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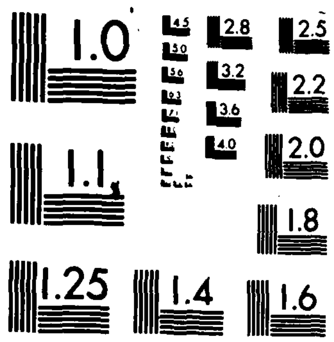

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US Army Corps
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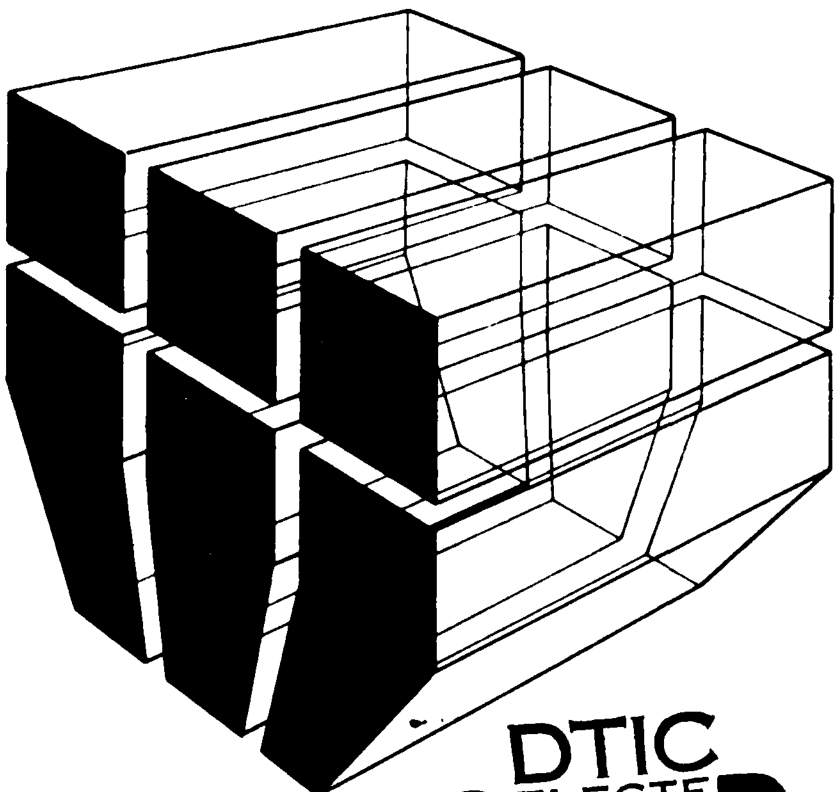
TECHNICAL REPORT N-16
January 198
Standard Methods to Assess Human an
Community Response for Impulse Nois

STRATEGIES FOR AND VALIDITY OF NOISE MONITORING IN THE VICINITY OF CIVILIAN AIRFIELDS AND ARMY INSTALLATIONS



by
Paul D. Schomer
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It is common practice to use computer-generated noise contours or noise zone maps to assess noise impact and perform noise related land-use planning. However, developers and other interested parties often question the accuracy of computer simulations and suggest direct measurement to "verify" the computer predictions. This report quantifies the temporal sampling requirements for and the accuracy and ability of directly measured sampled data to estimate the true yearly day/night average sound level (DNL). The results for civilian airports show that a precision (95 percent confidence) of ± 2 to ± 3

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decibels (dB) is generally achieved with 4 to 8 weeks of monitoring; 1 week from each eighth or 1 week from each quarter of the year, respectively. It does not appear possible to directly monitor blast noise with current instrumentation and techniques, even if the monitoring is done continuously for an entire year. Separating blast noise from other noise and incorporating a single-event threshold appear to be two of the main technological problems. Improved wind screens and multiple microphone arrays may alleviate these problems.

FOREWORD

This study was performed for the Directorate of Engineering and Construction, Office of the Chief of Engineers (OCE), under Project 4A162720A896, "Environmental Quality Technology"; Task A, "Installation Management Strategy"; Work Unit 019, "Standard Method to Assess Human and Community Response for Impulse Noise." The OCE Technical Monitor was Mr. Gordon Velasco, DAEN-ECE-I.

This study was conducted by the Environmental (EN) Division of the U.S. Army Construction Engineering Research Laboratory (CERL). Dr. R. K. Jain is Chief of CERL-EN.

COL Paul J. Theuer is Commander and Director of CERL, and Dr. L. R. Shaffer is Technical Director.

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1 INTRODUCTION

Background

It is common practice to use computer-generated noise contours or noise zone maps to assess noise impact and perform noise-related land-use planning. In the United States, noise zone maps are usually expressed in terms of the day/night average sound level (DNL) descriptor.[1] Most noise zone maps are created by computer simulation programs like the Federal Aviation Administration's (FAA's) Integrated Noise Model (INM), the Air Force's NOISEMAP, or the Army's BNOISE.[2]

When noise zone maps are used for noise assessment and especially land-use planning, developers and other interested parties often question the accuracy of the computer simulations and suggest direct measurement to "verify" the computer predictions. It is naturally assumed that direct measurement must be more accurate than computer simulation.

Purpose

The purpose of this report is to quantify the temporal sampling requirements for and the accuracy and the ability of directly measured sampled data to estimate the true yearly DNL.

Approach

The Army's main concern is the blast noise created by such operations as armor, artillery, and demolition. However most existing monitor data were gathered near major metropolitan airports. Thus, the analysis of monitoring accuracy with specific reference to blast noise proceeds along two parallel paths. For the first path, the results of limited blast noise monitoring near two Army installations are compared with computer simulation results and the results of attitudinal surveys of the community response to blast noise in the areas near these same installations. For the second path, metropolitan airport data are used. These data exist for a number of airports where continuous daily monitoring was performed for 1 year or more at several sites.[3] Studies and analyses are performed on these data to show, quantitatively, the accuracy that different sampling strategies would have achieved.

Attitudinal surveys are used to gauge or quantify the community response to some stimulus, such as noise. During the past 30 years, many attitudinal surveys have been conducted worldwide to better understand and assess human and community response to noise. These studies, which concentrate mainly on automobile and truck traffic and rail and fixed-wing aircraft noise, have resulted in a proliferation of noise assessment models or descriptors. In general, these descriptors, in one fashion or another, take into account the following:

1. Sound level of the noise events.

2. The frequency of the occurrence of the noise events.

3. The time of day at which the noise occurs.

In general, one major purpose of the attitudinal survey is to develop a highly correlated functional relation between some measure of community annoyance (the dependent variable) with one or another of these noise descriptors. Over the past few years, the scientific community has generally settled on the use of "high annoyance" as a measure of the community response, and the use of the day/night average sound level (DNL) as the noise descriptor. High annoyance is defined to be those respondents in an attitudinal survey

[1] *Guidelines for Considering Noise in Land Use Planning and Control* (Federal Interagency Committee on Urban Noise, June 1980).

[2] *Integrated Noise Model (INM)* (Department of Transportation, Federal Aviation Administration); *Community Noise Exposure Resulting From Aircraft Operations: Computer Program Description*, AMRL-TR-73-106 (Department of the Air Force, November 1974); and V. Pawlowska and L. Little, *The Blast Noise Prediction Program: User Reference Manual*, Technical Report N-75/ADA074050 (U.S. Army Construction Engineering Research Laboratory [CERL], August 1979).

[3] Richard E. DeVor, et al., "Development of Temporal Sampling Strategies for Monitoring Noise," *Journal of the Acoustical Society of America*, Volume 66, No. 3 (September 1979), pp 763-771; Paul D. Schomer and Richard E. DeVor, "Temporal Sampling Requirements for Estimation of Long-Term Average Sound Levels in the Vicinity of Airports," *Journal of the Acoustical Society of America*, Volume 69, No. 3 (March 1981), pp 713-719; and Paul D. Schomer, et al., "Sampling Strategies for Monitoring Noise in the Vicinity of Airports," *Journal of the Acoustical Society of America*, Volume 73, No. 6 (June 1983), pp 2041-2050. (Note: These papers are included as Appendices A, B, and C of this report.)

who rate themselves in the top two annoyance categories on a five-point adjectival scale when responding as to their overall annoyance to the noise environment. The five adjectival ratings are (1) extremely annoyed, (2) very much annoyed, (3) moderately annoyed, (4) a little annoyed, (5) and not at all annoyed. The independent variable (the noise environment described by DNL) is normally either predicted by computer simulation or directly measured. Frequently, direct measurements are used to spot check computer simulations. As indicated above, one purpose of this report is to investigate the applicability of direct measurement to check computer simulation.

For computer simulation, every noise source is tabulated and evaluated: every weapon firing, every target, every shell, etc. The directivity of each weapon for each firing is factored and a statistical distribution of the received amplitudes as a function of distance which reflects variable weather conditions is developed for each event. The received noise is added at a grid of rectangular points covering the installation and the surrounding area. The incremental noise from every source is added at each of these grid points. When the summation process is completed, equal noise contours are developed.

Impulse noise–the noise generated by armor, artillery, or demolition–is assessed using the C-frequency weighting. Noise events that generate sound levels which fall below a certain threshold are discarded. Both direct measurement and computer simulation must take into account this threshold and the C-weighting. Clearly, the computer simulation includes only blast noise produced by the Army installation. For direct measurement, care must be exercised to ensure that the noise monitoring results include only Army impulse noise and not other noise such as wind-generated noise, helicopter flybys, diesel trains or other nearby sources of high-level, C-weighted noise.

Figure 1 shows data the U.S. Army Construction Engineering Research Laboratory (CERL) has gathered which relate high annoyance and the computer-predicted C-weighted DNL in the vicinity of Fort Bragg and Fort Lewis. This figure also indicates the National Academy of Science's recommended function for relating community response to C-weighted DNL. These data indicate that if the noise environment at an installation is specified by computer-predicted DNL, then the resulting annoyance predicted by the National Academy of Science curve will likely underestimate the true annoyance by a small amount.

In analyzing the viability of using directly monitored impulse noise data, this report looks at the results of the attitudinal surveys and the community response in terms of high annoyance as rated against measured DNL levels and the National Academy of Science recommendations. The bottom line, in terms of the Army's interest, is accurate prediction of the community response to the noise environment around Army installations. When measured DNL improves the Army's ability to properly predict community annoyance, direct measurements should be used to augment computer prediction. However, when direct measurement correlates less well than computer prediction with community response and depreciates the Army's prediction capability, greater reliance must be placed on computer prediction and less on direct measurement.

As an approach to quantifying temporal sampling requirements, approximately 1 year of daily DNL (or CNEL) data were obtained from several major metropolitan commercial airports. These data were gathered by the airports using several fixed monitors at various locations around the airports. The time-series data are modeled and various statistical analyses are performed on these data to show, quantitatively, the accuracy that different sampling strategies would have achieved.

Mode of Technology Transfer

This report develops guidelines as to when direct measurement can be used to predict community response in the vicinity of Army installations and when only computer simulation should be used. Temporal sampling strategies are developed for use with direct measurement. The results of this report will be used by the Army Environmental Office and the Army Environmental Hygiene Agency to formulate their strategy for direct measurement as a part of Installation Compatible Use Zone (ICUZ) program mandated by Army Regulation (AR) 200-1, *Environmental Protection and Enhancement* (Department of the Army, 15 June 1982).

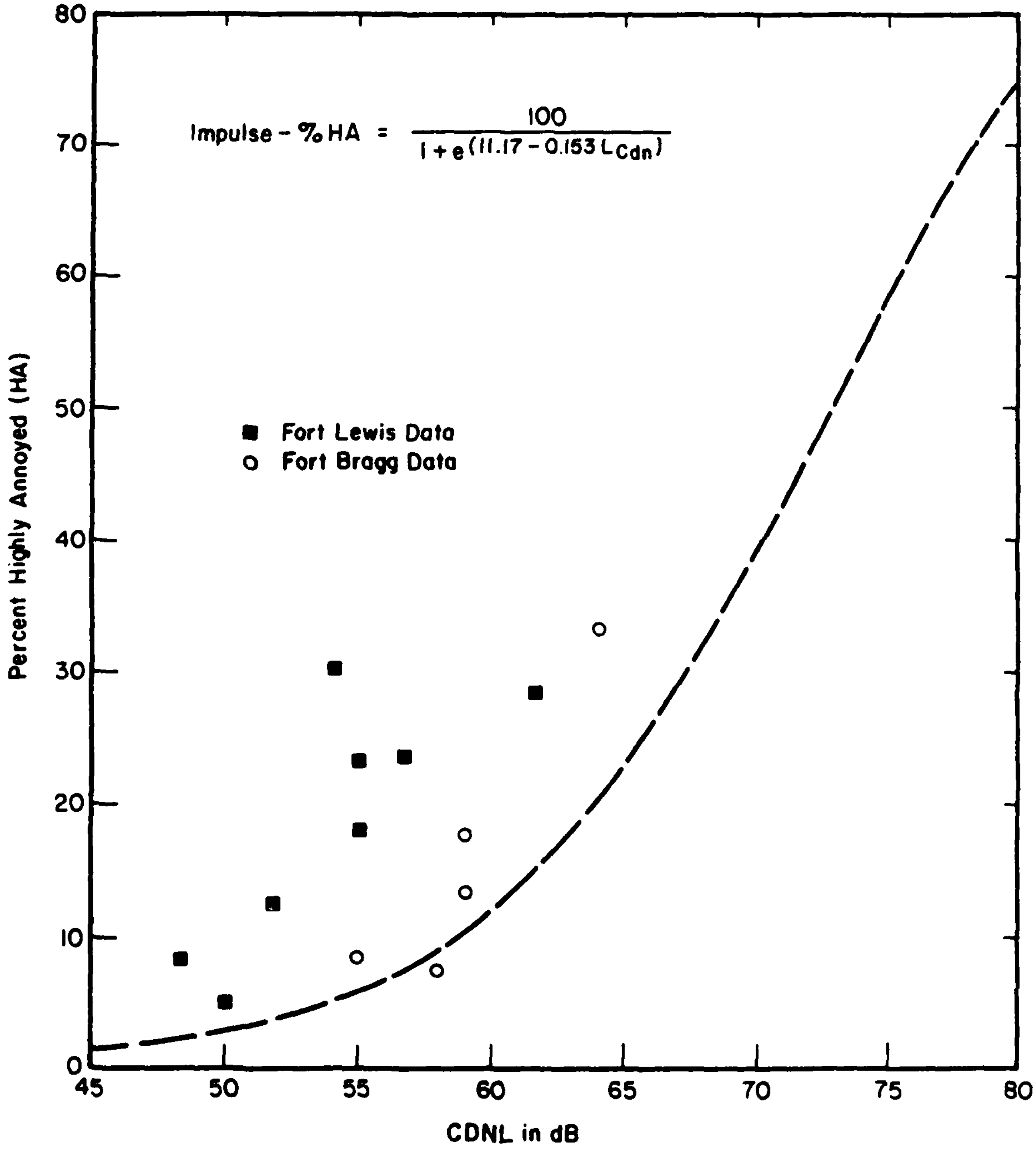

Figure 1. Fort Bragg and Fort Lewis data (based on computer prediction only).

2 ARMY INSTALLATION NOISE MONITORING

In 1978 and 1980, CERL administered attitudinal surveys of the community response to blast noise in the vicinity of Fort Bragg, NC, and Fort Lewis, WA.[4] At the same time the surveys were administered, CERL extensively monitored the actual blast noise produced by installation operations and prepared computer predictions for blast noise in the areas surrounding the installations. At both installations, the computer predictions correlated well with the measured community response. The results of direct noise monitoring at Fort Bragg generally correlated well with the computer predictions, except for areas distant from the installation and to the west or southwest.

The Fort Bragg study was performed in 1978, and the Fort Lewis study was performed in 1980. Thus, this chapter first describes the Fort Bragg results, then the Fort Lewis results. The details of these studies are discussed below; but based on the lessons learned at Fort Bragg, the attitudinal survey at Fort Lewis was conducted at eight clusters around eight fixed monitoring sites. This design was chosen to minimize movement of the monitors. To increase reliability, all monitors at Fort Lewis were powered from 110-V sources and the monitoring was performed for a 6-month period.

Fort Bragg Monitoring Results

In the vicinity of Fort Bragg, 24-hour monitoring was done at 17 sites. The number of complete 24-hour days of monitoring at each site ranged from 4 to 67, with 25 being a typical value. All C-weighted data recorded by CERL's monitoring equipment were extensively tested and checked to eliminate all but blast noise. All data were recorded in 6-minute blocks. To reduce the effects of noise generated by wind at the microphone, the monitors were turned off when the wind meter indicated the winds were blowing at more than about 18 km/hour. Whenever the monitors went above the preset peak level threshold of 105 dB (95 dB at night), an analog tape recorder and a special digital timer were turned on. If the wind threshold signal came on at any time when the recorder and timer were running, the data in that 6-minute block were discarded. If the threshold was exceeded for more than 2 seconds, a technician would listen to the analog tape to see if the signal was caused by impulses or by some other source, such as an aircraft or a helicopter. If the technician detected any other type of noise source on the analog tape, that 6-minute data block was also discarded. Thus, the only data included were those for which (1) the wind threshold was not triggered and (2) no other source could be heard or the event was less than 2 seconds long, or both.

Figure 2 shows the general outline of [illegible]e Fort Bragg study area, overlaid with comput[illegible]ed[illegible]cted C-weighted DNL (CDNL) contours for the [illegible]r before CERL's study. Also shown are 15 of the 17 [illegible]toring sites (two sites near the airfields measured [illegible] aircraft noise and are not shown). The figure grou[illegible]areas by their geographic area and noise zone. [illegible] off-installation areas in the same general region and noise zone are grouped separately. Table 1 lists the computer-predicted and directly measured noise levels by monitoring site.

At sites 1 and 2 the measured levels were much higher than predicted because units assigned firing points within 1 km of these monitors actually fired from much closer than 1 km. In the areas to the east, the monitored results ranged from 11 dB below to 3 dB above prediction. For the sites at which the measured levels were close to prediction in the east, the predominant noise all came in one to several days, each day characterized by a period of high noise caused by sound-focus conditions.* In contrast, monitor sites 5, 6, 8, and 9, to the south and west of the study area, exhibited no such focus days. As a result, Table 1 shows a much larger difference between the computer-predicted and the measured values for those locations.

The differences between prediction and measurement seem to follow a trend. Sites 1 and 2, which were very close to firing points, had measured data which were well above prediction. Sites 3 and 4, which were about 1 mile (1.6 km) from the nearest firing point, had measured data which were 2 to 4 dB above prediction. Sites to the east (both on and off the installation) had measured data which were somewhat below

[4] Paul D. Schomer, *Community Reaction to Impulse Noise: Initial Army Survey*, Technical Report N-100/ADA 101674 (CERL, June 1981); and Paul D. Schomer, *Community Response to Impulse Noise: A 10-Year Research Summary*, Technical Report N-167 (CERL, November 1983).

*The velocity of sound changes with altitude primarily because of changes in wind velocity and temperature with altitude. This sound velocity profile can focus sound much as a lens focuses light. The result is the possibility of very loud sounds focused at far distances (e.g., 2 to 25 miles) from the source.

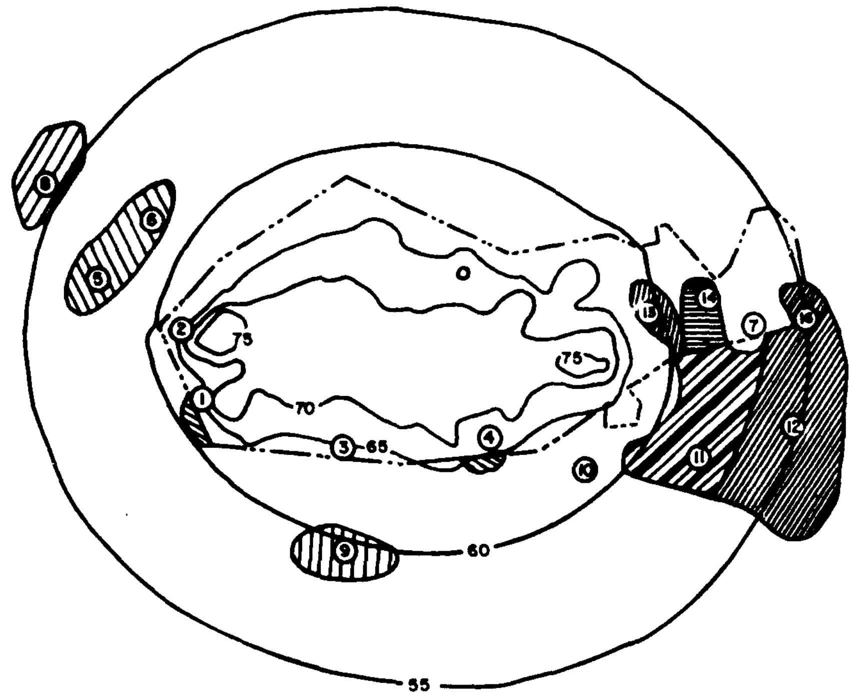

Figure 2. Predicted CDNL contours, monitor sites and predominant respondent groups in the Fort Bragg study area. (Circled numbers represent monitor locations; a table of metric grid coordinates can be found in CERL TR N-100.)

