Howard J. Taitel[1]
Graduate Research Assistant.

Kourosh Danai
Associate Professor. Mem. ASME.

Department of Mechanical Engineering,
University of Massachusetts,
Amherst, MA 01003

David Gauthier
Dynamics Engineer,
Sikorsky Aircraft,
Stratford, CT 06601

Helicopter Track and Balance With Artificial Neural Nets

Before a helicopter leaves the plant, it needs to be tuned so that its vibrations meet the required specifications. Helicopter track and balance is currently performed based on "sensitivity coefficients" which have been developed statistically after years of production experience. The fundamental problem with using these sensitivity coefficients, however, is that they do not account for the nonlinear coupling between modifications or their effect on high amplitude vibrations. In order to ensure the reliability of these sensitivity coefficients, only a limited number of modifications are simultaneously applied. As such, a number of flights are performed before the aircraft is tuned, resulting in increased production and maintenance cost. In this paper, the application of feedforward neural nets coupled with back-propagation training is demonstrated to learn the nonlinear effect of modifications, so that the appropriate set of modifications can be selected in fewer iterations (flights). The effectiveness of this system of neural nets for track and balance is currently being investigated at the Sikorsky production line.

1 Introduction

Helicopter track and balance is a tuning procedure for reducing both chassis vibration and the spread of rotor blades about a mean position. *Balance*, which is performed for the reduction of vibration, is the more important of the two since it directly affects the performance of the aircraft. *Track*, on the other hand, is performed mainly for aesthetic purposes as it has been found that well positioned rotor blades increase pilot confidence in the aircraft[2]. Both track and balance are performed by making modifications to the rotor blades of the aircraft. Thus, the tuning process consists of determining the blade modification, or the set of blade modifications, that will bring the chassis vibration within specification while simultaneously providing suitable rotor track. Since reduction of vibration is the main goal of the track and balance procedure, modifications are generally made in such a way that vibration characteristics are not compromised based on track considerations.

The current method of track and balance assumes that the effect of blade modifications on both track and balance is linear. As such, sensitivity coefficients are utilized to approximate the effect of individual modifications on track and balance. Although this method is generally effective in tuning the aircraft, it suffers from two major limitations. First, since the derived sensitivity coefficients are based on the assumption of linearity, they are valid for only a limited range of vibration and rotor track. Consequently, the effectiveness of the method diminishes for higher ranges of vibration and rotor track, where nonlinear effects may play a role. Second, the coupling effect of modifications (i.e., nonlinear interactions between modifications) is not taken into account by the sensitivity coefficients. As such, only a limited number of modifications are performed for each flight. Both of the above limitations contribute to an increase in the number of flights required to tune each aircraft, and thus result in increased production and maintenance costs.

In this paper, a system of neural networks trained with back-propagation learning is introduced for helicopter track and balance. Neural nets are particularly suited for nonlinear mapping of multiple inputs and multiple outputs. For this problem, a system of networks is designed to both select the set of modifications that will minimize vibration and rotor track, and predict the vibration and rotor track resulting from such modifications. The designed system, which is trained on actual track and balance data, is currently being tested on production aircraft at Sikorsky Aircraft Company.

[1]Presently with Mathworks Inc., Natick, MA.

[2]This research is concentrated mainly on vibrations at the frequency of once per blade revolution (1 per rev). Although track does not affect the 1 per rev vibrations, it has the potential to excite other main rotor harmonics such as 4 per rev.

Contributed by the Dynamic Systems and Control Division for publication in the JOURNAL OF DYNAMIC SYSTEMS, MEASUREMENT, AND CONTROL. Manuscript received by the DSCD September 1992. Associate Technical Editor: R. Shoureshi.

