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A comparison of main rotor smoothing adjustments using linear and neural network algorithms ☆

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Abstract

Helicopter main rotor smoothing is a maintenance procedure that is routinely performed to minimize destructive airframe vibrations induced by non-uniform mass and/or aerodynamic distributions in the main rotor system. This important task is both time consuming and expensive, so improvements to the process have long been sought. Traditionally, vibrations have been minimized by calculating adjustments based on an assumed linear relationship between adjustments and vibration response. In recent years, artificial neural networks have been trained to recognize non-parametric mappings between adjustments and vibration response. This study was conducted in order characterize the adjustment mapping of the Vibration Management Enhancement Program's PC-ground base system (PC-GBS), and compare it to the linear adjustment mapping used in the aviation vibration analyzer (AVA). Results show that, in a majority of situations, the neural network algorithms in PC-GBS produce adjustments that are identical to those produced by a linear algorithm similar to that used by AVA. Therefore, the use of neural networks for creating the mapping between adjustments and vibration response, provides no significant improvement over a linear mapping.
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1. Introduction

Since the earliest days of rotary wing aviation, helicopters have been known as much for their tendency to exhibit severe vibrations as for their ability to take off and land vertically. In addition to providing the principal source of lift for the helicopter, helicopter main rotors are also the principal source of some of the most destructive vibrations known to the aircraft industry. The principal sources of some of these vibrations

Abbreviation: PC-GBS, PC-ground base system; AVA, aviation vibration analyzer; RTB, rotor track and balance; HUMS, health usage and monitoring systems; VMEP, US Army's Vibration Management Enhancement Program; AEN, aviation evaluation network; VPN, vibration prediction network; TON, track optimization network; SOE, solution optimization network

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are mass and aerodynamic dissimilarities among the rotor blades. These dissimilarities result in vibratory forces that occur at the same frequency as the rotor speed, and are commonly known as 1/rev vibrations.

In recognition of the importance of minimizing 1/rev vibrations, for improving aircrew performance and passenger comfort, and minimizing airframe operating costs, many techniques have been developed to identify and correct blade-to-blade dissimilarities [1]. While lateral 1/rev vibrations primarily result from blade mass imbalances, which can be minimized by adjustment weights at either the rotor hub or blade tips, vertical 1/rev vibrations are primarily due to aerodynamic imbalances. Most early methods for reducing vertical 1/rev vibrations relied on the assumption that if the blades were aerodynamically identical, they would traverse the same path. It was thereby presumed that by "tracking" the blades, or making them all fly in the same path for all flight conditions, the vertical 1/rev vibrations could be minimized or eliminated. Thus, elimination of 1/rev vibrations has commonly been called rotor track and balance (RTB).

Field experience, backed up by mathematical modelling [2], has provided ample evidence that merely tracking helicopter rotor blades will not necessarily result in minimum 1/rev vertical vibrations [3]. Since blade track is not a reliable indicator of minimum vibratory loads, "rotor smoothing" techniques were developed to reduce 1/rev vertical vibrations. Helicopter main rotor smoothing is a technique under which vibration magnitude and phase are recorded both on the ground and in flight. Then, based on a predetermined relationship between vibrations and corrective adjustments, pitch link and trim tab adjustments are made to the blades. In order to reduce the vibrations to acceptable levels, this technique usually requires several flights, and is therefore both time consuming and expensive. It has been estimated that 5% of a helicopter's annual flight hours are devoted to eliminating 1/rev vibrations [4].

Efforts have long been made to improve main rotor smoothing techniques so as to decrease the number of required flights, and save time and money as a result. Over the years, vibration and track measuring equipment have become more accurate and reliable. Nonetheless, the methodology underlying many, or perhaps most, rotor smoothing implementations assumes that the mapping between vibrations and adjustments is linear, although corrections that account for statistical [5] or probabilistic [6] variations are often included. However, it has also been suggested that the linear assumption is overly simplistic; and that more sophisticated algorithms, which can account for nonlinearities, should be implemented [7]. Several algorithms, including neural networks [7–11], fuzzy logic [12], and interval modeling [13] have been investigated.

Rotor smoothing, which originally was performed by a stand-alone system, has recently been incorporated into health usage and monitoring systems (HUMS). The purpose of HUMS is to detect faults in many aircraft systems, including the rotor system. Like rotor smoothing algorithms, HUMS algorithms rely on measurements such rotating blade frequencies [10,14], hub forces and moments [11,12,15], blade response [11,12,15], and other quantities in addition to vibrations measurements; and serve as data sources for algorithms that make a determination as to which fault is causing the undesirable aircraft vibrations. Examples of operational HUMS installations are the US Army's Vibration Management Enhancement Program (VMEP) [8,9,16] and Goodrich Corporation's IMD HUMS [5].

In recent years, a substantial effort has been made to improve the HUMS software that is used to convert raw vibration measurements into corrective main rotor adjustments [7–9]. In doing so, the tasks performed by the maintainers have clearly become easier to accomplish. However, the question of whether the mapping between vibration measurements and blade adjustments is linear still remains. The intent of this investigation is to determine whether new algorithms, which are capable of accounting for nonlinear mappings between vibration measurements and blade adjustments, offer any significant advantage over standard linear methods. To this end, adjustments generated by the linear, aviation vibration analyzer coefficients will be compared to adjustments from the US Army's Vibration Management Enhancement Program neural network, for identical vibration measurements.

