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Identification of Helicopter Component Loads Using Multiple Regression

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Multiple regression analysis of helicopter flight data is used to develop prediction models for rotating system component loads from parameters measured in the fixed system. The data base that is analyzed contains load measurements for a helicopter performing several types of flight maneuvers, including symmetric pullouts, rolling pullouts, climbing turns, and level flight. The data are divided into two parts: one for model development and one to serve as a blind test of the model. For steady level flight, linear and nonlinear regression analyses are performed to predict main rotor pushrod and blade normal bending vibratory loads. Correlations above 95% were achieved on the test data for the steady level flight condition. For comparison, analytical results calculated using the CAMRAD/JA rotor analysis computer code for the helicopter in level flight are included. Regression models to predict vibratory loads during maneuvering flight are also developed. Evaluations on the test data indicate that correlations ranging from 79 to 95% are possible for the types of maneuvers contained in the data base.

Nomenclature

LF = load factor
LF$m\mu$ = product of LF, m, and μ
m = aircraft mass
p = roll acceleration
q = pitch acceleration
R = correlation coefficient, also rotor radius
ROC = rate-of-climb
r = yaw acceleration
SE = standard error
V = airspeed
$\ddot{x}$ = longitudinal acceleration
$\ddot{y}$ = lateral acceleration
δ_{1c} = perturbation in θ_{1c} from trim
δ_t = perturbation in θ_t from trim
θ_0 = collective swashplate input
θ_{1c} = lateral swashplate input
θ_{1s} = longitudinal swashplate input
θ_{stab} = stabilator incidence
θ_t = tail rotor collective
μ = advance ratio, $V/\Omega R$
Ω = main rotor rotation rate
ΩR = main rotor tip speed
$||$ = absolute value
$(\ )_{trim}$ = value in steady trim flight

Introduction

TO determine helicopter component fatigue life a knowledge of the component stress levels during operational use is required. Ideally, it would be desirable to have each critical component instrumented with strain gauges to continuously monitor the load level. This information, along with the fatigue characteristics of the particular part, could then be used to determine the accumulation of fatigue damage as the aircraft continues in service. However, extensive load monitoring via instrumentation in the rotating system is not practical for operational aircraft and is usually conducted only on specially instrumented flight test aircraft.

Currently, the life of component parts is based on a "worst case" scenario where all aircraft of a specific type and mission spectrum are assigned an identical fatigue life based only on the hours of usage. No adjustments due to actual usage or pilot technique are made. In an investigation of helicopter flight loads during aerial combat, it was found that significant variations in load level can exist for similar flight maneuvers due to differing pilot technique.[1] Continuous load monitoring would provide the means to make adjustments for actual usage and pilot technique which would result in extended life, lower operating costs, and ultimately safer aircraft. Load monitoring in real time could be used by the pilot to avoid subjecting the aircraft to damaging loads and to help define and extend the safe flight envelope.

The state-of-art in analytical prediction of rotating system loads is not sufficient to accurately predict these loads for many flight conditions from a purely theoretical basis. However, there have been some attempts to predict component loads in the rotating system from strain gauge measurements in the fixed system. This approach was applied to the SH-2 helicopter[2] and the AH-64A helicopter.[3] Both helicopters employ a similar main transmission mounting system consisting of several support tubes that are the primary load path for rotor loads entering the fuselage. High-frequency strain gauges located on the support tubes were used as a basis for predicting component loads in the rotating system. Results from these investigations indicate good agreement between the predicted loads calculated from strain gauge data and the actual measured loads.

A regression analysis to predict vibratory loads on an SH-60B helicopter as a function of fixed system parameters was conducted by the authors[4] and used different fixed system measurements from that of Refs. 2 and 3. Unlike the SH-2 and AH-64A, the SH-60B helicopter does not utilize support tubes for the main transmission support system. Therefore, the independent parameters of Ref. 4 consisted of pilot control stick positions, aircraft angular rates, velocity, and normal load factor. These parameters vary at a relatively low frequency compared to strain gauge data. Correlation between predicted and measured loads on the order of 95% were attainable for pushrod vibratory loads during symmetric pullout maneuvers and 90% for blade normal bending. The effects of various pilot techniques were included in the data.

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The present study extends the work of Ref. 4 by developing a regression model that is applicable for several different types of flight maneuvers. The maneuvers examined include, symmetric pullouts, rolling pullouts, climbing turns, and level flight. In addition, the choice of independent parameters that form the basis of the model was modified from those in Ref. 4. Instead of pilot control stick positions, swashplate servo positions are measured and used to directly calculate the main rotor swashplate collective and cyclic control inputs as well as the tail rotor collective. In this way, both the pilot control inputs and the control inputs from the stability augmentation system are included. Aircraft accelerations are used in place of angular rates. Regression models for the vibratory component of pushrod and main rotor blade normal bending loads are developed and evaluated for each of the four flight maneuvers using a "blind test" data base. The main rotor pushrod load and blade normal bending load were chosen for analysis because they are critical components. The results for these loads should be representative of other critical components in the rotating system.

