MODELING OF UH-60A PILOT VIBRATION USING NEURAL NETWORKS AND WIND TUNNEL DATA

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Abstract. In this study, full-scale flight test N/rev pilot floor vertical vibration is modeled using neural networks and ground based wind tunnel test data for low speed level flight conditions. Two full-scale UH-60A Black Hawk databases are used. The first database is the NASA/Army UH-60A Airloads Program flight test database. The second database is the low speed full-scale UH-60A rotor-only wind tunnel database that was recently acquired in the NASA Ames 80- by 120-Foot Wind Tunnel with the Large Rotor Test Apparatus (LRTA). This neural network based modeling or representation study involves the prediction of the helicopter flight-test peak N/rev pilot floor vertical vibration (PVV) from the wind tunnel rotating system hub accelerations, and separately, from the wind tunnel fixed system N/rev hub loads obtained from the LRTA dynamic rotor balance system. Since the measured wind tunnel data are being presented for the first time, the validation of the measured wind tunnel data is important and is considered prior to the prediction of the flight test PVV. The measured wind tunnel rotating system hub accelerations and the fixed system N/rev balance-system hub loads have been found to be of good quality. The results show that the measured wind tunnel rotating system hub accelerations and the operating parameters can be used to represent the flight test rotating system hub accelerations. The wind tunnel rotating system hub accelerations and the operating parameters can be used to represent the six components of the wind tunnel N/rev balance hub loads. The wind tunnel rotating system hub accelerations and the operating parameters can be used to represent the flight test PVV. The six components of the wind tunnel N/rev balance-system hub loads and the operating parameters can be used to represent the PVV. Based on the above two conclusions of this initial study, it appears that the wind tunnel rotating system hub accelerations can have a greater role than previously thought. The successful establishment of the present neural network based links between the wind tunnel data and the flight test data can significantly increase the value of wind tunnel testing.

1 NOTATION

Advance ratio	Nondimensional velocity representing either the forward speed of the helicopter or the airspeed in the wind tunnel
LRTA	Large Rotor Test Apparatus test stand/facility at NASA Ames

MIMO	Multiple-input, multiple-output
MISO	Multiple-input, single-output
N	Number of main rotor blades, N = 4 for the UH-60A
N/rev	Integer (N) multiple of main rotor speed
P	Per revolution
PVV	Peak, N/rev pilot floor vertical vibration, g's
Weight coefficient	Nondimensional coefficient representing helicopter weight
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
Solidity	Nondimensional coefficient, total blade area divided by the rotor disc area
Thrust coefficient	Nondimensional coefficient representing rotor thrust

2 INTRODUCTION

For rotorcraft, the reduction of vibration to minimum levels is important. Active controls through high frequency blade pitch inputs have been successfully used to reduce vibration. The creation of accurate identification models is the first step towards the eventual implementation of active control of vibration. Studies at NASA Ames Research Center[1, 2] have shown that neural networks can be used to model rotorcraft fuselage vibration. References 1 and 2 showed that the full-scale UH-60A Black Hawk rotor hub accelerations measured in flight can be used to represent the N/rev pilot floor vibration (where N is the number of rotor blades and N = 4 for the UH-60A). The above neural network based analyses[1, 2] were performed using only flight test data obtained from the NASA/Army UH-60A Airloads Program.[3]

The present neural network representation study introduces the use of ground based wind tunnel test data to model flight test pilot floor vibration in the vertical direction. The low speed full-scale UH-60A wind tunnel database[4, 5] that was acquired in the NASA Ames 80- by 120-Foot Wind Tunnel with the Large Rotor Test Apparatus (LRTA) is used. The successful establishment of such neural network based links (relationships) between the wind tunnel parameters and the flight test data can increase the value of wind tunnel testing. The consistent successful utilization of such links can quantify the anticipated benefits that could be obtained in flight testing prior to the actual flight testing. In the present study, the measured wind tunnel parameters under consideration include both rotating system parameters (the hub accelerations) and the fixed system parameters (the hub loads from the dynamic rotor balance system).

As background to the present study, a sample comparison of the (N-1)/rev (or 3/rev) tangential hub acceleration data from both wind tunnel and flight tests is shown in Fig. 1. Figure 1 shows that the wind tunnel and flight test data have similar trends. Using neural networks it was shown earlier[1, 2] that the flight test hub accelerations plus the advance ratio and gross weight could be used to model the pilot vibration. Based on the similarity seen in Fig. 1, the present neural network based study proceeds to link the wind tunnel hub accelerations to the flight test pilot floor vertical vibration. Subsequently, this study also considers additional wind tunnel data such as the fixed system rotor-generated balance-system loads. Procedurally, the wind tunnel and the flight test operating conditions are matched in a simple manner. The wind tunnel and flight test advance ratios are matched, and the flight test weight coefficient/solidity ratio and the wind tunnel thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle are matched. The present approach of relating the wind tunnel variables to the flight test variables is believed to be an adequate first pass approach for this initial study.

A successful conclusion of the present neural network effort may potentially facilitate the eventual development of active control vibration techniques in the wind tunnel that will also work in flight, and also the anticipated benefit in flight quantified from wind tunnel testing alone. The on-line or real-time implementation of active control requires that the neural networks and their associated training algorithms be of the type such that the neural networks can be built (trained) on-line. The building of neural networks in real-time is a separate research topic that is not addressed in the present study.

3 OBJECTIVES

This neural network based modeling or representation study involves the helicopter flight test peak, N/rev pilot floor vertical vibration (PVV), the wind tunnel rotating system hub accelerations, and separately, the wind tunnel fixed system hub loads obtained from a dynamic rotor balance system. The present study considers low speed level flight conditions. In the following, the wind tunnel advance ratio and the thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle are referred to as the wind tunnel operating condition parameters (the "operating parameters"). This study has the following four objectives:

1. Validate the measured wind tunnel hub accelerations in light of the previously validated flight test hub accelerations (that were validated in an earlier study), and separately, validate the six components of the measured wind tunnel fixed system N/rev balance hub loads.

