A More Accurate Characterization of UH-60A Pitch Link Loads Using Neural Networks

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A more accurate, neural-network-based characterization of the full-scale UH-60A maximum, vibratory pitch link loads (MXVPLL) was obtained. The MXVPLL data were taken from the NASA/Army UH-60A Airloads Program flight test database. This database includes data from level flights, and both simple and "complex" maneuvers. In the present context, a complex maneuver was defined as one which involved simultaneous, non-zero aircraft angle-of-bank (associated with turns) and aircraft pitch-rate (associated with a pull-up or a push-over). The present approach combines physical insight followed by the neural networks application. Since existing load factors do not represent the above-defined complex maneuver, a new, combined load factor ("present-load-factor") was introduced. A back-propagation type of neural network with five inputs and one output was used to characterize the UH-60A MXVPLL. The neural network inputs were as follows: rotor advance ratio, aircraft gross weight, rotor RPM, air density ratio, and the present-load-factor. The neural network output was the maximum, vibratory pitch link load (MXVPLL). It was shown that a more accurate characterization of the full-scale flight test pitch link loads can be obtained by combining physical insight with a neural-network-based approach.

Introduction

Helicopter rotor blade pitch link loads undergo large changes in magnitude due to varying flight conditions that range from the relatively benign level flight conditions to the more severe maneuver conditions (Refs. 1 and 2). Also, a typical rotor blade pitch link operates in a highly dynamic environment. Thus, the test pitch link load has associated with it a greater degree of uncertainty (Ref. 3). Analytical prediction of pitch link loads is thus difficult (Refs. 1 and 2), and methods that are more accurate than those currently available are highly desirable.

In Ref. 4, neural networks were used to model SH-60B pitch link loads. Apparently, no attempt was made in Ref. 4 to combine physical insight with the application of neural networks.

The present study attempts, first, to obtain physical insight, and second, to efficiently apply neural networks in order to characterize (model) helicopter rotor blade pitch link loads. The present neural-network-based approach accurately models rotorcraft pitch link loads and includes level flight and maneuver conditions data. The NASA/Army UH-60A Airloads Program flight test database (Refs. 5 and 6) was used in the present study. The present study uses the experience gained from the earlier neural-network-based studies conducted in the Army/NASA Rotorcraft Division at NASA Ames (Refs. 7 to 12). Neural networks have been successfully applied to rotorcraft aeromechanics problems (Ref. 7). These aeromechanics problems have included first, identification and control of rotor noise and hub loads (Refs. 8 to 11), and second, validation of tilt-rotor performance test data (Ref. 12). The test data validation study included the following: *data representation*, data quality assessment, and outdoor hover data wind-corrections formulation and implementation (Ref. 12). Overall, neural networks were found to be very useful in solving aeromechanics problems (Ref. 7).

References 7 and 12 showed that tilt-rotor wind tunnel test pitch link loads can be accurately modeled using the back-propagation type of neural network. In the preceding application of neural networks, the neural network inputs were the rotor shaft angle, the rotor advance ratio, and the rotor thrust coefficient. The neural network output was the oscillatory pitch link load.

References 7 and 12 also considered wind corrections procedures for correcting outdoor hover tilt-rotor performance test data. It was found that a neural-network-based procedure, based on a well-trained neural network, captured physical trends in the test data that had been missed by the existing, momentum-theory-based method.

Present Physics-Based Neural Network Approach

In the present approach, emphasis was placed on understanding the basic physics underlying helicopter rotor pitch link load variations during level flight and maneuver conditions. Subsequent application of neural networks used this fundamental knowledge. Pitch link load variations with several parameters were plotted so as to determine the important parameters that affected the pitch link load significantly (this is further discussed in the Results section). A "determining-parameter" list with six operating-condition and aircraft-state parameters was used. The six parameters were as follows: rotor advance ratio, aircraft gross weight, rotor RPM, density ratio, aircraft angle-of-bank (roll attitude), and the aircraft pitch-rate.

Present-Load-Factor

Using the basic physics of maneuvering aircraft, the present study introduced a new, single load factor that characterizes above-defined complex maneuvers. This load factor is discussed as follows. References 13 and 14 discuss simple maneuvers in which the aircraft is either turning or pitching. For the complex UH-60A maneuvers under consideration (simultaneous non-zero angle-of-bank and pitch-rate), the following new load factor was derived and used in the present study:

$$\text{Present-Load-Factor} = [\ 1\ /\ \text{cosine(angle-of-bank)}\ ] * [\ 1 + (\text{pitch-rate} * \text{airspeed}\ /\ g)\ ] \qquad (1)$$

where "g" is the acceleration due to gravity. Since both turning and pitch-rate effects are included in the present-load-factor, the number of "determining-parameters" was presently reduced to five from six.