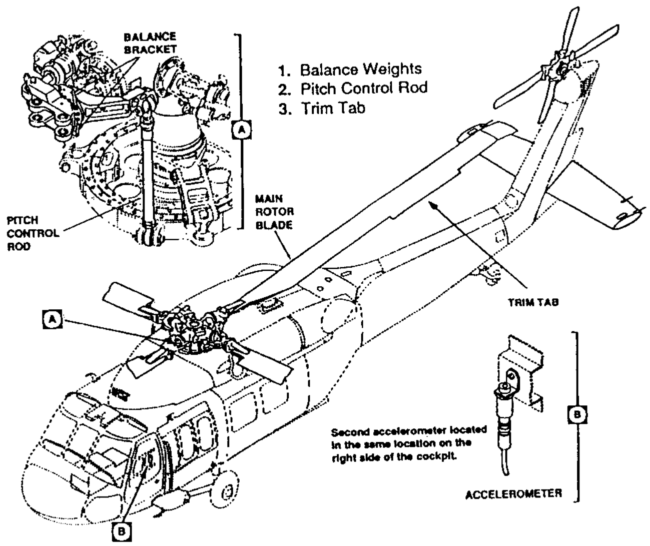

Fig. 1 Illustration of the position of accelerometers A and B on the aircraft, and the rotor blade modifications (push rod, tab, and hub weights)

Table 1 Typical track and balance data recorded during a flight

Flight regime	Vibration			
	A + B		A − B	
	Mag. (ips)	Phase (deg)	Mag. (ips)	Phase (deg)
fpm	0.19	332	0.38	272
hov	0.07	247	0.10	217
80	0.02	86	0.04	236
120	0.04	28	0.04	333
145	0.02	104	0.07	162
vh	0.10	312	0.12	211

Flight regime	Track (mm)			
	Blade #			
	1	2	3	4
fpm	−2	3	1	−2
hov	−1	3	0	−2
80	1	11	1	−13
120	2	13	−1	−14
145	5	18	−3	−20
vh	2	13	−1	−14

2 Track and Balance

Track and balance as applied to Sikorsky's H-60 Black Hawk helicopter is performed as follows. For initial measurements, the aircraft is flown through six different regimes during which measurements of rotor track and vibrations are recorded. Rotor track is measured by optical sensors which detect the vertical position of the blades. Vibration is measured at the frequency of once per blade revolution (1 per rev) by two accelerometers, "A" and "B," attached to the sides of the cockpit (see Fig. 1, detail B). The vibration data is vectorially combined into two components: A + B representing the vertical vibration of the aircraft and A − B representing its roll vibration. A sample of peak vibration levels for the six flight regimes, as well as the angular position of a reference blade corresponding to the peak vibration are given in Table 1, along with a sample of track data.

Table 2 Two sets of detailed modifications represented by a condensed set of modifications

Type of Modification	Blade Number	Detailed Set #1	Detailed Set #2	Blade Numbers	Cond. Set
Push Rod (notches)	1	2	1	Δ13	−2
	2	0	1	Δ24	2
	3	0	−1		
	4	2	3		
Tab (10^{-3} in.)	1	0	0.003	Δ13	−0.003
	2	0.001	0	Δ24	−0.001
	3	−0.003	0		
	4	0	−0.001		
Hub Weight (ounces)	1	5	2	Δ13	−5
	2	3	1	Δ24	−3
	3	0	−3		
	4	0	−2		

The six flight regimes in Table 1 are: ground (fpm), hover (hov), 80 knots (80), 120 knots (120), 145 knots (145), and maximum horizontal speed (vh). The track data indicates the vertical position of each blade relative to a mean position.

In order to bring track and 1 per rev vibration measurements within specification, three types of modifications can be made to the rotor system: pitch control rod adjustments, trim tab adjustments, and balance weight adjustments (see Fig. 1). Pitch control rods can be extended or contracted by a certain number of notches to alter the pitch of the rotor blades. Positive push rod modifications indicate extension. Trim tabs, which are adjustable surfaces on the trailing edge of the rotor blades, affect the aerodynamic pitch moment of the air foils and consequently their vibration characteristics. Tab adjustments are measured in thousandths of an inch, with positive and negative changes representing upward and downward tabbing, respectively. Finally, balance weights can either be added to or removed from the rotor hub to tune vibrations through changes in blade mass. Balance weights are measured in ounces with positive modifications representing the addition of weight. In the case of the Sikorsky H-60 helicopter, which has 4 main rotor blades, a total of twelve modifications can be made to tune the aircraft (i.e., three modifications per blade).

