the flight specification. The $C_{L,br}$ varies linearly; whereas, E_{br} and T_{br} vary nonlinearly. All these flight parameters drop during the cruise.

The best range and its endurance are obtained from Eqs. (16) and (17) by putting $\zeta = 0.3$, giving $x_{br} = 5078$ km, and $t_{br} = 6.66$ h.

The aircraft, therefore, flies at the best range airspeed of 762.5 km/h and covers the range of 5078 km in 6.66 h.

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Statistical Prediction of Maximum Buffet Loads on the F/A-18 Vertical Fin

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I. Introduction

IN a previous wind-tunnel investigation[1] of tail buffeting on the F/A-18, the vertical fin normal force was evaluated from a large number of pressure measurements on the fin surfaces. Steady and rms normal force coefficients were computed. For structural integrity considerations, it is of interest to know the peak load and frequency of occurrence. Some wind tunnels, such as the blowdown type used in Ref. 1, can only be operated for short running times. Similarly, in flight tests,[2] data collected within a certain angle of attack and dynamic pressure band are usually of short duration. A reliable statistical method to estimate maximum load encountered for long operating time of the aircraft using short duration experimental data is highly desirable.

A number of statistical approaches have been used successfully to predict maximum instantaneous distortion patterns of engine inlet total pressure. One that is especially suitable for predicting maximum buffet load is that of extreme value statistics, developed by Gumbel[3] and used by Jacocks[4,5] in inlet distortion studies. In this study, results using Gumbel's first and third asymptotic distributions are presented.

II. Gumbel's Extreme Value Statistics

In this section, steps of the procedure to apply Gumbel's asymptotic theory of extreme values to predict buffet loads are given.

If $X_1, X_2, X_3, \ldots, X_n$ denote n independent observations for the same parent population, and x is the maximum of X_i, Gumbel[3] gave three asymptotic distributions of x for large n.

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These can be expressed by a single equation given by the following generalized asymptotic initial distribution:

$$F(x) = \exp - \left[\frac{\alpha - \beta x}{\alpha - \beta \nu}\right]^{1/\beta} \tag{1}$$

where $\beta = 0$ corresponds to the first asymptote, $\beta < 0$ is the second asymptote, and $\beta > 0$ is the third asymptote. The ratio α/β is the maximum extreme value achievable, ν is the most frequently occurring extreme value level, and α represents the rate of increase of the extreme level with logarithm of time. Gumbel defined two variables; namely, the reduced variate t given as

$$t = -\ln \ln[1/F(x)] \tag{2}$$

and a return period T, which represents the operation time required to observe an extreme equal to or greater than x given by

$$T = 1/[1 - F(x)] = 1/\{1 - \exp[-\exp(-t)]\} \tag{3}$$

The parameters α, β, and ν can be estimated using the method of maximum likelihood. If the parent or initial distribution has a probability density function $f(X_i, \alpha, \beta, \nu)$, the likelihood function can be written as

$$L = \prod_{i=1}^{n} f(X_i, \alpha, \beta, \nu) = \prod_{i=1}^{n} \mathrm{d}[F(X_i, \alpha, \beta, \nu)]/\mathrm{d}x \tag{4}$$

The maximum likelihood estimates of α, β, and ν are obtained from the following equations:

$$\partial \ln L/\partial\alpha = H_1 = 0, \qquad \partial \ln L/\partial\beta = H_2 = 0,$$
$$\partial \ln L/\partial\nu = H_3 = 0 \tag{5}$$

which can be solved using a modified Gauss-Newton iteration scheme.

