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I, George Goley, hereby submit this original work as part of the requirements for the degree of:

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Committee Chair: J. Kim, PhD

J. Kim, PhD
Investigation and Improvement of Occupational and Military Noise Exposure Guidelines: Evaluation of Existing and Modified Noise Exposure Metrics Using Historical Animal Data

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By

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Miami University, December 2005
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Miami University, May 2008
ABSTRACT

Noise induced hearing loss is a significant problem in both the occupational and military settings. Current occupational noise guidelines use an energy based noise metric to predict the risk of hearing loss and thus ignore the effect of temporal characteristics of the noise. The practice is widely considered to underestimate the risk of a complex noise environment, where impulsive noises are embedded in a steady-state noise. A basic form for noise metrics is designed by combining the equivalent SPL and a temporal correction term defined as a function of kurtosis of the noise. Several noise metrics are developed by varying this basic form and evaluated utilizing existing chinchilla noise exposure data. It is shown that the kurtosis correction term significantly improves the correlation of the noise metric with the measured hearing losses in chinchillas. One of the investigated metrics, the kurtosis corrected A-weighted SPL, is applied to a human exposure study data as a preview of applying the metrics to human guidelines. A method to remove statistically unlikely outliers from the animal test data is also investigated. In addition to the basic temporal correction term for the characterization of complex noise exposures, a complex noise separation algorithm is explored to further characterize the exposure. In military noise settings, the effects of high intensity, impulsive noise on the auditory system are complex and difficult to quantify in a simple criterion. Several impulse noise criteria (e.g. MIL-STD 1474D, Pfander, Smoorenburg) are studied for their analytic structure to understand underlying basic assumptions. Then, these and other criteria are compared for their performance based on animal blast overpressure data. In occupational and military settings, a frequency-matched, weighted equivalent sound pressure level is investigated. The statistical correlations of this weight are compared with metrics currently in use. The possibility of developing a new noise
standards according to the approach adopted in this study as well as remaining challenges are discussed.
ACKNOWLEDGEMENTS

This work was partially supported by the National Institute for Occupational Safety and Health, Grant number R21 OH008510. The author thanks Roger Hamernik, Wei Qiu, James Patterson, and William Ahroon for providing chinchilla noise exposure study data and advice in interpreting the data.

The author also acknowledges William Murphy for his guidance throughout this research. He provided essential direction.

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Lastly, the author thanks his supportive and loving wife, Laura. Her endless encouragement was essential to my continued motivation and progress.
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I. INTRODUCTION

The overarching theme of this thesis is to improve current guidelines to better conserve the hearing of industrial and military personnel. The guidelines used in occupational and military settings differ greatly due to the vastly different characteristics of their noise exposures. This introduction provides an introduction to the anatomy and physiology of the auditory system, the biological mechanism of noise-induced hearing loss, an overview of both of these standards, particularly the areas that motivated this research, and provides an overview of the structure of the thesis.

A. Anatomy of the Auditory System

This section provides a basic overview of the anatomy and the physiology of the auditory system. This is not an exhaustive overview. From an engineering standpoint there are several motivations for the study of the auditory system including sound quality, hearing aid design, hearing conservation, etc… In addition, an engineer may study the auditory system in order to develop a finite element model, create a circuit analog, analyze the acoustic pathway, etc... These investigations all have merit. The brief investigation in this section is to provide the readers with some basic background knowledge of the auditory system and provide some insight as to the reasoning behind existing and the modified metrics used in the study.
FIG. 1. The anatomy of the auditory system (Flanagan, 1972).

The anatomy of the auditory system is typically divided into three distinct regions, the external or outer ear, the middle ear, and the inner ear, see FIG. 1. The external ear is comprised of the pinna and the external canal. The shape of the external ear passively amplifies the sound by its reverse horn design. The transfer function of this amplification is shown in FIG. 2. This function bears a resemblance to the A-weight function.
FIG. 2. The transfer function of the external ear (Henderson and Hamernik, 1995).

The external ear terminates at the tympanic membrane which is the start of the middle ear. The tympanic membrane oscillates which causes the middle ear ossicles to displace. The middle ear ossicles is comprised of, from the direction of the external ear to the inner ear, the malleus, incus, and stapes. These structures act as an impedance matching mechanism between the medium of the external ear, typically air, to the inner ear, fluid. The middle ear also includes the muscles that are responsible for the acoustic reflex. The acoustic reflex reduces the transmissibility of the middle ear thereby protecting the inner ear from potentially dangerous exposures. The acoustic reflex is the result of the contraction of two muscles, the stapedal muscle attached to the stapes and the tympani muscle attached to the malleus. If both muscles are activated, the middle ear attenuates the sounds below 2000 Hz (Henderson and Hamernik, 1995).
The external and middle ear are well-known and characterized. An analysis of numerous middle ear acousto-electric models exists (Song, 2010). The inner ear is significantly more complex and is the sensory organ of the auditory system. The stapes, which is attached to the oval window of the cochlea, moves in a piston like motion. This motion is approximately linear below 130 dB in the human organ and increasingly nonlinear thereafter (AHAAH, 2010). This nonlinearity acts as a limiting factor for the displacement of the stapes.

The motion of the stapes creates hydrodynamic motion in the cochlea. The cochlea includes two main compartments, or vestibules, and a basilar membrane separating them, see FIG. 3. The thickness and width of the basilar membrane vary along the axial direction of the cochlea. This results in different resonance frequencies of the basilar membrane depending on location. Simply, the location of the motion of the basilar membrane is dependent on the frequency of the sound. Pitches, or frequencies, are differentiated by the nervous system due to the frequency dependent characteristic of the basilar membrane. This behavior can be modeled by a series of loosely coupled filters, or SDOF systems.

Attached to the basilar membrane is the Organ of Corti, FIG. 4. The most essential cells in the Organ of Corti are the Outer and Inner Hair Cells. Protruding from the hair cells are stereocilia, or small hairs. When the basilar membrane displaces, shear flow between the Tectorial membrane and the Reticular membrane causes the stereocilia to displace, see FIG. 5. The mechanical energy of the stereocilia is then converted into electrical energy by the hair cell and transmitted to the nervous system.
FIG. 3. A cross-section of the cochlea (Kessell and Kardon, 1979).

FIG. 4. The Organ of Corti (Kessell and Kardon, 1979).
The biology of noise-induced hearing loss depends greatly on the intensity of the noise (Kopke et al., 2006). In moderate levels of noise exposures (85 to 140 dB SPL), the cause is primarily metabolic. As levels increase, the damage is more likely to be mechanical. In occupational type exposures the cause is metabolic, which results in a significant loss of hair cells.

It is believed that when the auditory system is exposed to moderate and persistent levels of noise, the hair cell is exposed to oxidative stress (Kopke et al., 2006). This oxidative stress overwhelms the antioxidant defenses of the cell. The essential structures of the cell now begin to
degnerate which eventually leads to cell death, see FIG. 6. After the cell dies, surrounding cells may also die as a result of apoptosis. Research currently exists to protect the cells that die due to apoptosis. In general, hair cells do not regenerate.

FIG. 6. A healthy hair cell, left, the defenses of the hair cell, middle, and the damaged hair cell, right (Kopke et al., 2006).

At higher noise levels, the damage is primarily mechanical. This ranges from the damage to the cochlea structures, the middle ear ossicles, and the tympanic membrane (Ritenour et al., 2008). A confounding result of the mechanical damage to the auditory pathway is a reduction in the efficiency of the transmissibility of the auditory pathway. The reduced efficiency can protect the downstream structures of the auditory system. In many cases, the mechanical damage to the upstream components of the auditory system does heal (Ritenour et al., 2008).
B. Occupational Noise

Most noise guidelines currently in use such as ISO 1999 (ISO-1999, 1990) recommend safe levels of noise exposure based on the equal energy hypothesis (EEH). The EEH assumes that hearing loss is a function of only the total exposure energy, independent of the temporal characteristics of the noise (Robinson, 1968; Prince et. al, 1997). The EEH based approach has been proved to be a very useful tool in establishing and implementing noise guidelines because of its simplicity. However, the approach is generally considered appropriate for steady-state noise but not complex noise, a steady-state noise embedded with impulsive noises (Ahroon et al., 1993). Some researchers have made arguments for the application of EEH in complex noise environments, (Atherley and Martin, 1971, Guberan et al., 1971, Atherley, 1973), which has largely been rebutted by laboratory studies (Dunn et al., 1991, Hamernik and Qiu, 2001, Lei et al., 1994, Hamernik et al., 1974) as well as epidemiological studies (Sulkowski and Lipowczan, 1982, Thiery and Meyer-Bisch, 1988).

The current NIOSH (National Institute for Occupational Safety and Health) guideline (NIOSH, 1998) suggests a 140-dB SPL limit be used for impulsive noise, and the 85-dBA permissible exposure limit (PEL) with a 3-dB exchange rule be used for complex noises. It also notes “[if] the effects are synergistic, the [85-dBA PEL and 3-dB exchange rule] would still be protective to a smaller extent [than for steady-state noise]”. This suggests the need for more research to determine (1) if synergistic effects exist in the complex noise problem, (2) a quantification of the synergistic effects to be included in future noise guidelines. The first issue, existence of synergetic effects was quite clearly confirmed by many animal noise exposure
studies (Dunn et al., 1991, Lei et al., 1994). The second issue, the need for quantification of synergetic effects, motivated this study.

Recent animal exposure studies (Hamernik and Qiu, 2001, Hamernik et al., 2003b) have shown that kurtosis calculated from the pressure time history of the noise is a very effective parameter to differentiate the risk of noises of the same energy level but different temporal characteristics. This suggests that the SPL combined with a kurtosis correction term may serve as a good noise metric for assessment of the risk of noise of widely different temporal characteristics. This approach, combining an energy based metric and a temporal correction term, was also applied concurrently to this study by Zhao et al. to human noise exposure study data (Zhao et al., 2010). In their work, the kurtosis correction was made through the exposure time. The correction term was determined to match dose-response relationship (DRR) of two groups respectively exposed to a complex noise environment and a Gaussian noise environment. Because the correction form was determined from only one set of data, validity of the correction form has yet to be established. In this work, the best form of the kurtosis corrected SPL is identified using chinchilla noise exposure test data, taking advantage of abundant dose response relationship (DRR) data obtained from direct, controlled experiments.

C. Military Noise

The problem of noise-induced hearing loss (NIHL) is a serious one in the military environment. Unlike industrial noises, which are typically moderate to high levels of steady-state noises embedded with comparatively lower peak level impulses (if any), military noises are highly impulsive of short time duration. NIHL is not only a lifestyle problem for victims but also an enormous long-term cost to society. These factors have motivated years of research that has
sought to classify damage biologically (Henderson and Hamernik, 1995, Garth, 1995), quantify impulse characteristics (Coles et al., 1968), model the auditory pathway\(^1\) (AHAAH, 2010, Patterson and Ahroon, 2004), correlate hearing loss with a variety of noise metrics (Patterson et al., 1993), and many others. In order to protect soldiers from NIHL due to military noises, in addition to hearing protectors, a variety of damage-risk criteria (DRC) exist. This research was motivated to evaluate existing DRCs in comparison to one another and propose a new DRC. The evaluation utilizes chinchilla exposure data set of 905 chinchillas to 137 different impulse noises. Unlike human data that measures NIHL in an indirect way, i.e., temporary threshold shift (TTS) not the permanent threshold shift (TTS), at relatively moderate levels, direct DRR data is obtained in chinchillas that enables quantitative comparison of the DRCs.

Historically several characteristics were used in the quantification of impulse noise in relation to hearing loss (Coles et al., 1968, Henderson and Hamernik, 1986), such as peak pressure, rise time, duration (A, B, C, and D), number of impulses, energy level and spectral characteristics (Price, 1979). Of these characteristics, peak-based noise metrics use the peak pressure, duration, and the number of impulses (Smoorenburg, 1981, Ward 1968). Hazard indicators (HI) of peak-based metrics have the following form:

\[
HI_p = L_{pk} + f(T) + g(N)
\]

where \(L_{pk}\) is the peak pressure level in dB, \(f(T)\) is a function of the duration of the impulses defined in various ways, and \(g(N)\) is an adjustment for the number of impulses. The peak-based metrics stemmed from the fact that the peak pressure is the main factor that distinguishes between the different mechanisms of hearing loss and other bodily injury.

