A STUDY OF SPEECH INTELLIGIBILITY AND INDOOR ENVIRONMENTAL ASSESSMENT IN HONG KONG CLASSROOMS

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PhD

The Hong Kong Polytechnic University

2021

The Hong Kong Polytechnic University

Department of Building Services Engineering

A Study of Speech Intelligibiliy and Indoor Environmental Assessment in Hong Kong Classrooms

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A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

November, 2020

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

_____________________________(Signed)

YANG Da (Name of student)

DEDICATION

To Qi, Wang, my wife, enormous patience and love during this phase of our lives.

To Yi-chen, my lovely son, for bringing happiness to the whole family.

To my parents, for their encouragement and continuous support.

ABSTRACT

Abstract of thesis entitled	:	A study of speech intelligibility and indoor environmental assessment in Hong Kong classrooms
Submitted by	:	Yang Da
For the degree of	:	Doctor of Philosophy

at The Hong Kong Polytechnic University in November, 2020

The indoor acoustical environment is not only related to productivity, health, and comfort, but also is related to acoustical quality in a space. The education of every citizen is essential to modern societies. Most formal education takes place in the classrooms, where a high level of acoustical quality is required. This thesis provides a systematic investigation of classroom speech intelligibility, sound field prediction, acoustical environment assessment, indoor environmental assessment with objective experiments, subjective questionnaires, and acoustic simulation methods in Hong Kong classrooms. To achieve the research objectives, several sub-works were conducted: (a) an investigation of the effects of speech transmission index (STI) on speech intelligibility; (b) the effects of acoustic descriptors on speech intelligibility; (c) a new combined sound field prediction method; (d) assessment model of acoustical environment; (e) assessment model of indoor environmental quality and its relationships with environmental factors.

In order to investigate the effects of STI, speech intelligibility tests were conducted in 9 middle school classrooms and 11 university classrooms in Hong Kong. Meanwhile, objective acoustical measurements were performed in each

listening position and testing conditions in each classroom. The relationship between subjective speech intelligibility scores (SI) an STI was discussed based on regression models. The effects of different age groups on the speech intelligibility were compared. The results show that SI increases with the increase of STI value for all age groups. The SI increase as the age increases under the same STI condition. The differences between age groups are decreased with the increase of STI values. English speech intelligibility scores in Hong Kong are always lower compared with native language studies under the same values of STI. Better STI values and better acoustical environment are needed because English is not the native language for students in Hong Kong but the official educational language.

In order to investigate the effects of acoustical descriptors, Speech intelligibility tests were conducted in 9 secondary school classrooms and 18 university classrooms, and the acoustical measurements were performed in these classrooms. Subjective speech intelligibility tests were obtained from phonetically balanced (PB) word lists on a total of 672 students and acoustic descriptors such as signal-to-noise ratio (SNR), early decay time (EDT), and sound clarity (C_{80}) were conducted in different listening positions in each classroom. The relationships between SI and acoustical descriptors were fitted based on non-linear curve fitting regression models. The "S" form regression model was selected with modification as the basic regression equation to describe the effects of SNR on speech intelligibility. The combination effects of SNR with reverberation condition and sound clarity condition on speech intelligibility were investigated. The impact of different age groups and linguistic environment on speech intelligibility were discussed. The results reveal that SI increases with the increase of SNR value for all age groups. The results indicate that nearly 0.06s increasing in EDT values will be correlated to a 1% decrease in SI.

Furthermore, the results also suggest that a 1 dB increasing in C_{80} values will be correlated to a 1.23% increase in speech intelligibility scores. The SI increases as the age increases under the same SNR condition. The speech intelligibility scores are always lower than the comparison research results with a constant reverberation value as well as sound clarity value for an equal SNR value.

Classroom acoustical parameters have a significant impact on speech intelligibility. In practice, applications of sound field predictions can provide the predicting level and spectral content of the sound in buildings, which are essential to acoustical design and acoustic environmental assessment. Therefore, a new combination method for sound field prediction is proposed for simulating sound fields during the whole audio frequency domain in small classrooms. An optimization approach based on the genetic algorithm is employed for optimizing the transition frequency of the combined sound field prediction method in classrooms. The selected optimization approach can identify the optimal transition frequency so that the combined sound field prediction can obtain more efficient and accurate prediction results. The proposed combined sound field prediction method consists of a wave-based method and geometric acoustic methods separated by the transition frequency. In low frequency domain (below the transition frequency), the sound field is calculated by the finite element method (FEM), while a hybrid geometric acoustic method is employed in the high frequency domain (above the transition frequency). The proposed combined prediction models are validated by comparing them with previous results and experimental measurements. The optimization approach is illustrated by several examples and compared with traditional combination results. Compared to existed sound field prediction simulations in classrooms, the proposed combination methods take the sound field in low frequencies into account. The results demonstrate the effectiveness of the proposed model.

Apart from the speech intelligibility investigations and sound prediction methods mentioned above, the overall acoustical environment satisfaction evaluation was developed. An assessment model based on a multi-layer fuzzy comprehensive evaluation method (FCE) of the classroom acoustical environment is proposed. The model classifies five major factors affecting the overall assessment model into several subsets alternatives. The weightings of these main criteria and alternatives were collected through questionnaires among students based on the analytic hierarchy process methodology (AHP). An evaluation score was calculated from the proposed model with the weightings generated from the AHP method. It indicates that classrooms in PolyU need to be improved. The weightings generated from the AHP method can be considered for the importance of each alternative. The assessment model can provide proper recommendations to universities for acoustic treatment so as to increase the acoustic quality of the educational environment.

As the acoustical environment is a key part of the indoor environment assessment. Indoor environmental quality (IEQ) is co-determined by several environmental factors (thermal, indoor air, lighting, and acoustics). In the last part, a four-layer IEQ assessment model for university classrooms was proposed based on fuzzy comprehensive evaluation (FCE) methods. The assessment model was evaluated based on a survey with a sample of 224 respondents in selected eight university classrooms in Hong Kong. Besides, objective measurements were performed in each classroom. Several parameters were included, such as operative temperature, CO_2 concentration, illuminance level, and A-weighted background noise level in the measurements. Then a set of prediction formulas were proposed to illustrate the relationships between IEQ and the environmental factors. The analysis results showed that the quality of the thermal environment was the most essential factor in the indoor environment. The results also discussed the significance rankings of sub-factors based on the weightings calculated from the analytic hierarchy process (AHP). The methods can give proper suggestions to authorities to manage the appropriate treatment and improve the indoor environmental quality. It is also useful for indoor environment design based on the proposed prediction formulas.

PUBLICATIONS ARISING FROM THIS THESIS

Journal Papers

2017 **Yang, D.**, Mak, C.M., 2017. An assessment model of classroom acoustical environment based on fuzzy comprehensive evaluation method. *Applied Acoustics*, 127, pp. 292-296.

2018 **Yang, D.**, Mak, C.M., 2018. An investigation of speech intelligibility for second language students in classrooms. *Applied Acoustics*, 134, pp. 54–59.

2020 **Yang, D.**, Mak, C.M., 2020. Relationships between indoor environmental quality and environmental factors in university classrooms. *Building and Environment*, 186, p.107331.

2020 **Yang, D.**, Mak, C.M., 2021. Effects of acoustical descriptors on speech intelligibility in Hong Kong classrooms. *Applied Acoustics*, 171, p.107678.

2021 **Yang, D.**, Mak, C.M., 2021. A new combined sound field prediction method in small classrooms. *Building Services Engineering Research and Technology*, In Revision.

Conference Papers

2019 **Yang, D.**, Mak, C.M., 2019. Effects of acoustical parameters on speech intelligibility for second language students in classrooms. Proceedings of the 26th International Congress on Sound and Vibration 2019, ICSV26, Montreal, Canada.

ACKNOWLEDGEMENTS

I would like to dedicate this thesis to my family, this thesis would have been not completed without their love, support and understanding.

Without the financial assistance and research techniques the Department of Building Services Engineering of the Hong Kong Polytechnic University provided, this thesis would have never been conducted.

My sincerest appreciation goes to my supervisor, Prof. Cheuk-ming Mak, for his tireless support, valuable suggestions, and continuous guidance during my PhD study. He sets a very good model for me in my future career by being modest, dedicated, earnest, and passionate.

I thank all my colleagues and friends in Hong Kong, especially Dr. Yu-wei, Dai, Dr. Zhen Wang, Mr. Guan-yu Fang and all the members in the Indoor Environmental Quality Laboratory for their valuable help and suggestions on my research. Their talents and diligence always inspire and encourage me. Thanks to all my friends who stand by to support me along the way during my PhD period.

I would also like to thank those anonymous journal reviewers and the thesis examiners for their constructive comments and suggestions, which have improved the quality of this thesis significantly.

Last but not least, I express my gratitude to Prof. Gen-shan, Jiang from North China Electric Power University for his care, encouragement and useful discussions throughout.

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NOMENCLATURE

Abbreviations

SNR	Signal-to-Noise Ratio
STI	Speech Transmission Index
RT	Reverberation Time
EDT	Early Decay Time
GA	Geometrical Acoustics
FEM	Finite Element Methods
BEM	Boundary Element Methods
FDTD	Finite Difference Time Domain methods
IAQ	Indoor Air Quality
IEQ	Indoor Environmental Quality
FCE	Fuzzy Comprehensive Evaluation method
AHP	Analytic Hierarchy Process
WIPI	Word Intelligibility by the Picture Identification
PB	Phonetically Balanced
SPL	Sound Pressure Level
SI	Speech Intelligibility Scores
S/N(A)	A-weighted Signal-to-Noise ratio

GTD	Geometrical theory of diffraction
UTD	Uniform theory of diffraction
PMV	Predicted Mean Vote
PDD	Predicted Percentage of Dissatisfied
SBS	Sick Building Syndrome
SD	Standard Deviation
BNL	Background Noise Level
ANL	Acceptable Noise Level
MLS	Maximum Length Sequence
RMS	Root-Mean-Square error
IS	Image Source method
CV	Coefficient of Variation
SA	Surface Area of each classroom facilities
HVAC	Heating Ventilation and Air conditioning
RH	Relative Humidity
ppm	parts per million
t_0	operative temperature
S_T	normalized satisfaction of the thermal environment
S_I	normalized satisfaction of the indoor air quality
C_{CO_2}	concentration of CO_2

S_L	normalized satisfaction of the lighting environment
E	illuminance level of the classroom
L_{Aeq}	A-weighted sound pressure level
S_A	normalized satisfaction of the acoustical environment

Greek symbols

α	Absorption coefficient
ω	Angular frequency
Δ	Laplacian operator
τ	Transit time or delay time
ρ	Density
ω_n	Weighting of the nth factors
σ_n	Standard derivation of the nth factors

Parameters

C_{80}	Sound Clarity in 80 ms
D_{50}	Definition
C_{50}	Sound Clarity in 50 ms
G	Strength
dB	Decibel
T_{30}	30-dB reverberation time
T_{60}	60-dB reverberation time

U_{80}	Useful-to-detrimental sound ratio
R^2	coefficient of determination
$h(t)$	Impulse response
c	Sound velocity (m/s)
$\overline{p}$	amplitude of the pressure wave.
k	angular wavenumber
j	Imaginary unit ($= \sqrt{-1}$)
p	Sound pressure (Pa)
Z_s	Acoustic surface impedance
$q(x)$	Density function
N	Integer
$\nabla, grad$	Gradient
K	Stiffness matrix
M	Mass matrix
D	strain rate tensor
F	Vector components
f_c	Schroeder frequency
A	Amplifier gain
Δt	time step size (s)
b_n	nth objective factors

C_{vn}	Coefficient of variation of the nth factors
h_max	Maximal size of the mesh element
f_0	Source frequency bandwidth
T_{total}	Total simulation time
M_{total}	Total memory costs
O	Overall comprehensive evaluation score
V	Evaluation index
R	Evaluation matrix
$\circ$	a kind of fuzzy operation symbol
Y	First hierarchy comprehensive evaluation

CHAPTER 1 Introduction

1.1 Background and motivation

The indoor acoustical environment is not only related to productivity, health, and comfort but also is related to acoustical quality in a space (Mak and Lui 2012, Wong, Mak et al. 2011, Mak 2007, To, Mak et al. 2015). The education of every citizen is essential to modern societies. Most formal education takes place in the classrooms, where a high level of acoustical quality is required (Lubman and Sutherland 2001). Evidence shows that poor room acoustics, such as excessive noise and reverberation, reduce speech intelligibility in a classroom, and interrupt verbal communication between teachers and students (Hygge, 2003). Speech intelligibility, acoustic comfort, and indoor environmental quality are highly correlated with classroom acoustic conditions.

Furthermore, acoustic modeling techniques were developed for predicting acoustic sound field conditions in classroom acoustics. In classroom acoustics, speech intelligibility is the basis for the classroom acoustical conditions criteria. Many acoustical descriptors were proved that had a significant impact on speech intelligibility. Bradley indicated that the signal-to-noise ratio (SNR) was the more crucial descriptor (Bradley, 1986). Steeneken and Houtgast developed speech transmission index (STI), which was based on the assumption that the degradation of speech intelligibility in rooms was related to the reductions in the amplitude modulations of speech signals by both room acoustics and ambient noise (Steeneken and Houtgast, 1999). Hodgson and Nosal proposed that, when the noise inside a classroom was taken into account, longer reverberation times (RT) were possible without compromising the speech intelligibility (Hodgson and Nosal, 2002). In recent years, several studies based on a specific linguistic environment were proposed to investigate the relationships between speech intelligibility and acoustical descriptors (Astolfi, Bottalico et al. 2012, Galbrun and Kitapci, 2016, Peng, Yan et al. 2015, Choi, 2020).

To associate with the impacts of acoustic descriptors on speech intelligibility mentioned above, it is necessary to investigate the acoustic modeling prediction techniques for predicting the sound field in classrooms. Auralization is a conception introduced to be used in analogy with visualization to describe rendering audible (imaginary) sound fields. Various acoustic modeling methods are available in architectural acoustics for this purpose (Kleiner, Dalenback et al. 1993). The general motivation for acoustic modeling is to predict the acoustical environment of constructions. These constructions included concert halls, theaters, and studios, where the acoustical environments are extremely important. Besides, the acoustic environment is also crucial in classrooms, buildings, and other public venues (Savioja and Svensson, 2015). The room acoustical simulations are commonly based on two main approaches, which are widely used in acoustical modeling based on acoustic wave propagation equation (wave-based method) and assumptions of geometrical acoustics (GA method). The wave-based methods discretize wave propagation equations into finite elements such as finite element methods (FEM) (Cai and Mak, 2016, Cai, Mak et al. 2017), boundary element methods (BEM) (Premat and Gabillet, 2000), and finite difference time domain methods (FDTD) (Kowalczyk and Walstijn, 2010, Savioja, 2010). Room acoustic simulation methods based on the two mentioned main approaches both had limitations in predicting acoustic characteristics. Therefore, some researchers attempt to combine the two approaches in room acoustic predicting. Wang et al. proposed a hybrid technique based on Finite difference time domain methods (FDTD) and ray tracing methods for site-specific modeling of indoor ratio wave propagation (Wang, Safavi-Naeini et al. 2000). Summers et al. combined the Boundary Element Method (BEM) and geometrical acoustics to assess the accuracy of aurilazation (Summers, Takahashi et al. 2004). Aretz proposed a combination method of Finite Element Methods (FEM) and ray tracing methods for simulating sound field in small rooms (Aretz, 2012).

Apart from speech intelligibility, acoustic comfort evaluation is another significant subjective criterion in classroom acoustics. Zannin and Zwirtes presented the evaluation results of acoustic comfort based on a standard design in Brazil (Zannin and Zwirtes, 2009). Puglisi et al. proposed an evaluation of acoustic quality through in-field measurements and self-reports in Italian high school classrooms (Puglisi, Cutiva et al. 2015). In recent years, various acoustic comfort evaluation methods were proposed based on subjective questionnaires and objective measurements (John, Thampuran et al. 2016, Dongre, Patil et al. 2017, Gramez and Boubenider, 2017, Chen and Kang 2017, Wu, Kang et al. 2020).

As the acoustic environment is one of crucial environmental factors affecting indoor environmental quality. A high level of indoor environmental quality (IEQ) is a crucial factor in achieving healthy environments in classrooms. As an expansion, it is necessary to investigate the impact of environmental factors on the assessment of indoor environmental quality. Each environmental factor independently contributed to indoor environments with different weighting factors (Wu, Wu et al. 2020). For instance, the thermal environment (Djongyang, Tchinda et al. 2010, Zhang, Arens et al. 2010), indoor air quality (Tham, 2016, Konsonen and Tan, 2004), lighting environment (Xue, Mak et al. 2016, Xue, Mak et al. 2016, Aries, 2005), and acoustic environment (Yang and Mak, 2017, Zhang, Zhang et al. 2018) on human perception were investigated by several researchers. From the results mentioned above, one can see that the relative importance of the four key aspects differs from one country to another. Different regions, cultures, and population densities make it impossible to develop a valid general formula to evaluate IEQ. Hong Kong is one of the most densely international cities where attracts numbers of international students from all over the world. Besides, Hong Kong is a special city in which English is not the native language for students but the official educational language. These conditions may have an impact on students' evaluation of acoustic environment and speech intelligibility in classrooms. This thesis focuses on classroom acoustic speech intelligibility measurements, acoustical environment assessments, classroom acoustic modeling, and indoor environmental quality assessments in Hong Kong classrooms. The speech intelligibility tests and measurements can summarize the relationship between speech intelligibility scores and various acoustical descriptors. The acoustical environment assessments can evaluate the acoustical environment satisfaction and distinguish the significance of each noise source. A combination prediction method is proposed in the acoustic modeling chapter. This sound field prediction method can provide the predicting level, and spectral content of the sound in buildings, which are essential to acoustical design and acoustic environmental assessment as the acoustic environment is one of the crucial environmental factors affecting indoor environmental quality. As an expansion, the assessment of indoor environmental quality can provide an evaluation of the overall indoor environmental quality satisfaction and its relationships with environmental factors.

1.2 Aim and objectives

Due to the limitation of the previous research about speech intelligibility, acoustic modeling, and indoor environment assessment, this thesis, therefore, aims to investigate speech intelligibility, acoustic modeling, acoustical environment assessment, and indoor environmental quality assessments using indoor measurement, speech intelligibility tests, environment evaluation questionnaires, and numerical method. The research objectives are presented as follows (see Figure 1.1 in detail):

1. Conduct a set of speech intelligibility tests and indoor acoustic measurements to investigate the impacts of acoustical descriptors on speech intelligibility.
2. Propose a mew combination sound field prediction model, which is a combined wave-based acoustic model and hybrid geometrical acoustic models separated by an optimized transition frequency. The optimized transition frequency is depended on the use of computation cost through a genetic algorithm.
3. Evaluate the influencing factors of the noise source to assess the quality of the classroom acoustical environment satisfaction.
4. Evaluate the influencing factors of the environmental factors to assess the overall indoor environmental quality satisfaction. The relationships between indoor environmental quality and environmental factors are proposed.

This study regarding subject investigation methods, experimental measurement, and numerical prediction to classroom acoustics and indoor environmental quality should contribute to improving the understanding of speech intelligibility and indoor environmental quality in the classroom environment. With the subjective investigation methods, it can obtain the speech intelligibility scores, indoor environmental quality satisfaction evaluation of the classroom environments. With the experimental measurement, it can provide the acoustic parameters, indoor environmental parameters of the classroom environment. With numerical simulation, it can provide detailed information of the numerical and modeling method for the acoustic sound field distribution of classroom environment.

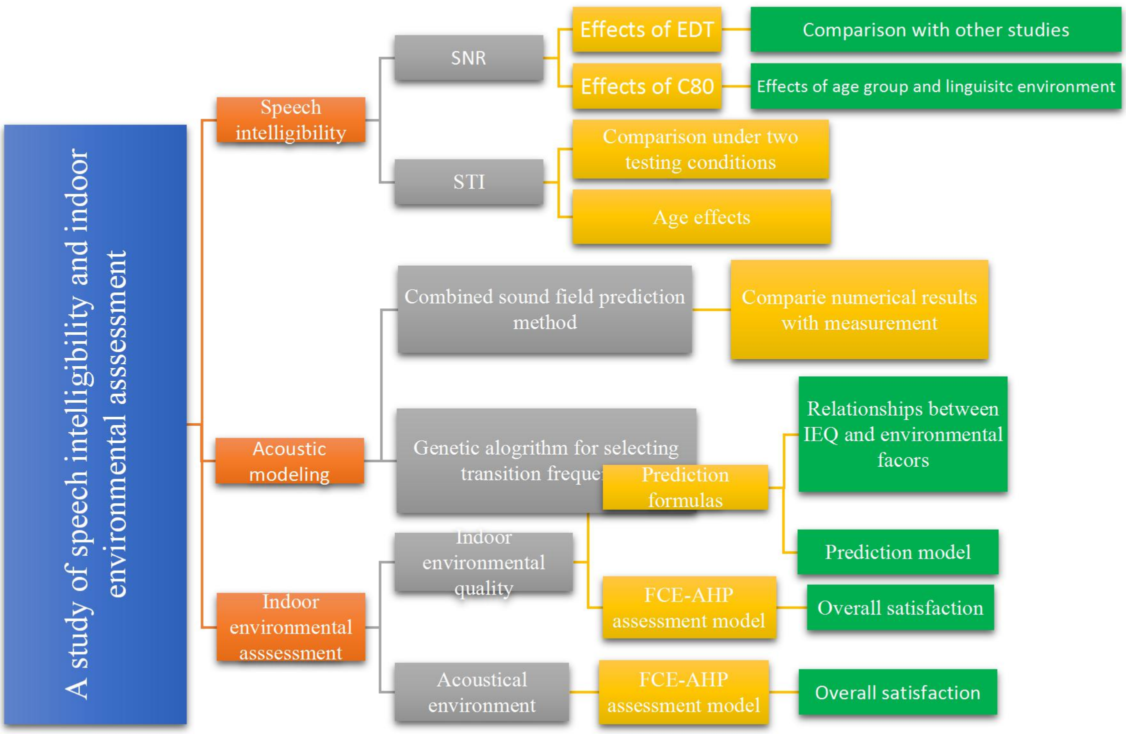

Figure 1.1 The outline of the research contents

1.3 Outline of the thesis

This Chapter introduces the background and the motivation and provides the objectives and significance of the research. Other chapters of this thesis are organized as follows.

Chapter 2 presents a comprehensive literature review, which includes four aspects: the impacts of acoustical descriptors on speech intelligibility, a combined sound field prediction method, acoustical environment assessment, and indoor environmental quality assessment and its relationship with environmental factors.

Chapter 3 describes an investigation of speech intelligibility for second language students in Hong Kong classrooms. This chapter aims to 1) propose a regression model to illustrate the relationship between speech intelligibility scores and speech transmission index (STI) in classrooms; 2) discuss the effects of age groups on speech intelligibility scores; 3) compare the differences of results under two testing conditions.

Chapter 4 discusses the influence of acoustical descriptors affecting speech intelligibility. This chapter aims to 1) propose a regression model to illustrate the relationship between speech intelligibility scores and signal-to-noise ratio (SNR) in classrooms; 2) discuss the effects of early decay time (EDT) on speech intelligibility scores; 3) discuss the effects of sound clarity (C_{80}) on speech intelligibility scores; 4) analyze the age effects and linguistic environment on speech intelligibility scores.

Chapter 5 proposes a new combination sound field prediction method. This chapter intends to predict sound fields in buildings that are essential to acoustical designs and acoustic environmental assessments.

Chapter 6 evaluates the overall acoustical environment satisfaction based on fuzzy comprehensive evaluation methods (FCE). This chapter extends the existing understanding of the significances of noise sources in classroom environments.

Chapter 7 presents the overall indoor environmental quality assessment and its relationships with environmental factors. This chapter uses regression models to describe the prediction formulas based on the principal component analysis.

Chapter 8 summarizes the main contributions of the work conducted in this PhD project and gives recommendations for future research on the subject concerned.

CHAPTER 2 Literature review

2.1 Speech intelligibility

Education develops a country's economy and society; therefore, it is the milestone of a nation's development. A high level of acoustical quality in classrooms is required (Lubman and Sutherland 2001). Evidence shows that poor room acoustics, such as excessive noise and reverberation, reduce speech intelligibility in a classroom and interrupt verbal communication between teachers and students (Hygge, 2003). Speech intelligibility is a measure of how comprehensible speech under given conditions in speech communication. Speech is considered the major communication method between humans. Speech intelligibility is affected by various acoustical descriptors. For instance, the level and quality of speech signal (speech-to-noise ratio SNR), reverberation conditions (reverberation time RT, early decay time EDT), energy balance between direct and delay sound (sound clarity C, definition D), and speech transmission index (STI), etc. Apart from the mentioned acoustical descriptors, many factors such as age, gender, linguistic environment, the acoustic condition can make impacts on speech intelligibility between speakers and listeners. The speech intelligibility score is a subjective evaluation index. Therefore, the speech intelligibility test is an efficient approach to obtain the speech intelligibility scores. Speech intelligibility tests should be developed highly depended on the standards from their language country. For instance, ANSI S3.2-1989 for English, GB 4959–85 for Chinese, Rapporto Tecnico 3C1286 for Italian (ANSI S3.2-1989, GB 4959–85, Bonaventura, Paoloni et al. 1986). In this thesis, as the special linguistic environment of Hong Kong, that is, English is not the native language for students but the official educational language. The test materials are selected based on ANSI S3.2-1989 for investigation. The materials used in the speech intelligibility tests should employ a representative sample of the critical speech sounds under all the conditions of speech communication under investigation. The test materials should have demonstrated validity and reliability and must permit the analysis of performance errors. The ability to diagnose specific transmission features of the system and the need to discriminate among highly intelligible systems are essential features. The economy of the testing and the potential for automation to simplify the administration of the tests and analysis of the results.

Various test material word lists are provided in each standard. Houtgast used a Fairbanks rhyme test, composed of meaningful consonant-vowel-consonant phonetically balanced word lists to obtain the speech intelligibility scores (Houtgast, 1981). Bradley and Sato (Bradley and Sato, 2008) conducted speech intelligibility tests by using WIPI (Word Intelligibility by the Picture Identification) test in rhythms. The same speech intelligibility tests were employed in the sequels of this work (Sato and Bradley, 2008, Yang and Bradley, 2009). Prodi et al. employed a bisyllabic diagnostic rhyme test using pairs of words in speech intelligibility tests

(Prodi, Visentin et al. 2010). Astolfi et al. used a diagnostic rhyme test based on the Fondazione U. Bordoni of Rome for Italian language speech intelligibility tests (Astolfi, Bottalico et al. 2012). Peng and his co-authors employed Chinese rhyme test word lists to obtain Chinese speech intelligibility scores. In this thesis, test materials were selected directly to compare the phonetically balanced (PB) word scores, according to ANSI S3.2-1989. The test material, which contained 50 six-word rows of similar-sounding English words were used.

2.2 Investigation of the relationships between speech intelligibility and acoustical descriptors in Hong Kong

In recent decades, many studies have investigated speech intelligibility and its relationships with acoustical descriptors for students in classrooms. In the following sections, a comprehensive literature review will be organized in several parts of acoustical descriptors.

2.2.1 Cases with STI

STI method was based on the assumption that the degradation of speech intelligibility in rooms was related to the reductions in the amplitude modulations of speech signals by both room acoustics and ambient noise (Houtgast and Steenken, 1984, Steenken and Houtgast, 1980). The STI method is a combination of both room acoustics and signal-to-noise component into an objective measure of speech intelligibility in rooms. Bradley and his co-workers (Bradley, 1986, Bradley and Sato, 2008, Sato and Bradley, 2008) investigated speech intelligibility using the English Fairbank rhyme test in occupied classrooms with RT from 0.39s to 1.20s for children aged 12 to 13 years old through a small loudspeaker with its directivity similar to human's mouth.

Astolfi et al. (Astolfi, Bottalico et al. 2012) investigated speech intelligibility tests and measurements in different reverberation times (RT) and types of noise in elementary school classrooms in Italy. 983 pupils from grade 2-5 (aged from 7-10) participated in the diagnostic rhyme tests. The authors proposed a logarithmic regression function curves of speech intelligibility scores and speech transmission index (STI).

Prodi et al. (Prodi, Visentin et al. 2010) conducted speech intelligibility tests on 80 pupils aged 8–10 in classrooms. The reverberation time of these classrooms was varied from 0.5 to 1.8 s. The test materials were based on a bisyllabic diagnostic rhyme test using pairs of words. The STI values in these classrooms were used for the analyses over a range of 0.23–0.72.

Peng and his co-workers (Peng, 2008, Peng, 2010, Peng, Bei et al. 2011, Peng, Yan et al. 2015) have investigated acoustical parameters (e.g., RT, SPL, STI, etc.) in the elementary classrooms and discussed the relationship between Chinese speech intelligibility and the acoustical parameters. The results indicated a high correlation between Chinese speech intelligibility and these acoustical parameters. Zhu et al. conducted Chinese speech intelligibility tests and in-situ measurements in four different rooms (office, laboratory, lecture hall, and semi-anechoic chamber) (Zhu, Mo et al. 2014).

2.2.2 Cases with SNR

Bradley pointed out that the signal to noise ratio (SNR) was an essential factor to affect speech intelligibility after the measurements of ten classrooms in Canada

(Bradley, 1986). The mean measured reverberation time in these classrooms was 0.7 s at 1 kHz, and ambient noise levels in occupied classrooms without student activity varied from 38 to 45 dBA. He also reported values of various room acoustics parameters and related intelligibility scores to combinations of reverberation time and signal-to-noise ratios. Neuman and Hochberg conducted speech intelligibility tests on 25 children (aged from 5 to 13). The authors summarized that increasing intelligibility scores with increasing age of the listeners and decreasing reverberation times with a constant S/N(A) value. A nonsense syllable speech test recorded by a male talker was reproduced to the respondents via headphones. The whole testing condition was under 0.4 to 0.6 s reverberation time conditions with a low ambient noise level (Neuman and Hochberg, 1983).

Yang and Bradley (Yang and Bradley, 2009) conducted measurements and speech intelligibility tests in elementary school classrooms. Subjects consisted of grade 1, 3, 6 students (aged 6, 8, and 11 years old) and adults. The authors recognized that reverberation time (RT) is not a complete descriptor of room acoustics conditions. Simulated conditions included realistic early-to-late arriving sound ratios as well as various reverberation time. The authors indicated that the speech intelligibility scores (SI) increased with decreasing RT for conditions of constant SNR, whereas for conditions including realistic increases in speech level with varied reverberation time for constant noise level, the intelligibility scores were nearly maximum for a range of reverberation times.

Two papers proposed by Bradley and Sato (Bradley and Sato, 2008, Sato and Bradley, 2008) described acoustical measurements and speech intelligibility tests in 41 classrooms in 12 different elementary schools. Acoustical parameters including SNR, RT, early decay time (EDT), clarity (C50), and strength (G) were discussed in the occupied and unoccupied classrooms. The results indicated that the +15 dB signal-to-noise ratio was not adequate for the youngest children. The study found, that on average, the students experienced: teacher speech levels of 60.4 dBA, noise levels of 49.1 dB A, and a mean speech-to-noise ratio of 11 dB A during teaching activities.

Astolfi et al. investigated speech intelligibility tests and measurements in different reverberation times (RT) and types of noise in elementary school classrooms in Italy. 983 pupils from grade 2-5 (aged from 7-10) participated in the diagnostic rhyme tests. The authors proposed a logarithmic regression function curves of speech intelligibility scores and signal-to-noise ratio (Astolfi, Bottalico et al. 2012).

Choi (Choi, 2020) focused on the effects of occupancy on acoustical conditions in 12 university classrooms in Korea. He compared two different groups of classrooms (6 reflective classrooms and six absorptive classrooms) to analyze the effect of added occupants. The author concluded that the occupants might contribute to achieving more ideal reverberation times for speech (typically 0.4–0.7 s in classrooms) in the more reflective classrooms, but not in the more absorptive classrooms.

Peng and his co-workers (Peng, 2010, Peng, Yan et al. 2015) investigated acoustical parameters (e.g., RT, sound pressure level (SPL), STI, etc.) in the elementary classrooms and discussed the relationship between Chinese speech intelligibility and the acoustical parameters. The results indicated a high correlation between Chinese speech intelligibility and these acoustical parameters.

2.2.3 The influence of linguistic environment

In a modern and globalized world, the interaction between multilingual and multicultural people in public, commercial and social spaces is gaining importance, and oral communication is at the center of this interaction (Galbrun and Kitapci, 2016). The differences in intelligibility among languages have been noticed. Houtgast and Steeneken indicated that language specification effects could be a factor causing disparity among 10 Western language tests (Houtgast and Steenken, 1984). Different linguistic environments and different educational modes may lead to different relationships between speech intelligibility and acoustical parameters. Kang compared the differences in intelligibility between English and Mandarin under reverberation conditions and noisy conditions (Kang, 1998). Other researchers reported the impact of room acoustical conditions on the speech intelligibility of different languages (Galbrun and Kitapci, 2016, Li, Xia et al. 2016). A number of other researchers also examined native and non-native speech intelligibility (Lecumberri and Cooke, 2006, Lecumberri and Cooke, 2010, Van Engen and Bradlow, 2007, Van Engen and Bradlow, 2010). Peng and Wang analyzed the effects of noise, reverberation and foreign accent on native and non-native listeners' performance of English speech comprehension (Peng and Wang, 2016, Peng and Wang, 2019). As for classrooms in Hong Kong, it is special with other classrooms that English as the second language among local citizens is widely used in education. Yang and Mak (Yang and Mak, 2018, Yang and Mak, 2021) proposed the regression models to describe the relationships between speech intelligibility scores and acoustical descriptors for second language students.

