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Exploring the Correlation Between Occupied and Unoccupied Noise Levels in K-12 Classrooms

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EXPLORING THE CORRELATION BETWEEN OCCUPIED AND UNOCCUPIED NOISE LEVELS IN K-12 CLASSROOMS

by

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Students learn in occupied spaces, yet acoustical standards specify recommendations for unoccupied levels. While some studies have quantified the relationship between occupied and background noise levels in classrooms, their definitions of background noise level were often inconsistent with those recommended by the standards. The research presented in this thesis examines the relationship between occupied and unoccupied levels in 110 classrooms in two Midwestern school districts. Acoustic levels were logged for a total of six days in each classroom. Occupied and unoccupied levels were parsed from the logged data using k-means clustering, an unsupervised statistical learning technique. The results from this research suggest that there is a significant correlation between general occupied and unoccupied levels ($r = 0.32$, $p < 0.05$) and a significant correlation between instructional and ventilation levels ($r = 0.58$, $p < 0.05$) in the measured classrooms. The results also suggest that the average instructional level in the measured classrooms increases 0.4 dBA for every 1 dBA of ventilation noise.

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Chapter 1

Introduction and Literature Review

Students learn in occupied spaces, yet acoustical standards specify recommendations for unoccupied conditions. While logic suggests that there is a relationship between occupied and unoccupied sound levels in classrooms, there is currently insufficient evidence to suggest the strength of that relationship. The goal of the research presented in this thesis is to further investigate the hypothesis that there is a linear relationship between occupied and unoccupied levels in classrooms.

This thesis is an acoustics sub-study of a much larger research project currently underway at the University of Nebraska-Lincoln. The study, ”Evidence-Based Interaction between Indoor Environmental Factors and Their Effects on K-12 Student Achievement,” has been funded by the United States Environmental Protection Agency from November 2014 through October 2018 (funding opportunity EPA-G2013-STAR-H1). The goal of this research is to determine how indoor environmental conditions in K-12 school buildings, including indoor air quality, thermal comfort, lighting, and acoustics, impact student

achievement. The results from this study will be used to develop evidence-based design recommendations intended to optimize student learning potential.

For the overall project, detailed environmental measurements are being collected in 220 classrooms across local K-12 school districts. These classrooms are composed of 3rd and 5th grade classrooms at the elementary level, and 8th and 11th grade math and language arts classrooms at the middle and high school levels. Classroom-level aggregate demographic and student achievement data are also being collected from these classrooms. The gathered data will be used in a statistical model to determine the impact and interactions of the built environment on student achievement outcomes.

While data for the project are still being collected, there are many questions that can be explored from the data already available to the research team. This thesis employs measured acoustic data from the first 110 classrooms to investigate the relationship between occupied and unoccupied sound levels. The goal of this research is to determine if the long-term continuous data can help determine if designing for unoccupied levels bears on occupied levels experienced by students. This goal will be accomplished by employing the in-situ acoustic data already available from 110 classrooms and determining a method for isolating different periods of activity during the school day.

This chapter begins with an overview of previous classroom acoustic literature then moves into a discussion of the literature most pertinent to this study. Motivations for this study and the methods used will be also be developed.

1.1 Background

There is a large body of research focused on classroom acoustics. Many studies have focused on determining preferable conditions and criteria for optimizing speech communication in classrooms as indicated by Picard and Bradley [2001] in their review of reverberation and ambient noise effects on speech. Their review helped summarized ideal and acceptable ambient noise levels for optimized speech recognition. *Ideal* levels are defined as those that allow uninhibited, clear speech recognition and *acceptable* levels are those that clearly alter speech recognition but are not thought to have deleterious effects on student achievement. They suggested that the ideal ambient noise level is 35 dBA and the ideal signal-to-noise ratio is 15 dB. Research conducted by Bistafa and Bradley [2000] suggested that ideal maximum classroom background noise levels are 25 dB below the voice level from 1 meter away from the talker whereas acceptable classroom background noise levels are 20 dB below the voice level under the same conditions. They concluded that a signal-to-noise ratio of 15 dB results from combining the “ideal” maximum background noise level and recommended reverberation time [Bistafa & Bradley 2000]. Later Bradley and Sato revisited these conclusions and suggested that a 15 dB signal-to-noise ratio might not be sufficient for younger students who need a higher level of speech intelligibility [Bradley & Sato 2008].

Recommended classroom acoustic criteria are presented in various building standards. The American National Standard for the classroom acoustic performance criteria and design guidelines and requirements recommends that the unoccupied

A-weighted level measured in an unoccupied classroom with ventilation (mechanical) systems on should not exceed 35 dBA [ANSI/ASA 2010]. This standard also states that the maximum reverberation time averaged over the 500, 1000, and 2000 Hz octave bands should only be permitted to be 0.6 seconds. The first edition of this standard provided perceptual, educational, and developmental rationale for the recommended criteria as well as the empirical evidence from which the criteria are derived. The rationale suggests verbal communication is essential to learning, developing language proficiency, and developing cognitive skills. Verbal communication can only successfully occur when there is a high degree of speech intelligibility especially when children are still developing their language skills. Minimizing the background noise level and the reverberation helps to create a clear communication channel between teachers and their students. Classroom speech levels are an important factor in determining the maximum recommended background noise levels. The American Speech-Language-Hearing Association [1995] recommends a signal-to-noise ratio of at least +15 dB to ensure high speech intelligibility for children with language and hearing impairments. A study by Pearsons et al. [1976] showed that the teachers A-weighed speech, sound level is 67 dBA at 1 meter in a quiet classroom. The ANSI standard suggests that with this 67 dBA speech level, sound levels could be as low as 50 dBA in the rear of the room. The criteria for the standard's recommended background noise level assumes a 50 dBA minimum speech sound level anywhere in the classroom, so a +15 dB signal-to-noise level will be achieved if the background noise level does not exceed 35 dBA [American National Standards Inst. 2002].

Many studies have shown that while the reverberation time recommendations are attainable, there are few classrooms that meet the unoccupied background noise level requirements [Picard & Bradley 2001]. In general these standards make noise level recommendations based on clear communication through increased speech intelligibility and not based on levels that negatively affect student achievement.

The purpose of specifying acoustic conditions in classrooms is to ensure that classrooms are appropriate learning environments. In other words, classroom acoustics are important because they can enhance or diminish educational outcomes. Various studies have examined these effects. In situ testing in two Midwestern public school districts was carried out to determine the relationship between acoustic criteria and student achievement [Ronsse 2011]. This study concluded that higher unoccupied background noise levels may have a negative impact on reading and language subject areas. Klatte has conducted multiple studies on student achievement and noise and has concluded that children's listening comprehension and speech perception is impaired by noise [Klatte et al. 2013]. She has also concluded that low levels of air traffic noise, not exceeding 60 dBA, have detrimental effects on reading scores [Klatte et al. 2016]. Shield and Dockrell [2008] studied the effects of noise on the academic achievement of elementary school and have found a correlation between test scores and occupied and unoccupied noise levels. They have determined that chronic exposure to noise generated internally in the school building has a detrimental effect on achievement and it is therefore necessary to diminish the background noise level in classrooms to mitigate this effect.

This remainder of this review is devoted to the discussion of previous research

that sought to characterize sources of noise levels and determine the relationship between occupied and background noise levels, and is the most pertinent to this thesis.

One of the challenges that arises from continuously logging sound levels in a classroom (or any room) is determining the source(s) of the measured levels. Hodgson et al. [1999] developed a method for determining speech, occupied background noise, and ventilation noise levels from recordings taken during 18 lectures in 11 university level classrooms. Hodgson hypothesized that there might be distinct distributions of A-weighted sound levels associated with each source of noise, shown in Figure 1.1.

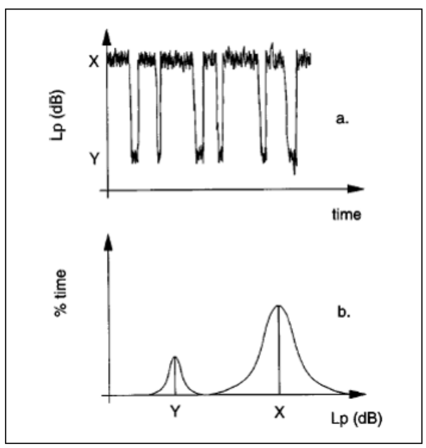


Figure 1.1: (a) Hypothesized time history of A-weighted levels in a classroom and (b) the distribution of the hypothesized levels [Hodgson et al. 1999].

This application of this method involved obtaining sound pressure levels from processed, digitized recordings and then fitting normal distribution curves to histograms of the A-weighted levels in order to isolate the various activities that compose the recording. The team measured the 18, 45-60 minute lectures in four positions in three 10-15 minute increments. The team determined there were three

components to the recorded sound content: speech signal, student activity noise, and ventilation noise. The lowest peak was associated with ventilation, middle peak was associated with student activity, and the highest peak was associated with teacher speech. Figure 1.2 shows a sample distribution measured by Hodgson et al. fit with normal distribution curves.

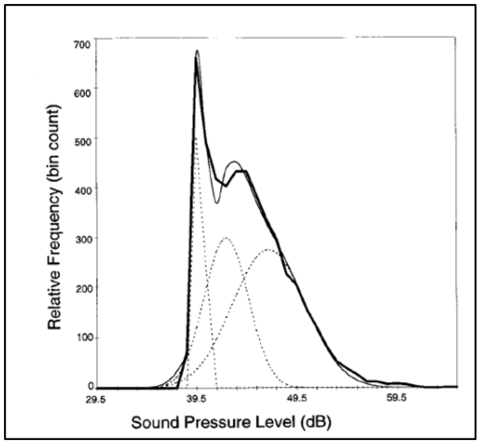


Figure 1.2: Sample of measured A-weighted sound pressure level distribution fit with normal distribution curves [Hodgson et al. 1999].

The activity and speech peaks were considered to be the energetic sum of activity and ventilation and energetic sum of speech, activity, and ventilation respectively. While most of the recordings followed a three peak pattern, some did not. Those that did not were hard for the researchers to interpret and were excluded from analysis. Results were determined and analyzed from each position in each lecture in each classroom which highlights a shortcoming. The recordings from the four positions in the student area of the classroom were analyzed separately, but it seems that mismatched interpretations are possible from position to position due to the change in noise level over distance. While ventilation noise was one of the isolated categories, this was not unoccupied ventilation noise. Unoccupied

ventilation noise was measured for verification purposes in one of the four positions but at a later time and date due to scheduling limitations. It was noted that these unoccupied background noise levels often poorly agreed with the ventilation noise calculated from the recordings, but this was assumed to be the result of varying ventilation noise from day to day and not as a result of the supposed ventilation noise during occupied hours not matching up with unoccupied ventilation noise. The results from these measurements were used to create empirical models that could be used predict speech and background levels, but the main purpose of this paper was introducing this technique.

There are a few shortcomings of this method. With the ability to playback the classroom recordings and revisit classroom observation notes, it seems that interpretation would have required less subjectivity and more matching to actual audio content;however, this method characterizes distinct noise sources from the mean of normal distribution curves fit to the data. This method does not classify individual observations thereby removing the interpretation from a temporal context making it conceivably more difficult to verify classification with temporal recordings. This method only used A-weighted sound pressure levels; however, the use of octave band data could have potentially improved interpretation of unexpected results. Their analysis of the recordings in octave bands was limited by computation time, but they expected that analysis of A-weighted levels was sufficient. Octave band levels could have been used to characterize the spectral characteristics of each of the normal distribution curves fit to the A-weighted levels. However, this might have only further complicated the interpretation because the normal distribution curves

fit to the A-weighted distribution could not be superimposed on the octave band distributions. Octave band analysis of the isolated observations contributing to each source identified by the researches could be useful for interpretation, but it is not possible with this method.

Many studies evaluating the effects of background noise on speech levels leverage the Lombard effect. The Lombard effect is the involuntary increase in vocal level in order to compensate for higher background noise levels originally observed by French otolaryngologist Etienne Lombard [Brumm & Zollinger 2011]. Lombard published his finding in 1911 in a paper entitled "Le signe de l'élévation de la voix" [Lombard 1911]. The Lombard effect is often cited as the reason occupied noise levels in classrooms should be correlated to the unoccupied noise levels.

Hodgson et al's method has been used by Sato and Bradley [2008] in their study of 27 traditional rectangular elementary school classrooms. They recorded 15-20 minutes of lessons when the teacher was frequently speaking to the students. Using Hodgson's method, they only found two peaks in the histograms of combined A-weighted levels and therefore only fitted two distribution curves to the data. They referred to one of the distributions as speech levels and the other as noise levels. They posited that the ambient student activity noise levels in elementary classrooms had broader ranges than those found in university classrooms thereby explaining the difference in the peaks between the studies and a limitation of the method. The Pearson correlation coefficient (r) was calculated to determine the strength of the linear correlations between the room-average speech and noise levels. The results of this study suggest that room-average speech and noise levels obtained

by the distribution technique are well correlated ($r = 0.82$, $p < 0.001$). They concluded that there is a 0.75 dB increase in speech level for every 1 dB of noise which is predicted by the Lombard effect [Sato & Bradley 2008]. It is important to note that this relationship does not characterize how the speech level is affected by unoccupied, ventilation noise. The study suggests that levels increase around 5-10 dBA between active student noise levels and inactive student noise levels measured in the same classroom. However, no exact correlation was given and these levels are still not directly representative of unoccupied ventilation levels.

Bottalico and Astolfi [2012] conducted an investigation into vocal doses of 40 primary school teachers in Italy. The teachers wore phonation monitors during four-hour periods over one, two, or three school days. From these samples, 54 traditional lessons were isolated for analysis. Ambient noise levels were monitored with a sound level meter placed close to the teacher's desk. Hodgson's method was then used to estimate the teacher's voice level and the noise level close to the teacher's desk during speech. Randomness in the activity level of the children prevented the researchers from using this technique on activity other than students sitting quietly at their desks during a lesson. This method was used to characterize the occupied A-weighted background noise level, but analysis suggested there were not significant differences between the A-weighted background noise found using Hodgson's method and the A-weighted level exceeded 90% of the time (L_{A90}), so L_{A90} was used instead. The study found a Lombard effect corresponding to a 0.72 dB increase in speech level per 1 dB of background noise level, L_{A90} [Bottalico & Astolfi 2012]. This study found similar results to Sato and Bradley; however,

occupied ambient levels are an insufficient representations of unoccupied levels.

Shield et al [2015] conducted an acoustic survey of 185 unoccupied secondary school classrooms in England and performed continuous monitoring during 247 occupied core subject lessons in 80 of those classrooms. The continuous logging was monitored by researchers which allowed them to exclude activities unrelated to the lesson (e.g. students or teachers leaving the classroom, disruptions outside the classroom, students talking amongst themselves when not related to group work, students shouting, items being dropped, etc.). The researchers broke the noise levels into four categories of activity: plenary (one person speaking at a time), individual work, group work, and watching or listening to video or audio playback. This study used A-weighted equivalent levels (L_{Aeq}) and the A-weighted level exceeded 90% of the time (L_{A90}) measured during plenary activity to characterize speech and noise for calculating a speech-to-noise ratio. Unoccupied, ambient noise levels were measured in these 80 classrooms. The researchers found a statistically significant correlation between the unoccupied ambient noise level and the occupied L_{Aeq} averaged over all lesson activity types ($r = 0.346$, $p < 0.01$). While this study establishes a relationship between occupied and unoccupied levels in classrooms it is not necessarily scalable because the methods used for analysis required researchers to observe the recorded lessons.

This thesis will suggest the use of k-means clustering as an alternative to Hodgson's technique for classifying sound levels because it does not necessarily require classroom observations or recording classroom audio content, makes use of octave band data for justifying interpretations, and is scalable. K-means clustering

is an unsupervised statistical learning method and is a popular data-mining technique. The applications of k-means clustering are varied. One marine, animal acoustics study used k-means clustering to group dolphin whistles by their spectral characteristics [Lu & Mellinger 2013]. A study of the use of computers to identify musical instruments used k-means clustering to determine whether sounds belonged to the oboe or saxophone class. Many speech recognition studies have implemented k-means clustering to isolate words and/or phonemes for broad categorization. A study of building energy performance benchmarking implemented k-means clustering to classify buildings based on building features. The buildings were grouped by the features that had the greatest impact on energy performance [Gao & Malkawi 2014]. While this is far from an exhaustive list of studies that implement k-means clustering, it illustrates some of the possible applications of the technique. In general, studies that implement k-means clustering, use observational data to validate the clusters using cross-validation.

There are challenges in determining the effect background noise levels have on occupied levels that include distinguishing between these levels when researchers are not present to observe classroom conditions. Previous researchers have proposed methods to mitigate some of these challenges, but they recorded short-term, specific, known classroom content and had researchers present to observe conditions. Prior research also used somewhat ambiguous and inconsistent definitions of background noise that did not necessarily meet those presented by acoustical standards. Continuous, unsupervised long-term logging of sound levels has not been leveraged for research of this kind. The goal of this research is to determine if the

long-term logging of continuous sound levels in a classroom can help determine if designing for unoccupied levels bears on occupied levels experienced by students. This goal will be accomplished using in-situ data measured over 6 days in 110 classrooms and implementing a novel application of k-means clustering to isolate different periods of activity during the school day.

1.2 Thesis Structure

Chapter 2 provides an overview of the measurement methods used in this study as well as descriptions of the measured classrooms. Data processing and analysis techniques are described in Chapter 3 as a case is made for the implementation of k-means clustering. Chapter 4 provides an overview of the initial clustering of the data and interpretation of the resulting clusters. Correlation results are presented in three sections: results of all classrooms averaged over the entire year, results by season, and results by district. Chapter 5 provides an overview of the results from the second round of clustering. These results are also presented by yearly average, by season, and by district. Discussion of the results along with brief comparisons to results reported in previous literature will be woven into Chapters 4 and 5. Conclusions from this study are presented in Chapter 6 along with suggestions for future investigation.

Chapter 2

Measurement Methods

This chapter describes measurement procedures and measurement equipment used for this thesis. This chapter also presents a description of the classrooms measured for this study.

2.1 Measurements

Measurements of indoor environmental conditions, including acoustics, lighting, thermal comfort, and indoor air quality, were carried out in 110 classrooms during the 2015-2016 academic year. This thesis will focus on the acoustic measurements. These 110 classrooms represent classrooms from two districts in the Omaha-Council Bluffs Metropolitan Area. Classrooms in the study were composed of 3rd and 5th grade classrooms as well as 8th and 11th grade math and language arts classrooms. These grade and subject levels were chosen because there is less variation in state standardized tests at these levels making achievement data more comparable across

districts in different states. It should again be noted that the analysis of the achievement data is an ongoing effort and will not be presented in this thesis. A breakdown of the grade levels by district is shown in Table 2.1.

Table 2.1: Breakdown of classrooms measured during the 2015-2016 academic year by grade level and school district

Grade Level	District A	District B
3rd Grade	25	18
5th Grade	20	22
8th Grade - Math	7	4
8th Grade - Language Arts	8	4
11th Grade - Math	0	1
11th Grade - Language Arts	0	1
Total	60	50

Measurements were repeated three times seasonally (fall, winter, and spring) to determine seasonal variation. The breakdown of these seasons is shown in Table 2.2.

Table 2.2: Breakdown of the seasonal time frames used during the 2015-2016 academic year

Season	Start Date	End Date
Fall	8-Sep-15	20-Nov-15
Winter	30-Nov-15	4-Mar-16
Spring	10-Mar-16	26-May-16

Seasonal weather changes result in switches between heating and cooling mode in HVAC (Heating, Ventilation, Air Conditioning) systems. These switches are expected to affect thermal comfort and indoor air quality in the classrooms. Noise levels may also be affected by the differences in these mechanical systems. The heating season for the measurements taken during the 2015-2016 academic year was determined to be October 29, 2015 to April 14, 2016. This was determined by indoor air quality and thermal comfort research team members using Heating Degree Days

(HDD) and the difference between the supply and room average temperature.

Two types of measurements were conducted in the classrooms and qualitatively can be described as occupied and unoccupied measurements.

2.1.1 Occupied Measurements

Occupied measurements took place during the school day and characterized the conditions that students actually experienced in their classroom. The acoustic measurements consisted of logging sound levels in the classroom for approximately 36 hours over two school days. Equipment was loaded into the classroom before students and teachers arrived. This research used two BSWA 309 Type 2/Class 2 sound level meters in each classroom. One sound level meter was placed at work-plane height inside of an open-air, metal cage as shown in Figure 2.1. This meter will be referred to as the "kit meter."

Figure 2.1: Occupied measurement equipment kit with the sound level meter on the left

The kit had an approximate 1.4 ft^2 footprint. Whenever possible, the kit was placed away from reflective surfaces such as walls and was preferentially placed against the teacher's desk with the sound level meter facing away from the desk. If the kit had to be placed against a wall, the kit meter's microphone was approximately 17 inches away from the wall. The kit's stand was 30 inches tall and the sound level meter in the kit was approximately 32 inches above the ground.

The second sound level meter was mounted to a hanging metal stand and was attached to the ceiling, as shown in Figure 2.2. This meter will be referred to as the "hanging meter."

Figure 2.2: Hanging sound level meter mounted in an acoustical tile ceiling

The base of the hanging meter's metal stand was two-feet long and could be set in an acoustical ceiling tile frame. For the classrooms that did not have drop-tile ceilings, C-clamps were used to mount the hanging meter on beams or light fixtures.

