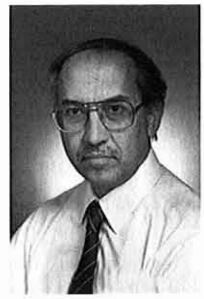
Neural Network Representation of External Tilt-Rotor Noise

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Results from a neural network study of the noise data from a full-scale XV-15 tilt-rotor are presented. Specifically, this database was acquired during the 1998 NASA Ames 80- by 120-foot wind tunnel test to establish the blade-vortex-interaction noise signature. The present study has three objectives: 1) To conduct a neural-network-based quality assessment of the noise data; 2) To obtain neural network representations of the noise data and to demonstrate their sensitivity to test conditions; 3) To obtain neural-network-based noise predictions. Overall, neural networks are successfully used to assess the quality of the noise data and to represent the complete database as well as to predict tilt-rotor noise using the minimal amount of input data. As major findings, the data quality is found to be acceptable, and accurate neural network representations are obtained for the test-condition-sensitivity cases.

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 by 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. Such representations could potentially be used to provide tilt-rotor pilots with near-real-time noise predictions of their aircraft noise exposure. This information could then be used to modify flight conditions and trajectories to minimize the exposure to noise sensitive areas. This would, in turn, help to insure the aircraft's acceptance by the nearby communities.

Rotorcraft noise measurement and prediction involve a high level of complexity, and it is difficult at times to know even heuristically the variation of the test data with changes in the operating conditions. Since the test data trends may be new and without precedent, it becomes difficult to isolate expeditiously 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 (SHCT) program. Moreover, neural network studies on rotorcraft performance and dynamics had also been initiated in the Army/NASA Rotorcraft Division at the NASA Ames Research Center; for details see Refs. 2 to 7. The present work on tilt rotor noise is motivated by the experience gained from these neural networks studies. The use of neural networks is justified because of their multi-dimensional, nonlinear curve fitting characteristics as well.

Significantly, the present work is a generic methodology, not restricted to the presently considered tilt-rotor configuration. The focus here is to demonstrate why this generic methodology offers considerable promise. Accordingly, the specific objectives are:

1) To conduct data quality assessment of the noise data in two parts: (a) coarse data quality checks, and (b) more involved fine data quality checks.

2) To obtain neural-network-based representations of the test data in two parts: (a) to demonstrate the sensitivity of the noise to test parameters such as advance ratio and thrust coefficient, and (b) to produce noise footprint plots, i.e., contour plots, using neural-network-based results, and separately, to study the implications of using 50% of the available data for neural network training purposes.

Based on a paper presented at the 6th American Institute of Aeronautics and Astronautics/Confederation of European Aerospace Societies Aeroacoustics Conference, Maui, Hawaii, June, 2000. Manuscript received January 2001; accepted February 2002.

3) 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) are 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 capture accurately 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. In the present wind tunnel noise application, the important physical parameters are associated with the wind tunnel test conditions. Thus, there are five neural network inputs: advance ratio, μ, shaft angle, α_s, thrust coefficient ratio, C_T/σ, the microphone traverse location, and the microphone position within the traverse. 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. 2–7) consists of first determining the best type of neural network to be used and then simplifying the network as much as 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 are used. For the back-propagation network, the hyperbolic tangent is used as the basis function and the extended-delta-bar-delta (EDBD) algorithm is used as the learning rule (Ref. 10).

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. The criteria used to determine that there are enough PEs is that the RMS error stops changing (and is sufficiently small). 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. The notation used in this paper to characterize a neural network is described as follows. An 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.

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, bad test data (or poor quality test data) may exist in the database (Ref. 2). 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 analyst should not solely rely on the neural network based correlation procedure to eliminate test data. This procedure, however, contributes to data assessment, and an example from a previous study is briefly discussed as follows. In Ref. 2 (Figs. 11 and 12, therein) the above procedure was applied to the experimental tilt-rotor blade flatwise bending moments. In the above Ref. 2 example, the subject test data points were not repeatable, possibly because of instrumentation problems.