2.3 Sound field prediction model

Auralization is a conception introduced to be used in analogy with visualization to describe rendering audible (imaginary) sound fields. Various acoustic modeling methods are available in architectural acoustics for this purpose (Kleiner, Dalenback et al. 1993). The general motivation for acoustic modeling is to predict the acoustical environment of constructions. These constructions included concert halls, theaters, and studios, where the acoustical environments are extremely important. Besides, the acoustical environment is also important in classrooms, buildings, and other public venues (Savioja and Svensson, 2015).

The sound field of constructions can be modeled based on two main approaches which are widely used in acoustical modeling based on acoustic wave propagation equation (wave-based methods) and assumptions of geometrical acoustics (GA methods). The wave propagation equation is the fundamental equation of acoustics. Therefore, wave-based methods will acquire the most accurate results in principle. However, widely used wave-based methods are element-based techniques, such as finite element method (FEM), boundary element method (BEM), Finite-difference time-domain method (FDTD) (Deckers, Atak et al. 2014). With the increases in frequency, the number of elements will be too large to cost much computing time. Comparing with wave-based methods, geometrical acoustics methods are less accurate while saving more computing time. In high frequency, the length of the sound wave is too short to be neglected compared to the dimensions of the surface. The sound is assumed to propagate as rays (beams or any other kinds of shapes), which are the basic assumption of the geometrical acoustic techniques. In practice, GA methods are widely used for predicting the sound field in mid-frequency and high frequency.

In geometrical acoustics, sound propagation was classified into three categories: specular reflection, diffusion, and diffraction. Actually, the sound field will typically tend to diffuse after early reflections instead of ideally specular reflection. Kuttruff first validated a part of reflected sound energy is dispersed into non-specular directions with the support of Monte Carlo simulations (Kuttruff, 1995). Sound diffraction occurred in outdoor and indoor acoustics propagation in a diffracting edge. For outdoor sound propagation on multiple residential buildings, separate parallel wide barriers with buildings (Min and Qiu, 2009). For indoor acoustics, stage ceilings reflectors, balcony edges, orchestra pits, the presence of pillars, and openings between sub-volumes should be considered the impact of sound diffraction (Kamisinski, Szelag et al. 2012, Torres, Svensson et al. 2001, Lovstad and Svensson, 2005). The geometrical theory of diffraction (GTD) and the Uniform theory of diffraction (UTD) were the models based on asymptotic diffraction equations.

Savioja et al. summarized the geometrical acoustic modeling techniques applied in acoustical prediction from algorithmic and computational viewpoints in recent years (Savioja and Svensson, 2015). The image source method and ray tracing method were the most representative and fundamental techniques based on geometrical acoustics widely used in room acoustic modeling simulation. Beam tracing, pyramid tracing, frustum tracing, radiosity method, and other hybrid methods were considered as the extensions and advanced techniques of the formerly mentioned methods (Funkhouser, Tsingos et al. 2004, Drumm and Lam, 2000, Chandak, Antani et al. 2009, Nosal, Hodgson et al. 2004).

Mak and Wang (Mak and Wang, 2015) reviewed the sound prediction methods in building acoustics from its application viewpoints in recent years. The authors pointed out that prediction methods in room acoustics and air-borne sound, structure-borne sound, and duct-borne sound are essential for assessing the acoustical environment or applying possible noise control measures (Yang and Mak, 2017, Mak, 2015).

Classrooms are essential places where formal education takes place. High levels of acoustical quality are required in classrooms. Sound prediction methods are essential to evaluate the acoustical environments as well as acoustical designs. Besides, wide frequency ranges of sound (from low frequencies to high frequencies) exist in classrooms. The purpose of the current study is to propose a hybrid model for predicting sound fields over the whole frequency in classrooms.

2.3.1 Finite element model

The finite element method (FEM) is a powerful numerical method for solving partial differential equations with given boundary conditions which are widely used in engineering and mathematical physics field. Typical applications in acoustics are almost based on wave propagation functions to deal with modal characteristics of enclosed spaces. Maluski and Gibbs applied FEM to simulate the low-frequency sound insulation in dwellings. The validation measurement justified the utilization of such a prediction method (Maluski and Gibbs, 2000). Pietrzyk investigated the sound field in small rooms by using a computer-aid FEM simulation (Pietrzyk, 1998). Cai and Mak used the FEM model to predict the dispersion characteristics of sound wave propagation in a periodic ducted Helmholtz resonator system (Cai and Mak, 2016). Gustavo et al. developed a model of surface absorption appropriate for a modal description of contained sound fields at low frequencies (Gustavo, Semir et al. 2006). Ou proposed a sound transmission loss prediction method based on the FEM model for stiffened building structures (Ou, 2015). Several researchers proposed an acoustic FEM model to solve constrained optimization problems using pressure response (Dhandole and Modak, 2012). The FEM model discretized wave propagation equations into finite elements. The FEM methods were regarded as the most accurate simulation methods. However, with the increase in the frequency, the number of elements increased, which lead to a large amount of computational cost.

2.3.2 Hybrid geometrical acoustic model

Under the basic assumption that the wavelength of sound was neglected at high frequency, the sound wave was assumed to be propagated as sound rays. Ray tracing methods were stochastic, which follow the principle of Monte Carlo sampling of possible reflection paths of sound rays. In recent years, the ray tracing technique was widely used in studying different sound reflection paths under different boundary conditions. Mehta et al. simulated the effect of a non-uniform distribution of absorption on reverberation time under the consideration of edge diffraction and specular reflections (Mehta and Mulholland, 1976). Several researchers presented novel algorithms for modeling interactive diffuse reflections and higher-order diffraction in large-scale virtual environments by using the ray-tracing technique (Schissler, Mehra et al. 2014). Heinz proposed an approach that was based on combinations of ray tracing method and image source method to predict the reverberant trail with diffused scattering walls (Heinz, 1993). Jeon et al. used ray-tracing methods as the simulation methods to evaluate the effect of sound absorption by orchestra members in a concert hall (Jeon, Jiang et al. 2018). The ray-tracing methods were appropriate for simulations under geometrical acoustic assumptions. While in small rooms, the geometrical method was omitted that it depended on Schroder frequency of the room. Astolfi et al. calculated the parameters for the acoustical characterization of classrooms by using geometrical acoustics methods with ODEON (Astolfi, Corrado et al. 2008). Zhu and his co-authors used geometrical acoustic simulation to study speech intelligibility tests based on binaural room impulse response in classrooms (Zhu, Mo et al. 2015). Yang and Hodgson validated auralization techniques in real and virtual classrooms. The authors found the results were reliable in the speech intelligibility tests in two real and virtual classrooms (Yang and Hodgson, 2007). Hodgson and his co-authors compared auralized sound fields by using CATT and ODEON in classrooms. The simulated results were also compared with measurement in real classrooms and were not accurate in the case of high noise and low reverberation (Hodgson, York et al. 2008).

2.3.3 Combination prediction methods

Room acoustic simulation methods based on the two mentioned main approaches both had limitations in predicting acoustic characteristics. Therefore, some researchers attempt to combine the two approaches in room acoustic predicting. Wang et al. proposed a hybrid technique based on Finite difference time domain methods (FDTD) and ray tracing methods for site-specific modeling of indoor radio wave propagation. (Wang, Safavi-Naeini et al. 2000). Summers et al. combined the Boundary Element Method (BEM) and geometrical acoustics to assess the accuracy of aurilazation (Summers, Takahashi et al. 2004). Aretz proposed a combination method of Finite Element Methods (FEM) and ray tracing methods for simulating sound field in small rooms (Aretz, 2012).

The previous studies proposed a low linear pass and high pass filters approach to combine the wave-based methods and geometric methods (Summers, Takahashi et al. 2004, Aretz, 2012). While in these studies, the authors proposed the combination methods focused on the combination of the results generated with both simulation techniques. They used a straightforward approach for combining both simulation results consist of low-pass/high-pass filtering the FE/ray-based results, both at the Schroeder frequency, and then simply adding the filtered frequency responses. The combination methods in the mentioned studies were effective for combining wave-based and ray-based prediction modeling in a real room. However, the computation costs seem not to be considered in the suggested approaches.

2.4 Assessment model of the acoustical environment

In rooms intended for speech communication, a good acoustical design is particularly important. Room size and shape, ambient noise level, and amount and location of sound-absorbing materials all affect how well such a room fulfills its purpose (Bradley, 1986). Han and Mak (Han and Mak, 2008) reported that increasing the absorption coefficient at the back wall could increase speech intelligibility to the largest extent in the classroom. To achieve a good acoustical environment from the beginning is to identify acoustical problems that can be found inside or outside the classrooms. In order to overcome the existing classroom acoustics problems and enhance speech intelligibility, classroom acoustic treatment is an effective way to improve the learning quality and learning outcomes. Besides, interactive teaching in the classroom is another main source of noise that can affect the educational quality in classrooms. It is, therefore, essential to have appropriate and accurate methods for assessing the acoustical environment in buildings. Mak and Wang (Mak and Wang, 2015) reported several assessment models used in building acoustics include analytical models, empirical models, and numerical models.

Many researchers evaluated some assessment of acoustic quality. Zannin et.al (Zannin, Zwirtes et al. 2012) evaluated reverberation time, sound insulation index, background noise, and assessment of speech transmission index. Subjective assessment of audio quality was conducted by Hoeg et.al (Hoeg, Christensen et al.

1997). Astolfi and Pellerey conducted a subjective assessment and an objective assessment of the acoustical and overall environmental quality of vernacular classrooms and modern classrooms (Astolfi and Pellerey, 2008). Madbouly et al. proposed an assessment model of classroom acoustics criteria based on the analytic hierarchy process (AHP) for enhancing speech intelligibility (Madbouly, Noaman et al. 2016). The model consisted of five main criteria that include classroom specifications, noise sources inside and outside the classroom, teaching style, and vocal effort. These five criteria covered twenty-eight alternatives that were considered the main factors that influenced classroom acoustics. AHP method can evaluate the priorities of the alternatives by conducting a number of pairwise comparisons. Mak et al. presented an approach to sustainable noise control system design using the AHP method to evaluate various noise control systems (Mak, To et al. 2015). However, the AHP cannot take into account uncertainty when assessing and tackling a problem effectively. Therefore, the combination of a fuzzy set of AHP methods can effectively tackle fuzziness or vague decision-making problem. Zadeh (Zadeh, 1965) first introduced fuzzy sets in 1965, which is a class of objects with a continuum of grades of membership. The fuzzy sets were pointed out because of the availability and uncertainty of information as well as the vagueness of human feeling and recognition. It is relatively difficult to provide exact numerical values for the criteria, make an exact evaluation and convey the feeling and recognition of objects for decision-makers. Fuzzy set theory has been applied in many systems in the latter scientific research (Doukas, Andreas et al. 2007, Wang, Jing et al. 2008, Mamlook, Akash et al. 2001, Mamlook, Akash et al. 2001, Goumas and Lygerou, 2000, Lee, Mogi et al. 2008). Fuzzy comprehensive evaluation method (FCE) is a multilayer comprehensive evaluation index system based on Fuzzy mathematics. Researchers presented many evaluation systems using the FCE method. In a multi-criteria decision-making problem, the FCE method has been used to trace urban development (Feng and Xu, 1999). In assessing Korean national competitiveness in the hydrogen sector, researchers conducted the hydrogen technology sectors of 30 nations, using fuzzy AHP relative weightings garners fuzzy triangular numbers. The studies mentioned above are all related to the assessment model based on fuzzy evaluation models.

2.5 Relationships between IEQ and environmental factors

Classrooms are essential places where most formal education takes place. A high level of indoor environmental quality (IEQ) is a crucial factor in achieving healthy environments in classrooms. Previous studies have shown that the IEQ had a significant effect on human comfort, productivity, effectiveness, health, and satisfaction (Abbaszadeh, Zagreus et al. 2006, Jones, 1999, Leaman, 1995, Wong, Mui et al. 2018, Vilcekova, Meciarova et al. 2017). It is necessary to investigate the impact of environmental factors on the assessment of indoor environmental quality. The latest review article proposed by Wu et al. (Wu, Wu et al. 2020) indicated that numbers of separate effects of single environmental factors were published in recent years. Each environmental factor independently contributed to indoor environments with different weighting factors. For instance, the thermal environment (Djongyang, Tchinda et al. 2010, Zhang, Arens et al. 2010), indoor air quality (Tham, 2016, Konsonen and Tan, 2004), lighting environment (Xue, Mak et al. 2016, Xue, Mak et al. 2016, Aries, 2005), and acoustic environment (Yang and Mak, 2017, Zhang, Zhang et al. 2018, Zannin and Marcon, 2007) on human perception were investigated by several researchers.

Nevertheless, occupants are subjected not to a single but multiple environmental factors simultaneously (Torresin, Pernigotto et al. 2018). Various combination of multiple indoor environmental factors affects their overall environmental satisfaction. Many studies have indicated that it is complicated to break down satisfaction into categories and determine how these categories contribute to overall satisfaction (Yang and Moon, 2019, Yang and Moon, 2018, Jin, Jin et al. 2020).

Xue et al. proposed a three-step structural approach of overall environment satisfaction in high-rise residential buildings in Hong Kong (Xue, Mak et al. 2016). The authors pointed out that the combined aspect of air quality and thermal comfort has the greatest influence on overall environment satisfaction in high-rise residential buildings, followed by luminous comfort and acoustic comfort. Kang et al. indicated a four-part IEQ assessment framework to investigate the impact of IEQ on work productivity in university open-plan research offices (Kang, Ou et al. 2017). Merabtine et al. showed a method combined to build energy audit, thermal, and IAQ assessment of a school building in France (Merabtine, Maalouf et al. 2018). The results indicate that increasing the indoor temperature by 1 °C can improve the indoor thermal sensation but lead to an increased energy consumption of about 12%. Yang and Moon (Yang and Moon, 2019) investigated the influence of multisensory interaction on acoustic comfort, thermal comfort, visual comfort, and indoor environmental comfort with three physical indoor environmental factors in South Korea. The authors concluded that the impact of acoustics on indoor environmental comfort was the greatest among the three environmental factors tested in the study. Ricciardi and Buratti (Buratti and Ricciardi, 2018) conducted a subjective and objective evaluation of thermal, acoustic, and lighting comfort in 7 university classrooms in Italy. The authors indicated that lighting indexes are higher than thermal and acoustical ones. Kim and de Dear (Kim and de Dear, 2012) estimated individual impacts of 15 IEQ aspects on occupants' overall satisfaction and distinguished linear and a non-linear relationship between those aspects and overall satisfaction in various climate zones (Australia, Canada, Finland, and the USA). Frontczak et al. found that noise level and sound privacy had a significant influence on office occupants' satisfaction (Frontczak, Schiavon et al. 2012, Frontczak, Andersen et al. 2012).

From the results mentioned above, one can see that the relative importance of the four key aspects differs from one country to another. Different regions, cultures, and population densities make it impossible to develop a valid general formula to evaluate IEQ. Hong Kong is one of the most densely international cities where attracts numbers of international students from all over the world. Besides, Hong Kong is a special city in which English is not the native language for students but the official educational language. These conditions may have an impact on students' evaluation of acoustic environment and speech intelligibility in classrooms.

2.5.1 Thermal quality

Thermal environment quality plays an essential role in students' satisfaction and productivity in classrooms (Horr, Arif et al. 2016, Wang, 2006, Li, Wargocki et al. 2011). According to the recent review paper (Djongyang, Tchinda et al. 2010), the authors summarize that two different approaches for the definition of thermal comfort coexist at present, the rational or heat-balance approach, and the adaptive approach. The most well-known prediction models based on the heat-balance approach are predicted mean vote (PMV) index and predicted percentage of dissatisfied (PPD) index (Fanger, 1970). PMV index is determined by six parameters, including four physical parameters (air temperature, relative humidity, air velocity and mean radiant temperature) and two human variables (clothing insulation and metabolic rate) (ISO 7730, 2005). Several adaptive analysis studies were proposed in recent years. Yao et al. presented an adaptive predicted mean vote model that took into account factors affected thermal comfort such as culture, climate, social, psychological, and behavioral adaptations (Yao, Li et al. 2009). Buratti and Ricciardi found a linear correlation between the PMV versus the difference between the Equivalent Uniform Temperature and the Comfort Uniform Temperature (Buratti and Ricciardi, 2009). At the same time, a second-degree polynomial relation was obtained between the PPD versus the absolute value of the same difference between temperatures in Italian university classrooms.

2.5.2 Indoor air quality

Indoor air quality (IAQ) is another environmental factor that has a high impact on indoor environmental quality as well as indoor productivity. A low degree of IAQ in classrooms can cause a reduction in students' productivity and even sick building syndrome (SBS) symptoms (Kosonen and Tan, 2004, Wargocki, Wyon et al. 2000). A multidisciplinary review (Sundell, Levin et al. 2011) of 27 scientific papers on the effects of ventilation rates on health reveals that SBS symptoms can be effectively reduced when the ventilation rate is up to approximately 25 L/s per person. The previous study illustrated that CO_2 level was related to a greater respiratory symptomology in Portugal schools (Fraga, Ramos et al. 2008). Xue et al. put the air odor/freshness as the subjective option for occupants to evaluate the IAQ. They pointed out that air freshness had a strongly positive correlation with IAQ (Xue, Mak et al. 2016). In recent years, a high level of CO_2 is still considered as the main factor affecting indoor air quality (Huang, Song et al. 2018). In a recent study, a long-term monitoring 24-h mean indoor CO_2 concentrations for different regions of China were conducted by several researchers (Liu, Dai et al. 2018). The results pointed out that the mean indoor CO_2 concentrations remained almost the same throughout the seasons in southern China except in regions Yangtze River Delta and Wu Han & Chang Sha. Lei et al. proposed a comprehensive evaluation method for evaluating indoor air quality based on rough sets and a wavelet neutral network (Lei, Chen et al. 2019).

2.5.3 Lighting quality

Lighting quality is a crucial factor for good indoor environmental quality in classrooms (Winterbottom and Wilkins, 2009). The assessments of the lighting quality are still the subject of discussion in scientific studies. A previous study pointed out that lighting quality was often limited to the evaluation of the quantity of light (illuminance and luminance) (Kruisselbrink, Dangol et al. 2018). Several researchers proposed assessment methods based on luminance values or illuminance values (Yacine, Noureddine et al. 2017, Bellia, Spada et al. 2015). Leccese et al. proposed an assessment model to assess the lighting quality in the educational room using the analytic hierarchy process (AHP) (Leccese, Salvadori et al. 2020). Natural lighting (daylight) and artificial lighting are the main light sources of indoor lighting. Xue et al. studied the effects of daylight and human behavior patterns on luminous comfort in residential buildings in Hong Kong (Xue, Mak et al. 2014). The authors illustrated that the degree of luminous comfort was most affected by satisfaction with daylight. However, daylight is much more satisfying for human preference. The artificial lighting system provides a visual condition for the place where the natural lighting is lack of adequate levels or not available. Hong Kong is one of the world's most densely populated cities, with many skyscrapers and high-rise buildings.

Actually, artificial lighting is widely used in Hong Kong university classrooms. Therefore, it is especially essential to assess the lighting quality in the current case study.

2.5.4 Acoustic quality

Some researchers have already pointed out the indoor acoustical environment is not only related to productivity, health, and comfort but also is related to acoustical quality in a space (Mak and Lui, 2012, Wong, Mak et al. 2011, Mak, 2002, To, Mak et al. 2015, Mak and Yang, 2000). Evidence showed that poor room acoustics, such as excessive noise and reverberation, reduced speech intelligibility in a classroom and interrupt verbal communication between teachers and students (Hygge, 2003).

The various existing types of noise becomes the major cause of annoyance in classrooms (Sala and Rantala, 2016, John, Thampuran et al. 2016, Zannin and Zwirtes, 2009). Yang and Mak (Yang and Mak, 2017) proposed an assessment model previously to evaluate the acoustical environment quality in university classrooms in Hong Kong. The model summarized almost all the noise sources that existed around the university affected the acoustical environment. Moreover, these adverse effects are caused by many acoustical factors. Yang and Mak (Yang and Mak, 2018) carried out the speech intelligibility test to middle school students (aged 12-16) and undergraduate students (aged 19-21). They found out the relationships between speech intelligibility scores and speech transmission index (STI) in Hong Kong. In lower STI conditions, Younger students performed worse and seemed to be affected easily by the acoustical environment. Besides, various studies indicated that reverberation time (RT), signal to noise ratio (SNR), sound insulation, and background noise level affected acoustic comfort (Peng, 2010, Astolifi and Pellerey, 2008).

2.6 Summary and scopes of the thesis

This chapter reviews the former studies related to the investigation of speech intelligibility and indoor environmental assessment in Hong Kong classrooms. The following research scopes of the thesis are leaded as following:

(1) Investigate the speech intelligibility for second language students in Hong Kong classrooms. Conduct speech intelligibility tests and acoustical measurements to find the relationships between speech intelligibility scores and acoustical descriptors. Discuss the age effects and impacts of linguistic environments on speech intelligibility.

(2) Propose a combination method of FEM and geometrical acoustic methods for predicting sound field in classrooms. Obtain the optimal transition frequency through genetic algorithms based on selection upon computation costs.

(3) Develop an assessment model for evaluating overall acoustical environment satisfaction. Distinguish the significance of noise sources affecting indoor acoustic quality.

(4) Evaluate the indoor environmental quality based on the proposed FCE-AHP methods. Select main criterion of environmental factor to find the relationships with indoor environmental quality.

The present study intends to provide investigations of (1) authentic speech intelligibility and acoustical parameter information in Hong Kong classrooms; (2)

improvement of the acoustical modeling simulation computation costs; (3) further understanding of the assessment of the acoustical environment and indoor environmental quality in university classrooms; (4) further relationships between indoor environmental quality and environmental factors.

CHAPTER 3 Investigation of speech intelligibility and speech transmission index

In this chapter, speech intelligibility in 9 classrooms of a middle school and 11 classrooms of a university in Hong Kong was investigated. The subjective speech intelligibility tests were conducted with students aged from 12 to 21 in these classrooms. Besides, objective acoustical measurements were performed in each listening position and testing conditions in each classroom. The relationship between subjective speech intelligibility scores and speech transmission index (STI) was discussed based on regression models. The effects of different age groups on speech intelligibility were compared. The results show that speech intelligibility scores increase with STI value for all age groups. The speech intelligibility scores increase as the age increases under the same STI condition. The differences between age groups are decreased with the increase of STI values. English speech intelligibility scores in Hong Kong are always lower compared with native language research under the same values of STI. Better STI values and a better acoustical environment are needed because English is not the native language for students in Hong Kong but the official educational language.

3.1 Description of the experimental campaign

3.1.1 Classrooms for investigation

In this chapter, 9 classrooms in a middle school and 11 classrooms in a university in Hong Kong were investigated. Classrooms in the middle school were not decorated with acoustical treatment (lime walls, cement floors, etc.). Classrooms in the university were well decorated with acoustical treatment (sound absorptive panels, sound absorptive ceilings, floor isolation mat, etc.). All the classrooms were rectangular in shape, and the temperature in Hong Kong during the investigation was around 27 ^{o}C, and the humidity was around 90%. The dimensions of the classrooms are shown in Table 3.1. Classrooms 3A, 3B, 3C, and 3D refer to Grade C (aged from 14 to 16). Classrooms 2A, 2C, and 2D refer to Grade B (aged from 12 to 14). Classrooms 1C and 1D refer to Grade A (aged from 12 to 13) in the middle school.

Table 3.1 The dimensions of all the classrooms

School	Classroom	Length*Width/ m^2	Height/m	Volume/m^3
	3C	6.981*7.535	2.983	156.91
	3B	6.965*7.549	2.962	155.73
	3A	6.994*7.540	2.993	157.84

Middle School	3D	6.968*7.513	2.963	155.11
	2A	6.796*7.496	2.980	151.81
	2C	6.953*7.523	2.975	155.61
	2D	6.966*7.529	2.944	154.40
	1C	6.968*7.567	2.944	155.23
	1D	6.959*7.529	2.991	156.71
University	A	10.988*8.224	2.534	228.99
	B	8.906*5.846	3.087	160.72
	C	8.836*8.335	2.458	181.03
	D	8.168*5.541	2.409	109.03
	E	8.259*6.022	2.524	125.53
	F	8.868*5.245	2.502	116.37
	G	9.845*7.202	2.991	212.07
	H	8.156*5.625	2.423	111.16
	I	8.298*5.864	2.465	119.95
	J	8.956*8.265	2.564	198.06
	K	8.532*6.658	2.523	143.32

Four listening positions were arranged in each classroom. A schematic drawing of classroom 3A was shown as an example in Fig. 3.1. Other desks and chairs were not shown in the classroom. Speech intelligibility tests were accomplished with junior students in middle school and undergraduates in university. The junior students aged from 13 to 15 years old and undergraduates aged from 19 to 21 years old (adults). Referring to the previous studies, the ages of participants had a significant influence on the performance of the speech intelligibility tests (Elliott, 1979, Klatte, Lachmann et al. 2010, Mayo, Florentine et al. 1997). Elliott reported the performance of children aged under 15 years old performed significantly poorer than adults (Elliott, 1979). In the current chapter, the speech intelligibility test results of junior students and undergraduates were used for discussing the differences between age groups.

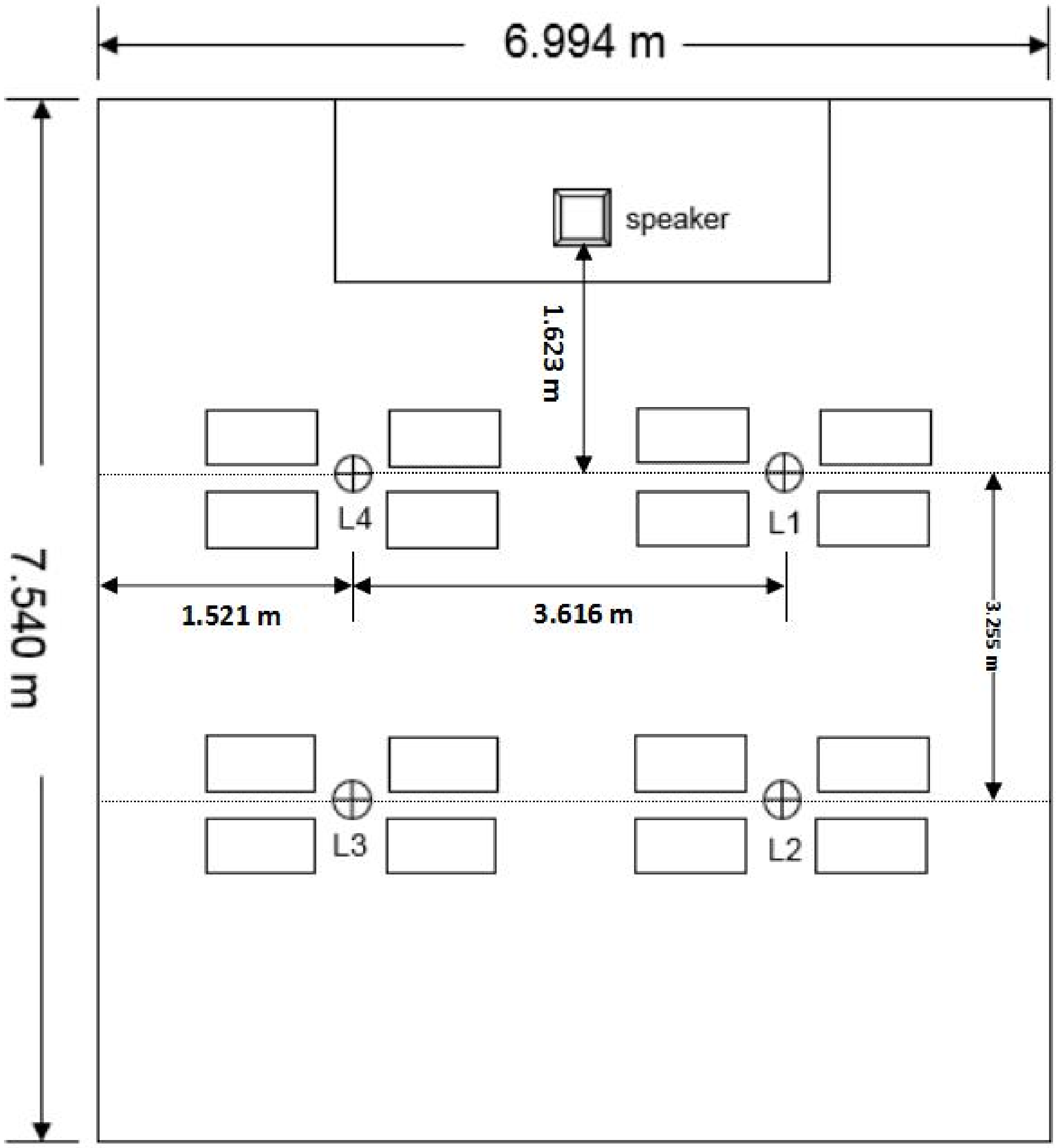

Figure 3.1 Schematic drawing of classroom 3A and showing of listening positions

3.1.2 Speech intelligibility test materials

In the current chapter, the speech intelligibility test word list was based on ANSI S3.2-1989 (ANSI S3.2-1989, 1982). Test materials were selected directly to compare the phonetically balanced (PB) word scores. The test signal material which contained 50 six-word rows of similar-sounding English words were used. The test words in the carrier phrase are “The x row reads y,” where x and y are replaced by the number of row and the pronunciation of the corresponding word. Readers were told to read the materials at a constant speed (4 words per second) and 65 dB sound pressure. One male and one female local resident who are English teachers in middle schools were chosen as readers in the experiment. The whole recording procedure was completed in the anechoic chamber of the Hong Kong Polytechnic University. As shown in Fig.3.2, a random-field microphone (B&K 4935) was placed at a distance of 0.5m from the speaker and 1.0m above the ground in the anechoic chamber. Meanwhile, the speaker sat on the chair and the microphone was placed on the tripod in front of the speaker. The signal was collected from pulse hardware (B&K 3160-B-042) into the computer. All of the children were native Cantonese speakers, and no medical reports of their hearing impairment were reported from them and their parents. They represented the typical general listening audiences.

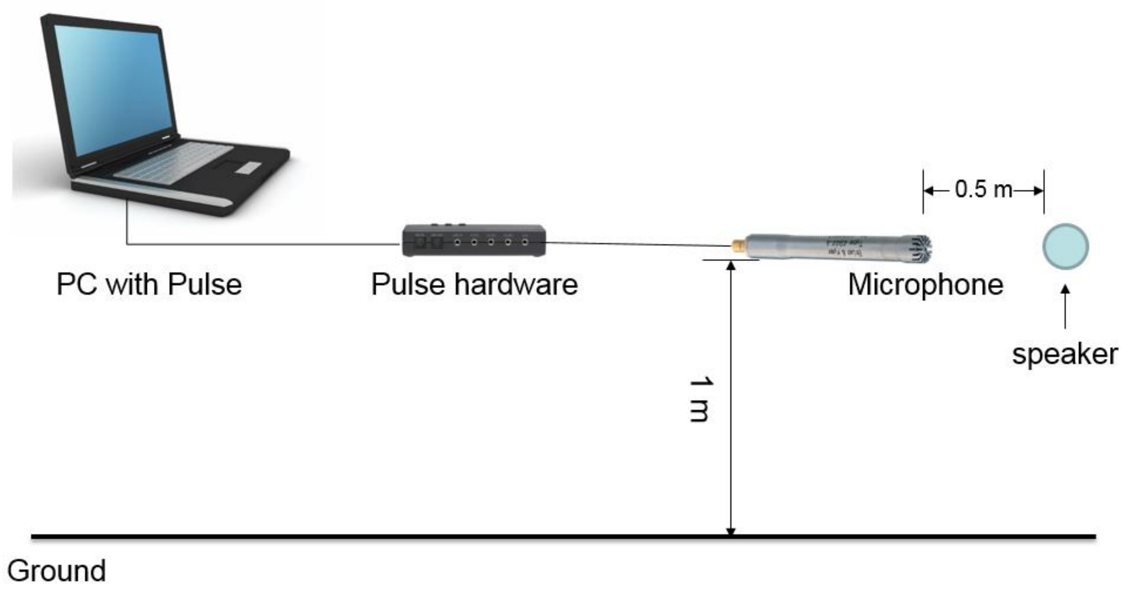

Figure 3.2 Schematic drawing of recording the test material

3.1.3 Speech intelligibility tests in classrooms

The speech intelligibility test signals recorded in the anechoic chamber were reproduced by a loudspeaker which is similar to the human mouth. The loudspeaker was located at the center of the platform where a teacher frequently stands and orients toward the students (location of the loudspeaker see Fig. 3.1). It was set 1.5m above the floor and 0.5m from the blackboard on the front wall. The speech level at 1m directly in front of the loudspeaker was set at 65 dBA by adjusting the volume of the loudspeaker when the subjects were seated around the listening positions. Two testing conditions were investigated in the experiment. The first condition was carried out with the mechanical ventilation system being switched off, but all the windows and doors being widely open. This case was the most usual operation condition of the classroom in autumn or winter in Hong Kong. The second condition was conducted with all the windows and doors being closed but all mechanical equipment for ventilation being switched on. This was the most usual operation condition of the classroom in spring or summer in Hong Kong. During the test period in middle school, nine classrooms, 288 students participated in the survey. The gender of all children was not taken into account, and the difference in the number of boys and girls was nearly negligible. Students come from Grade A (class 1C and 1D, aged from 12 to 13), Grade B (Class 2A, 2C, and 2D, aged from 12-14), Grade C (3A, 3B, 3C, and 3D, aged from 14-16). Besides, 195 undergraduates' participants aged from 19 to 21 were conducted in 11 classrooms. As shown in Fig. 3.1, four listening positions were arranged in each classroom, and four subjects were arranged to sit around each listening position. Therefore, a total of 16 subjects participated in the test in each classroom. For each testing condition, two test word lists (one with a male speaker, the other with a female speaker) were used. All the subjects received a few minutes of instruction prior to the test and were told that they should not communicate with each other while completing the word tests. The subjects were asked to mark the words they heard. The four subjects' English intelligibility scores at each listening position across all eight lists (4 children×2 talkers=8 lists) were calibrated according to ISO/TR 4870 (ISO/TR 4870, 1991), and the averaged speech intelligibility score was obtained for each test condition. The same procedure was completed in university classrooms.