Blade modifications for track and balance can be represented in two forms. The first form, the detailed form, is a list of all twelve blade modifications representing the total track and balance solution. If only vibration (balance) is considered, however, such a detailed specification of the modifications is not necessary. Due to symmetry of the rotor blades in four-bladed aircraft, changes in vibration realized by a modification to a specific blade may alternatively be realized by the negative modification to its opposite blade, or, more generally, by any set of modifications which maintain the relative adjustments to opposite blades. As such, the modifications required for vibration correction can be represented in a condensed form, including up to six relative modifications to pairs of opposite blades. The detailed representation, including all of the twelve modifications, is necessary when track is also considered. Two example sets of detailed modifications which have the same condensed representation are presented in Table 2. It can be seen that the condensed modifications are equivalent to the arithmetic difference of detailed modifications on opposite blade pairs 1 and 3, and 2 and 4[3].

[3]Condensed modifications on the 1 and 3 blade pair represent relative modifica-

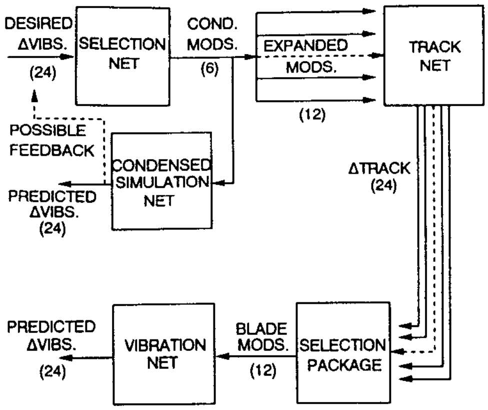

Fig. 2 Schematic of the track and balance system. The numbers inside parentheses represent the number of inputs or outputs of individual nets

3 Neural Net-Based Track and Balance

In practice, track and balance is performed by first specifying a condensed set of modifications to reduce vibrations, and then expanding these modifications into a detailed set to satisfy the track requirements. The detailed modifications are constrained by the condensed set as to maintain the integrity of the vibration solution. This sequential method is in contrast to a simultaneous solution of track and balance, which gives the same priority to both track and balance. In order to preserve the priority of vibration reduction, the proposed neural network-based system of track and balance utilizes the sequential method.

The system of track and balance consists of four neural nets as shown in Fig. 2. The first net in this system, the SELECTION NET, determines the condensed blade modifications (output) that will bring about a given change in vibration (input). To eliminate vibration, the negative of the vibration measurements from the flight are utilized as inputs to this net. The validity of the condensed modifications is then checked by predicting their effect on vibration via the CONDENSED SIMULATION NET. Theoretically, these simulated vibration changes should be the negative of the vibration measurements from the aircraft, so that their summation will generate a resultant vibration equal to zero. However, due to the inexactness of the neural net models and noise, the resultant vibration will most likely not be equal to zero. In cases where the resultant vibration is not within specifications (usually less than 0.20 ips), the condensed modifications may be refined by feeding the resultant vibration back into the SELECTION NET. This feedback is depicted in Fig. 2 by the dashed feedback line. It should be noted that the CONDENSED SIMULATION NET may also serve as a diagnostic tool by indicating out-of-norm behavior. For example, an aircraft with vibrations significantly different from those predicted by the net may suffer from deffective components.

Just as with the traditional approach, once the condensed solution has been specified, it needs to be expanded into detailed form to satisfy the rotor track requirements. As previously mentioned, the condensed set of modifications may be viewed as the constraint on detailed modifications so as to ensure that the vibration solution is not compromised for track. This constraint is satisfied by algebraic equations in the expansion program which generates detailed modifications from the condensed set (see Fig. 2):

$$\Delta 3 - \Delta 1 = \Delta 13 \tag{1}$$

$$\Delta 4 - \Delta 2 = \Delta 24 \tag{2}$$

In the above equations, $\Delta 3$, for example, represents the change in push rod, tab, or hub weight of blade #3, and $\Delta 13$ represents the change relative to the change of that parameter in the opposite blade #1. Each one of these detailed sets of modifications is a candidate for the final track and balance solution, and it is left to the TRACK NET and the SELECTION PACKAGE to determine which set of detailed modifications provides the best tracking performance. For selection purposes, the TRACK NET simulates the changes in track due to a candidate set of detailed modifications, and then adds these changes to the initial track measurements from the flight to estimate the resultant track. The set of detailed modifications that yields the smallest estimated track (i.e., smallest maximum blade spread) is selected as the solution to the track and balance problem. The selected set of detailed modifications is then checked via the VIBRATION NET, which similar to the CONDENSED SIMULATION NET, serves as an independent evaluator of the selected modifications. This validation is performed by simulating the effects of the selected modifications and adding them to the aircraft vibrations so as to estimate the resulting aircraft vibrations.