The calculation of the present-load-factor for a particular complex UH-60A maneuver under consideration involved special treatment for the helicopter pitch-rate. First, the individual flight test time-history of the pitch-rate was obtained using TRENDS (Ref. 15) and manually examined. For some maneuvers, the flight test pitch-rates varied with time. In the present study, a maneuver-specific representative-pitch-rate (based on the above flight test time-history) was calculated. Specifically, this representative-pitch-rate was estimated as follows: i) conducting a "reality check" on the pitch-rate sign and magnitude that were associated with the specific maneuver, and ii) ensuring consistency with the UH-60A flight test pilot's comments regarding the representative g-level encountered during the maneuver.

Neural Network Details

The five neural network inputs were as follows: advance ratio, gross weight, rotor RPM, density ratio, and the present-load-factor (Eq. 1). The neural network output was the maximum, vibratory pitch link load, MXVPLL. The presently-used back-propagation neural network had the same architecture as that used in the tilt-rotor performance application of neural networks (Ref. 12). The present back-propagation neural network architecture was referred to as "5-10-1." Here, the 5 and 1 respectively refer to the number of neural network inputs and the neural network output, and 10 refers to the number of processing elements in the neural network hidden layer.

Results

Neural Network Training Database

For present purposes, a portion of the complete UH-60A Airloads Program database was used The present neural network training database consisted only of those data points for which the maximum, vibratory test pitch link load MXVPLL > 1000 lb. This selection procedure resulted in a neural network training database consisting of approximately 80 data points (which account for both level flight and maneuver conditions, simple and complex). A lower limit of 1000 lb was imposed on the pitch link load for two reasons. First, data points with pitch link loads < 1000 lb would not really provide additional "information" of use in the training of the neural network. Second, by excluding the data points with maximum, vibratory pitch link load < 1000 lb, the neural network training database size became smaller. A smaller neural network training database not only facilitates the physical understanding of the maneuver-pitch-link-load trends, but also makes it easier to train the neural networks. Apparently, Ref. 4 did not involve any such physics-based considerations.

Present-Load-Factor

As an example of the type of functional dependencies presently involved, Fig. 1, a two-vertical-axes plot, shows the variations of the maximum, vibratory pitch link load (MXVPLL) and the present-load-factor with advance ratio. Figure 1 shows that the present composite load factor, which includes both the angle-of-bank and pitch-rate, has a high maximum value associated with it (≈ 4) as compared to a conventional load factor.

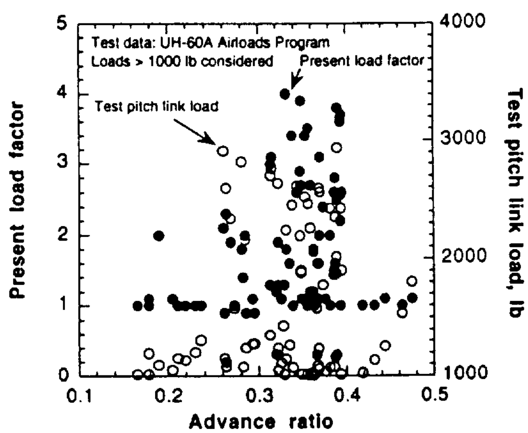

Fig. 1 Present-load-factor and pitch link load variations with advance ratio

Pitch Link Load Correlation

Figure 2 shows the correlation (scatter) plot from the above multiple-input, single-output (MISO) 5-10-1 back-propagation neural network. This correlation was considered to be very good. This is due to the fact that during a forward flight test condition, the rotor blade pitch links are subjected to high dynamic loading which is often due to nonlinear aerodynamic blade loading. The pitch link loads test data base would thus be expected to have an inherently lower level of repeatability. That is, the pitch link loads data base would have a wider "uncertainty band" due to the pitch links operating in an environment that is dynamic. In any case, it has been shown using neural networks that the quality of the present pitch link load test data is acceptable. Also, it is believed that the present physics-based approach using neural networks was able to produce a more accurate characterization of the UH-60A pitch link loads.

Concluding Remarks

The present study showed that a physics-based approach using neural networks was able to accurately predict helicopter pitch link loads during both level flight and complex maneuver conditions.

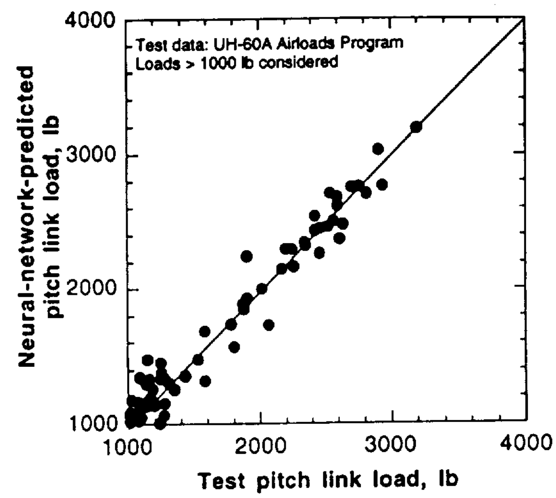

Fig. 2 Pitch link load correlation using neural networks

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