# Soundscape Evaluation and ANN Modelling in Urban Open Spaces

- Lei Yu

- A thesis submitted to the University of Sheffield in partial fulfilment of the requirements for the degree of Doctor of Philosophy

- School of Architecture, University of Sheffield

# Summary

There is an increasing public and academic interest in the environmental qualities of urban open spaces. The study in this thesis focuses on soundscape research in urban open spaces, which is within the paradigm of environmental psychology. It explores how to use the results of soundscape research in aiding the design process of urban open spaces with regard to the sonic environment. It is based on common notions that the acoustic aspect of urban open spaces should be considered in the same way as the visual dimensions.

The determinant of a soundscape is subjective evaluations, which depend on two acoustic aspects; one is the sound noise scales and the other is the effects of various sound sources. Based on data collected from a series of field studies and laboratory experiments, the subjective evaluations of sound-level and sound preference have been separately studied using statistical analyses, and the overall evaluations of soundscape and acoustic comfort have been examined. In order to provide a feasible tool to aid soundscape deigns, the study develops a modelling tool, namely artificial neural network (ANN), to present the subjective evaluations of potential users at the design stage. Based on the ANN models, soundscape maps can be produced.

The results of statistical analyses suggest that various factors influencing the subjective evaluations of sound level, sound preference and acoustic comfort are different in terms of a variation among case study sites and noticed sounds. Generally speaking, sound physical and psychological characteristics have the most influence on the subjective evaluations. The subjective evaluations of other physical environments are also much relevant to the soundscape evaluations, whereas social/demographical and behavioural factors are insignificant although some relationships have been found for certain factors. In addition to giving useful guidelines and information to soundscape research and design, the results are also crucial in selecting input variables for ANN prediction models.

For ANN model predictions, it is found that a general model for all the case study sites is less feasible due to the complex physical and social environments. Practical models for certain type of urban open spaces are more reliable. The performance of acoustic comfort models is considerably better than that of sound level models. It is also found that the key variables to determine the prediction performance of sound preference models are sound meanings and the sounds' physical and psychological characteristics. Furthermore, the prediction maps based on ANN models' outputs have been successfully produced in presenting the potential users' appraisals of a soundscape in developing urban open spaces.

# Acknowledgements

Firstly I wish to express my sincere appreciation to my supervisor, Professor J. Kang, for his valuably supervising and instantly encouraging me since my MSc study.

I would then like to thank my colleagues, Dr. M. Zhang and Dr. W. Yang for their supports and useful discussions in the whole study. It has been a pleasure to work with them as well as other colleagues, Dr. Y. Meng, Dr. C. J. Yu, B. Wang and H. Xie, in the acoustics groups of Sheffield University. I also enjoyed the time having spent with the interviewees in the Shanghai surveys for their cooperation.

My appreciation is also given to Dr. R. F. Harrison and Dr. K. Triantafyllopoulos for their professional support in the interdisciplinary parts of this study. I specially appreciate the helps from my friend S. Payne for the important discussions.

I am greatly indebted to my friends, Dr. A. Orrell, L. Cresswell, S. Payne, P. Allum, S. Bayliss, N. Awan, and ELT staffs who proofread my thesis and publications.

Last but not least, my deepest gratitude goes to my mother, my father and my sister for their understanding, encouragement and support.

# Table of Contents

## List of tables

# List of figures

# Abbreviations

| | |
|---|---|
| ADALINE | Adaptive Linear Neuron |
| ANN | Artificial Neural Network |
| AI | Artificial Intelligence |
| BP | Back Propagation |
| CV | Cross Validation |
| EDT | Early decay time |
| GA | Genetic Algorithms |
| JdP model | Jardin de Perolles model |
| MADALINE | Multi-layered Adaptive Linear Neuron |
| MLFF | Multilayer Feed Forward |
| MLP | Multi Layer Perceptron |
| MSE | Mean Squared error |
| PEs | Processing Elements |
| RMS | Root Mean Square |
| RT | Reverberation time |
| RUROS | Rediscovering the Urban Realm and Open Spaces |
| SANN | STATISTICA Automated Neural Networks |
| SPL | Sound pressure level |
| UOS | Urban Open Space |

# Chapter 1

# Introduction

## 1.1 Background

Nowadays, in order to obtain social well-being, high attention is paid to the comfort of physical environment (i.e. thermal, light, view, and sound environment) in urban open spaces. As an important part of physical environment, a significant amount of effort has been made to reduce the noise level within cities in past few decades; however, this has been proven to not always be efficient in providing a desirable sound environment especially in urban open spaces. From the prospective to ecological development, new contents have been rethought in building urban open spaces, where soundscape study is considered as an important complement in constructing social-well being in an urban open space.

Coined by Schafer 1960s, the term 'soundscape' is to describe the relationships between sound sources, aural responses, acoustic environments and its social contexts (Schafer, 1977). Similar to landscape, soundscape refers to the relationships between people, places and sounds around them. As it is concerned with the sound sources and the way people respond to sound, soundscape study and design is being paid more attention than noise attenuation by acousticians and social scientists. Nevertheless current acoustic strategies of outdoor space are mainly under the noise management paradigm, and the practice of soundscape designs and plans is far beyond which more effort needs to be made (Kang, 2006a; Schulte-Fortkamp, 2002).

In order to provide a satisfactory soundscape in urban open spaces, acoustic design is the premise while the subjective evaluation is crucial, which is determined by various physical and social factors. However, the subjective evaluation of soundscape is rather complicated as it not only relates to acoustic characters, but also other physical attributes as well as a user's social characteristics. As soundscape designs or plans are concerned with providing a desirable acoustic environment rather than a quiet world, delightful sound sources and the ecological 'scape' the sounds formed should be protected. In the meantime, the level of ambitious sound should be avoided or attenuated. The quality of a soundscape is mainly dominated by two factors: one is the level of sounds; the other is the sound preference. For the sound level, noise annoyance is the main sensory response, whereas for the individual sound, many sensations could be elicited, such as preference, noisiness, comfort and pleasantness.

Soundscape design is founded on the notion that the acoustic dimensions should be subjected to the design in the same way as the visual ones. However, there is an insufficient link between soundscape research and practical designs as lack of feasible tools at the design stage. Therefore, this study is going to explore a modelling approach for soundscape design/plan in urban open spaces based on a large scale social surveys and complementary laboratory study.

## 1.2 Aims and methodology

The main aim of this study is to use artificial neural network models to predict the subjective evaluations of soundscape, including the sound level, acoustic comfort and sound preference, in order to provide a communication tool for designers or planners of urban open spaces to understand users' requirement of a sonic environment.

To achieve this aim, the study is specifically focused on the following objectives:

(1) To investigate the relationships of various factors from physical and social aspects on the subjective sound level evaluations of the sound level, comfort evaluations of soundscape, and the preference evaluations of sound sources. This can be used for providing guidelines for soundscape researches and designers.

(2) To predict the subjective evaluations of sound level, acoustic comfort and the sound preference.

(3) To explore an approach of using prediction maps to connect designers/planners to the space users at the design stage.

Correspondingly, a system is expected to be established to minimise the differentia of planners/designers' ideas and user's perception.

This study may contribute in solving the contradiction between decision makers and spaces' users. It will provide an approach that could give an opportunity for users to involve in a place design which they are supposed to use.

The study is based on a large scale social surveys and complementary indoor experiment. It explores a broad range of factors that have an effect on the subjective evaluations of soundscape. In total, data which was collected from nineteen case study sites as well as laboratory experiment[a] were systematically analysed using statistic analyses. For the evaluations of the sound level and acoustic comfort, factors of sound pressure level, thermal, light element, subjects' social/demographic and acoustic experience background, on-site behavioural status, and psychological circumstance were examined; whilst for the subjective evaluations of sound preference, sound meanings and psychoacoustic influence have been considered for three kinds of sound: namely natural, human and mechanical sounds.

---

[a] The data used in this study come from 14 case study sites of RUROS project, two case study sites of a project in Beijing, three case study sites in Shanghai and laboratory experiment; the author did the surveys in Shanghai and the laboratory experiments.

Furthermore, this study explored Artificial Neural Network (ANN) techniques, and software packages Qnet and NeuroSolutions were introduced and employed to make ANN models. The input variables for ANN models were selected based on the significance results from the statistical analyses of the 19 case study sites and laboratory experiments. Consequently, based on the prediction results from ANN models, a mapping method was proposed to make useful tools in aiding designers or planners at the early designing/planning stage.

## 1.3 Thesis structure

This thesis is divided into eight chapters, including one chapter of introduction (Chapter 1), literature review (Chapter 2), methodology (Chapter 3), statistical analyses (Chapter 4 & 5), ANN prediction models (Chapter 6 & 7), and conclusions and future works (Chapter 8).

Chapter 2 reviews the literature of soundscape research and acoustic comfort in urban open spaces; it also discusses the relevant studies of environmental psychology and the computer simulation technique of ANN.

Chapter 3 focuses on the methodologies employed in this research. The chapter starts with description of the field studies, social surveys, and laboratory experiments, followed by a discussion of statistical analyses and ANN techniques that used in this research.

In Chapter 4 and Chapter 5, the subjective evaluations of sound level, acoustic comfort and sound preference are systematically discussed. In Chapter 4, following the preliminary field studies and laboratory experiments, the influence of various factors on the subjective evaluations of the sound level and acoustic comfort are statistically analysed. Also based on field studies and laboratory experiments, Chapter 5 examines the influence of various factors on the subjective evaluations of sound preference corresponding to three kinds of sounds, namely natural, human and mechanical sounds. In addition to contribute to the soundscape research and provide useful guidelines for the design of urban open spaces, the results detailed in Chapters 4 & 5 are important in selecting input variables for building ANN models in the following Chapters, 6 & 7.

Chapter 6 is dedicated to the process of building ANN models to predict the sound level and acoustic comfort evaluations. It also develops practical models for certain types of urban open spaces according to their locations or functions. Chapter 7 explores the development of models for predicting the subjective evaluations of sound preference for three sounds, namely birds, human speech and passing car. Based on the ANN models' prediction, an approach of mapping potential users' evaluation of soundscape has also been addressed in Chapters 6 & 7.

Chapter 8 is the end of thesis, in which a summary is given to draw all findings of this study together. It serves not only as a conclusion but also as a discussion for further applications of using ANN models in predicting subjective evaluations of other physical environments. Further discussion of using ANN prediction maps in building social well-being environment for urban development has been made. This chapter also discusses the potential use of ANN prediction maps in design and evaluation of open spaces in urban context.

## Chapter 2

# Literature Review

This chapter reviews the relevant literature in researching the subjective evaluations of soundscapes. Artificial neural network (ANN) theory and its applications are also reviewed. It begins with a description of urban open spaces, followed by a discussion of the physical and social environment in urban open spaces and its research methodology, environmental psychology, and then concludes with introductions of a new technique, ANN, in studying the soundscape in urban open spaces.

## 2.1 Urban open spaces

"*If you sit in one of the squares in the middle of Paris, no matter how small, you will be reminded of how much the design of public space affects life in the city*" (Aasen, 2002).

### 2.1.1 Definition of urban open spaces

Our collective perception of a city comes from the territory of open spaces. Currently, urban open space is considered important in improving social-well beings in a city; however, what is urban open space? Generally speaking, urban open spaces are the spaces left out by the buildings or constructions in a city.

As Gold (1980) described, open space is land and water area which is not covered by cars or buildings; Tankel (1963) suggested that open spaces are spaces above the uncovered lands, while Cranz (1982) also argued that open spaces are wide – open areas that can inter-flow into the city. However, in a view of users, urban open space is just a place where they can converse with others and escape from confined spaces which they are forced into. Correspondingly, urban open space is defined as being an arena that allows for different types of activities encompassing necessary, optional and social activities, which adds more social effects to an open space over its physical aspects (Gehl, 1987).

In our imagination, cities are more occupied by open spaces than by the buildings surrounding them. Just as Walzer (1986) suggested *"Public space is space where we share with strangers, people who aren't our relatives, friends or work associates. It is space for politics, religion, commerce, sport; space for peaceful coexistence and impersonal encounter"*. The most well known definition of urban open space relating to its use was developed some thirty years ago, which categorized the urban open space as public, semi – public, semi – private and private (Newman, 1972).

### 2.1.2 Development of urban open spaces

Historically, urban open spaces were used for many purposes such as religious or commercial events e.g. the temple square and market square in the Middle Eastern cities of 4000 years ago (Taylor, 1979). In the medieval time, the town square or piazza was often the heart of a city where people went to buy food, collect water, hear the news, talk politics, or watch the world going by (Marcus & Francis, 1997). Urban open spaces were described in the past only in terms of their size and dimensions. Today, that is a limited definition because the social use of open spaces has changed radically. Public life is being encouraged and reconstituted in the modern urban context. Faneuil Hall Market Place and Harbour Place are good examples of having lively public life in Boston and Baltimore (Lennards, 1987). In order to revitalize cities and towns, urban open spaces is vital in promoting a sense of well-beings for the inhabitants.

Nowadays, urban open spaces are complemented by new facilities such as recreation grounds and walking paths. Physically, open spaces can be defined by their legal ownership and boundaries, or socially, by activities of users (Schaudinischky, 1976). With many functions added, current urban open spaces are characterized by a term of 'either /or'. Urban open spaces are becoming more indeterminate spaces of possibility. Our understanding of public space has been becoming blurred. Urban open spaces can no longer be a quite clearly defined. Traditional images of urban open spaces have been modified. However, no matter how they have been changed, modern urban open spaces have their own meanings focusing on social activities and environmental qualities determined by an interaction between users and surrounding environments. Urban open spaces are not characterized merely by their original functions, but defined as a platform for activity.

### 2.1.3 Roles of urban open in modern city

With the speed of urbanization in 20$^{th}$ century, metropolitan cities emerged in our society. In the early 19$^{th}$ century, London was the only city in the world with a population of one million; however, by 1990 the world's largest 100 cities had a combined population of 540 million, 220 million of these live in the twenty largest cities (Girardet, 1996). It is expected that by the year 2025 half of the global population, approximate three billion people will be living in the cities (UNCHS, 1996). Unsurprisingly, quality of life in a city is an important issue for urban development, and becomes a more pressing concern with the emerging problems of crowding and air, light and noise pollution.

Nowadays, with renaissance of city centre, urban open spaces are re-conceptualized with "the new urbanity", re-migration to inner cities (Häußermann & Siebel, 1987). Urban open spaces are therefore rethought firstly from a historic perspective, and later from an ecological and urban renewal point of view. This process moved forward rapidly because of increasing use of urban open spaces by city-dwellers, who are looking for a more active form of urban living and leisure. The wild spaces experience in contrast to high-speed urban life experience is becoming more interesting to today's urban residents' life (Maorphet, 1994).

Urban open spaces in modern cities are supposed to provide good quality of life for urban citizens. Surely, people who use these spaces do not spend hours discussing definitions of the types of spaces they are using, but they do value and 'own' such spaces .They use them as part of their daily life, thus these spaces contribute greatly to an individual's and a community's quality of life in the urban context. There are a wide range of reasons for people using different types of open spaces at different stages. As children, playing games is the main aim in an urban open space; whereas quiet gardens and parks may be important to old people. If working in the city, opportunities for lunchtime breaks in plazas, squares or green spaces may help relieve the daily boredom, whilst transport corridors become increasingly important to those who spend many hours a day travelling. Different social groups get their own social benefits and opportunities in different types of open public spaces, which are themed as children's play, passive recreations, active recreation, community focus, cultural focus and educational opportunities. All these benefits can contribute to physical and mental health, termed as social well-beings, in contemporary cities (Woolley, 2003).

### 2.1.4 Constructing urban open spaces

Undeniably, urban open spaces play a relevant role in people's daily lives. They are places to create pleasure for urban societies which guarantee both its public character and its individuality. These spaces relate to urban "civilization" and have both social and physical environmental impacts. It requires urban planners and architects to provide enough quality open spaces in their planning and designing. The requirement varies according to the different users who are determinant factors for addressing location and function of an open space.

Primarily, urban open spaces have the potential to enhance citizens' physical and mental health, and so benefit our societies in a city. To build urban open space is not only to create physical surroundings but also how these surroundings communicate with the human subjects. New urban open spaces require the decision makers to consider both social activities and physical surroundings. Social activities may include children's play, greetings and conversations, communal activities and passive activities (e.g. watching, reading and communication), which take place only when the physical settings and environmental qualities are acceptable to participating individuals.

The design and management of urban open spaces can have a clear impact upon our societies. It has been confirmed by many researchers that there is a relationship between environment and behaviour, and whether it is conscious, this relationship has a beneficial or detrimental impact on both individuals and societies (Marcus & Francis, 1997; Greenhalgh, 1996). Developing open spaces needs to meet the corporate objectives of the authority in terms of regeneration, education and improving health and the quality of city dwellers lives (Greenhalgh, 1996). Urban open spaces are indentified by urban planners, left by building architects, and in order to provide a delightful space, landscape architects and environmental engineers have to work together to fill these spaces taking the physical and social environments into consideration.

Soundscape is 'scape' formed by interaction of the sound environment and its user psychological responses. It is an important socio-physical environment in the urban open spaces. Consequently, this thesis will study subjective evaluations of soundscape in urban open spaces. It is based on the notion that the auditory perceptions should be taken into account in the same way as the visual perceptions in constructing urban open spaces.

## 2.2 Physical social environment and its study method

For urban open spaces, subjects' physical comfort is affected by social, physical environment and the relationships between them. In order to study how to achieve physical comfort in an environment, it is essential to understand this physical-socio world.

### 2.2.1 Physical and social environment

First of all, what do physical and social environments include? The physical environment is usually composed of buildings, parks, streets, bodies of water and the atmosphere enclosed by these physical elements and physical items (e.g. climate, lighting, sound). The social environment is generally formed from the subjective character of individuals inside an environment, such as their demographical factors, culture background, and presently activity or psychological status. In the interactions between these two environments, individuals change the physical environment and at the same time their behaviour and experiences are changed by the physical environment conversely (Gifford, 2002).

### 2.2.2 Physical and social environment in urban open spaces

The city is a big environment; urban open spaces are a cluster of spots within it. With cities developed from ancient villages into modern megalopolises, dramatic population growth is seen as a crisis which will threaten the future of mankind (Bell & Tyrwhitt, 1972). Problems caused by density, industrialization and the increased use of cars in the modern city and therefore affect on social behaviours, are drawing more and more attention. A harmony between physical and social environment is therefore urgently to be achieved in a city especially in the city's activity spots - urban open spaces. However, the challenge is how to obtain individuals' physical comfort whilst respecting the natural environment. In order to achieve the goal of individual physical comfort in urban open spaces, the physical environment including thermal, light, visual and sound has to be considered as a whole.

### 2.2.3 Visual, thermal, lighting and sound environment

Numerous studies are related to visual comfort and most principles have been incorporated into design (Kooi & Toet, 2004; Fisher-Gewirtzman, Burt & Tzamir, 2003; Lozano, 1974; Bedwell, 1972). For example, human perception of various forms and colours has been considered in the design processes and knowledge is expanding with regard to good visual design.

Thermal comfort has also been broadly studied, and specific models have been proposed (Nikolopoulou, Lykoudis & Kikira, 2004). Details of temperature have been specified, wind-speed and humidity affecting thermal sensations either in a macro or micro environment (Lechner, 1991). For lighting comfort, glare is a significant issue influencing comfortable sensation which has been serially studied (Bennett, 1977; Tuaycharoen, 2006).

In the field of sound comfort, original studies focused on noise 'control' or 'abatement'. Noise management is the current paradigm for the acoustic environment. Most authors argued that noise reducing is not the way to provide sound comfort, instead discovering the aesthetic principles of sound environment can really improve the subject's aural comfort (Schafer, 1977; Kang, 2006a; Berglund, Lindvall & Schwela, 1999).

**2.2.4 What is environmental psychology?**

In order to study the interactions between social and physical environment, environmental psychology has been developed to solve problems caused by individuals and physical environment (Fisher, Bell & Baum, 1990). It is the study to make sure human's long-time impact on the environment is much more beneficial than harmful, and it searches for human satisfaction in response to the physical environment.

The field of environmental psychology may be traced back to the history of psychology. It emerged in the later half of the 1960s as a problem-focused discipline, responding to practical questions posed by architects and planners about real-world design decisions. In the early 1970s, environmental psychology was borne along on the first massive tide of environmentalism.

Environmental psychology has been defined as the discipline concerned with relationships between behaviour and the physical environments (Heimstra & McFarling, 1978); and also characterized as " the attempt to establish empirical and theoretical relationships between the behaviour and experience of the person and his built environment" (Proshansky, 1976). Environmental psychology is very concerned with the environment as a determinant or influence on behaviour and mood and the consequences of behaviour on the environment, more broadly, with larger scale environmental problems such as pollution, recycling and ecosystem issues (Heimstra & McFarling, 1978; Gärling & Golledge, 2003).

In the Handbook of Environmental Psychology, Stokols and Altman (1987) described it as "the study of human behaviour and well-being in relation to the socio-physical environment". It is also similarly narrated by Russell and Snodgrass (1987) as the "a branch of psychology concerned with providing a systematic account of the relationship between a person and the environment". Briefly, environmental psychology includes research and practice aimed at improving the process by which physical spaces are designed. It can contribute useful methods to study soundscape perception in urban open spaces.

### 2.2.5 Theories of environmental psychology

The theories of environmental psychology are classified as the Person Centred Theories: the environment viewed as a tool to support human goals; the Contrasts Theories: concentrating on preserving, conserving, and helping the natural environment; the Adaptation Theories: assuming a certain level of environmental stimulation as common, too much or little stimulation is the focus of arousal, overload, under-load, and stress theories that predict that a wide range of behaviours and experiences will be affected (Gifford, 2002).

Initial theories of environmental psychology have offered programmatic methods on the researches of crowding, cognitive development, environmental preference and spatial behaviour. The research methods of environmental psychology are known as experimental, correlational and descriptive (Fisher et al., 1990), which is different from psychology where laboratory is typical research method for many other research psychologists (Judith 1978).

A number of approaches have been established in the environmental psychology area to address the nature of the mechanisms that link people and environments, such as observation of behaviour, using interviews' questionnaires, and through analyzing historical and cross-cultural examples to trace patterns, regularities, and constancies etc (Mehrabian & Russell, 1974). Perception is designated as the information reception and processing of environment surrounding an individual (Gibson, 1986). Therefore, questioning subjective evaluation of physical environment is the direct way to obtain subject's perceptions.

However, no matter what theories or approaches are used, the final destination of socio-environmental study is to explore the subject's reactions of the environment and how the environment could be affected by the reactions (Gifford, 2002).

### 2.2.6 Environmental and noise stress

In contemporary cities, environmental stress is a big issue for environmental psychologists. The definition of stress is a psychological precursor of illness or as a catchall for anxiety reactions, discomfort, and the like (Baum, Singer & Baum, 1982). Although our bodies can cope with stress, repeated instances of adaptive demand under long-term exposure to stress can lead organism' depletion and cause physical dysfunction. Therefore, appraisal of stressors is very important in environmental research which has been systematic studied by Selye (1978) in his *General Adaptation Syndrome* (GAS).

In environmental psychology research, noise is widely regarded as a potential environmental stressor that has been specifically studied by various authors (Cohen, 1980; Glass & Singer, 1972). Tracor (1971) found that compared to physical indexes of noise, several attitudinal measures were more correlated with individual's noise annoyance. Moreover, Davis (1975) notes that noise level alone can only explain from one-tenth to one-third of annoyance. In a recent soundscape research in residential area, Schulte-Fortkamp (2006) pointed out there is an urgent need for modifying the current noise protection legislation by combining soundscape analysis.

### 2.2.7 Statistics

Mathematical statistics are commonly used in environmental study. It emerged from probability theory, which can be dated to the correspondence of Pierre de Fermat and Blaise Pascal (Mahoney, 1973). Christian Huygens gave the earliest known scientific treatment of the subject, while Abraham de Moivre (1756) treated the subject as a branch of mathematics.

The theory of errors may be traced back to Cotes's Opera Miscellanea (Cotes & Matsko, 1768), but a memoir prepared by Tipper and Simpson first applied the theory to the discussion of errors of observation (Tipper, Beighton, Heath, Simpson, Rollinson, Hutton, & Gregory, 1835). In 1783, Daniel Bernoulli introduced the principle of the maximum product of the probabilities of a system of concurrent errors (Bernoulli, 1954).

The method of least squares, which was used to minimize errors in data measurement, was published independently by Legendre (1805), Adrain (1808), and Gauss (1809). Gauss had used the method in his famous 1801 prediction of the location of the planetoid Ceres. Quetelet and Beamish (1839) introduced the notion of the "average man" as a means of understanding complex social phenomena. All mentioned theories and concepts are fundamental to the statistical analyses which will be used in analysing the collected data of field surveys and laboratory experiments in the late chapters of this thesis.

As one of several socio-physical environments, soundscape went into a range of research areas interested in sound environment. It appears that soundscape research is within environmental psychology realm, and statistics are the essential way to study it.

## 2.3 Soundscape

"*Sounds become soundscape when they are heard through the experience of everyday life*"; "*Soundscape is generated by the integration of sounds, time, place, era, fashion etc.*" - Schafer (1977).

### 2.3.1 What is soundscape?

With more attentions being paid to the urban environment, sounds and the 'scape' formed by them are attracting additional concerns than anytime in our society. The concept of soundscape can be tracked back to 1960s when Schafer (1977) coined this term in his book '*The Tuning of the World*'.

'Soundscape' specifically refers to a subjective sonic environment with an emphasis on the way the sounds are perceived and understood as a whole physical phenomenon by the individual, or by a society (Schafer, 1977). Various authors have defined the soundscape in different ways with concerning on its differential aspect; for instance, musicians thought soundscape is a cross-section of music domains (Schelemay, 2001); acousticians defined soundscape as a mix of ambient sounds and sound effects to create an aural environment (Traux, 1978); while linguists argued that soundscape are the subjective effects of complex sounds relying on semantic attributes (Dubois, Guastavino & Raimbault 2006). No matter how many different definitions there are; soundscape may be considered as an acoustic environment constituted by the mix of sound effects interacting with human's aural perceptions across some time and space. It contains sounds which have both physical and social aspects.

The history of soundscape can be seen as a history of aural culture. A soundscape has more to do with civilisation and is always undergoing change. As an aural landscape, a soundscape is simultaneously a physical environment and a way of perceiving that environment; it is a 'scape' combining both the physical world and the social environment formed by the cultural construction (Thompson, 2002). The physical aspects of a soundscape consist of not only the sounds, the waves they generated and the energy they penetrated into the atmosphere in which people live, but also the material objects that create those sounds and the effected space. The cultural aspects incorporate technical and aesthetic ways of listening, a listener's relationship to his environment, and social circumstances dictating who gets to hear what (See Barry Truax, Acoustic Communication). Soundscape exist in parallel, the acoustic and the perceived. The former is assessed by physical measuring instruments (acoustic properties) and the latter by perceptual scaling methods utilizing persons (perceptual features).

### 2.3.2 Development of soundscape along with noise control

Ever since human beings entered the industrial era, noise has become a big pollution problem in modern cities. Efforts have been made to noise control, but it has been proven not always efficient. Soundscape, therefore, has been promoted and entered the lexicons of a range of disciplines which educators are interested in (Traux, 1998).

Based on its concept, soundscape study is not limited to the engineering controls of noise but is also extended to enhance the sound aesthetic aspect. Schafer defined soundscape as the study of "acoustic ecology", describing it as "the scape on the physical responses or behavioural characteristics of creatures living within it" (Schafer, 1977). Soundscape study is to examine the effects of 'acoustic coloration' of the 'aural space' on individual's perceptions. Unlike visual space, aural space is non-locational, spherical and all-surrounding without obvious boundaries to emphasize a space (Yang & Kang, 2005a).

In the soundscape research field, the World Forum for Acoustic Ecology (WFAE) was founded in 1993, which is an ecologically balanced entity to represent the interdisciplinary study of scientific, social and cultural aspects of the natural and human-made sonic environment. Its journal, Soundscape – The Journal of Acoustic Ecology, was established in 2000, and then a number of national societies for acoustic ecology have been established (Whrightson, 2000).

### 2.3.3 Approaches of soundscape study

Undoubtedly, there is a growing interest in soundscape research in urban scope especially considering environmental and ecological development. Therefore, various authors have used diverse approaches to study soundscape over a range of disciplines for decades.

Since Torigeo introduced the term 'Soundscape' into Japan in 1980s, many Japanese musicologists, acousticians and philosophers have engaged in the soundscape research. Their study approach involved a large variety of disciplines connecting human sciences and acoustics (Torigeo, 1985). With their constant efforts, the soundscape concept has been translated from research area into design process and furthermore into education realm. After many years' preparation, the Soundscape Associated of Japan was eventually founded in 1993 (Hiramatus, 2006).

In Europe, multi-disciplines related to social, semantic, psychological, physical fields have been combined into soundscape research. Dubois et al. (2006) studied soundscape in a view of cognitive sciences. Berglund and Nilsson (2006) investigated soundscape quality by conducting on-site interviews in the Greater Stockholm. In his book "*Urban Sound Environment*", Kang (2006a) elaborated a systematic framework to study urban soundscapes. Moreover, Schulte-Fortkamp (2002), and Botteldooren and Coensel (2006) have used soundscape concept to cope with the environmental noise in communities.

Generally speaking, a person can gain two cognitions from a soundscape; one is the sound level perception of the background, and the other is the perception of foreground sounds. All approaches of soundscape study are therefore focused on dealing with the subjective perceptions of the level of background (also noise annoyance) or the subjective perceptions of foreground sound/s (sound preference). For the first perception, many studies have been intensively carried out and will be discussed in Section 2.3.4. Whilst for the second perception, characteristics of a sound will be more discussed in Section 2.3.5.

**2.3.4 Studies of noise annoyance**

It has been demonstrated by many studies that correlations between noise annoyance and the acoustic/physical factors are often not high. There are varied effects relating to social/demographic factors. Many other factors have also been studied, including income and economic status, general state of health, marital status, and the house size/type and family size, effect of length of residence, the time spent at home, and the type of occupancy. Noise experience, including exposure to noise at the place of work and over time, could affect residential noise annoyance as well as sleep process. Behaviour and habit is another important aspect which could affect annoyance, which includes, for example, opening and closing windows; using sleeping pills; using balconies or gardens; having their home sound insulated and frequently leaving for weekends. In a study over EU countries, $L_{eq90}$ is found to be an essential index to evaluate soundscape in urban open public spaces. It states that a lower $L_{eq90}$ value can make people feel quieter (Kang, 2006a).

Some evidence has proven that the study only focusing on the sound level attenuation is insufficient to reduce the noise annoyance and provide a good sound environment for communities (Brown & Muhar, 2004; Schulte-Fortkamp, 1996). As basic components, individual sounds also play an important role in determining the quality of soundscapes (Westerkamp, 2000).

### 2.3.5 Sound characteristics

As one essential way to perceive the world, sound with its visual counterpart plays an important role in determining the subjective aesthetic sensations of an environment (Schaudinischky, 1976). Technically, sound is a kind of waveform, a vibration in an elastic medium, and governed by some physical principles. It can be described by the term of frequency, a periodic event of the vibration, or by the parameter of sound pressure level.

Measurement of sound is based on sound pressure or intensity (Egan, 1988). However, human reaction to a sound is not just physical perception but also an aesthetic sensation which one receives from the environment (Gaver, 1993). Sound is a different subject to different investigators: to a sociologist, it is a stimulus to elicit subjective responses; to a physicist, it is a measurable phenomenon with varying propagation characters, to a structural engineer, vibration is the issue; to a mechanical engineer, it is noise control (Templeton & Sacre, 1997). No matter how many different aims exist for sound investigators, sound phenomenon can always be described by three parts: Source, Path and Receivers.

Because human beings are essential subjects to determine its effects, sound is also realized as a social element in our life. Apparently, sound effects on human's perception cause an informative aural sensation in our brains through the intermediary of the auditory mechanism (Moore, 1997). High intensity sound in prehistoric times was usually connected with some events which were threatening a life, such as the roar of predatory animals, a flash of lightning, eruption of a volcano. A comprehensive catalogue of the noises of nature that frighten human-beings can be found in Shakespeare's King Lear (ct Ш, Scene П).

For primary men, sounds were associated with danger, searching for food and tribal activities, and noise created by them was believed to be able to ward off wicked spirits. Many religious ceremonies accompanied by loud artificial 'sound phenomena' have remained to the present day. For examples, the custom of firecrackers on New Year eve in China is still popular for its intention of getting rid of evil; the tradition of breaking crockery on the wedding eve is performed in many German speaking communities; and also the breaking of a tumbler underfoot has also been a part of the Jewish wedding service (Schaudinischky, 1976). In these cases, sound is not only a physical phenomenon, but also a social context which is evolved with the development of human societies. The sound is created as an active function of helping people to change the original acoustic environment for the special purpose.

### 2.3.6 Soundscape in urban planning and design

In order to provide habitable environments, 'people' should be the top priority for architects (Kernohan, Gray & Daish, 1992). For decades, environmental researchers have made much effort to integrate their research results into architectural design. However, it is not easy to achieve such a goal, since many explicit and implicit factors are involved. Based on the notions of an ecological environment, the urban plan and design should take the acoustic aspects into account in the same way as the visual dimensions (Brown & Muhar, 2004).

Currently, a large body of practice and government authority has been involved in noise abatement or control. However, less effort has been made to acoustic design or soundscape planning. In contrast to noise control, soundscape planning is attempting to discover the principles by which the aesthetic qualities of the acoustic environment can be improved.

A good soundscape is achieved by reducing 'unwanted' sounds and supporting 'wanted' sounds. It is not always necessary to reduce the sound level to reach a better acoustic comfort, the characteristics of users, and other factors may play an important role in improving a soundscape when the SPL is below a certain value (Ballas, 1993; Gaver, 1993; Maffiolo, David, Dubois, Vogel, Castellengo & Polack, 1997; Yang & Kang, 2005b). Soundscape design seeks to provide a good sound environment based on the patterns of how sounds compose a wide array, in terms of cultural and cognitive processes, to the people inside it (Porteous & Mastin, 1985). Several studies have already been carried out of using the soundscape concept in environmental design (Hedfors & Grahn, 1998; Torigeo, 1993).

In order provide a delightful sonic environment, soundscape design is fundamental and the subjective evaluation is essential. The assessment of a soundscape is a part of sensory aesthetic research that is concerned with the sensory pleasure which one receives from the place he/she is located (Lang, 1988). The soundscape evaluation is a complex system, relating not only to acoustical and physical elements but also the subject's social and psychological factors (Kang, 2006a). From the point of view of users, the research of soundscape evaluations can provide essential guidelines to urban planners and designers, which is also one objective of the author's research.

## 2.4 Soundscape in urban open spaces

Previous researches in urban paradigm indicated that soundscape is playing an important role in determining the physical quality of urban open spaces (Ge & Hokao, 2004; Yang & Kang, 2005a&b; Zhang & Kang, 2007a). It was also argued that it is soundscape rather than noise annoyance that determines a community satisfaction of an acoustic environment, whilst the individual preference of foreground sounds in urban open spaces is important (Guastavino, 2006; Coensel & Botteldooren, 2006; Nilsson & Berglund, 2006).

### 2.4.1 Sound preference

Consistent efforts have been made by many authors to improve soundscape quality in open spaces (Bjork, 1985; Raimbault & Dubois, 2005; Kang, 2006a; Kull, 2006), which acoustic comfort is a criterion. Acoustic comfort in urban open spaces, however, could be better achieved by providing delightful foreground sounds with concerning the individual preference in a certain circumstance although the noise level cannot be ignored.

The importance of sound preference is being realized when making a decision of developing/redeveloping an urban open space, considering acoustic aspects. Natural sounds are more favoured in a comparison with man-made sounds, and sounds from traffic, construction or machine, are thought to be ugly and unwanted (Brown & Muhar, 2004; Yang & Kang, 2005a; Nilsson & Berglund, 2006). Southworth (1969) has studied the sonic environment in city centres and discovered that a cheerful sonic environment is also considerably associated with visual effects in urban open spaces. Moreover, many researchers have proved that aural and visual perceptions interact to contribute to human aesthetic sensations to an environment (Pheasant, Horoshenkov & Watts, 2008; Kang, 2006b; Fujiwara, 2006). Generally speaking, good views provide a better feeling to a sonic environment for human beings.

### 2.4.2 Studies of soundscape in urban open spaces

Because noise is not the only issue to impact individual's acoustic comfort in urban open spaces, efforts have been made in a broad way to cover various issues from social, acoustic and physical facets.

In Sweden, Nilsson and Berglund (2006) conducted questionnaire studies on soundscape quality in suburban green areas as well as city parks. Their results showed that a good soundscape could be reached when traffic noise exposure is below 50 dB while human sounds were generally not considered annoying but rather neutral or pleasant.

In Sheffield, UK, Yang and Kang (2005b) carried out an on-site study in open public spaces, and found considerable differences between the subjective evaluation of sound level and the acoustic comfort. A semantic differential study of soundscape has also been conducted in Sheffield by Kang and Zhang (2002). Their results showed that the subjective evaluations of soundscape in urban open spaces are complicated but several factors, including relaxation, communication, spatiality and dynamics, have been identified important.

In Japan, Ge and Hokao (2004) studied the sound environment in urban parks, and their findings suggested that except acoustic factors, many other factors which are from cultural, social and psychological aspects should be taken into account and brought into soundscape researches in public spaces.