2. Using the measured wind tunnel rotating system hub accelerations and the operating parameters, determine whether reasonably accurate neural network based models of the separately measured, but actual, pilot floor vertical vibration can be obtained.

3. Using the measured six components of the wind tunnel fixed system N/rev balance hub loads and the operating parameters, determine whether reasonably accurate neural network models of the pilot floor vertical vibration can be obtained.

4. Assess the results from the above Objectives 3 and 4 to determine whether a particular approach is markedly better than the others to predict the flight test measurements or whether alternative wind tunnel test measurements would be required.

4 FLIGHT TEST AND WIND TUNNEL DATABASES

The source of the flight test data was the NASA/Army UH-60A Airloads Program flight test database.[3] The flight test data were obtained with the (N-1)P bifilar vibration absorbers installed on the UH-60A. The creation of the peak, N/rev pilot floor vertical vibration, PVV, database has been described separately.[1] The present study considers the flight test rotating system hub accelerometers. Specifically, the (N-1)P and (N+1)P tangential hub accelerations and the NP vertical hub acceleration are considered. The appropriate hub acceleration values are taken as those corresponding to the peak, N/rev pilot floor vertical vibration under consideration.[1] The number of data points that are of present interest is approximately 60 (low speed level flight conditions).

The low speed full-scale UH-60A wind tunnel database[4,5] that was acquired in the NASA Ames 80- by 120-Foot Wind Tunnel with the Large Rotor Test Apparatus (LRTA) is used. The bifilar vibration absorbers were not installed during the above wind tunnel testing. The present study considers the (N-1)P and (N+1)P tangential hub accelerations and the NP vertical hub acceleration. Also, the six components of the N/rev hub loads from the LRTA dynamic rotor balance-system are considered. These six N/rev hub loads are given as follows: the normal force, the axial force, the side force, the pitching moment, the rolling moment, and the yawing moment. The number of experimental points that are of present interest is approximately 60. These low speed wind tunnel data points include variations in the advance ratio, the thrust coefficient, and the shaft angle. The variations in the shaft angle allow for simulation of flight conditions that include level flight, climb and descent conditions.

5 BASIC VARIATIONS

Figures 2 and 3 show the variations of the measured wind tunnel hub accelerations. The data shown in Figs. 2 and 3 use the above-mentioned 60-point wind tunnel database. In addition to the variation in the advance ratio covered in these figures, these data involve variations in the thrust coefficient and the shaft angle. As a result, many of these operating conditions do not simulate level flight. Figure 2 shows the variations of the wind tunnel (N-1)P and (N+1)P tangential hub accelerations versus the advance ratio. Figure 3 shows the variation of the wind tunnel NP vertical hub acceleration versus the advance ratio.

Figures 4 and 5 show the variations of the six components of the wind tunnel balance N/rev hub loads. The data shown in Figs. 4 and 5 use the above-mentioned 60-point wind tunnel database. In addition to the variation in the advance ratio covered in these figures, these data involve variations in the thrust coefficient and the shaft angle. Figure 4 shows the variations of the three N/rev balance hub forces (the normal force, the axial force, and the side force) versus the advance ratio. Figure 4 shows that the N/rev side force is the largest of the three N/rev forces. Figure 5 shows the variations of the three N/rev balance hub moments (the pitching moment, the rolling moment, and the yawing moment) versus the advance ratio. It appears from Fig. 5 that the N/rev rolling moment is larger than the other two N/rev moments. Note that the balance forces and moments are expressed at the hub location.

The conclusion from the above figures (Figs. 2-5) is that the variations of the N/rev pilot floor vertical vibration (PVV), the wind tunnel hub accelerations, and the wind tunnel balance hub loads may be considered to have similar trends with increasing advance ratio but there are obviously other important factors.

6 NEURAL NETWORK APPROACH

To accurately capture the required functional dependencies, the neural network inputs must be carefully selected and account for all important 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 inputs, the type, and the number of processing elements (PEs) and the number of hidden layers). The present overall neural network modeling approach is based on an earlier approach.[1] 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[6] is used. The required number of neural network PEs 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. In the present study, one to five PEs are added at each step in this process. 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 trained neural network 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.

For the notation used in this paper, a neural network architecture such as "2-10-5-1" refers to a neural network with two inputs, ten 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 low speed level flight full-scale helicopter flight test data and wind tunnel data has been conducted using the neural networks package NeuralWorks Pro II/PLUS (version 5.51) by NeuralWare.[6]

7 DATA VALIDATION

The validation of the measured wind tunnel data is particularly important because it has not been presented before. The validation (or the assessment of the data quality) of the measured wind tunnel data is considered prior to the prediction of the pilot floor vertical vibration. Consequently, the results of this study are presented in two parts, Sections 7 and 8, respectively. Section 7.1 of this study considers the validation of the measured wind tunnel rotating system hub accelerations in light of the previously validated flight test hub accelerations.[1] Separately, the validation of the measured wind tunnel fixed system balance loads is considered in Section 7.2. Section 8 of this study considers the prediction of the flight test pilot floor vertical vibration PVV using measured wind tunnel data.

The neural network results presented in this paper (Sections 7 and 8) are based on two full-scale UH-60A databases. The two UH-60A databases are the NASA/Army Airloads Program flight test database[3] and the low speed wind tunnel database[4] that was acquired in the NASA Ames 80- by 120-Foot Wind Tunnel with the LRTA. The present neural network based modeling study considers low speed level flight conditions and does not include the hover condition. The number of neural network training points is approximately 60. In the following, the rotating system (N-1)P and (N+1)P tangential hub accelerations and the NP vertical hub acceleration are referred to as the "<u>three relevant</u>" hub acceleration components. Also, the wind tunnel advance ratio and the thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle are referred to as the wind tunnel operating condition parameters (the "<u>operating parameters</u>").