4 System Training

Track and balance data for approximately one hundred and ten pairs of consecutive flights were used for training and testing of the system. Generally, two types of data were required for training the neural nets: 1) changes in vibration caused by blade modifications and 2) changes in track due to these modifications. Since vibration data are vector quantities (see Table 1), both their magnitude and phase components need to be taken into consideration. In order to keep all of the inputs on the same scale, the vibration vectors were represented to the net in cartesian coordinate form. As a result, the vibration data included 24 elements representing the changes in the x and y components of the A + B and A − B vibration in each of the six flight regimes (see Table 1). To ensure that the nets were properly trained, issues such as noise and generalization needed to be addressed.

4.1 Noise. Ideally, identical modifications made to any two helicopters should result in identical changes in vibration. In reality, however, this does not occur due to factors such as small differences between individual aircraft and variances in atmospheric flight conditions (i.e., weather). Prior to neural net training, the severity of the noise problem was investigated by studying the effect of identical modifications on vibration changes (Δvibrations) of different aircraft. One such set of results is shown in Fig. 3 where adjacent pairs of bars represent changes in the x (cos) and y (sin) components of A + B vibration that resulted from an identical set of modifications to two different aircraft. The results indicate that, as expected, large variations exist between the vibrations, and that in some cases the Δvibrations are so

tions of blade 3 with respect to blade 1 and modifications on the 2 and 4 blade pair represent relative modifications of blade 4 with respect to blade 2.

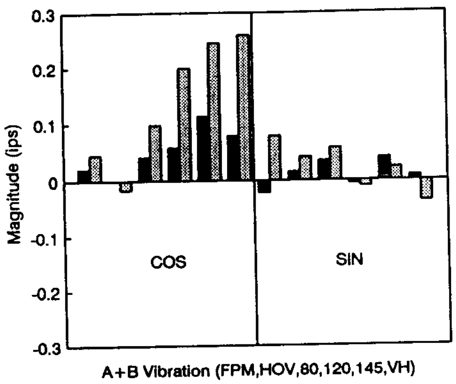

Fig. 3 Δvibrations of two aircraft caused by an identical set of modifications

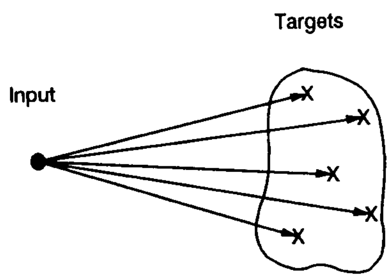

Fig. 4 Illustration of one-to-many mapping faced by the CONDENSED SIMULATION NET and VIBRATION NET due to noise

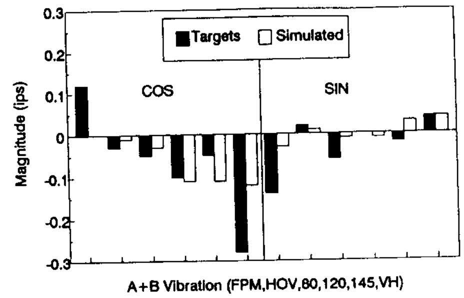

Fig. 5 Predicted Δvibrations by the CONDENSED SIMULATION NET compared with their target values

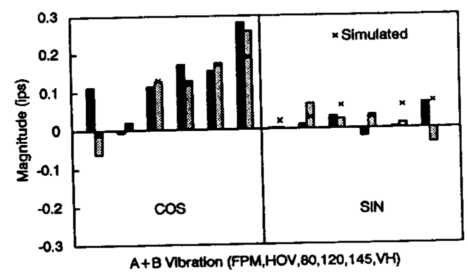

Fig. 6 Predicted Δvibrations by the CONDENSED SIMULATION NET (shown by the *x*) compared with their multi-targets (adjacent bars).

inconsistent that they actually differ in direction. This variation is caused by inevitable dissimilarities between various aircraft and rotor blades, and non-uniformity of flight conditions due to variations in weather. (Similar variations are observed in A − B vibration measurements.)