The sound level meters were operated by external, rechargeable batteries and

therefore did not need to be plugged in to the wall. This means that equipment placement was only dictated by convenience and unobtrusiveness and not additionally dictated by electrical outlets. Removing the dependence on electrical outlets eliminated tripping hazards and inconvenient equipment placement. Whenever possible, the sound level meters were placed close to the "lecture position" and above the farthest listening position; however, when this was not possible, the meters were placed on opposite sides of the room to achieve a representative room average. Care was taken to avoid placing the hanging sound level meter next to sources of steady-state noise like ventilation diffusers and projectors. Placement decisions were made in the field by trained research team members.

Research team members arrived at the school before students, set up and turned on all equipment, and then left before class began. Team members returned the following afternoon to pick up the equipment. Because these measurements were repeated throughout the year, equipment layouts were noted during the first visit to the classroom and then referenced for the second and third visit to ensure the comparability of results from season to season. An example of this equipment layout is shown in Figure 2.3. Figure 2.4 shows the equipment installed in the classroom from the example layout.

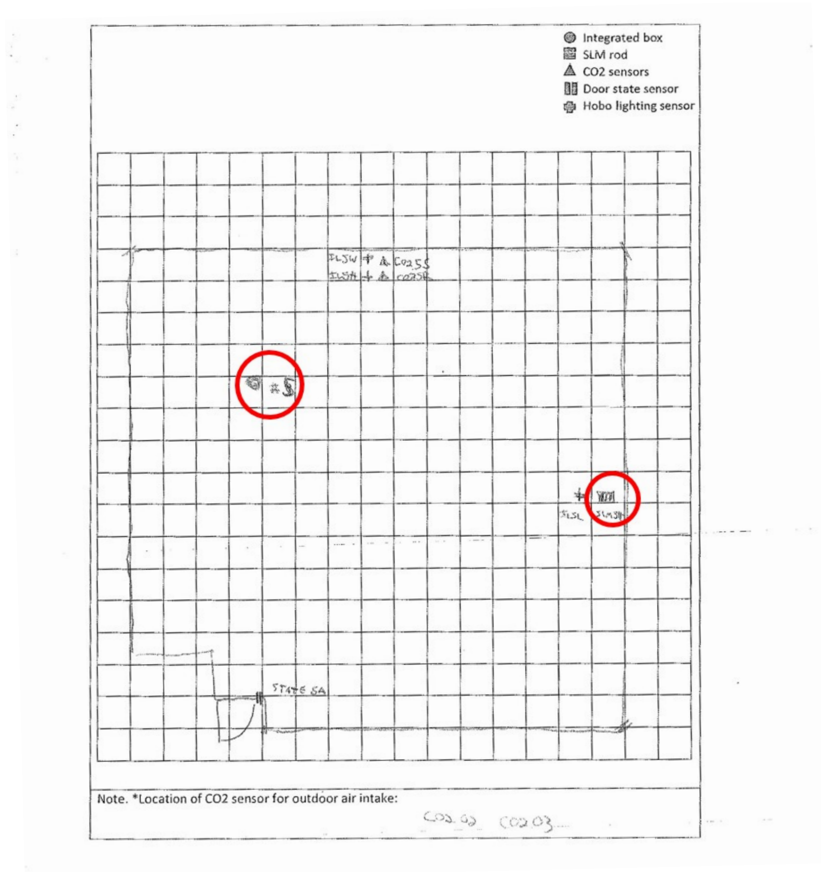


Figure 2.3: Example of the measurement equipment layout drawings used by team members

Figure 2.4: Example of equipment installed in a classroom. The hanging sound level meter is shown on the left and the kit containing the kit sound level meter is shown next to the teacher's desk on the right.

The sound level meters were set up to log equivalent levels every ten seconds

with an integration period of ten seconds. The sound level meters reported A, B, C, and Z-weighted equivalent levels in addition to equivalent octave band levels with center frequencies ranging from 32 Hz to 16 kHz. The microphone used by the meter had a published frequency range of 20 Hz 12.5 kHz, so results were only analyzed up to 8 kHz.

Once data were collected, the equipment was brought back to the lab where data were downloaded to the project computer.

2.1.2 Unoccupied Measurements

Unoccupied measurements took place when students were not occupying the space and served to measure characteristics of the room that are not expected to change greatly based on occupancy. As mentioned in Chapter 1, the ANSI/ASA standard for classroom acoustics specify the measurement of unoccupied background noise levels with mechanical systems on [ANSI/ASA 2010]. In order to characterize the unoccupied noise level, one-minute A-weighted equivalent levels of the background noise were measured using a Larson-Davis 831 Sound Level Meter with slow time detection in an unoccupied classroom with the mechanical systems on. These measurements will be referred to as the background noise levels or BNLs. Team members recorded these measurements in the morning when they were loading in the occupied measurement equipment. The measurement was recorded in the same position as the kit sound level meter.

For the 2016-2017 academic year, these background noise levels were measured

during every season; however, these measurements were implemented halfway through the second season for the 2015-2016 academic year. For that reason, some of the classrooms only have one background noise level data point while others have two.

For the larger project, acoustic unoccupied measurements also included impulse responses (IRs) that have been used to determine the reverberation time, clarity, and other room acoustic metrics. The IR/room acoustic results are not the focus of this thesis and will not be reported.

2.2 Classroom Descriptions

Schools in the study are representative of a variety of building conditions. Tables 2.3–2.9 list the schools, the year each school was built, the year of the most recent building renovation, and the project identification number, volume, and floor plan type of the classrooms in each school by grade level. The information for 3rd grade classrooms is in Tables 2.3 and 2.4. The information for 5th grade classrooms is in Tables 2.5 and 2.6. The information for 8th grade classrooms is in Tables 2.7 and 2.8, and the information for 11th grade classrooms is in Table 2.9.

On average, the volume of measured 3rd grade classrooms in District B (7,543 ft^3) are 1,160 ft^3 larger than those measured in District A (6,383 ft^3).

Elementary classrooms have similar building materials and furnishings within each district. All of the measured 3rd and 5th grade classrooms had at least one exterior window, but most had an entire wall of exterior windows. Most of the

Table 2.3: Descriptions of 3rd grade classrooms in District A

School ID	Year Opened	Year of Most Recent Rennovation	ID #	Volume (ft3)	Floor Plan Type
A-ES-1	1950	2011	001	6864	Closed
			002	6514	Closed
			003	5664	Closed
A-ES-2	1939	2011	006	6183	Closed
			007	6583	Closed
			008	6453	Closed
A-ES-3	1952	2012	011	5942	Closed
			012	6076	Closed
			013	6915	Closed
A-ES-4	1975	2013	016	6942	Closed
			017	7061	Closed
			018	7040	Closed
A-ES-5	1924	2013	021	4578	Closed
			022	6304	Closed
			026	7020	Closed
A-ES-6	1971	2012	023	5031	Closed
			024	4919	Closed
			025	5099	Closed
A-ES-7	1924	2010	033	6160	Closed
A-ES-8	1950	2011	038	7823	Closed
A-ES-9	1958	2007	036	5403	Closed
A-ES-10	2011	2011	041	7933	Closed
			042	8098	Closed
			043	6610	Closed
A-ES-11	1957	2014	044	6370	Closed

Table 2.4: Descriptions of 3rd grade classrooms in District B

School ID	Year Opened	Most Recent Renovation	ID #	Volume (ft^3)	Floor Plan Type
B-ES-1	1954	2005	061	5814	Closed
			062	5862	Closed
B-ES-2	1927	1996	066	7244	Closed
			067	7970	Closed
			068	7811	Closed
B-ES-3	1959	1982	071	9562	Closed
			072	9198	Closed
B-ES-4	1959	2005	076	5727	Closed
			077	7941	Closed
			078	9747	Closed
B-ES-5	1956	1997	084	8377	Closed
B-ES-6	1958	1998	079	7722	Closed
			080	7997	Closed
B-ES-7	1932	1997	088	6579	Closed
B-ES-8	1956	1997	091	6384	Closed
			092	6430	Closed
B-ES-9	1962	1992	093	7453	Closed
B-ES-10	1961	2003	098	7954	Closed

classrooms in District A have thin carpet, acoustical tile ceilings, and gypsum board walls. Figure 2.5 shows an example of a typical District A elementary classroom. Elementary classrooms in District B have some unique features and building materials. Some of these features include brick walls, sloped ceilings, wood beams, and ceilings that have not been treated with absorption. Figure 2.6 shows a picture of a classroom in District B with most of the unique features that have been listed, and Figure 2.7 shows a picture of a more “conventional” classroom in District B.

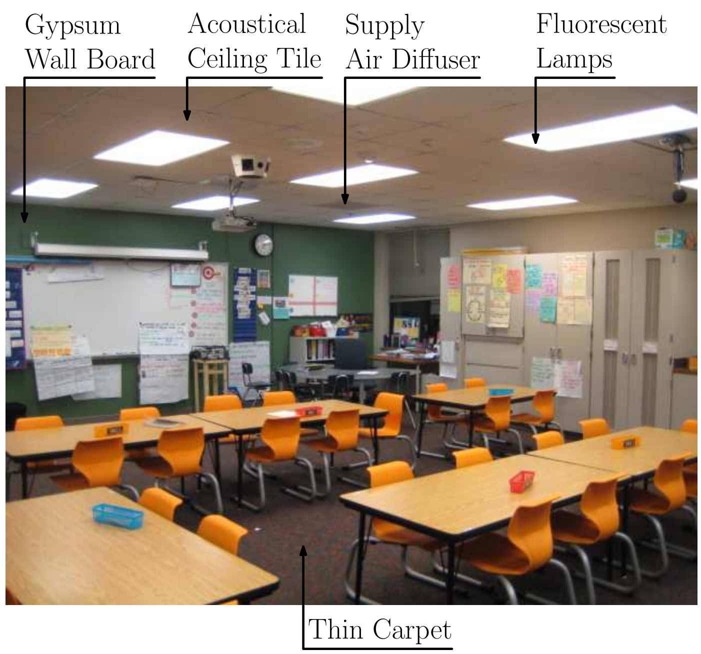


Figure 2.5: Example of a typical elementary classroom in District A.

Figure 2.6: Example of an elementary classroom in District B with unique features.

Figure 2.7: Example of a typical elementary classroom in District B with the window ventilation unit shown.

The elementary classrooms in both districts have dry-erase boards, bulletin boards, cabinetry, and bookcases. Most walls are decorated with educational and

motivational materials.

Table 2.5: Descriptions of 5th grade classrooms in District A

School ID	Year Opened	Year of Most Recent Rennovation	ID #	Volume (ft3)	Floor Plan Type
A-ES-1	1950	2011	004	7289	Closed
			005	6854	Closed
A-ES-2	1939	2011	009	5372	Closed
			010	6592	Closed
A-ES-3	1952	2012	014	7566	Closed
			015	7306	Closed
A-ES-4	1975	2013	019	7664	Closed
			020	7237	Closed
A-ES-5	1924	2013	027	7304	Closed
			031	7544	Closed
			032	7017	Closed
A-ES-6	1971	2012	028	5960	Closed
			029	5895	Closed
			030	5853	Closed
A-ES-7	1924	2010	034	7026	Closed
			035	6260	Closed
A-ES-8	1950	2011	039	7182	Closed
			040	5481	Closed
A-ES-9	1958	2007	037	5382	Closed
A-ES-11	1957	2014	045	6606	Closed

On average, the volume of measured 5th grade classrooms in District B (7,532 ft^3) are 863 ft^3 larger than those measured in District A (6,670 ft^3).

Figure 2.8 shows a typical 8th grade classroom in District A while Figure 2.9 shows a typical 8th grade classroom in District B.

Table 2.6: Descriptions of 5$^{\text{th}}$ grade classrooms in District B

School ID	Year Opened	Most Recent Renovation	ID #	Volume (ft^3)	Floor Plan Type
B-ES-1	1954	2005	063	5993	Closed
			064	5951	Closed
			065	5979	Closed
B-ES-2	1927	1996	069	7254	Closed
			070	7450	Closed
B-ES-3	1959	1982	073	8852	Closed
			074	8883	Closed
			075	8852	Closed
B-ES-4	1959	2005	081	7846	Closed
			082	7337	Closed
			083	6451	Closed
B-ES-5	1956	1997	085	8467	Closed
B-ES-6	1958	1998	086	8076	Closed
			087	7997	Closed
B-ES-7	1932	1997	089	5984	Closed
			090	6365	Closed
B-ES-8	1956	1997	096	6919	Closed
			097	6720	Closed
B-ES-9	1962	1992	094	10188	Closed
			095	10111	Closed
B-ES-10	1961	2003	099	7016	Closed
			100	7018	Closed

Table 2.7: Descriptions of 8th grade classrooms in District A. *Spot renovations only

School ID	Year Opened	Year of Most Recent Rennovation	ID #	Subject	Volume (ft3)	Floor Plan Type
A-MS-1	1979	2017*	046	Lang Arts	3564	Closed
			047		7040	Closed
			048		4932	Closed
			049		6668	Closed
			050	Math	6290	Closed
			051		6689	Closed
			052		6658	Closed
A-MS-2	1961	2016*	053	Lang Arts	6181	Closed
			054		7701	Closed
			055		6548	Closed
			056		6838	Closed
			057	Math	7308	Closed
			058		6552	Closed
			059		7560	Closed
			060		7056	Closed

Table 2.8: Descriptions of 8th grade classrooms in District B

School ID	Year Opened	Most Recent Renovation	ID #	Subject	Volume (ft^3)	Floor Plan Type
B-MS-1	1961	1995	101	Math	6736	Closed
			102		5984	Closed
			103		6461	Closed
			104		6631	Portable, Closed
			105	Lang Arts	6407	Closed
			106		7372	Closed
			107		8180	Closed
			108		6027	Closed

Figure 2.8: Typical 8^{th} grade classroom in District A.

Figure 2.9: Typical 8^{th} grade classroom in District B.

On average, the volume of measured 8^{th} grade classrooms in District B (6,725 ft^3) are 219 ft^3 larger than those measured in District A (6,506 ft^3).

Table 2.9: Descriptions of 11th grade classrooms in District B

School ID	Year Opened	Most Recent Renovation	ID #	Subject	Volume (ft^3)	Floor Plan Type
B-HS-1	1952		109	Math	8620	Closed
			110	Lang Arts	6661	Closed

Figure 2.10: Typical high school classroom in District B.

Overall, the classrooms in District A have ducted ventilation and most of the classrooms in District B have unit ventilators. HVAC units were typically running while the classrooms were occupied. The mechanical systems in District A have programmed set points ranging from 67-70° F while the unit ventilators in District B are individually controlled by facility managers and teachers. Figure 2.11 shows a window ventilation unit found in a typical classroom in District B.

Figure 2.11: Window ventilation unit found in a typical District B classroom.

All of the measured classrooms have closed floor plans. Classroom 104 in school B-11 is in a portable building while the rest of the classrooms presented in this thesis are in traditional buildings. Portable classrooms are better represented in the measurements from the 2016-2017 academic year.

2.3 Concluding Remarks

This chapter provided an overview of the measurement techniques used to gather the data presented in subsequent chapters of this thesis. Classroom descriptions were also introduced to provide context for the results.

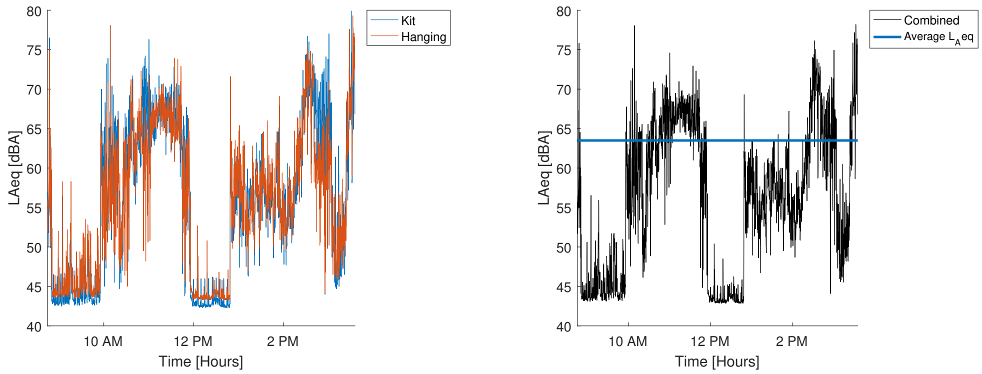
Chapter 3

Data Analysis

This chapter provides an overview of data processing and analysis techniques used in the investigation of the relationship between occupied and unoccupied classroom noise levels.

3.1 Preliminary Data Processing

Data processing routines have been developed in MathWorks MATLAB R2016a. Routines are performed in batches to load data from cloud storage and prepare it for analysis. These routines include importing the raw data into a data structure, extracting and storing the data that were recorded during the school day, and calculating room energy-averages to be used in analysis. The school day has been defined according to the published academic hours for each school. The purpose of isolating the data recorded during the school day was to roughly determine the "occupied" condition that students experience since detailed occupancy information



(a) Time history of data logged from both meters.

(b) Time history of energy-averaged meter data.

Figure 3.1: Example of the A-weighted equivalent level plotted over time from (a) both the kit and hanging meters, and (b) from the energy-averaged meter data. The energy-average of the data is shown in (b).

was not available. Data recorded overnight were not used in formal analysis for unoccupied levels because many schools do not keep mechanical systems running overnight or do not keep them running on the highest setting.

Data are energy-averaged at multiple levels for every classroom. The first level is a room energy-average of the school day data averaged between the two sound level meters at every point in time shown in Figure 3.1. The second level is a seasonal energy-average which is an energy-average of the room energy-averaged data. The third and final level used in this thesis is a yearly energy-average which is an energy-average of the three seasonal energy-averages.

3.1.1 Data Removal/Exclusion

With a data set and project of this size (110 classrooms x 2 meters x 3 seasons = 660 possible files each with 36 hours of logged data), occasional missing data, equipment malfunctions, and operator mistakes are unavoidable. Importing routines have been

programmed to create a log of missing files and missing data. Files that are present but have fewer than two hours of data are also flagged. Appendix A presents the log of missing data. During processing, if data meet certain conditions (e.g. the A-weighted equivalent level energy-average for a given meter on a given day is above 90 dBA) they are flagged for review, and excluded from subsequent averaging.

As stated in Chapter 2, the one-minute BNLs were taken in unoccupied classrooms with mechanical systems on. When this was not possible because the students had already arrived for school, or because mechanical systems were suspected to be off, etc., team members made notes in the written measurement log for that classroom, and then those data were excluded from the sample. These one-time BNL measurements were plotted against the time log of the A-weighted equivalent level for each classroom for each season and visually inspected to ensure that the BNLs measurements were reasonable characterizations of the true background noise level. Those measurements that were not deemed reasonable were excluded from analysis. More on this process and which samples were removed can be found in Appendix A.

3.2 Initial Investigation of Correlation

Data processing prepared the data for an investigation of correlation between unoccupied and occupied levels. The Pearson Correlation Coefficient, r, was chosen as the criteria for correlation because it tests if a linear relationship exists between

two variables. The correlation coefficient is calculated using equation (3.1)

$$r = \frac{cov_{xy}}{s_x s_y} = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{(N-1)s_x s_y} \tag{3.1}$$

where cov_{xy} is the covariance of the data in x and y, s_x is the standard deviation of the data in x, s_Y is the standard deviation of the data in y, x_i is a single point in x, y_i is a single point in y, $\bar{x}$ and $\bar{y}$ are the means of x and y, and N is the number of sampled data points [Field et al. 2012]. Before calculating the correlation, the data were tested for normality. The coefficient of determination, R^2, was also calculated when there was a statistically significant correlation to determine the amount of shared variance between the two variables [Field et al. 2012]. Initially, the yearly energy-averages of school day data were used as the "occupied" levels and the one-minute background noise levels were used as the unoccupied levels. Figure 3.2 shows a scatter plot of the yearly A-weighted energy-averages ("occupied") against the unoccupied one-minute A-weighted BNL.