Analytical Approach

Stepwise multiple regression[5] is used to statistically analyze flight test data for moderate to high-speed level flight and for several types of flight maneuvers. A relationship between the rotating component loads (dependent variable) and the fixed system parameters (predictor variables) is desired. The form of the linear regression model is

$$Y(t_i) = a_0 + \sum_{j=1}^{N} a_j X_j(t_i) + \varepsilon(t_i) \qquad (1)$$

where Y is the dependent variable (pushrod and blade normal bending load in this study) at time t_i, and $X_1, \ldots, X_N$ are the predictor variables such as swashplate control inputs, aircraft accelerations, rate-of-climb, and airspeed. The term ε is the error, and the $a_0, \ldots, a_N$ are unknown regression coefficients.

In matrix notation, Eq. (1) can be written as

$$\{Y\} = [X]\{a\} + \{\varepsilon\} \qquad (2)$$

The method of least squares is used to obtain a solution for $\{a\}$. This method consists of minimizing the term $\{\varepsilon\}^T\{\varepsilon\}$ with respect to $\{a\}$. That is, minimize

$$|\{Y\} - [X]\{a\}|^2 = \{\varepsilon\}^T\{\varepsilon\} \qquad (3)$$

Differentiating Eq. (3) with respect to $\{a\}$ and setting the result equal to zero, yields the solution

$$\{a\} = ([X]^T[X])^{-1}[X]^T\{Y\} \qquad (4)$$

A "weighted" least-squares solution of Eq. (2) can be determined by minimizing the term $\{\varepsilon\}^T[w]\{\varepsilon\}$, where $[w]$ is a diagonal matrix of weighting factors. Weighting of the data is used to increase or decrease the influence of certain data points in the analysis. Although Eq. (1) is linear in X_j, it is possible to choose a nonlinear model by selecting the X_j as nonlinear functions of the desired variables.

Because the actual magnitude of the regression coefficients are dependent on the units in which the X_j are measured, it is inappropriate to interpret the regression coefficients as an indication of the relative importance of the X_j. Only if all of the predictor variables are measured in the same units are their coefficients directly comparable. One way to make regression coefficients more comparable is to calculate a standardized regression coefficient A_j, defined as

$$A_j = a_j(S_X/S_Y) \qquad (5)$$

where S_X is the standard deviation of the predictor variable X_j, and S_Y is the standard deviation of the dependent variable. The standardized regression coefficient is a nondimensional quantity that can be used to judge the relative importance of each predictor variable. The A_j, however, are contingent on the other variables in the equation, and therefore do not reflect the importance of any predictor variable in an absolute sense.

In stepwise regression, variables are entered and removed from the regression equation in steps based on the significance of the F statistic. A tolerance limit is also specified to control multicollinearity. Multicollinearity is the condition where one or more of the regression parameters can be expressed as a linear combination of the other regression parameters. Severe multicollinearity will cause numerical errors when solving for the regression coefficients, resulting in large standard deviations associated with these coefficients. The tolerance value represents the degree to which a variable to be entered in the regression equation can be predicted by variables already in the regression equation. The tolerance limit and the significance level were adjusted to find a satisfactory regression model. A thorough discussion of multiple regression analysis is available in Ref. 5.

In addition to multiple linear regression, nonlinear univariate regression is also employed. During steady level flight a nonlinear velocity model was chosen to fit the data. For this model an iterative solution technique was required to solve for the unknown regression coefficients.

To evaluate the regression models the data is divided into two parts, one for model development (referred to as "model data") and one to serve as a blind test of the model (referred to as "test data"). The correlation coefficient R and standard error of the model SE help to characterize how well the model fits the data. R is a measure of the linear relationship between two variables. If two variables are perfectly correlated, R will be equal to 100%. A low value of R indicates that the linear correlation between the two variables is weak. The SE of the model is defined as the standard deviation of the error between the predicted and actual loads and provides a measure of the scatter between the predicted and measured load. A regression model is desired that possesses a large correlation R between predicted and actual load and a small SE.