Table 1
Measured vs Predicted CDNL at Fort Bragg

Site*	Number of Monitoring Days**	*Computer-* Predicted During the Monitoring Period (CDNL)	Measured (CDNL)	Difference	Computer-Predicted for the Entire Year (CDNL)
1	11	63	103	−40	66
2	84	67	88	−11	64
3	34	68	70	−2	64
4	81	69	73	−4	66
5	81	61	46	+15	58
6	12	60	49	+11	58
7	78	60	49	+11	58
8	44	59	42	+17	55
9	42	61	49	+12	59
10	34	64	53	+11	62
11	26	59	58	+1	57
12	12	51	51	+6	55
13	28	64	54	+10	61
14	33	60	55	+5	58
15+					
16	80	58	61	−3	55
17+					

*See Figure 1 for site locations.
**During the days that the monitoring occurred.
+Aircraft noise site; blast noise not monitored.

or at the predicted level. Sites to the south and west had measured data which were far below the predicted levels. The very high levels at Sites 1 and 2 are believed to have been caused by Marine units which fired from other than the locations they listed. (Large percentage errors in small distances and firing points closer than 300 m to monitors are beyond the scope of CERL's noise contour prediction computer program.)

For those sites where the measured data agree with prediction, most of the sound energy comes during 1 to 2 hours over a few days when focus conditions existed that would cause high noise levels. During other times, the monitors measured much lower noise levels. These results are in accordance with the statistical nature of sound propagation resulting from the extreme variations caused by weather conditions. The sites to the west and southwest measured levels well below prediction. At the time of the Fort Bragg study, it was thought that this occurred because the monitoring was not performed for a long enough time.

Fort Lewis Monitoring Results

At Fort Lewis, 24-hour monitoring was done at eight sites for 6 months before the attitudinal survey was administered (11 January to 30 June 1980). In comparison, the monitoring duration at Fort Bragg was about 5 months at 17 sites, most of which alternated weekly. To minimize the equipment problems encountered at Fort Bragg associated with moving monitoring locations, eight fixed locations were chosen for the Fort Lewis study. All of the Fort Lewis sites were powered by 110-V lines and included the normal uninterruptible power supply in the CERL monitor. As at Fort Bragg, the data were tested to ensure that only blast noise was included in the monitored results. The same wind speed and peak amplitude thresholds were used at Fort Lewis as at Fort Bragg. This modified equipment setup improved the overall performance of the study by increasing the number of successfully completed monitoring days by at least 100 percent and reducing equipment failures by at least 200 percent.

Figure 3 shows the general outline of the Fort Lewis study area overlaid with computer-predicted CDNL contours for 1 year preceding the monitoring period. The figure also shows the eight monitoring sites; these sites were chosen to include a range of community types (i.e., small town, city, suburban, and cantonment area).

Table 2 lists the computer-predicted and measured CDNLs by monitor location. Although the predicted and monitored levels tend to correlate, they do not agree. With one exception, the measured levels fall far below prediction. These same results were found to the south and west at Fort Bragg. Apparently, the poor Fort Bragg results to the south and west were not due merely to "not measuring long enough," as had been assumed.

Although a number of theories can be advanced to explain these poor results, none by itself gives a satisfactory answer. These theories include:

1. Blast noise was lost by deleting data when high winds occurred (above 18 km/hour).

2. Sound focusing conditions failed to occur at the eight Fort Lewis monitor sites during the measurement period.

3. The peak threshold (105 dB for daytime and 95 dB for night) deleted meaningful data.

4. The monitoring equipment is fundamentally incorrect in its operation.

5. The monitored results are correct and the prediction and measures used to assess community response are incorrect.

Table 2
Measured vs Predicted CDNL at Fort Lewis

Site*	Computer-Predicted During the Monitoring Period** (CDNL)	Measured (CDNL)	Difference	Computer-Predicted for the Entire Year (CDNL)
1	44	34	+10	45
2	45	30	+15	47
3	59	46	+13	61
4	53	46	+7	53
5	56	43	+13	56
6	53	37	+16	53
7	49	53	4	50
8	54	44	+10	54

*See Figure 3 for site locations.
**All stations ran for the entire 6 months with only a few scattered days of data lost.

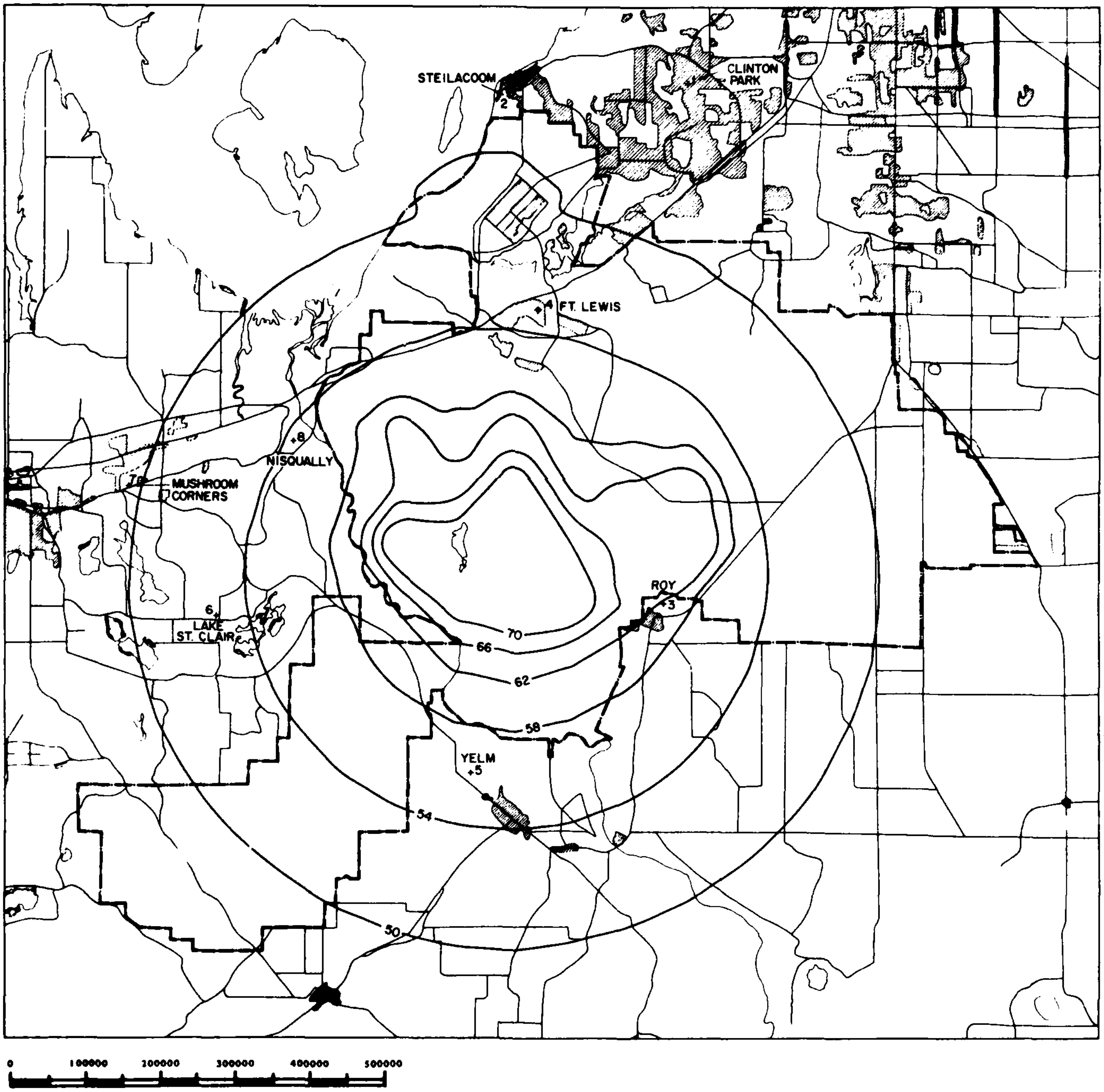

Figure 3. Predicted CDNL contours, monitor sites and predominant respondent groups in the Fort Lewis study area.

Figure 4 arrays the attitudinal survey results in terms of community response (i.e., high annoyance) vs the monitored DNL. This figure also includes the National Academy of Science's recommended function for predicting community response based on CDNL. Clearly, if a measured DNL value is plugged into the recommended National Academy of Science relation for predicting community response, then community annoyance is greatly underestimated as compared with the results from the attitudinal surveys. In the discussion which follows, this result (i.e., that annoyance prediction based on measured levels greatly underestimates true annoyance) and the corresponding results for computer simulation and the data in Figure 1 are used to analyze some of the causes to explain the discrepancy between results obtained by computer simulation and by direct measurement.

Fort Bragg and Fort Lewis Results – Discussion

1. *Can the monitoring be correct and the computer predictions and the attitudinal survey results be incorrect?* The following facts are known: training, including artillery fire, mortars, and demolition, occurred at a more or less normal rate (perhaps at a somewhat decreased rate) during the Fort Lewis monitoring period. The attitudinal survey results in terms of community annoyance correlate well with the predicted noise environment and are in general agreement with the previous survey results and prediction at Fort Bragg. Thirty percent of about 1500 respondents interviewed at Fort Lewis report hearing blast noise either daily or several times per week, and two-thirds of these respondents say that the blast noise is much louder than ordinary conversation. The survey interviewers also occasionally reported that they heard

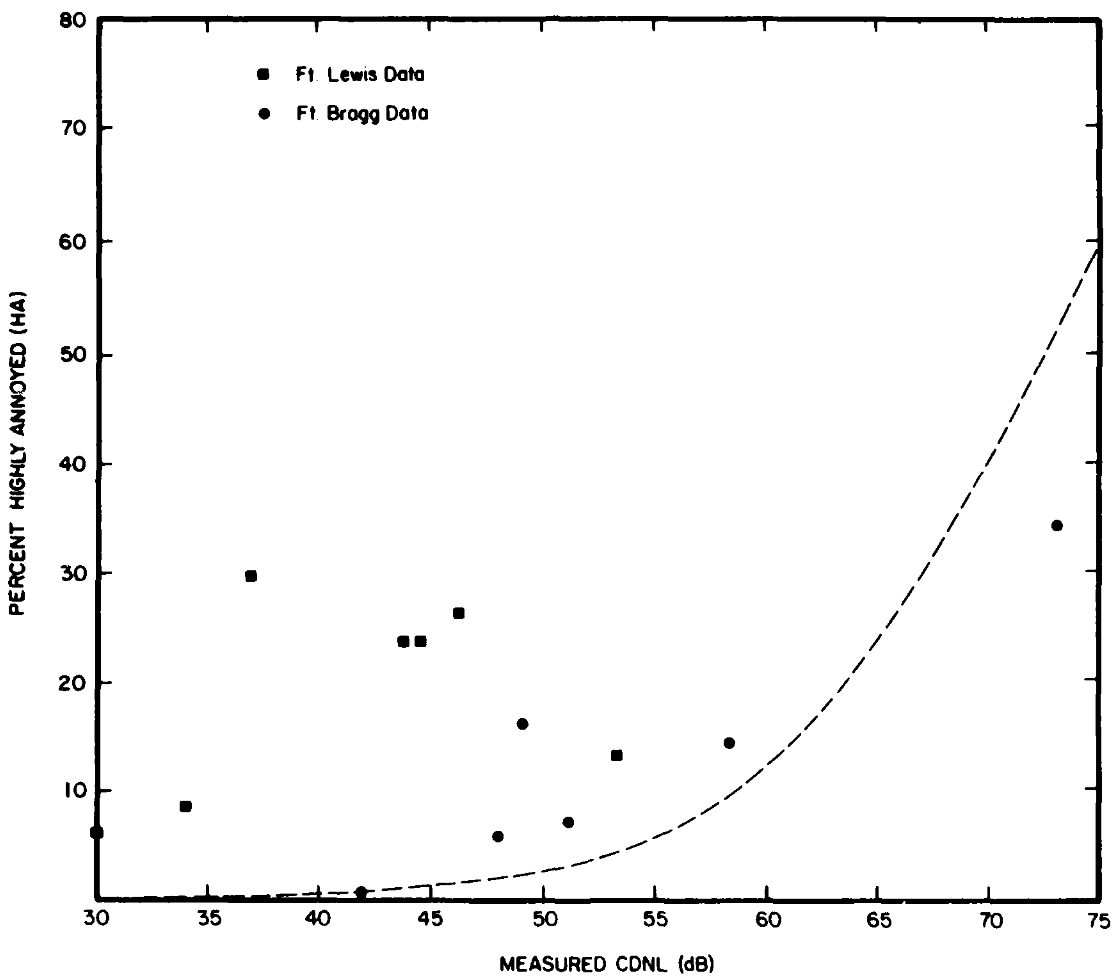

Figure 4. Survey data, percent highly annoyed (HA) vs measured CDNL. The dashed line is the CHABA recommended relation.

blast noise when they conducted interviews; sometimes during an interview, the building would shake from blast noise excitation. These facts seem to indicate that the answer cannot lie wholly in the statement that no noise existed. Rather, it appears there was a failure to properly record some of the blast noise data.

2. *Does the noise monitoring equipment properly measure impulse noise?* CERL has had about 4 years of experience with this equipment. It has been tested in comparison with every major commercial noise monitor and always equals or betters any commercial equipment in terms of measuring a known noise source. It has measured blast noise at Fort Bragg and Fort Carson using the same general techniques. It has been used successfully for Army source noise measurements and for many Army sound propagation measurements. It is designed and operated in accordance with all applicable American National Standards Institute standards. A basic flaw in the equipment or general operation does not appear to be a reasonable explanation for the poor results obtained from these studies.

3. *Does deletion of "windy data" delete important blast noise data?* The general monitoring procedure used at Fort Bragg and Fort Lewis was to delete all blocks of data for which the wind exceeded 18 km/hour. This was done because wind turbulence generated at the microphone can cause readings which will appear as blast noise. The known facts indicate the following: there were not many windy days during the monitoring period at Fort Lewis, so little data were deleted because of the wind threshold. On the other hand, blast propagation measurements conducted by CERL at Fort Leonard Wood showed that the greatest sound propagation occurred on 1 day during the 4-week test period when a wind shear occurred at about 1000 ft (305 m) above ground level.[5] Thus, it may be that some blast noise data were lost because of the wind threshold. However, the respondent-reported frequency of hearing blast noise substantially exceeds the rate at which windy days occurred at Fort Lewis during the monitoring period. So the full answer cannot lie in deletion of "windy data."

4. *Can the 104-dB peak threshold be deleting blast noise data?* The 105-dB peak threshold corresponds to a blast having about an 85-dB sound exposure level. This is the threshold set as the recommended practice of the National Academy of Science Committee on Hearing, Biocoustics and Biomechanics (CHABA). Mathematically, there would have to be between 100 and 1000 of these "just missed" events per day to bring the measured values into general agreement with the predicted levels. So, while it also may be true that the CHABA procedure should not incorporate this 85-dB threshold, the numbers are so small that the total answer cannot lie with the threshold. In the case of Fort Lewis, there are not enough firings to even theoretically explain the discrepancy on the basis of the 85-dB threshold.

5. *Did all of the monitors fail to be located at focus points?* The sound levels received in the community vary statistically. Weather conditions can focus high-amplitude sound at distant locations. For example, the Army Environmental Hygiene Agency recorded an instance of a noise complaint at one installation where a woman reported her house shaking from artillery noise. Sometime within the 20 minutes it took someone from the installation to go out to the woman's house, her house stopped shaking. But the barn, a few hundred feet away from the house, had begun shaking. The point of this anecdote is that sound focuses can, at times, be very localized in nature. It may be that none of the eight Fort Lewis monitors regularly received these sharply focused sounds, although some percentage of the population near these monitors did receive the sharply focused sounds. However, this explanation does not seem very likely.

Summary

The directly measured blast noise results at Fort Lewis, and to some extent Fort Bragg, do not agree with computer prediction or with the community response in terms of annoyance or reported frequency of hearing blast noise. Many reasons can be advanced for these discrepancies, but none appear to fully explain them. However, three of the potential sources of discrepancy can be mitigated:

1. The wind threshold and the peak amplitude threshold can be altered if windscreens are improved and if a multiple microphone technique can be developed to separate wind-induced noise from blast noise.

2. With windscreen improvements and a multiple microphone array, it may be possible to set the peak threshold at 95 or 100 rather than 105 dB; the wind speed deletion level could then be set at perhaps 30 instead of 18 km/hour.

[5] P. D. Schomer, et al., *The Statistics of Amplitude and Spectrum of Blasts Propagated in the Atmosphere*, Technical Report N-13, Volume 1 (ADA033475) and Volume 2 (ADA 033361) (CERL, November 1976).

3. The only answer to the question, "Are we measuring long enough to obtain a good statistical sample of what the weather effects are likely to be on the sound propagation?" is to measure for a very long time, and clearly this can be done.

The general results of the Fort Bragg and Fort Lewis studies seem to dictate that no more monitoring be performed for noise contour verification purposes (except possibly near to the sources) until the windscreens used with the noise monitoring equipment are improved and until a multiple microphone technique is developed which can better separate wind effects from true blast noise data. Also, any future monitoring should be done for at least 1 year in order to better account for the extreme variation in sound propagation and focus location.

3 SAMPLING STRATEGIES FOR MONITORING NOISE IN THE VICINITY OF CIVILIAN AIRPORTS

Introduction

When one can monitor blast noise, such as near an installation, then a temporal sampling strategy must be developed. This chapter uses commercial airport data to develop a notion about temporal sampling requirements in general. The next chapter relates the airport results to the Army situation.

The general problem underlying temporal sampling requirements for estimating long-term average sound levels at civilian airports is the associated statistical assessment of the precision of the estimates of mean sound level. With only a few exceptions, most techniques in use today for sampling community noise call for sampling over relatively short periods of time, i.e., from a few minutes to perhaps a single day. However, the time varying nature of noise data when viewed as a time series (hourly or daily averages) suggests that short-term sampling may lead to serious inaccuracies in the estimation of a long-term (yearly) mean noise level. For example, the 24-hour periodic pattern in hourly mean sound level may vary from about 40 to 85 dB. The Community Noise Equivalent Level (CNEL) and DNL noise descriptors both commonly vary from 45 to 80 dB. These wide ranges for sound level, together with the fact that the data in general exhibit high positive autocorrelation and high coefficients of variation, suggest that small or short sampling periods or both may provide imprecise and inaccurate mean value estimates.

The techniques of time series modeling generally provide a powerful method for assessing mean level estimation precision and for formulating sampling strategies. Appendix A fully describes the use of the Dynamic Data System (DDS) for doing analyses based on fitting Autoregressive-Moving Average (ARMA) time series models to the daily average noise level data. The analysis in Appendix A uses about 1 year's daily CNEL data gathered at several sites around San Diego's Lindbergh Field and Miramar Naval Air Station and shows a high degree of positive autocorrelation in CNEL values from day to day. This day-to-day positive autocorrelation is to be expected because of prevailing winds, slowly varying weather fronts, and the relatively constant set of daily operations and fleet mix at commercial airports. The autocorrelated nature of the data, particularly the degree of positive autocorrelation among neighboring observations, increases the amount of consecutive sampling required to estimate the long-term mean level with a given level of precision over sampling where independence is assumed.

In Appendix B, the DDS method is used to model about 8 months of daily CNEL data gathered at 12 sites near Los Angeles International Airport. The results given in Appendices A and B form a set of guidelines for sampling strategies near civilian airports. However, these results use only CNEL data and are only for west coast airports.

Appendix C extends the analysis to east coast airports and to the use of the DNL noise descriptor. Specifically, about 13 months of daily DNL data were obtained for 15 sites near Boston's Logan Airport, and about 9 months of daily DNL data were obtained for nine sites near the Washington, DC, Dulles Airport and 14 sites near the Washington, DC, National Airport. The DDS method was again used to model these daily DNL data. Monte Carlo simulations were performed to verify the sampling requirements obtained from the DDS data modeling and to study alternatives to consecutive sampling. The results of these analyses, along with the results given in the other two appendices, are used to form a set of guidelines for sampling strategies in the vicinity of civilian airports.