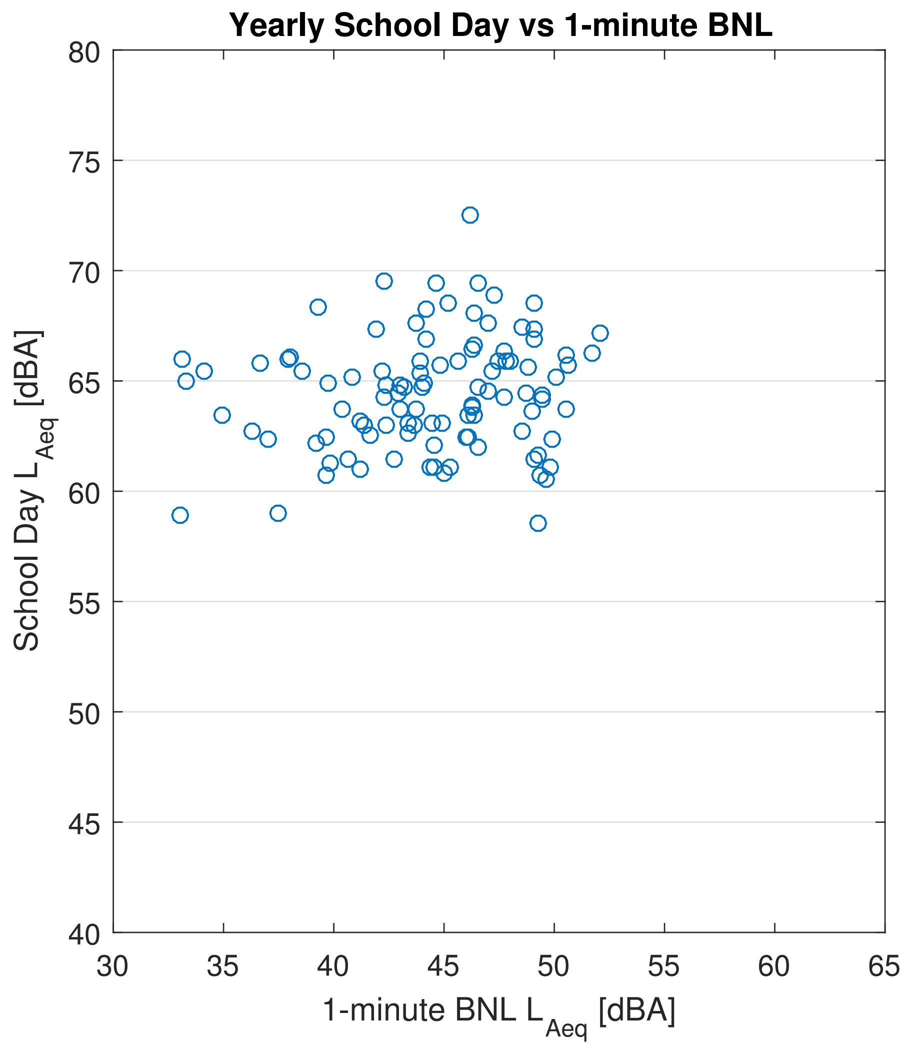


Figure 3.2: Scatter plot of the yearly A-weighted energy-avarages against the one-minute BNL for each classroom

The correlation coefficient between these two metrics is 0.16 ($r = 0.16$, $p > 0.05$). This correlation is not strong and is not considered statistically significant because the p-value is not less than an alpha value of 0.05. One reason that this correlation may not be strong is that the occupied level has been characterized by one number that encompasses approximately 30,240 data points (7 school day hours x 60 minutes x 6 measurements/minute x 2 days x 2 meters x 3 seasons). Defining the "occupied" condition as encompassing the entire school day (even when students

may vacate the classroom for lunch, recess, music, etc.) may be the cause of the weak correlation.

The assumption used to justify the exploration presented in the rest of this thesis is that the method of defining occupancy as the entire school day does not accurately account for periods of inactivity and vacancy that ultimately affect the yearly energy-average. The periods of vacancy and activity vary from classroom to classroom and therefore have an unpredictable effect on the actual occupied levels. This method may include enough periods of inactivity and vacancy that there is little correlation to the baseline unoccupied background noise level. Thus, additional methods have been implemented to categorize the occupancy of the classroom to determine if the correlation changes due to the definition of occupied time.

3.3 K-means Clustering

K-means clustering is an unsupervised statistical learning technique that categorizes observations into a specified (K) number of clusters while minimizing the within cluster variation. The best choice of K will also maximize the distance between clusters. This method is useful for predicting qualitative results (a response) from a set of quantitative observations when the associated response is unavailable to "supervise" the results [James et al. 2014].

There are two properties that apply to all clustered data sets: (1) each observation must belong to at least one of the K clusters; and (2) none of the clusters overlap meaning each observation only belongs to one of the K clusters

[James et al. 2014]. Because all of the observations belong to one and only one cluster, the definition of a *good* cluster is one where the variation between its observations is minimal. While there are a variety of ways to define the variation within a cluster, this thesis presents squared Euclidean distance which is the most commonly used method. In this case, the within-cluster variation, $W(C_k)$ for the k^{th} cluster is defined as the sum of all the pairwise squared Euclidean distances between observations in that cluster, divided by the total number of observations in that cluster,$|C_k|$:

$$W(C_k) = \frac{1}{|C_k|} \sum_{i,i' \in C_k} \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2 \tag{3.2}$$

The overall goal is to partition the data into K clusters so as to minimize the total within-cluster variation summed over all clusters [James et al. 2014]. Equation (3.3) presents an optimization formula.

$$\underset{C_1,\ldots,C_K}{minimize} \{ \sum_{k=1}^{K} \frac{1}{|C_k|} \sum_{i,i' \in C_k} \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2 \} \tag{3.3}$$

However, the formula is somewhat challenging to solve as there are almost K^n ways to partition n observations into K clusters [James et al. 2014]. For the data presented in this thesis, there are approximately 5,040 observations for a classroom during the combined academic days during a given season. That means that for every season and every classroom, the number of ways to partition the data into two clusters would be on the order of 10^{1517} (K^n: 2^{5040}). The computation time required for each classroom would be astronomical (about 32 trillion years using the current fastest supercomputer which can perform 10^17 operations per second). Luckily, a

simple algorithm can be shown to provide a local optimum to this optimization problem. The k-means clustering algorithm follows the approach shown in Figure 3.3.

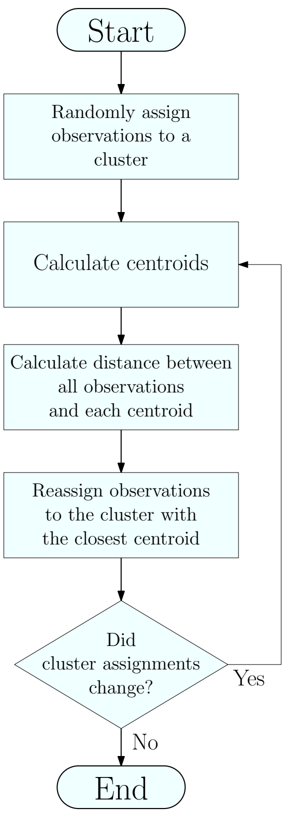


Figure 3.3: Flowchart of the k-means clustering algorithm

The first step in the initialization procedure is to randomly assign a number, from 1 to K, to each of the observations. These random assignments serve as the initial cluster assignments. Once the initialization is complete, the iterative process begins. Cluster centroids are calculated to be 1-by-p vectors of the mean of each feature for each cluster. Next, the observations are reassigned to the cluster with the closest centroid; in this case *closest* is defined using squared Euclidean distance. This process continues until a solution converges to a local optimum and the cluster

assignments stop changing. The algorithm simplifies equation (3.2) as follows:

$$\frac{1}{|C_k|}\sum_{i,i'\in C_k}\sum_{j=1}^{p}(x_{ij}-x_{i'j})^2 = 2\sum_{i\in C_k}\sum_{j=1}^{p}(x_{ij}-\bar{x}_{kj})^2 \tag{3.4}$$

where $\bar{x}_{kj} = \frac{1}{|C_k|}\sum_{i\in C_k} x_{ij}$ is the mean for feature j in cluster C_k [James et al. 2014]. The algorithm seeks to minimize the within cluster variation by minimizing the distance between every observations in a cluster and the centroid of that cluster.

While less computationally intensive, this algorithm produces a local optimum and not global optimum solutions. Local optima depend on the initialization conditions; therefore, it is important to run the algorithm multiple times with different random initial conditions. The local optima are calculated for each repetition and the best (smallest) solution is selected.

The algorithm results in observations that are organized into K distinct clusters. Every observation will have a cluster assignment from 1 to K and every k^{th} cluster will have observations assigned to it. Clusters will be found every time the clustering algorithm is performed. However, there is no universally agreed upon way to determine if the found clusters represent the true subgroups in the data or if they are clusters of noise. Cluster specification is important because k-means forces each observation into a cluster which can result in outliers being assigned to clusters to which they do not really belong. The problem is there is no direct way to determine the optimum number of clusters for a given data set. As of yet, there is no consensus on the best approach for assessing whether there is more evidence for a cluster than one would expect due to chance.

3.4 Application of K-means Clustering

For this study, k-means clustering was performed on observations of the energy-averaged sound level meter data using octave bands as the features. This means that k-means clustering was performed on 9-dimensional observations where each dimension was a different octave band. Octave bands (centers at 32 Hz-8 kHz) were chosen over weighted equivalent levels because they provide more detailed information. The observations used for clustering only included observations logged during the academic day. Clustering was performed in this manner for every season and every classroom.

Data were parsed into academic days prior to clustering and did not include overnight data. While the overnight data should include a large amount of unoccupied time, it was excluded for the initial clustering because it could hypothetically increase the number of initial clusters needed for broad strokes. Most of the schools do not run their mechanical/HVAC systems overnight so realistically, the levels recorded during an unoccupied and overnight period would differ from those recorded during a daytime unoccupied period. The spectral signature of the mechanical system would be absent and could ultimately confuse the clustering method.

Initially, clustering was performed to categorize the data by occupancy. Upon further investigation, follow-up clustering was performed on each initial category in an attempt to discern various levels of activity.

All clustering was performed in MathWorks MATLAB 2016a using the *kmeans*

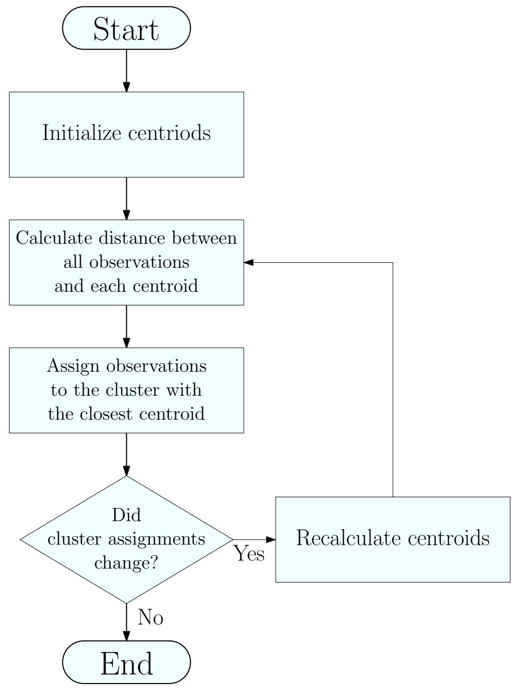


Figure 3.4: Flowchart of the k-means clustering algorithm using *kmeans++* for initialization

function. While cluster numbers varied depending on the objective (i.e. occupancy or activity), all other parameters remained consistent between test types. The measure of difference was always chosen to be squared Euclidean distance and five repetitions were performed. Initial centroids were chosen using the *k-means++* algorithm. Instead of randomly assigning each observation to a cluster, *kmeans++* chooses K centroid starting positions using an heuristic. The centroids are 1-by-p vectors, where p is the number of features (or columns) in the data to be clustered. This method improves the algorithm and outperforms methods that use random seeding [Arthur & Vassilvitskii 2007]. This change to the flow of the algorithm is reflected in Figure 3.4.

The *kmeans* function returns the cluster identity assigned to each observation; however, the cluster identification numbers do not hold inherent meaning and are

therefore not directly comparable between classrooms without some interpretation. For instance, cluster 1 from classroom 001 could be interpreted as the occupied cluster while cluster 1 from classroom 002 could be interpreted as the unoccupied cluster. The cluster assignments stem from the randomization of the initial conditions: the cluster number is determined by the order in which the centroid seeds were initialized. While the clustered observations are meaningful, the number given to that cluster is arbitrary. This randomization has been accounted for by reassigning the cluster numbers from 1 to K so the 1^{st} cluster has the highest mean and the k^{th} cluster has the lowest mean. This acts as an initial interpretation of the results and allows for more direct comparison between classrooms and seasons. The use of this initial interpretation of the results was chosen over clustering all of the classrooms together because clustering the data together finds trends for the entire data set and dilutes the possibility of finding meaningful results at the classroom level. The best clustering for the entire data set may not be the best clustering for individual classrooms.

3.4.1 Sample of Validation

While unsupervised learning does not require measured response variables, the clustering can still be checked for validity if response variables are available. For this study, clusterings for a sample number of classrooms have been compared to their class schedules to provide some means of verifying accuracy. Figure 3.5 shows the logged A-weighted equivalent level, color coded by cluster assignment, over one

school day. The scheduled class time is also displayed on this plot to provide a means of comparing the clustering results to expected occupied time.

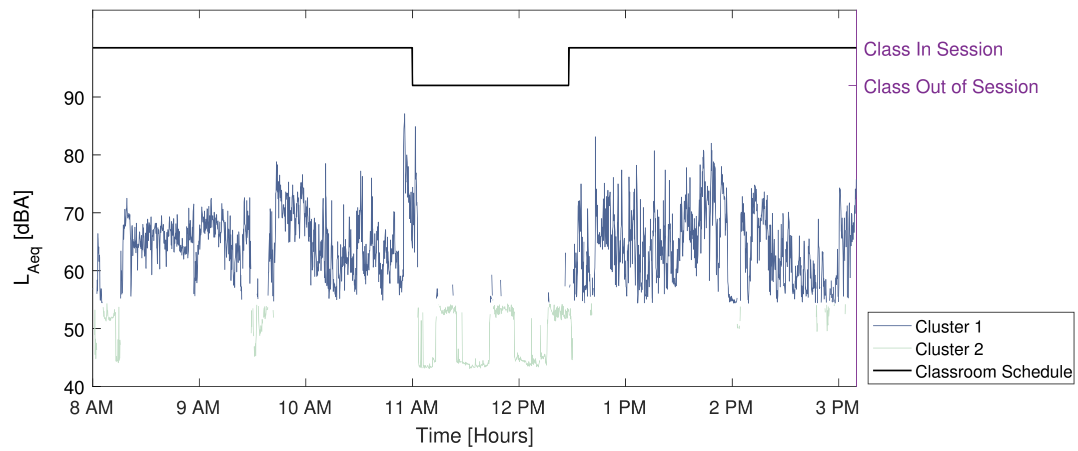


Figure 3.5: A-Weighted equivalent level, color coded by cluster assignment, logged during one school day with the scheduled class time displayed

Figure 3.6 shows the confusion matrix for the sampled data. The "true" classification of the data is taken from the classroom schedule and is assumed occupied when class was scheduled to be in session and unoccupied otherwise. The top left and bottom right corners represent the correct classification rate, the bottom left corner represents the false occupied classification rate, and the top right corner represents the false unoccupied classification rate.

For this classroom, k-means clustering correctly predicted occupied periods 91% of the time and unoccupied periods 89% of the evaluated time. 10.4% of the time the classroom was scheduled to be out of session, the algorithm predicted the classroom was occupied. This false occupied rate could have resulted from noisy students in hallways or adjacent classrooms during passing periods or the presence of the teacher in the classroom. The algorithm predicted the room was unoccupied

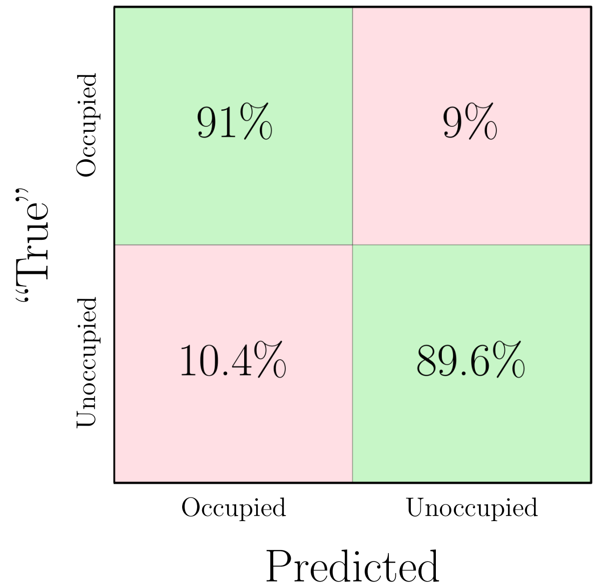


Figure 3.6: Confusion matrix for the clustered data presented in Figure 3.5.

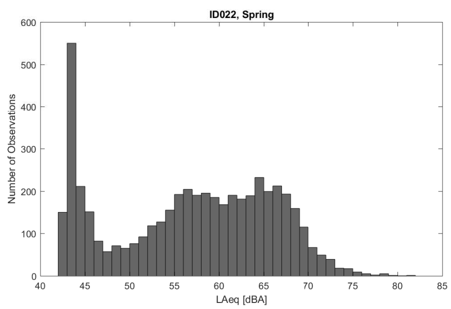
9% of the time class was scheduled to be in session. This could have resulted from an absence of speech and limited noise while students were taking a test or quiz or from vacancy during passing periods. Overall, the clustering agreed with the classroom schedule 90.6% of the evaluated time. It is important to note that the classroom schedule is not a perfect response because it does not give an exact account of the occupancy for the given measurement day. Results from other sampled classrooms were consistent with those presented.

While logged data from additional environmental variables (temperature, CO_2, illuminance, etc.) are available, they were determined to be less useful/accurate in distinguishing occupied and unoccupied periods of time, due to two possible reasons. One, the resolution of all other data logged in the classroom is five minutes while the resolution of acoustic data is 10-seconds. Two, there is a lag in the response time for observing variations in indoor air quality and thermal comfort metrics that

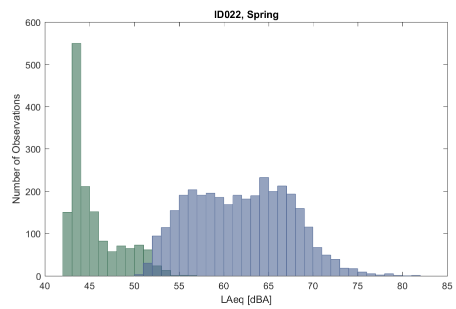
is not present in acoustic metrics. The lag in the response time could potentially be accounted for, but is ultimately not easy to do and requires simulations to validate.

3.4.2 Comparison to Hodgson et al. [1999]

The results of this method can be viewed as histograms and a sample of these clustered and un-clustered histograms is shown in Figure 3.7.



(a) Overall distribution



(b) Clustered distribution

Figure 3.7: Distribution of the logged A-weighted equivalent level measured in one classroom over two school days

These histograms are similar to those used in Hodgson et al.'s method for predicting typical speech and background noise levels presented in Figures 1.1 and 1.2 in Chapter 1. In Hodgson et al.'s method, normal distribution curves had to be fit to a histogram of the A-weighted sound pressure levels in order to obtain predictions for the noise source levels. Hodgson et al.'s method was only applied to the A-weighted levels, and, unlike k-means clustering, was not automated. The clustered distribution shown in Figure 3.7(b) is theoretically stronger than if normal distribution curves had been fit to the overall A-weighted equivalent level distribution because this method was applied in 9-dimensions (to all the octave bands between 32 Hz and 8 kHz) simultaneously. While the results from k-means

clustering can be viewed as distributions of the logged A-weighted equivalent levels, the distributions are not necessary for the clustering process. Histograms of the clustered results are meaningful and similar to results from Hodgson's method because k-means clustering seeks to minimize the within-cluster variation while maximizing the between-cluster variation thereby creating distinct distributions. Once k-means clustering is programed, it does not require human interaction to obtain results and it can be applied in multiple dimensions simultaneously in fractions of a second. The clustered results retain their ordered, temporal context, but can also be viewed in many ways (e.g. time history, histogram, etc.) which helps with the interpretation and validation.

3.5 Concluding Remarks

The previous sections presented the initial correlation between the one-minute unoccupied BNL and the yearly average of the measured school days. The correlation was determined to be weak and not statistically significant (r = 0.16, p > 0.05). In order to determine if this definition of unoccupied and occupied was insufficient or if there is not a strong correlation between unoccupied and occupied noise levels, k-means clustering will be used to isolate occupied an unoccupied observations. The methodology of k-means clustering was introduced in Section 3.3, and Section 3.4 illustrated how it would be applied to data sets used in this study. A sample validation of the k-means clustering results was also provided.

Chapter 4

Investigation of Occupancy

An initial clustering of K = 2 was performed to separate the data into two broad categories. The hypothesis was that the most prominent difference in observations would be the difference between the spectral characteristics of occupied time and unoccupied time. While there may be varying levels of activity during occupied time periods, those activities should have similar spectral characteristics and be different enough from the unoccupied or inactive time periods that they are properly clustered with other occupied observations.

While the k-means clustering algorithm is performed on the octave band data, it is easier to visualize the clustering applied to the A-weighted levels. Figure 4.1 shows an example of the logged A-weighted equivalent level, energy-averaged between both sound level meters, plotted over time with the overall energy-average and one-minute BNL plotted as horizontal lines for reference. Figure 4.2 shows the same plot with the data broken up into the assigned clusters as well as the energy-average of each cluster.

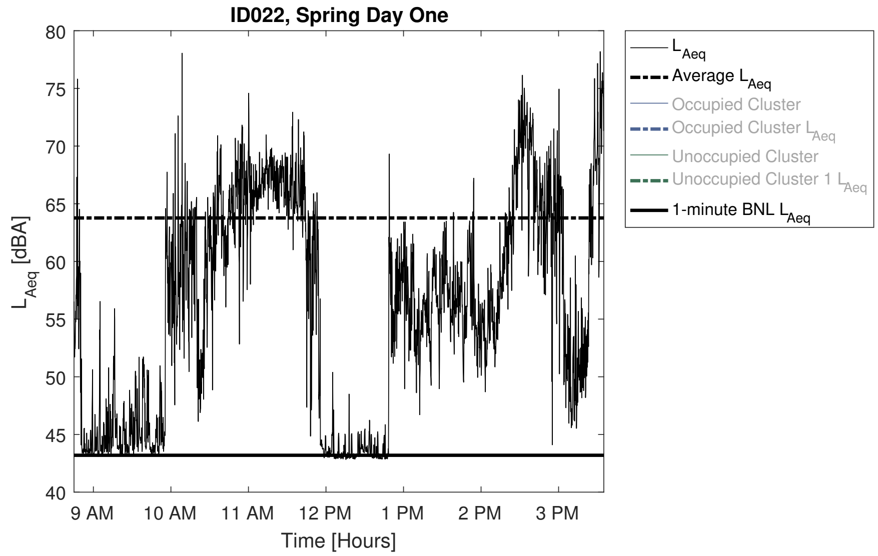


Figure 4.1: Room energy-averaged A-weighted equivalent level for a single school day shown with the seasonal school day average L_{Aeq} and one-minute BNL.