Flight Test Data Base

A flight test program was conducted on a Navy SH-60B helicopter to measure component loads for various flight maneuvers and aircraft configurations. In the present study, 35 individual maneuvers lasting from 10 to 90 s each are analyzed. The types of maneuvers include, symmetric pullouts, left and right rolling pullouts, left and right climbing turns, and level flight at various airspeeds from 65 to 155 kt. All of the 35 flights were conducted on the same day and at the same altitude and nominal gross weight (16,500 lb).

Strain gauge data for component loads were processed to obtain the peak-to-peak loads for each rotor revolution. Because the frequency of rotating system loads is primarily 1/rev, processing in this manner allows the frequency content of the data to be removed. The vibratory component of load is defined from the peak loads as

$$\text{vibratory load} = (\max - \min)/2$$

The vibratory load is an approximation of the amplitude of the 1/rev component of load and is used in fatigue calculations. The focus of this study is to predict the variation in the vibratory component of the load during a given maneuver. Specifically, the main rotor pushrod load and the blade normal bending load at the 15% radial station are examined.

In addition to component loads, control inputs to the main rotor and tail rotor and the aircraft state parameters including six accelerations, airspeed, and rate-of-climb were measured. These parameters form the basis of the regression models. A

Table 1 Independent parameters

Parameter	Abbreviation
Accelerations	
Load factor	LF
Longitudinal	$\ddot{x}$
Lateral	$\ddot{y}$
Pitch	q
Roll	p
Yaw	r
Airspeed	V
Aircraft mass	m
Rate-of-climb	ROC
Rotor rotation rate	Ω
Swashplate controls	
Collective	θ_0
Longitudinal	θ_{1s}
Lateral	θ_{1c}
Tail rotor	θ_t
Stabilator position	θ_{stab}

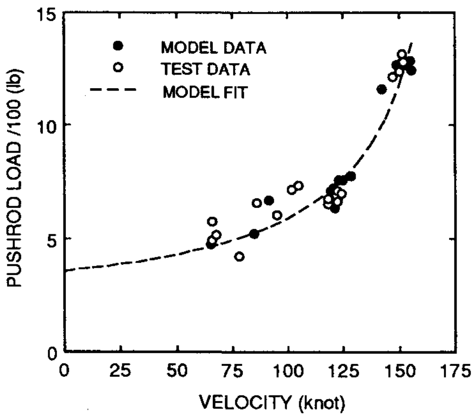

Fig. 1 Main rotor pushrod load of SH-60B helicopter in steady level flight.

summary of the parameters and abbreviations are given in Table 1.

Results

Steady Level Flight

Regression analysis was conducted for steady level flight to investigate parameters that can be used to predict vibratory loads in this condition. The flight data contain fluctuations even in level flight due to small variations in pilot input, gust conditions, and measurement noise. These fluctuations were removed by averaging the data over each time segment. The mean value for a time segment was chosen as a discrete data point, if the following criteria were met: 1) a mean load factor between 0.98 and 1.02 with a standard deviation less than 0.02; 2) pitch, roll, and yaw accelerations less than 7.5 deg/s^2 in magnitude; and 3) longitudinal and lateral accelerations less than 0.15 g and 0.05 g, respectively. This resulted in a total of 41 level flight data points. For these 41 data points, the standard deviation was 3–4% for the pushrod load and 5–7% for the blade normal bending load. Therefore, scatter in a prediction model is expected to be of this level if the correct predictor variables are used.

Pushrod and blade normal bending vibratory loads for the level flight data points are shown in Figs. 1 and 2. An obvious nonlinear relationship between vibratory load and velocity exists. To fit a model that contains only velocity through these data, a rational polynomial approximation was chosen of the form

$$\text{load} = (a_1V + a_2)/(a_3V + a_4) \qquad (6)$$

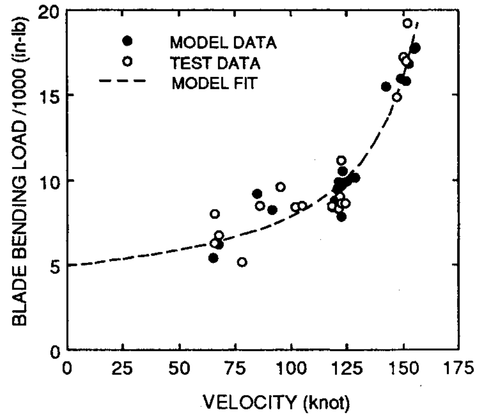

Fig. 2 Main rotor blade normal bending load at 15% radial station in steady level flight.