The DDS method can be used to develop parametric stochastic time series models of the ARMA class. Daily sound exposure (Eq 1), when viewed as a time series of values $X_1, X_2, \ldots, X_N$, has been shown to be well characterized by such models (Appendices A and B). This makes it possible to determine the precision associated with an estimate of the yearly mean sound exposure level when the observed daily values X_t are autocorrelated.

The general ARMA model is given by

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots \phi_n X_{t-n} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_n a_{t-m} \qquad \text{[Eq 1]}$$

where:

X_t is the noise level (daily average) for day t.

a_t is the random disturbance for day t.

$\phi_1, \dots, \phi_n$ are autoregressive parameters.

$\theta_1, \dots, \theta_m$ are moving average parameters.

Given the time series X_t, the appropriate order of the ARMA model (the proper values for n and m) may be determined and the parameters of the model may be estimated by the method of least squares.[6]

Most of the fitted ARMA models obtained for the data analyzed in this report are of relatively low order. For example:

$$\text{AR (1)}: X_t = \phi_1 X_{t-1} + a_t$$

$$\text{AR (2)}: X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + a_t$$

$$\text{ARMA (1, 1)}: X_t = \phi_1 X_{t-1}\ a_t - \phi_1 a_{t-1}$$

The ARMA models fit to the daily sound exposure time series X_t may be used to estimate the precision associated with the sample mean $\bar{X}$. It can be shown (Appendix B) that the variance estimate of the sample mean is given by

$$\widehat{\text{Variance}}(\bar{X}) = \frac{\hat{\sigma}_a^2}{N} \left[\frac{(1 - \sum_{i=1}^{m} \hat{\theta}_i)}{(1 - \sum_{j=1}^{n} \hat{\phi}_j)} \right]^2 \qquad \text{[Eq 2]}$$

where σ_a^2 is the residual mean square for the fitted ARMA model. Given the above variance estimate, 100 $(1-\alpha)$ percent confidence intervals of the form

$$\bar{X} \pm t_{N-(n+m),\,1-\alpha/2} [\widehat{\text{Variance}}(\bar{X})]^{1/2} \qquad \text{[Eq 3]}$$

may be obtained for the true yearly mean sound exposure level, thereby providing an estimate of the precision associated with the sample mean $\bar{X}$.

Discussion

In summing the modeling results across the Boston and Washington Airports (Appendix C), it becomes apparent that a number of the sites exhibit nonstationary behavior; i.e., the mean level changes over the year. As a result, long-term consecutive sampling requirements are very large, often constituting more than one-third of a year. This result is much different than the sampling requirements analysis for the west coast airports which exhibit, in general, a stationary stochastic structure over an entire year's data. In attempting to delineate differences in the characteristics of the east and west coast airports and the sampled data obtained, two observations can be noted: (1) the west coast airports are one-direction, one-runway airports, and (2) the monitoring sites for the west coast airports are generally closer to the runways. The results relative to the east coast airports suggest that any analysis should be confined to data covering substantially a period of 1 year.

Figure 5 summarizes the results for all of the airports modeled (airport sites only), including Dulles, National, and Logan from Appendix C and Los Angeles (including one site from Lindberg Field) from Appendices A and B. This figure graphically represents the similarities and differences among the airports in terms of their sampling characteristics. The results generally show that the west coast airports (typically one-direction because of prevailing winds off the ocean) tend to have lower coefficients of variation and comparable autocorrelation factors relative to the multirunway or multidirection (variable wind) or both characters of east coast airports. These results produce overall sampling requirements for the west coast airports which are generally lower than those for the east coast airports.

Because of the presence of nonstationary trends and large sampling requirements for some of the data, Monte Carlo sampling experiments were performed with the Los Angeles, Boston, and Washington data. Through such simulations, generalized sampling strategies, including alternatives to consecutive

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[6] S. M. Pandit and S. M. Wu, *Time Series and System Analysis: Modeling Applications* (John Wiley and Sons, 1982).

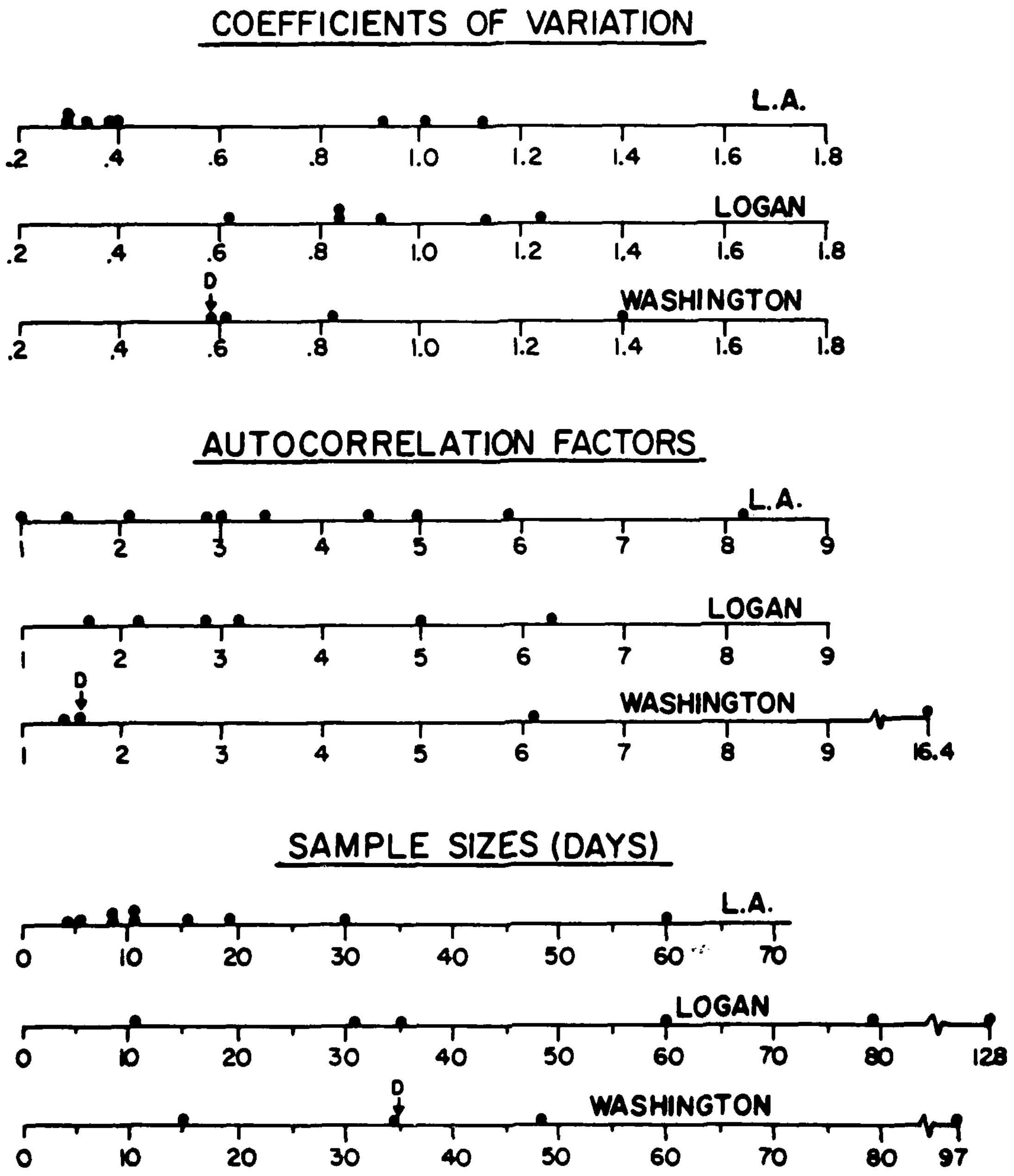

Figure 5. Results of all airports modeled in Appendices A, B, and C

sampling, may be examined. Such alternate strategies may require fewer total samples than consecutive sampling and provide a means to accommodate trends.

Sampling experiments were performed on those sites with 1 year of reasonably continuous data. In the first set of experiments, the total number of samples taken to estimate the mean noise level for each strategy was 28 days; in the second experiment, the total number of days was 56.

Figures 6a through 6h show the Monte Carlo simulation for Los Angeles, Boston, National, and Dulles airports, respectively. For Los Angeles, periodic sampling indicates a slight but not marked improvement in predictive precision over consecutive sampling. With the exception of two sites, the Los Angeles results show that a ± 50 percent precision can be attained with 28 samples, regardless of the sampling strategy chosen. For the Boston and Washington airports, significant improvements in the predictive precision can be achieved by periodic sampling, e.g., 1 week from each quarter over the year. This is particularly true for those sites which exhibited nonstationary behavior. To guarantee a ± 60 percent precision level for these airports, it is required to sample 1 week from each quarter over the entire year.

In considering the results of the simulation experiments involving requirements of 56 days of sampling, it is noted that for Los Angeles, ± 35 percent precision is attainable for all sites regardless of the sampling strategy except for Sites 12 and W3. For these two sites ± 35 percent precision is obtainable by sampling for 1 week out of each eighth of the year. For the Boston and Washington airports, ± 40 percent precision can be achieved for all sites if eight 1-week samples are taken, one from each eighth of the year.

For Los Angeles, the DDS modeling consecutive sampling requirements and those obtained from the Monte Carlo simulations are generally about the same (see Table 3). These sites exhibit a stationary stochastic structure for the entire year and the simulations verify the DDS modeling results. The same comparison holds for Boston sites 1, 5, 8; Dulles site 8; and National sites 15 and 20. These sites exhibit stationary behavior.

Table 3
Comparison of DDS and Monte Carlo Simulation Results

Site		DDS Modeling Results Consecutive Samples For P = ±50%	Monte Carlo Simulation Results % P for 28 Consecutive Samples	Monte Carlo Simulation Results % P for 56 Consecutive Samples
L.A.X.	A1	6	26.0	17.0
L.A.X.	A2	19	32.0	22.0
L.A.X.	E1	4	24.0	15.0
L.A.X.	E2	8	32.0	24.0
L.A.X.	12	30	77.0	47.0
L.A.X.	L2	11	35.0	18.0
L.A.X.	W2	16	36.0	25.0
L.A.X.	W3	60	81.0	52.0
L.A.X.	W4	11	40.0	28.0
BOSTON	1	11	40.0	25.0
BOSTON	3	60	71.0	78.0
BOSTON	4	128	121.0	116.0
BOSTON	5	35	65.0	49.0
BOSTON	6	79	93.0	42.0
BOSTON	8	31	51.0	39.0
DULLES	1	90	57.0	46.0
DULLES	4	Nonstationary	74.0	47.0
DULLES	6	158	93.0	56.0
DULLES	7	34	47.0	24.0
DULLES	8	10	32.0	20.0
DULLES	10	62	55.0	39.0
NATIONAL	13	48	72.0	46.0
NATIONAL	14	97	55.0	52.0
NATIONAL	15	15	47.0	35.0
NATIONAL	18	14	96.0	90.0
NATIONAL	20	10	26.0	20.0
NATIONAL	21	67	74.0	57.0
NATIONAL	22	159	80.0	66.0

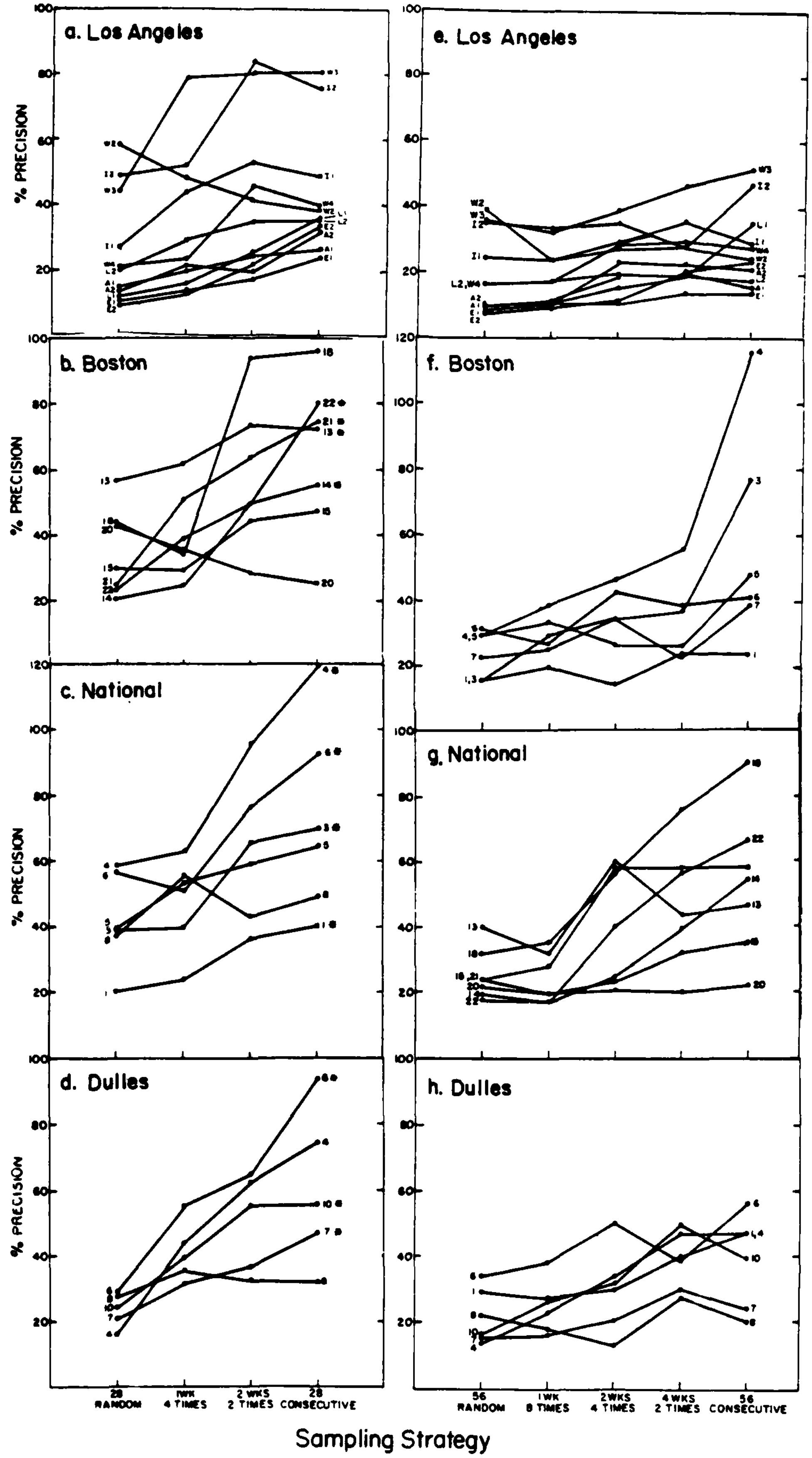

Figure 6. Monte Carlo simulation results for Los Angeles, National, and Dulles airports.

For the sites exhibiting nonstationary behavior at Boston, Dulles, and National, the comparison of the DDS modeling and simulation results are not always consistent. In particular, the DDS models may over-quote the consecutive sampling requirements needed for a particular level of precision when compared with the simulation results. This is particularly true for site 6 at Boston, site 6 at Dulles, and sites 14 and 22 at National.

Summary

The results generally show that the west coast airports tend to have lower coefficients of variation and comparable autocorrelation factors relative to the multirunway and/or multidirection (variable wind) east coast airports. These results produce overall consecutive sampling requirements for the west coast airports which are generally lower than those for the east coast airports.

A precision (95 percent confidence) of ±2 to ±3 dB is generally achieved with 4 to 8 weeks of monitoring; 1 week from each eighth or 1 week from each quarter of the year, respectively.

4 EXTENSION OF THE AIRPORT TEMPORAL SAMPLING RESULTS TO ARMY INSTALLATIONS

The airport results (Chapter 3) show that a precision (95 percent confidence) of ±2 to ±3 dB is generally achieved with 4 to 8 weeks of monitoring; 1 week from each eighth or 1 week from each quarter of the year, respectively.

The point of closest approach of airplanes to any noise monitor is never more than a few thousand feet. The operations at civil aviation airports are quite regular throughout the year; that is, the airport schedule remains relatively constant. In contrast, training operations at an Army base are much less regular and the "point of closest approach" from firing points to monitors may be at distances of 5 miles or more.

Since precision is proportional to the square of the number of samples, an increase in variability of only a factor of 2 in the Army case over the public airport case implies sampling strategies requiring 16-64 weeks out of the year. In effect, due to the variability in day-to-day operations coupled with the variability of sound propagation over long distances, the only way to estimate the yearly CDNL in the vicinity of an Army base with any degree of precision is to measure the CDNL for the entire year.

5 CONCLUSIONS

1. The airport results (Chapter 3) show that a precision (95 percent confidence) of ±2 to ±3 dB is generally achieved with 4 to 8 weeks of monitoring; 1 week from each eighth or 1 week from each quarter of the year, respectively.

2. The results in Chapter 2 show that monitored levels may differ substantially from computer simulation predictions. In view of the community response data which correlate well with computer simulation and which indicate the presence of substantial impulsive noise, it can only be concluded that either the current monitoring techniques are inadequate to measure the true impulsive noise and that the current results are biased to the low side or that the computer predictions are high and communities respond adversely to much lower levels of impulsive noise than is commonly believed. The former seems to be the more reasonable conclusion.

Because the extrapolation of the airport data (Chapter 4) indicates impulsive noise monitoring must be continuous to properly measure the CDNL and because survey data show that even continuous monitoring will generally be biased to the low side (except near base boundaries), the general recommendation is that monitoring not be performed until monitoring techniques can be improved and a good correlation achieved between monitoring and attitudinal survey results. Until then, it is recommended that reliance be placed only on computer simulation since these results correlate better with attitudinal surveys.

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APPENDIX A: DEVELOPMENT OF TEMPORAL SAMPLING STRATEGIES FOR MONITORING NOISE

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This paper addresses the problem of the estimation of the long-term (yearly) mean of the Community Noise Equivalent Level (CNEL) or day/night average sound level (L_{DN}). Recent environmental noise standards have emphasized the significance of this problem. While it is possible to continually monitor the noise level, it is not necessarily desirable or practical. It is desirable to sample the level over a relatively short period of time and use this information to draw reliable inferences about the long term mean level. Examination of daily average noise levels (either in mean square pressure or in decibel units) shows that while the data may be stationary with respect to mean level over a several month period, they exhibit a strong pattern of autocorrelation in which positive correlation predominates. As a result, the sample sizes required to achieve a desired level of precision in the sample mean estimate are much larger than they would otherwise be if the data were uncorrelated serially in time. To assess the level of autocorrelation in the data, autoregressive-moving average (ARMA) models are developed for the noise data via the Dynamic Data System (DDS) approach to time series analysis. These models are then used to derive estimates of the sample mean variance and therefore to establish sampling strategies. For the data examined, to obtain an estimate of the mean level within a 5-dB range (±50% of the mean in mean square pressure units), sample sizes in the range of 20–50 consecutive daily averages would be required. If the daily averages were uncorrelated in time, only 5–15 consecutive daily averages would be required. The data used in this study were obtain from continuous monitoring at a number of sites in the vicinity of a busy Naval Air Station. Some data obtained from a large commercial airport were also analyzed and found to have even stronger positive autocorrelation, and therefore requiring even larger sample sizes for mean value estimation.

PACS numbers: 43.50.Sr, 43.50.Qp, 43.50.Lj

LIST OF SYMBOLS

X_t	A daily CNEL at time t
$\mathrm{Var}(\bar{X})$	The variance of the sample mean, $\bar{X}$
γ_0	The variance of the X_t's
N	The number of observations
k	Time lag
γ_k	kth lag covariance between X_t and X_{t+k}
ϕ_i	ith autoregressive parameter
θ_i	ith moving average parameter
G_i	ith Green's function value
a_t	Random shock occurring at time t
σ_a^2	The variance of the random shocks a_t
B	The backward shift operator
$z_{1-\alpha/2}$	Unit normal statistic at the α significance level

INTRODUCTION

Assessment of community noise is an important data analysis problem currently receiving considerable attention in both the public and private sectors.[1,2] In this paper, we will examine the fundamental problem of estimating the long term average noise level based on measurements of the Community Noise Equivalent Level (CNEL). Due to the close correspondence between CNEL and the day/night average sound level L_{DN}, the results herein should be equally applicable to monitoring L_{DN}. In this regard, the appropriate sample interval size and the total amount of information collected for the specified sample interval are the sampling parameters of interest.

