Neural Network Based Representation of UH-60A Pilot and Hub Accelerations

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Neural network relationships between the full-scale, experimental hub accelerations and the corresponding pilot floor vertical vibration are studied. The present quantitative effort represents an initial, systematic study on the UH-60A Black Hawk hub accelerations. The NASA/Army UH-60A Airloads Program flight test database is used. A physics-based "maneuver-effect-factor (MEF)," derived from the roll-angle and the pitch-rate, is used as well. Three neural network based representation-cases are considered. The pilot floor vertical vibration is considered in the first case and the hub accelerations are separately considered in the second case. The third case considers both the hub accelerations and the pilot floor vertical vibration. Neither the advance ratio nor the gross weight alone can be used to predict the pilot floor vertical vibration. However, the advance ratio and the gross weight together can be used to predict the pilot floor vertical vibration over the entire flight envelope. The hub accelerations data are modeled and found to be of acceptable quality. The hub accelerations alone cannot represent the pilot floor vertical vibration. The hub accelerations and the advance ratio can be used to represent the pilot floor vertical vibration. Also, the hub accelerations along with the advance ratio and the gross weight can be used to represent the pilot floor vertical vibration. Thus, the hub accelerations are clearly a factor in determining the pilot floor vertical vibration.

Notation

MEF	Maneuver effect factor, Equation (1)
MIMO	Multiple-input, multiple-output
MISO	Multiple-input, single-output
PVV	Peak, 4P pilot floor vertical vibration, g's
R	Linear regression correlation (an R close to 1 indicates that a regression-based relationship exists between the test data and the neural network predictions)
RMS error	Root mean square error between the test data and the neural network predictions, g's
SISO	Single-input, single-output

Introduction

For helicopters, the relationships between the rotor hub accelerations and the fuselage vibration may be linear or nonlinear and involve many variables. Here, fuselage vibration is defined as the N/rev fuselage acceleration at the pilot location, where N is the number of main rotor blades (presently, $N = 4$). For the UH-60A flight test data that were considered in Ref. 1, one of the conclusions was that the fuselage vibration trends qualitatively matched those of the hub accelerations. Reference 1 did not present any quantitative representations for the hub accelerations. Also, in Ref. 1, the relationships between the hub accelerations and the fuselage vibrations were not quantified.

The present study is the first systematic effort that considers hub accelerations in a quantitative manner, and attempts to identify numerical relationships between the hub accelerations and the fuselage vibrations. Also, this study has been undertaken to obtain a better understanding of the basic dynamics underlying the main rotor-dependent fuselage vibration and the associated hub accelerations. This study builds up on previous neural network studies that were conducted at NASA Ames in the areas of rotorcraft performance, acoustics, and dynamics (Refs. 2–8). Flight test data from the NASA/Army UH-60A Airloads Program (Refs. 9, 10) are used. For purposes of modeling the UH-60A peak, 4P pilot floor vertical vibration (PVV) and the hub accelerations, two neural network related databases are created. The first database includes only level flight data. The second database includes data from the entire flight envelope, including unsteady (time varying) maneuver conditions.

The neural network based modeling of the UH-60A PVV for real-time applications was studied in Ref. 4. The peak value of the pilot floor vertical vibration was used so as to better represent time varying maneuvers, such as a pull-up maneuver. Compared to Ref. 4, the additional considerations present in this study are the effects due to the hub accelerations.

The use of neural networks is justified because neural networks can perform multi-dimensional, nonlinear curve fitting. The above feature is useful in this representation study that seeks to identify smoothly varying relationships. This work is considered to be a generic methodology and is not specific to the presently considered UH-60A configuration.

Objectives

The present neural-network-based representation or modeling study involving the helicopter N/rev peak, pilot floor vertical vibration (PVV) and the hub accelerations has four objectives:

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1) Create a neural network training database for the hub accelerations. The hub acceleration values are taken as those corresponding to the peak, pilot floor vertical vibration values, PVVs. If the peak, pilot floor vertical vibration occurs at a time $t = \tau$, then the subject hub acceleration is defined as that also occurring at time $t = \tau$.

2) Using the advance ratio and the gross weight, conduct exploratory studies to determine whether reasonably accurate analytical representations of the PVV can be obtained.

3) Assess the data quality of the hub accelerations and obtain their neural network based representations.

4) Using the hub accelerations and flight condition parameters such as the advance ratio and gross weight, determine whether reasonably accurate analytical representations of the PVV can be obtained.

Hub Acceleration and Pilot Vertical Vibration Databases

The source of the hub accelerometer data was the NASA/Army UH-60A Airloads Program flight test database (Refs. 9, 10). The creation of the corresponding PVV database was described in Ref. 4. For purposes of this dynamics related study, the following categories of flights from Refs. 9 and 10 are presently considered: "Steady and Maneuvering Airloads" and "Maneuvers." The following flight conditions are included: level flight, rolls, pushovers, pull-ups, autorotations, and landing flares. These conditions approximate the entire UH-60A flight envelope.

The UH-60A hub accelerometers were mounted on a triaxial block glued to the main rotor shaft 4.5 inches from the center of rotation (Ref. 1). Three accelerometers (radial, tangential, and vertical) were used. Following Ref. 1, the tangential accelerometer measurements are used to present the in-plane response because it has a smaller centrifugal acceleration value than the radial sensor.