There are other researches from Coensel and Botteldooren (2006) and, Brambilla and Maffei (2006), who involved their works of investigating soundscape quality in open spaces along the line of the European Environmental Noise Directive. Whilst Coensel and Botteldooren (2006) focused their works on characterizing soundscapes in quiet areas with multi-criteria assessments, Brambilla and Maffei (2006) conducted their works on finding the congruence of the subject's hearings with the sound environment, and found that the more congruent it is, the less annoyance is evoked.

Acoustic design of open public spaces is rather different from noise control as it approaches sounds as sustainable resources; ones whose depletion or degradation has to be avoided, which in another word is to mostly achieve delightful sounds and avoid nuisance noise (Brown & Muhar, 2004). Soundscape design of urban open spaces should be based on understanding people's general perceptions of the sonic environment surrounding them. Soundscape quality will be increased when incident sounds are novel, informative, and responsive to personal action or culturally approved.

**2.4.3 Aural and visual interactions**

Because aural and visual sensations are fundamental for a person to experience the world around them, their interaction is crucial to the study of soundscape evaluations in urban open spaces. Using natural/semi-natural settings in urban green spaces, Carles, Barrio and Delucio (1999) researched the sound effects in the landscape and their findings suggested that sound could provide additional information to visual images where the conservation of sound environment is essential. Their results also showed that on a landscape value, there is a rank of preference from natural to man-made sounds with information content or meaning of the sound.

The study of sound function in blind and deaf people suggested that sound has important social and psychological influences in our living spaces. Blind people rarely develop stable images of a space but at best have images of common trips, whereas for deaf people, the whole space seems unchanged and could become boring since no sound evoke attentions and loss of sound cut their links with their lives (Southworth, 1976).

As close interaction exists between aural and visual effects, a number of studies have been made of the visual effects of carrying sound meanings (Sekuler, Sekuler & Lau, 1997; Zetzsche, Röhrbein, Hofbauer & Schill, 2002; Watanabe & Shimojo, 2002; Shin, Ji-Hyeon, Chan & Sun-Woo, 2007; Alais, Burr & Carlile, 2007). The soundscape study would be most valuable if it could be made in a similar way to visual representations. As such, Kull (2006) produced a continuous soundscape spectrum from purely natural to extremely urban context analogous to the visual light spectrum. Consequently, soundscape combined with landscape has been identified as a main dimension to determine an environmental aesthetic quality in urban open spaces, which is judged by the aesthetic response of mixed feelings of pleasure, excitement and relaxation (Nasar, 1989).

### 2.4.4 Subjective evaluations in the soundscape design

In urban design processes, it has been found that the sound field of a complex urban space is generally similar to that of the typologically classifiable forms, for instance, the SPL is very much related to the shape, size, opening and material of the typologically classifiable forms (Kang, 2000; 2001; 2002). Thus, the sound level distribution can not be ignored when considering individual sound effecting; however, when the sound level is not excessive or dominant, individual sounds may play an obvious role.

Intentionally designed elements of pleasing sound can generate aesthetic aural perceptions for the space's users. Soundscape design in urban open spaces is more emphasized on emotional than stressful terms. Consequently, understanding users' appraisals of a soundscape in an urban open space is essential in the design process, where the agreement of the design criteria with the subjective evaluation of soundscape is important. The subjective evaluation of soundscape is one kind of subjective responses to the whole physical environment in urban open spaces.

When designing urban open spaces, a sustainable ecosystem is required. This will be achieved only if urban planners/designers understand the requests of users – the subjective evaluations in advance. The policy of developing an urban open space should reflect public requests and integrate them into the space's topological and morphological forms whilst respecting its historical evolution.

In the short term, acoustic comfort seems not that urgent in a space's plan/design; but a serious problem might be caused by it after the space used for long-term, and this could cost more to repair than initially imagined; for an instance, a quiet workplace can support healthier workers taking fewer sick days to bring up more profit for the company, even if it costs more money to make a quiet environment (Cohen & Weinstein, 1982). The key point of providing a good soundscape in urban open spaces is to invest for our future generations. Acoustic comfort in urban open spaces can benefit mental health and cognitive development for citizens, economic relationships of social and physical environment, and ecological development of a city. A good soundscape should tie a sonic environment together with social well-beings.

### 2.4.5 Relationships amongst various aspects

The relationship of urban open spaces, space's users, the soundscape evaluations and design-makers can be briefly described in Fig. 2.1. It shows the relationships between various stakeholders in determining the soundscape designs in urban context.

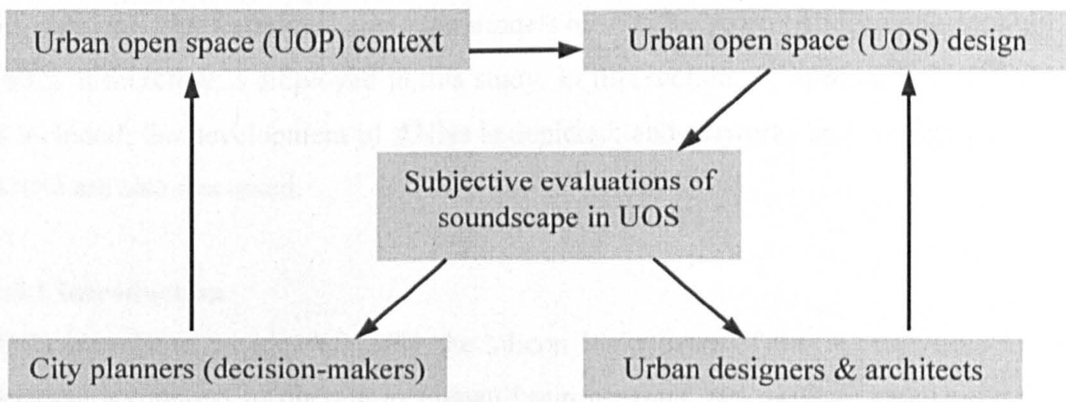



*Fig. 2.1 The role of subjective evaluations of soundscape in urban design/planning*

The study of subjective evaluations of soundscape in urban open spaces provides information to the decision makers. Meanwhile, urban designers or landscape architects design a soundscape based on the users' requirements. After the space has been designed and built, it is used and evaluated by its users, and the post occupied information should be returned back to the decision makers. In sum, the users determine which soundscapes are appropriate for them, while the urban planners/designers decide who are suitable to use some urban open space in terms of different soundscape qualities. Based on the users' group, the locations and functions of urban open spaces can be furthermore assigned.

## 2.5 Artificial neural networks (ANNs)

Whilst the subjective evaluation of soundscape should be imported into the design/plan process of an urban open space with respect to acoustic effects, there is lack of a bridge to link the user's appraisal with the design communities. A cyclical system as shown in Fig. 2.1 is needed to qualitatively assemble and manipulate the quantitative data from on-site studies in order to deliver useful information to the decision-makers. This may be achieved by the implementation of a computer simulation to predict the soundscape evaluation in urban open spaces, for examples, Yu and Kang (2005a&b; 2006; 2007; 2009a) suggested that models based on ANNs are useful to make predictions for helping urban planners/designers in soundscape design.

Benefitted by the method of mimicking brain work patterns, ANNs are able to solve the problems that traditional computer models have failed to do (Anderson & McNeill, 1992). It therefore is employed in this study. In this section, an introduction of ANNs is included; the development of ANNs is depicted; and networks and configuration of ANNs are also discussed.

### 2.5.1 Introduction

ANN introduces an idea of using the silicon logic gates of the microprocessors in personal computers to operate as human brain neurons. Neurons are small cells that receive stimuli from multiple sources and respond by generating electrical impulses which are transmitted to other neurons. A biological neuron is composed of a nucleus, a cell body, numerous dendrites links providing input "connections" from other neurons through synapses, and an axon trunk that carries an action potential output to other neurons through terminal links and synapses.

Approximately 10% of the neurons are input (afferent) and output (efferent). The remaining 90% of neurons are interconnected with other neurons which store information or perform various transformations on the signals being propagated through the network. The connections between two neurons are made through two general types of synapses: excitatory and inhibitory. Neuronal activity is related to the creation of an internal electric potential called a membrane potential depending on its neural construction. This potential may be increased or decreased by the input activity received from other neurons through the synapses. If the cumulative inputs raise the potential above a threshold value, the neuron "fires" by propagating a sequence of action potential spikes down the axon to either excite or inhibit other neurons, and then sends a message to other neurons.

Following the neuron's "firing", there is a silent period lasting about 10 ms during which the neuron cannot fire again (Patterson, 1996). The development of biological synapses has been described as being synonymous with plasticity (referred to as "adaptive" in ANNs), which permits the brain to adapt to the surrounding environment (Sejnowski & Churchland, 1992). In this sense, neuron function can be modelled by a computer as a simple threshold function - activation function.

### 2.5.2 Historical perspective

ANN theory is based on the pioneering work of Ramón y Cajál (1911) who introduced the idea of neurons as structural constituents of the brain. The network was first established by McCulloch and Pitts (1943), who introduced a logical calculus of neural networks based on the theory of the processing unit. The McCulloch and Pitts network was improved in the neural learning process by Hebb (1949), who firstly suggested that connectionist architecture represents knowledge existing in distributed neuron assemblies, which is now known as "Hebbian learning".

The first computer simulations of ANNs were reported by Rochester, Holland, Haibt and Duda (1956) at the Dartmouth summer conference, which is now recognized as the official beginning date of Artificial Intelligence (AI). Rosenblatt (1958) developed the Hebb's model by introducing the normalization of weights to prevent unbounded growth in some synapse weights. The most accomplishment of Rosenblatt is the perceptron convergence theorem which stated that after a finite number of iterations the error between the target and the network function will reach a minimum state, i.e. the optimisation state. An alternative model was proposed by Widrow and Hoff (1988), who developed a simple neural element similar to the Rosenblatt's Perceptron model which is called ADALINE (ADAptive Linear Neuron). This model led to the networks of MADALINE –the first multi-layered neural network structure. In addition, Widrow and Hoff (1988) also introduced the least mean square (LMS) algorithm to formulate the ADALINE, which is a similar statistical structure to the perceptron, but differs in the nature of the training procedure.

The perceptron network, however, was seriously criticized by Minsky and Papert (1969) who argued capabilities and more importantly the limitations of the computational power of perceptrons and showed what logical functions the simple perceptrons could and could not compute. Consequently, most research funding for further neural networks was cut and all efforts were reduced. Later work by Grossberg and his colleagues focused on the mathematical dynamic properties of ANNs and this led to an important theorem on the global convergence of dynamic networks (Cohen & Grossberg, 1983). In addition, Hopfield (1982) used the concept of an energy function to formulate a way of understanding neuronal computation that had previously been reported as being problematic due to the credit assignment problem by Minsky and Papert. Such renaissance was continued by Kirkpatrick, Gelatt and Vecchi (1983) who developed the procedure of simulations for solving optimisation problems.

**2.5.3 Networks**

The idea provided a statistical approach of assigning credits to hidden neurons in multi-layered networks which were used by Ackley, Hinton and Sejnowski (1985) in the Boltzmann machine. One of the most important developments of recent neural network research is the discovery of a learning technique with the back propagation (BP) algorithm (Rumelhart, Hinton & Williams, 1986) to adjust the weights in multilayer feed forward networks (also referred to as multilayer perceptrons). A typical network of this model is shown in Fig. 2.2.

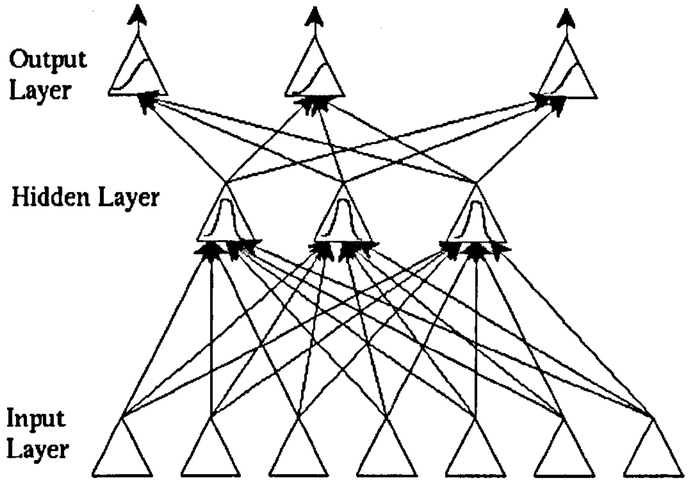



*Fig 2.2 Typical neural network (BP -back propagation) architecture (http://www.cs.stir.ac.uk/~lss/NNIntro/InvSlides.html#what)*

A multilayered BP network was highlighted as the best approach to use by Jones and Franklin (1990). Moreover, Maier and Dandy (1998) found that these networks performed better when the data to be modelled was derived for real – life applications, e.g. environmental modelling. Currently, the multilayer feed-forward (MLFF) network, also called Multilayer Perceptron, with BP learning is by far the most popular network to be used. Most of the other neural network structures represent models for "thinking" that are still being evolved in the laboratories (Anderson & McNeill, 1992). The basic structure units of this network are artificial neurons (called processing elements or PEs), which simulate the functions of natural neurons.

The more recent network other than MLFF is the neocognitron, which is a hierarchical feed forward network that learns through either supervised or unsupervised methods. Developed by supervised learning techniques, support vector machines were developed by lots of researchers (Boser, Guyon & Vapnik, 1992; Vapnik, 1998; Cortes & Vapnik, 1995).

Besides the problems which can be solved by the above networks, the remaining unexplored part is the problems of chaos. Freeman (1995) expected that chaotic dynamics can offer a basis for solving the problems of chaos. The chaotic dynamics describes the conditions that are required for self-organization of patterns in and amongst populations of neurons. Therefore, Freeman suggested that the next generation of neural networks will be able to learn highly chaotic systems such as those found in environmental modelling problems. Since $21^{st}$ century, the utility of ANN models has been broadly explored in many areas (Jayasundara, 2002; Huntingdon, 2003; Beltran et al., 2004; Farooq & Cherif, 2008); however, the theoretical development has been rather limited.

**2.5.4 ANNs configuration**

Functionally, artificial neurons are made up of three types of cells: input, output and hidden. Each of these input cells (x(n)) is multiplied by a connection weight. These weights are represented by w(n). If the cumulative inputs exceed a threshold, then the unit is fired and passes on an impulse to the response layer (hidden or output layers). Each input link i (i=1, 2, 3) has an associated input stimulus $x_i$ and a corresponding weight $w_i$–a sort of filter that is part of the linkage connecting the input to the ANN neuron.

Like the human brain, ANN models learn by examples. Adjustments to the synaptic connections between the neurons are important in the learning process in biological systems and the same learning process happens to ANNs as well. This 'learning' process lends itself to the physical implementation on a large scale, albeit in a small package, with utilizing different summing functions as well as different transfer functions (Anderson & McNeill, 1992). Correspondent to the flexible interactions between the perceptrons of layers (Haykin, 1994), artificial neural nets are 'dynamic' nets to be able of recognizing sequences in the real world. For ANNs, adaptive are achieved through learning algorithms that develop 'weight' and build up interconnections between the PEs. A weight is simply a floating-point number and is adjusted when comes to train the network. It can be either negative or positive to provide excitatory or inhibitory, and can be modified in order to minimize the difference between the desired response and the actual response of the network produced by the input signal regarding with an appropriate statistical criterion until there is no further significant change (Hecht- Nielsen, 1990).

Through a learning process, ANNs are able to predict pattern recognition or data classification. The learning function of MLFF network is usually nonlinear just as human brains. In ANN models, each PE is considered to be a binary threshold device with n inputs such as $x_1, x_2, \ldots, x_n$, and one output y, as well as n synaptic weights as $w_1, w_2, \ldots, w_n$ accounting for the different efficiencies. With these weights, the synapses can affect the neural learning's potentiality. Each input is multiplied by a corresponding weight, analogous to synaptic strengths. The weighted inputs are summed to determine the activation level which is relied to the learning functions. Then, the model can be summarized as $Y=f(\Sigma w_i xi- \theta)$, where f (.) is the unit step function, where the learning is to find a weight matrices w.

To generate satisfied models, ANN uses error function to represent the amount by which the output differs from the required output via iterative learning procedures. A concept of mean was defined for fault tolerance (Hecht – Nielsen, 1990). Under the supervised learning method, the mean squared error (MSE) between the network output and the desired response is calculated to adjust the network's accuracy. In sequence, for a particular problem, the network has learnt from the training examples by mapping the input-output patterns.

**2.5.5 Discussions**

It is improper to think that ANNs can do almost anything as the neural brain does. ANNs are relatively crude electronic models mimicking biological brains. The biological neurons are far more complicated with having over one hundred different classes of neurons with a myriad of parts, sub-systems, and control mechanisms. They convey information via a host of electrochemical pathways (Sejnowski & Churchland, 1992). "*It is estimated that the human brain contains over 100 billion neurons and more than 1000 synapses on the input and output of each neuron in its nervous system. Although the biological neurons operation is slower than silicon logic gates, which is* *on a scale of milliseconds ($10^{-3}$ s) compared to nanoseconds ($10^{-9}$ s), human neurons are super with its massive number of interconnections (estimated as 60 trillion connections) as it is more synonymous with plasticity, permitting the brain to adapt to the surrounding environment, than a computer*" (Shepherd & Koch, 1990).

Nowadays, advances in biological research promise an initial understanding of the natural learning mechanism, which is suitable for ANNs configurations (Mehrotra, Mohan & Ranka, 1996). Unlike the traditional computing programs, ANNs create massively parallel networks and trains them to solve specific problems (Anderson & McNeill, 1992). They are networks of highly interconnected neural computing elements that have the ability to respond to input stimuli, and then learn to adapt to the environment (Patterson, 1996).

## 2.6 Applications of ANNs in various areas

The applied fields of ANNs cover a range of issues from cloning human speeches, to commercial, scientific and engineering practices, as well as medicine and AI disciplines of pattern recognition (Bishop, 1995). It is even used in the sports area for equine breeding, auto racing setups, performance evaluations, handicapping and more. The very common applications of ANNs are classification, identification and prediction or diagnosis (Swingler, 1996).

### 2.6.1 Applications in medical and environmental area

In medical area, ANNs have been used to predict psychological reactions of patients admitted to accident and emergency (Jayasundara, 2002). In their study, Jayasundara compared ANNs with standard statistical techniques and the results showed that combined with Genetic Algorithms (GA), ANN models have been found to be the best ones to predict the patterns of psychological outcomes.

Many works of using ANNs to predict environmental pollutions have already been provided in recent time (Badran & Thiria, 1991; Boznar, Lesjak & Mlakar, 1993; Zhang & Stanley, 1997). Using ANNs to forecast colour at water treatment is one example (Huntingdon, 2003). Huntingdon's work explored ANN models to anticipate the colour of water located in upland peat catchments. His research showed that after careful consideration of the nature of modelling problem, the successful model could be made to forecast the water colour in different upland peat catchments.

### 2.6.2 Applications in building science

In building science area, ANN models have been used to diagnose structure-damage problems (Szewczyk & Hajela, 1994; Elkordy, Chang & Lee, 1994; Karunanithi, Grenney, Witley & Bovee, 1994), either to estimate construction-operation productivity (Chao & Skibniewski, 1994) or to predict design-building project performance (Ling & Liu, 2004).

It was also concluded by Vanluchene and Sun (1990) that ANNs might be able to solve three kinds of structural engineering problems: pattern recognition, a simple beam design, and a rectangular plate analysis. In structural engineering area, ANN models have been broadly applied to detect and monitor the structure performance by various researches (Tong & Steven, 2000; Chase & Aktan, 2001; Lee, Lee, Yi, Yun & Jung, 2005).

### 2.6.3 Applications in building acoustics

Nannariello and Fricke (1999; 2001a, 2001b&c; 2002) have carried out a number of works of using ANN models in building acoustic researches and also extended their works to the other architecture and building disciplines. They successfully established networks to predict reverberation time, which was as good as, or better than existing formulae (Nannariello & Fricke, 1999). Their study also explored to predict the acoustic parameters in concert halls (Nannariello & Fricke, 2001a&b), and to predict the speech levels in classrooms (Nannariello & Fricke, 2001c). The prediction of the early inter-aural cross-correlation coefficient ($IACC_{E3}$) for auditoria using ANNs is another achievement by them (Nannariello & Fricke, 2002).

Furthermore, a comparison of using ANNs with using the other computer simulations (Kang, 2002; 2004) in calculating reverberation time (RT30), early decay time (EDT) and sound pressure level (SPL), was made by Yu (2003).

### 2.6.4 Applications in design area

There is a broad application of using ANN models in the design area of textile manufactures (Cheng & Adams, 1995; Shamey & Hussain, 2003; Beltran, Wang & Wang, 2004; Farooq & Cherif, 2008). In the area of architectural design, however, ANN application is rather limited.

The application of using ANNs in the area of architectural design has been explored, and there have been some pioneering studies. For instance, Rebaño-Edwards (2007) tried using neural network approach to predict building quality at design stage. Based on the notions that people within a culture commonly share the similar attitudes of their buildings, they explored the capability of ANN models to anticipate potential users' evaluations for the qualities of un-designed buildings in terms of post-occupancy evaluations surveys as well. Boubekri, Yin and Guy (1997) employed it in solving a design problem of light shelf; and Fricke (1999) applied a neural network analysis to architectural design.

### 2.6.5 Applications in soundscape study

Besides to predict the physical acoustic parameters, ANNs have also been used to predict the soundscape quality in residential areas by Berglund, Nilssona and Pekalab (2004). In one of their researches in Sweden, ANNs were employed to diagnose green labelling degree of a soundscape via inputting 1/3-octave-band spectra to aural perceptions. Berglund et al. (2004) suggested a radial network to understand perceived soundscape both indoor and outdoor, and it was found that the well trained network could successfully diagnose the soundscape quality and be possible to classify and label soundscapes in residential area.

## 2.7 ANN software

The concept of ANNs has been discussed for nearly 50 years, but its applications have not been broadly developed to handle practical problems until the last 20 years. Corresponding to the objectives of this study, some software packages have been reviewed and examined in this section.

### 2.7.1 Qnet and NeuroSolutions

As their priority of multi-layered neural network (MLFF) structure with back propagation algorithms, Qnet (Vesta, 2000) and NeuroSolutions (NeuroDimension, 1995) were considered to develop ANN models for predicting the soundscape evaluations.

Qnet is developed by Vesta (2000), it offers virtually unrestricted model sizes and makes it easier to train, maintain and implement large numbers of models. Qnet model interconnects processing elements using nodes and layers (input, hidden and output) as shown in Fig. 2.3.

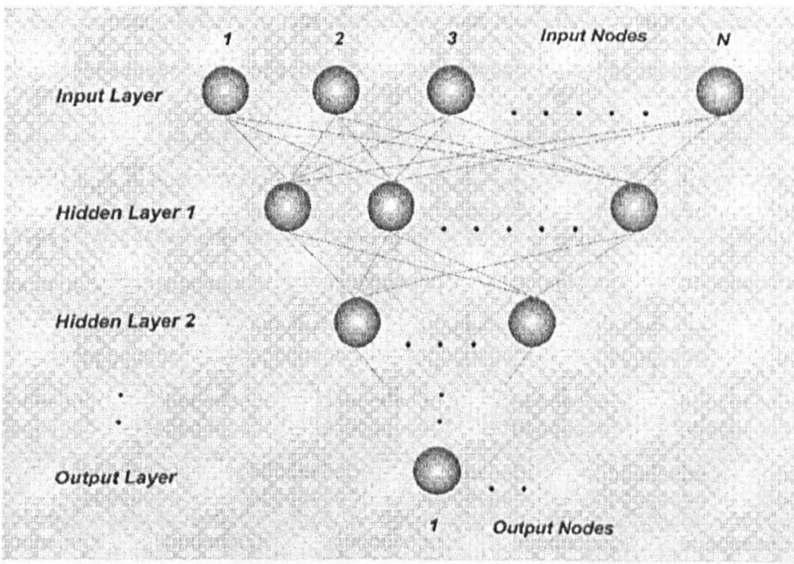


*Fig. 2.3 Network construction in Qnet (Vesta, 2000)*

In Qnet, there are many analysis tools available to monitor the overtraining and interrogating the model's quality, including root-mean-square (RMS) error history plot, correlation history plot, test tolerance history plot, learning rate history plot, targets/network outputs plots, input node plots, input interrogator, input colour contours, node analyzer, network information check, statistics, tolerance check, threshold check and divergence check. Amongst all these analysis tools, the correlation coefficients and RMS error are commonly used to determine the model performance (Vesta, 2000).

Issued by NeuroDimension Inc., NeuroSolutions, as another ANN software package, is also employed in this study. It is a high graphical neural network which is ease to create networks for various dataset (NeuroDimension, 1995). It combines a modular design interface with advanced learning procedures, giving flexibility to design the neural network. As a powerful network, NeuroSolutions is broadly used in various markets covering data prediction, data classification and data mining problems in research, business and industrial environments, such as assisting patients to receive pressure support ventilation, predicting chemical analysis of beer flavours, power plant coal quality analysis, seabed recognition and texture classification.

The network of the NeuroSolutions module, Multi-Layer Perceptron (MLP), is constructed by interconnecting several neural objects, also called components. NeuroSolutions has approximately 100 components that can be interconnected to an unlimited variety ANN models. There are four kinds of probes, namely BarChart, DataGraph, MatrixViewer and DataWriter, could be added into a network to monitor its performance. The final finished construction of a NeuroSolutions' MLP network is shown in Fig. 2.4, which is used in this study.

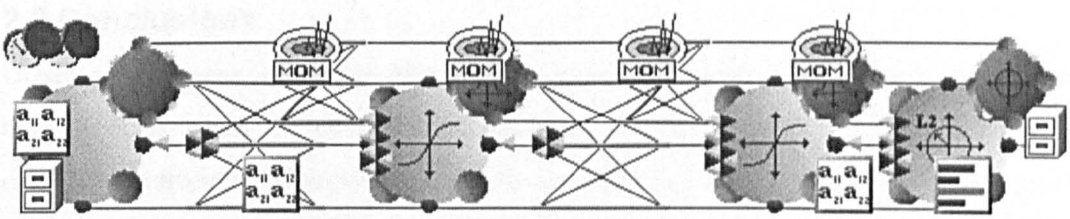



*Fig. 2.4 Network construction in NeuroSolutions (Neurodimension, 1995)*

### 2.7.2 BrainMaker and STATISTICA

BrainMaker is a frequently used ANN software package, designed by nine Caltech mathematicians and scientists of California Scientific Software (http://www.calsci.com/BrainIndex.html). It includes Netmaker and Brainmaker Neural Network Development System which is easy to be used by even novices. Propriety algorithms including Data Correlator, Cyclic Analysis, Sensitivity Analysis, Global Network Analysis, Contour Analysis, Hypersonic Training and even Genetic Training have been offered by BrainMaker professional. 'BrainMaker's carefully chosen defaults and automated functions save time and make design easy. The training process is similar to using a deck of flash cards, and the network learns to recognize patterns and make predictions using examples that have been collected or created. Although BrainMaker hasn't been used in this study, it was successfully applied by Nannariello and Frick (2001a&b&c; 2002) to predict acoustic indoor parameters.

Developed in STATISTICA, STATISTICA Automated Neural Networks (SANN) is ANN software often used (http://www.statsoft.com/products/stat_nn.html). It is issued by StatSoft. SANN is fully integrated with the STATISTICA system, where allows a large selection of tools for editing data for analyses. It is a comprehensive, state-of-the-art network which is integrated the pre- and post-processing to solve classification, regression and time series problems. It is a powerful tool for automation (automatically perform neural network analyses inside *MS Excel* spreadsheets, or incorporate neural network procedures in custom applications developed in C++, *C#*, *Java*, etc.). SANN program can be "connected" to remote databases via the tools for in-place-database processing, or linked to active data so that models can be retrained or applied automatically every time the data change.

## 2.8 Conclusions

Urban open spaces are active elements in improving social lives in modern cities as they mediate urban life rhythms and assist in the renaissance of city centres. With merging environmental problems, such as air, light and noise pollutions, the design of urban open spaces has to be reconsidered from an ecological perspective where the social-physical environments and their interactions have been taken into account.

Subjective physical comfort is regarded as being a key component of a delightful environment in an urban open space (Nikolopoulou et al., 2004). Numerous studies have investigated the interactions of visual and thermal environments with their social contents, and the findings of these studies have already been incorporated into the design stage in developing urban open spaces. In contrast, aural aspect has rarely been studied in the design process. Currently, acoustic design simply focuses on noise control. Various parties from decision makers to landscape architects take noise management as the main approach to improve acoustic environments; however, this is not an efficient way to provide delightful sound environments. Soundscape design is considered more important.

First coined by Schafer (1977), soundscape refers to a sonic environment emphasising on perception and understanding of sounds as a whole physical phenomenon "*by an individual, or a society*". The concept of soundscape is therefore a mix of ambient sounds and sound subjective effects. Soundscape design is different from noise control since it takes sounds as active elements to be designed, not negative ones to be eliminated. Soundscape concerns the subjective reactions of a sound and the evaluations it evokes. Hence soundscape is considered to be a socio-physical environment, which focuses on sounds and the environment they created both physically and socially.

As it deals with a socio-physical environment, the soundscape study is within the environmental psychology paradigm, where social survey is commonly used and laboratory experiment is often employed as supplement. Mathematical statistics is an efficient method to be used in exploring useful information for soundscape research and design. However, statistical analyses cannot provide a practical tool in aiding urban planners and designers at design stage. Consequently, ANNs have been introduced in this chapter.

ANN technique has been broadly reviewed in Section 2.5. Numerous studies of ANNs demonstrated that with their robust learning ability, ANN models are capable of being used in various areas from commercial estimations to scientific practices. They have also been applied for diagnosing the soundscape quality in residential areas (Berglund et al., 2004). Various applications of ANNs have shown that ANN models can learn from the actual data from the real world and make predictions for a future position. As the best networks used for classification and prediction issues, the multilayered BP networks are considered suitable for this study, where ANN software, Qnet and NeuroSolutions, has been specially reviewed. Based on their merits of Multilayer Perceptron with BP learning, Qnet and NeuroSolutions will be used in Chapters 6 & 7 for predicting the subjective evaluations of sound level, acoustic comfort and sound preference in urban open spaces in this study.

# Chapter3

# Methodology

In this chapter, methodologies of studying the subjective evaluation of soundscape in urban open spaces have been explored. As soundscape research is within the environmental psychology realm, field study and social surveys were first adopted and discussed in Section 3.1. Limited by the on-site conditions, laboratory experiments were also employed to study the subjective evaluation of sound preference (Section 3.2). Following the description of the field study and the laboratory experiment methods, in Section 3.3, initial statistical analyses are made to the data collected in the field studies and the laboratory experiments in terms of data population and distribution. This is followed by Section 3.4, which discusses ANN models to predict the subjective evaluation with an emphasis on Qnet and NeuroSolutions. Finally, in Section 3.5, a summary of the whole chapter is made.

## 3.1 Field studies

As field study and social surveys are common methods in psychological environment (Gifford, 2002), it is then used in soundscape research. In order to carry out an efficient field study, planning for operation is the most important, including designing questionnaires, selecting the field study sites, and managing a series scientific measurement in real life settings (Fiedler, 1978).

In this study, data collected in two funded previous projects and an extension study were statistically analysed and used for establishing ANN models. Funded by EU, the first project, Rediscovering the Urban Realm and Open Spaces (RUROS), was carried out by a number of partners in a series of urban open spaces in the EU cities to explore the physical comfort in urban open spaces, where the Sheffield group worked on the soundscape part (Nikolopoulou et al., 2004). The second project was supported by British Academic; it was undertaken in Beijing, China by the Sheffield colleagues, also with an aim of exploring the quality of physical environment with an emphasis on soundscape. As an extension study, field studies and social surveys were also carried out by the author in Shanghai, China.

### 3.1.1 Questionnaires for the EU field studies

Questionnaires for the RUROS project were developed by environmental researchers in seven EU institutes, including the countries of Greece, Italy, UK, Germany, and Switzerland. Questions about the subjective evaluation of soundscape were systematically designed; the whole project, however, was focused on investigating the physical comfort in urban open spaces where acoustic comfort was one part of it.

The questionnaire of RUROS project included two parts: the observation sheet and the survey sheet; the questions related to the subjective evaluations of soundscape were designed by Kang, Yang & Zhang (2004). They included the questions about the subjective evaluation of acoustic comfort on-site, subject's tranquillity feelings of sound-level on-site, individual preference of incident sound on-site, and subjective evaluation of home sound level etc., whilst the interviewee's social/demographic characteristics, and the interviewee's on-site behaviour such as read/write, watching distance status were included in the observation sheet (see Appendix I: questionnaires for the EU surveys). In Sheffield, more in-depth questions were made for soundscape study, including the subjective evaluation of on-site acoustic comfort and the preference evaluations for the sounds which are often heard in urban open spaces rather than the just on-site noticed sounds. Based on the study of Sheffield, semantic differential analysis was made (Kang & Zhang 2002).

All questionnaires were developed in English and then translated into different languages for different case study sites. In total, the social surveys were carried out in 14 EU case study sites, including 1: Germany Kassel, Bahnhofsplatz; 2: Germany Kassel, Florentiner;

3: Greece Athens, Karaiskaki; 4: Greece Athens, Seashore; 5: Greece Thessaloniki, Kritis; 6: Greece Thessaloniki, Makedonomahon; 7: Italy Milan, IV Novembre; 8: Italy Milan, Piazza Petazzi; 9: Switzerland Frobourg, Jardin de Perolles; 10: Switzerland Frobourg, Place de la Gare; 11: UK Cambridge, All Saint's Garden; 12: UK Cambridge, Silver Street; 13: UK Sheffield, Barkers Pool; and 14: UK Sheffield, Peace Gardens. Followed by the EU field studies of the RUROS project, similar field studies were carried out in China, which will be described in the next section. Table 3.1 shows a summary of all the case study sites from both EU and China field studies.

***Table 3.1** Summary of case study sites in the EU*

| Country | City | Site | | | |
|---|---|---|---|---|---|
| | | Code | Description | Location | Interview |
| Germany | Kassel | 1 | Bahnhofsplatz | Railway station | 418 |
| | | 2 | Florentiner | Tourist spot | 406 |
| Greece | Athens | 3 | Karaiskaki | City centre | 655 |
| | | 4 | Seashore | Tourist spot | 848 |
| | Thessaloniki | 5 | Kritis | Residential | 777 |
| | | 6 | Makedonomahon | City centre | 1037 |
| Italy | Milan | 7 | IV Novembre | City centre | 574 |
| | | 8 | Piazza Petazzi | Residential | 599 |
| Switzerland | Frobourg | 9 | Jardin de Perolles | Residential | 888 |
| | | 10 | Place de la Gare | Railway station | 1041 |
| UK | Cambridge | 11 | All Saint's Garden | Tourist spot | 459 |
| | | 12 | Silver Street | Tourist spot | 489 |
| | Sheffield | 13 | Barkers Pool | City centre | 499 |
| | | 14 | Peace Gardens | City centre | 510 |
| China | Beijing | 15 | Chang Chun Yuan Square | Residential | 307 |
| | | 16 | Xi Dang Square | City centre | 304 |
| | Shanghai | 17 | Century Square | Tourist spot | 62 |
| | | 18 | Nanjing Road Square | City centre | 79 |
| | | 19 | Xu Jia Hui Park | Residential | 79 |

### 3.1.2 Questionnaires for the Chinese field studies

Similar to the EU field studies, social surveys for investigating people's physical comfort in urban open spaces were conducted in China (Zhang & Kang, 2007b). Questionnaires of the Chinese field studies were slightly changed with an emphasis on the soundscape study. More questions aiming at examining the interviewee's aural experience have been added, whereas questions of subject's drinking appetites, glaring problems have been omitted. The questionnaires in China were firstly developed in English, and then translated into Chinese (see Appendix II: questionnaire for the Chinese surveys). Five studied sites were carefully selected in two cities: Beijing and Shanghai, where two are in Beijing, namely site 15- Chang Chun Yuan Square and site 16- Xi Dan Square and three are in Shanghai, which are site 17- Century Square, site 18- Nanjing Road Square and site 19- Xu Jia Hui Park (also see Table 1).

The questionnaire was designed according to the principles of conducting social surveys in the field study (Peterson, 2000). In order to obtain original information from the interviewees, non-rhetorical open-ended or semi-open-ended questions were used, such as the question of "which kind of sounds are often heard in your living place", or giving "other" option to the question "where are you living?", "Do you like the soundscape of your home?", "What kind of factor you would care more if taking a place to rest in this open space?" etc. One principle of question design is to make the purposes of the study not be easily aware by the respondents, therefore, the questions were designed randomly according to attract the interviewees' interests rather than directly seek the answers. In this way, quantitative questions of interviewee's situations have been assembled. Questions about the subjective evaluation of on-site physical environment have been asked using closed-end questions with offering a linear 5 points scales explained by verbal descriptions, which is often employed in social surveys (McCormack & Hill 1997). For example, the scale ranged from 'very cold' to 'very hot' was used for temperature evaluation, and from 'very dark' to 'very bright' for brightness evaluation. Although 5 points scales were usually made for eliciting the subjective evaluations, 3-points scaled for sound preference (favourable, neither favourable nor annoying, and annoying) and binary 'yes and no' question for the overall physical comfort were also used.