7.1 Validation of wind tunnel data

7.1.1 Validation of wind tunnel hub accelerations

The measured wind tunnel rotating system three relevant hub accelerations are validated in the same manner as was done previously for the flight test hub accelerations.[1] In the present study the quality of the measured wind tunnel hub accelerations has been assessed relative to the quality of the flight test hub accelerations. The two 60-point low speed experimental databases, namely, the flight test database and separately, the wind tunnel test database, are used.

For comparative purposes specific to the present validation effort, the previously validated flight test hub accelerations database is reconsidered in the following manner. A neural network, trained from the flight test database, is used. This neural network uses two flight condition operating conditions to predict the three in-flight hub accelerations. The two neural network inputs are the flight test advance ratio and the weight coefficient/solidity ratio. The three outputs are the three relevant flight test hub accelerations, namely, the rotating system (N-1)P and (N+1)P tangential hub accelerations and the NP vertical hub acceleration.

For the validation of the measured wind tunnel hub accelerations, a second separate neural network is trained from the wind tunnel test database, and uses two wind tunnel test operating conditions to predict the three wind tunnel hub accelerations. The wind tunnel operating parameters are used as the two neural network inputs. The two neural network inputs are the wind tunnel advance ratio and the thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle. The three relevant measured wind tunnel hub accelerations are the three neural network outputs. These three outputs are the wind tunnel rotating system (N-1)P and (N+1)P tangential hub accelerations and the NP vertical hub acceleration.

Two different MIMO 2-10-5-3 back-propagation neural networks are used, one for the flight test hub accelerations and the other for the measured wind tunnel hub accelerations. The neural network associated with the flight test accelerations has been trained for 1 million iterations and the neural network associated the measured wind tunnel hub accelerations has been trained for 4 million iterations. Table 1 below shows the resulting correlations, i.e., the R's and the nondimensional RMS errors. The nondimensional RMS errors are obtained as follows. The dimensional RMS error under consideration is divided by the maximum value of its respective hub acceleration component. Table 1 shows that the correlations for the flight test hub accelerations and the measured wind tunnel hub accelerations are similar, thus validating the measured wind tunnel hub accelerations. From this study, the measured wind tunnel rotating system hub accelerations have been found to be of good quality.

7.1.2 Relationships between measured wind tunnel and flight test hub accelerations

As shown above, the measured wind tunnel hub accelerations have been found to be of good quality. As an additional indicator of consistency, the measured wind tunnel hub accelerations are used to model the flight test hub accelerations. A simple MIMO 5-2-3 back-propagation neural network is used. The five wind tunnel inputs are as follows: the three relevant wind tunnel hub accelerations, the advance ratio, and the thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle (the latter two inputs are the same as the wind tunnel operating parameters). The three outputs are the three relevant flight test hub accelerations. Procedurally, the above inputs (measured wind tunnel quantities) are available at the wind tunnel operating conditions. Since the subject outputs (the flight test hub accelerations) are originally from the flight test database, appropriate values of the flight test based hub accelerations have to be obtained at the wind tunnel operating condition values. This intermediate step is accomplished via a neural network that is not described in this paper since it is a procedural detail. Subsequently, the above back-propagation neural network has been trained for 50,000 iterations and the resulting R's and RMS errors are as follows. For the 3P tangential hub acceleration correlation, R = 0.98 and RMS error = 0.01 g's. For the 5P tangential hub acceleration correlation, R = 0.95 and RMS error = 0.01 g's. For the 4P vertical hub acceleration correlation, R = 0.97 and RMS error = 0.01 g's. Clearly this trained neural network can easily capture the direct relationships between the wind tunnel hub accelerations and the flight test hub accelerations.

7.2 Validation of wind tunnel balance loads

In this section, the quality of the measured wind tunnel fixed system N/rev balance-system hub loads is assessed. The six components of the N/rev hub loads from the dynamic rotor balance system are modeled using the measured wind tunnel hub accelerations. It has been shown in Section 7.1 that the wind tunnel hub accelerations are valid (of good quality) and consistent. A MIMO 5-4-6 back-propagation neural network is used. The five wind tunnel inputs are as follows: the three relevant wind tunnel hub accelerations, the advance ratio, and the thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle (the latter two inputs are the same as the wind tunnel operating parameters). The six outputs are the wind tunnel N/rev balance-system hub loads, namely, the three N/rev forces (normal, axial, and side forces) and the three N/rev moments (pitching, rolling, and yawing moments). The above back-propagation network has been trained for 400,000 iterations. The resulting R's and RMS errors are shown in Table 2. Figures 6-11 show the resulting correlation plots for the above balance N/rev hub loads.

Overall, the quality of the measured wind tunnel N/rev balance-system hub loads is assessed as being good. Figures 6-11 show that the three relevant wind tunnel hub accelerations and the operating parameters can represent the six components of the low speed wind tunnel N/rev balance-system hub loads. This implies that numerical relationships (the identification model) relating the full-scale measured wind tunnel fixed system balance loads to the measured wind tunnel rotating system hub accelerations has been obtained. Finally, the successful completion of the above data validation effort gives the necessary reality/consistency checks associated with the wind tunnel rotating system hub accelerations and the corresponding fixed system balance hub loads.

8 PREDICTION OF PILOT FLOOR VERTICAL VIBRATION, PVV

In this part of the study, the flight-test peak N/rev pilot floor vertical vibration PVV is predicted using neural networks and measured ground based wind tunnel data. These measured wind tunnel data include the three relevant rotating system hub accelerations and separately, the fixed system N/rev balance-system hub loads. The low speed level flight full-scale PVV values of current interest were obtained earlier[1] from the NASA/Army UH-60A Airloads Program flight test database.[3] Since the PVV values are originally from a flight test database, for present purposes, the appropriate values of the PVV have to be obtained at the wind tunnel operating condition values. This intermediate step is accomplished via a neural network. The PVV values at the wind tunnel operating conditions are referred to as the "flight test PVV" values. These "flight test PVV" values are obtained as follows. A MISO 2-10-5-1 back-propagation neural network is trained from the flight test database. The flight test advance ratio and the weight coefficient/solidity ratio are the two inputs, and the single output is the actual pilot floor vertical vibration, PVV. The above back-propagation network has been trained for 1 million iterations with resulting R = 0.82 and RMS error = 0.02 g's. The above neural network model is similar to the model that was obtained earlier[1] (Fig. 7 of Reference 1). Figure 12 shows the above flight test PVV variation with the advance ratio where the above neural network has been executed using the wind tunnel operating parameters as the inputs.