2. Technical background

Due to the complexity of the dynamics involved with a main rotor system, simplifying assumptions have been introduced when defining the relationship between vibrations and corrective adjustments [1]. One such assumption is that the relationship between main rotor adjustments and vibration changes is linear, and may be described mathematically as

$$[C]_{NxM}\{\text{Adj}\}_{Mx1} = \{\Delta\text{Vib}\}_{Mx1}. \tag{1}$$

This assumption has allowed for the development of straightforward main rotor smoothing algorithms, at the core of which are empirically derived, linear sensitivity coefficients ([C] in Eq. (1)). Sensitivity coefficients are determined, using Eq. (2), over a series of test flights during which changes in vibrations are measured for single adjustment moves.

$$C_{n,m} = \frac{\text{Vib}_n^{\text{before}} - \text{Vib}_n^{\text{after}}}{\text{Adj}_m}. \tag{2}$$

While the linear methodology has produced acceptable results, it has been proposed that improved performance can be obtained by relaxing the linear assumption and allowing for a nonlinear relationship between vibrations and adjustments [7].

To this end, a new paradigm was introduced into the practice of main rotor smoothing. Artificial neural networks have been trained to recognize the relationship between main rotor adjustments and the resulting changes in vibrations. In the late 1990s, Wroblewski et al. [8] implemented a software system based on neural networks as part of the South Carolina Army National Guard and US Army's Vibration Management Enhancement Program (VMEP). The PC-ground base system (PC-GBS) is used today by several helicopter units in the US Army for rotor smoothing operations.

At the core of the PC-GBS are four neural networks. These are the adjustment evaluation network (AEN), the vibration prediction network (VPN), the track optimization network (TON), and the solution optimization expert (SOE). Each of these neural networks performs a specific function that contributes to finding the optimum set of adjustments to minimize the vibration levels.

The purpose of the adjustment evaluation network is to convert measured vibration data into a set of candidate adjustments known as reduced adjustment vectors. These reduced adjustment vectors are defined by a positive magnitude, and a phase angle that is oriented with the helicopter frame of reference, much like the vibration vectors. Each reduced adjustment vector may be applied to the main rotor system as defined by the adjustment evaluation network, or as the negative of the adjustment magnitude with a 180° phase shift. Either way, the adjustments will achieve the same change in predicted vibrations. The only difference between applying the positive versus the negative adjustment magnitude is the change in blade track.

Vibration levels that will result from the application of the reduced adjustments vectors generated by the adjustment evaluation network are predicted by the vibration prediction network. These predicted vibration levels provide a basis for comparing the effectiveness of the reduced adjustment vectors.

One of the purposes of the track optimization network is to apply the reduced adjustment set to the main rotor in a manner that minimizes the main rotor blade track split. The track optimization network does this as it converts a reduced adjustment vector to a detailed adjustment set on actual rotor blades.

The function of the solution optimization expert is to select a set of adjustments from the list of candidates, which will reduce vibration magnitudes below desired thresholds with as few adjustment moves as possible. This principle makes the solution optimization expert very effective in minimizing the chances for human error because it has been observed that, on average, 20% of adjustments are applied in the wrong direction or to the wrong blade [8].

One of the goals of this study is to characterize the mapping between vibrations and adjustments in the PC-GBS neural networks. Of the four networks that make up the rotor smoothing function in the PC-GBS, it appears that only the adjustment evaluation network and the vibration prediction network contain the vibration/adjustment mappings of interest. Throughout the course of this study it has been assumed that the adjustment evaluation network and vibration prediction network have been fully trained for the UH-60 Blackhawk, AH-64A Apache, and AH-64D Longbow Apache helicopters.

3. Analysis

The Blackhawk, Apache, and Longbow Apache were studied for a broad spectrum of vibration magnitudes. Vibration data were downloaded from an online VMEP database compiled and maintained by Intelligent

Automation Corporation (IAC). For each aircraft type, 20 flights were downloaded from the IAC database, 5 in each of four vibration categories, as shown in Table 1.

The vibration data from the IAC database was analyzed using PC-GBS version 3.0, Build 439, Service Pack 2. All adjustment sets were calculated by stipulating that the maximum number of adjustment moves be used, thus negating the effects of the solution optimization network. This allowed the adjustment evaluation network to produce the most highly defined adjustment sets possible.

For each flight, an entry consisting of vibration vectors (magnitude and phase), predicted vibration vectors, and detailed adjustment values was made in a spreadsheet. The values for each entry were recorded directly from the Vibration tab and the Rotor Smoothing Solution tab of the PC-GBS.

In addition to the analysis performed using PC-GBS, a linear algorithm was created for each aircraft based on the sensitivity coefficients of the US Army's Aviation Vibration Analyzer (AVA). Fig. 1 is a histogram of the 20 UH-60 flights considered in this study. The histogram represents the percent difference between the set of adjustments from PC-GBS to one from the AVA-based algorithm. Only the pitch link and trim tab adjustments can be compared directly, since AVA does not produce weight adjustments based on flight data for the UH-60. It is obvious that there are significant differences between the two adjustment sets. Note that in

Table 1
Vibration categories

Category		UH-60	AH-64A/D
Good	Vert (Lat)	0.0–0.25 (0.0–0.2)	0.0–0.3 (0.0–0.2)
Above	Vert (Lat)	0.25–0.5 (0.2–0.5)	0.3–0.5 (0.2–0.5)
Caution	Vert (Lat)	0.5–0.8 (0.5–0.8)	0.5–0.8 (0.5–0.8)
Exceed	Vert (Lat)	>0.8 (>0.8)	>0.8 (>0.8)

Values are given in inches per second (ips).