Results

The application of neural networks to full-scale tilt-rotor noise data is conducted using the neural networks package NeuralWorks Pro II/PLUS (version 5.2) by NeuralWare (Ref. 10). The present neural network RMS error is dimensionless and based on the squares of the errors for each processing element (PE) in the output layer. Any large differences in the magnitudes of the neural network variables are mitigated by appropriate scaling. In the present application, the cost function used in minimizing the RMS error has 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 is 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 has 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 is obtained by considering the complete noise database. This complete database includes over 4000 data points, which are used as training data for the neural networks. The five wind tunnel test parameters used as the neural network inputs are: 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 is relatively larger. Thus, the present data quality assessment procedure is split up into two steps. The first step involves coarse correlation curve fits. The second step involves fine correlation curve fits, and involves 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 are $+/-4$ 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 is 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 are judged as the bad test data points. These bad test data points are denoted in

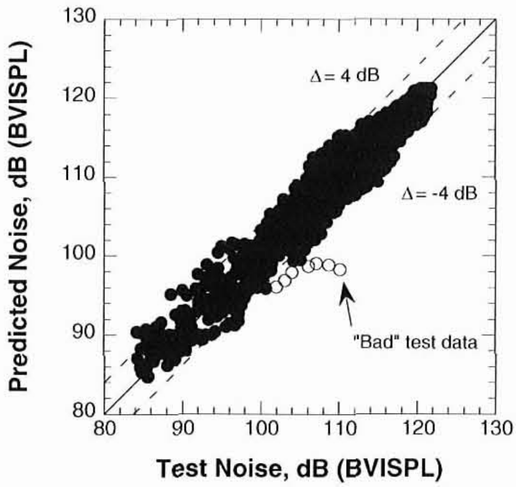


Fig. 1. Coarse correlation, complete noise database (over 4000 points).

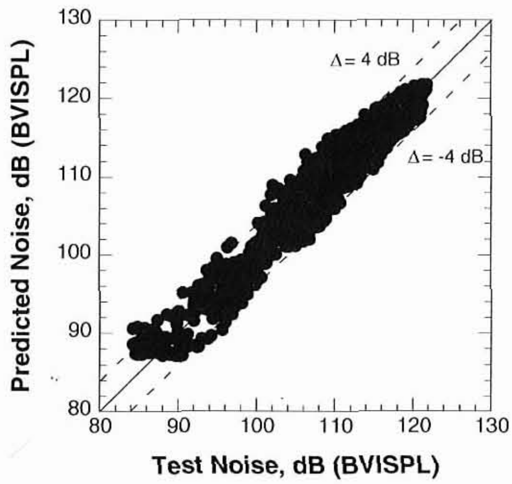


Fig. 2. Coarse correlation, eight points ($\alpha_s = -15$ deg, point 25, run 139) omitted.

the figure by the open circle symbols. A detailed examination of the noise database shows that these bad points are from test point 25 of run 139. The test parameters for this test condition are: $\mu = 0.169$, $\alpha_s = -15$ deg, and $C_T/\sigma = 0.06$. 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 in an open circuit wind tunnel.

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 ($\alpha_s = -15$ deg) are omitted from the complete training database. In this figure the correlation plot from a MISO 5-25-5-1 RBF neural network are shown. The RBF network is 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 $\alpha_s = -15$ deg points (152 in number) are omitted from the complete training database. The correlation plot is from a MISO 5-25-5-1 RBF neural network. The RBF network is trained for 4 million iterations with a final RMS error of 0.08. Figures 2 and 3 are similar in that no outstanding bad points can be seen. Thus, the bad data points (open circles) seen in Fig. 1 are associated with only one test condition, point 25 of run 139. Figures 1 to 3 demonstrated the ability of neural networks to identify noise data of poor quality.