3.1.4 Acoustical measurements in the classrooms

The classroom impulse responses were measured by using an e-sweep signal generated from an internal DIRAC e-sweep source at the four listening positions with subjects in classrooms after the subjective questionnaire investigation. The e-sweep signal was generated from the same loudspeaker which was placed at the same location as the subjective questionnaire tests. Acoustical parameters such as reverberation time (T_{30}), early decay time (EDT), speech transmission index (STI), and early-to-late sound energy ratio (C_{80}). In the meantime, the background noise level was measured by B&K 2270 sound analyzer for each listening position. Table 2 shows the statistics of acoustical parameters in 20 classrooms. $EDT_{(500-1000Hz)}$, $T_{30(500-1000Hz)}$ and $\mathrm{C}_{80(500-1000\mathrm{Hz})}$ is the average value from 500Hz to 1000Hz octave band for each parameter.

Table 3.2 Statistics of acoustical parameters in 20 classrooms

	Parameters	Mean	SD	Min	Max
Grade A	$EDT_{(500-1000Hz)}$/s	1.022	0.29	0.39	1.41

($\mathbf{1}_{st}$condition)	$T_{30(500-1000Hz)}/s$	0.996	0.27	0.46	1.38
	$C_{80(500-1000Hz)}/dB$	3.318	2.65	-0.56	6.86
	STI/-	0.572	0.06	0.53	0.67
Grade A	$EDT_{(500-1000Hz)}/s$	0.833	0.28	0.41	1.35
($\mathbf{2}_{nd}$condition)	$T_{30(500-1000Hz)}/s$	0.852	0.26	0.45	1.38
	$C_{80(500-1000Hz)}/dB$	4.251	2.85	-0.21	9.21
	STI/-	0.645	0.07	0.59	0.75
Grade B	$EDT_{(500-1000Hz)}/s$	1.138	0.26	0.36	1.39
($\mathbf{1}_{st}$condition)	$T_{30(500-1000Hz)}/s$	1.167	0.24	0.42	1.40
	$C_{80(500-1000Hz)}/dB$	2.717	2.22	-0.68	7.21
	STI/-	0.577	0.07	0.48	0.71
Grade B	$EDT_{(500-1000Hz)}/s$	0.926	0.31	0.45	1.28
($\mathbf{2}_{nd}$condition)	$T_{30(500-1000Hz)}/s$	0.945	0.25	0.42	1.22
	$C_{80(500-1000Hz)}/dB$	3.825	2.54	-0.98	8.68
	STI/-	0.617	0.08	0.51	0.75
Grade C	$EDT_{(500-1000Hz)}/s$	1.187	0.29	0.44	1.35

($\mathbf{1}_{st}$condition)	$T_{30(500-1000Hz)}/s$	1.196	0.29	0.46	1.36
	$C_{80(500-1000Hz)}/dB$	2.613	1.96	-0.18	5.88
	STI/-	0.568	0.08	0.46	0.69
Grade C ($\mathbf{2}_{nd}$condition)	$EDT_{(500-1000Hz)}/s$	0.956	0.31	0.42	1.38
	$T_{30(500-1000Hz)}/s$	0.979	0.28	0.46	1.32
	$C_{80(500-1000Hz)}/dB$	3.664	2.14	-0.48	7.98
	STI/-	0.634	0.09	0.51	0.79
Adults ($\mathbf{1}_{st}$condition)	$EDT_{(500-1000Hz)}/s$	0.353	0.18	0.32	0.54
	$T_{30(500-1000Hz)}/s$	0.405	0.16	0.36	0.53
	$C_{80(500-1000Hz)}/dB$	9.131	2.28	0.96	12.81
	STI/-	0.813	0.06	0.73	0.90
Adults ($\mathbf{2}_{nd}$condition)	$EDT_{(500-1000Hz)}/s$	0.327	0.15	0.28	0.52
	$T_{30(500-1000Hz)}/s$	0.365	0.18	0.29	0.55
	$C_{80(500-1000Hz)}/dB$	9.826	2.92	1.81	13.96
	STI/-	0.873	0.05	0.78	0.93

3.2 Results and discussions

3.2.1 Regression model

The relationship between speech intelligibility scores and acoustical parameters was the main focus studied by researchers. Bradley and Sato proposed a third-order polynomial equation to simplify the speech intelligibility scores with the A-weighted speech–noise level (S/N(A)) and useful-to-detrimental sound ratio (U_{80}) (Bradley and Sato, 2004, Bradley and Sato, 2008). The normal third-order polynomial equation is:

$$\mathrm{SI} = \mathrm{a} + \mathrm{bSTI} - \mathrm{cSTI}^2 + a\mathrm{STI}^3 \tag{3.1}$$

A logarithmic model was used to simulate the relationship between the speech intelligibility scores and STI in investigations in Italy primary school (Astolfi, Bottalico et al. 2012).

The normal logarithmic equation is:

$$\mathrm{SI} = \mathrm{a} - \mathrm{bln}(\mathrm{STI} + \mathrm{c}) \tag{3.2}$$

Peng and his co-workers (Peng, Yang et al. 2015) discussed that the “S” form model was more suitable in comparison of Chinese speech intelligibility with the STI.

The normal “S” form equation is:

$$\mathrm{SI} = 100(1 - 10^{-\frac{STI}{a}})^b \tag{3.3}$$

According to Equations (3.1), (3.2), speech intelligibility score can be more than 100% with the value of STI increased to a certain value. This case would not occur in the model of “S” form fitting equation. Therefore, the “S” form model was selected to simplify the relationship between speech intelligibility score and STI in classrooms in Hong Kong.

3.2.2 Relationships between speech intelligibility and STI

Fig. 3.3 shows the speech intelligibility scores obtained from students in grade A in middle school (aged from 12 to 13) under two testing conditions which are plotted against the STI value from different listening positions. The first condition was carried out with the mechanical ventilation system being switched off, but all the windows and doors being widely open. The second condition was conducted with all the windows and doors being closed, but all mechanical equipment for ventilation being switched on. The lines shown in the figure is the result of “S” form model equation based on the non-linear least square fitting method. The regression parameters, standard deviation, and correlation coefficient are shown in Table 3.3. The value of R^2 refers to a high correlation between speech intelligibility scores and STI value. The STI can explain 80.5% and 84.3% the variance of speech intelligibility scores under two testing conditions in classrooms, respectively.

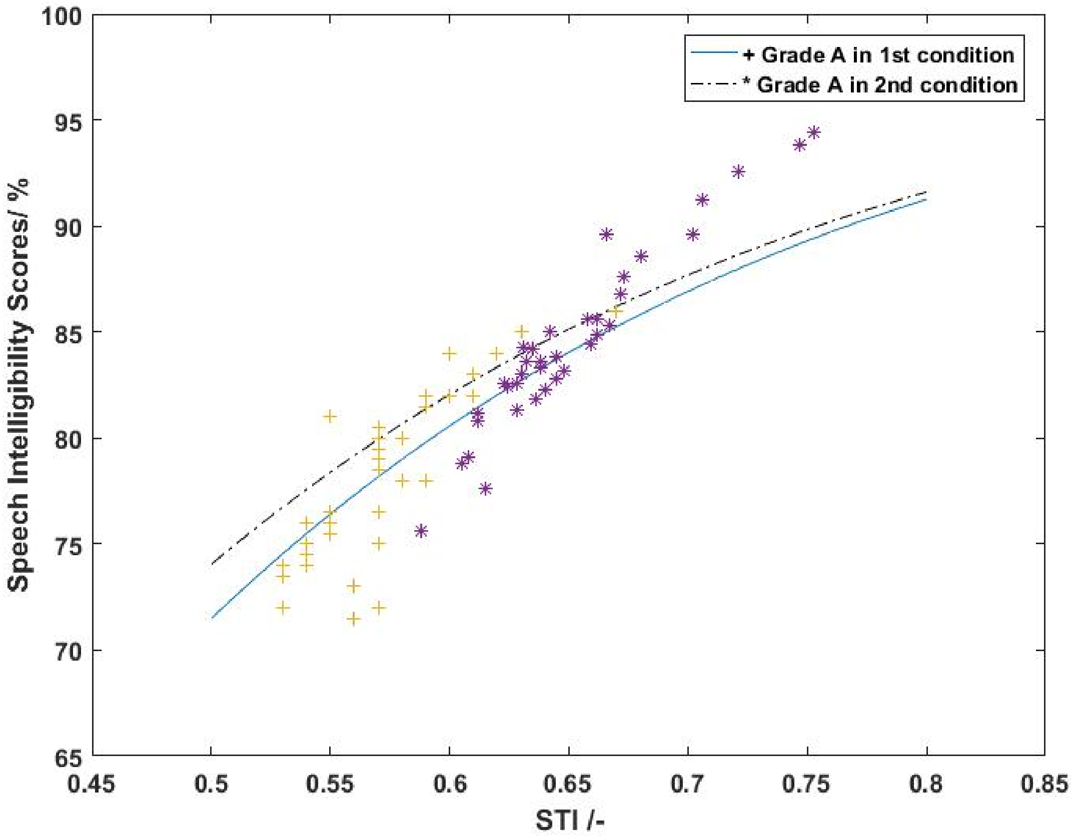

Figure 3.3 The relationship between speech intelligibility scores and STI for grade A students.

Fig. 3.3 shows the regression results based on the non-linear least-square fitting method completed with MATLAB. The standard deviation (SD) and coefficient of determination R^2 were calculated to account for independent variables.

Table 3.3 shows that the values of variables, standard deviation (SD), and coefficient of determination R^2 . The value of R^2 refers to the independent variables in the regression analysis.

Table 3.3 Results of each variable in the regression models.

Variables	a	b	R	SD	R^2
Values in 1st condition	0.552	2.535	0.897	6.02	0.805
Values in 2nd condition	0.586	1.989	0.918	6.52	0.843

3.2.3 Comparison with results under two testing conditions

Referring to the two testing conditions mentioned, the first condition was the most usual operation condition of the classrooms in autumn or winter in Hong Kong. The second condition was the most usual operation condition of the classrooms in spring or summer in Hong Kong. However, these two conditions have different influences on speech intelligibility in classroom education. Fig. 3.3 shows the best-fit curves between speech intelligibility scores and STI value for Grade A students under both two testing conditions. Both the best-fit curves were used "S" form-fitting model curves. The speech intelligibility scores increase as the STI increases under each testing condition. Moreover, under the same STI value, from the views of the regression curves, the speech intelligibility scores may be affected more in values under the first test conditions. Besides, the second test condition i.e., closing all windows and switching on ventilation systems, can achieve higher STI values and the corresponding speech intelligibility scores in classrooms. This means that a mechanical ventilation system may have a lower influence on speech intelligibility than road traffic noise. This may be an explanation for the fact that most schools in

Hong Kong have been badly affected by noise from road traffic. A school insulation program to redress the noise problem for a quieter learning environment for students was implemented by the Hong Kong Environment Protection Department (EPD) in 1999 (EPD, 1999). The program proposed several stages to insulate road traffic noise. To et al. investigated road traffic noise levels compared with the Acceptable Noise Levels (ANLs) in the whole day in Hong Kong (To, Mak et al. 2015). They proposed that most daytime hourly outdoor noise levels and all the nighttime hourly outdoor noise levels were at or above ANLs. Therefore, closing windows is an effective mode for insulating heavy road traffic noise in Hong Kong.

3.2.4 Effects of different age groups

Referring to previous studies, younger children always have greater difficulty in understanding speech and require less noisy acoustical conditions (Elliott, 1979). To compare speech intelligibility scores under the same STI value for different age groups. Fig. 3.4 shows the best-fit curves between speech intelligibility scores and STI value for different age groups under the first testing condition. Grade A, B, and C are three different grades in the middle school investigated in the study. Students from grade A, B, and C aged normally 13, 14 and 15, respectively. The undergraduates' curves represent the participants from university aged from 19 to 21 (adults). All the best-fit curves were used "S" form-fitting model curves. The speech intelligibility scores increase as the age increases under the same STI condition. With the increase of the STI value, the gap between each curve narrowed, which indicates the differences between age groups decreased. This finding indicates that students have greater difficulty in understanding speech in noisy acoustical conditions. The differences between grade A and B are greater than that in grade B and C curves. This finding indicates that the younger students were more affected by acoustical environment. In most cases shown in Table 3.2, the reverberation is longer in a lower STI condition. Masking by reverberation reduces the amount of acoustical information available to students. Children are less flexible in their auditory sensitivity and their ability to separate sounds even under quite complex listening condition (Werner, 2007).

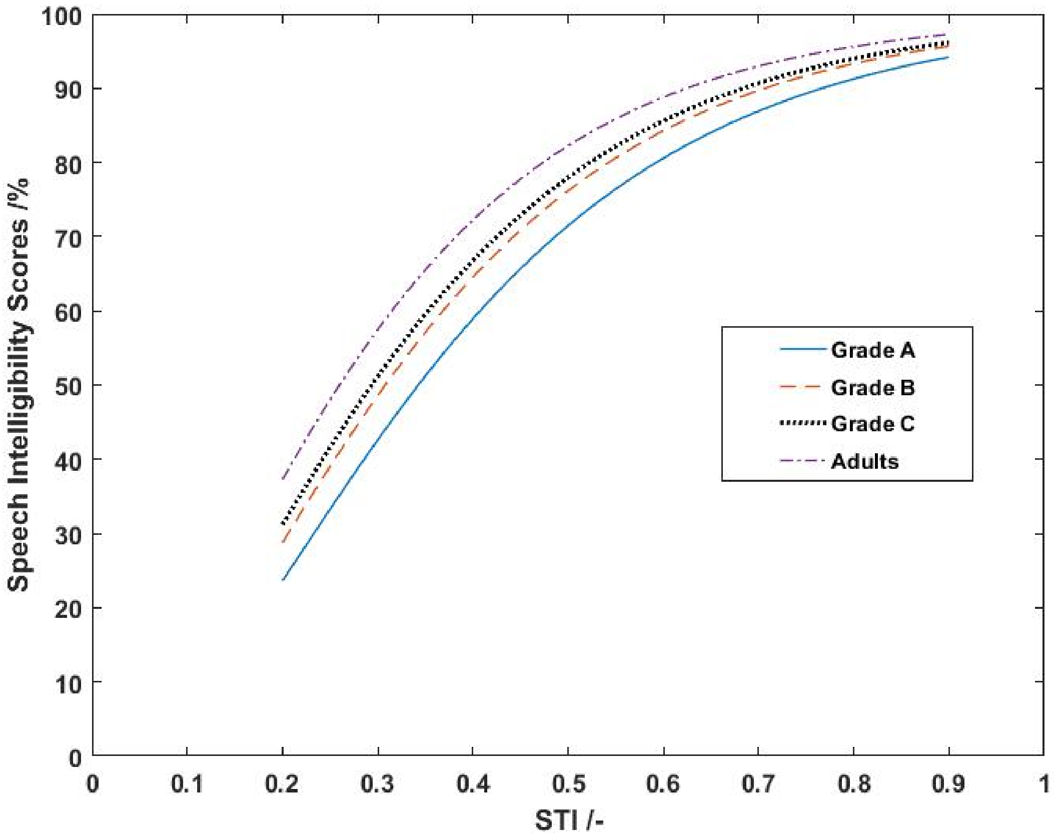

Figure 3.4 Relationships between speech intelligibility and STI for different age groups under the first condition.

3.2.5 Comparison with other studies

Speech intelligibility scores for students were investigated to relate to S/N(A), sound pressure level (SPL), speech intelligibility metric U_{50} in previous studies (Bradley, 1986, Peng, 2010, Han and Mak, 2008). The relationships between these parameters and speech intelligibility scores cannot directly compared because STI and other indices are different acoustical objective parameters to evaluate speech intelligibility in rooms. Therefore, different relationships between speech intelligibility scores and STI under different language conditions were compared. As shown in Fig. 3.5, the fitting curves between two indices obtained by Astolfi et al. and Peng et al. were compared (Astolfi, Bottalico et al. 2012, Peng, Yan et al. 2015). Astolfi et al. used a diagnostic rhyme test to investigate the Italian speech intelligibility scores, and different types of noise were added to the test signals to create different listening conditions (Astolfi, Bottalico et al. 2012). The best-fit curve between two indices for grade 3-5 elementary students was described by a logarithmic curve.

Peng et al. (Peng, Yan et al. 2015) used Chinese rhyme test word lists which is similar to the modified rhyme test of English, to obtain the relationship between the two indices. 9 primary schools and 27 classrooms were investigated. The best-fit curve between speech intelligibility scores and STI for grade 6 was simulated by an "S" form curve.

In order to avoid the influence of age groups, students from grade A (aged 12-13) were selected to compare with the other two studies. Both two testing conditions were not mentioned in these two studies. The first condition was assumed to choose for comparison with other studies.

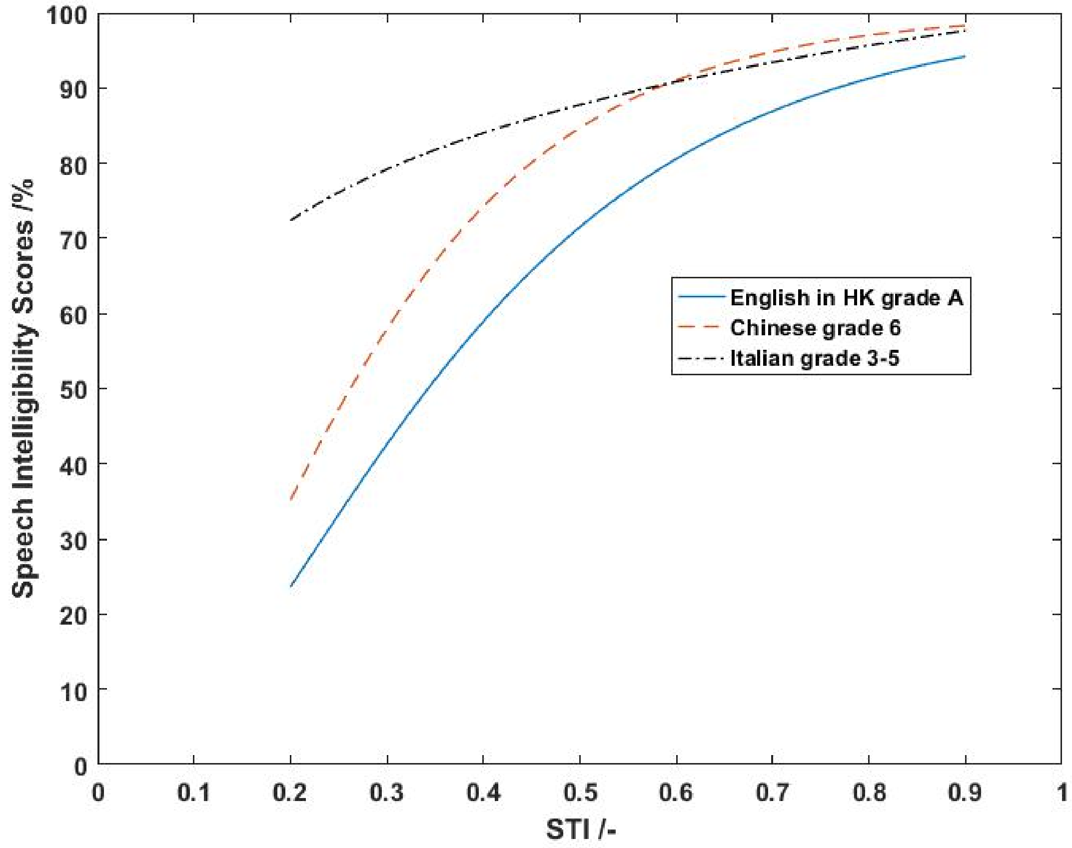

Figure 3.5 Comparison of the regression curves between speech intelligibility scores and STI values with other studies

It can be seen in Fig. 3.5 that all these three curves indicate speech intelligibility scores increase with STI value. As for the English curve in Hong Kong, it can be seen in Fig. 3.5 that English speech intelligibility scores in Hong Kong are always lower than another two cases under the same values of STI. This means that better STI values and better acoustical environments are needed in Hong Kong to obtain high speech intelligibility scores. This may be an explanation of the fact that English is not the native language for students in Hong Kong but the official educational language. In addition, the reverberation time measured from middle school classrooms (shown in Table. 3.2) was almost higher than that in Chinese and Italian classrooms. All these factors will influence the lower English speech intelligibility scores obtained in Hong Kong classrooms.

3.3 Summary

This chapter investigated speech intelligibility in middle school and university classrooms. Speech intelligibility tests were conducted in 9 middle school and 11 university classrooms, and the acoustical measurements were performed in these classrooms. Subjective speech intelligibility tests were obtained from PB word lists, and STI values were conducted in different listening positions and testing conditions in each classroom. The regression model was fitted based on the non-linear least square fitting method. The effects of different age groups on speech intelligibility and findings from different studies were also discussed. The conclusions can be drawn as follows:

(1) Speech intelligibility scores increase with the increase of STI value for all the age groups.

(2) The speech intelligibility scores increase as age increases under the same STI condition.

(3) The differences between age groups are decreased with the increase of STI values.

(4) Speech intelligibility scores in Hong Kong are always lower than another two cases, in Italy and China, under the same values of STI.

(5) Better STI values and a better acoustical environment are needed because English is not the native language for students in Hong Kong but the official educational language.

CHAPTER 4 Effects of acoustical descriptors on speech intelligibility

This chapter investigated the effects of classroom acoustics on speech intelligibility in secondary school and university classrooms. Speech intelligibility tests were conducted in 9 secondary school classrooms, and 18 university classrooms and the acoustical measurements were performed in these classrooms. Subjective speech intelligibility tests were obtained from phonetically balanced (PB) word lists on a total of 672 students and acoustic descriptors such as signal-to-noise ratio (SNR), early decay time (EDT), and sound clarity (C_{80}) were conducted in different listening positions in each classroom. The relationships between speech intelligibility scores (SI) and acoustical descriptors were fitted based on non-linear curve fitting regression models. The "S" form regression model was selected with modification as the basic regression equation to describe the effects of SNR on speech intelligibility. The combination effects of SNR with reverberation condition and sound clarity condition on speech intelligibility were investigated. The impact of different age groups and linguistic environment on speech intelligibility were discussed.

The results reveal that SI increases with the increase of SNR value for all age groups. The results indicate that nearly 0.06s increasing in EDT values will be correlated to a 1% decrease in SI. Furthermore, the results also suggest that a 1 dB increasing in C_{80} values will be correlated to a 1.23% increase in speech intelligibility scores. The SI increases as the age increases under the same SNR condition. The speech intelligibility scores are always lower than the comparison research results with a constant reverberation value as well as sound clarity value for an equal SNR value.

4.1 Description of the Experimental procedure

4.1.1 Classrooms in case studies

In this chapter, 9 classrooms in a secondary school and 18 classrooms in a university were investigated in Hong Kong. Classrooms in secondary school were without acoustical treatment, while classrooms in the university were well decorated with acoustical treatment. A comparative table of the decorating materials of classrooms in secondary school and the university was given in Table 4.1. All the classrooms were rectangular in shape. The dimensions of the selected classrooms are shown in Table 4.2. Classrooms 3A, 3B, 3C, and 3D are the classrooms of Grade C students (aged from 14 to 16). Classrooms 2A, 2C, and 2D are the classrooms of Grade B students (aged from 12 to 14). Classrooms 1C and 1D are the classrooms of Grade A students (aged from 12 to 13) in secondary school.

Table 4.1 Decorated materials of classrooms comparison

Sides	Secondary School classrooms	University classrooms
Floor	Concrete floor	Loop pile tufted carpet
Sidewalls	Painted concrete walls	Painted concrete walls
Ceiling	Painted concrete walls	Metal perforated plates
Windows	Double glazing windows	Double glazing windows
Door	Solid wooden door	Solid wooden door
Front and rear walls	Painted concrete walls	Wooden perforated plates

Table 4.2 Dimensions of selected classrooms

School	Classroom	Length*Width/ m^2	Height/m	Volume/m^3
	3C	6.981*7.535	2.983	156.91
	3B	6.965*7.549	2.962	155.73
	3A	6.994*7.540	2.993	157.84
	3D	6.968*7.513	2.963	155.11
	2A	6.796*7.496	2.980	151.81
	2C	6.953*7.523	2.975	155.61
Secondary School	2D	6.966*7.529	2.944	154.40
	1C	6.968*7.567	2.944	155.23
	1D	6.959*7.529	2.991	156.71
	A	10.988*8.224	2.534	228.99
	B	8.906*5.846	3.087	160.72
	C	8.836*8.335	2.458	181.03
	D	8.168*5.541	2.409	109.03
	E	8.259*6.022	2.524	125.53
	F	8.868*5.245	2.502	116.37

University	G	9.845*7.202	2.991	212.07
	H	8.156*5.625	2.423	111.16
	I	8.298*5.864	2.465	119.95
	J	8.956*8.265	2.564	198.06
	K	8.532*6.658	2.523	143.32
	L	7.121*7.182	2.633	134.66
	M	12.113*7.682	3.621	336.94
	N	11.265*7.842	3.251	287.19
	O	7.843*3.849	2.682	80.96
	P	16.525*12.648	5.028	1050.89
	Q	8.175*5.538	2.492	112.82
	R	11.488*9.025	3.136	325.14

According to the sizes of the chosen classrooms, four listening positions (L1-L4) were selected in each classroom. As shown in Fig 3.1, an example (Classroom 3A) was given (Other specifications were hidden in this classroom). Speech intelligibility tests were accomplished with junior students in secondary school classrooms and undergraduates in university classrooms. The junior students from the secondary schools were aged from 12 to 16, while undergraduates were aged from 19 to 23 (adults). In the current chapter, the speech intelligibility test results of the mentioned respondents were studied for discussing the effects of different age groups.

4.1.2 Speech intelligibility test materials

In this paper, the speech intelligibility test materials were highly dependent on the American National Standard ANSI S3.2-1989 (ANSI S3.2-1989, 1982). The phonetically balanced (PB) word lists were chosen as the test materials for the respondents. This test word list consisted of 50 rows of six-word similar-pronouncing English words. The test lists in the carrier phrase were "The x row reads y," where x and y were replaced by the rows number and the pronunciation of the corresponding word. A male and a female local English teacher in secondary schools were invited as readers for recording the test materials. Readers were asked to read the prepared test materials at a constant speed (4 words per second) and a continuous SPL (65 dBA). The whole recording procedure was conducted in the anechoic chamber. A random-field microphone (B&K type 4935) was settled at a 0.5m distance from the reader and a 1.0m height above the floor in the anechoic chamber. Meanwhile, the reader was asked to sit on a chair, and the microphone was settled on the tripod in front of the reader. The recording signal was collected through pulse hardware (B&K type 3160-B-042) and passed to the notebook (see Fig 4.1).

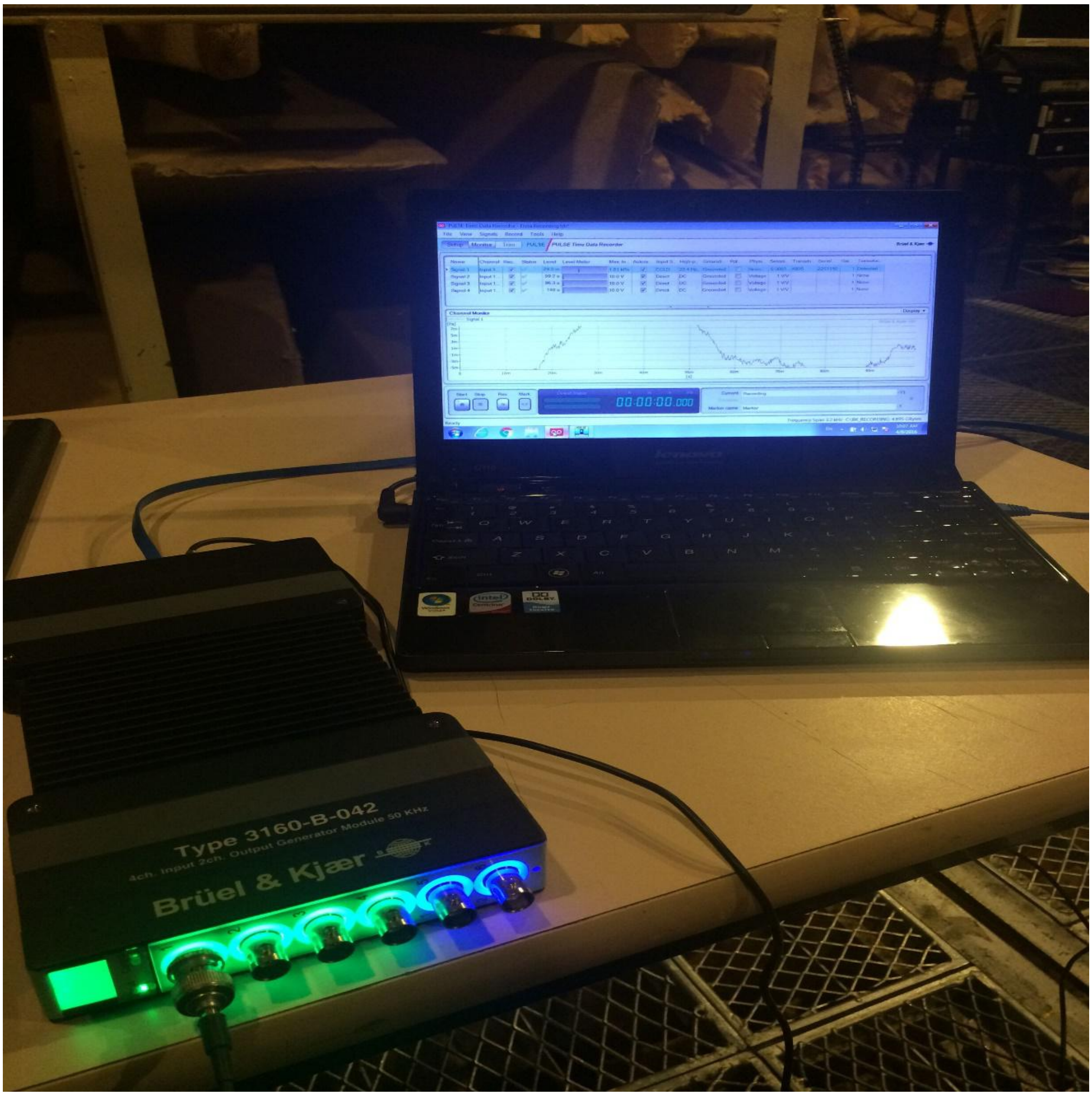

Figure 4.1 B&K Pulse system for signal recording in the anechoic chamber

4.1.3 Speech intelligibility tests in the classrooms

The speech intelligibility test signals which were recorded in the anechoic chamber were arranged to reproduce by an echo speech source (B&K Type 4720), which is a mouth directivity sound source. The sound source was placed at the platform center. This simulated that a teacher stood and oriented toward the students (the sound source location is given in Fig. 3.1). The sound source was settled a 1.5m distance above the ground and a 0.5m distance front the blackboard. In the objective measurement, different speech sound pressure levels (SPLs) were controlled from 30 dBA to 90 dBA by changing the speech source (B&K 4720), which includes the possible changing range of the speech levels in the classrooms. The speech intelligibility tests were conducted in classrooms with the background noise level (BNL) varied from 31.5 dBA to 57.6 dBA. The SNR changes in the current chapter were varied from -8.5 dBA to 32.4 dBA.

284 students from 9 secondary classrooms participated in the survey. Students came from Grade A (aged from 12 to 13), Grade B (aged from 12-14), Grade C (aged from 14-16). Besides, 388 undergraduate participants aged from 19 to 23 participated in the speech intelligibility tests in 18 university classrooms. The gender of the students was not taken into account in this paper, and the difference in the number of genders was nearly negligible. Four listening positions (L1-L4 shown in Fig. 3.1) were selected in each classroom. In addition, four students were asked to sit around every listening position. Two different test word lists (one with the male reader, the other with the female reader) were used for asking the respondents in each testing condition. Instruction prior to the tests was given to the respondents. Besides, they were told not to communicate with others while answering the speech intelligibility tests. During the tests, the respondents were told to choose the words they heard from the sound source. The four respondents' speech intelligibility scores (SIs) at every proposed listening position across all 8 lists (4 students×2 readers=8 lists) were calculated according to ISO/TR 4870 (ISO/TR 4870, 1991), and the mean SI was obtained. In these speech intelligibility tests, all students were native Cantonese speakers. Besides, there are no medical reports about their hearing impairment that

were provided from them. They roughly represented the typical listening audiences in classrooms.