To rationally embrace the problem posed above, it is necessary to reveal the probabilistic nature of the noise level signal as it evolves serially in time. This is so since the techniques of estimation and statistical inference brought to bear on such a problem are dependent upon the underlying statistical characteristics of the data, in particular, the serial correlation of the data. The inherent time-varying behavior of the data suggests that its stochastic nature should be fully revealed. In fact, it becomes clear after only a cursory examination of the signal to be sampled that time series analysis of one form or another will be required to obtain a valid and efficient temporal sampling strategy.

In recent years, time series modeling via the class of autoregressive-moving average (ARMA) models has received considerable attention both in modeling strategy development and modeling applications. Recently, Pandit and Wu[3-5] have proposed a new strategy for time series modeling referred to as Dynamic Data System (DDS). The DDS approach combines the modeling of deterministic trends including periodicities by a generalized Laplace transform and the modeling of the remaining stochastic variation including stochastic trends and periodicities by the general class of autoregressive-moving average models. Since the models developed are parametric in nature, they have the advantage of being able to describe the autocorrelated nature of the data in simple, closed forms which greatly facilitates the mean level estimation and inference problem.

In this paper, we will examine the use of ARMA models as an approach to the characterization of community noise level data. This approach is considered to have significant potential, since it not only contributes to the solution of the sampling strategy problem for CNEL mean level estimation and inference, but also can provide a methodology for monitoring and modeling noise level for the detection of significant shifts in level, and can serve as a basis for the analysis of the relationship between noise level and other physical phenomena. In the formulation of the sampling strategies presented here, an analysis is conducted on CNEL data obtained from several sites in the vicinity of NAS Miramar, San Diego, CA. The paper is presented in four main sections. The first section provides a discussion of the problems which autocorrelated data pose to the mean level inference problem and formulates the problem mathematically via the ARMA class of stochastic models. The second section briefly describes the DDS modeling methodology, and its application to the problem at hand. In the third section, modeling results are presented for two noise time series and an assessment of the precision of the estimation of the mean noise level is provided. The precision assessment developed via the DDS modeling method is compared to results obtained under the assumption that the noise data are uncorrelated in time. Finally, the fourth section summarizes the sampling strategy requirements and discusses the varying results over the several sites from which noise data were obtained and analyzed.

I. THE MEAN LEVEL INFERENCE PROBLEM

At the outset of this study, it was proposed to formulate a strategy for sampling the noise level signal at a given location and using the data obtained to estimate the *yearly* average noise level with some prespecified level of precision. While this information may be quite useful from an environmental impact point of view, it will be both insightful and necessary to carefully examine the time-varying nature of the signal over the entire year. This will not only impact the estimation and inference problem, but strongly influence the practical interpretation given to an average or mean level estimate.

A. Autocorrelated nature of the data

If a series of observations $X_1, X_2, \ldots, X_N$ is used to estimate the average yearly noise level, the specific nature of the autocorrelation in the data will impact the precision of this estimate. The precision of the estimate of the true mean level is given by

$$\mathrm{Var}(\bar{X}) = \frac{1}{N}\left[\gamma_0 + 2\sum_{k=0}^{N-1}\left(1 - \frac{|k|}{N}\gamma_k\right)\right], \tag{1}$$

where $\gamma_0 = \mathrm{Var}(X_t)$, k = time lag, N = sample size, and γ_k = kth lag auto covariance between X_t and X_{t+k}.

If the data are uncorrelated, then $\gamma_k = 0$ for $k \geq 1$ and

$$\mathrm{Var}(\bar{X}) = \gamma_0/N. \tag{2}$$

Therefore, a $(1-\alpha)100\%$ confidence interval for $\bar{X}$ will be given by

$$\bar{X} \pm z_{1-\alpha/2}[\mathrm{Var}(\bar{X})]^{1/2}. \tag{3}$$

Strictly speaking, the t distribution should be used instead of the unit normal, z distribution to account for the uncertainty in estimating the variance of the sample mean. However, for the sample sizes encountered in this paper, the t distribution is closely approximated by the z distribution. While the X_t need not be Gaussian, they should fluctuate about a fixed mean level with a constant pattern of irregularity, i.e., be stationary.

If the data are autocorrelated, then Eq. (1) may be rewritten as

$$\mathrm{Var}(X) = (\gamma_0/N)C, \tag{4}$$

where C is a factor which varies with and accounts for the specific autocorrelated nature of the data. In general, for positively correlated data the autocorrelation factor C will be greater than 1.0 while for negatively correlated data it will be between 0.0 and 1.0. This phenomenon can be appreciated intuitively by examination of Fig. 1. It is clear that for positively correlated data the excursions or runs above and below the mean produce sample averages with wider dispersion about the true mean than if the data were random. Similarly, negatively correlated data are characterized by successive high and low values which tend to "average" to values quite closely clustered about the true mean. These characteristic behaviors may be quantified by the autocorrelation factor, which for the modeling technique used herein can be shown to be solely a function of the parameters of an autoregressive-moving average model for the data.

B. Mathematical statement of the problem

Consider a finite set of discrete measurements, X_1, $X_2, \ldots, X_N$ obtained by uniformly sampling a continuous

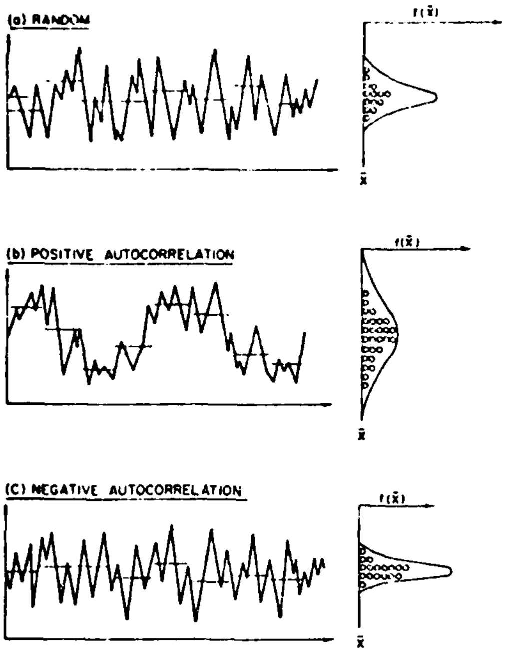

FIG. 1. Autocorrelated structures in time series and their impact on sample mean precision.

signal $X(t)$ at equispaced intervals Δt. Let us assume that:

(1) The sample interval size Δt is a prespecified constant and is of a size sufficient to capture the structure of the continuous signal.

(2) $\{X_t\}$ constitutes a *stationary* time series, i.e., fluctuates about a fixed mean with a constant pattern of irregularity and

(3) The length of record $N\Delta t$ is sufficient to adequately encompass the significant long-term features of the continuous signal.

The problem to be addressed is, then, to determine the precision with which the sample mean $\bar{X}$ based on N observations estimates the true mean level, or alternatively to specify the length of record (number of observations) needed to estimate the true mean μ by $\bar{X}$ within a certain prespecified interval at a given level of statistical significance.

For a stationary time series, the $\{\gamma_k\}$ converge to zero as k increases so that for large N, Eq. (1) reduces to the approximation,

$$\mathrm{Var}(\bar{X}) \approx \frac{1}{N} \sum_{k=1-N}^{N-1} \gamma_k . \tag{5}$$

The problem of mean value inference then reduces to the estimation of $\{\gamma_k\}$.

We will be concerned with the use of parametric stochastic models of the autoregressive-moving average (ARMA) class for the estimation of the $\{\gamma_k\}$. This approach provides both a mathematically sound and practically appealing approach to the problem.

II. TIME SERIES MODELING BY DYNAMIC DATA SYSTEM (DDS)

A. The DDS modeling approach

Modeling of stochastic phenomena by the general class of autoregressive-moving average (ARMA) models has found a tremendous growth in applications in the areas of forecasting and control in recent years. Several unified strategies have been proposed to facilitate this modeling with varying philosophies on the model building procedure, physical interpretation of models, and the manner in which both deterministic and stochastic trends are modeled. The Dynamic Data System (DDS) methodology has particular appeal for several reasons which go beyond the scope of this paper. In particular, the modeling and interpretation of physical systems is greatly enhanced by this approach.

When only stochastic variation is evident in the data (no deterministic trends such as periodicities) the general class of ARMA models given by Eq. (6) is employed for modeling,

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_n X_{t-n} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_m a_{t-m}, \tag{6}$$

where X_t is the observation in the time series at time t, a_t is normally and independently distributed: $\mathrm{NID}(0, \sigma_a^2)$, $\phi_1, \ldots, \phi_n$: n autoregressive parameters, and $\theta_1, \ldots, \theta_m$: m moving average parameters. In the *DDS modeling methodology*, m is generally defined to be $n-1$ although the final appropriate fitted model may have $m < (n-1)$. It can be shown[5] by employing the elementary theory of linear operators on Hilbert space that any stationary stochastic system can be approximated by an autoregressive moving average model of order $(n, n-1)$.

For the use and interpretation of the ARMA$(n, n-1)$ model class it is useful to consider two important characterizations of the model: (i) Green's function, and (ii) autocovariance function. According to Wold's decomposition, X_t may be expressed as a sum of orthogonal vectors $G_j a_{t-j}$, in an infinite dimensional space, i.e.,

$$X_t = \sum_{j=0}^{\infty} G_j a_{t-j} . \tag{7}$$

The weights G_j may be determined for any ARMA$(n, n-1)$ model by equating coefficients of like powers of the backward shift operator B in,

$$(G_0 - G_1 B - G_2 B^2 - \cdots -) = \frac{(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_{n-1} B^{n-1})}{(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_n B^n)} . \tag{8}$$

For stable systems, only a relatively few number of vectors need to be added to obtain X_t. The weights G_j are referred to as Green's function and are expressable in terms of the ϕ's and θ's of the model. Physically, Green's function may be thought of describing the nature of the dynamic response of the system to a random disturbance a_t. If the forcing function a_t is removed, the system response decays to the mean level according to G_j. The Green's function characterization of the stochastic process is most useful in deriving statistical properties of the process as will be seen later.

The autocovariance function for the general ARMA($n, n-1$) model form may be derived from Eq. (6), noting that the kth lag autocovariance γ_k is given by

$$\gamma_k = E(X_t \cdot X_{t-k}) . \quad (9)$$

The fact that the autocovariances $\{\gamma_k\}$ can be expressed solely in terms of the model parameters, ϕ, θ, and σ_a^2 is found to be most useful later when an estimate of the variance of the sample mean is to be obtained given an appropriate ARMA model for the data. The Appendix provides the equations which define the $\{\gamma_k\}$ as functions of ϕ, θ, and σ_a^2.

In the DDS methodology, the appropriate model for a given set of data is determined by successively fitting models of progressively higher order by the method of least squares until a satisfactory fit is obtained. Analysis of variance is performed for each model, and the F test is employed to determine when the reduction in the residual sum of squares from one model to the next is statistically significant. Initially, an ARMA(2, 1) model, i.e.,

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + a_t - \theta_1 a_{t-1} , \quad (10)$$

is fit to the data. Models of the form ARMA(4, 3), ARMA(6, 5), ..., ARMA($2n, 2n-1$) are then successively fit. The model is incremented by steps of two, i.e., ARMA($2n, 2n-1$) so that the roots of the model can be either real or complex at any time, thereby not forcing a real root to be present in a model for a process which does not physically have that characteristic. Modeling is terminated when the F test fails to show significance when the next higher-order model is fit. Individual model parameters near zero may be examined for significance by computing their $(1-\alpha)100\%$ confidence intervals. Insignificant parameters are dropped and the remaining parameters are reestimated. In general, an ARMA(n, m) model results.

B. Estimation of the $\{\gamma_k\}$ from the ARMA model parameters

By employing the ARMA model class to characterize a time series of noise data, the $\{\gamma_k\}$ for these data [and in Eq. (5)] can be estimated by functions of the model parameters alone. In particular,

$$\mathrm{Var}(\bar{X}) = \frac{\sigma_a^2}{N} \left[\frac{\left(1 - \sum_{j=1}^{m} \theta_j\right)}{\left(1 - \sum_{i=1}^{n} \phi_i\right)} \right]^2 . \quad (11)$$

The variance of the disturbances σ_a^2 may be calculated by recursively calculating the $\hat{a}_t$'s from the fitted model and then substituting into Eq. (12):

$$\hat{\sigma}_a^2 = \frac{\sum_{t=1}^{N} (\hat{a}_t)^2}{N - (2n + m)} . \quad (12)$$

The approach to assessing the confidence associated with the sample mean $\bar{X}$ of the autocorrelated sequence $X_1, X_2, \ldots, X_N$ is then as follows:

(1) Use the DDS modeling methodology to find by successive fitting the appropriate ARMA(n, m) model for the data. Since, in general, the models are nonlinear in the parameters, an interative nonlinear least squares routine is required to estimate the parameters.

(2) Based on the fitted model and estimated parameters $\hat{\phi}$, $\hat{\theta}$, and $\hat{\sigma}_a^2$, estimate the variance of the sample mean from Eqs. (11) and (12).

(3) Establish a $(1-\alpha)100\%$ confidence interval for the true mean μ from Eq. (3).

It should be noted that in all of the modeling of noise data which follows, the data are modeled and precision estimates in the sample mean are determined in units of sound exposure or mean-square pressure. Confidence intervals determined in mean-square pressure are then transformed to sound exposure level (SEL) in decibels by the transformation,

$$\mathrm{SEL} = 10 \log_{10}(\text{mean-square pressure}) . \quad (13)$$

III. ANALYSIS OF NOISE DATA

To illustrate the modeling technique employed and its use in the mean level estimate precision assessment problem, two sets of noise data are examined. One is derived from a site in the vicinity of NAS Miramar, San Diego, CA (site 30) while the second was obtained by nearby Lindberg Field (site W50), the commercial San Diego Airport. Both sets of data were recorded between January and June of 1976. Figure 2 shows a map of NAS Miramar and the locations of several monitoring sites around the airfield. Figures 3 and 4 show the data in units proportional to mean-square pressure. Each data point is a time-weighted 24-hour average noise level referred to as the Community Noise Equivalent Level (CNEL). CNEL values are determined from the equation,

$$\mathrm{CNEL} = 10 \log \frac{1}{P_0^2 T} \left[\int_0^{25\,200} 10 P_a^2(t) dt + \int_{25\,200}^{79\,200} P_a^2(t) dt + \int_{79\,200}^{86\,400} 10 P_a^2(t) dt \right] , \quad (14)$$

where $P_0 = 20$ micropascal and $T = 86\,400$ s.

A. DDS modeling

The DDS modeling methodology was applied to the data to obtain an adequate ARMA(n, m) model. For the NAS Miramar data successive fitting and testing for adequacy via the F test revealed that an ARMA(8, 7) model is required to describe the data. For the Lindberg Field data, an ARMA(2, 1) model was found to provide an adequate representation.

Table I provides the fitted models and statistical para-

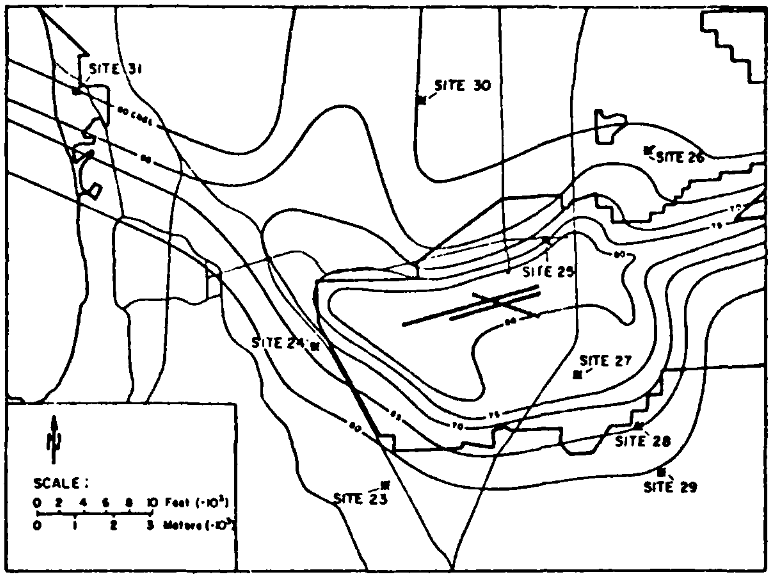

FIG. 2. Map of monitoring sites at NAS Miramar.

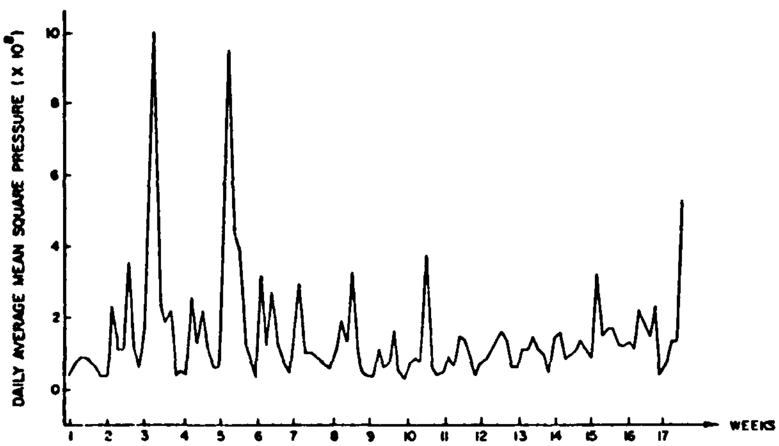

FIG. 3. NAS Miramar—data from site 30.

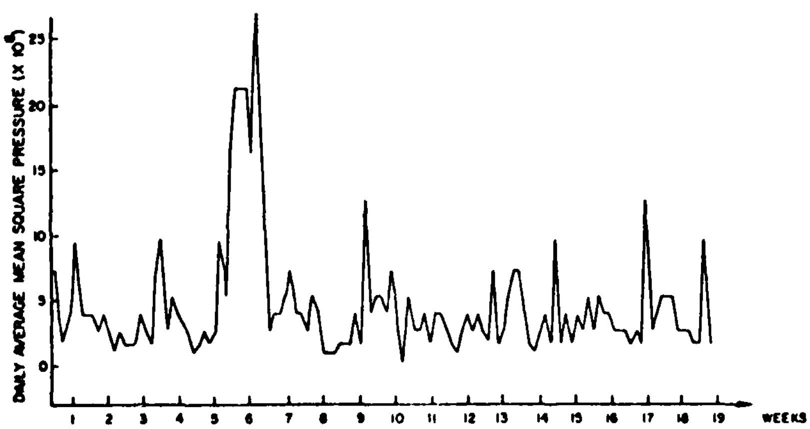

FIG. 4. Lindberg Field—data from site W50.

TABLE I. Fitted models and parameter estimates for the CNEL mean square pressure data for sites 30 and W50.

Site	Fitted ARMA(n, m) model	$\bar{X}$	$\hat{\gamma}_0$	$\hat{\sigma}_a^2$	N
NAS Miramar site 30	$X_t = 0.616X_{t-1} - 0.330X_{t-2} + 0.159X_{t-3}$ $+ 0.118X_{t-4} - 0.132X_{t-5} + 0.065X_{t-6}$ $-0.156X_{t-7} - 0.011X_{t-8} + a_t + 0.563a_{t-1}$ $-0.528a_{t-2} + 0.046a_{t-3} + 0.483a_{t-4}$ $-0.149a_{t-5} + 0.137a_{t-6} - 0.693a_{t-7}$	1.69×10^6	2.54×10^{12}	1.75×10^{12}	105
Lindberg Field site W50	$X_t = 0.633X_{t-1} + 0.135X_{t-2}$ $+ a_t + 0.202a_{t-1}$	51.9×10^6	1186.57×10^{12}	750.21×10^{12}	182

meter estimates for both the site 30 and site W50 data. As can be seen from the table, the two noise level time series appear to vary considerably in terms of both their average levels and stochastic structure. For site 30, the mean level is equivalent to 61.4 dB while for site W50 it is considerably higher, 76.0 dB. The differences in the autocorrelated structure will be more fully revealed when an assessment in the precision of the sample mean $\bar{X}$ is made.

B. Mean level precision assessment

To assess the precision of the estimate of the sample mean, a $(1-\alpha)100\%$ confidence interval for the true mean μ may be determined. For the site 30 data, using Eq. (11), and $\hat{\sigma}_a^2$ from Table I,

$$\hat{\text{Var}}(\bar{X}) = 4.80 \times 10^{10}.$$

A 95% confidence interval for μ is then given by Eq. (3),

$$1.69 \times 10^6 \pm 4.29 \times 10^5.$$

In decibel units, the mean estimate is 62.3 dB and the 95% confidence interval is bounded by 61.0 dB and 63.3 dB. The interpretation of this interval is that we are 95% confident that the true mean for these data is estimated within about ± 25% in mean-square pressure which is about minus 1.3, plus 1.0 dB.