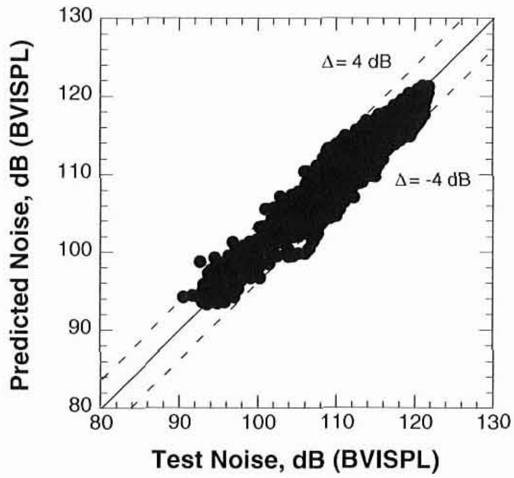


Fig. 3. Coarse correlation, all $\alpha_s = -15$ deg points omitted.

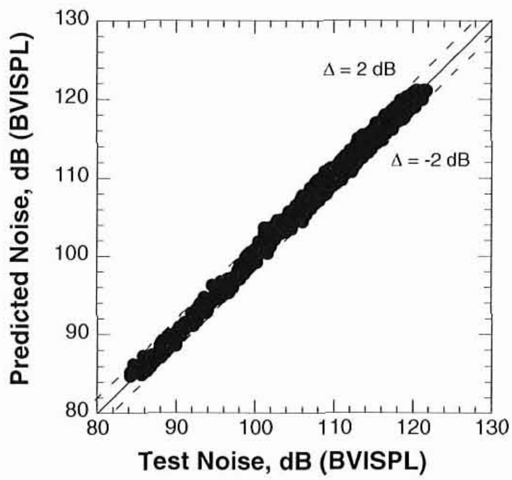


Fig. 4. Fine correlation, database same as in Fig. 2, over 4000 points.

Fine data-quality-assessment. Figure 4 shows the fine correlation plot obtained by using the same database as that was used in Fig. 2. The eight microphone measurements arising from test point 25 of run 139 ($\alpha_s = -15$ deg) are omitted from the complete training database. The correlation plot is from a MISO 5-75-25-1 back-propagation neural network. This more complex back-propagation network is trained for 8 million iterations (double the number used in the coarse correlation step) with a final RMS error of 0.02. It is seen that the quality of the noise data is 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 in Fig. 4 also demonstrates the ability of neural networks to represent the experimental noise data within an acceptable level of accuracy (+/−2 dB), and involves 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 are separately treated. A near maximum BVI condition ($\mu = 0.170$, $\alpha_s = 3$ deg, and $C_T/\sigma = 0.091$) is taken as the baseline test condition about which the variations are considered.

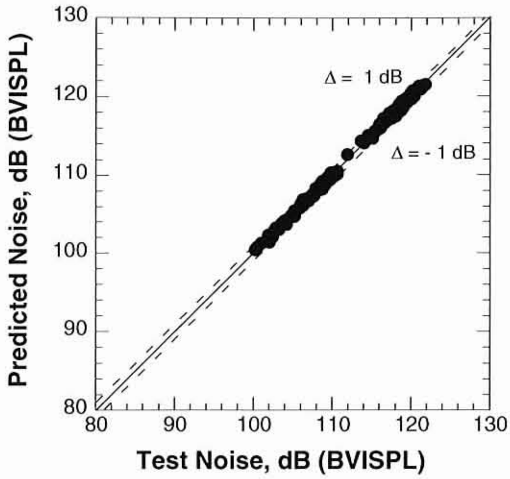


Fig. 5. Correlation, forward speed variation.