The implication of noise for neural net training is illustrated in Fig. 4 where the target for a set of inputs is not unique, but consists of many targets due to the inconsistency of the data. The fact that one input is mapped to various targets makes learning difficult, and the best that the net can do in such cases is to provide mapping to a target that represents the average of all of the targets.

4.2 Generalization and Net Structure. Generalization is defined as the ability of a trained net to correctly classify patterns not included in the training set. Since, in general, only a finite number of input-output data is available for training, the ability of the net to generalize to patterns it has not "seen" will ultimately determine its effectiveness. In some cases, a net's inability to generalize in the presence of noise may be caused by overfitting the data during training (Hertz et al., 1991). The issue of overfitting is particularly important in the case of helicopter vibration because of the high level of noise in the training data.

The complexity of the functions which can be learned by neural net models is directly related to the number of hidden units. Therefore, an important factor in generalization is the number of hidden units of the neural net (Kung and Hu, 1991; Rumelhart et al., 1991). In general, the "best" number of hidden units is not known a priori and needs to be determined. The usual method of trial and error was used to determine the optimal number of hidden units for each net. In these trials, the criteria for "best network performance" was the sum of the absolute error on a set of ten test patterns (i.e., patterns not used during training). As an example of generalization ability, test results for the CONDENSED SIMULATION NET, in which 14 hidden units were used, are presented in graphical form in Fig. 5. It can be seen that although some of the Δvibrations are accurately predicted by the net, others, the "FPM" regime for example, are not well predicted. Such absolute comparison, however, is not appropriate in view of the large amount of noise present in the data. In order to study these results in the context of the existing noise, predicted Δvibrations from the CONDENSED SIMULATION NET (represented by the "*x*") are compared against two target sets of Δvibrations that resulted from the same set of modifications (depicted by adjacent bars) in Fig. 6. The results indicate that the net's output lies within the range of variability of its target values, and given the inconsistancy of the data is in fact providing reasonable generalization. Note that the targets here are from test cases that have not been "seen" before by the net.

Many alternatives to the method of trial and error for determining the number of hidden units have been proposed. Some notable methods include determining the optimal number of hidden units 'a priori' through unsupervised learning (Sanger, 1991), pruning procedures (Rumelhart et al., 1991; Kung and Hu, 1991; Hertz et al., 1991), and various cross-validation techniques (Wada and Kawato, 1991; Utans and Moody, 1991). Pruning procedures reduce model complexity either by removing low activation units (i.e., units that contribute little to the output) or by removing unnecessary weights, or connections, between units. The effectiveness of pruning weights was investigated through the weight decay algorithm (Hertz et al., 1991). However, upon close inspection of the trained networks it was found that the

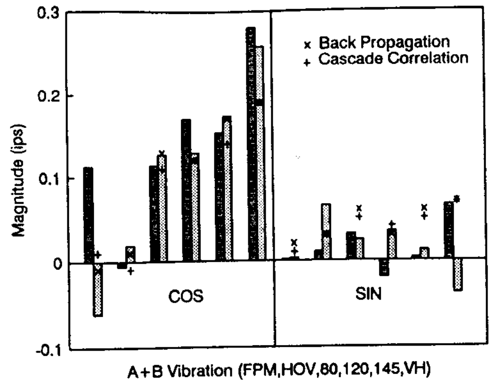

Fig. 7 Test results comparing the generalization capability of the cascade correlation algorithm with back-propagation

majority of the weights were relatively small, and since weight decay was targeted at removing the smaller network weights, it resulted in the removal of most of the internal structure of the net. The remaining larger weights were unable to compensate for the removed weak connections, and, as a result, the performance of the net deteriorated.