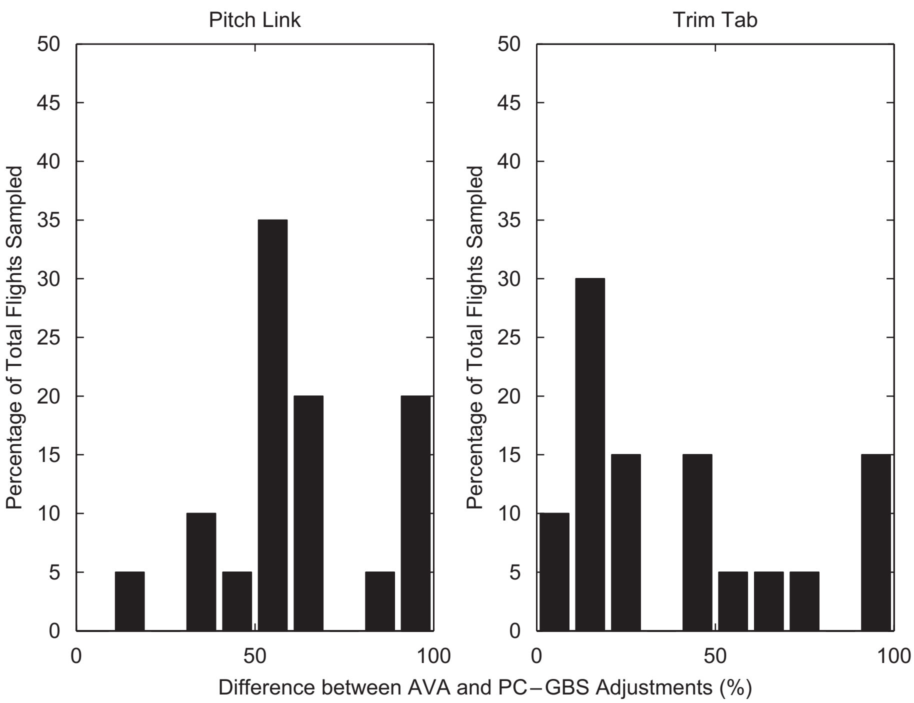

Fig. 1. Histogram of percent difference between PC-GBS adjustments and AVA adjustments for the UH-60, for the weight and pitch link.

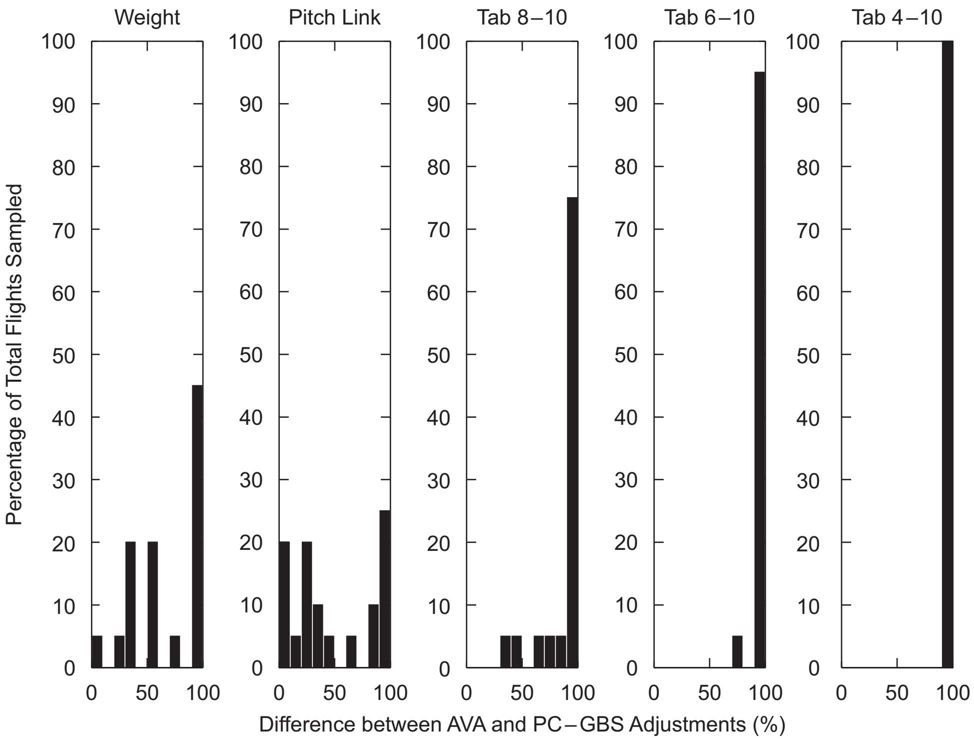

Fig. 2. Histogram of percent difference between PC-GBS adjustments and AVA adjustments for the AH-64A for the weight, pitch link, tab 8–10, tab 6–10 and tab 4–10.

these histograms, when a comparison is said to differ by 90–100%, differences that exceed 100% are also included.