The following sections describe three different methods of predicting the flight test PVV. In order to predict the flight test PVV, the first method uses the flight test rotating system hub accelerations. The second method uses the measured wind tunnel rotating system hub accelerations, and the third method uses the measured wind tunnel fixed system N/rev balance-system hub loads.

8.1 PVV prediction using flight test rotating system hub accelerations

In this section, the original 60-point flight test database (Section 4) and a smaller 29-point flight test database derived from the above 60-point flight test database are used to predict the PVV. In the 60-point flight test database, the advance ratio range is 0.002 to 0.20. The 29-point flight test database envelope contains data only for operating conditions that closely match the measured 60-point wind tunnel database envelope. Both the 29-point flight test database and the 60-point measured wind tunnel database have an advance ratio range 0.09 to 0.19.

First, using the 60-point flight test database, a simple MISO 5-9-1 back-propagation neural network is trained. The five flight test inputs are as follows: the three relevant actual flight test hub accelerations, the advance ratio, and the weight coefficient/solidity ratio. The single output is the actual flight test PVV. The above back-propagation network has been trained for 1.2 million iterations with resulting R = 0.994 and RMS error = 0.00 g's. Figure 13a shows the resulting correlation plot for the PVV. In order to show a representative variation with advance ratio, a weight coefficient/solidity ratio (or equivalently, the wind tunnel thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle) = 0.08 is considered. Figure 13b shows the predicted PVV with advance ratio at constant thrust using this neural network.

Second, using the 29-point flight test database, a simple MISO 5-5-1 back-propagation neural network is trained. The five flight test inputs are as follows: the three relevant actual flight test hub accelerations, the advance ratio, and the weight coefficient/solidity ratio. The single output is the actual flight test PVV. The back-propagation network has been trained for 425,000 iterations with resulting R = 0.996 and RMS error = 0.00 g's. Figure 14a shows the resulting correlation plot for the PVV. Figure 14b shows the predicted PVV with advance ratio using the 29-point flight test database for the same representative operating condition as in Fig. 13b (weight coefficient/solidity ratio = 0.08). For comparison, Fig. 14b also includes the corresponding 60-point variation from Fig. 13b. Figure 14b shows that there is a significant difference between the PVV predictions obtained using the 60-point and the 29-point flight test databases when using the rotating system flight test hub accelerations.

To understand the differences in the predicted PVV using the two different neural networks, the predicted flight test PVV derived from Fig. 12 is considered. In Fig. 12, a 60-point flight test database has been used but the only inputs were the advance ratio and the weight coefficient/solidity ratio. Figure 15 shows the resulting PVV variation with advance ratio derived from Fig. 12 (from the neural network used to obtain Fig. 12) along with the above two variations using the flight test rotating system hub accelerations (from Fig 13b, using the 60-point trained network, and Fig. 14b, using the 29-point trained network). The PVV variation using the advance ratio and the weight coefficient (derived from Fig. 12) appears to be a mean variation for the PVV as compared to the other two PVV variations obtained by using the flight test rotating system hub accelerations (60-point and 29-point databases, Figs. 13b and 14b, respectively). Table 3 shows the measured flight test PVV for two low speed operating conditions that are practically the same. However, the measured PVV values are significantly different (0.15 g's and 0.05 g's, Table 3). The two neural network based PVV predictions using the flight test rotating system hub accelerations are sensitive to the above large difference in the PVV values that have been used in the training sets. The neural network based PVV prediction using the advance ratio and the weight coefficient (derived from Fig. 12) gives a mean value and this PVV variation may likely be more representative. In the following sections, the PVV variation derived from Fig. 12 is therefore used as the standard PVV variation for purposes of comparison.

8.2 PVV prediction using measured wind tunnel rotating system hub accelerations

A simple MISO 5-2-1 back-propagation neural network is used. The five wind tunnel inputs are as follows: the three relevant wind tunnel hub accelerations, the advance ratio, and the thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle (the latter two inputs are the same as the wind tunnel operating parameters). The single output is the flight test PVV. The above back-propagation network has been trained for 5000 iterations with resulting R = 0.997 and RMS error = 0.00 g's. Figure 16a shows the resulting correlation plot for the PVV. In order to show a representative variation with advance ratio, a weight coefficient/solidity ratio (or equivalently, the wind tunnel thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle) = 0.08 is considered. Figure 16b shows the resulting variation of the flight test PVV (derived from Fig. 12) and the predicted PVV with advance ratio. Figures 16a and 16b show that the three relevant measured wind tunnel hub accelerations and the operating parameters can likely accurately characterize and quantify the low speed level flight PVV.

8.3 PVV prediction using measured wind tunnel balance-system hub loads

A simple MISO 8-2-1 back-propagation neural network is used. The eight wind tunnel inputs are as follows: the six measured wind tunnel fixed system N/rev balance-system hub loads, the advance ratio, and the thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle (the latter two inputs are the same as the operating parameters). The single output is the flight test PVV. The above back-propagation network has been trained for 5500 iterations with resulting R = 0.997 and RMS error = 0.00 g's. Figure 17a shows the resulting correlation plot for the PVV. In order to show a representative variation with advance ratio, a weight coefficient/solidity ratio (or equivalently, the wind tunnel thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle) = 0.08 is considered. Figure 17b shows the variation of the flight test PVV (derived from Fig. 12) and the predicted PVV with advance ratio. Figures 17a and 17b show that the six components of the measured wind tunnel N/rev balance-system hub loads and the operating parameters can very accurately represent the low speed level flight PVV.

