Predicting activity noise levels in occupied classrooms by means of cluster analysis

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ABSTRACT

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Educators have developed innovative teaching strategies in order to maximize learning outcomes in classrooms. Active learning classrooms are new learning spaces that facilitate the teaching strategies with enhanced students' engagement and collaborative discussions. Previous studies showed that the design of learning spaces impacts on students' achievement. However, acoustic requirements of the active learning classrooms have not been investigated yet. This study aims to estimate activity noise levels by means of unsupervised learning methods, while active learning is practiced in classrooms. Three clustering algorithms, including K-means clustering, Gaussian mixture model, and spectral clustering algorithms, are employed to analyze the continuous one-third octave band sound pressure levels (SPLs). The data were being collected from five active learning classes and two traditional lecture classes at Concordia University in Montreal, Canada. Based on the spectral characteristics of the speech and non-speech signals, and by using the results of previous studies, a unique decision chart is developed in this study in order to assign the activities in to the clusters obtained from the algorithms. Employing the algorithms along with the decision chart, predicts the acoustic levels of assorted

class activities such as lecturer's speech, students' group work and ambient condition. The predicted activities and their corresponding acoustic levels are then compared with the actual results obtained by the researcher during the measurements and the performance of each algorithm is evaluated. Lastly, this study compares the developed method to predict activity noise levels in occupied classrooms with the two other methods proposed in previous studies and the advantages and disadvantages of the developed method are further discussed. The results obtained from employing the Gaussian Mixture Model (GMM) along with the developed decision chart, indicates the best performance among the other methods investigated in this study.

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1 CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

From childhood to adulthood, students spend a considerable amount of their life in classrooms. The time individuals spend in these spaces has an important role in their personal and professional growth. Students develop part of their personality at school and also gain knowledge and skills toward building a successful future. Accordingly, a proper learning environment plays a significant role in helping students achieve their future goals. If a learning space is poorly designed, it can adversely affect students' creativity or feeling toward the learning process [1]. The impact of positive feeling in learning process is investigated in recent studies by Um et al. [2] and Heidig et al.[3]. Based on their conclusion on the role of the emotional regulation system in learning process, people are most likely to learn and remember things which stimulate positive feelings or arouse interest in them. Others discussed the importance of a comfortable learning environment by demonstrating its effects on learning process and students' performance [4], [5].

The necessity of acoustic comfort in learning environments and the impact it has on students' learning capacity has been known for years. Numerous studies in this context, sought to determine regulations and standards in order to keep the acoustic comfort in core learning spaces on a satisfactory level. Knowing that the perception of teaching/leaning methods has not remained the same throughout time, an important question would be whether implementing new pedagogies has impacted the acoustic condition of new learning spaces significantly. If there is an impact, it is important to recognize the required measures in order to keep the acoustic comfort in a desired level in new learning spaces.

Traditionally, a learning space is a classroom with fixed seats towards the front of the room while the teacher positions themselves in the front of the classroom towards the students. These arrangements serve the purpose of traditional classes. This is because the teacher is the main speaker and subsequently the focal point in traditional classroom settings [6]. Introducing new teaching/leaning methods has inevitably imposed changes on the traditional arrangements of classrooms. Open plan classrooms, circle/semi circle seat arrangements etc. are some of the manifestations of the newly developed teaching spaces.

Active Learning is among the newly developed pedagogies that employ students' capacities by encouraging active participation in the teaching and learning process rather than being passive listeners and observers. Active learning methods require students to think, write and discuss their approaches in solving problems [7], [8]. Group discussions in classrooms are among the most common, yet effective strategies in promoting active learning. Movable furniture in circle arrangement facilitates students' engagement in group discussions. Not only the layouts of classrooms are affected by new learning and teaching methods, but also the environmental factors such as acoustic comfort might be influenced by new teaching practices. The active learning techniques that require talking with nearby peers, such as Think-Pair-Share (TPS)[9], may increase the occupied sound pressure levels of learning spaces.

This study aims to propose a method to predict the activity noise levels from the long term sound pressure levels of occupied classrooms, with focus on conditions in which active learning methods are practiced. For the purpose of the study, the data were being collected from five active learning classes which were being held in three active learning spaces, and two traditional lecture style classes in two lecture rooms at Concordia University. Unsupervised learning is employed in order to identify the long term activity sound pressure levels in classrooms (i.e.

student silent activity, active learning activities and lecturer's speech), from the long term one-third octave band occupied sound pressure levels logged in 5 seconds intervals.

1.2 Thesis Structure

Chapter 2 reviews the importance of proper classroom acoustics as well as the impact of inappropriate acoustic conditions, e.g. excessive noise levels, on both students and teachers, based on previous studies done on the subject. The recent studies on the acoustic characteristics of modern learning spaces are reviewed in this chapter as well.

Chapter 3 provides an overview of the measurement methods, including brief descriptions on the characteristics of the acoustically measured classrooms, the number of microphones and their locations in each room, as well as the equipment used to collect the occupied sound pressure levels in both active learning and traditional lecture classrooms. The theoretical framework of the three clustering algorithms employed, including K-means clustering, Gaussian Mixture Model and Spectral clustering are reviewed and their implementation in this study is discussed.

Chapter 4 provides the results of the measurements and the algorithm analysis and discusses them in details. Moreover, the performances of the algorithms are evaluated and the disadvantages of the method proposed are discussed in this chapter.

In Chapter 5 the main findings of the study are summarized.

2 CHAPTER 2: LITERATURE REVIEW

2.1 Impacts of Acoustic Quality on Students and Instructors

Despite all the technological developments, speech communication is still the most important tool in the learning process. As much as 60% of classroom activities involve in speech communication either between teachers and students or between students [10]. Therefore, proper environments that support clear communication should be recognized.

In general, inappropriate acoustic characteristics of classrooms such as high levels of background noise and reverberation, and low signal to noise ratios can affect stress level, the ability to be concentrated on a subject and academic performance of students in all different age groups. In a research discussion by Crandall and Sandino in 2000 [11], it is concluded that the off standard acoustical variables such as noise level, reverberation time and sound to noise ratio, adversely influence not only speech perception of both hearing impaired and normal students, but also their psycho educational and psychosocial achievements. Moreover, in young kids in particular, reading and spelling ability as well as their social behaviors are negatively influenced. These adverse effects are more detrimental to students with hearing impairment, learners of a second language and those with attention problems [12]–[15]. Based on a study conducted by Green et al. [16], excessive background noise in schools is negatively related to reading scores in elementary-school students. Similar to younger kids, adolescent students with additional learning needs have been reported to be affected by poor classroom acoustics [1], [17].

Improper acoustic conditions do not only affect students. Teachers in noisy and reverberant environments have to constantly raise their voices in order to be heard by the students. Being under this condition, over time, results in vocal fatigue, voice problems, increased level of stress and also cognitive fatigue which decrease teachers' performances at schools [18]–[21]. According to a subjective study conducted by Ahlander et al. [22], noise produced by the activity of pupils, ventilation and other equipment in the building was perceived disturbing by the majority of the teachers participating in the research. In a research from 2000 to 2006, a mixed team of acousticians, occupational health- and medical-scientists and pedagogues investigated the impact of classroom acoustic conditions on work and communication behavior in two elementary schools. It was observed that the heart rates of teachers increased due to the stress reaction caused by the noise level. Students were shown to have the same reactions [19].

2.2 Activity Noise and Speech to Noise Ratio (SNR) in Occupied Classrooms

There are numbers of studies, investigated the occupied conditions of classrooms in order to identify the occupied sound pressure levels associated with different activities during class time. Identifying the sound pressure levels of these activities including, teacher's speech level and students' activity noise, has been of interest for many years in order to evaluate and estimate the SNR in real time occupied conditions.

In 1985, Markids [23] investigated the speech levels and speech to noise ratios of both teachers and students during class time in schools for deaf and partially hearing children. For the purpose of the study, he acoustically measured 12 classrooms in 5 schools for hearing impaired children. Both teachers' and students' speech levels were measured at 2m distance from their mouth. Students' speech levels were measured for one student in each classroom by random selection, when they were responding to their teacher or commenting on other students. Three type of environmental background noise were measured for these spaces. Short duration noise was associated with noise generated from footsteps, banging doors and etc. Non-stationary long term noise reflected the 'chatter' and speech like noise of the students and Quasi-stationary noise was related to the long term noise from machinery, cars, aircraft and etc. The results indicated that the mean A-weighted speech levels of the teachers and students were relatively low and measured to be 57.5 dBA and 52 dBA respectively, while the levels of background noise were unacceptably high, from 44.6 dBA (stationary noise) to 76.5 dBA (short-duration noise).

In 1991, Pekkarinen et al. [24] conducted a study in order to evaluate the acoustic conditions for speech communication in 31 classrooms in 26 schools in Finland. The occupied sound pressure level measurement in each classroom was carried out for 20 to 30 minutes while the microphone was located at the front of the classroom, approximately 2 to 3 meter away from the teachers' desks. The SNRs were calculated as the difference between the A-weighted equivalent continuous sound pressure levels, L_{Aeq} (considered as speech level) and L_{90} (considered as occupied ambient noise level). The mean A-weighted L_{90} and L_{Aeq} were reported to be 49(±6) dBA and 67(±5) dBA respectively. The mean SNR through all the measurements was calculated to be 18 dBA. For most of the spaces the SNRs were reported 15 dBA or higher. The authors concluded that the vocal effort of the teachers increased as the occupied background noise reached 40 dBA or above.

In 1998, Hodgson et al. [25] proposed a method to identify speech and ambient noise levels during lecture time by fitting three distributions into the frequency distributions of long term sound pressure levels of classrooms. The mean values of the 3 distributions were associated with the long term sound pressure levels of ventilation noise, students' activity noise and speech. To collect data, they acoustically recorded 18 occupied classrooms at the University of British Columbia. Classrooms were lecture and seminar rooms with 10 to 291 seats and 6 to 254 students present during the measurements. To perform the measurements, classroom spaces were divided into three blocks, including front, middle and back. The recordings were conducted in each block for 10 to 15 minutes at the beginning, middle and the end of class time. The recordings were then post processed and the short term mean squared pressures were calculated in 200 millisecond (ms) intervals. The A- weighted sound pressure level frequency distribution (in statistical sense, indicating the proportion of time for which the level took given values) for each measurement location was plotted. The obtained distributions were then fitted by one, two or more normal distributions. They concluded that fitting two curves resulted in a significantly good outcome with adjusted $R^2 = 0.95$ and fitting 3 curves usually led to even better results with adjusted $R^2 = 0.99$. Based on the similarities between the distribution of unoccupied sound pressure level (SPL) measurements and the lowest level curves obtained from the developed method, they associated the lowest level distributions to long term ventilation noise levels. The differences between the measured A-weighted equivalent unoccupied SPLs and the mean value of their corresponding distributions were up to 5 dBA. In the next step, by referring to the long term speech levels published in other studies, the highest level curves were associated with the instructors' long term speech levels. Subsequently, the middle distributions were considered as long term students' activity noise. The average ventilation noise was reported to be at 40.9(±3.9) dBA. The mean values of the second and the third distributions associated with the average students' activity noise levels and instructors' speech levels, were 41.9(±4.0) and dBA 50.8(±3.7) dBA respectively. The values obtained for the mean students' activity noise level and speech level were a few dB lower than the results reported in previous studies. They concluded that the level differences happened due to the age of the students as well as the inclusion of discussion classes in the measurements. Finally, they reported the A-weighted SNRs for different measurement locations to vary from 2.1 to 14.8 dBA with the average of 7.3 dBA. At no measurement point the calculated SNR, based on their developed method, exceeded 15 dBA.

In 2003, Shield and Dockrell [26] measured the external and internal noise levels of 16 schools in London area, UK. Overall, they measured 200 locations in these schools, from which 110 were in occupied classrooms during class time. The occupied noise levels were divided into 6 categories based on the activities that were taking place during the measurements. To have the least interference with the class environment, each activity was measured for two minutes with a hand-held sound level meter. Based on their observations, on average the difference between the noisiest and the quietest student activity was 20 dBA while the average ambient noise level was relatively high and measured to be 56 dBA.

Sato & Bradley [27] measured the occupied noise levels and teachers speech levels at four measurement points in 28 elementary school classrooms in Ottawa, Canada. Using the distribution fitting method suggested by Hodgson et al. [25], the continuous sound pressure levels of 118 cases of occupied recording were averaged in 200ms intervals and the long term SPLs' frequency distributions were fitted by two normal distributions representing speech and occupied noise levels. The mean A-weighted speech and noise level averaged over 28 classrooms' recordings were found to be at 59.5 dBA and 49.1dBA respectively. Based on their results, only 2% of the cases met the 15 dBA speech to noise ratio requirement for speech communication [10]. In addition, they investigated the Lombard effect[1] on the teachers' voice levels when the occupied ambient noise level increased. The two were reported to be highly correlated.

[1] Lombard effect is an unintentional tendency in a speaker, who is talking in a noisy environment, to increase their voice level for noise compensation [43]

In 2011 Greenland and Shield [28] acoustically measured the noise levels in 42 open plan classrooms in 12 primary schools in England with a focus on activities involving speech. Multiples 2-minute recordings at three positions in each open plan class-base were collected. In total 561 samples were analyzed and activity sound levels, considering three main speech type activities took place during class time, were calculated. The $L_{Aeq,2min}$ when one person (teacher or students) were talking in the main class-base and while students were working at their tables were reported to be 47.4 (±4.8) dBA and 53 (±5.5) dBA respectively. The highest activity noise level was associated with students work while moving between the tables at 57 (±4.8) dBA. Their results indicated a general trend in increasing the activity noise levels by getting farther from the teacher at the front of the room and being closer to the openings to adjacent activities at the back of the room. A significant positive correlation between the noise levels of the adjacent activities and the average intrusive noise was observed.

In part of a large-scale in-situ study carried out in 2016 in University of Nebraska, Brill and Wang [29] investigated the correlation between occupied and unoccupied noise levels in 110 K-12 classrooms. The occupied sound level measurements were conducted for 36 hours in two school days. K-means clustering were used to categorize the collected data into occupied and unoccupied conditions. The results suggested a significant correlation between the occupied and unoccupied sound pressure levels with increase of 0.3 dBA in occupied sound levels for every 1 dBA increase in unoccupied sound levels. Furthermore, K-means clustering was performed on observations associated with occupied conditions in order to identify the instructional activities. The sub-clusters obtained were associated with classroom activity sound levels and ventilation noise levels. A linear model between the classroom activity sound levels and ventilation noise levels indicated an increase of 0.4 dBA in instructional sound levels for every 1 dBA increase in ventilation noise.

Sala & Rantala [2] investigated the activity noise in 40 classrooms in 14 elementary schools in Finland. The occupied sound pressure levels were measured for the whole duration of the classes. Results indicated that the noise levels during the lectures were highly dependent on the activity which was taking place at the time of the measurement. The averaged L_{Aeq}, L_{10} and L_{90} of all the measurements were calculated to be 68 dBA, 55 dBA and 42 dBA respectively.

In 2017, Peng et al. [30] conducted a study to investigate the teaching speech levels and background noise levels in Chinese elementary schools. In total, 46 classrooms in three elementary schools were measured during three courses of Chinese, mathematics and English. In each classroom, data were collected from the front and back of the rooms for 15 minutes or more. The authors then calculated the mean A-weighted teaching SPL and background noise level by employing the distribution fitting method proposed by Hodgson et al. [25]. In 59 cases that the SRS (Sound Reinforcement System) were not used during the measurements, the mean A-weighted background noise level and teacher's speech level were reported to be 62.8 (±4.7) dBA and 72 (±5.5) dBA respectively. The results illustrated a significant correlation between the background noise levels and the teachers' speech levels.

Following the previous studies in the field, the purpose of this study is to investigate the occupied conditions, including occupied ambient noise level, teachers' speech levels and students' activity levels in classrooms, while active learning methods are practiced, by means of unsupervised learning methods. Furthermore, this study aims to investigate the probable differences between the activity SPLs in active learning practices and traditional lecturing. For the purpose of the study, unsupervised learning methods are employed to predict the sound pressure levels of the activities, and the results are compared with the previous methods proposed in similar subjects. The real time SNRs are investigated to evaluate the speech communication quality in these new learning spaces.

3 CHAPTER 3: METHODOLOGY

3.1 General Overview

A measurement setup was developed in order to do the acoustic measurement in occupied conditions. The locations of equipment were chosen based on the probable location of teacher and students in a classroom. A detailed description of each set up is provided in the following section. The long-term occupied sound pressure level measurements were conducted in both active learning and traditional classrooms. This chapter describes the methodologies utilized to obtain and analyze the data.

3.2 Occupied Classroom Measurement

The occupied sound pressure level measurement was conducted in the five active learning classrooms and two lecture-style classrooms, located at Sir George William campus, Concordia University. From these five active learning classes, four of them were held in three recently renovated active learning spaces and 1 took place in a traditional learning space. Traditional classrooms were chosen to have the most similarities to the active learning classrooms in terms of volumes and capacities.

Table 1 lists some general characteristics of the measured classrooms such as the volume of the room, capacity, materials of the interior surfaces, classroom ID and the location of each classroom.

For both active learning and traditional classrooms, the continuous sound pressure levels were measured at four locations in each classroom by using B&K LAN-XI system and 4 ½-inch free-filed microphones. All microphones where mounted at 0.5m under the ceilings. The microphones locations were determined as; Microphone 1 is placed in above the teacher's desk. Microphone 2 is placed next to the nearest students' desk. Microphone 3 is placed in 6 meter from teacher's desk. Microphone 4 is placed next to the farthest students' desk.

To have the least interfere with the classes' natural flows, all the microphones were mounted 0.5m under the ceilings.

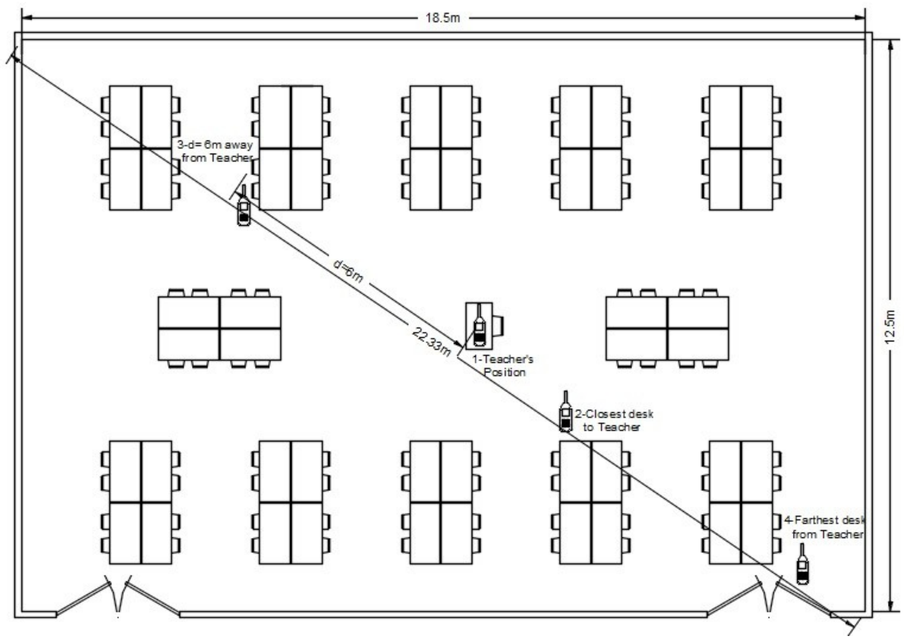
Table 1: General descriptions of measured occupied active learning and traditional classrooms

	Name	Classroom Layout	Volume (m^3)	Dimension L×W×H(m)	#No of participant	Capacity	Surface material
4 Active Learning Classes	H603	ALC	323	13.1×9×2.75	25	65	ACT, drywall, white boards
	H605	ALC	351	14.3×9×2.75	59	65	ACT, drywall, white boards
	H654-1	ALC	636	18.5×12.5×2.7	46	96	ACT, drywall, smart boards
	H654-2	ALC	636	18.5×12.5×2.7	30	96	ACT, drywall, smart boards
	H509	Traditional	336	13.8×8.8×2.75	52	84	ACT, drywall,
Traditional Lectures	MB.2.270	Traditional	546	15.6×11.3×3	67	80	ACT, drywall, acoustical wall panels
	H561	Traditional	326	13.5×8.8×2.75	56	84	ACT, drywall

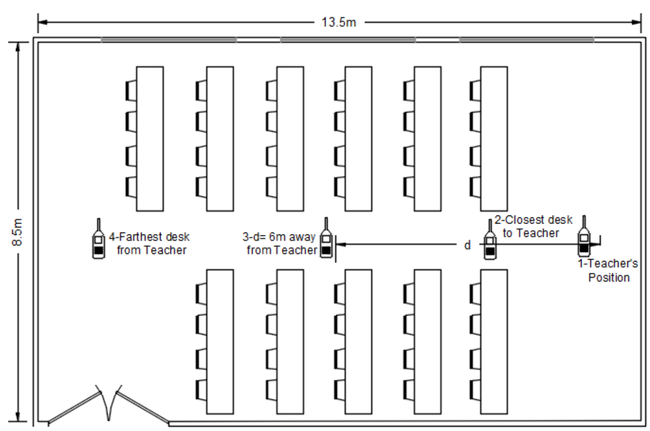
Figure 1 shows the schematic plans of the measured classrooms. In active learning classrooms, the teacher's desk might be in the front or in the middle of the room. As shown in *Figure 1*, whenever teacher's position was in the middle, the microphones were positioned diagonally in the room to follow the same criteria mentioned above.

Prior to the commencing of the class, the equipment was placed in their locations. In order to capture the sound levels from all over the room uniformly, four microphones connected to the

LAN-XI (Type 3056) - a multi channel data acquisition hardware-, were mounted from under the ceilings of the classrooms. The locations of the microphones in the classrooms are as described above.



a)



b)

Figure 1: a) Teacher's position in the middle-Active learning classroom H654.b) Teacher's position in the front-Traditional classroom H561

For each classroom, the occupied continuous SPLs were monitored for the whole duration of the class. The researcher was present during each class to observe and note the activities and their durations as well as any occurrences of sudden high level noises and their related sources. The researcher recorded the name of the courses, the dates and times of the measurements and the numbers of students present during the measurements. Based on the observations, the measurement durations were allocated to three activities including:

- Student individual silent work (e.g. quiz) which is referred to as 'Ambient' in this document
- Teachers speaking which is referred to as 'Lecture' in this document
- Student group work which is referred to as 'Active Learning Activity' in this document
- Media playing session which is referred to as 'Active Learning Activity' in this document

During the measurements LAN-XI Data Acquisition Hardware was connected to a lap top running BK Connect software where the audios were captured and stored. The post-processing of data was later performed by using BK Connect. For all classrooms, the signal recorded at each measurement location was processed. The one-third Constant Percentage Bandwidth (CPB) versus time analysis applied on the recorded signals and the one-third octave band un-weighted sound pressure levels (SPL), using linear averaging with "slow" time constant, logged in 5s intervals, were exported to Microsoft Excel data sheets.

To collect data in occupied classrooms, an ethics certification acquired from the Concordia University Human Research Ethics Committee. The certificate number is 30011510.

The analyses of the one-third octave band sound pressure levels were performed using MathWorks MATLAB 20167b in order to identify the mean sound levels as well as the duration of each activity in the occupied classrooms. Three different clustering algorithms were applied to 28 sets of 31-dimentional observations (1/3rd octave band frequencies from 16Hz to 16 kHz). The average duration of the recordings was 94 (± 28) minutes in each classroom and the numbers of observations ranged from 606 to 1465 with the average of 1124 (± 331). The utilized clustering algorithms and their applications in this study are explained in details in the following section.

4.1 Clustering

Clustering analysis is the most commonly used method in unsupervised learning which aims to group the observations in a manner that maximize similarities in the same group and minimize similarities between the observations in different groups. Clustering analysis can be classified as hard and soft clustering. In hard clustering each observation can only belong to one cluster while in soft clustering (also known as fuzzy clustering or soft K-means) an observation can exist in multiple clusters at the same time. In soft clustering, a membership weight is assigned to each observation. The membership weight of each observation indicates to what degree the observation belongs to each cluster [31]. In order to identify the activities in occupied classrooms, in this study it is assumed that each observation can only belong to one activity at the time. Therefore, to assigns the data collected from the classrooms to each activity, hard clustering is implemented by means of three common clustering algorithms, including K-means clustering, Gaussian Mixture Model and spectral clustering. The following sections explain the theory and fundamentals of each algorithm.

4.1.1 K-means Clustering

Combinatorial cluster analysis is a method to investigate data points and picking up the best fit for the optimized target function from all possible data arrangements in a search space. K-means is considered to be one the most typical among the algorithms of combinatorial cluster analysis [32]. MacDueen [33] first proposed K-means method about 50 years ago, a method which is still among the ten most important algorithms in data mining on account of its simplicity and wide range of application.

K-means clustering is an unsupervised learning method to partition a set of N-dimensional observation into K predefined non-overlapping clusters in a way that minimize the inner-cluster variation. [34]. To perform K-means clustering, the number of clusters (K) should be known in advance. Two remarkable properties of clustered set of data using K-means clustering that must be satisfied are as follow:

1. Each data should at least belong to one cluster.(For a set of n observations, if $C_1, C_2, \ldots, C_k$ denote sets containing indices of the observations in each cluster, then $C_1 \cup C_2 \cup \ldots \cup C_k = \{1,2,\ldots,n\}$)
2. There is no overlap between any two clusters. It means no data belong to more than one cluster. (If $k \neq k'$, then $C_k \cap C_{k'} = \emptyset$)

If $W(C_k)$ is defined as a measure to specify within cluster variation of data, the purpose of K-means clustering is to minimize the summation of $W(C_k)$ through all K clusters [34].

$$\underset{C_1,\ldots,C_K}{\text{minimize}} \left\{ \sum_{k=1}^{K} W(C_k) \right\} \tag{1}$$

The *Equation* (1) denotes that in order to partition a set of n data sets into K clusters using K-means clustering, within cluster variations, summed over all K clusters should be minimized. Within cluster variation $W(C_k)$ may be defined in a variety possible ways, but in this study it is defined by squared Euclidean distances between observations in each cluster, as by far this is the most common method.

Within cluster variation $W(C_k)$ for cluster k is defined as the summation of the all pair-wise squared Euclidean distances between the data in cluster k, divided by the numbers of data belong to that cluster [34].