\(^1\) The website cited above provides numerous other references. In addition the Bibliography provides additional references (Price, 2007a, Price 2007b)
A second form of hazard indicator is an energy-based metric, such as equivalent sound pressure level, $L_{eq}$. These metrics have the following format:

$$HI_{SPL} = H_{eq}(W) + g(N)$$  \hspace{1cm} (2)

where $H_{eq}$ is the equivalent SPL with some frequency weight $W$. $L_{eq}$ has been the standard in industrial noise exposure guidelines since the 1950s and proven quite useful in this application, especially in the A-weighted form. Frequency weighting can be applied in the time domain using either an analog or digital filter or in the frequency domain. The noise data used in this study has the complete time history, which allows for the application of frequency weighting in the frequency domain. This procedure and its MATLAB implementation are explained in the Appendix A.

The last form of hazard indicator is the model-based approach that assesses the risk through simulation. Although some other auditory models exist, the Auditory Hazard Assessment Algorithm for Humans (AHAAH) is the only model tested in relation to noise-induced hearing loss (AHAAH, 2010). The AHAAH model calculates the displacement of the basilar membrane from the free field waveform. The AHAAH model also accounts for the nonlinearity of the annular ligament in the middle ear, which limits the motion of the stapes to high level exposures. The AHAAH model, a human model, is applied to chinchilla data in this work; therefore, the AHAAH model’s performance would likely be higher if a chinchilla version model existed. The result of the AHAAH model is the Auditory Risk Units, or ARUs. This is the result of the maximum of the time integrated basilar membrane displacements. This indicator has the following form:
The research in this thesis on military noise exposures takes advantage of existing chinchilla test data in order to make comparisons of current military DRCs. This study will conduct a brief analytical comparison of the metrics used in the DRCs to understand how they are designed. The data from the animal experiment is used to compare these metrics for their correlations with the damage data. Then, these metrics are modified by finding the best-fit coefficients for the number and duration functions. In addition to the aforementioned metrics, two other equivalent sound pressure levels are investigated, $L_{peq,8hr}$ and $L_{eq,5,1234}$. The goal of this study is to provide a new metric design that is easily evaluated from the given waveform, and easy to be incorporated to current guidelines, and investigate the meaning of various predictors used in current DRCs.

D. Overview

This thesis is comprised of five chapters in addition to the introduction. Chapter II is the body of a manuscript that was submitted the Journal of the Acoustical Society of America. This chapter investigates how including the temporal characteristics of noise exposure in a noise metric can better predict hearing loss in chinchillas. This study also investigates an equivalent sound pressure that is frequency matched to hearing loss indicator. Chapter III describes a procedure that was used to identify outliers in the occupational noise animal experiment used in Chapter II. Chapter IV is the body of a manuscript that is in process and will be submitted to a journal yet to be determined. This chapter investigates current military noise guidelines and proposes some new metrics. Chapter V describes a complex noise separation procedure that was
used to extract more information from the exposures used the occupational noise animal experiment. Chapter VI summarizes the results and describes potential future work in this area.
II. KURTOSIS CORRECTED SOUND PRESSURE LEVEL AS A NOISE METRIC

This chapter uses an experiment that exposed chinchillas to occupational complex type noises to design a new noise metric that corrects for the temporal characteristics of the noise. In addition to the temporal correction, an equivalent sound pressure level which uses only energy from the same frequency range of the hearing loss indicator is investigated. This study begins with an overview of the experimental data, describes the design of and results from the new metrics, and applies the new metrics to a comparable human study.

A. Experimental Data

Provided by collaborators in SUNY Plattsburgh, noise exposure data for 273 chinchillas of 23 groups are used for current study. Each group consisting of 9-16 chinchillas was exposed to a specially designed, different noise environment. 18 groups were exposed to 100-dBA noises (1 Gaussian, 17 complex), 2 groups to 95-dBA noises (1 Gaussian and 1 complex) and 3 groups to 90-dBA noises (1 Gaussian and 2 complex). Animals were exposed to a given noise for 24-hour per day, for five consecutive days. The hearing threshold level (HTL) was measured from the auditory evoked potential (AEP) at 0.5, 1, 2, 4, 8, 16 kHz for each animal before the test, daily during the test and 30 days after the completion of the test. From the AEP data, permanent threshold shift (PTS) and temporary threshold shift (TTS) are calculated. Outer hair cell (OHC) losses and inner hair cell (IHC) losses in 0.5, 1, 2, 4, 8, 16 kHz bands were also measured. The noise data digitally recorded for 5-minutes with the 48 kHz sampling was given as a part of the data to the author. More detailed descriptions of the noises and experimental protocols are
available in various publications (Hamernik et al., 1989, Hamernik et al., 2003a, Hamernik et al., 2007). The PTS data is used as the primary measure in the current research because it is used as the basis for the noise induced hearing loss (NIHL) in most noise guidelines.

TABLE I. The overall and frequency-by-frequency equivalent SPLs and kurtosis of the 23 noises.

<table>
<thead>
<tr>
<th>Group Index</th>
<th>Overall</th>
<th>0.5 kHz</th>
<th>1 kHz</th>
<th>2 kHz</th>
<th>4 kHz</th>
<th>8 kHz</th>
<th>16 kHz</th>
<th>kurtosis</th>
<th>PTS&lt;sub&gt;5124&lt;/sub&gt; (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>G-44</td>
<td>101.08</td>
<td>80.70</td>
<td>92.94</td>
<td>92.96</td>
<td>95.40</td>
<td>93.31</td>
<td>93.85</td>
<td>32.65</td>
<td>34.09</td>
</tr>
<tr>
<td>G-49</td>
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<td>85.40</td>
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<td>93.36</td>
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<td>14.81</td>
<td>24.99</td>
</tr>
<tr>
<td>G-63</td>
<td>103.07</td>
<td>94.20</td>
<td>93.56</td>
<td>89.56</td>
<td>90.23</td>
<td>95.36</td>
<td>95.54</td>
<td>58.41</td>
<td>30.48</td>
</tr>
<tr>
<td>G-64</td>
<td>99.88</td>
<td>69.30</td>
<td>74.33</td>
<td>99.31</td>
<td>91.08</td>
<td>82.19</td>
<td>75.16</td>
<td>77.42</td>
<td>8.30</td>
</tr>
<tr>
<td>G-65</td>
<td>101.46</td>
<td>85.20</td>
<td>92.31</td>
<td>92.64</td>
<td>95.63</td>
<td>93.22</td>
<td>93.56</td>
<td>27.14</td>
<td>27.73</td>
</tr>
<tr>
<td>G-66</td>
<td>92.40</td>
<td>80.65</td>
<td>79.34</td>
<td>78.17</td>
<td>81.95</td>
<td>86.35</td>
<td>86.59</td>
<td>2.95</td>
<td>3.33</td>
</tr>
<tr>
<td>G-67</td>
<td>92.56</td>
<td>75.90</td>
<td>87.24</td>
<td>84.98</td>
<td>84.39</td>
<td>83.41</td>
<td>84.30</td>
<td>33.25</td>
<td>7.77</td>
</tr>
</tbody>
</table>
Availability of the digitally recorded noise time histories makes the exposure data obtained by Hamernik et al. highly valuable as it enables re-processing of the noise to study the data from different angles. The analytic wavelet transform (AWT) developed by Zhu and Kim (Zhu and Kim, 2006, Zhu et al., 2009) was applied in this work to obtain time histories of the full octave frequency components at 0.5, 1, 2, 4, 8, 16 KHz. From these time histories, equivalent SPL of the frequency components were calculated as listed in TABLE I. Kurtosis of the noise was calculated from the original pressure time histories.

Kurtosis is defined as the 4\textsuperscript{th} standardized moment about the mean of the data:

\[
\frac{E(x - \mu)^4}{s^4}
\]  

(4)

where, \( s \) is the standard deviation of \( x \), \( E(t) \) represents the expected value of quantity \( t \), \( \mu \) is the mean of \( x \). Kurtosis is used to determine the “peakedness” of a distribution and was first used as a measure of impulsiveness by Erdreich (1985). Kurtosis, an energy-independent metric, has been used to study the effect of temporal characteristics of the noise on hearing loss due to noise exposures (Hamernik and Qiu, 2001). Kurtosis of Gaussian noises (G-61, G-47, G-57) is approximately 3 as seen in Table 1.

### B. Development of the New Noise Metric
The performance of the noise metric is evaluated by its correlation with the NIHL defined in a way most compatible with the definition used in human guidelines. The level of unacceptable occupational hearing loss in the NIOSH guideline (NIOSH, 1999) is defined as material hearing impairment, defined as having a 25-dB or higher HTL averaged for 1, 2, 3, and 4 kHz. The closest definition to this that can be made from the currently available chinchilla data is the average of PTS at 0.5, 1, 2, and 4 kHz measured in chinchillas. Therefore, PTS\textsubscript{5124} defined as follows is adopted as the NIHL indicator in the correlation study.

\[
PTS_{5124} = \frac{1}{4} (PTS_5 + PTS_1 + PTS_2 + PTS_4).
\]  

where, PTS\textsubscript{5}, PTS\textsubscript{1}, PTS\textsubscript{2}, PTS\textsubscript{4} are the average PTS measured at 0.5, 1, 2, 4 kHz from chinchillas in each group. PTS\textsubscript{5124} of each of the 23 groups of chinchillas is shown in the last column of Table 1.

1. Design of the noise metric

While kurtosis is a very good differentiator of the risk of noises of the same energy but different temporal characteristics, it cannot be used as a noise metric by itself because it is an energy-independent parameter. For example, Gaussian noises of 50-dBA and 100-dBA, which clearly have different noise risks, have the same kurtosis value. Therefore, it is logical to design the noise metric by combining the SPL with a kurtosis correction term. After testing several forms for the correction term, the basic form of the new metric was determined as follows:

\[
L'_{eq} = L_{eq} + \lambda \log_{10} \frac{\beta}{\beta_G}.
\]
where, $L'_\text{eq}$ is the corrected SPL, $\lambda$ is a positive constant to be determined from the dose-response correlation study, $\beta$ is the kurtosis of the noise and $\beta_G$ is the kurtosis of the Gaussian noise. Notice that no correction is made for a Gaussian noise. A complex noise has a kurtosis higher than $\beta_G$; therefore, has a positive correction term that represents the higher risk of the noise. Four new noise metrics obtained by varying the definition in Eq. (6) are compared to one another along with two traditional metrics, $L_{eq}$ and $L_{Aeq}$. As it is shown in Table 2, the first two metrics are the $L_{eq}$ and $L_{Aeq}$. The third metric, $L_{eq,5124}$, is defined as:

$$L_{eq,5124} = \frac{1}{4}(L_{eq,5} + L_{eq,1} + L_{eq,2} + L_{eq,4}).$$

(7)

where $L_{eq,5}, L_{eq,1}, L_{eq,2}, L_{eq,4}$ are equivalent SPLs of the 0.5, 1, 2, and 4 kHz full octave components respectively. $L_{eq,5124}$ is chosen by matching its form with the form of the NIHL defined in Eq. (7) based on the cochlea position theory (Price, 1979, Zwislocki and Nguyen, 1999). Six metrics were evaluated: the first three metrics have no kurtosis correction term, the last three are obtained by adding the kurtosis correction term to the first three metrics. The coefficient $\lambda$ is determined from regression analysis create the optimal corrected SPL metric in terms of correlation with the NIHL of chinchillas.

2. Correlation study

The correlation between the noise metric and the NIHL indicator, $PTS_{5124}$, is calculated from a linear regression analysis applied to 23 pairs of $L'_\text{eq}$ and $PTS_{5124}$ data. The linear regression equation for the first three metrics in Table 2 is, for example that of $L_{eq}$ is:
\[ PTS_{5124} = b_0 + b_1 L_{eq} + \epsilon \] 

(8)

where, \( \epsilon \) is the error to be minimized. Multiple predictor regression models are constructed for the last three metrics in Table 2. For example the regression equation for \( L'_{eq} = L_{eq} + \lambda \log_{10} \frac{\beta}{\beta_G} \) becomes:

\[ PTS_{5124} = b_0 + b_{Leq} L_{eq} + b_{k1} \log_{10} \frac{\beta}{\beta_G} + \epsilon \] 

(9)

The regression analysis obtains the best values for \( b_0, b_{Leq} \) and \( b_{k1} \) that minimizes \( \epsilon \).

\[ \lambda = \frac{b_{Leq}}{b_{k1}} \]

and corresponding \( r^2 \) values are obtained for each metric. The correlation study result is summarized in TABLE II.

TABLE II: Results of regression analysis of the noise metrics as a function of the average PTS.