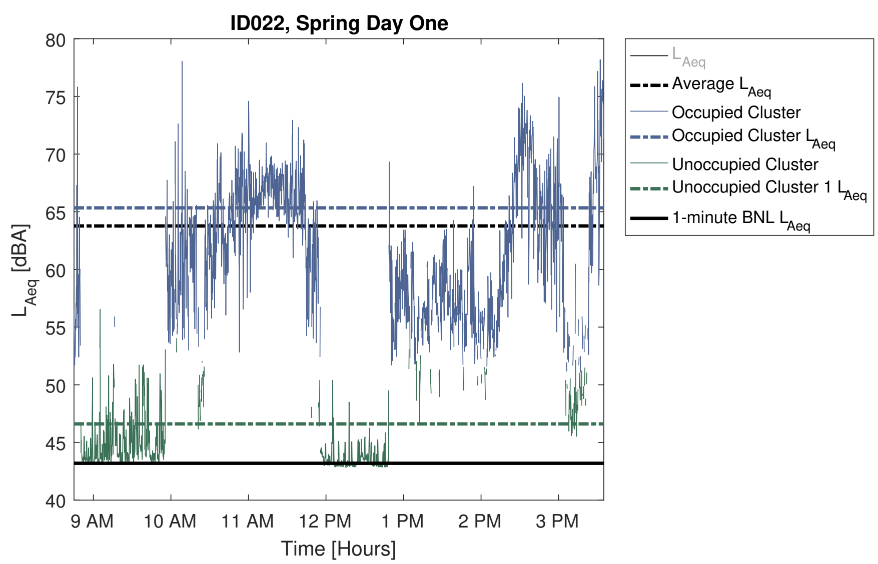


Figure 4.2: Room energy-averaged A-weighted equivalent level for a single school day broken up into two clusters shown with the seasonal school day average and seasonal cluster averages, and one-minute BNL.

While the data are the same, there is a gap in the plotted data in Figure 4.2 because the clusters were plotted separately meaning that connecting lines between the clusters were eliminated. The calculated cluster energy-averages for this

classroom are visually different from the calculated school day energy-average and one-minute BNL. In this classroom, the school day energy-average for the spring was 63.8 dBA while the occupied cluster energy-average was 65.3 dBA. There is a 1.5 dB difference. The measured one-minute BNL was 43.2 dBA while the unoccupied cluster energy-average was 46.6 dBA. The difference between the measured BNL and the calculated unoccupied level is 3.4 dB. From examining Figure 4.2, it appears that the one-minute BNL is the baseline level in this room.

4.1 Spectral Characteristics

As previously stated, k-means clustering was performed on each season and classroom separately, so the routine was programmed to determined each cluster's A-weighted average and then reassign the cluster numbers so that the clustered observations with the highest average was assigned to the 1st cluster and the clustered observations with the lowest average were assigned to the k^{th} cluster. While A-weighted level is not sufficient for clustering, it is sufficient for this initial "interpretation" because it is more indicative of human speech perception and places more of an emphasis on octave bands that are associated with speech than with mechanical systems. This process helped ensure comparable results from classroom to classroom. While spectral characteristics of mechanical systems and occupant voices may vary from room to room, there should be some distinction between the two on a room by room basis.

Box plots of the yearly energy-averaged A-weighted and octave band levels for

each cluster have been examined in order to interpret the clustering based on differences in spectral characteristics. In the box plots presented, the top of the box represents the 75^{th} percentile of the data, the horizontal line inside the box represents the median (or 50^{th} percentile) of the data, and the bottom of the box represents the 25^{th} percentile of the data. 25% of the data is represented between adjacent lines (e.g. top whisker and 75^{th} percentile, 75^{th} percentile and median, etc.). The cross-marks sometimes seen above or below the whiskers are outliers. Box plots are an efficient means of simultaneously visualizing the distribution of data from multiple categories. Overall spectral characteristics will be presented by season and district as well.

4.1.1 Overall

Figure 4.3 shows box plots of the energy-averaged A-weighted and octave band levels for the one-minute BNLs across 110 classrooms. This plot is used as a baseline for the unoccupied measurement comparisons.

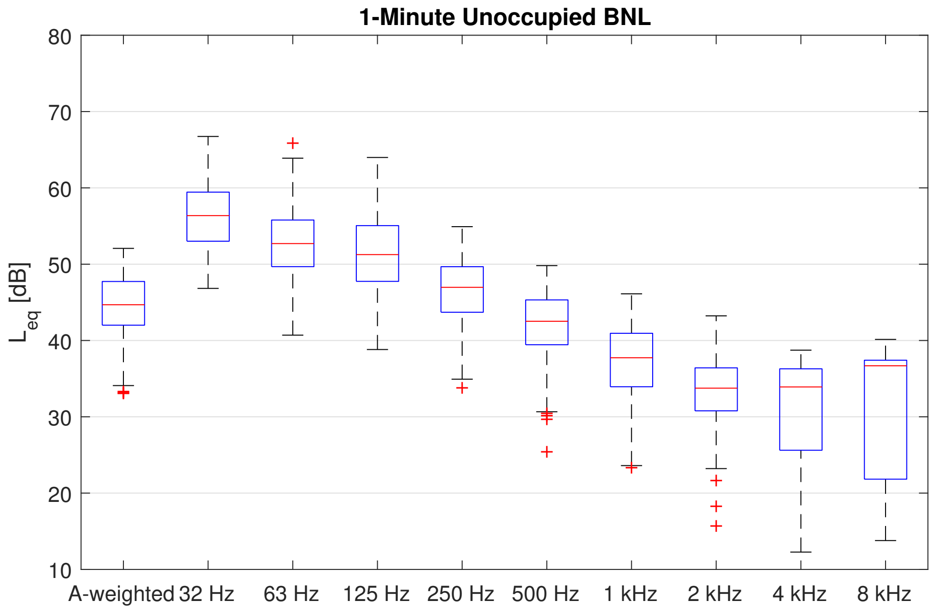


Figure 4.3: Box plot of energy-averaged A-weighted and octave band equivalent sound levels from the one-minute BNLs.

Figure 4.4 shows box plots representative of the yearly energy-averaged A-weighted and octave band levels for all 110 classrooms averaged over the clustered time periods with the highest average A-weighted level (cluster 1) and lowest average A-weighted level (cluster 2).

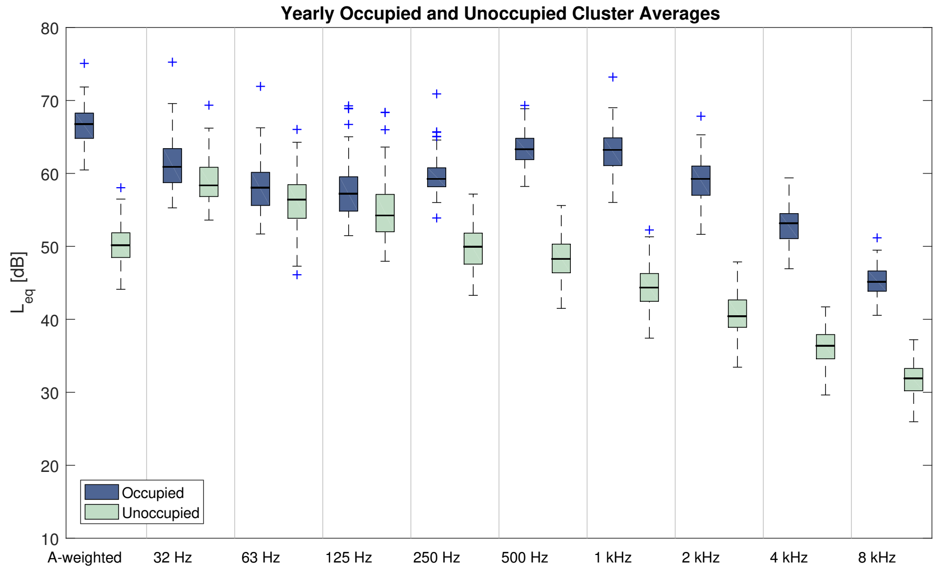


Figure 4.4: Box plot of energy-averaged A-weighted and octave band equivalent sound levels from the clusters interpreted to be representative of occupied and unoccupied conditions.

Between the clusters presented in Figure 4.4, it is logical to interpret the observations from Cluster 1 as occupied and the observations from Cluster 2 as unoccupied. Frequencies in the 500, 1000, 2000, and 4000 Hz octave bands are associated with speech content. The octave band levels of the occupied cluster do not follow the somewhat more continuous downward slope of the unoccupied cluster. Fundamental voice frequencies range from 85-180 Hz for men, 165-255 Hz for women, and 250-650 Hz for children [Baker & Orlikoff 2000]. Cluster 1's octave band averages begin increasing at the 250 Hz octave band which corresponds to fundamental voice frequencies of humans. Because the increase in energy-average octave band levels is consistent with characteristic of speech, it is logical to interpret Cluster 1 as the occupied cluster. With the exception of the 4 kHz and 8 kHz octave bands, the pattern of the results from Cluster 2 matches the results from the

one-minute BNLs presented in Figure 4.3. Consequently, cluster 2 was interpreted to be representative of unoccupied observations.

Now that an interpretation of the clusters has been established, the spectral characteristics of each cluster will be examined by season and district.

4.1.2 Seasonal

Figure 4.5 shows a box plot of the seasonal occupied cluster energy-averages for the A-weighted equivalent level and octave band levels in all 110 classrooms.

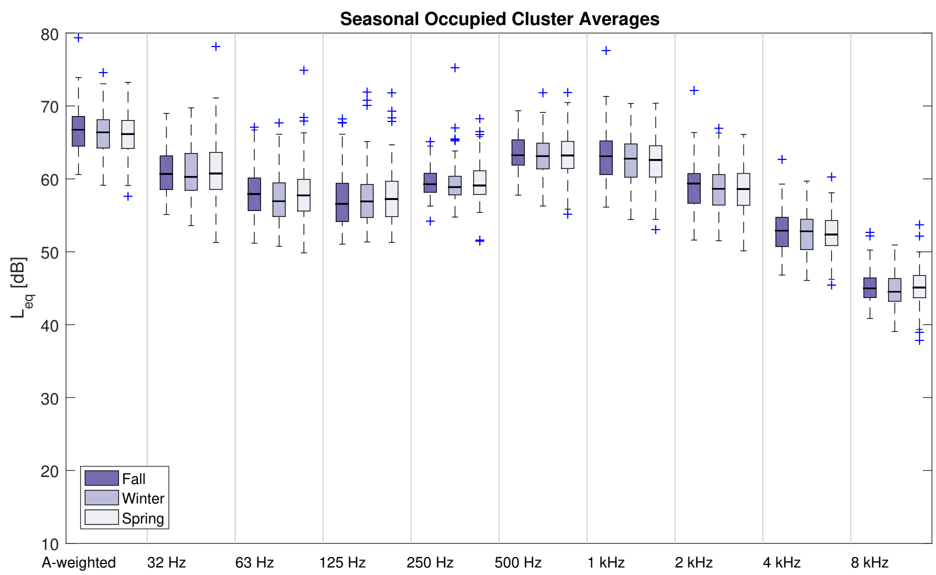


Figure 4.5: Box plot of the seasonal energy-averaged A-weighted and octave band equivalent sound levels from the cluster determined to be representative of occupied conditions.

The seasonal results follow the same trend as the yearly results. Yearly levels have a slightly tighter range than individual levels for each season.

Differences between the yearly occupied cluster average A-weighted equivalent level and the seasonal occupied cluster average A-weighted equivalent level were calculated as an initial way to examine seasonal differences. In the fall, only eight

classrooms had differences between 3 dBA and 6 dBA. Twelve classrooms in the winter had differences greater than 3 dBA and one classroom had a difference greater than 6 dBA. In the spring, nine classrooms had differences greater than 3 dBA from the yearly average and two classrooms had differences greater than 6 dBA.

Figure 4.6 shows a box plot of the seasonal unoccupied cluster energy-averages for the A-weighted equivalent level and octave band levels for all 110 classrooms.

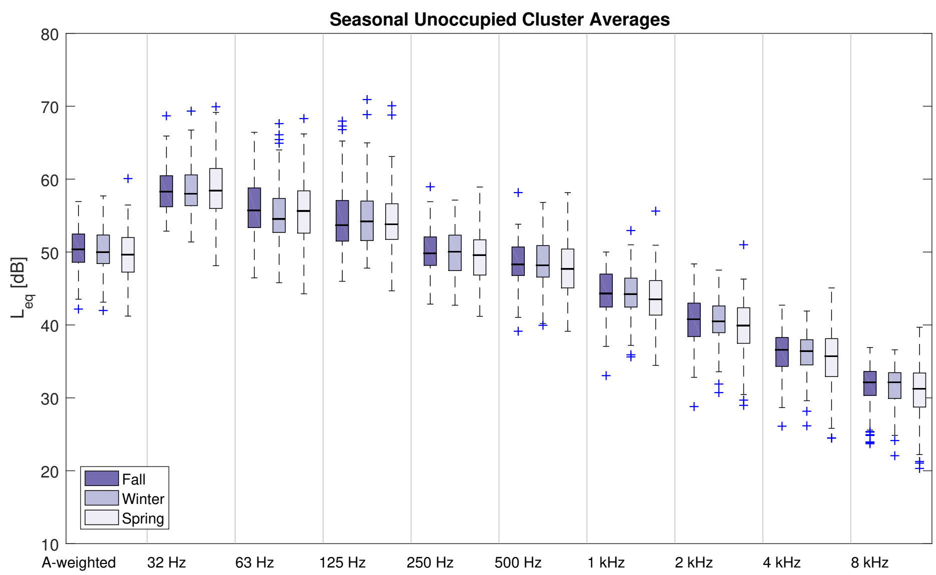


Figure 4.6: Box plot of the seasonal energy-averaged A-weighted and octave band equivalent sound levels from the cluster determined to be representative of unoccupied conditions.

Again, the energy-average seasonal levels follow the same trend as the yearly energy-averaged levels. In the fall, only four classrooms had differences between 3 dBA and 6 dBA. In the winter, three classrooms had differences between 3-6 dBA and one classroom had differences between 6-9 dBA. In the spring, thirteen classrooms had differences between 3-6 dBA and one classroom had a difference between 6-9 dBA.

4.1.3 District

Figure 4.7 shows a box plot of the yearly occupied cluster energy-averaged A-weighted level and octave band levels for Districts A and B.

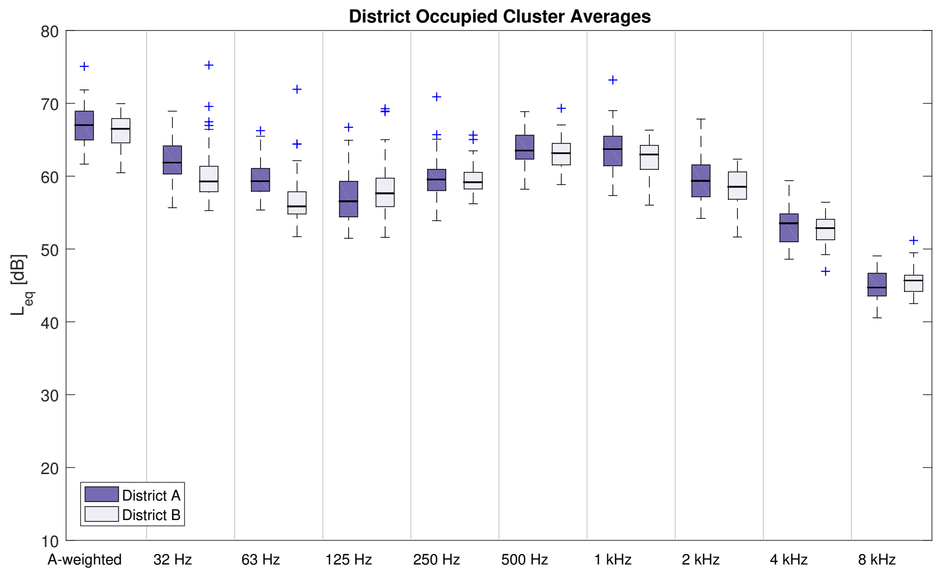


Figure 4.7: Box plot of the yearly energy-averaged A-weighted and octave band equivalent sound levels determined to be representative of occupied conditions split by district

While the speech frequency characteristics are present in the occupied clusters from both districts, there is less energy in the 63 Hz octave band than in the 125 Hz octave band in District B. There is a dip in the 63 Hz octave band in District B while there is a dip in the 125 Hz octave band in District A. District A visually lines up a little more closely to the yearly average.

Figure 4.7 shows a box plot of the yearly occupied cluster energy-averaged A-weighted level and octave band levels for Districts A and B.

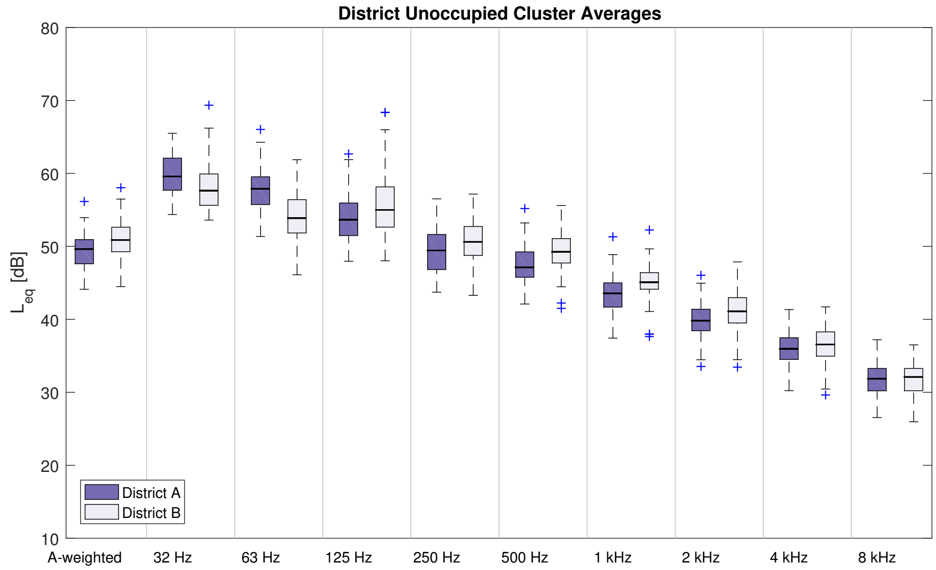


Figure 4.8: Box plot of the yearly energy-averaged A-weighted and octave band equivalent sound levels determined to be representative of occupied conditions split by district

The spectral curves are fairly consistent. There is more energy in the 63 Hz octave band in District A than there is in District B. This pattern is consistent between the clusters. Energy in the lower frequency octave bands is more associated with mechanical noise; therefore, the differing pattern between districts is likely characteristic of the noise emanated by the mechanical systems in each district.

4.2 Investigation of Correlation Between Clusters

Once an interpretation of the clustered observations was established, the next step was to investigate the relationship of the clusters. The Pearson Correlation Coefficient, r, was chosen as the criteria for correlation because it establishes the strength of a linear relationship between two variables. The coefficient of determination, R^2, was also calculated when there was a statistically significant

correlation to determine the amount of shared variance between the two variables. These methods were presented in Chapter 3.

4.2.1 Yearly Correlation

The relationship between the one-minute BNLs and the occupied cluster was the first to be investigated. Figure 4.9 shows a scatter plot of the yearly occupied L_{Aeq} against the one-minute unoccupied L_{Aeq}.

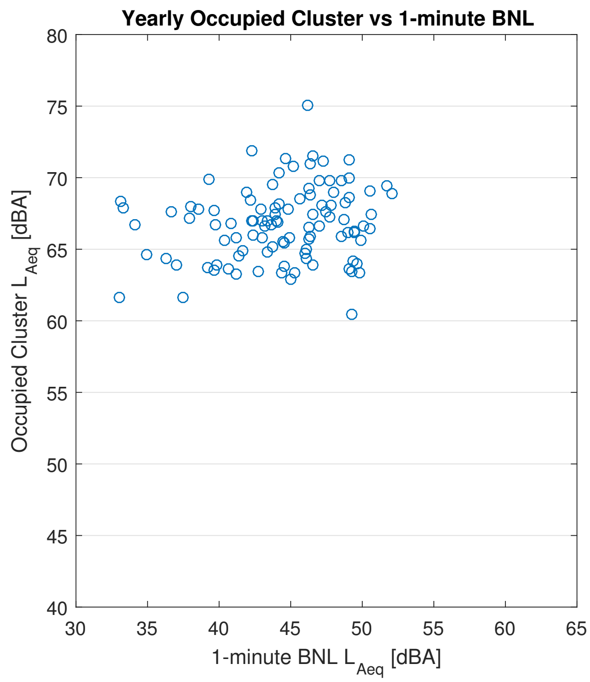


Figure 4.9: Scatter plot of the yearly occupied cluster energy-average A-weighted level against the one-minute BNL for each classroom

There is a non-significant correlation between the variables ($r = 0.19$, $p > 0.05$). This is not necessarily surprising since the one-minute BNL measurement was taken in the same position as the kit meter and the averages are based off of the energy average of the kit and hanging meters. As the A-weighted one-minute background noise levels increase, the energy averages of the occupied clusters do not

uniformly increase. The average level of the occupied clusters stays within a range of 60-73 dBA no matter the BNL.