4.1.4 Classroom acoustic measurements

The classroom acoustic measurement system in the current chapter was using DIRAC (B&K Type 7841) 6.0 system (as shown in Fig 4.2). DIRAC software is a widely used architecture acoustic software that is based on measurements and analysis of impulse response. In the current chapter, the impulse responses were measured by using MLS (Maximum Length Sequence) signal generated from internal DIRAC MLS source at the four listening positions in occupied and unoccupied classrooms. Impulse response was measured in one pass using intermittent MLS stimulus followed by an equally long period of silence. USB Audio Interface B&K ZE-0948 is a sound device for line-level interface to microphone and speaker systems. A sound level meter (B&K 2250) and an echo speech source (B&K 4720) were selected in the measurement. In the meantime, B&K 2270 sound analyzer was employed for measuring the BNLs at selected listening positions.

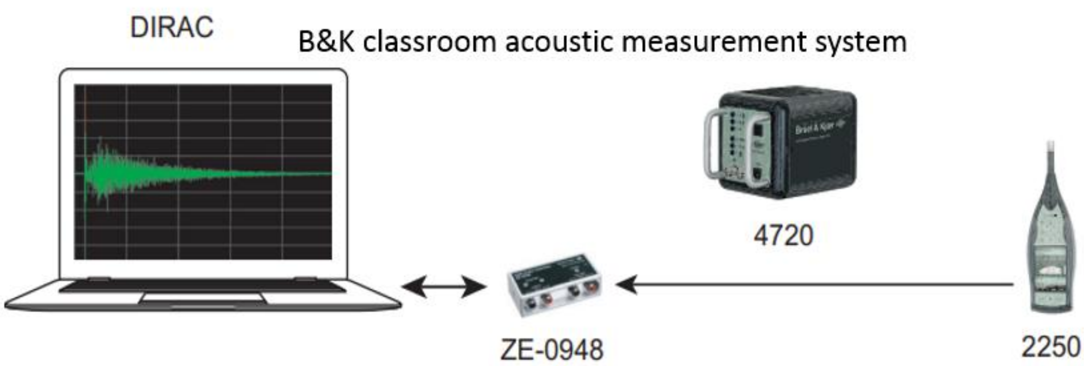

Figure 4.2 Dirac classroom acoustic measurement system (figure from B&K users' menu)

4.2 Results and discussions

4.2.1 Regression model

In order to clearly distinguish the effects of acoustical descriptors on speech intelligibility, regression models were discussed and studied variously in previous studies. Three primary forms of non-linear curve fitting regression models were employed in fitting curves in classroom acoustics. Bistafa and Bradley proposed a third-order polynomial equation to simplify the SIs with the SNR and other acoustic parameters (Bistafa and Bradley, 2000). Astolfi et al. pointed out a logarithmic model as the best fitting model to illustrate the relationships between speech intelligibility scores and acoustic descriptors (Astolfi, Bottalico et al. 2012). Peng et al. revealed an "S" form regression function to describe the relationship between Chinese SIs and speech transmission index (STI) (Peng, Yan et al. 2015). In this paper, the mentioned three regression models were employed and compared to describe the relationships between SIs and acoustical descriptors. The basic model functions of the mentioned three regression models were as follows:

$$y = a + bx + cx^2 + dx^3 \tag{4.1}$$

$$y = a + bln(x) \tag{4.2}$$

$$y = 100(1 - 10^{-x/a})^b \tag{4.3}$$

where a,b,c, and d are the regression parameters generated from the fitting process. Fig 4.3 shows the fitting curves based on the three mentioned regression models for the description of SIs and SNR values in university classrooms. The regression parameters and statistical characteristics were given in Table 4.3.

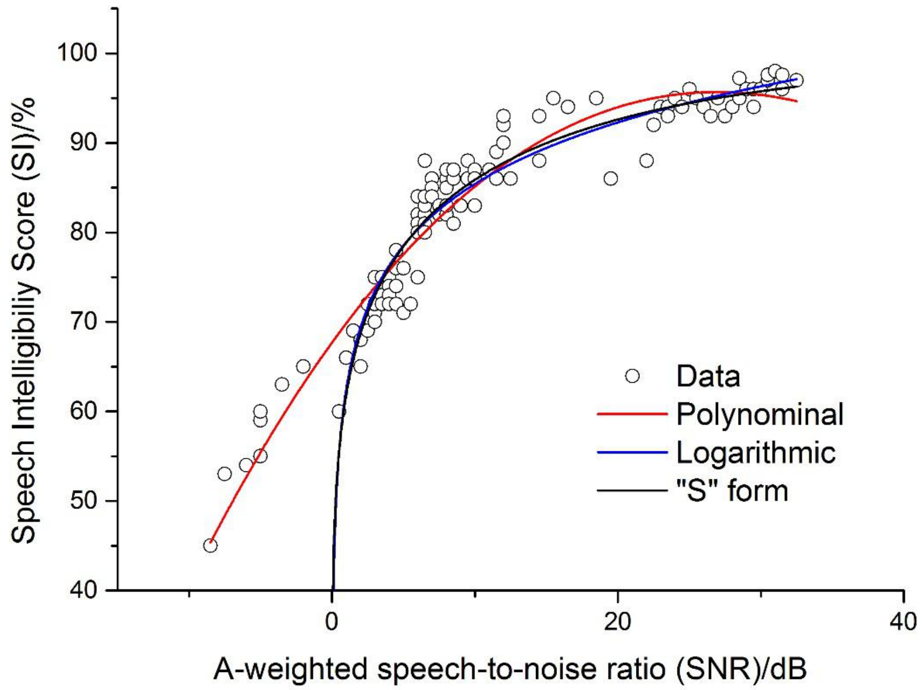

Figure 4.3 Comparison results of three regression models in university classrooms

Table 4.3 Regression parameters of the three regression models and statistical characteristics

	$\boldsymbol{a}$	$\boldsymbol{b}$	$\boldsymbol{c}$	$\boldsymbol{d}$	Adj. $\boldsymbol{R^2}$
Third-order polynomial	67.702	2.206	-0.481	0.002	0.924
Logarithmic	9.927	62.559			0.789
***"S"* form**	48.790	0.156			0.786

Where Adj. R^2 denotes the adjusted R^2 which reveals the effects of the number of regression parameters and the fitting quality. As shown in Fig 4.3, the logarithmic model and "S" form model are significantly deviate from the plotted data when the

SNR value approaches zero. The logarithmic regression model equation (4.2) was proposed by Astolfi et al. to describe the relationship between SIs and STI values. The STI values were constantly above zero in real classrooms. However, the SNR values are able to below zero in classroom measurements. Therefore, Eq. (4.2) needs to be modified to be appropriate for evaluating SIs and SNR values. As for the *"S"* form regression equation (4.3), the basic formula was similarly proposed by Peng et al. to illustrate the relationship between SIs and STI. According to the regression parameter results in Table 4.4, the values of a and b are both above zero. Therefore, two conditions should be discussed, x (SNR value) > 0 and $x < 0$, respectively. When $x > 0$, $0 < x/a < 1$. This condition is similar to that in evaluating STI. While $x < 0$, $x/a < 0$, $10^{-x/a} > 1$. Therefore, Eq. (4.3) needs to be modified to be appropriate for evaluating SIs and SNR values. According to the previous analysis, the modifications of Eq. (4.2) (4.3) can be added to a constant c to avoid the mentioned derivate phenomenon as well as improve the fitting goodness. The modification regression models are given as follows:

$$y = a + bln(x + c) \tag{4.4}$$

$$y = 100(1 - 10^{-(x+c)/a})^b \tag{4.5}$$

Fig 4.4 shows the fitting curves based on the two modification regression models for the description of speech intelligibility scores and SNR values in university classrooms. The corresponding regression parameters and statistical characteristics were given in Table 4.4.

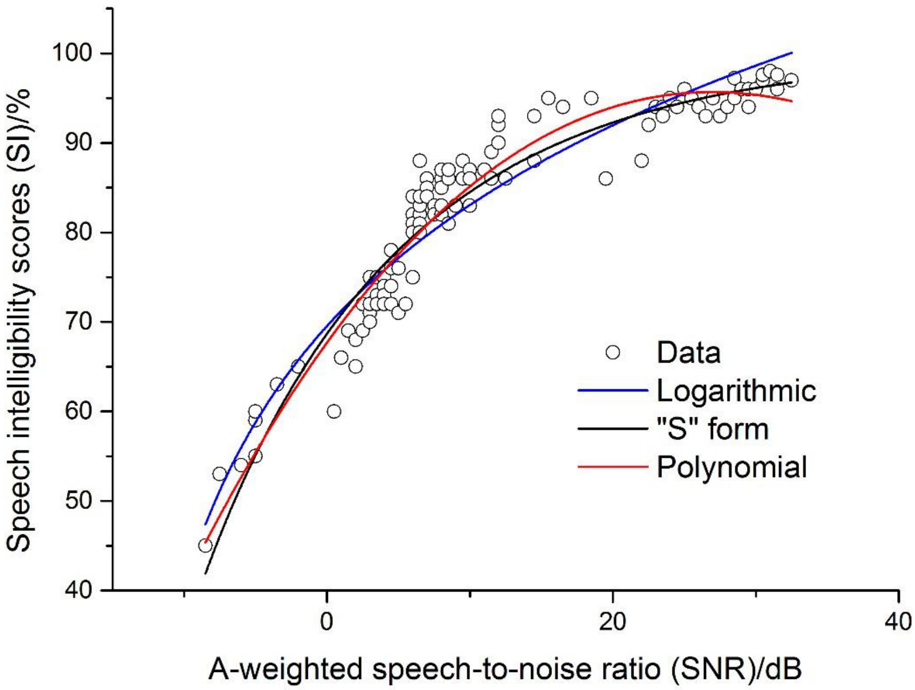

Figure 4.4 Comparison results of three modified regression models in university classrooms

Table 4.4 Regression parameters of the three regression models and statistical characteristics

	$\boldsymbol{a}$	$\boldsymbol{b}$	$\boldsymbol{c}$	$\boldsymbol{d}$	Adj. $\boldsymbol{R^2}$
Third-order polynomial	67.702	2.206	-0.481	0.002	0.924
Logarithmic	-2.174	26.482	13.879		0.893
***"S"* form**	33.455	0.853	15.125		0.914

The modification regression fitting curves are plotted with data collected from university classrooms in Fig.4.4. Besides, the regression parameters are given in Table 4.4. The third-order polynomial regression curve (red line in Fig 4.4) can obviously be seen that it is not monotonically increased with the increase of SNR.

The SIs in the logarithmic fitting curve (blue line in Fig 4.4) will be more than 100% when the SNR is greater than a certain value. Therefore, in the current chapter, the *"S"* form regression fitting model is employed to describe the relationships between SIs and SNR as well as other acoustic descriptors.

4.2.2 Effects of SNR on speech intelligibility

SNR is a critical factor in affecting speech intelligibility. The average SIs at listening positions versus A-weighted speech-to-noise ratios were plotted in Fig 4.5. They are plotted separately for the results collected from the occupied secondary school classrooms (Grade A, B, and C) and university classrooms.

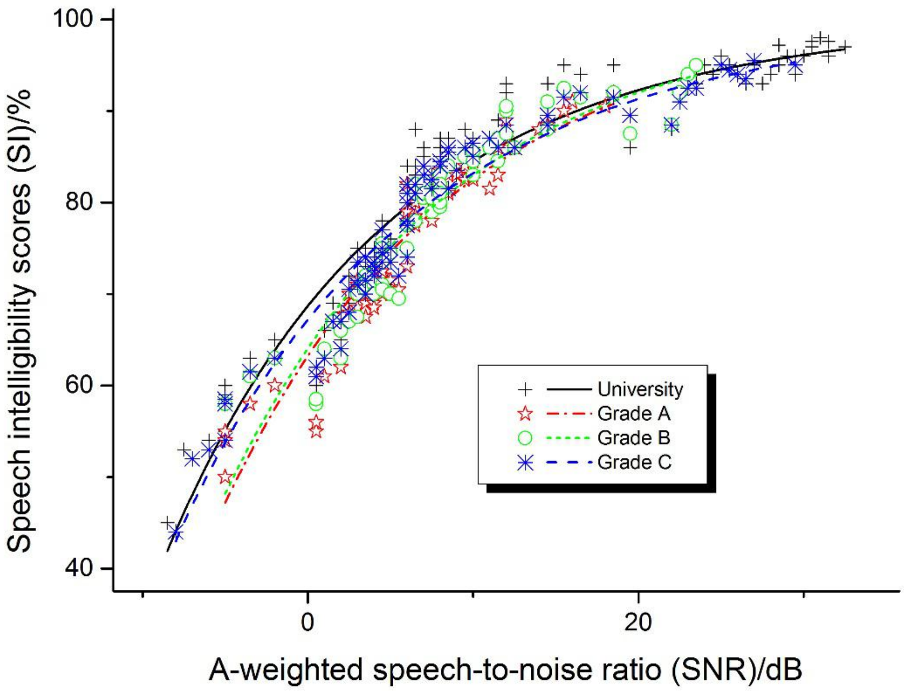

Figure 4.5 Relationships between speech intelligibility scores and SNR

The regression parameters and statistical characteristics are given in Table 4.5. An analysis of variance (ANOVA) indicated that there were highly significant main effects of age ($p<0.001$) and SNR ($p<0.001$) and a highly significant interaction effect of these two independent variables ($p<0.001$).

Table 4.5 Regression parameters of the results and statistical characteristics

	a	b	c	Adj. R^2	Root-MSE
University	33.455	0.853	15.125	0.914	3.433
Grade C	30.173	1.196	12.889	0.891	3.261
Grade B	30.112	1.166	13.815	0.884	3.378
Grade A	35.396	0.840	14.096	0.934	3.057

Where “Root-MSE” is an abbreviation of root-mean-square error.

Students from grade A, B, and C normally aged 13, 14, and 15, respectively. The undergraduates’ curves represent the participants from university aged from 19 to 23 (adults). Therefore, the younger students need significantly higher SNR values to obtain the same SIs as the older students in these classrooms.

4.2.3 Effects of early decay time (EDT) on speech intelligibility

The relationship of the SIs and SNR analyzed above excludes the effect of other acoustic descriptors. These acoustic descriptors include those parameters associated with the nature of reverberation (RT, EDT) and those parameters of energy balance between direct and delayed sound (Sound clarity C, Definition D). Multiple regression analyses were employed to analyze SNR values and one of the room acoustics parameters to investigate the additional effects of classroom acoustic parameters on SIs. EDT is defined as the time in which the first 10 dB fall of a decay curve occurs, multiplied by a factor 6. Since the EDT is strongly influenced by the early energy (which can vary significantly from seat-to-seat), the EDTs for a given space vary in value more than RT. A short EDT provides an acoustical advantage for communicating in a reverberant space. Fig 4.6 illustrates the multiple regression analyses fitting results for speech intelligibility scores versus SNR and EDT values.

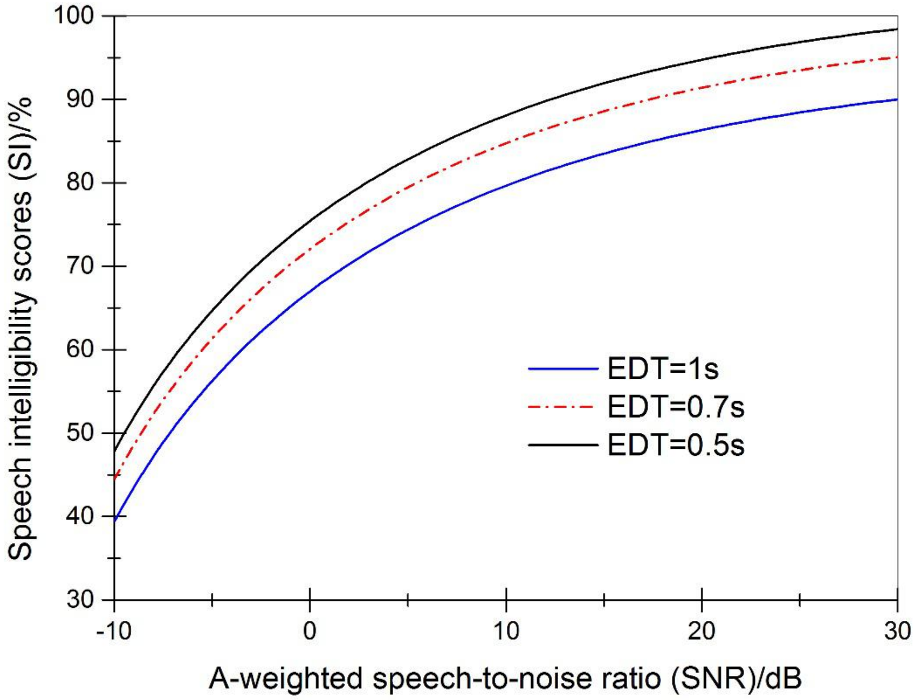

Figure 4.6 Combination effects of SNR and EDT on SIs

The regression equation in Fig 4.6 is given as follows:

$$y = 100(1 - 10^{-(SNR+14.8)/41.5})^{0.57} - 16.78EDT + 11.6 \qquad (4.6)$$

The regression curves in Fig 4.6 were based on this same regression equation. SIs in university classrooms versus SNR and 1000Hz EDT values of 0.5s, 0.7s, and 1s, were plotted separately. The results indicate that nearly 0.06s increasing in EDT values will be correlated to a 1% decrease in SIs.

4.2.4 Effects of sound clarity (C_{80}) on speech intelligibility

C_{80} is expressed in dB, and it is related to the attribute clarity. It is an objective descriptor of clarity or speech intelligibility. The basis for C_{80} is the fact that late reflections are unfavorable for speech intelligibility because it causes speech sounds to merge, making speech unclear. However, if the delay does not exceed a certain time limit, the reflections will contribute positively to the intelligibility. The definition of C_{80} is shown as follows:

$$C_{80} = 10log\frac{\int_0^T h^2(t)dt}{\int_T^\infty h^2(t)dt}$$

Where "T" is time (80ms) elapsed after the arrival of the direct sound wave, and $h(t)$ is the impulse response. Fig 4.7 illustrates the multiple regression analysis fitting results for speech intelligibility scores versus SNR and C_{80} values.

$$y = 100(1 - 10^{-(SNR+15.2)/35.7})^{0.72} + 1.23C_{80} - 7.81 \qquad (4.7)$$

The regression curves in Fig 4.7 were based on this same regression equation. SIs in university classrooms versus SNR and 1000Hz C_{80} values of 3 dB, 6 dB, and 9 dB were plotted separately. The results indicate that a 1 dB increasing in C_{80} values will be correlated to a 1.23% increase in speech intelligibility scores.

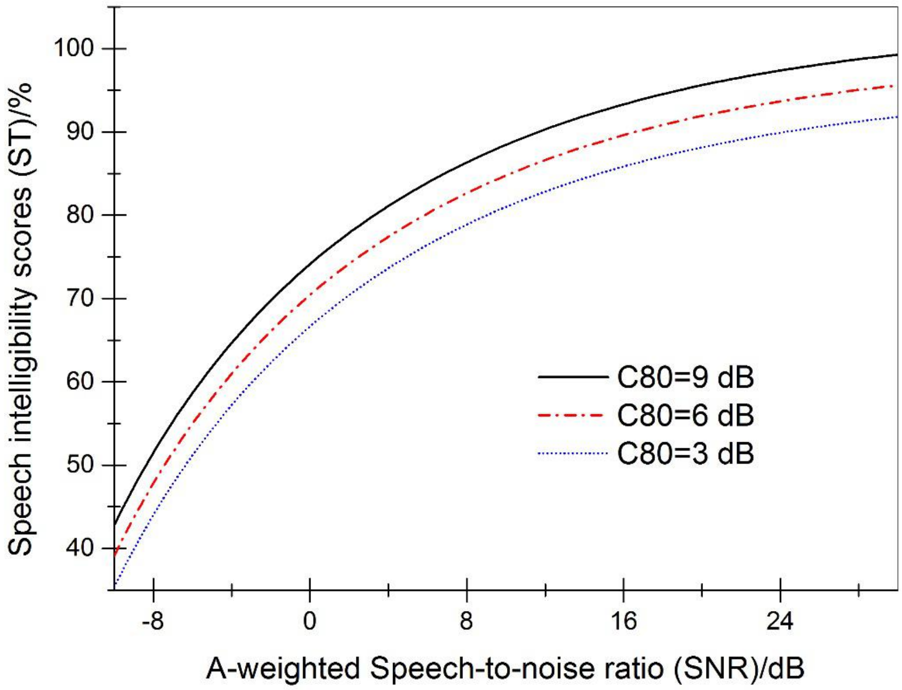

Figure 4.7 Combination effects of SNR and C_{80} on SIs

4.2.5 Comparison with other studies

A set of comparisons of the proposed regression curves with other studies were discussed in the following section. However, these studies used different sample sizes, age groups of the respondents, the language, and test materials from the current work. Both similarities and differences were listed for a comparison between the previous studies and the current study.

Previous studies proposed regression curves for evaluating SNR as well as RT effects on speech intelligibility scores. Bradley (Bradley, 1986) used a Fairbanks rhyme test to obtain English speech intelligibility results from Grade 7-8 students (12-13 years old) in ten classrooms in Canada. The regression curve was described by the quadratic regression curve to evaluate the results. Peng used Chinese rhyme test word lists to obtain Chinese speech intelligibility scores from undergraduate students (aged 20-24) in China (Peng, 2010). The regression equation was similarly described by the quadratic regression curve. The regression equations of the mentioned studies were given as follows:

Bradley (1986): $$\mathrm{SI} = 2.26\mathrm{SNR} - 0.0888\mathrm{SNR}^2 - 13.95RT + 95 \tag{4.8}$$

Peng (2010): $$\mathrm{SI} = 3.12\mathrm{SNR} - 0.064\mathrm{SNR}^2 - 6.15RT + 57.2 \tag{4.9}$$

As shown in Eq. (4.8) (4.9), combined effects of SNR and RT were concluded by using quadratic regression curves in previous studies. Although the regression models were selected differently, the basic increasing trends of the SNR and RT (EDT) values were similar to the current results. The better SNR values and less RT (EDT) values are needed to obtain higher speech intelligibility scores. However, the significance of reverberation values is distinct in the regression equation (4.6) (4.8) (4.9). As shown in Eq. (4.6), nearly 0.06s increasing in EDT values will be correlated to a 1% decrease in SIs. The value of changing of RT in Eq. (8) (9) is 0.07s and 0.16s, respectively. This means in the current chapter, the reverberation condition of the classrooms more easily influences the students. Since the quadratic regression model is a parabola curve. The symmetry axis in Eq. (4.8) (4.9) are SNR= 12.7dB and 24.4dB respectively. This means under a constant RT condition, and the speech intelligibility scores will decrease with the increase of SNR values, which are above the corresponding symmetry axis. This conclusion was different from the results in the current chapter. Eq. (4.6) reveals that the speech intelligibility scores will increase continuously with the increase of SNR values under a constant EDT condition. As shown in Fig 4.6, the slope of the regression curve will decrease with the increase of SNR values under a constant EDT condition. This means that with the increase of SNR values, the rate of the increase of speech intelligibility scores will be reduced.

The combination effects of SNR and sound clarity (C_{50},C_{80}) were investigated on speech intelligibility scores in several studies. Bradley and Sato used Word Identification by Picture Identification (WIPI) test to obtain English speech intelligibility results from Grade 1, 3, and 6 students in 41 classrooms of twelve different schools in Canada (Bradley and Sato, 2008). A quadratic regression model was employed for evaluating the results. Choi used Korean standard-monosyllabic tests to obtain Korean speech intelligibility results from 12 university classrooms in Korea (Choi, 2020). A linear regression model was employed for evaluating the results. The regression equations of the mentioned studies were given as follows:

Bradley and Sato (2008): $\mathrm{SI} = 0.772\mathrm{SNR} - 0.0189\mathrm{SNR}^2 + 1.53C_{50} + 74.46$ (4.10)

Choi (2020): $\mathrm{SI} = 14.69\mathrm{SNR} + 2.92C_{50} + 34.91$ (4.11)

As shown in Eq. (4.10) (4.11), the regression results for the effects of SNR and sound clarity were proposed by various regression models. Similarly, the primary trend effects of the two independent variables in the mentioned formulas are the same as the proposed equation (Eq. 4.7) in this work. The better SNR values and better C_{50} (C_{80}) values are positive to obtain higher speech intelligibility scores. However, the significance of sound clarity values is distinct in the regression equations (4.7) (4.10) (4.11). As shown in Eq. (4.7), nearly 1dB increasing in C_{80}

values will be correlated to a 1.23% increase in SIs. While the values changing of C_{50} in Eq. (4.10) (4.11) are predicted to 1.53% and 2.92% increase in speech intelligibility scores respectively. This means in the current research, and the students are uneasily influenced by the sound clarity of the classrooms. As the regression results of Eq. (4.10) is a parabola curve with a constant sound clarity value. The symmetry axis of Eq. (4.10) is SNR= 20.4dB under a constant sound clarity value. Since the sound clarity values can hardly reach 20.4 dB in the measurements of real classrooms. The Eq. (4.10) can be seen as a monotonically increasing function with a constant sound clarity value. It is similar to the results in Eq. (4.7) (4.11) with a constant sound clarity value. However, the changes in slopes in the three mentioned equations are distinguished. In Eq. (4.11) proposed by Choi, the slope of the SNR regression curve with a constant sound clarity value is constant. While in Eq. (4.7) (4.10), the slopes are gradually decreased with the increase of SNR under a constant sound clarity condition. This means that with the increase of SNR values, the rate of the increase of SIs will be reduced in Eq. (4.7) (4.10).

4.2.6 The influence of age effects and linguistic environment on speech intelligibility

The best-fit curves between SIs and SNR value for different age groups were given in Fig 4.5. The regression parameters are given in Table 4.5. The undergraduates' curves represent the participants from university aged from 19 to 23 (adults). "S" form-fitting model curves were used as the regression models. It is seen from Fig 4.5 that the SIs increase as the age increases under the same SNR condition. Fig 4.8 compared the proposed regression curves for the combination of reverberation condition and SNR with those curves obtained by Bradley (Bradley, 1986) and Peng (Peng, 2010). Furthermore, Fig 4.9 compared the proposed regression curves for the combination of sound clarity and SNR with those curves obtained by Bradley and Sato (Bradley and Sato, 2008). Results are given for RT (EDT) values (0.5s and 1s) and C_{80} (C_{50}) values (3dB and 6 dB), which are roughly corresponding to the range of frequently found conditions in the measured classrooms. It is obviously shown from Fig 4.8 that speech intelligibility scores are always lower than the comparison research results with a constant RT (EDT) value for an equal SNR value. Similar results can be obtained from Fig 4.9 that speech intelligibility results are always lower than the results in the reference with a constant sound clarity value for an equal SNR value. As the results in the mentioned references were obtained from their native language speech intelligibility tests. The results in the current chapter were obtained from English speech intelligibility tests. It is mainly because English is the official educational language in Hong Kong, while it is not the native one. The special linguistic environment results in a better acoustical environment that are needed for students in Hong Kong.

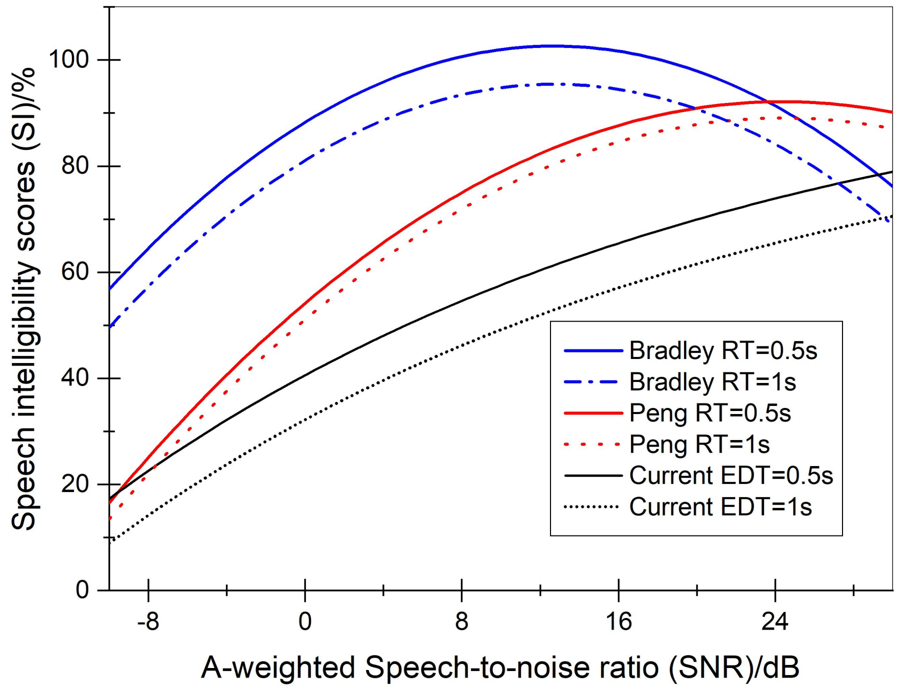

Figure 4.8 Comparison of combination effects of SNR and reverberation condition

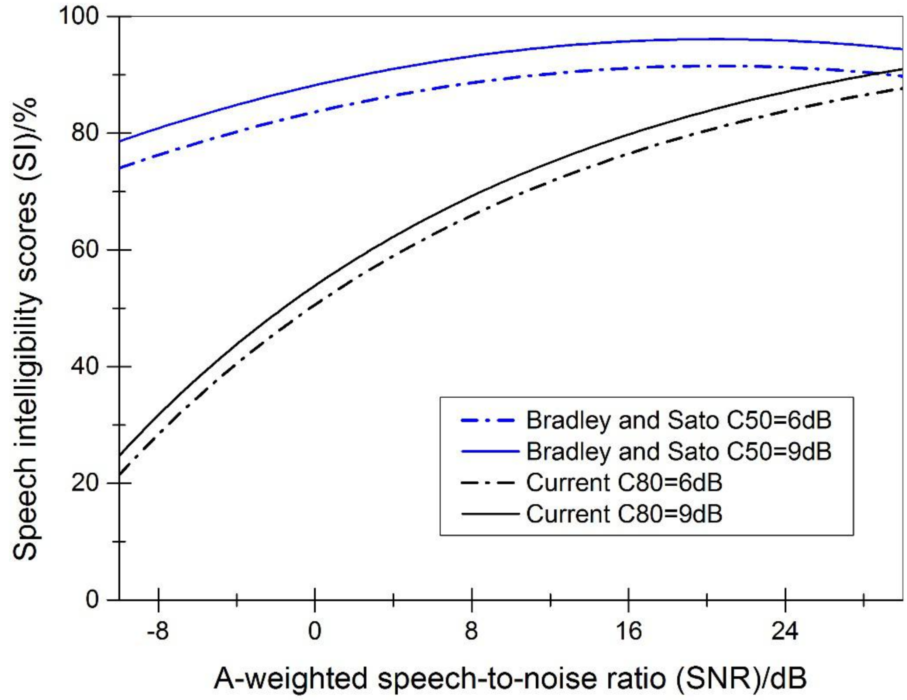

Figure 4.9 Comparison of combination effects of SNR and sound clarity

4.3 Summary

This chapter proposes data analyses that describe the speech intelligibility of students from secondary school and university to understand speech with noise and reverberation in real classrooms. 9 secondary school classrooms and 18 university classrooms were selected for speech intelligibility tests on total 672 students in Hong Kong. PB word lists were employed for speech intelligibility tests, while objective acoustical measurements were conducted in the same classrooms. Several findings emerged from the data analyses as follows:

(1) Three basis regression models were compared in the current work for evaluating the relationship between SIs and SNR values. *"S"* form regression curves were selected to describe SI versus SNR for grade A, B, C, and university students.

(2) Combined effects of SNR and EDT, as well as C_{80} were discussed based on *"S"* form regression curves. The results indicate that nearly 0.06s increasing in EDT values will be correlated to a 1% decrease in SIs. Furthermore, the results also indicate that 1 dB increasing in C_{80} values will be correlated to a 1.23% increase in SIs.

(3) The influence of age effects and linguistic environment were also discussed. The SIs increase as the age increases under the same SNR condition. The SIs are always lower than the comparison research results with a constant reverberation value as well as sound clarity value for an equal SNR value.

CHAPTER 5 A new combined sound field prediction method in small classrooms

In this chapter, a new combination method for sound field prediction is proposed. An optimization approach based on the genetic algorithm is employed for optimizing the transition frequency of the combined sound field prediction method in classrooms. The selected optimization approach can identify the optimal transition frequency so that the combined sound field prediction can obtain more efficient and accurate prediction results. The proposed combined sound field prediction method consists of a wave-based method and geometric acoustic methods that are separated by the transition frequency. In low frequency domain (below the transition frequency), the sound field is calculated by the finite element method (FEM), while a hybrid geometric acoustic method is employed in the high frequency domain (above the transition frequency). The proposed combined prediction models are validated by comparing them with previous results and experimental measurements. The optimization approach is illustrated by several examples and compared with traditional combination results. Compared to existed sound field prediction simulations in classrooms, the proposed combination methods take the sound field in low frequencies into account. The results demonstrate the effectiveness of the proposed model.