Let θ_1, θ_2, θ_3 represent α, β, and ν and $\theta = \theta(\theta_1, \theta_2, \theta_3)^T$, $H(\theta) = H(H_1, H_2, H_3)^T$. A function $Q(\theta)$ is defined as

$$Q(\theta) = H^T(\theta)H(\theta) = \sum_{i=1}^{3} H_i^2(\theta) \tag{6}$$

$H(\theta)$ can be expanded in a Taylor series about the initial value θ_0 as follows:

$$H(\theta) = H(\theta_0) + H'_\theta(\theta_0)\Delta\theta_0 \tag{7}$$

where

$$H'_\theta = (\partial H_i/\partial\theta_j) \quad \text{for} \quad i = 1, 2, 3; \qquad j = 1, 2, 3 \tag{8}$$

and $\Delta\theta_0 = \theta - \theta_0$. The function $Q(\theta)$ is minimized under the condition

$$\text{grad } Q(\theta) = \text{grad } H^T(\theta)H(\theta) = 0 \tag{9}$$

and $\Delta\theta_0$ is obtained by solving the following equation:

$$H_\theta'^T(\theta_0)H'_\theta(\theta_0)\Delta\theta_0 = -H_\theta'^T(\theta_0)H(\theta_2) \tag{10}$$

Consider the function

$$Q(v) = Q(\theta_k + v\Delta\theta_k) \quad \text{for} \quad 0 \le v \le 1 \tag{11}$$

where the subscript k denotes the kth iteration. Let V_m be the value of v when $Q(v)$ is a minimum in the interval $0 \le v$

≤ 1. V_m can be estimated by solving the following equations:

$$Q(v) = \sum_{i=1}^{3} H_i^2(\theta_k + v\Delta\theta_k) \quad \text{at} \quad v = 0 \quad \text{and} \quad v = 1 \tag{12}$$

$$d[Q(v)]/dv = \sum_{i=1}^{3} d[H_i^2(\theta_k + v\Delta\theta_k)]/dv = s \quad \text{at} \quad v = 0 \tag{13}$$

where

$$s = 2\Delta\theta_k^T H_\theta'^T H \tag{14}$$

V_m can be obtained from the following equation[6]:

$$V_m = \frac{-s}{2[Q(1) - Q(0) - s]} \tag{15}$$

Substituting V_m into $Q(\theta_k + v\Delta\theta_k)$, the new minimum $Q(\theta_k + V_m\Delta\theta_k)$ is compared with $Q(\theta_k)$. If the value decreases, the next step iteration of Eq. (7) is carried out using $\theta_{k+1} = \theta_k + V_m\Delta\theta_k$, otherwise the $Q(v)$ approximation step is operated over $0 \leq V \leq V_m$ where $Q(1)$ is set to $Q(\theta_k + V_m\Delta\theta_k)$, $s = V_m s$ and V_m is recomputed until the new minimum is smaller than $Q(\theta_k)$. The iterations using Eq. (7) are then repeated until the desired convergence is satisfied.

III. Results and Discussion

In the wind-tunnel investigation[1] of the F/A-18 tail buffet, results for various Mach numbers and angles of attack α were obtained. However, only data for $M = 0.6$ and three α at 25, 30, and 35 deg are presented in this article. These cases are considered to be of particular interest because they represent locations of the center of the mean vortical flow to be just outboard of the vertical fin and between the vertical fins, respectively. The LEX fence was installed in this test.

Gumbel's first asymptotic distribution theory for the peak absolute value of C_N is shown in Fig. 1 using 1.56 s of wind-tunnel data. The time intervals were divided into 100 segments each having 1250 data points. The last data point of the results for each value of α taken at 12.5 s is also included in the graph for comparison with the predicted values. Various time segments and samples per segment were studied and the results presented are typical when the segments and samples per segment are neither too large nor too small. Using an operating time of 1.56 seems to be near the limit when the last data point can be predicted reasonably close to experiment. The inadequacy of the first asymptotic theory to predict extreme values is obvious from this figure.

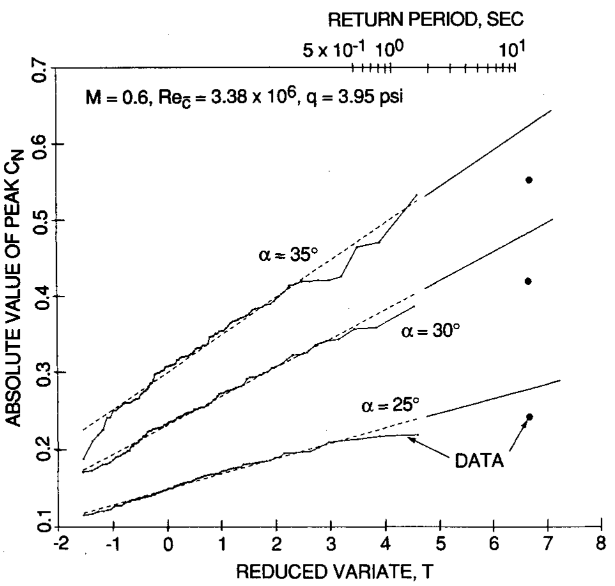

Fig. 1 Estimation of peak buffet loads from the first asymptote.