It is interesting to compare the result above to the parallel result obtained if we assume that the daily average noise levels ordered in time are independent. In this case, using Eq. (2),

$$\hat{\text{Var}}(\bar{X}) = 2.419 \times 10^{10}.$$

A 95% confidence interval is given by

$$1.69 \times 10^6 \pm 0.305 \times 10^6,$$

which says that we can estimate the mean within ± 18% in units of mean-square pressure. Hence, by neglecting the effect of autocorrelation in the data we get the impression that for a fixed sample of data (here, approximately one-third of a year) we can estimate the mean more precisely than what we really can.

When analyzing the Lindberg Field (site W50) data, the effect of autocorrelation is even more pronounced. Accounting for the autocorrelated nature of the data,

$$\hat{\text{Var}}(\bar{X}) = 4876.37 \times 10^{10}.$$

Assuming independence,

$$\hat{\text{Var}}(\bar{X}) = 652.0 \times 10^{10}.$$

The corresponding 95% confidence intervals are given by

(i) Assuming the data are autocorrelated;

$$51.9 \times 10^6 \pm 6.98 \times 10^6.$$

(ii) Assuming the data are independent;

$$51.9 \times 10^6 \pm 2.60 \times 10^6.$$

In other words, while an uncorrelated analysis would suggest a mean level estimate within ± 5% based on the 182 data points, the autocorrelated analysis shows that our precision is really only about ± 13.4%.

For the site W50 (Lindberg Field) data it is clear that the effect of autocorrelation in the data is more dramatic in terms of the precision assessment of the long run sample mean. The specific effect in terms of the formulation of sampling strategies will now be examined.

IV. DEVELOPMENT OF SAMPLING STRATEGIES FOR ESTIMATION OF MEAN NOISE LEVELS

A. Comparision of sample size requirements: Independence versus autocorrelated analysis

The question of practical significance to the acoustician studying environmental noise problems is: "How long must I monitor noise at a particular site to be able to estimate the long run mean level with a given level of precision?" In terms of the data we are examining here this question asks, "How many days must be monitored?" For example, how large of a sample of daily averages must we obtain? The answer to this question may be sought in an effort to validate the predictions of a noise level model used in the vicinity of a military installation or to assess and detect possible noise level shifts over a period of time.

Using the data from several sites around NAS Miramar and vicinity, we will attempt to answer the above question and lend some insight to the general problem of sampling environmental noise and estimating mean levels with some prespecified level of precision required.

Returning to the site 30 and site W 50 data previously modeled, the question is asked: "How many successive daily average values would have to be obtained to estimate the mean level within ± 50% in units of mean-square pressure?" Assuming a 95% confidence interval of size ± 0.50$\bar{X}$ (50% precision in the mean level estimate) is required, we have that

$$\pm 0.50\bar{X} = \pm Z_{1-\alpha/2}[\hat{\mathrm{Var}}(\bar{X})]^{1/2}. \quad (15)$$

For the site 30 data, answers to this question are compared assuming independence of the data and accounting for the autocorrelated structure in the data:

(i) Independence analysis
Combining Eqs. (2) and (15), and solving for N, the sample size, we find that $N = 12$ satisfies the precision requirement.

(ii) Autocorrelated analysis
In this case, combining Eqs. (11) and (15), we find that $N = 23$ samples (daily averages) are required.

When the site W50 data are examined with respect to this precision requirement, the comparison is even more dramatic. While an independence assumption produces a sample size requirement of one week (7 days), correctly accounting for the autocorrelated nature of the data produces a sample size requirement of over *seven* weeks (50 days). When the autocorrelation is strong, as is the case for the Lindberg Field data, the effect of neglecting autocorrelation in the data is quite severe in terms of grossly underestimating *the length of time the* noise level must be monitored to assess the mean level precision within a given prespecified range.

B. Summary of modeling results and sample size requirements

In addition to the two sites analyzed above, data were obtained from two other sites (23, 31) in the area of NAS Miramar. For one of these additional sites (site 31) two time series of CNEL measurements were formed over different time periods to examine the stationarity and homogeneity of the data over an extended period of time. Figure 2 shows a map of the NAS Miramar and the location of the sites examined. CNEL contours are also shown on this figure.

Figures 5 and 6 show portions of the data analyzed for sites 23 and 31. Visual inspection of these two noise time series seems to indicate a marked difference in the time-varying nature of the data. The data for site 23 seem much more random in nature than those at site 31, which appears to have more of a positive correlation pattern (almost a weekly pattern) with two large "spikes" around the fourth and sixth weeks.

Modeling by DDS showed that for the site 31 data (both noise time series) an ARMA(4,3) model appeared to adequately describe the autocorrelated structure of the data. For site 23, autocorrelated structure of any significance only seemed to appear at lags 7 and 14 (weekly periodic-type structure). A model of the following form was fit to these data:

$$X_t = -0.667X_{t-7} - 0.315X_{t-14} + a_t + 0.355a_{t-1}. \quad (16)$$

When the parameters of the above fitted model are used to determine the variance estimate of the sample mean an interesting result is obtained. Contrary to the results from all other sites, the use of Eq. (11) to estimate $\mathrm{Var}(\bar{X})$ versus the independence assumption [Eq. (2)] show that *smaller* sample sizes are required when we recognize autocorrelation than when we assume independence. In summary,

$$\hat{\mathrm{Var}}(\bar{X}) = 10.4\times 10^{12} \text{ (autocorrelated)},$$

$$\hat{\mathrm{Var}}(\bar{X}) = 24.4\times 10^{12} \text{ (independence)}.$$

This suggests that this data is predominated by negative correlation which in fact explains the somewhat oscillatory appearance of the data in Fig. 5. It is also noted that the general variance of this data γ_0 is quite small relative to the data from the other sites (0.31×10^{12} vs 2.33 and 2.73×10^{12} for sites 30 and 31, respectively). Hence, it is not surprising that the sample size re-

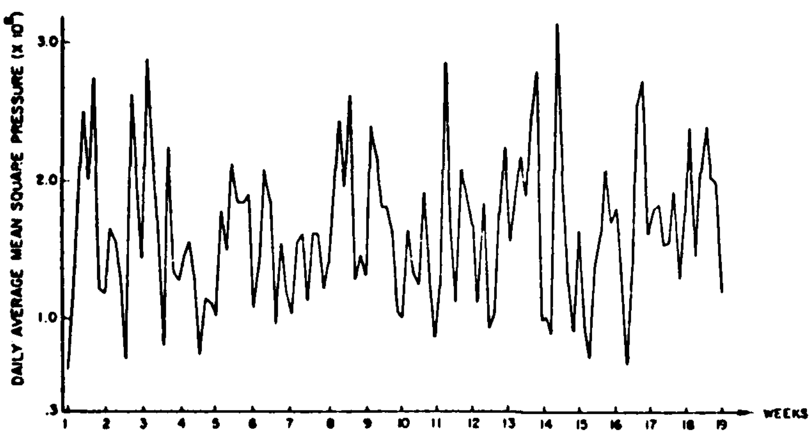

FIG. 5. NAS Miramar—data from site 23.

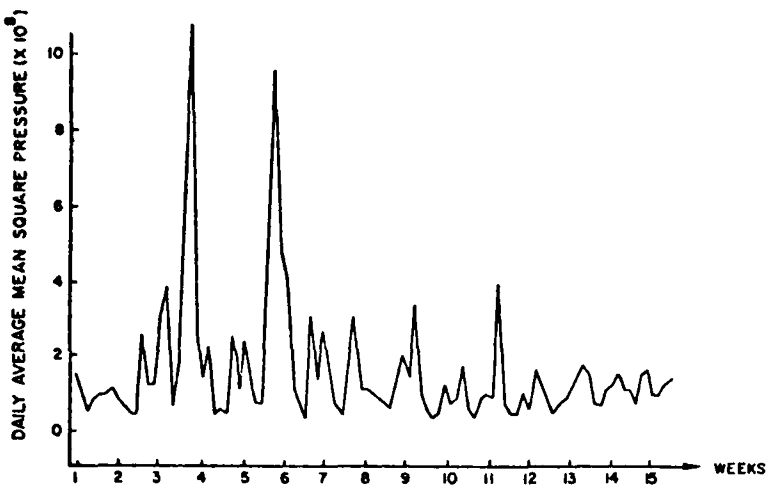

FIG. 6. NAS Miramar—data from site 31.

quirements for mean level precision assessment at site 23 are quite low. In fact, for a ± 50% precision in the mean level estimate (in units of mean-square pressure) only one daily average is required (two daily averages if autocorrelation is neglected). To obtain a ± 25% precision, only three daily readings are required (seven daily readings if autocorrelation is neglected).

Table II summarizes the modeling and sampling strategy analysis for all of the sites evaluated. It is interesting to observe the wide variation in the autocorrelated nature of the data from these four sites and its concommittant impact on the sample size requirements. The following observations are summarized:

(1) Sites 30 and 31 (Figs. 3 and 6) are typified by data which have two structural components visible in the time series: (i) irregular runs of average length of about 7 days, and (ii) a few very sharp spikes indicating that high mean square pressure levels occur somewhat infrequently over an extended period of time. Table II indicates that the time series modeling approach responded to these data characteristics by conveying a general positive correlation content which produced sample size requirements in access of those required under the assumption of no correlation in the data. Sample size requirements are about 100% greater than would be called for assuming independence of the data.

(2) For site W50 (Lindberg Field), Fig. 4 shows the same general patterns as sites 30 and 31 except that the irregular runs (above, below the mean) seem longer. This suggests even stronger positive correlation. The DDS model for this site confirms this general appearance by producing very high sample size requirements relative to the assumption of independence (50 days versus 7 days).

(3) For site 23 (Fig. 5) the data are quite uniform in variation level (no large spikes) and have much more of an oscillatory pattern as opposed to a pattern of longer, irregular runs. The DDS model conveys this mathematically by producing a sample size requirement which is: (i) much lower than for the other sites, and (ii) such that actually fewer samples are required, relative to assuming independence.

V. CONCLUSIONS

In this paper, a method for developing strategies for temporal sampling of environmental noise has been presented. Data were examined from several sites in the

TABLE II. Summary of sample size requirements.

Site	Model	$\bar{X}$ (10^6)	$\hat{\gamma}_0$ (10^{12})	$\hat{\sigma}_a^2$ (10^{12})	Number of data pts.	Var($\bar{X}$) Eq. (12) (10^{10})	± 50% of $\bar{X}$ precision: Sample size required (Autocorrelated)	Sample size required (Independence)
23	See Eq. (16)	1.69	0.308	0.28	126	0.104	1 (3, ± 25%)	2 (7, ± 25%)
30	ARMA(8,7)	1.84	2.535	1.75	105	4.80	23	12
31	ARMA(4,3)	1.58	2.332	1.80	140	4.58	33	15
31A	ARMA(4,3)	1.63	2.734	1.92	107	5.23	33	16
W50	ARMA(2,1)	51.9	1186.57	750.21	182	4264.15	50	7

area of NAS Miramar and a site from Lindberg Field, San Diego. These data are typified by a strong autocorrelated structure. This autocorrelated structure greatly influences the estimation of the variance of the sample mean and must be accounted for in the development of valid sampling strategies. The Dynamic Data System approach was used to develop stochastic autoregressive-moving average models capable of capturing this structure in a closed parametric form. The parameters of these models are used in the estimation of the sample mean variance. While the specific sampling plans obtained may be peculiar only to the airports studied, the modeling and inference techniques presented may be applied to a wide range of mean level inference problems when data are autocorrelated.

For the data examined, comparisons of the sampling requirements assuming independence and accounting for autocorrelation show that, in general, more samples are required accounting for autocorrelation due to the predominance of positive autocorrelation in the data. By neglecting the effect of autocorrelation in the data, the impression is given that for a fixed sample of data, one can estimate the mean more precisely than what one really can. For example, when the site W50 data are examined the independence assumption produces a sample size requirement of one week (7 days), while correctly accounting for the autocorrelated nature of the data produces a sample size requirement of over seven weeks (50 days).

Wide differences in the autocorrelation structure and the sampling requirements from site to site at the same airport, NAS Miramar, were noted. Further work is being done to study the effects of weather, flight patterns, and monitor location on the problem of mean sound level assessment.

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APPENDIX

$$\gamma_0 = \phi_1\gamma_1 + \phi_2\gamma_2 + \cdots + \phi_n\gamma_n + \sigma_a^2(1 - \theta_1 G_1 - \theta_2 G_2 - \cdots - \theta_{n-1}G_{n-1}),$$

$$\gamma_1 = \phi_1\gamma_0 + \phi_2\gamma_1 + \cdots + \phi_{n-1}\gamma_{n-1} + \sigma_a^2(-\theta_1 - \theta_2 G_1 - \cdots - \theta_{n-1}G_{n-2}),$$

$$\vdots$$

$$\gamma_{n-1} = \phi_1\gamma_{n-2} + \phi_2\gamma_{n-3} + \cdots + \phi_n\gamma_1 - \theta_{n-1}\sigma_a^2,$$

$$\gamma_k = \phi_1\gamma_{k-1} + \phi_2\gamma_{k-2} + \cdots + \phi_n\gamma_{k-n} \quad \text{for } k \geq n.$$

[1] D. C. Pies and L. C. Sutherland, "Evaluation of Spatial Sampling Techniques for Community Noise Surveys," Wyle Research, El Segundo, CA, Report #WR77-5 (for the U. S. Environmental Protection Agency), 1977.

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APPENDIX B: TEMPORAL SAMPLING REQUIREMENTS FOR ESTIMATION OF LONG-TERM AVERAGE SOUND LEVELS IN THE VICINITY OF AIRPORTS

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Community noise temporal sampling requirements in general, and in the vicinity of airports or other large noise producers in particular, are not well understood. Frequently, the purpose is to sample and estimate the true yearly Day/Night Average Sound Level (DNL) or Community Noise Equivalent Level (CNEL). This being the case, it is important to note that day-to-day samples are not independent, but, in fact, the time series formed by these day-to-day samples exhibits an autocorrelated structure. For this reason, sampling requirements are 4 to 8 times larger than are calculated by assuming purely random day-to-day data. Moreover, the data may exhibit weekly and yearly deterministic trends. As a result of those factors, the analysis herein shows that sampling requirements sufficient to achieve a precision of +2 to −3 dB of the true yearly CNEL or DNL value with a 95% confidence level can be summarized as 14 days of totally random sampling throughout the year, or 3-4 weeks of quasi-random sampling taken one week at a time, or at least 30 days of totally continuous sampling.

PACS numbers: 43.50.Lj, 43.50.Sr, 43.50.Nm

INTRODUCTION

Recently, increasing attention has been given to the problems associated with high sound exposure levels in the immediate vicinity of installations such as civil airports and military bases. From an acoustical point of view, work is proceeding on several fronts in the areas of improved equipment design, better operations planning and new techniques for noise abatement. An important element of the overall problem is the measurement of noise levels and the associated statistical assessment of the precision of mean level estimates. Most techniques in use today[1,2] for sampling community noise call for sampling over relatively short periods of time, e.g., from a few minutes to perhaps a single day. However, the time varying nature of noise data when viewed as a time series (hourly or daily averages) suggests that short-term sampling may lead to serious inaccuracies in the estimation of a long-term (yearly) average noise level. For example, the 24-h periodic pattern in hourly average sound level may vary from about 40 to 85 dB. The Community Noise Equivalent Level (CNEL) or Day/Night Average Sound Level (DNL) both commonly vary from 45 to 80 dB. These wide ranges for sound level, together with the fact that the data in general, exhibit high positive autocorrelation and high coefficients of variation suggests that small and/or short sampling periods may provide both imprecise and inaccurate mean value estimates.

The techniques of time series modeling, in general, provide a powerful methodology for an assessment of mean level estimation precision and the formulation of sampling strategies. In a recent paper,[3] the authors have described the use of the Dynamic Data System (DDS) for performing these analyses based on the fitting of Autoregressive-Moving Average (ARMA) time series models to the daily average noise level data. The previous paper utilized approximately one year's daily CNEL data gathered at several sites around San Diego's Lindbergh Field and Miramar Naval Air Station. Analysis of these data showed a high degree of positive correlation in CNEL values from day to day. This autocorrelated nature of the data, particularly the degree of positive correlation between neighboring observations, increases the amount of consecutive sampling required to estimate the long-term mean level with a given level of precision over sampling where independence is assumed.

In this paper, the dynamic data system method is used to model approximately eight months of daily CNEL data gathered at 12 sites in the vicinity of the Los Angeles International Airport (LAX). The results of this analysis, along with the previous results, are used to form a set of guidelines for sampling strategies in the vicinity of airports. Of necessity, this paper uses CNEL data. However, as stated in several references,[4,5] the correspondence and correlation between CNEL and DNL are so close as to make the results equally applicable to DNL data.

I. THE DATA BASE

Continuous daily monitored CNEL values were supplied by LAX for the period from 1 May 1977 to 31 December 1977 for the 12 monitoring locations indicated in Fig. 1. These daily CNEL were transformed to values denoted by X, on a linear scale, proportional to daily sound exposure (SE) as shown in (1).

$$X = 10^{CNEL/10} . \tag{1}$$

Figure 2 illustrates the resulting data plotted as a function of day of the year for these 12 sites after transforming the data as described in Eq. 1. It must be noted that these X values are used because one is interested in estimating the yearly mean DNL or CNEL value which by definition is estimated by the sample

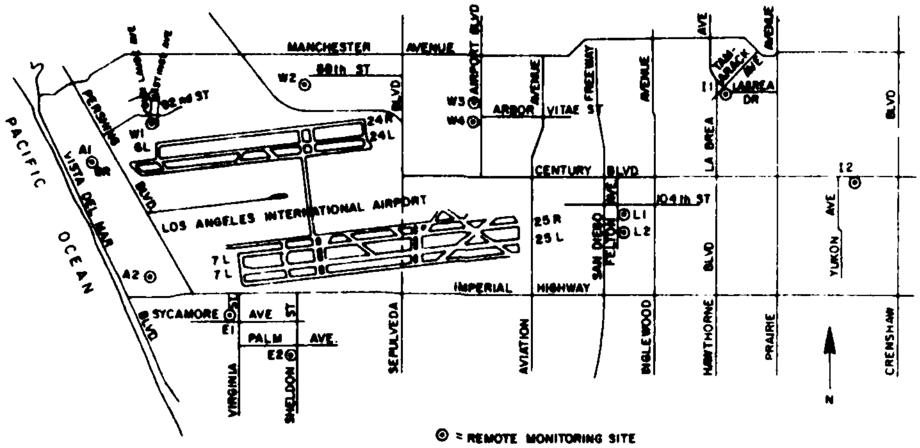

FIG. 1. Location of monitor sites in the vicinity of Los Angeles International Airport.

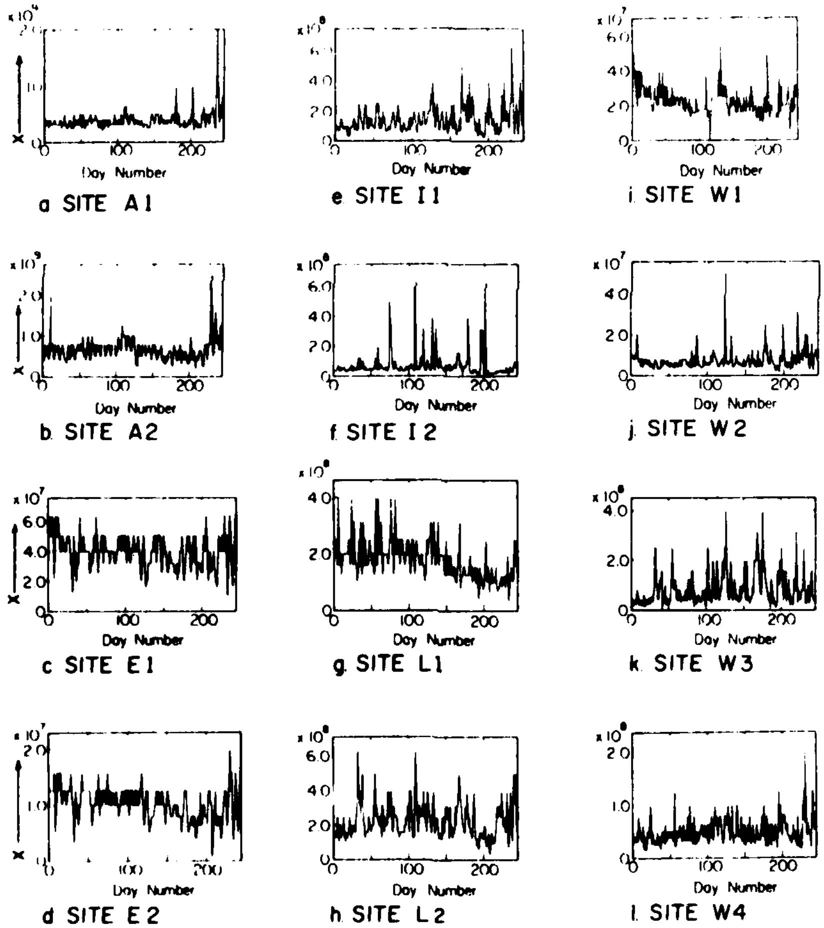

FIG. 2. The quantity X time series (dimensionless) developed from the monitor data at Los Angeles International Airport. (Point 1 corresponds to 1 May 1977 and point 245 corresponds to 31 December 1977).