Fig. 2 shows the differences between the VMEP neural network and linear AVA adjustment sets for the AH-64A. Again, for the 20 flights considered, the differences between the neural network and the linear solutions are often large. This does not imply that the mapping in the vibration prediction network is nonlinear. It only means that the AVA and PC-GBS algorithms produce very different adjustments for the same vibration vector.

Fig. 3 shows the differences between the VMEP neural network and linear AVA adjustment sets for the AH-64D. Unlike the previous comparisons, the adjustment sets generated by the neural network and linear algorithms are identical. This clearly indicates that the PC-GBS has learned a linear mapping for the AH-64D that is a near perfect match to the AVA coefficients. While this simple analysis is sufficient to characterize the VMEP neural network mapping for this one aircraft type, a different method must be used to characterize the other two.

In order to characterize the mappings for the UH-60 and the AH-64A, *ad hoc* sensitivity coefficients were developed for every flight. These *ad hoc* coefficients were determined using Eq. (2) with the $\mathrm{Vib}_n^{\mathrm{before}}$ set as the measured vibration vector. $\mathrm{Vib}_n^{\mathrm{after}}$ was set to the vibration level predicted by the VPN, read from the Vibration Values tab of PC-GBS after applying a single ‘‘manual’’ adjustment move of the smallest size (see Table 2). This procedure is identical to the procedure described above for obtaining linear coefficients; except in this case, the VPN was used as a flight simulator.

The *ad hoc* coefficients were then used in the same manner as the AVA coefficients to calculate adjustment sets for each of the 20 flights. The *ad hoc* adjustments were then compared to the adjustments generated by the AEN. Fig. 4 shows the polar plots of the UH-60 weight adjustment sets as determined by the *ad hoc* coefficients and by the PC-GBS. These adjustments are based on measured vibrations ranging from ‘‘good’’ to ‘‘exceed’’.

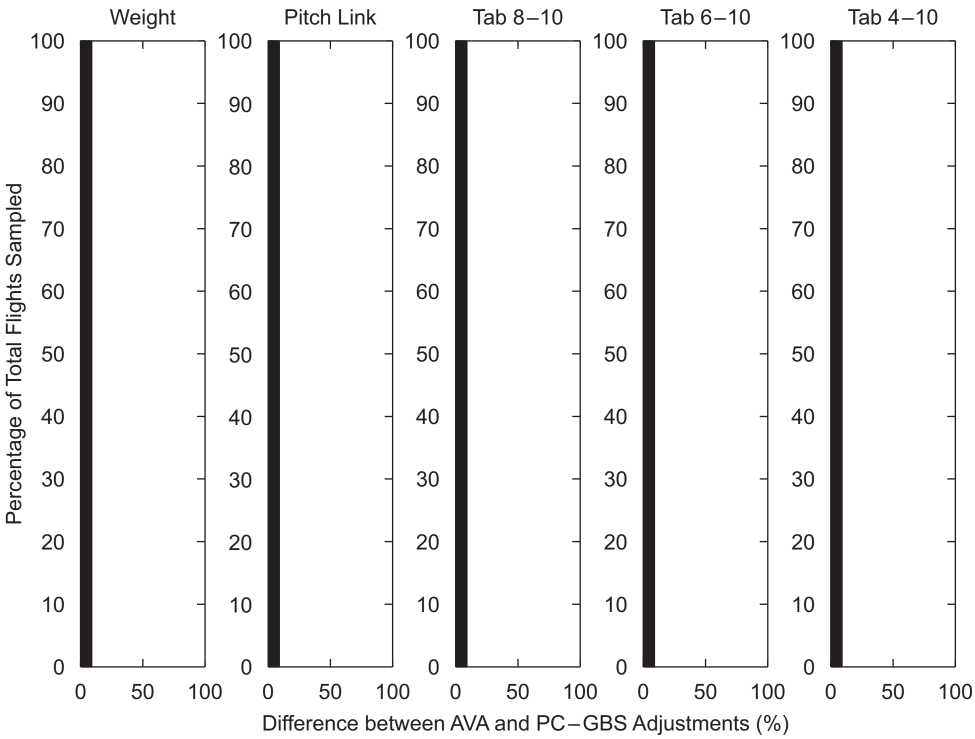

Fig. 3. Histogram of percent difference between PC-GBS adjustments and AVA adjustments for the AH-64D for the weight, pitch link, tab 8–10, tab 6–10 and tab 4–10.

Table 2
Minimum and maximum adjustment moves allowable in PC-GBS

	UH-60		AH-64A/D	
	Smallest	Largest	Smallest	Largest
Weight	5 oz	80 oz	113 g	1017 g
Pitch link	1 notch	30 notches	0.5 flats	12 flats
Trim tab bend	2 mils	20 mils	0.5°	5.0°

For the majority of flights, the PC-GBS and *ad hoc* adjustments are on top of one another, indicating that the PC-GBS and the *ad hoc* linear coefficients produce nearly identical sets of adjustments. This shows that the *ad hoc* linear coefficients accurately reproduce the neural network mapping in the neighborhood of each of the flight conditions.