5.1 Theory

5.1.1 Finite element method in room acoustics

In the current paper, the Finite Element Method (FEM) was selected as the wave-based solution for calculating the sound field in low frequencies (frequency lower than transition frequency). FEM is a powerful tool for the numerical solution of partial differential equations with given boundary conditions. Besides, FEM is a representative wave-based model in room acoustic simulation. Typical applications in acoustics deal with the prediction of the modal characteristics of structure-borne, airborne, and also coupled sound fields in enclosed spaces (Mak and Wang, 2015). The basic starting equation is sound wave propagation function:

$$\mathrm{c}^2 \Delta p = \frac{\partial^2 p}{\partial t^2} \tag{5.1}$$

with the assumption of harmonic time law for pressure, velocity, and so on ($p(x,t) = p(x)e^{-j\omega t}$). The sound wave propagation function transfers to the Helmholtz equation (homogeneous) as follows:

$$\Delta p + k^2 p = 0 \text{ with } k = \frac{\omega}{c} \tag{5.2}$$

where ω refers to the angular frequency, k is the angular wavenumber.

A Plane-wave solution could be given for the homogeneous Helmholtz equation in free space as follows:

$$p(x) = \overline{p}e^{-jkx} \tag{5.3}$$

where $\overline{p}$ is the amplitude of the pressure wave.

If a sound source is placed inside the volume, the inhomogeneous Helmholtz equation will be replaced:

$$\Delta p + k^2 p =- j\omega\rho_0 q(x) \tag{5.4}$$

which is defined as room acoustics FEM basic equation.

The wave propagation in an enclosed cavity Ω will be described by the inhomogeneous Helmholtz equation with mix boundary conditions on the boundary S_z and Neumann boundary condition on the boundary S_V. According to the Galerkin Method, an equivalent integral form will be derived by an arbitrary weighting function $\overline{\omega}$ multiplied the Helmholtz equation with acoustical boundaries integral form:

$$\iiint_{\Omega} \overline{\omega}(\Delta p + k^2 p + j\omega\rho_0 q) d\Omega + \oint_{S_V} \overline{\omega}(\frac{\partial p}{\partial \mathrm{n}} - j\omega\rho_0 v_n)\, dS_V + \oint_{S_z} \overline{\omega}(\frac{-\partial p}{\partial \mathrm{n}} - \frac{j\omega\rho_0}{Z_s}.p)\, dS_Z = 0 \tag{5.5}$$

According to Green first identity:

$$\iiint_{\Omega} (\psi\Delta\varphi + \nabla\psi\nabla\varphi)\, d\Omega = \oint_{\Gamma} \psi(\frac{\partial\varphi}{\partial n})\, d\Gamma \tag{5.6}$$

where ψ and φ are scalar functions of which φ is twice continuously differentiable, Ω is a region in R with boundary Γ and n is the outward pointing surface normal on Γ.

Equation 5.5 is equivalent to:

$$\iiint_{\Omega} -\nabla\bar{\omega}\nabla p + \bar{\omega}(k^2 p + j\omega\rho_0 q)d\Omega - \oint_{S_V} \bar{\omega}(j\omega\rho_0 v_n)\, dS_V - \oint_{S_z} \bar{\omega}(\frac{j\omega\rho_0}{Z_s}.p)\, dS_Z \tag{5.7}$$

The next step is the discretization of Equation 5.7:

$$\bar{p} = [N]\{p\}_e = [N_1,N_2\cdots N_m]\begin{Bmatrix} p_1 \\ p_2 \\ \vdots \\ p_m \end{Bmatrix} \tag{5.8}$$

where $N_1,N_2\cdots N_m$ are the serial numbers of discretized units. $p_1,p_2\cdots p_m$ are the nodal sound pressures. Then substitute Equation 5.8 into Equation 5.7:

$$\sum_e \int_{V_e} (\{p\}_e^T[N]^T[\nabla N]\{p\}_e - k^2\{p\}_e^T[N]^T[\nabla N]\{p\}_e - j\omega\rho_0\{p\}_e^T[N]^T q)dV_e + \sum_e \int_{S_e} \frac{j\omega\rho_0}{Z_s}\{p\}_e^T[N]^T[\nabla N]\{p\}_e dS_e = 0 \tag{5.9}$$

Simplify Equation 5.9

$$\sum_e \int_{V_e} ([N]^T[\nabla N])dV_e\{p\}_e - \sum_e \int_{V_e} k^2[N]^T[\nabla N]\, dV_e\{p\}_e - \sum_e \int_{V_e} j\omega\rho_0[N]^T\, q)dV_e\,\{p\}_e + \sum_e \int_{S_e} \frac{j\omega\rho_0}{Z_s}[N]^T[\nabla N]dS_e\,\{p\}_e \tag{5.10}$$

With the abbreviations

$$[\mathrm{k}]_e = \int_{V_e} ([\nabla N]^T[\nabla N])dV_e \tag{5.11}$$

$$[\mathrm{m}]_e = \int_{V_e} [N]^T[N]\, dV_e \tag{5.12}$$

$$[\mathrm{d}]_e = \rho_0 c Z_s \int_{S_e} [N]^T [N] dS_e \tag{5.13}$$

$$[\mathrm{f}]_e = \int_{V_e} j\omega\rho_0 [N]^T \, q dV_e \tag{5.14}$$

Equation 5.10 can be simplified

$$\sum_e ([\mathrm{k}]_e + jk - k^2 [\mathrm{m}]_e) \{p\}_e = \sum_e [\mathrm{f}]_e \tag{5.15}$$

where $[\mathrm{k}]_e$,$[\mathrm{m}]_e$,$[\mathrm{d}]_e$,$[\mathrm{f}]_e$ are stiffness unit matrix, mass unit matrix, damping unit matrix, and single-column unit matrix, respectively. Then Equation 5.15 can be rewritten as a matrix equation:

$$([\mathrm{K}] + \mathrm{j}k[\mathrm{D}] - k^2[\mathrm{M}])\{p(r)\} = \{F(r)\} \tag{5.16}$$

The matrix components K, M, D, and F, are calculated element by element, which is an integration of the discretization. This equation is the FEM method used in the time domain.

The following system of FEM equations can be derived for the frequency domain:

$$\left([\mathrm{K}] + \mathrm{j}\omega[\mathrm{D}] - \omega^2[\mathrm{M}]\right)p = j\omega f \tag{5.17}$$

The FEM simulations in this paper were carried out by a commercial software COMSOL Multiphysics 5.4. COMSOL Multiphysics is a general-purpose simulation software in all fields of engineering for solving partial differential equations (COMSOL Multiphysics, 2014). The FEM methods were employed in predicting sound fields at low sound frequencies. These low sound frequencies referred to those frequencies below the transition frequency (which will be discussed in Chapter 5.1.3). The main purpose of using the FEM methods was to avoid the effects of standing waves, diffraction, and interference in small rooms.

5.1.2 *Hybrid geometric acoustic methods*

Comparing with the expensive computation of the wave-based method, it is often more appropriate to resort to faster but less accurate techniques such as those based on geometric acoustic (GA) methods. Most geometrical acoustics simulation tools use hybrid algorithms that combine an image source (IS) method for a precise calculation of the early specular reflections in a room impulse response with a computation efficient ray-tracing algorithm to calculate the late diffuse exponential sound decay (Savioja and Svensson, 2015). The fundamental geometrical acoustic assumption is that the length of the sound wave is too short to be neglected compared to the dimensions of the surface at high frequencies. The IS method is based on the principle that the sound field generated by a point source in front of an extended planar surface. The surface can be represented in good approximation by the superposition of the sound field, which was generated by the original point source and the additional secondary source. In the ray tracing method, the sound wave is assumed to propagate as rays that are cast from the sound source and reflected specularly and diffusely according to the boundary conditions. Each ray carries information about its energy. Whenever modes, the rays are reflected, and the energy will be attenuated due to the material properties of the boundary. The energy information could be performed in frequency bands. Correspondingly, the sound absorption coefficient of the boundary material is defined in the same frequency bands. The sound rays are eventually terminated when its energy has decayed below the given constants for each frequency band. Besides, the sound rays will eventually be terminated when it reached a predefined maximum traveling distance. The hybrid geometrical acoustic methods were employed in predicting sound fields at high sound frequencies. These high sound frequencies referred to those frequencies above the transition frequency (which will be discussed in Chapter 5.1.3). The main purpose of using geometrical acoustic methods was to obtain efficient results that occupied less computation time and CPU memories compared to the FEM methods.

In this chapter, the hybrid geometrical acoustic simulation was carried out by the geometric acoustic module of the commercial software COMSOL Multiphysics 5.4. The same commercial software chosen as the FEM method is convenient for the combination procedure.

5.1.3 Combination of wave-based method and the geometric acoustic method

In this chapter, a combination method that is based on a wave-based method and geometric method is proposed. The aim to propose the combined model is to predict the sound field over the whole audible frequency range efficiently and accurately. With the increases in the frequency, the number of elements will be too large to cost much of computing time as well as memories. The wave-based method is more accurate at low frequencies. Comparing with the wave-based method, the geometric acoustic method saved more computing time and memories at mid-frequencies and high frequencies. In order to develop an efficient and accurate prediction method over the whole frequency domain. The separated calculation is a necessary approach for combining the two mentioned prediction methods. The two mention methods are separated by a transition frequency. The transition frequency limits the applicable frequency higher than the Schroeder frequency. Schroeder and Kuttruff proposed a crossover frequency (Schroeder frequency) that marked the transition from the individual, well-separated resonances to many overlapping normal modes (Schroeder and Kuttruff, 1962). Which was given by:

$$f_c = 2000\sqrt{T/V} \tag{5.18}$$

where T is 60-dB reverberation time (T_{60}), V is the volume of the enclosure.

To select the optimal transition frequency in the current chapter, a novel optimized approach is employed to search the transition frequency. This transition frequency can be regarded as a combination point to combine the mentioned two methods.

5.2 Optimization Methodology

The objective of the current chapter is to optimize the efficiency and accuracy of the proposed combination methods so as to make transition frequency to be of their corresponding target values simultaneously. This is a multi-objective optimization problem since more than one parameter is to be optimized at the same time. Every slight change of the separation frequency leads to new values of computation time, memories, and RMS error. Therefore, a global search algorithm genetic algorithm is applied for searching the optimal separation frequency.

5.2.1 Genetic algorithm

The genetic algorithm is a metaheuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms. Genetic algorithm is commonly used to generate high-quality solutions to optimization and relying on biological inspired operators such as mutation, crossover, and collection (Mitchell and Melanie, 1996). Ou et al. employed a genetic algorithm combined with FEM and BEM for calculating the optimized natural frequency of plate structure (Ou and Mak, 2017, Ou and Mak, 2018, Ou, 2018).In a genetic algorithm, four bio-inspired operators, including initialization, crossover, selection, and mutation, are the main procedure to search for optimized results. The initialization process generates the initial population randomly. The selection operator selects excellent individuals in the current generation for breeding the next generation of individuals. To avoid local convergence, the mutation operator changes one or more gene values in a chromosome for individuals in the next generation. In the whole process, the fitness quality is calculated by the fitness function. The fitness function is a key concept to evaluate the fitness of individuals in the search process.

5.2.2 Fitness function

The genetic algorithm optimized the effects of computation time, memory, and RMS error to achieve the desired separation frequency. It is a multi-objective optimization problem since three factors can avoid the results simultaneously. The most straightforward multi-objective fitness function can be given as follows:

$$Minimize\ F = \sum \omega_n\, b_n \tag{5.19}$$

where ω_n is the weighting of the nth factors, which represents the importance of the nth objective. b_n is the nth objective factors which affect the selection of the optimization frequency. b_n is consists of computation time, CPU memory, and RMS error. Therefore, it is obvious that when F is minimized, the optimal results can be obtained. In this paper, the weighting schemes are based on the method of the coefficient of variation. The coefficient of variation (CV) is defined as follows:

$$C_{vn} = \frac{\sigma_n}{\mu_n} \tag{5.20}$$

Where σ_n denotes the standard derivation of the nth factors. μ_n denotes the mean value of the nth factors. C_{vn} denotes the coefficient of variation of the nth factors. The weighting scheme is defined as follows:

$$\omega_n = \frac{C_{vn}}{\sum C_{vn}} \tag{5.21}$$

5.2.3 Optimization transition frequency approach

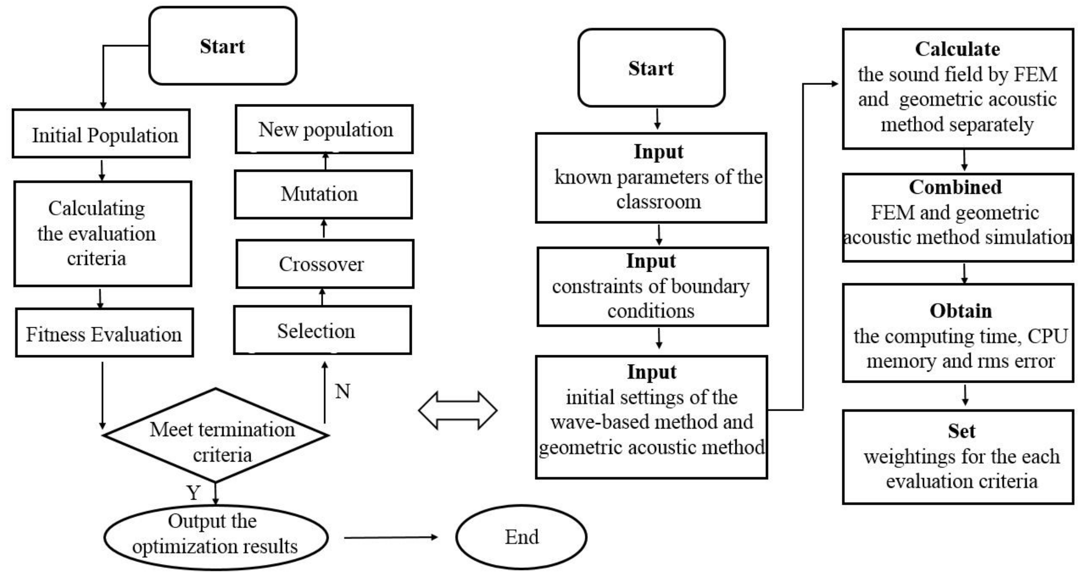

Figure 5.1 Flowchart of the genetic algorithm procedure

The flowchart of the optimization frequency approach accompany with the combined FEM and geometric acoustics prediction methods is shown in Fig. 5.1. It is shown that the genetic algorithm optimization model is given on the left side while the combination sound prediction methods are given on the right side. The whole optimal transition procedure is as follows: (1) input the known classroom characteristics, such as the classroom's length, width, height. (2) Input and boundary constraints, such as the boundary materials including the absorption coefficients scattering coefficients at different frequencies. (3) Input general settings for FEM and geometric acoustics methods in COMSOL servers. (4) Calculate the sound field by FEM and geometric acoustic separately under the concerned separation frequency. (5) Combined the proposed FEM and geometric acoustics methods results and obtain the computation cost factors (including computation time, CPU memory costs, and RMS value). (6) Set the termination criteria for the genetic algorithm. For instance, set the maximum tolerable error and maximum generations in the genetic algorithm.

(7) Run the genetic optimization algorithm program to search the optimal frequency results.

5.3 Case studies and experimental validation

In this chapter, a package of genetic algorithm code was utilized for the optimization process, as shown in Fig. 5.1. Based on the proposed methods, several case studies were conducted in real classrooms in the Hong Kong Polytechnic University (PolyU). The general characteristics of the selected classrooms were given in Table 5.1. In the genetic optimization algorithms, the initial population and max numbers of generation are 100 and 500, respectively. The crossover and mutation rates are 0.8 and 0.08, respectively. The computation costs were generated by the COMSOL FEM server. The general information for the FEM server was shown in Table 5.2.

As for the experimental measurements, the room acoustical parameters were measured by using architecture acoustic software *DIRAC 6.0* (B&K Type 7841). The sound source used in the experiment was the Echo Speech source (B&K Type 4720). The signal collecting device was a pre-polarized free-field 1/2-inch microphone with B&K 2270 handheld sound level meter. Yang and Mak reported the investigation of speech intelligibility and acoustical measurements by using *DIRAC*. *DIRAC* software was commercial software based on the measurement and analysis of room impulse response (Yang and Mak, 2018). In the current chapter, the classroom impulse response was generated by an internal e-sweep source. A comparison between the numerical results and measurement results were discussed in Chapter 5.4.4.

5.3.1 Case study 1

In this case, a small well-decorated (with acoustic treatments) rectangular classroom in PolyU was selected as the objective enclosure (see Fig. 5.2). The information of the classroom, materials of the classroom walls, general settings of the combined prediction methods are shown in Table 5.1. The absorption coefficients of the classroom boundaries at different frequencies were shown in Appendix A. A Gaussian impulse was used as the impulse response in the FEM methods. The characteristics of the Gaussian impulse was given in Table 5.2.

Figure 5.2 The schematic drawing of rooms in case 1(left) and photos of case 2(right).

Table 5.1 Classroom characteristic in the case 1

Length/m	Width/m	Height/m	Volume/m3	Number of seats
7.12m	7.88m	2.63m	147.558m3	40

Materials on each side of the classroom

Floor	**Side Walls**	**Ceiling**	**Windows**	**Door**	**Front and rear walls**
Loop pile	Painted	Metal	Double	Solid wooden	Wooden perforated

tufted carpet	concrete walls	perforated plates	glazing windows	door	plates

Table 5.2 General settings of wave-based methods and geometric acoustic methods

Finite Element Methods	h_max	N	Δt/total time	f_0	A	c_air
	0.12m	4	0.7ms/3s	f_c	4	343m/s
Geometric acoustic methods	Start frequency	Nrays	Δt/total time	Ray direction vector	Source power	c_air
	f_0	10000	0.1ms/3s	spherical	0.04W	343m/s

Where h_max is the maximal size of the mesh element. N is the number per wavelength required to resolve a harmonic wave with some accuracy. Δt is the size of the time-step. f_0 is the source frequency bandwidth, f_c is the upper cut-off frequency of f_0. A is the sound source amplitude.

The known parameters, boundary conditions, general settings, and optimal results are listed in the mentioned tables. The optimized approach procedure is the same as the one shown in Chapter 5.1.3. It can be seen from the tables that the optimal transition frequency can be found according to the restriction conditions obtained from the combination methods. In this chapter room, the wall was decorated with double glazing windows, as shown in Fig. 5.2. The information of the classroom, general settings of the combined prediction methods is shown in Table 5.1 and 5.2 respectively.

5.3.2 Case study 2

In this case, a small rectangular glass-decorated study room in PolyU was selected as the objective enclosure (see Fig. 5.2). The information of the classroom, general settings of the combined prediction methods, and parameters in the genetic algorithms are shown in Table 5.3. The general settings of the combined prediction methods were the same as Case 1 in Table5. 2.

Table 5.3 Classroom characteristics in case 2

Length/m	Width/m	Height/m	Volume/m3	Number of seats	
7.84m	3.85m	2.68m	80.893m3	20	
			Materials on each side of the classroom		
Floor	**Side Walls**	**Ceiling**	**Windows**	**Door**	**Front and rear walls**
Loop pile tufted carpet	The double-glazing glass wall	Metal perforated plates	Double glazing windows	Solid wooden door	Painted concrete walls

5.4 Results and discussions

5.4.1 Optimization of the computation costs

A normal desktop manufactured in 2016, 8GB of memory, and Intel R Core (TM) i7-6800K processor (6 cores, 3.6GHz) was used for calculating the simulation cases. During the whole combined prediction model calculation process, the CPU and memory were less than 50% and 56%, respectively. The target of the optimization process was to minimize the computation costs to obtain the optimized separation frequency in the combined prediction methods.

The case studies introduced in Chapter 5.3 show the effective, optimized results of the proposed combination methods. For sound field prediction in a given classroom, the computation costs and accuracy are essential factors that affect to be considered. The proposed combination methods combined the wave-based methods and geometric acoustic methods. The proposed genetic algorithm optimization approach is used to search the balanced optimized results. By using the proposed methods, users can set the computation costs and accuracy error conditions according to the calculation results of the combination methods and identify the optimal results.

Table 5.4 Optimization results

		Case 1	Case 2
Schroeder frequency		112Hz	131Hz
Optimized frequency		118Hz	133Hz
Weightings		$\omega_1 = 0.09, \omega_2 = 0.13, \omega_3 = 0.78$	$\omega_1 = 0.09, \omega_2 = 0.13, \omega_3 = 0.78$
Optimization Results	T_{total}	12993s	8228s
	M_{total}	19.82 GB	12.26GB
	RMS	2.03	2.88

In Table 5.4, "T_{total}" denotes the total simulation time (computation time of FEM and geometric acoustic methods) of the numerical approaches. "M_{total}" denotes the total memory costs (CPU memory costs of FEM and geometric acoustic methods) during the numerical computation process. "RMS" denotes the root-mean-squared error between the combined simulation results and measurements. "$\omega_1, \omega_2, \omega_3$"

denotes the weightings of the computation time, memory cost, and RMS, respectively.

In these cases, the weightings of computation costs criteria are predefined by the coefficient of variation. Besides, the proposed methods can obtain optimal results, which depend on the weighting coefficients. The criteria for computation costs need to be normalized before an input in the optimization process.

5.4.2 Effectiveness of computation cost at optimization frequency

In Table 5.5, the effectiveness of the proposed combined optimization results was compared with the separated approaches. According to the equation stated in Chapter 5.1.3, the Schroder frequency in Case 1 and Case 2 are 112Hz and 131Hz, respectively. The selected separation frequency is required to be higher than the Schroder frequency. In Table 5.5, the optimization process and results of several selected representative separation frequency in case study 1 are shown as follows.

Table 5.5 Comparison of computation cost among optimization frequency and selected frequency.

	Wave-based model		**GA model**		**Combination model**		
Freq.	T_{sim}	***Memory***	T_{sim}	***Memory***	T_{total}	M_{total}	***RMS***
Schroeder	12708s	18.88GB	74s	784MB	12782s	19.65GB	2.82
125Hz	13445s	19.63GB	69s	702MB	13514s	20.34GB	1.86

200Hz	13513s	20.51GB	68s	685MB	13581s	21.18GB	1.58
250Hz	13714s	21.22GB	65s	680MB	13779s	21.88GB	1.44
Optimized	12922s	19.11GB	71s	735MB	12993s	19.82GB	2.03

In Table 5.5, "$Freq.$" denotes the separation frequency for the separated approaches. "T_{sim}" denotes the total simulation time of each numerical approach. "$Memory$" shows the memory cost during the computation process. "T_{total}" denotes the total simulation time (computation time of FEM and geometric acoustic methods) of the numerical approaches. "M_{total}" denotes the total memory costs (CPU memory costs of FEM and geometric acoustic methods) during the numerical computation process. "RMS" denotes the root-mean-squared error between the combined simulation results and measurements.

5.4.3 Comparison with other studies

A set of comparisons of the proposed regression curves with other studies were discussed in the following section. Previous studies on acoustic sound filed simulations of normal-sized classrooms were always based on the hybrid geometrical acoustic methods (Jeon, Jiang et al. 2012, Astolfi, Corrado et al. 2008, Zhu, Mo et al. 2015, Yang and Hodgson, 2017, Hodgson, York et al. 2008). However, when it comes to small rooms, geometrical acoustic prediction methods appear to be flawed due to the inherent negligence of important low frequency wave effects, such as standing waves, diffraction, and interference. In order to assess the aural significance of using more accurate low-frequency modeling and applied in a real room. Several combined wave-based and geometric studies were proposed in the previous study (Wang, Safavi-Naeini et al. 2000, Summers, Takahashi et al. 2004, Aretz, 2012). While in these studies, the authors proposed the combination methods focused on the combination of the results generated with both simulation techniques. They used a straightforward approach for combining both simulation results consist of low-pass/high-pass filtering the FE/ray-based results, both at the Schroeder frequency, and then simply adding the filtered frequency responses.

The combination methods in the mentioned studies were effective for combining wave-based and ray-based prediction modeling in a real room. While the computation costs seem not considered in the mentioned approaches. In this paper, the proposed genetic algorithm optimization method was used to search the optimal frequency, which was the transition frequency for separating the wave-based methods and geometric acoustic methods. The FEM methods were employed as wave-based methods for calculating the sound field in that frequency domain lower than the transition frequency. And geometric acoustic methods were employed in that frequency domain high than the transition frequency. Computation costs were the main criteria in the mentioned genetic algorithm optimization methods. Therefore, the main difference between the approaches in previous studies and the ones in this paper is the consideration of the computation costs.

5.4.4 Comparison of measurements and simulations

The Comparison between numerical predicted acoustical parameters and experimental acoustical parameters in Case study 1 were shown in Fig. 5.3-5.6. A summary of the results was given as follows:

For the results of RT and EDT: as expected, good agreement was found between the RT's in real and virtual classrooms. Compared to the measured values, the expected RT values were very similar, generally within 0.1 s, especially at low frequency (63Hz) within 0.15s. The EDT results were similar to RT, except that at low frequency (63Hz), prediction values up to 0.15s lower than measured results at lower frequencies.

For the results of C80: the results are as expected, given that C80 is inversely related to RT and EDT, the results of the combined prediction model are generally within 1 dB different from the measurement, except at which it is up to nearly 2 dB lower at 8000 Hz. Prediction is up to 1dB higher than measurement at low frequency but within 2 dB higher than measurement at high frequency.

For the results of D50: the results are as expected, good agreement was found between the D50's in the real and virtual classrooms. The results of the combined prediction model are generally within 0.05 different from the measurement. Prediction is up to 0.05 lower than measurement at low frequency but within 0.05 higher than measurement at high frequency

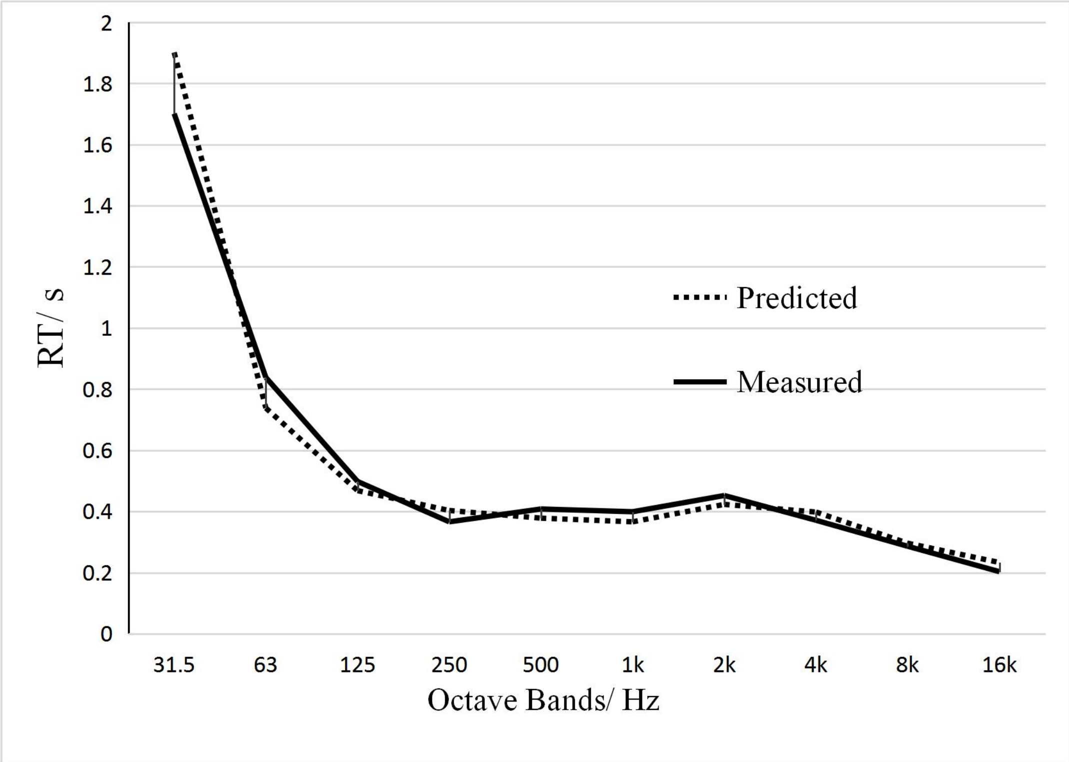

Figure 5.3 Comparison between predicted and measured results of RT

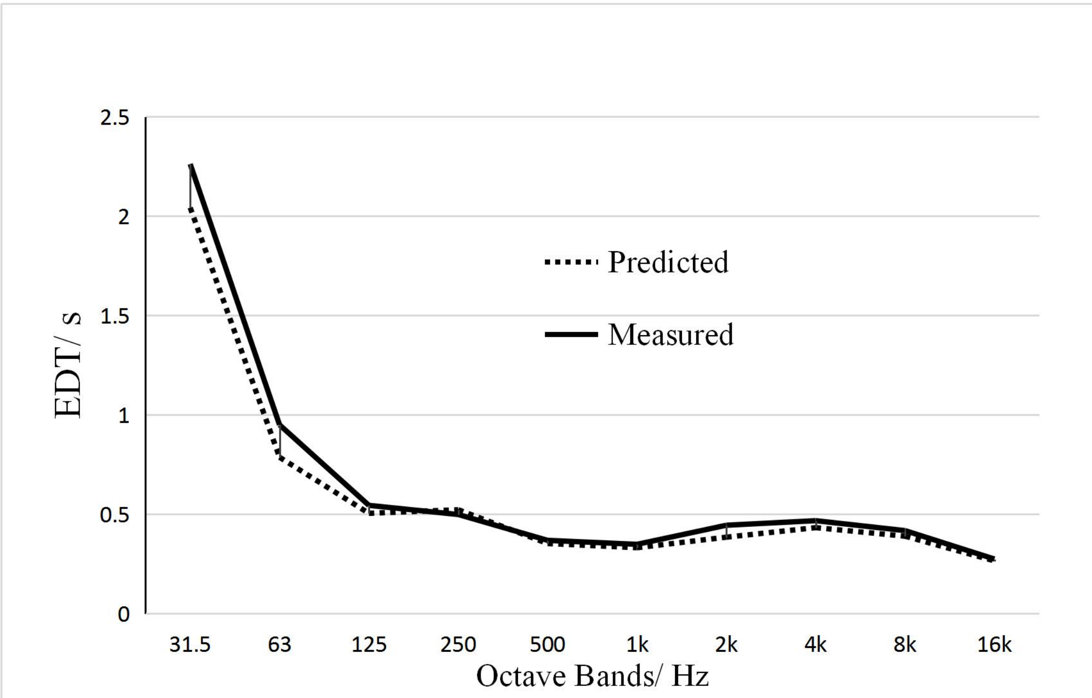

Figure 5.4 Comparison between predicted and measured results of EDT

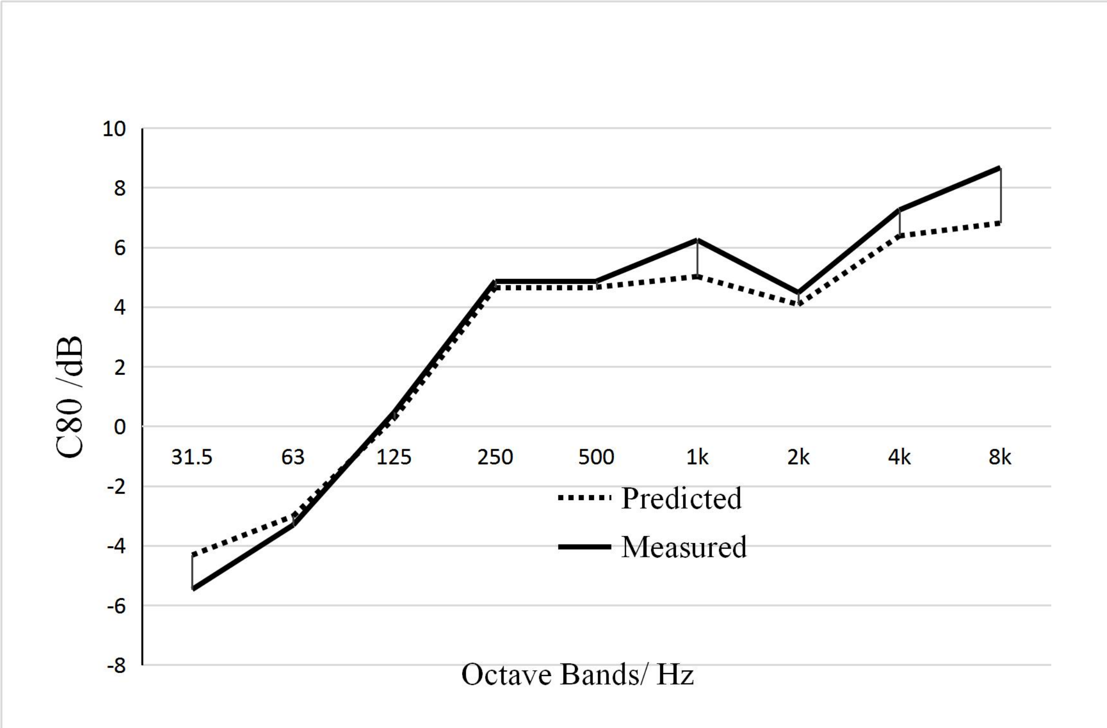

Figure 5.5 Comparison between predicted and measured results of C80

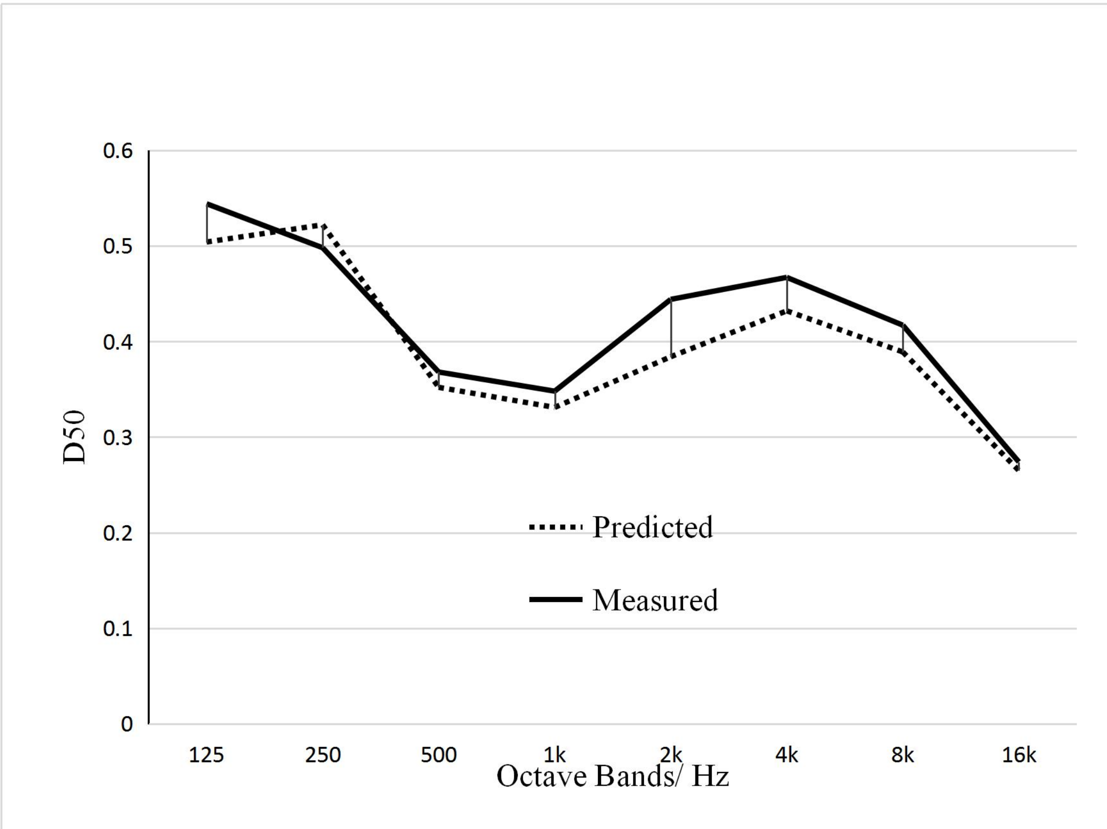

Figure 5.6 Comparison between predicted and measured results of D50

5.5 Limitations

In spite of the high relevance of simulated prediction data and experimental validation results, there still remain limitations for discussion. Some limitations in the simulation methods and classroom geometric models exist in the theoretical fundamentals. The following discussions are the factors influencing the simulation quality.

