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NEURAL NETWORK REPRESENTATION OF EXPERIMENTAL TILT-ROTOR NOISE

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Summary

Results from a neural network study of full-scale experimental XV-15 tilt-rotor noise are presented. An XV-15 database, acquired during the 1998 NASA Ames 80- by 120-Foot Wind Tunnel test, was used. This existing database was acquired to establish the blade vortex interaction (BVI) noise signature of a full-scale tilt-rotor. The present study had the following three objectives. The first objective was to assess, using neural networks, the quality of the noise data. The second objective was to obtain neural network representations of the noise data and demonstrate their sensitivity to test conditions. The third objective was to obtain neural-network-based noise predictions, while using a minimum amount of input data. Neural networks were successfully used to assess the quality of noise data. The quality of the experimental noise data was found to be acceptable. Neural networks were successfully used to represent the complete, experimental tilt-rotor noise database. Accurate neural network representations were obtained for the test-condition-sensitivity cases. Neural networks were successfully used to predict tilt-rotor noise using a small amount of input data. Both the radial-basis function (RBF) and the back-propagation types of neural networks were used. For contour plots, the RBF neural network was found preferable over the back-propagation neural network.

Notation

A	Rotor disc area, πR^2, m^2
BVI	Blade vortex interaction
BVISPL	Blade vortex interaction sound pressure level, 30th to 150th rotor harmonics, dB
C_T	Rotor thrust coefficient, thrust / $\rho A V^2_{tip}$
MIMO	Multiple-input, multiple-output
MISO	Multiple-input, single-output
PE	Neural network processing element
R	Rotor radius, m
RBF	Radial-basis function
V	Wind tunnel airspeed, m/s
V_{tip}	Blade tip speed, ΩR, m/s
α_s	Rotor shaft angle, positive nose up, deg
μ	Rotor advance ratio, $V \cos \alpha_s/(\Omega R)$
σ	Rotor solidity ratio
Ω	Rotor rotation speed, rad/sec

Introduction

Growing public sensitivity to rotorcraft noise has forced the rotorcraft community (industry, government, and academia) to be innovative in reducing rotorcraft external noise (Ref. 1). Tilt-rotors are in a class in themselves, and their acceptance by the public is a very important and a much-awaited milestone. To facilitate tilt-rotor noise reduction efforts, it is important to develop an analytical capability that enables data quality assessment and representation of experimental tilt-rotor noise databases.

The advantages of rotorcraft wind tunnel testing include cost and safety benefits, as the rotorcraft model is rigorously evaluated prior to its first flight test. By allowing significant operational variations to be systematically introduced into the test conditions, wind tunnel tests of experimental models provide valuable data. Further, these wind tunnel test conditions can be well outside the flight envelope. Thus, a wind tunnel test can encompass a larger test envelope compared to a flight test, making wind tunnel testing indispensable.

Rotorcraft noise measurement and prediction involve a high level of complexity, and it is difficult at times to even heuristically know the variation of the test data with changes in operating conditions. Since the test data trends may be new and without precedent, it becomes difficult to expeditiously isolate "bad" data points from the "good" points. As such, it is more difficult to interpret the quality of the measured data and the trends projected by wind tunnel tests.

This paper presents results from a neural network study conducted to assess the quality of full-scale wind tunnel tilt-rotor noise data, and also to represent such data. These wind tunnel data were acquired from a test performed in support of NASA's Short Haul Civil Tilt-rotor (SH(CT)) program. In the present study, the use of neural networks is justified because of their multi-dimensional, nonlinear curve fitting characteristics. The present work is considered to be a generic methodology and is not specific to the presently considered tilt-rotor configuration. Neural network studies on rotorcraft performance and dynamics were initiated in the Army/NASA Rotorcraft Division at NASA Ames Research Center, as discussed in Refs. 2 to 7. The experience gained from these neural network studies was very useful in the present study on tilt-rotor noise.

Objectives

The present neural-network-based, full-scale XV-15 tilt-rotor noise study had the following objectives:

1. Assessment of Test Data Quality Using Neural Networks

   a. Conduct "coarse" data quality checks.

   b. Conduct more involved "fine" data quality checks.

2. Representation of Test Data Using Neural Networks

   a. Demonstrate sensitivity of the noise to test parameters, for example, the advance ratio and separately, the thrust coefficient.

   b. Produce contour-plots using neural-network-based results, and study the implications of using half the available data for neural network training purposes.