<table>
<thead>
<tr>
<th>Metric Number</th>
<th>Metric</th>
<th>( \lambda )</th>
<th>( r^2 ) value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( L_{eq} )</td>
<td>N/A</td>
<td>0.41</td>
</tr>
<tr>
<td>2</td>
<td>( L_{Aeq} )</td>
<td>N/A</td>
<td>0.46</td>
</tr>
<tr>
<td>3</td>
<td>( L_{eq,5124} )</td>
<td>N/A</td>
<td>0.61</td>
</tr>
<tr>
<td>4</td>
<td>( L'<em>{eq} = L</em>{eq} + \lambda \log_{10} \frac{\beta}{\beta_G} )</td>
<td>4.80</td>
<td>0.54</td>
</tr>
<tr>
<td>5</td>
<td>( L'<em>{Aeq} = L</em>{Aeq} + \lambda \log_{10} \frac{\beta}{\beta_G} )</td>
<td>4.04</td>
<td>0.54</td>
</tr>
<tr>
<td>6</td>
<td>( L'<em>{eq,5124} = L</em>{eq,5124} + \lambda \log_{10} \frac{\beta}{\beta_G} )</td>
<td>3.07</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Between the traditional metrics, \( L_{Aeq} \) has a slightly better \( r^2 \) value than \( L_{eq} \), which supports the practice of using \( L_{Aeq} \) over \( L_{eq} \) in noise guidelines. \( L_{eq,5124} \) shows by far the best
correlation among uncorrected noise metrics, which may be expected if the cochlea position
theory is considered.

Kurtosis corrections improve correlations of all three metrics $L_{eq}$, $L_{Aeq}$, and $L_{eq,5124}$. Overall, $L'_{eq,5124}$ shows the best correlation with the NIHL. In fact, the best two metrics are $L_{eq,5124}$ and $L'_{eq,5124}$. The kurtosis correction term does not improve $L_{Aeq}$ and $L_{eq,5124}$ as much as it does $L_{eq}$. TABLE III shows the cross correlation of the correction term with $L_{eq}$ variations which shows the lowest cross-correlation between the correction term and $L_{eq}$. This explains the largest improvement of the correlation obtained by adding the correction term to $L_{eq}$.

TABLE III. Cross-correlation $r^2$ values of the predictors variables.

<table>
<thead>
<tr>
<th></th>
<th>$L_{eq}$</th>
<th>$L_{Aeq}$</th>
<th>$L_{eq,5124}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda \log_{10} \frac{\beta}{\beta_G}$</td>
<td>0.09</td>
<td>0.36</td>
<td>0.18</td>
</tr>
</tbody>
</table>

FIG. 7 compares the scatter plots of the PTS$_{5124}$ values against the metric values with the regressed line. Each point represents the PTS$_{5124}$ - metric pair of the 23 animal groups. A), C), and E) plot the uncorrected $L_{eq}$, $L_{Aeq}$ and $L_{eq,5124}$, respectively. B), D), and F) plot the corresponding corrected $L'_{eq}$, $L'_{Aeq}$ and $L'_{eq,5124}$.

The third best metric, $L'_{Aeq}$ has an advantage because it is correcting $L'_{Aeq}$, the noise metric used in most current noise guidelines. That is, a current noise guideline can be used without any changes except adopting $L'_{Aeq}$ in place of $L_{Aeq}$. For example, NIOSH guidelines can use $L_{Aeq,8hr} = 85$-dBA and 3-dB exchange rule only by adopting $L'_{Aeq,8hr} = 85$-dBA.
FIG. 7. Plots of the actual $PTS_{5124}$ values against the actual metric values with the regressed predicted correlations. A): against $L_{eq}$, B): against $L'_{eq}$, C): against $L_{Aeq}$, D): against $L'_{Aeq}$, E) against $L_{eq,5124}$, F): against $L'_{eq,5124}$.

C. Application to Human Data

The corrected A-weighted SPL developed in this study was tested against the human data gathered by Hamernik and his collaborators in China (Zhao et al., 2010). $L_{eq,5124}$ and $L'_{eq,5124}$ could not be tested because the digital noise exposure time histories of the noises were not available to the author. Among 195 subjects who participated in the survey, 32 subjects were exposed to complex noise of the average kurtosis of 44 for $12.3 \pm 7.1$ years and 163 subjects were exposed to a Gaussian noise ($\beta = 3$) for $12.7 \pm 8.4$ years. The adjusted high frequency NIHL (AHFNIHL) was used as the NIHL, which is defined as having a higher HTL by 30 dB or more than the 50$^{th}$ percentile of the age and gender matched population found in the International Standard Organization (ISO-1999, 1990) standard in Annex B in either ear at 3, 4 or 6 kHz. The cumulative noise exposure (CNE) index, the noise metric (dose), was defined:

$$CNE = L_{Aeq,8hr} + 10\log_{10} T$$

(10)

where, $T$ is the exposure duration measured in years.

Similar to the procedure adopted in the study by Zhao et. al, the subjects are separated into 5-dB CNE bins (2010). The results are shown in Fig. 2 in a plot of AHFNIHL percentage – CNE relationship. It is clearly seen that the complex noise shows higher NIHL for the same
value of CNE, uncorrected noise metric than the Gaussian noise in all but the 90-dB CNE case, in which no subject showed significant hearing loss in the complex noise case and there were no subjects exposed to Gaussian noise at this level.

In their study (Zhao et. al, 2010), \( CNE' \), the kurtosis corrected metric was defined as follows.

\[
CNE' = L_{Aeq,8hr} + \frac{\ln(\beta) + 1.9}{\log(2)} \log_{10} T
\]  

(11)

The correction in Eq. (11) was determined so that the metric (CNE' or CNE) – NIHL (AHFNIHL) relationships of the complex noises (\( \beta = 44 \)) and the Gaussian noises are best matched, and the form reduces to Eq. (10) for a Gaussian noise (\( \beta = 3 \)). The correction form in Eq. (11) was determined to make the two sets of the data match with each other. Therefore, the validity of the kurtosis correction form in Eq. (11) is not known.

Because the correction scheme previously developed in this study (see Eq.(6)) applies to \( L_{Aeq} \), independent of the exposure time length, the correction of the CNE is as follows.

\[
CNE' = L_{Aeq,8hr}' + 10 \log_{10} T = L_{Aeq,8hr}' + \lambda \log_{10} \frac{\beta}{\beta_C} + 10 \log_{10} T
\]  

(12)

where \( \lambda = 4.02 \) as it was identified for \( L_{Aeq}' \) previously. The relationship between the corrected AHFNIHL percentage and CNE’ of the complex noises is shown using a different symbol in FIG. 8. Improvement using the kurtosis correction term is obvious from the figure. The metric – NIHL
relationships of the Gaussian and complex noises have become much closer to each other, which implies that the corrected metric CNE’ will estimate risk of complex noises more accurately. For example, before correction, a noise of CNE = 105 is predicted to cause NIHL to 50% of the population if no correction is made (i.e., following to the curve of the Gaussian noise), which actually caused NIHL to 90% of the population. With the correction term, the noise with CNE’ = 105 is predicted to cause NIHL to 70% of the population. Therefore, the corrected CNE’ will reflect the risk of complex noises more accurately. It is also noted that $L'_{eq,5124}$ showed much better performance than $L'_{Aeq}$; therefore its application is expected to improve the result even more.

FIG. 8: Effect of kurtosis correction on predicting NIHL risk of human.
D. Discussion

1. Basic Hypotheses Used in Development of New Noise Metrics

The approach adopted in this work is developing new noise metrics by using chinchilla noise exposure data, then applying them to assess the risk of human noise exposure. The approach takes advantage of abundant, directly measured noise exposure study data. The approach obviously involves errors because it uses the chinchilla data for human application. Besides the expected differences in the DRR of the human and chinchilla, definitions of the dose and response (NIHL) are different. For example, NIOSH guideline defines dose as 30-year, 8-hour exposure, while chinchillas were exposed to 5-days continuous exposures; response in the NIOSH guideline is defined as having 25-dB or higher HTL averaged for 1, 2, 3, 4, KHz, while it is defined as the PTS averaged for 0.5, 1, 2, 4 KHz in chinchillas. Therefore, the approach in this work implicitly adopts the following hypotheses.

(1) Human and chinchillas have similar DRR in a relative sense. That is, if a given noise causes higher NIHL than the other noise in chinchillas, the same will occur in human.

(2) Long-term and short-term exposures have similar DRR in a relative sense. That is, if one noise causes higher NIHL than the other noise in a short-term exposure, the same will occur in a long-term exposure.

The above hypotheses are plausible if the similarity of the auditory systems of human and chinchillas is considered, while they will ultimately have to be validated empirically. The first hypothesis can be validated by using animal tests, for example by showing that the noise metric developed from chinchilla data applies very well to guinea pigs. The second hypothesis will have
to be validated by applying the new noise metric to a number of human exposure study data. The human study for this purpose will have to record the time history of the noise so that kurtosis of the noise can be calculated. The validation will still be indirect and limited because of the nature of the human data. For example, it is highly unlikely that the noise to which workers are exposed will remain the same over a long duration, e.g. 30 years; there are many uncontrollable factors such as exposure to recreational noises or effects of other illnesses.

2. **Reference kurtosis $\beta_G$**

The basic form of the new noise metric, $L'_eq = L_{eq} + \lambda \log_{10} \frac{\beta}{\beta_G}$, was designed so that Gaussian noises are not corrected. Current noise guidelines may be considered as the result of empirical data accumulated for a long period of time for most common occupational noise environments, which may have higher kurtosis than $\beta_G$. In this case, using $\beta_G$ as the reference kurtosis in the correction may result in over-evaluation of the risk of complex noises. A better reference kurtosis may be identified by surveying “typical” occupational noise environments.

3. **Modification of $L'_{eq,5124}$ to utilize it in human guidelines**

$L'_{eq,5124}$ was adopted because PTS, NIHL, of chinchillas was measured at 0.5, 1, 2, 4 kHz, not at 1, 2, 3, 4 kHz that most human guidelines adopt to define NIHL. Therefore, $L'_{eq,1234}$ may be used for human application instead of $L'_{eq,5124}$, while using the same $\lambda$ value identified for $L'_{eq,5124}$ from the chinchilla data.

4. **Potential application of the new noise metrics to human guidelines**
Among the three best noise metrics, $L'_{Aeq}$ is the easiest to apply in human guidelines. Because $L'_{Aeq}$ is a temporally corrected $L_{Aeq}$, the noise metric used in most noise guidelines, no other change is necessary to use $L'_{Aeq}$ in place of $L_{Aeq}$. However, some manipulation is necessary to use $L'_{eq,1234}$ because it does not represent the overall SPL. It can be viewed as a type of weighting. One option is using $L''_{eq,1234}$, a scaled $L'_{eq,1234}$ defined as follows:

$$L''_{eq,1234} = L'_{eq,1234} + (L_{eq,A,G} - L_{eq,1234,G}) \approx L''_{eq,1234} + 9.2 \quad (13)$$

where, $(L_{eq,A,G} - L_{eq,1234,G})$ is the difference of the A-weighted SPL and $L_{eq,1234}$ of the Gaussian-white noise. If the noise is Guassian-white noise, $L'_{eq,1234} = L_{eq,1234,G}$; therefore, $L''_{eq,5124}$ reduces to $L_{Aeq}$. $L_{eq,A,G} - L_{eq,1234,G}$ is approximately 9.2-dB, independent of the level of the noise. $L''_{eq,1234}$ defined in Eq. (13) can be used in place of $L_{Aeq}$ in the noise guideline, which requires no other changes. $L''_{eq,1234}$ is expected to give the best result.
III. OUTLIER IDENTIFICATION

This chapter suggests, explains, and implements a procedure for quantifying and indentifying outliers in NIHL experiments with chinchillas. Using a multifaceted approach, the procedure uses all known data to establish a score for each subject in an attempt to retain the expected individual variability but identify subjects that exhibit conflicting and statistically improbable results. This procedure uses pre-exposure thresholds, correlations of hair cell losses and permanent threshold shifts (PTS), as well as comparisons of the group PTS with individual PTS results. Combining these measures into a normalized outlier score for each subject allows the researcher to set a tolerance level, investigate subjects marked as outliers by this tolerance level, and remove these outliers.

The process of identifying and eliminating outliers is extremely difficult when subject to subject variation is large. However, large and unlikely variations in subject results provide great barriers when attempting to produce a convincing statistical model. Unlike other statistical methods, such as regression analysis or hypothesis testing, outlier identification is less well-defined. Defining an outlier for a sample set depends on the sample variation, the researcher’s goals, and others. In this case the researchers’ goal was outlined and investigated in Chapter II. The goal of this procedure is to identify subjects whose variation is not only statistically improbable but also contains conflicting data, which could indicate measurement error.