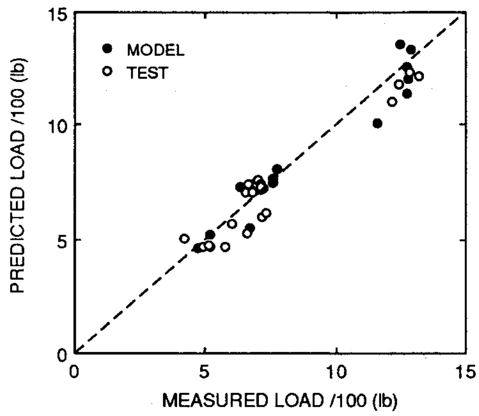

Fig. 3 Pushrod load using nonlinear velocity model.

Because Eq. (6) is nonlinear in V, an iterative nonlinear regression analysis is required to calculate the unknown coefficients $a_1, \ldots, a_4$. To evaluate the model, the 41 data points were divided into two sets. The model data set consists of 22 points and is used to solve for the a_i (solid symbols in Figs. 1 and 2). The remaining 19 points are used as a blind test of the model (open symbols in Figs. 1 and 2). The model represented by Eq. (6) is indicated by the dashed line in Figs. 1 and 2. This nonlinear velocity model is a good approximation of the overall velocity trend found in the flight test data. The correlation coefficient between measured and predicted pushrod load is 97% for the model data and 96% for the test data. Figure 3 is a plot of predicted pushrod load vs measured pushrod load and shows the linear correlation more clearly.

For a given velocity, scatter in the data greater than the expected value (approximately 5%) is evident. For example, in Fig. 1 at about 80–90 kt the scatter is approximately ±100 lb, whereas the average load is just over 500 lb. The SE of the model provides a measure of the scatter between the predicted and measured loads, which for the pushrod load is 74 lb; the SE of the blade normal bending load is 1275 in.-lb. There are several reasons for this scatter. First, it is not possible to achieve an ideal steady level flight condition, where the rate-of-climb and all accelerations are exactly zero. Also, at a given airspeed, the aircraft trim orientation may vary, resulting in a different sideslip angle or roll attitude. Last, the gross weight of the aircraft varies about 3% above and below the nominal value due to fuel burn. Inspection of the swashplate control settings also revealed scatter similar to that shown in Figs. 1 and 2.

To reduce model error, several models based on swashplate control positions are investigated. The first set of models examined are one-term linear models of the form

$$\text{load} = a_1X_1 + a_0 \qquad (7)$$

where X_1 consists of (θ_{1s}) for pushrod load and θ_0 for blade normal bending load. The correlation and standard error for the models are shown in Table 2. The SE for these models applied to the test data increased, indicating they are no better than the velocity model.

The next set of models includes coupling of the collective and longitudinal control inputs. Earlier findings suggested that coupling of the control positions may help to improve the correlation of the regression model.[4] For both pushrod and blade normal bending loads, the product of collective and longitudinal swashplate input $(\theta_0\theta_{1s})$ produced a high correlation. Figure 4 shows the results of a one-term linear model based on this control parameter for pushrod load. An improvement can be seen as compared to the nonlinear velocity model (Fig. 3). For both pushrod and blade normal bending load, the SE was reduced by 20–28%, using $(\theta_0\theta_{1s})$ as the predictor variable instead of velocity (see Table 2). This indicates that a one-term solution using $(\theta_0\theta_{1s})$ is a better representation of load in steady level flight than the one-term nonlinear velocity model.

Table 2 Model results for steady level flight

	Model data		Test data	
Pushrod models	R, %	SE, lb	R, %	SE, lb
Nonlinear velocity	96.9	69	96.4	74
θ_{1s}	97.6	61	96.3	82
$\theta_0\theta_{1s}$	99.3	33	98.0	59
$\theta_{1s}V$, θ_{1c}, m	99.5	27	99.4	31
Blade normal bending models	R, %	SE, in.-lb	R, %	SE, in.-lb
Nonlinear velocity	96.6	983	95.2	1275
θ_0	97.0	923	92.2	1564
$\theta_0\theta_{1s}$	97.4	863	97.4	909

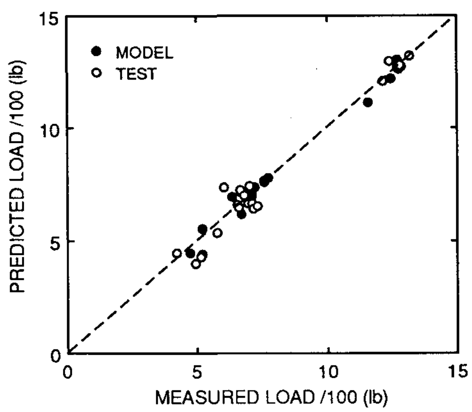

Fig. 4 Pushrod load predicted from linear model using one coupling term $(\theta_0\theta_{1s})$.