In general, to obtain a time varying, step-by-step simulation of the pilot vibration during a maneuver, a neural network based time-series method can be used. However, such methods are complex. In the present, initial modeling study using neural networks, a static-mapping approach involving the peak vibration level is followed. This implies that each flight condition is characterized by its peak vibration. The possibility of utilizing the peak-vibration-based static mapping in a quasi-static manner to simulate time varying maneuvers was investigated in Ref. 4. A quasi-static approach will not capture all dynamic effects, and may miss the prediction of relevant maximums and their associated phases. Also, a time-series analysis using neural networks will capture the maximums and phases more accurately, compared to a quasi-static approach. The present study considers the 3P and 5P tangential hub accelerations and the 4P vertical hub acceleration. The appropriate hub acceleration values are taken as those corresponding to the peak, 4P pilot floor vertical vibration PVV. Let this peak vibration PVV occur at a time $t = \tau$. The hub acceleration at time $t = \tau$ is defined as the corresponding or appropriate hub acceleration. In general, the peak vibration time τ is different for different maneuvers, and has to be individually determined.

Maneuver effect factor

The MEF, a non-dimensional parameter, is used to characterize helicopter maneuvers involving *simultaneous* non-zero roll-angle and pitch-rate, and the MEF is used as one of the neural network inputs. The MEF is derived by a consideration of the vertical force changes arising because of the roll-angle and the pitch-rate. The changes in the lift due to both the roll-angle and the acceleration due to the pitch-rate are accounted for. The MEF is subsequently defined by the following equation:

$$\text{Maneuver effect factor, MEF} = [1/\cos(\text{roll-angle})] * [1 + (\text{pitch-rate} * \text{airspeed}/g)] \quad (1)$$

where "g" is the acceleration due to gravity. The purpose of the MEF is to compactly represent complex maneuvers using a single, physics-based parameter. Depending on the reference axes system used, other parameters can be derived, and this would result in slightly different formulations.

The number of the neural network training data points in the present study is over 200. These points represent the entire database. Each training data point represents a single flight condition. The maximum advance ratio is 0.48. The gross weight range encountered is from 14,749 lbs to 17,720 lbs. Approximately 25% of the training database involve maneuver related points. Here, maneuver related refers to a flight condition for which the maneuver effect factor MEF is not equal to 1. The level flight cases are defined as those involving an approximately constant RPM (255 to 256) and an MEF = 1. Approximately 80 points are involved in the level flight cases.

Basic Variations: Hub Accelerations and Pilot Vertical Vibration

Figures 1–4 show the variations of the flight test hub accelerations and the PVV versus the advance ratio. The data shown in Figs. 1–4 use the 200 point flight database. Thus, in addition to the variation in the advance ratio covered in the figures, overall, these data involve variations in the gross weight, the main rotor RPM, the density ratio, the MEF, and the ascent/descent rate (and variations in the cyclic and collective stick positions).

Figure 1 shows the 3P tangential hub acceleration variation with the advance ratio. These data were obtained with the 3P bifilars installed on the UH-60A (Ref. 9). In Fig. 1, the low speed "hump" due to rotor wake effects can be seen around an advance ratio of 0.09 (approximately 40 knots). Figure 2 shows the 5P tangential hub acceleration variation with the advance ratio. Compared to the 3P hub acceleration data in Fig. 1, the 5P hub acceleration data in Fig. 2 appear to contain more scatter. This could be due to the fact that the 3P bifilars bring in a forced response behavior that tends to smooth out the 3P accelerations. In the UH-60A Airloads Program, the UH-60A did not have 5P bifilars installed. Figure 3 shows the 4P vertical hub acceleration variation with the advance ratio. Figure 4 shows the peak, 4P pilot floor vertical vibration, PVV, versus the advance ratio.

Neural Network Approach

To accurately capture the required functional dependencies, the neural network inputs must be carefully selected and account for all important

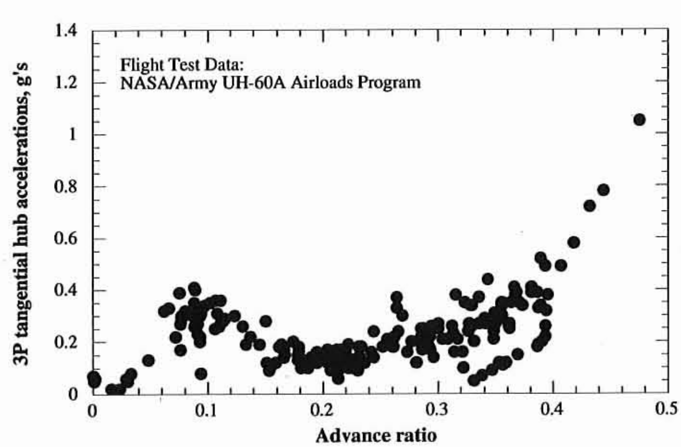

Fig. 1. UH-60A 3P tangential hub acceleration variation with advance ratio.

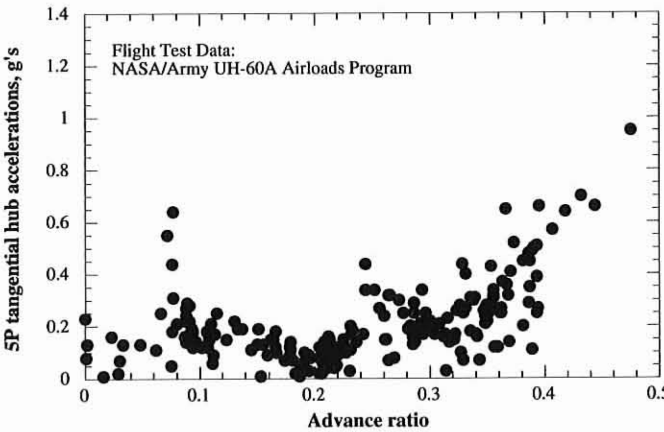

Fig. 2. UH-60A 5P tangential hub acceleration variation with advance ratio.