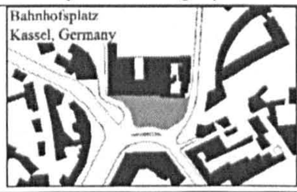
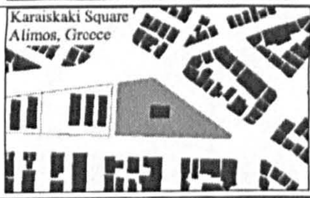
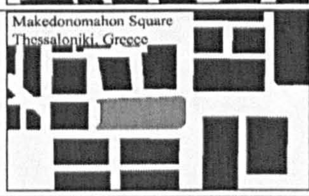
### 3.1.3 Case study sites in the EU

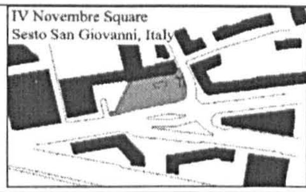
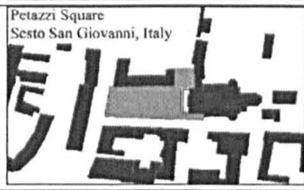
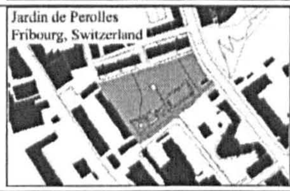
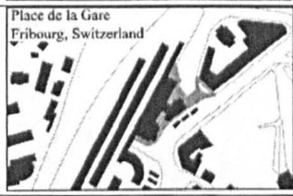
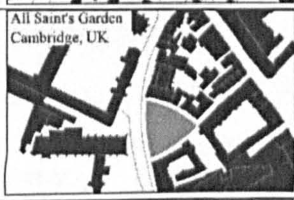
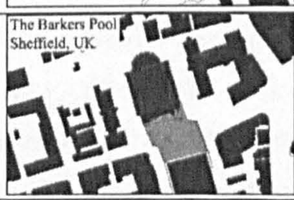
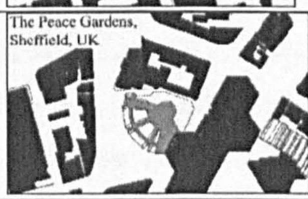
From summer 2001 to spring 2002, a series of field studies were carried out in four seasons in 14 urban open spaces (Kang et al., 2004). The field studies covered seven cities in Five European countries as already shown in Table 3.1. The locations of the seven case study cities are shown in Fig. 3.1. The questionnaires of social surveys for the field study have been discussed in Section 3.1.1. In this section, details of field study sites and the conditions in which the social surveys were undertaken will be introduced.


***Figure 3.1** Locations of seven case study cities in the EU (Yang, 2005)*

The case study sites were located in varied urban open areas, including residential area, Tourist spot, city centre, and railway station as shown in Table 3.1. The site plan and size of all the 14 case study sites in EU are shown in Table 3.2. It can be seen that the size of all 14 case study sites are rather limited, ranging from 4,500 $m^2$ to 700 $m^2$, except the site 9- Jardin de Perolles, which has a area of 1,5000$m^2$. Besides, most sites are rather enclosed or half enclosed, except the site 4- Seashore and 12- Silver Street, which are almost open.

***Table 3.2** Plan and basic information of 14 case study sites in the EU (Kang, 2006a)*

| Site | Plan<br>Surveys areas in grey | Size |
|---|---|---|
| 1- Bahnhofsplatz,<br>Kassel; Germany |  | 40x25m (approx.1,000$m^2$) |
| 2- Florentiner<br>Kassel; Germany |  | 35x20m (approx. 700$m^2$) |
| 3- Karaiskaki<br>Athens; Greece |  | 80x50m (approx. 4,000$m^2$) |
| 4- Seashore<br>Athens; Greece |  | 85x25m (approx.2,100$m^2$) |
| 5- Kritis<br>Thessaloniki; Greece |  | 85x85m (approx.4,500$m^2$) |
| 6- Makedonomahon<br>Thessaloniki; Greece |  | 90x45m (approx. 4,000$m^2$) |

| | | |
|---|---|---|
| 7- IV Novembre<br>Milan; Italy |   | 80x35m (approx. 3,000m²) |
| 8- Piazza Petazzi<br>Milan; Italy |   | 70x40m (approx. 2,600m²) |
| 9- Jardin de Perolles<br>Frobourg; Switzerland |   | 170x100m (approx. 1,5000m²) |
| 10- Place de la Gare<br>Frobourg; Switzerland |   | 80x20m (approx. 1,400m²) |
| 11- All Saint's Garden<br>Cambridge; UK |   | 38x35m (approx. 1,000m²) |
| 12- Silver Street<br>Cambridge; UK |   | 30x18m (approx. 500m²) |
| 13- Barkers Pool<br>Sheffield; UK |   | 50x50m (approx. 2,500m²) |
| 14- Peace Gardens<br>Sheffield; UK |   | 70x50m (approx. 3,000m²) |

### 3.1.4 Case study sites in Beijing

In the summer 2005 and the spring 2006, similar field studies on the physical comfort in urban open spaces concerning on the soundscape quality were carried out in Beijing. Subsequent studies were conducted in Shanghai. The locations of these two cities are shown in Fig.3.2.

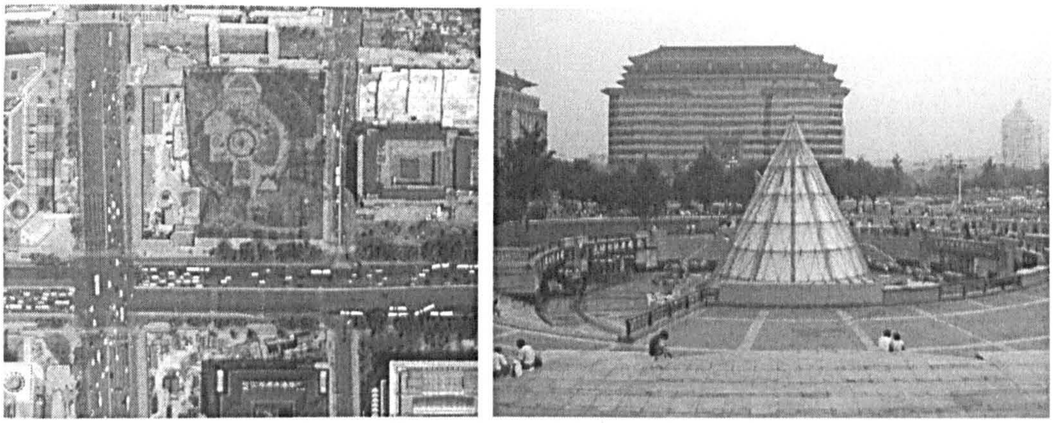

*Figure 3.2 Locations of the two case study cities in China (Source: U.S. Central Intelligence Agency, China map)*

Field studies in Beijing were undertaken in two case study sites carried out by Zhang with a group of students from Beijing University (Zhang & Kang, 2007b). One case study site is located in a residential area of Beijing, named Chang Chun Yuan. The Chang Chun Yuan Square is within Chang Chun Yuan residential area, which is located in Beijing Haidian district. Haidian is a cultural and educational district of Beijing, where many famous universities and institutes are located, such as the Peking (Beijing) University and Qinghua University. There is a main city road near the square but separated by a green zone. The shape of the whole place is not flat which is featured with a small hill around the north-west and the south-west part, and a concrete playground is in the middle. More green spaces can be found in the east part and table tennis activity area is arranged in the north-west corner. The satellite plan of the site is shown in Fig. 3.3 (a), and the people's activities in the site can be seen in Fig. 3.3 (b). Compared to the EU case study sites, the size of the Chang Chun Yuan Square is rather large, which is roughly 300m x 300m. The main function of the square is for the local people's recreation and relaxing.

(a) (b)

***Fig. 3.3*** *Beijing Chang Chun Yuan Square: (a) the satellite plan (source: www.maps.google.com); (b) people activities (Picture supplied by Dr. Zhang, School of East Asian Studies, the University of Sheffield)*

The Xi Dan Square is within Xi Dan commercial district, which is a central shopping place of Beijing. It is a culture plaza located in the corner of Xidan road towards the north-east direction. The whole square has two levels; one is on the ground and the other is under the ground. The two levels are connected by a glazing tunnel. The whole square is decorated as a chessboard by a group of green grass and ground tiles. The centre is a sunken square which is featured by a high toughened glass cone as the site's landmark. The Xi Dan Square is rather large with an area of 15,000 $m^2$. It provides a rest space for the peoples who are shopping in the Xi Dan area and also is a concourse for social activities and a junction for transportations. Fig. 3.4 (a) shows the site's satellite plan and Fig 3.4 (b) presents the centre part of the site.



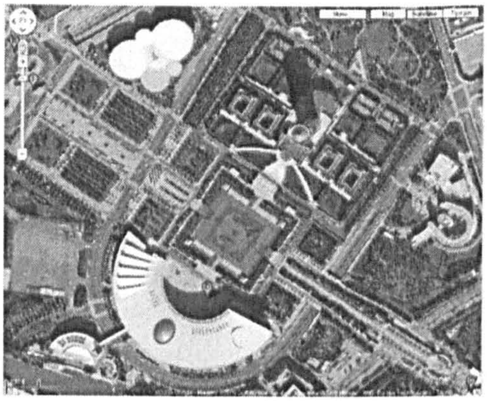
(a) (b)

*Fig. 3.4 Beijing Xi Dan Square: (a) the satellite plan (source: www.maps.google.com); (b) the centre part (Picture supplied by Dr. Zhang, School of East Asian Studies, the University of Sheffield)*

### 3.1.5 Case study sites in Shanghai

In addition of Beijing field studies, more study cases of China have been added in order to compare with the EU field studies. Three urban squares in Shanghai, namely , the Nanjing Road Square and Xu Jia Hui Park, were selected to undertake social surveys for exploring the physical comfort in urban open spaces also with an emphasis on soundscape. These three case study sites were chosen because they are typical urban squares in Shanghai and have similar functions with the other case study sites. In addition, Shanghai is an important city parallel to Beijing but it is situated in the southern part of China.

As shown in Fig. 3.5, the Century Square of Shanghai is laid on the southern side of the Century Road located in the Pu Dong business district in Shanghai. It is named as 'Time Square' that means it is a square for the new era and also decorated by a sculpture of this theme. It is also the biggest open square in Shanghai which attracts many citizens for entertainment and tourists for visit. The whole square is composed of three open spaces, and the case study site is situated in the middle, which is an open space surrounded by hedges and far away from the heavy traffic roads. The size of the site is 50mx50m, which is relatively large compared to the other case study sites.


(a)

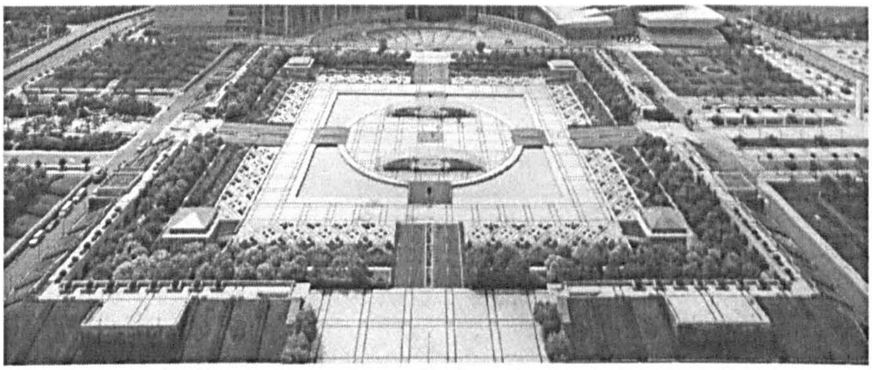
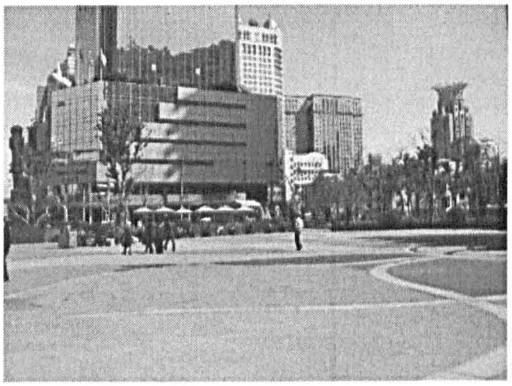

(b)

***Fig.3.5*** *Shanghai Century Square; (a) the satellite plan (source: www.maps.google.com); (b)a model of the whole site (source: www.shanghaidaily.com)*

The Nanjing Road Square is also called the Nanjing Road Century Square. It is situated in the famous shopping pedestrian street, Shanghai Nanjing Road. As the Nanjing Road is located in the pedestrian street, there is no passing through traffic except one traffic road, Zhejiang Zhong Road is on one side of several meters far. The whole square is nearly 8,000m$^2$ with a movable stage in the centre and green spaces are surrounded outside. The square is mostly used for public celebration in some important days or festivals, such as New Year. It is also a rest place for people who shop or work around the area. Fig.3.6 shows the satellite plan and the central part of the square where a fountain is placed hidden in the ground; the fountain is similar as the one in another case study site, the Peace Gardens of Sheffield, UK.


(a)

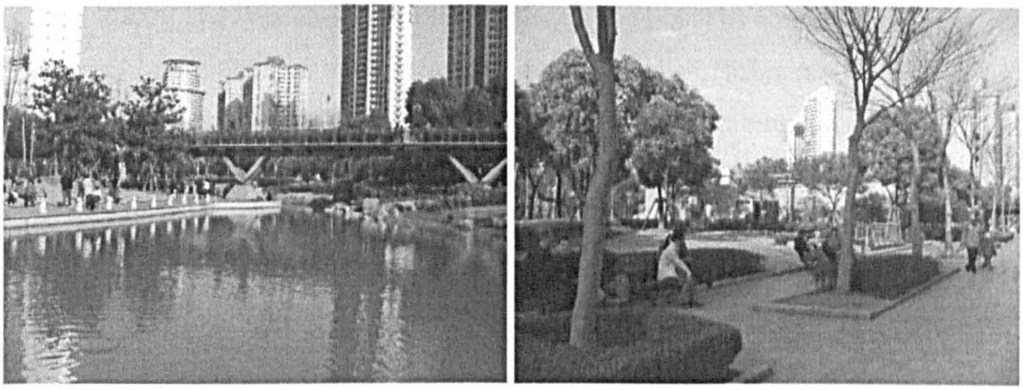



(b)

***Fig. 3.6*** *Shanghai Nanjing Road Square, (a) the satellite plan (source: www.maps.google.com); (b) the central square*

The Xu Jia Hui Park is an urban park situated in the luxury residential area of Shanghai, Xu Jia Hui. Its four sides are surrounded by four main roads of Shanghai, which is the Hen San Road in the north, the Zhao Jia Bing Road in the south; the Tian Ping Road is on the western side and the Wan Ping Road is on the eastern side. The satellite plan of the park is shown in Fig. 3.7(a). The whole park occupies approximately 72,700m$^2$ areas, and the surveys were mainly undertaken in the lake area which is shown in Fig. 3.7(b). As all the traffic roads are surrounded the outside of the park, the field study area is rather quiet as it is in the inner part near an artificial lake. The main function of Xu Jia Hui Park is to provide various refresh and recreation places for the residents. The field study site is a place for people to look around, chat and play with children.

(a)



(b)

*Fig. 3.7 Shanghai Xu Jia Hui Park, (a) the satellite plan (source: www.maps.google.com); (b) main site of the field study*

### 3.1.6 Interviewees and duration of field studies

The interviewees in all the field surveys were randomly selected in terms of their social/demographic background and on-site behaviours.

A wide variation of the physical conditions and urban morphology were considered in all the surveys. The duration of EU survey covered four seasons. However, limited by the project funding, the surveys in Beijing and Shanghai were carried out only in one season, which was summer for the surveys in Beijing and spring for the surveys in Shanghai because these two seasons are a common time for people to use urban open spaces. The time of all the surveys except Nanjing Road Square (site 18) was varied in a day- time from the morning to the evening, which could be roughly separated into four periods, the morning (10:00 – 11:59), the midday (12:00 – 14:59), the afternoon (15:00 – 17:59) and the evening (18:00 – 20:59). The surveys in Nanjing Road were undertaken only in the middle day due to the time limitation.

### 3.1.7 Sound levels in field study sites

In order to monitor the sound pressure level (SPL) during the social surveys, a one-minute Leq (equivalent continuous noise levels) was recorded for each interviewee around the time he/she filled the questions. A sound level monitoring instruction was designed by Kang et al. (2004) in the RUROS project according to *Noise Guidance* (Environment Agency, 2000), and was also used in the Chinese surveys. The sound level meter used for each survey was calibrated before and after taking the measurement. The average SPL for each case study site was calculated according to the one-minute Leq measured for all interviewees. The results are summarised in Table 3.3.

***Table 3.3** The average SPL of 19 case study sites*

| Code | Case study site | Average of SPL | Location |
|---|---|---|---|
| Site 1 | Bahnhofsplatz, Kassel, Germany | 64.7 | Railway station |
| Site 2 | Florentiner, Kassel, Germany | 61.3 | Tourist spot |
| Site 3 | Karaiskaki, Athens; Greece | 62.8 | City centre |
| Site 4 | Seashore, Athens; Greece | 64.4 | Tourist spot |
| Site 5 | Kritis, Thessaloniki; Greece | 66.0 | Residential |
| Site 6 | Makedonomahon, Thessaloniki; Greece | 69.3 | City centre |
| Site 7 | IV Novembre, Milan, Italy | 69.1 | City centre |
| Site 8 | Piazza Petazzi, Milan, Italy | 66.2 | Residential |
| Site 9 | Jardin de Perolles, Frobourg; Switzerland | 55.9 | Residential |
| Site 10 | Place de la Gare, Frobourg; Switzerland | 67.9 | Railway station |
| Site 11 | All Saint's Garden, Cambridge, UK | 72.4 | Tourist spot |
| Site 12 | Silver Street, Cambridge, UK | 80.7 | Tourist spot |
| Site 13 | Barkers Pool, Sheffield, UK | 60.2 | City centre |
| Site 14 | Peace Gardens, Sheffield, UK | 67.4 | City centre |
| Site 15 | Chang Chun Yuan Square, Beijing, China | 61.4 | Residential |
| Site 16 | Xi Dan Square, Beijing, China | 70.0 | City centre |
| Site 17 | Century Square, Shanghai, China | 49.3 | Tourist spot |
| Site 18 | Nanjing Road Square, Shanghai, China | 54.9 | City centre |
| Site 19 | Xu Jia Hui Park, Shanghai, China | 50.2 | Residential |

It can be seen that the average SPL for all the case study sites varied considerably, from 50.2dBA (site 19) to 80.7dBA (site 12). The SPL of the studied cases in EU was generally higher than the studied cases in China, which was usually above 60dBA for the studied cases in EU; for the studied cases in China, however, the SPL of Beijing was considerably higher than that of Shanghai, which was 61.4 dBA and 70dBA respectively for the two studied cases in Beijing, but was less than55dBA for the three studied cases in Shanghai. This may be caused by the quieter background where *the site is situated* as discussed in Section 3.1.5.

Table 3.3 also shows the location of each case study site. It can be seen that the SPL was also greatly varied corresponding to where the case study site is located. For all the 19 case study sites, 7 are located in the city centres (site 3, 6, 7, 13, 14, 16 and 18), 2 are near the railway stations (site 1 and 10), and 5 are situated in the residential areas (site 5, 8, 9, 15 and 19) as well as in the tourist spots (site 2, 4, 11, 12 and 17). Generally speaking, the SPL was relatively high in the case study sites near the railway stations; however, for the case study sites in the city centres, it is found that the SPL was even higher than at the railway stations if one or more heavy traffic roads are nearby, such as site 6- Makedonomahon square in Thessaloniki, Greece, site 7- IV Novembre square in Milan, Italy, site 14- Peace Gardens in Sheffield, UK, and site 16- Xi Dan Square in Beijing, China. But, for the case study sites in the residential areas, the SPL was relatively low except site 5- Kritis in Thessaloniki, Greece, and site 8- Piazza Petazzi Square in Milan, Italy. This might be caused by the high sound levels of the urban area where the case study sites are located, as it can be seen in Table 3.3, that the SPL of the studied cases in residential areas in Thessaloniki and Milan are higher than the studied residential cases in the other cities. The same reason might also explain why the SPL of the two case study sites in the tourist spots in Cambridge are higher than those of the tourist spot cases in the other cities.

In summary, the investigation of the SPL for all the 19 case study sites during the survey period showed that the sound level in an urban open space might be firstly determined by the acoustic characteristics of a district, in which the urban open space is located, and then determined by a location at which the urban open space is situated, such as in residential areas, tourist spots, city centres, or railway stations.

### 3.1.8 Sound sources in the case study sites

In terms of sound sources, individual single sounds derived from natural, human and mechanical sources were examined in social surveys of 19 case study sites. These sounds were birdsong, water and insect sounds; people's speech, footsteps and children shouting; and cars passing, buses passing, vehicles parking and construction sounds. From case study site 1 to site 12, only the noticed sound were investigated and the interviewees were asked to evaluate the sound preference; however, from case study site 13 to site 19, in order to completely study the subjective preference of various sounds, all the above sounds were required to be evaluated. A summary of the sound distribution of noticed sound is shown in Table 3.4.

In Table 3.4, it can be seen that traffic noise existed in nearly all the case study sites, although less so in some sites; such as site 15- Chang Chun Yuan Square in Beijing; site 17- Century Square in Shanghai; site 18- Nanjing Road Square in Shanghai; site 19- Xu Jia Hui Park in Shanghai. These sites are all located in China and all have a relatively low SPL (see Table 3.3). Soundscapes in most case study sites were noticed by people speech. The sound of footsteps was often noticed in the sites located in city centres. Seven case study sites were featured by water sound, including the site 2- Florentiner in Kassel, Germany, site 4- Seashore in Athens, Greece, Site 7- IV Novembre in Milan, Italy, site 12- Silver Street in Cambridge, UK, site 14- Peace Gardens in Sheffield, UK, site 18- Nanjing Road Square in Shanghai, China, and site 19- Xu Jia Hui Park in Shanghai, China. Other commonly noticed sounds included water (noticed in site 1, 7, 12, 14, 18, 19), bird (noticed in site 9, 11, 15, 19), and children shouting (noticed in site 3-6, 8, 9, 14, 15, 19). A number of other unique sound elements contributed to the soundscapes of several case study sites has also been examined, such as music in site 13- Barkers Pool in Sheffield, UK, church bells in site 8- Petazzi Square in Milan, Italy, construction/demolition sounds in site 5- Kritis Square and site 6- Makedonomahon Square in Thessaloniki, Greece, as well as site 14- Peace Gardens in Sheffield, UK. Some sport activity sound has also been notably realized, such as skateboard in site 19- Century Square in Shanghai, China.

***Table 3.4*** *Noticed sounds (marked by √) in the case study sites*

| Site | Natural sounds | | | Human sounds | | | Mechanical sounds | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Traffic | | | Construction |
| | Bird | Water | Insect | Speaking | Footstep | Children shouting | Car | Bus | Parking | |
| Site 1 | | √ | | √ | √ | | √ | √ | | |
| Site 2 | | | | √ | √ | | √ | | | |
| Site 3 | | | | √ | √ | √ | √ | | | |
| Site 4 | | | | √ | √ | √ | √ | | | |
| Site 5 | | | | √ | | √ | √ | √ | | √ |
| Site 6 | | | | | | √ | √ | √ | | √ |
| Site 7 | | √ | | √ | | | √ | √ | | |
| Site 8 | | | | √ | | √ | √ | | | |
| Site 9 | √ | | | √ | | √ | √ | | | |
| Site 10 | | | | √ | √ | | √ | √ | | |
| Site 11 | √ | | | √ | | | √ | √ | | |
| Site 12 | | √ | | √ | √ | | √ | √ | | |
| Site 13 | | | | √ | √ | | √ | √ | | |
| Site 14 | | √ | | √ | | √ | √ | √ | √ | √ |
| Site 15 | √ | | √ | √ | | | √ | √ | | |
| Site 16 | | | √ | √ | √ | | √ | √ | √ | |
| Site 17 | | | | √ | √ | | √ | √ | | |
| Site 18 | | √ | | √ | | | √ | √ | √ | |
| Site 19 | √ | √ | √ | √ | | | √ | √ | | |

The grey areas indicate where the variables are not available.

## 3.2 Laboratory experiments

Although field studies are commonly to be used in soundscape research, laboratory experiment is necessary when field studies are not possible to isolate the psychoacoustic indices of a sound on the case study site. It is therefore utilised in this study as a complement of field study in investigating the subjective evaluation of sound preference.

Following the field studies in EU and China, laboratory experiments were undertaken by the author in order to further explore the relationship between sound meaning, psychoacoustic parameters, loudness and sharpness, and the sound preference evaluations. Psychoacoustic parameters are the physical dimensions used to describe the sound psychological effecting on a listener (Howard & Angus, 2001), where loudness and sharpness are two important components. Loudness is an essential psychoacoustic magnitude to judge feelings about noise, and sharpness is defined as the ratio of high frequency component in the whole sound spectrum (Zwicker & Fastl, 1999), both of which are considered significantly related to the subjective evaluations of a sound.

### 3.2.1 Experimental procedures

The laboratory experiments were divided into three parts. In Part I, the participants were asked to give their evaluations in terms of 3-point scales, 'favourable', 'neither favourable nor annoyance' and 'annoyance', amongst nine individual sounds without playing any sound. The laboratory experiments of this part were an extension and connection of the previous mentioned field studies, because it used the same questions and similar sounds as those in the field studies. The purpose of the study in this part was to elicit the subjective evaluations of a sound based on its verbal meaning. It also aimed to re-examine the results of the field studies in laboratory conditions.

In Part II, ten pre-recorded sounds were presented to the participants. Of those, six were from a variety of natural, human and mechanical sound sources. In order to eliminate the impact of sound meaning on the subjective evaluations, the remaining four sounds repeated two sound sources; birdsong and cars passing, at levels 10dBA higher than their original level or 10dBA lower than their original level. Also in this part, the traffic sound was repeated in order to test the accuracy of the experiments. The participants were required to evaluate these ten sounds based on their listening experience. The first criterion for this evaluation was the effect on the listeners; it replicates questions asked in the previous mentioned field studies and Part I laboratory experiments. Participants were also asked to rate each sound for noisiness, comfort, and pleasantness on a scale of -2 to 2.

The criteria for these evaluations, however, were only elicited in Part II & III of the laboratory experiments. Overall, this part of experiments focused on exploring the impact of psychoacoustic parameters and the sound meaning on the sound preference evaluation.

In Part III, five sounds with audio plus video records were presented to the participants. The audio record of a sound was firstly played back to the participants, and this was followed by playing the video record of the same sound. The sounds were randomly played back with a 4.5 seconds gap for the participants to answer the questions. In this part, participants were asked to evaluate these five sounds based on their listening or watching experience. The main aim of Part III is to compare the aural and visual effects of a sound.

### 3.2.2 Sound samples recording

In the Part II & III experiments, most studied sounds were recorded in the field study sites, such as the Peace Gardens in Sheffield and the Century Square in Shanghai. Only two sounds were recorded from other urban open spaces and the birdsong was obtained from a professional website (www.naturesongs.com) because it is unavailable to be isolated from the real world. While the studied sounds were recorded with different equipments or obtained from different sources, their levels were so adjusted to represent a reasonable level of the original sounds. Eventually, all the sounds were edited into a sound file using the program Coolpro2.0 and were included in a CD.

The main equipment used for recording the sounds was a digital Fostex FR-2 field DAT recorder with Dummy Head Neumann KU100. Two portable recorders, namely Canon IXUS digital camera and SHWY Digital MP3 Player, were also used because they would not draw attentions to the interviewees compared to a professional one. In order to know the difference of the sound recordings between these portable recorders and professional equipment, a comparison was made before editing these sounds into one file and presenting to the participants. The comparison was undertaken in the anechoic room at the School of Architecture, University of Sheffield. A one-minute sound was played and recorded by the two portable recorders and the professional equipment simultaneously. The sounds obtained from the above three recorders were analysed using 01dB System. The spectra are shown in Fig. 3.8. While it was expected that the professional equipment can record a wider range of frequencies than the portable recorders, for the sounds interested in this study, no significant difference has been found between the three sets of equipment. Hence, in this study, all the sound records were considered effective.

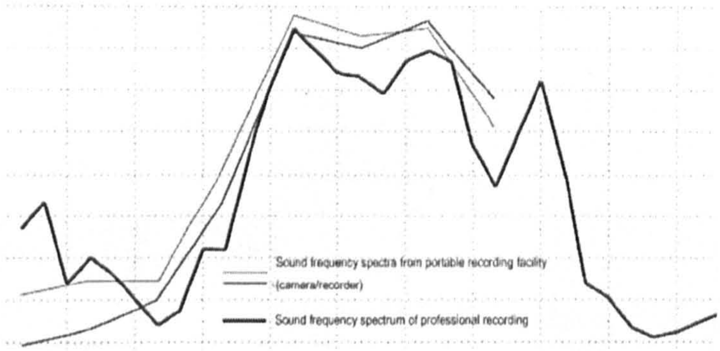



***Fig. 3.8*** *Comparison of white noise recorded amongst the Canon IXUS digital camera, the SHWY Digital MP3 Player and Fostex FR-2 field DAT recorder with Dummy Head Neumann KU100*

### 3.2.3 Studied sounds

As mentioned in Section 3.2.1, the number of studied sounds in each part of the laboratory experiments was different. All the studied sounds are summarised in Table 3.5. Generally speaking, these sounds can be classified into two categories, single sounds and combined sounds. Single sounds can also be divided into natural sounds, human sounds and mechanical sounds.

In Table 3.5, it can be seen that in Part I experiment, all studied sounds are single sounds, most of which are the same sounds as explored in the above mentioned field studies. More added sounds are skateboard and traffic, whereas water, footsteps, and cars and buses passing sounds are excluded. In one word, the sounds often heard in urban open spaces are examined, including natural sounds of bird and insect, human sounds of people speech and children shouting, and mechanical sounds of traffic and construction. Some man-made but not mechanical sounds are also examined, which are music played in a street, church bell and skateboard, which are also classified as human sounds.

*Table 3.5 Studied sounds in the laboratory experiments*

| Sounds | | Part I (without playing a sound) | Part II (with an audio record) | Part III (with an audio and a video record) |
|---|---|---|---|---|
| Single sounds | Natural sounds | Bird | Bird | Waterfall |
| | | Insect | Bird -10dBA | |
| | | | Bird + 10dBA | |
| | Human sounds | People speech | Children shouting | Skateboard |
| | | Children shouting | | |
| | | Music played in a street | | |
| | | Church bell | | |
| | | Skateboard | | |
| | Mechanical sounds | | Cars passing | |
| | | | Cars passing -10dBA | |
| | | Traffic | Cars passing + 10dBA | |
| | | Construction | Traffic | |
| Combined sounds | | | Birdsong & Cars passing | Fountain & Song |
| | | | Church bell & Speaking | Fountain & Children shouting |
| | | | | Fountain & Construction |

In Part II of the laboratory experiments, two studied sounds are combined sounds, whereas the others are single sounds. In Part III of the laboratory experiments, two single sounds and three combined sounds were included, whilst no single mechanical sound was examined.

In total, sixteen sounds were studied in the laboratory experiments. Eleven of them are single sounds, including natural sounds of birdsong, insect singing, waterfall; human sounds of people speech, children shouting, music played in a street, church bell and skateboard; mechanical sounds of traffic, cars passing and construction. Five of them are combined sounds, including birdsong mixed with cars passing, church bell mixed with people speech, fountain mixed with song, fountain mixed with children shouting, and fountain mixed with construction. Questionnaires of laboratory experiments are shown in Appendix III: questionnaire for the laboratory experiments.

### 3.2.4 Subjects

The total people participated in the laboratory experiments were 56. Compared with the number of subjects interviewed in the field studies, the subject's social/demographical backgrounds of the laboratory experiments were rather narrowed. The subject's age ranged from younger than 12 years to 55 years. The number of male subjects was 31 and that of female was 25, which was rather equal. Nineteen subjects were primary/secondary students from the King Edward IIV School; twenty-five were undergraduates/postgraduates in the University of Sheffield; and twelve were social workers from the Organisation of Family Actions. Based on the subject's social backgrounds, two groups were defined according to their occupations; students and workers. In terms of education level, the subjects were split into three groups in the same way as they were used in the social surveys. It is noted that a direct comparison between the results of field surveys and those of the laboratory experiments may not be always feasible as some differences exist.

## 3.3 Statistical analyses

Statistics is a mathematical science pertaining to the collection, analysis, interpretation, explanation, and presentation of data collected in the field studies. It is an intriguing study of how an unknown world can be described by opening a few windows on it (Wonnacotts, 1990). As it allows researchers to estimate population tendency and explain the facts behind the samples drawn from the real world, it is suitable to be applied in this study to examine the relationships of various factors and the subjective evaluations which were obtained from the social surveys and laboratory experiments.

A common goal for a statistical analysis is to investigate the relationship of cause and effect and draw a conclusion based on experimental studies and observational studies. It is important to discover the independent variable/s on the behaviour of the dependent variable/s (Wonnacotts, 1990). In this study, various variables were designed as the factors which possibly have a relation with the soundscape evaluations; these factors were the physical and psychological effects of sound, the physical and environmental attributes, and the social/demographical factors involved in the soundscape.

The dependent variables were assigned as the subjective evaluations of soundscape in urban open spaces, including the evaluations of sound level, acoustic comfort and sound preference. It is noted that in this study, the term 'sound level' evaluation has been used, instead of using 'loudness', 'noisiness', 'tranquility' or 'quietness'. This is because loudness and noisiness have rather specific definitions and calculation methods, referring to subjectively perceived sound and noise levels (Kryter, 1970; Goldstein, 1979; Zwicker & Fastl, 1999). Tranquility and quietness often emphasize the positive aspect of a quiet environment. Sound level evaluation seems to be rather neutral, which is more appropriate for this study. The population/ distribution of studied independent and dependent variables have been explored and discussed in the following sections

### 3.3.1 The variables and data issues

This section describes the data from various variables collected in the field studies and laboratory experiments. A definition of studied variables and categorization of obtained data are drawn out. This is necessary when seeking the facts hidden behind the variables before conducting statistical analyses.

Soundscape research is rather complicated and related to various disciplines; therefore, numerous variables were examined in this study. Descriptions of each variable and data categorization have then been made and shown in Table 3.6. It can be seen that all the studied variables were categorised into four elements; physical, behavioural, social/demographical, and psychological elements. The measurements of the physical conditions and when the surveys were carried out (season and time of day), were categorised as physical elements. The subjects' on-site activities and behavioural status were categorised into behavioural elements. The subject's age, gender, occupation, education et al., was assigned as social/demographical elements. The subject's preference of the sites together with all subjective evaluations were categorised into psychological elements. In total, eight physical elements, seven behavioural elements, six social/demographic elements and ten psychological elements have been included in this study, which are thirty-one variables.

Table 3.6 shows that a 5-point scales, with assigned adjective, were used for the subjective evaluations. These included the subjective evaluations of acoustic comfort, the sound level, the sound level at home, thermal, humidity, wind, and brightness. The subjective evaluations of noise, comfort and pleasantness, which were used in the laboratory experiments, also employed a 5-point scale. This was to show the variation in people's assessments of sound feelings across one dimension. Unlike the above evaluations, 'the view assessment' used a 3-point scale, as pilot studies have shown that this scale is more efficient in distinguishing the visual effects on different people than other scales. A 3-point scale was also designed for the subjective evaluations of sound effects on the listeners for the same reason. Two antonymous adjectives were used for the evaluations of an overall physical comfort, which are comfortable and uncomfortable. All these subjective evaluations were categorised into the psychological elements.