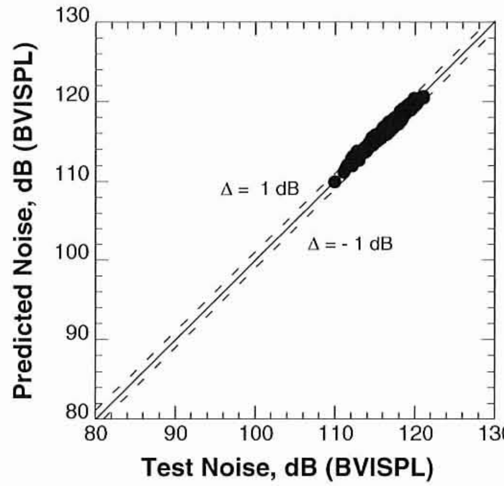


Fig. 6. Correlation, thrust variation.

Forward speed variation. Three advance ratios are considered ($\mu = 0.125$, 0.170, and 0.200), each with $\alpha_s = 3$ deg and $C_T/\sigma = 0.091$. The three neural network inputs are 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 is trained for 1 million iterations with a final RMS error of 0.02. The neural network representation is acceptable to within $+/-1$ dB.

Thrust variation. Four thrust coefficient ratios are considered ($C_T/\sigma = 0.060$, 0.075, 0.091, and 0.100), each with $\mu = 0.170$ and $\alpha_s = 3$ deg. The three neural network inputs are 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 is trained for 1 million iterations with a final RMS error of 0.04. Here as well, the neural network representation is acceptable to within $+/-1$ dB.

Contour plots. Neural-network-based contour plots are obtained at a tilt-rotor operating condition involving maximum blade vortex interaction ($\mu = 0.200$, $\alpha_s = 4$ deg, and $C_T/\sigma = 0.075$). The corresponding experimental noise contour with 96 data points is shown in Fig. 7(a) (the approximate rotor circle is also shown in the figure). A particular contour point is identified by its microphone number (1 to 8) and its traverse location. This case involves 96 neural network training points. The microphone traverse location and the microphone position are the two neural network inputs. The BVISPL noise measure is the single neural network output.

Figure 7(b) 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). Specifically, the contour plot from a MISO 2-28-7-1 RBF neural network is shown. The RBF network is trained for 4 million iterations with a final RMS error of 0.02. This RBF neural network representation is accurate.

Figure 8(a) shows the representation for the 50% case using an RBF neural network and training data from six traverse locations (involving 48 test points). This 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 are selected by starting out with the 275-inch traverse location and selecting every other location. Here also, the contour plot from a MISO 2-28-7-1 RBF neural network is shown. The RBF network is trained for 200,000 iterations with a final RMS error of 0.02. This RBF neural network representation is accurate.

Figure 8(b) shows a representation for the 50% case using a back-propagation neural network. In particular, the contour plot from a MISO 2-28-12-1 back-propagation neural network is presented. The back-propagation network is trained for 800,000 iterations with a final RMS error of 0.02. The secondary hot spot in Fig. 8(b) (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. 8(a), is closer to the test data. The back-propagation neural network representation is thus not as accurate as the RBF neural network representation.