3. Prediction of Noise Using Neural Networks

   Use neural networks to predict tilt-rotor noise at a test condition not included in the neural network training database. This includes the following: modeling and prediction of multiple noise variations using a minimum amount of input data. The input data consist of the defining test condition parameters and the corresponding, unique "reference" noise curves.

Tilt-Rotor Test Database Description

Full-scale XV-15 tilt-rotor noise test data for forward flight conditions (Ref. 8) were analyzed in this paper. As noted in Ref. 8, the overall objective in acquiring the above data was to establish the blade vortex interaction (BVI) noise signature of a full-scale tilt-rotor. The wind tunnel testing approach was described in Refs. 8 and 9. The 25-ft diameter right hand, three-bladed tilt-rotor was installed on the NASA Ames Rotor Test Apparatus and tested in the Ames 80- by 120-Foot Wind Tunnel. The shaft angle was varied from -15 deg (nose down) to +15 deg, from a vertical orientation. The present study considers noise test data with a rotor tip Mach number of 0.69.

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 or back-propagation network, etc.) and its complexity (i.e., the number of processing elements (PEs) and the number of hidden layers). The present overall neural network modeling approach (Refs. 2 to 7) consists of first determining the best type of neural network to be used and then simplifying the network as much as is practical.

Determining the best type of neural network usually involves selecting either a radial-basis function (RBF) or a back-propagation network. Reference 10 notes that the RBF network (Moody-Darken version) "can be used in most situations in which one would consider using a back-propagation network." In the present study, both types of networks were used.

Simplifying the network involves reducing the number of PEs and in a few cases, the number of hidden layers. The number of PEs required depends on the specific application. The determination of the appropriate number of PEs is done by starting with a minimum number of PEs. Additional PEs are added to improve neural network performance by reducing the RMS error between the test data and the neural network predictions. Typically, five PEs are initially added at each step in this process. Adding two or three PEs at a time "fine-tunes" the neural network.

If the correlation plot, comparing measured and predicted values, shows only small deviations from the 45-deg reference line, the neural network has produced an acceptable representation of the subject test data. If the plot shows points well off of the 45-deg line, the presence of "bad" test data is assumed. A detailed examination of the subject test database is then required to identify the source(s) of the errors associated with these test data.

The notation used in this paper to characterize a neural network is described as follows. A neural network architecture such as "4-25-5-1" refers to a neural network with four inputs, twenty five processing elements (PEs) in the first hidden layer, five PEs in the second hidden layer, and one output.

Results

The application of neural networks to full-scale tilt-rotor noise data was conducted using the neural networks package NeuralWorks Pro II/PLUS (version 5.2) by NeuralWare (Ref. 10). The present neural network RMS error was dimensionless and based on the squares of the errors for each processing element (PE) in the output layer. Generally, the RMS error was characterized by a monotonic decrease with the number of training iterations (Ref. 7). Also, any large differences in the magnitudes of the neural network variables were mitigated by appropriate scaling. In the present application, the "cost function" used in minimizing the RMS error had equally weighted individual contributions.

The results from the neural network study using full-scale XV-15 tilt-rotor noise data are presented below. The noise was characterized using a BVISPL measure (blade vortex interaction sound pressure level, 30th to 150th rotor harmonics, dB). For test conditions involving traverse sweeps, the corresponding database consisted of 96 points (measurements at 12 traverse locations using 8 microphones). The largest ("complete") noise database considered in this study had over 4000 data points (Ref. 8). The neural network inputs and output(s) depend on the specific application under consideration and are given later.

Neural Network Based Data Quality Assessment

An overall assessment of the quality of the wind tunnel noise data was obtained by considering the complete noise database. This complete database included over 4000 data points, which were used as training data for the neural networks. The five wind tunnel test parameters used as the neural network inputs were as follows: advance ratio, μ, shaft angle, α_s, thrust coefficient ratio, C_T/σ, the microphone traverse location, and the microphone position within the traverse. Since the positions of the eight microphones are fixed with respect to the traverse, an equivalent "microphone number" can also be used.

Compared to the neural network tilt-rotor performance application reported in Ref. 2, which involved approximately 300 training data points, the present, complete, experimental noise database was relatively large. Thus, the present data quality assessment procedure was split up into two steps. The first step involved "coarse" correlation curve fits. The second step involved "fine" correlation curve fits, and involved more complex networks and a larger number of training iterations. In contrast to a representation type of application, the "coarse" data quality assessment application does not require the neural networks to produce accurate curve fits. In the data quality assessment examples that follow, the coarse and fine error bands were +/- 4 dB and +/- 2 dB, respectively.