*Table 3.6 Description & categorization of variables*

| Elements | Attribute factors | Measures of the attributes |
|---|---|---|
| Physical | Phy1-Season | 1-winter; 2- autumn; 3- spring; 4- summer |
| | Phy2-Time of day | 1-night>21pm; 2- evening:18.00-20.59pm; 3- morning:9.00am-11.59pm; 4- afternoon:15.00-17.59pm; 5- midday: 12.00-14.59pm |
| | Phy3-Air temperature | Measurement of air temperature: $^0$C |
| | Phy4-Wind speed | Measurement of wind speed: m.sec$^{-1}$ |
| | Phy5-Relative humidity | Measurement of relative humidity: % |
| | Phy6-Horizontal luminance | Measurement of horizontal luminance: Klux (EU); lux (China) |
| | Phy7-Sun shade | 0-interviewee not standing in the sun; 1- interviewee standing in the sun |
| | Phy8-Sound pressure level | Measurement of sound pressure level: dB(A) |
| Behavioural | B1-Whether wearing earphones | 0-not wearing earphone; 1- wearing earphone |
| | B2-Whether reading or writing | 0-neither reading nor writing; 1- either reading or writing |
| | B3-Whether watching somewhere | 0-not watching anywhere; 1- watching somewhere |

| | | |
|---|---|---|
| | B4-Movement statuses | 1-sitting; 2- standing; 3- walking; 4- playing with kids; 5- sporting |
| | B5-Frequency of visiting the site | Scale 1-5; 1- first time; 2- occasion; 3- sometime; 4- often; 5-every day |
| | B6-Reason for visiting the site | 1-the equipment/services of the site; 2- children playing and social meetings; 3- business/meeting/break; 4-attending social events; 5- passing by |
| | B7-Grouping | 0-without company; 1- with 1 person; 2- with more than 1 person |
| Social/ demographical | S1-Age | 1<12; 2=12-17; 3=18-24; 4=25-34; 5=35-44; 6=45-54; 7=55-64; 8>65 |
| | S2-Gender | 1-male; 2- female |
| | S3-Occupation | 1-students; 2- working people; 3- others (e.g. unemployed and pensioners) |
| | S4-Education | 1-primary; 2- secondary; 3- high level |
| | S5-Residential status | 0- non local; 1- local |
| | S6-Home sound level evaluation | Scale-2 to 2, with -2 as very quiet and 2 as very noisy |
| Psychological | Psy1-Site preference | 0-not like the site for certain reasons; 1- like the site |
| | Psy2-View assessment | Scale from -1 to 1, with -1 as negative and 1 as positive |
| | Psy3-Heat evaluation | Scale from -2 to 2, with -2 as very cold and 2 as very hot |
| | Psy4-Wind evaluation | Scale from -2 to 2, with -2 as stale and 2 as too much wind |
| | Psy5-Humidity evaluation | Scale from -2 to 2, with -2 as very damp and 2 as very dry |
| | Psy6-Brightness evaluation | Scale from -2 to 2, with -2 as very dark and 2 as very bright |
| | Psy7-Overall physical evaluation | 0-not comfortable; 1 - comfortable |
| | Psy8-Sound level evaluation | Scale from -2 to 2, with -2 as very quiet and 2 as very noisy |
| | Acoustic comfort evaluation | Scale from -2 to 2, with -2 as very discomfort and 2 as very comfort |
| | Sound preference evaluation | Scale from -1 to 1; -1- favourite; 0- neutral; 1- annoyance |
| | | Scale from -2 to 2, with -2 as very uncomfortable and 2 as very comfortable |
| | | Scale from -2 to 2, with -2 as very quiet and 2 as very noisy |
| | | Scale from -2 to 2, with -2 as very pleasant and 2 as very unpleasant |

In statistics, data are generally divided into four types, namely nominal, ordinal, interval, and ratio. Nominal data have no meaningful rank order among categories; ordinal data have imprecise differences between consecutive values but a meaningful order to those values; interval data have meaningful distances between measurements but no meaningful zero value; ratio data also called continues data, is like internal data but with a meaningful zero, thus providing the most analytical power (Coolican, 1996). In this study, most physical variables are ratio data except season and time of day, which are interval data. Most behavioural variables are nominal data; however 'frequency of visiting the site' and 'grouping' are interval; 'movement statuses' is ordinal. Besides 'gender' and 'resident status', which are nominal binary data, many social/demographical variables are ordinal data. Most psychological variables are also ordinal data, although the variable 'site preference' and 'overall physical evaluation' are nominal binary.

### 3.3.2 The sample distributions

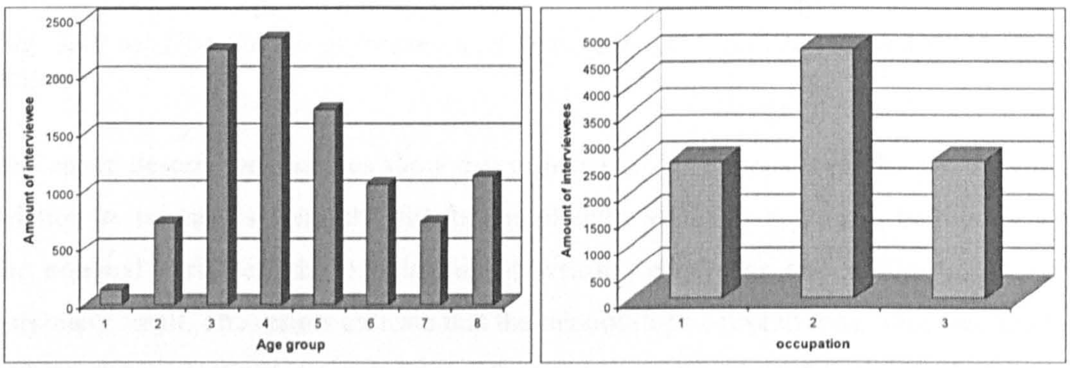
For measures of central tendency, four items are useful, which are the mode (the most frequent value), the median (the midpoint of the data), the mean (sum of scores, divided by number of items), and the standard deviation (a measure of the spread of values). Amongst them, the mean is the one which takes the total data into account, whilst the standard deviation is important to describe how data spread out or varied (Wonnacotts, 1990). Both of them are often used to elucidate the distribution of samples. Mode, however, is often used to describe the majority of nominal data. As powerful and easy handled, Statistical Package for the Social Sciences (SPSS) was employed in this study (Pallant, 2005).

The population of collected samples for social/demographical and behavioural variables was explored and the result is shown in Table 3.7. It shows the mean, median, mode, and standard deviation for all above mentioned variables. For the social/demographical variables, the standard deviation of age is higher than that of occupation and education. The mode of both gender and residential status is 1, which means that more male and local people come to use the space. The percentage shows that 53.4% interviewees are male and 57.3% are local people.

As age has been found with a higher standard deviation than that of the other social/demographical variables, further analyses should be made. The distribution histogram of age is shown in Fig. 3.9 (a). It can be seen that the distribution of age is nearly normal excluding group 8, with most interviewees being aged 18-34. For another social/demographical variable, occupation, whose standard deviation is also rather high, its distribution is normal, as shown in Fig. 3.9 (b).

***Table 3.7*** *Populations of social/demographical and behavioural variables*

| Variables | Valid N. | Mean | Median | Mode | Std. Deviation | Percentage of mode |
|---|---|---|---|---|---|---|
| Age | 10015 | 4.64 | 4 | 4 | 1.80 | |
| Gender | 10007 | | | 1 | | 53.4% |
| Occupation | 9866 | 1.93 | 2 | 2 | 0.80 | |
| Education | 9811 | 2.28 | 2 | 2 | 0.69 | |
| Residential status | 9972 | | | 1 | | 57.3% |
| Whether wearing earphones | 10013 | | | 0 | | 99.2% |
| Whether reading or writing | 10016 | | | 0 | | 93% |
| Whether watching somewhere | 10023 | | | 0 | | 55.3% |
| Movement status | 10008 | 1.98 | 2 | 1 | 1.04 | |
| Frequency of visiting the site | 9783 | 3.85 | 4 | 5 | 1.28 | |
| Reason for visiting the site | 9730 | | | 2 | | 67% |
| Grouping | 10014 | 1.76 | 2 | 1 | 0.81 | |

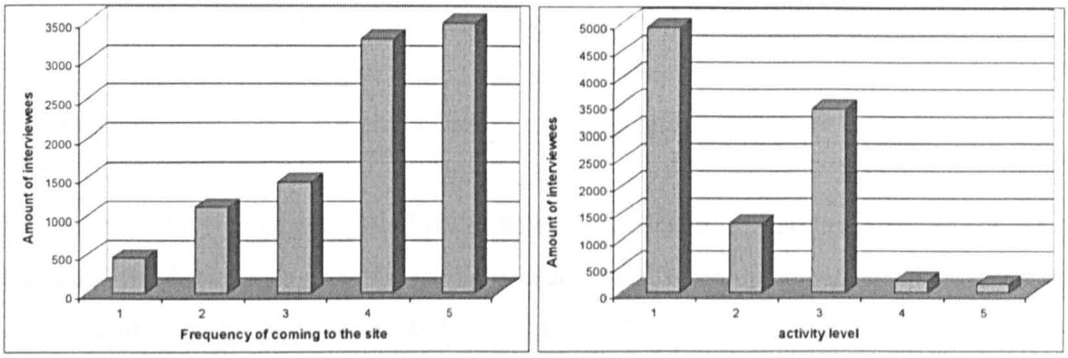



(a) (b)

***Fig. 3.9*** *(a) Distribution of age; (b) Distribution of occupation*

Table 3.7 also shows the populations of behavioural variables. A small number of wearing earphones and reading/writing have been found. It can be seen that there are only 83 samples of wearing earphones in 4 of 19 case study sites and only 703 samples of reading/writing, meaning over 90% of the interviewees were not wearing earphones and reading/writing. The mode of reason for visiting the site is 2, indicating most people come to the site for accompanying their children or for social events.

In Table 3.7, a rather high standard deviation has been found for movement status and frequency of visiting the site, hence the distribution histograms have also been made for these two variables and shown in Fig. 3.10 (a) & (b). It can be seen that the distributions of both variables are not normal. An ascending tendency is discovered regarding the frequency of visiting to the site, implying the major interviewees visit the site often. For the movement statues, more people have been found sitting or walking.




(a) (b)

*Fig. 3.10 (a) Distribution of frequency of visiting the site; (b) Distribution of movement statues*

The above descriptive analyses show that distributions of various variables are varied. In relation to the interval data, the distribution of some variables is normal, but not all. For the nominal variables, the populations of wearing earphones and reading/writing are extremely small. The results indicate that the relationships between some variables and the soundscape evaluations are non-linear. Therefore, non-linear models are needed, where ANNs are suitable.

### 3.3.3 Use of statistical techniques in this study

The purpose of description statistics is to provide useful information for inferential statistics for probing the patterns between independent and dependent variables. Pearson/Spearman correlations were commonly used in this study to investigate the correlations between various factors and the soundscape evaluations. Independent t-test was applied for the binary data, whilst Chi-square test was used for the nominal data.

The correlation is to measure how closely a change in one variable is tied to the change in another variable, and vice versa (Newbold, 1991). The values of the correlation analyses are varied from -1 to 1, where -1 means a 'perfect negative correlation' and 1 means a 'perfect positive correlation', in the middle 0 represents 'no correlation' or 'no relationship' between two variables. Independent t-tests are useful to explore the differences between the binary independent variable and dependent variable, by comparing the means of these two variables. Chi-square tests can be used for nominal data. When sample size within a category is too small, some categories have been combined to continue chi-square tests, e.g. the variable 'reason for visiting the site'.

In statistics, the significance level is defined as probability of making a decision to reject the null hypothesis. The decision is often made using the p-value; the smaller the p is, the more significant the result, the less likely the null hypothesis, will be true. Confidence is commonly used to show how significant exists. $P<0.05$ (95% confidence) or $p<0.01$ (99% confidence), it is said that the result reached a significance level. For the correlation analyses, the significant level indicates the significant confidence of the correlation coefficient between two variables. For independent t-test and Chi-Square test, the significant level defines the significant difference between the variables (Hinton, 2004).

The main objective of the analysis is to select suitable input factors for the ANN models. As ANN has a robust learning capability to model nonlinear relationships, many input factors can be used in the network as far as there are sufficient training samples. However, since the sample sizes vary considerably among different case study sites, it is important to limit the input factors so that the network size can be kept reasonable for a good prediction. On the other hand, if the input factors are selected too strictly, namely only those factors which are highly related to the output are used, the advantage of ANN modeling compared to a simple multiple regression would not be significant. As a result, in this study, the level of significant correlations or differences, namely $p$ values derived from statistical analyses, is used for limiting the input factors, whereas a threshold in terms of correlation coefficient is not applied since this may limit the number of input factors too strictly. Such methods have also been used in other studies (Ling & Liu, 2004).

Using significant levels to select relevant factors as input variables is important in establishing ANN models in this study, as will be shown in Chapters 6 & 7. Inferential statistical analyses are essential in finding the significant levels; correlations, independent t-test and chi-square test are used and discussed in Chapters 4 & 5.

## 3.4 ANN model system and application software

As ANN has a robust learning capability to produce fairly accurate predictions, it is used in this study to predict the subjective evaluation of soundscape in urban open spaces, including the subjective evaluation of sound level, acoustic comfort and sound preference. Technically, a multi-layer back propagation network is chosen because such a network is suitable to deal with classification and prediction problems. Instead of developing a network program, commercial software, Qnet and NeuroSolutions are employed and illustrated in this section.

### 3.4.1 A modelling framework

Before building prediction models, a modelling framework has been established as a numerous variables could affect the subjective evaluation of soundscape in urban open spaces. The framework is designed based on the multi-layer conception of ANN networks. It looks like a tree system as shown in Fig. 3.11.

The working procedure of the modelling framework is from sub-models to an overall model. Three types of sub-models are suggested in the framework, which are the sound level evaluation model for background noise, the sound preference evaluation models for each foreground sound and the models for the subjective evaluation of other physical environments including thermal, lighting and visual and overall physical comfort. The overall model in the framework is the subjective evaluation of a soundscape, which in this study, is assigned as the subjective evaluation of acoustic comfort in an urban open space.

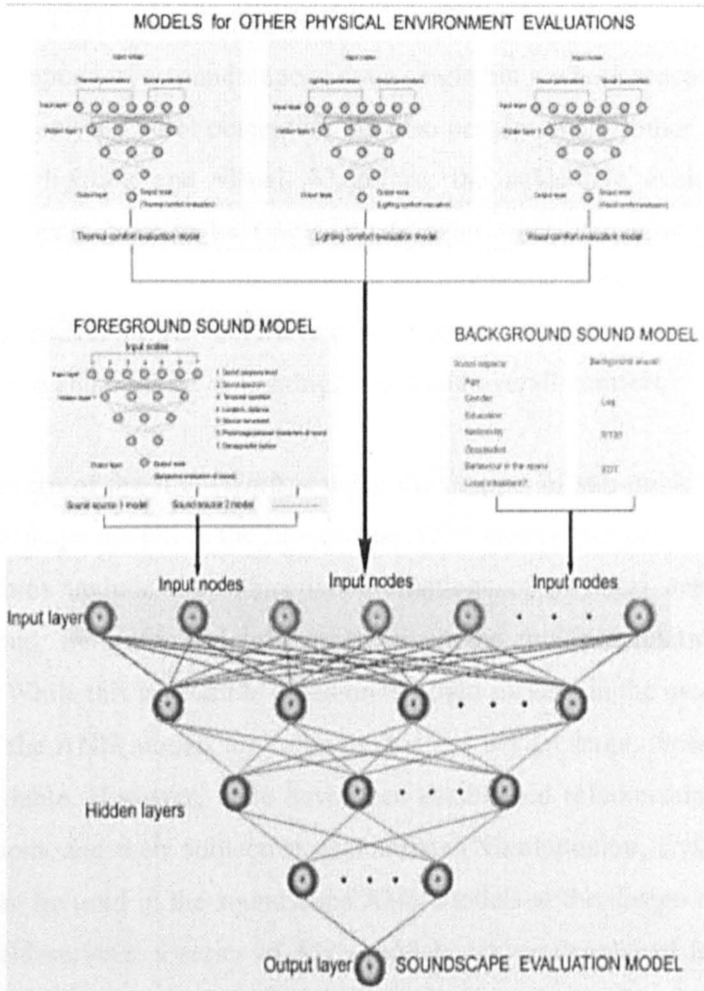



*Fig. 3.11 A modelling framework*

For an urban open space, the sound level of background noise is unique but there might be several noticed foreground sounds. Hence, there is only one sound level model in an overall soundscape model, but might be several sound preference models according to how many sounds are notable in an urban open space. A typical foreground sound model should take as many sound features into account as possible, no matter whether it is physical or psychological. A sound level model, however, only concerns the physical sound pressure level (SPL). But, for both sub-models, factors of the subject's social, cultural, psychological, behavioural aspects and the physical environmental conditions are considered.

The people's perception of a soundscape is not a single but a whole sensory process which is determined not only by aural perception but also perceptions of other physical stimuli, such as thermal, lighting and visual. Therefore, the subjective evaluations of these physical environments have to be taken into account when constructing a soundscape evaluation model. Thus, the third sub-model in the modelling framework of a soundscape evaluation is the models for the subjective evaluations of other physical comfort including thermal (heat, wind and humidity), lighting, visual and overall comfort.

The working pattern of the framework is using the outputs of sub-models to be inputs in the overall soundscape model. In the soundscape ANN models presented late in this thesis, the input variables include the subjective evaluations of physical conditions such as temperature, wind, humidity and brightness, given the multiple relationships between various factors. While this is possible based on the field surveys in the model development in this study, if the ANN models are to be used at the design stage, those input variables will not be available. However, there have been established relationships between these physical conditions and their subjective evaluations (Nikolopoulou, Lykoudis & Kikira, 2004), which can be used in the soundscape ANN models at the design stage. Moreover, based on the field surveys, a series of ANN models can be developed for the subjective evaluation of these physical conditions, which could be used as sub-models for soundscape ANN models, although this is not within the scope of this thesis.

### 3.4.2 Qnet model

As introduced in Chapter 2, Qnet is a typical multi-layers feed forward (MLFF) neural network using back propagation error learning. In this study, it has been used to develop ANN models for predicting the subjective evaluations of sound level and subjective evaluations of acoustic comfort. It has also been used to build prediction models for birdsong evaluations in comparison with the NeuroSolutions models.

The network of a Qnet model is formed by one input layer, several hidden layers, and one output layer. In this study, the nodes in the input layer are determined by the input variables, and the node in the output layer is the soundscape evaluations. An example has been made here is the network for the sound level evaluation model of Kassel Florentiner as shown in Fig. 3.12. The input variables of this model are six and the output is only one, the subjective evaluations of sound level. This model contained two hidden layers, with four hidden nodes in layer1 and two in layer2. The numbers of hidden layers and nodes were adjusted by the learning complexity in this model. More details of the model will be discussed in Chapter6.

The learning procedure of ANN model was via comparing the network outputs and the real targets. For each model built in Qnet, a minimum of 10% of the samples has been set for testing the network performance. In order to process data from input to output, the transfer functions are important; sigmoid function has been used. In relation to selecting the optimal network for each model, an optimizing training process is used which is based on establishing and running a large number of networks from the simple to the complex ones. The optimal networks for all the ANN models were obtained through this optimizing process. The root-mean square (RMS) errors between outputs (model's prediction) and targets (real evaluations obtained from field surveys in this study) along with the correlation coefficient between the outputs and targets were used to observe the prediction performance of these networks.

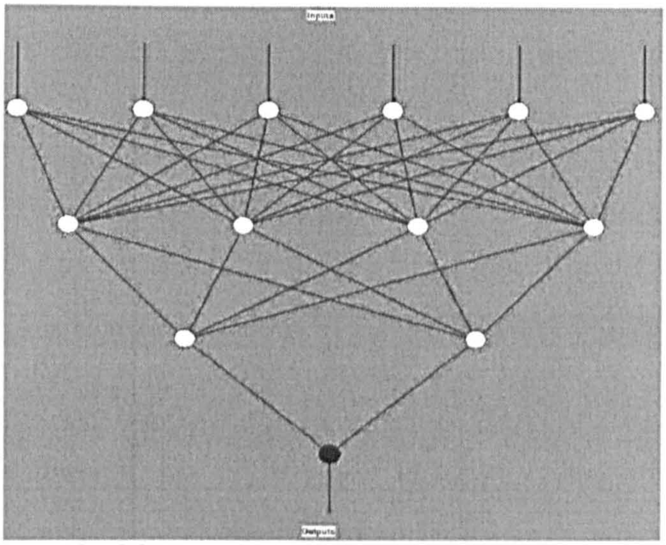
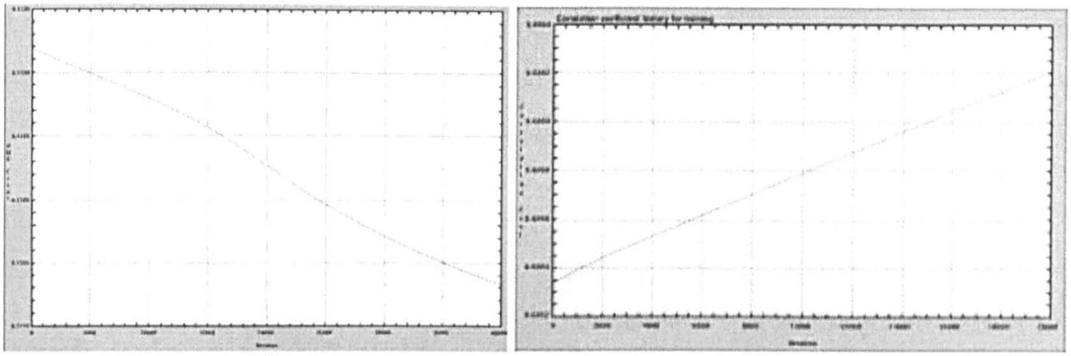


***Fig. 3.12** Network of the sound level evaluation model for Kassel Florentiner*

In Qnet, prediction performance of each model can be observed by several analysis tools, for instance, the plot of error history and correlation history are commonly used, and examples are shown in Fig. 3.13 from the same model as mentioned above. The error history is for determining when learning has reached its maximum level. It ranges from 0 to 1. The minimal global RMS error for test set is the point to terminate the training process; the more it closes to 0 the better the training has been done. Fig 3.13 (a) shows that the learning process of the model was successful as a good convergence has been gained and no overtraining has been found. The range of the correlation coefficient for model predictions is from 0 to 1. The closer it is to 1, the more accurate the prediction is. The correlation history plot shown in Fig. 3.13 (b) illustrates how well the network predictions trend with the targets. It can be seen that this model reached its highest correlation level in its training process.



(a) (b)

*Fig. 3.13 History plot of RMS error and correlation coefficient for test set of the sound level evaluation model for Kassel Florentiner; (a) RMS error history plot for test set; (b) Correlation history plot*

### 3.4.3 NeuroSolutions model

NeuroSolutions is a popular neural network program applied in various areas as mentioned in Section 2.7.1. It has been mainly used in this study to predict the sound preference evaluations as well as make comparison with Qnet for the models of sound level evaluations. There are many network modules in NeuroSolutions, where the MLP is appropriate for predictions, and has been employed in this study.

As an example of MLP network, the JdP model is shown in Fig. 3.14; it is a model for predicting the subjective evaluations of sound preference based on case study site 9-Jardin de Perolles in Frobourg, Switzerland, it will be discussed in details in Section 7.1. It can be seen that it works as data flow machine, which manages and operates the input information with two types of component: the Axon and Synapse. Axons represent a layer of PEs and implement the transfer functions. An axon at its input is fully connected to another axon at its output by a FullSynapse, a member of the Synapse family; however, input axon is only connected by a FullSynapse at its output and output axon can only be connected at its input. Before running a network, a data file at the input as well as output has to be added with a file component that can normalize and segment the data file. In training process, a backprop plane is used to transmit error information from the output to the network. The transfer function used in this model is sigmoid same as Qnet models. A generic algorithm is tagged to optimize the parameters when it is possible to be used. Like the test set of Qnet models, a sub-set has been set for internally testing the training process of this model, which is called cross validation (CV) in NeuroSolutions.

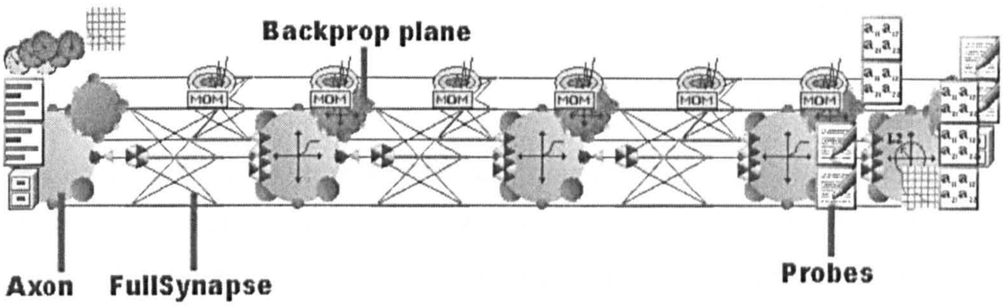



*Fig. 3.14 Network of MLP in NeuroSolutions*

In terms of the NeuroSolutions models for the soundscape evaluation in this study, analysis tools to monitor the network performance are probes. Four probes are available in NeuroSoltions, which are data graph, data writer, bar chart, and matrix viewer. The most used probe is data graph. A typical data graph for above mentioned sound preference model is shown in Fig. 7.1 (b). It can be seen that a good convergence has been achieved; the CV learning line declines with the training learning line and reaches its minimal error. The most used parameters for observing the models of sound preference evaluation in this study is Mean Square Error (MSE) and correlation coefficient between the outputs and targets. In this case, MSE (NeuroSolutions) differs from RMS error (Qnet) in the root, both of which are used for guiding over training and ensuring the training reaches its minimal error of the network outputs and the targets. The closer MSE is to 0 the better the training has been done. In addition, the correlation coefficient presents how well predicted the trend of the outputs towards the targets is between network predictions and the targets. The range of the correlation coefficient of model predictions is from 0 to 1. The closer it is to 1, the more accurate the prediction will be.

## 3.5 Conclusions

Field study and social surveys are the main methodology employed in this study. 19 case study sites were chosen with a wide range of European countries and China. In social surveys, the subjective evaluations of soundscape include sound levels, sound preference and acoustic comfort.

Following the field studies, the laboratory experiments were also undertaken to explore the subjective evaluations of sound preference. In total, 16 sounds which are commonly heard in urban open spaces and 56 subjects randomly selected were included in the laboratory experiments, which is in order to investigate the relationships between sound meanings, psychoacoustic parameters and the subjective evaluations of sound preference.

In this study, a number of factors possibly relating on the soundscape evaluations are explored. These factors can be categorised into four elements, namely physical, behavioural, social/demographical, and psychological. It is evident that the distribution of some social/demographical variables is normal, but not all.

Consequently, non-linear modelling techniques, such as ANNs, are suitable to be used. A modelling system for predicting subjective evaluation of soundscape was established in this chapter. Based on the significance levels of relationships between various factors and the subjective evaluations, Qnet and NeuroSolutions models were developed to predict the evaluations of sound level, acoustic comfort and sound preference. This will be specifically discussed in Chapter 6 & 7.

## Chapter 4

# Sound Level and Acoustic comfort Evaluation

Based on the literature review, it is known that various factors from physical and social environments are important for the subjective evaluations of soundscape in urban open spaces. The importance of sound pressure level, other physical conditions, social/demographical elements, behavioural and psychological factors on the subjective evaluations of sound level and acoustic comfort is discussed in this chapter. The chapter starts with examining the relationships between various social/demographical factors, followed by the statistical analysis of the importance of various factors on the subjective evaluations of sound level and acoustic comfort in urban open spaces, and finally proposes a mapping method to represent the subjective evaluations of potential users.

## 4.1 Relationships amongst social/demographical factors

In order to analyse the importance of various factors for the subjective evaluations of soundscape, it is essential to study the correlations amongst them. In this section, relationships amongst some social/demographical factors are examined; they are age, gender, occupation, education, and residential status.

Based on the data description in Section 3.3, it can be seen that population of age, occupation and education is generally normal distributed, for which the Person/Spearman correlation r is appropriate to be used to investigate their relationships, whilst for gender and resident status (local or non-local), independent t-test can be used, and the significant difference or correlation will be marked as * and ** , with * representing confidence $p<0.05$ and ** representing $p<0.01$.

### 4.1.1 Age, occupation and education

The relationships between age and occupation as well as between age and education in the 19 case study sites are shown in Table 4.1, in terms of the Pearson correlation coefficient r and the significance level. In Table 4.1 it can be seen that in most case study sites there is generally a significant correlation between age and occupation as well as between age and education. The correlation coefficients between age and occupation are generally rather high, around 0.5 to 0.7, and are predominately positive. Between age and education the correlation coefficients are relatively low, typically around 0.3-0.4, and include both positive and negative values.

***Table 4.1** Relationships amongst age and occupation, education, gender, residential status*

| Site | Correlation/Significance | | | | Mean difference/Significance (male - female; local - non-local) | |
|---|---|---|---|---|---|---|
| | Age/Occupation | | Age/Education | | Age/Gender | Age/Residential |
| | Pearson | Spearman | Pearson | Spearman | | |
| 1 | 0.74 (**) | 0.75(**) | 0.13 (**) | 0.12(*) | 0.09/0.17 | -0.023/0.88 |
| 2 | 0.69 (**) | 0.68(**) | 0.26 (**) | 0.27(**) | 0.25/0.10 | -0.19/0.21 |
| 3 | 0.67 (**) | 0.61(**) | -0.29 (**) | -0.26(**) | 0.56/0.00 (**) | -0.45/0.00 (**) |
| 4 | 0.65 (**) | 0.61(**) | -0.30 (**) | -0.27(**) | 0.35/0.00 (**) | -0.40/0.00 (**) |
| 5 | 0.56 (**) | 0.55(**) | -0.42 (**) | -0.44(**) | 0.49/0.00 (**) | -0.90/0.00 (**) |
| 6 | 0.66 (**) | 0.68(**) | -0.40 (**) | -0.38(**) | -0.03/0.82 | -0.80/0.00 (**) |
| 7 | 0.74 (**) | 0.75(**) | -0.33 (**) | -0.30(**) | 0.73/0.00 (**) | -0.45/0.00 (**) |
| 8 | 0.74 (**) | 0.75(**) | -0.40 (**) | -0.41(**) | 0.26/0.10 | -0.61/0.01 (*) |
| 9 | 0.72 (**) | 0.72(**) | 0.01 | 0.02 | -0.33/0.01 (**) | -0.46/0.00 (**) |
| 10 | 0.67 (**) | 0.69(**) | -0.05 | -0.01 | 0.09/0.42 | -0.02/0.82 |
| 11 | 0.50 (**) | 0.48(**) | 0.11 (*) | 0.14(**) | 0.32/0.02 (*) | 0.53/0.00 (**) |
| 12 | 0.65 (**) | 0.63(**) | -0.13 (**) | -0.10(*) | 0.20/0.17 | 0.47/0.01 (**) |
| 13 | 0.65 (**) | 0.60(**) | -0.01 | 0.09(*) | -0.21/0.19 | -0.71/0.00 (**) |
| 14 | 0.71 (**) | 0.70(**) | -0.12 (**) | -0.07 | -0.04/0.80 | -0.10/0.59 |
| 15 | -0.15 (**) | -0.10 | -0.05 | 0.02 | -0.29/0.08 (*) | -1.36/0.00 (**) |
| 16 | 0.08 | 0.12(*) | 0.31 (**) | 0.34(**) | 0.16/0.10 | 0.35/0.00 (**) |
| 17 | 0.72 (**) | 0.75(**) | 0.57 (**) | 0.56(**) | -0.74/0.04 (*) | 0.18/0.68 |
| 18 | 0.62 (**) | 0.53(**) | 0.22 | 0.34(**) | 0.41/0.26 | 1.04/0.01 (**) |
| 19 | 0.56 (**) | 0.56(**) | 0.31 (**) | 0.35(**) | 0.05/0.90 | 0.89/0.04 (*) |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

### 4.1.2 Gender, occupation, education and residential status

Table 4.1 also shows the difference between males and females as well as between local and non-local residents in terms of age. Between males and females, the difference is at a significance level in 8 of 19 case study sites, and between local and non-local residents significant differences exist in 14 of 19 case study sites, which indicated that the space users were rather even for male and female but not for residential status.

*Table 4.2 Relationships amongst gender and occupations, education, residential status*

| Site | Mean difference/Significance (male - female) | | |
|---|---|---|---|
| | Gender/Occupation | Gender/Education | Gender/Residential |
| 1 | 0.07/-0.51 | 0.02/0.76 | -0.04/0.41 |
| 2 | 0.03/0.09 | 0.07/0.29 | 0.09/0.08 |
| 3 | -0.13/0.01 (**) | 0.09/0.09 | 0.00/0.10 |
| 4 | -0.11/0.01 (**) | 0.03/0.57 | -0.03/0.31 |
| 5 | -0.08/0.16 | -0.14/0.01 (*) | -0.06/0.09 |
| 6 | -0.13/0.01 (**) | -0.04/0.37 | -0.01/0.66 |
| 7 | 0.16/0.01 (**) | -0.20/0.00 (**) | 0.03/0.51 |
| 8 | -0.06/0.36 | -0.04/0.48 | -0.03/0.30 |
| 9 | -0.17/0.00 (**) | 0.04/0.43 | -0.08/0.01 (**) |
| 10 | 0.05/0.25 | 0.08/0.04 (*) | -0.02/0.50 |
| 11 | 0.05/0.48 | 0.13/0.01 (**) | 0.01/0.84 |
| 12 | -0.00/0.98 | 0.08/0.10 | 0.14/0.00 (**) |
| 13 | -0.01/0.86 | -0.04/0.48 | -0.02/0.50 |
| 14 | 0.11/0.12 | 0.05/0.30 | 0.02/0.59 |
| 15 | 0.28/0.00 (**) | -0.05/0.43 | -0.15/0.01 (*) |
| 16 | 0.04/0.40 | 0.04/0.51 | -0.13/0.03 (*) |
| 17 | -0.56/0.00 (**) | -0.38/0.01 (**) | -0.09/0.47 |
| 18 | 0.03/0.77 | 0.17/0.21 | -0.02/0.86 |
| 19 | 0.08/0.61 | -0.09/0.53 | -0.20/0.09 |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

The difference between males and females in terms of occupation, education and residential status are shown in Table 4.2, based on independent samples t-test. Significant differences between genders in terms of occupation are found in seven case study sites. In case study site 17, the mean difference is 0.56. In terms of education, only five case study sites show significant differences between genders and the mean differences are rather low, suggesting that gender and education are generally unrelated variables in these urban open spaces. Similarly, in terms of residential status, only four case sites show significant differences between genders while the mean difference is usually less than 0.15, which indicates that gender and residential status can be generally regarded as unrelated variables in the study.

### 4.1.3 Occupation and education

The relationships between occupation and education, as well as the differences between local and non-local residents in terms of occupation and education are shown in Table 4.3. It can be seen that between occupation and education, the relationships are significant in fifteen case study sites, with correlation coefficients generally around 0.3, either positive or negative. In terms of occupation, significant differences exist between local and non-local residents in ten case study sites, and in terms of education, seven study sites present significant differences between local and non-local residents.

***Table 4.3** Relationships between occupation and education as well as between residential status and occupation and education*

| Site | Correlation/Significance | | Mean difference/Significance (local - non-local) | |
|---|---|---|---|---|
| | Occupation/Education | | Residential/Occupation | Residential/Education |
| | Pearson | Spearman | | |
| 1 | 0.07/0.14 | 0.07/0.17 | 0.00/0.10 | 0.04/0.56 |
| 2 | 0.16/0.00 (**) | 0.17/0.00(**) | 0.09/0.19 | -0.12/0.08 |
| 3 | -0.32/0.00 (**) | -0.33/0.00(**) | -0.23/0.00 (**) | 0.22/0.00 (**) |
| 4 | -0.31/0.00 (**) | -0.31/0.00(**) | -0.10/0.03 (*) | -0.01/0.86 |
| 5 | -0.43/0.00 (**) | -0.44/0.00(**) | -0.61/0.00 (**) | 0.46/0.00 (**) |
| 6 | -0.41/0.00 (**) | -0.41/0.00(**) | -0.32/0.00 (**) | 0.37/0.00 (**) |
| 7 | -0.35/0.00 (**) | -0.35/0.00(**) | -0.21/0.00 (**) | 0.40/0.00 (**) |
| 8 | -0.45/0.00 (**) | -0.47/0.00(**) | -0.21/0.04 (*) | 0.40/0.00 (**) |
| 9 | -0.08/0.02 (*) | -0.09/0.01(**) | -0.22/0.00 (**) | 0.08/0.13 |
| 10 | -0.20/0.00 (**) | -0.18/0.00(**) | 0.08/0.10 | -0.11/0.01 (**) |
| 11 | -0.15/0.00 (**) | -0.140.00 (**) | -0.00/0.96 | 0.02/0.72 |
| 12 | -0.08/0.11 | -0.08/0.10 | -0.07/0.32 | -0.07/0.24 |
| 13 | -0.23/0.00 (**) | -0.23/0.00(**) | -0.17/0.06 (*) | -0.08/0.23 |
| 14 | -0.26/0.00 (**) | -0.26/0.00(**) | 0.04/0.66 | -0.02/0.76 |
| 15 | -0.07/0.27 | -0.12/0.051 | 0.26/0.00 (**) | -0.24/0.00 (**) |
| 16 | -0.28/0.00 (**) | -0.29/0.00(**) | 0.11/0.03 (*) | -0.00/0.95 |
| 17 | 0.40/0.00 (**) | 0.41/0.00 (**) | 0.08/0.69 | -0.11/0.51 |
| 18 | 0.24/0.06 | 0.26/0.04 (*) | 0.21/0.08 | 0.21/0.14 |
| 19 | -0.05/0.68 | 0.02/0.87 | 0.20/0.20 | 0.07/0.65 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

### 4.1.4 Summary

In Table 4.4, the percentage and number of the case study sites, where the correlations among the social/demographical factors exist, are shown. Although the aim of this thesis is not to examine the differences between individual case study sites, it is important to consider these relationships because this is useful when selecting input variables for the prediction models of soundscape evaluations.

***Table 4.4** Percentage (number) of the case study sites where significant correlations or differences exist between pairs of social/demographical factors*

| | Age | Gender | Occupation | Education | Residential |
|---|---|---|---|---|---|
| Age | - | 42% (8) | 95% (18) | 74% (14) | 74% (14) |
| Gender | | - | 37% (7) | 26% (5) | 21% (4) |
| Occupation | | | - | 74% (14) | 53% (10) |
| Education | | | | - | 37% (7) |
| Residential | | | | | - |

## 4.2 Social/demographical factors

In this section, the importance of social/demographical factors on the subjective evaluations of sound level and acoustic comfort has been analysed.