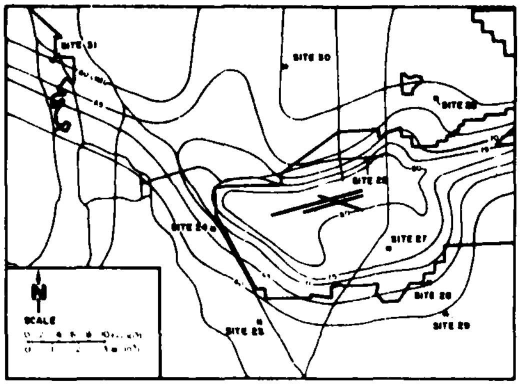

FIG. 3. Location of monitor sites in the vicinity of Miramar Naval Air Station.

yearly mean (arithmetic average), $\bar{X}$. Monitored data is frequently measured for far less than one year's time period, and it is the purpose of this paper to address the validity of techniques to estimate this yearly mean.

In order to draw the most complete conclusions possible, the data developed in the previous paper will be utilized for the analysis herein along with the LAX data. Figure 3 illustrates the location of two monitoring points utilized in the vicinity of Miramar Naval Air Station. Other sites at Miramar Naval Air Station were either outside the noise contour area and measuring other noise (e.g., site 23) or they had significant gaps in the data when ordered serially. A third set of previous data comes from a monitor located approximately one mile west of the main runway at San Diego's Lindbergh Field.

Using the DDS method, ARMA models of various orders were developed for 15 of the 16 above time series of the quantity X. For details of the modeling methods and terminology, the reader is referred to the author's previous paper.[1] One of the LAX time series (I1, the location of which is shown in Fig. 1) was found to contain strong deterministic trends and thus was not modeled using the DDS stochastic models. Using the method described in the previous paper, the estimated parameters of the fitted ARMA models were employed to determine the autocorrelation factors for each of the time series and thereafter estimate the variance of the sample means. Table I summarizes the model type and autocorrelation factor for each of the time series modeled. This Table also contains the sample mean and sample variance derived from these time series. To aid in interpretation, the coefficient of variation, which is the ratio of the standard deviation to the mean, is also included in Table I.

Based on the assumption of independence of the data (no autocorrelation on a day-to-day basis), one can calculate the number of samples required to estimate the long-term (yearly) mean for any desired level of precision. In this paper, an estimation precision of ±50% of the mean with a 95% confidence level has been chosen as typical values for illustrative purposes. It must be noted that a plus-minus 50% band in the estimation of mean $\bar{X}$ corresponds to a plus 2- to minus 3-dB band on the estimation of yearly mean DNL or CNEL. However, the fitting of an ARMA model to a time series indicates that the series possesses a positive autocorrelative structure. And hence, sample sizes determined assuming independence will underestimate, in some cases, by a considerable amount, the actual sample size requirements. When the autocorrelation factors are rightfully applied, the correct sample size requirements emerge. Table I also provides the sample size requirements for the estimation

TABLE I. Modeling results, summary statistics, and sample size requirements for each site.

Site	Model	Mean $\bar{X}$	Variance	Coefficient of variation	Autocorrelation factor	Sample size[a] requirement (independence)	Sample size[a] requirement (autocorrelation)
A1	ARMA(2, 1)	3.89×10^{8}	2.46×10^{16}	0.403	2.140	3	6
A2	ARMA(5, 5)	6.60×10^{8}	6.38×10^{16}	0.383	8.189	3	19
E1	AR(1)	3.88×10^{7}	1.17×10^{14}	0.279	3.010	2	4
E2	ARMA(4, 3)	1.03×10^{7}	8.76×10^{12}	0.287	5.842	2	8
I2	AR(1)	7.03×10^{7}	6.48×10^{15}	1.140	1.475	20	30
L2	AR(1)	2.27×10^{8}	1.03×10^{16}	0.448	3.353	4	11
W1	ARMA(2, 1)	2.21×10^{7}	5.14×10^{13}	0.333	4.980	2	8
W2	Random	7.44×10^{6}	5.71×10^{13}	1.050	1.000	16	16
W3	ARMA(2, 1)	8.90×10^{7}	6.85×10^{15}	0.929	4.517	14	60
W4	ARMA(1, 1)	5.03×10^{7}	6.12×10^{14}	0.492	2.850	4	11
30[b]	ARMA(8, 7)	1.84×10^{6}	2.53×10^{12}	0.865	1.98	12	23
31[b]	ARMA(4, 3)	1.58×10^{6}	2.33×10^{12}	0.967	2.35	15	33
W50[c]	ARMA(2, 1)	5.19×10^{7}	1.19×10^{15}	0.663	7.48	7	50

[a] Sample size refers to the number of consecutive sample days needed to predict the long-term mean level within plus 2 to minus 3 dB of the true value with 95% confidence based on the quantity X in Eq. 1. (Independence) means sample sizes based on the assumption of serially independent data. (Autocorrelation) means sample sizes based on the assumption of serially autocorrelated data.

[b] Sites at Miramar Naval Air Station.

[c] Site at Lindbergh Field, San Diego, California.

of the mean noise level for both the cases of assumed independence and correctly accounting for the autocorrelated structure in the data. In the Table, the autocorrelation factor relationship is not precisely evident because the sample numbers have always been rounded up to the next highest integer in order to guarantee the stated precision. Table I also provides summary statistics and sample size requirements for the two monitor sites at Miramar Naval Air Station and the one site at Lindbergh Field. These results were previously reported in Ref. 3 and are included here to demonstrate the similarity in the results across the three airports.

In summary, Table I lists the monitor sites, the model type, the mean, and the standard deviation for the original time series, the coefficient of variation, the number of independent samples required for ±50% accuracy (+2 to −3 dB), the autocorrelation factor and the true number of samples required for ±50% accuracy when the autocorrelated nature of the time series is taken into account.

Operational data were also supplied by the Los Angeles Department of Airports for landings per day by runways on 25R, 25L; 24R and 24L; and by runway pairs for 6L and 6R; and for 7L and 7R. Takeoff data were supplied per day by runway pair for 25L and 25R, 24L and 24R, 6L and 6R, and for 7L and 7R. Operations at LAX, Miramar, and Lindbergh are typically westward due to prevailing winds off the ocean. Occasionally winds are such that the normal direction of operations must reverse and takeoffs and landings are to the east.

To test the relation of the monitored data in the vicinity of LAX with operations, various correlation pairs were developed and are listed in Table II. In each case, correlation coefficients (i.e., the zeroth lag cross-correlations) between the X time series and the corresponding runway operations time series in terms of total daily approaches, departures, and the sum of approaches and departures were determined. As can be seen from the descriptions in the Table, data pairs have been selected to emphasize the predominant type of operation likely to be encountered at any given monitoring location. For example, because of the westbound nature to the traffic flow, site L2 should predominantly measure landings on 25L and location E2 should measure both takeoffs and landings in either direction on the south complex (where "complex" defines either the northern or southern pair of runways at LAX). Table II provides only those estimated cross-correlations which were deemed significant in magnitude. While many site noise-operations pairs were correlated, those not found in the Table resulted in small (effectively zero) correlation coefficients. Based on the amount of data available, correlation coefficients in excess of approximately plus or minus 0.15 would be considered statistically significant at the 0.05 level of significance. However, for purposes of explaining the data and analysis herein, only the major significant correlations are presented and discussed. As explained later in this paper, 0.3 is chosen as the value to define major significant correlations.

II. DISCUSSION OF RESULTS

Examination of the data in Table I shows a wide range of sampling requirements from site to site depending on relative location and proximity to the runways. In many cases, the sample size requirements are quite

TABLE II. Zeroth lag cross-correlation between noise level recorded at a site and operations in the vicinity of the site.

Site	Operations strongly correlated with	Correlation coefficient
A1	None	...
A2	EB/APP/7 + WB/DEP/25[a]	0.481
E1	WB/APP/25	0.308
	WB/DEP/25	0.312
E2	WB/APP/25	0.408
	WB/DEP/25	0.323
I1	WB/APP/24R[b]	0.731
	WB/APP/24	0.639
	WB/APP/24 + EB/DEP/6	0.611
I2	None	...
L1	WB/APP/25	0.436
	WB/APP/25 + EB/DEP/7	0.406
L2	WB/APP/25L	0.716
W1	None	...
W2	None	...
W3	WB/APP/24R[b]	
	WB/APP/24	0.499
	WB/APP/24 + EB/DEP/6	0.439
W4	WB/APP/24R[b]	0.419
	WB/APP/24	0.432
	WB/APP/24 + EB/DEP/6	0.473

[a] EB/APP/7 + WB/DEP/25 denotes the sum of eastbound approaches on the 7 complex and westbound departures on the 25 complex.

[b] 24R denotes the 24 complex, right runway.

large. The large sample numbers may be due to the presence of strong positive autocorrelation, large overall noise series variability from day to day, or both. One could hope to observe that the number of autocorrelated sample days required grows smaller as the sample site approaches the airport. Unfortunately, this is not evident since stations A2, W2, and W3 each require substantial numbers of days. However, careful examination of these data, the operational data, and weather conditions indicates possible explanations for the greater variability found in two of these three stations.

Site W3 has an autocorrelation factor of 4.5, which is typical of the values found for all the monitoring sites in close proximity to the runways (except for A2 and W2 which are the other two sites near the runways which have relatively large sampling requirements). Site W3, however, exhibits a much higher coefficient of variation than do the other sites in the vicinity of the airport (except for site W2 which is again one of the three sites under discussion and site I2 which will be discussed later). Examination of the number of landings per day on runway 24R, the operations which most influence the noise received at Site W3, indicates a high degree of variation from day to day. The correlation coefficient between the landings on runway 24R and the noise measured at Site W3 is 0.678. Although not shown herein, the number of landings per day on 24R are much more variable than are the numbers of landings per day on the other three runways (24L, 24R, and 25L). Thus the high coefficient of variation in the X data from Site W3, in reality, likely reflects the high variation in the operations data.

Site A2 exhibits a coefficient of variation which is much in line with the other stations near to the runways (except W2 and W3). At this site, however, the autocorrelation factor is 8.2—a value which is much higher than the value for most of the other sites. Examination of this time series shows that the noise level generally rises during the warmer summer months. Typically at Los Angeles, there are 12 days in which the high temperature exceeds 90 °F.[6] This site measures predominantly takeoff noise and is some 4000 ft further from start of roll than is site A1. Thus this site is the only site which will be influenced by the average temperature since temperature strongly affects the efficiency of the turbojet engines—requiring longer takeoff rolls and lower altitudes over site A2 during warm weather. In fact, this is the exact trend strongly evident in the data; i.e., the average sound level goes up during the warm weather months. Referring to Table II, this conclusion is further supported by the fact that the cross-correlation between noise level monitored at site A2 and the combination of eastbound approaches and westbound departures on the south complex is quite high, a value of 0.481.

Site A2 exhibits two predominant peaks in the data in addition to the general trend discussed above. One peak appears on the 10th of May (day 10) and the other on the 16th of December (day 230). Many of the stations exhibit peaks in the mid-to-end of December time period. This time period was a period of heavy cloud cover, variable winds, and rain.[7] No explanation can be found in the weather or the operations for the peak exhibited on May 10. Similarly, examination of the data at site W2, the other "problem site," exhibits a very strong peak on the 16th of July (day 77). Again, no weather-related or operations-related explanation can be found. The two series of quantity X values derived from the monitored CNEL values at these two sites were remodeled with the data for July 16 deleted from the series at site W2 and the data for May 10 deleted at site A2, respectively.

At site W2, removal of the spike on July 16 did not change the model. That is, the site noise series remained totally random and removal of the spike only served to decrease the variance, changing the sampling requirement from 20 to 16 days. Similarly, at site A2, removal of the spike on May 10 did little to change its results. However, removing both the spike on May 10 and the spike on December 16 substantially altered the characteristics of the time series but did little to change the ultimate sampling requirements. Removal of these two spikes revealed a model with a strong deterministic trend. The time series strongly demonstrated a 7-day weekly cycle to the data in addition to the yearly cycle discussed above. Because of this strong weekly cycle, the autocorrelation factor actually rose from its already high value of 8 to almost 25. Similar results were found in the author's previous paper.[3] However, removal of the spike at December 16 may not be justified because its presence can be explained by weather-related factors.

Examination of the cross-correlation data between operations and measured noise levels reveals some correlations to be as expected and others to present some significant departures from expectations. The correlations between noise levels in the vicinity of the east end of the north complex (24), and the corresponding north complex operations exhibit the most regularity and are most as expected. That is, the landings on 24R are highly correlated with the data measured at W3, the landings on 24L are well correlated with data measured at site W4. Also the data measured at these two sites correlate well with the total operations over the east end of the north complex. The correlations with the data measured at site I1, indicate that landings on 24R correlate with these measurements but not the landings on 24L. This also is a reasonable result. It is noted that the cross-correlations between operations on the 24 complex and site W2 (to the north-side of the complex) are generally small (effectively zero). This site is typified statistically as a random noise series with high coefficient of variability (1.05).

Unfortunately, landings on the 25 complex do not exhibit the same regularity and expected results as described above for the 24 complex. Landings on 25L are well correlated with the noise measured at site L2, but landings on 25R were not found to be correlated with the data measured at site L1. However, the total of all operations or the total number of landings to the east of the south complex are both well correlated with the data measured at site L1. This would seem to indicate that site L1 is such that it is located more nearly acoustically midway between the operations on 25L and 25R, rather than as indicated in Fig. 1. On the other hand, the lower correlation for site L2 with overall operations and the generally higher correlation with the specific landing operations on 25L indicate that it is more nearly in line with 25L. Station I2 exhibits no correlation with any of the operations either taken singly or in combination and like site W2, its noise series exhibits weak autocorrelation and a high coefficient of variation.

It must be noted that correlations developed between numbers of operations and measured data cannot be expected to be extremely high because the measured data are being correlated with operations which may represent a variety of noise levels. For example, correlations have been calculated with landings alone when in reality on certain days the landings may be very low and the takeoffs very high with the resulting noise levels also high. On the other hand, correlations have been developed with total operations where there is no guarantee that these operations do not produce systematically differing CNEL on differing days that is not reflected merely in the total number of operations. As a result, correlation coefficients in excess of approximately 0.3 are considered significant at this stage of analysis.

The monitored data at sites I2 and W2 exhibit no significant correlation with operations in their respective vicinities. In addition, they share the same common characteristics of weak or no autocorrelation in the noise series and high levels of variability relative to their mean levels. This raises a question about the actual noise these sites are measuring; i.e., is this *monitored noise really strongly related to airport* operations? In terms of sampling requirements, however, these sites are quite consistent with the other sites, while the low autocorrelation tends to reduce the sample size requirements, the high variability brings them back in line with those sites with strong autocorrelation.

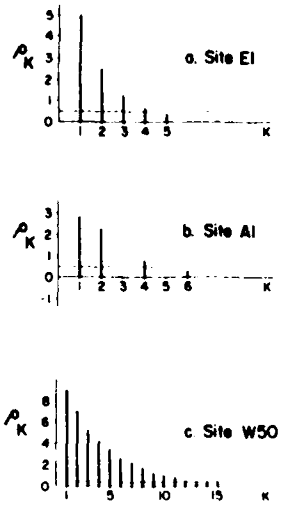

FIG. 4. Theoretical autocorrelation functions.

III. AN ALTERNATE SAMPLING STRATEGY

The rather large sampling *requirements revealed* by the analysis above suggest that an alternate strategy might be sought to reduce the amount of sampling. When several sites are to be monitored at a given facility, it may become practical to induce independence in the sample data by spacing successive observations by a sufficient lag distance. The theoretical autocorrelation function for the ARMA model at a given site can be used to estimate the spacing *required to* approximately validate the independence assumption.

For site E1, the model was AR(1) with $\phi_1 = 0.5$. The theoretical autocorrelation function for an AR(1) process is given by $\rho_0 = 1$, $\rho_K = \phi_1^K$, $K = 1, 2, 3, \ldots$. Hence, $\rho_1 = 0.5$, $\rho_2 = 0.25$, $\rho_3 = 0.125$, $\rho_4 = 0.0625$, $\rho_5 = 0.0312$, etc., and therefore, for practical purposes, observations spaced by 5 or more lags are uncorrelated. In the case of site A1, the model was ARMA (2,1) and the theoretical autocorrelation function is given by:

$$\rho_0 = 1,$$

$$\rho_1 = (\phi_1 - \theta_1\sigma_a^2/\gamma_1)/(1 - \phi_2),$$

$$\rho_K = \phi_1\rho_{K-1} + \phi_2\rho_{K-2}, \quad k \geq 2.$$

Based on the model parameters for site A1, $\rho_1 = 0.28$, $\rho_2 = 0.23$, $\rho_3 = 0.00$, $\rho_4 = 0.08$, $\rho_5 = -0.03$ and again observations spaced by 5 or more days are approximated uncorrelated. Figure 4 shows the theoretical autocorrelation functions for sites E1, I1, and W50. In developing sampling requirements based on induced independence, the theoretical autocorrelations are assumed to be effectively zero when the correlation coefficients damp to less than 0.05 in absolute value.

A similar strategy can be developed for randomly spaced groups of days such as weekly blocks of data.

IV. CONCLUSIONS

In the vicinity of airports, the data indicate that 30 continuous days of monitoring is a reasonable estimate of the number of days required to achieve a precision of +2 to −3 dB of the true yearly CNEL (or DNL) value with a 95% confidence level. Moreover, the autocorrelation factors appear to be on the order of 4 to 5 for sites in the immediate vicinity of the airport. However, in worst-case situations such as when the total operations on a runway become highly variable (such as runway reversals) when seasonal load or weather factors become significant, or when there is a weekly cycle to the data, then these numbers can become significantly greater than 30 and 4, respectively. These data indicate a worst-case requirement of 60 continuous days in the vicinity of airports and a worst-case autocorrelation factor on the order of 8.

Because of the autocorrelation factor generally exhibited in most of the data series, the number of sampling days can be significantly reduced by inducing randomness in the selection of days sampled. That is, sample days can be selected sufficiently far apart to induce randomness in the data gathered, rather than performing continuous monitoring over the total number of days. Also, because of the common sense potential for long-term seasonal effects, it is recommended that samples be selected from throughout the entire year. A variety of strategies can be employed based on this analysis. For example, one could:

(a) Sample for a continuous period of 30 days or more.

(b) Sample 14 days chosen randomly throughout the year, subject to the constraint that no two sample days be less than 8 calendar days apart.

(c) Sample approximately 3 one-week periods chosen randomly throughout the year, subject to the constraint that no two sample weeks be consecutive.

The above can be used to achieve a precision of +2 to −3 dB of the true yearly CNEL or DNL at a 95% level of confidence.

While the above analysis pertains only to airports in Southern California, subsequent analysis currently underway indicate that these sampling requirements are approximately valid in the vicinity of major commercial airports on the east coast as well.

ACKNOWLEDGMENT

The authors are deeply indebted to W. V. Collins and the Los Angeles Department of Airports for graciously supplying the data contained herein for analysis.

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APPENDIX C:
SAMPLING STRATEGIES FOR MONITORING NOISE IN THE VICINITY OF AIRPORTS

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This paper is the third in a series dealing with the development of temporal sampling strategies for estimation of mean noise levels in the vicinity of airports. It extends the previous analysis for westcoast, one-direction airports (due to prevailing winds) to eastcoast, multidirection airports (Boston Logan, Washington Dulles, and National). The results show that the data for many of the eastcoast airport sites are nonstationary in the mean level and the corresponding consecutive sampling requirements predicted by the Dynamic Data System (DDS) methodology are very large, at times exceeding 1/3 of a year. When the data are stationary, Monte Carlo simulations using the data produce sampling requirements comparable to the values obtained by the DDS methodology. However, the DDS methodology tends to overestimate sampling requirements for nonstationary data. The simulations demonstrate that nonconsecutive sampling strategies reduce the overall sampling requirements for nonstationary data. In general, the results reveal the following: (a) Westcoast (one-direction): ± 50% precision—four weeks, any sampling strategy, ± 35% precision—eight weeks, any sampling strategy. (b) Eastcoast (multidirection): ± 60% precision—four weeks, one from each quarter, ± 40% precision—eight weeks, one from each eighth.