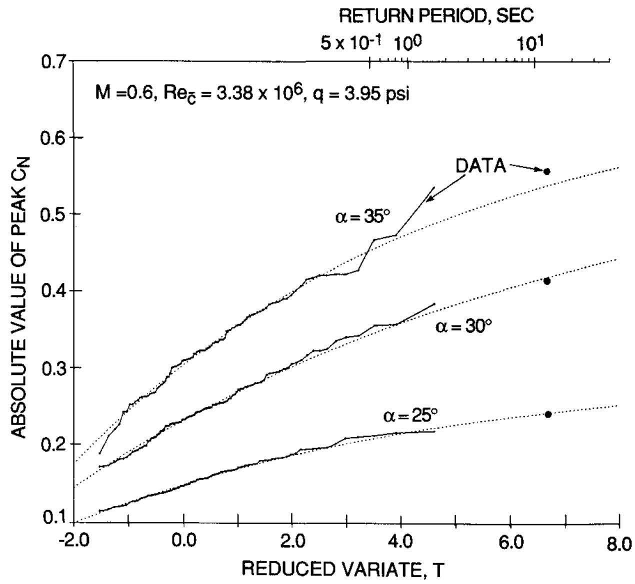

Fig. 2 Estimation of peak buffet loads from the third asymptote.

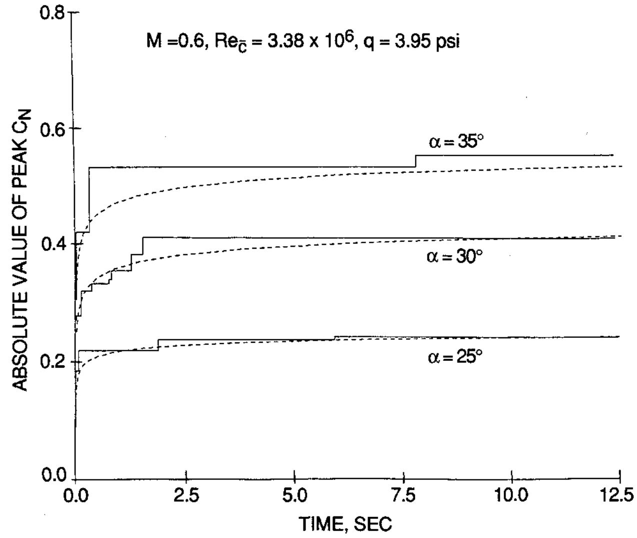

Fig. 3 Comparisons of observed and predicted peak buffet loads from the third asymptote.

The third asymptotic distribution gives much closer agreement with results at large operating times, as seen in Fig. 2. This is to be expected because the first asymptote has an initial distribution of the exponential type, unlimited to the right with all moments existing. The third asymptote has an initial distribution that is limited to the right. Figure 3 shows the peak absolute value of C_N vs time. The stepped curves are the progression of relative increase with time in the peak absolute value of C_N observed in 12.5 s of operation. The dashed lines are obtained from Gumbel's third asymptote and they show very good agreement with observed peak absolute C_N.

IV. Concluding Remarks

Gumbel's extreme value statistics can be used to predict peak loads in aerodynamic applications. Wind-tunnel examples of peak buffet loads on the F/A-18 vertical tail show that the third asymptotic theory predicts extreme values very accurately. The short time period of 1.56 s is sufficient to estimate maximum peak load for long operating time. This is extremely useful for testing in blowdown wind tunnels where operating costs can be cut down for short runs. In flight tests, long operating time of the aircraft in a given angle of attack and dynamic pressure band is usually difficult to maintain and a reliable method for estimation of extreme load levels from short time data is very useful.