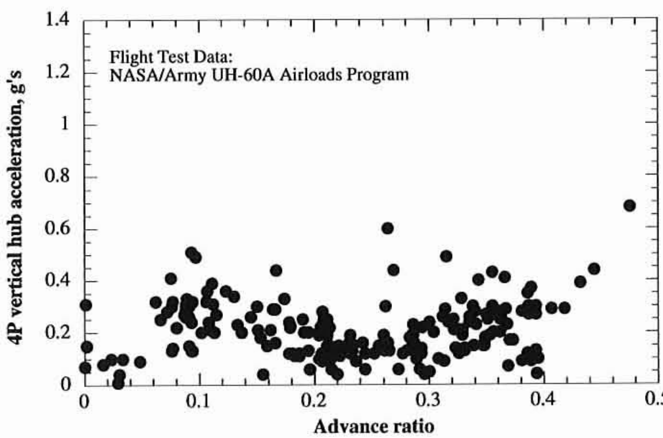

Fig. 3. UH-60A 4P vertical hub acceleration variation with advance ratio.

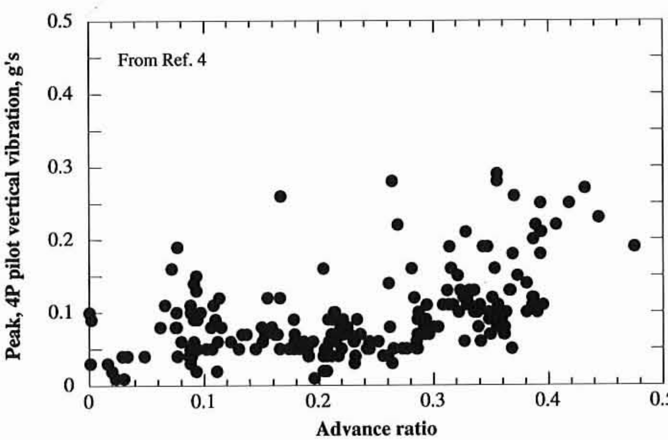

Fig. 4. UH-60A peak, 4P pilot floor vertical vibration, PVV, variation with advance ratio.

physical traits that are specific to the application. The important attributes of a neural network are its type (radial-basis function network, back-propagation network, recurrent network, etc.) and its complexity (i.e., the number of processing elements (PEs) and the number of hidden layers). The present overall neural network modeling approach is based on the approach followed in Refs. 2–8. The back-propagation type of network with a hyperbolic tangent as the basis function, and the extended-delta-bar-delta (EDBD) algorithm as the learning rule (Ref. 11) is used.

The number of neural network PEs required depends on the specific application. The determination of the appropriate number of PEs is done by starting with a minimum number of PEs. Additional PEs are added to improve neural network performance by reducing the RMS error between the test data and the neural network predictions. Typically, five PEs are added at each step in this process. The addition of two or three PEs at a time refines the neural network. A more automated method of determining the optimum neural network architecture would be desirable, and this subject is an active area of research.

If the correlation plot, comparing measured and predicted values, shows only small deviations from the 45-deg reference line, the neural network has produced an acceptable representation of the subject test data. If the plot shows points well off of the 45-deg line, poor quality test data may exist in the database. A detailed examination of the subject test database is then required to identify the source(s) of the errors associated with any poor quality test data. The analyst should not solely rely on the neural network based correlation procedure to eliminate poor quality test data.

This procedure, however, contributes to data assessment, and two examples from previous studies are briefly discussed as follows. First, in Ref. 2 (Figs. 11 and 12 in Ref. 2) the above procedure was applied to experimental tilt-rotor blade flatwise bending moments. In the Ref. 2 example, the subject test data points were not repeatable, possibly due to instrumentation problems. Second, in Ref. 3 (Fig. 1 in Ref. 3) the above procedure was applied to experimental wind tunnel tilt-rotor noise data. In the Ref. 3 example, the conclusion was that the presence of gusty winds, affecting the wind tunnel flow quality (flow unsteadiness) and the thrust coefficient, may have adversely affected quality of the subject data. In the present *initial* study, the PVV correlation points well off of a $+/-0.05$ g's error band are further examined for poor quality.

For the notation used in this paper, a neural network architecture such as "4-25-5-1" refers to a neural network with four inputs, twenty five processing elements (PEs) in the first hidden layer, five PEs in the second hidden layer, and one output. The present application of neural networks to full-scale helicopter flight test vibration and hub accelerations data has been conducted using the neural networks package NeuralWorks Pro II/PLUS (version 5.2) by NeuralWare (Ref. 11).

In the present work, three basic studies (taken up in order of increasing complexity) have been conducted, and are described as follows:

i) An initial exploratory study has been conducted to determine the relationships between the PVV and the advance ratio and the gross weight. Two sets of results, one for level flight and the other for all flights (entire database including maneuvers) have been obtained.

ii) A hub accelerations representation study has been conducted.

iii) A study has been conducted on using the hub accelerations along with the advance ratio and the gross weight to model the PVV. Here, the entire database is involved. The expectation is that the results from this third study may be of help in determining whether the hub accelerations can be used to obtain the PVV.

Results

Pilot vertical vibration exploratory study

This exploratory study has two parts. The first part involves level flight conditions and the second part involves the entire database including maneuver conditions. In this exploratory study, the PVV is the single neural network output.