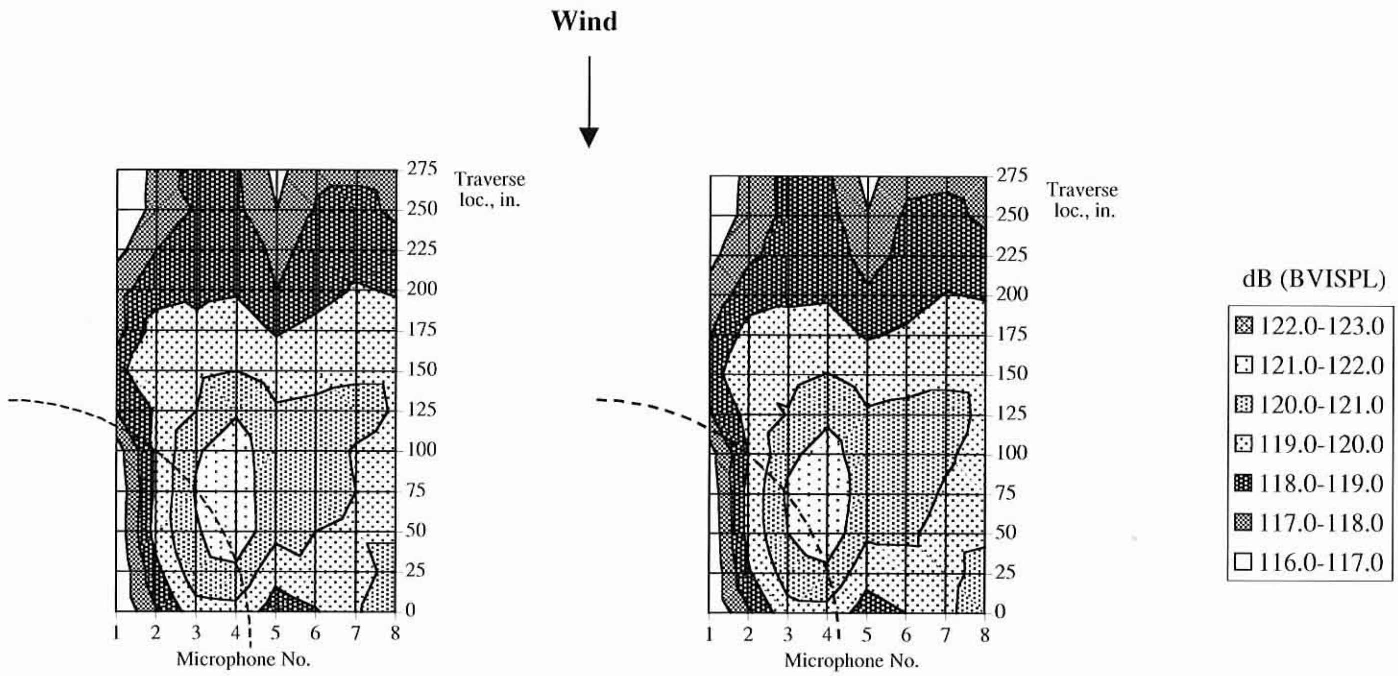
It should be noted that Fig. 7(a) shows a $+/-1$ dB-resolution contour plot based on test data acquired at the maximum BVI condition. The corresponding contour plot extracted from the $+/-2$ dB neural network representation of the complete database (discussed earlier, Fig. 4) is shown in Fig. 9. The neural-network-based contour obtained using the complete, experimental database is considered to be reasonable and to have captured the essential hot spot.

Prediction of noise

In this section, neural networks are used to predict noise at a test condition not included in the neural network training database. This is illustrated as follows.