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

By combining *Equation* (1) and *Equation* (2), K-means clustering is defined as an optimization problem as below:

$$\underset{C_1,\ldots,C_K}{\text{minimize}} \left\{ \sum_{k=1}^{K} \frac{1}{|C_k|} \sum_{i,i' \in C_k} \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2 \right\} \tag{3}$$

Solving *Equation* (3) is very difficult and time consuming as there are almost K^n ways of partitioning a set of n data into K cluster. A simple way of solving this equation is to write an algorithm to find the local optimum for this optimization problem. After specifying the number of clusters, the first step in clustering process is to randomly assign an index from 1 to K to each of the observations. As the initial random assignment is complete, the iterative process begins. This process continues until the solution converges to a local optimum and the cluster indices stop changing. In this process, the *Equation* (2) is simplified into *Equation* (4).

$$W(C_k) = 2 \sum_{i \in C_k} \sum_{j=1}^{p} (x_{ij} - \bar{x}_{kj})^2 \quad (4)$$

Where $W(C_k) = \frac{1}{|C_k|} \sum_{i \in C_k} x_{ij}$; is the mean for feature j in cluster C_k [34].

The algorithm results in assigning observations in to 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.

4.1.1.1 Implementation of K-means Clustering

In this study, K-means clustering algorithm was applied to 28 sets of 31- dimensional (one-third octave band) time-averaged sound pressure levels in 5s intervals. Clustering was performed on data obtained from all four measurement locations in each classroom separately in order to identify the mean A-weighted sound pressure level of each activity during class time. Cluster centriods which represent the A-weighted sound pressure levels of the activities are then calculated by acoustical averaging of the observations in each cluster.

The analyses were performed in MATLAB 2017 using `Kmeans` function. Initial centriods were chosen using the `k-means++` algorithm in MATLAB 2017. `Kmeans++` chooses K centroids starting positions based on heuristic instead of random assignments. For this purpose, the first cluster center is chosen randomly from the data points that are being clustered, after which, each subsequent cluster center is chosen from the remaining data points with probability proportional to its squared distance from the closest existing cluster center. Applying `kmeans++` avoids the sometimes poor clustering found by the standard K-means algorithm and improves the algorithm and outperforms methods that use random seeding [35].

4.1.2 Gaussian Mixture Model

While using a clustering method, the focus might be on the population, from which a set of data is clustered, rather than the actual set of data itself. This population can be defined as a sum of statistical models which describe the observations in each cluster [32].

A mixture model is a probabilistic model that illustrates the presence of clusters within a population. If K distributions with density functions $f(x)_1, \ldots, f(x)_K$ are mixed in proportions $\pi_1, \ldots, \pi_K$, the density function of the mixture distribution is defined as given by the *Equation* (5) [36].

$$f(x) = \sum_{k=1}^{K} \pi_k \, f_k(x) \tag{5}$$

A Gaussian Mixture Model (GMM) is defined as a parametric density function, consists of finites numbers of weighted Gaussian subpopulations densities. It is defined as shown in *Equation* (6).

$$p(X|\lambda) = \sum_{k=1}^{K} \pi_k \, N_k(X|\pi_k, \mu_k, \Sigma_k) \tag{6}$$

In the equation above, X is N-dimensional continuous-valued data set. For $k = 1, \ldots, K$ when K is the numbers of clusters, π_k, μ_k, Σ_k are the mixture proportion, mean value and the covariance matrix of the component k respectively. The $\lambda = \{\pi_k, \mu_k, \Sigma_k\}$, represents the complete set of parameters for a mixture model with K components.

$p_k(X| \pi_k, \mu_k, \Sigma_k)$ illustrates the Gaussian densities of the components for $k = 1, \ldots, K$, and can be calculated as given in *Equation* (7) [36].

$$p_k(X|\lambda_k) = \frac{1}{(2\pi)^{N/2}|\Sigma_k|^{1/2}} \exp\left\{-\frac{1}{2}(x-\mu_k)'\Sigma_k{}^{-1}(x-\mu_k)\right\} \tag{7}$$

4.1.2.1 Expectation Maximization (EM)

In order to solve the *Equation* (7), an optimization method should be implemented to find the parameters, (i.e. π_k, μ_k, Σ_k) of a mixture model which maximize the likelihood of the observed data. To estimate the parameters of a Gaussian Mixture Model(GMM) that maximize the likelihood of the observations, a common method is to use EM algorithm, a maximum likelihood method developed by Dempster et al. for a set of incomplete data [36], [32].

In a mixture model, the assumption is each vector x_i is generated by a single component k. the uncertainty about which of the K component generates vector x_i is given by the *Equation* (8) which reflects the "membership weight" of data vector x_i [32].

$$w_{ik} = p(z_{ik} = 1|x_i, \lambda) = \frac{N_k(x_i|z_k, \lambda_k).\pi_k}{\sum_{m=1}^{K} N_m(x_i|z_m, \lambda_m).\pi_m}, \quad 1 \le m \le K, \quad 1 \le i \le N \tag{8}$$

The EM (Expectation-Maximization) algorithm is an iterative algorithm that starts from some initial estimate of mixture model parameters π_k, μ_k, Σ_k and then proceeds to iteratively update them until convergence is detected. Iterations consist of two steps called E-step and M-step as defined in the following.

E-Step: Denote the current parameter values. Compute membership weights w_{ik}, using the *Equation* (8), for all data vectors x_i , $1 \le i \le N$ and all mixture components $1 \le k \le K$. Note that for each data vector x_i, the membership weights are defined such that $\sum_{m=1}^{K} w_{ik} = 1$. This yields an N × K matrix of membership weights, where each of the rows sums to 1.

M-Step: By using the membership weights and the data, new parameter values are calculated. The effective number of data points assigned to component k is defined as $N_k = \sum_{i=1}^{N} w_{ik}$, i.e. the sum of the membership weights for the k^{th} component.

The new parameters are calculated based on w_{ik};

$$\pi_k^{new} = \frac{N_k}{N}, \quad 1 \leq k \leq K \tag{9}$$

$$\mu_k^{new} = \left(\frac{1}{N_k}\right) \sum_{i=1}^{N} w_{ik} \, . \, x_i, \quad 1 \leq k \leq K \tag{10}$$

And;

$$\Sigma_k^{new} = \left(\frac{1}{N_k}\right) \sum_{i=1}^{N} w_{ik} \, . \, (x_i - \mu_k^{new})(x_i - \mu_k^{new})^t, \quad 1 \leq k \leq K \tag{11}$$

After computing all of the new parameters, the M-step is complete and the iteration of the E-step and M-step and updating the parameters continue, till convergence [36].

4.1.2.2 Implementation of GMM Clustering

In this study, GMM clustering algorithm was applied to 28 sets of A-weighted 31-dimensional (one-third octave band) time-averaged sound pressure levels in 5s intervals. The analyses were performed in MATLAB 2017 by using `fitgmdist` function. First the optimal numbers of clusters is calculated by using Silhouette value. Silhouette measure is later explained in this document in details. The initial labels of the observations are assigned by using `Kmean++` algorithm. The covariance type for each set of data was determined to be full and unshared among the clusters. The maximum numbers of iterations for the Expectation Maximization (EM) steps are set at 1000. *Figure 2* illustrates the flowchart of GMM employed in this study.

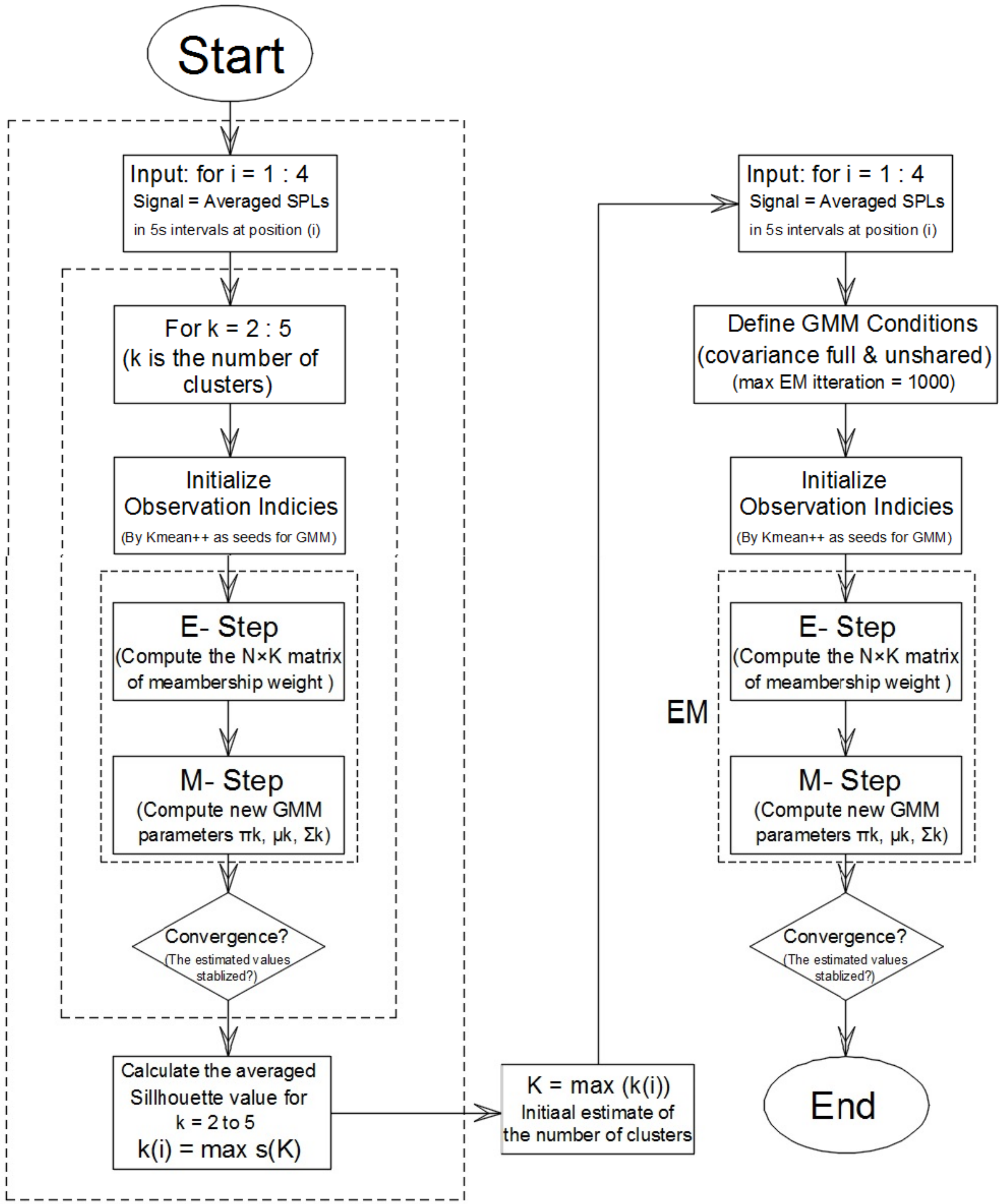


Figure 2: flowchart of GMM algorithm in order to solve the GMM optimization problem plus estimation of the initial values for number of clusters (K) by using Silhouette values.

4.1.3 Spectral Clustering

Spectral clustering is referred to a class of techniques for clustering that are based on pair-wise similarity relations among data points. In spectral clustering the data clustering is treated as a graph partitioning problem while no assumption is made on the form of the clusters. The method makes use of dimension reduction of data by employing Eigenvalues and Eigenvectors of the graph Laplacian [32]. Prior to explaining the algorithm, the mathematical objects used by spectral clustering are introduced briefly.

The ultimate goal of clustering is to divide data into several clusters in a way that similar points are in the same cluster and dissimilar points are in different clusters. For a given set of n data points , $x_1, \dots, x_n$, where x_i is a N-dimensional row vector, data set can be represented as similarity graph $G = (V, E, W)$; where V is the set of vertices and vertex $v_i \in V$ represents the row vector x_i, E is a vector representing the edges between the vertices and W is the generalized adjacency matrix. In this study, it is assumed that G is a weighted graph where the edge e_{ij}, between two vertices v_i and v_j carries a non-negative weight $w_{ij} \geq 0$. The entry w_{ij} indicates the similarity between vertices v_i and v_j [32], [37].

There are several popular methods to construct a similarity graph for a given set $x_1, \dots, x_n$, of data, in order to model the local neighborhood relationships between the data points. In this study, the similarity graph is formed by using ***The fully connected graph*** method [37] which is explained in the following.

The fully connected graph: similarity graph is constructed by connecting all points with positive similarity to each other, and weight all edges with w_{ij} by using a similarity function. A common function to construct such a similarity matrix is the Gaussian kernel similarity function which is defined as *Equation* (12), where σ is a user-defined parameter that controls the width of the neighborhoods. In this study, by trial and error, σ is considered as the difference between the maximum and minimum A-weighted equivalent sound pressure levels averaged in 5s intervals, at their corresponding measurement locations.

$$w_{ij} = \exp\left(-\frac{\| x_i - x_j \|^2}{2\sigma^2}\right) \tag{12}$$

The degree matrix D of graph G is defined as the diagonal matrix with the degrees $d_1, \ldots, d_n$, on the diagonal and 0 value for off-diagonal elements [37].

If graph $G = (V, E)$ is an udirected weighted graph and $V = \{v_1, \ldots, v_n\}$ and $E = \{e_{ij}\}$; $i, j = 1, \ldots, n$ are its sets of vertices and edges respectively, each e_{ij} which is the edge between vertices v_i and v_j carries a non-negative weight $w_{ij} \geq 0$. The adjacency matrix for graph G is defined as $W = [\, w_{ij}]$; $i, j = 1, \ldots, n$. Since the graph is undirected, for each i and j, $w_{ij} = w_{ji}$. If there is no edge between vertices v_i and v_j, then $w_{ij} = w_{ji} = 0$ [32], [37].

For graph $G = (V, E)$, the degree of a vertex $v_i \in V$ is defined as shown in *Equation* (13).

$$d_i = \sum_{j=1}^{n} w_{ij} \tag{13}$$

The *degree matrix D* of graph G is defined as the diagonal matrix with the degrees $d_1, \ldots, d_n$, on the diagonal and 0 value on off-diagonal elements [37].

Graph cut is removing edges connecting two parts of the graph G in order to partition the graph $G = (V, E)$ into two disjoint sets of connected vertices A and B in a way that;

$$A \cup B = V \tag{14}$$

$$A \cap B = \emptyset$$

For two disjoint clusters (sub-graph) A and B the following terms are defined:

– The sum of weight connections between two clusters (*Equation* (15))

$$\mathrm{Cut}(A, B) = \sum_{i \in A, j \in B} w_{ij} \tag{15}$$

–The sum of weight connections within cluster A *(Equation* (12)):

$$\mathrm{Cut}(A, A) = \sum_{i \in A, j \in A} w_{ij} \tag{16}$$

– The total weights of edges originating from cluster *(Equation* (17)):

$$\mathrm{Vol}(A) = \sum_{i \in A} d_i \tag{17}$$

The objective of Min-Cut method is to find two sets (clusters) A and B which have the minimum weight sum connections.

$$J_{\mathrm{MinCut}} = \mathrm{Cut}(A, B) \tag{18}$$

It is easy to prove that such equation can be written as:

$$J_{\mathrm{MinCut}} = \frac{1}{4} f^T (D - W) f \tag{19}$$

$f_i \in R^n$ is the indicator vector of vertices belonging to clusters A and B such that:

$$f_i = \begin{cases} +1 & i \in A \\ -1 & j \in B \end{cases} \tag{20}$$

By relaxing the indicator vector f to real values, it is proved that, the solution minimizing the objective function will be equivalent to solve the following equation :

$$(D - W)f = \lambda f \tag{21}$$

Graph Laplacian matrices are essential measures to portion a graph, based on different cut methods. In this study the un-normalized graph Laplacian is utilized [37].

The un-normalized graph Laplacian matrix is defined as:

$$L = D - w \tag{22}$$

Proposition 1: The matrix L satisfies the following properties:

1- For every vector $f \in R^n$:

$$f^T L f = \frac{1}{2}\sum_{i,j=1}^{n} w_{ij}(f_i - f_j)^2 \tag{23}$$

2- L is a symmetric matrix, positive and semi-definite.

3- The smallest Eigenvalue of L is 0, corresponds to a constant eigenvector with elements of 1.

4- L has n non-negative, real-valued eigenvalues $0 = \lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_n$

Proposition 2: Number of connected components and the spectrum of L

For undirected graph $G = (V, E)$; with non-negative weights, the multiplicity k of the eigenvalue 0 of L equals the number of connected components $A_1, A_2, \ldots, A_k$ in the graph. The Eigenspace of Eigenvalue 0 is spanned by the indicator vectors $\mathbb{1}_{A_1}, \ldots, \mathbb{1}_{A_k}$ of the components.

4.1.3.1 Implementation of Spectral Clustering Algorithm

In this study, spectral clustering algorithm was applied to 28 sets of A-weighted 31-dimensional (one-third octave band) time-averaged sound pressure levels in 5s intervals.

The algorithm used on this study is summarized bellow [37];

Input: Similarity matrix W $\in R^{n\times n}$, in order to partition data into K number of clusters.

• Construct a fully connected similarity graph by using the Gaussian Kernel density function while W is its weighted adjacency matrix.

• Compute the un-normalized Laplacian L by using *Equation* (22).

• Compute the first k eigenvectors $v_1, \dots, v_k$ of L while V $\in R^{n\times k}$ is the matrix containing the vectors $v_1, \dots, v_k$ as columns.

• For $i = 1, \dots, n,\ y_i \in R^k$ be the vector corresponding to the i_{th}row of V.

• Cluster the points (y_i) in R^k with the k-means algorithm into clusters $C_1, \dots, C_k$.

Output: Clusters $A_1, \dots, A_k$ with $A_i = \{j | y_j \in C_i\}$.

4.2 Optimal Number of Clusters

To have and initial evaluation of the proper numbers of clusters, Silhouette measure [38] was employed. Silhouette is a graphical method to evaluate the within cluster consistency by looking at the tightness and separation of observations within their clusters. The average Silhouette width is among the common measures has been used to decide about the optimal numbers of clusters for clustering analysis in which the proximities are in ratio scale (as in cases of Euclidean distances).

To construct Silhouette for n observation divided into K>1 clusters, for any observation $i \in A$ when A is the cluster that *i* is assigned to and contains other observations rather than *i*;

$a(\mathrm{i})$: Average dissimilarity between *i* and other observations in A

If C is any other cluster which is different from A;

$\mathrm{d(i, c)}$: Represent the average dissimilarity between i and all other observations in C. in another word, it is the average of all lines going from i to C.

For all clusters $C \neq A$, the smallest average distance $\mathrm{d(i, c)}$ is represented by $\mathrm{b(i)}$ as shown in *Equation* (24).

$$b(i) = minimum_{C \neq A}\, d(i, c) \tag{24}$$

Accordingly, the closest neighboring cluster of each observation which is also, the second-best option for that observation, is determined. The term $s(i)$ is calculated by *Equation* **(**25).

$$s(i) = \frac{b(i) - a(i)}{max\{a(i), b(i)\}} \tag{25}$$

As *s(i)* get closer to 1, the within cluster dissimilarity *a(i)* is much smaller than *b(i)*, meaning observation *i* is well-clustered. For different K, the average of *s(i)*s of all observations can be considered as an indicator of the "appropriate' number of clusters.

In this study, for $2 \leq K \leq 5$, the K with the largest averaged Silhouette value is calculated for all measurement locations in each room. K obtained this way might be different among measurement locations in a classroom. Because it is expected that the number of activities remains the same among different measurement locations, the maximum K between four measurement locations was taken as the initial estimate for the appropriate number of clusters.

4.3 Identification of Clusters

The activities noted by the researcher during the measurement were generalized into three categories, including 'Lecture', 'Ambient' and 'Active Learning Activity'.

Table ***2*** explains all the possible combinations of these three activities based on number of K;

Table 2: possible combinations of the defined 3 activities, including 'Lecture', 'Ambient' and 'Active Learning Activity', based on calculated optimal K

#K	Activities
2	Ambient- Lecture Lecture- Active Learning Activity
3	Ambient- Lecture- Active Learning Activity Lecture- Active Learning Activity 1 - Active Learning Activity 2
4	Ambient- Lecture- Active Learning Activity1 - Active Learning Activity 1

Criteria and assumptions employed to assign clusters to activities are defined in the following, based on the results of the previous studies [25], [39], [40], [9], [11]. The main assumptions are;

1- 'Lecture' is always one of the activities.

2- 'Lecture' and 'Active Learning Activity' mean SPLs are always higher than 'Ambient' noise levels.

3- 'Lecture' is more likely to be the most frequent activity taking place which takes the largest portion of class duration comparing to other activities [25],[39].

The Criteria used are:

1- Assuming the teacher' location is in the front and students are uniformly distributed in the classroom, it is expected to observe drops in mean 'Lecture' SPL from the front to the back of the room while 'Ambient' noise levels and 'Active Learning Activity' sound pressure levels should be more uniform over the four microphone locations in the room.

2- Based on the averaged standard speech frequency spectra developed by Byrne et al. [40], and the results of a study by Weisser et al. [41] on the effect of noise on real time speech spectrums, the minimum frequency roll-off (or slope) for the speech spectra, at maximum 1.5m from the speaker, from 630Hz to 16KHz, is determined to be -15 dB/decade[2].

Table 3: Averaged standard speech frequency spectra[40]

Fr [Hz]	Male	Female	Combined
630	60.6	60.4	60.5
800	55.7	58	56.8
1000	53.1	54.3	53.7
1250	53.7	52.3	53
1600	52.3	51.7	52
2000	48.7	48.8	48.7
2500	48.9	47.3	48.1
3150	47	46.7	46.8
4000	46	45.3	45.6
5000	44.4	44.6	44.5
6300	43.3	45.2	44.3
8000	42.4	44.9	43.7
10 000	41.9	45	43.4
12 500	39.8	42.8	41.3
16 000	38.9	37.8	40.7

[2] The unit to measure frequency ratio in logarithmic scale in called 'decade'. dB/decade is defined as the unit of frequency roll-off.

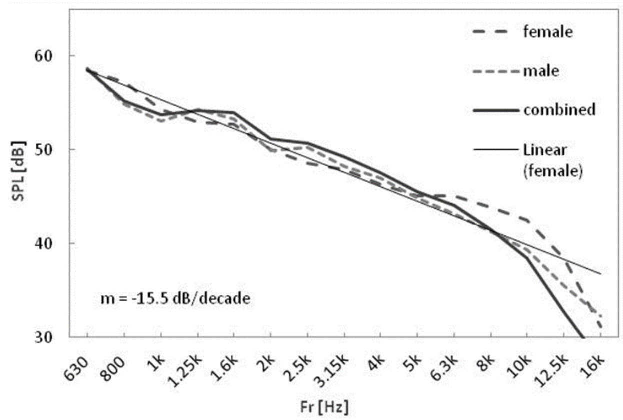


Figure 3 : Standard speech spectrum frequency roll-off from 630Hz to 16 KHz for female speakers

To assign clusters obtained from the results of the algorithms, for each classroom, the frequency spectrums of the clusters at measurement location1 (teachers' desk) and measurement location 2 (closest students' desk at 1.2m to 1.5m away from teacher's desk), the clustered time history of the continuous un-weighted sound pressure levels averaged in 5s intervals and trends of changes in cluster SPLs from measurement location 1 to measurement location 4 are investigated. *Figure 4* indicates the decision chart used to assign the activities, mainly 'Lecture' and 'Ambient', into clusters. The implementation of the chart is explained in detail in the next chapter.

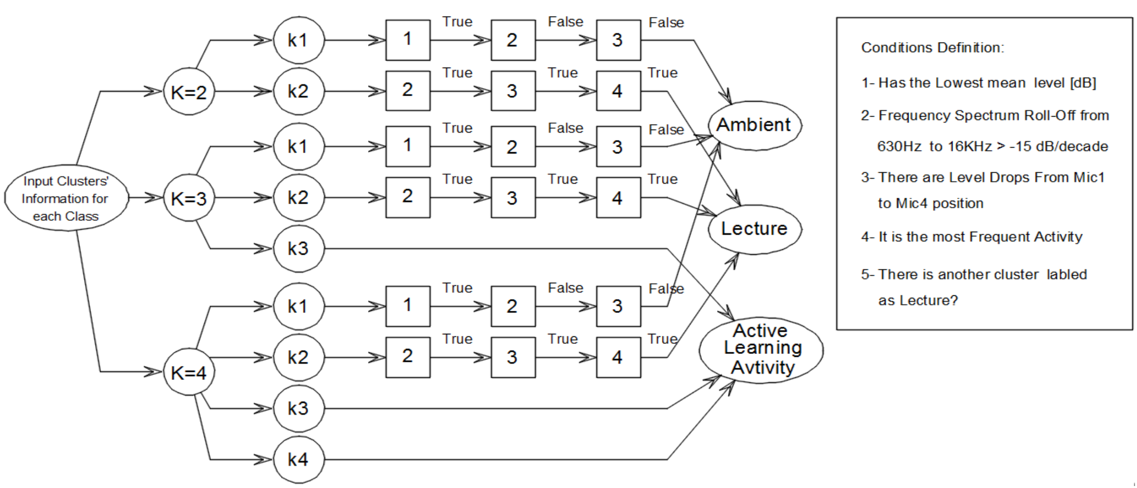


Figure 4: Conditions and criteria that are considered for each cluster to be associated to an activity for different possible number of clusters

4.4 Clustering Performance Evaluation

Typical objective functions in clustering are to attain high inter-cluster and low intra-cluster similarities. This is an internal criterion for the quality of a clustering, but good scores on an internal criterion do not necessarily translate into good effectiveness in an application.

External criterion evaluates how well the clustering matches the standard classes. Setting of classes in an evaluation benchmark is ideally produced by human judges with a good level of inter-judge agreement. In this study, as the actual clustering index for each observation is known by the researcher, three external criterions, including Accuracy, Precision and Recall are used to evaluate the performance of the algorithms. The following explains these measures in detail.

In machine learning, a confusion matrix is a main source to evaluate the performance of a clustering algorithm. In the common configuration of a confusion matrix, the rows and the columns represent the predicted and the actual classes respectively. *Table 4* illustrates the common configuration of confusion matrices.

Table 4: An example of a common confusion matrix

		Actual Classes	
		Positive	Negative
Predicted Classes	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

In general, two observations are in the same group if and only if they are similar. A true positive (TP) decision assigns two similar observations to the same cluster while a true negative (TN) decision assigns two dissimilar observations to different clusters. There are two types of errors to be considered in cluster evaluation. A (FP) decision assigns two dissimilar observations to the same cluster and a (FN) decision assigns two similar observations to different clusters.