Level flight. The first part of this exploratory study involves level flight conditions, with varying gross weight and a constant RPM.

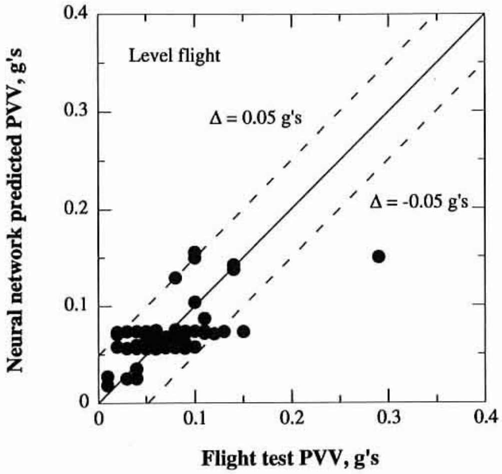

Fig. 5. PVV correlation using advance ratio, level flight.

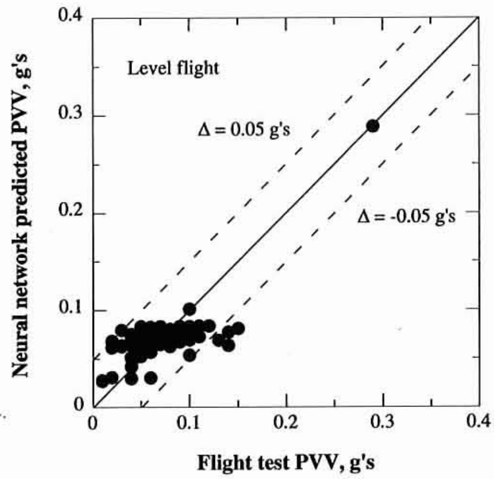

Fig. 6. PVV correlation using gross weight, level flight.

Approximately 80 points are involved. Figures 5–7 show the results for these level flight cases.

Figure 5 shows the correlation plot from a SISO 1-10-5-1 back-propagation neural network in which the advance ratio is the single input. The above back-propagation network has been trained for 5 million iterations with resulting $R = 0.65$ and RMS error $= 0.03$ g's. There does not appear to be a unique relationship between the advance ratio and the PVV.

Figure 6 shows the correlation plot from a SISO 1-10-5-1 back-propagation neural network in which the gross weight is the single input. The above back-propagation network has been trained for 5 million iterations with resulting $R = 0.74$ and RMS error $= 0.03$ g's. Again, not surprisingly, there does not appear to be a unique relationship between the gross weight and the PVV.

Figure 7 shows the correlation plot from a MISO 2-10-5-1 back-propagation neural network in which the advance ratio and the gross weight are the two inputs. The above back-propagation network has been trained for 1 million iterations with resulting $R = 0.89$ and RMS error $= 0.02$ g's. Figure 7 shows that the advance ratio and the gross weight can represent the PVV for level flight conditions. The trained neural network, Fig. 7, can typically predict the PVV to within $+/-0.05$ g's, knowing only the advance ratio and the gross weight.

All-flights (entire database). The second part of this exploratory study involves all flight conditions, i.e., the entire database is used (200 points,

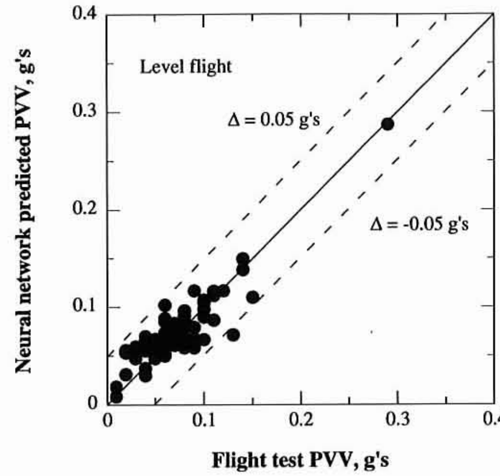

Fig. 7. PVV correlation using advance ratio and gross weight, level flight.

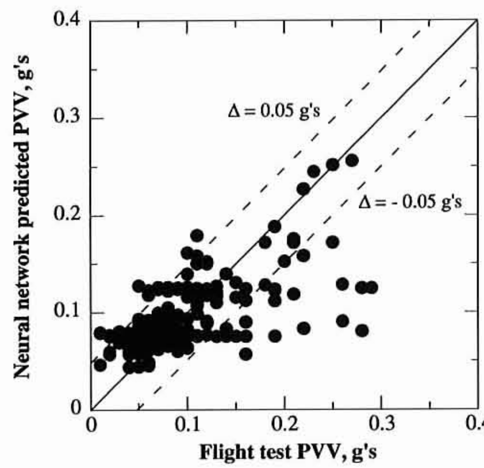

Fig. 8. PVV correlation using advance ratio.

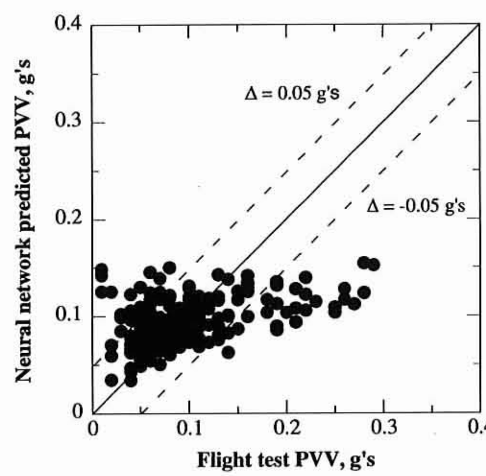

Fig. 9. PVV correlation using gross weight.

including maneuvers). Figures 8–10 show the corresponding results. Even though the above level flight results show that neither the advance ratio nor the gross weight alone can represent the PVV, these two cases are included in the All-Flights study also. This is done both for completeness and also to build up to the third case involving both the advance ratio and the gross weight.