PACS numbers: 43.50.Lj, 43.85.Fm, 43.50.Qp

INTRODUCTION

This paper represents the third in a series dealing with *temporal sampling requirements for estimation for long-term average sound levels.*[1,2] The general problem is the associated statistical assessment of the precision of estimates of mean sound level. With only a few exceptions such as the California Airport Noise Regulation,[3] most techniques in use today[4,5] for sampling community noise call for sampling over relatively short periods of time, e.g., from a few minutes to perhaps a single day. However, the time varying nature of noise data when viewed as a time series (hourly or daily averages) suggests that short-term sampling may lead to serious inaccuracies in the estimation of a long-term (yearly) mean noise level. For example, the 24-h periodic pattern in hourly mean sound level may vary from about 40 to 85 dB. The Community Noise Equivalent Level (CNEL) or Day/Night Average Sound Level (DNL) both commonly vary from 45 to 80 dB. These wide ranges for sound level, together with the fact that the data in general, exhibit high positive autocorrelation and high coefficients of variation suggest that small and/or short sampling periods may provide both imprecise and inaccurate mean value estimates.

The techniques of time series modeling, in general, provide a powerful methodology for assessment of mean level estimation precision and the formulation of sampling strategies. In the first paper, the authors have described the use of the Dynamic Data System (DDS) for performing these analyses based on the fitting of Autoregressive-Moving Average (ARMA) time series models to the daily average noise level data. This previous paper utilized approximately one year's daily CNEL data gathered at several sites around San Diego's Lindbergh Field and Miramar Naval Air Station. Analysis of these data showed a high degree of positive autocorrelation in CNEL values from day-to-day. This day-to-day positive autocorrelation is to be expected because of prevailing winds, slowly varying weather fronts, and the relatively constant set of daily operations and fleet mix at commercial airports. This autocorrelated nature of the data, particularly

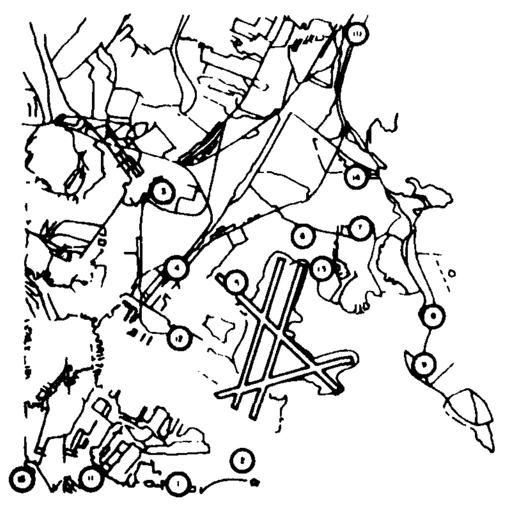

FIG. 1. Boston Logan International Airport—locations of noise monitoring sites.

the degree of positive autocorrelation between neighboring observations, increases the amount of consecutive sampling required to estimate the long-term mean level with a given level of precision over sampling where independence is assumed.

In the second paper, the dynamic data system method was used to model approximately eight months of daily CNEL data gathered at 12 sites in the vicinity of the Los Angeles International Airport. The results from these first two papers were used to form a set of guidelines for sampling strategies in the vicinity of airports. These first papers used CNEL data and were for westcoast airports only.

The present paper extends the analysis to eastcoast airports and to the use of DNL. Specifically, approximately 13 months of daily DNL data were obtained for 15 sites in the vicinity of Boston's Logan Airport and approximately nine months of daily DNL data were obtained for nine sites in the vicinity of Washington's Dulles Airport and 14 sites in the vicinity of Washington's National Airport. The dynamic data system method was again used to model these daily DNL data. Monte Carlo simulations were performed to verify the sampling requirements obtained from the DDS modeling of the data and to study alternatives to consecutive sampling. The results of these analyses, along with the results of the two previous papers are used to form a set of guidelines for sampling strategies in the vicinity of airports.

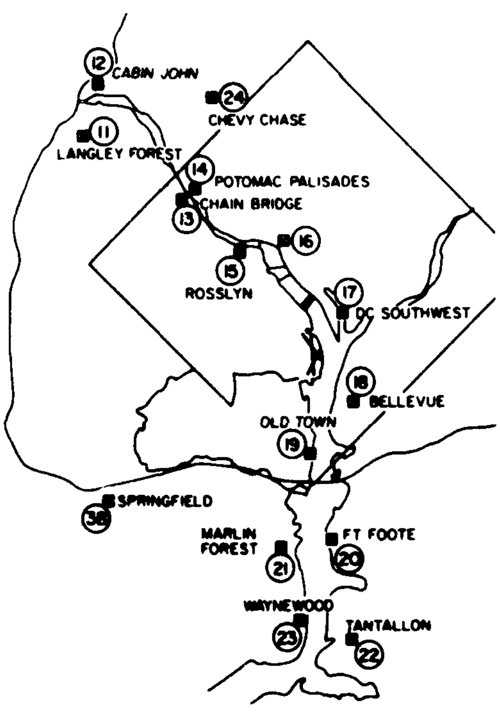

FIG 2 Washington National Airport—locations of noise monitoring sites

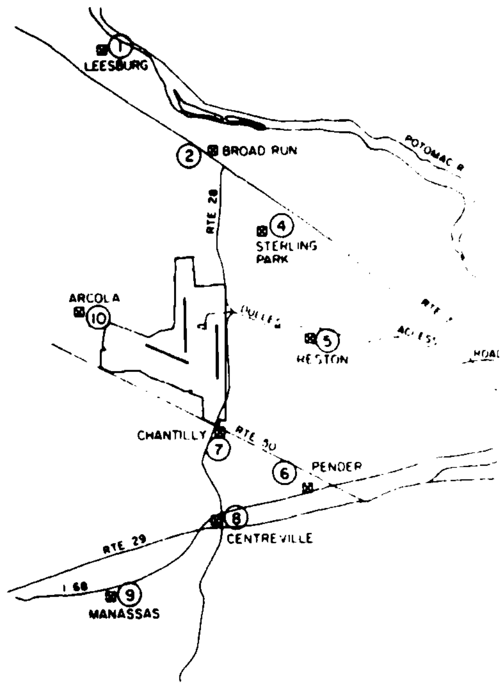

FIG 3. Washington Dulles Airport—locations of noise monitoring sites

I. THE DATA BASE

Continuous daily monitored DNL values were supplied by Logan Airport for the period from 1 October 1978 to 31 October 1979 for the 15 monitoring locations indicated in Fig. 1. These daily DNL data were transformed to values denoted by X, on a linear scale, proportional to time-weighted daily sound exposure as shown in Eq. (1),

$$X = 10^{(DNL/10)} . \quad (1)$$

As noted in earlier papers, these X values are used because one is interested in estimating a yearly mean DNL or CNEL value which by definition is estimated by the sample yearly mean (arithmetic average) $\bar{X}$. Monitored data are frequently measured for far less than one year's time period, and it is the purpose of this research to address the validity of techniques to estimate this yearly mean.

The time series of X values at some of the locations were divided into part A and part B at a gap in the data around the halfway mark. Due to sizeable gaps in some of the sites' data, only about one-half year of continuous data were available and modeled. Using the DDS method, ARMA models of various orders were developed for 15 of the 16 above time series of the quantity X. (For a brief review of the modeling methods and terminology, the reader is referred to Appendix A.) The estimated parameters were used to determine the autocorrelation factor, coefficient of variation, and appropriate sampling requirements for mean-level estimation

The partitioning of the data, as mentioned above, provides for the opportunity to examine the homogeneity of the stochastic structure of the data over the entire period of one year. Although the DDS models do not reveal seasonal variations, modeling data in different times of the year does show some differences in stochastic structure at certain sites. This fact leads to the postulation of several alternate sampling strategies including sampling in each of the four seasons. This will be discussed in detail later in the paper.

Runway operations data were unavailable at Boston Logan, but all the sites were evaluated and the monitored levels found to exceed reasonable estimates of the community noise in the absence of aircraft. Thus the monitored data were assumed to be predominantly aircraft noise and subject to a constant set of prevailing operations.

Data were analyzed from Washington National and Dulles Airports for the period of 17 March 1978 to 14 December 1978. At Dulles Airport, the daily number of arrivals and departures are significantly less than at Los Angeles or Boston, and for both Washington Airports, the monitoring sites were generally positioned farther from the airport (see Figs. 2 and 3). For the Washington Airports, it was attempted to determine whether each site was monitoring predominately aircraft or community noise. Monthly Federal Aviation Administration noise level plots (Fig. 4) served as the basis for this classification process. The sample plot in Fig. 4 shows the airport noise level (indicated by the LEQA hatching) standing clearly above the background community noise level of about 65 dB. Plots of this type were studied for all of the National and Dulles sites. In some cases, a site could be unquestionably classified as either an airport or a community noise site, but in other cases it was necessary to classify a site as a mixed airport and community noise site.

II. DISCUSSION OF MODELING RESULTS

A. Boston's Logan sites

For Boston's Logan Airport, frequency histograms and time series plots were developed and can be found in Ref. 6. The DDS modeling results are listed in Table I for all sites at Boston. For those sites whose data were divided into approximately two equal parts, modeling results are given for each part and for the entire data set. Most of the data were found to follow AR(1) time series models, with autocorrelation factors commonly ranging from 1.3 to 3.0. The required sample sizes for estimation of the mean within a $\pm 50\%$ of $\bar{X}$ (+2, −3 dB) at the 95% confidence level commonly varied from 10 to 80 days. Site 4A was the most extreme exception, with a very high autocorrelation factor of 6.35 and a correspondingly large sample size of 134 days. Sites 3 and 4 (in the same general area) also have higher than average autocorrelation factors. Almost all the coefficients of variation range from 0.6 to 1.3.

The data which were divided into two parts are used to more carefully examine the long-term (yearly) sound characteristics (Table I). In some cases (sites 1, 5, and 8), the modeling results are very similar in terms of both autocorrelation factor and coefficient of variation, giving rise to very similar sampling requirements. For others (sites 3, 4, and 6), the results are somewhat different. Of particular interest is the fact that modeling of the combined data for sites 3, 4, and 6 produces sampling requirements generally larger than for either part. For site 3, the main difference in the modeling results is the autocorrelation factor. For this site, examination of the data [Fig. 5(a)] reveals a gradual upward trend from the middle of the second part of the data. This nonstationary tendency increases the order of the model and produced a higher autocorrelation factor due to a model root approaching 1.0. For site 6, the second half of the data has a more random structure with corresponding autocorrelation factor equal to 1.0. In examining site 4, it is seen in Table I that the model for the first part of the year gives rise to a very large sampling requirement, 134 days. This is 2.5 times greater than any other site. Examination of the data [Fig. 5(b)] shows a large downward shift in the mean level of the data after about the first two months. This nonstationarity has produced a model with high autocorrelation factor. Al-

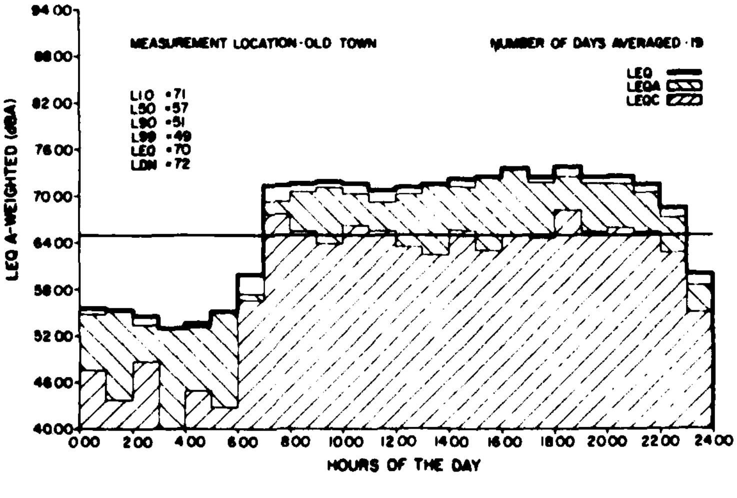

FIG. 4. Typical FAA monthly data summary at a Washington monitoring site. In this FAA figure, "LEQA" are the equivalent levels (by hour) resulting from aircraft noises. "LEQC" are the equivalent levels resulting from (nonaircraft) community noises, and LEQ are the total equivalent levels resulting from the combination of community and aircraft noises.

TABLE I. Boston Logan DDS modeling results

Site	Model	Coefficient of variation	Autocorrelation factor	Sample size
1A	AR(1)	0.68	1.94	17
1B	AR(1)	0.56	1.31	7
1	AR(1)	0.62	1.66	11
2	ARMA(3, 2)	0.47	3.03	50
3A	AR(1)	0.86	2.48	29
3B	ARMA(3, 1)	0.85	4.11	48
3	AR(3)	0.87	4.96	60
4A	ARMA(2, 1)	1.15	6.35	134
4B	ARMA(2, 1)	0.93	3.85	54
4	AR(2)	1.13	6.28	128
5A	AR(1)	0.88	2.51	32
5B	AR(1)	0.84	2.48	29
5	ARMA(7, 7)	0.88	2.77	35
6A	AR(1)	1.14	2.50	53
6B	White noise	1.24	1.00	25
6	ARMA(1, 1)	1.25	3.17	79
7	AR(1)	0.99	1.61	26
8A	AR(1)	0.87	1.95	27
8B	AR(1)	0.90	1.94	25
8	ARMA(3, 2)	0.93	2.18	31
9	AR(1)	1.56	1.64	64
10	White noise	0.21	1.00	16
11	AR(1)	0.98	1.43	22
12	AR(1)	0.91	1.44	20
13	AR(1)	0.84	1.34	16
14	AR(1)	1.43	2.05	68
15	AR(1)	0.85	1.99	24

though no records are available to the authors such a data trend could be caused by a marked and sustained change in runway activity or flight patterns or, perhaps instrumentation problems. The combined model appears dominated by the trend in the first part of the data and shows large sampling requirements.

B. Washington Dulles and National sites

DDS modeling was performed for each site in the vicinity of Dulles and National Airports. Site classification and modeling results are summarized in Tables II, III, and IV (airport sites, community sites, and mixed sites, respectively). Low-order models resulted for most of the sites, with a first-order autoregressive model, AR(1), being common. The sampling requirements for all the Washington sites are generally similar to those for the Logan sites.

Tables II, III, and IV indicate that several Washington Dulles and National sites exhibit wide differences in modeling results when each part and the combined data are examined separately. In particular, for seven sites (Dulles 1, 6, 7, and 10 and National 14, 21, and 22), DDS modeling results vary considerably from one part of the data to the other and sampling requirements based on the combined data models are generally larger than for either part. Examination of the time series data show nonstationary trends either within or across both parts of the data. These trends can again be characterized as a shifting of the mean level of the data. The extreme case is Dulles site 6 which has small sampling requirements for each half ($N = 5$) but a very large requirement ($N = 158$) for the combined data. This site's data [Fig. 5(c)] show a marked shift in the mean level at about the midyear point.

III. COMPARISON OF EASTCOAST AND WESTCOAST AIRPORTS

In summarizing the modeling results across the Boston and Washington Airports, it becomes apparent that a num

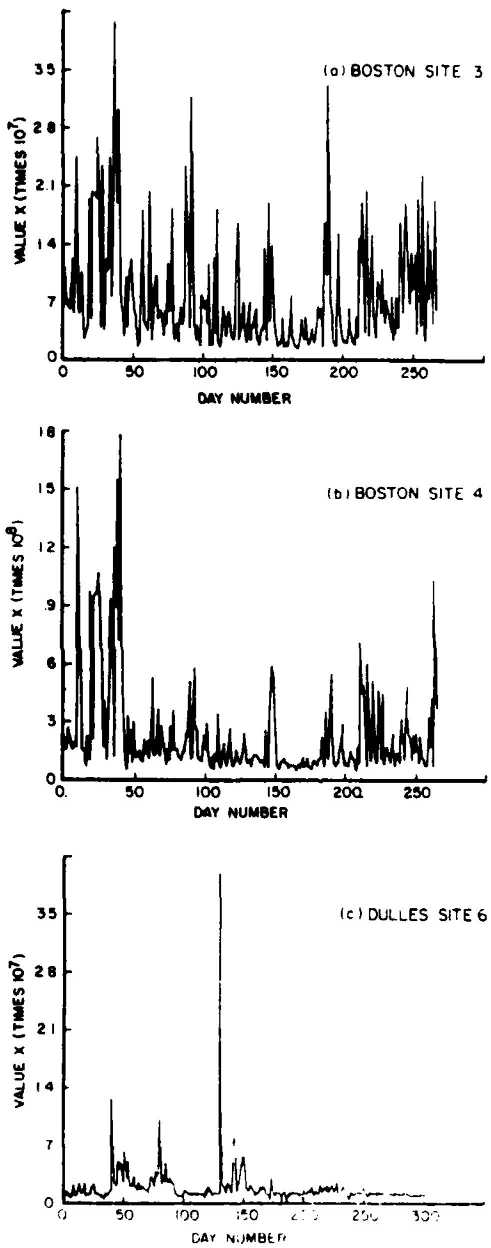

FIG. 5. Site specific time-series data of [illegible]

TABLE II. Washington National and Dulles Airport sites—DDS modeling results on original data.

Airport	Site	Model	Coefficient of variation	Autocorrelation factor	Sample size
Dulles	7A	AR(1)	0.51	1.49	7
Dulles	7B	AR(1)	0.65	2.50	17
Dulles	7	ARMA(3, 3)	0.58	6.17	34
National	13A	White noise	1.83	1.00	54
National	13B	AR(2)	0.66	3.25	23
National	13	ARMA(4, 3)	1.40	1.47	48
National	14A	AR(1)	0.47	1.49	6
National	14B	AR(1)	0.62	3.09	19
National	14	ARMA(2, 2)	0.61	16.38	97
National	15A	White noise	0.86	1.00	13
National	15B	AR(1)	0.80	1.79	19
National	15	AR(1)	0.83	1.36	15
National	16	AR(1)	0.53	2.56	12
National	19	AR(1)	0.92	1.82	25

TABLE III. Washington National and Dulles community sites—DDS modeling results.

Airport	Site	Model	Coefficient of variation	Autocorrelation factor	Sample size
Dulles	1A	White noise	0.52	1.00	5
Dulles	1B	AR(1)	0.95	2.06	31
Dulles	1	ARMA(1, 1)	0.88	7.24	90
Dulles	4	Nonstationary	0.53	...	...
Dulles	5	AR(3)	0.64	10.28	67
Dulles	9	AR(1)	0.48	1.77	7
National	24	AR(1)	0.43	5.14	14

TABLE IV. Washington National and Dulles mixed sites—DDS modeling results.

Airport	Site	Model	Coefficient of variation	Autocorrelation factor	Sample size
National	3B	AR(2)	0.36	2.65	6
Dulles	6A	White noise	1.47	1.00	5
Dulles	6B	AR(1)	0.37	2.11	5
Dulles	6	ARMA(1, 1)	1.44	4.78	158
Dulles	8A	White noise	1.55	1.00	9
Dulles	8B	White noise	2.02	1.00	11
Dulles	8	White noise	0.71	1.18	10
Dulles	10A	AR(1)	0.76	2.62	25
Dulles	10B	Nonstationary	0.62	...	...
Dulles	10	ARMA(3, 3)	0.70	8.02	62
National	11	ARMA(2, 2)	0.80	11.00	112
National	12	AR(2)	0.65	3.80	26
National	18	White noise	0.92	1.00	14
National	20A	White noise	0.85	1.00	11
National	20B	AR(1)	0.51	1.67	7
National	20	White noise	0.74	1.05	10
National	21A	Nonstationary	0.62	...	...
National	21B	AR(1)	1.03	1.85	32
National	21	ARMA(3, 1)	0.62	5.51	67
National	22A	AR(1)	0.83	1.30	15
National	22B	AR(2)	0.80	4.83	50
National	22	ARMA(1, 1)	0.82	14.79	159

ber of the sites exhibit nonstationary behavior, viz., changing mean level over the year. As a result, long-term consecutive sampling requirements are very large, often constituting more than one-third of a year. This result is much different than the sampling requirements analysis for the westcoast airports which exhibit, in general, stationary stochastic structure over an entire year's data. In attempting to delineate differences in the characteristics of eastcoast and westcoast airports and the sampled data obtained, two observations can be noted: (1) the westcoast airports are one-runway-direction airports, and (2) the monitoring sites for the westcoast airports are generally located closer to the runways.