A more severe departure from standard back-propagation is the cascade correlation algorithm (Fahlman and Labiere, 1990) which takes the approach of "growing" a neural net. This algorithm starts with no hidden units and adds additional ones as training progresses. Each new unit is selected so as to maximize the correlation between its output and the residual training error. Once a unit has been added, the input weights to that unit are not changed. It has been argued that this "freezing" of weights may yield improved generalization (Whitley and Karunanithi, 1991). Also, since in the cascade correlation algorithm the error is not back-propagated, this algorithm is expected to learn orders of magnitude faster than the standard back-propagation algorithm. Fahlman and Labiere's cascade correlation algorithm (1990) was used to train the CONDENSED SIMULATION NET. The test results for A + B vibrations from this algorithm are compared with those produced by the back-propagation algorithm in Fig. 7, where the pairs of bars represent the actual changes in vibration of two different helicopters resulting from identical modifications, and the *x*s and +s represent the predictions by the back-propagation and cascade correlation nets, respectively. The results indicate that the generalization performance of cascade correlation is virtually the same as that of back-propagation. Consequently, the use of cascade correlation was not pursued.

Overtraining also causes poor generalization due to overfitting the data (Rumelhart et al., 1991; Matsuoka, 1991). To avoid overtraining, in-training cross-validation was employed, which consists of periodically monitoring the performance of the net on the test set so that training can be stopped once generalization (test set error) begins to deteriorate.

The number of hidden units and learning parameters for the four nets in the Track and Balance system are given in Table 3. Some typical test results for the SELECTION NET are also shown in Table 4 indicating that the performance of the net is quite good. Note that the SELECTION NET, contrary to the simulation nets, performs many-to-one mapping of small regions ("clouds") of input space to specific outputs. So, it provides better prediction.

Table 3 Topology of the nets used in the system of track and balance

Neural net	Hidden units	Learning rate	Momentum coefficient	Sigmoid range
Selection Net	10	0.3	0.6	0 – 1
Cond. Sim. Net	14	0.3	0.6	0 – 1
Track Sim. Net	10	0.3	0.6	0 – 1
Vibration Net	8	0.3	0.6	0 – 1

Table 4 Test results comparing the output of the SELECTION NET with its target values

	Push Rod (notches)		Tab (10^{-3} inches)		Hub Weights (ounces)	
Simulated	0	−2	0	0.005	0	0
Actual	0	−2	0	0.005	0	0
Simulated	0	−2	0	0.004	0	0
Actual	0	−1	0	0.004	0	0
Simulated	−5	5	0.010	−0.010	0	0
Actual	−6	5	0.010	−0.009	0	0
Simulated	0	−4	0.001	0	0	0
Actual	0	−5	0.004	0	0	0

5 Results

Ideally, the performance of the neural net-based system of track and balance should be evaluated "side by side" against that of the traditional method. However, such an evaluation would entail flying the aircraft with the modifications from one method, measuring the vibration and track, undoing the changes, and flying the aircraft with the modifications from the other method, so that their vibration and track measurements can be compared. Unfortunately, such an exercise is prohibitively costly and cannot be justified in production environment. A less ideal approach would be to evaluate the performance of the system based on the existing track and balance data, by comparing the system's simulated vibrations and track with those obtained from the modifications of the traditional method. However, that approach would have the problem of being biased toward the neural net-based system by ignoring the inaccuracies of the simulated results. In order to avoid misleading conclusions, the overall performance of the neural net-based system was evaluated independently in production.

Track and balance data from an aircraft before the application of the system are shown in Table 5 in which the A + B "145" knots and "VH" vibrations are above the acceptable limit of 0.2 ips. To determine the required blade modifications, the negative of the measured vibrations were specified as the "desired Δvibration" for the Track and Balance System (see Fig. 2). The modifications determined by the system and subsequently performed on the aircraft are shown in Table 6, and the vibration and track of the aircraft after these modifications are shown in Figs. 8 and 9, respectively. The results indicate that all twelve vibration measurements are within the acceptable range (below the dashed line in Fig. 8), and that the majority of the track measurements have been reduced[4]. The results obtained are indicative of the

[4]These results were obtained from one pass through the Selection Net.