The Accuracy measures the overall percentage of decisions that are correct. It is calculated as the ratio of total number of decisions that correctly assigned similar observations to the same cluster (TP) and dissimilar observations to different clusters (TP) to the total number of assignments. *Equation* **Error! Reference source not found.**) indicates the formula to calculate he accuracy [42].

$$ACC = \frac{TP + TN}{TP + FP + FN + TN} \tag{26}$$

Precision is calculated by dividing the correctly assigned decisions (TP) by the total of positive counts. Recall which is also known as Sensitivity is calculated by dividing the true positive assignments (TR) by the total number of true positive (TP) and incorrectly considered negative decisions (FN). Recall and Precision formulas are indicated in *Equation* ((27) [42].

$$Precision = \frac{TP}{TP + FP} \tag{27}$$

$$Recall = \frac{TP}{TP + FN}$$

Table 5 summarizes the methods of collecting and analyzing the data in to 7 steps.

Table 5: The summarized methods of collecting and analyzing the data

Audio Measurement & Post processing

1-	Audio recordings are collected from 4 measurement locations in each classrooms and the activities which were taking place during the measurements were noted by the researcher in 5 seconds intervals
2-	Post processing is performed on the audio files of each measurement location by using BK-Connect software and 1/3 octave band sound pressure levels logged in 5 seconds intervals were exported to Excel data sheets (31 dimensional data sets ranged from 660 to 1500 observations in each set)
Clustering Analysis	
3-	The optimal numbers of clusters were evaluated by using GMM and Silhouette values. 1/3 octave band sound pressure levels stored in Excel sheets are used as inputs of the algorithm
4-	1/3 octave band sound pressure levels stored in Excel sheets and the optimal number of cluster for each classrooms are used as inputs of GMM, KM and Spectral clustering
5-	Indices corresponding to the observation are obtained by each clustering method and observations in each cluster are acoustically averaged in order to calculate the mean value of each cluster
6-	By using the decision chart developed in this study, clusters in each classroom are associated with the activities (including 'Ambient', 'Lecture', 'Active Learning Activity')

Clustering Performance Evaluation	
7-	Based on the actual labels of the observations noted by the researcher during the measurement the performance of each algorithm is evaluated

5 CHAPTER 4: RESULTS & DISCUSSION

5.1 Long-term Sound Pressure Levels of Classroom Activities

Table 6 provides the mean A-weighted activities sound pressure levels for each classroom, based on the labels assigned to each observation by the researcher during the measurements. For each classroom, the SPLs are averaged acoustically over four measurement locations.

Table 6: the mean A-weighted activities' sound pressure levels for each classroom, based on the labels assigned to each observation

Mean A-weighted SPL [dBA]	H509	H603	H605	H654-1	H654-2	H561	MB2-270
Ambient noise	49.1	46.8	45.7	47.5	45.0	47.5	46.3
Lecture (including Q/A sessions)	56.9	62.6	61.9	57.4	55.9	62.2	60.9
Active learning activity1 (Group talk)	63.1	56.5	70.2	59.5	57.6	-	-
Active learning activity2 (Media)	67.3	-	73.2	-	-	-	-
L_{Aeq} (equivalent continuous sound pressure level)	64.5	61.4	68.5	57.4	56.1	62	63.8
L_{10}	68.6	62.2	71.8	60.1	60.6	65.4	67.4
L_{90}	45.9	44.9	44.7	45.3	49.3	43.6	44.4
Speech to Noise Ratio (SNR)	7.8	15.8	16.2	9.9	10.5	14.7	14.6

The mean A-weighted 'Ambient' noise level for the classrooms included in the measurements is 46.8 (±0.7) dBA and no significant difference is observed between the ambient noise levels in active learning and traditional lecture spaces. The mean A-weighted 'Lecture' SPL in traditional classrooms and active learning classrooms are 61.4 (±1.2) dBA and 59.8 (±3.1) dBA respectively. The mean A-weighted 'Active Learning Activity' is measured to be 63.9 (±4.2) dBA. The highest and lowest mean A-weighted 'Active Learning Activities' are 57.5 dBA and 73.2 dBA respectively.

By comparing the mean A-weighted equivalent continuous sound pressure level in MB2-270 (63.8 dBA) and with H605 (68.5 dBA),(considering there is no significant difference between 'Ambient' noise levels and 'Lecture' speech levels in these two spaces and the numbers os students in both classes were almost the same), one may conclude that the difference between their equivalent A-weighted sound pressure levels is due to students' activities. Meaning, the active Learning classrooms experience higher sound pressure levels compared to traditional classrooms. More samples need to be investigated in order to draw stronger conclusions on this matter.

The Speech to Noise Ratios (SNRs), averaged over measurement locations, in each classroom, indicate that four out of seven measured classrooms fulfill the 15 dB requirement [8] for speech communication. All four classrooms have been recently renovated. However, by investigating the SNRs at each measurement location, it is observed that only H605 met the requirements for SNR at the back of the classroom. H509 has the highest 'Ambient' noise level and the lowest speech to noise ratio at all measurement locations among the measured classrooms. During the measurement the researcher, who was sitting at the back of the room, could clearly hear the voice of the teacher lecturing in the next door classroom. *Table 7* provides the SNRs calculated at each measurement location for all the classrooms.

Table 7: SNRs calculated at each measurement location for the measured classrooms

Mean A-weighted SNR for each cluster	Actual Result			
	Teacher's desk	Closest Student desk	d = 6m	Farthest Student desk
H509	10.7	7.8	4.7	3.6
H603	17.9	15.7	13.3	13.6
H605	17.8	15.5	15.7	15.3
H654(Han)	9.9	11.9	10.5	5.8
H654(LYN)	12.7	12.2	9.1	8.9
H561	18.6	17.6	13.2	9.3
MB2-270	16.0	15.3	14.0	12.9

In classroom H654 which is a large space, during both of the measurements, the teachers were moving in the classroom in order to be better heard by the students. Accordingly the SNR obtained in these two classes are likely to be underestimated at measurement location 1 and 2. Attaching a microphone to teachers during the measurements may help resolve this issue,

A linear regression analysis is performed to investigate the potential correlations between the number of students per square meters of the classrooms (density of population) and the mean A-weighted activity sound pressure levels. Although the lack of sufficient samples makes it difficult to have a firm conclusion on this matter, the results obtained (*Figure 5*) suggest that the 'Active Learning Activity' sound pressure levels (Group work) in active learning classrooms are highly correlated (R^2 = 0.72) to the number of students per square meter. In addition, There is a correlation between the 'Lecture' speech levels and number of students per square meter in all classrooms involved in the measurements ($R^2 = 0.42$) while for occupied 'Ambient' noise levels, no significant correlation is observed between the two terms. More samples need to be investigated in order to have a more reliable conclusion on this matter.

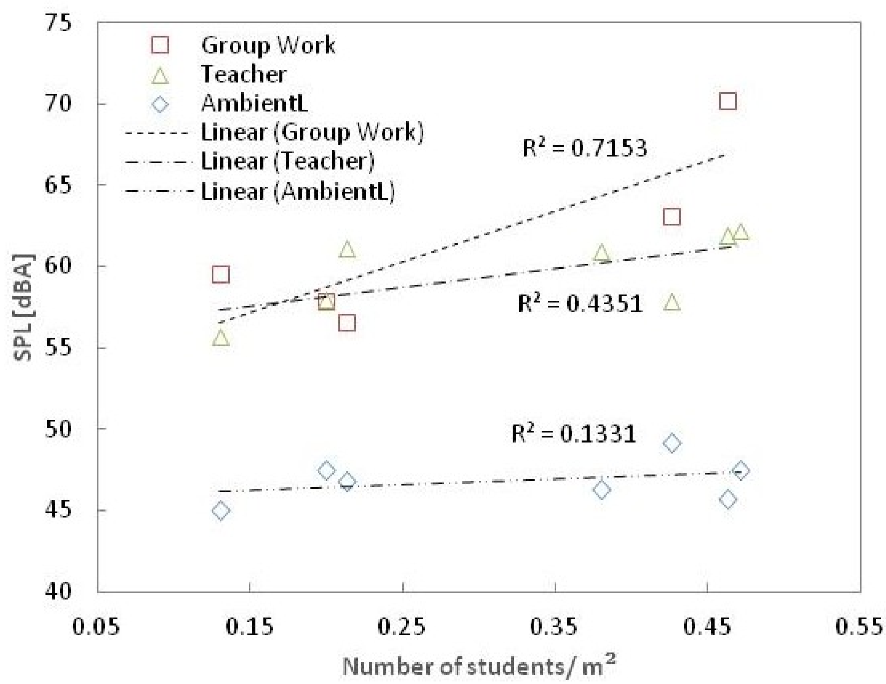
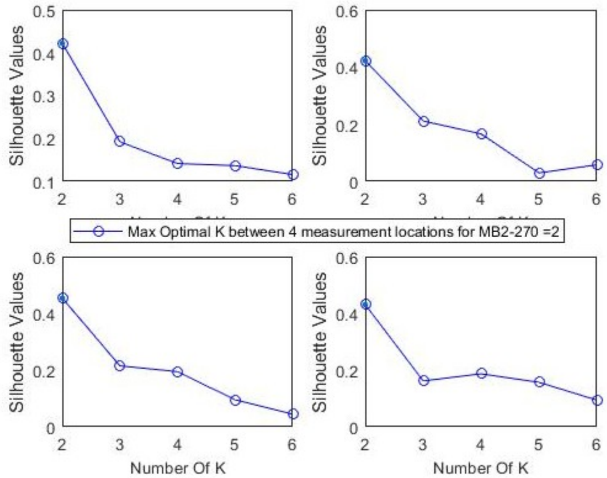


Figure 5: Regression analysis between the 'Active Learning Activity' sound pressure levels [dBA], 'Lecture' speech levels [dBA], 'Ambient' noise levels and the number of students per square meter present during the measurements

In the next step, to perform the clustering analysis, the initial estimations of the number of clusters in each classroom were made by using the maximum number of clusters proposed by

Silhouette values over the four measurement locations.



MB2-270

Figure 6 illustrates the number of clusters obtained by using Silhouette criteria over four measurement Locations in each classroom.

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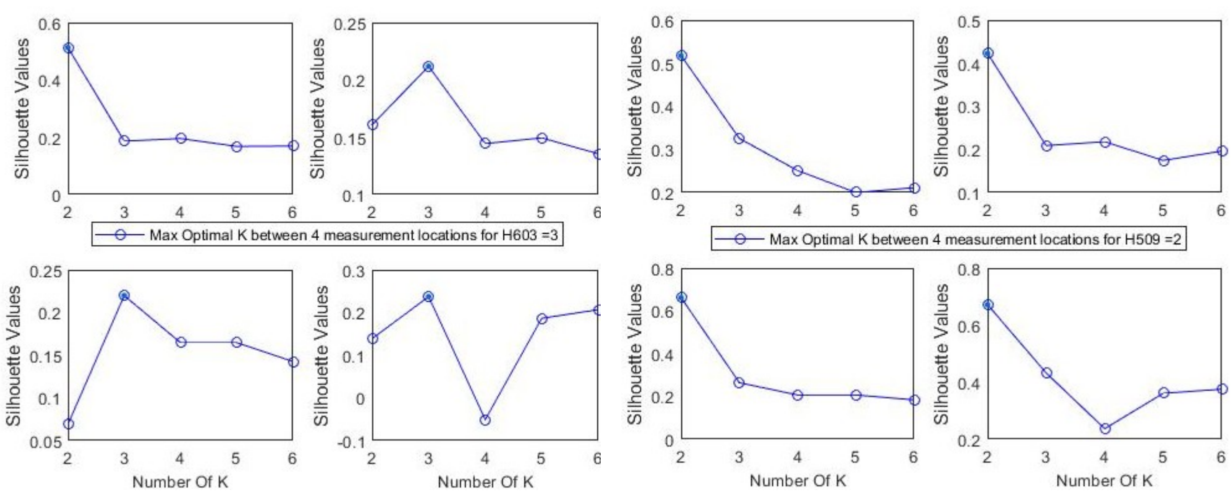
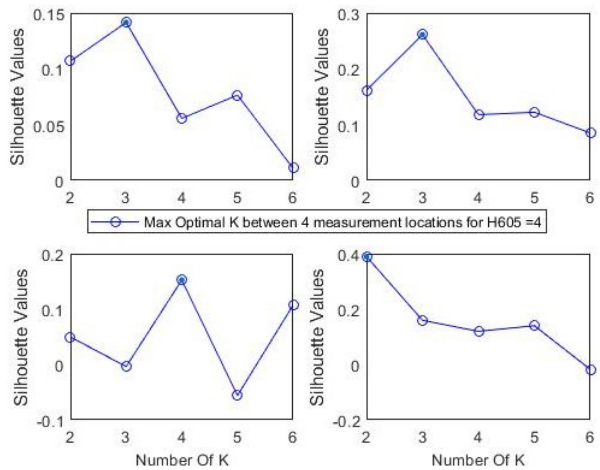
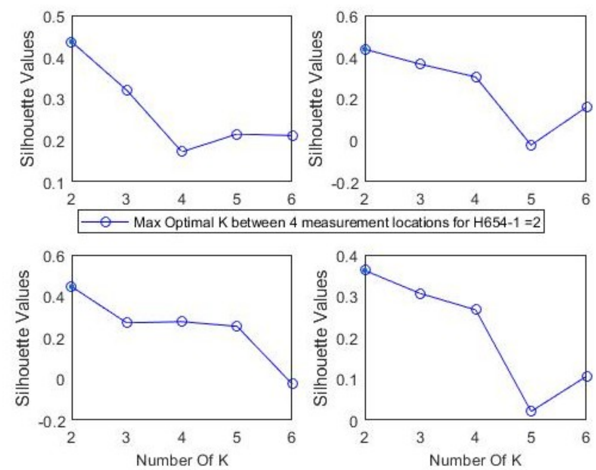


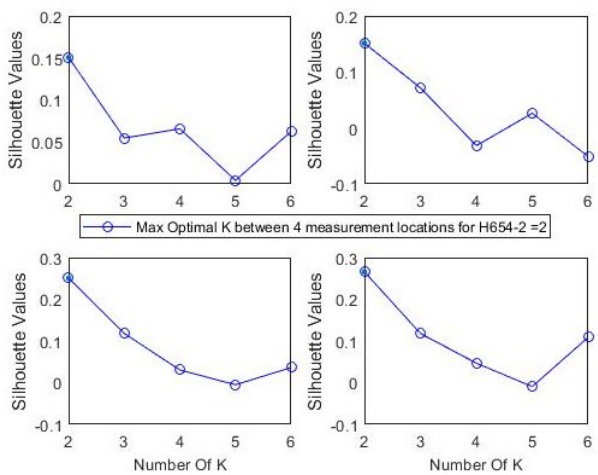
a) H603 b) H509



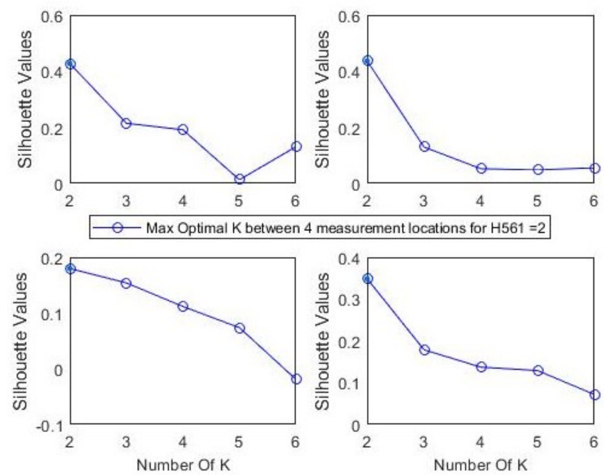
c) H605



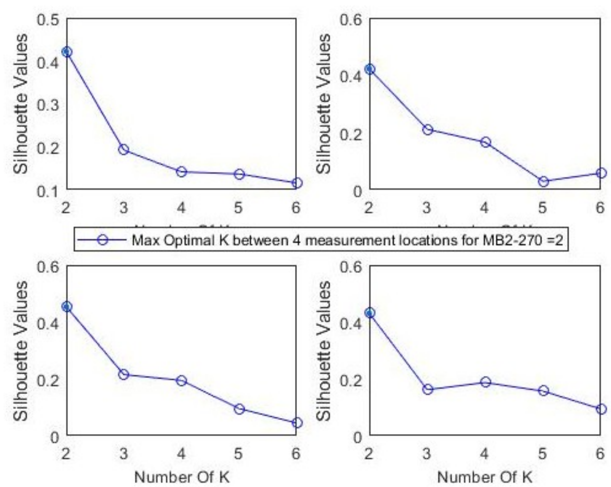
d) H654-1



e) H654-2



f) H561



g) MB2-270

Figure 6: Maximum optimal number of clusters over four measurement locations, evaluated by Silhouette values for each classroom.

Based on the results obtained, Silhouette failed to identify the true number of clusters in classroom H509 and H654-1. The number of clusters suggested by Silhouette values for these two classrooms is 2 while the true number of clusters for both classrooms is 3.

According to *Figure 6*, the final number of clusters (k) chosen to perform clustering on the data obtained from each classroom is illustrated in *Table 8* . In a traditional lecture classroom, i.e. classroom H561 and MB2-270, no 'Active Learning Activity' is expected; hence in these spaces the number of clusters is determined to be 2 (this assumption is confirmed with the number of k calculated by using Silhouette values for these spaces).

Table 8: Number of clusters (k) considered to perform clustering for each classroom by using Silhouette values

	H509	H603	H605	H654-1	H654-2	H561	MB2-270
Number of Clusters (k)	2	3	4	2	2	2	2

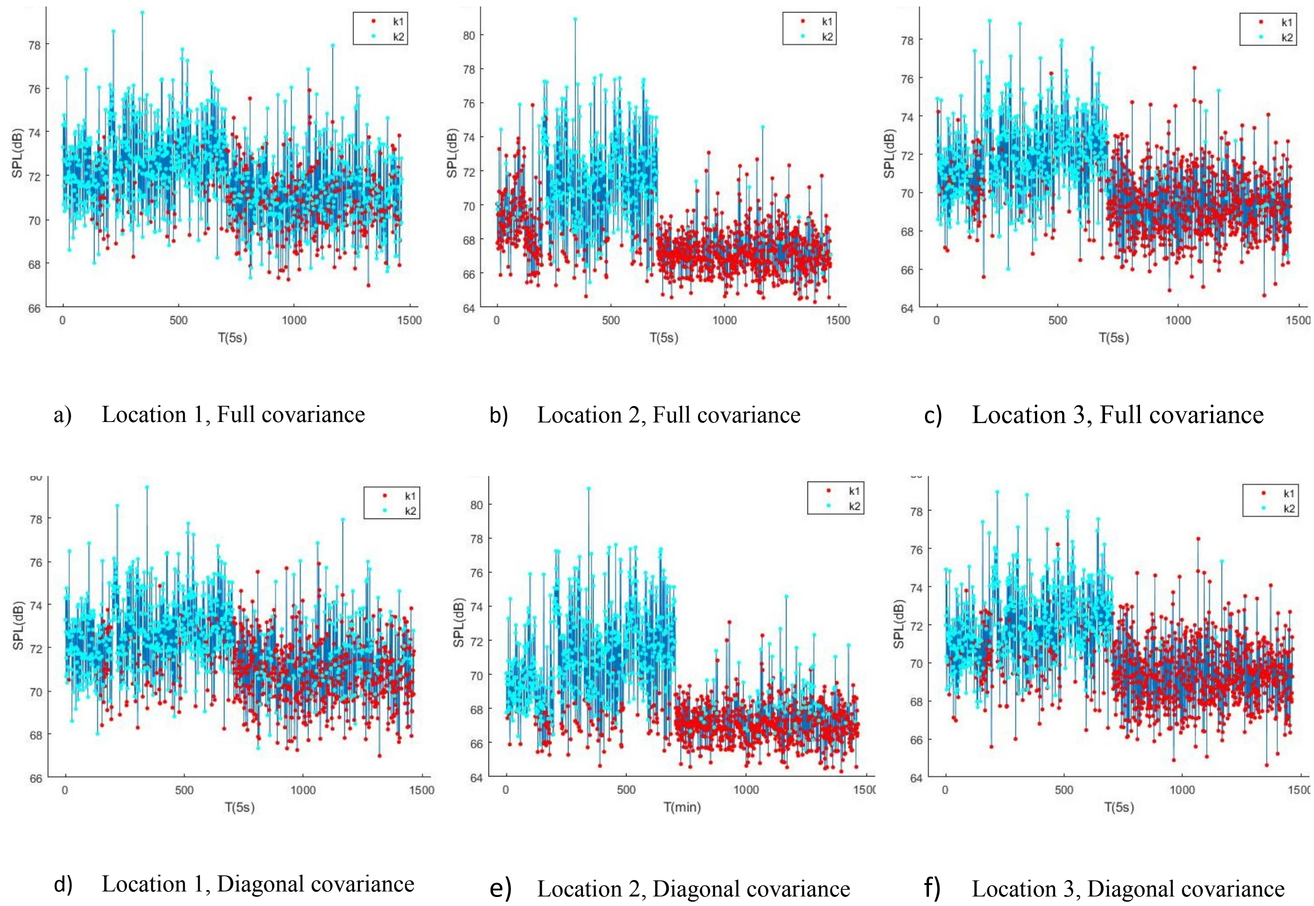
Table 9 provides the mean A-weighted sound pressure levels of the activities in each classroom, calculated by using 3 clustering methods, including K-means clustering Gaussian Mixture model and Spectral clustering.

Table 9: A-weighted mean sound pressure levels of the clusters obtained from algorithm analysis in each classroom

Mean A-weighted SPL [dBA]		H509	H603	H605	H654-1	H654-2	H561	MB2-270
K-means Clustering	k1	52.5	46.6	47.4	48.1	52.1	50.3	49.3
	k2	66.8	56.6	58.6	59.9	59.2	64.3	62.9

	k3	-	64.0	69.2	-	-	-	-
	k4	-	-	72.9	-	-	-	-
GMM Clustering	k1	52.5	46.5	46.5	46.8	52.0	49.1	47.3
	k2	66.8	56.3	59.2	58.8	59.1	63.4	62.4
	k3	-	63.1	68.5	-	-	-	-
	k4	-	-	72.8	-	-	-	-
Spectral Clustering	k1	52.2	46.3	46.3	47.5	52.2	49.4	48.9
	k2	66.8	55.6	57.0	59.6	59.2	64.0	62.8
	k3	-	63.3	67.1	-	-	-	-
	k4	-	-	72.0	-	-	-	-

Among three algorithms, K-means clustering is the most convenient to be implemented while there were limitations in application of GMM and spectral clustering. One of the initial assumptions was that the covariance matrices of the GMM components were full. However, it was observed that this assumption did not necessarily lead to consistent clusters at some measurement locations. Therefore, for classrooms H654-2 and H509 the covariance matrices were determined to be diagonal. *Figure 7* provides an example of this, by comparing the results obtained for H509 when the covariance matrices of the clusters are full to when they are diagonal.



a) Location 1, Full covariance
b) Location 2, Full covariance
c) Location 3, Full covariance

d) Location 1, Diagonal covariance
e) Location 2, Diagonal covariance
f) Location 3, Diagonal covariance

Figure 7 : Time history of long term A-weighted sound pressure levels averaged in 5s interval for classroom H509, a) , b) and c) at measurement location 1, 2 and 3 respectively , obtained by using GMM when covariance matrices of the clusters are considered to be full, d), e) and f) when covariance matrices of the clusters are considered to be diagonal.

Using spectral clustering analysis, in classrooms H654-1 and H654-2, the σ values that control the width of the neighborhoods, were determined to be equal to two times the difference between the maximum and minimum A-weighted equivalent sound pressure level averaged in 5s intervals.

5.2 Identification of Activities

By using the developed decision chart (*Figure 4*), the clusters obtained from the algorithms are associated with the activities defined in methodology. The efficiency of employing algorithms along with the developed decision chart in identifying the activities and their corresponding sound pressure levels and durations, is then evaluated by using three evaluation measures.

The results of GMM algorithm for all the classrooms are investigated. For classroom H509, the time history of the equivalent un-weighted sound pressure levels, averaged in 5s intervals and the frequency spectrums of the clusters at measurement locations 1 and 2 are illustrated in *Figure 8*. Moreover, it indicates the trends of changes in cluster SPLs over different measurement locations. At measurement location 1, which was above the teacher's desk, the frequency roll-offs for k1 and k2 are calculated to be -18 dB/decade and -24 dB/decade respectively. At measurement location 2 above the closest students' desk, those values were calculated to be -16.4dB/decade and -24.7dB/decade respectively. Accordingly, both k1 and k2 indicate the characteristics of a speech type activities. Based on *Figure 8*, k1 illustrates a drop of 3.5 dBA while k2 indicates a more uniform pattern with a slight rise at measurement location 2. Considering that k1 is the most frequent activity with the lowest mean sound pressure level over measurement locations, 'Lecture' is assigned to k1 and 'Active Learning activity' is assigned to k2. It is expected that the activities remain the same in the entire classroom and subsequently through different measurement locations; hence, for measurement location 3 and 4, 'Lecture' is assigned to k1 and 'Active Learning Activity' is assigned to k2 as well.