Because there was not a strong correlation between the one-minute BNLs and the occupied cluster, the relationship between the one-minute BNLs and the unoccupied cluster was investigated in order to justify the interpretation by establishing that the unoccupied cluster was indicative of known unoccupied conditions measured by the one-minute BNLs. Figure 4.10 shows a scatter plot of the yearly unoccupied L_{Aeq} against the one-minute unoccupied BNL.

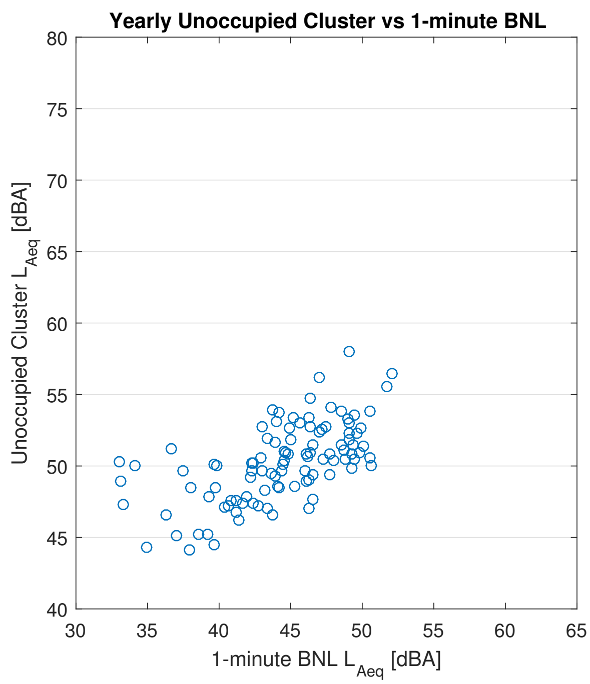


Figure 4.10: Scatter plot of the yearly unoccupied cluster energy-average A-weighted level against the one-minute BNL for each classroom

These variables have a strong, statistically significant correlation and accounts for 38% of the shared variance ($r = 0.62$, $R^2 = 0.38$ $p < 0.05$). This strong correlation justifies the interpretation and provides a reason to investigate the correlation between the unoccupied and occupied clusters.

Figure 4.11 shows a scatter plot of the yearly L_{Aeq} of the occupied cluster against the yearly L_{Aeq} of the unoccupied cluster.

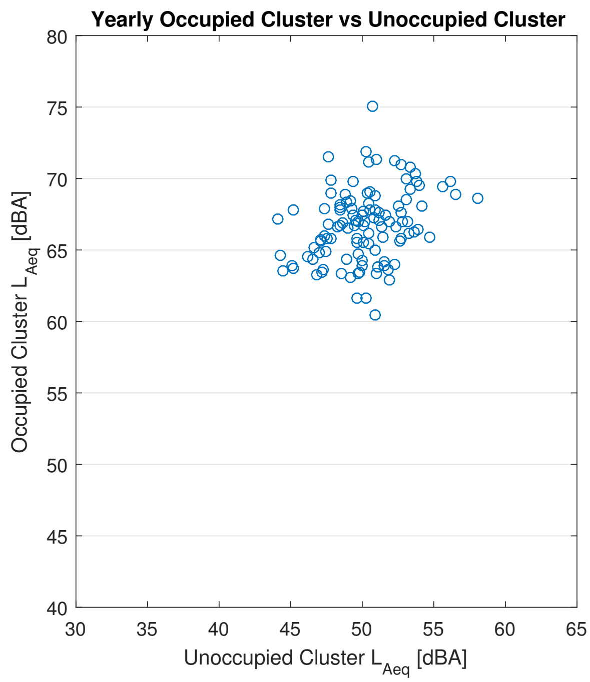


Figure 4.11: Scatter plot of the yearly occupied cluster energy-average A-weighted level against the yearly unoccupied cluster energy-average A-weighted level

These two variables have a statistically significant correlation, but only accounts for 10% of the shared variance ($r = 0.32$, $R^2 = 0.10$, $p < 0.05$). A linear model of the suggests that there is a 0.304 dBA increase in occupied noise level for every 1 dBA increase in unoccupied noise level. While this correlation is stronger than the correlation between the one-minute BNLs and the occupied cluster, it is still not particularly strong. Team members in the field determined if the mechanical systems were on or off which also introduces some error into the accuracy. As previously stated, the BNLs are not a room average. While the Larson-Davis 831 sound level meters are more precise and accurate than the BSWA

309 meters used during continuous logging, they are only used to capture one minute of data. The increased strength in correlation can likely be attributed to a longer sample as well as the clustered results being more comparable because they are both composed of room energy-averaged data on the same types of meters.

This 0.32 statistically significant correlation is similar to the the 0.35 statistically significant correlation found in a similar study conducted by Shield et al. presented in Chapter 1 [Shield et al. 2015]. The increased strength in the correlation found by Shield et al. could be partially explained by their exclusion of occupied times that were observed to be intrusions to lesson activities.

4.2.2 Seasonal Correlation

These tests can be repeated for seasonal averages of each cluster. Additional statistical tests can be applied to determine if there were any significant differences.

Figure 4.12 shows a scatter plot of the occupied cluster energy-averaged A-weighted equivalent levels plotted against the unoccupied cluster energy-averaged A-weighted equivalent levels for the fall measurement season.

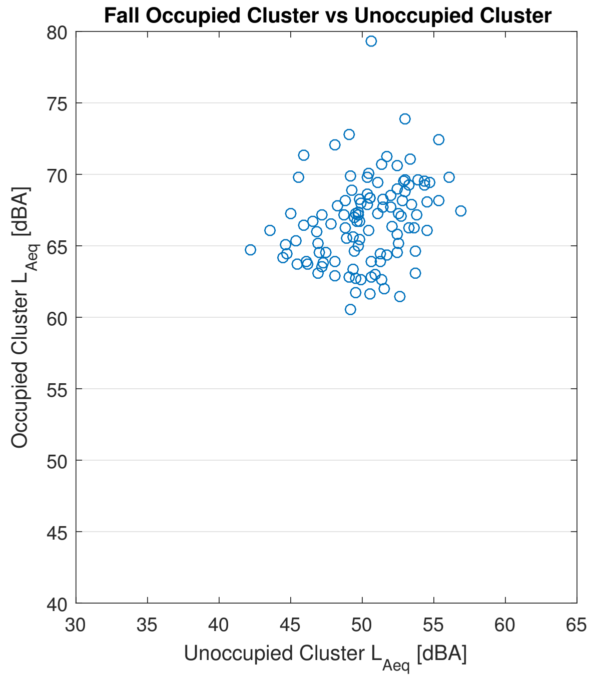


Figure 4.12: Scatter plot of the Fall occupied cluster energy-average A-weighted levels against the Fall unoccupied cluster energy-average A-weighted levels

There is a statistically significant correlation between the fall occupied and unoccupied energy-averaged A-weighted equivalent levels that accounts for 8% of the shared variance ($r = 0.29$, $R^2 = 0.08$, $p < 0.05$). The difference between the yearly and fall correlation coefficients was determined to be insignificant.

Figure 4.13 shows a scatter plot of the occupied cluster energy-averaged A-weighted equivalent levels plotted against the unoccupied cluster energy-averaged A-weighted equivalent levels for the winter measurement season.

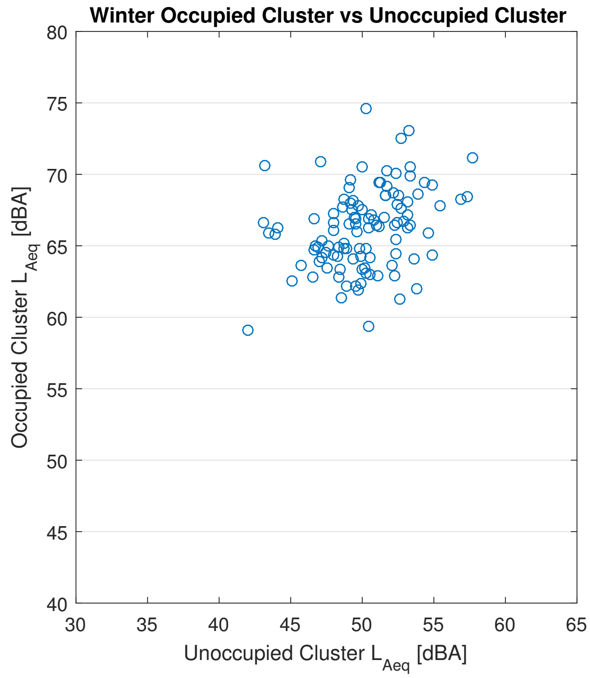


Figure 4.13: Scatter plot of the Winter occupied cluster energy-average A-weighted levels against the Winter unoccupied cluster energy-average A-weighted levels

There is a statistically significant correlation between the winter occupied and unoccupied energy-averaged A-weighted equivalent levels that accounts for 11% of the shared variance ($r = 0.33$, $R^2 = 0.11$, $p < 0.05$). The difference between the yearly and winter correlation coefficients was determined to be insignificant using the Fisher r-to-z transformation [Field et al. 2012].

Figure 4.14 shows a scatter plot of the occupied cluster energy-averaged A-weighted equivalent levels plotted against the unoccupied cluster energy-averaged A-weighted equivalent levels for the spring measurement season.

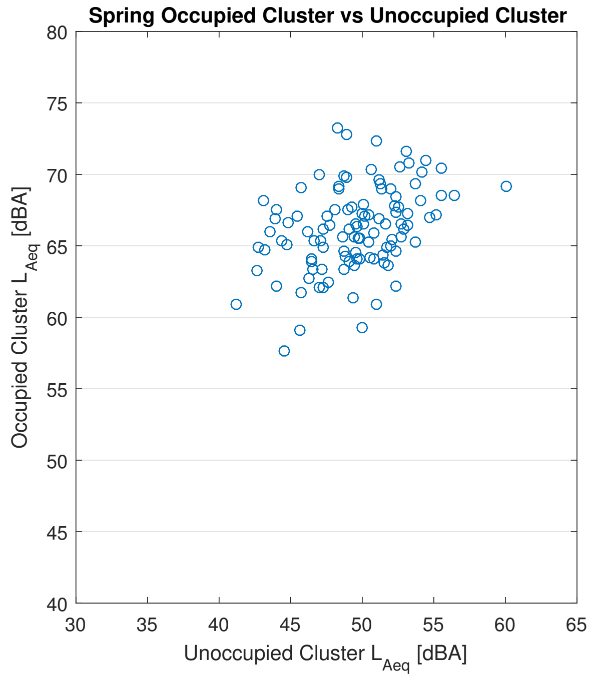


Figure 4.14: Scatter plot of the Spring occupied cluster energy-average A-weighted levels against the Spring unoccupied cluster energy-average A-weighted levels

There is a statistically significant correlation between the spring occupied and unoccupied energy-averaged A-weighted equivalent levels that explains 15% of the shared variance ($r = 0.39$, $R^2 = 0.15$, $p < 0.05$). The difference between the yearly and spring correlation coefficients was determined to be insignificant.

Data from three seasons were available and used to calculate an average representative of the school year. A repeated measures analysis of variance (ANOVA) was conducted to assess the relationship between A-weighted equivalent level, occupancy, and season with occupancy and season as the independent variables and A-weighted equivalent level as the dependent variable. A repeated measures ANOVA was chosen because it allows the analysis of categorical independent variables when observations are nonindependent because they are linked or grouped

in some way [Judd et al. 2009]. In this case they are grouped by season.

Five orthogonal contrast codes were used to assess the relationships (two for season, one for occupancy, and two for the interactions between the two). The two seasonal contrast codes were designed to test one: if there was a linear relationship between the seasonal observations, and two: if there was a quadratic relationship between the seasonal observations. The linear contrast code was designed to test if A-weighted equivalent levels followed a significant linear trend from the fall to the spring. The quadratic contrast code was designed to test if A-weighted equivalent levels in the winter were significantly greater than those in the fall and spring (hence following a quadratic pattern). The results from the tests are presented in Table 4.1.

Table 4.1: Source table for repeated measures ANOVA with three seasons and two states of occupancy for each season

Source	*SumSq*	*df*	*MeanSq*	*F*	*pValue*
Between classrooms	2839.78	104	27.31		
Within classrooms					
Linear seasons	47.78	1	47.78	9.25	0.00
Linear seasons error	537.23	104	5.17		
Quadratic seasons	0.01	1	0.01	0.00	0.97
Quadratic seasons error	502.13	104	4.83		
Occupancy	41885.75	1	41885.75	3391.24	0.00
Occupancy error	1284.52	104	12.35		
Linear seasons x Occupancy	0.73	1	0.73	0.27	0.60
Linear seasons x Occupancy error	276.31	104	2.66		
Quadratic seasons x Occupancy	10.13	1	10.13	3.40	0.07
Quadratic seasons x Occupancy error	310.28	104	2.98		
Total within	44854.86	525			
Total	47695	629			

The results of this analysis suggest that there is a statistically significant increase in A-weighted equivalent level within classrooms from fall to spring ($F(1{,}104) = 9.25$, $p < 0.05$). The results also suggest that occupancy effects on

A-weighted equivalent level are statistically significant ($F(1{,}104) = 3391.24$, $p < 0.05$). The occupancy effect on A-weighted equivalent level are independent of season ($F(1{,}104) = 0.27$, $p > 0.05$). While there are significant effects, the difference in yearly and seasonal correlation coefficients was not shown to be significant.

4.2.3 District Correlation

Correlation between yearly averaged occupied and unoccupied levels were also examined by district.

Figure 4.15 shows a scatter plot of the occupied cluster yearly energy-averaged A-weighted levels against the unoccupied cluster yearly energy-averaged A-weighted levels for District A.

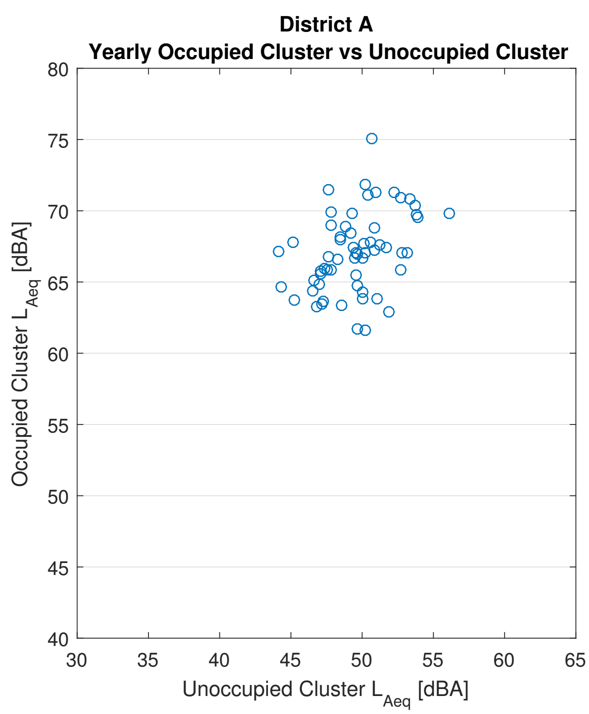


Figure 4.15: Scatter plot of the District A yearly occupied cluster energy-average A-weighted level against the yearly unoccupied cluster energy-average A-weighted level

There is a statistically significant correlation between the occupied and unoccupied energy-averaged A-weighted equivalent levels in District A that accounts for 15% of the shared variance ($r = 0.39$, $R^2 = 0.15$, $p < 0.05$).

Figure 4.16 shows a scatter plot of the occupied cluster yearly energy-averaged A-weighted levels against the unoccupied cluster yearly energy-averaged A-weighted levels for District B.

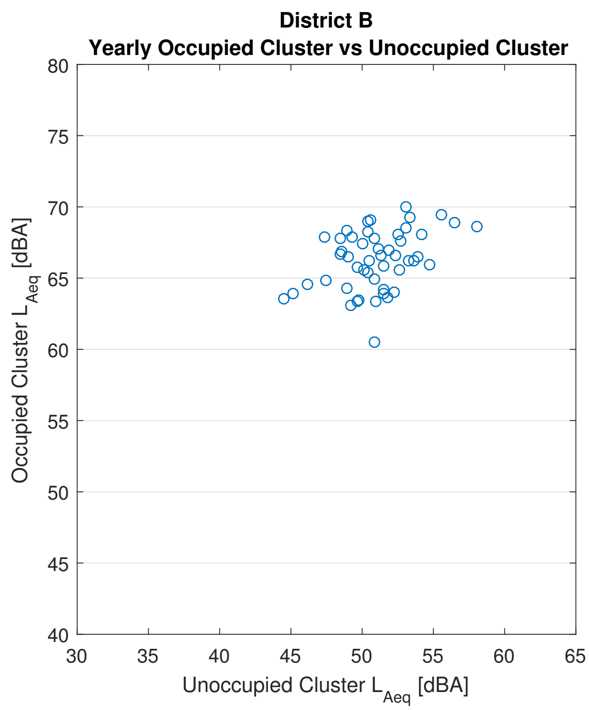


Figure 4.16: Scatter plot of the District B yearly occupied cluster energy-average A-weighted level against the yearly unoccupied cluster energy-average A-weighted level

There is a statistically significant correlation between the occupied and unoccupied energy-averaged A-weighted equivalent levels in District B that accounts for 15% of the shared variance ($r = 0.40$, $R^2 = 0.16$, $p < 0.05$).

Correlation at the district level seems to be stronger than overall. However, The differences between the yearly and district correlation coefficients were

determined to be insignificant.

A two-way factorial ANOVA was conducted with A-weighted equivalent level as the dependent variable and occupancy and district as the independent variables. The results show that occupancy has significant effects on A-weighted equivalent level ($F(1{,}216) = 2296.47, p < 0.05$), while district alone does not have significant effects on A-weighted equivalent level ($F(1{,}216) = 0.85$, $p > 0.05$). The results also show that the effects of occupancy are dependent on district ($F(1{,}216) = 10.91$, $p < 0.05$).

A more in depth analysis shows that unoccupied A-weighted levels in District A are significantly different from unoccupied A-weighted levels in District B (as shown in Figure 4.17).

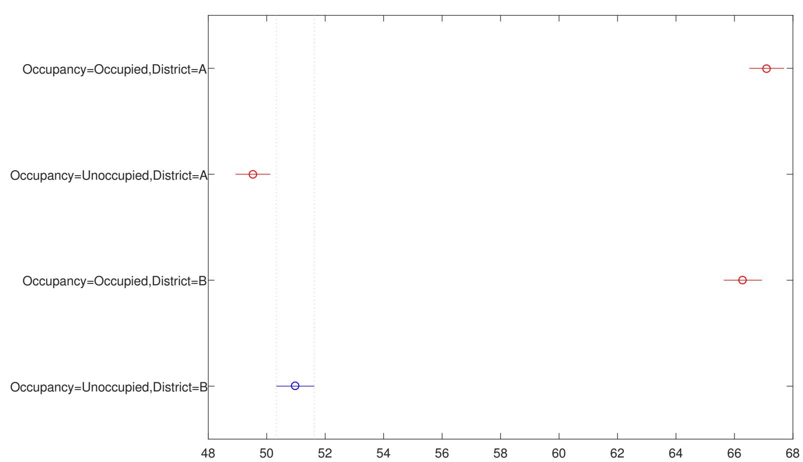


Figure 4.17: Comparison of population marginal means for occupied and unoccupied conditions in Districts A and B.

These results mean that the difference in the correlation between occupied and unoccupied levels between districts is statistically significant. This difference can be explained by the difference in unoccupied A-weighted levels between district. The

unoccupied A-weighted levels help characterize the background noise level, HVAC noise is the main component of unoccupied background noise levels in classrooms, so the unoccupied A-weighted levels should be heavily influenced by the mechanical system. Mechanical systems are different between District A and District B, so it is reasonable that the unoccupied A-weighted levels would be significantly different.

4.3 Concluding Remarks

This chapter provided an initial investigation of correlation between occupied and unoccupied results extracted from a combined six days of data logging. Results were presented at the yearly, seasonal, and district level. These results show that the use of clusters to define occupied and unoccupied conditions affected the correlation. By using k-means clustering, the correlation between unoccupied and occupied A-weighted equivalent levels has shifted to a statistically significant 0.32 correlation from an insignificant 0.16 correlation when occupied was defined as the overall school day average and unoccupied was defined as the 1-minute unoccupied BNL. However, there is not a statistically significant difference between these correlation coefficients as determined by an r-to-z transformation.

Chapter 5

Investigation of Activity

The hypothesis that led to the use of clustering was that the overall energy average did not sufficiently account for periods of inactivity. This hypothesis can be modified and implemented again to determine if there are distinct activity levels that might have different effects on the correlation.

A follow up clustering was performed on each initial cluster to parse out distinguishable activity levels. While k-means clustering is an unsupervised learning technique, there are still some methods to determine the optimal choice of K. A method for determining the optimal number of sub-clusters was implemented. Observations will be split into any number of clusters specified and the observations will be forced into the "most appropriate" cluster; however this does not mean that it's the best fit. For instance, if a set of observations had two underlying characteristics and was then fit into three clusters, observations that had a distinct characteristic would be forced into a separate cluster that could be a mix of observations expressing different characteristics, it could be a subset of one of the

two characteristics, or it could force clusters that do not correspond to either of the characteristics. The choice to perform k-means on the school day observations with K=2 was somewhat more straightforward and easier to evaluate and verify with classroom schedules; however, at this point, there's no way to validate activity levels in the classrooms measured during the 2015-2016 academic year. Work is underway to validate measurements levels taken during the 2016-2017 academic year.