Similar polar plots could be generated for the remaining adjustments on the UH-60 and each adjustment on the AH-64A and AH-64D. However, a more concise technique for observing similarities in parallel adjustment sets is to tabulate the largest magnitude of dissimilarity for each adjustment type (weight, pitch link, trim tab). For every flight, a delta vector separating parallel adjustments was determined. Table 3 contains the magnitude of the largest delta vector per adjustment type. For reference, the table also contains the minimum adjustment unit that is mechanically allowable on the UH-60. Tables 4 and 5 contain similar information for the AH-64A and AH-64D.

For all three aircraft, it can be seen that the largest adjustment difference is usually greater than the basic adjustment unit. This indicates that the PC-GBS may, under some circumstances, produce slightly different

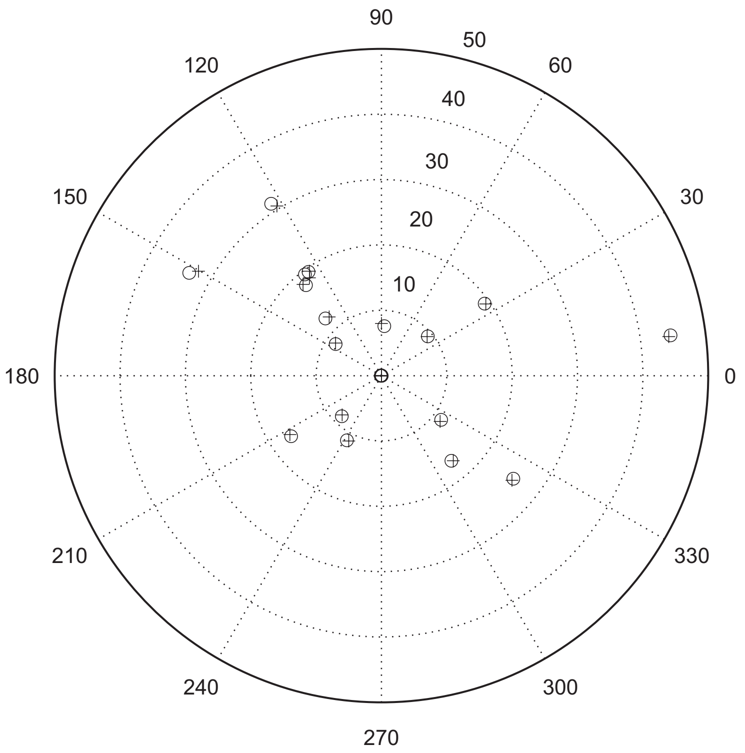

Fig. 4. Weight adjustments for UH-60 as calculated by PC-GBS (+) and by rms small move (○) *ad hoc* coefficients.

Table 3
Largest difference between UH-60 *ad hoc* adjustment sets and PC-GBS adjustment sets

UH-60	Weight (oz)	Pitch link (notch)	Trim tab (mil)
Largest difference	2.178	1.253	4.699
Basic unit	1	1	1

Table 4
Largest difference between AH-64A *ad hoc* adjustment sets and PC-GBS adjustment sets

AH-64A	Weight (g)	Pitch link (flat)	Tab 8–10 (deg)	Tab 6–10 (deg)	Tab 4–10 (deg)
Largest difference	43.78	0.417	0.960	0.838	0.471
Basic unit	52	0.25	0.5	0.5	0.5

Table 5
Largest difference between AH-64D *ad hoc* adjustment sets and PC-GBS adjustment sets

AH-64D	Weight (g)	Pitch link (flat)	Tab 8–10 (deg)	Tab 6–10 (deg)	Tab 4–10 (deg)
Largest difference	96.37	0.492	2.063	1.248	0.437
Basic unit	52	0.25	0.5	0.5	0.5

adjustment sets than the *ad hoc* linear coefficient algorithm. Since the PC-GBS mapping for the AH-64D has already been shown to behave like the AVA mapping, and still has magnitude differences exceeding the minimum adjustment unit, the values noted in these tables should not be interpreted as proof of nonlinearity in the adjustment evaluation or vibration prediction network.

During the course of this analysis, it was observed that the *ad hoc* coefficient matrices were virtually identical from flight to flight. In order to quantify the similarities in the matrices, the *ad hoc* coefficient matrices were summed into a single root-mean-square (rms) coefficient matrix for each type aircraft. All flights for each aircraft were then reevaluated using the appropriate single rms matrix. Tables 6–8 are analogous to Tables 3–5 in that they show the maximum difference between the PC-GBS solution and the *ad hoc* rms solution. When compared to Tables 3–5, it is apparent that the largest difference from the rms matrix adjustments is smaller than the difference from the individual matrix adjustments. The most important observation from examining these tables is that, for each type of helicopter, a single set of linear sensitivity coefficients is capable of producing adjustment sets that are nearly identical to those from the adjustment evaluation network of PC-GBS.

The preceding analysis included an equal distribution of flights from each of the four vibration categories. The results of that analysis showed the mappings in the adjustment evaluation and vibration prediction networks were essentially linear with respect to measured vibration magnitude. The *ad hoc* coefficient matrices that were calculated for each aircraft used the minimum adjustment magnitudes to generate the coefficients. The next part of the analysis addresses the effect of using large adjustment magnitudes to generate *ad hoc* coefficient matrices from the vibration prediction network.