Coarse Data-Quality-Assessment The results from the coarse correlation step are shown in Figs. 1 to 3. Figure 1 shows the correlation plot from a MISO 5-25-5-1 RBF neural network using the complete, experimental noise database as the training database. The RBF network was trained for 4 million iterations with a final RMS error of 0.07. For the results shown in Fig. 1, correlation points far away from the 45 deg correlation line were judged as "bad" test data points. A detailed examination of the noise database showed that these "bad" points were from test point 25 of run 139. The test parameters for this test condition were: μ = 0.169, α_s = -15 deg, and C_T/σ = 0.06. The test Run Log for run 139 notes the presence of "gusty south winds affecting μ and C_T/σ," which could adversely affect data quality.

Figure 2 shows the coarse correlation plot obtained by using a training database in which the eight microphone measurements from test point 25 of run 139 (α_s = -15 deg) were omitted from the complete training database. Figure 2 shows the correlation plot from a MISO 5-25-5-1 RBF neural network. The RBF network was trained for 4 million iterations with a final RMS error of 0.06. Figure 2 does not contain the "bad" points seen in Fig. 1.

Figure 3 shows the coarse correlation plot obtained by using a training database in which all α_S = -15 deg points (152 in number) were omitted from the complete training database. Figure 3 shows the correlation plot from a MISO 5-25-5-1 RBF neural network. The RBF network was trained for 4 million iterations with a final RMS error of 0.08. Figure 2 and 3 were similar to each other in that no outstanding "bad" points can be seen. Thus, the "bad" data seen in Fig. 1 were associated with only one test condition, point 25 of run 139. Figures 1 to 3 demonstrated the ability of neural networks to indicate noise data of poor quality.

Fine Data-Quality-Assessment Figure 4 shows the fine correlation plot obtained by using the same database as that used in Fig. 2. The eight microphone measurements arising from test point 25 of run 139 (α_S = -15 deg) were omitted from the complete training database. Figure 4 shows the correlation plot from a MISO 5-75-25-1 back-propagation neural network. This more complex back-propagation network was trained for 8 million iterations (double the number used in the coarse correlation step) with a final RMS error of 0.02. Figure 4 showed that the quality of the noise data was acceptable, to within a +/- 2 dB band. The representation aspects of this result are discussed below.

Neural Network Representations

Complete, Test Database Representation The preceding result, Fig. 4, also demonstrated the ability of neural networks to represent the experimental noise data within an acceptable level of accuracy (+/- 2 dB), and involved over 4000 data points. The Contour Plots section given later contains a comparison of the neural-network-based contour based on the above "+/- 2 dB" representation with the test data contour.

Sensitivity to Test Conditions Variations in advance ratio and thrust coefficient were separately considered. A near maximum BVI condition (μ = 0.170, α_S = 3 deg, and C_T/σ = 0.091) was taken as the "baseline" test condition about which the variations were considered.

Forward Speed Variation. Three advance ratios were considered (μ = 0.125, 0.170, and 0.200), with α_S = 3 deg and C_T/σ = 0.091. The three neural network inputs were the advance ratio, the traverse location, and the microphone position. Figure 5 shows the correlation plot from a MISO 3-15-5-1 back-propagation neural network involving approximately 300 training data points. The back-propagation network was trained for 1 million iterations with a final RMS error of 0.02. The neural network representation was acceptable, to within +/-1 dB.

Thrust Variation. Four thrust coefficient ratios were considered (C_T/σ = 0.060, 0.075, 0.091, and 0.100), with μ = 0.170 and α_S = 3 deg. The three neural network inputs were the thrust coefficient ratio, traverse location, and the microphone location. Figure 6 shows the correlation plot from a MISO 3-15-5-1 back-propagation neural network involving approximately 400 training data points. The back-propagation network was trained for 1 million iterations with a final RMS error of 0.04. The neural network representation was acceptable, to within +/-1 dB.

Contour Plots Neural-network-based contour plots were obtained for at a tilt-rotor operating condition involving maximum blade vortex interaction (μ = 0.200, α_S = 4 deg, and C_T/σ = 0.075). The corresponding experimental noise contour with 96 data points is shown in Fig. 7 (the approximate rotor circle is also shown in the figure). The contour points are identified by their microphone number (1 to 8) and the traverse location, Fig. 7. This case involved 96 neural network training points. The microphone traverse location and the microphone position were the two neural network inputs. The BVISPL noise measure was the single neural network output

Figure 8 shows the representation for the "100%" case using a radial-basis function (RBF) neural network and training data from all 12 traverse locations (involving 96 test points). Figure 8 shows the contour plot from a MISO 2-28-7-1 RBF neural network. The RBF network was trained for 4 million iterations with a final RMS error of 0.02. This RBF neural network representation is accurate. Also, equally good results were obtained for the above "100%" case using a back-propagation neural network. These back-propagation results are not shown in this paper.