9 CONCLUDING REMARKS

Using only flight test data, it was shown earlier[1, 2] that the rotating system hub accelerations are clearly a factor in determining the pilot vibration. The above earlier result involving the flight test hub accelerations allowed for the identification of more general neural network relationships between the experimental data such as the hub accelerations obtained from wind tunnel testing and the experimental pilot floor vibration data obtained from flight testing.

The present neural network representation study introduces the use of full-scale measured ground based wind tunnel test data to model the full-scale flight test pilot floor vibration in the vertical direction. The measured wind tunnel parameters under consideration include both rotating system parameters (the hub accelerations) and the fixed system parameters (the N/rev hub loads from a dynamic rotor balance-system). Specifically, the low speed level flight full-scale peak N/rev pilot floor vertical vibration (PVV) obtained from flight testing is considered in this initial study for modeling purposes. In the following, the wind tunnel advance ratio and the thrust coefficient/solidity ratio multiplied by the cosine of the rotor shaft angle are referred to as the wind tunnel operating condition parameters (the operating parameters). Specific conclusions are as follows:

1) The measured wind tunnel rotating system hub accelerations and the six components of the fixed system N/rev balance-system hub loads have been found to be of good quality.

2) The measured wind tunnel rotating system hub accelerations and the operating parameters can be used to represent the flight test rotating system hub accelerations.

3) The measured wind tunnel rotating system hub accelerations and the operating parameters can be used to represent the six components of the measured wind tunnel fixed system N/rev balance-system hub loads.

4) The measured wind tunnel rotating system hub accelerations and the operating parameters can be used to represent the low speed PVV.

5) The six components of the measured wind tunnel fixed system N/rev balance-system hub loads and the operating parameters can be used to represent the low speed PVV.

Based on the above Conclusions 4 and 5 of this initial study, it appears that the wind tunnel rotating system hub accelerations can have a greater role than previously thought. In order to model the flight test PVV, compared to the use of the fixed system balance-system hub loads, the successful use of the rotating system hub accelerometers may entail less effort. This would be because the use of a fixed system balance-system involves the associated calibration of the balance.

In the future, the present neural network based study involving the pilot floor vibration in the vertical direction will be extended to include the pilot floor vibration in the other two directions also, namely, the lateral and longitudinal directions. The successful establishment of such neural network based links (relationships) between the wind tunnel parameters and the flight test data can significantly increase the value of wind tunnel testing.

10 REFERENCES

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Table 1: Correlation results for full-scale flight test and measured wind tunnel hub accelerations.

Hub acceleration component	**R**		**RMS error** (non dimensional)	
	Flight test	**Wind tunnel test**	**Flight test**	**Wind tunnel test**
(N-1)P Tangential	0.94	0.96	0.08	0.06
(N+1)P Tangential	0.89	0.84	0.08	0.09
NP Vertical	0.88	0.96	0.09	0.06

Table 2: Correlation results for full-scale measured wind tunnel balance loads.

N/rev Hub load	**R**	**RMS error**
Normal Force	0.99	39 lb
Axial Force	0.97	97 lb
Side Force	0.98	158 lb
Pitching Moment	0.98	96 ft-lb
Rolling Moment	0.96	163 ft-lb
Yawing Moment	0.99	116 ft-lb

Table 3: Flight test data, pilot floor vertical vibration.

Advance ratio	**Weight coefficient/solidity**	**Measured PVV, g's**
0.093	0.080	0.15
0.094	0.081	0.05

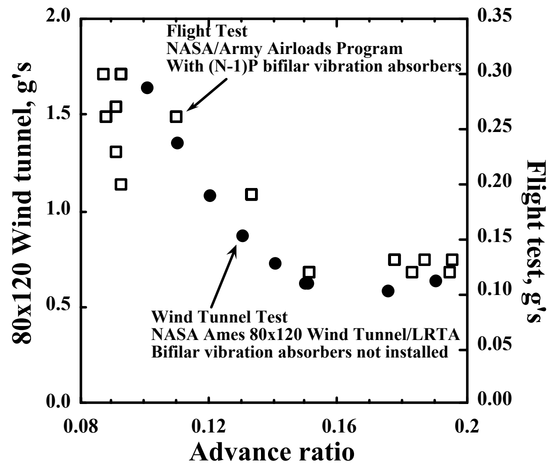

Figure 1: UH-60A wind tunnel and flight test full-scale (N-1)P tangential hub acceleration.

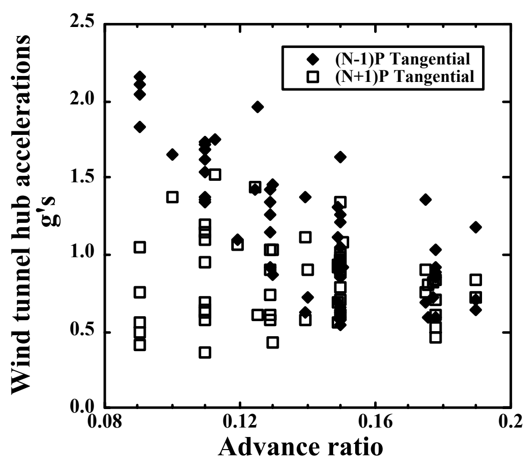

Figure 2: UH-60A wind tunnel (N-1)P and (N+1)P tangential hub accelerations.