Cluster choice is important because k-means clustering forces every observation into a cluster regardless of whether or not an observation actually belongs to a cluster or an interpretation of that cluster actually exists or is meaningful. Clustering evaluation techniques were used to determine the optimal number of sub-clusters in each cluster. Clustering evaluation techniques are available in MATLAB using the function *evalclusters*. Four clustering evaluation criterion are available in this function: Calinski-Harabasz index, Davies-Bouldin index, gap statistic, and silhouettes. For the most part, index values are indicative of the clusters separation and tightness. The optimal choice for K will be where the within-cluster variation is minimized and the between cluster distance is maximized. A routine to evaluate the optimal number of sub-clusters for the occupied and unoccupied clusters was performed on the data from each season for each criterion. The function was fed the octave data to be clustered using k-means as well as an array of K values (1:6) to be tested. While each criterion was tested, gap statistic was too computationally intensive and was not always able to converge to a solution in a reasonable amount of time. For these reasons, the limited results were not taken into consideration.

All of the evaluated techniques indicated $K=2$ as the optimal sub-cluster choice for over 90% of the classrooms for both the occupied and unoccupied clusters for every season. K-means clustering was then performed on the occupied and unoccupied clusters with $K=2$ to isolate sub-clusters in the observations.

A sub-cluster labeling convention has been established to concisely and clearly label and discuss the sub clusters. Sub-clusters will be denoted by Occ for "occupied" and $Unocc$ for "unoccupied." The sub-cluster number will be denoted by a subscript one or two. Sub-clusters with a higher average have ones as the subscript while sub-clusters with a lower average have twos as the subscript. For example, the second occupied sub-cluster will be denoted as Occ_2 and the energy-average of that sub-cluster will be denoted as $\overline{Occ_2}$.

Figure 5.1 shows an example of the time logged A-weighted equivalent level broken into occupied and unoccupied sub-clusters.

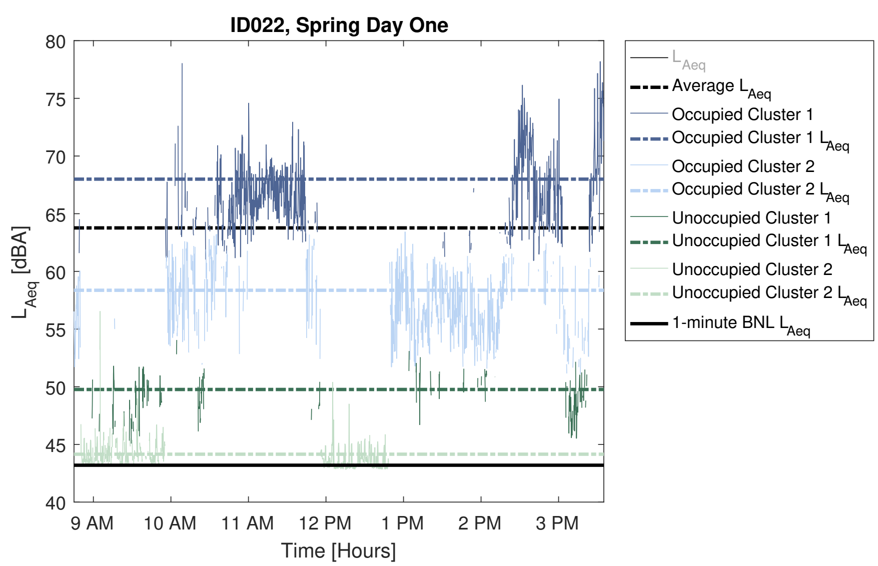


Figure 5.1: Room energy-averaged A-weighted equivalent level for a single school day broken up into two clusters shown with the overall average and cluster averages, and one-minute BNL.

The calculated sub-cluster energy-averages for this classroom are visually different from the calculated school day energy-average and one-minute BNL. In this classroom, the school day energy-average for the spring was 63.8 dBA while $\overline{Occ_1}$ was calculated to be 68.0 dBA, and $\overline{Occ_2}$ was calculated to be 58.4 dBA. There is a 4.2 dB and 5.4 dB absolute difference between the school day and the first and second occupied sub-clusters respectively. The measured one-minute BNL was 43.2 dBA while $\overline{Unocc_1}$ was calculated to be 49.8 dBA, and $\overline{Unocc_2}$ was calculated to be 44.2 dBA. The difference between the measured BNL and the calculated $\overline{Unocc_1}$ is 6.6 dB while the difference between the measured BNL and the calculated $\overline{Unocc_2}$ is 1 dB.

5.1 Spectral Characteristics

5.1.1 Overall

Box plots of the classrooms yearly energy-averaged A-weighted and octave band levels for each cluster have been examined in order to interpret the clustering based on differences in spectral characteristics and are all shown in Figure 5.2.

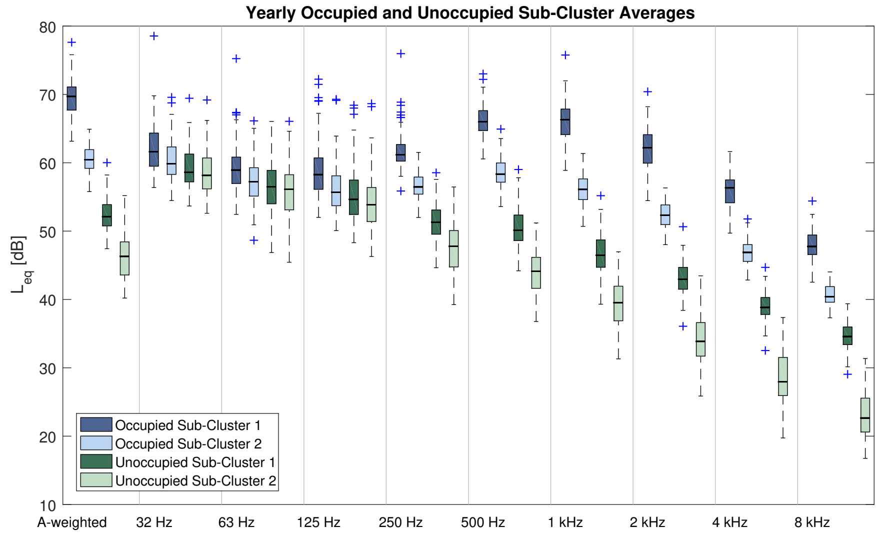


Figure 5.2: Box plot of enery-averaged equivalent sound levels from all of the occupied and unoccupied sub-clusters.

Figure 5.3 shows a box plot representative of the yearly energy-averaged A-weighted and octave band levels for all 110 classrooms averaged over the occupied sub-clusters.

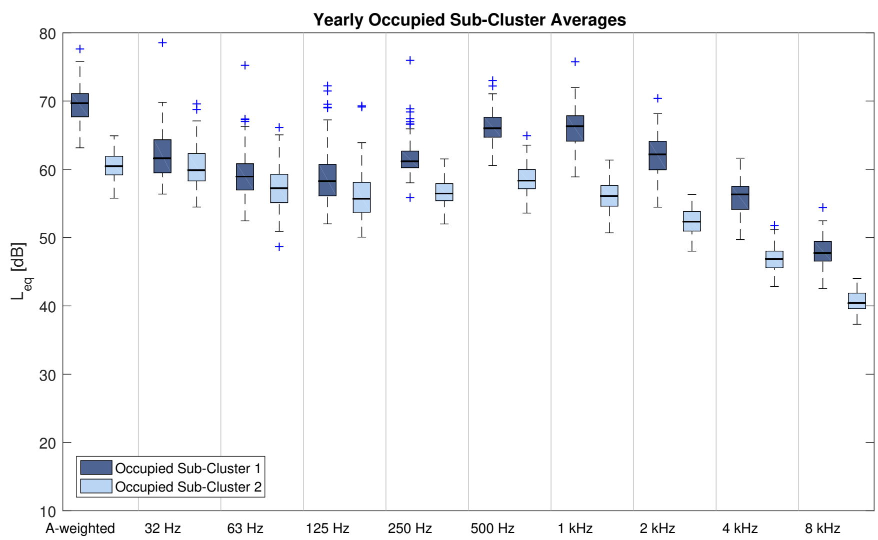


Figure 5.3: Box plot of energy-averaged equivalent sound levels from the occupied sub-clusters.

One interpretation of the first occupied sub-cluster could be periods of time when students were engaged in hands-on or group activities (group learning). The

basis for this interpretation is the raised levels in 1000 Hz octave band. In the overall occupied cluster averages seen in Figure 4.4, the octave band with the highest average was 500 Hz. Since the fundamental frequency of children's voices is higher than adults', it makes sense that the 1000 Hz octave band would be raised during periods of group learning. Whispering would also raise this level. Data from this sub-cluster will be interpreted as group levels.

One interpretation of the second occupied sub-cluster could be periods of instruction or single speakers. The peak octave band is 500 Hz which would correspond more with adult fundamental frequencies; however, this cluster could also encompass periods of time when a single student was talking. Picard and Bradley [2001] summarized long term average A-weighted speech levels from approximately 183 teachers compiled from eight different studies and calculated the mean speech level to be 60.1 dBA. These studies had a mixture of known and unknown source (teacher)-receiver distances. The mean of the energy-averaged A-weighted levels from this sub-cluster is 60.5 dBA. Data from this sub-cluster will be interpreted as instructional or single-speaker levels.

Figure 5.4 shows a box plot representative of the yearly energy-averaged A-weighted and octave band levels for all 110 classrooms averaged over the unoccupied sub-clustered time periods with the highest and lowest average A-weighted levels respectively.

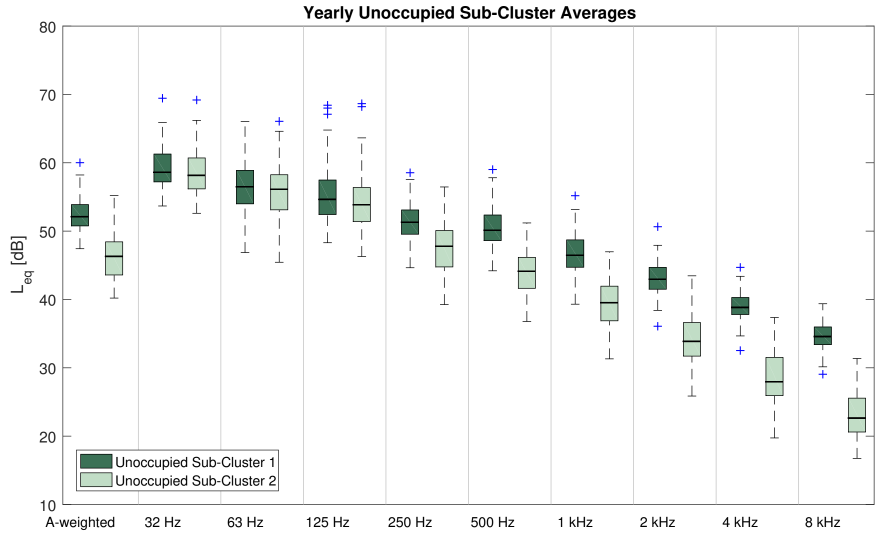


Figure 5.4: Box plot of energy-averaged sound levels from the unoccupied sub-clusters.

Hodgson [1994], showed that student generated background noise due to movement and not speech can raise the noise floor by approximately 5 dB. The first unoccupied sub-cluster has been interpreted to be periods of silent occupancy while the second unoccupied sub-cluster has been interpreted to be representative of the unoccupied, ventilation background noise level.

Now that an interpretation of the sub-clusters has been established, the spectral characteristics of each sub-cluster will be examined by season and district.

5.1.2 Seasonal

Spectral characteristics at the seasonal level were also examined in order to determine differences that might affect the yearly averages.

Figure 5.5 shows a box plot of energy-averaged A-weighted and octave band levels from the first occupied sub-cluster during the fall, winter, and spring.

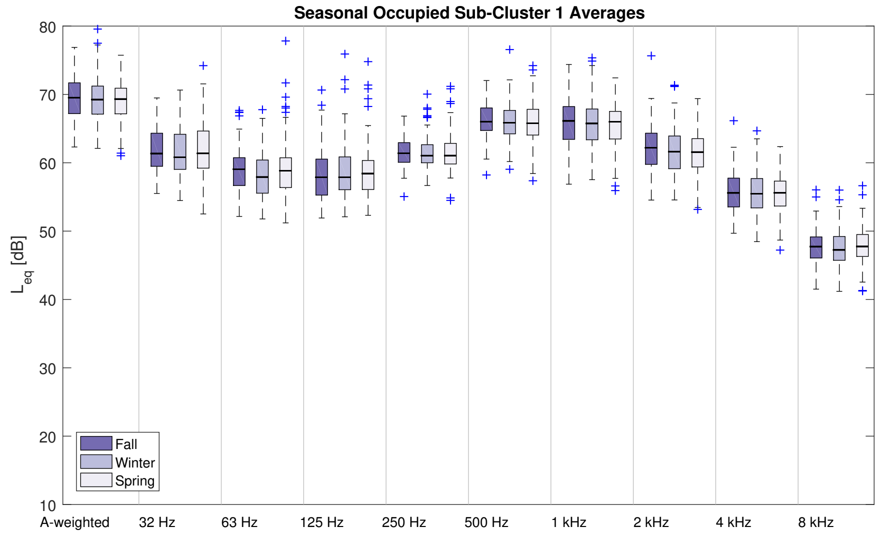


Figure 5.5: Box plot of the seasonal energy-averaged equivalent sound levels from the occupied sub-cluster with the highest average A-weighted equivalent level.

In the fall, nine classrooms have a 3-6 dBA difference from the yearly first occupied sub-cluster, and one classroom has a difference between 6-9 dBA. In the winter, eighteen classrooms have a difference between 3-6 dBA from the yearly average and one classroom has a difference between 6-9 dBA. In the spring, ten classrooms have a difference between 3-6 dBA and three classrooms have a difference between 6-9 dBA.

Figure 5.6 shows a box plot of energy-averaged A-weighted and octave band levels from the second occupied sub-cluster during the fall, winter, and spring.

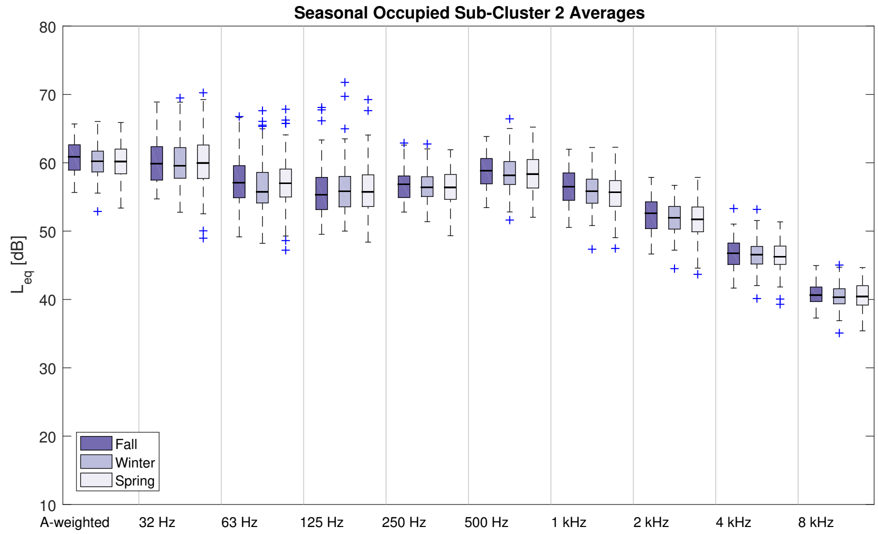


Figure 5.6: Box plot of the seasonal energy-averaged equivalent sound levels from the occupied sub-cluster with the second highest average A-weighted equivalent level.

In the fall, four classrooms have differences between 3-6 dBA compared to the yearly average. In the winter, three classrooms have differences between 3-6 dBA compared to the yearly average. In the spring, seven classrooms have differences between 3-6 dBA and one classroom has a difference between 6-9 dBA compared to the yearly average.

Figure 5.7 shows a box plot of the seasonal energy-averaged A-weighted and octave band levels from the first unoccupied sub-cluster with the highest A-weighted equivalent level.

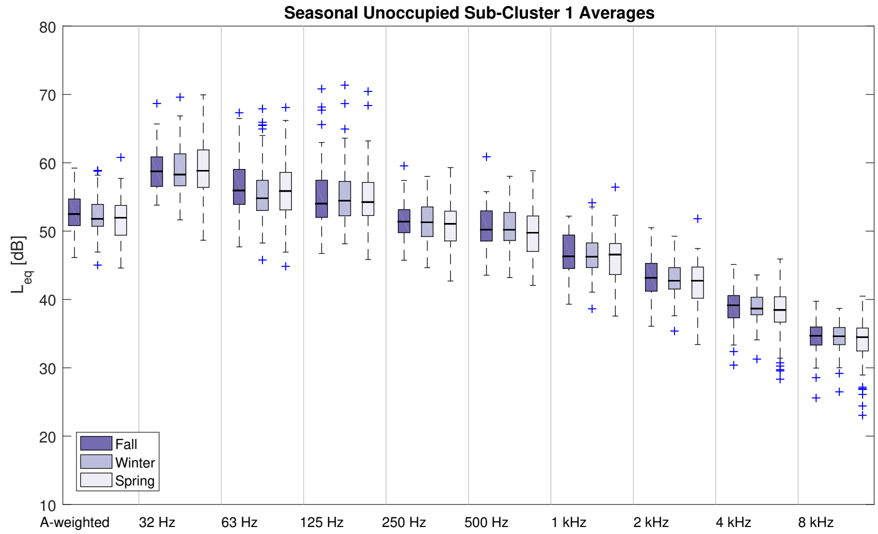


Figure 5.7: Box plot of the seasonal energy-averaged equivalent sound levels from the unoccupied sub-cluster with the highest average A-weighted equivalent level.

In the fall, five classrooms have differences between 3-6 dBA from the yearly average. In the winter, one classroom has a difference between 6-9 dBA. In the spring, ten classrooms have differences between 3-6 dBA and one classroom has a difference between 6-9 dBA.

Figure 5.8 shows a box plot of energy-averaged A-weighted equivalent and octave band levels from the second unoccupied sub-cluster.

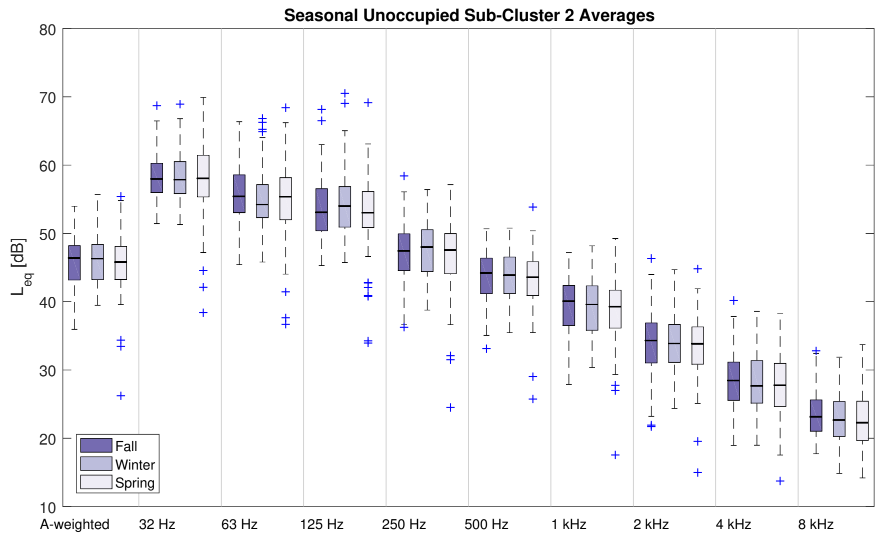


Figure 5.8: Box plot of the seasonal energy-averaged equivalent sound levels from the occupied sub-cluster with the lowest average A-weighted equivalent level.

In the fall, two classrooms have differences between 3-6 dBA and two classrooms have differences greater than 9 dBA relative to the yearly average. In the winter, one classroom has a relative difference between 3-6 dBA, one classroom has a relative difference between 6-9 dBA, and one classroom has a relative difference greater than 9 dBA. In the spring, three classrooms have relative differences between 3-6 dBA, three classrooms have relative differences between 6-9 dBA, and two classrooms have relative differences greater than 9 dBA.

5.1.3 District

Figure 5.9 shows the yearly energy-averaged A-weighted and octave band equivalent levels of the first occupied sub-cluster plotted by district.

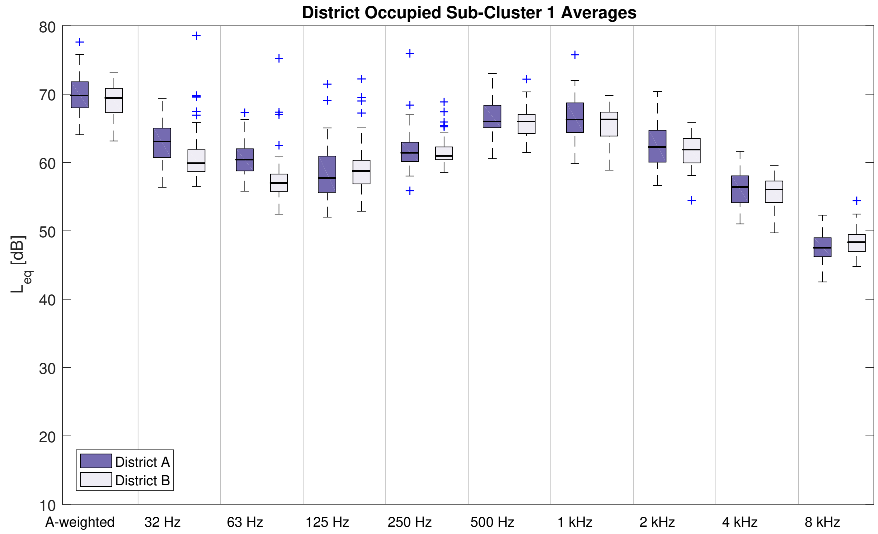


Figure 5.9: Box plot of yearly energy-averaged equivalent sound levels from the occupied sub-cluster with the highest average A-weighted level plotted by district.