Figure 9 shows the representation for the "50%" case using an RBF neural network and training data from six traverse locations (involving 48 test points). The "50%" case is important because halving the number of traverse locations reduces the run time by approximately 50% per traverse sweep. The six traverse locations were selected by starting out with the 275-inch traverse location and selecting every other location. Figure 9 shows the contour plot from a MISO 2-28-7-1 RBF neural network. The RBF network was trained for 200,000 iterations with a final RMS error of 0.02. This RBF neural network representation is accurate.

Figure 10 shows representation for the "50%" case using a back-propagation neural network. Figure 10 shows the contour plot from a MISO 2-28-12-1 back-propagation neural network. The back-propagation network was trained for 800,000 iterations with a final RMS error of 0.02. The secondary "hot spot" in Fig. 10 (120 to 121 dB range) has erroneously "spread out" near the 0-inch traverse location. It erroneously involves an additional microphone, No. 4. Consequently, the RBF "50%" representation, Fig. 9, was closer to the test data. The back-propagation neural network representation was thus not as accurate as the RBF neural network representation. For contour plots, the RBF network was preferable compared to the back-propagation network.

It should be noted that Fig. 7 showed a +/- 1 dB-resolution contour plot based on test data acquired at the maximum BVI condition. The corresponding contour plot extracted from the +/- 2 dB neural network representation of the complete database (that was discussed earlier, Fig. 4) is shown in Fig. 11. The neural-network-based contour obtained using the complete, experimental database was considered to be reasonable, and to have captured the essential "hot spot," Fig. 11.

Prediction of Noise

The objective in this part of the study was to use neural networks to predict noise at a test condition not included in the neural network training database. This is illustrated as follows.

The presently considered, complete, experimental noise database included 21 sets of data obtained from traverse sweeps (corresponding to 21 test conditions). A single test condition was presently defined by the following three parameters: μ, α_S, and C_T/σ. The noise curve based on an eight-microphone measurement acquired at the 125-inch traverse location was taken as the "reference curve." The three test condition parameters and the eight "reference curve" noise values formed the neural network inputs, thus uniquely "defining" the complete noise map. In the present prediction study, the subject neural network thus had 11 inputs. Noise predictions (neural network outputs) were required at 11 traverse locations (i.e., at traverse locations other than the reference traverse location). Thus, the subject neural network with the eight-microphone setup had 88 outputs. The above definition of the subject "problem" was direct and involved the smallest amount of input data. Also, the present neural network tilt-rotor noise-application with 11 inputs and 88 outputs, was a good "test case." The "test case" results would determine whether neural networks could efficiently model and predict the full-scale tilt-rotor, multi-dimensional, nonlinear noise variations.

An examination of the above 21 test conditions showed that the following near maximum BVI test condition with $\mu = 0.170$, $\alpha_S = 3$ deg, and $C_T/\sigma = 0.091$ was an appropriate choice for a neural-network-based prediction of the noise. This selection was based on the availability of test data at $\mu = 0.125$, 0.170, and 0.200 at the above shaft angle and thrust coefficient ratio. The neural network training database consisted of noise data from 20 test conditions, excluding the above selected condition. The neural network model was obtained from a MIMO 11-25-10-88 back-propagation neural network. The back-propagation network was trained for 50,000 iterations with a final RMS error of 0.02. Subsequently, it was found that the present neural network predictions and the experimental noise data at the selected test condition were within +/- 1 dB of each other. The corresponding correlation plot is shown in Fig. 12. This shows the ability of neural networks to predict tilt-rotor noise.

Conclusions

Specific conclusions from the present neural-network-based data-quality-assessment and representation study on full-scale experimental tilt-rotor noise data were as follows:

1. Neural networks were successfully used to assess the quality of noise data.

2. Neural networks were successfully used to represent the complete, experimental tilt-rotor noise database.

3. Neural networks were used to accurately represent the noise data for the cases involving varying test conditions ("test-condition-sensitivity").

4. Neural networks were successfully used to predict tilt-rotor noise using a small amount of input data.

5. Both the radial-basis function (RBF) and the back-propagation types of neural networks were used in the present noise study. It was found that the RBF neural network was preferable over the back-propagation neural network for noise contour plots.