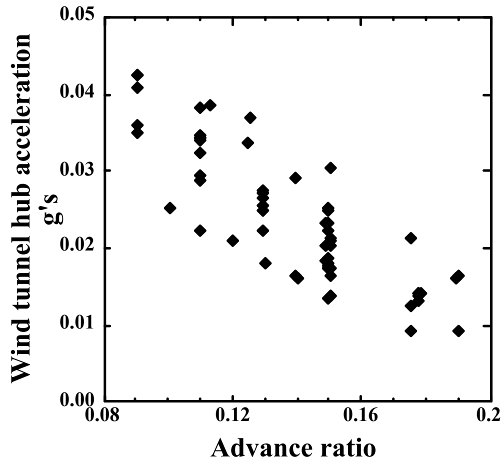

Figure 3: UH-60A wind tunnel NP vertical hub acceleration.

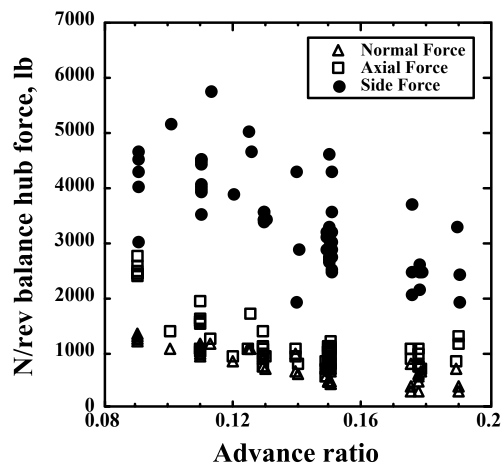

Figure 4: UH-60A LRTA N/rev balance-system hub forces.

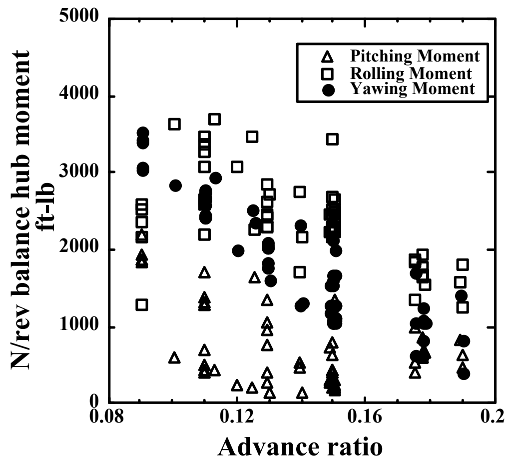

Figure 5: UH-60A LRTA N/rev balance-system hub moments.

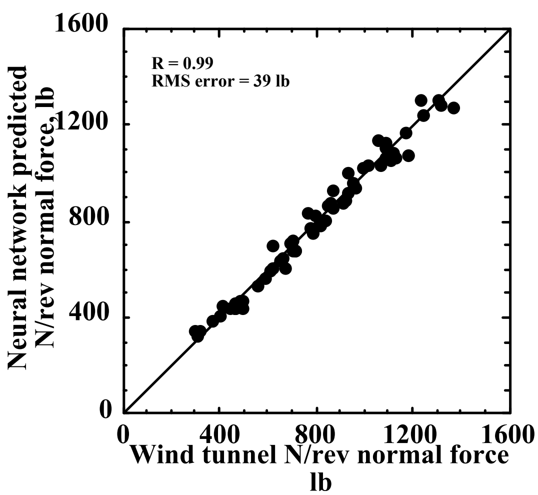

Figure 6: Normal force correlation using wind tunnel hub accelerations and operating parameters.

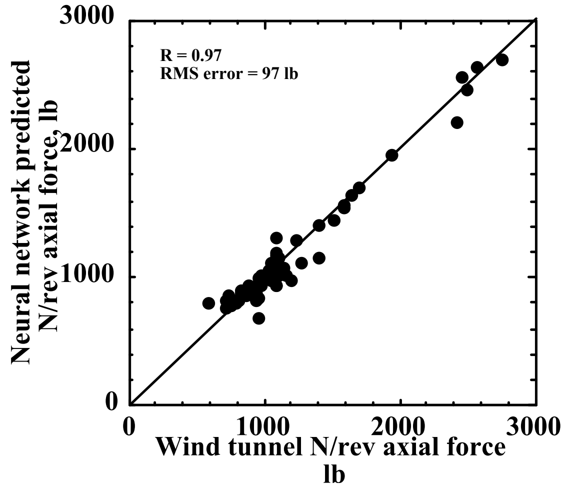

Figure 7: Axial force correlation using wind tunnel hub accelerations and operating parameters.

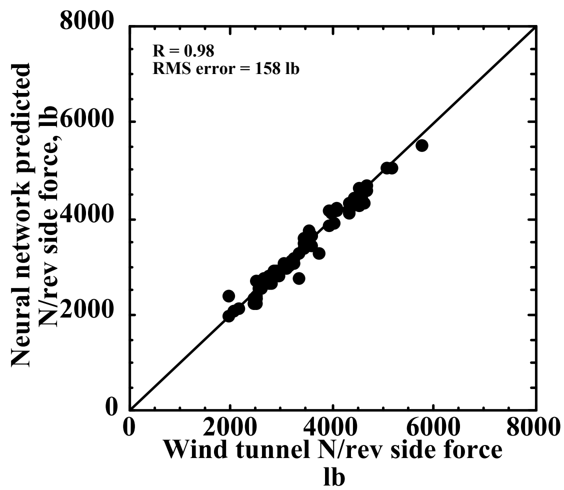

Figure 8: Side force correlation using wind tunnel hub accelerations and operating parameters.

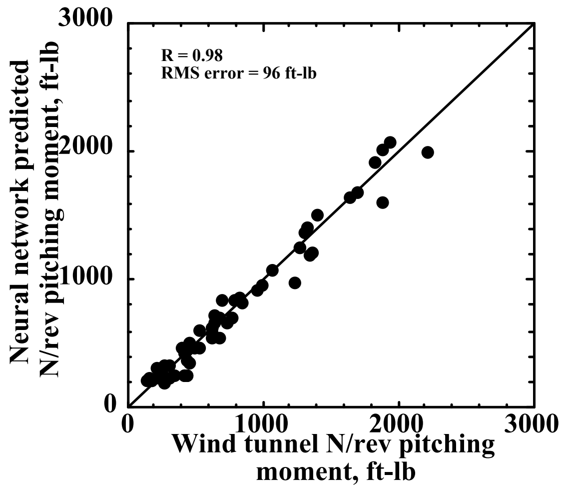

Figure 9: Pitching moment correlation using wind tunnel hub accelerations and operating parameters.