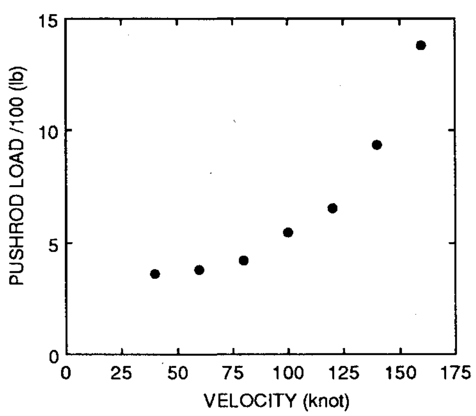

Fig. 5 Pushrod load calculated from CAMRAD/JA.

Table 3 Predictor variables for maneuvering flight

Controls	θ_0, θ_{1s}, δ_{1c}, δ_t, θ_{stab}
Accelerations	$\lvert q\rvert$, $\lvert p\rvert$, $\lvert r\rvert$, $\lvert qp\rvert$, $\lvert qr\rvert$, LF$\ddot{x}$
Force terms	$\lvert\ddot{x}\rvert m$, $\lvert\ddot{y}\rvert m$, LF$m\mu$
Control couples	$(\theta_0\theta_{1s})$, $(\theta_0\delta_{1c})$, $(\theta_0\delta_t)$, $(\theta_{1s}\delta_{1c})$
Velocity couples	$(\theta_0 V)$, $(\theta_{1s}V)$, $(\delta_{1c}V)$, $(\delta_t V)$
Miscellaneous terms	V, ROC, m, μ, Ω

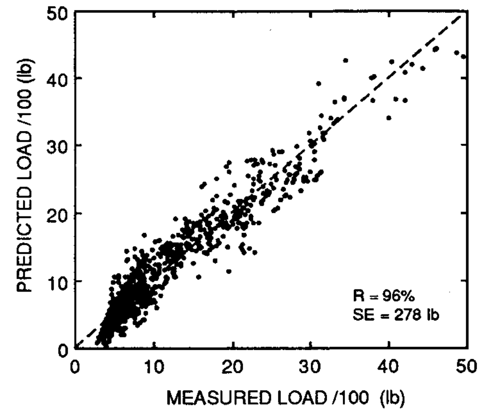

Fig. 6 Model results for pushrod load in maneuvering flight.

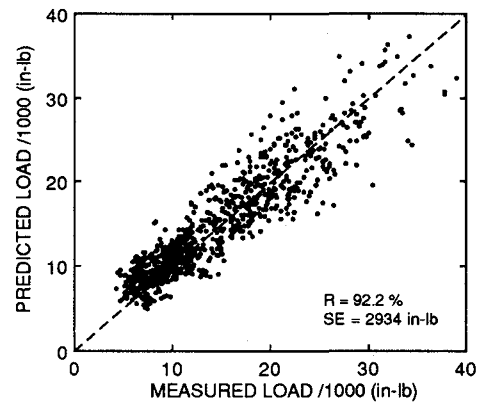

Fig. 7 Model results for blade normal bending load in maneuvering flight.

To substantiate these results, the SH-60B helicopter was modeled using the comprehensive rotorcraft analysis code CAMRAD/JA.[6] Main rotor pushrod peak-to-peak load and trim control settings were calculated for airspeeds ranging from 40 to 160 kt. Figure 5 is a plot of calculated pushrod vibratory load vs airspeed. These results are in good agreement with the flight test data (Fig. 1). A one-term regression model consisting of the parameter $(\theta_0\theta_{1s})$ was fitted to the analytical results and confirmed the strong linear relationship between pushrod load and the term $(\theta_0\theta_{1s})$.

In addition to the univariate models, models with several predictor variables were evaluated using stepwise multiple regression. Even with the addition of more predictor variables, a further improvement in blade normal bending load could not be achieved. A model with improved correlation and lower SE for pushrod load, however, was found of the form

$$\text{pushrod load} = f(\theta_{1s}V, \theta_{1c}, m)$$

The results of this model (Table 2) show a good predictive capability for both the model data and the test data. Results for the level flight models are summarized in Table 2.