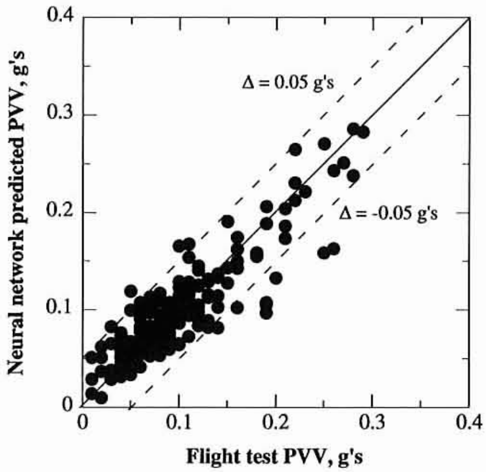

Fig. 10. PVV correlation using advance ratio and gross weight.

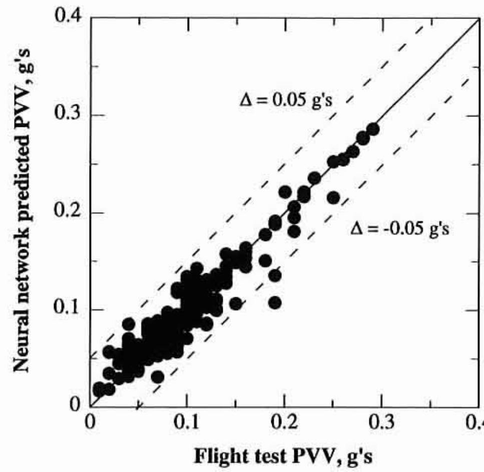

Fig. 11. PVV correlation using maneuver effect factor, MEF.

Figure 8 shows the correlation plot from a SISO 1-10-5-1 back-propagation neural network in which the advance ratio is the single input. The above back-propagation network has been trained for 5 million iterations with resulting $R = 0.63$ and RMS error $= 0.04$ g's. There does not appear to be a unique relationship between the advance ratio and the PVV.

Figure 9 shows the correlation plot from a SISO 1-10-5-1 back-propagation neural network in which the gross weight is the single input. The above back-propagation network has been trained for 5 million iterations with resulting $R = 0.43$ and RMS error $= 0.05$ g's. There does not appear to be a unique relationship between the gross weight and the PVV.

Figure 10 shows the correlation plot from a MISO 2-10-5-1 back-propagation neural network in which the advance ratio and the gross weight are the two inputs. The above back-propagation network has been trained for 5 million iterations with resulting $R = 0.89$ and RMS error $= 0.03$ g's. Figure 10 shows that the advance ratio and the gross weight can reasonably predict the PVV for the entire flight database, maneuvers included. Compared to the entire database correlation shown in Fig. 10, the level flight correlation shown in Fig. 7 is "cleaner." The good correlation seen in Fig. 10 is encouraging, even though the neural network inputs (advance ratio and gross weight) do not account for maneuver effects. This result has been included in order to show a way to obtain the UH-60A PVV in a simple manner.

A correlation result based on a more complex physical model (with far more inputs) that accounts for maneuver effects (and other effects noted below) is shown in Fig. 11. Figure 11 shows the correlation plot from a MISO 6-10-5-1 back-propagation neural network. The six inputs are: advance ratio, gross weight, main rotor RPM, density ratio, MEF, and ascent/descent rate. The above back-propagation network has been trained for 5 million iterations with resulting $R = 0.96$ and RMS error $= 0.02$ g's. Figure 12 shows the corresponding successful, quasi-static modeling of the time varying PVV for a pull-up maneuver at 120 knots (also, see discussion on quasi-static modeling in the section on "Hub Acceleration and Pilot Vertical Vibration Databases"). Such fidelity in predicting the pilot floor vertical vibrations shows considerable promise in using neural networks to obtain the UH-60A fuselage vibrations.

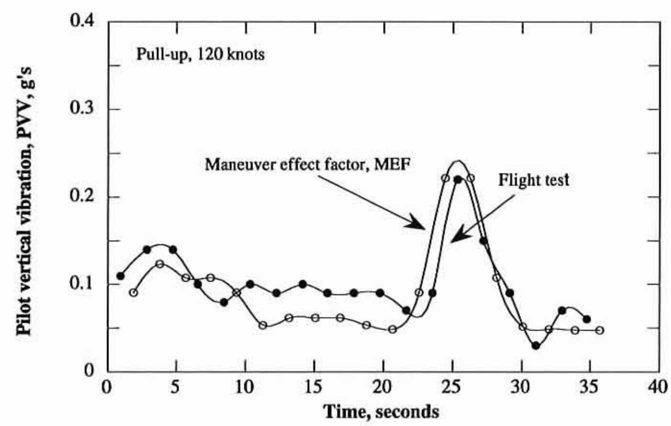

Fig. 12. Quasi-static prediction of PVV using MEF, unsteady pull-up.