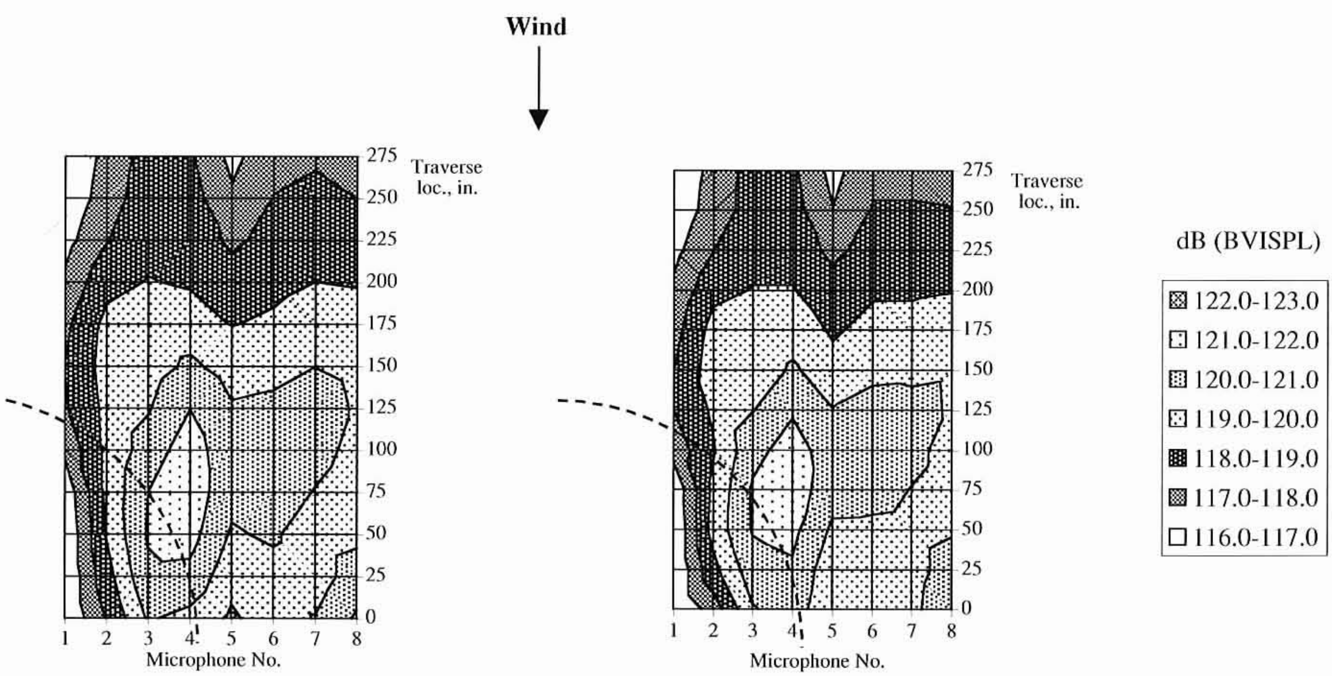
The presently considered, complete, experimental noise database includes 21 sets of data obtained from traverse sweeps (corresponding to 21 test conditions). A single test condition is presently defined by the three parameters: μ, α_s, and C_T/σ. The noise curve based on an eight-microphone measurement acquired at the 125-inch traverse location is taken as the reference curve. These three test condition parameters and the eight reference curve noise values formed the neural network inputs, thus uniquely defining the complete noise map. Thus, the subject neural network has 11 inputs. Noise predictions (neural network outputs) are required at 11 traverse locations (i.e., at traverse locations other than the reference traverse location), and the subject neural network with the eight-microphone setup has 88 outputs. The above definition of the subject problem is direct and involves the smallest amount of input data. Also, the present neural network tilt-rotor noise-application with 11 inputs and 88 outputs, is 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 shows that the following near maximum BVI test condition with $\mu = 0.170$, $\alpha_s = 3$ deg,



(a) (b)

Fig. 7. (a) Experimental tilt-rotor noise at maximum BVI condition. (b) Radial-basis function (RBF) neural network tilt-rotor noise at maximum BVI condition, "100%" case.



(a) (b)

Fig. 8. (a) Radial-basis function neural network tilt-rotor noise at maximum BVI condition, "50%" case. (b) Back-propagation neural network tilt-rotor noise at maximum BVI condition, "50%" case.

and $C_T/\sigma = 0.091$ is an appropriate choice for a neural-network-based prediction of the noise. This selection is 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 test data used to evaluate the predictive capability is not used in the training. The neural network training database consists of noise data from 20 test conditions, excluding the above selected condition. The neural network model is obtained from a MIMO 11-25-10-88 back-propagation neural network. The back-propagation network is trained for 50,000 iterations with a final RMS error of 0.02. Subsequently, it is found that the present neural network predictions and the experimental noise data at the selected test condition are within $+/-1$ dB of each other. The corresponding correlation plot is shown in Fig. 10(a).