Figure 5.10 shows the yearly energy-averaged A-weighted and octave band levels of Occ_2 for Districts A and B respectively.

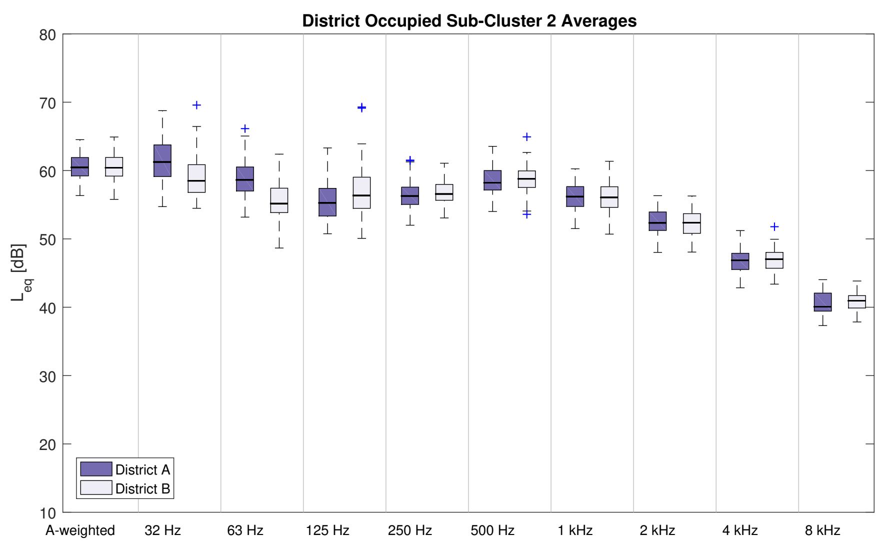


Figure 5.10: Box plot of yearly energy-averaged equivalent sound levels from the occupied sub-cluster with the second highest average A-weighted level plotted by district.

The results from the occupied sub-clusters are visually consistent across

district.

Figure 5.11 shows the yearly energy-averaged A-weighted and octave band levels of the first unoccupied sub-cluster plotted by district.

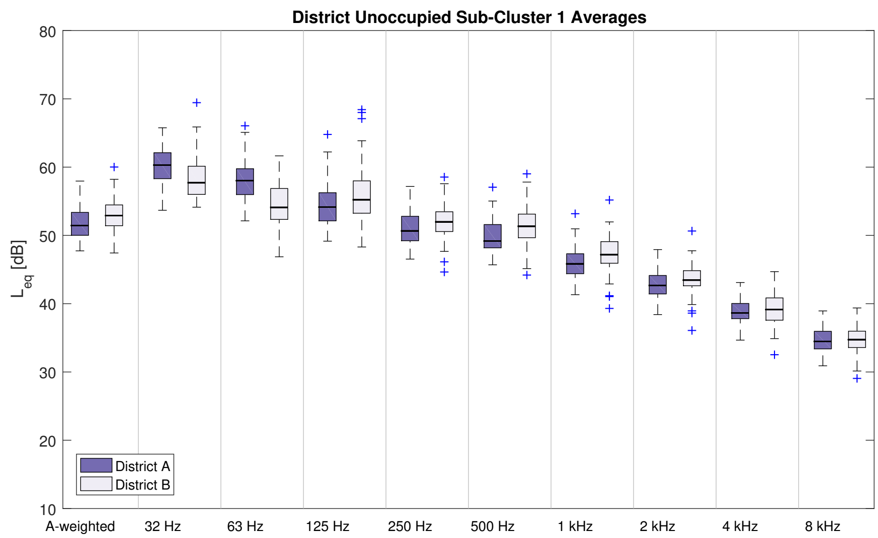


Figure 5.11: Box plot of yearly energy-averaged equivalent sound levels from the unoccupied sub-cluster with the highest average A-weighted level plotted by district.

Figure 5.12 shows the yearly energy-averaged A-weighted and octave band levels of the second unoccupied sub-cluster plotted by district.

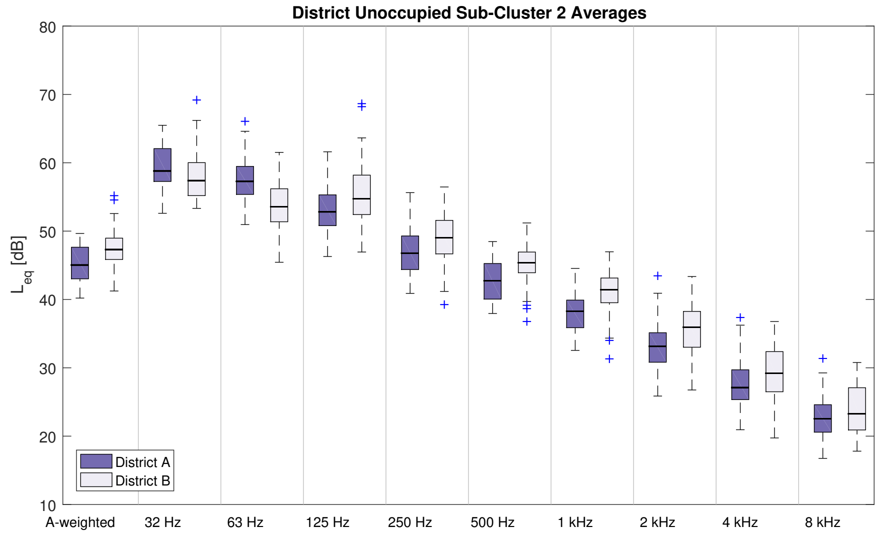


Figure 5.12: Box plot of energy-averaged equivalent sound levels from the unoccupied sub-cluster with the second highest average A-weighted level plotted by district.

Overall, the spectral characteristics between districts are comparable. However, as presented in Section 4.2.3, there is less energy in the 63 Hz octave band relative to 32 and 125 Hz in District B than in District A. In the second unoccupied sub-cluster, there is more energy in District B between 125 Hz-8 kHz than in District A. This is likely a characteristic of the mechanical systems in District B as compared to those in District A.

5.2 Investigation of Correlation Between Sub-Clusters

Once an interpretation of the sub-clustered observations was established, the next step was to investigate the relationships between the sub-clusters. The Pearson Correlation Coefficient, r, was chosen as the criteria for correlation because it

establishes the strength of a linear relationship between two variables. The coefficient of determination, R^2, was also calculated when there was a statistically significant correlation to determine the amount of shared variance between the two variables. These methods were presented in Chapter 3.

5.2.1 Yearly Correlation

Figure 5.13 shows a scatter plot of the yearly, energy-averaged A-weighted levels of the sub-cluster indicative of group activity (Occ_1) plotted against the one-minute BNLs.

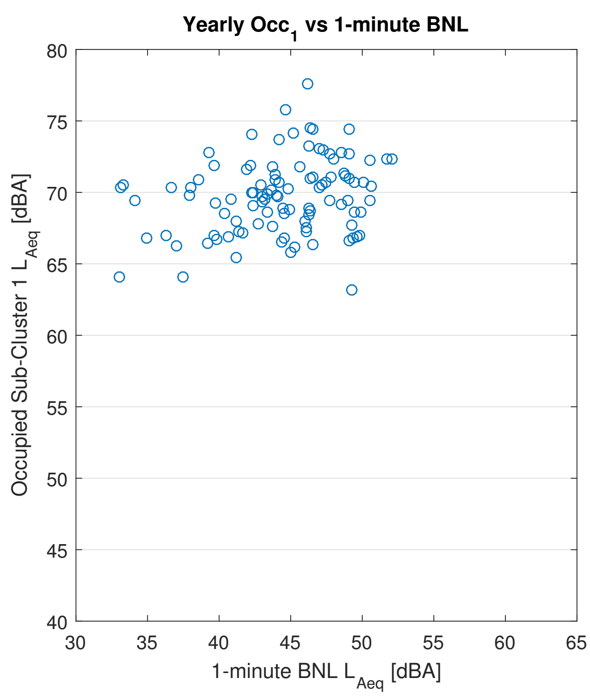


Figure 5.13: Scatter plot of the yearly first occupied sub-cluster energy-average A-weighted levels against the one-minute BNL for each classroom

There is a significant correlation between the variables, but only accounts for 6% of the shared variance between the variables ($r = 0.25$, $R^2 = 0.06$, $p < 0.05$). Again, this is not necessarily surprising since the one-minute BNL measurement was

taken in the same position as the kit meter and the averages are based off of the energy average of the kit and hanging meters.

Figure 5.15 shows a scatter plot of the yearly, energy-averaged A-weighted levels of the sub-cluster indicative of instructional activity (Occ_2) plotted against the one-minute BNLs.

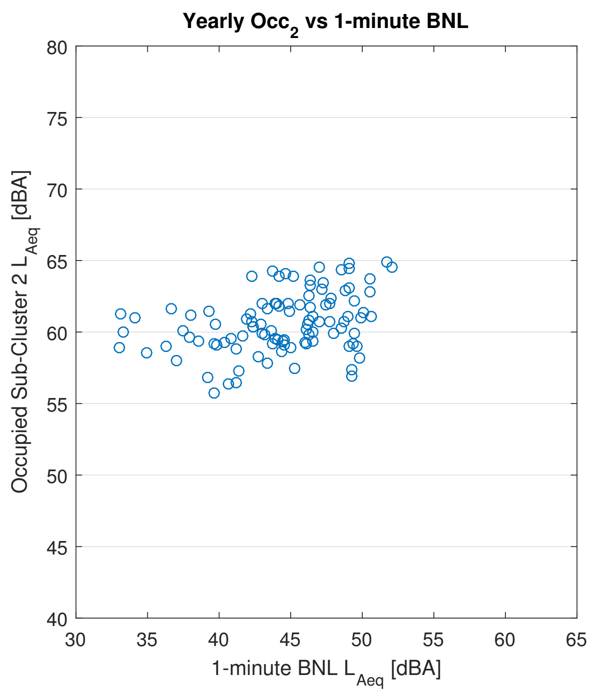


Figure 5.14: Scatter plot of the yearly second occupied sub-cluster energy-averaged A-weighted level against the one-minute BNL for each classroom

There is a significant correlation between instructional and one-minute BNL A-weighted levels that explains 13% of the shared variance (r = 0.37, R^2 = 0.13, p < 0.05). While this correlation is significant, the correlation might be improved by correlating the occupied sub-clusters to the unoccupied su-clusters as seen in the previous chapter. In order to justify the interpretation of the unoccupied sub-clusters, the correlation was calculated between the one-minute BNL and each

unoccupied sub-cluster.

Figure 5.15 shows a scatter plot of the yearly, energy-averaged A-weighted levels of the sub-cluster indicative of quiet occupants ($Unocc_1$) against the one-minute BNL.

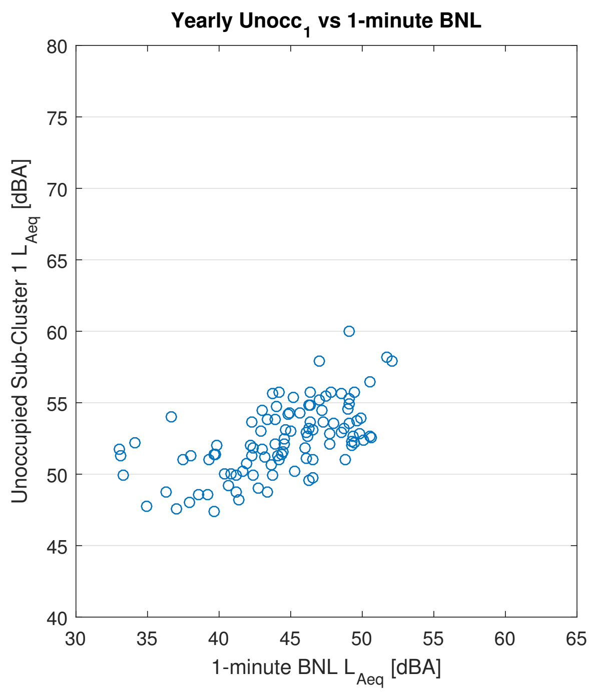


Figure 5.15: Scatter plot of the yearly first unoccupied sub-cluster energy-average A-weighted equivalent level against the one-minute BNL for each classroom

There is a strong correlation between $Unocc_1$ and one-minute BNL A-weighted levels that explains 36% of the shared variance ($r = 0.60$, $R^2 = 0.36$, $p < 0.05$).

Figure 5.16 shows a scatter plot of the yearly, energy-averaged A-weighted equivalent levels of the sub-cluster indicative of unoccupied, ventilation noise ($Unocc_2$) against the one-minute BNL.

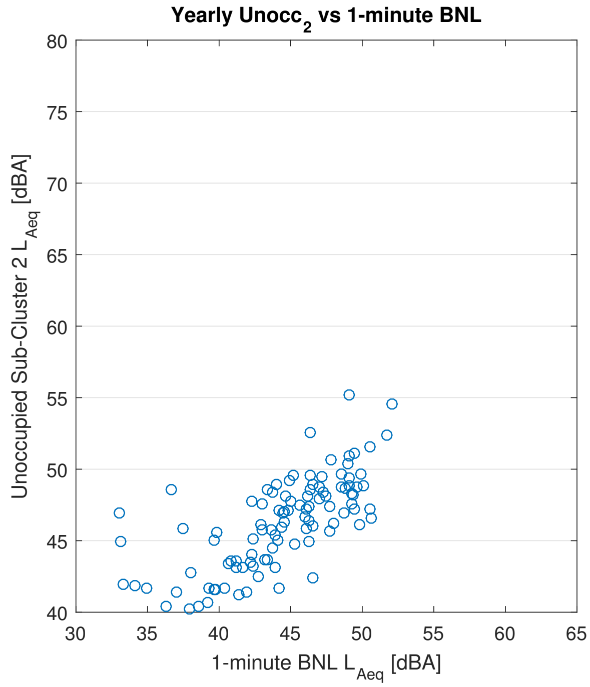


Figure 5.16: Scatter plot of the yearly second unoccupied sub-cluster energy-average A-weighted equivalent level against the one-minute BNL for each classroom

There is a significant correlation between $Unocc_2$ and one-minute BNL A-weighted levels that explains 50% of the shared variance (r = 0.70, R^2 = 0.50, p < 0.05). This strong correlation suggests that the there is reason to interpret this cluster as average unoccupied background noise.

As before, correlations were next calculated between cluster averages. Figure 5.17 shows a scatter plot of the yearly, energy-averaged A-weighted group activity level against the yearly, A-weighted energy-averaged unoccupied, ventilation level.

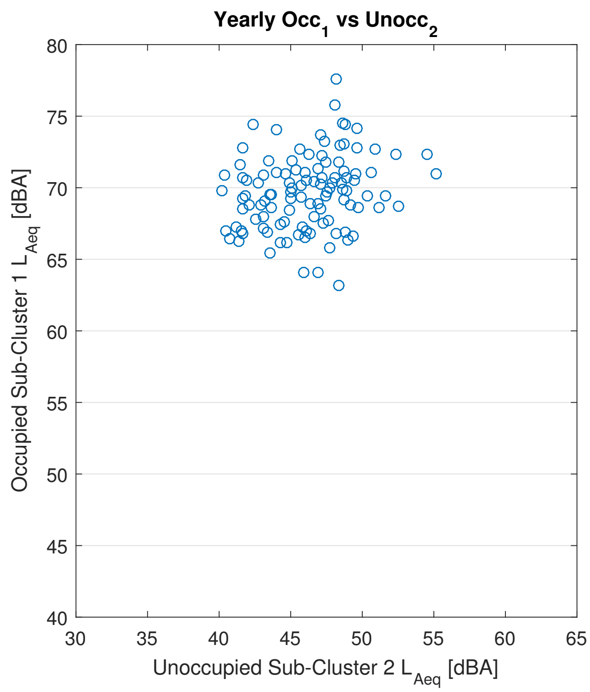


Figure 5.17: Scatter plot of the yearly first occupied sub-cluster energy-average A-weighted equivalent level against the second unoccupied sub-cluster for each classroom

There is a statistically significant correlation between the group activity level and the unoccupied, ventilation level, but it only accounts for 5% of the shared variance ($r = 0.23$, $R^2 = 0.05$, $p < 0.05$). Based on the interpretation of these sub-clusters, this weak correlation seems reasonable and would seem to depend more on the type of activity and the number of students in the classroom than the background noise level.

Figure 5.18 shows a scatter plot of the yearly, instructional energy-average A-weighted equivalent level against the yearly, A-weighted energy-averaged unoccupied, ventilation level.

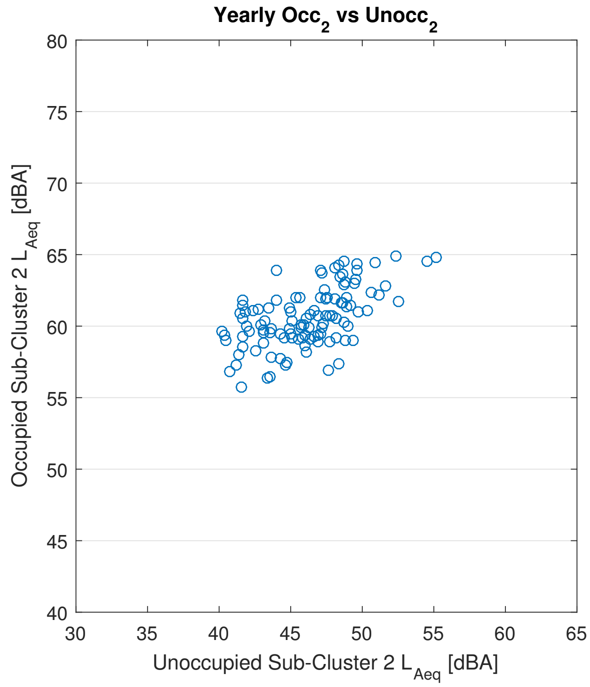


Figure 5.18: Scatter plot of the yearly second occupied sub-cluster energy-average A-weighted equivalent level against the second unoccupied sub-cluster for each classroom

There is a significant correlation between the instructional activity level and the unoccupied, ventilation level that accounts for 33% of the shared variance. A linear model suggests that the instructional levels increase by 0.4 dBA for every 1 dBA increase in ventilation noise ($r = 0.58$, $R^2 = 0.33$, $p < 0.05$). This correlation is stronger than the correlation between the occupied and unoccupied clusters presented in Chapter 4. The correlation between ventilation noise level and group activity levels are ultimately not as pertinent to this research as the correlation between ventilation and instructional levels. For this reason, the correlation between the second unoccupied sub-cluster and the second occupied sub-cluster will be presented by season and district.

5.2.2 Seasonal Correlation

Figure 5.19 shows a scatter plot of the energy-averaged A-weighted instructional levels (Occ_2) against the A-weighted energy-averaged unoccupied, ventilation levels ($Unocc_2$) measured during the fall.

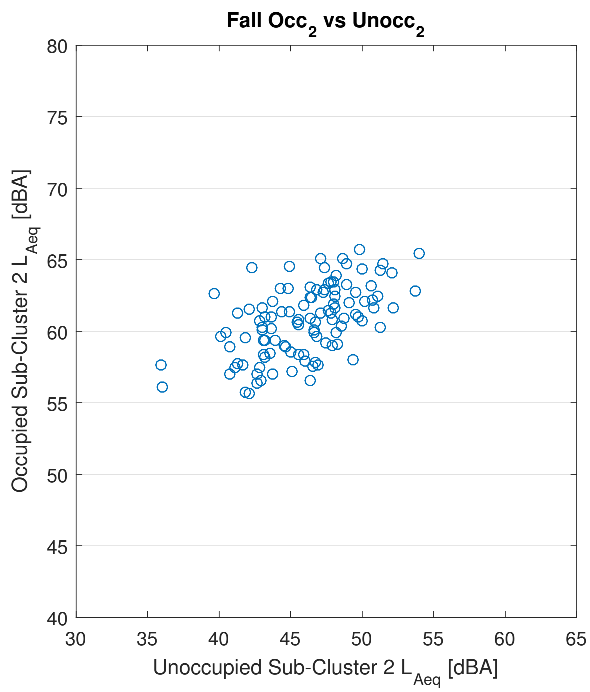


Figure 5.19: Scatter plot of the second occupied sub-cluster energy-average A-weighted equivalent level against the second unoccupied cluster for each classroom during the fall.

There is a significant correlation between the instructional activity level and the unoccupied ventilation level measured during the fall that accounts for 32% of the shared variance ($r = 0.57$, $R^2 = 0.32$, $p < 0.05$). There is not a significant difference between the yearly and fall correlation coefficients for data of this type.

Figure 5.20 shows a scatter plot of the energy-averaged A-weighted instructional levels (Occ_2) against the A-weighted energy-averaged unoccupied, ventilation levels ($Unocc_2$) measured during the winter.