This procedure uses as much meaningful information as was available to the researchers and is common in NIHL animal experiments. The array of information used provides multi-faceted information on the subject, thus providing the researchers with a strong argument to eliminate an outlying subject. This procedure uses a comparison of pre-exposure thresholds to
the chinchilla audiogram, the comparison of group permanent threshold shift (PTS) to that of the individual, and the correlation between sensory cell loss, or inner and outer hair cells, with PTS.

This procedure is part of a larger research project to create a NIHL assessment procedure. The result of the outlier procedure is a dataset that can be used to make stronger correlations between PTS and noise metrics. If these correlations are improved the noise risk metrics will have stronger correlations and be more accurate in predicting hearing loss.

A. Procedure

The procedure is divided into the following steps, see FIG. 9 for a diagram of the steps (1), (2), and (3):

(3) Score subjects’ pre-exposures (iPRE), OHC\(_s\), IHC\(_s\), and gPTS. The subscript ‘s’ denotes that these are not the actual outer and inner hair cell losses but the score associated with the loss. The four types of scores will be described in the subsequent sections.

(4) Normalize scores

(5) Combine scores using weighting constants (e.g. IHC\(_{WC}\)) to create a Normalized Outlier Score (NOS) for each subject

(6) Select a tolerance level.

(7) Investigate outliers.

(8) Remove outliers.
FIG. 9. Diagram of the outlier identification procedure.
1. **Pre-Exposure Scores**

The pre-exposure score is calculated as the number of standard deviations that the subjects’ pre-exposure threshold is from the audiogram mean for each frequency. The audiogram was the mean pre-exposure thresholds for the population of 273 chinchillas. The frequency scores are then added together to represent one \(iPRE\) score for each subject. The \(iPRE\) scores are normalized by the maximum \(iPRE\) score of the population.

\[
iPRE(i) = \frac{1}{6} \sum_{j=0.5}^{16} \left| \frac{\mu_j - p_{RE,i,j}}{\sigma_j} \right|
\]  

(14)

where \(i\) – subject number, \(j\) – frequency (in this case 0.5, 1.0, 2.0, 4.0, 8.0, 16.0 Hz), \(\mu\) – the mean pre-exposure threshold for the chinchilla at the \(j\)th frequency, \(\sigma\) – the standard deviation of the pre-exposure threshold for the chinchilla at the \(j\)th frequency.

The \(iPRE\) scores were calculated for the entire population, see FIG. 10. The scores are continuous variables and show high concentration from 0 to about 1, moderate concentration between 1 and about 1.4 and much lighter concentration for higher scores. This observation is clearer in the box plot, see FIG. 10. The median is approximately .8, the inter-quartile range is .6 to .95, and the plot shows 7 subjects greater than \(Q_3 + 1.5IQR\) where \(Q_3\) is the 75th percentile and \(IQR\) is the inter-quartile range. Recall that each subject’s score is the summation of each frequency component, thus the subjects with great \(iPRE\) scores showed consistent aberrations from the mean pre-exposure threshold for the chinchilla.
2. **Hair Cell Scores**

The hair cell scores include both the inner outer hair cell scores. As described in Chapter I, loss of sensory cells is often the cause of hearing loss due to occupational noise exposure. Thus, it is likely that permanent threshold hold shifts accompany a corresponding level of hair cell loss. This part of the procedure finds discrepancies between the hair cell losses and permanent threshold shifts. The calculation of these two scores follows the same procedure:

1. **Regression**
   - Regress the hair cell losses with the PTS for the entire population for a given frequency.
   - Calculate the residuals.
   - Add the absolute value of the residual to the HC score.

This procedure is calculated for each frequency. The total HC outlier score is then divided by the number of frequencies. The regression function used in both cases is exponential and has the following definition where PTS is $x$, the percent of hair cell loss is the $y$, and $a$ and $b$ are regression constants:
The HC scores are calculated as follows:

\[ y = \frac{100}{a-x} \]  \hspace{1cm} (15)

The HC scores are calculated as follows:

\[ HC_s(i) = \frac{1}{6} \sum_{j=0.5}^{16} r(i,j) \]  \hspace{1cm} (16)

where

\[ r(i,j) = |y(i,j)_{pred} - y(i,j)_{actual}| \]  \hspace{1cm} (17)

The hair cell scores are continuous variables ranging from approximately 2 to 70 for OHC scores, and 1 to 49 for IHC scores, see FIG. 11. Recall, these scores are averages of all the frequencies for one subject. The two hair cell scores have tightly grouped data at low average residual levels. The data becomes less scattered at higher scores until each show a subject with extremely high average residuals, in each case it is subject 3076.
FIG. 11. The hair cell scores, left, and box plots of the hair cell scores.

3. \textbf{gPTS Scores}

Unlike the other outlier scores the \textit{gPTS} scores are calculated on a group by group basis. The \textit{gPTS} scores compare the PTS of the subject against the PTS of subjects exposed to the same noise waveform. Subject to subject variation is expected in any animal test; however, extreme subject to subject variation can help the researcher identify potential outliers. The \textit{gPTS} scores are calculated in the following manner:
The $gPTS$ scores are continuous random variables as seen in FIG. 12. Notice that the concentration of scores is extremely high below a score of approximately 1.4. The box plot in FIG. 12 shows 5 subjects greater than $Q_3 + 1.5IQR$. This is an indication of extreme variation of these subjects.

4. Combining the Scores

Next the four scores are normalized, weighted and combined. The researcher at this time uses weighting factors for each of the scores to weight some of the scores more heavily than others. In this study, three different sets of weighting factors are investigated. After the scores are weighted and added together the normalized outlier score (NOS) is plotted and a tolerance level is chosen. A tolerance level is difficult to calculate based on statistical evidence, such as standard deviations or residuals, since the NOS is a combination of a large amount of data (6 frequencies for each score and four scores). Thus, the researcher can decide which score he/she wishes to
accentuate for a variety of reasons, such as sensor specifications or experimental procedure. The points above the tolerance are then removed.

### B. Results

The results used three different sets of weighting factors, see TABLE IV. Set A highlights the hair cell scores, set B highlights the $gPTS$ score, and set C highlights the $iPre$ score. The correlation coefficient, $r^2$, for the same metrics used in the kurtosis correction study, see Chapter II are compared. The resulting data set used with outliers removed is used to recalculate the regression factors and is compared to those calculated with the full data set. For each set of weighting factors the scatter plots of the outlier scores with the chosen tolerance level, the data for each marked outlier and the new correlation coefficients are shown.

<table>
<thead>
<tr>
<th></th>
<th>$OHC_{wc}$</th>
<th>$IHC_{wc}$</th>
<th>$gPTS_{wc}$</th>
<th>$iPre_{wc}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.75</td>
<td>1.25</td>
<td>.5</td>
<td>.5</td>
</tr>
<tr>
<td>B</td>
<td>.75</td>
<td>.75</td>
<td>1.75</td>
<td>.75</td>
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<tr>
<td>C</td>
<td>.75</td>
<td>.75</td>
<td>.75</td>
<td>1.75</td>
</tr>
</tbody>
</table>
FIG. 13. Set A

TABLE V: Set A

<table>
<thead>
<tr>
<th>Group</th>
<th>Animal #</th>
<th>OHC</th>
<th>IHC</th>
<th>gPTS</th>
<th>iPRE</th>
</tr>
</thead>
<tbody>
<tr>
<td>249.0</td>
<td>2825</td>
<td>0.419</td>
<td>0.523</td>
<td>0.386</td>
<td>0.392</td>
</tr>
<tr>
<td>251.0</td>
<td>2881</td>
<td>0.442</td>
<td>0.309</td>
<td>0.305</td>
<td>0.951</td>
</tr>
<tr>
<td>255.0</td>
<td>2939</td>
<td>0.558</td>
<td>0.597</td>
<td>0.114</td>
<td>0.356</td>
</tr>
<tr>
<td>263.0</td>
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<td>0.800</td>
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</tr>
<tr>
<td>263.0</td>
<td>3075</td>
<td>0.336</td>
<td>0.459</td>
<td>0.762</td>
<td>0.475</td>
</tr>
<tr>
<td>263.0</td>
<td>3076</td>
<td>1.000</td>
<td>1.000</td>
<td>0.362</td>
<td>0.172</td>
</tr>
<tr>
<td>258.0</td>
<td>2997</td>
<td>0.399</td>
<td>0.332</td>
<td>1.000</td>
<td>0.416</td>
</tr>
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</table>

Correlation Coefficient Comparison

<table>
<thead>
<tr>
<th></th>
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<th>Outlier Dataset</th>
<th>Corrected (Full Dataset)</th>
<th>Outlier Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_{eq}$</td>
<td>(0.41) 0.42</td>
<td></td>
<td>(0.54) 0.54</td>
<td></td>
</tr>
<tr>
<td>$L_{Aeq}$</td>
<td>(0.46) 0.46</td>
<td></td>
<td>(0.54) 0.54</td>
<td></td>
</tr>
<tr>
<td>$L_{eq,5124}$</td>
<td>(0.61) 0.61</td>
<td></td>
<td>(0.67) 0.66</td>
<td></td>
</tr>
</tbody>
</table>
**FIG. 14. Set B**

**TABLE VI: Set B**

<table>
<thead>
<tr>
<th>Group</th>
<th>Animal #</th>
<th>OHC</th>
<th>IHC</th>
<th>gPTS</th>
<th>iPRE</th>
</tr>
</thead>
<tbody>
<tr>
<td>251</td>
<td>2869</td>
<td>0.230</td>
<td>0.244</td>
<td>0.951</td>
<td>0.527</td>
</tr>
<tr>
<td>252</td>
<td>2898</td>
<td>0.258</td>
<td>0.479</td>
<td>0.827</td>
<td>0.400</td>
</tr>
<tr>
<td>260</td>
<td>3041</td>
<td>0.308</td>
<td>0.086</td>
<td>0.653</td>
<td>1.000</td>
</tr>
<tr>
<td>260</td>
<td>3135</td>
<td>0.259</td>
<td>0.324</td>
<td>0.733</td>
<td>0.441</td>
</tr>
<tr>
<td>263</td>
<td>3075</td>
<td>0.336</td>
<td>0.459</td>
<td>0.762</td>
<td>0.475</td>
</tr>
<tr>
<td>263</td>
<td>3076</td>
<td>1.000</td>
<td>1.000</td>
<td>0.362</td>
<td>0.172</td>
</tr>
<tr>
<td>265</td>
<td>3102</td>
<td>0.278</td>
<td>0.474</td>
<td>0.787</td>
<td>0.379</td>
</tr>
<tr>
<td>266</td>
<td>3123</td>
<td>0.252</td>
<td>0.491</td>
<td>0.684</td>
<td>0.342</td>
</tr>
<tr>
<td>268</td>
<td>3164</td>
<td>0.201</td>
<td>0.521</td>
<td>0.787</td>
<td>0.489</td>
</tr>
<tr>
<td>270</td>
<td>3216</td>
<td>0.297</td>
<td>0.401</td>
<td>0.699</td>
<td>0.383</td>
</tr>
<tr>
<td>258</td>
<td>2997</td>
<td>0.399</td>
<td>0.332</td>
<td>1.000</td>
<td>0.416</td>
</tr>
</tbody>
</table>

The following subjects will be removed:

- Animal #260
- Animal #268
- Animal #270
- Animal #251

The following subjects will be removed:

<table>
<thead>
<tr>
<th>Group</th>
<th>Animal #</th>
<th>OHC</th>
<th>IHC</th>
<th>gPTS</th>
<th>iPRE</th>
</tr>
</thead>
<tbody>
<tr>
<td>251</td>
<td>2869</td>
<td>0.230</td>
<td>0.244</td>
<td>0.951</td>
<td>0.527</td>
</tr>
<tr>
<td>252</td>
<td>2898</td>
<td>0.258</td>
<td>0.479</td>
<td>0.827</td>
<td>0.400</td>
</tr>
<tr>
<td>260</td>
<td>3041</td>
<td>0.308</td>
<td>0.086</td>
<td>0.653</td>
<td>1.000</td>
</tr>
<tr>
<td>260</td>
<td>3135</td>
<td>0.259</td>
<td>0.324</td>
<td>0.733</td>
<td>0.441</td>
</tr>
<tr>
<td>263</td>
<td>3075</td>
<td>0.336</td>
<td>0.459</td>
<td>0.762</td>
<td>0.475</td>
</tr>
<tr>
<td>263</td>
<td>3076</td>
<td>1.000</td>
<td>1.000</td>
<td>0.362</td>
<td>0.172</td>
</tr>
<tr>
<td>265</td>
<td>3102</td>
<td>0.278</td>
<td>0.474</td>
<td>0.787</td>
<td>0.379</td>
</tr>
<tr>
<td>266</td>
<td>3123</td>
<td>0.252</td>
<td>0.491</td>
<td>0.684</td>
<td>0.342</td>
</tr>
<tr>
<td>268</td>
<td>3164</td>
<td>0.201</td>
<td>0.521</td>
<td>0.787</td>
<td>0.489</td>
</tr>
<tr>
<td>270</td>
<td>3216</td>
<td>0.297</td>
<td>0.401</td>
<td>0.699</td>
<td>0.383</td>
</tr>
<tr>
<td>258</td>
<td>2997</td>
<td>0.399</td>
<td>0.332</td>
<td>1.000</td>
<td>0.416</td>
</tr>
</tbody>
</table>