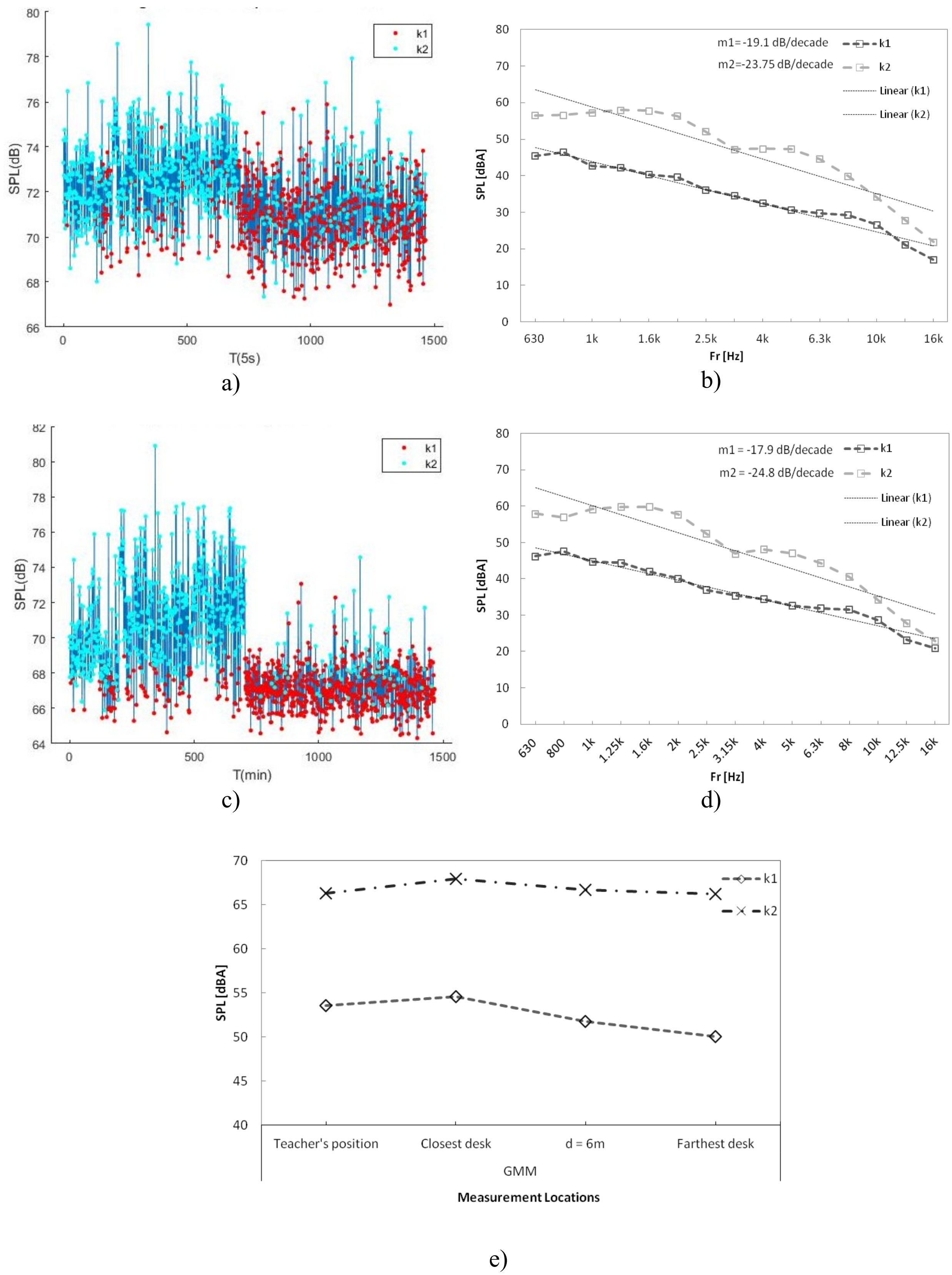
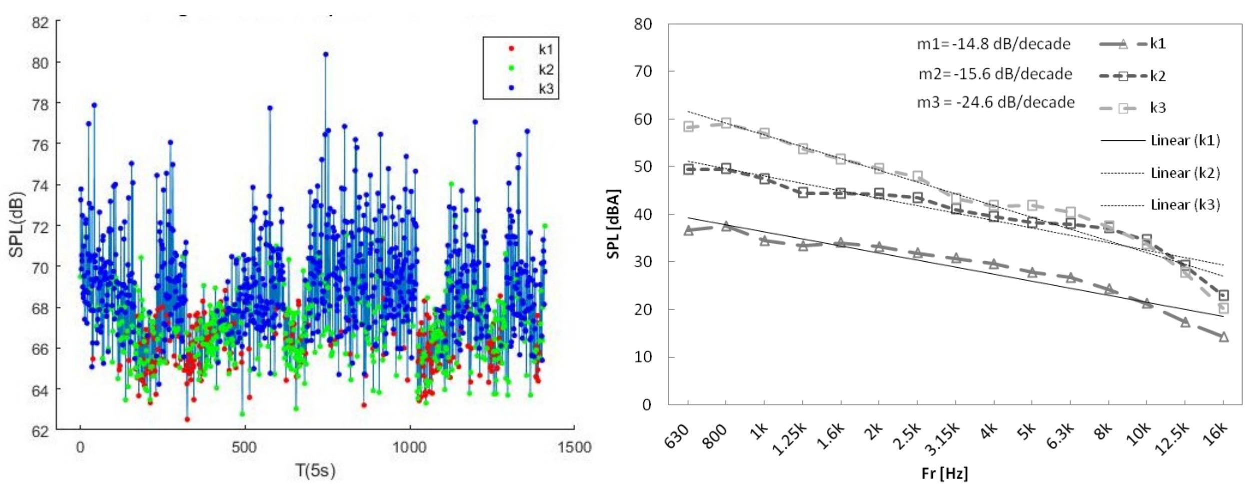
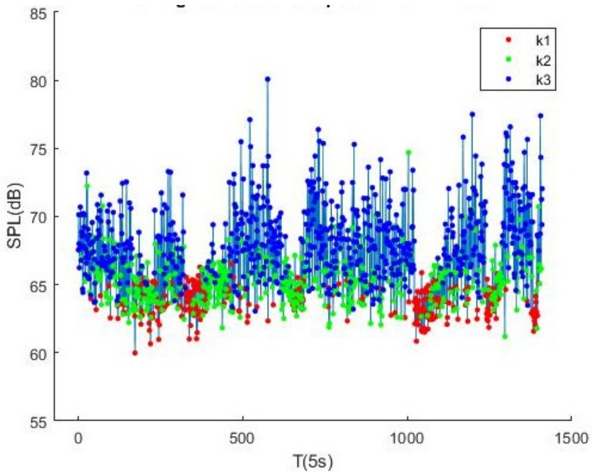

SPL(dB)
T(5s)
k1
k2
a)
m1=-19.1 dB/decade
m2=-23.75 dB/decade
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]
b)
SPL(dB)
T(min)
c)
m1 = -17.9 dB/decade
m2 = -24.8 dB/decade
Fr [Hz]
d)
Teacher's position
Closest desk
d = 6m
Farthest desk
GMM
Measurement Locations
e)

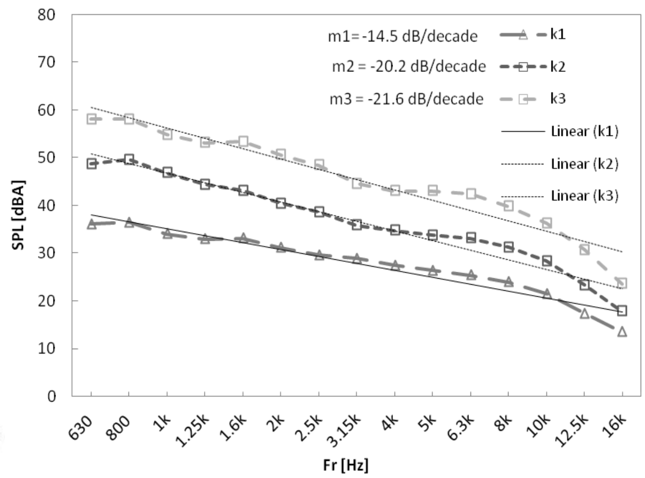
Figure 8: Classroom H-509 a) The clustering results of the long-term sound pressure levels at measurement location 1. b) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. c) The clustering results of the long-term sound pressure levels at measurement location 1. d) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. e) The trends of changes in A-weighted activity sound pressure levels over different measurement locations.

For classroom H603, the continuous equivalent un-weighted sound pressure levels in 5s intervals and the frequency spectrums of the clusters at measurement locations 1 and 2 are illustrated in *Figure 9*. At measurement locations 1 and 2, the frequency roll-offs from 630 Hz to 16 kHz for k1 are -14 dB/decade and -13.9 dB/decade respectively. Moreover, k1 has the lowest mean sound pressure level over different measurement locations. Based on *Figure 9* k1 illustrates more of a uniform pattern over different measurement positions. Accordingly, 'Ambient' is assigned to k1. At measurement locations 1 and 2, cluster k2 and k3 indicate the characteristic of a speech type activity with frequency spectrum roll-offs greater than -15 dB/decade. Considering that cluster 3 is the most frequent activity, 'Lecture' is assigned to k3. Subsequently 'Active Learning Activity; is assigned to k2.

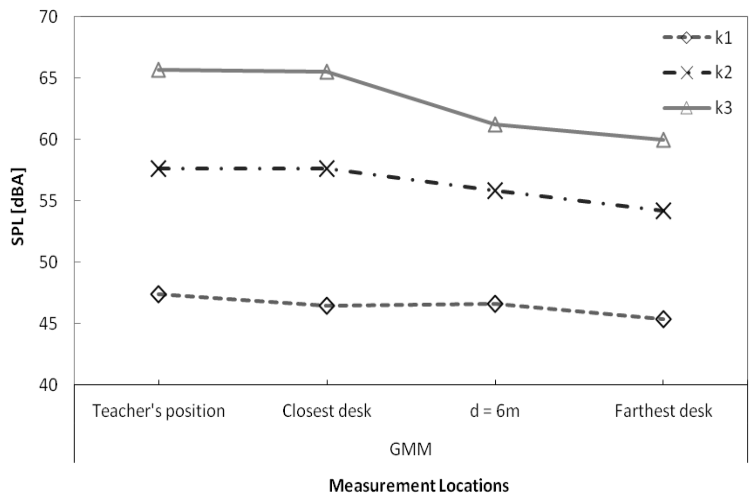


a) b)





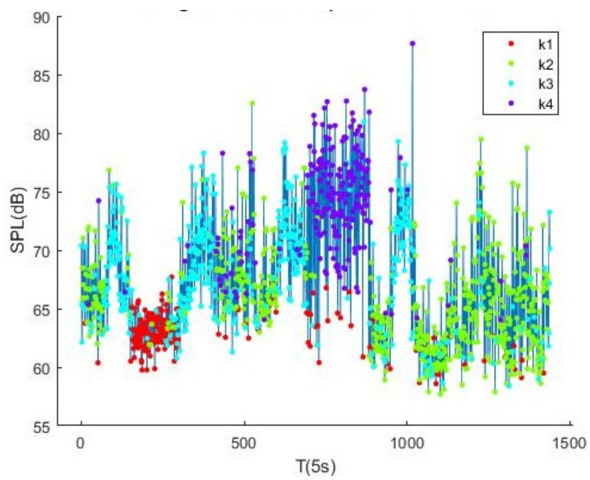
c) d)



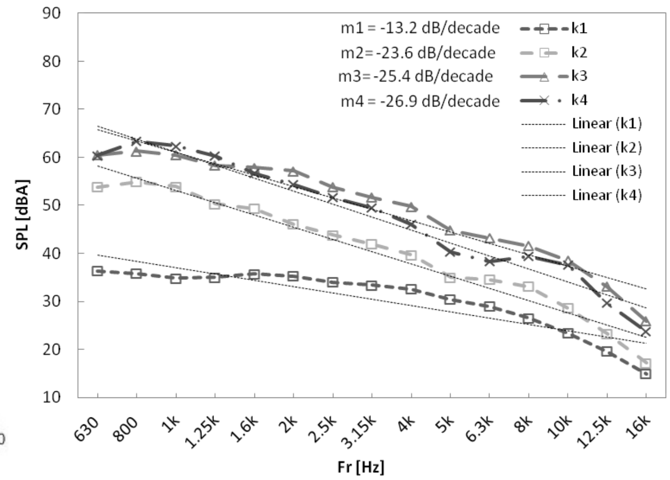
e)

Figure 9: Classroom H-603 a) The clustering results of the long-term sound pressure levels at measurement location 1. b) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. c) The clustering results of the long-term sound pressure levels at measurement location 1. d) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. e) The trends of changes in A-weighted activity sound pressure levels over different measurement locations.

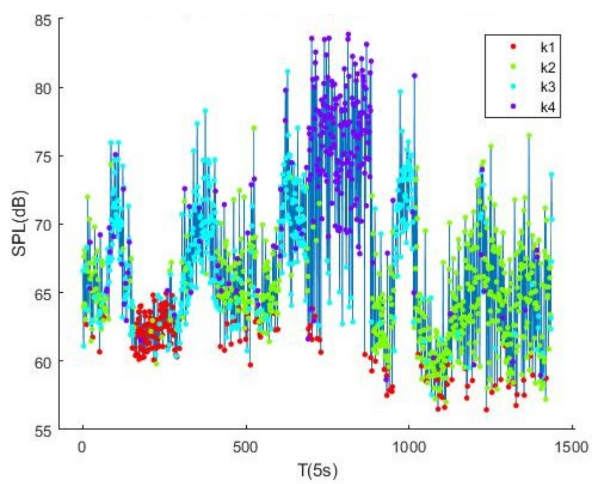
In classroom H605 (*Figure 10*), at measurement location 1 and 2, the frequency roll-offs from 630 Hz to 16 kHz for k1 are -14.8 dB/decade and -14.5dB/decade respectively. k1 has the lowest mean sound pressure level and illustrates more of a uniform pattern over different measurement locations. Accordingly, 'Ambient' is assigned to k1. At measurement locations 1 and 2, cluster k2 indicates the characteristic of a speech type activity with frequency spectrum roll-offs greater than -15 dB/decade. Considering that k2 is the most frequent activity, 'Lecture' is assigned to k2. Subsequently 'Active Learning Activity is assigned to k3 and k4.



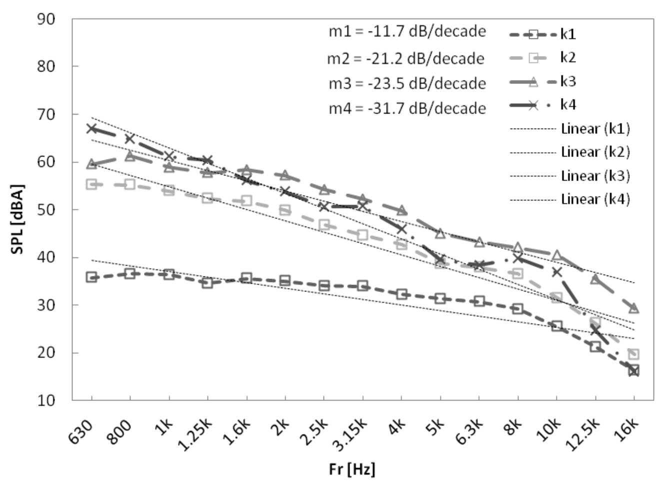
a)



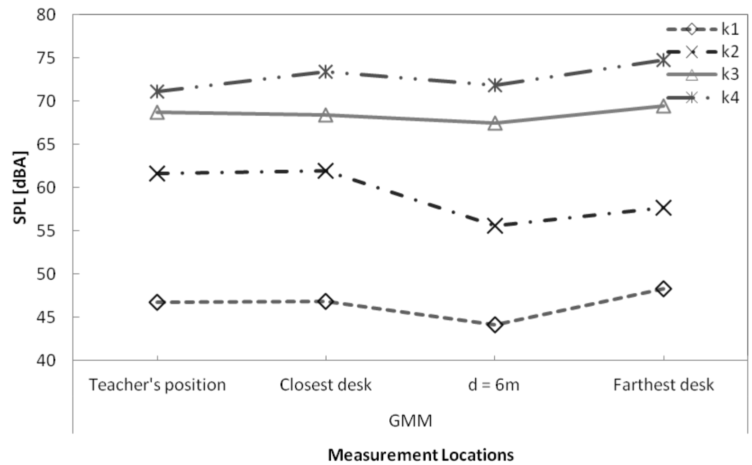
b)



c)



d)

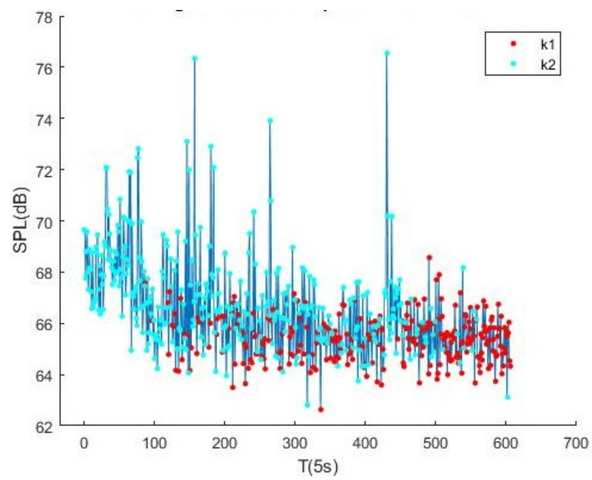


e)

Figure 10: Classroom H-605 a) The clustering results of the long-term sound pressure levels at measurement location 1. b) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. c) The clustering results of the long-term sound pressure levels at measurement location 1. d) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. e) The trends of changes in A-weighted activity sound pressure levels over different measurement locations.

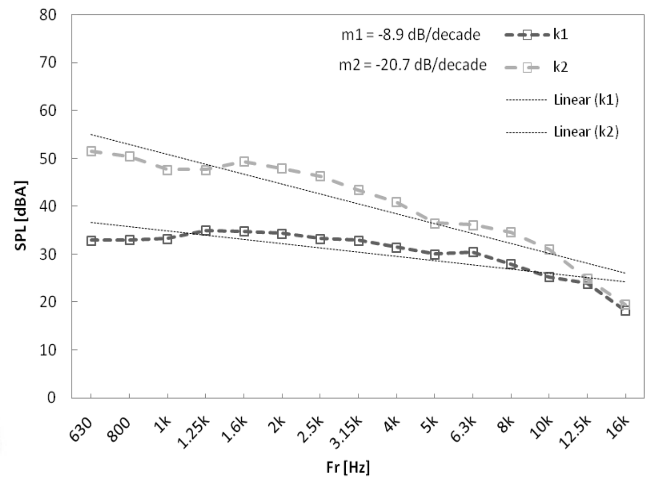
Figure 11 indicates that in classroom H564-1, the frequency roll-offs from 630 Hz to 16 kHz for k1 are -8.9 dB/decade and -11.3 dB/decade respectively. In addition, k1 does not illustrate sound level drops through measurement locations; hence 'Ambient' is assigned to k1. Based on assumption1, 'Lecture' is assigned to k2.

Considering *Figure 11*, the frequency roll-offs from 630 Hz to 16 kHz for k2 at measurement location 1 and 2 are -20.7 dB/decade and -21.7 dB/decade respectively which indicate the characteristic of a speech type activity. k2 is the most frequent activity with sound level drops over measurement locations. These two observations confirm the assignment of 'Lecture' to k2.



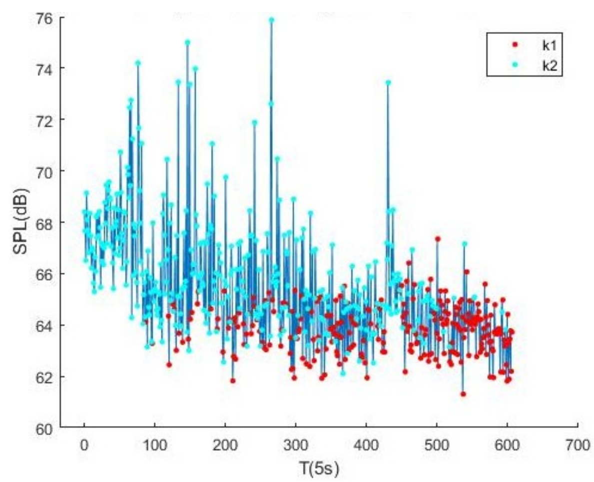
k1
k2
SPL(dB)
T(5s)

a)



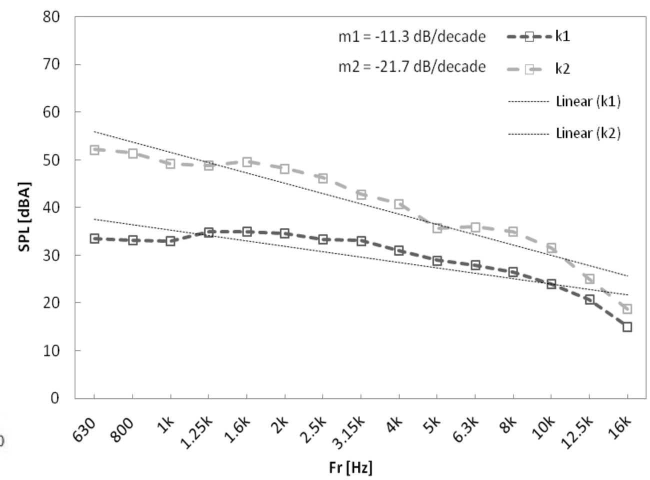
m1 = -8.9 dB/decade
m2 = -20.7 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

b)



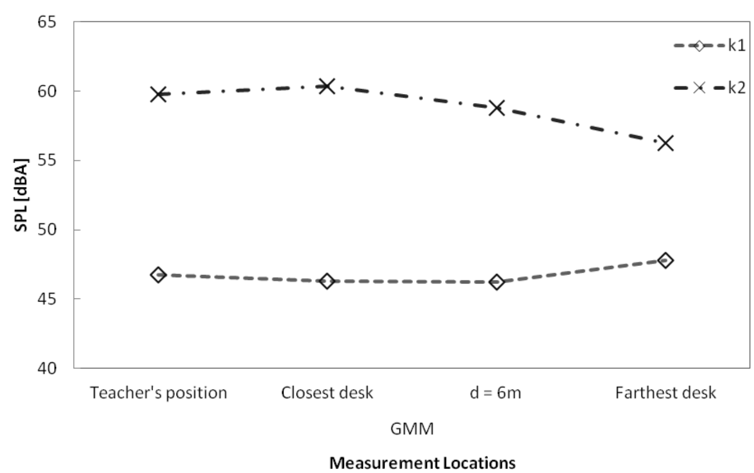
k1
k2
SPL(dB)
T(5s)

c)



m1 = -11.3 dB/decade
m2 = -21.7 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

d)

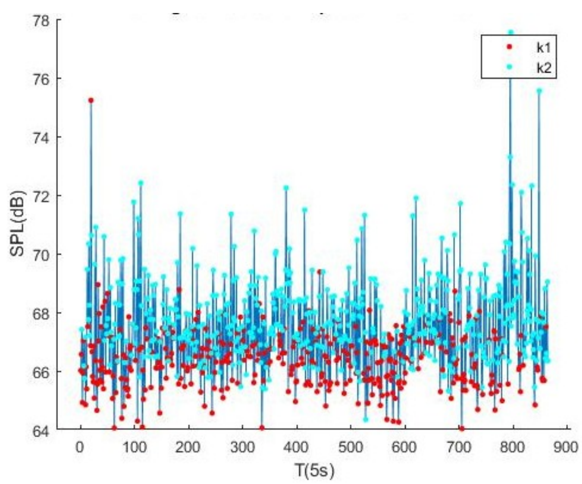


k1
k2
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
GMM
Measurement Locations

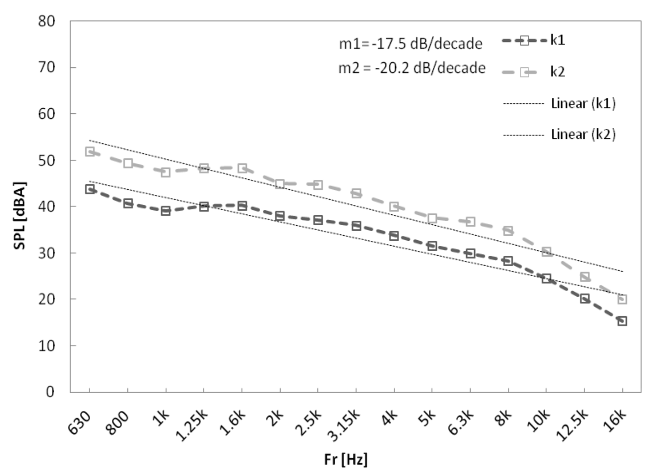
e)

Figure 11: Classroom H-654-1 a) The clustering results of the long-term sound pressure levels at measurement location 1. b) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. c) The clustering results of the long-term sound pressure levels at measurement location 1. d) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. e) The trends of changes in A-weighted activity sound pressure levels over different measurement locations.

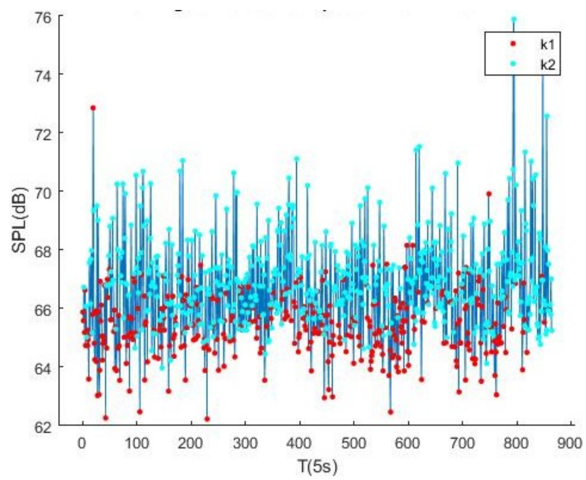
In classroom H654-2, the frequency roll-offs from 630 Hz to 16 kHz for k1 are -17.5 dB/decade and -16.8 dB/decade respectively (*Figure 12*). The frequency roll-offs from 630 Hz to 16 kHz for k2 are -20.2 dB/decade and -20.0 dB/decade respectively. Although none of the two clusters indicate meaningful sound level drops over measurement locations, because k2 is the most frequent activity by considering assumption 1 and 3, 'Lecture' is assigned to k2. Subsequently, 'Active Learning Activity' is assigned to k1.