### 4.2.1 Age, occupation and education re. the sound level evaluations

Table 4.5 shows the significance level of age, occupation and education on the subjective evaluations of sound level. It is found that age is less important for subjective evaluations of the sound level. Among the 19 case study sites only 4 show significant correlations between age and sound level evaluations, and the coefficient values are rather low, around -0.1. The negative correlations in these 4 case study sites suggest that with increasing age, people tend to be slightly more tolerant. A possible reason is that these sites are featured by children shouting and the main function is recreation and relaxation.

In terms of the relationship between occupation and subjective evaluations of the sound level, significant correlations are shown in 7 case study sites, including site 3, 4, 5, 6, 9, 11 and 14. It is interesting to note that all these 7 sites are in the EU and the correlation coefficients are negative in 6 sites. In terms of the effect of education on sound level evaluations, it is also found that 7 case study sites show significant correlations. This includes sites 5, 6, 9, 10, 12, 14 and 16, where 4 sites are the same as those for occupation. The possible reason for this is that occupation and education are correlated factors in these sites, as shown in Table 4.4. The correlation coefficients between sound level evaluations and education are all positive in 7 sites where a significance level exists, although the r values are less than 0.2. It implies that people with a higher education level show less noise tolerance in urban open spaces.

***Table 4.5** Relationships between age, occupation, education, gender, residential status and the sound level evaluations*

| Site | Correlation/Significance | | | | | Mean difference/Significance (male - female; local - non-local) | |
|---|---|---|---|---|---|---|---|
| | Age | Occupation | | Education | | Gender | Residential |
| | | Pearson | Spearman | Pearson | Spearman | | |
| 1 | -0.04 | 0.02 | 0.01 | 0.09 | 0.08 | -0.15/0.02 (*) | -0.12/0.06 |
| 2 | -0.09 | -0.04 | -0.05 | 0.02 | 0.02 | 0.04/0.57 | -0.05/0.40 |
| 3 | 0.07 | 0.11 (**) | 0.09(*) | -0.04 | -0.02 | -0.03/0.66 | -0.11/0.16 |
| 4 | -0.12 (**) | -0.10 (**) | -0.10(**) | 0.06 | 0.06 | 0.00/0.97 | 0.06/0.9 |
| 5 | -0.06 | -0.11 (**) | -0.11(**) | 0.07 (*) | 0.08(*) | -0.01/0.92 | 0.08/0.3 |
| 6 | -0.12 (**) | -0.12 (*) | -0.13(**) | 0.12(**) | 0.12(**) | 0.17/0.00 (**) | 0.02/0.7 |
| 7 | 0.07 | 0.06 | 0.05 | 0.00 | 0.00 | 0.05/0.59 | -0.05/0.60 |
| 8 | -0.01 | 0.00 | -0.00 | -0.04 | -0.02 | -0.08/0.27 | -0.20/0.08 |
| 9 | -0.09 (**) | -0.12 (**) | -0.13(**) | 0.12(**) | 0.13(**) | -0.03/0.57 | 0.13/0.00(*) |
| 10 | 0.04 | 0.03 | 0.04 | 0.08(**) | 0.07(*) | -0.17/0.00 (**) | -0.09/0.08 |
| 11 | -0.04 | -0.19(**) | -0.21(**) | 0.06 | 0.07 | -0.04/0.65 | 0.08/0.31 |
| 12 | -0.06 | -0.01 | 0.01 | 0.10 (*) | 0.11(*) | -0.15/0.06 | 0.34/0.00 (**) |
| 13 | -0.00 | -0.03 | -0.04 | -0.03 | -0.03 | -0.01/0.84 | -0.08/0.39 |
| 14 | -0.12 (**) | -0.12 (**) | -0.12(**) | 0.10 (*) | 0.12(**) | 0.05/0.58 | -0.16/0.09 |
| 15 | 0.00 | 0.02 | 0.05 | 0.03 | 0.02 | -0.09/0.26 | 0.02/0.85 |
| 16 | 0.08 | -0.11 | -0.09 | 0.17 (**) | 0.18(**) | -0.01/0.95 | -0.05/0.56 |
| 17 | -0.06 | 0.01 | -0.03 | 0.09 | 0.08 | -0.22/0.21 | -0.33/0.10 |
| 18 | 0.07 | -0.11 | -0.09 | 0.03 | 0.06 | -0.05/0.71 | 0.03/0.85 |
| 19 | 0.09 | 0.07 | 0.05 | 0.23 | 0.20 | 0.09/0.60 | 0.30/0.06 |
| % of Sig. | 4/19 | 7/19 | 7/19 | 7/19 | 7/19 | 3/19 | 2/19 |
| Ratio | 21% | 37% | 37% | 37% | 37% | 16% | 11% |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

### 4.2.2 Gender and residential status re. the sound level evaluations

Previous studies suggested that the effect of gender on sound annoyance evaluations is generally insignificant (Fields, 1993; Miedema & Vos, 1999), although it was reported that males might be less tolerant than females to low-frequency noise (Verzini, Frassoni & Oritiz, 1999). From Table 4.5 it can also be seen that there is generally no significant difference between males and females in terms of sound level evaluations except in three case study sites. Nevertheless, it is also shown that the mean differences are negative in 13 case study sites; namely, the evaluations score of females is slightly higher than males, or in other words, males might be more tolerant than females, although the differences are not at a significance level. The standard deviations (STD) of the sound level evaluations of males and females are shown in Fig. 4.1. It is interesting to note that in majority of the case study sites the STD of males is higher than that of females. This suggests that males tend to have a wider range of evaluations range than females, although the differences between males and females are not considerable compared with the standard deviations among males or females, which are both around 0.6-1.

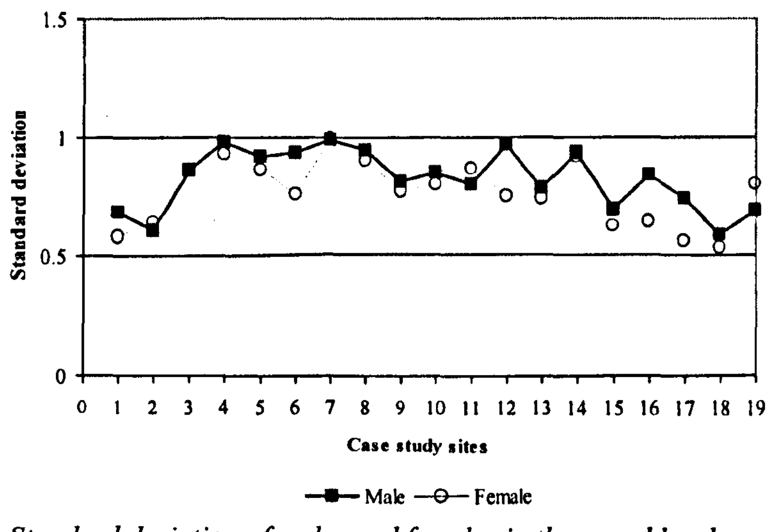



*Fig. 4.1 Standard deviation of males and females in the sound level evaluations*

The effect of residential status is generally insignificant, as can be seen in Table 4.5, where only two case study sites have significant difference between local and non-local residents. In site 12, namely Cambridge Silver Street, the difference is significant, at 0.34

in average, which is probably because in this site there are two distinguish groups, namely local students and overseas tourists. Whilst the standard deviations among locals and non-locals are rather high in the case study sites, at around 0.6-1, as shown in Fig. 4.2, between the two groups there is generally no significant difference.

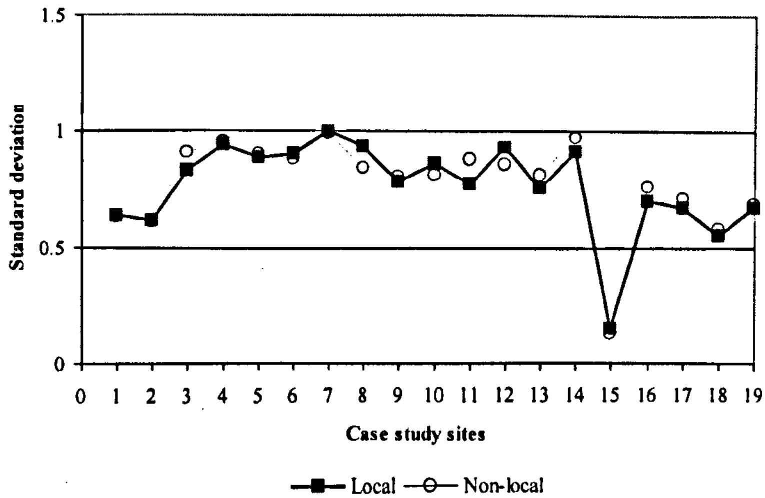



*Fig. 4.2 Standard deviation of locals and non-locals in the sound level evaluations*

### 4.2.3 Long-term sound experience re. the sound level evaluations

Long-term sound experience is another important factor for the evaluations of sound quality in urban areas (Bertoni, Franchini, Magnoni, Tartoni & Vallet, 1993; Schulte-Fortkamp & Nitsch, 1999). The importance of the sound levels in the interviewees' living place for the sound level evaluations on-site has also been investigated in this section as shown in Table 4.6 & 4.7. Correlation coefficient between the sound level evaluations at case study sites and at home is shown in Table 4.6. It can be seen that statistically significant correlations are reached in 6 case study sites and 5 correlation coefficients are positive. This implies that people living in noisy homes might be less tolerable in the urban open spaces, although the correlation coefficient values are all below 0.49.

Correspondingly, Figure 4.3 and 4.4 show the differences in mean evaluations score and the difference in the standard deviation of evaluations scores between home and the case study sites, respectively. It is interesting to note that the mean evaluations score at home is generally lower than that in the case study sites, by over 0.5 in average, except 4 sites where the differences are all less than 0.2. This indicates that usually the home environment is quieter than in urban open spaces. Moreover, the STD for the home sound level evaluations is mostly greater than that in the case study sites, by 0.18 in average, except site 5 and 14, suggesting that people have more diversity when evaluating the home environment.

***Table 4.6*** *Relationships between the sound level evaluations at home and the sound level evaluations on-site*

| Site | Correlation/Significance |
|---|---|
| 1- Germany Kassel, Bahnhofsplatz | -0.12/0.02(*) |
| 2- Germany Kassel, Florentiner | -0.06/0.22 |
| 3- Greece Athens, Karaiskaki | 0.05/0.20 |
| 4- Greece Athens, Seashore | 0.09/0.01(*) |
| 5- Greece Thessaloniki, Kritis | 0.07/0.04(*) |
| 6- Greece Thessaloniki, Makedonomahon | -0.01/0.81 |
| 7- Italy Milan, IV Novembre | 0.02/0.65 |
| 8- Italy Milan, Piazza Petazzi | 0.18/0.00 (**) |
| 9- Switzerland Fribourg, Jardin de Perolles | 0.04/0.22 |
| 10- Switzerland Fribourg, Place de la Gare | 0.03/0.31 |
| 11- UK Cambridge, All Saint's Garden | -0.02/0.68 |
| 12- UK Cambridge, Silver Street | -0.03/0.47 |
| 13- UK Sheffield, Barkers Pool | 0.33/0.00 (**) |
| 14- UK Sheffield, Peace Gardens | 0.49/0.00 (**) |
| 15- China Beijing, Chang Chun Yuan Square | 0.05/0.39 |
| 16- China Beijing, Xi Dan Square | 0.03/0.63 |
| 17- China Shanghai, Century Square | -0.12/0.38 |
| 18- China Shanghai, Nanjing Road Square | -0.15/0.20 |
| 19- China Shanghai, Xu Jia Hui Park | 0.21/0.07 |
| % of Sig. | 6/19 |
| Ratio | 32% |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

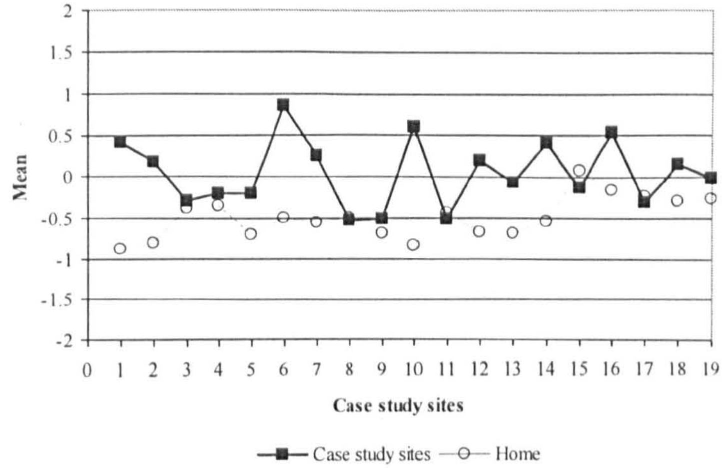



*Fig. 4.3 Comparison in sound level evaluations between home and case study sites*

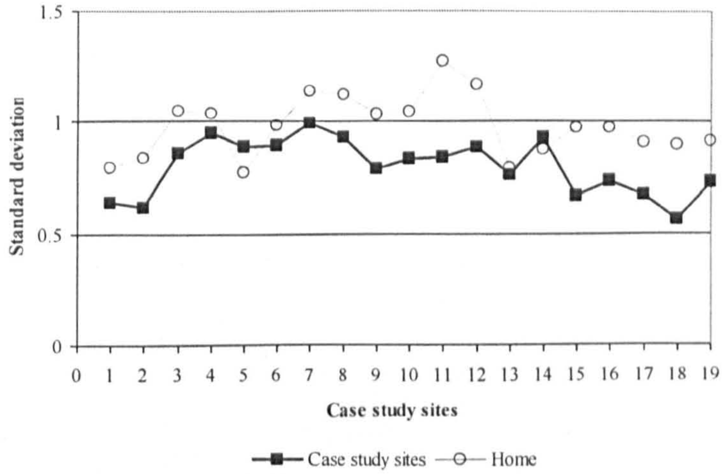



*Fig. 4.4 Comparison in the standard deviation of sound level evaluations between home and case study sites*

Table 4.7 shows the correlation coefficients between the subject's evaluations of home sound level and its age, occupation and education, as well as the mean differences between males and females and between local and non-local residents in terms of the subjective evaluations of home sound level. The table also compared with the significance levels of the sound level evaluations between case study sites and home. It is interesting to note that for those sites with significance levels, the home sound level evaluations is generally not significantly correlated with the social/demographical factors, and *vice versa*, except at three sites, namely site 6- Makedonomahon Square in Thessaloniki, site 9-

Jardin de Perolles in Frobourg and site 14- the Peace Gardens in Sheffield, where two of them, site 6 and 9, are located residential areas. This generally suggests that the difference between the sound level evaluations at home and at the case study sites could not be from those social/demographical factors.

*Table 4.7 Relationships between the sound level evaluations at home and age, occupation, education, gender, residential status*

| Site | Correlation/Significance | | | | | | Mean difference/Significance (male-female; local - non-local) | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Age | | Occupation | | Education | | Gender | | Residential | |
| | Home | Site | Home | Site | Home | Site | Home | Site | Home | Site |
| 1 | 0.04/0.45 | | 0.05/0.32 | | 0.04/0.37 | | 0.04/0.60 | (*) | -0.21/0.01(**) | |
| 2 | 0.03/0.61 | | 0.00/0.99 | | 0.11/0.03 (*) | | 0.04/0.68 | | -0.22/0.01(*) | |
| 3 | -0.05/0.21 | | 0.02/0.67 | (**) | 0.03/0.45 | | -0.18/0.03(*) | | -0.05/0.61 | |
| 4 | -0.05/0.13 | (**) | -0.00/0.95 | (**) | -0.06/0.11 | | -0.06/0.44 | | 0.41/0.00(**) | |
| 5 | 0.09/0.01(*) | | 0.04/0.33 | (**) | 0.00/0.95 | (*) | 0.06/0.25 | | 0.01/0.90 | |
| 6 | 0.09/0.00(**) | (**) | 0.08/0.01 (*) | (*) | -0.09/0.00(**) | (**) | -0.07/0.23 | (**) | -0.36/0.00(**) | |
| 7 | 0.06/0.17 | | 0.08/0.05 (*) | | -0.11/0.01(**) | | 0.36/0.00(**) | | -0.25/0.02(*) | |
| 8 | 0.05/0.26 | | 0.05/0.23 | | -0.06/0.13 | | 0.09/0.33 | | -0.30/0.04 | |
| 9 | -0.02/0.58 | (**) | 0.04/0.19 | (**) | -0.10/0.00(**) | (**) | -0.10/0.15 | | -0.51/0.00(**) | (*) |
| 10 | -0.09/0.01(**) | | -0.05/0.09 | | -0.03/0.33 | (**) | 0.00/0.98 | (**) | -0.35/0.00(**) | |
| 11 | -0.10/0.04(*) | | -0.03/0.51 | (**) | -0.10/0.03 (*) | | -0.25/0.04(*) | | -0.28/0.02(*) | |
| 12 | 0.19/0.00(**) | | 0.10/0.03(*) | | -0.03/0.50 | (*) | 0.01/0.91 | | 0.16/0.21 | (**) |
| 13 | -0.060/0.18 | | -0.11/0.02 (*) | | -0.00/0.95 | | 0.07/0.34 | | 0.02/0.79 | |
| 14 | -0.06/0.17 | (**) | -0.13/0.00(**) | (**) | 0.15/0.00 (**) | (*) | 0.13/0.10 | | -0.06/0.53 | |
| 15 | -0.17/0.00(**) | | 0.03/0.61 | | -0.04/0.45 | | 0.16/0.16 | | 0.12/0.31 | |
| 16 | -0.07/0.26 | | 0.02/0.79 | | -0.10/0.10 | (**) | 0.05/0.66 | | -0.08/0.51 | |
| 17 | -0.18/0.19 | | -0.02/0.90 | | -0.28/0.04 (*) | | 0.28/0.25 | | 0.40/0.14 | |
| 18 | -0.26/0.03(*) | | -0.33/0.01(**) | | -0.10/0.39 | | -0.24/0.25 | | 0.43/0.06 | |
| 19 | -0.02/0.88 | | -0.05/0.71 | | 0.15/0.21 | | -0.04/0.84 | | 0.18/0.39 | |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

### 4.2.4 Social/demographical factors re. the acoustic comfort evaluations

In terms of the subjective evaluations of acoustic comfort, only 7 case study sites in Sheffield and China have been studied as the acoustic comfort evaluations were not investigated in other case study sites. Table 4.8 shows the relationships between social/demographical factors and the acoustic comfort evaluations. Unlike the sound level evaluations, there is a rather limited relation between the acoustic comfort evaluations and occupation and education, because a significance level has only been found in 1 of 7 case study sites. Similar as the sound level evaluations, variables of age, gender and residential are related less to the acoustic comfort evaluations yet as none or one significance level has been found. In Table 4.8, it can also be seen that the evaluations of sound level at home, which has been found to be closely related to the sound level evaluations, has limited relation with the acoustic comfort evaluations. Only 2 of 7 case study sites have a significance level. However, in Sheffield Peace Gardens (site 14) and Shanghai Xu Jia Hui Park (site 19), a negative relationship between this two factors has been found.

***Table 4.8*** *Relationships between social/demographical factors and the acoustic comfort evaluations*

| Site | Age | Gender | Occupation | Education | Local, non-local residential | Sound level evaluations at home |
|---|---|---|---|---|---|---|
| 13 | 0.05 | -0.00 | 0.07 | 0.08 | 0.08 | 0.01 |
| 14 | 0.01 | -0.17 | 0.02 | 0.02 | -0.02 | -0.55(**) |
| 15 | 0.02 | 0.11 | 0.01 | 0.00 | 0.03 | 0.02 |
| 16 | -0.01 | 0.11 | 0.19(**) | -0.15(**) | 0.05 | 0.06 |
| 17 | 0.01 | 0.22 | 0.06 | -0.10 | 0.19 | -0.21 |
| 18 | -0.27(*) | 0.16 | -0.07 | 0.03 | 0.15 | 0.09 |
| 19 | -0.15 | -0.01 | -0.03 | -0.22 | -0.19 | -0.42(**) |
| % of Sig.. | 14.3 | 0.0 | 14.3 | 14.3 | 0.0 | 28.6 |
| Ratio | 1/7 | 0/7 | 1/7 | 1/7 | 0/7 | 2/7 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

In terms of the correlations between occupation, education and the acoustic comfort evaluations, it is interesting to note that a significance level exists in the same case study site for both factors. This might be because these two factors are closely correlated as shown in Table 4.3. In terms of the sound level evaluations at home and the acoustic comfort evaluations, it is found that a significance level exists in two case study sites and both of them are located in the tourist spots. In three case study sites, a negative correlation between the sound level evaluations at home and the acoustic comfort evaluations has been found, all with a relatively high value. With the other four remaining sites, a positive correlation is found but the value is considerably low. This result implies that people from quiet places might feel less acoustically comfortable in urban open spaces.

## 4.3 Acoustic/physical factors

The importance of acoustic factor, SPL, and other physical factors, including season; time of day; air temperature; wind speed; relative humidity; horizontal luminance and whether in sun-shade place; on the sound level evaluations as well as the acoustic comfort evaluations were examined. The results are shown in Table 4.9.

***Table 4.9** Relationships between acoustic/physical factors and the sound level evaluations*

| Site | Season | Time of day | Temperature | Wind speed | Humidity | Luminance | Sun-shade | SPL |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.04 | 0.04 | 0.09 | 0.02 | -0.02 | 0.02 | 0.06 | 0.11(*) |
| 2 | 0.05 | 0.05 | 0.11(*) | -0.09 | -0.12(*) | 0.03 | 0.07 | 0.21(**) |
| 3 | -0.25(**) | -0.26(**) | -0.23(**) | 0.08(*) | 0.21(**) | 0.19(**) | -0.02 | 0.30(**) |
| 4 | -0.24(**) | -0.25(**) | -0.15(**) | -0.07(*) | 0.07(*) | -0.05 | -0.10 | 0.27(**) |
| 5 | 0.04 | 0.03 | 0.02 | -0.08(*) | -0.02 | -0.16(**) | 0.04 | 0.06 |
| 6 | -0.10(**) | -0.10(**) | -0.05 | 0.05 | -0.04 | 0.06 | -0.05 | 0.14(**) |
| 7 | 0.03 | 0.04 | 0.01 | -0.00 | 0.05 | 0.13(**) | 0.17 | 0.07 |
| 8 | 0.05 | 0.04 | 0.06 | -0.12(**) | 0.04 | -0.10(*) | 0.05 | 0.17(**) |
| 9 | -0.01 | -0.01 | -0.01 | -0.07(*) | 0.09(**) | -0.11(**) | 0.18(**) | 0.22(**) |
| 10 | 0.03 | 0.03 | 0.06(*) | 0.10(**) | -0.08(**) | 0.07(*) | -0.11(*) | 0.14(**) |
| 11 | 0.02 | 0.03 | -0.06 | -0.12(*) | 0.11(*) | 0.08 | -0.18(*) | 0.12(*) |
| 12 | -0.07 | -0.05 | -0.12(**) | -0.08 | 0.01 | -0.03 | -0.21(*) | 0.06 |
| 13 | 0.02 | 0.02 | -0.04 | -0.02 | -0.05 | 0.03 | -0.10 | 0.30(**) |
| 14 | -0.14(**) | -0.13(**) | -0.06 | -0.06 | 0.04 | 0.07 | 0.06 | 0.43(**) |
| 15 | | -0.02 | -0.04 | -0.15(**) | 0.19(**) | 0.08 | | -0.01 |
| 16 | | -0.08 | -0.04 | -0.01 | 0.02 | -0.10 | | 0.11 |
| 17 | | -0.01 | -0.19 | 0.21 | 0.06 | -0.11 | | 0.77(**) |
| 18 | | | -0.01 | 0.12 | 0.04 | -0.03 | | 0.79(**) |
| 19 | | -0.10 | 0.06 | 0.01 | 0.02 | 0.30 (**) | | 0.80(**) |
| % of Sig. | 28.6 | 22.2 | 26.3 | 42.1 | 36.8 | 36.8 | 28.6 | 73.7 |
| Ratio | 4/14 | 4/18 | 5/19 | 8/19 | 7/19 | 7/19 | 4/14 | 15/19 |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

### 4.3.1 Acoustic/physical factors re. the sound level evaluations

Table 4.9 shows the relationships between acoustic/physical factors and the sound level evaluations. The grey areas indicate where the variables are not available. The SPL is different from the other physical factors, where it is found that it has the strongest correlation with the sound level evaluations as 14 of 19 case study sites are marked with

* (p>0.05) or **(p>0.01). Moreover, the correlation values of SPL with the sound level evaluations are generally higher than those of other physical factors.

Amongst 19 case study sites, the highest correlation between SPL and the sound level evaluations has been found in 3 Shanghai case study sites as shown in Table 4.9. This might be related to the low SPL, as a low value has been found in all the Shanghai case study sites as can be seen in Fig. 4.5 (values are also shown in Table 3.3).

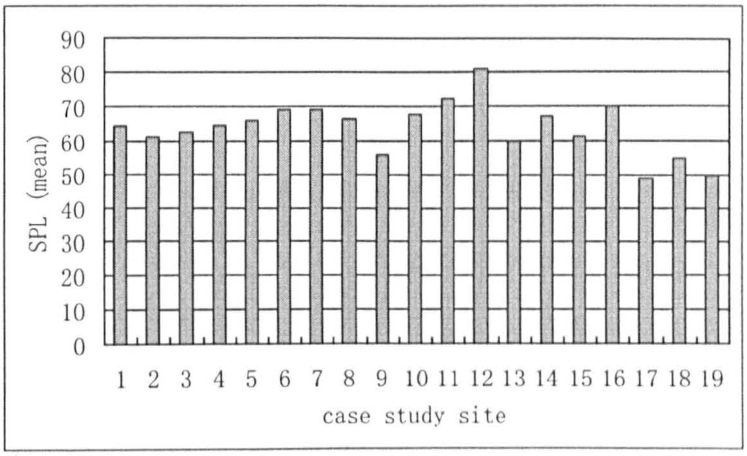



***Fig. 4.5*** *SPL (mean) distribution for 19 case study sites*

Table 4.9 also showed the importance of air temperature, wind speed and relative humidity on the sound level evaluations. It can be seen that significant values have been found in 5 of 19, 8 of 19 and 7 of 19 case study sites respectively. It indicates that these thermal factors have some relations with the sound level evolutions especially wind speed and relative humidity. However, both positive and negative correlations have been found between these two factors and the sound level evaluations. This might be related to the subjects' social background and individual experience.

For other two physical factors, season and time of day, it is found that their influence on the sound level evaluations is limited, because a significance level has only been found in 4 of 19 case study sites. It is interesting to note that the significance level of both factors on the sound level evaluations exists in the same case study sites, implying these two factors may also be correlated.

In Table 4.9, the relationship between lighting conditions and the sound level evaluations has also been examined, including the horizontal luminance and whether subjects under sun-shade. It can be seen that the horizontal luminance has some relation with the sound level evaluations as 7 of 19 case study sites have been found with a significance level with a either positive or negative correlation. However, the influence of sun-shade on the sound level evaluations is limited as 4 of 14 case study sites have been found having a significant difference between the people who are under a sun-shade and those who are not. It is also noted that the case study sites with a significance level are usually located in the same city, such as Milan and Frobourg, or the same country, e.g. Greece; or situated in similar locations, residential area or city centres. This result implies that such influence may be related to culture differences.

**4.3.2 Acoustic/physical factors re. the acoustic comfort evaluations**

Following the above analyses, the correlations between the acoustic/physical factors and the acoustic comfort evaluations have also been analysed and shown in Table 4.10. Like its effect on the sound level evaluations, SPL has also been found closely related to the acoustic comfort evaluations because significance levels exist in 5 out of 7 case study sites. It has also been found that all the correlations with significance levels were negative, which means people felt less comfortable with a higher SPL. Comparing the relation of SPL with the sound level evaluations and with the acoustic comfort evaluations, it is interesting to note that a distinct difference exists in two case study sites, site 15- Chang Chun Yuan Square of Beijing and site 17- Century Square of Shanghai. In the Chang Chun Yuan Square, SPL is not significantly correlated with the sound level evaluations but it is significantly correlated with the acoustic comfort evaluations; however, an opposite situation has been found in the Century Square. This might be related to the differences in users. The users of Chang Chun Yuan Square usually reside around the area and become less sensitive to the sound level in the Square, whereas the users of the Century Square are not residents near the place as there is no residential complex around it.

Table 4.10 also shows that the correlation of the thermal factors (temperature, wind speed, relative humidity), season and time of day, with the acoustic comfort evaluations is weak, because only one significant case has been found for all the factors except two for the relative humidity with a low *r* value. Although only 2 case study sites could be used to analyse the relations of season with the acoustic comfort evaluations, and the analyses of the relationship between time of day and the acoustic comfort evaluations may be useful in understanding the relationships between season and the acoustic comfort evaluations because both factors are highly correlated. In Table 4.12, a positive correlation between air temperature and the acoustic comfort evaluations have also been found, indicating that interviewees generally felt acoustically uncomfortable with high temperature in the case study sites. It is noted that this result is limited to a certain temperature range, which does not include very high or very low ranges.

The correlations of lighting factors, horizontal luminance, whether under a sun-shade, with the acoustic comfort evaluations have also been analysed as shown in Table 4.10. Generally speaking, their correlations were considerably less because at most one case was found with a significant difference or at a significance level. A negative correlation between horizontal luminance and the acoustic comfort evaluations has been found in 3 of 5 case study sites, and comparing with the positive correlation, the value of the negative is relatively high. This result may imply that people felt more acoustic comfortable in a bright place. This is also limited by the range of the horizontal luminance which was measured in the case study sites.

*Table 4.10 Relationships between acoustic/physical factors and the acoustic comfort evaluations*

| Site | Season | Time of day | Air temperature | Wind speed | Humidity | Luminance | Sun-shade | SPL |
|---|---|---|---|---|---|---|---|---|
| 13 | -0.02 | 0.01 | 0.12 | -0.04 | -0.04 | | -0.04 | -0.15(*) |
| 14 | -0.37(**) | 0.22(**) | 0.02 | 0.13(**) | -0.21(**) | | -0.01 | -0.17(**) |
| 15 | | 0.01 | 0.08 | 0.07 | 0.00 | -0.05 | | -0.14(*) |
| 16 | | 0.06 | 0.13(*) | -0.11 | -0.16(**) | 0.02 | | 0.00 |
| 17 | | -0.08 | 0.08 | -0.28 | -0.12 | 0.00 | | 0.08 |
| 18 | | | 0.01 | -0.27 | 0.05 | -0.10 | | -0.25(*) |
| 19 | | 0.03 | 0.11 | -0.18 | 0.15 | -0.24(*) | | -0.37(**) |
| % of Sig.. | 50 | 16.7 | 14.3 | 14.3 | 28.6 | 20.0 | 0.9 | 71.4 |
| Ratio | 1/2 | 1/6 | 1/7 | 1/7 | 2/7 | 1/5 | 0/2 | 5/7 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

## 4.4 Behavioural factors

### 4.4.1 Earphones, reading/writing re. the sound level evaluations

Table 4.11 shows the difference of the sound level evaluations between people wearing and not-wearing earphones, as well as between people who were reading/writing and not reading/writing in the case study sites. For the factor, whether wearing earphones, only a few samples exist in several case study sites as mentioned in Section 3.3. So, the analyses have been made not only for individual case study site but also for a combination of EU, China and all studied sites. The results shown in Table 4.11 present that there is no significant difference in any of the above case. For the factor, whether reading/writing, a significant difference has only been found in 2 of 19 case study sites, namely site 6-Makedonomahon in Thessaloniki, Greece, and site 14- Peace Gardens in Sheffield, UK. This result suggests the behavioural factor, whether reading/writing, is insignificant related with the sound level evaluations.

***Table 4.11*** *Relationships between whether wearing earphones, whether reading/writing and the sound level evaluations*

| Site | Mean difference/Significance (not-wearing - wearing; not-reading/writing - reading/writing) | |
|---|---|---|
| | Earphones | Reading/Writing |
| 1: Germany Kassel, Bahnhofsplatz | 0.02/0.95 | -0.05/0.68 |
| 2: Germany Kassel, Florentiner | | -0.02/0.90 |
| 3: Greece Athens, Karaiskaki | | 0.25/0.06 |
| 4: Greece Athens, Seashore | | 0.12/0.48 |
| 5: Greece Thessaloniki, Kritis | | 0.23/0.08 |
| 6: Greece Thessaloniki, Makedonomahon | 0.26/0.27 | 0.26/0.03 (*) |
| 7: Italy Milan, IV Novembre | | -0.16/0.19 |
| 8: Italy Milan, Piazza Petazzi | | 0.30/0.07 |
| 9: Switzerland Fribourg, Jardin de Perolles | -0.07/0.79 | -0.21/0.15 |
| 10: Switzerland Fribourg, Place de la Gare | 0.38/0.05 | 0.07/0.65 |
| 11: UK Cambridge, All Saint's Garden | | 0.15/0.12 |
| 12: UK Cambridge, Silver Street | | 0.22/0.10 |
| 13: UK Sheffield, Barkers Pool | | -0.20/0.18 |
| 14: UK Sheffield, Peace Gardens | | 0.46/0.01 (**) |
| 15: China Beijing, Chang Chun Yuan Square | | 0.15/0.18 |
| 16: China Beijing, Xi Dan Square | | -0.35/0.08 |
| 17: China Shanghai, Century Square | | -0.33/0.35 |
| 18: China Shanghai, Nanjing Road Square | | 0.16/0.78 |
| 19: China Shanghai, Xu Jia Hui Park | | 0.20/0.41 |
| EU | -0.05/0.67 | |
| China | 0.34/0.16 | |
| Overall | -0.00/0.99 | |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

Following the analyses of the influence of reading/writing on the sound level evaluations, Table 4.12 tracks the difference between people who were reading/writing and not reading/writing in terms of social/demographical factors including age, gender, occupation, education, and residential status. Bold texts emphasize two case study sites where a significant difference between the people who were reading/writing and who were not reading/writing exists. It can be seen that in site 14- Peace Gardens, reading/writing is an independent factor, and people who were reading/writing have a lower evaluation score, by 0.46 in averages. However, in site 6- Makedonomahon, social/demographical factors including age, gender, education and residential status also significantly affect the differences between those who were reading/writing or not reading/writing, so that reading/writing is not an independent factor to influence the sound level evaluations in this site and may be masked by social/demographical factors. The interactions between reading/writing and social/demographical factors in other seventeen case study sites are also shown in Table 4.12. It can be seen that reading/writing relates to age, gender and education in 6 to 7 case study sites, more than that to occupation and residential status, which is only significant in 3 to 4 sites.

***Table 4.12** Relationships between whether reading/writing and age, gender, occupation, education, residential status*

| Site | Mean difference/Significance ( not-reading/writing - reading/writing) | | | | |
|---|---|---|---|---|---|
| | Age | Gender | Occupation | Education | Residential |
| 1 | 0.26/0.37 | -0.09/0.31 | 0.13/0.27 | -0.06/0.59 | 0.18/0.03 |
| 2 | -0.26/0.38 | 0.00/1.00 | -0.14/0.27 | -0.18/0.19 | -0.02/0.90 |
| 3 | 0.46/0.10 | 0.08/0.33 | 0.20/0.03 (**) | -0.33/0.00 (**) | 0.01/0.06 |
| 4 | 0.89/0.00 (**) | -0.11/0.22 | 0.26/0.02 (**) | -0.24/0.04 (**) | 0.18/0.03 (**) |
| 5 | 1.90/0.00 (**) | -0.12/0.10 | 0.12/0.30 | -0.16/0.17 | 0.14/0.04 (**) |
| **6** | **0.56/0.02 (**)** | **-0.22/0.00 (**)** | **0.10/0.36** | **-0.33/0.00 (**)** | **0.30/0.00 (**)** |
| 7 | -0.27/0.17 | 0.05/0.37 | -0.12/0.17 | -0.13/0.11 | 0.28/0.00 (**) |
| 8 | -0.08/0.82 | 0.22/0.01 (**) | 0.02/0.89 | -0.26/0.02 (**) | 0.10/0.09 |
| 9 | 0.75/0.03 (**) | -0.25/0.01(**) | 0.24/0.08 | -0.14/0.24 | 0.10/0.22 |
| 10 | 0.22/0.49 | -0.02/0.85 | 0.23/0.08 | -0.26/0.02 (**) | 0.08/0.38 |
| 11 | -0.58/0.00 (**) | 0.14/0.01(**) | -0.13/0.10 | -0.13/0.03 (**) | -0.01/0.93 |
| 12 | 1.05/0.00 (**) | -0.14/0.07 | 0.44/0.00 (**) | 0.05/0.56 | 0.08/0.19 |
| 13 | -0.13/0.71 | -0.15/0.13 | 0.08/0.61 | -0.18/0.10 | -0.08/0.28 |
| **14** | **-0.30/0.42** | **-0.09/0.35** | **-0.13/0.40** | **-0.19/0.08** | **-0.03/0.77** |
| 15 | -0.07/0.77 | 0.17/0.05 (**) | 0.18/0.10 | -0.19/0.05 (**) | 0.03/0.69 |
| 16 | -0.50/0.03(**) | 0.08/0.56 | 0.23/0.08 | -0.10/0.46 | 0.18/0.21 |
| 17 | -0.21/0.78 | 0.20/0.45 | 0.15/0.68 | -0.34/0.32 | 0.02/0.95 |
| 18 | -0.99/0.54 | 0.44/0.39 | 0.09/0.84 | -0.49/0.41 | 0.32/0.51 |
| 19 | 0.49/0.40 | 0.43/0.01 (**) | 0.35/0.10 | 0.21/0.27 | -0.03/0.88 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

### 4.4.2 Watching, movement statues re. the sound level evaluations

A number of previous studies have suggested that aural and visual aspects are closely related, both contributing to the identification and interpretation of the surrounding spaces (Lang, 1988; Carles, Bernaldez & Delucio, 1992; Pheasant, et al., 2006). Therefore, the behavioural factor, watching, related to the visual effect, has been specifically studied and results are shown in Table 4.13.