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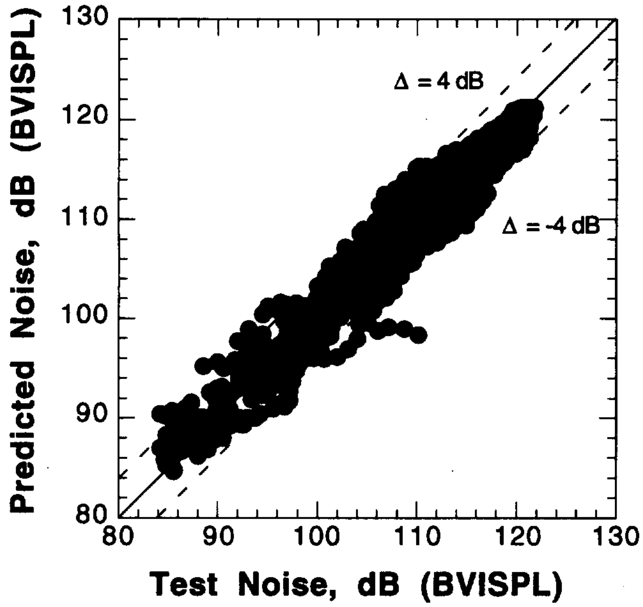

Fig. 1. Coarse correlation, complete noise database (over 4000 points).

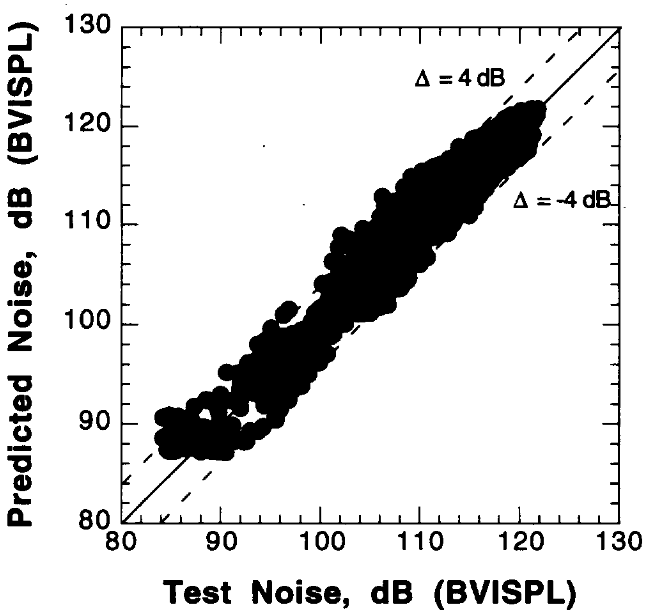

Fig. 2. Coarse correlation, eight points (α_s = -15 deg, point 25, run 139) omitted.

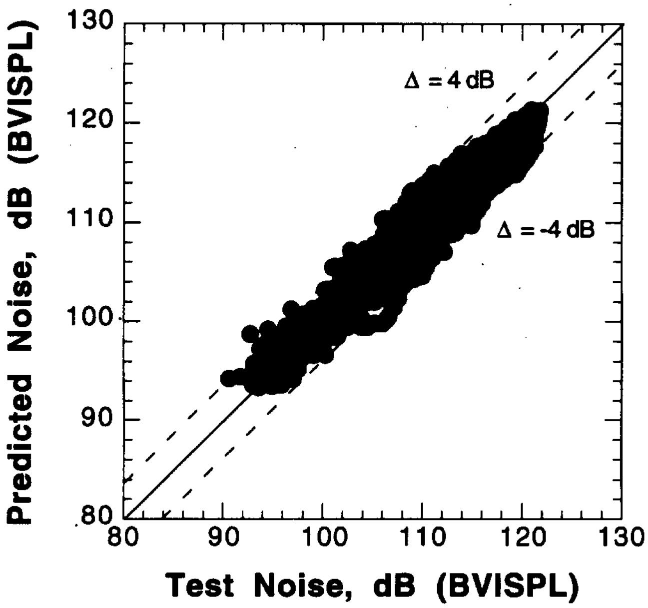

Fig. 3. Coarse correlation, all α_s = -15 deg points omitted.