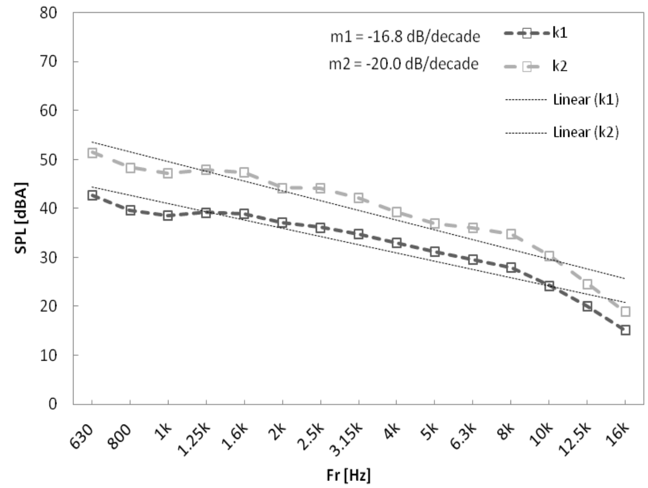
a)



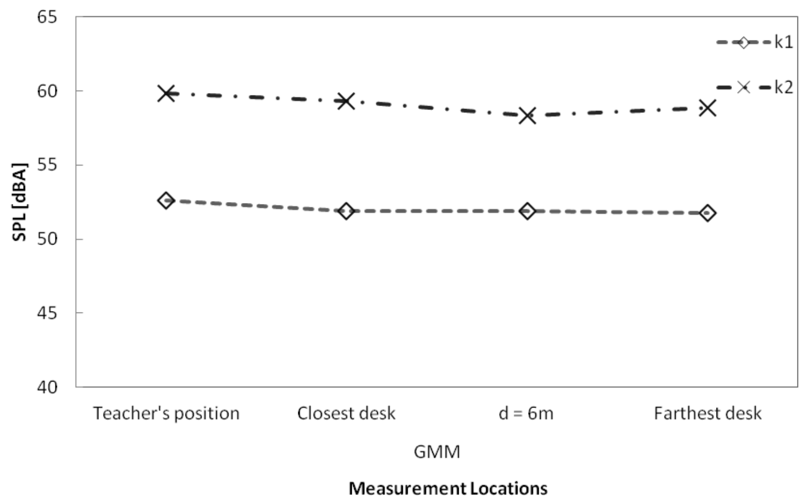
b)



c)



d

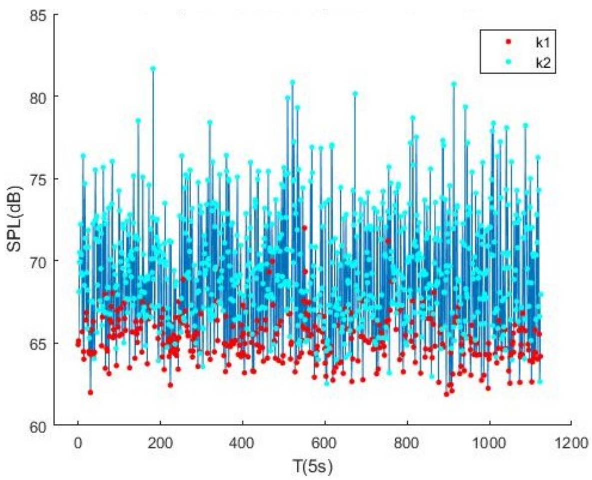


c)

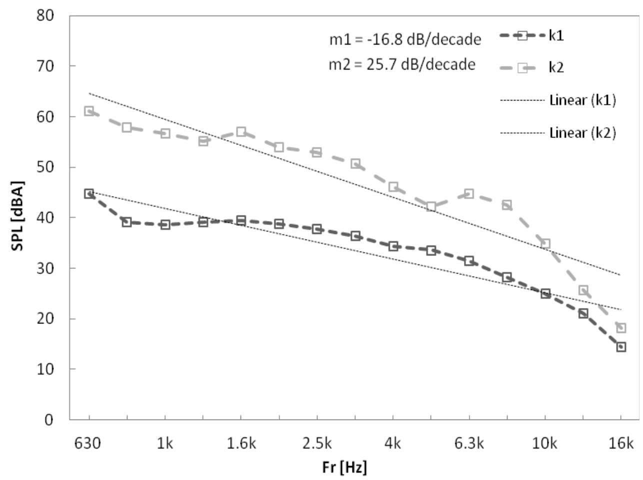
Figure 12: Classroom H-654-2 a) The clustering results of the long-term sound pressure levels at measurement location 1. b) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. c) The clustering results of the long-term sound pressure levels at measurement location 1. d) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. e) The trends of changes in A-weighted activity sound pressure levels over different measurement locations.

In traditional lecture classrooms, the number of clusters were determined to be k=2. For these spaces, k1, which is the lowest activity, represents the ambient noise levels and k2 is associated with speech (i.e. 'Lecture' SPLs). These assumptions are aligned with the optimal number of clusters obtained by applying Silhouette measure for traditional lecture classes.

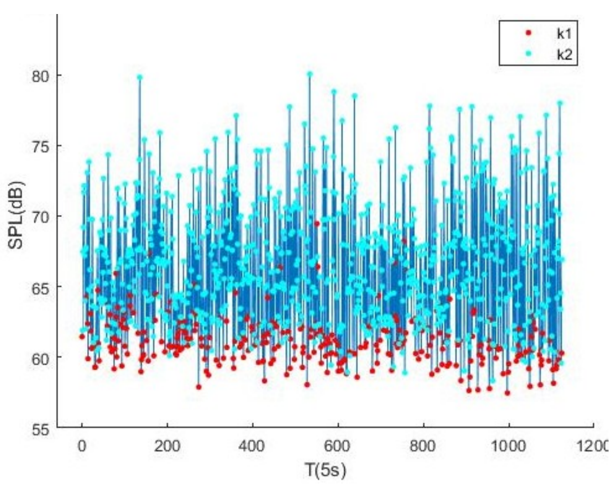
Figure 13 illustrates that in classroom H561, at measurement location 1 and 2, the frequency roll-offs from 630 Hz to 16 kHz for k1 are -16.8 dB/decade and -14.3 dB/decade. This suggests that the algorithm failed to detect 'Ambient' at measurement location 1. For measurement location 2 to 4, based on *Figure 13*, 'Lecture' is assigned to k2. Subsequently, 'Ambient' is assigned to k1.



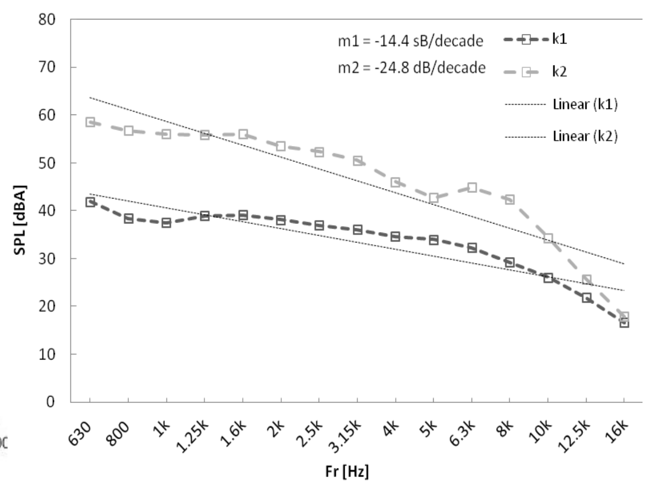
a)



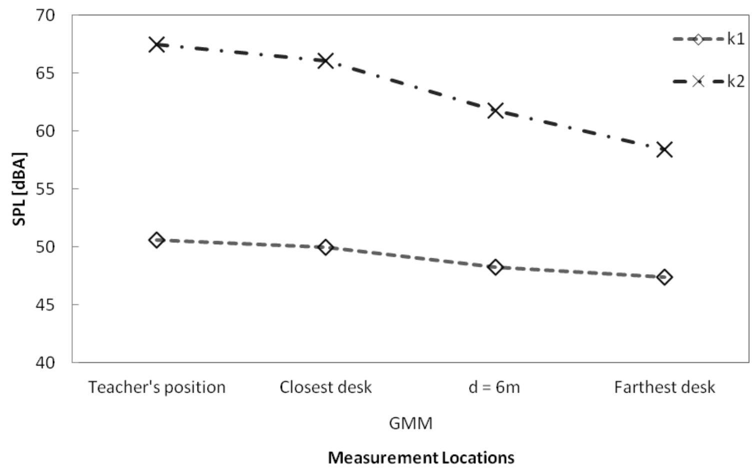
b)



c)



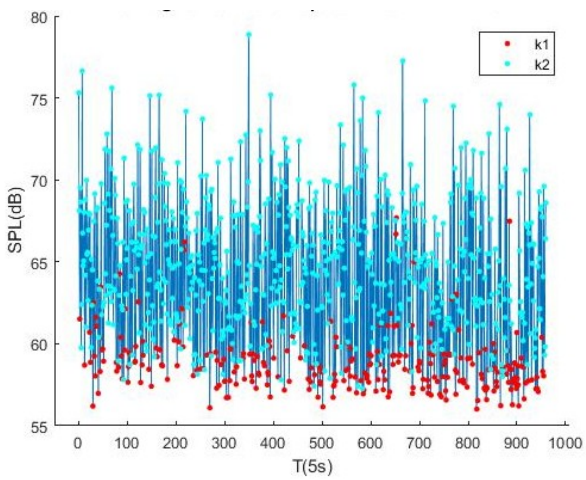
d)



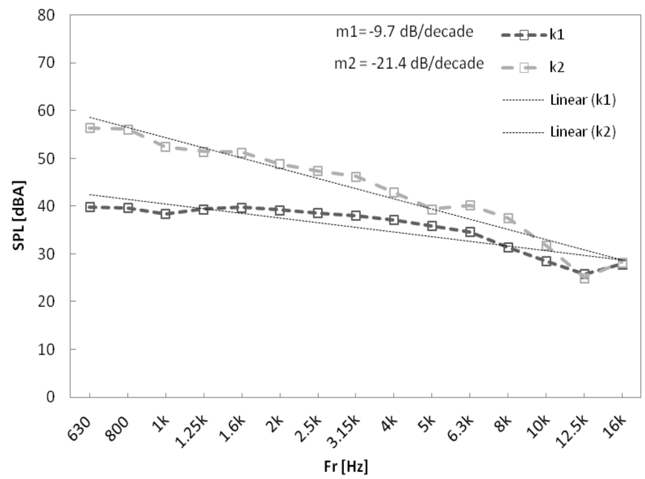
e)

Figure 13: Classroom H-561 a) The clustering results of the long-term sound pressure levels at measurement location 1. b) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. c) The clustering results of the long-term sound pressure levels at measurement location 1. d) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. e) The trends of changes in A-weighted activity sound pressure levels over different measurement locations.

In classroom MB2-270, results from *Figure 14* indicate that at measurement location 1 and 2, the frequency roll-offs from 630 Hz to 16 kHz for k1 are $-9.7\ \mathrm{dB/decade}$ and $-10.9\ \mathrm{dB/decade}$ respectively, hence 'Ambient' is assigned to k1. Subsequently, 'Lecture' is assigned to k2.



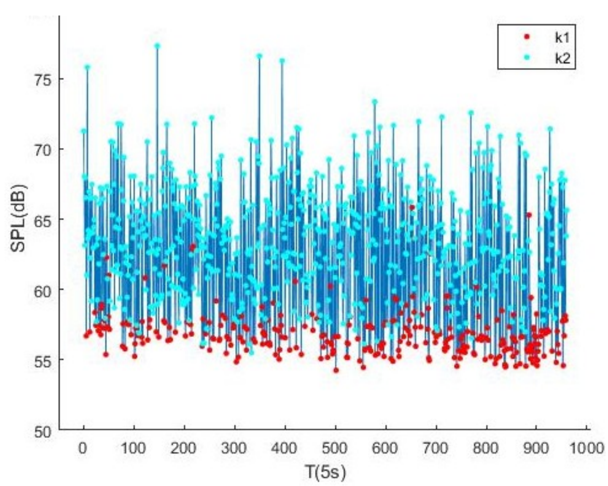
k1
k2
SPL(dB)
T(5s)



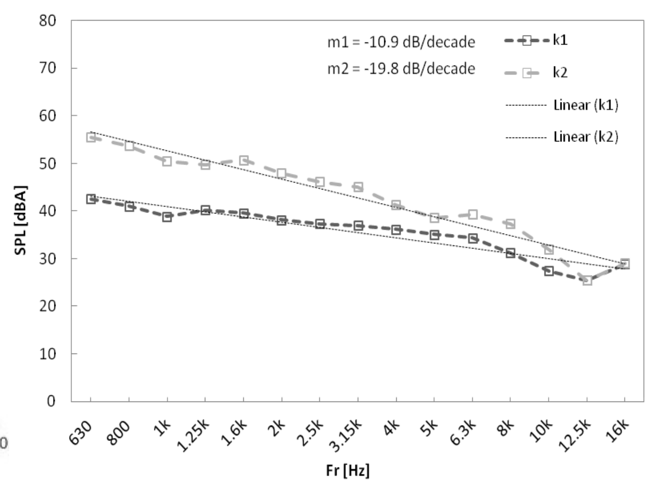
m1= -9.7 dB/decade
m2 = -21.4 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

a)

b)



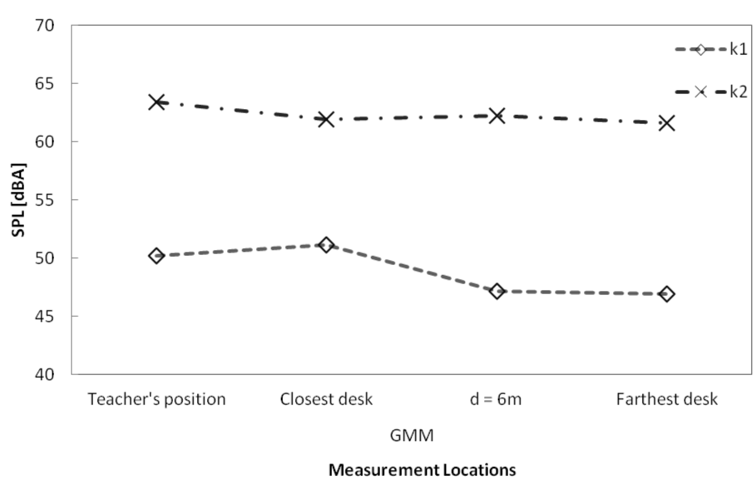
k1
k2
SPL(dB)
T(5s)



m1 = -10.9 dB/decade
m2 = -19.8 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

d)

e)



k1
k2
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
GMM
Measurement Locations

e)

Figure 14: Classroom MB2-270 a) The clustering results of the long-term sound pressure levels at measurement location 1. b) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. c) The clustering results of the long-term sound pressure levels at measurement location 1. d) The frequency spectrum roll-offs from 630 Hz to 16 kHz, for the clusters at measurement location 1. e) The trends of changes in A-weighted activity sound pressure levels over different measurement locations.

By following the same procedure for the results obtained from K-means clustering and spectral clustering algorithms, activities assigned to clusters in all classrooms. To avoid repetition, the process is not explained. The detail information about the implementation of the decision chart for all three algorithms is provided in Appendix.

The finalized activities considered in each classroom, based on explanations above, are summarized in *Table 10*.

Table 10: Activities assigned to clusters in each classroom

	H509	**H603**	**H605**	**H654-1**	**H654-2**	**H561**	**MB2-270**
k1	Lecture	Ambient	Ambient	Ambient	Active Learning	Ambient	Ambient
k2	Active Learning	Active Learning	Lecture	Lecture	Lecture	Lecture	Lecture
k3	-	Lecture	Active Learning	-	-	-	-
k4	-	-	Active Learning	-	-	-	-

5.3 Performance Evaluation of the Algorithms and the Decision Chart

To compare the performance of the clustering algorithms on estimating the long term sound pressure levels of the activities at each measurement location, linear regression analysis was performed between the actual mean A-weighted activity levels (as indicated in *Table 6*). *Figure*

15 visualizes the regression analysis between the results obtained from the algorithms and the actual mean A-weighted sound pressure levels of the activities.

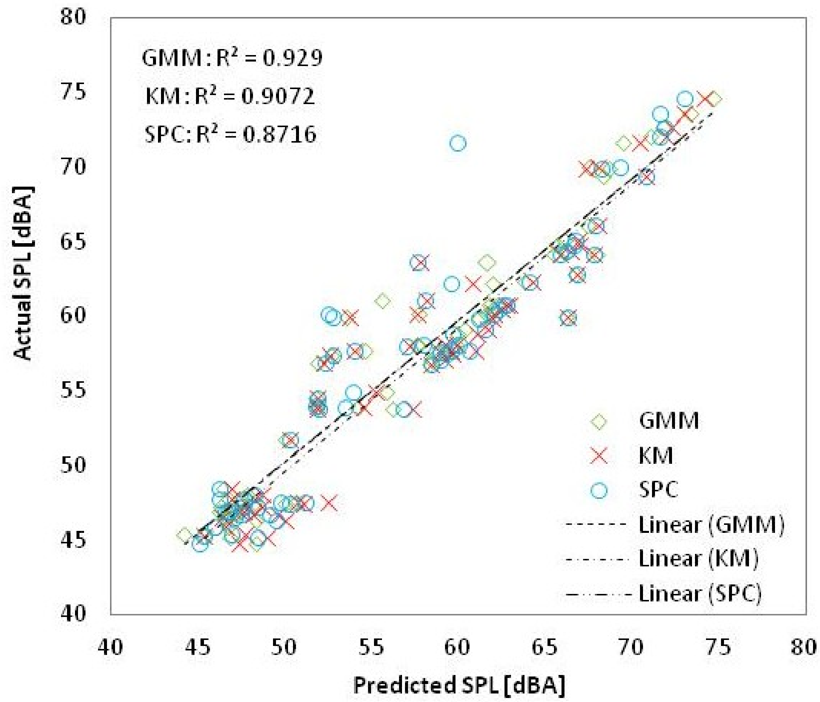


Figure 15: Linear regression between the actual mean A-weighted activity levels and calculated mean A-weighted sound levels of the clusters

Based on the results of the analysis, GMM results with the highest coefficient of determination (R^2=0.9204) predicts the mean activity levels better than the other two algorithms. K-means clustering performed slightly worse (R^2=0.9072) followed by spectral clustering results with the coefficient of determination to be R^2=0.8242.

The performance of the algorithms and the developed decision criteria in identifying the activities in measured classrooms were then evaluated by calculating the Accuracy (ACC), Precision (PRC) and Recall (REC) for the assigned activities to clusters, at all the measurement positions in each classroom. *Table 11* provides the results of the performance evaluations of the three clustering algorithms averaged over measured classrooms.

Table 11 : Results of performance evaluation for K-means, GMM and Spectral clustering algorithm by calculating the Accuracy (ACC), Precision (PRC) and Recall (REC

	Activity	ACC	PRC	REC
GMM	Ambient	82%	40%	78%
	Lecture	67%	87%	63%
	Active Learning	74%	54%	70%
	Overall	76%	69%	69%
K-means	Ambient	72%	30%	86%
	Lecture	63%	87%	58%
	Active Learning	68%	40%	49%
	Overall	72%	63%	63%
Spectral Clustering	Ambient	72%	26%	77%
	Lecture	59%	86%	55%
	Active Learning	66%	44%	49%
	Overall	71%	61%	61%

The results indicate that GMM performs the best among three algorithms. By employing GMM and applying the decision chart presented in this study, the highest average accuracy which belongs to identifying the 'Ambient' is 82%. It is followed by 'Active Learning Activity' that is identified accurately 74% of the time. The lowest accuracy is related to 'Lecture' which was identified correctly 67% of the time. The lowest accuracy in identifying 'Lecture' was related to classroom H654-2 (35%). The measurement performed in H654-2 was during a practice class (i.e. the session was not a regular class) in which 'Lecture' was not the dominant activity. The results of H654-2 suggests that assumption 3 in the decision chart might be misleading if the measurements are conducted in practice sessions in which most of the class duration is spent on students' activities. Overall, employing GMM along with the decision chart identify the activities discussed in this study in 76% of time.

One-third octave band frequency spectrums of the 'Ambient' noise levels and 'Lecture' SPLs, obtained from the actual results, indicate that in all the classrooms the frequency spectrum roll-offs from 630 HZ to 16 kHz for 'Ambient' noise levels are lower than -15 dB/decade and for 'Lecture' sound levels are higher than -15 dB/decade. Therefore, the second criteria of the decision chart developed in this study, is promising to be applied to future studies on similar subjects.

5.4 Comparison with the Methods Proposed in Previous Studies

The efficiency of the method proposed in this study in identifying the different sound sources and their corresponding mean sound levels, in comparison with other similar studies, is investigated. Two methods previously employed in studies by Pekkarinen et al. [24] and Hodgson et al. [25] are applied to the long-term occupied A-weighted sound pressure levels of the classrooms averaged in 5s intervals . Pekkarinen et al., associated the L_{90} and the L_{Aeq}, obtained from the long term continuous sound pressure level measurements in occupied classrooms, with the 'Ambient' noise level and 'Lecture' speech level respectively. Following their method, in this study, L_{90} and L_{Aeq}, calculated from the long term A-weighted continuous sound pressure levels averaged in 5s intervals at each measurement location, are associated with the long-term 'Ambient' and 'Lecture' sound levels respectively. The other method, proposed by Hodgson et al, predicts the long-terms 'Lecture' sound pressure level and 'Ambient' noise level during lecture time by fitting three distributions into the long term sound pressure level frequency distributions of classrooms. The mean values of the three distributions were associated with the long-term sound pressure levels of ventilation noise, student activity noise and speech.

The average of the mean values of ventilation noise and student activity noise was considered as the 'Ambient' noise level in occupied classrooms. In order to duplicate their proposed method, in this study, the frequency distributions of the occupied long-term A-weighted sound pressure levels averaged in 5s intervals at each measurement location, is fitted with two normal distributions. The mean value of the higher distribution is associated with 'Lecture' sound level and the mean value of the lower curve is to represent the occupied 'Ambient' noise level. *Figure 16* illustrates the results obtained from the distribution fitting method, for classroom H603 at measurement location 2, as an example.

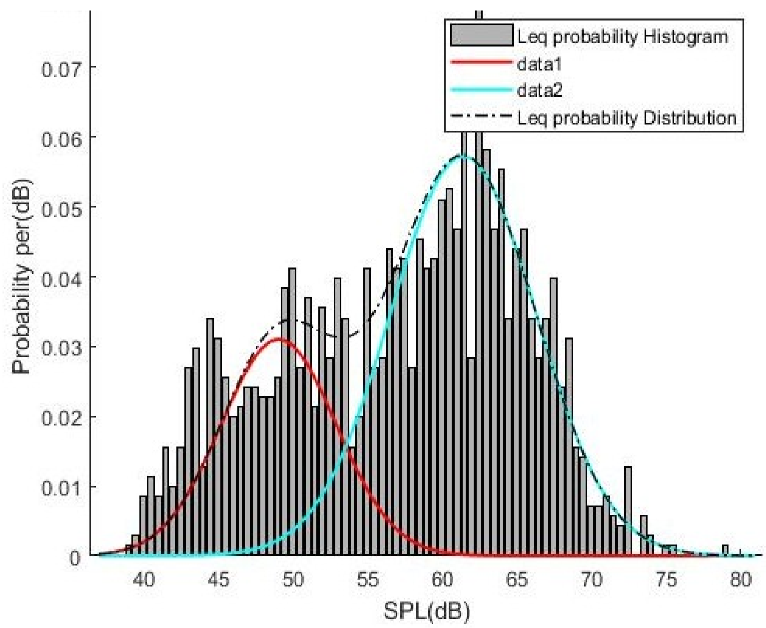


Figure 16: probability density plot for the A-weighted long term sound pressure levels averaged in 5s intervals at measurement location 2 in classroom H603, fitted by two normal distributions representing 'Ambient' and 'Lecture

To investigate the efficiency of the methods in predicting the 'Ambient' and 'Lecture' sound levels, Linear regression analysis was performed between the actual mean A-weighted sound pressure levels of 'Ambient' and 'Lecture' activity and the values predicted by GMM algorithm, L_{90}/L_{Aeq} and distribution fitting methods. *Figure 17* illustrates the linear regression between the actual 'Ambient' and 'Lecture' sound levels and the values predicted by using the methods explained above.

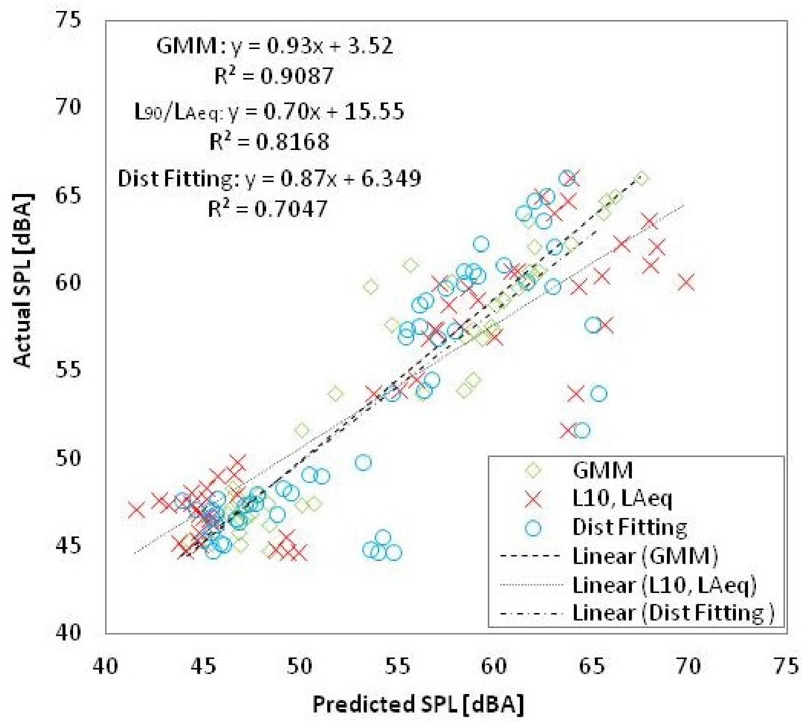


Figure 17: Linear regression between the actual 'Ambient' and 'Lecture' A-weighted sound pressure levels and the levels predicted by using GMM algorithm, L_{90} and L_{Aeq} and distribution-fitting methods

Furthermore, Speech to Noise Ratio (SNR) is calculated at each measurement location by subtracting 'Ambient' noise levels from 'Lecture' sound levels. The actual SNRs are plotted against predicted SNRs by using GMM and the methods explained above. *Figure 18* illustrates the linear regression between the actual SNRs and the values predicted by using GMM algorithm, L_{90} and L_{Aeq} and distribution-fitting methods.