**Correlation Coefficient Comparison**

- Uncorrected (Full Dataset) Outlier Dataset: $L_{eq} = 0.41$, $L_{Aeq} = 0.46$, $L_{eq,5124} = 0.61$
- Corrected (Full Dataset) Outlier Dataset: $L_{eq} = 0.54$, $L_{Aeq} = 0.54$, $L_{eq,5124} = 0.67$
FIG. 15. Set C
TABLE VII: Set C

<table>
<thead>
<tr>
<th>Group</th>
<th>Animal #</th>
<th>OHC</th>
<th>IHC</th>
<th>gPTS</th>
<th>iPRE</th>
</tr>
</thead>
<tbody>
<tr>
<td>244.0</td>
<td>2739</td>
<td>0.237</td>
<td>0.302</td>
<td>0.468</td>
<td>0.655</td>
</tr>
<tr>
<td>249.0</td>
<td>2829</td>
<td>0.187</td>
<td>0.324</td>
<td>0.498</td>
<td>0.670</td>
</tr>
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<td>249.0</td>
<td>2833</td>
<td>0.108</td>
<td>0.096</td>
<td>0.498</td>
<td>0.827</td>
</tr>
<tr>
<td>251.0</td>
<td>2869</td>
<td>0.230</td>
<td>0.244</td>
<td>0.951</td>
<td>0.527</td>
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<tr>
<td>251.0</td>
<td>2881</td>
<td>0.442</td>
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<td>0.951</td>
</tr>
<tr>
<td>252.0</td>
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<td>0.258</td>
<td>0.479</td>
<td>0.827</td>
<td>0.400</td>
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<td>254.0</td>
<td>2918</td>
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<td>0.459</td>
<td>0.762</td>
<td>0.475</td>
</tr>
<tr>
<td>263.0</td>
<td>3076</td>
<td>1.000</td>
<td>1.000</td>
<td>0.362</td>
<td>0.172</td>
</tr>
<tr>
<td>268.0</td>
<td>3164</td>
<td>0.201</td>
<td>0.521</td>
<td>0.787</td>
<td>0.489</td>
</tr>
<tr>
<td>258.0</td>
<td>2997</td>
<td>0.399</td>
<td>0.332</td>
<td>1.000</td>
<td>0.416</td>
</tr>
</tbody>
</table>

Correlation Coefficient Comparison

<table>
<thead>
<tr>
<th></th>
<th>Uncorrected (Full Dataset)</th>
<th>Outlier Dataset</th>
<th>Corrected (Full Dataset)</th>
<th>Outlier Dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_{eq}$</td>
<td>(0.41)</td>
<td>0.42</td>
<td>(0.54)</td>
<td>0.52</td>
</tr>
<tr>
<td>$L_{Aeq}$</td>
<td>(0.46)</td>
<td>0.45</td>
<td>(0.54)</td>
<td>0.52</td>
</tr>
<tr>
<td>$L_{eq,5124}$</td>
<td>(0.61)</td>
<td>0.60</td>
<td>(0.67)</td>
<td>0.64</td>
</tr>
</tbody>
</table>

C. Discussion

The outlier removal procedure produced no improvement over the entire data set. Since the goal of this correlation study is a relative study of metric quality of fit, it is unlikely that removing outliers will impact the conclusions of the correlation study. This is the case since this was a comparative study, so poor data points will likely affect all of the metrics in the same way.
This approach does have merit in evaluating the quality of the experimental data and determining if a particular group of subjects exhibits numerous outliers as calculated by this procedure. If this is the case, it is likely that there was an error in some part of the experimental process. The weighting factors could also be used as a diagnostic tool to decide which type of data caused the additional variation.

Since the motivation of this study was for a correlation study that used an average hearing loss over multiple frequencies, the outlier study used an average of the various frequencies of the data. In use for other studies a frequency by frequency approach may be more appropriate and provide more meaningful results.
IV. MILITARY NOISE DRC COMPARISON AND EVALUATION

This chapter takes advantage of existing chinchilla test data in order to make comparisons of current DRC of military blast noise. This study will conduct a brief analytical comparison of the metrics used in the DRCs to understand how they are designed. The data from the animal experiment is used to compare these metrics for their correlations with the damage data. Then, these metrics are modified by finding the best-fit coefficients for the number and duration functions. In addition to the aforementioned metrics, two other equivalent sound pressure levels are investigated, $L_{eq,8hr}$ and $L_{eq,5124}$. The goal of this study is to provide a new metric design that is easily evaluated from the given waveform, easy to incorporate to current guidelines, and investigate the meaning of various predictors used in current DRCs.

A. Experimental Data

The experimental data used in this study was conducted by The Auditory Research Laboratory of the State University of New York at Plattsburg, New York (Hamernik et al., 1998a, Hamernik et al., 1998b). The data includes 905 chinchillas exposed to 137 different exposures. The 137 exposures vary by impulse, or stimulus, type, number of impulses, and inter-peak intervals. Descriptions of the stimuli are found in TABLE VIII.
TABLE VIII: Stimuli descriptions

<table>
<thead>
<tr>
<th>Stimulus Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 – 3</td>
<td>Conventional shock tube, nonreverberant</td>
</tr>
<tr>
<td>4 – 6</td>
<td>Fast-acting valve (5”), nonreverberant</td>
</tr>
<tr>
<td>7 – 9</td>
<td>Fast-acting valve (3.5”), nonreverberant</td>
</tr>
<tr>
<td>10 – 12</td>
<td>Spark gap, nonreverberant</td>
</tr>
<tr>
<td>13 – 15</td>
<td>Conventional shock tube, reverberant</td>
</tr>
<tr>
<td>16 – 18</td>
<td>Fast-acting valve (3.5”), reverberant</td>
</tr>
<tr>
<td>19 – 20</td>
<td>260 Hz Narrow-band impact</td>
</tr>
<tr>
<td>21 – 23</td>
<td>775 Hz Narrow-band impact</td>
</tr>
<tr>
<td>24 – 27</td>
<td>1025 Hz Narrow-band impact</td>
</tr>
<tr>
<td>28 – 30</td>
<td>1350 Hz Narrow-band impact</td>
</tr>
<tr>
<td>31 – 34</td>
<td>2450 Hz Narrow-band impact</td>
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<tr>
<td>35 – 38</td>
<td>3550 Hz Narrow-band impact</td>
</tr>
<tr>
<td>39 – 40</td>
<td>2075 Hz Narrow-band impact</td>
</tr>
<tr>
<td>41 – 42</td>
<td>146 dB peak SPL and 138 dB peak SPL</td>
</tr>
<tr>
<td>43, 45 &amp; 47</td>
<td>290C driver, High peak wave, USAARL Report 86-7</td>
</tr>
<tr>
<td>44, 46, &amp; 48</td>
<td>290C driver, Low peak wave, USAARL Report 86-7</td>
</tr>
<tr>
<td>49</td>
<td>290C driver, 131 peak SPL, 100x , USAARL Report 85-3</td>
</tr>
<tr>
<td>50</td>
<td>USAARL Conventional shock tube, nonreverberant (unpublished)</td>
</tr>
</tbody>
</table>

The data used in this paper was analyzed in the past by several researchers. In a report, Hamernik conducted extensive nonlinear regression of peak-based models as well as weighted SPLs (Hamernik et al., 1998a, Hamernik et al., 1998b). In Hamernik’s results he found that the P-weighted energy-based metrics were best correlated with PTS. The P-weighting function was
created by Patterson (Patterson et al., 1993) and now has several modified forms. Hamernik used a nonlinear regression analysis function.

Chan used the SUNY/USAARL chinchilla dataset to develop a human impulse noise injury model for unprotected ears (Chan and Ho, 2005). Chan et al. used a logit model to regress the peak-based metrics and A-weighted SPL against $PTS_{124}$. The model was used to estimate the probability that an ear would be injured immediately or permanently following a given exposure. A 10 dB shift was used to adjust the model from chinchillas to humans. The current study differs in that the AHAAH model is also compared to other metrics, a frequency matched SPL is investigated, and best-fit metrics are found.

Recently, Murphy et al. used nonlinear regression to compare five standard metrics, MIL-STD-1474D, Pfander, Smoorenburg, $L_{Aeq,8hr}$, and AHAAH, (Murphy et al., 2010). The analysis is briefly repeated here to enable comparison to new hazard indicators.

**B. Types of Metrics**

This section defines the various metrics to be analyzed. In addition, this section also provides an analysis of the peak-based metrics.

1. **Peak-based Metrics**

Peak-based metrics are the foundation of numerous military standards. The relationship between the maximum peak level and duration length in the Pfander and Smoorenburg metrics approximate the 85 or 90 dB maximum exposure limit for an 8 hour work day (Smoorenburg, 1981). These metrics were likely developed due to the historical characterization of highly
impulsive noise as well as the availability of data during their development (Smoorenburg et al., 2003).

Three widely used current peak-based metrics are MIL-STD-1474D (1991), Pfander (Pfander et al., 1980), and Smoorenburg (Smoorenburg, 1981). Although they are defined in different forms in respective standards, the forms of the metrics are represented as in Eq. (2) (Chan et al., 2001).

\[
\begin{align*}
L_M &= L_{pk} + 6.64 \log_{10} \frac{T_B}{200} + 5 \log_{10} N \\
L_P &= L_{pk} + 10 \log_{10} T_C + 10 \log_{10} N \\
L_S &= L_{pk} + 10 \log_{10} T_D + 10 \log_{10} N
\end{align*}
\]

where, \(L_M\) is the metric used by the MIL-STD-1474D guideline, \(L_P\) by the Pfander guideline, \(L_S\) by the Smoorenburg guideline; \(T_B\), \(T_C\), and \(T_D\) are the B, C, and D-duration in ms. The durations were calculated in MATLAB using code developed by Zechmann (2009). The definitions of the durations is shown in FIG. 16.
Some studies have shown that these metrics do not perform as well as energy-based metrics in both animal and human studies (Chan et al., 2001, Hamernik et al., 1998a, Hamernik et al., 1998b). Examining the physical meaning of their mathematical definitions provides a possible explanation of their shortcomings. For example, from Eq. (2), the Pfander metric with $N = 1$ becomes:

$$L_P = L_{pk} + 10 \log_{10} T_c + 10 \log_{10} N \quad (20)$$

The C-duration is equivalent, in its discrete implementation, to the product $C(\Delta t)$ where $\Delta t$ is defined in milliseconds, or as shown below as $\Delta t$ added $C$ times. Also, for simplicity let us assume that $N = 1$. 