5.5.1 Limitations due to simulation methods

The finite element method is based on wave propagation equations that cover all relevant sound wave characteristics. Therefore, the simulation quality is mainly depended on the geometrical dimensions of the classroom model and boundary material sound coefficient data. However, the impedance boundary approach is limited by assuming the locally reacting boundary condition for a porous material. Dragonetti and Romano estimated errors in assuming the locally reacting boundary condition for porous materials (Dragonetti and Romano, 2017). The authors proved that the acoustic surface impedance depended on airflow resistivity, the type of wavefront impinging on its surface, the angle of wave incidence, and the thickness of the porous material.

In contrast to the FEM method, the ray tracing method (geometrical acoustics method) used many simplifications, assuming the sound propagation and sound reflection modes in the classroom. Possible problems in the reflection pattern of the impulse response can be attributed to the negligence of diffraction effects and the uncertainty of determining realistic low frequency scattering coefficients for boundary materials.

5.5.2 Limitations due to the classroom geometric model

As mentioned in the previous section, the classroom geometric model was built from detailed architectural structures and acoustically relevant features of the real classrooms. In this chapter, the classroom geometric model neglected some small objects and geometric details in the classroom. Even if we believed that these small objects and geometric details would not generally affect the simulation results, another limitation due to the classroom geometric model was several desks and chairs existing in the classroom. The reflection and diffraction effects at the positions of desks and chairs were possible reasons influencing the simulation quality. The limitations mentioned above are uncertainties in the classroom geometric model.

5.6 Summary

In the current chapter, a combined wave-based and geometric acoustics prediction method is proposed in two small classrooms in university. A genetic algorithm is employed for searching the optimal transition frequency in view of the consideration of computation cost. FEM method is selected as the representative wave-based method applied at frequencies below the transition frequency. Hybrid geometric acoustic methods are applied at frequencies above the transition frequency. The proposed combination model offers the possibility to simulate the sound field in the whole audible frequency range in real small rooms. Several comparisons with other studies are discussed in the current chapter. Validation experiments are conducted in the same classroom. High correlation coefficient values between the combined prediction method and experimental measurements. The proposed combined prediction model was proved optimal methods for predicting the sound field in the classroom over the whole audio frequency domain in this chapter. The wave-based FEM part at low frequencies is useful and efficient for predicting the low-frequency sound fields. In practice, applications of the proposed combined prediction model can provide the predicting sound fields in buildings that are essential to acoustical designs and acoustic environmental assessments.

CHAPTER 6 Assessment model of classroom acoustical environment

In this chapter, an assessment model based on multi-layer fuzzy comprehensive evaluation method (FCE) of the classroom acoustical environment is proposed. The model classifies five major factors affecting the overall assessment model into several subsets alternatives. The weightings of these main criteria and alternatives were collected through questionnaires among students based on the analytic hierarchy process methodology (AHP). An evaluation score was calculated from the proposed model with the weightings generated from the AHP method. In this paper, classrooms in the Hong Kong Polytechnic University were used to develop the assessment model. The result shows that the evaluation score of PolyU classrooms is about 87.2, which refers to a “Good” evaluation set. It indicates that classrooms in PolyU need to be improved. The weightings generated from the AHP method can be considered for the importance of each alternative. The assessment model can provide a proper recommendation to universities for acoustic treatment so as to increase the acoustic quality of the educational environment.

6.1 Description of evaluation criteria and alternatives

An assessment model of the classroom acoustic criteria is established in Fig.6.1.

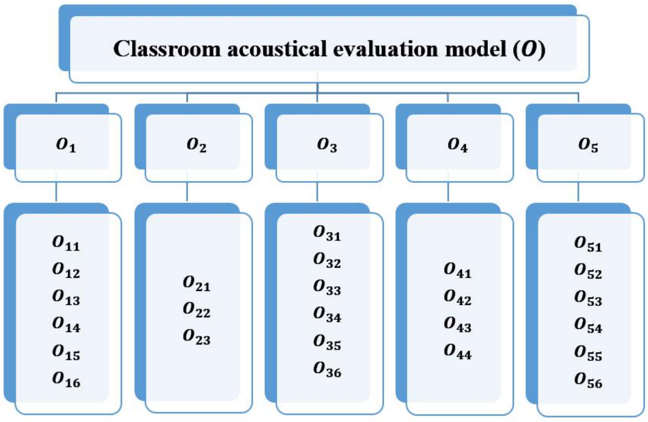

Figure 6.1 An assessment model for assessing acoustical criteria and alternatives

Refer to previous studies, the assessment model should consist of five main criteria. Each of these criteria is made up of some independent indexes. Therefore, a three-layer comprehensive evaluation index system is proposed (Madbouly, Noaman et al. 2016, Brandewie, 2012). The index system consider the overall classroom acoustical criteria comprehensive evaluation score (O) determined by five main evaluation indexes: the classroom facility(O_1), inside classroom noise(O_2), outside classroom noise(O_3), Interactive teaching(O_4), and vocal effort(O_5).

O_1 represents the classroom facility, which influence the education quality. This criterion includes six sub-factors named O_{11} to O_{16}.

Acoustical properties (O_{11}): such as the acoustical design of walls and ceilings, which are used to preserve reverberation time and keep ambient noiseless. Lighting (O_{12}): both low lights level and too much lighting are problems for inside classroom education. Equipment (O_{13}): facilities includes data projector, projection screen, teacher's computer and network connection for students' computer and laptops. Ventilation (O_{14}): proper ventilation in the classroom will promote optimum conditions for students in study, listening, reading, and interaction. Classroom specification (O_{15}): this criterion is mainly referring to the classroom size. Insufficient classroom space may influence students in daily education. Classroom architecture (O_{16}): such as shape and style of the classroom, the location of the classroom. All of these are important factors that affect students learning process and education quality.

O_2 is further determined by three alternatives. Heating Ventilation and Air-condition (HVAC) system (O_{21}) are the main sources of noise inside the classroom. The system includes air handlers and fans, acoustical treatment of ducts, returns, and diffusers. Besides, students' activity and interacting (O_{22}) can increase the noise level inside the classrooms. In addition, another factor that contributed to the noise inside the classroom is the lighting system (O_{23}).

Corresponding to O_2, noise sources outside the classroom (O_3) is another important criterion of the classroom acoustics. O_3 is further considered by the following six criteria: traffic noise (O_{31}), noise generated from neighboring classroom (O_{32}), noise from corridor, hallway, and lobby (O_{33}), the noise coming from surrounding playgrounds (O_{34}), mechanical equipment noise (O_{35}), noise generated from the nearby building (O_{36}).

Universities aim to increase the effectiveness of teaching students so that the teaching methods and styles (O_4) play an important role in classroom education. These teaching methods and styles mainly include practice work (O_{41}), group work (O_{42}), blackboard teaching (O_{43}) and multimedia techniques (O_{44}). Different ways of communication between students and speakers affect different learning experience.

Traunmüllera and Eriksson defined "Vocal effort" as the communication distance estimated by a group of listeners for each utterance (Traunmüllera and Eriksson, 2000). Therefore, vocal effort (O_5) becomes the fifth criterion of the classroom acoustical assessment model. Six alternatives are included in O_5 as follows: acoustical treatment (O_{51}), sound reinforcement system (O_{52}), classroom size (O_{53}), the position of students inside the classroom (O_{54}), lecturer position inside the classroom (O_{55}) and the numbers of students (O_{56}).

6.2 Fuzzy multi-layer evaluation methodology

6.2.1 FCE theory

In the real world, precise data pertaining to measurement indicators is very hard to extract from human judgments. This is because human preferences encompass a degree of uncertainly, and decision-makers may very well be reluctant or unable to assign crisp numerical values to comparison judgments. Decision-makers also prefer natural language expressions over exact numbers when assessing criteria and alternatives. The fuzzy set theory deals with ambiguous or not well-defined situations. The AHP leads from simple pairwise comparison judgments to priorities arranged within a hierarchy. The AHP cannot take into account uncertainly when assessing and tackling a problem effectively. However, the fuzzy comprehensive evaluation method can tackle fuzziness or the problem of vague decision-making more efficiently by using fuzzy scales with lower, median, and upper values. This can be contrasted with the AHP's crisp 9-point scale and synthesis of the relative weights using fuzzy sets, membership functions, and fuzzy members.

Fuzzy multi-layer assessment model generally classifies those major factors affecting overall assessment model into several subsets alternatives. Assuming the set of evaluation criteria $O = [O_1, O_2, ... O_n]$. Since $O_i (i \in [1,2 ... n])$ is composed of n_i sub-criteria,

$O_i = [O_{i1}, O_{i2}, ... O_{in}]$. The evaluation index set V is composed of all evaluation indexes. V is divided into k subsets, i.e., $V = [V_1, V_2, ... V_k]$ which satisfy the following:

$$\bigcup_{i=1}^{k} V_i = V, V_i \cap V_j = \emptyset, \ i,j \in [1,2 ... n].$$

Next, assuming that the evaluation index set $V = [V_1, V_2, ... V_k]$ has n_i evaluation indexes, the eigenvalue of n_i evaluation matrix R_i can be represented as follows,

$$R_i = \begin{Bmatrix} r_{11}^{(i)} \, r_{12}^{(i)} \cdots r_{1m}^{(i)} \\ r_{21}^{(i)} \, r_{22}^{(i)} \cdots r_{2m}^{(i)} \\ \vdots \quad \vdots \quad \vdots \quad \vdots \\ r_{ni1}^{(i)} \, r_{ni2}^{(i)} \cdots r_{nim}^{(i)} \end{Bmatrix}$$

Assuming that $A_i = [a_1{}^{(i)}, a_2{}^{(i)}, ..., a_{n_i}{}^{(i)}]$ is the weighting coefficient evaluation matrix.

The result set of a comprehensive evaluation is as follows,

$$B = A \circ R = (b_1, b_2, ..., b_m),$$

where ° represent a kind of fuzzy operation symbol, the computational formula is

$$b_j = \sum_{i=1}^{n} (a_i r_{ij}).$$

6.2.2 *Model evaluation*

Refer to the multi-criteria assessment model, the combination of the AHP method and FCE method are needed to calculate the model. The AHP enables decision-makers to structure complex problems in a simple hierarchical form and to evaluate a large number of quantitative and qualitative factors in a systematic manner despite the presence of multiple conflicting criteria. In order to collect information about classroom acoustical properties, a set of survey questionnaires was conducted at the Hong Kong Polytechnic University (PolyU). Twenty students (both undergraduates and postgraduates are included) participated in the survey. They were asked to compare every two factors of one main criterion and to give scale according to the importance. Besides, participants were asked about the quality of the acoustical environment in PolyU. In terms of each criterion, students can choose an evaluation score from the assessment system. They were told to answer each question independently. They were arranged to complete the questionnaires in prescript classrooms. These classrooms were selected in a different building in PolyU. This condition aimed to cover the whole university.

Table 6.1 Pairwise comparisons among classroom facilities alternatives.

	$\boldsymbol{O_{11}}$	$\boldsymbol{O_{12}}$	$\boldsymbol{O_{13}}$	$\boldsymbol{O_{14}}$	$\boldsymbol{O_{15}}$	$\boldsymbol{O_{16}}$	**Weightings**
$\boldsymbol{O_{11}}$	1.00	3.58	5.66	2.21	4.80	5.12	41.44%
$\boldsymbol{O_{12}}$	0.28	1.00	0.50	0.26	1.12	2.05	7.83%
$\boldsymbol{O_{13}}$	0.18	2.00	1.00	0.45	4.06	4.60	14.98%
$\boldsymbol{O_{14}}$	0.45	3.85	2.22	1.00	3.54	6.80	25.21%

O_{15}	0.21	0.89	0.25	0.28	1.00	1.20	6.00%
O_{16}	0.20	0.49	0.22	0.15	0.83	1.00	4.54%

Table 6.2 Pairwise comparisons among inside classroom noise alternatives.

	O_{21}	O_{22}	O_{23}	**Weightings**
O_{21}	1.00	0.40	0.67	19.66%
O_{22}	2.50	1.00	2.10	53.01%
O_{23}	1.50	0.48	1.00	27.33%

Table 6.3 Pairwise comparisons among outside classroom noise alternatives.

	O_{31}	O_{32}	O_{33}	O_{34}	O_{35}	O_{36}	**Weightings**
O_{31}	1.00	0.28	0.40	0.58	1.15	1.88	10.71%
O_{32}	3.57	1.00	0.62	2.86	2.12	2.04	26.53%
O_{33}	2.50	1.61	1.00	2.16	2.96	1.91	28.03%
O_{34}	1.72	0.35	0.46	1.00	3.32	1.85	16.34%
O_{35}	0.87	0.47	0.34	0.30	1.00	0.67	8.14%
O_{36}	0.53	0.49	0.52	0.54	1.50	1.00	10.25%

Table 6.4 Pairwise comparisons among interactive teaching alternatives.

	O_{41}	O_{42}	O_{43}	O_{44}	**Weightings**
O_{41}	1.00	0.36	4.21	1.98	25.35%
O_{42}	2.78	1.00	4.56	4.13	52.72%
O_{43}	0.24	0.22	1.00	0.38	7.44%
O_{44}	0.51	0.24	2.63	1.00	14.49%

Table 6.5 Pairwise comparisons among vocal effort alternatives.

	O_{51}	O_{52}	O_{53}	O_{54}	O_{55}	O_{56}	**Weightings**
O_{51}	1.00	2.05	4.22	5.02	2.86	3.69	37.47%
O_{52}	0.49	1.00	3.06	2.88	1.66	2.92	22.91%
O_{53}	0.24	0.33	1.00	2.14	3.06	0.88	12.55%
O_{54}	0.20	0.35	0.47	1.00	1.08	2.00	9.14%
O_{55}	0.35	0.60	0.33	0.93	1.00	0.41	7.77%
O_{56}	0.27	0.34	1.14	0.50	2.44	1.00	10.16%

Table 6.6 Pairwise comparisons among five major criteria.

	O_1	O_2	O_3	O_4	O_5	**Weightings**
O_1	1.00	1.21	1.67	1.58	2.15	28.11%
O_2	0.83	1.00	1.34	1.63	2.08	24.87%
O_3	0.60	0.75	1.00	1.16	1.80	18.87%
O_4	0.63	0.61	0.86	1.00	1.42	16.40%
O_5	0.47	0.48	0.56	0.70	1.00	11.76%

Assuming that the evaluation index set:

$$V = [V_1, V_2, V_3, V_4, V_5] = ["Excellent", "Good", "Medium", "Poor", "Very\ Poor"],$$

where "Excellent" refers to a score more than 90, "Good" refers to a score between 80 and 90, "Medium" refers to a score from 70 to 80, "Poor" refers to a score from 60 to 70, and "Very Poor" refers to score up to 60.

Table 6.7 The results of classroom acoustic quality from students

Main Criteria	**Sub-criteria**	**Excellent** V_1	**Good** V_2	**Medium** V_3	**Poor** V_4	**Very Poor** V_5
	Acoustical properties	12	6	2	0	0

	(O_{11})					
The classroom facility $(\mathbf{O_1})$	Lighting (O_{12})	8	8	3	1	0
	Equipment (O_{13})	4	6	5	4	1
	Ventilation (O_{14})	6	6	4	3	1
	Classroom specification (O_{15})	2	8	8	2	0
	Classroom architecture (O_{16})	4	12	3	1	0
Inside classroom noise $(\mathbf{O_2})$	HVAC system (O_{21})	8	8	2	2	0
	Students' activity and interacting (O_{22})	14	5	1	0	0
	lighting system (O_{23})	12	5	2	0	1
Outside classroom noise $(\mathbf{O_3})$	Traffic noise (O_{31})	8	4	7	1	0
	Noise generated from neighboring classroom (O_{32})	14	6	0	0	0
	Noise from corridor, hallway, and lobby (O_{33})	10	8	2	0	0

	Noise coming from surrounding playgrounds (O_{34})	16	1	2	1	0
	Mechanical equipment noise (O_{35})	10	4	4	1	1
	Noise generated from nearby building (O_{36})	8	8	2	1	1
Interactive teaching ($\mathbf{O_4}$)	Practice work (O_{41})	10	4	4	1	1
	Group work (O_{42})	8	6	4	2	0
	Blackboard teaching (O_{43})	4	8	4	4	0
	Multimedia techniques (O_{44})	9	5	5	1	0
Vocal effort ($\mathbf{O_5}$)	Acoustical treatment (O_{51})	15	4	1	0	0
	Sound reinforcement system (O_{52})	12	3	2	1	2
	Classroom size (O_{53})	8	8	4	0	0
	Position of students inside classroom (O_{54})	14	2	2	2	1
	Lecturer position inside	12	4	3	1	0

the classroom (O_{55})					
The numbers of students (O_{56})	10	6	3	1	0

From the survey results, the sub-criteria evaluation matrix is:

$R_{11} = [0.6, 0.3,0.1,0,0]$ $R_{12} = [0.4, 0.4,0.15,0.05,0]$

$R_{13} = [0.2, 0.3,0.25,0.2,0.05]$ $R_{14} = [0.3, 0.3,0.2,0.15,0.05]$

$R_{15} = [0.1,0.5,0.4,0.1, 0]$ $R_{16} = [0.2,0.6,0.15,0.05, 0]$

The second hierarchy evaluation matrix is:

$$R_1 = \begin{bmatrix} 0.6, 0.3, 0.1, 0, 0 \\ 0.4, 0.4,0.15,0.05,0 \\ 0.2, 0.3,0.25,0.2,0.05 \\ 0.3,0.3,0.2,0.15,0.05 \\ 0.1, 0.5, 0.4, 0.1, 0 \\ 0.2,0.6,0.15,0.05, 0 \end{bmatrix}$$

$A_1 = [0.4144, 0.0783, 0.1498, 0.2521, 0.006, 0.0454]$ is the weighting coefficient evaluation matrix calculated from AHP method.

The result set of the second hierarchy comprehensive evaluation is as follows,

$B_1 = A_1 \circ R_1$= [0.3952, 0.3064, 0.1503, 0.0746, 0.0201]

Similarly,

$$B_2 = [0.6737,0.2795,0.0735,0.0197,0.0137]$$

$$B_3 = [0.5811,0.2786,0.1084,0.0227,0.0092]$$

$$B_4 = [0.4177,0.2748,0.2072,0.0875,0.0127]$$

$$B_5 = [0.6301, 0.2147, 0.1028, 0.0296, 0.0229]$$

$$B = \begin{Bmatrix} B_1 \\ B_2 \\ B_3 \\ B_4 \\ B_5 \end{Bmatrix} = \begin{Bmatrix} 0.3952, 0.3064, 0.1503, 0.0746, 0.0201 \\ 0.6737, 0.2795, 0.0735, 0.0197, 0.0137 \\ 0.5811, 0.2786, 0.1084, 0.0227, 0.0092 \\ 0.4177, 0.2748, 0.2072, 0.0875, 0.0127 \\ 0.6301, 0.2147, 0.1028, 0.0296, 0.0229 \end{Bmatrix}$$

According to Table 6.6, the weighting coefficient evaluation of main criteria

$$A = [0.2811, 0.2487, 0.1887, 0.1640, 0.1176]$$

The first hierarchy comprehensive evaluation Y is

$$Y = A \circ B = [0.5309, 0.2785, 0.1271, 0.0480, 0.0156]$$

Assuming that the evaluation index set V:

$$V = [V_1, V_2, V_3, V_4, V_5] = ["Excellent", "Good", "Medium", "Poor", "Very\ Poor"],$$

where “Excellent” refers to a score more than 90, “Good” refers to a score between 80 and 90, “Medium” refers to a score from 70 to 80, “Poor” refers to a score from 60 to 70, and “Very Poor” refers to score up to 60. In order to calculate the value of the overall assessment of the classroom environment. “Excellent” refers to score 95, “Good” refers to score 85, “Medium” refers to score 75, “Poor” refers to score 65, and “Very Poor” refers to score 30. Therefore, the evaluation index value set N defines:

$$N = [N_1, N_2, N_3, N_4, N_5] = ["Excellent", "Good", "Medium", "Poor", "Very\ Poor"$$

$$N = [95, 85, 75, 65, 30]$$

The overall assessment score of the classroom environment F is:

$$F = Y * N' = [0.5309, 0.2785, 0.1271, 0.0480, 0.0156] \begin{bmatrix} 95 \\ 85 \\ 75 \\ 65 \\ 30 \end{bmatrix} = 87.2251$$

Therefore, the overall assessment score in PolyU classrooms is 87.2251, which refers to "Good".

6.3 Findings and discussions

Tables 6.1-6.5 show pairwise comparisons among each major criterion based on the AHP method. The weightings column represents a significant proportion of each alternative. Table 6.1 shows Acoustical properties (O_{11}), Ventilation (O_{14}), Equipment (O_{13}) are the main classroom facilities to avoid classroom acoustical environment. Table 6.2 shows those students' activity and interacting (O_{22}) generates most noise inside the classroom. Table 6.3 shows that noise from corridor, hallway, and lobby (O_{33}), noise generated from the neighboring classroom (O_{32}), the noise coming from surrounding playgrounds (O_{34}) are the main noise sources outside the classroom. Table 6.4 shows group work (O_{42}) in interactive teaching generates most noise. As for vocal effort, Table 6.5 shows that acoustical treatment (O_{51}), sound reinforcement system (O_{52}) are the main source of the noise.

As shown in Table 6.6, five main criteria can be ranked from O_1-O_5 based on the weights calculated from the AHP method. The FCE assessment model input the weightings based on AHP and finally output the evaluation score. This evaluation score can intuitively show the quality of the classroom acoustical environment. The FCE assessment model not only can assess the acoustical condition in the classroom, but also can give the weightings of each alternative. Besides, the model can give proper recommendations to universities. In the evaluation survey, as shown in Table 6.7, some students choose the “poor” or “very poor” option to evaluate the objective alternatives. For example, there are three students considering that ventilation system (O_{14}) in PolyU generates a poor acoustical environment, and even one student chooses “very poor”. Universities are suggested to reduce the noise generated from the ventilation system in order to improve the acoustical environment. For our case study, the evaluation score of PolyU is 87.2, which refers to a “Good” educational environment. In order to increase the evaluation score, university authority may consider improving the following alternatives based on the FCE assessment model. First is the noise from the equipment and facilities that include a data projector, projection screen, teacher’s computer, and network connection for students’ computers and laptops. Second is the noise from the ventilation system. The third is the seating of the students inside the classroom and the sound reinforcement system. Fourth is the mechanical equipment noise and the noise generated from a nearby building.

6.4 Summary

The work in this chapter proposed an assessment model of the classroom acoustical environment. The model based on the Fuzzy comprehensive evaluation method and applied in PolyU classrooms. The data is collected from students in the university. The weighting coefficient was calculated from the Analytic hierarchy process method. The model is a combination of qualitative and quantitative, which is more accurate and reliable. It can be used in other universities and schools' assessment. It can help universities comprehend the experience of students about the acoustical environment. Besides, it can help manage the proper treatment and improve acoustical facilities in a proper way.

CHAPTER 7 Relationships between IEQ and environmental factors

Indoor environmental quality (IEQ) is co-determined by several environmental factors (thermal, indoor air, lighting, and acoustics). In this chapter, a four-layer IEQ assessment model for university classrooms was proposed based on fuzzy comprehensive evaluation (FCE) methods. The assessment model was evaluated based on a survey with a sample of 224 respondents in selected eight university classrooms in Hong Kong. Besides, objective measurements were performed in each classroom. Several parameters were included, such as operative temperature, CO_2 concentration, illuminance level, and A-weighted background noise level in the measurements. Then a set of prediction formulas were proposed to illustrate the relationships between IEQ and the environmental factors. The analysis results showed that the quality of the thermal environment was the most essential factor in the indoor environment. The results also discussed the significance rankings of sub-factors based on the weightings calculated from the analytic hierarchy process (AHP). The methods can give proper suggestions to authorities to manage the appropriate treatment and improve the indoor environmental quality. It is also useful for indoor environment design based on the proposed prediction formulas.

7.1 Methodology

7.1.1 Classrooms for investigation

In this chapter, eight classrooms in the Hong Kong Polytechnic University (PolyU) were investigated. All the classrooms were well decorated with acoustical treatment (sound absorptive panels, sound absorptive ceilings, floor isolation mat, etc.). The criteria of the selected classrooms contained the following considerations. Firstly, the selected classrooms were located in different buildings with different dimensions and characteristics. These conditions aim to cover the whole university. Secondly, the classrooms were selected to cover both modes of the light source (Combination of natural and artificial or artificial) in university. Thirdly, several classrooms near the street were chosen to obtain the data under high background noise levels. Fourthly, the classrooms with different volumes, windows surfaces area, exposures, etc. were taken into account to have a significant sample. The descriptions of the classrooms are shown in Table 7.1. The characteristics are shown in the following table, including essential issues which may affect the indoor environmental quality.

Table 7.1 Classroom characteristics in case study

Classroom	1	2	3	4	5	6	7	8
Width[m]	7.12	7.84	12.11	8.91	11.26	8.17	16.53	10.99
length[m]	7.18	3.85	7.68	6.85	7.84	5.54	12.65	8.22
Height[m]	2.63	2.68	3.62	3.09	3.25	2.41	5.03	2.53
Volume[m3]	134.45	80.89	336.68	188.59	286.90	109.08	1051.80	228.56

No of seats	40	20	118	54	86	32	208	72
No of doors	2	1	2	2	2	1	2	2
No of windows	3	3	5	3	4	2	0	0
SA of windows[m2]	9.79	7.78	18.12	9.79	13.06	6.53	0	0
SA of doors [m2]	4.2	2.1	4.2	4.2	4.2	2.1	4.2	4.2
Light source	Artificial and natural						Artificial	
No of fluorescent tubes	20	8	48	28	32	12	64	40
Type of artificial lighting	Fluorescent tubes							
Materials of ceilings	Metal perforated plates							
Materials of floors	Loop pile tufted carpet							
Materials of surface walls	Sidewalls: Painted concrete walls Front and rear walls: Wooden perforated plates							
Materials of windows	Double glazing windows							
Building Services system	HVAC							

Where "No" denotes the numbers of each classroom facilities. "SA" denotes the surface area of each classroom facilities.

7.1.2 Subjective Questionnaires and assessment method

7.1.2.1 Questionnaire survey

A pilot study with 300 respondents in 8 mentioned classrooms in PolyU participated in the questionnaire survey. A total of 273 questionnaires returned, out of 224 were valid (valid rate 82%). The valid results referred to the ones passed the consistency checking process. These participants include undergraduates, postgraduates, PhD students, and academic staff (assistant professors, associate professors, and professors). General information of respondents is given in Table 7.2. The surveys were conducted from September 2018 to June 2019. The participants were asked to compare every two factors of one main criterion and to give scale according to the importance. They were asked to answer the questionnaire according to their feeling in prescript classrooms in PolyU. These classrooms were selected in different buildings in PolyU. In terms of each criterion, participants can choose the evaluation score from the assessment system. They were told to answer each question independently.

Table 7.2 General Information of respondents participated in the questionnaire survey

Classification	Gender		Students			Staffs
	Male	Female	Undergraduates	Postgraduates	PhD	
Number	135	89	116	92	12	4
Proportion (%)	60.27	39.73	51.79	41.07	5.35	1.79
Total	224			224		

7.1.2.2 Combined Fuzzy comprehensive evaluation (FCE) and analytic hierarchy process (AHP) method

In the real world, precise data on measurement indicators are tough to extract from human judgments. This is because human preferences encompass a degree of uncertainly, and decision-makers may very well be reluctant or unable to assign crisp numerical values to comparison judgments. Fuzzy comprehensive evaluation method (FCE) is a multi-layer comprehensive evaluation index system based on Fuzzy mathematics, which has been applied in various fields (Yang, Xu et al. 2018, Zheng, Li et al. 2019, Wu, Su et al. 2018, Zhang, Wang et al. 2020). The analytic hierarchy process (AHP) leads from simple pairwise comparison judgments to priorities arranged within a hierarchy (Mak, To, et al. 2015). The AHP's crisp 9-point scale and synthesis of the relative weights are appropriate for calculating fuzzy sets, membership functions, and fuzzy members. Yang and Mak have proposed an assessment model to evaluate the acoustical environment quality using the FCE-AHP method (Yang and Mak, 2017). In this chapter, a more complex multi-layer assessment model, including indoor environmental quality, is proposed.

The FCE method involves five steps as following:

The fuzzy multi-layer assessment model generally classifies those major factors affecting the overall assessment model into several subsets alternatives. Assuming the set of evaluation criteria $O = [O_1, O_2, \ldots O_n]$. Since $O_i (i \in [1,2 \ldots n])$ is composed of sub-criteria, $O_i = [O_{i1}, O_{i2}, \ldots O_{in}]$

The evaluation index set V is composed of all evaluation indexes. V is divided into subsets, i.e., $V = [V_1, V_2, \ldots V_k]$ which satisfy the following:

$$\cup_{i=1}^{k} V_i = V, V_i \cap V_j = \emptyset,\ i,j \in [1,2 \ldots n].$$

Next, assuming that the evaluation index set $V = [V_1, V_2, ... V_k]$ has n_i evaluation indexes, the eigenvalue of n_i evaluation matrix R_i can be represented as follows,

$$R_i = \begin{Bmatrix} r_{11}^{(i)} & r_{12}^{(i)} & \cdots & r_{1m}^{(i)} \\ r_{21}^{(i)} & r_{22}^{(i)} & \cdots & r_{2m}^{(i)} \\ \vdots & \vdots & \vdots & \vdots \\ r_{ni1}^{(i)} & r_{ni2}^{(i)} & \cdots & r_{nim}^{(i)} \end{Bmatrix}$$

Assuming that $A_i = [a_1{}^{(i)}, a_2{}^{(i)}, ..., a_{n_i}{}^{(i)}]$ is the weighting coefficient evaluation matrix.