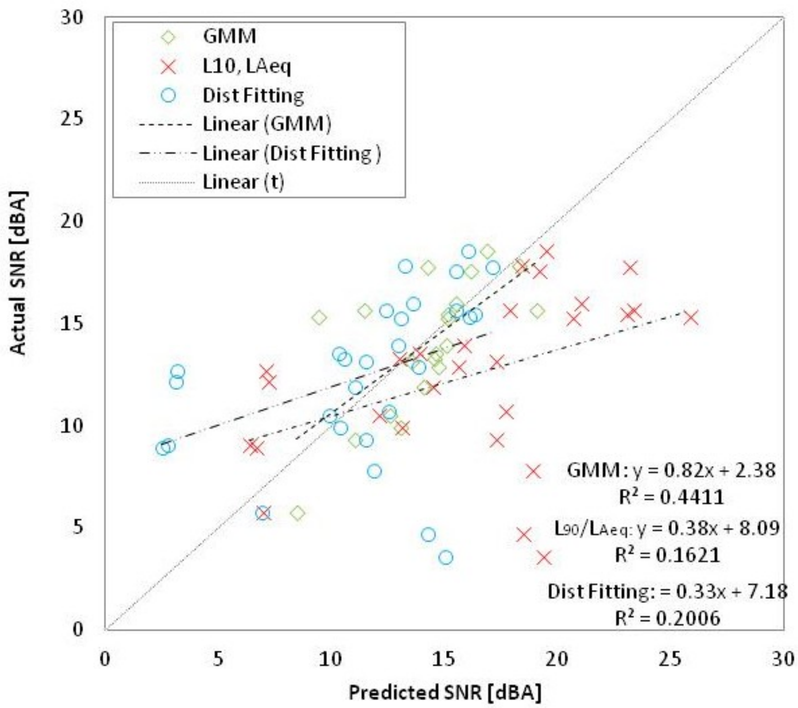


Figure 18: Linear regression between the actual SNRs and the values predicted by using GMM algorithm, L90 and LAeq and distribution-fitting methods

From *Figure 17*, GMM indicates the best performance in predicting 'Ambient' noise levels and 'Lecture' sound levels (R^2=0.9087). L90/LAeq method indicates a tendency to overestimate the mean activity sound levels (R^2=0.8398). Based on *Figure 18*, among three methods, GMM predicts the SNR values better than the other two (R^2=0.4411) while the same pattern of overestimating SNRs is observed in the values obtained from the L90/LAeq method. Distribution fitting method performs the worst in those classes where the duration of time that silent activities took place was proportionally too small compared to other activities. Accordingly in these spaces, 'Ambient' cannot be assigned to a distribution. For instance, in H509, the method proposed by Hodgson et al, assigned the lowest distribution to 'Ambient' while based on the actual results, it is associated with 'Lecture' sound levels.

Overall, using the GMM algorithm along with the decision criteria developed in this study performs better in predicting the sound pressure levels of the activities in occupied classrooms compared to the L_{90}/ L_{Aeq} and distribution-fitting methods explained. Despite the fact that the decision criteria proposed in this study fails to distinguish between different active learning activities, it successfully recognizes the presence of them and with a good level of accuracy (74%) assigns their corresponding observations to these activities. The distribution-fitting method proposed by Hodgson et al., indicates two major drawbacks in comparison with GMM method, specifically in active learning classrooms. One major issue is that the distribution-fitting method dismisses the underlying 'Active Learning Activity' in active learning classrooms and merges all the potential existing activities into 'Lecture' and 'Ambient'. Second, it fails to assign the observations to activities; therefore, it does not provide information on the location of the activities in the time history of the measurements, nor does it determine the proportion of the total class time that belongs to each activity.

6 CHAPTER 5: CONCLUSION

In this study, the occupied activity sound pressure levels in active learning classrooms are investigated by using three unsupervised learning algorithms. The occupied sound pressure level measurements were conducted in five active learning and two traditional lecture classes at four measurement locations in the classrooms (overall 28 cases). During the measurements, the researcher noted the type of the activity and its corresponding duration. Based on the observations of the researcher, as well as the results of the previous studies, three main activities are considered to be detected in active learning classrooms, including ‘Ambient’, ‘Lecture’, ‘Active Learning Activity’. The one-third octave band continuous sound pressure levels averaged in 5s intervals obtained at each measurement location are analyzed by using three clustering methods, including K-means clustering, Gaussian Mixture Model and Spectral clustering. In order to detect the number of activities in each classroom, Silhouette value is employed as an indicator to estimate the initial number of clusters in clustering analysis. Furthermore, by using the results of the previous studies, a decision chart has been developed in order to assign the clusters to activities. The performance of the algorithms in detecting the activities is evaluated by calculating the Accuracy, Precision and Recall for each activity. The results of the three algorithms are compared with the actual results through linear regression analysis. Gaussian Mixture model indicated a better performance (R^2 =0.929) among three in predicting the occupied activity sound pressure levels. Overall GMM illustrated a better performance in assigning the observations to their corresponding activities. Moreover, the results obtained from GMM are compared to previously developed methods in similar subject. L_{90}/L_{Aeq} and distribution fitting method were applied to the one-third octave band SPLs collected from the classrooms. Results suggest that both methods lose accuracy in predicting the 'Ambient' noise level and 'Lecture' speech level due to dismissing the other underlying activities.

Overall GMM algorithm along with the decision criteria developed, perform better than the other methods investigated in this study in identifying the underlying activities and their corresponding sound pressure levels while active learning is practiced in classrooms. Although the proposed method is promising to be applied to future studies, silhouette measure proposed in this method indicates limitations in determining the optimal number of activities. In addition, assumption 3 of the decision chart was misleading in identifying the 'Lecture' speech levels in practice or discussion classes that the teacher may not be the main speaker. Further research directions will focus on Limitations and down sides of the method, such as detecting the number of activities. Introducing supervised learning methods may potentially improve the assumptions and criteria developed to assign activities to clusters.

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Appendix

Implementation of the decision chart on GMM results:

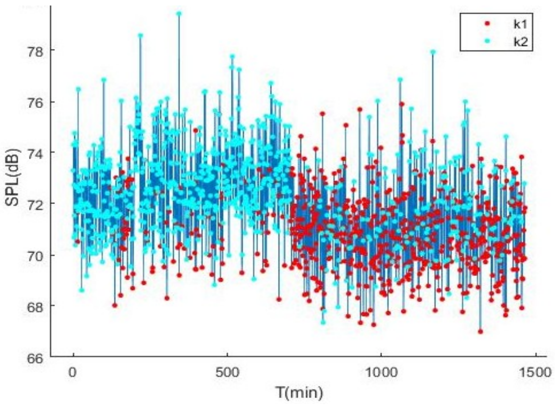
H509								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	-			TRUE	-		
Condition 2	TRUE	-			TRUE	-		
Condition 3	TRUE	-			TRUE	-		
Condition 4	TRUE	-			TRUE	-		
Condition 5	N/A	-			N/A	-		
Activity	Lecture	Active Learning Activity			Lecture	Active Learning Activity		
H603								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A	N/A		TRUE	N/A	N/A	
Condition 2	FALSE	TRUE	TRUE		FALSE	TRUE	TRUE	
Condition 3	FALSE	TRUE	TRUE		FALSE	TRUE	TRUE	
Condition 4	N/A	FALSE	TRUE		N/A	FALSE	TRUE	
Condition 5	N/A	N/A	FALSE		N/A	N/A	FALSE	
Activity	Ambient	Active Learning Activity	Lecture		Ambient	Active Learning Activity	Lecture	
H605								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A	-	-	TRUE	N/A	-	-
Condition 2	FALSE	TRUE	-	-	FALSE	TRUE	-	-
Condition 3	FALSE	TRUE	-	-	FALSE	TRUE	-	-
Condition 4	N/A	TRUE	-	-	N/A	TRUE	-	-
Condition 5	N/A	FALSE	-	-	N/A	FALSE	-	-
Activity	Ambient	Lecture	Active Learning Activity	Active Learning Activity	Ambient	Lecture	Active Learning Activity	Active Learning Activity
H654-1								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A			TRUE	N/A		
Condition 2	FALSE	TRUE			FALSE	TRUE		
Condition 3	FALSE	TRUE			FALSE	TRUE		

Condition 4	N/A	TRUE			N/A	TRUE		
Condition 5	N/A	FALSE			N/A	FALSE		
Activity	Ambient	Lecture			Ambient	Lecture		
H654-2								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A			TRUE	N/A		
Condition 2	TRUE	TRUE			TRUE	TRUE		
Condition 3	FALSE	TRUE			FALSE	TRUE		
Condition 4	FALSE	TRUE			FALSE	TRUE		
Condition 5	N/A	FALSE			N/A	FALSE		
Activity	Active Learning Activity	Lecture			Active Learning Activity	Lecture		
H561								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A			TRUE	N/A		
Condition 2	TRUE	TRUE			FALSE	TRUE		
Condition 3	FALSE	TRUE			FALSE	TRUE		
Condition 4	FALSE	TRUE			N/A	TRUE		
Condition 5	N/A	FALSE			N/A	FALSE		
Activity	-	Lecture			Ambient	Lecture		
MB2-270								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A			TRUE	N/A		
Condition 2	FALSE	TRUE			FALSE	TRUE		
Condition 3	FALSE	TRUE			FALSE	TRUE		
Condition 4	N/A	TRUE			N/A	TRUE		
Condition 5	N/A	FALSE			N/A	FALSE		
Activity	Ambient	Lecture			Ambient	Lecture		

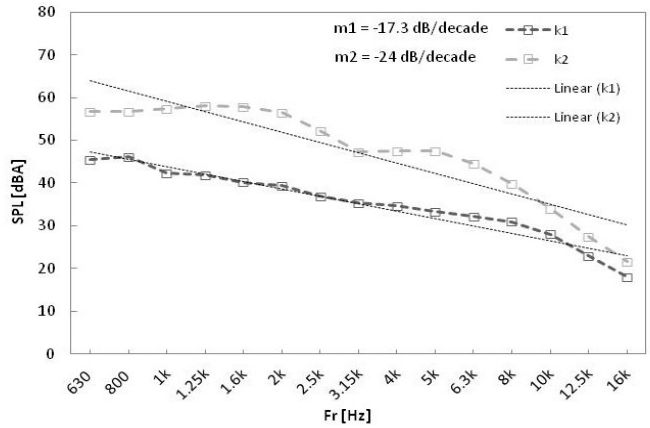
Implementation of the decision chart on KM and SPC results:

Graph and Figures from KM results:

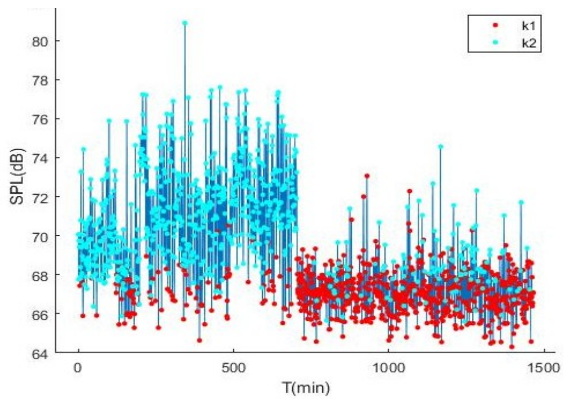
H509:



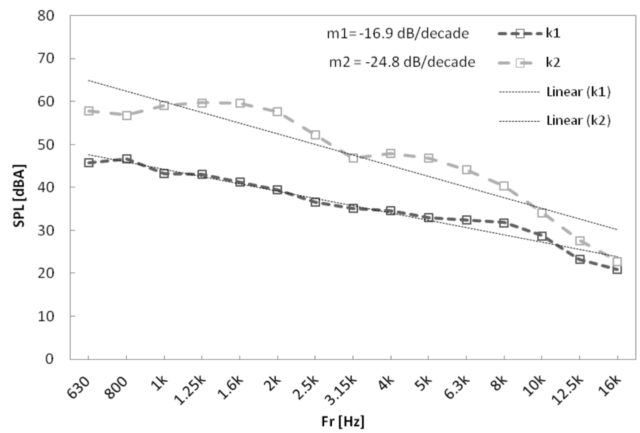
a)



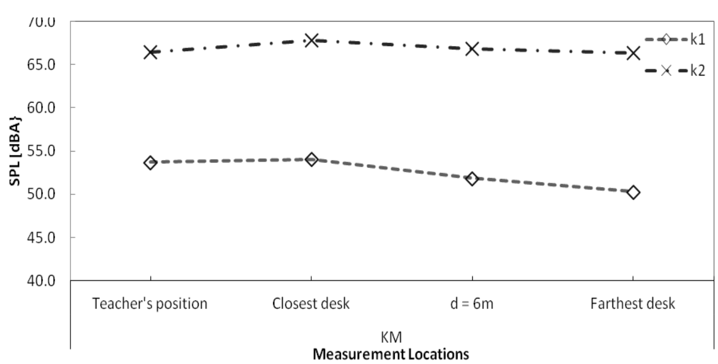
b)



c)

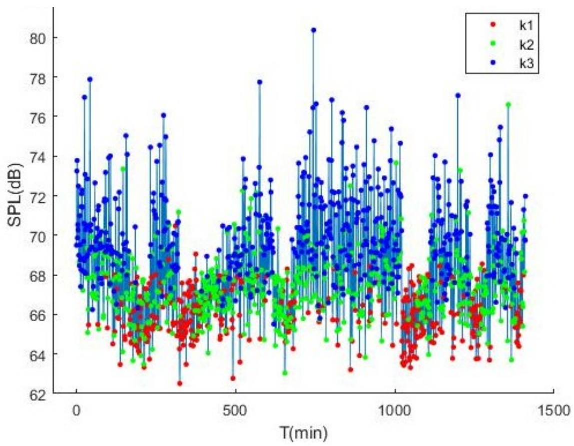


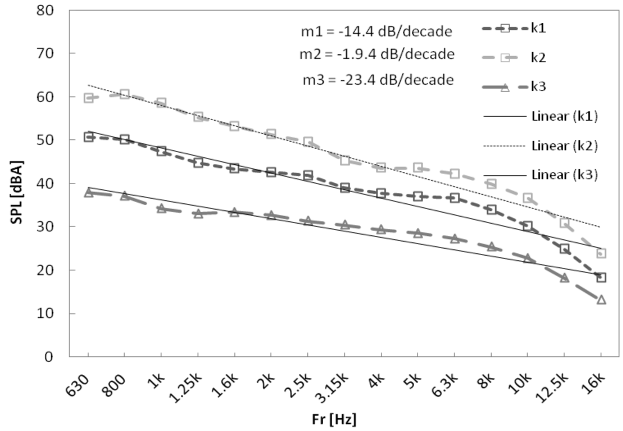
d)



e)

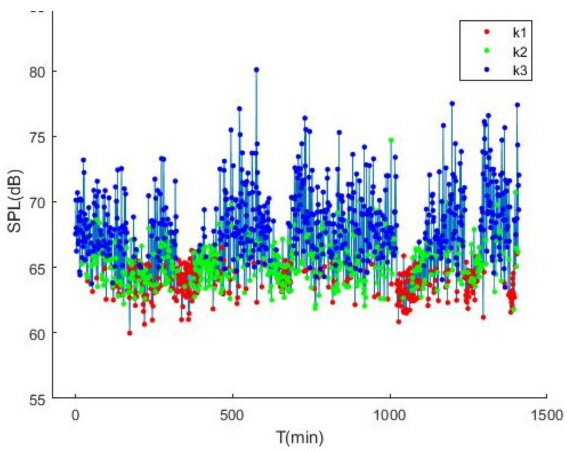
H603:

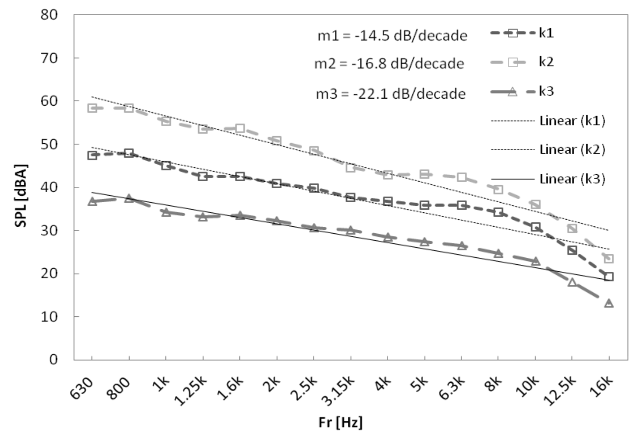

k1
k2
k3
SPL(dB)
T(min)


m1 = -14.4 dB/decade
m2 = -1.9.4 dB/decade
m3 = -23.4 dB/decade
k1
k2
k3
Linear (k1)
Linear (k2)
Linear (k3)
SPL [dBA]
Fr [Hz]

a)

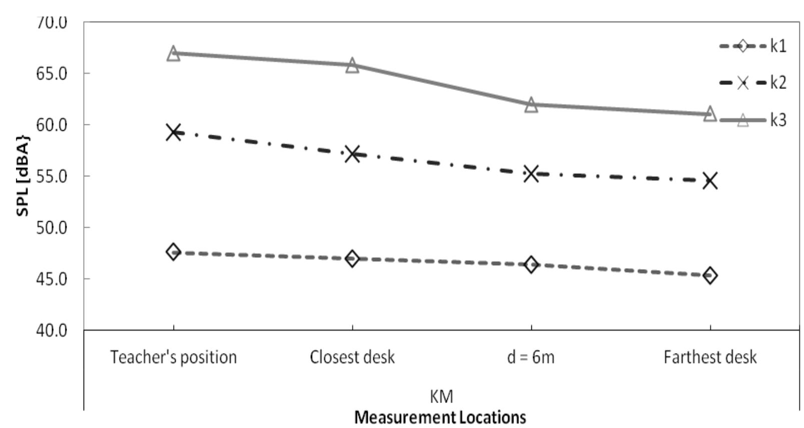
b)


k1
k2
k3
SPL(dB)
T(min)


m1 = -14.5 dB/decade
m2 = -16.8 dB/decade
m3 = -22.1 dB/decade
k1
k2
k3
Linear (k1)
Linear (k2)
Linear (k3)
SPL [dBA]
Fr [Hz]

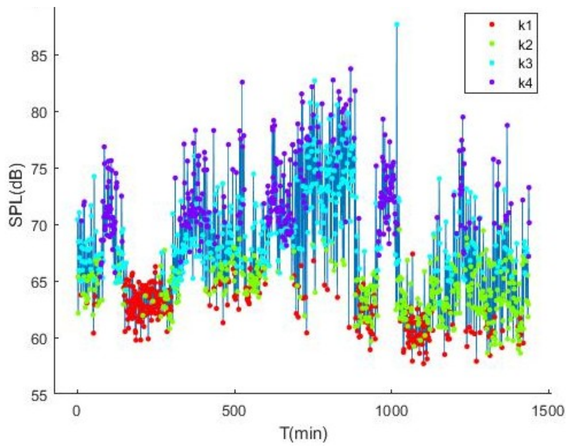
c)

d)

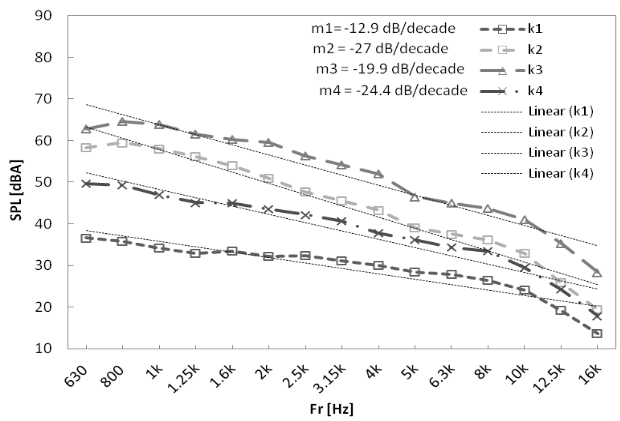

k1
k2
k3
SPL [dBA}
Teacher's position
Closest desk
d = 6m
Farthest desk
KM
Measurement Locations

e)

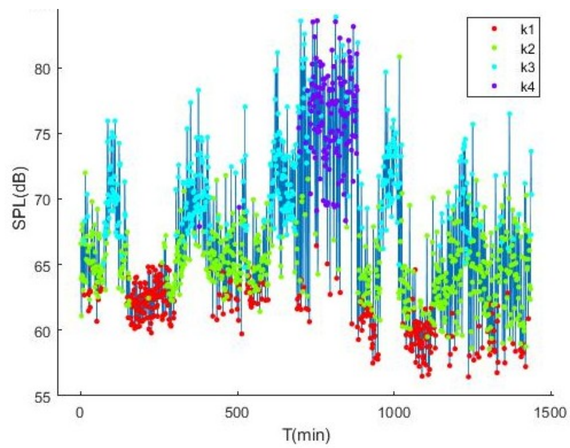
H605:


k1
k2
k3
k4
SPL(dB)
T(min)

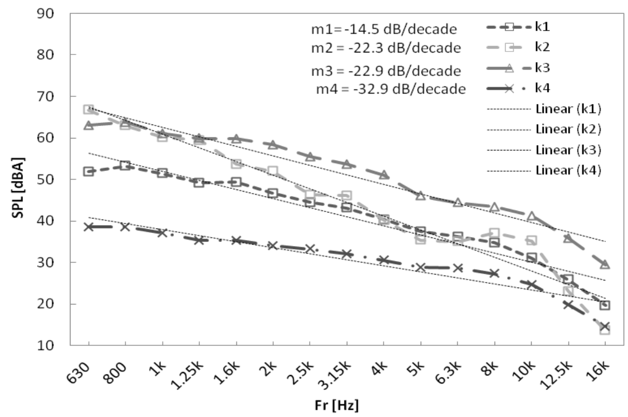
a)


m1= -12.9 dB/decade
m2 = -27 dB/decade
m3 = -19.9 dB/decade
m4 = -24.4 dB/decade
k1
k2
k3
k4
Linear (k1)
Linear (k2)
Linear (k3)
Linear (k4)
SPL [dBA]
Fr [Hz]

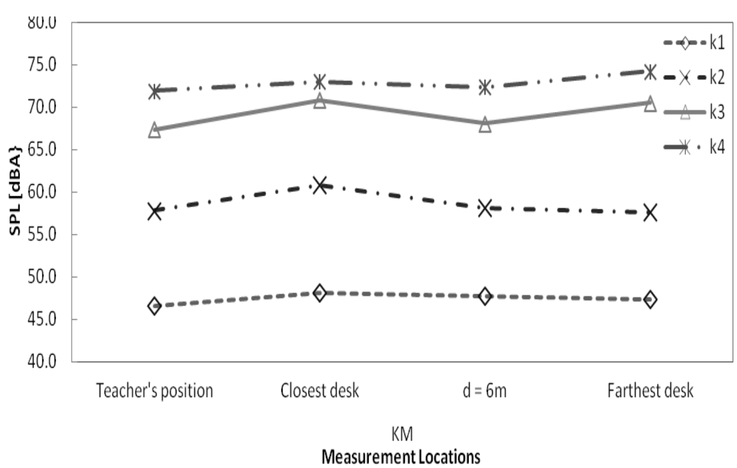
b)


k1
k2
k3
k4
SPL(dB)
T(min)

c)

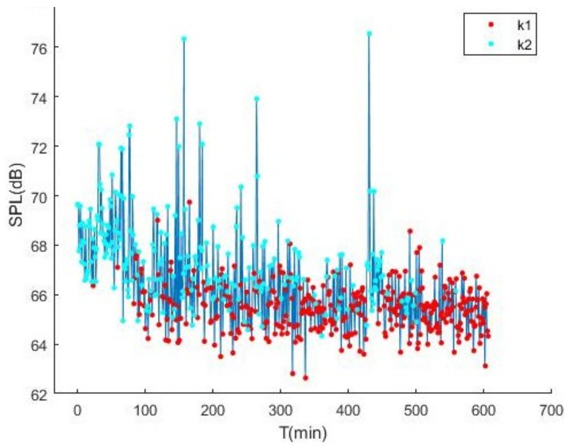

m1= -14.5 dB/decade
m2 = -22.3 dB/decade
m3 = -22.9 dB/decade
m4 = -32.9 dB/decade
k1
k2
k3
k4
Linear (k1)
Linear (k2)
Linear (k3)
Linear (k4)
SPL [dBA]
Fr [Hz]

d)


k1
k2
k3
k4
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
KM
Measurement Locations

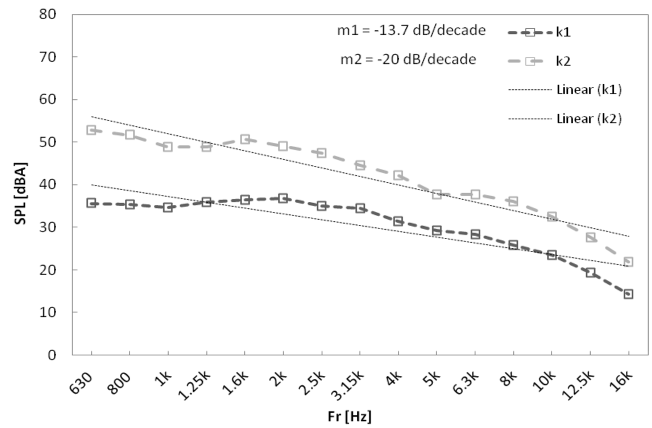
e)

H654-1:



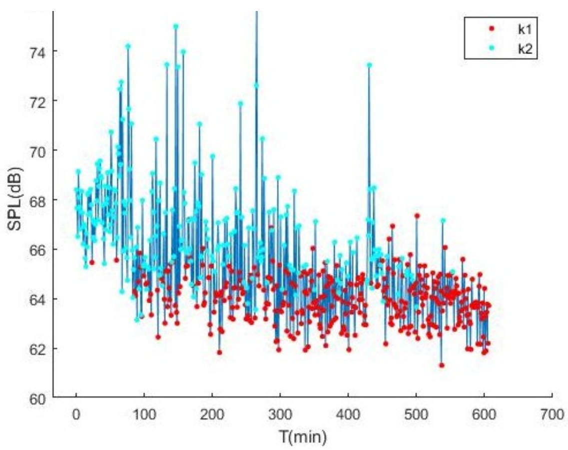
k1
k2
SPL(dB)
T(min)

a)



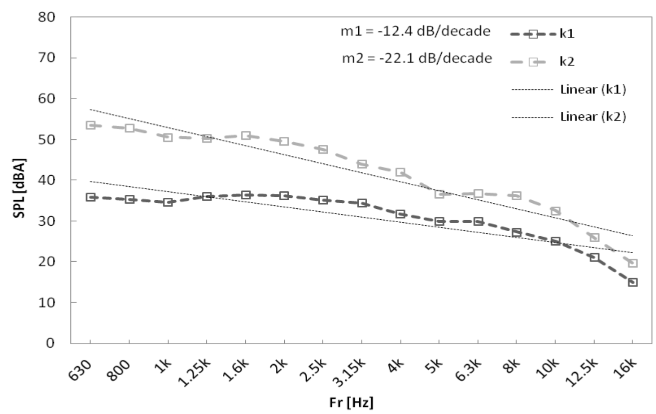
m1 = -13.7 dB/decade
m2 = -20 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

b)