Acknowledgments

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Wind-Tunnel Compressor Stall Monitoring Using Neural Networks

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Introduction

ROTATING stall and stall surge of an axial compressor are two distinct types of aerodynamic instabilities that can severely limit a compressor's performance. Both rotating stall and surge may cause the rotor and stator blades to begin vibrations and the internal compressor temperatures to rise rapidly. The large dynamic stresses on the blades may induce severe mechanical damage. For the case of the C3 rotor blades of 16S compressor, the stall will produce potentially destructive levels of vibratory stress after approximately 10 revolutions (or 1 s) following "onset" of the stall. Rotating stall, which will be the prevalent type in the C-1 compressor of 16T, builds to a peak stress level and the decays in periods of two revolutions (0.2 s). It is apparent that a system is required that can detect and warn rapidly of the first symptoms of stall and have the capability to activate corrective actions automatically.[1] At the present, the open-loop technique is essentially in the monitoring mode based on observation from many years of experience. The engineer will perform the corrective action to avoid the compressor stall. A closed-loop stall avoidance incorporating a control system to move the compressor operation point away from the stall line is the ultimate goal.

To accomplish detection of stall for compressor requires speed and an automatic process for both open-loop and closed-loop modes. The neural network is a new information processing technology to classify data, process signals, and model and forecast events. The performance of neural networks in the task of classifying data has speed, accuracy, and high noise tolerance; therefore, neural networks techniques are suitable and selected in the present study to detect and monitor compressor instabilities.

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Compressor Stall Monitoring

Stall monitoring for the compressor in the Arnold Engineering Development Center (AEDC) 16-Foot Transonic/Supersonic (16T/S) wind tunnel is investigated. The primary monitoring data are based on the time traces of rotor blade stresses during the operation of 16T/S compressors. The sensor data are recorded in the Compressor Monitoring System disk records and Compressor Monitoring Room oscillograph traces. Some typical rotor/stator stress data are recorded as oscillograph traces, as shown in Fig. 1. An early stall warning and detection expert system is to be constructed utilizing these time traces data and other auxiliary parameters.

Testing Data Acquisition and Simulator

The data of normal runs for rotors and stators of Compressor C-1 of 16T at AEDC were recorded for various flow conditions. The flow Mach numbers covered include 0.6, 0.9, and 1.2. The original data from stress sensors were recorded

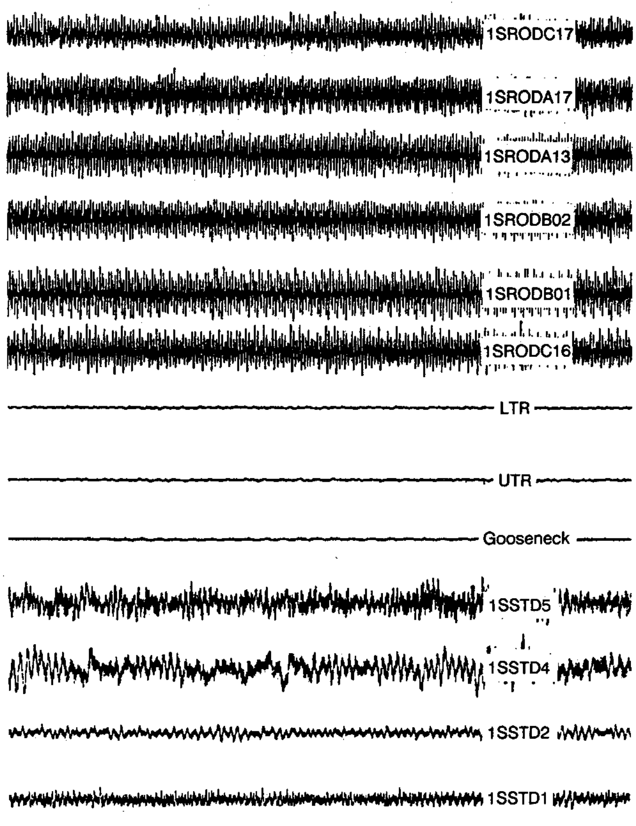

Fig. 1 Typical C-1 compressor stress traces.