***Table 4.13** Relationships between whether watching somewhere, movement statuses and the sound level evaluations*

| Site | Mean difference/Significance (not-watching - watching; not-moving - moving) | | Correlation/Significance |
|---|---|---|---|
| | Watching | Movement statuses | Movement statuses |
| 1 | 0.07/0.38 | 0.11/0.23 | -0.01/0.81 |
| 2 | 0.08/0.23 | 0.19/0.01(**) | -0.10/0.04 (*) |
| 3 | 0.13/0.05 (*) | -0.09/0.34 | 0.05/0.24 |
| 4 | 0.30/0.00 (**) | -0.08/0.37 | 0.06/0.06 |
| 5 | -0.31/0.00 (**) | -0.04/0.53 | 0.03/0.41 |
| 6 | 0.12/0.17 | 0.10/0.09 | -0.03/0.29 |
| 7 | -0.18/0.03 (*) | 0.16/0.11 | 0.02/0.57 |
| 8 | 0.05/0.51 | 0.26/0.01 (**) | -0.12/0.00 (**) |
| 9 | 0.01/0.85 | 0.06/0.30 | -0.04/0.24 |
| 10 | 0.00/0.95 | -0.02/0.79 | 0.00/0.90 |
| 11 | 0.20/0.03 (*) | -0.33/0.13 | 0.05/0.31 |
| 12 | 0.48/0.00 (**) | -0.21/0.06 | 0.06/0.18 |
| 13 | 0.21/0.18 | 0.07/0.32 | -0.03/0.50 |
| 14 | -0.49/0.01 (**) | -0.01/0.95 | 0.02/0.70 |
| 15 | -0.08/0.42 | 0.07/0.57 | -0.04/0.53 |
| 16 | 0.54/0.07 | 0.18/0.44 | -0.06/0.35 |
| 17 | 0.23/0.24 | 0.12/0.54 | -0.05/0.66 |
| 18 | 0.14/0.28 | -0.05/0.85 | -0.05/0.66 |
| 19 | -0.09/0.65 | 0.25/0.51 | 0.00/0.98 |
| % of Sig. | 37% | 11% | 11% |
| Ratio | 7/19 | 2/19 | 2/19 |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

Table 4.13 shows that there is a significant difference of the sound level evaluations between the people who were watching and who were not watching in 7 case study sites. This means that watching behaviour is more related to the sound level evaluations compared to other two behaviours, wearing earphones and reading/writing. It is interesting to note that all the 7 sites are in Europe, two each in Athens and Cambridge, and one each in Thessaloniki, Milan and Sheffield. In the case study sites in Athens and Cambridge, the watching people gave lower evaluations than non-watching people did, indicating that the watching people felt quieter. A possible reason is that these four case study sites are located in historic and tourist cities and visually attractive, so that the tranquillity perception is enhanced. In the other three case study sites, conversely, watching people felt nosier than non-watching people, probably because the views from the nearby traffic could bring certain acoustic nuisance. Overall, among the 19 case study sites, only five have negative mean difference, generally indicating that watching people tend to feel quieter.

Table 4.14 shows the differences between people who were watching and not watching in terms of social/demographical factors are shown, including age, gender, occupation, education and residential status. It can be seen that watching behaviour is related, at a significance level, to age, education and occupation in 7, 6 and 5 case study sites respectively, whereas the effect of gender and residential status is only significant in 1 and 2 case study sites respectively.

By comparing Table 4.13 and 4.14, it can be seen in the seven case study sites with significant difference in sound level evaluation between watching and non-watching people, the relationships between social/demographical factors and the sound level evaluations are generally not significant, suggesting that the effects of watching behaviour are not from social/demographical factors.

Table 4.13 also shows the differences of the sound level evaluations between the people who were moving and not moving in the case study site in terms of sound level evaluations, as well as the correlation coefficients of the movement statuses and the sound level evaluations. It can be seen that the significant differences and corrections are only found in 2 case study sites, site 2- Florentiner in Kassel, Germany, and site 8- Piazza Petazzi in Milan, Italy. The mean differences are around 0.2 and the correlation coefficients are around -0.1, which are both not high.

***Table 4.14** Relationships between whether watching somewhere and age, gender, occupation, education, residential status*

| Site | Mean difference/Significance ( not-watching - watching) | | | | |
|---|---|---|---|---|---|
| | Age | Gender | Occupation | Education | Residential |
| 1 | -0.55/0.01(**) | 0.16/0.01(**) | -0.20/0.02(*) | 0.02/0.78 | -0.05/0.37 |
| 2 | 0.05/0.76 | -0.01/0.84 | 0.11/0.12 | 0.08/0.30 | 0.08/0.23 |
| **3** | **0.46/0.00** | **0.01/0.85** | **0.13/0.01(**)** | **-0.02/0.68** | **-0.06/0.12** |
| **4** | **-0.26/0.04(*)** | **0.03/0.38** | **-0.06/0.20** | **0.14/0.01(**)** | **0.01/0.86** |
| **5** | **-0.66/0.00(**)** | **-0.01/0.86** | **-0.17/0.06** | **-0.00/0.98** | **0.01/0.82** |
| 6 | -0.62/0.00(**) | -0.02/0.70 | -0.26/0.00(**) | 0.30/0.00(**) | -0.09/0.07 |
| **7** | **-0.25/0.08** | **0.00/0.96** | **-0.07/0.23** | **-0.02/0.75** | **-0.00/0.97** |
| 8 | -0.63/0.00(**) | -0.00/0.94 | -0.22/0.00(**) | 0.11/0.03(*) | -0.02/0.42 |
| 9 | -0.04/0.75 | 0.05/0.13 | -0.03/0.54 | 0.07/0.13 | -0.01/0.65 |
| 10 | -0.07/0.54 | 0.00/0.93 | -0.01/0.78 | 0.03/0.44 | 0.08/0.02(*) |
| **11** | **-0.17/0.29** | **-0.02/0.66** | **0.07/0.35** | **0.23/0.00(**)** | **0.16/0.00(**)** |
| **12** | **-0.84/0.00(**)** | **0.01/0.75** | **-0.24/0.00(**)** | **-0.05/0.29** | **0.00/0.99** |
| 13 | 0.15/0.67 | 0.04/0.73 | 0.06/0.69 | 0.07/0.55 | 0.07/0.35 |
| **14** | **0.16/0.65** | **0.04/0.71** | **0.07/0.63** | **0.22/0.03(*)** | **-0.06/0.48** |
| 15 | 0.33/0.12 | 0.10/0.19 | 0.12/0.21 | 0.03/0.70 | 0.12/0.10 |
| 16 | 0.07/0.84 | 0.07/0.74 | 0.12/0.62 | 0.13/0.53 | 0.24/0.24 |
| 17 | -0.35/0.39 | -0.13/0.37 | -0.36/0.06 | -0.35/0.04(*) | -0.03/0.82 |
| 18 | -0.82/0.02(*) | 0.05/0.67 | 0.01/0.96 | -0.05/0.71 | 0.11/0.31 |
| 19 | -0.37/0.46 | 0.02/0.89 | 0.22/0.21 | -0.02/0.93 | -0.09/0.51 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.0; Bold figures indicate that in these case study sites, a significant difference of sound level evaluations exists between the subjects who watched somewhere and who did not.*

In order to explore how these difference are influenced by the social/demographical factors, in Table 4.15 the correlations between moving activities and various social/demographical factors are shown, including age, gender, occupation, education and residential status. It can be seen that in site 2- Florentiner Square in Kassel, Germany, the movement statuses are also significantly correlated with age, education and gender; although in site 8- Petazzi Square in Milan, Italy, only occupation is significant correlated. In other case study sites there are some correlations between movement statuses and social/demographical factors, with a significance level in eight sites for gender, seven sites for occupation and education, five sites for residential status and four sites for age, but the correlation coefficients are generally rather low.

*Table 4.15 Relationships between movement statuses and age, gender, occupation, education*

| Sites | Correlation/Significance | | | Mean difference/Significance (male-female; local-non-local) | |
|---|---|---|---|---|---|
| | Age | Occupation | Education | Gender | Residential |
| 1 | 0.19/0.00 (**) | 0.13/0.10 | 0.10/0.04 (*) | -0.01/0.84 | -0.07/0.30 |
| **2** | **0.20/0.00 (**)** | **0.09/0.07** | **0.15/0.00 (**)** | **0.27/0.00(**)** | **-0.07/0.48** |
| 3 | 0.07/0.08 | 0.08/0.04 (*) | 0.06/0.15 | -0.09/0.30 | -0.21/0.02 (*) |
| 4 | -0.08/0.03 (*) | -0.04/0.26 | 0.14/0.00 (**) | -0.20/0.00(**) | 0.03/0.63 |
| 5 | -0.09/0.02 (*) | -0.08/0.03 (*) | -0.02/0.56 | -0.05/0.49 | -0.01/0.92 |
| 6 | -0.06/0.05 (*) | -0.06/0.06 | -0.01/0.81 | 0.05/0.45 | -0.04/0.58 |
| 7 | -0.06/0.16 | -0.08/0.07 | 0.04/0.33 | 0.15/0.03(*) | -0.04/0.60 |
| **8** | **-0.04/0.32** | **-0.08/0.05 (*)** | **0.05/0.26** | **0.05/0.43** | **0.16/0.13** |
| 9 | 0.08/0.02 (*) | 0.00/0.90 | -0.09/0.01(**) | 0.07/0.31 | -0.38/0.00 (**) |
| 10 | 0.03/0.32 | 0.01/0.66 | -0.03/0.40 | -0.04/0.32 | -0.02/0.65 |
| 11 | -0.01/0.85 | -0.02/0.76 | 0.12/0.01 | 0.03/0.49 | -0.08/0.09 |
| 12 | 0.11/0.02 (*) | 0.14/0.00 (**) | 0.13/0.00 (**) | 0.15/0.03(*) | -0.02/0.83 |
| 13 | -0.07/0.10 | -0.17/0.00 (**) | -0.03/0.56 | -0.04/0.69 | -0.02/0.89 |
| 14 | -0.03/0.50 | -0.04/0.38 | 0.07/0.13 | -0.19/0.02(*) | 0.21/0.03 (*) |
| 15 | 0.18/0.00 (**) | -0.05/0.43 | 0.09/0.14 | -0.14/0.02(*) | -0.17/0.01 (**) |
| 16 | -0.06/0.29 | -0.08/0.17 | 0.02/0.72 | -0.07/0.01(**) | -0.02/0.44 |
| 17 | -0.44/0.00 (**) | -0.46/0.00 (**) | -0.49/0.00 (**) | 1.66/0.00(**) | -0.11/0.83 |
| 18 | -0.21/0.06 | -0.04/0.77 | -0.18/0.12 | -0.01/0.92 | -0.40/0.00 (**) |
| 19 | 0.05/0.75 (*) | -0.16/0.17 | -0.05/0.69 | 0.02/0.88 | -0.13/0.39 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

### 4.4.3 Frequency, reason and grouping re. the sound level evaluations

The behavioural factors, wearing earphones, reading/writing, watching, and moving activity are related with people's behaviour on-site, whereas the factors of frequency of visiting the site, reason for visiting the site and grouping are related with individual's behavioural habit. The importance of these factors for the subjective evaluations of sound level was analysed and the results are shown in Table 4.16.

Whilst correlations were made for the factors, frequency of visiting the site and grouping, Pearson Chi-Square was used for the factor reason for visiting the site. It can be seen that significant differences have been found between the people with different reasons for visiting the site, as a significant value exists in 43.8% (7 of 16) case study sites. It can also be seen that the frequency of visiting the site and grouping have less importance for the sound level evaluations, as significance levels have been found in 5 of 19 (26.3%) and 4 of 19 (21.1%) case study sites, respectively.

***Table 4.16** Relationships between frequency of visiting the site, reason for visiting the site, grouping and the sound level evaluations*

| Site | Frequency | Reason | Grouping |
|---|---|---|---|
| 1 | 0.05 | 0.44 | 0.01 |
| 2 | 0.08 | 0.01(*) | 0.03 |
| 3 | 0.00 | 0.06 | 0.07 |
| 4 | -0.10(**) | 0.00(**) | 0.12(**) |
| 5 | -0.11(**) | 0.37 | -0.03 |
| 6 | 0.10(**) | 0.01(**) | -0.02 |
| 7 | 0.15(**) | 0.02(*) | -0.04 |
| 8 | 0.01 | 0.04(*) | 0.10(*) |
| 9 | -0.07(*) | 0.78 | 0.00 |
| 10 | 0.00 | 0.55 | -0.09(**) |
| 11 | -0.06 | 0.00(**) | 0.03 |
| 12 | -0.00 | 0.01(**) | -0.05 |
| 13 | -0.00 | 0.76 | 0.06 |
| 14 | -0.04 | 0.83 | 0.10(*) |
| 15 | -0.10 | 0.40 | 0.09 |
| 16 | -0.01 | 0.10 | -0.10 |
| 17 | 0.13 | | 0.00 |
| 18 | 0.05 | | 0.11 |
| 19 | -0.05 | | -0.04 |
| % of Sig. | 26.3 | 43.8 | 21.1 |
| Ratio | 5/19 | 7/16 | 4/19 |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

### 4.4.4 Behavioural factors re. the acoustic comfort evaluations

The importance of behavioural factors, including reading/writing, watching, movement statuses, frequency of visiting the site, reason for visiting the site, and grouping, on the subjective evaluations of acoustic comfort have been analysed and the results are shown in Table 4.17. Another behavioural factor, whether wearing earphones, was not analysed as its influence on the acoustic comfort evaluations was not examined in any case study site.

In Table 4.17, it can be seen that no significance level of the influence of on-site behavioural factors (reading/writing, watching, and movement statuses) on the acoustic comfort evaluations exists in any case study sites, although watching is important to affect the sound level evaluations. For the factors, frequency of visiting the site and reason for visiting the site, a significance level has been found in only one case study site. Two case study sites have been found with a significance level of the grouping influencing the acoustic comfort evaluations.

***Table 4.17** Relationships between various behavioural factors and the acoustic comfort evaluations*

| Site | Reading / writing | Watching | Moving | Frequency | Reason | Grouping |
|---|---|---|---|---|---|---|
| 13 | | | -0.01 | -0.03 | 0.15 | -0.17(**) |
| 14 | | | -0.10 | 0.00 | 0.24 | -0.13(*) |
| 15 | 0.18 | -0.17 | 0.04 | -0.19(**) | 0.00(**) | 0.07 |
| 16 | 0.34 | 0.01 | -0.10 | 0.07 | 0.37 | -0.09 |
| 17 | 0.10 | 0.06 | -0.01 | -0.09 | | 0.16 |
| 18 | | -0.33 | -0.04 | -0.01 | | -0.05 |
| 19 | -0.06 | -0.08 | -0.05 | -0.02 | | 0.09 |
| % of Sig. | 0.00 | 0.0 | 0.00 | 14.3 | 25.0 | 28.6 |
| Ratio | 0/4 | 0/5 | 0/7 | 1/7 | 1/4 | 2/7 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

## 4.5 Psychological factors

An individual's psychological status is important in influencing how a person perceives this world. In this section, therefore, analyses have been made for the influence of various psychological factors on the sound level and acoustic comfort evaluations, also based on the 19 case study sites. The examined factors are, individual's preference of the case study site, view assessment, and the subjective evaluations of heat, wind, humidity, brightness, overall physical and sound level.

### 4.5.1 Site preference and view assessment re. the sound level evaluations

Table 4.18 shows the relationships between the site preference, view assessment and the sound level evaluations. For the site preference, only samples from EU case study sites are included as this factor was not explored in Chinese case study sites.

***Table 4.18*** *Relationships between site preference, view assessment and the sound level evaluations*

| Site | Site preference | View assessment |
|---|---|---|
| 1 | -0.12 | -0.10(*) |
| 2 | -0.04 | -0.04 |
| 3 | -0.19(**) | 0.03 |
| 4 | 0.04 | -0.04 |
| 5 | 0.16(*) | -0.16(**) |
| 6 | -0.31(**) | -0.18(**) |
| 7 | -0.30(**) | 0.03 |
| 8 | -0.15(*) | -0.05 |
| 9 | -0.14(*) | -0.07(*) |
| 10 | -0.28(**) | -0.13(**) |
| 11 | -0.07 | 0.02 |
| 12 | -0.21(*) | -0.04 |
| 13 | -0.13 | -0.11(*) |
| 14 | -0.25(**) | -0.09 |
| 15 | | -0.09 |
| 16 | | -0.13(*) |
| 17 | | -0.29(*) |
| 18 | | -0.14 |
| 19 | | -0.03 |
| % of Sig. | 64.3 | 42.1 |
| Ratio | 9/14 | 8/19 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

In Table 4.18, it can be seen that the site preference is important for the sound level evaluations as a significant difference between the people who liked the site and did not like the site exists in 9 of 14 (64.3%) case study sites. A negative value has been found in 12 of 14 case study sites, indicating that people would feel quieter if they like the site compared if they do not like the site. However, there are two exceptions, which are site 4- Seashore in Athens, Greece, and site 5- Kritis in Thessaloniki, Greece, where a positive value has been found in both case study sites. For site 4- Seashore, the positive value of the difference between the people who liked site and did not like the site is low, which is only 0.04. For site 5- Kritis, a positive significant difference has been found, which may be caused by the morphology of this case study site. As shown in Fig. 4.6, this site is located in a nearly enclosed residential area with buildings surrounding the four sides;

therefore, it is possible that the people who have a preference for this site are more sensitive to the sound levels there.

The influence of view assessment on the sound level evaluations is also shown in the Table 4.18. It can be seen that this factor is important in influencing the sound level evaluations, because a significance level has been found in 8 of 19 case study sites. A negative correlation has been found in 16 of 19 case study sites, indicating that the better the view is, the quieter people felt.

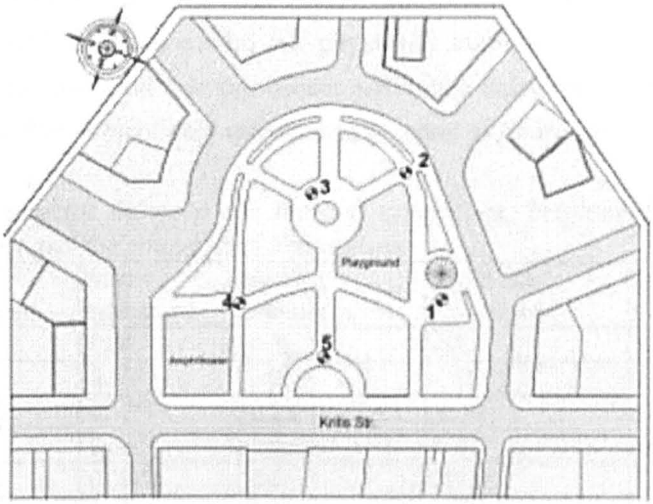



*Fig. 4.6 Plan of site 5- Kritis, Thessaloniki, Greece*

**4.5.2 Thermal conditions, brightness and overall physical comfort evaluations re. the sound level evaluations**

In Table 4.19, the relationships between the subjective evaluations of thermal conditions (including heat, wind and humidity), brightness, overall physical comfort and the sound level evaluations are shown. It can be seen that for the evaluations of thermal conditions, the subjective evaluations of heat and wind are more important for the sound level evaluations than the subjective evaluations of humidity, as for the subjective evaluations of heat and wind, a significance level exists in 6 and 7 of 19 case study sites respectively, whereas for the subjective evaluations of humidity, a significance level only exists in 3 of 19 case study sites. Both positive and negative correlations have been found, suggesting that the relationships between the evaluations of thermal conditions and the sound level evaluations vary in terms of the different case study sites.

In terms of the subjective evaluations of brightness and overall physical comfort, Table 4.19 also shows their relationships with the sound level evaluations. Some relations between these two factors and the sound level evaluations have been found. A significance level exists in 6 out of 19 case study sites for both factors. Negative correlation of the brightness evaluations and the sound level evaluations have been found in 13 out of 19 case study sites, whereas a difference between the people who did not feel physically comfortable and those who felt physically comfortable has been found in 11 out of 19 case study sites, and this significant difference exists in all the case study sites. The results suggest that subjectively quieter and brighter sites are often correlated.

***Table 4.19*** *Relationships between the thermal conditions, brightness, overall physical comfort evaluations and the sound level evaluations*

| Site | Heat evaluations | Wind evaluations | Humidity evaluations | Brightness evaluations | Overall physical evaluations |
|---|---|---|---|---|---|
| 1 | 0.04 | -0.04 | -0.05 | -0.01 | 0.10 |
| 2 | 0.07 | -0.10(*) | 0.03 | -0.02 | -0.06 |
| 3 | 0.10(**) | -0.17(**) | -0.13(**) | 0.09(*) | 0.15 |
| 4 | -0.01 | -0.08(*) | -0.09(*) | 0.01 | 0.15 |
| 5 | -0.08(*) | 0.08(*) | -0.07 | -0.13(**) | 0.26(**) |
| 6 | 0.03 | 0.12 | 0.04 | -0.09(*) | 0.26(**) |
| 7 | -0.09(*) | 0.10(*) | -0.02 | 0.05 | -0.09 |
| 8 | 0.05 | -0.01 | 0.09(*) | -0.23(**) | 0.26(**) |
| 9 | -0.04 | -0.05 | -0.05 | -0.07 | -0.03 |
| 10 | 0.09(**) | 0.05 | 0.04 | 0.03 | -0.04 |
| 11 | 0.04 | -0.05 | 0.09 | -0.03 | 0.18 |
| 12 | -0.10(*) | 0.02 | 0.05 | 0.06 | -0.01 |
| 13 | -0.06 | 0.05 | 0.05 | -0.02 | -0.15 |
| 14 | -0.02 | -0.11 | -0.11 | 0.03 | -0.01 |
| 15 | 0.11 | -0.12(*) | -0.07 | -0.07 | 0.44(**) |
| 16 | 0.15(**) | -0.01 | -0.03 | -0.19(**) | 0.45(**) |
| 17 | 0.13 | 0.35(**) | -0.09 | -0.27(*) | -0.20 |
| 18 | 0.12 | -0.01 | -0.14 | -0.10 | 0.23 |
| 19 | -0.04 | -0.03 | 0.06 | -0.17 | 1.78(*) |
| % of Sig. | 31.6 | 36.8 | 15.8 | 31.6 | 31.6 |
| Ratio | 6/19 | 7/19 | 3/19 | 6/19 | 6/19 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

### 4.5.3 Site preference and view assessment re. the acoustic comfort evaluations

In Table 20, the relationships between site preference, view assessment and the acoustic comfort evaluations are shown. The relationship between site preference and the acoustic comfort was only examined in two case study sites and neither of them was found to have a significant difference. It is found that site preference is less importance for the acoustic comfort evaluations compared to the sound level evaluations.

There is a strong correlation between view assessment and the acoustic comfort evaluations because a significant correlation has been found in all case study sites. In addition, it is found that this correlation value is positive for all the case study sites where the relationship of view assessment and the acoustic comfort evaluations were explored. This result suggests that a good view of the site could largely improve the comfortable feelings of a soundscape in an urban open space. Comparing its influence on the sound level evaluations, view assessment is more related to the acoustic comfort evaluations.

***Table 4.20*** *Relationships between site preference, view assessment and the acoustic comfort evaluations*

| Site | Site preference | View assessment |
|---|---|---|
| 13 | -0.07 | 0.14(*) |
| 14 | 0.15 | 0.14(*) |
| 15 | | 0.27(**) |
| 16 | | 0.26(**) |
| 17 | | 0.46(**) |
| 18 | | 0.35(**) |
| 19 | | 0.33(**) |
| % of Sig. | 0.0 | 100.0 |
| Ratio | 0/2 | 7/7 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

### 4.5.4 Thermal conditions, brightness and overall physical comfort evaluations re. the acoustic comfort evaluations

Table 4.21 shows the effects of the subjective evaluations of thermal conditions, brightness and overall physical comfort on the acoustic comfort evaluations. For the subjective evaluations of thermal conditions, a significant correlations exist in 3 out of 7 case study sites for the heat evaluations, 1 out of 7 case study sites for the wind evaluations, and none case study site for the humidity evaluations. The result means that the relations between the subjective evaluations of thermal conditions and the acoustic comfort evaluations are very weak; their relationships are insignificant.

Table 4.21 also shows the importance of the subjective evaluations of brightness and overall physical comfort for the acoustic comfort evaluations. A significance level has been found in all seven case study sites. The correlations between the brightness evaluations and the acoustic comfort evaluations are considerably higher than the correlations between other evaluations and the acoustic comfort evaluations, which are from 0.30 to 0.50 for the seven case study sites. A positive correlation between these two factors was found in all seven case study sites. This means that in a range of studied conditions, the brighter the people felt a site to be, the better the acoustic comfort; or *vice versa*.

***Table 4.21** Relationships between the thermal conditions, brightness, overall physical comfort evaluations and the acoustic comfort evaluations*

| Site | Heat evaluations | Wind evaluations | Humidity evaluations | Brightness evaluations | Overall physical evaluations |
|---|---|---|---|---|---|
| 13 | 0.14(*) | -0.07 | 0.09 | 0.23(**) | -0.39(**) |
| 14 | 0.15(*) | 0.15(*) | -0.01 | 0.19(**) | -0.21(**) |
| 15 | -0.06 | 0.06 | 0.10 | 0.31(**) | -0.39(**) |
| 16 | -0.16(*) | 0.09 | 0.03 | 0.30(**) | -0.38(**) |
| 17 | 0.07 | 0.10 | 0.06 | 0.30(**) | -0.20 (*) |
| 18 | -0.21 | 0.02 | 0.15 | 0.40(**) | -0.30(**) |
| 19 | -0.11 | -0.04 | 0.02 | 0.50(**) | -0.50(**) |
| % of Sig. | 42.9 | 14.3 | 0.0 | 100.0 | 100.0 |
| Ratio | 3/7 | 1/7 | 0/7 | 7/7 | 7/7 |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

A difference between the people who ticked 'physically comfortable' and 'physically uncomfortable' has been found for the acoustic comfort evaluations in all seven case study sites. The former group has a lower evaluation score. All reached a significance level. This suggests that people who felt physically uncomfortable in an urban open space would feel less acoustically comfortable in the same place.

### 4.5.5 The sound level evaluation re. the acoustic comfort evaluation

As a part of the soundscape evaluations, the relation between sound level evaluations and the acoustic comfort evaluations has been explored and the result is shown in Table 4.22. It can be seen that a high correlation exists, because a significance level has been found in all the 6 case study sites with a high *r* of 0.2 to 0.5. The correlations are negative for all the case study sites, suggesting that the noisier the people felt the less acoustic comfort they had on-site.

***Table 4.22** Relationships between the sound level evaluations and the acoustic comfort evaluations*

| Site | Sound level evaluations |
|---|---|
| 13 | -0.39(**) |
| 14 | -0.21(**) |
| 15 | -0.39(**) |
| 16 | -0.38(**) |
| 17 | -0.20(*) |
| 18 | -0.30(**) |
| 19 | -0.50 (**) |
| % of Sig. | 100.0 |
| Ratio | 7/7 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

### 4.5.6 The sound preference evaluations re. the acoustic comfort evaluations

The relationship of sound preference evaluations and acoustic comfort evaluations has been analysed using Spearman correlation. Subjective evaluations of commonly heard sounds in urban open spaces, including birdsong, water, people speech, footsteps, children shouting, music from the surrounding stores, car passing, and bus passing, have been studied. The results are shown in Table 4.23.

***Table 4.23*** *Relationships between the sound preference evaluations and the acoustic comfort evaluations, the grey areas indicate that the sounds were not noticed.*

| Site | Natural sound | | Human sound | | | | Mechanical sound | |
|---|---|---|---|---|---|---|---|---|
| | Bird | Water | People speech | Footsteps | Children shouting | Store-music | Car passing | Bus passing |
| Site 13 | | | | -0.01 | | 0.03 | -0.07 | |
| Site 14 | | -0.01 | | | -0.00 | | -0.05 | -0.04 |
| Site 15 | -0.01 | | 0.01 | -0.13(*) | | | -0.03 | |
| Site 16 | | | -0.02 | 0.02 | | -0.12(*) | 0.01 | -0.13 (*) |
| Site 17 | | | -0.06 | 0.07 | -0.14 | | | |
| Site 18 | | 0.14 | 0.14 | | | -0.14 | -0.10 | 0.01 |
| Site 19 | -0.05 | | 0.02 | 0.11 | | | | |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

In Table 4.23, it can be seen that the relation between the sound preference evaluations and the acoustic comfort evaluations is unimportant, because a significance level has been found in at most one case study site in terms of various sounds. An important reason is that in the field surveys, the evaluation of sound preference was not necessarily based on the sound the interviewees heard during the time of filling questionnaires. Therefore, in chapter 7, when building the overall models, the models of acoustic comfort evaluations, the sound preference evaluations are not included.

## 4.6 Social/demographical factors and, physical, behavioural, psychological factors

Whilst the relationships between social/demographical, physical, behavioural, psychological factors and the sound level/acoustic comfort evaluations have been analysed above, it is also useful to examine the relationships between the social/demographical factors and other factors in order to understand the overlap correlations of these factors with the soundscape evaluations. In this section, relationships between social/demographical and, physical, behavioural and psychological factors are examined. Table 4.24 summarises the percentages of the case study sites in which a significance level exists. More details can be seen in Appendix IV.

In Table 4.24, it can be seen that age generally has strong correlations with physical/behavioural/psychological factors, in 55.6% of the sites in terms of time of day, 47.4% of the sites in terms of frequency of using the site, and 50% of the sites in terms of the site preference. It is also shown that occupation is more related with frequency of using the site, education level is highly related with the site preference, and the residential status is closely related to the frequency of using the site. Conversely, the significance of gender is rather weak. By comparing various physical/behavioural/psychological factors, it is seen that frequency of using the site and the site preference are most related to various social/demographical factors, whereas season is the least related.

***Table 4.24*** *Percentage (number) of the case study sites where significant correlations or differences exist between social/demographical factors and some physical, behavioural and psychological factors*

| | Season | Time | Frequency | Site preference |
|---|---|---|---|---|
| Age | 28.6% (4/14) | 55.6% (10/18) | 47.4% (9/19) | 50.0% (7/14) |
| Gender | 28.6% (4/14) | 16.7% (3/18) | 21.1% (4/19) | 21.4% (3/14) |
| Occupation | 28.6% (4/14) | 38.9% (7/18) | 52.6% (10/19) | 42.9% (6/14) |
| Education | 21.4% (3/14) | 11.1% (2/18) | 42.1% (8/19) | 78.6% (11/14) |
| Residential | 21.4% (3/14) | 27.8% (5/18) | 84.2% (16/19) | 35.7% (5/14) |

## 4.7 Conclusions

Based on a series of social surveys in the 19 case study sites, this chapter has explored various factors, including acoustic, physical, social/demographical, behavioural and psychological factors, in terms of their importance for the sound level and acoustic comfort evaluations.

The relationships between social/demographical factors including age, gender, occupation, education, and residential status are firstly studied. There are generally considerable correlations, although the correlation coefficients may not be high. It is important to note that amongst age, occupation and education, there is a closer relationship which needs to be taken into account when building the sound level evaluations models.

In the study of the importance of social/demographical factors (age, gender, occupation, education, residential status) for the subjective evaluations of sound level, it is found that all factors are generally insignificant with the sound level evaluations, although occupation and education are more correlated to the sound level evaluations than other social/demographical factors. Sound level experience at home is an important factor to relate with the sound level evaluations in urban open spaces. People from noisier homes showed less acoustic tolerance on-site. Notable variations have been found in different case study sites in terms of the correlations of social/demographical factors with the sound level evaluations.

The study also shows notable variations in different case study sites in terms of the relationships between social/demographical factors and the acoustic comfort evaluations. Compared to its importance for the sound level evaluations, the importance of social/demographical factors for the acoustic comfort evaluations is weaker and more insignificant. Unlike its importance for the sound level evaluations, sound level experience at home has less importance for the acoustic comfort evaluations.

Importance of physical factors for the sound level and acoustic comfort evaluations has been analysed. It is shown that SPL is an important factor related to both the sound level evaluations and the acoustic comfort evaluations. Season, time of day, air temperature, wind speed, relative humidity, horizontal luminance, and sun-shade, was less influence on the sound level evaluations, although some relations exist. However, the influence of these physical factors on the acoustic comfort evaluations is rather limited. To the factors, season and time of day, their influence on either the sound level evaluations or the acoustic comfort evaluations is limited and lesser than the any other physical factors' influence.

For the behavioural factors, it is found that the influence of whether wearing earphones, whether reading/writing, and movement statuses on the sound level evaluations is generally insignificant. However, watching and reason for visiting the sites are more related to the sound level evaluations. The influence of frequency of visiting the site and grouping on the sound level evaluations is rather limited. All these behavioural factors have been found insignificantly related with the acoustic comfort evaluations.

In this chapter, the relationships between psychological factors, including site preference, view assessment, and the subjective evaluations of heat, humidity, wind, brightness, and overall physical comfort, and the sound level and the acoustic comfort evaluations have also been explored. The result shows that all the psychological factors are related with the sound level evaluations except one factor humidity evaluations. The result suggests that a good view, a bright feeling and overall physical comfort can improve quiet feelings in urban open spaces. The correlation of the evaluations of thermal conditions with the sound level evaluations is notably varied in terms of a diversity of case study sites. Significantly close correlations have been found between view assessment, the brightness evaluations, overall physical comfort evaluations, the sound level evaluations, with the acoustic comfort evaluations. A suggestion has been made that a good view, a bright/quiet feeling, and overall physical comfort can largely improve the acoustic comfort in urban open spaces.

In summary, this chapter explored various factors influencing the sound level and acoustic comfort evaluations. It showed the importance of social/demographic, behavioural, psychological and other physical factors on subjective evaluations of soundscape due to varied culture backgrounds. The outcomes of this chapter are also important in selecting input variables in order to develop ANN models in Chapter 6.

# Chapter 5

# Sound preference evaluation

People's evaluation of a soundscape is not only determined by the sound level but also their preference of incident sounds. Sound preference is the aesthetic response that people have to the sound environment in an urban open space. This chapter investigates the importance of various factors for the preference evaluation of sounds in urban open spaces. Section 5.1 studies the relationships between various types of sound source and the subjective evaluation of sound preference. Section 5.2 investigates the importance of psychoacoustic indices, loudness and sharpness for the sound preference evaluation. In Section 5.3, the importance of social/demographic factors for the sound preference evaluation is systematically examined. This is followed by Section 5.4, where the physical, behavioural, psychological factors together with home sound experience are all studied with the relationships between them and the sound preference evaluations. Finally, a summary of the studies in this chapter is made in Section 5.5.

## 5.1 Effect of types of sound sources

The literature reviewed in Chapter 2 showed that the subjective evaluation of a sound is complicated where many factors could play a role in determining the sound preference evaluation. However, amongst the various factors, sound meaning has been taken as the first determinant (Dubois et al., 2006). In this section, based on the indoor experiments as well as field surveys as described in Chapter 3, the effect of sound meaning on the sound preference evaluation has been investigated.

### 5.1.1 Effect of sound category

In terms of verbal description, the effect of sound meaning (categorised into natural, human and mechanical) on the sound preference evaluation was studied in Part I experiment and 19 outdoor field studies (see Section 3.1 & 3.2). In Fig. 5.1, the subjective preference evaluations of ten studied sounds, including bird, water, insect, speak, footsteps, children playing, cars passing, buses passing, vehicle parking and construction, are examined based on the percentage of all case study samples. It can be seen that the natural sounds (bird, water, insect) are more preferred, whereas the mechanical sounds (cars passing, buses passing, vehicle parking and construction) are more annoying; however, the human sounds (speak, footsteps, children playing) are more neutral. The result suggests that people prefer natural sounds, are annoyed by mechanical sounds and have a neutral attitude to human sounds.