In order to determine whether large adjustment magnitudes result in nonlinear vibration predictions from the vibration prediction network, a second set of *ad hoc* coefficients were created for each flight, using the maximum allowable adjustment magnitudes from Table 2. It was anticipated that if any nonlinear mappings had been learned by the neural network, these new coefficients would produce different sets of adjustments, compared to the previous coefficients generated by using small moves. As shown in Tables 9–11, this is not the case. These tables tabulate the magnitude of the largest difference vector, comparing adjustments determined by the PC-GBS and the *ad hoc* coefficients created using large moves. They also contain the largest difference

Table 6
Largest difference between UH-60 rms *ad hoc* adjustment sets and PC-GBS adjustment sets

UH-60	Weight (oz)	Pitch link (notch)	Trim tab (mil)
Largest difference	1.402	0.475	1.166
Basic unit	1	1	1

Table 7
Largest difference between AH-64A rms *ad hoc* adjustment sets and PC-GBS adjustment sets

AH-64A	Weight (g)	Pitch link (flat)	Tab 8–10 (deg)	Tab 6–10 (deg)	Tab 4–10 (deg)
Largest difference	33.901	0.410	0.426	0.363	0.337
Basic unit	52	0.25	0.5	0.5	0.5

Table 8
Largest difference between AH-64D rms *ad hoc* adjustment sets and PC-GBS adjustment sets

AH-64D	Weight (g)	Pitch link (flat)	Tab 8–10 (deg)	Tab 6–10 (deg)	Tab 4–10 (deg)
Largest difference	14.698	0.066	0.219	0.125	0.043
Basic unit	52	0.25	0.5	0.5	0.5

Table 9
Largest difference between UH-60 large move *ad hoc* adjustment sets and PC-GBS adjustment sets

UH-60	Weight (oz)	Pitch link (notch)	Trim tab (mil)
Largest difference	1.069	0.392	0.394
Largest rms difference	0.779	0.393	0.523
Basic unit	1	1	1

Table 10
Largest difference between AH-64A large move *ad hoc* adjustment sets and PC-GBS adjustment sets

AH-64A	Weight (g)	Pitch link (flat)	Tab 8–10 (deg)	Tab 6–10 (deg)	Tab 4–10 (deg)
Largest difference	37.938	0.672	0.596	0.333	0.366
Largest rms difference	39.219	0.647	0.486	0.360	0.318
Basic unit	52	0.25	0.5	0.5	0.5

Table 11
Largest difference between AH-64D large move *ad hoc* adjustment sets and PC-GBS adjustment sets

AH-64D	Weight (g)	Pitch link (flat)	Tab 8–10 (deg)	Tab 6–10 (deg)	Tab 4–10 (deg)
Largest difference	16.369	0.076	0.259	0.106	0.063
Largest rms difference	9.786	0.041	0.151	0.055	0.026
Basic unit	52	0.25	0.5	0.5	0.5

between the PC-GBS adjustment and the adjustments based on the single rms matrix of the large move, *ad hoc* coefficients.

These tables show that for the UH-60 and the AH-64D, the respective rms matrices of the large moves coefficients produced adjustment sets that were virtually identical to those of the PC-GBS. Fig. 5 illustrates why the large difference exists for AH-64A pitch link adjustments. The small move rms adjustments are also plotted in the figure.

Fig. 5 shows that as the magnitudes of the calculated adjustments grow, so do the differences between large move *ad hoc* adjustments and PC-GBS adjustments. On the other hand, the small move adjustments tend to track well with those of the PC-GBS. This means that the adjustment/vibration mapping of the vibration prediction network closely matches that of the AEN for low adjustment magnitudes but differs at higher magnitudes, thus indicating that nonlinear behavior is present in the AH-64A vibration prediction network for pitch link adjustments. In order to accurately reproduce adjustment sets from the adjustment evaluation network using a linear algorithm, coefficients based on small adjustment moves would be the most appropriate choice for determining pitch link adjustments.

In Fig. 6, the large and small move rms adjustments are an excellent match to each other but consistently produce adjustment magnitudes less than those of the adjustment evaluation network. This indicates that the vibration/adjustment mapping of the vibration prediction network differs slightly from that of the adjustment evaluation network but remains linear at all adjustment magnitudes. The weight, tab 6–10, and tab 4–10 adjustments for the AH-64A all behave in a linear fashion on par with those of the AH-64D and UH-60.

Overall, the rms *ad hoc* coefficients based on large adjustment moves appear, in most cases, to produce adjustment sets that are virtually identical to those offered by the adjustment evaluation network. One final justification for this is demonstrated in Table 12. This table lists the standard deviations of the differences between PC-GBS adjustments and those produced with the rms coefficients of the large move, *ad hoc*