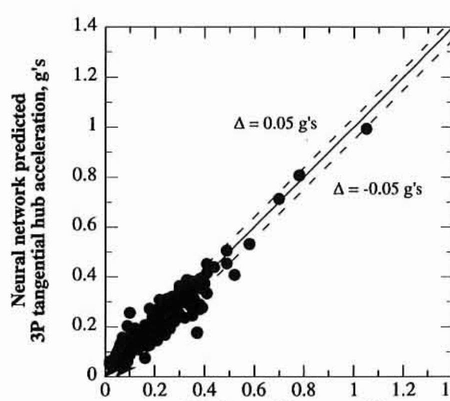

Fig. 13. 3P tangential hub acceleration correlation using maneuver effect factor.

Hub accelerations representation

In the present study, the quality of the hub accelerations flight test data has been assessed, and the numerical representations of the flight test data have been obtained. The entire database is used (200 points, including maneuvers). There are six inputs which are the same as those used for Fig. 11, and these inputs are: advance ratio, gross weight, main rotor RPM, density ratio, MEF, and ascent/descent rate. The three neural network outputs are as follows: the 3P and 5P tangential hub accelerations and the 4P vertical hub acceleration. Figures 13–15 show the correlation plots obtained using a MIMO 6-15-5-3 back-propagation neural network. The above back-propagation network has been trained for 5 million iterations and the resulting R's and RMS errors are as follows. For the 3P tangential hub acceleration correlation (Fig. 13), $R = 0.94$ and

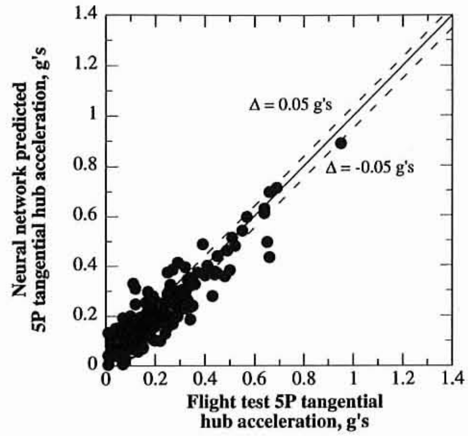

Fig. 14. 5P tangential hub acceleration correlation using maneuver effect factor.

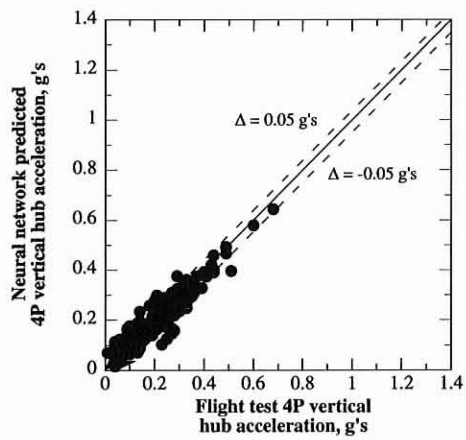

Fig. 15. 4P vertical hub acceleration correlation using maneuver effect factor.

RMS error = 0.04 g's. For the 5P tangential hub acceleration correlation (Fig. 14), R = 0.91 and RMS error = 0.06 g's. For the 4P vertical hub acceleration correlation (Fig. 15), R = 0.93 and RMS error = 0.04 g's.

Overall, the hub acceleration flight test "data quality" is assessed as being acceptable (Figs. 13–15). There are no identifiable poor quality data points such as those discussed earlier (Neural Network Approach). As noted in Ref. 2, the analyst should not solely rely on the neural network based correlation to eliminate poor quality test data. The present process does, however, contribute to data assessment. Finally, the results shown in Figs. 13–15 imply that for the UH-60A, numerical relationships (the identification model) relating the hub accelerations to the flight condition parameters have been obtained.

Relationships between hub accelerations and pilot vertical vibration

The objective is to represent the PVV using the 3P and 5P tangential hub accelerations and the 4P vertical hub acceleration as the three core inputs. The PVV is the single neural network output, and the entire database is used (200 points, including maneuvers). Three cases are created, with their inputs listed as follows:

Case 1 inputs: three hub accelerations (3 inputs).
Case 2 inputs: three hub accelerations and advance ratio (4 inputs).
Case 3 inputs: three hub accelerations, advance ratio and gross weight (5 inputs).

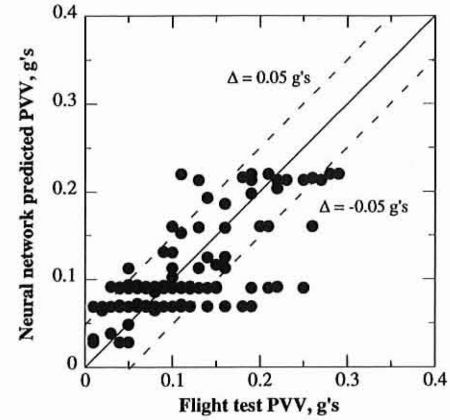

Fig. 16. PVV correlation using hub accelerations.

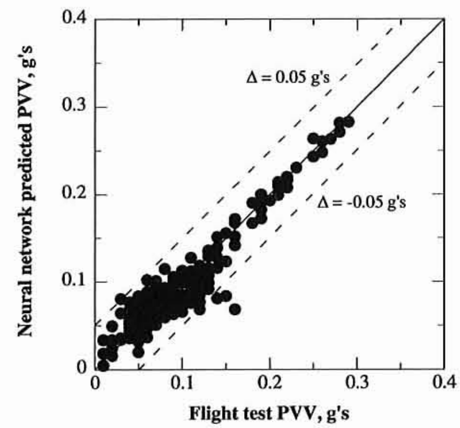

Fig. 17. PVV correlation using hub accelerations and advance ratio.