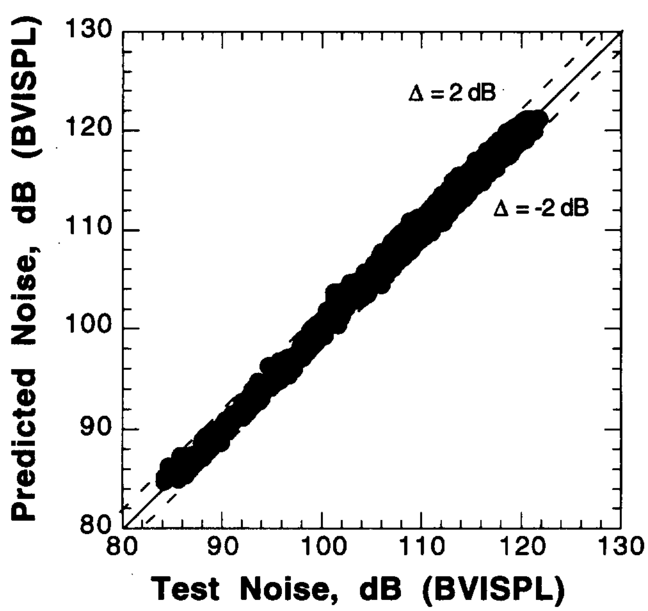

Fig. 4. Fine Correlation, database same as in Fig. 2, over 4000 points.

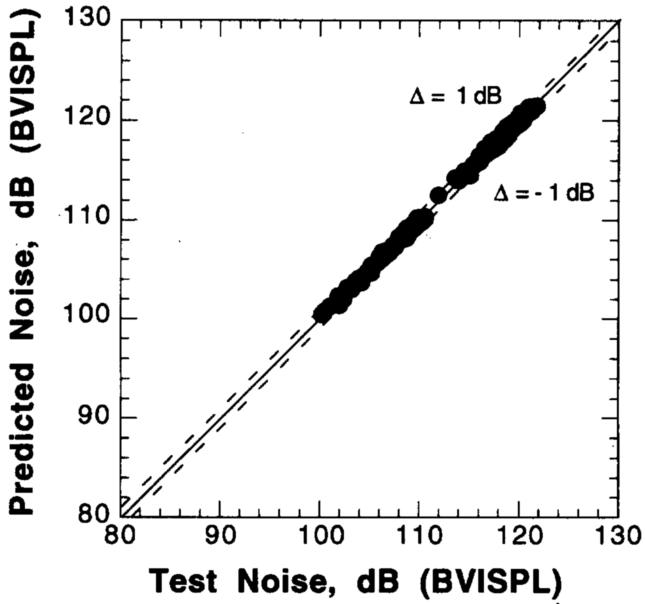

Fig. 5. Correlation, forward speed variation.

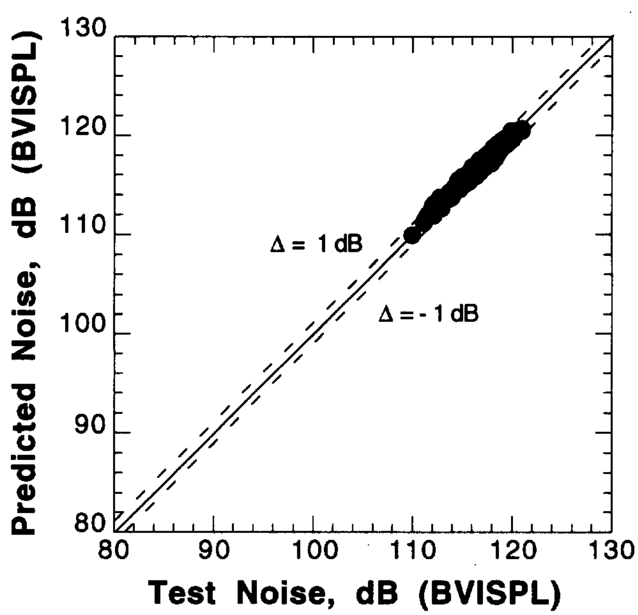

Fig. 6. Correlation, thrust variation.

Wind

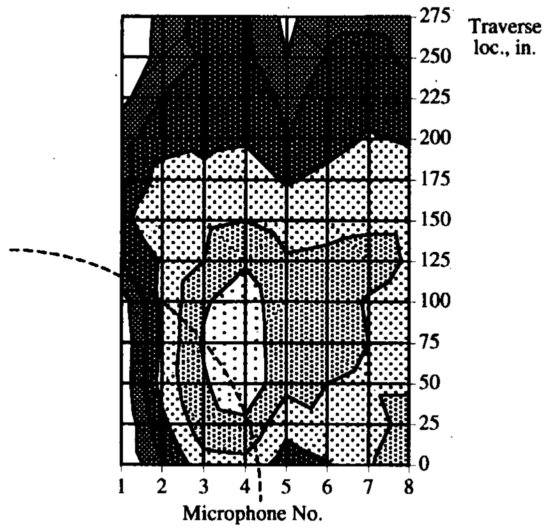

Fig. 7. Experimental tilt-rotor noise at maximum BVI condition.