The result set of a comprehensive evaluation is as follows,

$$B = A \circ R = (b_1, b_2, ..., b_m),$$

where ° represent a kind of fuzzy operation symbol, the computational formula is

$$b_j = \sum_{i=1}^{n} (a_i r_{ij})$$

In the current chapter, A four-layer overall indoor environmental quality assessment model (O) is established in Fig.7.1. Each of these criteria is made up of some independent indexes.

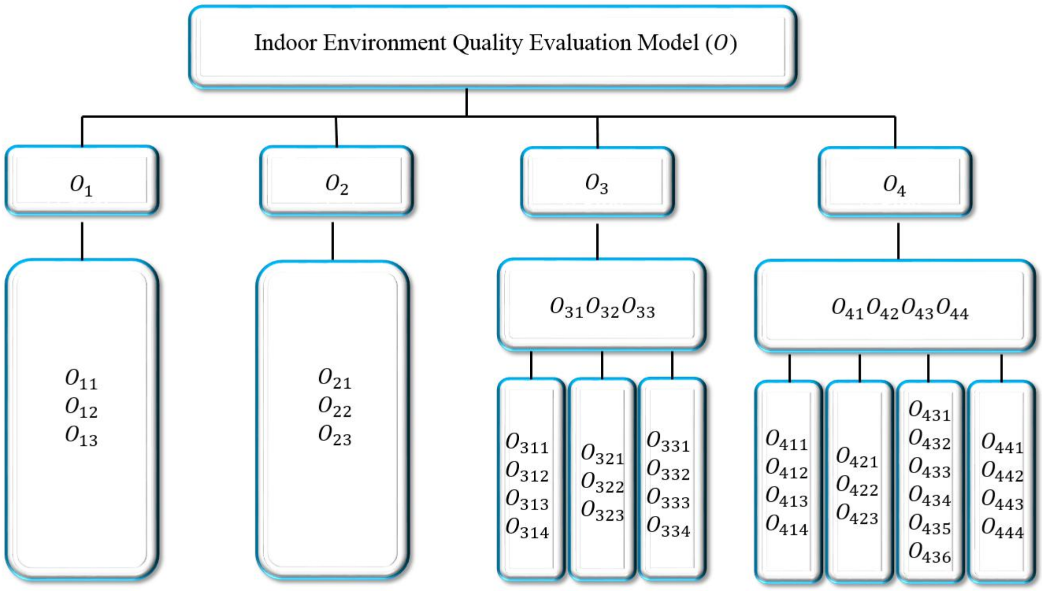

Figure 7.1 assessment model framework of indoor environmental quality

As shown in Fig. 7.1, the indoor environmental quality FCE-AHP assessment model consists of 4 main criteria. These four main criteria are including thermal quality (O_1), indoor air quality (O_2), lighting quality (O_3), and acoustic quality (O_4).

Thermal quality (O_1) includes three sub-factors O_{11} *to* O_{13}. O_{11} represents the feelings of temperature for the subjects in the classrooms. O_{12} represents the feeling s of relative humidity for the subjects in the classrooms. O_{13} represents the effect of the clothing insulation for the subjects in the classrooms.

Indoor air quality (O_2) includes three sub-factors O_{21} *to* O_{23}. O_{21} represents the feelings of natural ventilation conditions for subjects in the classrooms. O_{22} represents the feelings of air-conditioning ventilation conditions for subjects in the classrooms. O_{23} is the feeling of the air freshness for subjects in the classrooms.

Lighting quality (O_3) includes three sub-factors O_{31} *to* O_{33}. O_{31} represents the quality of the artificial lighting system in classrooms. This criterion includes four sub-factors named O_{311} to O_{334}. O_{311} is the illuminance level of the classrooms. O_{312} is the illuminance uniformity of the classrooms. O_{313} is the feeling of uncomfortable glare for subjects in classrooms. O_{314} is the feelings of visual comfort for subjects to evaluate the artificial lighting system in classrooms. O_{32} represents the quality of natural lighting in classrooms. This criterion includes four sub-factors named O_{321} to O_{324}. O_{321} is the amount of daylight. O_{322} is the hours of the daylight. O_{323} is the sunlight reflection off the walls, blackboard, floors, and desk in classrooms. O_{324} is direct solar radiation in classrooms. O_{33} represents the quality of the performance of the fluorescent tubes in classrooms. This criterion includes four sub-factors named O_{331} to O_{334}. O_{331} is the color rendition in classrooms. O_{332} is the color temperature in classrooms. O_{333} is the color rendering index. O_{334} is the lighting power density of the fluorescent tubes.

Acoustic quality (O_4) is determined by four evaluation indexes: the classroom facility(O_{41}), inside classroom noise(O_{42}), outside classroom noise(O_{43}), Interactive teaching (O_{44}) . O_{41} represents the noise effects of the classroom facility. This criterion includes six sub-factors named O_{411} to O_{414}. Acoustical properties *(O_{411})*: such as the acoustical design of walls and ceilings. Equipment (O_{412}) : facilities includes data projector, projection screen, teacher's computer and network connection for students' computer and laptops. Classroom specification (O_{413}): this criterion is mainly referred to as the classroom size. Insufficient classroom space may influence students in daily education. Classroom architecture (O_{414}): such as shape and style of the classroom, the location of the classroom. All of these are essential factors that affect students learning process and education quality. O_{42} is further determined by three alternatives. Heating Ventilation and Air conditioning (HVAC) system (O_{421}) are the primary sources of noise inside the classroom. The system includes air handlers and fans, acoustical treatment of ducts, returns, and diffusers. Besides, students' activity and interacting (O_{422}) can increase the noise level inside the classrooms. Besides, another factor that contributed to the noise inside the classroom is the lighting system (O_{423}). Corresponding to O_{42}, noise sources outside the classroom (O_{43}) is another important criterion of the classroom acoustics. O_{43} is further considered by the following six criteria: traffic noise (O_{431}), noise generated from the neighboring classroom (O_{432}), noise from corridor, hallway, and lobby (O_{433}), the noise coming from surrounding playgrounds (O_{434}), mechanical equipment noise (O_{435}), noise generated from the nearby building (O_{436}).

Universities aim to increase the effectiveness of teaching students so that the teaching methods and styles (O_{44}) play an essential role in classroom education. These teaching methods and styles mainly include practice work (O_{441}), group work (O_{442}), blackboard teaching (O_{443}) and multimedia techniques (O_{444}). Different ways of communication between students and speakers affect the different learning experiences.

7.1.3 Objective experimental measurement

In order to measure the indoor environment variables, different kinds of instruments were used in the objective experimental measurements. The authors have already investigated the acoustic conditions in university classrooms and middle school classrooms (Yang and Mak, 2018). However, other aspects, apart from acoustic conditions, need to be taken into account for evaluating overall indoor environmental quality in classrooms. In this work, the investigation is extended to analyze also the thermal, indoor air, and lighting quality environment. General information of instruments used in the measurements was shown in Table 7.3.

Table 7.3 Information of instruments in IEQ measurements

IEQ aspect	Parameter	Instrument	Unit	Range	Accuracy
Thermal	Temperature	HOBO data logger	°C	-20-100	0.45°C
	Air velocity	Dantec Low Air velocity Meter	m/s	0.05-5.00	2% or 0.02m/s of reading
IAQ	RH	HOBO data logger	%	0-100	5%
	CO_2 concentration	Telaire 7001 CO_2 sensor	ppm	0-10,000	50ppm or 5% of reading
Lighting	Illuminance level		lux	0-50,000	5%
	Illuminance Uniformity	Luntron LX-101A	N/A	0.000-1.000	N/A
Acoustic	L_{Aeq}	B&K 2270	dB	0-123	1.5dB
	T_{30}	B&K 7841 Dirac	s	0.02-100	N/A
	STI	B&K 7841 Dirac	N/A	0-1	N/A

In Table 7.3, "RH" denotes relative humidity. "L_{Aeq}" denotes to A-weighted Noise Continuous Equivalent Level. "T_{30}" denotes to Reverberation Time related to the decay from - 5 dB to - 35 dB. "STI" means Speech Transmission Index.

7.2 Evaluation results

Refer to the multi-criteria assessment model (see Fig.7.1), a combination of the AHP method and the FCE method is employed to calculate the model. The AHP enables decision-makers to structure complex problems in a simple hierarchical form and to evaluate a large number of quantitative and qualitative factors systematically despite the presence of multiple conflicting criteria. The participants were asked to compare every two factors of one main criterion and to give scale according to the importance. Besides, respondents were asked about the quality of indoor environmental quality in PolyU. In terms of each criterion, students can choose an evaluation score from the assessment system. They were told to answer each question independently. They were arranged to complete the questionnaires in prescript classrooms. The statistical results of the results were shown in the following tables.

Table 7.4 The subjective results of thermal and indoor air quality in classrooms

Main Criteria	Sub-criteria	Excellent V_1	Good V_2	Medium V_3	Poor V_4	Very Poor V_5
Thermal environment quality(O_1)	Temperature (O_{11})	38	95	72	14	5
	Relative Humidity (O_{12})	23	106	58	31	6
	Clothing insulation (O_{13})	69	76	63	12	4
Indoor Air	Natural	8	25	42	102	47

quality (O_2)	ventilation condition (O_{21})					
	Air-conditioning ventilation condition (O_{22})	88	53	51	22	10
	air freshness (O_{23})	27	76	72	36	13

Table 7.5 The subjective results of lighting quality in classrooms

Main Criteria	Sub-criteria	Excellent V_1	Good V_2	Medium V_3	Poor V_4	Very Poor V_5
Quality of the artificial lighting system (O_{31})	Illuminance level (O_{311})	41	108	60	12	3
	Illuminance uniformity(O_{312})	12	92	66	43	11
	Uncomfortable glare (O_{313})	34	102	47	25	16
	Visual comfort (O_{314})	42	80	58	32	12
Quality of natural	Amount of daylight (O_{321})	12	32	77	66	37

lighting (O_{32})	Sunlight reflection effects (O_{322})	53	86	52	18	15
	Direct solar radiation (O_{323})	55	43	82	35	9
Performance of the fluorescent tubes (O_{33})	Color rendition (O_{331})	65	73	67	12	7
	Color temperature (O_{332})	106	66	30	21	1
	Color rendering index (O_{333})	102	72	36	10	4
	Lighting power density (O_{334})	103	46	42	25	8

Table 7.6 The subjective results of acoustic quality in classrooms

Main Criteria	Sub-criteria	Excellent V_1	Good V_2	Medium V_3	Poor V_4	Very Poor V_5
The classroom facility	Acoustical properties (O_{411})	141	65	12	4	2
	Equipment (O_{412})	48	66	58	34	18
	Classroom	32	88	78	22	4

(O_{41})	specification (O_{413})					
	Classroom architecture (O_{414})	42	150	18	12	2
Inside classroom noise (O_{42})	HVAC system (O_{421})	80	82	27	22	13
	Students' activity and interacting (O_{422})	182	31	12	1	0
	lighting system (O_{423})	142	55	20	6	1
Outside classroom noise (O_{43})	Traffic noise (O_{431})	93	42	67	18	4
	Noise generated from neighboring classroom (O_{432})	168	46	10	0	0
	Noise from corridor, hallway, and lobby (O_{433})	100	82	36	4	2
	Noise coming from surrounding playgrounds (O_{434})	177	12	20	10	5
	Mechanical equipment noise (O_{435})	113	43	41	14	13
	Noise generated from the nearby building (O_{436})	98	79	26	12	9

Interactive teaching (O_{44})	Practice work (O_{441})	106	49	42	23	4
	Group work (O_{442})	89	65	44	23	3
	Blackboard teaching (O_{443})	52	76	48	42	6
	Multimedia techniques (O_{444})	99	53	45	18	9

The results of 224 valid FCE questionnaires in every part of indoor environmental quality were summarized in Table 7.4-7.6. Besides, the AHP pairwise comparison results and weightings were shown in Table 7.7-7.15. Assuming that the evaluation index set:

$$V = [V_1, V_2, V_3, V_4, V_5] = ["Excellent", "Good", "Medium", "Poor", "Very\ Poor"],$$

where "Excellent" refers to a score more than 90, "Good" refers to a score between 80 and 90, "Medium" refers to a score from 70 to 80, "Poor" refers to a score from 60 to 70, and "Very Poor" refers to score up to 60.

Table 7.7 Pairwise comparisons among thermal quality assessment

	$\boldsymbol{O_{11}}$	$\boldsymbol{O_{12}}$	$\boldsymbol{O_{13}}$	**Weighting**

O_{11}	1.00	1.62	1.23	41.24%
O_{12}	0.62	1.00	0.85	26.47%
O_{13}	0.81	1.18	1.00	32.28%

Table 7.8 Pairwise comparisons among indoor air quality assessment

	O_{21}	O_{22}	O_{23}	Weighting
O_{21}	1.00	0.43	0.70	20.94%
O_{22}	2.32	1.00	1.77	50.04%
O_{23}	1.43	0.56	1.00	29.02%

Table 7.9 Pairwise comparisons among artificial lighting systems quality alternatives

	O_{311}	O_{312}	O_{313}	O_{314}	Weighting
O_{311}	1.00	1.56	2.47	0.80	30.70%
O_{312}	0.64	1.00	1.62	0.54	20.04%
O_{313}	0.40	0.62	1.00	0.38	12.84%
O_{314}	1.25	1.84	2.65	1.00	36.42%

Table 7.10 Pairwise comparisons among natural lighting quality alternatives

	O_{321}	O_{322}	O_{323}	Weighting

O_{321}	1.00	0.48	0.65	20.87%
O_{322}	2.08	1.00	2.39	52.53%
O_{323}	1.54	0.42	1.00	26.61%

Table 7.11 Pairwise comparisons among fluorescent tubes performance alternatives.

	O_{331}	O_{332}	O_{333}	O_{334}	**Weighting**
O_{331}	1.00	0.34	4.75	2.38	26.84%
O_{332}	2.98	1.00	4.26	3.83	51.89%
O_{333}	0.21	0.23	1.00	0.35	7.11%
O_{334}	0.42	0.26	2.83	1.00	14.16%

Table 7.12 Pairwise comparisons among three major criteria in lighting quality assessment

	O_{31}	O_{32}	O_{33}	**Weighting**
O_{31}	1.00	0.54	1.67	29.77%
O_{32}	1.85	1.00	2.44	50.92%
O_{33}	0.60	0.41	1.00	19.31%

Table 7.13 Pairwise comparisons among classroom facilities alternatives

	O_{411}	O_{412}	O_{413}	O_{414}	**Weighting**
O_{411}	1.00	3.26	4.39	2.56	50.59%
O_{412}	0.31	1.00	0.45	0.28	9.32%
O_{413}	0.23	2.22	1.00	0.52	14.48%
O_{414}	0.39	3.57	1.92	1.00	25.62%

Table 7.14 Pairwise comparisons among inside classroom noise alternatives.

	O_{421}	O_{422}	O_{423}	**Weighting**
O_{421}	1.00	2.55	2.83	57.28%
O_{422}	0.39	1.00	1.25	23.33%
O_{423}	0.35	0.80	1.00	19.39%

Table 7.15 Pairwise comparisons among outside classroom noise alternatives.

	O_{431}	O_{432}	O_{433}	O_{434}	O_{435}	O_{436}	**Weighting**
O_{431}	1.00	0.27	0.36	0.49	1.25	1.96	9.74%
O_{432}	3.68	1.00	0.60	2.88	3.71	3.94	30.15%
O_{433}	2.76	1.66	1.00	2.08	2.86	2.91	29.54%
O_{434}	2.06	0.35	0.48	1.00	2.32	2.55	15.69%

O_{435}	0.80	0.27	0.35	0.43	1.00	0.83	7.57%
O_{436}	0.51	0.25	0.34	0.39	1.20	1.00	7.31%

Table 7.16 Pairwise comparisons among interactive teaching alternatives.

	O_{441}	O_{442}	O_{443}	O_{444}	**Weighting**
O_{441}	1.00	1.28	1.16	0.76	24.82%
O_{442}	0.78	1.00	0.83	0.44	17.58%
O_{443}	0.86	1.20	1.00	0.54	20.75%
O_{444}	1.32	2.25	1.85	1.00	36.85%

Table 7.17 Pairwise comparisons among four sub-criteria of acoustic quality.

	O_{41}	O_{42}	O_{43}	O_{44}	**Weighting**
O_{41}	1.00	1.33	1.79	1.52	33.55%
O_{42}	0.75	1.00	1.39	1.60	27.55%
O_{43}	0.56	0.72	1.00	1.22	20.31%
O_{44}	0.66	0.63	0.82	1.00	18.60%

Table 7.18 Pairwise comparisons among four main criteria alternatives of IEQ

	$\boldsymbol{O_1}$	$\boldsymbol{O_2}$	$\boldsymbol{O_3}$	$\boldsymbol{O_4}$	Weighting
$\boldsymbol{O_1}$	1.00	1.88	1.36	1.15	31.77%
$\boldsymbol{O_2}$	0.53	1.00	0.65	0.59	16.29%
$\boldsymbol{O_3}$	0.74	1.54	1.00	0.82	23.86%
$\boldsymbol{O_4}$	0.87	1.69	1.22	1.00	28.08%

As the results are shown in Table 7.4-7.6, the normalized sub-criteria evaluation matrix of the thermal quality R_1, the normalized sub-criteria evaluation matrix of the indoor air quality R_2, the normalized sub-criteria evaluation matrix of the lighting quality $R_{31} - R_{33}$, the normalized sub-criteria evaluation matrix of the acoustic quality $R_{41} - R_{44}$.

$$R_1 = \begin{bmatrix} 0.170, 0.424, 0.321, 0.062, 0.023 \\ 0.103, 0.473, 0.259, 0.138, 0.277 \\ 0.308, 0.339, 0.281, 0.054, 0.018 \end{bmatrix}$$

$$R_2 = \begin{bmatrix} 0.036, 0.112, 0.187, 0.455, 0.210 \\ 0.393, 0.237, 0.228, 0.098, 0.044 \\ 0.121, 0.339, 0.321, 0.161, 0.058 \end{bmatrix}$$

$$R_{31} = \begin{bmatrix} 0.183, 0.482, 0.268, 0.054, 0.013 \\ 0.053, 0.411, 0.295, 0.192, 0.049 \\ 0.152, 0.455, 0.210, 0.112, 0.071 \\ 0.188, 0.357, 0.259, 0.143, 0.054 \end{bmatrix}$$

$$R_{32} = \begin{bmatrix} 0.054, 0.143, 0.344, 0.295, 0.165 \\ 0.237, 0.384, 0.232, 0.080, 0.067 \\ 0.245, 0.192, 0.366, 0.157, 0.040 \end{bmatrix}$$

$$R_{33} = \begin{bmatrix} 0.290, 0.326, 0.299, 0.054, 0.031 \\ 0.473, 0.295, 0.134, 0.094, 0.004 \\ 0.455, 0.321, 0.161, 0.045, 0.018 \\ 0.460, 0.205, 0.188, 0.112, 0.036 \end{bmatrix}$$

$$R_{41} = \begin{bmatrix} 0.629, 0.290, 0.054, 0.018, 0.009 \\ 0.214, 0.295, 0.259, 0.152, 0.080 \\ 0.143, 0.393, 0.348, 0.098, 0.018 \\ 0.187, 0.670, 0.080, 0.054, 0.009 \end{bmatrix}$$

$$R_{42} = \begin{bmatrix} 0.357, 0.366, 0.121, 0.098, 0.058 \\ 0.813, 0.138, 0.054, 0.005, 0.000 \\ 0.634, 0.246, 0.089, 0.027, 0.004 \end{bmatrix}$$

$$R_{43} = \begin{bmatrix} 0.415, 0.188, 0.299, 0.080, 0.018 \\ 0.750, 0.205, 0.045, 0.000, 0.000 \\ 0.446, 0.366, 0.161, 0.018, 0.009 \\ 0.790, 0.054, 0.089, 0.045, 0.022 \\ 0.504, 0.192, 0.183, 0.063, 0.058 \\ 0.437, 0.353, 0.116, 0.054, 0.040 \end{bmatrix}$$

$$R_{44} = \begin{bmatrix} 0.473, 0.219, 0.187, 0.103, 0.018 \\ 0.397, 0.290, 0.197, 0.103, 0.013 \\ 0.232, 0.339, 0.214, 0.188, 0.027 \\ 0.442, 0.237, 0.201, 0.080, 0.040 \end{bmatrix}$$

The pairwise comparison results of the thermal quality assessment were given in Table 7.7. $A_1 = [0.4124, 0.2647, 0.3228]$ is the weighting coefficient evaluation matrix calculated from the AHP method for thermal quality.

The result set of the comprehensive evaluation of thermal quality is as follows,

$$B_1 = A_1 \circ R_1 = [0.1968, 0.4095, 0.2916, 0.0795, 0.0886]$$

Similarly, the result set of the comprehensive evaluation of indoor air quality is:

$$B_2 = A_2 \circ R_2 = [0.2393, 0.2404, 0.2464, 0.1910, 0.0828]$$

The result set of the second hierarchy comprehensive evaluation of lighting quality is:

$$B_{31} = A_{31} \circ R_{31} = [0.1548, 0.4188, 0.2627, 0.1215, 0.0426]$$

$$B_{32} = A_{32} \circ R_{32} = [0.2010, 0.2827, 0.2911, 0.1454, 0.0803]$$

$$B_{33} = A_{33} \circ R_{33} = [0.4208, 0.2924, 0.1879, 0.0823, 0.0168]$$

$$B_3 = \begin{Bmatrix} B_{31} \\ B_{32} \\ B_{33} \end{Bmatrix} = \begin{bmatrix} 0.1548, 0.4188, 0.2627, 0.1215, 0.0426 \\ 0.2010, 0.2827, 0.2911, 0.1454, 0.0803 \\ 0.4208, 0.2924, 0.1879, 0.0823, 0.0168 \end{bmatrix}$$

The result set of the second hierarchy comprehensive evaluation of acoustic quality is:

$$B_{41} = A_{41} \circ R_{41} = [0.4068\ 0.4048, 0.1223, 0.0513, 0.0169]$$

$$B_{42} = A_{42} \circ R_{42} = [0.5171, 0.2895, 0.0992, 0.0625, 0.0340]$$

$$B_{43} = A_{43} \circ R_{43} = [0.5923, 0.2370, 0.1265, 0.0289, 0.0152]$$

$$B_{44} = A_{44} \circ R_{44} = [0.3982, 0.2630, 0.1995, 0.1122, 0.0271]$$

$$B_4 = \begin{Bmatrix} B_{41} \\ B_{42} \\ B_{43} \\ B_{44} \end{Bmatrix} = \begin{bmatrix} 0.4068\ 0.4048, 0.1223, 0.0513, 0.0169 \\ 0.5171, 0.2895, 0.0992, 0.0625, 0.0340 \\ 0.5923, 0.2370, 0.1265, 0.0289, 0.0152 \\ 0.3982, 0.2630, 0.1995, 0.1122, 0.0271 \end{bmatrix}$$

Referring to Table 7.12, the pairwise comparison and weighting coefficient evaluation of three sub-criteria of lighting quality was given. The weighting matrix A_3 is as follows:

$$A_3 = [0.2977, 0.5092, 0.1931].$$

The overall lighting quality C_l is:

$$C_l = A_3 \circ B_3 = [0.2297, 0.3251, 0.2627, 0.1261, 0.0568]$$

Referring to Table 7.17, the pairwise comparison and weighting coefficient evaluation of four sub-criteria of acoustic quality was given. The weighting matrix A_4 is as follows:

$$A_4 = [0.3355, 0.2755, 0.2031, 0.1860].$$

The overall acoustic quality C_a is:

$$C_a = A_4 \circ B_4 = [0.4733, 0.3126, 0.1312, 0.0612, 0.0232]$$

Referring to Table 7.18, the pairwise comparison and weighting coefficient evaluation of four main criteria of indoor environmental quality were given. The weighting matrix A is as follows:

$$A = [0.3177, 0.1629, 0.2386, 0.2808].$$

The result set of the first hierarchy comprehensive evaluation of IEQ is:

$$C = \begin{Bmatrix} B_1 \\ B_2 \\ C_l \\ C_a \end{Bmatrix} = \begin{bmatrix} 0.1968, 0.4095, 0.2916, 0.0795, 0.0886 \\ 0.2393, 0.2404, 0.2464, 0.1910, 0.0828 \\ 0.2297, 0.3251, 0.2627, 0.1261, 0.0568 \\ 0.4733, 0.3126, 0.1312, 0.0612, 0.0232 \end{bmatrix}$$

The overall indoor environmental quality Q is as follows:

$$Q = A \circ C = [0.2892, 0.3346, 0.2323, 0.1036, 0.0617]$$

In order to calculate the value of the overall assessment of indoor environmental quality in classrooms. The authors defined the evaluation index "Excellent" refers to score 95, "Good" refers to score 85, "Medium" refers to score 75, "Poor" refers to score 65, and "Very Poor" refers to score 30. These are mainly because the definition scores were depended on the mean score in the corresponding evaluation interval. Therefore, the evaluation index value set N defines:

$$N = [N_1, N_2, N_3, N_4, N_5] = ["Excellent", "Good", "Medium", "Poor", "Very\ Poor"$$

$$N = [95,85,75,65,30]$$

The overall assessment score of the IEQ in classrooms S is:

$$S = Q * N^{'} = [0.2892, 0.3346, 0.2323, 0.1036, 0.0617]\begin{bmatrix}95\\85\\75\\65\\30\end{bmatrix} = 81.9274$$

Therefore, the overall assessment score of IEQ in PolyU classrooms is 81.9274, which refers to "Good."

Since the matrix A represents and weighting coefficient evaluation of four main criteria of indoor environmental quality. Therefore, the indoor environmental quality satisfaction formula is as follows:

$$O = 0.3177O_1 + 0.1629O_2 + 0.2386O_3 + 0.2808O_4 \qquad (7.1)$$

7.3 Relationship between IEQ and environmental factors in classrooms

In addition to the subjective surveys in the university classrooms, objective measurements of indoor environmental quality were synchronously conducted in the mentioned classrooms. The detailed information about classrooms and instruments are shown in Table 7.1 and Table 7.3, respectively. During the survey, mean daily outdoor temperatures ranged from 24.6 °C to 35.8 °C. The outdoor relative humidity ranged from 60% to 86%.

In order to obtain the relationships between indoor environmental quality factors with the residential satisfaction in university classrooms, the regression analysis model was employed in a separate field. Several single parameters in each area were selected for analyzing the relationships between the quantitative and qualitative results. The underlying data (mean value) of the selected eight classrooms were given in Table 7.19. The overall satisfaction scores in the following sections were normalized. The regression analysis calculation and graphical representation were performed using MATLAB R2016a.

Table 7.19 The underlying data (mean value) of selected eight classrooms

Classroom	1	2	3	4	5	6	7	8
Temperature (°C)	19.0	20.9	23.1	25.0	25.9	27.0	28.1	30.0
Air velocity (m/s)	0.53	0.42	0.40	0.39	0.36	0.38	0.44	0.45
Relative humidity (%)	50.2	48.5	55.6	62.3	59.2	68.5	66.3	72.6
CO_2 concentration (ppm)	971	1641	521	554	843	1183	449	640
Illuminance level (lux)	533	309	919	645	505	458	724	239
L_{Aeq} (dB)	59.5	54.9	60.2	46.6	54.9	49.9	51.7	57.9
T_{30} (s)	0.41	0.35	0.49	0.43	0.41	0.39	0.64	0.44
STI (-)	0.72	0.86	0.65	0.76	0.77	0.79	0.71	0.75

7.3.1 Thermal environment

Referring to previous studies (Ncube and Riffat, 2012, Cao, Ouyang et al. 2012, Huang, Zhu et al. 2012), the operative temperature, which was comprised of the convection and radiation, was used as an indoor temperature index. During the survey, the operative temperature in eight classrooms ranged from 19 °C to 30 °C. The indoor relative humidity ranged from 48.5% to 72.6%. The air velocity was 0.36m/s-0.53m/s. The overall satisfaction was calculated by subjective questionnaires in each classroom followed the mentioned FCE process (Chapter 7.2). The relationship between overall satisfaction (normalized) and the operative temperature was shown in Fig 7.2.

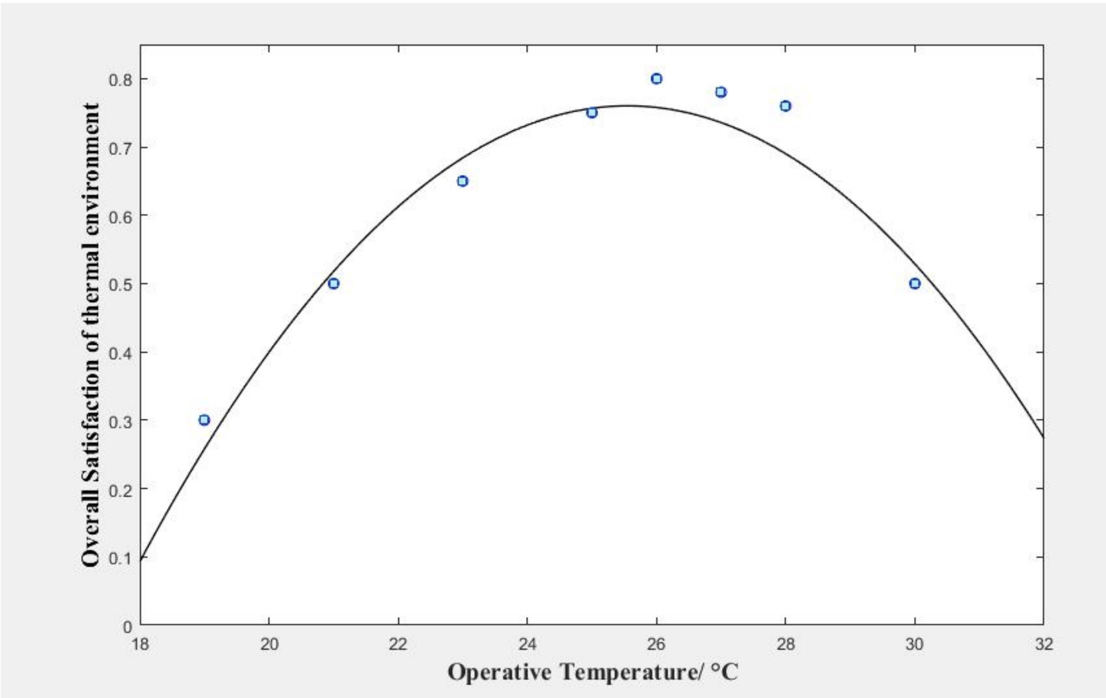

Figure 7.2 Relationship between thermal satisfaction and operative temperature

Fig. 7.2 shows the relationship between the overall satisfaction of the thermal environment and the operative temperature. Each dot represents the average value of the overall satisfaction at the corresponding operative temperature in a classroom. The corresponding polynomial equation is written as follows:

$$S_T = -0.0117{t_0}^2 + 0.5979t_0 - 6.878 \; R^2 = 0.9509 \qquad (7.2)$$

Where t_0 denotes the operative temperature, S_T is the normalized satisfaction of the thermal environment.

For the proposed polynomial equation, F-test was used for verifying the validation. The results show there are statistically significant differences between the overall satisfaction of the thermal environment and operative temperature (F= 48.403, p<0.01).

7.3.2 Indoor air quality

Many kinds of environmental parameters are factors affects the indoor air quality, such as $CO, CO_2, NO_x, NH_3, and\ O_3$ (GB/T 18883, 2002). Since the target buildings in the current chapter are mainly used for studying and teaching. CO_2 As the primary production by the human body is considered the most essential factor for evaluating indoor air quality. During the survey, the concentration of CO_2 in eight classrooms ranged from 449 ppm to 1641 ppm (parts per million). The relationship between overall satisfaction scores of IAQ and concentration of CO_2 are shown as follows:

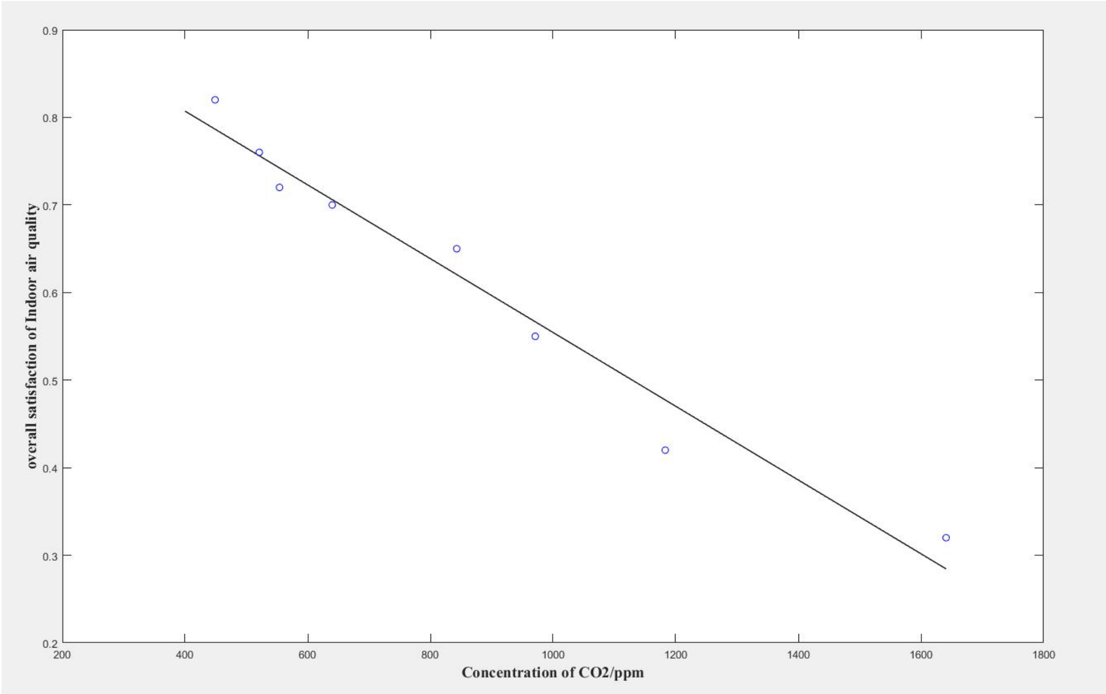

Figure 7.3 Relationship between indoor air satisfaction and CO_2 concentration

Fig. 7.3 shows the relationship between the overall satisfaction of the indoor air quality and the operative temperature. Each dot represents the average value of the overall satisfaction at the corresponding concentration of CO_2 in a classroom. The corresponding linear equation is written as follows:

$$S_I = -\,0.0004212 C_{CO_2} + 0.9756 \; R^2 = 0.9652 \qquad (7.3)$$

Where C_{CO_2} denotes the concentration of CO_2, S_I is the normalized satisfaction of the indoor air quality.