Table 5 Track and balance data recorded during an initial flight

Flight regime	Vibration			
	A + B		A − B	
	Mag. (ips)	Phase (deg)	Mag. (ips)	Phase (deg)
fpm	0.06	92	0.15	96
hov	0.05	155	0.03	289
80	0.04	268	0.04	350
120	0.16	346	0.01	344
145	0.35	325	0.06	261
vh	0.54	330	0.16	274

Flight regime	Track (mm)			
	Blade #			
	1	2	3	4
fpm	−4	6	−7	5
hov	−5	4	−4	5
80	−1	6	−8	4
120	2	11	−17	4
145	5	6	−28	17
vh	12	−2	−33	22

Table 6 Modifications selected to zero the vibration and adjust the track of Table 5

Push rod (notches)				Tab (10^{-3} in.)				Hub Weights (ounces)			
0	0	−3	0	0	0	0.008	−0.003	0	0	0	0

system's ability to tune the aircraft within one flight, which could be rarely achieved with the traditional method.

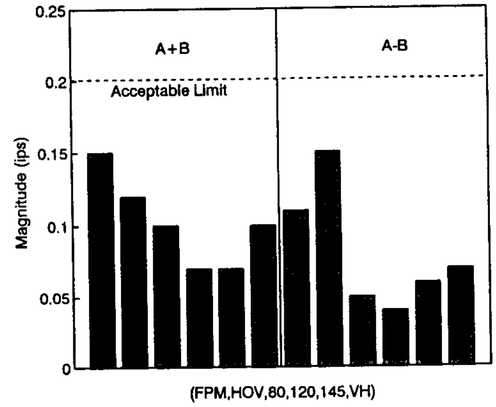

Fig. 8 Resultant aircraft vibration (magnitude only) due to modifications in Table 6

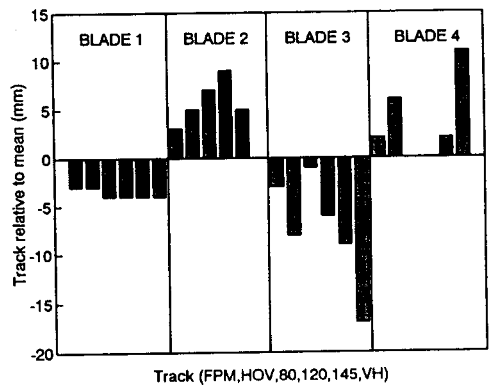

Fig. 9 Resultant aircraft track due to modifications in Table 6

References

Fahlman, S. E., and Lebiere, C., 1990, "The Cascaded-Correlation Learning Architecture," Technical Report No. CMU-CS-90-100, School of Computer Science, Carnegie Mellon University.

Hertz, J. A., Krogh, A. S., and Palmer, R. G., 1991, *Introduction to the Theory of Neural Computation*, Addison-Wesley, Redwood City, CA.

Jordan, M. I., and Rumelhart, D. E., 1992, "Forward Models: Supervised Learning with a Distal Teacher," *Cognitive Science*, in print.

Kung, S. Y., and Hu, Y. H., 1991, "A Frobenius Approximation Reduction Method (Farm) for Determining Optimal Number of Hidden Units," *Proc. IJCNN*, IEEE, Seattle, WA, July, pp. 163–168.

Matsuoka, K., 1991, "An Approach to the Generalization Problem in the Backpropagation Method," *Systems and Computers in Japan*, Vol. 22, No. 2, pp. 897–905.

Rumelhart, D. E., Weigend, A. S., and Huberman, B. A., 1991, "Generalization by Weight-Elimination applied to Currency Exchange Rate Prediction," *Proc. IJCNN*, IEEE, Seattle, WA, July, pp. 837–841.

Sanger, T. D., 1991, "Optimal Hidden Units For NonLinear FeedForward Neural Networks," *Pattern Recognition and Artificial Intelligence*, Vol. 5, No. 4, pp. 545–561.

Utans, J., and Moody, J., 1991, "Selecting Neural Network Architectures via the Prediction Risk: Application to Corporate Bond Rating Prediction," *Proc. First International Conference on Artificial Intelligence Application on Wall Street*.

Wada, Y., and Kawato, M., 1991, "Estimation of Generalization Capability by Combination of New Information Criterion and Cross Validation," *Proc. IJCNN*, IEEE, Seattle, WA, July, pp. 1–6.

Whitley, D., and Karunanithi, N., 1991, "Generalization in Feed Forward Neural Networks," *Proc. IJCNN*, IEEE, Seattle, WA, July, pp. 77–82.