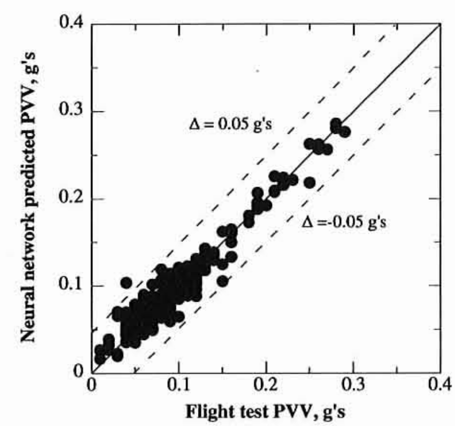

Fig. 18. PVV correlation using hub accelerations along with advance ratio and gross weight.

Figures 16–18 show the correlation plots obtained using the above three input lists. Figure 16 shows the correlation plot from a MISO 3-10-5-1 back-propagation neural network with the case 1 inputs (three hub accelerations). Figure 16 shows the results with the above back-propagation network trained for 3 million iterations with resulting R = 0.74 and RMS error = 0.04 g's. For this case, increasing the number of iterations to 5 million results in a slightly larger error (using the extended-delta-bar-delta (EDBD) algorithm, Ref. 11). Only the 3-million iteration results are reported in this paper. Figure 16 shows that there does not appear to exist a unique relationship between the hub accelerations and the PVV.

At the same time, it can be suggested that the hub accelerations inherently contain some basic information that depends on the flight condition.

Figure 17 shows the correlation plot from a MISO 4-10-5-1 back-propagation neural network with the case 2 inputs (three hub accelerations and advance ratio). The above back-propagation network has been trained for 5 million iterations with resulting R = 0.94 and RMS error = 0.02 g's. Figure 17 shows that the hub accelerations and advance ratio can represent the PVV. The Fig. 17 correlation is very encouraging because it appears that, for all airspeeds, the physics of the PVV variation with airspeed is being captured by the advance ratio (in combination with the hub accelerations). This result is encouraging also because both the hub accelerations and advance ratio are parameters that can be easily measured (note that the measurement of the hub accelerations involves the use of slip rings).

Figure 18 shows the correlation plot from a MISO 5-10-6-1 back-propagation neural network with the case 3 inputs (three hub accelerations along with advance ratio and gross weight). The above back-propagation network has been trained for 5 million iterations with resulting R = 0.97 and RMS error = 0.01 g's. Figure 18 shows that the hub accelerations along with advance ratio and gross weight can represent the PVV. Compared to the Fig. 17 correlation (involving hub accelerations and advance ratio), the Fig. 18 correlation is not unexpected. This is because the hub accelerations may contain substantial basic information and very little additional information (e.g., advance ratio) is required to produce neural network based representations. Also, the correlation shown in Fig. 11 uses the maneuver effect factor MEF whereas the correlation shown in Fig. 18 uses the hub accelerations (along with advance ratio and gross weight). Both correlation results have been presently obtained such that they fall within a +/−0.05 g's error band and thus are comparable to each other. Hence, it can be suggested that the hub accelerations contain maneuver effects information reflecting load factor effects.

Selected results are shown in Table 1 in numerical form to show typical neural network predictions. The flight test PVV's for four specific flight conditions and the corresponding four neural network based PVV's are shown in Table 1. The present neural network models for which the predictions have been obtained are noted in Table 1. These models are as follows: the advance ratio and gross weight model (Fig. 10), the MEF model (Fig. 11), and the hub accelerations along with advance ratio and gross weight model (Fig. 18). From Table 1 it can be directly observed that the present neural network based models are accurate to within +/−0.05 g's of the corresponding flight test values for high-speed level flight, descent, climb, and a constant turn flight condition. The model that used the MEF and present model that used the hub accelerations along with advance ratio and gross weight give the best PVV predictions.

Neural Network Validation

The full UH-60A Airloads Program database has been explored till now for modeling the PVV and the hub accelerations using the present, neural network related entire database (200 point database). If additional data were available beyond the 200 point database, then these data could be used to test (validate) the neural networks. The neural networks could be applied to other operating conditions. However, additional data are not available. Consequently, the validation of the neural networks is done by working with the entire 200 point database, and splitting it into a training database and a testing (validation) database, and subsequently verifying that the testing results are acceptable. Approximately 80% of the entire database's 200 points are used to create a training database and the remaining approximately 20% are used to create a separate testing database. The validation results are summarized as follows.

For cases with the PVV as the single output, the PVV training RMS error is ≤0.02 g's (with R ranging from 0.89 to 0.98). The PVV testing RMS error is ≤0.04 g's (with R ranging from 0.73 to 0.81) for all of the above cases except for one case that is noted below. The case with the advance ratio and the gross weight as the inputs has a PVV testing RMS error of 0.05 g's (R = 0.70). Additionally, two sample validation (testing) plots, with the PVV as the single output, are presented in Figs. 19a–19b.

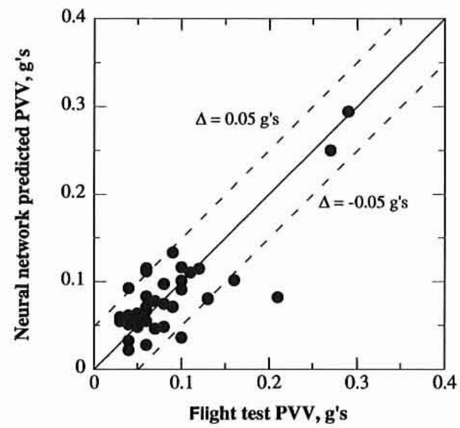

Fig. 19a. Validation plot, six inputs including MEF, associated with Fig. 11.