Maneuvering Flight

To develop a general load model that is valid for several different types of flight maneuvers, the model data must re-

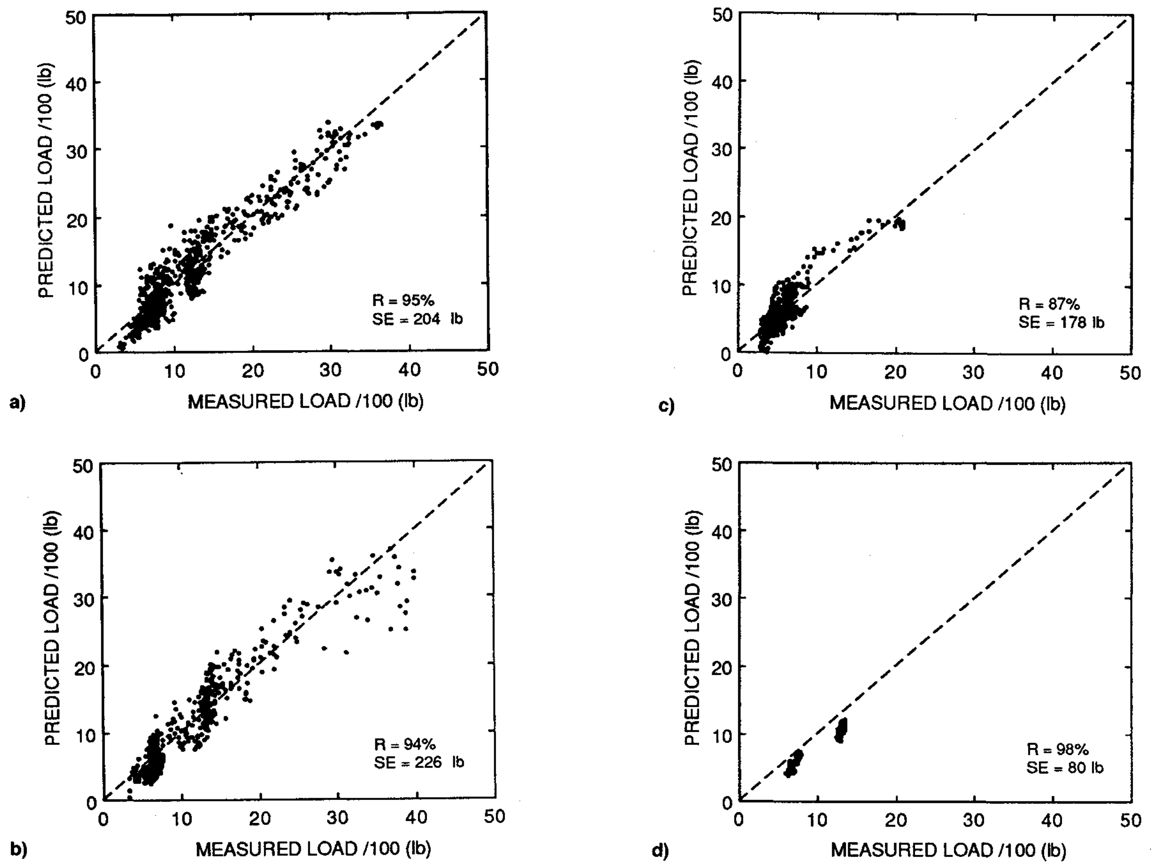

Fig. 8. Eleven-term pushrod load model test cases for a) symmetric pullouts, b) rolling pullouts, c) climbing turns, and d) level flight.