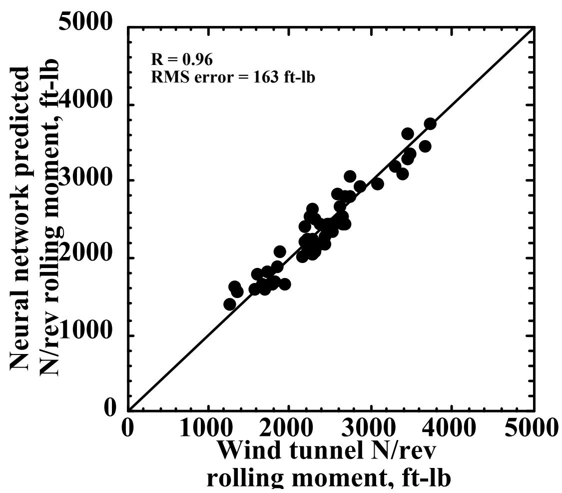

Figure 10: Rolling moment correlation using wind tunnel hub accelerations and operating parameters.

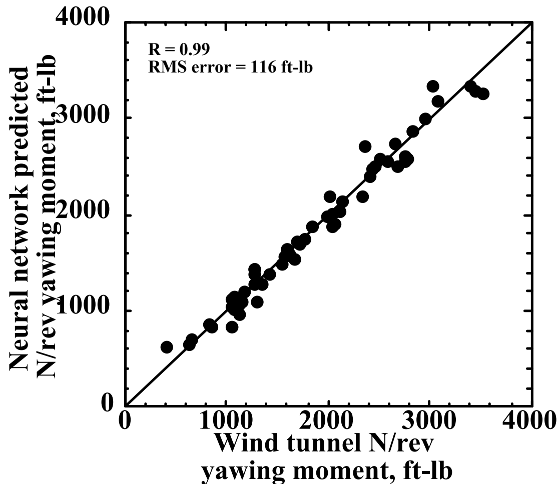

Figure 11: Yawing moment correlation using wind tunnel hub accelerations and operating parameters.

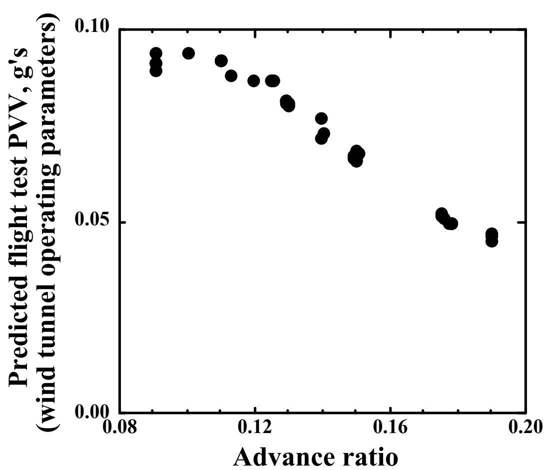

Figure 12: Predicted flight test PVV obtained using advance ratio and weight coefficient.

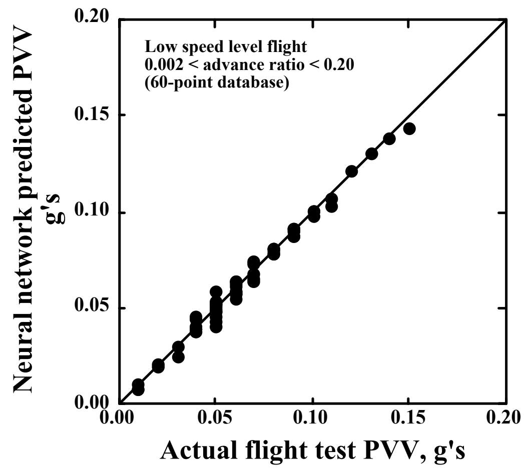

Figure 13a: PVV correlation using flight test rotating system hub accelerations and operating parameters, 60-point database.

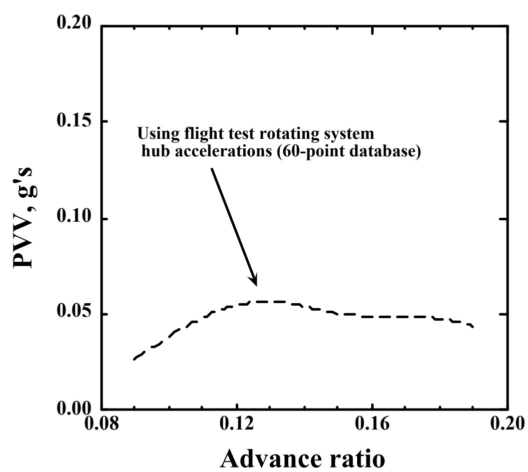

Figure 13b: PVV prediction using flight test rotating system hub accelerations and operating parameters, 60-point database (weight coefficient/solidity = 0.08).

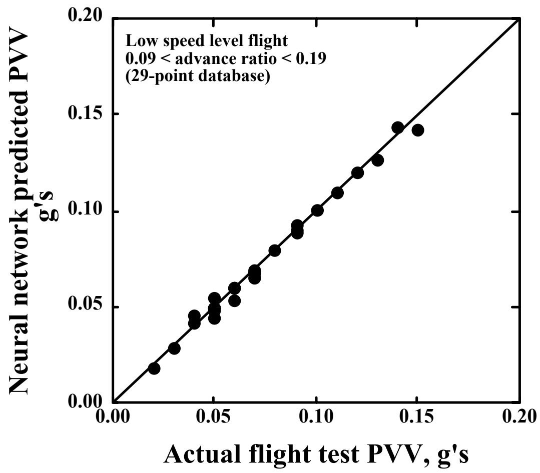

Figure 14a: PVV correlation using flight test rotating system hub accelerations and operating parameters, 29-point database.