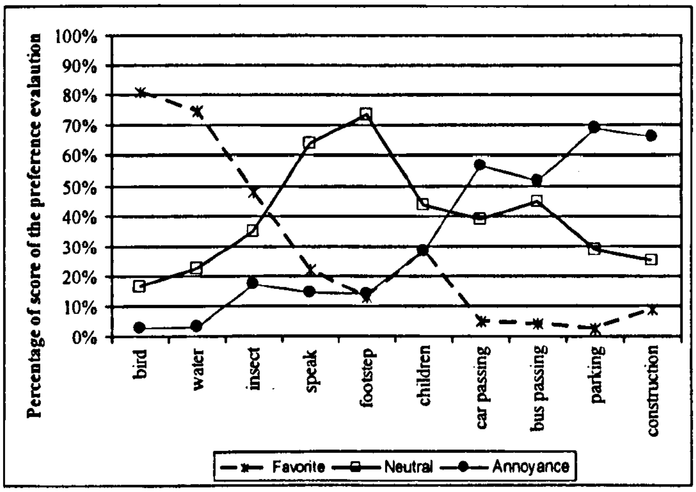



*Fig.5.1 Percentage of the score of the preference evaluations for studied sounds*

In order to understand how preference for a sound changes when the sound changes from natural to mechanical, a comparison of the means of the preference evaluations to various sounds is made and illustrated in Fig. 5.2. The mean of every sound is calculated based on all subject's responses of the sound preference gathered in 19 case study sites and the laboratory experiment. Under the given circumstance, with the studied groups, the results showed that the subjective evaluation of sound preference decreased when a sound moved from natural to mechanical. A possible reason might be that the study was focused on urban open spaces.

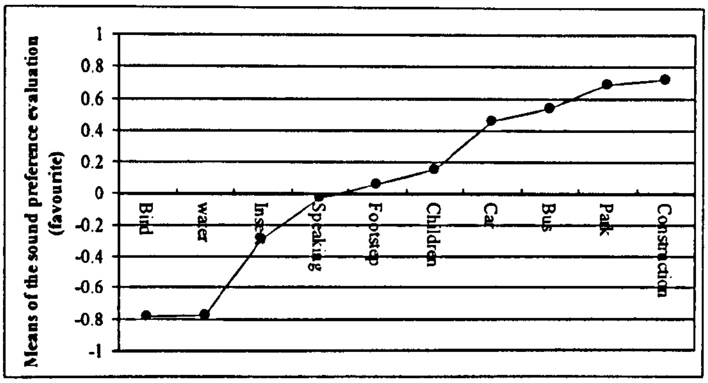
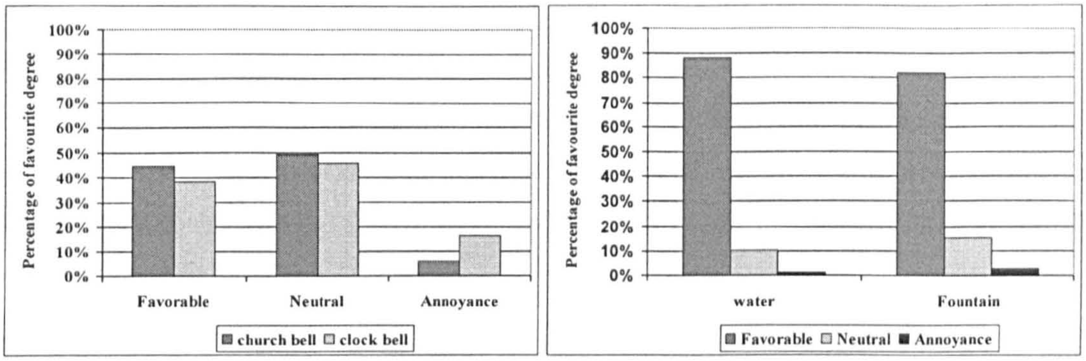



*Fig.5.2 Means of sound preference evaluations for all sound samples*

### 5.1.2 Effect of sound subcategory

Besides the effect of sound category, the effect of sound subcategory, which is the same sound source but with a different function or action, is also found to have some influence on the subjective evaluations of a sound (Dubios et al., 2006). Therefore, the subjective evaluation for the same sound source but with different function or action is studied, such as bell of clock and bell of church, twittering water and fountain, and the music played in the street, in the store and the music from a passing car. Here the same sound source means the verbal definition of a sound is same, having same noun.

The results are shown in Fig. 5.3 & 5.4. In Fig. 5.3 (a), a comparison of the sound preference evaluations between a church bell and a clock bell is made. It shows that the church bell was slightly more preferred than the clock bell. This might be related to the culture of conventional soundscape, as a church bell was a mark of life before Industrial Revolution. Fig. 5.3 (b) shows that there is little evaluation difference between a sound of water twittering and a fountain.




(a) (b)

*Fig. 5.3 A comparison between (a) church bell and clock bell; (b) water and fountain*

Subjective evaluation of three kinds of music from different areas, street, store and a passing car have been studied and compared in Fig. 5.4. It can be seen that the music from a passing car was perceived to be the most annoying, whereas the music in street was more favourable than the others. The same result has also been obtained by Yang (2005).

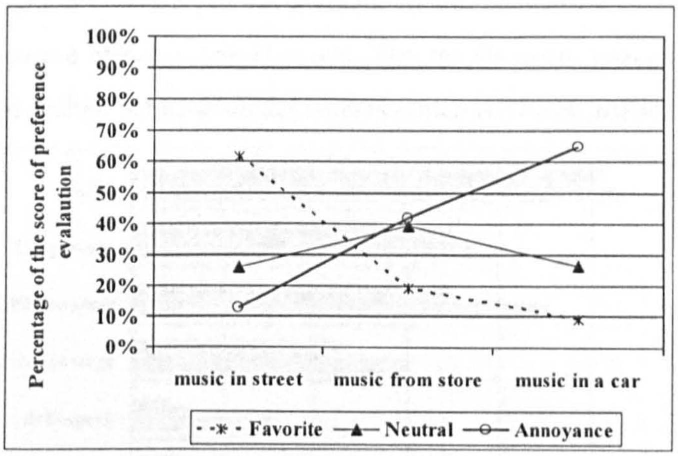



*Fig. 5.4 A comparison amongst music in street, music from store and from a passing car*

In the laboratory experiments, an interesting example was found in that one participant marked the sound of loud cars passing as a favourable sound although it was perceived as annoying by all other participants. The participant said '*I know it is a traffic sound, but it sounds like a kind of music I love*'. It is the same sound, cars passing, but to different receivers, it was perceived differently, having an opposite effect on the preference evaluation.

### 5.1.3 Effect of sound meaning on subjective evaluations

Six sounds (bird, church bell mixed with speech, bird mixed with nearby cars passing, children playing, cars passing and a combined sound of various traffic noises) ranging from natural to mechanical (either single or combined) were examined in Part II and III experiments (see Section 3.2).

The subjective evaluations of sounds in terms of preference, noisiness, comfort and pleasantness have been examined in Part II of the laboratory experiments as shown in Fig. 5.5. It can be seen that the birdsong has generally the lowest evaluation scores which indicates it was preferred by most participants. The sound of various traffic noises has the highest scores showing it was the least preferred sound. A notable preference tendency in the sound evaluations is noticed when the sound meaning moves from natural to artificial, nevertheless a slight difference has been found in the evaluation of noisiness, and this might be related to the effect of sound levels. The results again prove that people prefer natural sounds and dislike the mechanical sounds which are more artificial.

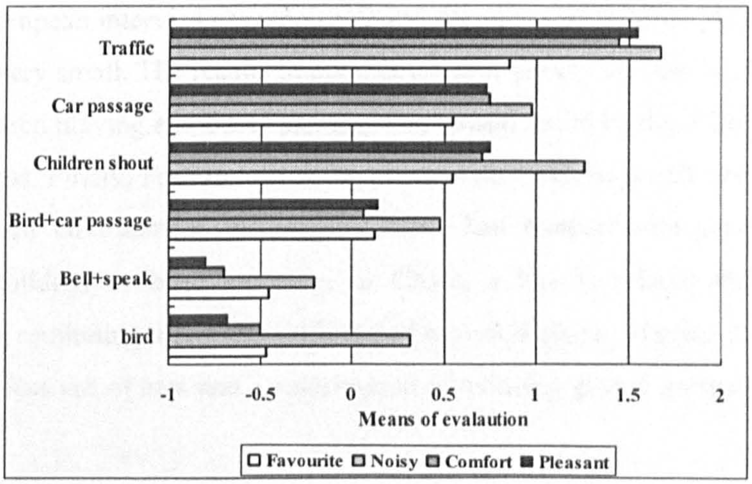



*Fig. 5.5 The subjective evaluations of studied sounds in Part II of the laboratory experiments*

In Part III laboratory experiment, the sound of waterfall was not recognized by most participants before presented a video record. Hence, it is used to study the effect of sound meaning on the subjective evaluation through a comparison between the evaluations of audio listening and video watching. With the independent t-test, the subjective evaluation of waterfall has been evaluated by comparing who recognised this sound and who did not. The difference is significant ($p<0.01$) in the evaluation of preference, comfort and pleasantness; however for the evaluation of noisiness, the difference is not significant. This result suggests that the effect of sound meaning on the evaluations of preference, comfort and pleasantness is stronger than the noisiness evaluation. In other words, the evaluation of noisiness is perhaps related more to loudness rather than sound meaning.

### 5.1.4 Differences between the EU and China

The difference in the sound preference evaluation between the EU and China has been examined in this section, as shown in Fig. 5.6 & 5.7.

In Fig 5.7, it can be seen that the sound of children playing was more annoying for the Chinese interviewees than for the European interviewees, and the sound of buses passing caused more annoyance for the Chinese interviewees too. However, the numbers of Chinese or European interviewees who preferred the sound of children playing are similar and both are very small. The results imply that Chinese people are less likely to prefer the sound of children playing and buses passing. The reason might be the differences between the two cultures. Firstly, because of the big population, Chinese people are more exposed to noise in their environment and might become less tolerant with generators of loud sound, e.g. children or bus. Secondly, in China, a bus is related more to a work transportation, reminding a narrow, shifting and crowded space, whereas in the EU, a bus may suggests less use of cars and a contribution to reducing global warming (Guastavino, 2006).

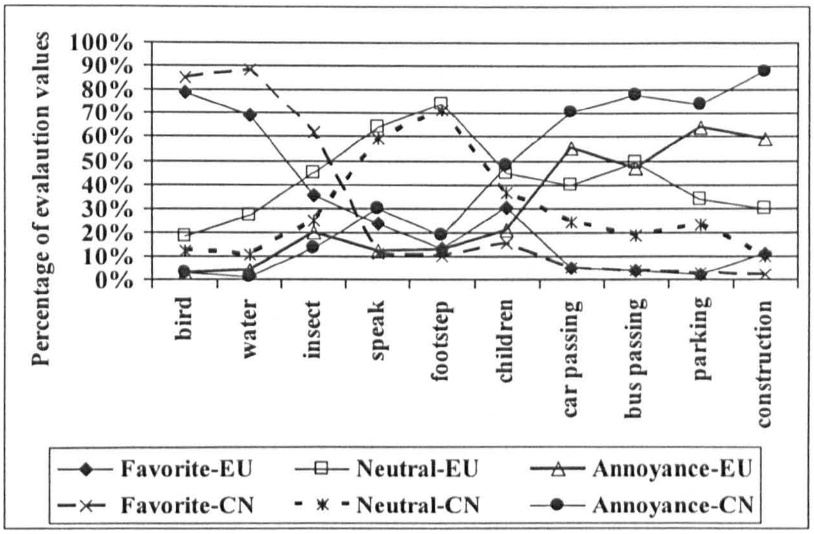



*Fig. 5.6 The differences of sound preference evaluations between the EU and China*

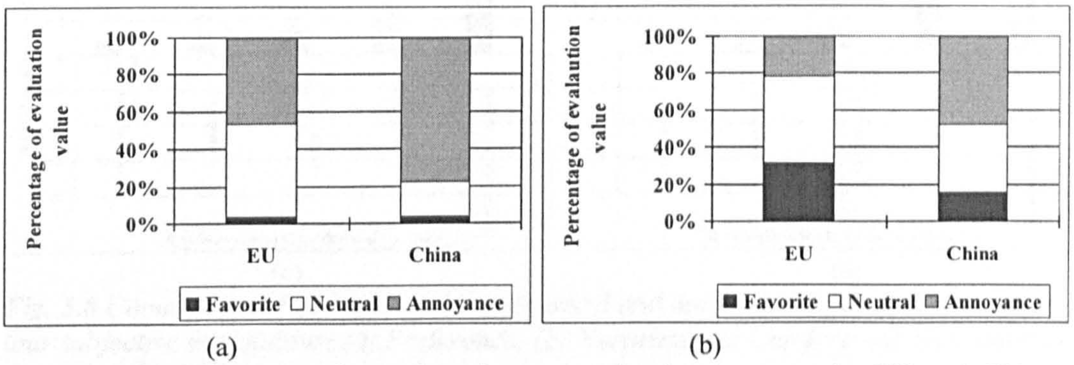



*Fig. 5.7 The differences of sound preference evaluation between the EU and China in terms of (a) children playing; (b) buses passing*

### 5.1.5 Aural and visual interactions

As visual perception is a direct way of understanding the sound meanings, its effect on the sound preference evaluation was explored in Part III laboratory experiment, and the results are shown in Fig. 5.8. It shows the difference in the personal evaluations of sounds between audio listening and video watching in terms of the evaluations of preference, noisiness, comfort and pleasantness. The evaluation means are compared and it can be seen that visual effect is positively related to the sound preference evaluations in usual, as lower values have been given by the participants after they watched a video with two exceptions, the preference evaluations of skateboard and fountain mixed with construction.

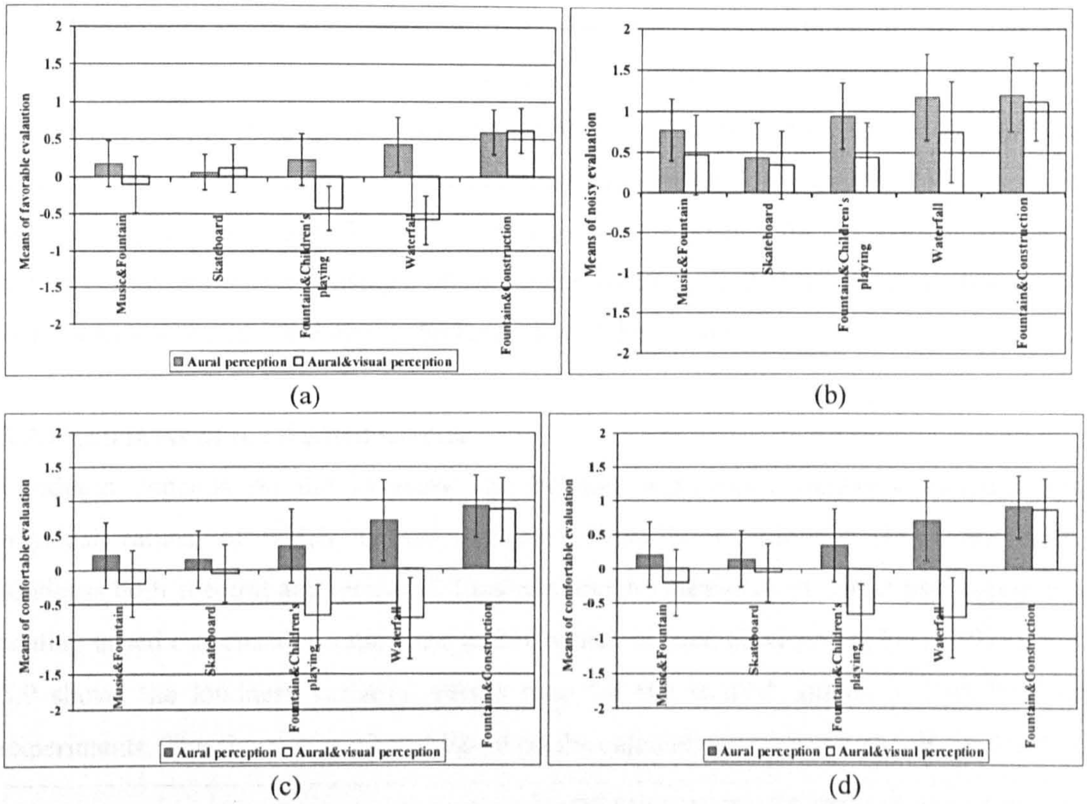



*Fig. 5.8 Comparison of evaluations between aural and aural-visual perception in terms of four subjective evaluations; (a) Preference; (b) Noisiness; (c) Comfort; (d) Pleasantness*

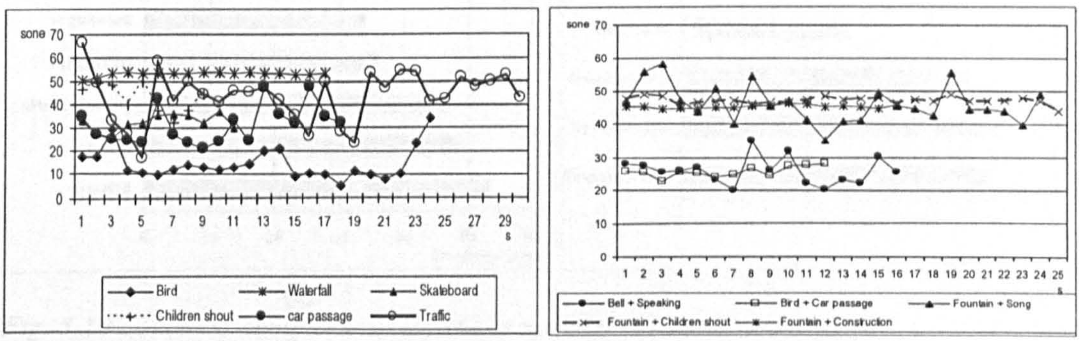
In Fig. 5.8 (a), it can be seen that the evaluation of skateboard is worse after watching the video and less difference has been found in the evaluation of fountain with construction after watching the video. Fig 5.8 shows that the evaluation of audio listening is distinct from the video watching in all four evaluations. It is also interesting to note that positive scenery can enhance the sound preference evaluation whereas negative scenery could damage it. However, in Fig. 5.8, it is also found that visual effect is closely related to three evaluations: preference, comfort and pleasantness. Its relation to the noisiness evaluation is not as strong as to the other evaluations. This might be due to the sound physical-psychological effect, of which loudness is one. This will be particularly examined in the next section.

## 5.2 Psychoacoustic parameters: loudness and sharpness

As soundscape is related more to the subjective perception than the objective measurements, the psychoacoustic features of a sound are supposed to have some influence on the sound preference evaluation. Hence the effects of psychoacoustic indices, loudness and sharpness, on the sound preference evaluation are examined in this section. In the study, loudness and sharpness magnitudes are extracted for the studied sounds of the laboratory experiments using 01dB software (01dB-Stell, 2001). Other psychoacoustic indices were not examined due to the limitation of the software.

### 5.2.1 Loudness of the studied sounds

Loudness depends on the intensity and belongs somewhere between sensation and physical values, of which, partial masking effects have been considered and make loudness both spectral and temporal. Loudness can be measured by direct psychophysical scaling based on sensation ratios, the unit of which is sone (Zwicker & Fastl, 1999). Fig. 5.9 shows the loudness variation versus time for the studied sounds in Part II & III experiments. The figure was plotted based on the calculations by 01dB (01dB-Stell, 2001).

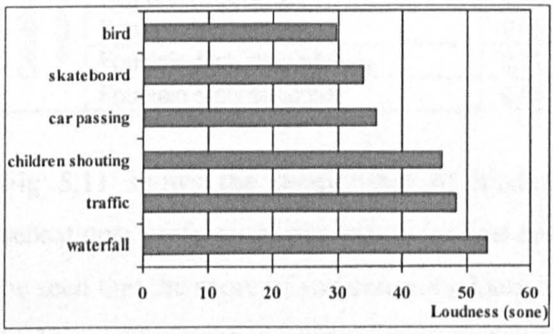



(a) (b)

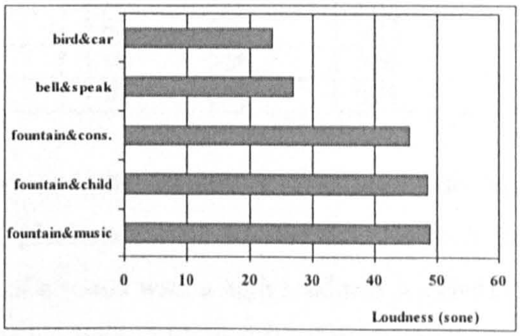
*Fig. 5.9 Loudness variation versus time, (a) single sounds; (b) combined sounds*

In Fig. 5.9 (a), it can be seen that for the studied single sounds, the loudness of birdsong is the lowest, whereas the sound of waterfall was ranked the highest. It is noted that such comparison is based on the samples obtained from the laboratory experiments, where the sound levels were already adjusted. In other words, direct comparison of the original sounds is not appropriate. For the combined sounds as seen in Fig. 5.9 (b), the loudness variation of the sound of the bell with speech and the sound of the birdsong with cars passing is similar. Both are ranked quieter than the other three sounds of fountain with music, children playing and construction which also have similar loudness variation. Fig. 5.9 also illustrates the variation of loudness is stable for the sound of waterfall, the sound of a fountain with children playing, and the sound of a fountain with construction.

Fig. 5.10 shows a comparison of average loudness for the studied sounds in parts II & III of the laboratory experiments. The studied natural sounds do not always have lower loudness than the mechanical sounds, such as the loudness of waterfall is higher than the traffic and cars passing sound as can be seen in Fig. 5.10 (a). The loudness of the sound of a fountain with music is slightly higher than the loudness of the sound of a fountain with construction as shown in Fig. 5.10 (b). It can be seen that the natural sounds, such as waterfall does not always have low loudness whereas the mechanical sounds, such as cars passing does not always have high loudness. Again, all these comparisons are based on the sound levels adjusted in the laboratory experiments.



(a)



(b)

*Fig. 5.10 Loudness comparison: (a) single sounds; (b) combined sounds*

### 5.2.2 Loudness re. the subjective evaluations of the studied sound

Table 5.1 shows the subjective evaluations of four sensations after the participants listened to the sounds. It is found that the sound of waterfall is more preferred than the sound of traffic, although the loudness of waterfall is higher than that of traffic as shown in Fig. 5.10 (a). The same result can also be found between the birdsong with the cars passing and the bell with the speech. This means that a sound with more natural meanings could be preferred more than a sound with more artificial meanings although the former one may have higher loudness. However, this might be also because the difference in loudness between these sounds is not big. As shown in Fig. 5.10, the difference in the loudness of the waterfall and the traffic, the bell with the speech and the birdsong with the cars passing are not distinct.

***Table 5.1** Means of the subjective evaluations of preference, noisiness, comfort and pleasantness for studied sounds in Part II & III experiments*

| | Sound | Preference | Noisiness | Comfort | Pleasantness |
|---|---|---|---|---|---|
| Single sound | Low bird | -0.60 | -0.70 | -1.08 | -1.11 |
| | Bird | -0.46 | 0.32 | -0.50 | -0.68 |
| | Loud bird | 0.34 | 1.28 | 0.74 | 0.49 |
| | Skateboard | 0.13 | 0.29 | 0.21 | 0.16 |
| | Children playing | 0.55 | 1.27 | 0.71 | 0.75 |
| | Waterfall | 0.50 | 1.34 | 0.77 | 0.63 |
| | Low cars passing | 0.06 | 0.32 | 0.11 | 0.26 |
| | Car passing | 0.55 | 0.98 | 0.75 | 0.73 |
| | Loud cars passing | 0.87 | 1.60 | 1.55 | 1.53 |
| | Traffic | 0.86 | 1.68 | 1.45 | 1.55 |
| Combined sound | Bell & speak | -0.45 | -0.20 | -0.70 | -0.80 |
| | Bird & cars passing | 0.13 | 0.48 | 0.07 | 0.14 |
| | Fountain & music | -0.05 | 0.66 | 0.00 | -0.13 |
| | Fountain & children playing | 0.31 | 1.14 | 0.46 | 0.59 |
| | Fountain & construction | 0.46 | 1.18 | 0.71 | 0.73 |

Fig 5.11 shows the relationship of loudness and the subjective evaluations in four sensations: preference, noisiness, comfort and pleasantness for all studied sounds. It can be seen that the score of subjective evaluation of a sound with a high loudness is generally higher, indicating that a lower sound preference has been achieved. It is interesting to note that amongst the four evaluations, the evaluation of noisiness is rather closer to loudness than others as it has a steeper trend line with $R^2$=0.765. This again proves that loudness has more influence on the evaluation of noisiness than the evaluations of preference, comfort and pleasantness as also have discussed in Section 5.1. It is interesting to note that the relationship between loudness and the evaluations of comfort/pleasantness is closer than those between loudness and the evaluations of preference and noisiness.

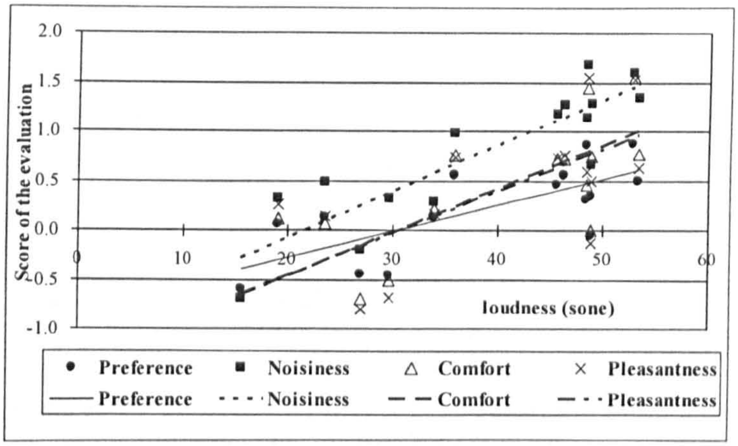


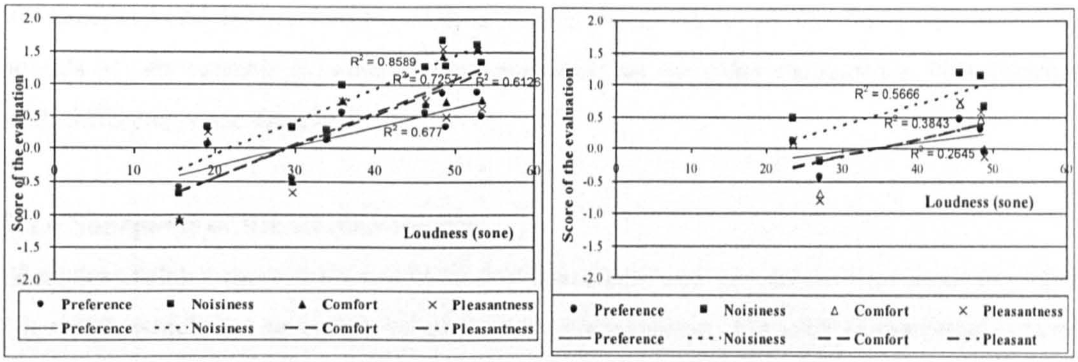

***Fig. 5.11*** *The relationships between loudness and the subjective evaluations of preference, noisiness, comfort, and pleasantness for all studied sounds*

Fig. 5.12 (a) & (b) show that the effect of loudness on the subjective preference evaluations for single sounds and combined sounds. It can be seen that the correlation between loudness and the subjective evaluations of single sounds is higher than that of the combined sound as $R^2$ is usually higher for the single sounds. Furthermore, Pearson correlation in Table 5.2 showed that the relationship between the loudness of single sounds and the subjective evaluations of preference, noisiness, comfort and pleasantness is significant ($p<0.05$) but not for the loudness of the combined sounds and the subjective evaluations. A possible reason might be that a combined sound contains more meanings than a single sound. This might distract the subjects' attentions as to how loud a sound is.

***Table 5.2*** *Pearson correlations between the means of the evaluation scores and the loudness magnitudes of studied sounds*

| Subjective evaluations | Single sounds | | Combined sounds | |
|---|---|---|---|---|
| | Correlation | Sig. level | Correlation | Sig. level |
| Preference | 0.82 | 0.00 (**) | 0.45 | 0.44 |
| Noisiness | 0.93 | 0.00 (**) | 0.70 | 0.19 |
| Comfort | 0.85 | 0.00 (**) | 0.56 | 0.32 |
| Pleasantness | 0.78 | 0.01 (**) | 0.49 | 0.41 |

Fig. 5.12 shows again that the relationships between loudness and the evaluations of comfort/pleasantness are closer than those between loudness and the evaluations of preference/noisiness.

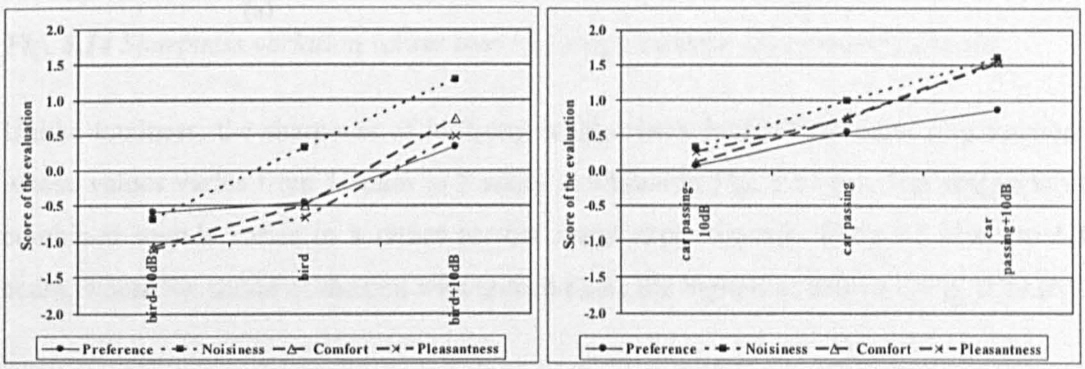



(a) (b)

*Fig. 5.12 The relationships between loudness and the subjective evaluations of preference, noisiness, comfort, and pleasantness for (a) single sounds, (b) combined sounds*

### 5.2.3 Loudness re. the subjective evaluations of different sound levels

As the effect of loudness on the single sounds is relatively weaker, it is assumed to be affected by the effect of the sound meaning. Investigation of the effect of loudness on the same sound source but at three levels, the original, 10dB higher, and 10dB lower has been made. Fig. 5.13 (a) shows the effect of loudness on the subjective evaluation of the birdsong, and Fig. 5.13 (b) illustrates the effect of loudness on the subjective evaluation of the sound of cars passing.



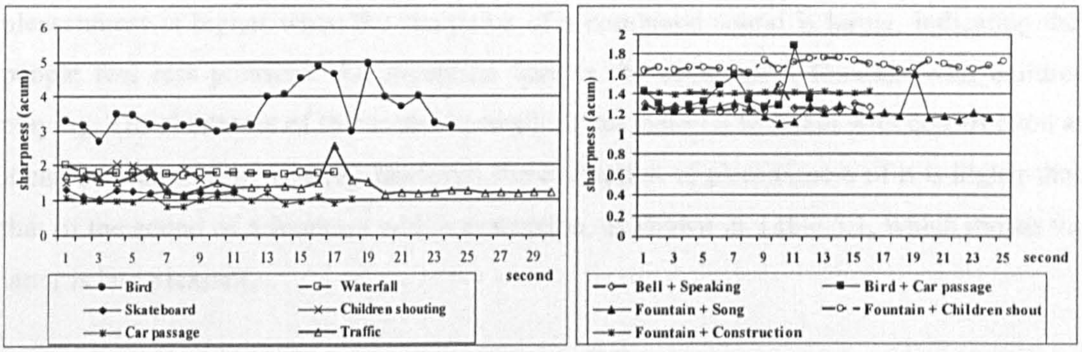

(a) (b)

*Fig. 5.13 The relationships between loudness and the subjective evaluations of preference, noisiness, comfort, and pleasantness for (a) birdsongs; (b) sounds of cars passing*

It can be seen that for both sound sources, when the sound level increases from -10dB to +10dB, the subjective evaluation generally increases as well, which means that people preferred the sound with lower levels. It is interesting to note that the relationship between the loudness and the evaluation of noisiness is linear either for the birdsongs or for the sounds of cars passing; however it does not occur for the other evaluations. Nevertheless, such differences are not significant.

### 5.2.4 Sharpness of the studied sounds

Sharpness relates more with sound timbre characters and can be used to describe sound "density", which is a sensation called sensory pleasantness. The unit of sharpness is acum (Zwicker & Fastl, 1999). In Fig. 14, the sharpness variation versus time to (a) single sounds, and (b) combined sounds are shown. The figure was also plotted based on the calculations by 01dB (01dB-Stell, 2001).

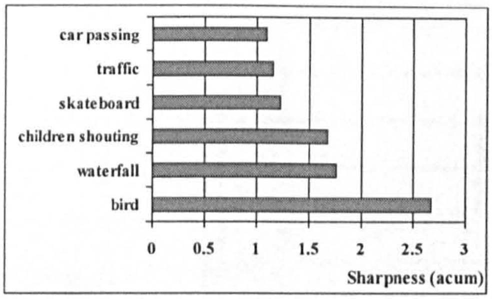


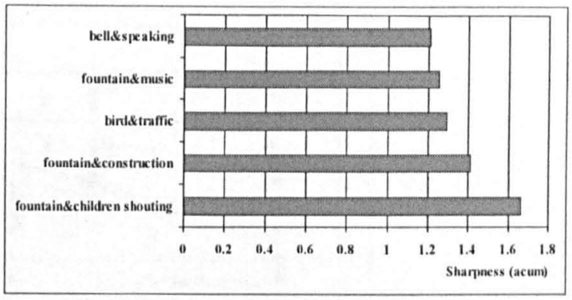

(a) (b)

*Fig. 5.14 Sharpness variation versus time: (a) single sounds; (b) combined sounds*

Unlike loudness, the sharpness of birdsong is apparently higher than other single sounds whose values varies from 1 acum to 2 acum as shown in Fig. 5.14 (a). The sharpness of combined sounds varies in a rather narrow range approximately from 1.2 acum to 1.8 acum, where the sound of the bell with speech ranks the highest as shown in Fig. 5.14 (b).

Fig. 5.15 shows the comparison of average sharpness magnitude for the studied sounds in Part II & III experiments. In Fig. 5.15 (a), it can be seen that there is a positive relation between sharpness and natural sound, within the limited range of the studied sounds. But, for the combined sounds, no relationship between sharpness and the sound meaning/type has been found. In Fig. 5.15 (b), it is found that the sound of the bell with speech has the lowest sharpness and the sound of fountain with the children playing has the highest.




(a) (b)

***Fig. 5.15** A comparison of sharpness for: (a) single sounds; (b) combined sounds*

### 5.2.5 Sharpness re. the subjective evaluations of the studied sound

Based on Fig. 5.15 (b) and Table 5.1, it is noted that the subjective evaluation of pleasantness is higher when the sharpness of a combined sound is larger, indicating that people feel less pleasure. An exception here is the sound of a fountain with children playing. The sharpness of this sound is smaller than that of a fountain with construction as it can be seen in Fig. 5.16 (b); however, the evaluation of pleasantness of it is higher than that of the sound of a fountain with construction, as shown in Table 5.1, which means the latter is less pleasant.

The relationship between sharpness and the subjective evaluations is also presented in Fig. 5.16. A slightly negative relationship between the sharpness and the subjective evaluation of preference, noisiness, comfort, and pleasantness is found. The result indicates that the sharper the sound is the more it is preferred. However, the increase of the subjective evaluation along with the sharpness magnitude is weak as the trend lines are relatively flat especially for the evaluation of pleasantness. Further investigations are therefore made for the single sounds and the combined sounds separately.

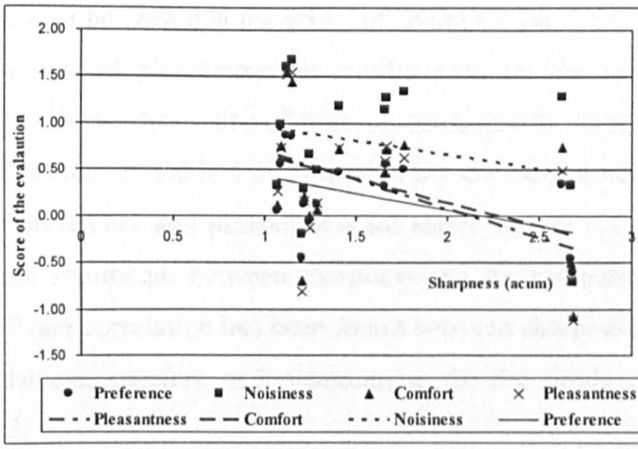
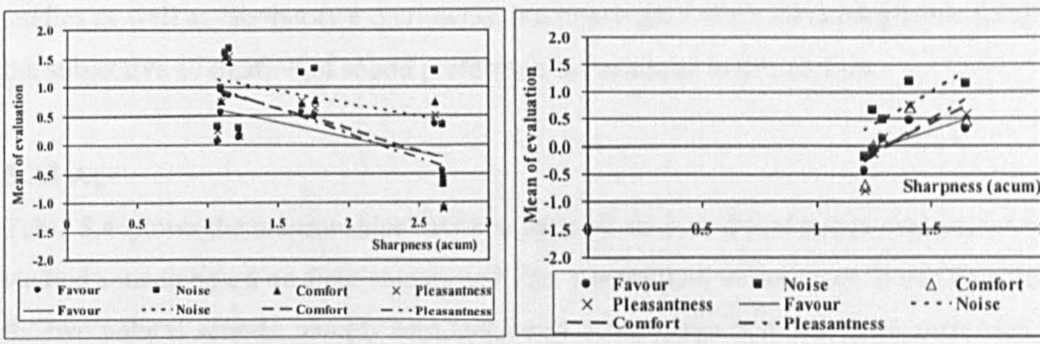



*Fig. 5.16 Relationships between sharpness and the subjective evaluations of preference, noisiness, comfort, and pleasantness for all studied sounds*

Fig. 5.17 shows the relationships between sharpness and the subjective evaluations of the single and the combined sounds respectively. When comparing Fig. 5.17 (a) with (b), it is interesting to find that the effect of sharpness on the subjective evaluation of single sounds and combined sounds is opposite. For the single sounds, as shown in Fig. 5.17 (a), the relationship of sharpness and the sound evaluations (preference, noisiness, comfort and pleasantness) is negative, but for the combined sounds as shown in Fig. 5.17 (b), it is positive. This means that the larger the sharpness is the more a single sound is preferred, whereas the larger the sharpness is the less a combined sound is preferred.