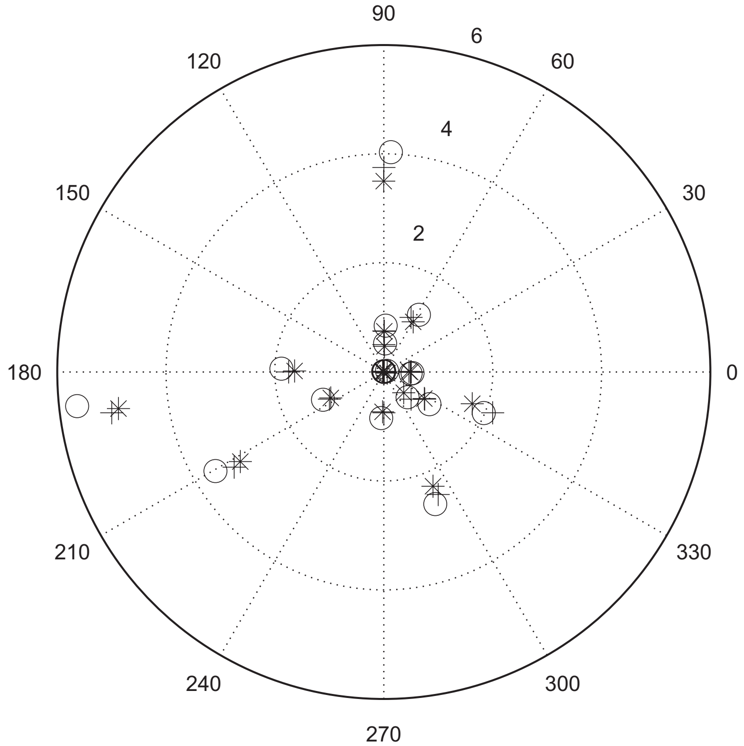

Fig. 5. Pitch link adjustments for AH-64A as calculated by PC-GBS (+) and by rms large move (○) and small move (∗) *ad hoc* coefficients.

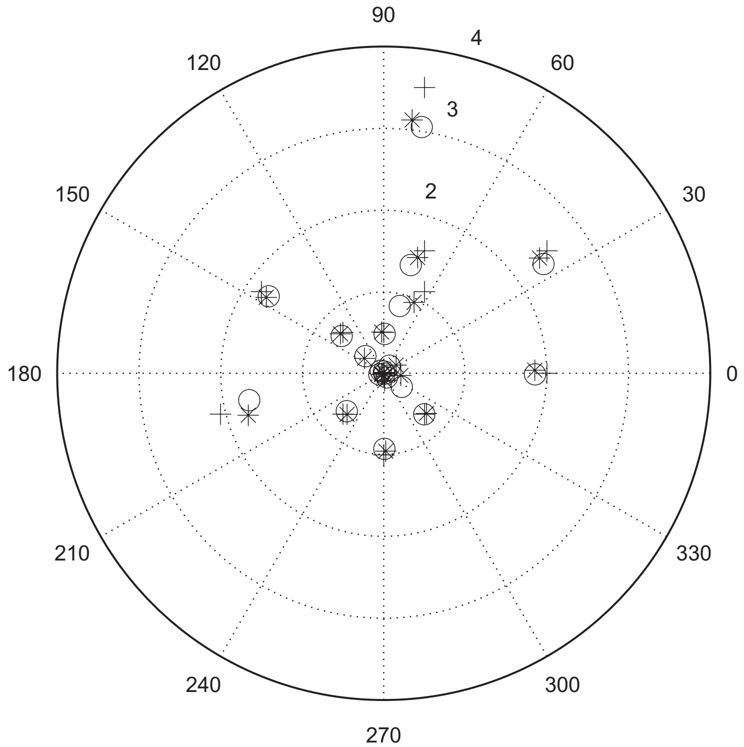

Fig. 6. Tab 8–10 adjustments for AH-64A as calculated by PC-GBS (+) and by rms large move (○) and small move (∗) *ad hoc* coefficients.

Table 12
Standard deviation of the difference in parallel adjustments as determined by PC-GBS and large move, rms *ad hoc* coefficients

	Weight (oz)	Pitch link (notch)	Trim tab (mil)		
UH-60	0.266	0.1	0.1		
	Weight (g)	Pitch link (flat)	Tab 8–10 (deg)	Tab 6–10 (deg)	Tab 4–10 (deg)
AH-64A	8.55	0.15	0.14	0.10	0.07
AH-64D	4.47	0.02	0.06	0.03	0.02

Table 13
UH-60 sensitivity coefficients as determined by large move, rms *ad hoc* coefficients

UH-60	Weight		Pitch link		Trim tab	
	Magnitude	Phase	Magnitude	Phase	Magnitude	Phase
FPG100 (A − B)	0.012437	335.1	0.061253	119.9	0.014479	146.7
Hover (A − B)	0.003777	258.1	0.062257	140.9	0.008360	128.8
Hover (A + B)	5.73e − 06	15.6	0.013415	278.9	0.004451	243.3
80 kts (A − B)	0.003672	261.0	0.027964	114.8	0.005148	99.7
80 kts (A + B)	1.78e − 05	309.2	0.043495	187.9	0.016227	197.2
120 kts (A − B)	0.003595	250.2	0.042692	127.8	0.007671	116.6
120 kts (A + B)	5.66e − 05	273.8	0.068672	176.9	0.026840	191.4
145 kts (A − B)	0.003700	249.2	0.046724	132.0	0.008472	139.5
145 kts (A + B)	4.11e − 05	311.3	0.081355	182.9	0.040795	190.3

Table 14
AH-64A sensitivity coefficients as determined by large move, rms *ad hoc* coefficients. Pitch link coefficients determined using small move, rms *ad hoc* coefficients