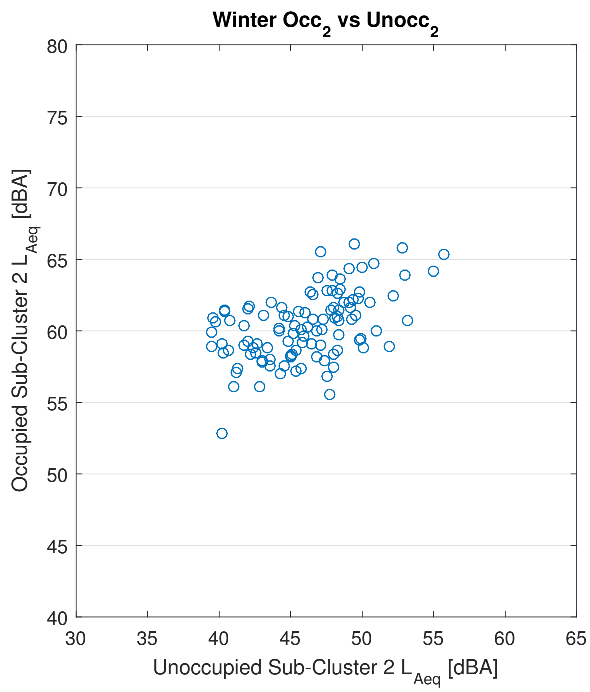


Figure 5.20: Scatter plot of the second occupied sub-cluster energy-average A-weighted equivalent level against the second unoccupied cluster for each classroom during the winter.

There is a significant correlation between the instructional activity level and the unoccupied ventilation level measured in the winter that accounts for 26% of the shared variance ($r = 0.51$, $R^2 = 0.26$, $p < 0.05$). There is not a significant difference between the yearly and winter correlation coefficients for data of this type.

Figure 5.21 shows a scatter plot of the energy-averaged A-weighted instructional levels (Occ_2) against the A-weighted energy-averaged unoccupied, ventilation levels ($Unocc_2$) measured during the spring.

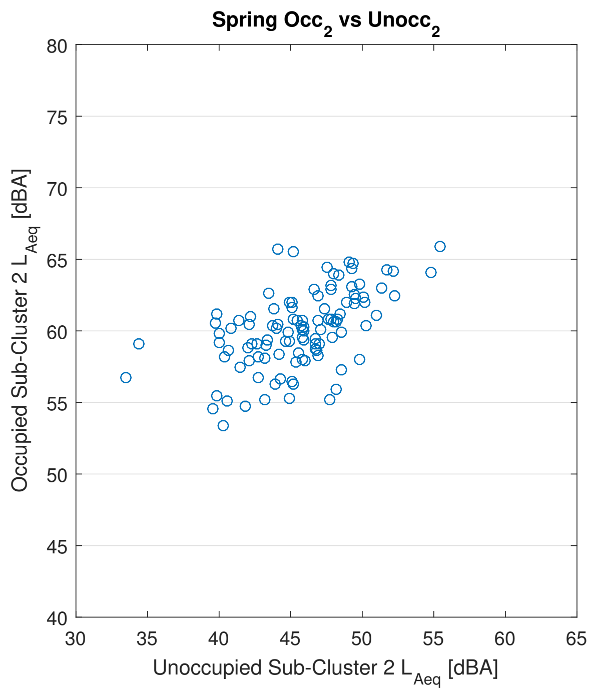


Figure 5.21: Scatter plot of the second occupied sub-cluster energy-average A-weighted equivalent level against the second unoccupied cluster for each classroom during the spring.

There is a significant correlation between the instructional activity level and the unoccupied ventilation level measured in the spring that accounts for 25% of the shared variance ($r = 0.5$, $R^2 = 0.25$, $p < 0.05$). There is not a significant difference between the yearly and spring correlation coefficients for data of this type.

A repeated measures ANOVA was conducted using the same approach presented in Section 4.2.2. The results from this analysis are presented in Table 5.1.

The results of this analysis suggest that there is a statistically significant increase in A-weighted equivalent level within classrooms from fall to spring ($F(1,104) = 5.23$, $p < 0.05$). The results also suggest that occupancy effects on A-weighted equivalent level are statistically significant ($F(1,104) = 3255.56$, $p < 0.05$). The occupancy effect on A-weighted equivalent level are independent of

Table 5.1: Source table for repeated measures ANOVA with three seasons and two states of more specific occupancy for each season

Source	*SumSq*	*df*	*MeanSq*	*F*	*pValue*
Between classrooms	3528.68	104	33.93		
Within classrooms					
Linear seasons	39.10	1	39.10	5.23	0.02
Linear seasons error	776.84	104	7.47		
Quadratic seasons	1.95	1	1.95	0.43	0.51
Quadratic seasons error	467.75	104	4.50		
Occupancy	33016.79	1	33016.79	3255.56	0.00
Occupancy error	1054.73	104	10.14		
Linear seasons x Occupancy	0.00	1	0.00	0.00	0.99
Linear seasons x Occupancy error	335.71	104	3.23		
Quadratic seasons x Occupancy	9.04	1	9.04	3.88	0.05
Quadratic seasons x Occupancy error	242.57	104	2.33		
Total within	35944.50	525			
Total	39473	629			

season ($F(1,104) = 0.00$, $p > 0.05$). Although there are significant effects, there is not a significant difference between the yearly and seasonal correlation coefficients.

5.2.3 District Correlation

Correlation between yearly averages of the second occupied sub-cluster and second unoccupied sub-cluster were also examined by district.

Figure 5.22 shows a scatter plot of the energy-averaged A-weighted instructional levels (Occ_2) against the A-weighted energy-averaged unoccupied, ventilation levels ($Unocc_2$) measured in District A.

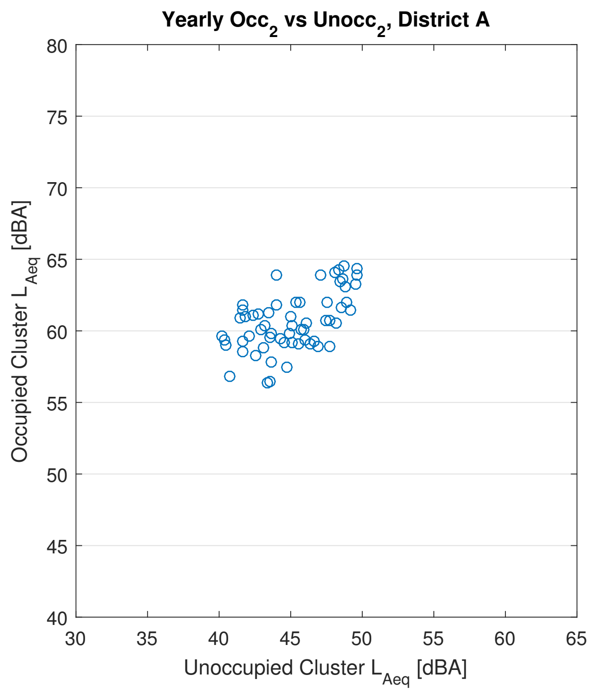


Figure 5.22: Scatter plot of the second occupied sub-cluster energy-average A-weighted equivalent level against the second unoccupied cluster for each classroom in District A.

There is a significant correlation between the instructional activity level and the unoccupied ventilation level measured in District A that accounts for 32% of the shared variance ($r = 0.57$, $R^2 = 0.32$, $p < 0.05$). The difference between the yearly and District A correlation coefficient is not significant.

Figure 5.23 shows a scatter plot of the energy-averaged A-weighted instructional levels (Occ_2) against the A-weighted energy-averaged unoccupied, ventilation levels ($Unocc_2$) measured during in District B.

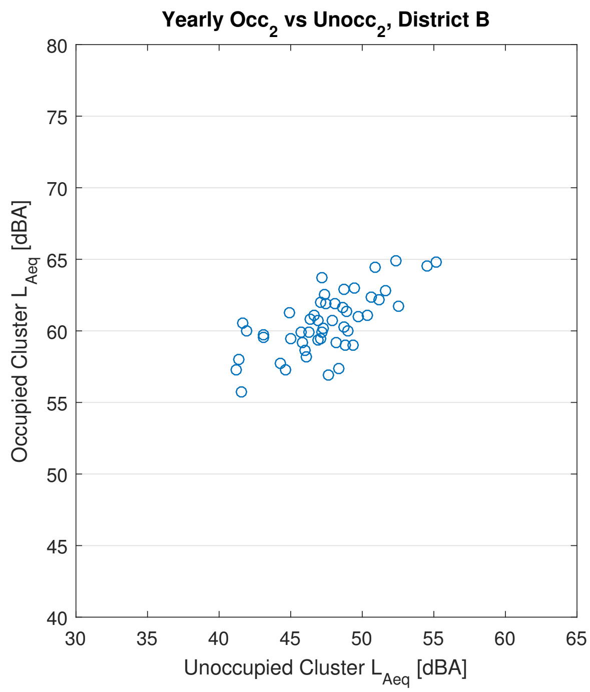


Figure 5.23: Scatter plot of the second occupied sub-cluster energy-average A-weighted level against the second unoccupied cluster for each classroom in District B.

There is a significant correlation between the instructional activity level and the unoccupied ventilation level measured in District B that accounts for 47% of the shared variance ($r = 0.69$, $R^2 = 0.47$, $p < 0.05$). The difference between the yearly and District B correlation coefficients is not statistically significant.

Although the district level correlation coefficients seem different, the difference is not statistically significant.

A two-way factorial ANOVA was conducted with occupancy and district as the independent variables and A-weighted equivalent levels from the second sub-clusters as the dependent variable. The results of this analysis show that occupancy effects on A-weighted equivalent level are, again, significant ($F(1,216) = 1715.84$, $p < 0.05$), the occupancy effects are, again, dependent on district effects ($F(1,216) =$

11.94, $p < 0.05$), and in this case, the district effects on A-weighted equivalent level are significant (F(1,216) = 10.48, $p < 0.05$). These results mean that occupied and unoccupied levels are significantly different from one another and that the levels measured in District A are significantly different than those measured in District B. The interaction of these two effects could possibly help explain the difference in correlation of occupied levels and unoccupied levels between District A and District B. Although there are significant district effects, there is not a significant difference between the district correlation coefficients.

5.3 Concluding Remarks

This chapter provided an investigation of correlation between occupied and unoccupied sub-clusters interpreted to be representative of activity levels. Results were presented at the yearly, seasonal, and district level. These results show that the use of clusters to characterize occupied and unoccupied activity sound levels affected the correlation found between occupied and unoccupied conditions. The correlation between yearly unoccupied ventilation levels and occupied instructional levels was calculated to be 0.58 ($p < 0.05$). A linear regression of these yearly A-weighted equivalent levels indicated that instructional levels increase 0.4 dBA for every 1 dBA increase in ventilation noise.

Chapter 6

Conclusion and Recommendations for Future Work

6.1 Conclusion

The work presented in this thesis characterized the relationship between occupied and unoccupied levels in 110 K-12 classrooms in two Midwestern school districts. The definition of occupied and unoccupied conditions affected the correlation. Three definitions of occupied and unoccupied conditions were used. First, occupied levels were defined as the energy-average of the A-weighted equivalent levels measured during the school day and unoccupied levels were defined as the one-minute, unoccupied BNL. The correlation between these two conditions was not statistically significant ($r = 0.16$, $p > 0.05$). K-means clustering was used to categorize the observations from each classroom and season to establish occupied and unoccupied conditions. The correlation between the clusters interpreted to be indicative of

occupied and unoccupied conditions was significant ($r = 0.32$, $p < 0.05$). This result is consistent with the 0.35 correlation found by Shield et al. [2015]. A linear model of this data suggests that there is a 0.3 dBA increase in occupied levels for every 1 dBA increase in unoccupied levels. In order to determine how speech is affected by increasing background noise levels, k-means clustering was performed once again to isolate sub-categories in each cluster in order to define distinct activities. The correlation between the sub-clusters interpreted to be indicative of instructional activities and ventilation levels was significant ($r = 0.58$, $p < 0.05$). A linear model of this data suggests that there is a 0.4 dBA increase in instructional level for every 1 dBA increase of ventilation level. Unlike some of the previous studies, background noise levels were defined as unoccupied so as to be consistent with ANSI standards.

This research also indicates that the differences in correlation between the yearly results and seasonal or district results are not statistically significant meaning that the yearly results are sufficiently representative.

This research used k-means clustering to classify distinct sources of noise in long-term logging of sound level measurements. This method is useful because it does not require measurement observation which allows for longer data logging sessions to be carried out in a larger sample of classrooms without adding a significant amount of time to the analysis. This method is also useful because it is able to cluster the observations across all octave bands simultaneously unlike the method proposed by Hodgson et al. [1999], and it is easier to interpret because it can be viewed in multiple contexts (e.g. time history, distribution, etc.).

Students learn in occupied spaces, yet acoustical standards specify

recommendations for unoccupied conditions. Steps were taken to determine the relationship between the unoccupied conditions standards specify and the levels students actually experience during the school day. The standard recommends an unoccupied background noise level of 35 dBA to ensure a +15 dB signal-to-noise ratio assuming the teacher's voice level is at least 50 dBA at any position in the room. This recommendation is meant to provide the signal-to-noise ratio that children need for uninhibited speech comprehension. However, this recommendation assumes that the unoccupied noise level due to mechanical systems is the only noise source in the room that a teacher must compete with. Based on this research, a linear relationship does not fully account for the variance between unoccupied and occupied levels. The evidence does not strongly suggest that occupied noise levels are only affected by unoccupied noise levels which means that the assumptions made in the standard are not completely realistic. Specifically, this means that there is not a strong foundation to assume the occupied background noise level will be the same as or proportionally increased from the unoccupied background noise level which means that assuming a minimum teacher level of 50 dB anywhere in the room may not provide a +15 dB signal-to-noise ratio.

6.2 Recommendations for Future Work

While these results are significant and are representative of the measured classrooms, there is not enough evidence to determine if they are representative of the population. An empirical model for predicting the occupied levels from the

unoccupied levels is already available, but it cannot be used to predict levels outside the measured range. In this study, the minimum level calculated for the unoccupied cluster was 44 dBA and the minimum level calculated for the second unoccupied sub-cluster (interpreted to be representative of ventilation noise) was 40 dBA. The ANSI standard recommends that unoccupied BNLs should not exceed 35 dBA. Therefore, a model for predicting occupied levels from unoccupied levels generated from this study would not necessarily be representative of classrooms that meet the ANSI standard. More measurements in classrooms that meet the ANSI standard are needed to generate a more representative model. Measurements are already underway to increase the sample size from 110 to 220 classrooms. The next step for this study will be investigating the relationship between occupied levels, unoccupied levels, and student achievement.

K-means clustering is a popular, computationally efficient, unsupervised learning technique that was employed in this thesis. However, more work is needed to validate the interpretation of the clusters. While spectral characteristics of the clusters and sub-clusters provide justification for the interpretations, it is not a substitute for cross-validation. A sample validation was presented in Section 3.4.1, but it is not perfect because it relied on the assumption that the classroom schedule was a perfect indication of occupancy. In order to validate the cluster interpretations, observations of the actual occupancy and activities will need to be collected from a sample number of classrooms. Depending on informed consent, video cameras could also be used to record classroom content; however, it is not a method being explored to validate cluster interpretations for this study. For this

research, validation will likely be carried out using data collected from occupancy sensors, infrared cameras, or classroom observation sessions. Cluster validation is still a work in progress.

Future work could avoid the use of k-means clustering or unsupervised statistical learning methods altogether. A small computer with a video camera, like a Raspberry Pi, could perform feature extraction in the field to count the number of people and determine activity levels without ever storing the video. Locally processing the video eliminates the collection of personally identifiable information. Eliminating personally identifiable information and storing only objective data limits the need for informed consent making it easier to implement in classroom research and research in other public spaces. This type of system uses supervised learning techniques and requires training to refine the predictive models. Training would require recording video in a sample number of classrooms which would require informed consent.

While this study has investigated the relationship between averaged occupied and unoccupied noise levels and averaged instructional and ventilation levels, it may be more useful to understand the impacts of ventilation levels on ambient occupied noise levels. Lower unoccupied background noise levels are important because they contribute to the occupied ambient levels, but more work should be done to understand the relationship between unoccupied noise levels, occupied noise levels, and the signal-to-noise ratio in order to understand how specifying unoccupied noise levels can meaningfully impact the signal-to-noise ratio.

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Appendix A

Missing Data

Table A.1: Log of error messages found during data import for the fall. Highlighted rows indicate absence of data from both meters.

ID	**Meter**	**Message**
ID002	Hanging	File has less than two hours of data or not enough data categories.
ID003	Hanging	File has no data
ID004	Hanging	No data from the hanging SLM, only data from 004-Fall-SLM.OCT
ID005	Hanging	File has less than two hours of data or not enough data categories.
ID005	Kit	No data from the kit SLM, only data from 005-Fall-SLM-H.SWN
ID005	Both	Neither of the meters have data
ID006	Kit	No data from the kit SLM, only data from 006-Fall-SLM-H.OCT
ID008	Hanging	File has no data
ID051	Hanging	No data from the hanging SLM, only data from 051-Fall-SLM-5.OCT
ID054	Hanging	No data from the hanging SLM, only data from 054-Fall-SLM-3.OCT
ID062	Hanging	No data from the hanging SLM, only data from 062-Fall-SLM-3.OCT
ID076	Hanging	No data from the hanging SLM, only data from 076-Fall-SLM-2.OCT
ID077	Kit	File has less than two hours of data or not enough data categories.
ID097	Kit	No data from the kit SLM, only data from 097-Fall-SLM-5H.OCT
ID099	Hanging	No data from the hanging SLM, only data from 099-Fall-SLM-2.OCT
ID110	Kit	No data from the kit SLM, only data from 110-Fall-SLM-5H.OCT

Table A.2: Log of error messages found during data import for the winter. Highlighted rows indicate absence of data from both meters.

ID	Meter	Message
ID006	Hanging	No data from the hanging SLM, only data from 006-Winter-SLM-2.OCT
ID014	Kit	File has less than two hours of data or not enough data categories.
ID020	Hanging	No data from the hanging SLM, only data from 020-Winter-SLM-4.OCT
ID021	Hanging	No data from the hanging SLM, only data from 021-Winter-SLM-3.OCT
ID036	Hanging	No data from the hanging SLM, only data from 036-Winter-SLM-2.OCT
ID039	Kit	File has no data
ID043	Hanging	No data from the hanging SLM, only data from 043-Winter-SLM-2.OCT
ID051	Hanging	No data from the hanging SLM, only data from 051-Winter-SLM-2.OCT
ID054	Kit	No data from the kit SLM, only data from 054-Winter-SLM-5H.OCT
ID071	Kit	File has no data
ID083	Kit	File has less than two hours of data or not enough data categories.
ID089	Kit	File has no data
ID097	Both	Neither of the meters have data
ID097	N/A	ID has 0 SLM files. Follow up
ID109	N/A	ID has 0 SLM files. Follow up
ID109	Both	Neither of the meters have data

Table A.3: Log of error messages found during data import for the spring. Highlighted rows indicate absence of data from both meters.

ID	Meter	Message
ID003	Hanging	File has no data
ID003	Kit	No data from the kit SLM, only data from 003-Spring-SLM-4H.OCT
ID003	Both	Neither of the meters have data
ID006	Kit	No data from the kit SLM, only data from 006-Spring-SLM-4H.OCT
ID044	Kit	File has no data
ID047	Kit	File has less than two hours of data or not enough data categories.
ID069	Hanging	No data from the hanging SLM, only data from 069-Spring-SLM-2.OCT
ID072	Hanging	No data from the hanging SLM, only data from 072-Spring-SLM-4.OCT
ID075	Kit	File has no data
ID077	Hanging	File has no data
ID089	Kit	File has no data
ID092	Kit	No data from the kit SLM, only data from 092-Spring-SLM-5H.OCT
ID100	Kit	No data from the kit SLM, only data from 100-Spring-SLM-5H.OCT
ID110	Kit	File has no data

Table A.4: Log of flagged BNLs.

File	ID	Season	Meter	Message
013-BNL	ID013	Spring	831	BNL is between 32-35 dBA
024-BNL	ID024	Spring	831	BNL is between 32-35 dBA
034-BNL	ID034	Spring	831	BNL is between 32-35 dBA
074-BNL (SystemsOff)	ID074	Spring	831	BNL is between 32-35 dBA
091-BNL	ID091	Winter	831	BNL is less than or equal to 32 dBA
091-BNL	ID091	Spring	831	BNL is less than or equal to 32 dBA
092-BNL (SystemsOff)	ID092	Spring	831	BNL is less than or equal to 32 dBA
096-BNL (SystemsOff)	ID096	Winter	831	BNL is less than or equal to 32 dBA
096-BNL	ID096	Spring	831	BNL is less than or equal to 32 dBA
097-BNL (makeup-SystemsOff)	ID097	Winter	831	BNL is less than or equal to 32 dBA
097-BNL (SystemsOff)	ID097	Winter	831	BNL is less than or equal to 32 dBA
097-BNL	ID097	Spring	831	BNL is less than or equal to 32 dBA
109-BNL	ID109	Winter	831	BNL is between 32-35 dBA
109-BNL	ID109	Spring	831	BNL is between 32-35 dBA

Table A.5 shows data that was flagged because the levels seemed unreasonable. Meter energy-averages of a single day that were greater than or equal to 90 dBA were flagged and omitted. These levels were not actually recorded in these classrooms and resulted from a human calibration error.

Table A.5: Log of data flagged for unreasonable levels.

ID	Season	Meter	Message
ID038	Spring	Hanging	Average LAeq for either days exceeds 90 dBA
ID042	Spring	Hanging	Average LAeq for either days exceeds 90 dBA
ID045	Spring	Hanging	Average LAeq for either days exceeds 90 dBA
ID047	Spring	Hanging	Average LAeq for either days exceeds 90 dBA
ID048	Spring	Hanging	Average LAeq for either days exceeds 90 dBA