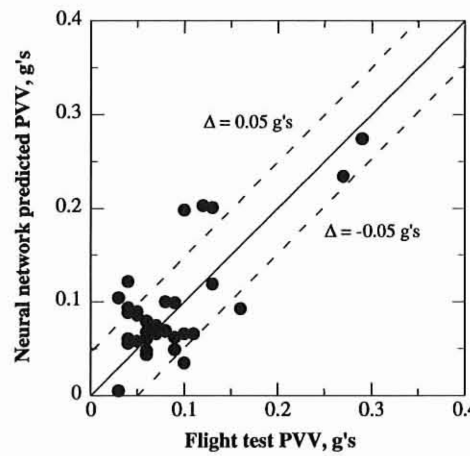

Fig. 19b. Validation plot, five inputs including hub accelerations, advance ratio and gross weight, associated with Fig. 18.

Table 1. Neural network based results for pilot floor vertical vibration, PVV, g's

Flight Condition	Flight Test	Advance Ratio + Gross Weight (Fig. 10)	Maneuver-Effect-Factor (Fig. 11)	Hub Accels. + Advance-Ratio + Gross Weight (Fig. 18)
Level flight, 135 knots	0.10	0.10	0.10	0.11
Descent, 160 knots	0.25	0.27	0.24	0.26
Climb, 62 knots	0.12	0.10	0.12	0.12
Turn, 45 deg, 120 knots	0.13	0.08	0.18	0.14

Table 2. Parametric study, varying percentage ratio of training to testing data points (associated with Fig. 18)

	Training		Testing	
Ratio	R	RMS error	R	RMS error
50/50	1.00	0.00 g's	0.50	0.06 g's
67/33	0.98	0.01 g's	0.61	0.05 g's
80/20	0.98	0.01 g's	0.74	0.04 g's
90/10	0.97	0.01 g's	0.80	0.04 g's
100/0	0.97	0.01 g's	-	-

Table 3. Training ("80%") error and testing ("20%") error for hub accelerations, 6 inputs, 3 outputs (associated with Figs. 13–15)

	Training		Testing	
Hub Accel.	R	RMS error	R	RMS error
3P Tang.	0.93	0.05 g's	0.85	0.07 g's
5P Tang.	0.90	0.06 g's	0.76	0.10 g's
4P Vert.	0.92	0.04 g's	0.75	0.07 g's

These two validation cases are associated with two important correlations that have been considered earlier in the present study, namely, those shown in Figs. 11 and 18, respectively. In the first sample validation case there are six inputs, listed as follows: advance ratio, gross weight, main rotor RPM, density ratio, MEF, and ascent/descent rate. The corresponding validation plot is shown in Fig. 19a (R = 0.81, RMS error = 0.04 g's). In the second sample validation case there are five inputs, listed as follows: three hub accelerations along with advance ratio and gross weight. The corresponding validation plot is shown in Fig. 19b (R = 0.74, RMS error = 0.04 g's).

In addition to the above validation study for the PVV using an 80/20 split ratio, a parametric study has also been conducted in which this split ratio was varied as follows: 50/50, 67/33, 80/20 as above, and 90/10. The parametric study has been conducted for the validation case associated with Fig. 18 in which there are five inputs (the three hub accelerations along with advance ratio and gross weight) and the PVV is the single output. The validation results are given in Table 2, which shows that a 80/20 training/testing validation ratio is appropriate.

Validation results for the hub accelerations using a 80/20 training/testing validation ratio are given in Table 3. These validation results are associated with Figs. 13–15.

Finally, the above validation results for the PVV and the hub accelerations prove that the neural networks used in the present study have predictive capability.

Concluding Remarks

Full-scale, flight test based peak, 4P pilot floor vertical vibration (PVV) and the corresponding hub accelerations are considered in this initial study for modeling purposes. The present quantitative effort represents the first systematic study involving hub accelerations. The flight conditions considered in the present study are as follows: level flight, rolls, pushovers, pull-ups, autorotations, and landing flares. Specific conclusions from the present neural network representation study are as follows:

1) Neither the advance ratio nor the gross weight alone can be used to represent the peak, 4P pilot floor vertical vibration (PVV).

2) The advance ratio and the gross weight can be used to represent the PVV of virtually the entire database of the UH-60A Airloads Program.

3) The quality of the hub accelerations data has been found to be acceptable.

4) The hub accelerations data have been successfully modeled using the following six inputs: advance ratio, gross weight, RPM, density ratio, MEF, and ascent/descent rate.

5) The relationships between the hub accelerations and the PVV have been studied, and the resulting conclusions are as follows:

a) The hub accelerations alone cannot represent the PVV.

b) The hub accelerations along with advance ratio can be used to represent the PVV.

c) The hub accelerations along with advance ratio and gross weight can be used to represent the PVV. Conclusion 5c) involving hub accelerations is complementary to conclusion 2) above. The additional inclusion of the hub accelerations (in addition to advance ratio and gross weight) brings in maneuver effects (e.g., load factor effects) into the neural network model that may help in predicting the maneuver PVVs.

The focus of the future work is discussed as follows. Practically, the present results involving hub accelerations potentially allow for the identification of neural network relationships between the experimental hub accelerations obtained from wind tunnel testing and the experimental pilot floor vertical vibration data obtained from flight testing. A successful establishment of the above neural network based link between the wind tunnel hub accelerations and the flight test vibration data can increase the value of wind tunnel testing.

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