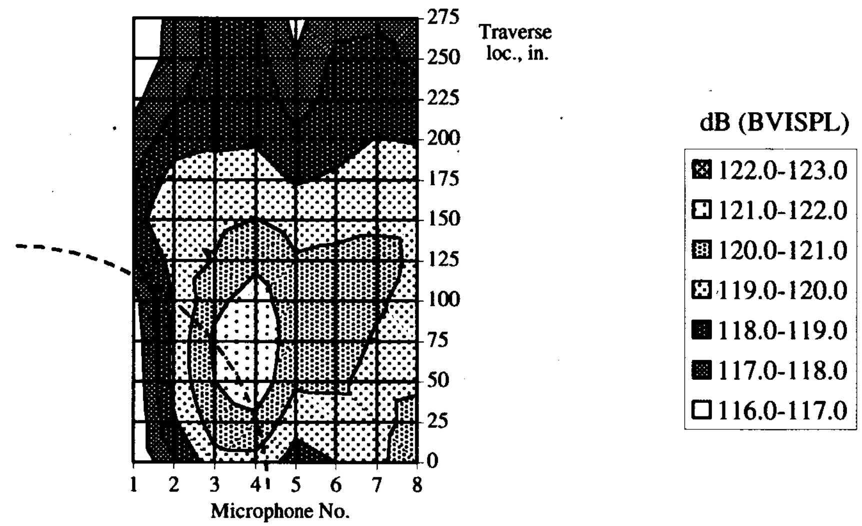

Fig. 8. Radial-basis function (RBF) neural network tilt-rotor noise at maximum BVI condition, "100%" case.

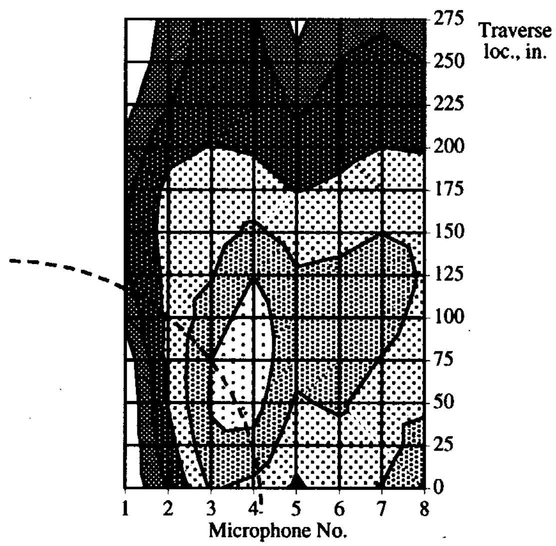

Fig. 9. Radial-basis function neural network tilt-rotor noise at maximum BVI condition, "50%" case.