The results relative to the eastcoast airports suggest that any analysis should be confined to data covering substantially a period of a year. Thus the remainder of this paper will focus only on sites for which a full year's data were available.

Figure 6 summarizes the results for all of the airports modeled (airport sites only), including Dulles, National, and Logan from this paper and Los Angeles (including one site from Lindberg Field) from the author's previous papers. This figure was constructed to more graphically represent the similarities and differences among the airports in terms of their sampling characteristics. The results generally show that the westcoast airports (typically one-direction, due to prevailing winds off the ocean) tend to have lower coefficients of variation and comparable autocorrelation factors relative to the multirunway and/or multidirection (variable wind) eastcoast airports. These results produce overall sampling requirements for the westcoast airports which are generally lower than those for the eastcoast airports.

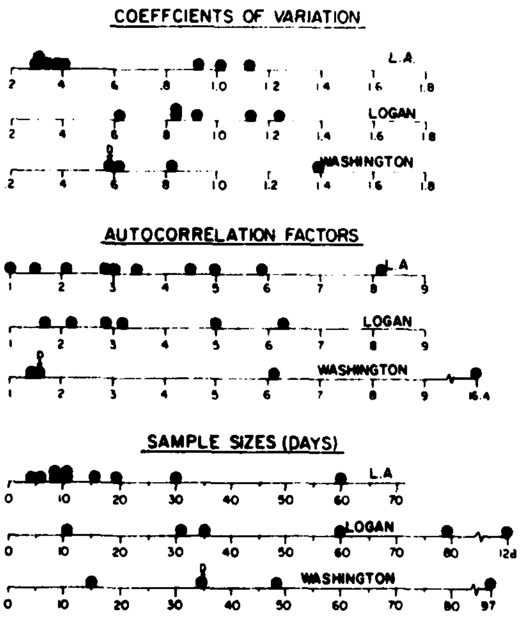

FIG. 6. Airport modeling results. The "D" in the Washington Airport data indicates Dulles sites and the "S" in the Los Angeles Airport data indicates the Lindberg Field site.

Data and modeling results from the Dulles and National community sites and mixed sites are surprising in that they do not appear to differ significantly from the airport data. That is, the autocorrelation factors, coefficients of variation and therefore overall sample size requirements do not appear to differ significantly among types of sites.

IV. MONTE CARLO STUDY OF GENERALIZED SAMPLING STRATEGIES

Because of the presence of nonstationary trends and large sampling requirements for some of the data, Monte Carlo sampling experiments were performed with the Los Angeles, Boston, and Washington data. Through such simulations, generalized sampling strategies including alternatives to consecutive sampling may be examined. Such alternate strategies may require fewer total samples than consecutive sampling and provide a means to accommodate trends in the airport noise data over a period of about one year.

Sampling experiments were performed on those sites with one year of reasonably continuous data. In the first set of experiments, the total number of samples taken to estimate the mean noise level for each strategy was 28 days. Four sampling strategies were investigated: (1) 28 days randomly spaced throughout the year, (2) one week of consecutive sampling in each quarter of the year, (3) two weeks of consecutive sampling in each half of the year, and (4) 28 consecutive days.

For each strategy, the starting date was selected randomly for each sample or group of samples. For each site, the sampling strategy was repeated 20 times. For each trial, the sample mean noise level was calculated, and the variability in means among the trials was used to estimate the variance of sample means. This variance estimate together with the appropriate t statistic ($t_{19,0.975} = 2.039$) was used to develop an estimate of predictive precision as a percentage of the population mean at the $\alpha = 0.05$ significance level. For the time series approach, it was desired to determine the requirements for consecutive sampling to estimate the mean noise level within $\pm 50\%$ of the mean at the 95% confidence level. For these Monte Carlo sampling experiments, the percent precision P for each sampling strategy is computed.

In a second set of experiments a total of 56 samples were taken. Five sampling strategies were considered: (1) 56 days randomly spaced throughout the year, (2) one week of consecutive sampling in each eighth of the year, (3) two weeks of consecutive sampling in each quarter of the year, (4) four weeks of consecutive sampling in each half of the year, and (5) 56 consecutive days.

Figure 7(a) through 7(g) show the Monte Carlo simulation results for Los Angeles, Boston, National, and Dulles Airports, respectively. In examining these figures, a number of important observations are noted. For Los Angeles, periodic sampling does indicate a slight but not marked improvement in predictive precision over consecutive sampling. With the exception of two sites, the Los Angeles

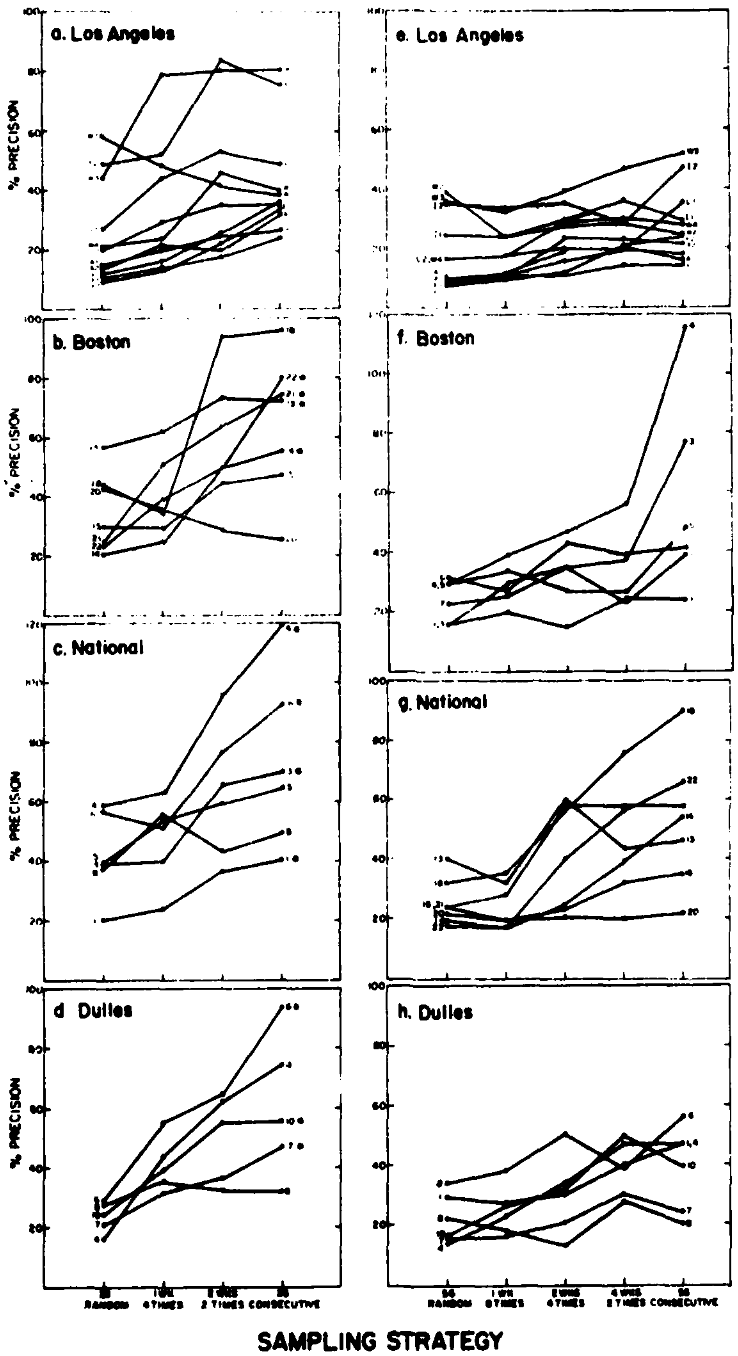

FIG. 7. Results from the Monte Carlo experiments. The "*" indicates sites exhibiting nonstationary behavior. The left-hand column shows the results of the 28-day experiments and the right-hand column shows the results of the 56-day experiments.

results show that a $\pm 50\%$ precision can be attained with 28 samples, regardless of the sampling strategy chosen. For Boston Logan and the Washington Airports significant improvements in the predictive precision can be achieved by periodic sampling, e.g., one week from each quarter over the year. This is particularly true for those sites which exhibited nonstationary behavior. To guarantee a $\pm 60\%$ precision level for these airports it is required to sample one week from each quarter over the entire year.

In considering the results of the simulation experiments involving requirements of 56 days of sampling it is noted that for Los Angeles, $\pm 35\%$ predictive precision is obtained for all sites regardless of the sampling strategy except for sites I2 and W3. For these two sites $\pm 35\%$ precision is attainable by sampling for one week out of each eighth of the year. For the Boston and Washington Airports, $\pm 40\%$ precision can be achieved for all sites if eight one-week samples are taken, one from each eighth of the year.

For Los Angeles, the DDS modeling consecutive sampling requirements and those obtained from the Monte Carlo simulations are generally about the same (see Table V). These sites exhibit stationary stochastic structure for the entire year and the simulations verify the credibility of the DDS modeling results. The same comparison holds for Boston sites 1, 5, 8, Dulles site 8, and National sites 15 and 20. These sites exhibit stationary behavior.

TABLE V. Comparison of DDS and Monte Carlo simulation results.

Site		DDS modeling results consecutive samples for $P = \pm 50\%$	Monte Carlo simulation results %P for 28 consecutive samples	Monte Carlo simulation results %P for 56 consecutive samples
LAX	A1	6	26.0	17.0
LAX	A2	19	32.0	22.0
LAX	E1	4	24.0	15.0
LAX	E2	8	32.0	24.0
LAX	I2	30	77.0	47.0
LAX	L2	11	35.0	18.0
LAX	W2	16	36.0	25.0
LAX	W3	60	81.0	52.0
LAX	W4	11	40.0	28.0
Boston	1	11	40.0	25.0
Boston	3	60	71.0	78.0
Boston	4	128	121.0	116.0
Boston	5	35	65.0	49.0
Boston	6	79	93.0	42.0
Boston	8	31	51.0	39.0
Dulles	1	90	57.0	46.0
Dulles	4	Nonstationary	74.0	47.0
Dulles	6	158	93.0	56.0
Dulles	7	34	47.0	24.0
Dulles	8	10	32.0	20.0
Dulles	10	62	55.0	39.0
National	13	48	72.0	46.0
National	14	97	55.0	52.0
National	15	15	47.0	35.0
National	18	14	96.0	90.0
National	20	10	26.0	20.0
National	21	67	74.0	57.0
National	22	159	80.0	66.0

For the sites exhibiting nonstationary behavior at Boston, Dulles, and National, the comparison of the DDS modeling and simulation results are not always consistent. In particular, the DDS models may overquote the consecutive sampling requirements necessary to achieve a particular level of precision when compared with the simulation results. This is particularly true for site 6 at Boston, site 6 at Dulles and sites 14 and 22 at National. For a comprehensive examination of the Monte Carlo simulation results, the reader is directed to the Appendix.

V. CONCLUSIONS

The results generally show that the westcoast airports (typically one-direction due to prevailing winds) tend to have lower coefficients of variation and comparable autocorrelation factors relative to the multirunway and/or multidirection (variable wind) eastcoast airports. These results produce overall consecutive sampling requirement for the westcoast airports which are generally lower than those for the eastcoast airports.

Many of the eastcoast airport sites exhibit nonstationary trends. This nonstationary condition is evidenced by vastly different models and resulting sampling requirements for the data as whole or for one part of the data when compared with the other part. Typically, the sampling requirements for the entire year's data greatly exceed the requirements derived for one or both parts.

Monte Carlo simulations using the data show similar results to the DDS methodology when the data are stationary. However, the DDS methodology overestimates the sampling requirements for nonstationary data. Moreover, the Monte Carlo simulations show that nonconsecutive sampling strategies for nonstationary data reduce the overall sampling requirements.

These results can be generalized to the eastcoast and westcoast airports as follows: (a) Westcoast (one-direction); $\pm 50\%$ precision—four weeks, any sampling strategy, $\pm 35\%$ precision—eight weeks, any sampling strategy. (b) Eastcoast (multidirection); $\pm 60\%$ precision—four weeks, one from each quarter, $\pm 40\%$ precision—eight weeks, one from each eighth.

In general, the stationary airport sites are modeled as AR(1) processes. Occasionally, there are white noise sites and, occasionally, there are nonstationary sites. The community sites and the mixed sites also are generally AR(1) models.

ACKNOWLEDGMENTS

The authors are indebted to Boston's Logan Airport and to the FAA (Dulles and National Airports) for graciously making available the data used in this study.

APPENDIX A: STOCHASTIC MODELING BY THE DYNAMIC DATA SYSTEM (DDS) METHOD

The method of dynamic data system (DDS) provides for the development of parametric stochastic time series models of the autoregressive—moving average (ARMA) class. Daily sound exposure [Eq. (1)] when viewed as a time series of values $X_1, X_2, \ldots, X_N$ has been shown to be well characterized by such models[1,2] which makes it possible to determine the precision associated with an estimate of the yearly mean sound exposure level when the observed daily values X_t are autocorrelated.

The general ARMA model is given by

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_n X_{t-n} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_m a_{t-m},$$

where X_t is the noise level (daily average) for day t, a_t is the random disturbance for day t, $\phi_1, \ldots, \phi_n$ are autoregressive parameters, and, $\theta_1, \ldots, \theta_m$ are moving average parameters. Given the time series X_t, the appropriate order of the ARMA model, viz., the proper values for n and m, may be determined and the parameters of the model may be estimated by the method of least-squares. For details of the modeling procedures, the reader is referred to Ref. 7. The majority of the fitted ARMA models obtained for the data analyzed in this paper are of relatively low order, e.g.,

$$\text{AR(1)}: X_t = \phi_1 X_{t-1} + a_t,$$

$$\text{AR(2)}: X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + a_t,$$

$$\text{ARMA(1,1)}: X_t = \phi_1 X_{t-1} + a_t - \theta_1 a_{t-1}$$

The ARMA models fit to the daily sound exposure time series X_t may be used to estimate the precision associated with the sample mean $\overline{X}$. It can be shown[1] that the variance estimate of the sample mean is given by

$$\widehat{\text{Variance}}(\overline{X}) = \frac{\hat{\sigma}_a^2}{N}\left[\left(1 - \sum_{i=1}^{m} \hat{\theta}_i\right) \Big/ \left(1 - \sum_{i=1}^{n} \hat{\phi}_i\right)\right]^2,$$

where σ_a^2 is the residual mean square for the fitted ARMA model. Given the above variance estimate, $100(1-\alpha)\%$ confidence intervals of the form

$$\overline{X} \pm t_{N-(n+m),1-\alpha/2}\,[\widehat{\text{Variance}}(\overline{X})]^{1/2}$$

may be obtained for the true yearly mean sound exposure level, thereby providing an estimate of the precision associated with the sample mean $\overline{X}$.

APPENDIX B

		Sampling strategy			
Site		One week four times per year %P	Two weeks two times per year %P	28 consecutive days %P	28 random days %P
Los Angeles	A1	20.0	23.0	26.0	15.0
Los Angeles	A2	21.0	20.0	32.0	14.0
Los Angeles	E1	14.0	18.0	24.0	11.0
Los Angeles	E2	13.0	22.0	32.0	10.0
Los Angeles	I1	44.0	54.0	49.0	27.0
Los Angeles	I2	52.0	83.0	77.0	49.0
Los Angeles	L1	16.0	25.0	37.0	12.0
Los Angeles	L2	31.0	35.0	35.0	20.0
Los Angeles	W2	48.0	42.0	36.0	58.0
Los Angeles	W3	78.0	81.0	81.0	45.0
Los Angeles	W4	24.0	46.0	40.0	21.0
Boston	1	24.0	37.0	40.0	21.0
Boston	3	40.0	66.0	71.0	39.0
Boston	4	63.0	96.0	121.0	59.0
Boston	5	54.0	59.0	65.0	39.0
Boston	6	53.0	77.0	93.0	57.0
Boston	8	56.0	43.0	51.0	38.0
Dulles	1	41.0	57.0	57.0	30.0
Dulles	4	44.0	62.0	74.0	16.0
Dulles	6	55.0	64.0	93.0	30.0
Dulles	7	32.0	37.0	47.0	21.0
Dulles	8	35.0	32.0	32.0	28.0
Dulles	10	39.0	55.0	55.0	25.0
National	13	62.0	74.0	72.0	57.0
National	14	25.0	50.0	55.0	21.0
National	15	29.0	45.0	47.0	30.0
National	18	34.0	94.0	96.0	44.0
National	20	35.0	29.0	26.0	43.0
National	21	53.0	64.0	74.0	25.0
National	22	39.0	50.0	80.0	23.0

Site		Sampling strategy				
		One week eight times per year %P	Two weeks four times per year %P	Four weeks two times per year %P	56 consecutive days %P	56 random days %P
Los Angeles	A1	12.0	19.0	20.0	17.0	10.0
Los Angeles	A2	11.0	24.0	23.0	22.0	11.0
Los Angeles	E1	11.0	13.0	15.0	15.0	10.0
Los Angeles	E2	12.0	16.0	21.0	24.0	9.0
Los Angeles	I1	24.0	30.0	37.0	30.0	25.0
Los Angeles	I2	34.0	35.0	29.0	47.0	35.0
Los Angeles	L1	10.0	12.0	21.0	36.0	8.0
Los Angeles	L2	18.0	20.0	19.0	18.0	17.0
Los Angeles	W2	24.0	28.0	29.0	25.0	39.0
Los Angeles	W3	33.0	39.0	47.0	52.0	36.0
Los Angeles	W4	18.0	29.0	30.0	28.0	17.0
Boston	1	21.0	15.0	25.0	25.0	16.0
Boston	3	30.0	35.0	38.0	78.0	16.0
Boston	4	39.0	47.0	56.0	116.0	25.0
Boston	5	34.0	27.0	27.0	49.0	25.0
Boston	6	27.0	43.0	39.0	42.0	31.0
Boston	8	26.0	35.0	25.0	39.0	23.0
Dulles	1	27.0	30.0	40.0	46.0	29.0
Dulles	4	23.0	34.0	47.0	47.0	14.0
Dulles	6	38.0	51.0	39.0	56.0	34.0
Dulles	7	16.0	21.0	31.0	24.0	15.0
Dulles	8	17.0	13.0	27.0	20.0	22.0
Dulles	10	27.0	32.0	50.0	39.0	16.0
National	13	32.0	60.0	43.0	46.0	40.0
National	14	17.0	25.0	39.0	52.0	19.0
National	15	19.0	23.0	32.0	35.0	24.0
National	18	35.0	56.0	75.0	90.0	32.0
National	20	20.0	21.0	21.0	20.0	22.0
National	21	28.0	58.0	58.0	57.0	24.0
National	22	18.0	40.0	56.0	66.0	18.0

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Philadelphia 19106
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Norfolk 23510
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Savannah 31402
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Chicago 60604
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Rock Island 61201
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ATTN: Chief, ED-D
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ATTN: Chief, SPKED-D
Far East 96301
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Seattle 98124
ATTN: Chief, EN-DB-ST
Walla Walla 99362
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North Atlantic 10007
ATTN: Chief, NADEN-T
Middle East (Rear) 22601
ATTN: Chief, MEDED-T
South Atlantic 30303
ATTN: Chief, SADEN-TS
Huntsville 35807
ATTN: Chief, HNDED-CS
ATTN: Chief, HNDED-SR
Ohio River 45201
ATTN: Chief, Engr Div
Missouri River 68101
ATTN: Chief, MRDED-T
Southwestern 75202
ATTN: Chief, SWDED-T
South Pacific 94111
ATTN: Chief, SPDED-TG
Pacific Ocean 96858
ATTN: Chief, Engr Div
North Pacific 97208

6th US Army 94129
ATTN: AFKC-EN

7th Army Combined Arms Trng. Cntr. 09407
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Armament & Dev. Command 21005
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USA ARRADCOM 07801
ATTN: DRDAR-LCA-OK

DARCOM 22333
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Ft. Clayton, Canal Zone 34004
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Ft. Detrick, MD 21701

Ft. Leavenworth, KS 66027
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Human Engineering Lab. 21005 (2)

USA-WES 39181

Army Environmental Hygiene Agency 21005

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Naval Air Systems Command 20360

US Naval Oceanographic Office 39522

Naval Surface Weapons Center 22485
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Naval Undersea Center, Code 401 92152 (2)

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AFESC/TST

Wright-Patterson AFB, OH 45433 (3)

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Transportation Research Board 20418

Dept of Housing and Urban Development 20410

Dept of Transportation Library 20590

Illinois EPA 62706 (2)

Federal Aviation Administration 20591

Federal Highway Administration 22201
Region 15

NASA 23365 (2)

National Bureau of Standards 20234

Office of Noise Abatement 20590
ATTN: Office of Secretary

USA Logistics Management Center 23801

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