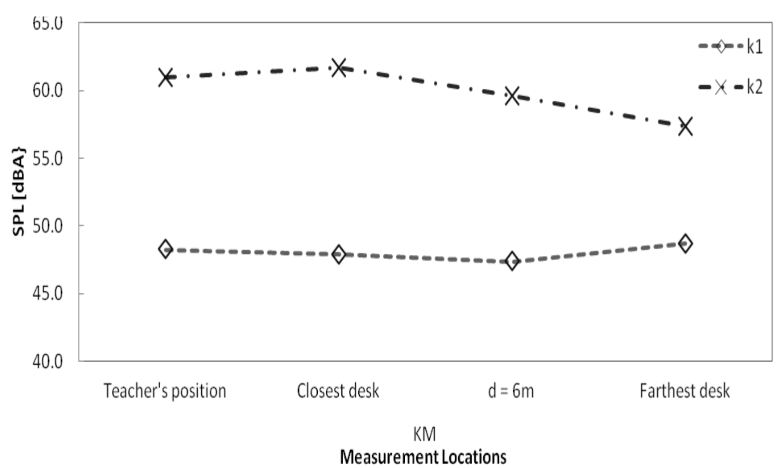
k1
k2
SPL(dB)
T(min)

c)



m1 = -12.4 dB/decade
m2 = -22.1 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

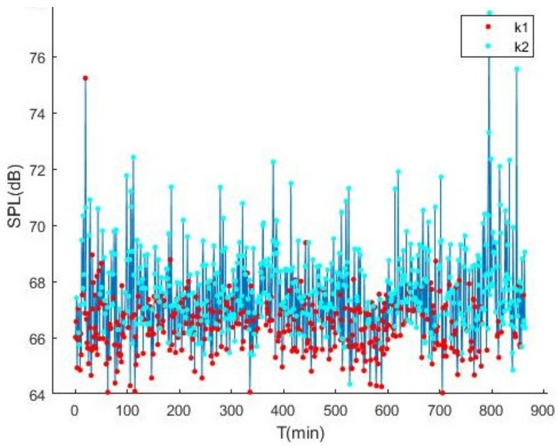
d)



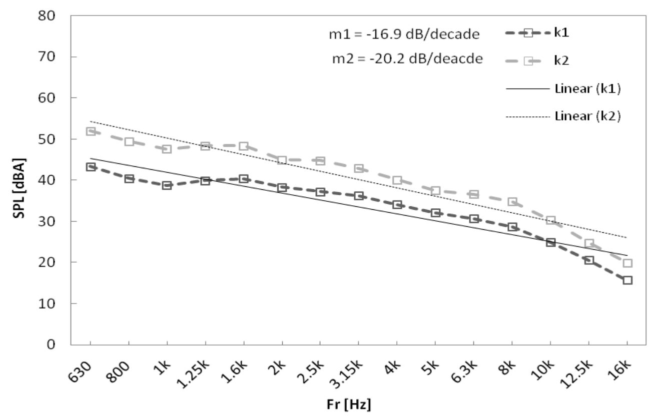
k1
k2
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
KM
Measurement Locations

e)

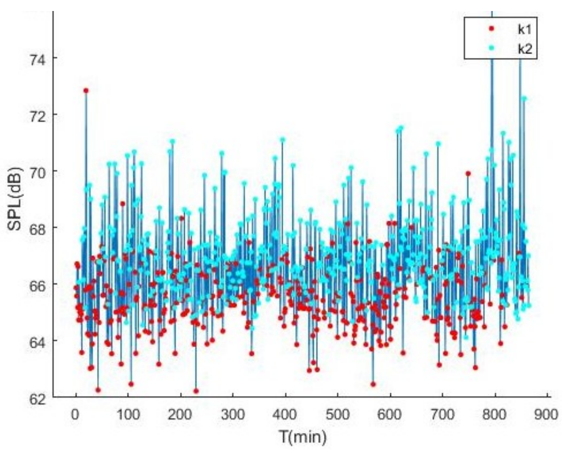
H654-2:


k1
k2
SPL(dB)
T(min)

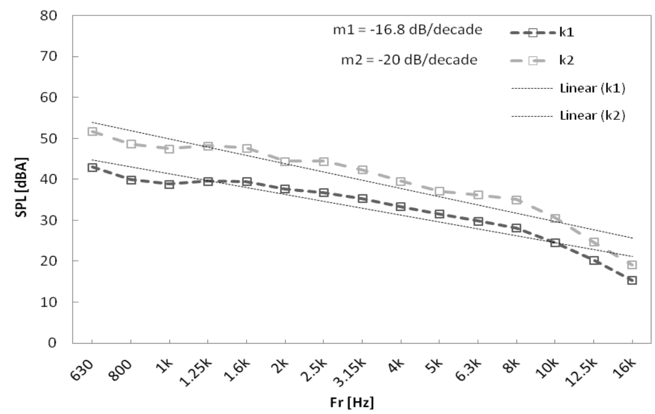
a)


m1 = -16.9 dB/decade
m2 = -20.2 dB/deacde
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

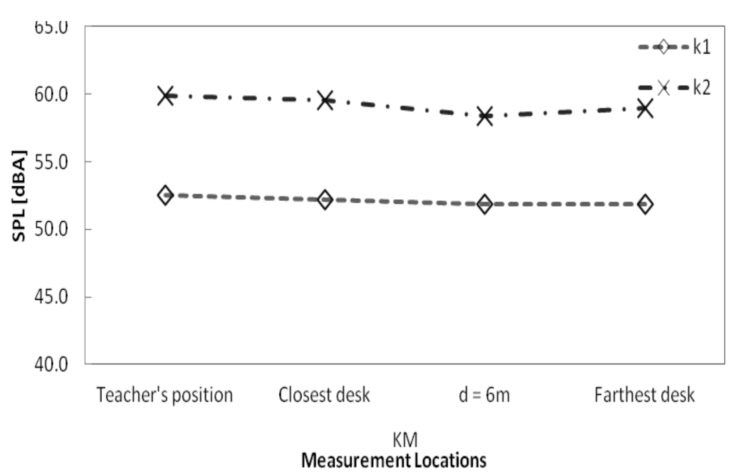
b)


k1
k2
SPL(dB)
T(min)

c)

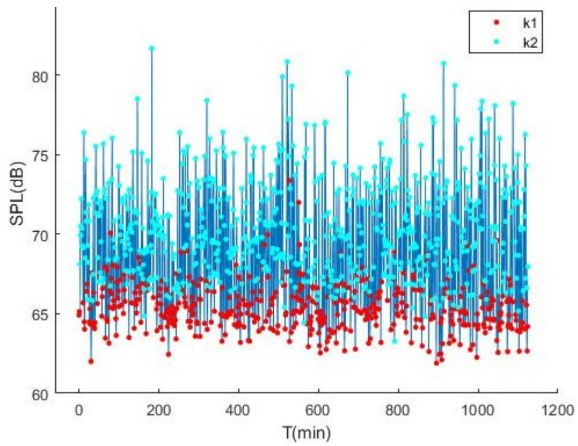

m1 = -16.8 dB/decade
m2 = -20 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

d)

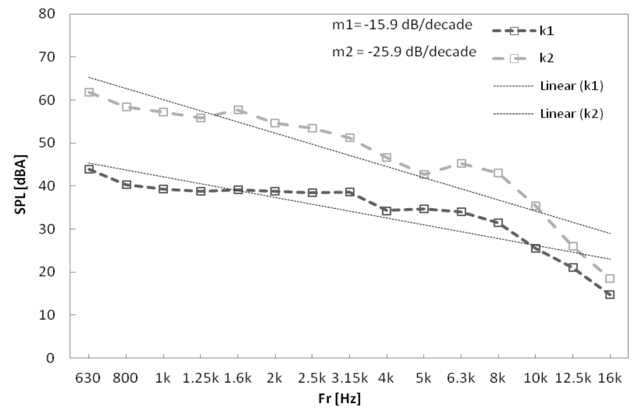

k1
k2
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
KM
Measurement Locations

e)

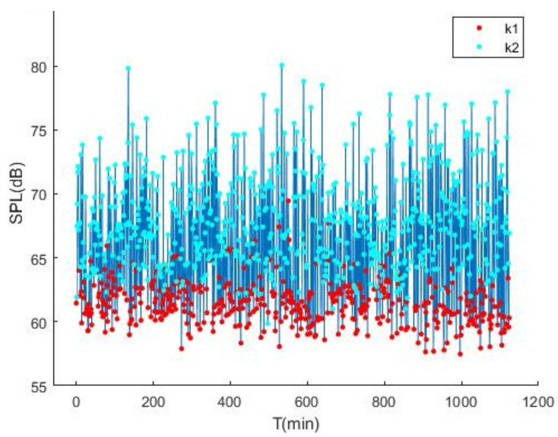
H561:


k1
k2
SPL(dB)
T(min)

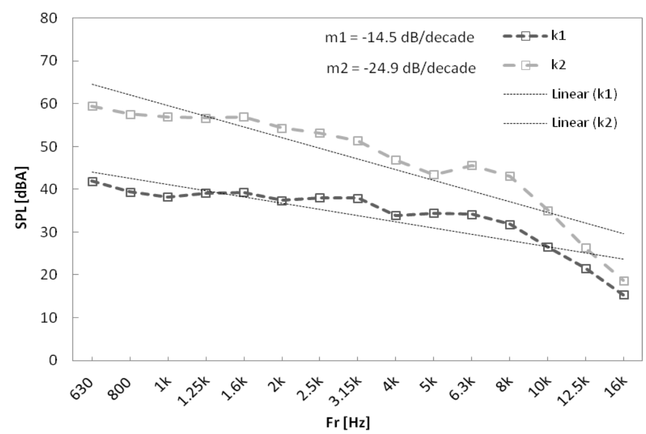
a)


m1= -15.9 dB/decade
m2 = -25.9 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
630 800 1k 1.25k 1.6k 2k 2.5k 3.15k 4k 5k 6.3k 8k 10k 12.5k 16k
Fr [Hz]

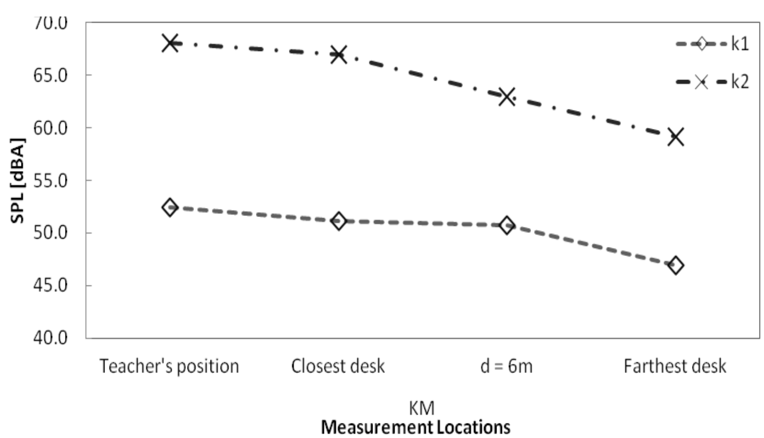
b)


k1
k2
SPL(dB)
T(min)

c)

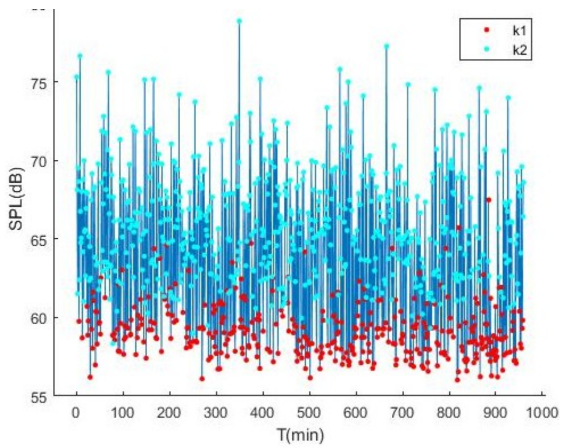

m1 = -14.5 dB/decade
m2 = -24.9 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
630 800 1k 1.25k 1.6k 2k 2.5k 3.15k 4k 5k 6.3k 8k 10k 12.5k 16k
Fr [Hz]

d)

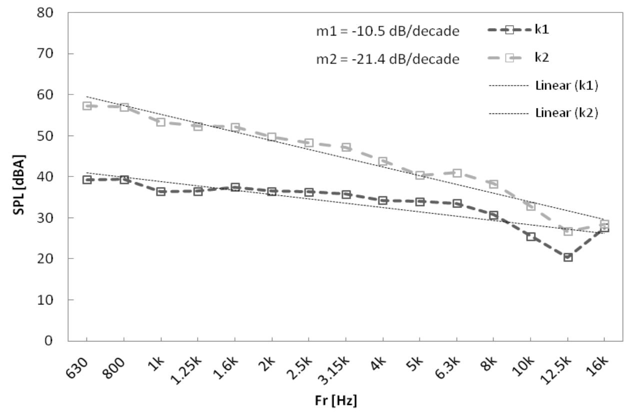

k1
k2
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
KM
Measurement Locations

e)

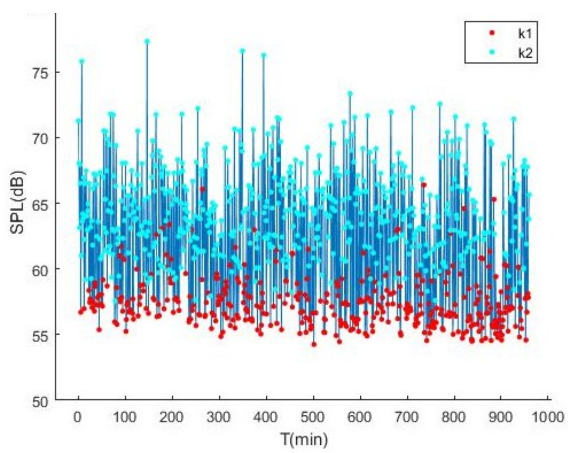
MB2-270:



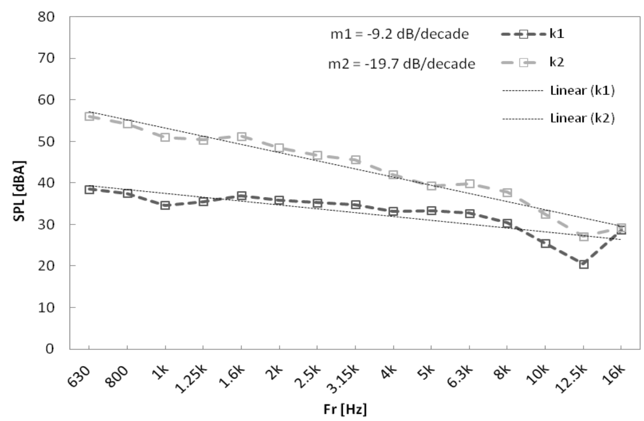
a)



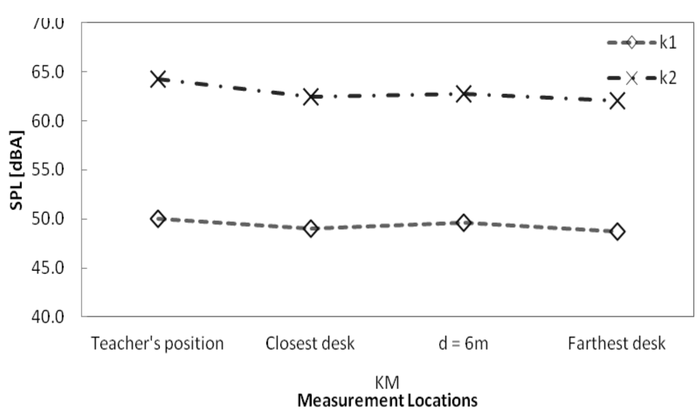
b)



c)



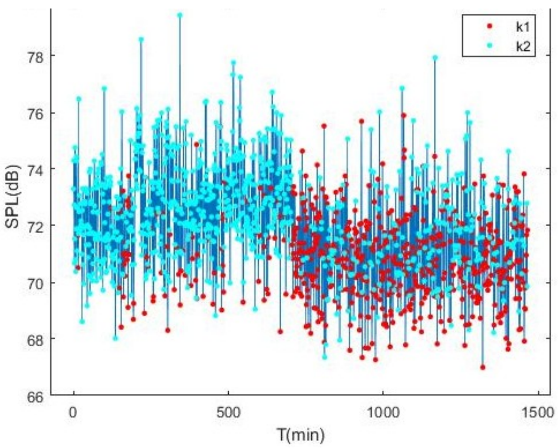
d)



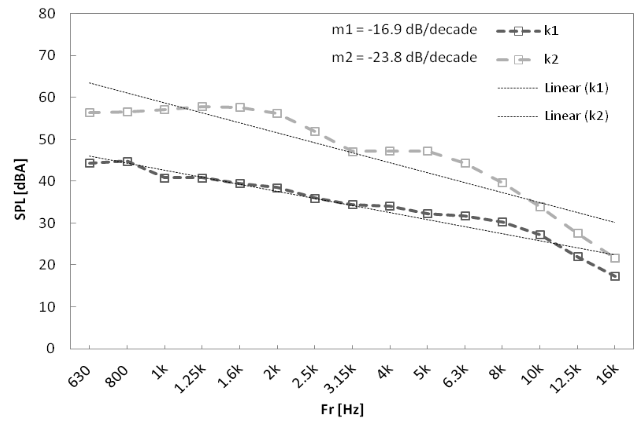
e)

Graph and Figures from SPC results:

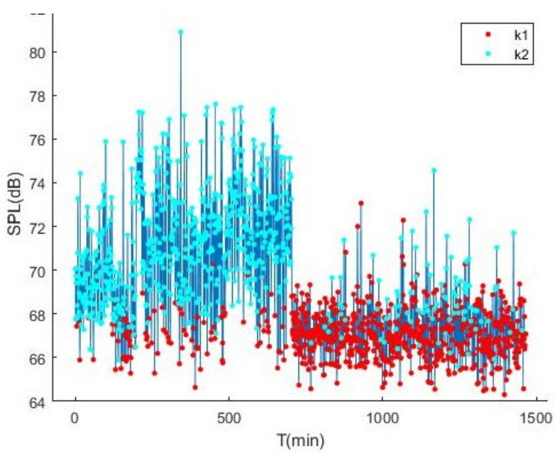
H509:



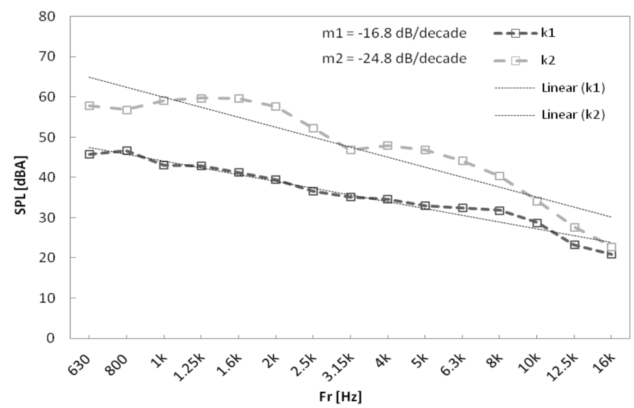
a)



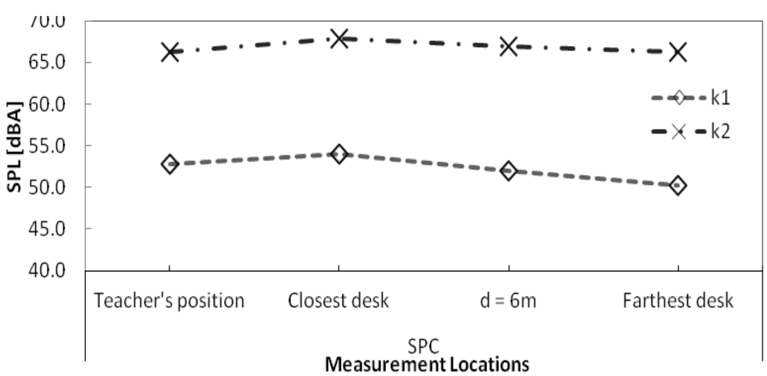
b)



c)

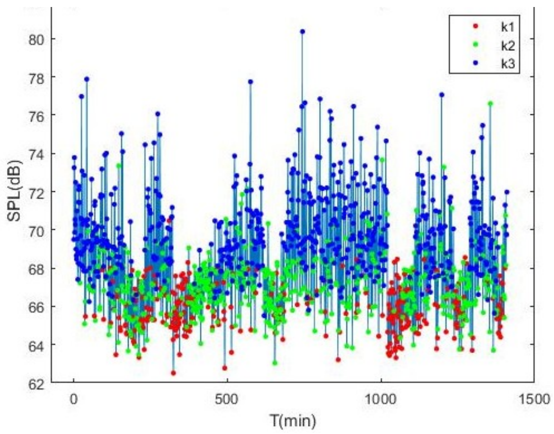


d)



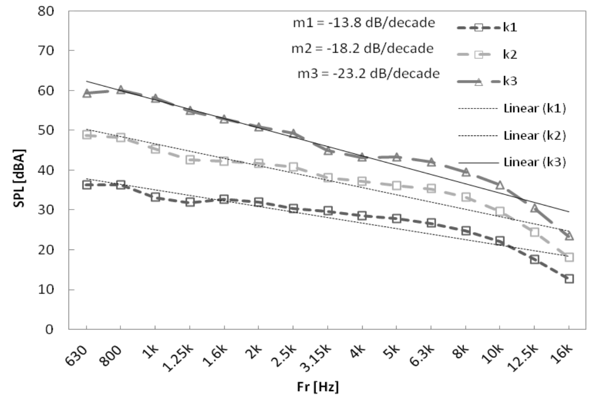
e)

H603:



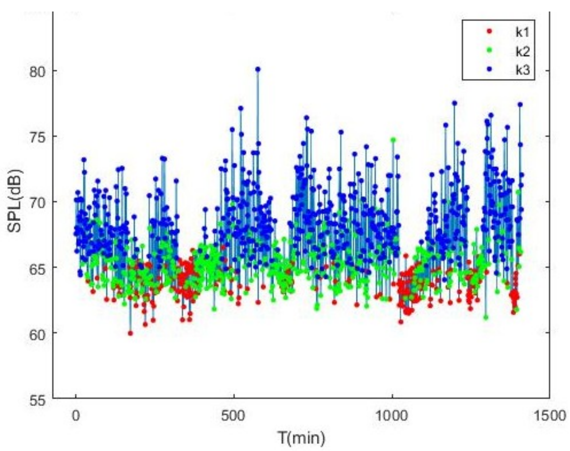
k1
k2
k3
SPL(dB)
T(min)

a)



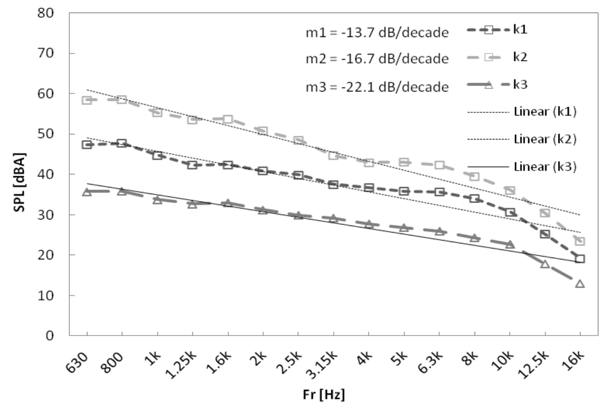
m1 = -13.8 dB/decade
m2 = -18.2 dB/decade
m3 = -23.2 dB/decade
k1
k2
k3
Linear (k1)
Linear (k2)
Linear (k3)
SPL [dBA]
Fr [Hz]

b)



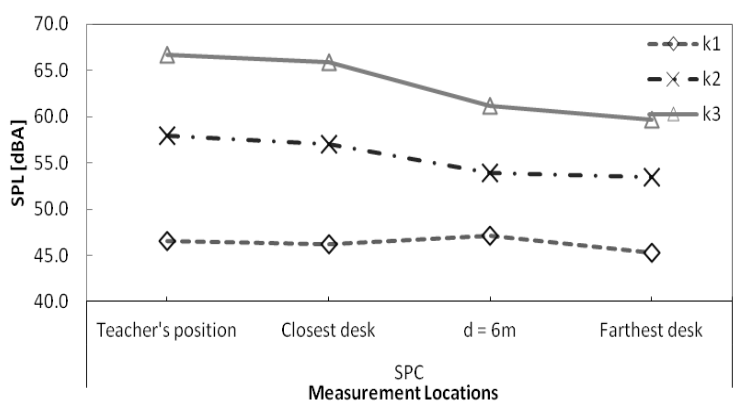
k1
k2
k3
SPL(dB)
T(min)

c)



m1 = -13.7 dB/decade
m2 = -16.7 dB/decade
m3 = -22.1 dB/decade
k1
k2
k3
Linear (k1)
Linear (k2)
Linear (k3)
SPL [dBA]
Fr [Hz]

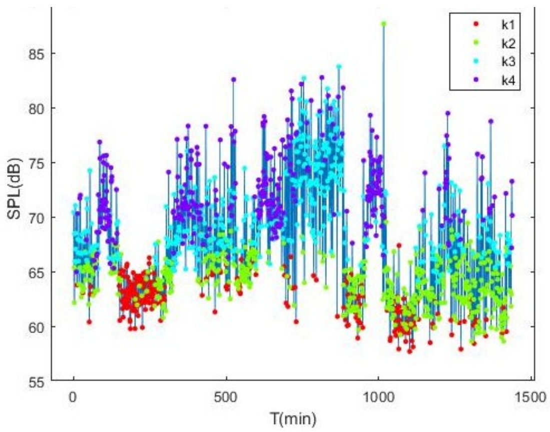
d)



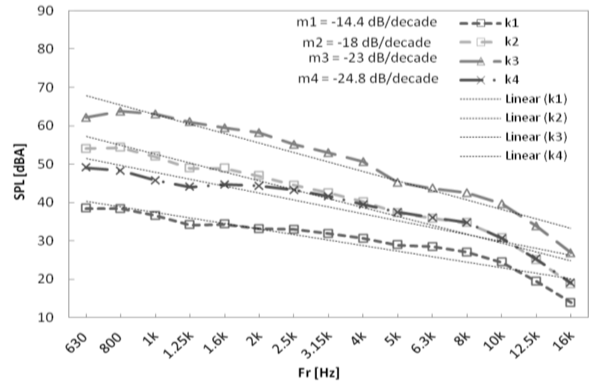
k1
k2
k3
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
SPC
Measurement Locations

e)