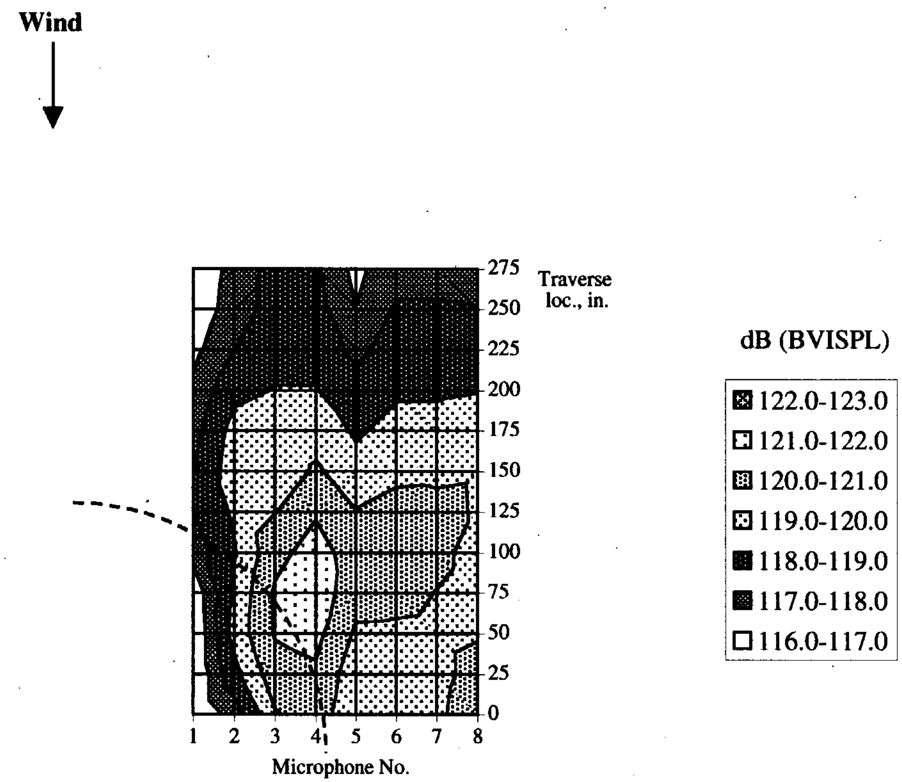

Fig. 10. Back-propagation neural network tilt-rotor noise at maximum BVI condition, "50%" case.

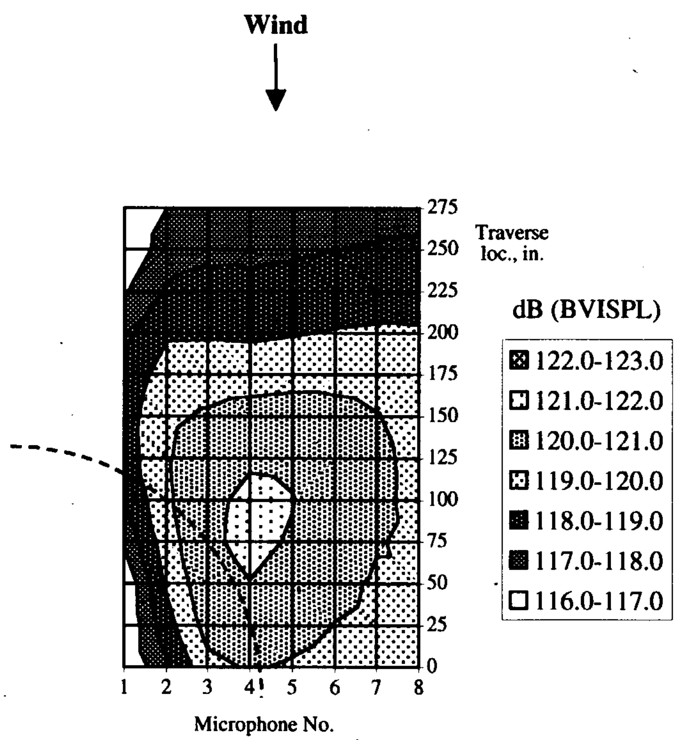

Fig. 11. Back-propagation neural network noise extracted from "+/- 2dB" representation of complete, experimental database, Fig. 4, maximum BVI condition, test data shown in Fig. 7.

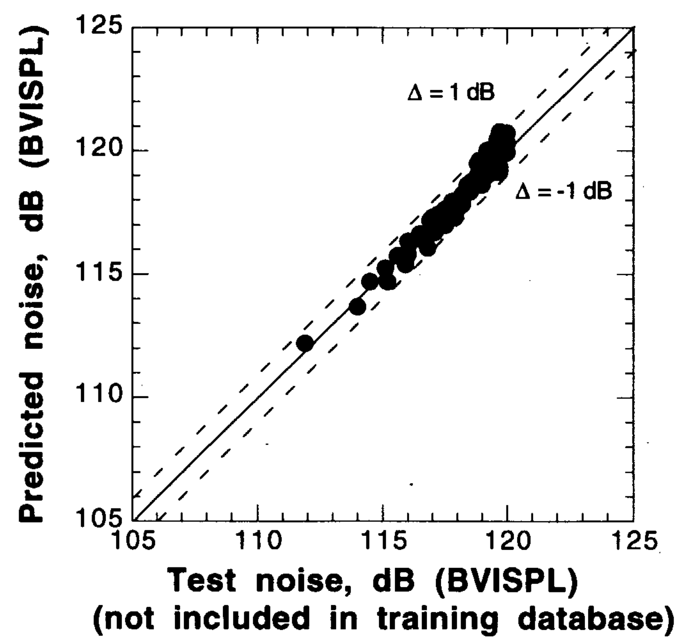

Fig. 12. Noise prediction using MIMO back-propagation neural network.