simulation are: (1) wing root bending moment, (2) wing root torque, (3) engine lateral acceleration, and (4) c.g. normal acceleration. Peak values of these loads are subsequently used in the computation of a fitness, or objective function. Figure 3 shows a schematic of the nonlinear model while Figure 4 shows the results of applying the turbulent gust shown in Figure 2 to the nonlinear aircraft model.

Figure 3: The nonlinear aircraft model shown in the schematic above receives a time-varying turbulent gust as its input and computes a load response vector that includes time-varying values of wing bending moment, wing torque, engine lateral acceleration, and normal acceleration at the center of gravity.

III. THE BASIC SEARCH APPROACH

Once a mechanism has been identified for (a) defining a gust using a set of coefficients and (b) using those coefficients to compute the dynamic loads on an aircraft, a search approach to solving the problem at hand can be defined. Recall that the problem of interest is to employ an EA to determine the worst-case or critical gust profile for pre-defined loading conditions on a specific aircraft model. This worst-case gust is one that results in maximum values of one of four loads in a given aircraft model when the given gust is used as the forcing function in the model. The four loads that are generally considered are again: (1) wing root bending moment, (2) wing root torque, (3) engine lateral acceleration, and (4) center-of-gravity (c.g.) normal acceleration.1

The basic approach used in the current study is summarized in Figure 5. This approach has at least two very desirable

1 Although in the current effort the four aircraft loads are considered independently, they could be combined into a more complex multi-objective optimization problem.
attributes. First, the approach is applicable to both linear and nonlinear aircraft models. Second, the method is easily adapted to account for a variety of definitions of “worst-case” gusts, e.g., the designer can easily incorporate a variety of criteria for determining exactly what a worst-case gust is. The fundamental methodology is implemented with the genetic-based search procedure that maximizes the peak values in a given aircraft load quantity, thereby determining the associated critical gust profile.

The dynamic EA simultaneously uses more than one crossover and mutation operator to drive its search and generate the next generation of solutions or population [12]. While simultaneously applying genetic operators in the genetic process, the applied ratios (or probabilities of applying the individual operators from the pool of available operators) are dynamically adjusted according to the evaluation results of the respective offspring’s in the next generation. The dynamic EA can be transformed into a traditional EA by setting the initial ratios of the applied crossover and mutation operators as the assigned values and the initial ratios of the other operators (not applied) to zero. The flow diagram shown in Figure 6 gives an overview of the dynamic EA process that has been implemented for this study.

A dynamic EA was run with four separate fitness functions. The four fitness functions used to achieve the optimization goals were defined simply to be the maximum values of the four loads computed:

- Fitness function 1 = Wing Bending Moment,
- Fitness function 2 = Engine Lateral Acceleration,
- Fitness function 3 = Wing Torque,
- Fitness function 4 = Aircraft Normal Acceleration.

Figure 6: The algorithm for the dynamic EA is basically the same as for more standard EAs except for the fact that multiple crossover and mutation operators are available for use. The probability of using a specific operator is controlled by the applied ratio values, which are themselves determined based on the relative success of individuals previously produced using a given operator.

IV. THE EVOLUTIONARY ALGORITHM

The optimization algorithm chosen for this study is a dynamic EA [8]. The underlying philosophy behind the operation of a dynamic EA is the same as most traditional genetic algorithms, i.e., they are based on the ideas and the techniques from genetic and evolution theory [9] and utilize the principle of survival-of-the-fittest to search for improved solutions in the search space. A dynamic EA differs from traditional genetic algorithms in the way it utilizes genetic operators for production of successive generations and populations in the algorithm.

Traditional evolutionary algorithms use only one crossover and one mutation operator to generate the next generation. It is important to note that the choosing effective genetic operators from the plethora of different kinds of operators that exist in the evolutionary literature is not trivial. In fact, the selection of specific operators is usually decided either based exclusively on the experience of the person who is applying an EA to a specific problem, or by trial-and-error. There have been studies showing that for most applications the form of the crossover and mutation operators plays a key role in the success of the evolutionary algorithms [10], [11].
A dynamic EA was used to search for the worst-case gust parameters, i.e., a gust described using four pulses. Twelve parameters characterize the four-pulse excitation waveform. All of the parameters were coded as real numbers, and their ranges are shown in Table 2.