**FIG. 16.** Definition of impulse noise durations (Smoorenburg, 1992).
Using basic logarithmic operations we can combine the peak pressure and duration.

\[ L_p = 10 \log_{10} \left( \frac{p^2_{pk}}{p^2_{ref}} \right) + 10 \log_{10} \left( \sum_{i=1}^{c} \Delta t \right) \]  \hfill (21)

This now becomes quite similar to a calculation of equivalent sound pressure level based on the discrete time signal.

\[ L_p = 10 \log_{10} \left( \sum_{i=1}^{c} \frac{\Delta t}{p^2_{ref}} \frac{p^2_{pk}}{p^2_{ref}} \right) \]  \hfill (22)

\[ L_p = 10 \log_{10} \left( \frac{\Delta t}{p^2_{ref}} \sum_{i=1}^{c} p^2_{pk} \right) \]  \hfill (23)

With the exception of \( T_{bhr} \), which is simply a constant, the Pfander calculation can be viewed as a reduction of the waveform to a square wave with an amplitude equal to the peak and a period equal to the duration associated with that particular standard, see FIG. 17. In other words the Pfander peak-based metric is similar to a poor integrator of the time signal or as the equivalent sound pressure level of a corresponding square wave. The Smoorenburg HI is identical if C-duration is exchanged with D-duration. The MIL-STD-1474D is similar but has a different coefficient on the duration logarithm. This will result in a reduction of the period of the square wave. It is clear that from a correlation perspective, \( L_{Aeq,bhr} \) will likely perform better since it better differentiates between the impulses than these standards. Since the standards reduce the information provided by the waveform to a square wave with an amplitude equal to the peak and a period equal to the duration of interest.
Peak-based metrics implicitly assume that the hearing damage occurs primarily due to the mechanical failure of the hearing organ; therefore, the peak-level metrics counts the effect of the noise when the level only within 10 or 20-dB of the peak level by applying the crude integration shown above to estimate the associated energy. Because of this definition, the peak-level based metrics ignore the dynamic response characteristics of the hearing organ, unlike $L_{Aeq}$ that reflect the frequency response characteristics. Due to the transient nature of highly impulsive noise, the temporal and spectral characteristics of the noise are not independent but interwoven (Zhu et al., 2009). A reverberant noise will likely have a longer duration than a non-reverberant impulsive noise with the same peak level. This creates a trade-off effect that the longer duration produces longer exposure to high pressure levels but also is largely composed of low frequency noise that is more easily attenuated by the auditory system. This likely leads to the relationship seen in the Chan et. al. study of the Albuquerque data where the best fit model actually had a negative coefficient on the duration factor (2001).

**FIG. 17.** Example waveform and square wave approximation result from Pfander peak-based HI.

### 2. Energy-based Metrics
$L_{eq}$ is the standard in industrial noise exposure guidelines and has been since the 1950’s. It is typically calculated based on the A-weighted pressure time history. The $L_{Aeq}$, or A-weighted equivalent sound pressure level, can be normalized to a given time length, such as 8 hours, to be related to a standardized dose level for workers. More recently, $L_{Aeq}$ has been used as the hazard indicator for highly impulsive DRCs (Dancer, 2003). The standard $L_{Aeq,8hr}$ metric is defined as:

$$L_{Aeq,8hr} = 10 \log_{10} \left( \frac{1}{t_1 - t_2} \int_{t_1}^{t_2} \frac{p_A^2(t)}{p_0^2} \, dt \right) + 10 \log_{10} \left( \frac{t_2 - t_1}{T_{8hr}} \right) + 10 \log_{10} N \tag{25}$$

In addition to the A-weighted equivalent sound pressure level, the $L_{Peq,8hr}$, or P-weighted equivalent sound pressure level, is investigated. The P-weighting function was defined to better correlate to high level exposures with hearing loss in chinchillas (Patterson et al., 1993). The standard P-weighted metric is the same form as $L_{Aeq,8hr}$ shown in Eq. (25) with $p_P(t)$ in place of $p_A(t)$.

A third energy-based metric $L_{eq,5124}$ is included in the study, see (7). Since the noise time histories are fully observable transients, $L_{eq,5}, L_{eq,1}, L_{eq,2}, L_{eq,4}$ can be estimated easily in the frequency domain. The standard metric for $L_{eq,5124}$ is defined as:

$$L_{eq,5124} + 10 \log_{10} N \tag{26}$$

Kurtosis which was investigated in Chapter II, was also investigated for military noise types. The military exposures can be viewed as extreme cases of complex noise, if a low level Gaussian noise is assumed to exist during the inter-peak interval. The benefit of a kurtosis correction term was also explored, but the results were inconclusive and are not included. The
calculation of kurtosis with long inter-peak intervals is not trivial and is shown in Appendix B. The relationship between kurtosis and IPI is interesting and should be explored further.

3. The AHAH Model

The unwarned condition was used to calculate the ARUs, Auditory Risk Units. In addition, due to the wide spread of $ARU(N)$ the logarithm of the metric was taken and included in this analysis. The standard forms of these two metrics are defined as:

$$ARU(N)$$

(27)

$$\log_{10} ARU + 10 \log_{10} N$$

(28)

C. Comparison of Noise Metrics by Statistical Analysis

Performances of various metrics are compared by their correlations with the damage observed in chinchillas.

1. The Hearing Loss Indicator

Temporary threshold shifts (TTS) are used as the damage indicator in human experiments as PTS cannot be used as the damage indicator for obvious ethical reasons. Instead, the damage is defined in terms of the TTS as in the Albuquerque test (Chan et al., 2001), either their exact, continuous value or filtered into a Boolean value of failure (Chan et al., 2001, Prince et al., 1997) given some gate value, such as 15 dB. In order to replicate the damage caused to the speech range the average of PTS values at 0.5, 1, 2, and 4 kHz was used in this study similar to Chapter
II, see Eq. (5). Due to large subject to subject variation the group means for each exposure condition were used.

2. **Statistical Analysis**

The statistical analysis is divided into two sections:

(13) The metrics in their standard form

(14) The metrics with the coefficients of additional terms determined for best correlation by least-squares analysis

In each analysis correlations of the metrics with the damage defined by $PTS_{5124}$ and its log form are used to compare the metrics. The log form of the damage $PTS_{5124}^-$ is defined as follows.

$$PTS_{5124}^- = \log_{10}(\phi(PTS_{5124}) + 1)$$  \hspace{1cm} (29)

where

$$\phi(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

The form in Eq. (29) is to ensure the damage is defined as a positive quantity.

*Analysis of Standard Metrics*

The following standard metrics evaluated in this study include $L_{A_{eq,8hr}}$, MIL-STD-1474D, Pfander, and Smoorenburg, $L_{eq,5124}$, $L_{peq,8hr}$, and AHAHA. The standard metric definitions for these metrics are given in the previous section. The regression models used are shown in Eqns. (30) and (31). The coefficients of determination, $r^2$, for the metrics are shown in TABLE IX. A subset of the regression fits are shown in FIG. 18.
\[ PTS_{5124} = a_0 + a_1 M \]  \hspace{1cm} (30)

\[ PTS'^{c}_{5124} = a_0 + a_1 M \]  \hspace{1cm} (31)

where \( M \) is the standard metric.

TABLE IX. The results of the regression analysis for the standard metrics.

<table>
<thead>
<tr>
<th>Metric</th>
<th>( r^2 ) value</th>
<th>( PTS_{5124} )</th>
<th>( PTS'^{c}_{5124} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( L_{Aeq,8hr} )</td>
<td>0.44</td>
<td>0.50</td>
<td></td>
</tr>
<tr>
<td>MIL-STD</td>
<td>0.07</td>
<td>0.07</td>
<td></td>
</tr>
<tr>
<td>Pfander</td>
<td>0.21</td>
<td>0.27</td>
<td></td>
</tr>
<tr>
<td>Smoorenburg</td>
<td>0.15</td>
<td>0.20</td>
<td></td>
</tr>
<tr>
<td>( ARU \cdot N )</td>
<td>0.29</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>( \log_{10}(ARU \cdot N) )</td>
<td>0.50</td>
<td>0.62</td>
<td></td>
</tr>
<tr>
<td>( L_{eq,5124} )</td>
<td>0.50</td>
<td>0.61</td>
<td></td>
</tr>
<tr>
<td>( L_{Peq,8hr} )</td>
<td>0.34</td>
<td>0.41</td>
<td></td>
</tr>
</tbody>
</table>
FIG. 18. $L_{Aeq,8hr}$, $L_{eq,5124}$, and log (ARU) fits against $PTS_{5124}$ and $PTS'^{e}_{5124}$. 
**Analysis of the Metrics with Best-Fit Coefficients**

The best-fit analysis treats the number and duration terms as separate predictors allowing the co-efficients to be determined by a least-squares solution. The regression is then re-calculated similar to the analysis shown above in TABLE IX. For example, the best-fit regression models for the Pfander and $L_{Aeq,8hr}$ metrics are:

$$PTS_{5124} = a_0 + a_1 L_{pk} + a_T \log_{10} T_c + a_N \log_{10} N$$  \hspace{1cm} (32)

$$PTS_{5124} = a_0 + a_1 L_{Aeq,8hr} + a_N \log_{10} N$$  \hspace{1cm} (33)

The results of the best-fit metrics also show the coefficients for the main term ($a_1$), either $L_{pk}$, $L_{eq}$ (with a variety of frequency weighting applied), or $ARU$, as well as the time and number term coefficients. Instead of showing this information as coefficients themselves the ratio is calculated – $a_N/a_1$. This is a better comparison to the standard metric form. For example, the best-fit $L_{Aeq,8hr}$ metric, Eq. (33), is equivalent to Eq. (34). In this form it is obvious that the ratio of $a_N/a_1$ corresponds to the factor of 10 in the standard metric form. The coefficients of determination as well as the regression coefficients are shown in TABLE X and a subset of the regression fits are shown in FIG. 19

$$PTS_{5124} = a_0 + a_1 \left( L_{Aeq,8hr} + \frac{a_N}{a_1} \log_{10} N \right)$$  \hspace{1cm} (34)
TABLE X. The results of the best-fit metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>$PTS_{5124}$</th>
<th>$PTS^*_5124$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r^2$</td>
<td>$a_1$</td>
</tr>
<tr>
<td>$L_{Aeq,8hr}$</td>
<td>0.45</td>
<td>0.75</td>
</tr>
<tr>
<td>MIL-STD</td>
<td>0.34</td>
<td>0.30</td>
</tr>
<tr>
<td>Pfander</td>
<td>0.34</td>
<td>0.37</td>
</tr>
<tr>
<td>Smoorenburg</td>
<td>0.34</td>
<td>0.31</td>
</tr>
<tr>
<td>$ARU (N)$</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>$\log_{10}(ARU(N))$</td>
<td>0.52</td>
<td>13.70</td>
</tr>
<tr>
<td>$L_{eq,5124}$</td>
<td>0.50</td>
<td>1.00</td>
</tr>
<tr>
<td>$L_{Peq,8hr}$</td>
<td>0.41</td>
<td>0.75</td>
</tr>
</tbody>
</table>
FIG. 19. Results for the best-fit versions of $L_{eq,8hr}$, $L_{eq,5124}$, log (ARU) against $PTS_{5124}$.
3. Discussion of Statistical Results

In general, the relative goodness-of-fit between the metrics and $PTS_{5124}$ are similar between the linear and log dependent variables. In other words, if metric A performs better when regressed against $PTS_{5124}$ than metric B, it will likely perform better when regressed against $PTS^c_{5124}$. In each case, with the exception of $ARU$, the regression is improved when $PTS^c_{5124}$ is used. Since the log transform results in better correlations between the metrics, only these results will be discussed hereafter. The standard metrics show a clear delineation between the peak-based metrics and the other metrics. The peak-based metrics clearly perform worse than the others. The AHAH model also performs quite poorly unless a log transformation is applied. If the AHAH metric is transformed then it has the best correlation with $L_{eq,5124}$ and $L_{Aeq,5124}$ just slightly worse.

The best-fit metrics are very similar to the standard metrics except for the peak-based metrics and $L_{Peq,8hr}$. The best-fit peak-based metrics have identical $r^2$ statistics. This is the result of the number of impulses and $L_{pk}$ explaining the variance of $PTS^c_{5124}$ with the duration metrics adding little additional information. The p-value for the duration coefficients in the peak-based metrics is significant, $p \gg 0.05$. Thus, the duration terms should be removed from the model.

The P-weighted equivalent sound pressure level improves dramatically between the standard form and the best fit form. $L_{eq,5124}$ showed the best correlation when in the best-fit form is compared to the other energy-base metrics.
V. COMPLEX NOISE SEPARATION ALGORITHM: IN DEPTH ANALYSIS OF IMPULSES EMBEDDED IN STEADY-STATE NOISE

This chapter describes a procedure that was created by the author to evaluate the impulses embedded in steady-state noise. The procedure requires a user to initially select a region of the noise that only contains the steady-state component. After this selection is made, the impulses in the noise are found without any further user input. The procedure results in removal of the impulse time history from the steady-state time history to allow for further calculations of the exposure. This chapter will first describe the procedure then show a sample of the impulse characteristics. The complex noise time histories from the experiment in Chapter II are used.

A. Complex Noise Separation Procedure

Initially, a reasonable length window of the pressure time history is selected, in this study ten seconds was suitable, see FIG. 20. This window should provide a visible and selectable section of steady-state noise. The larger the section of selected steady-state noise the more statistical evidence available for further analysis and, thus, it is likely more characteristic of the remaining segments of steady-state noise in the signal.