AH-64A	Weight	Pitch link	Tab 8–10	Tab 6–10	Tab 4–10
Magnitude	ips/gm	ips/flat	ips/deg	ips/deg	ips/deg
FPG100 (Lat)	0.000588	0.014779	6.39e − 06	1.42e − 05	1.42e − 05
Hover (Lat)	0.000509	0.185371	0.030085	0.063803	0.104823
60 kt (Vert)	0.000369	0.030565	0.154106	0.254046	0.298218
80 kt (Vert)	2.94e − 08	0.079075	0.342480	0.506208	0.756329
100 kt (Vert)	5.48e − 08	0.129714	0.366005	0.552828	0.803414
120 kt (Vert)	3.66e − 08	0.159954	0.452708	0.664427	0.970470
140 kt (Vert)	5.94e − 08	0.235513	0.576983	0.833208	1.330095
Phase	deg	deg	deg	deg	deg
FPG100 (Lat)	169.1	20.7	263.2	64.5	66.7
Hover (Lat)	166.9	54.7	71.0	60.9	50.9
60 kt (Vert)	225.1	220.0	248.1	246.0	258.8
80 kt (Vert)	117.6	268.5	252.1	263.9	261.9
100 kt (Vert)	111.4	267.4	262.1	256.0	260.0
120 kt (Vert)	93.3	248.6	253.0	256.0	260.0
140 kt (Vert)	112.4	246.1	244.0	250.0	238.0

coefficient matrices. These standard deviation values are all smaller than the size of the basic adjustment unit. Tables 13–15 show the *ad hoc* coefficients as determined from calculating the rms of the large move, *ad hoc* coefficients for all flights.

Table 15
AH-64D sensitivity coefficients as determined by rms of large move, *ad hoc* coefficients

AH-64A	Weight	Pitch link	Tab 8–10	Tab 6–10	Tab 4–10
Magnitude	ips/gm	ips/flat	ips/deg	ips/deg	ips/deg
FPG100 (Lat)	0.000491	0.044240	0.000000	0.000000	0.000000
Hover (Lat)	0.000456	0.155225	0.000000	0.000000	0.000000
60 kt (Vert)	0.000468	0.038996	0.159772	0.336765	0.647302
80 kt (Vert)	0.000452	0.063262	0.170617	0.287326	0.735197
100 kt (Vert)	0.000480	0.113166	0.187719	0.314955	0.655976
120 kt (Vert)	0.000451	0.180973	0.214903	0.372574	0.695178
140 kt (Vert)	0.000449	0.242108	0.305237	0.444347	0.903616
Phase	deg	deg	deg	deg	deg
FPG100 (Lat)	163.0	15.5	165.9	165.9	165.9
Hover (Lat)	171.1	57.6	238.3	238.9	238.9
60 kt (Vert)	212.0	286.3	263.6	270.5	256.0
80 kt (Vert)	204.7	273.2	261.6	261.3	259.2
100 kt (Vert)	216.0	262.1	258.7	268.3	256.7
120 kt (Vert)	219.7	256.1	255.8	258.7	255.0
140 kt (Vert)	235.7	247.3	250.3	260.4	250.6

4. Concluding remarks

The principal objective of this study was to characterize the vibration/adjustment mapping as it is known to a trained neural network. This goal was achieved through analysis of the adjustment evaluation network and vibration prediction network of the PC-based ground based system. The results of this analysis show that the adjustment evaluation network and the vibration prediction network (with one exception) behave linearly over all vibratory categories (Table 1) and over the full range of adjustment magnitudes (Table 2). By studying multiple flights on multiple airframes over a broad range of vibration and adjustment magnitudes, it was determined that the PC-GBS mappings can be accurately described by linear sensitivity coefficients. Therefore, it can be concluded that the vibration/adjustment mapping is linear; and that neural networks offer no significant advantage over linear algorithms.

This conclusion may also be extended to other algorithms that might be used to identify nonlinear vibration/adjustment mappings. If the true mapping between vibrations and adjustments were nonlinear, the training of the neural network would have identified those nonlinearities and incorporated them into the network. Since results from the neural network and the linear coefficients were nearly identical, the neural network training did not identify any significant nonlinearities. One can then safely conclude that the vibration/adjustment mappings are linear, and any other algorithm would yield the same result.

The assumption that the vibration/adjustment mapping is linear has been used in the development of rotor smoothing equipment for quite some time, and has substantial support. However, the results of this investigation provide the first quantitative evidence that the linear assumption is indeed valid. It also suggests that inadequacies in the performance of linear rotor smoothing equipment is more likely due to inadequacies in the underlying data used to generate the coefficients.

A study conducted by Wroblewski et al. [8] found that the PC-GBS algorithm outperformed the AVA algorithm by consistently producing adjustment sets for the AH-64 with fewer moves, which resulted in lower predicted vibrations. It is now apparent that the success that the PC-GBS has enjoyed is most likely not due to a unique, nonlinear mapping between vibration levels and adjustments, but rather to improved mapping accuracy, the effects of the solution optimization expert, and other improvements in processing the vibration data and adjustment results. Use of the solution optimization network has resulted in major improvements by decreasing the chances of human error in the main rotor smoothing iterations. This improvement is the result of selecting adjustment sets with a minimum number of moves. While there is a slight degradation in predicted vibration levels, the tradeoff is more than justified when the adjustment moves are applied correctly the first time.

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