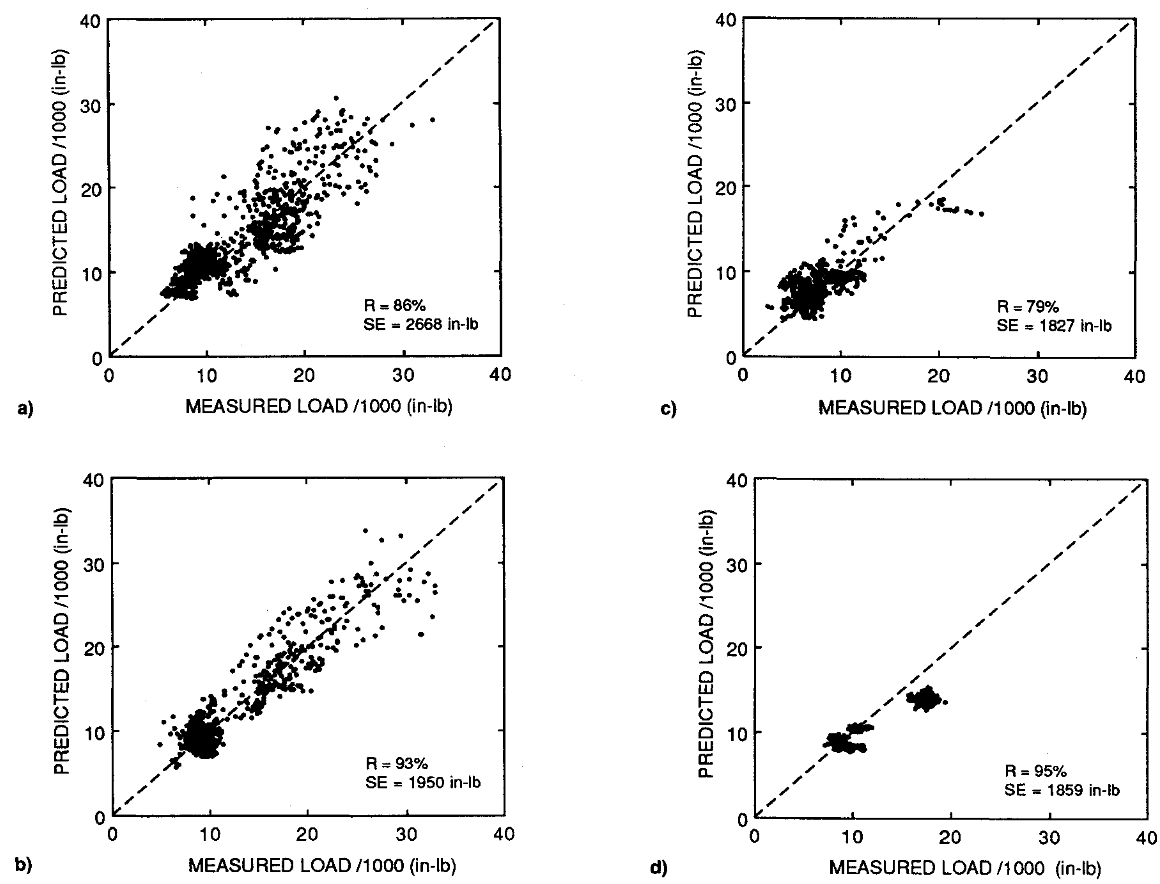

Fig. 9. Twelve-term blade normal bending load model test cases for a) symmetric pullouts, b) rolling pullouts, c) climbing turns, and d) level flight.

flect all the flight conditions the model will be used to predict. The data should not be biased towards any specific flight condition. The model data selected consist of 13 individual flights. These flights include six symmetric pullouts, three left rolling pullouts, two right rolling pullouts, and two climbing turn maneuvers. A symmetric pullout is a maneuver in which the pilot begins from level flight and then pitches the helicopter nose up pulling positive g's while maintaining a nearly constant roll attitude (zero roll acceleration). In a rolling pullout maneuver the pilot begins from level flight with a large roll attitude to one side. The pilot then begins the maneuver by rolling the helicopter back toward zero roll attitude and simultaneously pitches the helicopter nose up. In this way the aircraft pulls positive g's and undergoes coupled pitch and roll accelerations. The symmetric and rolling pullout maneuvers in the data base are flown at high load factors with maximum g levels ranging from 2.5 to 3.3 g. In comparison, climbing turn maneuvers are more benign. The maximum g level attained during the climbing turns used in the regression model is 1.8 g.

In addition to different maneuvers, the model data should also reflect differences in pilot technique for a given maneuver. Of the six symmetric pullouts included, three different pilot techniques are used to accomplish the maneuver: 1) fixed collective input, 2) top collective input, and 3) 25% collective drop. The velocity range of the model data is from 50 to 160 kt with a mean value of 98 kt.

The helicopter undergoes significant accelerations during maneuvering flight that result in loads significantly above those found even in high-speed level flight. Of the parameters listed in Table 1, the most significant in predicting loads for maneuvering flight is the aircraft load factor. Unlike steady flight where the load increases with velocity, during symmetric and rolling pullout maneuvers, the aircraft typically slows down as the loads increase during the pullout maneuver. The regression load models for maneuvering flight are therefore based around load factor.

Stepwise multiple regression is used to develop a load model from the predictor variables. The predictor variables are derived from the independent parameters found in Table 1 by taking the absolute value of the parameters, by coupling the parameters, and by taking perturbations from the parameter value in steady level flight. Table 3 contains the list of predictor variables considered in this study. The variables in Table 3 consist of several different sets of parameters. These parameter sets were developed using guidance from the level flight results and by numerous applications of regression analysis on the model data.

Table 3 shows five control inputs including two control perturbations δ_{1c} and δ_t. These perturbations are defined as the absolute value of the control input from the steady level flight value for a given velocity:

$$\delta_{1c} = |\theta_{1c} - (\theta_{1c})_{\text{trim}}|$$

$$\delta_t = |\theta_t - (\theta_t)_{\text{trim}}|$$

To determine the parameters δ_{1c} and δ_t, a regression model of lateral and tail rotor inputs as a function of velocity for steady level flight was performed.