The largest segment of the steady-state noise is selected. This steady-state noise is then split into contiguous bins of sequential time points and the standard deviation of the pressure in the bins is calculated. The mean and standard deviation of the bins’ statistics are also calculated.
This will provide a basis for impulse detection in the following steps of the process. The size of the bins is an important variable in this process, in this study fifty time points worked well.

![Initial complex noise signal](image)

**FIG. 20.** The initial complex noise signal

After the steady-state noise is evaluated, the complete signal is also divided into bins of the same size as the steady-state noise. Similar to the above process, the standard deviation of the pressure is calculated for all of the bins, see FIG. 21. This process not only accentuates the visible and numerical differences between the steady-state and impulsive noise types, it also removes any negative values in the time history and many of the oscillations found in the impulse time history. The removal of the oscillations in the impulsive time history allows for automated or manual detection of the approximate beginning and end of the impulse.

In the automated detection, the procedure involves three main steps:
(15) Find one bin for each impulse that defines the location of the impulse using a very insensitive threshold.

(16) For each impulse, using a more sensitive threshold find the start and end bins of each impulse.

(17) Evaluate each time point of the start and end bins for each impulse against an even more sensitive threshold to find the start and end time points for each impulse.

The thresholds are based on the standard deviation and mean of the steady-state noise bins’ standard deviation: \( \tau = m_{ss} + \gamma s_{ss} \), where \( m_{ss} \) is the mean of the standard deviation of the steady-state bins and \( s_{ss} \) is the standard deviation of the bins’ standard deviation statistic. The \( \gamma \) coefficient can be adjusted as the researcher sees fit, but in this implementation a value of 20 was used and had accurate results. This threshold should contain no false alarms as a chi-squared variance test of such a sample is infinitesimal, closer to zero than numerical precision. Note in FIG. 21, the black horizontal line represents this threshold, it is approximately 2.5.
FIG. 21. The standard deviation of the bins of the one second time history shown in FIG. 20.

1. **Step 1**

   The bins are now evaluated iteratively from the start of the time history. If a bin’s standard deviation is above the threshold, the bin is flagged. If a neighboring bin, adjacent or with only one bin separating the current with another, the next bin is flagged. These two bins are considered part of the same impulse and the flag of the impulse is marked at the most recent bin. Once the next two bins are both below the threshold, the index for the impulse has been found. This process is continued until the end of the time history.

2. **Step 2**

   Next, the starting and ending bins of each impulse are found. The starting bin is found by comparing starting at the impulse’s index and observing the previous bin. If the previous bin’s standard deviation is below a now more sensitive threshold, this previous bin is determined to be
the start of the impulse. This process creates some excess before the start of the impulse that is later removed. The last bin of the impulse is found in a similar way but moving in the opposite direction with respect to time with a more sensitive threshold since the end of the impulse is less abrupt than the start. This process will also leave excess at the end of the impulse that will be removed in the next step.

3. **Step 3**

   The start of the impulse is trimmed by starting at the initial *time point* of the impulse’s starting *bin*. The next point is evaluated and compared to a threshold value, now three standard deviations above the maximum value found in the initial user-selected steady-state noise. The first point found that is above this threshold is determined to be the start of the impulse. A similar procedure is conducted for the end point of the impulse but starts with the last point in the impulse and proceeds in the opposite direction. Now, the exact time points of the beginning and the end of the impulse have been found and can be analyzed.

   The need to start with an extremely high threshold and then lower it to obtain more specific and accurate starting and ending time is to avoid falsely identifying impulses. Since the steady-state background noise is Gaussian in this case, and there are many time points, values significantly greater than the mean are possible although statistically improbable. For example, if a threshold of 3 standard deviations above or below the mean were used for the time history, there is a probability of approximately 0.9% for each sample point that it would exceed the threshold. Given only one second of steady-state noise, or 48000 time samples in this case, a the expected value of a type I errors, or false alarms, given this threshold is 425.
4. Results

The complete set of results are shown in Appendix C. The impulse and the steady-state noise, over the first 100 seconds, for group G-44 are shown below in FIG. 22. In view of Appendix C, the algorithm was able to find all of the impulses with no noticeable false alarms.

FIG. 22. The separated noise for the exposure G-44. The left are the impulses laid out contiguously and right is the remaining noise component.

B. Impulse Analysis

The impulses can are now analyzed in a variety of ways. Prior research has shown that there are many important characteristics that define an impulse: a) rise time, b) peak SPL, c) $L_{eq}$, d) duration, e) background SPL, f) frequency distribution. Many of these metrics are trivial to implement and their implementation will not be discussed in much depth in this thesis. Classically, duration of an impulse is defined in one of four ways, A, B, C, and D-durations, see FIG. 16. These duration calculations depend on the length of time before the pressure decreases to some level below the peak. However, in the complex noise scenario the impulses are embedded in steady-state noise and the apparent impulse is actually the resultant pressure of a
combination of an impulsive noise with the steady-state noise. So, in the complex noise case the
duration of the impulse is ill-defined.

FIG. 23. The frequency spectrums from two different noises. The energy in the G-44 impulse is
clearly centered at 3 bands. The energy of G-49 impulses is more broadband.

The implementations of several of the characteristics are somewhat trivial. These
characteristics are described below and their results are shown in TABLE XI.

**Frequency distribution:** The frequency distribution of two group’s impulses is shown in FIG. 23.
This shows the vastly different spectral structures of the two exposures. Frequency distribution is
difficult to distill down to a single value and beyond the scope of this study.

**Background SPL:** The equivalent sound pressure level for the steady-state noise is found by
applying the $L_{eq}$ to the steady-state noise after the impulses have been removed.

**Peak SPL:** The peak SPL is the maximum pressure of the impulse.
**Interpeak Interval:** The interpeak interval, unlike in the military noise exposure data, are random in complex noise. Due to this, an average interpeak interval is calculated.

**TABLE XI:** Impulse characteristics of the noise groups used in the complex noise study.

<table>
<thead>
<tr>
<th>Group</th>
<th>β</th>
<th>Full Signal</th>
<th>Average Peak SPL</th>
<th>Largest Peak SPL</th>
<th>Background SPL</th>
<th>Average IPI</th>
</tr>
</thead>
<tbody>
<tr>
<td>G-44</td>
<td>32.65</td>
<td>107.10</td>
<td>124.18</td>
<td>97.48</td>
<td>1.21</td>
<td></td>
</tr>
<tr>
<td>G-49</td>
<td>33.23</td>
<td>104.52</td>
<td>122.09</td>
<td>95.95</td>
<td>1.08</td>
<td></td>
</tr>
<tr>
<td>G-50</td>
<td>20.80</td>
<td>106.60</td>
<td>118.76</td>
<td>99.59</td>
<td>1.81</td>
<td></td>
</tr>
<tr>
<td>G-51</td>
<td>101.81</td>
<td>105.50</td>
<td>125.66</td>
<td>91.73</td>
<td>1.04</td>
<td></td>
</tr>
<tr>
<td>G-52</td>
<td>52.90</td>
<td>110.32</td>
<td>128.91</td>
<td>97.72</td>
<td>1.17</td>
<td></td>
</tr>
<tr>
<td>G-53</td>
<td>97.88</td>
<td>108.27</td>
<td>123.60</td>
<td>95.70</td>
<td>2.96</td>
<td></td>
</tr>
<tr>
<td>G-54</td>
<td>35.87</td>
<td>108.31</td>
<td>125.82</td>
<td>98.45</td>
<td>1.31</td>
<td></td>
</tr>
<tr>
<td>G-55</td>
<td>25.59</td>
<td>108.43</td>
<td>127.97</td>
<td>97.83</td>
<td>1.07</td>
<td></td>
</tr>
<tr>
<td>G-59</td>
<td>30.90</td>
<td>105.97</td>
<td>125.80</td>
<td>97.74</td>
<td>1.63</td>
<td></td>
</tr>
<tr>
<td>G-60</td>
<td>35.59</td>
<td>108.00</td>
<td>124.00</td>
<td>97.00</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>G-61</td>
<td>2.98</td>
<td>102.00</td>
<td>104.00</td>
<td>102.67</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>G-63</td>
<td>117.12</td>
<td>103.67</td>
<td>131.18</td>
<td>77.94</td>
<td>1.16</td>
<td></td>
</tr>
<tr>
<td>G-64</td>
<td>8.37</td>
<td>107.13</td>
<td>124.64</td>
<td>100.86</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td>G-65</td>
<td>118.77</td>
<td>110.39</td>
<td>128.94</td>
<td>77.97</td>
<td>6.84</td>
<td></td>
</tr>
<tr>
<td>G-66</td>
<td>14.81</td>
<td>105.36</td>
<td>128.99</td>
<td>95.43</td>
<td>0.86</td>
<td></td>
</tr>
<tr>
<td>G-68</td>
<td>58.41</td>
<td>113.35</td>
<td>129.07</td>
<td>99.07</td>
<td>2.11</td>
<td></td>
</tr>
<tr>
<td>G-69</td>
<td>77.42</td>
<td>99.46</td>
<td>126.55</td>
<td>77.07</td>
<td>1.15</td>
<td></td>
</tr>
<tr>
<td>G-70</td>
<td>27.14</td>
<td>102.58</td>
<td>126.18</td>
<td>96.81</td>
<td>0.96</td>
<td></td>
</tr>
<tr>
<td>G-47</td>
<td>2.95</td>
<td>93.00</td>
<td>95.00</td>
<td>92.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>G-48</td>
<td>33.25</td>
<td>99.36</td>
<td>116.69</td>
<td>88.61</td>
<td>1.57</td>
<td></td>
</tr>
<tr>
<td>G-56</td>
<td>35.94</td>
<td>96.64</td>
<td>115.72</td>
<td>86.97</td>
<td>1.16</td>
<td></td>
</tr>
<tr>
<td>G-57</td>
<td>2.97</td>
<td>98.00</td>
<td>100.00</td>
<td>97.33</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>G-58</td>
<td>41.53</td>
<td>102.38</td>
<td>121.31</td>
<td>92.18</td>
<td>0.78</td>
<td></td>
</tr>
</tbody>
</table>

**C. Discussion**

The characteristics of the impulses provide researchers and practitioners with a tremendous amount of information. This information could lead to several diagnoses, such as
unsafe peak levels despite a safe overall SPL. In addition, knowing the spectrum of the impulse could lead to manufacturers altering equipment or procedures to move energy to frequencies that are less dangerous to the auditory system.

The connection between inter-peak interval and kurtosis was shown to be significant and counter-intuitive in the military noise study, see Appendix B. The information in this chapter could be used in the future as the basis for a sensitivity analysis of this relationship. The applicability of kurtosis as a good indicator of the increased risk of complex noise exposures is likely only reasonable given some inter-peak interval and/or background to impulse SPL ratio.

Although this algorithm is quite robust when applied to the time histories used in this study, it has not been thoroughly tested against changes in parameters. An obvious limitation is that the algorithm assumes that the parameters that define the steady-state noise are constant throughout the time history. If the mean and/or standard deviation of the steady-state noise were to change throughout the time history, significant errors would result. In addition, the sensitivity of the thresholds is not known beyond their ability to detect impulses in this dataset.
VI. CONCLUSION AND FUTURE WORK

A. Summary and Conclusions

Several tasks were completed in the goal of improving the guidelines for both occupational and military noise guidelines. In terms of occupational noise, a new form of noise metric with a temporal correction term was designed as $L'_{eq} = L_{eq} + \lambda \log_{10} \frac{\beta}{\beta_G}$, where $\beta$ and $\beta_G$ are kurtosis values of the given and Gaussian noises. The basic form was designed so that no correction is made for Gaussian noises and higher corrections are made for more impulsive noises. Several new noise metrics were developed by varying the basic form were evaluated utilizing chinchilla noise exposure test data for their correlations with the noise induced hearing loss (NIHL) in chinchillas. Evaluation showed that the kurtosis correction term generally improves correlations of the metric with NIHL.

In addition to the pragmatic advancement of the standard, a method for the evaluation of animal exposure tests was developed. Although this method did not have an immediate impact on the analysis herein, the method is a novel one for the identification of outliers. This method may be helpful in future tests and analyses.

In order to characterize complex noise exposures, an algorithm for the separation of impulses from the steady-state background noise was established. This allowed for further posteriori characterization of these noise environments. This allowed the researchers to better understand quantitatively the noise exposures. This method can be applied to an exposure with numerous impulses without significant time required by the researcher.
In terms of the military noise guidelines, this study verified the previous studies of this same data set as well as the study performed by Chan et al. that the peak-based metrics do not correlate well with hearing loss (Chan et al., 2001). It is interesting to note that both in the Albuquerque study and this study, a negative coefficient fit was the best least-squares fit for the B-duration. In addition, the analysis showed that the regression fit was insensitive to the type of duration used. This was due to the fact that the duration metrics provided no additional information to the regression after considering peaking pressure and the number of impulses. This confirms what prior studies have shown experimentally and this study showed analytically, that the peak and duration metric or peak-based metrics are not good predictors of hearing loss. In addition to their poor performance, the duration metrics had significant p-values if the peak pressure and number of impulse variables were included in the model.