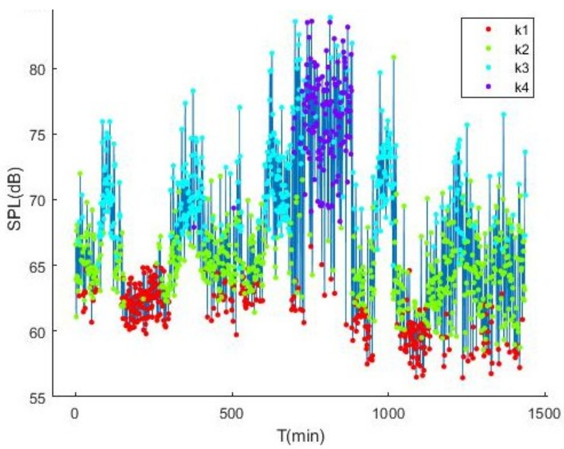
H605:


k1
k2
k3
k4
SPL(dB)
T(min)

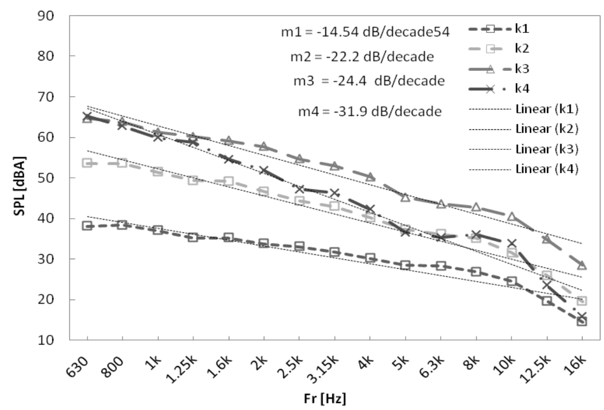
a)


m1 = -14.4 dB/decade
m2 = -18 dB/decade
m3 = -23 dB/decade
m4 = -24.8 dB/decade
k1
k2
k3
k4
Linear (k1)
Linear (k2)
Linear (k3)
Linear (k4)
SPL [dBA]
Fr [Hz]

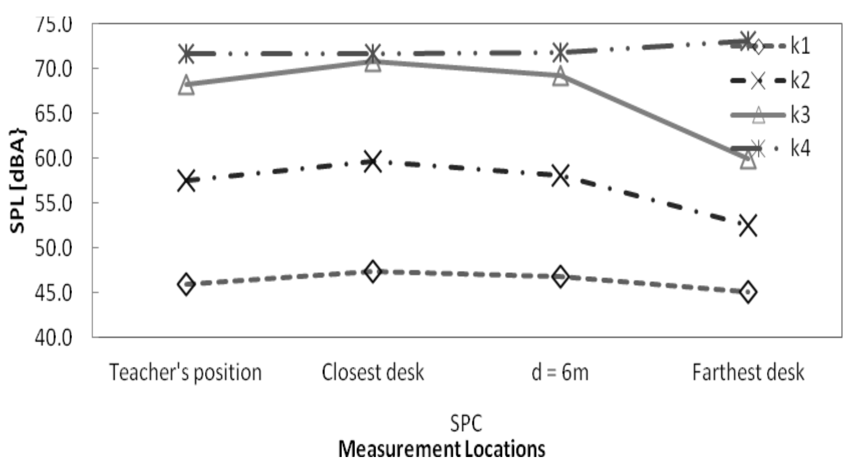
b)


k1
k2
k3
k4
SPL(dB)
T(min)

c)

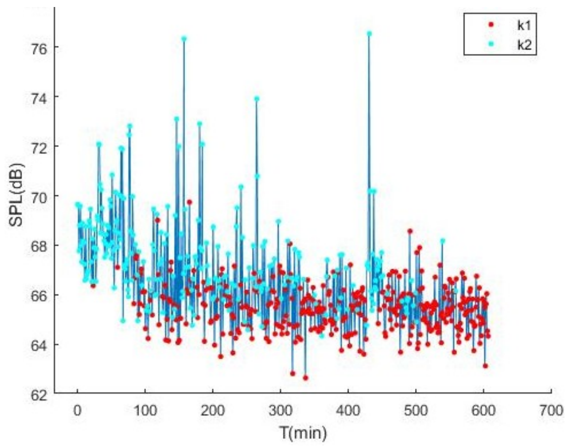

m1 = -14.54 dB/decade54
m2 = -22.2 dB/decade
m3 = -24.4 dB/decade
m4 = -31.9 dB/decade
k1
k2
k3
k4
Linear (k1)
Linear (k2)
Linear (k3)
Linear (k4)
SPL [dBA]
Fr [Hz]

d)


k1
k2
k3
k4
SPL [dBA}
Teacher's position
Closest desk
d = 6m
Farthest desk
SPC
Measurement Locations

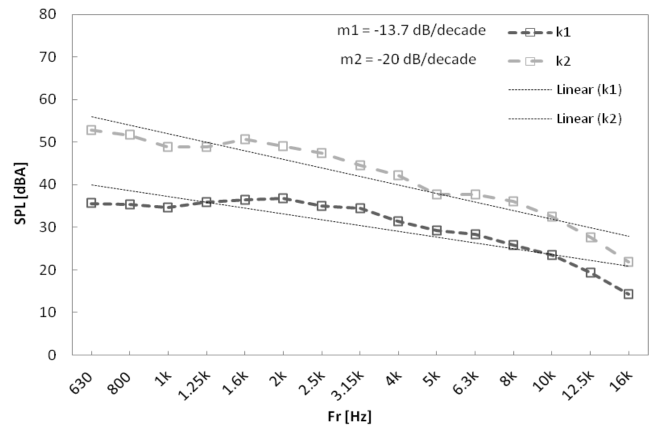
e)

H654-1:



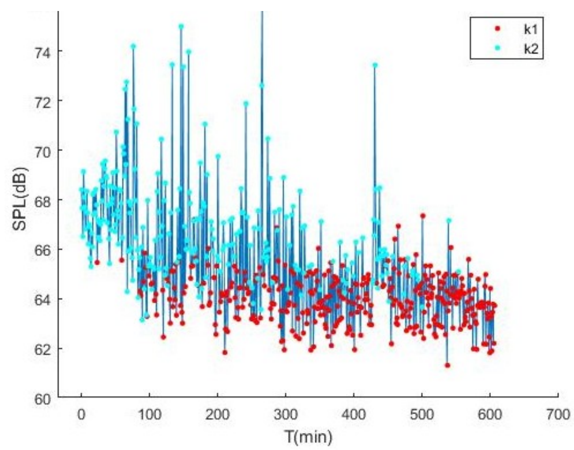
k1
k2
SPL(dB)
T(min)

a)



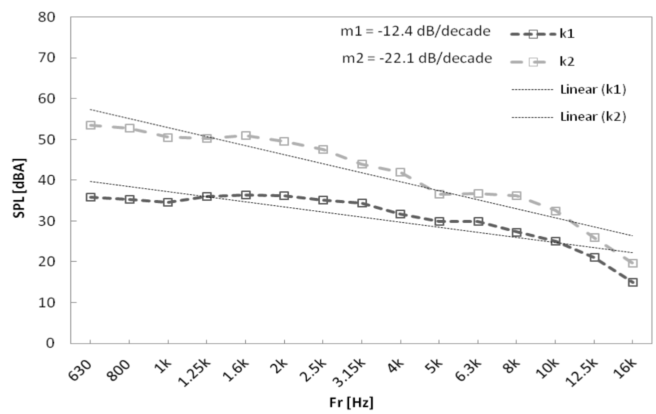
m1 = -13.7 dB/decade
m2 = -20 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

b)



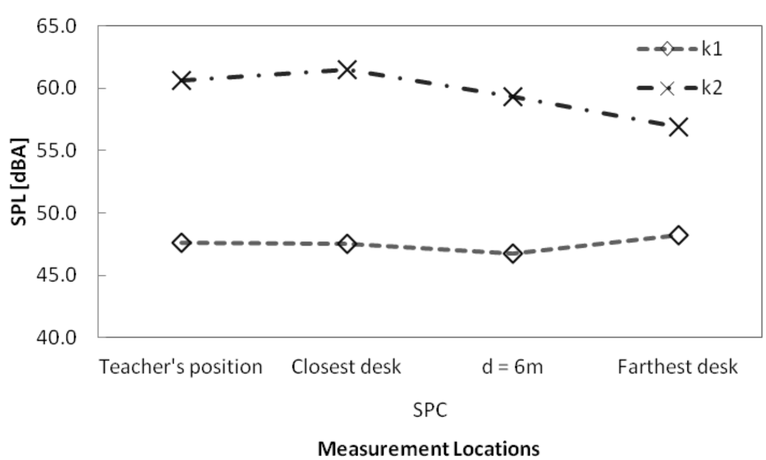
k1
k2
SPL(dB)
T(min)

c)



m1 = -12.4 dB/decade
m2 = -22.1 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

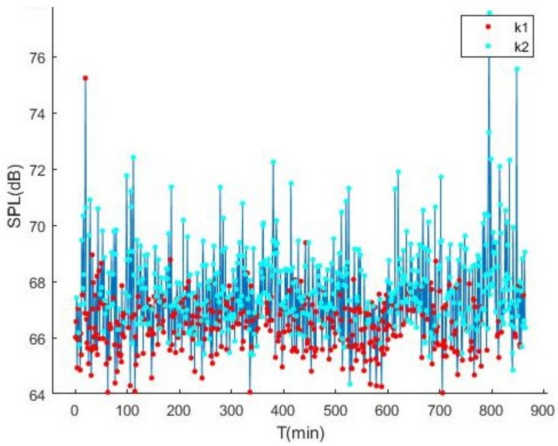
d)



k1
k2
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
SPC
Measurement Locations

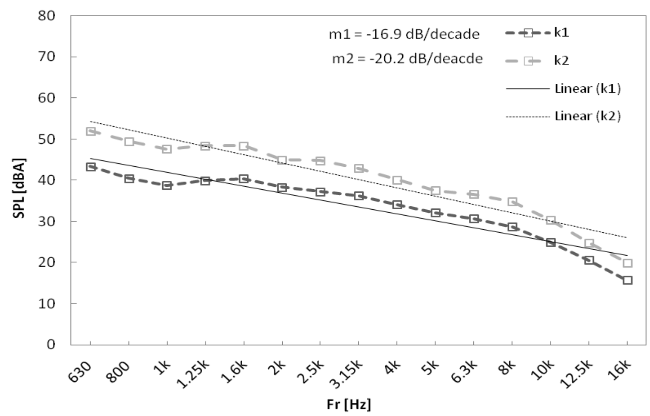
e)

H654-2:



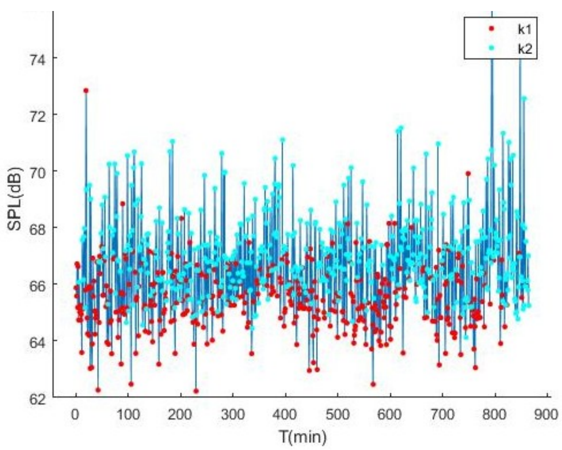
k1
k2
SPL(dB)
T(min)

a)



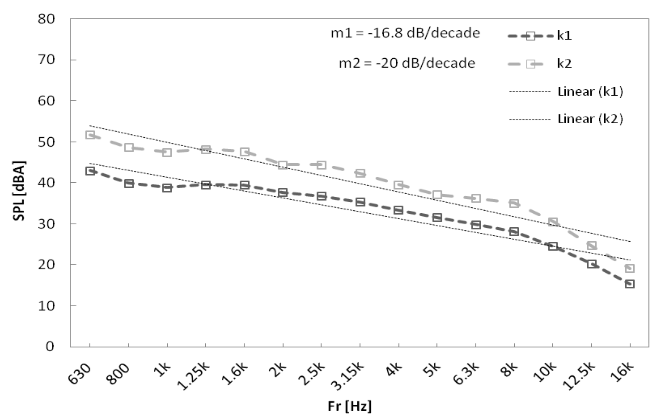
m1 = -16.9 dB/decade
m2 = -20.2 dB/deacde
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

b)



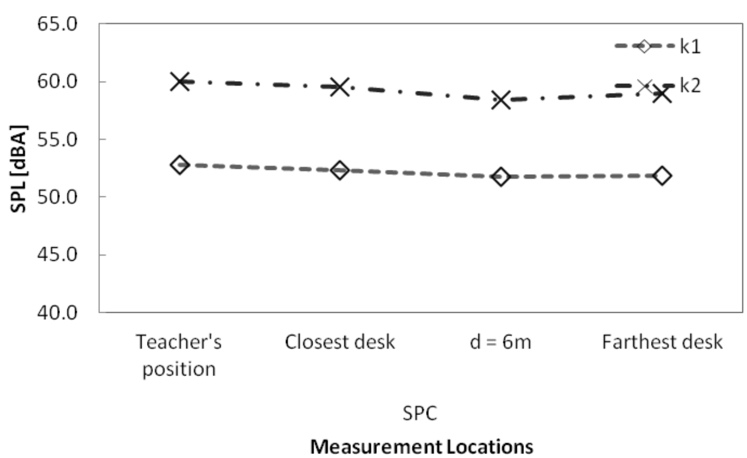
k1
k2
SPL(dB)
T(min)

c)



m1 = -16.8 dB/decade
m2 = -20 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

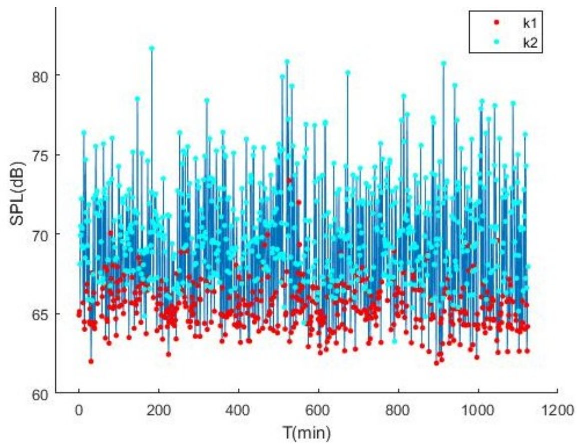
d)

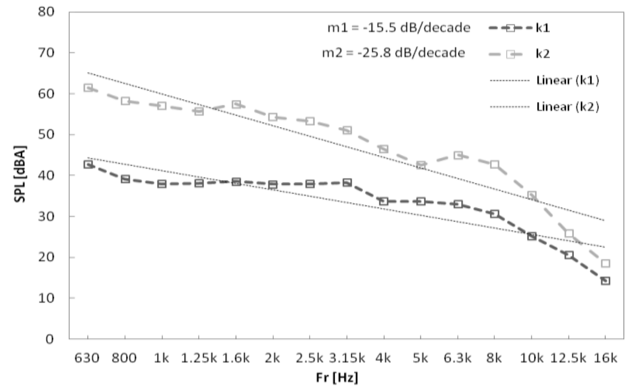


k1
k2
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
SPC
Measurement Locations

e)

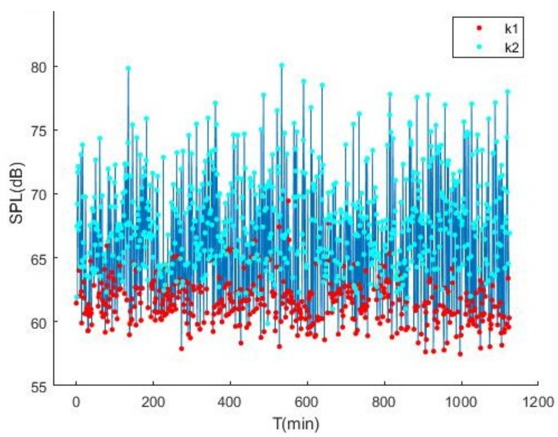
H561:

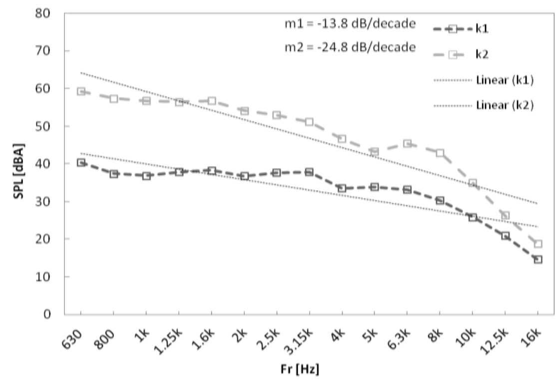

k1
k2
SPL(dB)
T(min)


m1 = -15.5 dB/decade
m2 = -25.8 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

b)

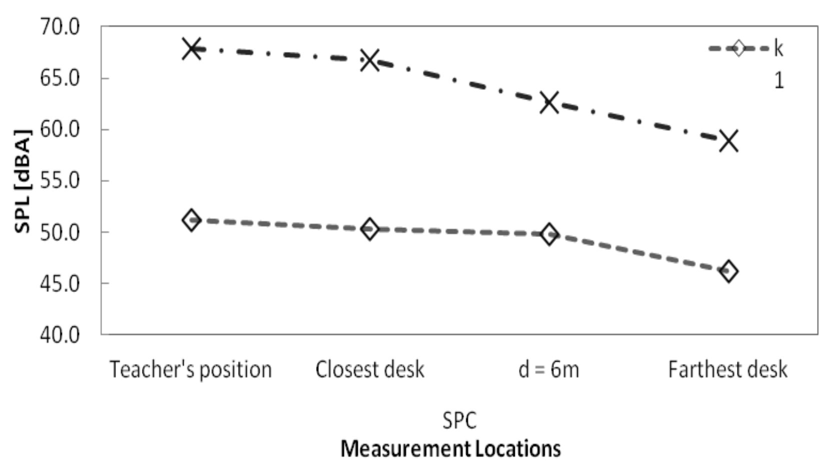
a)


k1
k2
SPL(dB)
T(min)


m1 = -13.8 dB/decade
m2 = -24.8 dB/decade
k1
k2
Linear (k1)
Linear (k2)
SPL [dBA]
Fr [Hz]

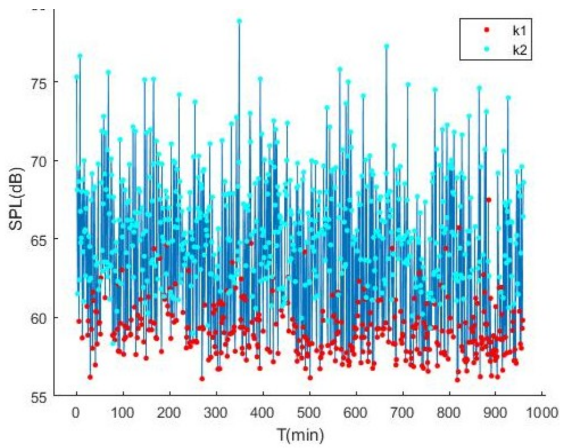
d)

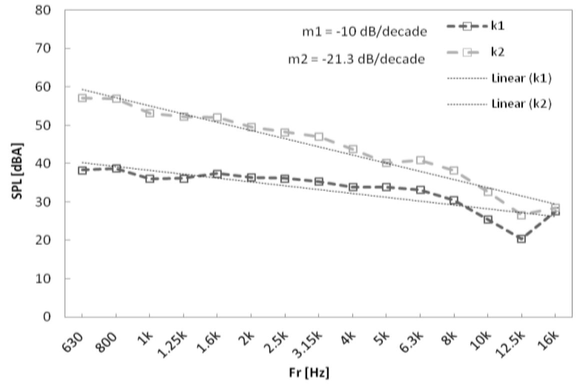
c)


k
1
SPL [dBA]
Teacher's position
Closest desk
d = 6m
Farthest desk
SPC
Measurement Locations

e)

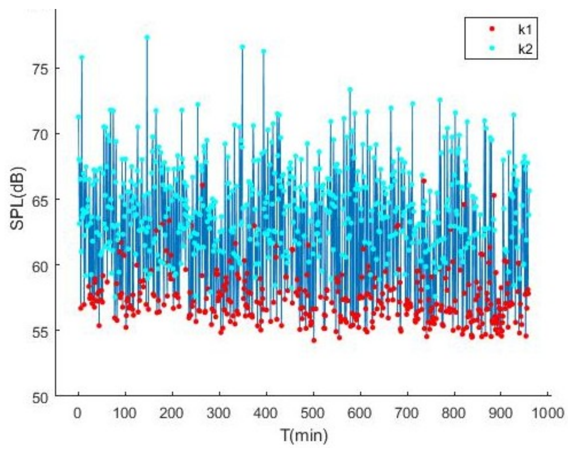
MB2-270:

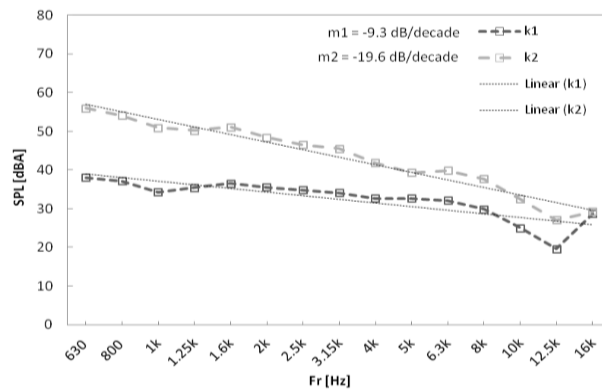




b)

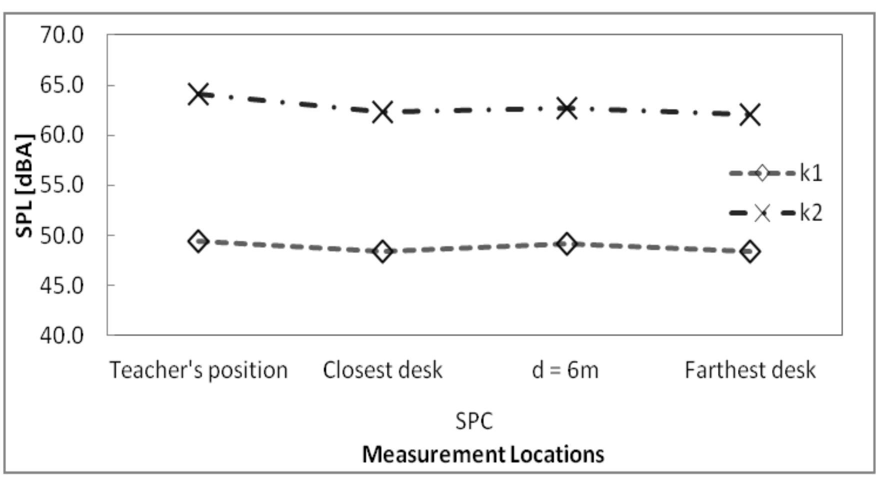
a)





d)

c)



e)

H509								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	-			TRUE	-		
Condition 2	TRUE	-			TRUE	-		
Condition 3	TRUE	-			TRUE	-		
Condition 4	TRUE	-			TRUE	-		
Condition 5	N/A	-			N/A	-		
Activity	Lecture	Active Learning Activity			Lecture	Active Learning Activity		

H603								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A	N/A		TRUE	N/A	N/A	
Condition 2	FALSE	TRUE	TRUE		FALSE	TRUE	TRUE	
Condition 3	FALSE	TRUE	TRUE		FALSE	TRUE	TRUE	
Condition 4	N/A	FALSE	TRUE		N/A	FALSE	TRUE	
Condition 5	N/A	N/A	FALSE		N/A	N/A	FALSE	
Activity	Ambient	Active Learning Activity	Lecture		Ambient	Active Learning Activity	Lecture	

H605								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A	-	-	TRUE	N/A	-	-
Condition 2	FALSE	TRUE	-	-	FALSE	TRUE	-	-
Condition 3	FALSE	TRUE	-	-	FALSE	TRUE	-	-
Condition 4	N/A	TRUE	-	-	N/A	TRUE	-	-
Condition 5	N/A	FALSE	-	-	N/A	FALSE	-	-
Activity	Ambient	Lecture	Active Learning Activity	Active Learning Activity	Ambient	Lecture	Active Learning Activity	Active Learning Activity

H654-1								
	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A			TRUE	N/A		
Condition 2	FALSE	TRUE			FALSE	TRUE		
Condition 3	FALSE	TRUE			FALSE	TRUE		
Condition 4	N/A	TRUE			N/A	TRUE		
Condition 5	N/A	FALSE			N/A	FALSE		
Activity	Ambient	Lecture			Ambient	Lecture		

H654-2

	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A			TRUE	N/A		
Condition 2	TRUE	TRUE			TRUE	TRUE		
Condition 3	FALSE	TRUE			FALSE	TRUE		
Condition 4	FALSE	TRUE			FALSE	TRUE		
Condition 5	N/A	FALSE			N/A	FALSE		
Activity	Active Learning Activity	Lecture			Active Learning Activity	Lecture		

H561

	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A			TRUE	N/A		
Condition 2	TRUE	TRUE			FALSE	TRUE		
Condition 3	FALSE	TRUE			FALSE	TRUE		
Condition 4	FALSE	TRUE			N/A	TRUE		
Condition 5	N/A	FALSE			N/A	FALSE		
Activity	-	Lecture			Ambient	Lecture		

MB2-270

	Measurement Location 1				Measurement Location 2			
	k1	k2	k3	k4	k1	k2	k3	k4
Condition 1	TRUE	N/A			TRUE	N/A		
Condition 2	FALSE	TRUE			FALSE	TRUE		
Condition 3	FALSE	TRUE			FALSE	TRUE		
Condition 4	N/A	TRUE			N/A	TRUE		
Condition 5	N/A	FALSE			N/A	FALSE		
Activity	Ambient	Lecture			Ambient	Lecture		