For the proposed linear equation, F-test was used for verifying the validation. The results show there are statistically significant differences between the overall satisfaction of indoor air quality and CO_2 concentration (F=166.463, p<0.01).

7.3.3 Lighting environment

In the current chapter, the illuminance level is selected as the main parameter to evaluate the lighting environment in university classrooms. During the survey, the illuminance levels in eight classrooms ranged from 239 lx to 919 lx. The relationship between overall satisfaction scores of the lighting environment and illuminance level is shown as follows:

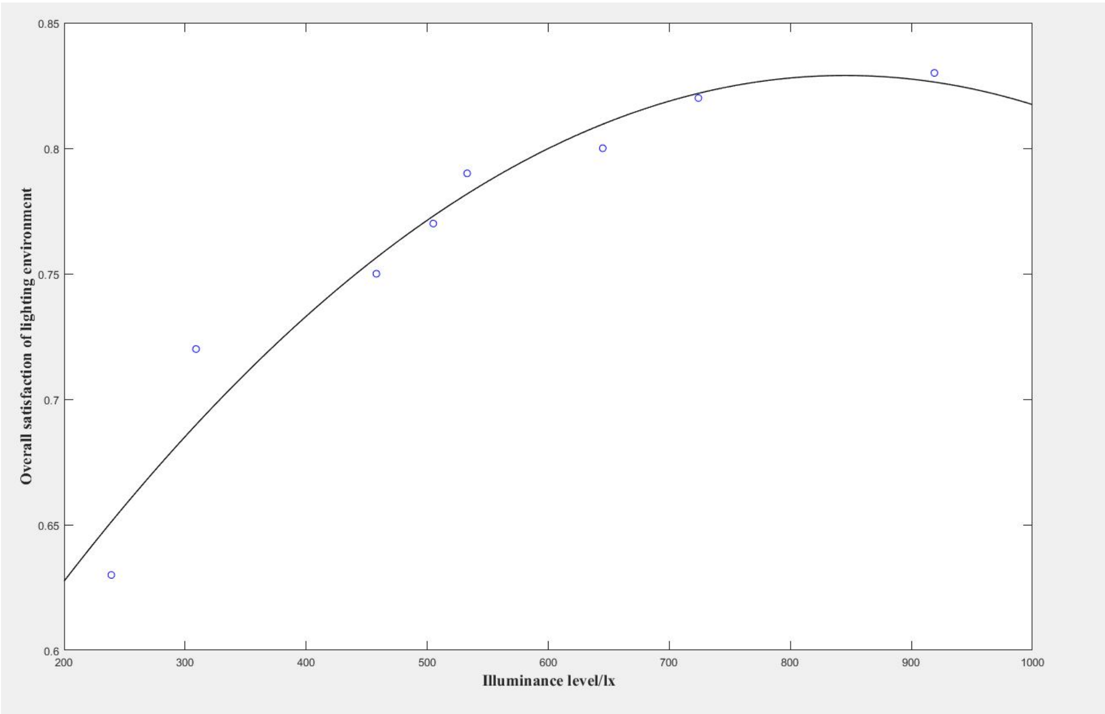

Figure 7.4 Relationship between lighting satisfaction and illuminance level

Fig. 7.4 shows the relationship between the overall satisfaction of the lighting environment and illuminance levels in university classrooms. Each dot represents the average value of the overall satisfaction at the corresponding illuminance level in a classroom. The corresponding polynomial equation is written as follows:

$$S_L = -4.838 \times 10^{-7}E^2 + 8.179 \times 10^{-4}E + 0.4833 \quad R^2 = 0.9465 \quad (7.4)$$

Where E denotes the illuminance level of the classroom, S_L is the normalized satisfaction of the lighting environment.

For the proposed polynomial equation, F-test was used for verifying the validation. The results show there are statistically significant differences between the overall satisfaction of the lighting environment and the illuminance level ($F = 44.245$, $p<0.01$).

7.3.4 Acoustic environment

The classrooms in the case study were well decorated with acoustical treatments. Materials of the side surfaces are given in Table 7.1. Therefore, the main parameter that affects the acoustical environment is the background noise level. The subject survey for assessing the acoustical environment is to evaluate the noise sources. During the survey, the background noise levels in eight classrooms ranged from 46.6 dB to 60.2 dB. The reverberation time (T_{30}) ranged from 0.36 to 0.51. The speech transmission index (STI) ranged from 0.71 to 0.88. The relationship between overall satisfaction scores of the acoustical environment and background noise levels are shown as follows:

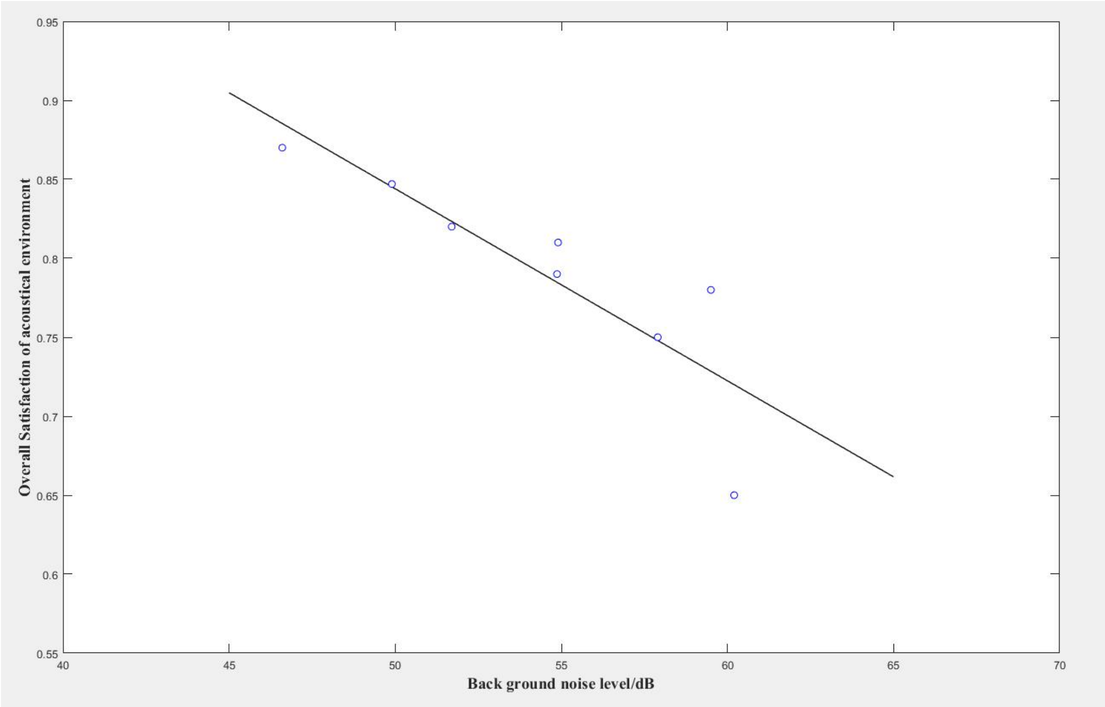

Figure 7.5 Relationship between acoustic satisfaction and background noise level

Fig. 7.5 shows the relationship between the overall satisfaction of the acoustical environment and background noise levels in university classrooms. Each dot represents the average value of the overall satisfaction at the corresponding background noise level in a classroom. The corresponding linear equation is written as follows:

$$S_A = -0.01216L_{Aeq} + 1.452 \quad R^2 = 0.7369 \qquad (7.5)$$

Where L_{Aeq} denotes the A-weighted sound pressure level of the background noise, S_A is the normalized satisfaction of the acoustical environment.

For the proposed linear equation, F-test was used for verifying the validation. The results show there are statistically significant differences between the overall satisfaction of the acoustical environment and background noise level (F=16.804, p<0.01).

7.3.5 Relationship between indoor environmental quality and various parameters

To obtain the final relationship between indoor environmental quality and various parameters, a combination equation is integrated from Eq. (7.2-7.5) to Eq. 7.1.

$$O = 0.3177 \times (-0.0117{t_0}^2 + 0.5979t_0 - 6.878) + 0.1629 \times (-0.0004212C_{CO_2} + 0.9756) + 0.2386 \times (-4.838 \times 10^{-7}E^2 + 8.179 \times 10^{-4}E + 0.4833) + 0.2808 \times (-0.01216L_{Aeq} + 1.452) \qquad (7.6)$$

The meaning of the above equation is that, in a particular indoor environment, the overall satisfaction of indoor environmental quality can be predicted by the four representative parameters. This is helpful for those authorities or architects as references in a design stage. Besides, the proposed assessment methods can be employed in other regions to evaluate the indoor environmental quality.

7.3.6 The acceptable range of each environmental factor

Referring to the China Standard GB 50019-2003, GB/T 18883-2002, GB 50034-2004, and GBJ 118-1988 (GB 50019, 2003, GB/T 18883, 2002, GB 50034, 2004, GBJ 118, 1988), each environmental factor is suggested to be at an acceptable range in buildings. The standards suggested that the acceptable range of temperature is between 22 °C and 28 °C for air conditioning in summer. The acceptable range of CO_2 concentration should be lower than 1000 ppm, the acceptable level of illumination is above 300 Lux, and the acceptable level of noise is below 50 dB. In the current paper, since the subject questionnaire is based on the FCE evaluation method, the acceptable option for respondents to select corresponds to "Medium." The corresponding satisfaction score is 70, which normalized 0.7 in the prediction formulas. Therefore, in this chapter, the acceptable range of temperature is between

23.3 °C and 27.8 °C, the acceptable range of CO_2 concentration should be lower than 654.3 ppm, the acceptable level of illumination is above 329 Lux, and the acceptable level of noise is below 61.77 dB.

7.4 Findings and discussions

7.4.1 The significance of second hierarchy alternatives in the assessment model

Referring to the mentioned 224 questionnaire survey, thermal environment quality is an essential factor for respondents in university classrooms. The next is acoustic environment quality, lighting environment quality, and indoor air quality, respectively. As for the second hierarchy criteria, the values of the column of the weightings related to the proposed IEQ model by multiplying weightings related to the criterion by the weighting of the quality of the alternative. The results are shown in the following bar chart.

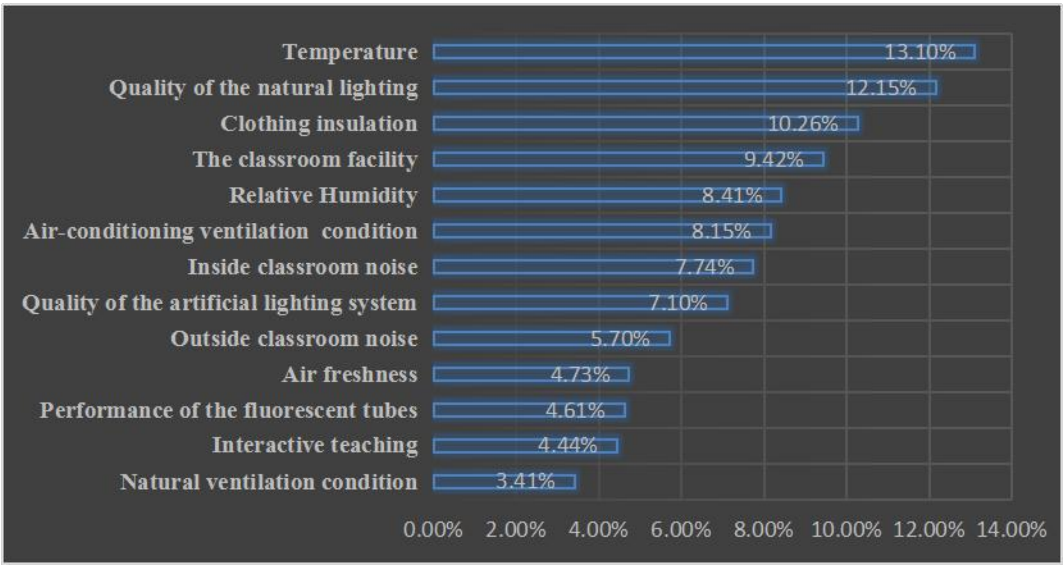

Figure 7.6 AHP results: bar chart of the second hierarchy criteria weightings

Fig 7.6 illustrates the weightings of second hierarchy alternatives ranked related to the IEQ assessment model. These findings show that the temperature of classrooms, natural lighting quality in classrooms, and students' appropriate clothes are the most critical factors to affect the feelings of the respondents in university classrooms. The reason for these findings is that in Hong Kong, the temperature is always high, nearly all read round. Students and teachers care more about the temperature and their clothing inside classrooms. Besides, Hong Kong is one of the most densely populated cities; high-rise buildings are a common type of buildings, including university buildings. Therefore, the natural lighting condition in university classrooms is another essential factor for respondents.

Furthermore, results also show that air freshness of the classrooms, the fluorescent tubes' performance, interactive teaching style, and natural ventilation conditions are with lower values of weightings in the questionnaires. The reasons for these findings are that classrooms at PolyU have a good quality of air freshness and fluorescent tubes. As for natural ventilation condition, it is mainly because that classrooms in Hong Kong are more rely on the HVAC systems. The interactive teaching style is acceptable for students so that it is not an essential factor in the survey.

7.4.2 The sub-criteria alternatives evaluation results based on the maximum membership principle

In the Fuzzy set theory, several defuzzification methods are included in consulting fuzzy problems. In the mentioned FCE evaluation model process, the weighted average method was employed in calculating the evaluation scores. The maximum membership principle is another defuzzification method, which is widely used for its simplify and intuition. The maximum membership principle is also known as the height method, which can be given by algebraic expression as:

$$u(z^*) \geq u(z)\ for\ all\ z \in Z$$

Where z^* is the output point (defuzzified value). In the current chapter, the evaluation results of each sub-criteria are intuitive for users to analyze. For instance, in the acoustic environment assessment survey, "Excellent" was chosen in most sub-criteria except for O_{412}, O_{413}, O_{414} and O_{443}. These results can easily be considered to enhance the achievement of a high-quality acoustic education environment. In the lighting environment assessment survey, most respondents chose "Good" in assessing natural and artificial lighting system quality, "Excellent" in assessing fluorescent tubes' performance. However, the amount of daylight (O_{321}) and direct solar radiation (O_{323}) are less dissatisfied compared to other sub-criteria. These results are useful for improving the lighting environment for university authorities. The most interesting sub-criteria in the FCE assessment survey is natural ventilation conditions in classrooms. Near half of the respondents (45.53%) selected "Poor" to express the dissatisfaction of the factor. While in the AHP comparison survey, they think it is less important than the other two factors for indoor air quality. The reason was mentioned in the formal part, that natural ventilation condition highly depends on the outdoor climate condition. The specific location of Hong Kong is classified as a Subtropical monsoon climate with high temperature and high relative humidity nearly all year round (Climate of Hong Kong).

7.4.3 Comparison with other studies in prediction formulas

In this chapter, two parts of the prediction models are proposed. One is predicting overall satisfaction from the individual factor satisfaction. The other is introducing the prediction formulas to present the relationship between environmental factors and individual results.

Various weightings schemes and different regression functions are the main factors in assessing the overall prediction formulas. A summary of the previous studies is shown in the following Table 7.20 for comparison.

Table 7.20 Summary of prediction models with weighting schemes in previous studies

Studies	Respondents	Analysis method	Prediction model
Cao et al. (2012)	500 respondents in Beijing and Shanghai	Multivariate linear regression	$S_O = 0.0075 + 0.316S_T + 0.118S_I + 0.171S_L + 0.224S_A$
Astolfi & Pellerey (2008)	852 students from secondary school in Turin (Italy)	Pearson's coefficient with overall satisfaction	Renovated classrooms(702): S_T:0.5,S_I:0.32,S_L:0.29,S_A:0.39 Nonrenovated classrooms(150): S_T:0.28,S_I:0.31,S_L:0.25,S_A:0.5
Fassio et al. (2014)	17 occupants in a university classroom in Roma (Italy)	Multivariate linear regression	$S_O = 0.02S_T + 0.12S_I + 0.56S_L + 0.31S_A$ (9.45 am) $S_O = 0.33S_T + 0.10S_I + 0.38S_L + 0.18S_A$ (11.30 am)

		Multivariate logistic regression	$S_O = 0.33S_T + 0.16S_I + 0.25S_L + 0.26S_A$ (9.45 am) $S_O = 0.30S_T + 0.12S_I + 0.30S_L + 0.28S_A$ (11.30 am)
Wong et al. (2008)	293 occupants in offices in Hong Kong	Multivariate logistic regression	$1 - \frac{1}{1 + \exp(15.02 + 6.09S_T + 4.88S_I + 3.7S_L + 4.74S_A)}$
Buratti et al. (2018)	928 university students in Italy	Ask directly by students	$S_O = 0.35S_T + 0.3S_L + 0.35S_A$
Ncube & Riffat (2012) [63]	68 occupants in the UK	Multivariate linear regression	$S_O = 0.3S_T + 0.36S_I + 0.16S_L + 0.18S_A$
Chiang & Lai (2002)	12 experts in Taiwan	AHP method	$S_O = 0.208S_T + 0.29S_I + 0.164S_L + 0.203S_A + 0.135S_{EMF}$
The current chapter	224 respondents in university classrooms in Hong Kong	FCE method	$S_O = 0.3177S_T + 0.1629S_I + 0.2386S_L + 0.2808S_A$

Several previous studies were listed in Table 7.20, in which different weighting schemes and regression functions were proposed. The data were collected in various regions and were analyzed using different statistical methods. Therefore, direct comparisons are difficult to be performed in results. However, it is possible to compare the weighting distributions in each study. In this paper, a new multi-criteria assessment model of indoor environmental quality criteria is developed based on the fuzzy comprehensive evaluation method (FCE). The analytic hierarchy process (AHP) method is used to calculate the weightings of the secondary layer index. The Multi-criteria FCE method combines with the weightings from the AHP method. The fuzzy set theory deals with ambiguous or not well-defined situations. The AHP leads from simple pairwise comparison judgments to priorities arranged within a hierarchy. The AHP cannot take into account uncertainly when assessing and tackling a problem effectively. However, the fuzzy comprehensive evaluation method can tackle fuzziness or the problem of vague decision-making more efficiently by using fuzzy scales with lower, median, and upper values. This can be contrasted with the AHP's crisp 9-point scale and synthesis of the relative weights using fuzzy sets, membership functions, and fuzzy members.

It is found that the weighting of the thermal environment is higher than other factors in most studies. Similar results are also observed in the current chapter. As for the other indoor environmental factors, there are no conclusive results for indoor environment comfort rating in field studies.

Table 7.21 Summary of prediction formulas for evaluating single parameters in previous studies

Studies	Respondents	Prediction formulas
Cao et al. (2012)	500 respondents in Beijing and Shanghai	$S_T =- 0.0063{t_0}^2 + 0.287t_0 - 2.934$ $S_I =- 0.0002C_{CO_2} + 0.244$ $S_L =- 5 \times 10^{-7}E^2 + 0.0011E - 0.106$ $S_A =- 0.0230L_{Aeq} + 1.382$

Ncube & Riffat (2012)	68 occupants in the UK	$S_T = 100 - PPD$ $S_I = 100 - 395e^{-15.15C_{CO_2}^{-0.25}}$ $S_L =- 176.16X^2 + 738.4X - 690.29$ $\{X = \ln(\ln(lux))\}$ $S_A = 100 - 2(\text{Actual}_{SPL} - \text{Design}_{SPL})$
Wong et al. (2008)	293 occupants in offices in Hong Kong	$S_T = 1 - \frac{1}{PPD}$ $S_I = 1 - 0.5\left(\frac{1}{1+\exp(3.118 - 0.00215C_{CO_2})} - \frac{1}{1+\exp(3.23 - 0.00117C_{CO_2})}\right)$ $S_L = 1 - \frac{1}{1+\exp(-1.017 + 0.00558E)}$ $S_A = 1 - \frac{1}{1+\exp(9.54 - 0.134L_{Aeq})}$
Guo et al. (2017)	76 participants in Qingdao (China)	$S_T =- 0.1394{t_0}^2 + 6.843t_0 - 84.130$ $S_L =- 9.206 \times 10^{-6}E^2 + 0.012E - 4.573$ $S_A =- 0.101L_{Aeq} + 6.011$
Huang et al. (2012)	120 subjects in offices in Beijing	$S_T =- 0.0108{t_0}^2 + 0.5541t_0 - 6.8587$ $S_L =- 0.7844I^2 + 1.8886I - 0.497$ $S_A =- 0.0524L_{Aeq} + 2.6$
The current chapter	224 respondents in university classrooms	$S_T =- 0.0117{t_0}^2 + 0.5979t_0 - 6.878$ $S_I =- 0.0004212C_{CO_2} + 0.9756$

	in Hong Kong	$S_L =- 4.838 \times 10^{-7}E^2 + 8.179 \times 10^{-4}E + 0.4833$ $S_A =- 0.01216L_{Aeq} + 1.452$

A summary of prediction equations among single environmental factors and satisfaction scores were listed based on several previous studies in Table 7.21 as the data in each study was collected in various regions and different satisfaction evaluation methods. Similarly, it is difficult to compare directly with the prediction equations. However, the acceptable range of every single factor can be discussed and compared. The acceptable range of the selected study is summarized in Table 7.22.

Table 7.22 Summary of the acceptable range of environmental factors in previous studies

Studies	The acceptable range of environmental factors			
	Temperature	C_{CO_2}	**Illuminance**	L_{Aeq}
Cao et al. (2012)	22 ~ 28 °C	$\leq 1200\ ppm$	100~2100 lx	$\leq 58\ dB$
Wong et al. (2008)	24 ~ 26 °C	Not given	$\geq 500\ lx$	$\leq 60\ dB$
Guo et al. (2017)	21.5 ~ 27 °C	Not given	$\geq 250\ lx$	$\leq 65\ dB$
Huang et al. (2012)	20.9 ~ 30.4 °C	Not given	$\geq 300\ lx$	$\leq 49.6\ dB$
The current chapter	23.3 ~ 27.8 °C	$\leq 654.3\ ppm$	$\geq 329\ lx$	$\leq 61.77\ dB$

It is found that the acceptable range of CO_2 concentration is obviously lower than the other studies and China Standard GB/T 18883-2002 mentioned in Chapter 7.3.2. As we know that if the concentration is too high, people may feel tired, and their productivity during work and study will be negatively affected. The low acceptable range of CO_2 concentration may be due to the small-sized university classrooms with full students are normal statuses in Hong Kong.

7.5 Future work and limitations

In the current chapter, several single environmental factors that were considered as the most significant impact on the corresponding sub-environmental satisfaction were selected for analysis. The prediction formulas were proposed to describe the relationships between sub-environmental satisfaction and the single environmental factors in Eq (7.2-7.5). This idea roots in principal component analysis in the statistical field. However, the influences of other environmental factors were not included in the proposed prediction formulas. Therefore, the integrated Eq. (7.6) for describing the relationship between indoor environmental quality and various parameters that were needed to add a correction. The limitations mentioned above are uncertainties in the prediction formulas. Furthermore, the interplay between the environmental factors was not considered in the current work. It is a valuable project to study the multisensory interactions of the four environmental factors on indoor environmental quality. Besides, the relationships between indoor environmental quality and the combined effects of environmental factors should be investigated in future work

7.6 Summary

In this chapter, indoor environmental quality (IEQ) is co-determined by various environmental factors (Thermal, indoor air, lighting, and acoustics). Studies of IEQ and human satisfaction assessment are needed to consider the comprehensive influence of the four mentioned factors. The proposed fuzzy comprehensive evaluation (FCE) models are efficient methods to avoid the overall satisfaction results absolutely influenced by one single factor in extremely poor conditions (i.e., too hot or too noisy). Besides, the weighting schemes are calculated by the analytic hierarchy process (AHP) layer by layer. These conditions are essential to transfer the qualitative questionnaires into quantitative data. Besides, a set of prediction formulas are proposed to illustrate the relationship between respondents' satisfaction scores and single environmental factors. These single environmental factors are selected as the representative parameters which have the most significant impacts on the corresponding sub-environment (thermal, indoor air, lighting, and acoustics). The proposed model is effective for assessing the overall satisfaction in university classrooms. It can help authorities manage the proper treatment and improve the indoor environmental quality. The methods can also be employed in other universities and schools. It is also useful for indoor environment design based on the proposed prediction formulas.

CHAPTER 8 Conclusions and recommendations for future work

8.1 Summary of main contributions

This thesis studied speech intelligibility, sound field prediction methods and indoor environmental quality assessment in Hong Kong classrooms with indoor measurements, subjective questionnaires, and numerical simulations. The main contributions are summarized below:

(a) An investigation of speech intelligibility and acoustical descriptors (STI, SNR, EDT, C_{80}, etc.) has been conducted to investigate the relationships between these two factors. Speech intelligibility tests were completed obtained from phonetically balanced (PB) word lists in secondary and university classrooms. The effects of age groups and linguistic environment were discussed.

(b) A new combined sound field prediction method has been proposed for predicting sound field over the whole audio domain. The proposed combined sound field prediction method consists of a wave-based method and geometric acoustic methods that are separated by the transition frequency. An optimization approach based on the genetic algorithm is employed for optimizing the transition frequency of the combined sound field prediction method in classrooms. Applications of the proposed combined prediction model can provide the predicting sound fields in buildings that are essential to acoustical designs and acoustic environmental assessments.

(c) An assessment model for evaluating acoustical environment satisfaction has been proposed based on FCE methods. This study provides detailed criteria for evaluating acoustical environment from views of noise sources in classroom environment. The assessment model can provide proper recommendation to universities for acoustic treatment so as to increase the acoustic quality of the educational environment.

(d) A four-layer FCE-AHP assessment model has been developed for evaluating overall indoor environmental quality satisfaction. The relationships between IEQ and environmental factors were investigated through regression models. Several prediction formulas were proposed to illustrate the relationship between respondents' satisfaction scores and single environmental factors. These single environmental factors are selected as the representative parameters which have the most significant impacts on the corresponding sub-environment (thermal, indoor air, lighting, and acoustics). The results of this study are useful for indoor environment design based on the proposed prediction formulas.

8.2 An investigation of speech intelligibility and STI

Speech intelligibility in middle school and university classrooms were investigated. Speech intelligibility tests were conducted in 9 middle school and 11 university classrooms and the acoustical measurements were performed in these classrooms. Subjective speech intelligibility tests were obtained from PB word lists and STI values were conducted in each listening positions and testing conditions in each classroom. The regression model was fitted based on non-linear least square fitting method. The effects of different age groups on the speech intelligibility and findings from different studies were also discussed.

Speech intelligibility scores increase with the increase of STI value for all the age groups. The speech intelligibility scores increase as age increases under the same STI condition. The differences between age groups are decreased with the increase of STI values. Speech intelligibility scores in Hong Kong are always lower than another two cases, in Italy and China, under the same values of STI. Better STI values and better acoustical environment are needed because English is not the native language for students in Hong Kong but the official educational language.

8.3 Effects of acoustical descriptors on speech intelligibility

This chapter proposes data analyses that describe the speech intelligibility of students from secondary school and university to understand speech with noise and reverberation in real classrooms. 9 secondary school classrooms and 18 university classrooms were selected for speech intelligibility tests on total 672 students in Hong Kong. PB word lists were employed for speech intelligibility tests, while objective acoustical measurements were conducted in the same classrooms. Several findings emerged from the data analyses as follows:

(1) Three basis regression models were compared in the current work for evaluating the relationship between SIs and SNR values. "S" form regression curves were selected to describe SI versus SNR for grade A, B, C, and university students.

(2) Combined effects of SNR and EDT, as well as C_{80} were discussed based on "S" form regression curves. The results indicate that nearly 0.06s increasing in EDT values will be correlated to a 1% decrease in SIs. Furthermore, the results also indicate that 1 dB increasing in C_{80} values will be correlated to a 1.23% increase in SIs.

(3) The influence of age effects and linguistic environment were also discussed. The SIs increase as the age increases under the same SNR condition. The SIs are always lower than the comparison research results with a constant reverberation value as well as sound clarity value for an equal SNR value.

8.4 A combined sound field prediction method

A combined wave-based and geometric acoustics prediction method are proposed in two small classrooms in the university. A genetic algorithm is employed for searching the optimal transition frequency in view of the consideration of computation cost. FEM method is selected as the representative wave-based method applied at frequencies below the transition frequency. Hybrid geometric acoustic methods are applied at frequencies above the transition frequency. The proposed combination model offers the possibility to simulate the sound field in the whole audible frequency range in real small rooms. Several comparisons with other studies are discussed in the current chapter. Validation experiments are conducted in the same classroom. High correlation coefficient values between the combined prediction method and experimental measurements. The proposed combined prediction model was proved optimal methods for predicting the sound field in the classroom over the whole audio frequency domain in this chapter. The wave-based FEM part at low frequencies is useful and efficient for predicting the low-frequency sound fields. In practice, applications of the proposed combined prediction model can provide the predicting sound fields in buildings that are essential to acoustical designs and acoustic environmental assessments.

8.5 An assessment model of classroom acoustical environment

An assessment model of the classroom acoustical environment was proposed. The model based on the fuzzy comprehensive evaluation method and applied in PolyU classrooms. The data is collected from students in the university. In this model, it has been classified by five major factors affecting the overall assessment model into several subsets alternatives. The weighting coefficient was calculated from the Analytic hierarchy process method. The model is a combination of qualitative and quantitative, which is more accurate and reliable. The weightings generated from the AHP method can be considered for the importance of each alternative. The assessment model can provide proper recommendations to universities for acoustic treatment so as to increase the acoustic quality of the educational environment. It can help universities comprehend the experience of students about the acoustical environment. Besides, it can help manage the proper treatment and improve acoustical facilities in a proper way.

8.6 Relationships between IEQ and environmental factors

In this chapter, indoor environmental quality (IEQ) is co-determined by various environmental factors (Thermal, indoor air, lighting, and acoustics). Studies of IEQ and human satisfaction assessment are needed to consider the comprehensive influence of the four mentioned factors. The proposed fuzzy comprehensive evaluation (FCE) models are efficient methods to avoid the overall satisfaction results absolutely influenced by one single factor in extremely poor conditions (i.e., too hot or too noisy). Besides, the weighting schemes are calculated by the analytic hierarchy process (AHP) layer by layer. These conditions are essential to transfer the qualitative questionnaires into quantitative data. Besides, a set of prediction formulas are proposed to illustrate the relationship between respondents' satisfaction scores and single environmental factors. These single environmental factors are selected as the representative parameters which have the most significant impacts on the corresponding sub-environment (thermal, indoor air, lighting, and acoustics). The proposed model is effective for assessing the overall satisfaction in university classrooms. It can help authorities manage the proper treatment and improve indoor environmental quality. The methods can also be employed in other universities and schools. It is also useful for indoor environment design based on the proposed prediction formulas.

8.7 Recommendations for future work

Despite the obtained findings of this thesis, there are still several limited or incomplete aspects in this thesis, which are recommended for future work.

(a) For the investigation of speech intelligibility and acoustical descriptors in classrooms, this study only considers several representative acoustical descriptors (STI, EDT, SNR, C_{80}). Other factors (e.g. occupancy, Strength G, useful-to-detrimental ratio U, etc.) should also be investigated to study their effects on speech intelligibility. Thus, studies including such influence factors should be conducted in the future.

(b) The combined sound field prediction method proposed in Chapter 5 has been applied in small classrooms. In real classroom conditions, classrooms have different shapes, dimensions, decorations, and even a couple of styles. All these factors could influence the results in this thesis, and these will be explored in future studies.

(c) In Chapter 6, the proposed method is an overall satisfaction assessment model for evaluating the acoustical environment. The influences of noise sources were summarized in the proposed model. However, the measurements of these noise generated sources are not included and its relationship with the overall acoustical environment quality are needed to study in the future work.

(d) In Chapter 7, the interplay between the environmental factors was not considered in the current work. It is a valuable project to study the multisensory interactions of the four environmental factors on indoor environmental quality. Besides, the relationships between indoor environmental quality and the combined effects of environmental factors should be investigated in future work.

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