The military noise study also compared energy-based metrics with the AHAAH metric. The AHAAH metric performed poorly without the use of a log transformation. However, with the log transformation the AHAAH metric performs quite well. Given several types of frequency weighted equivalent sound pressure level, the AHAAH performs roughly on par or slightly better than the energy based metrics. For a variety of reasons, the AHAAH metric requires more investigation. Unlike the other metrics, the AHAAH was specifically designed for the humans, not chinchillas. If a similar model was developed for the chinchilla, it is likely that the metric would perform better. In addition, there are several other factors to consider when using the AHAAH model, such as warned and unwarned conditions and the position of the microphone. If all these conditions are optimized it is possible that the performance of the AHAAH could improve. Yet, this introduces a challenge to the potential implementation of the AHAAH model. The complexities of its implementation could produce challenges for practitioners. Before the
AHAAH model is adopted it is necessary to streamline its implementation as well as consider the benefits of using a dB scale, analogous to a log transform, for the ARU calculation.

In both military and occupational studies, the results showed that a frequency-matched equivalent sound pressure level, $L_{eq,5124}$, where $L_{eq,5124}$ is the average of $L_{eq}$ of 0.5, 1, 2, 4 kHz components of the noise, and its kurtosis corrected form performed better than the other weighting functions. This metric has the advantage of being quite similar to a metric that is currently in use, $L_{Aeq,8hr}$, making a noise guideline based on this metric comparatively easy to implement.

**B. Future Work**

In several of the impulses evaluated as part of the complex noise separation procedure, the amplitude of the impulses appeared to clip at high levels. This should be further investigated by estimating the $\Delta A$, or the smallest change in amplitude. This could then be used to estimate the bit-range given a likely 16 or 24 bit ADC.

This $L_{eq,5124}$ function should be further evaluated for other noise exposures and data sets. In addition, it is necessary to obtain a reference level, similar to 85 dB with a 3 dB exchange rate for occupational noise, for the $L_{eq,5124}$ in impulsive and complex noise exposures. This will allow this metric to be included in a guideline and implemented by practitioners.

It was noted that the kurtosis correction term, when applied to military noise exposures, did not perform well. The kurtosis term, as shown in Appendix B, behaved in a manner that is somewhat counterintuitive. The kurtosis of the noise exposures generally increased with inter-
peak interval. This relationship suggests the need for a sensitivity analysis on kurtosis, inter-peak interval, and hearing loss. This can be accomplished with complex noise separation algorithm described above and military noise exposures.

The peak-based metrics were shown to reduce the waveform to a square wave. This can be seen as an assumption that the risk of the actual wave is equivalent to the corresponding square wave. This assumption can be checked for its validity by viewing the cochlea as series of SDOF systems. The response of these systems to a square wave, or gate function, is well known. This may further illuminate these metrics.

In general, the findings for new or modified metrics found above require further validation and refinement. A second species, such as cat, mouse or guinea pig, test may be used as an intermediary step before epidemiological human studies. If these metrics are validated, it is necessary to determine the implemented form. This requires a reference level, or permissible limit, with reduced exposure time for increasing exposure levels.

In addition, the AHAHAH metric showed some promise in its application to military noise. It is also suggested above that AHAHAH would likely perform better if a chinchilla model were defined. One important aspect of this conversion is the nonlinearity of the annular ligament in the middle ear. This ligament would reduce the damage caused by higher peak levels. As a starting point FIG. 24 shows the relationship of peak pressure and $PTS_{5124}$ for 100 impulse exposures. From this plot it appears that there is a piecewise relationship. This needs to be further investigated for the chinchilla through autopsy and testing.
FIG. 24. Peak pressure (dB) against $PTS_{S124}$
BIBLIOGRAPHY


APPENDIX A: APPLICATION OF SPECTRAL WEIGHTS

Historically, in the area of noise meters spectral weighting is applied using either an analog or digital filter. These allow for real-time weighting, or are causal – they depend only on past and present inputs. In this case, the researchers have the luxury of knowing the complete time history. This allows the transformation of the time data into the frequency domain using the Fourier transform. Once the data is in the frequency domain, the weighting functions are applied using their frequency domain formulae. After the weighting functions are applied the sound pressure level is obtained from integration in the frequency domain, avoiding any errors associated with an inverse Fourier transform.

The derivation of the frequency domain integration of equivalent sound pressure level is as follows:

$$L_{eq} = 10 \log_{10} \frac{1}{T} \int_0^T \frac{p(t)^2}{p_{ref}} dt = 10 \log_{10} \frac{1}{p_{ref}} \int_0^T p(t)^2 dt = 10 \log_{10} \frac{1}{p_{ref}} p_{rms}^2$$

(35)

The above is a helpful simplification for the rest of the derivation. Note that given two uncorrelated harmonic sounds, $p_1$ and $p_2$, of different frequencies $p_{rms}^2$ can be calculated as follows:

$$p_{rms}^2 = \frac{1}{T} \int_0^T (p_1(t) + p_2(t))^2 dt$$

(36)

Since $p_1$ and $p_2$ are harmonic, they are defined by their amplitude ($P_1, P_2$), frequency and phase.
Due to the orthogonality condition of sine and cosine the above is reduced to:

\[
= \left(\frac{1}{T}\right)\left(\frac{T}{2}\right) (P_1^2 + P_2^2) = p_{rms1}^2 + p_{rms2}^2
\]  

(38)

Since the whole time history is known, it is possible with the Fourier transform to obtain the Fourier coefficients, \(C_n\), or magnitude of the Fourier transform, of the time history, \(p(t)\).

\[
p(t) = \sum_{n=-L/2}^{L/2} C_n e^{j\omega_0 t}
\]  

(39)

where

\[
C_n = \frac{2}{T} \sum_{n=-L/2}^{L/2} p(t)e^{-j\omega_0 t} \Delta t
\]  

(40)

By substituting, Eq. (39) into Eq. (36):

\[
p_{rms}^2 = \frac{1}{T} \int_0^T \left( \sum_{n=-L/2}^{L/2} C_n e^{j\omega_0 t} \right)^2 \Delta t
\]  

(41)

\[
p_{rms}^2 = \frac{1}{2} \sum_{n=-L/2}^{L/2} C_n^2
\]  

(42)
Lastly, by substituting Eq. (42) into Eq. (35):

\[
L_{eq} = 10 \log_{10} \frac{1}{P_{\text{ref}}} \sum_{n=-L/2}^{L/2} C_n^2
\]  

(43)

Now that the equivalent sound pressure level is defined in the frequency domain, spectral weighting is applied by multiplying the Fourier coefficients by the weight that corresponds to their frequency component, \( n\omega_0 \).

\[
L_{Aeq} = 10 \log_{10} \frac{1}{2P_{\text{ref}}} \sum_{n=0}^{N} C_n^2 A(n\omega_0)^2
\]  

(44)

Where \( A(\omega) \) is the A-weighting function defined in the frequency domain. This weighting function can easily be replaced with other types of spectral weighting, such as P-weighting. If the signal is completely observable during \( T \) or periodic in \( T \), the above procedure will be exact. If not, the signal can be padded with zeros to simulate a completely observable transient.

**A. MATLAB Code**

The following code assumes that the time history being weighted is defined as the variable \( \text{th}_p \). The code also invokes a program \( \text{a_weight.m} \) which defines the weighting functions.

```matlab
% pad waveform with zeros to create a one second wave form
zLength = 0; %Fs-L;
p = [th_p;zeros(zLength,1)];

% redefine variables for new waveform
L = length(p);
Tlong = L/Fs;
dt = 1/Fs;
t = 0:dt:Tlong;
```
Fny = Fs/2;

% transform time signal to frequency domain
P = fft(p)./(L/2);
Pp = P(1:end/2);            % positive frequencies
freq = linspace(0,Fny,L/2); % frequency vector

% find prms^2 and weight with A-weighting and P-weighting
Prms   = Pp.*conj(Pp)./2;
PrmsA  = Pp.*conj(Pp)./2.*a_weight(freq,1).^2.;
PrmsP  = Pp.*conj(Pp)./2.*a_weight(freq,5).^2.;

% sum
Ptrms  = sum(Prms(2:end));
PtrmsA = sum(PrmsA(2:end));
PtrmsP = nansum(PrmsP(2:end));
Ptrms5124 = sum(Prms(floor(500/df):ceil(4000/df)));
PtrmsLF = sum(Prms(2:ceil(500/df)));

% reference pressure
Pref   = 20*10^-6;

% decibel conversion
Peq    = Tlong/Tshort*Ptrms./Pref^2;
Leq    = 10.*log10(Ptrms./Pref.^2) + 10*log10(Tlong/Tshort);
LAeq   = 10.*log10(PtrmsA./Pref.^2) + 10*log10(Tlong/Tshort);
LPeq   = 10.*log10(PtrmsP./Pref.^2) + 10*log10(Tlong/Tshort);
Leq5124= 10.*log10(Ptrms5124./Pref.^2) + 10*log10(Tlong/Tshort);
LeqLF  = 10.*log10(PtrmsLF./Pref.^2) + 10*log10(Tlong/Tshort);
[dum, idx] = max(Prms(2:end));
Fpeak  = freq(idx+1);
c1f
semilogy(freq,Prms);
APPENDIX B: KURTOSIS CALCULATION OF IMPULSIVE NOISES WITH LONG INTERPEAK INTERVALS

In order to extend the success of kurtosis into highly impulsive noises, the kurtosis of the entire time history was calculated, $k_{IPI}$. However, $k_{IPI}$ is somewhat more difficult, specifically when the IPI becomes long, such as 600s. In order to overcome the computational challenges associated with analyzing a long signal, an approximation of kurtosis was computed. Kurtosis for long waveforms which are comprised of a short impulse, or numerous short impulse imbedded in a relatively long Gaussian background noise can be reduced in the following way:

$$\frac{E(X - \bar{X})^4}{\sigma^2}$$

(45)

where $I$ is the number of points in the impulse, $G$ is the number of points in the background noise. If we assume that the Gaussian noise is significantly longer than the impulse, in the case of an IPI of only 6 seconds with a sampling rate of 500 k-Hz, the Gaussian noise is comprised of $3.0 \times 10^6$ points versus the impulse of waveform 1 which is 16384, then $\bar{X} \approx 0$. Also, $G \gg I$, so, Eq (46) is approximately:

$$\frac{\sum_{i=G}^{I+G}(X_i - \bar{X})^4}{I + G}$$

(46)

$$= \frac{\sum_{i=1}^{I+G}(X_i - \bar{X})^4}{(\frac{\sum_{i=1}^{I+G}(X_i - \bar{X})^2}{I + G})^2}$$
In a Gaussian noise, \( \frac{\sum_{i=1}^{l+G} X_i^4}{G} \approx 3 \) and \( \frac{\sum_{i=1}^{l+G} X_i^2}{G} \approx 1 \). Thus:

\[
\frac{\sum_{i=1}^{l}(X_i)^4}{G} + 3 = \frac{\sum_{i=1}^{l}(X_i)^2}{G} + 1
\]

This allows us to calculate the kurtosis of an impulse with an interval of Gaussian noise or a number of exposures with inter-peak intervals quite fast. The accuracy of the approximation is shown in the following figures. These figures used the waveform from stimulus code #1. In the figure to the left the exact and approximate calculations are too close to be distinguished. The figure on the right shows the error as a percentage of the exact kurtosis. At an IPI of 50 seconds the error is already below 0.01%.
FIG. 25: a) the approximated kurtosis for various IPI and b) the error of the estimated kurtosis.

There is an obvious strong correlation between kurtosis and IPI. This relationship is not identical, however, for all impulsive noise types. The figure below shows the IPI against kurtosis plot for all fifty waveforms.

FIG. 26: The kurtosis of all the waveforms at a variety of IPIs.
APPENDIX C: THE RESULTS FROM THE NOISE SEPARATION PROCEDURE

G-44

G-44

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G-48

G-49
FIG. 27. The impulses for each time history, left. The remaining signal for each time history is on the right. If a no left plot exists it is due to the fact that the noise was not complex. Only the first ten seconds of the time histories were used.