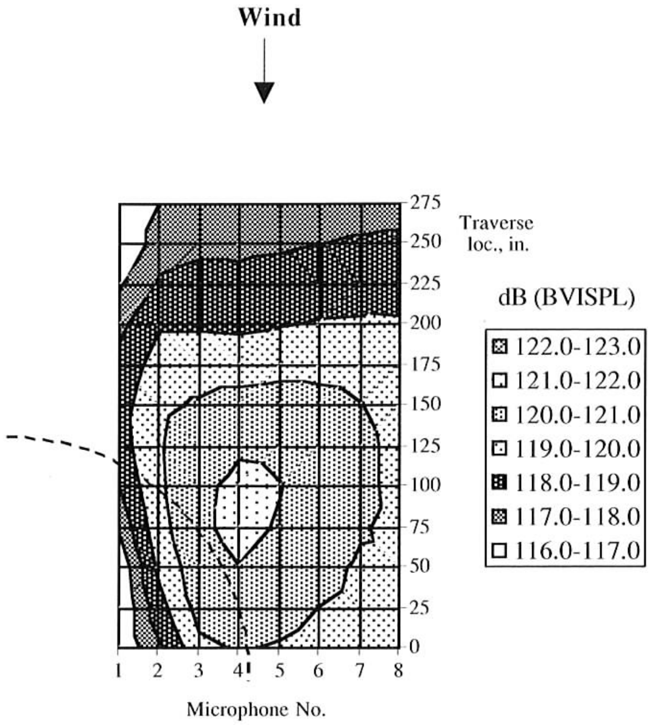


Fig. 9. Back-propagation neural network noise extracted from "+/−2 dB" representation of complete, experimental database, Fig. 4, maximum BVI condition, test data shown in Fig. 7(a).

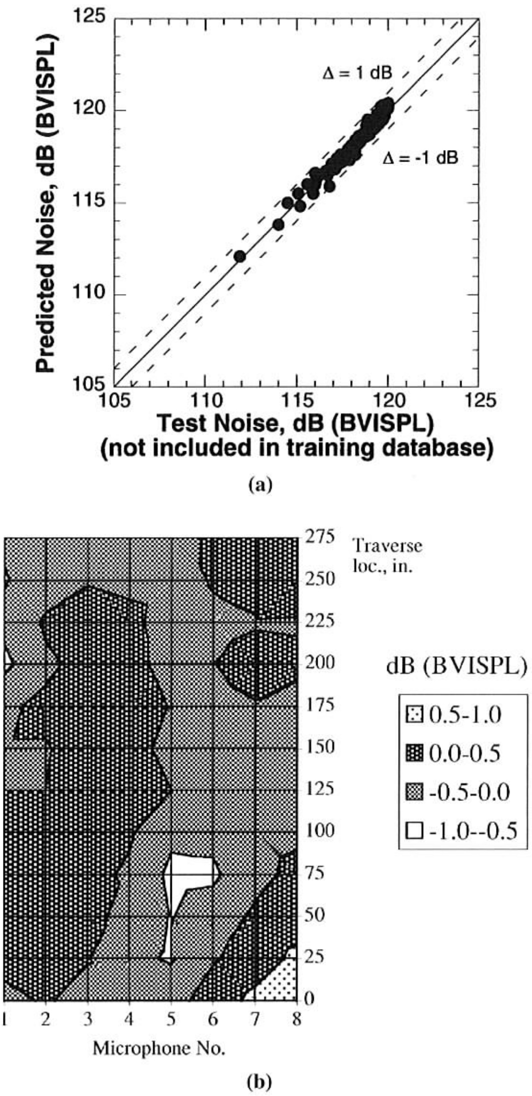


Fig. 10. (a) Noise prediction using MIMO back-propagation neural network. (b) Contour map of error between test data and neural network predictions for Fig. 10(a) prediction.

Figure 10(b) shows the contour map of the error between the test data and the neural network predictions. Figures 10(a) and 10(b) show 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 are as follows:

Neural networks were successfully used to assess the quality of noise data as well as to represent the complete, experimental tilt-rotor noise database. Neural networks were used to represent accurately the noise data for the cases involving varying test conditions (test-condition-sensitivity). Finally, neural networks were successfully used to predict tilt-rotor noise within +/−1 dB using the minimal amount of input data.

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