### Table 2

**LIMITS ON THE DECISION VARIABLES**

<table>
<thead>
<tr>
<th>Pulse</th>
<th>Range</th>
<th>Start Time</th>
<th>Width</th>
<th>Amplitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pulse 1</td>
<td>1.0 ≤ x ≤ 5.0</td>
<td>1.0 ≤ x ≤ 5.0</td>
<td>0.1 ≤ x ≤ 1.0</td>
<td></td>
</tr>
<tr>
<td>Pulse 2</td>
<td>0.5 ≤ x ≤ 8.0</td>
<td>1.1 ≤ x ≤ 2.0</td>
<td>0.15 ≤ x ≤ 0.95</td>
<td></td>
</tr>
<tr>
<td>Pulse 3</td>
<td>2.0 ≤ x ≤ 8.0</td>
<td>0.1 ≤ x ≤ 1.0</td>
<td>≤ 0.095 ≤ x ≤ 0.15</td>
<td></td>
</tr>
<tr>
<td>Pulse 4</td>
<td>2.0 ≤ x ≤ 7.0</td>
<td>0.1 ≤ x ≤ 1.0</td>
<td>≤ 0.095 ≤ x ≤ 0.15</td>
<td></td>
</tr>
</tbody>
</table>

Simulation runs were made for the four specific objective functions stated in the section above using the EA parameters shown in Table 3.

### Table 3

**DYNAMIC EA PARAMETERS**

<table>
<thead>
<tr>
<th>GA Parameters</th>
<th>Dynamic EA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population Size</td>
<td>50</td>
</tr>
<tr>
<td>Number of Gens</td>
<td>100</td>
</tr>
<tr>
<td>Selection Scheme</td>
<td>Tournament</td>
</tr>
<tr>
<td>Crossover Scheme</td>
<td>ArithXover, HeuristicXover, SimpleXover</td>
</tr>
<tr>
<td>Mutation Scheme</td>
<td>Uniform Mutation, Gaussian Mutation, Random Mutation</td>
</tr>
</tbody>
</table>

### V. RESULTS

There are no proven techniques for solving the problem of determining the worst-case gust for a particular nonlinear aircraft. However, the wavelet analysis method of Jones and his co-workers [3], [4] is applicable to problems in which a linear aircraft model is used. Thus, the first step in validating the current method of using a dynamic EA was to compare results with those obtained using the wavelet analysis method on a linear problem. Table 4 shows the results of this exercise. Note that in each of the four fitness function cases, the dynamic EA found a gust that produced a greater load than the gusts determined using the wavelet analysis method. These results are considered a validation of the current method.

### Table 4

**RESULTS**

<table>
<thead>
<tr>
<th>Load Quantity (for linear aircraft model)</th>
<th>Wavelet-analysis method</th>
<th>Dynamic EA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engine Lateral Acceleration (g)</td>
<td>1.4774</td>
<td>2.0166</td>
</tr>
<tr>
<td>Wing Bending Moment (lb ft)</td>
<td>3.1902E+06</td>
<td>6.495E+06</td>
</tr>
<tr>
<td>Wing Torque (lb ft)</td>
<td>2.4078E+05</td>
<td>2.738E+05</td>
</tr>
<tr>
<td>Aircraft Normal Acceleration (g)</td>
<td>1.3288</td>
<td>3.3857</td>
</tr>
</tbody>
</table>

The next step was to solve the problem defined initially of determining the worst-case gust for a particular nonlinear aircraft. Table 5 shows the results of this exercise. Aside from the values of the loads associated with the worst-case gusts determined using the dynamic EA, it is also interesting to consider the performance of the dynamic EA. To this end, Figure 7 is included below showing the convergence behavior of a dynamic EA compared to a standard EA run using the same EA parameters. Notice in this figure that the dynamic EA tends to consistently perform better than the standard EA.

### Table 5

**LOADS FOR WORST-CASE GUSTS**

<table>
<thead>
<tr>
<th>Load Quantity</th>
<th>Dynamic EA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Engine Lateral Acceleration</td>
<td>2.594 g</td>
</tr>
<tr>
<td>Wing Root Bending Moment</td>
<td>11.50E+06 lb ft</td>
</tr>
<tr>
<td>Wing Root Torque</td>
<td>2.122E+06 lb ft</td>
</tr>
<tr>
<td>Aircraft Normal Acceleration</td>
<td>5.894 g</td>
</tr>
</tbody>
</table>

Figure 7: As can be seen from the above figure, the dynamic EA converges more quickly and to a higher fitness value than does the “standard” EA run using the same parameters.
VI. CONCLUSIONS

The stated purpose of the current paper was to use an evolutionary algorithm to determine the worst-case gust loading on a particular aircraft. The details of the application have been set forth in the paper and results have been presented indicating that this approach to solving the very difficult problem is effective. This approach should be of interest both to aircraft designers and to the FAA.

Acknowledgments

The authors would like to acknowledge the support of the Federal Aviation Administration (FAA) through University of Alabama Contract number: 98-G-018, TASK F and the Sterling Dynamics Ltd. for the research.

References