The absolute value of acceleration was used because the loads generally increase during rapid acceleration, regardless of the direction. Two terms coupling pitch acceleration with roll and yaw acceleration are also present. Longitudinal and lateral acceleration and LF were multiplied with aircraft mass to produce force terms. The LF term was further multiplied with advance ratio because this term produced a higher correlation with the data. In the level flight analysis, coupling of the control inputs with one another and with velocity helped to improve the regression model. For maneuvering flight, eight coupling terms involving swashplate control inputs were derived.

In stepwise regression analysis, the predictor variables are entered into the model one at a time depending on their correlation with the load, their significance level, and their correlation with variables already in the model. Therefore, not all of the predictor variables in Table 3 will necessarily be entered into the model. For the maneuvering flight models, weighted stepwise multiple regression is conducted on the model data base. Each data point is weighted according to the weighting factor w_i defined as

$$w_i = \frac{\text{load}}{(\text{mean load of model data base})}$$

This weighting technique allows the high load data points to have a greater influence on the solution of the regression coefficients a_i.

Figures 6 and 7 show the results of the analysis for pushrod and blade normal bending loads for the model data. A correlation of 96% and SE of 278 lb is achieved for the pushrod load and a correlation of 92% and SE of 2934 in.-lb is achieved for blade normal bending load. The pushrod regression model consists of 11 terms; the blade normal bending model consists of 12 terms. Terms contained in the load models in order of relative importance are

$$\text{pushrod} = f(\text{LF}m\mu,\ \theta_0\theta_{1s},\ V,\ \theta_0\delta_{1c},\ \delta_t,\ |qp|,\ |q|,\ |p|,\ |\ddot{y}|m,\ m,\ \text{ROC})$$

$$\text{blade bending} = f(\text{LF}m\mu,\ \delta_{1c},\ \theta_0\theta_{1s},\ \theta_{1s}\delta_{1c},\ V,\ \delta_t,\ \Omega,\ \text{LF}\ddot{x},\ |qr|,\ \text{ROC},\ |q|,\ |\ddot{y}|m)$$

Influential parameters for the pushrod load include LF$m\mu$, $(\theta_0\theta_{1s})$, V, $(\theta_0\delta_{1c})$, δ_t, and $|qp|$. The rest of the parameters in the equation had standardized regression coefficients less than 0.10. Influential parameters with standardized regression coefficients greater than 0.10 for the blade normal bending load include LF$m\mu$, δ_{1c}, $(\theta_0\theta_{1s})$, $(\theta_{1s}\delta_{1c})$, V, and δ_t.

To evaluate these models, a blind test for each maneuver type was conducted. The symmetric pullout test data set consists of nine symmetrical pullouts with maximum load factors ranging from 2.6 to 3.1 g and with three different pilot techniques. A rolling pullout test set contains two left and two right rolling pullouts, a climbing turn test data set contains three climbing turns, and a level flight data set contains six level flights with airspeed ranging from 90 to 155 kt. In total, the load models are evaluated on 22 individual maneuvers containing over 3000 data points.

Figures 8a–8d show the test results for the pushrod model plotted for each of the four test data sets. The correlation of the model for symmetric and rolling pullouts is 94–95%. For climbing turns the correlation is 87%, and for level flight the correlation is 98%. The largest SE for each of these test cases is 226 lb.

Figures 9a–9d show the test results for the blade normal bending load model. Correlations range from 79 to 95% with climbing turns having the lowest correlation, possibly due to the lower load level for this type of maneuver. The maximum SE is 2668 in.-lb for all of the test cases. In comparing Figs. 8 and 9 it is seen that a larger degree of scatter is present for the blade normal bending load model.

Conclusions

Level Flight

For the data used in this study, velocity is a primary parameter in predicting pushrod and blade normal bending loads during steady level flight. A nonlinear velocity model in the form of a first-order rational polynomial was fitted to the data with a correlation of 95%. Each of the control positions is also strongly correlated with velocity; however, the control positions can be changed while holding airspeed fixed. As a result, the coupling term ($\theta_0\theta_{1s}$) was found to have a higher correlation with load than any other single term evaluated, including velocity. The correlation could be improved by using control inputs in place of velocity and by coupling the control inputs with one another and with velocity.

Maneuvering Flight

A model was created for pushrod and blade normal bending loads that is valid for several different types of flight maneuvers including symmetric pullouts, rolling pullouts, climbing turns, and level flight. For the data used in this study, the single most significant term was the product of load factor with aircraft mass and advance ratio. Correlations from 87 to 95% were achieved for pushrod vibratory load; while correlations from 79 to 93% were achieved for blade normal bending loads.

Acknowledgments

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