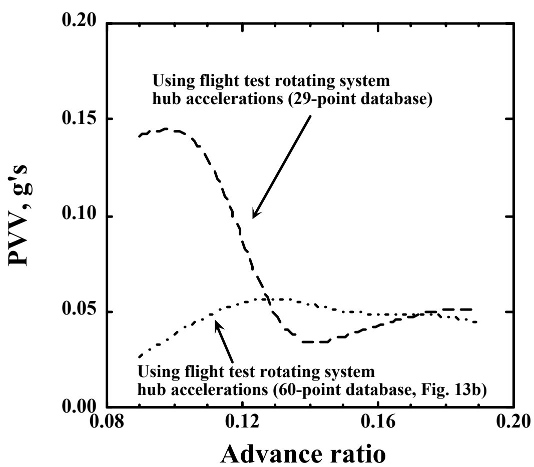

Figure 14b: PVV prediction using flight test rotating system hub accelerations and operating parameters, 29-point database (weight coefficient/solidity = 0.08).

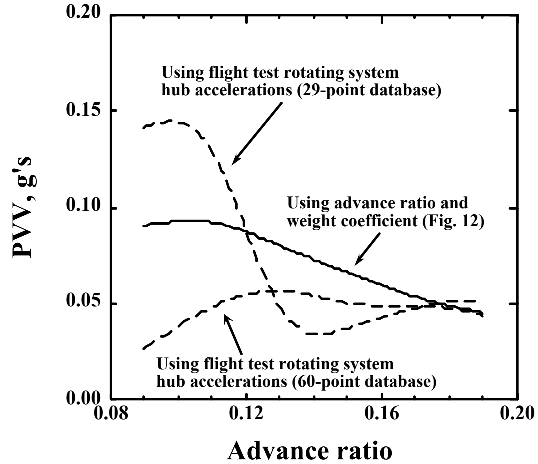

Figure 15: Comparison of PVV predictions (weight coefficient/solidity = 0.08).

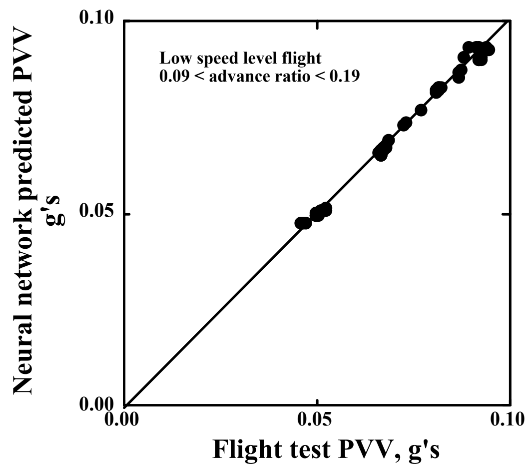

Figure 16a: PVV correlation using wind tunnel rotating system hub accelerations and operating parameters.

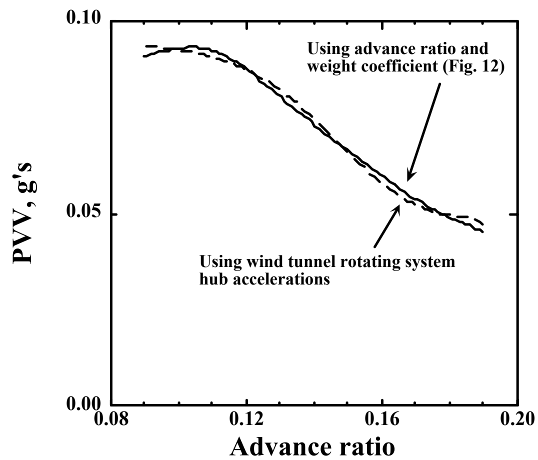

Figure 16b: PVV prediction using wind tunnel rotating system hub accelerations (weight coefficient/solidity = 0.08).

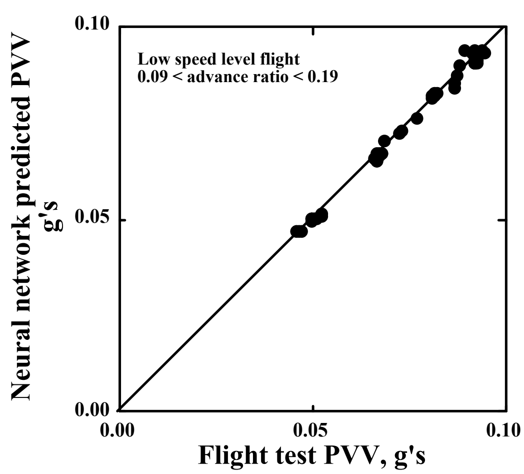

Figure 17a: PVV correlation using the six components of N/rev balance-system hub loads.

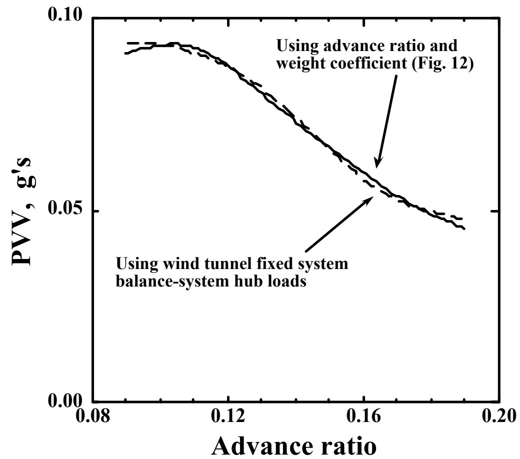

Figure 17b: PVV prediction using the six components of N/rev balance-system hub loads. (weight coefficient/solidity = 0.08).