(a) (b)

*Fig. 5.17 Relationships between sharpness and the subjective evaluations of preference, noisiness, comfort, and pleasantness for (a) single sounds; (b) combined sounds*

In Fig. 5.17, it can also be seen that the effect of sharpness on the evaluations of comfort and on the evaluations of pleasantness is similar both for the single sounds and the combined sounds, as the tendency line of both are considerably close. Moreover, analyses of the Pearson correlation in Table 5.3 shows that the correlation between sharpness and the evaluations of preference and pleasantness for single sounds are significant ($p<0.05$); however, it was not significant between sharpness and the evaluations of noisiness and comfort. No significant correlation has been found between sharpness and the evaluations of preference, noisiness, comfort, and pleasantness for the single combined sounds as shown in Table 5.3.

***Table 5.3** Pearson correlations between the means of the evaluation scores and the sharpness magnitudes of studied sounds*

| Subjective evaluations | Single sounds | | Combined sounds | |
|---|---|---|---|---|
| | Correlation | Sig. level | Correlation | Sig. level |
| Preference | -0.67 | 0.03 (*) | 0.04 | 0.95 |
| Noisiness | -0.41 | 0.24 | 0.29 | 0.64 |
| Comfort | -0.62 | 0.06 | 0.14 | 0.83 |
| Pleasantness | -0.70 | 0.02 (*) | 0.06 | 0.93 |

## 5.3 Social/demographical factors

In Chapter 4, it has been found that some relations exist between certain social/demographic factors and the sound level evaluations. Therefore, based on the field studies as well as laboratory experiments, the importance of social/demographic factors on the subjective evaluation of sound preference is examined in this section.

### 5.3.1 Age

Table 5.4 shows the relationships between age and the sound preference evaluations of the studied sounds based on field studies and Part 1 laboratory experiment. It can be seen that for two natural sounds, namely bird and insect sounds, age is rather more correlated with the sound preference, as 6 out of 11, and 3 out of 8 studied cases have been found with a significance level although $r$ is not high.

With the increase of age, the sound preference for bird and insect sounds also increases, reflected by the negative correlation coefficients in most the studied cases, and in case of the positive correlations, the coefficients are small and statistically insignificant. It is interesting to note that for the natural sound, water, only one out of ten studied cases show statistically significant correlations between age and the sound preference evaluation. In other words, age has less importance on the sound preference of water. The importance of age for the sound preference of two human sounds, namely speech and footsteps is generally less compared with that for natural sounds including bird and insect sounds. It is noted, however, for children playing, age is strongly correlated with the sound preference, as 7 out of 15 studied case having statistically significant correlations.

***Table 5.4*** *Relationships between age and the sound preference evaluations*

| | Bird | Water | Insect | Speech | Footsteps | Children playing | Car passing | Bus passing | Vehicle parking | Construction |
|---|---|---|---|---|---|---|---|---|---|---|
| Site1 | | -0.13 | | 0.01 | 0.01 | | -0.03 | 0.07 | | |
| Site2 | | | | -0.10 | -0.01 | | -0.09 | | | |
| Site3 | | | | -0.18(**) | -0.09(*) | -0.28(**) | 0.11(*) | | | |
| Site4 | | | | -0.05 | -0.02 | -0.09(*) | 0.05 | | | |
| Site5 | | | | 0.11 | | -0.01 | -0.05 | 0.09(*) | | -0.05 |
| Site6 | | | | | | 0.07(*) | -0.05 | -0.06 | | 0.00 |
| Site7 | | -0.04 | | -0.08(*) | | | -0.14(**) | -0.11(**) | | |
| Site8 | | | | 0.08 | | -0.20(**) | -0.01 | | | |
| Site9 | -0.22(**) | | | -0.06 | | -0.20(**) | -0.09(**) | | | |
| Site10 | | | | 0.09(*) | 0.04 | | 0.00 | -0.11(**) | | |
| Site11 | 0.05 | | | -0.14(**) | | | -0.14(**) | 0.00 | | |
| Site12 | | 0.00 | | 0.03 | -0.38(**) | | -0.13(**) | -0.07 | | |
| Site13 | -0.03 | -0.02 | -0.03 | 0.03 | -0.02 | 0.01 | 0.13(**) | 0.08 | 0.11(**) | 0.01 |
| Site14 | 0.06 | 0.10 | 0.07 | 0.14(**) | -0.10(*) | 0.11(*) | 0.16(**) | 0.13(**) | 0.17(**) | 0.13(*) |
| Site15 | -0.13(*) | 0.01 | -0.23(**) | -0.09 | -0.09 | -0.01 | 0.04 | 0.03 | 0.08 | 0.08 |
| Site16 | -0.15(**) | -0.00 | -0.16(**) | -0.12(*) | -0.05 | -0.21(**) | -0.11 | -0.13(*) | -0.02 | -0.05 |
| Site17 | -0.27(*) | -0.32(**) | -0.37(**) | 0.21 | 0.07 | 0.03 | 0.18 | 0.19 | 0.18 | 0.23 |
| Site18 | -0.10 | 0.06 | -0.19 | -0.02 | 0.19 | -0.22 | -0.13 | -0.06 | 0.07 | -0.02 |
| Site19 | -0.14 | -0.11 | -0.17 | 0.06 | 0.07 | -0.11 | 0.19 | 0.06 | 0.19 | 0.06 |
| Lab01 | -0.31(*) | | -0.21 | -0.03 | | -0.24 | | | | 0.18 |
| Lab02 | -0.35(*) | | | | | -0.09 | | | | |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

For mechanical sounds including cars passing, buses passing, vehicle parking and construction, the importance of age on the sound preference is also relatively low. In Table 5.4, it is also interesting to note that the correlation coefficients for the sound of vehicle parking are all positive except one site (site 16, Beijing Xi Dan Square), suggesting that with the increase of age, people may become slightly more annoyed by this sound. For the sound of construction, it is noted that a significant correlation is only found in one site, namely site 14 (Sheffield Peace Gardens), indicating that age is barely related to the subjective preference evaluation of this sound.

The importance of age for the subjective evaluations of preference, noisiness, comfort and pleasantness has also been investigated in Part II & III of the laboratory experiments and the result is shown in Table 5.5.

***Table 5.5** Relationships between age and the subjective evaluations of preference, noisiness, comfort and pleasantness*

| Sound | | Preference | Noisiness | Comfort | Pleasantness |
|---|---|---|---|---|---|
| Single sound | Low bird | -0.50(**) | -0.24 | -0.36(**) | -0.43(**) |
| | Bird | -0.35 (**) | -0.28(*) | -0.37(**) | -0.40(**) |
| | Loud bird | -0.37(**) | 0.03 | -0.31(*) | -0.46(**) |
| | Skateboard | 0.03 | -0.03 | 0.01 | -0.15 |
| | Children playing | -0.09 | -0.05 | -0.17 | -0.23 |
| | Waterfall | -.037 | -0.32(*) | -0.01 | -0.08 |
| | Low cars passing | 0.17 | 0.13 | 0.15 | -0.10 |
| | Car passing | 0.20 | 0.18 | 0.15 | -0.00 |
| | Loud cars passing | 0.32(*) | 0.42(**) | 0.36(**) | 0.16 |
| | Traffic | -0.04 | 0.14 | -0.00 | -0.24 |
| Combined sound | Bell & speak | 0.02 | -0.10 | -0.08 | -0.01 |
| | Fountain & song | 0.26 | 0.23 | 0.15 | 0.01 |
| | Fountain & children playing | -0.31(*) | -0.34(*) | -0.21 | -0.37(**) |
| | Bird & cars passing | -0.24 | 0.05 | -0.06 | -0.35(**) |
| | Fountain & construction | 0.26 | 0.04 | 0.32(*) | 0.20 |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

It shows again that age is much relevant to the subjective evaluation of birdsong. Significant correlation is found in all evaluations for the normal birdsong with a negative *r* at least higher than 0.28, in the meanwhile, significant correlation is also found in 3 of 4 case study sites for the evaluations of the low birdsong and the loud birdsong. However, in terms of the loud birdsong, the relationship between age and the noisiness evaluation is considerably weaker, where a relatively low $r$=0.03 is found. This differs from the relationships between age and other evaluations, namely preference, comfort and pleasantness. It is also found in Table 5.5 that the importance of age for the evaluations of other sounds is rather limited as less significance is found except for the sound of loud cars passing and the sound of fountain mixed with children playing.

### 5.3.2 Education

Table 5.6 shows the correlations of education and the sound preference evaluation of the studied sounds based on Part I & II of the laboratory experiments and field surveys. It can be seen that compared to age, education and the sound preference evaluation are more related and their relation varies with different sounds. The importance of education for the sound preference evaluation is generally more significant for mechanical sounds compared to natural and human sounds. It can be explained that mechanical sounds are usually related to the sensation of noisiness, and education is the most influencing factor on the sound level evaluation compared to other social/demographic factors (Yu & Kang, 2008a).

Also from Table 5.6, it can be seen that in most studied cases with mechanical sounds, the correlation coefficients are positive, and for the small number of negative coefficients the correlations are generally low and not at a significant level. This suggests that people with a higher education level are more annoyed by mechanical sounds. For natural sounds, conversely, the correlation coefficients are predominately negative, suggesting that with the increase of education level people tend to prefer natural sounds more. For human sounds, there are mixed positive and negative correlation coefficients.

***Table 5.6** Relationships between education and the sound preference evaluations*

| Site | Bird | Water | Insect | Speech | Footsteps | Children playing | Car passing | Bus passing | Vehicle parking | Construction |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | 0.03 | | -0.01 | -0.21 | | 0.17(**) | 0.12 | | |
| 2 | | | | -0.09 | -0.17 | | 0.07 | | | |
| 3 | | | | 0.05 | 0.05 | 0.09(*) | -0.07 | | | |
| 4 | | | | 0.09(*) | 0.02 | 0.06 | -0.03 | | | |
| 5 | | | | -0.21(*) | | 0.12(**) | -0.04 | -0.03 | | -0.08(*) |
| 6 | | | | | | -0.11(**) | -0.06(*) | -0.07(*) | | -0.09(**) |
| 7 | | 0.06 | | 0.01 | | | 0.18(**) | 0.17(**) | | |
| 8 | | | | -0.10(*) | | 0.03 | -0.01 | | | |
| 9 | -0.09(*) | | | -0.12(**) | | -0.18(**) | 0.12(**) | | | |
| 10 | | | | -0.11(**) | -0.06 | | 0.08(**) | 0.07(*) | | |
| 11 | -0.26(**) | | | -0.01 | | | 0.04 | 0.19(*) | | |
| 12 | | -0.02 | | -0.09 | 0.44(**) | | 0.12(**) | 0.15(**) | | |
| 13 | -0.02 | 0.01 | -0.05 | 0.03 | 0.03 | 0.00 | 0.08 | 0.09(*) | 0.03 | 0.03 |
| 14 | -0.09(*) | -0.12(*) | -0.11(*) | -0.11(*) | -0.06 | -0.11(*) | -0.05 | -0.05 | -0.05 | -0.07 |
| 15 | 0.02 | -0.14(*) | 0.00 | 0.12(*) | 0.11 | 0.10 | 0.24(**) | 0.15(*) | 0.18(**) | 0.22(**) |
| 16 | -0.10 | -0.05 | -0.04 | 0.00 | -0.03 | -0.01 | 0.20(**) | 0.15(**) | 0.13(*) | 0.13(*) |
| 17 | -0.42(**) | -0.56(**) | -0.46(**) | 0.04 | -0.19 | -0.24 | 0.19 | 0.04 | 0.08 | 0.11 |
| 18 | -0.14 | -0.11 | -0.20 | 0.25(*) | 0.37(**) | -0.12 | 0.40(**) | 0.03 | 0.09 | 0.02 |
| 19 | -0.28(*) | -0.28 (*) | -0.16 | 0.32(**) | 0.24(*) | 0.15 | 0.33(**) | 0.36(**) | 0.47(**) | 0.31(**) |
| Lab01 | -0.35(**) | | -0.18 | -0.02 | | -0.19 | | | | 0.32(**) |
| Lab02 | -0.28(*) | | | | | 0.10 | | | | |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

Unlike age, the relationships between education and the evaluations of preference, noisiness, comfort, and pleasantness based on Part II & III of the laboratory experiments were not studied as limited by the samples.

### 5.3.3 Gender

Table 5.7 shows the mean differences between males and females' evaluation on the sound preference. It is found that the importance of gender for the sound preference evaluation is limited for all studied sounds except the sound of bird, as seven out of eleven studied cases have a significant difference between the sound preference evaluation of males and females. However, it is noted that the differences contain both positive and negative values, suggesting there is no consistent tendency. A possible reason for this might be cultural differences, as the negative values are from the Sheffield sites as well as the laboratory experiments in Sheffield, whereas the positive values are mainly from the Shanghai sites. In other words, females in Sheffield preferred bird sounds less than males, whereas females in Shanghai preferred bird sounds more than males. For other sounds there are also mixed positive and negative values in terms of the differences between genders. For other sounds there are also mixed positive and negative values in terms of the differences between genders.

***Table 5.7** Relationships between gender and the sound preference evaluations*

| Site | Bird | Water | Insect | Speech | Footsteps | Children playing | Car passing | Bus passing | Vehicle parking | Construction |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | 0.12 | | -0.08 | -0.03 | | -0.08 | -0.11 | | |
| 2 | | | | -0.06 | -0.12 | | -0.13(*) | | | |
| 3 | | | | -0.08(*) | -0.04 | -0.17(*) | -0.01 | | | |
| 4 | | | | -0.02 | -0.06(*) | 0.06 | -0.09(**) | | | |
| 5 | | | | 0.18 | | -0.10 | 0.01 | 0.01 | | 0.11 |
| 6 | | | | | | -0.04 | 0.08(**) | 0.09(**) | | 0.07(*) |
| 7 | | -0.02 | | 0.06 | | | -0.03 | -0.02 | | |
| 8 | | | | 0.05 | | 0.24(**) | -0.04 | | | |
| 9 | 0.03 | | | 0.04 | | 0.06 | -0.05 | | | |
| 10 | | | | 0.03 | -0.05 | | -0.05 | -0.13(**) | | |
| 11 | 0.18(*) | | | 0.00 | | | -0.05 | 0.08 | | |
| 12 | | -0.03 | | -0.19(**) | -0.2 | | 0.16(**) | 0.12(*) | | |
| 13 | -0.29(*) | 0.24 | -0.35(**) | -0.29(*) | -0.25(*) | -0.09 | -0.21(*) | -0.19(*) | -0.21(*) | -0.29(*) |
| 14 | -0.45(**) | -0.40(**) | -0.45(**) | -0.29 | -0.44(*) | -0.25(*) | -0.27(*) | -0.30(**) | -0.20(*) | -0.11 |
| 15 | 0.00 | 0.00 | 0.02 | -0.03 | -0.04 | 0.03 | 0.08 | 0.01 | -0.08 | 0.02 |
| 16 | -0.03 | -0.02 | -0.07 | -0.12 | -0.07 | -0.09 | -0.01 | 0.04 | -0.01 | 0.05 |
| 17 | 0.31(*) | 0.21 | 0.26 | -0.12 | -0.05 | 0.07 | -0.50(**) | -0.10 | -0.20 | -0.09 |
| 18 | 0.22(*) | 0.10 | 0.02 | 0.14 | 0.18 | -0.20 | -0.10 | -0.08 | -0.05 | -0.06 |
| 19 | 0.09 | 0.18(*) | 0.18 | 0.04 | -0.17 | -0.05 | 0.10 | 0.10 | 0.10 | -0.08 |
| Lab01 | -0.26(*) | | -0.06 | 0.16 | | -0.07 | | | | -0.11 |
| Lab02 | -0.41(*) | | | | | -0.08 | | | | |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

Table 5.8 shows that relationships between gender and the evaluations of preference, noisiness, comfort and pleasantness for the studied sounds in Part II & III experiments. Apparently, the differences between male and female on the subjective evaluations of preference, noisiness, comfort or pleasantness are small, as at most two significant difference cases have been found. The sound of low cars passing has been found much more effected by gender, because significant differences between males and females on the evaluations of preference, noisiness, comfort and pleasantness was found with a positive value, which means the male participants felt less preference of this sound.

***Table 5.8** Relationships between gender and the sound preference evaluations in terms of preference, noisiness, comfort and pleasantness*

| | Sound | Preference | Noisiness | Comfort | Pleasantness |
|---|---|---|---|---|---|
| Single sound | Low bird | 0.01 | -0.00 | 0.33 | 0.26 |
| | bird | -0.41(*) | -0.07 | -0.33 | -0.29 |
| | Loud bird | -0.01 | -0.04 | -0.08 | 0.02 |
| | skateboard | 0.14 | 0.24 | 0.19 | 0.38 |
| | Children playing | -0.08 | -0.17 | -0.16 | -0.31 |
| | Waterfall | 0.08 | 0.12 | 0.19 | -0.02 |
| | Low cars passing | 0.33(**) | 0.49(*) | 0.28 | 0.39(*) |
| | Car passing | -0.01 | 0.40 | 0.05 | 0.31 |
| | Loud cars passing | -0.08 | -0.09 | -0.11 | -0.07 |
| | Traffic | 0.18 | 0.21 | 0.01 | 0.06 |
| Combined sound | Bell & speak | 0.13 | 0.15 | -0.03 | -0.15 |
| | Fountain & music | 0.27 | 0.33 | 0.22 | 0.21 |
| | Fountain & children playing | 0.03 | 0.11 | -0.03 | -0.02 |
| | Bird & cars passing | 0.30 | 0.37 | 0.06 | 0.19 |
| | Fountain & construction | 0.05 | -0.30 | -0.03 | -0.00 |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

### 5.3.4 Occupation

Table 5.9 traces the importance of occupation for the sound preference evaluation using Spearman correlation or Independent t-test (only for the data of laboratory experiment) based on the collected data in field studies and Part I & II experiments. Similar to gender, occupation and the sound preference evaluations is related less. It can be seen that there are far fewer case study sites where a significance level of correlation between occupation and the sound preference evaluation exists. In Table 5.9, it is also seen that the correlation coefficients are mixed with positive and negative values.

***Table 5.9*** *Relationships between occupation and the sound preference evaluations*

| Site | Bird | Water | Insect | Speech | Footsteps | Children playing | Car passing | Bus passing | Vehicle parking | Construction |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | -0.19(*) | | 0.08 | -0.04 | | 0.03 | 0.08 | | |
| 2 | | | | -0.05 | 0.05 | | -0.02 | | | |
| 3 | | | | -0.10(*) | -0.03 | -0.15(**) | 0.04 | | | |
| 4 | | | | -0.02 | -0.03 | -0.09(*) | 0.05 | | | |
| 5 | | | | 0.10 | | -0.01 | 0.03 | 0.02 | | 0.04 |
| 6 | | | | | | 0.07(*) | 0.00 | 0.00 | | 0.01 |
| 7 | | -0.05 | | -0.03 | | | -0.14(**) | -0.11(**) | | |
| 8 | | | | 0.11(**) | | -0.18(**) | 0.01 | | | |
| 9 | -0.08(*) | | | 0.01 | | -0.16(**) | -0.11(**) | | | |
| 10 | | | | 0.07 | 0.08(**) | | -0.01 | -0.08(**) | | |
| 11 | -0.13 | | | -0.19(**) | | | -0.08 | -0.03 | | |
| 12 | | -0.09 | | 0.12(*) | -0.08 | | -0.01 | 0.02 | | |
| 13 | -0.10(**) | -0.09(*) | -0.08 | -0.08 | -0.08 | -0.09(*) | -0.03 | -0.05 | -0.01 | -0.06 |
| 14 | - 0.01 | 0.01 | -0.01 | 0.06 | 0.01 | 0.04 | 0.02 | 0.02 | 0.07 | 0.05 |
| 15 | 0.07 | -0.03 | 0.02 | 0.12(*) | 0.14(*) | 0.00 | -0.01 | 0.03 | 0.11 | -0.04 |
| 16 | 0.04 | -0.03 | -0.02 | -0.11 | -0.01 | -0.07 | -0.07 | -0.08 | -0.06 | -0.03 |
| 17 | -0.34(*) | -0.29(*) | -0.34(*) | 0.09 | 0.09 | -0.02 | 0.21 | 0.16 | 0.19 | 0.20 |
| 18 | -0.10 | 0.00 | 0.09 | 0.16 | 0.26(*) | -0.16 | -0.01 | -0.10 | 0.10 | -0.05 |
| 19 | -0.05 | 0.17 | 0.12 | -0.03 | 0.11 | -0.09 | 0.13 | -0.08 | -0.03 | -0.19 |
| Lab01 | -0.76 | | 0.21 | 0.24 | | 0.02 | | | | -0.06 |
| Lab02 | 0.32 | | | | | -0.00 | | | | |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

Briefly, Table 5.10 shows the percentage/number of the studied cases where significant correlations or differences exist. It is found that significance between occupation and the sound preference evaluation exists in 3 of 11 studied cases for the sound of bird, 3 of 10 for the sound of water, 1 of 8 for the sound of insect, 5 of 19 for the sound of speech, 3 of 13 for the sound of footsteps, 6 of 15 for the sound of children playing, 2 of 19 for the sound of cars passing, and 2 of 16 for the sound of buses passing, which are mostly below 30%, except for the sound of children playing. Compared to the importance of age and education for the sound preference evaluation, the importance of occupation is relatively lower, which implies that the importance of occupation for the sound preference evaluation is insignificant.

Same as the education, the relationships between occupation and the subjective evaluations of preference, noisiness, comfort, and pleasantness has not been examined yet because of the sample limitation.

*Table 5.10 Percentage (number) of the studied cases where significant correlations or differences exist between social/demographic factors and the sound preference evaluations*

| Sound | | Age | Gender | Occupation | Education | Residence |
|---|---|---|---|---|---|---|
| Natural sound | Bird | 54.5% (6/11) | 63.6% (7/11) | 27.3% (3/11) | 63.6% (7/11) | 11.1% (1/9) |
| | Water | 10.0% (1/10) | 20.0% (2/10) | 30.0% (3/10) | 40.0% (4/10) | 0.0% (0/10) |
| | Insect | 37.5% (3/8) | 25.0% (2/8) | 12.5% (1/8) | 25.0% (2/8) | 28.6% (2/7) |
| Human sound | Speech | 31.6% (6/19) | 15.8% (3/19) | 26.3% (5/19) | 47.4% (9/19) | 16.7% (3/18) |
| | Footsteps | 23.1% (3/13) | 23.1% (3/13) | 23.1% (3/13) | 23.1% (3/13) | 0.0% (0/13) |
| | Children playing | 46.7% (7/15) | 20.0% (3/15) | 40.0% (6/15) | 33.3% (5/15) | 15.4% (2/13) |
| Mechanical sound | Car passing | 36.8% (7/19) | 36.8% (7/19) | 10.5% (2/19) | 52.6% (10/19) | 21.1% (4/19) |
| | Bus passing | 35.7% (5/14) | 35.7% (5/14) | 14.3% (2/14) | 57.1% (8/14) | 14.3% (2/14) |
| | Vehicle parking | 28.6% (2/7) | 28.6% (2/7) | 0.0% (0/7) | 42.9% (3/7) | 0.0% (0/7) |
| | Construction | 10.0% (1/10) | 20.0% (2/10) | 0.0% (0/10) | 60.0% (6/10) | 33.3% (3/9) |

### 5.3.5 Residential status

Mean differences between non-local and local residents' evaluation on the sound preference is presented in Table 5.11, and summarised in Table 5.10 as well. In Table 5.10, it can be seen that for all studied sounds less than 34% studied cases have been found with significant differences between local and non-local residents in terms of the sound preference evaluation.

In Table 5.11, it shows that the importance of residence status for the sound preference evaluation is also not strong generally because significance exists in a small number of case study sites for the sound of bird, the sound of insect, the sound of speech, the sound of children playing, the sound of cars passing, the sound of buses passing, and the sound of construction.

*Table 5.11 Relationships between residential status and the sound preference evaluations*

| Site | Bird | Water | Insect | Speech | Footsteps | Children playing | Car passing | Bus passing | Vehicle parking | Construction |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | 0.04 | | 0.03 | 0.22 | | -0.05 | -0.14 | | |
| 2 | | | | 0.11 | 0.03 | | 0.09 | | | |
| 3 | | | | -0.03 | -0.05 | 0.04 | -0.02 | | | |
| 4 | | | | 0.05 | 0.05 | 0.02 | 0.05 | | | |
| 5 | | | | 0.33(*) | | -0.19(*) | 0.23(**) | -0.01 | | 0.34(**) |
| 6 | | | | | | -0.04 | 0.09(**) | 0.15(**) | | 0.12(**) |
| 7 | | 0.05 | | 0.10(*) | | | -0.04 | -0.07 | | |
| 8 | | | | 0.07 | | 0.07 | 0.07 | | | |
| 9 | 0.01 | | | -0.01 | | 0.02 | -0.04 | | | |
| 10 | | | | 0.04 | -0.02 | | 0.01 | -0.02 | | |
| 11 | 0.14 | | | 0.00 | | | 0.18(**) | 0.09 | | |
| 12 | | 0.02 | | -0.03 | -0.24 | | 0.15(**) | 0.28(**) | | |
| 13 | 0.13 | 0.04 | 0.02 | 0.12 | -0.03 | 0.09 | -0.06 | -0.06 | -0.06 | -0.09 |
| 14 | -0.18 | -0.09 | 0.04 | 0.01 | -0.07 | -0.03 | -0.03 | 0.01 | -0.04 | -0.01 |
| 15 | -0.09 | -0.06 | -0.16(*) | 0.02 | -0.05 | 0.06 | 0.11 | -0.09 | 0.06 | 0.13(*) |
| 16 | 0.13(*) | 0.07 | 0.19(*) | 0.14 | 0.11 | 0.23(**) | 0.07 | 0.04 | 0.08 | -0.01 |
| 17 | -0.18 | -0.14 | -0.06 | 0.04 | -0.12 | -0.17 | 0.19 | 0.15 | 0.21 | 0.22 |
| 18 | -0.12 | 0.03 | 0.04 | -0.34(**) | 0.00 | 0.30 | -0.03 | 0.08 | -0.01 | 0.08 |
| 19 | -0.10 | -0.12 | -0.04 | 0.10 | 0.14 | -0.25 | -0.09 | -0.03 | 0.06 | 0.12 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

Fig. 5.18 shows the mean difference of all the studied cases between local and non-local residents in terms of the sound preference evaluation. It is interesting to note that from natural sounds to mechanical sounds, the mean difference between local and non-local residents is getting higher, which suggests that non-local people are more annoyed by mechanical sounds in urban squares, especially construction sounds.

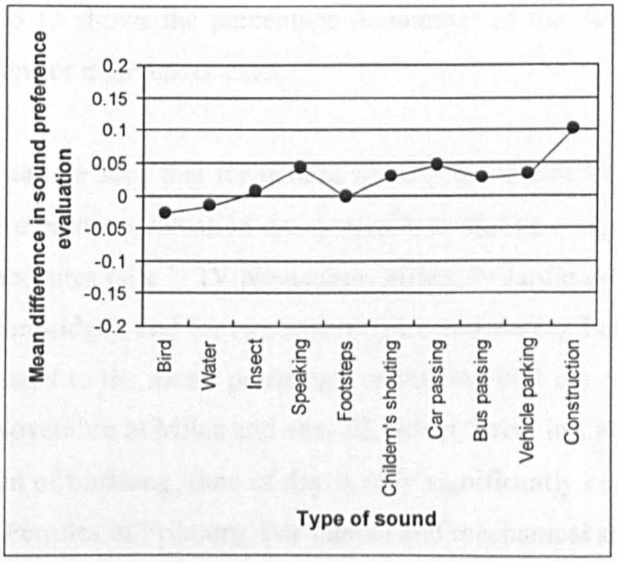



*Fig. 5.18 Mean difference of all studied cases between local and non-local residents in terms of the sound preference evaluations*

## 5.4 Physical, behavioural/psychological factors and home sound experience

This section illustrates the importance of physical and behavioural/psychological factors for the sound preference evaluation, focusing on season, time of day, frequency of using the site, reason for visiting the site, and site preferences. Corresponding to the study of Section 5.3, ten sounds ranging from natural to mechanical sounds are examined, including bird, water, insect, speech, footsteps, children playing, cars passing, buses passing, vehicle parking, and construction. However, as it is impossible to investigate these factors in laboratory experiment, all analyses in this section are based on the field studies.

### 5.4.1 Physical conditions

In Table 5.12, the effects of season and time of day on the sound preference evaluation are shown. For the Chinese sites, since the surveys were carried out in summer only, the effect of season is not examined. In Shanghai Nanjing Road Square (site 18) all the surveys were carried out in midday and thus, the effect of time of day was not examined for that site. Table 5.13 shows the percentage or number of the case study sites where significant correlations or differences exist.

From Table 5.12 it can be seen that for natural sounds, the effects of season and time of day on the sound preference evaluation are generally trivial as a significance level only shows in three studied sites (site 7- IV Novembre, Milan; 9- Jardin de Perolles, Frobourg; 12- Silver Street, Cambridge), and for two sounds (bird and water). For the sound of water, season is closely related to the sound preference evaluation in 2 out of 5 case study sites, namely site- 7, IV Novembre in Milan and site- 12, Silver Street in Cambridge, and for the preference evaluation of birdsong, time of day is only significantly correlated with it only in site- 9, Jardin de Perolles in Fribourg. For human and mechanical sounds, the effects of season and time of day are relatively higher, but the number/percentage of the case study sites with a significant level is still rather low, generally less than 30%, as can be seen in Table 5.11, except for speech, footsteps and vehicle parking, where the percentage is 46.2%, 37.5% and 50%, respectively, in terms of the season effect.

In Table 5.12, it is interesting to note that in three Greek case study sites, including Athens Seashore Square (site 4), Thessaloniki Kritis Square (site 5), and especially, Thessaloniki Makedonomahon Square (site 6), the effect of season and time of day is considerably greater than that of other sites, suggesting the importance of considering cultural and physical conditions.

*Table 5.12 Relationships between season, time of day and the sound preference evaluations*

| Site | Natural sounds | | | | | | Human sounds | | | | | | Mechanical sounds | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bird | | Water | | Insect | | Speech | | Footsteps | | Children playing | | Car passing | | Bus passing | | Vehicle parking | | Construction | |
| | Season | Time | Season | Time | Season | Time | Season | Time | Season | Time | Season | Time | Season | Time | Season | Time | Season | Time | Season | Time |
| 1 | | | 0.02 | -0.05 | | | -0.27(*) | -0.19 | -0.16 | -0.22 | | | -0.16(**) | 0.04 | -0.12 | -0.08 | | | | |
| 2 | | | | | | | -0.34(**) | 0.08 | -0.23(*) | -0.21 | | | 0.01 | 0.01 | | | | | | |
| 3 | | | | | | | 0.03 | -0.02 | 0.08 | -0.03 | 0.04 | 0.01 | -0.1 | 0.03 | | | | | | |
| 4 | | | | | | | -0.17(**) | 0.07 | 0.20(**) | -0.17(**) | -0.06 | 0.05 | -0.15(**) | 0.04 | | | | | | |
| 5 | | | | | | | 0.76(**) | -0.08 | | | 0.32(**) | -0.08(*) | -0.06 | 0.04 | 0.22(**) | -0.10(*) | | | -0.05 | 0.07(*) |
| 6 | | | | | | | | | | | 0.29(**) | -0.10(**) | -0.23(**) | 0.09(**) | -0.22(**) | 0.09(**) | | | -0.23(**) | 0.10(**) |
| 7 | | | -0.11(**) | 0.04 | | | 0.26(**) | -0.01 | | | | | 0.02 | -0.02 | -0.02 | 0.05 | | | | |
| 8 | | | | | | | 0.27(**) | -0.18(**) | | | 0.06 | -0.01 | 0.02 | 0.03 | | | | | | |
| 9 | -0.02 | 0.12(**) | | | | | -0.07 | 0.10(*) | | | 0.02 | 0.14(**) | 0.06 | 0.07(*) | | | | | | |
| 10 | | | | | | | 0.03 | -0.03 | 0.05 | 0.00 | | | 0.05 | 0.01 | -0.02 | 0.04 | | | | |
| 11 | 0.15 | 0.12 | | | | | -0.04 | -0.08 | | | | | -0.29(**) | -0.03 | -0.39 | -0.05 | | | | |
| 12 | | | 0.14(**) | -0.11 | | | 0.08 | 0.04 | -0.24(*) | 0.10 | | | -0.07 | -0.09(*) | -0.05 | -0.24(**) | | | | |
| 13 | 0.04 | 0.04 | 0.01 | 0.00 | 0.04 | 0.04 | -0.01 | -0.02 | 0.04 | 0.04 | 0.01 | 0.00 | 0.03 | 0.02 | 0.03 | 0.02 | 0.03 | 0.02 | 0.00 | -0.00 |
| 14 | 0.06 | 0.05 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 | 0.01 | 0.01 | 0.01 | -0.01 | -0.02 | 0.05 | 0.05 | 0.05 | 0.05 | 0.09(*) | 0.08 | 0.03 | 0.02 |
| 15 | | 0.01 | | -0.06 | | 0.05 | | -0.00 | | 0.02 | | 0.03 | | -0.08 | | -0.02 | | -0.08 | | -0.06 |
| 16 | | 0.03 | | -0.02 | | 0.03 | | 0.01 | | 0.01 | | -0.06 | | -0.02 | | -0.02 | | 0.08 | | -0.03 |
| 17 | | -0.06 | | -0.05 | | 0.00 | | 0.03 | | 0.16 | | -0.01 | | 0.14 | | -0.03 | | -0.02 | | 0.07 |
| 18 | | | | | | | | | | | | | | | | | | | | |
| 19 | | 0.07 | | 0.02 | | 0.03 | | 0.03 | | -0.13 | | -0.15 | | -0.02 | | -0.14 | | -0.11 | | -0.06 |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

***Table 5.13*** *Percentage (number) of the case study sites where significant correlations or differences exist between sound preference and physical, behavioural and psychological factors*

| | Sound | Season | Time | Frequency | Site preferences | Reason |
|---|---|---|---|---|---|---|
| Natural sounds | Bird | 0.0% (0/4) | 12.5% (1/8) | 0.0% (0/4) | 0.0% (0/2) | 0.0% (0/3) |
| | Water | 40.0% (2/5) | 0.0% (0/9) | 16.7% (1/6) | 25.0% (1/4) | 0.0% (0/4) |
| | Insect | 0.0% (0/2) | 0.0% (0/6) | 0.0% (0/3) | | 50.0% (1/2) |
| Human sounds | Speech | 46.2% (6/13) | 11.8% (2/17) | 33.3% (6/18) | 23.1% (3/13) | 6.7% (1/15) |
| | Footsteps | 37.5% (3/8) | 8.3% (1/12) | 11.1% (1/9) | 14.3% (1/7) | 0.0% (0/8) |
| | Children playing | 25.0% (2/8) | 25.0% (3/12) | 37.5% (3/8) | 42.9% (3/7) | 14.3% (1/7) |
| Mechanical sounds | Car passing | 28.6% (4/14) | 16.7% (3/18) | 15.8% (3/19) | 64.3% (9/14) | 18.8% (3/16) |
| | Bus passing | 22.2% (2/9) | 23.1% (3/13) | 14.3% (2/14) | 44.4% (4/9) | 18.2% (2/11) |
| | Vehicle parking | 50.0% (1/2) | 0.0% (0/6) | 33.3% (1/3) | 100% (1/1) | 0.0% (0/2) |
| | Construction | 25.0% (1/4) | 25.0% (2/8) | 66.7% (2/3) | 33.3% (1/3) | 66.7% (2/3) |

### 5.4.2 Behavioural factors

Table 5.14 shows the effects of frequency of using the site and reason for visiting the site on the subjective evaluation of sound preference, and the summary of the percentages or numbers of the case study sites with significant levels can also be seen in Table 5.13. Unlike the study of the physical factors, only noticed sounds in the case study sites are included in the study of the behavioural factors' effecting on the sound preference evaluation, since unnoticed sounds are considered less relevant to these behavioural factors for the case study sites. In Table 5.14, it can be seen that between frequency of using the site and the sound preference evaluation, the correlation is not significant for natural sounds. But for human and mechanical sounds, significant correlations exist in a small percentage of the sites as shown in Table 5.13; however, the analyses for the sound of construction were only based on three case study sites, where the construction sound were noticed.

For all studied sounds no matter natural or mechanical, it is found that the importance of reason for visiting the site for the sound preference evaluation is insignificant as significant level has been found in less than three case study sites as shown in Table 5.13. For the sound of construction, the percentage of the case study sites where a significant level exists is relatively high, say as 67.7%, but based on three case study sites 2 of 3 case study sites the same as frequency of visiting the site. In Table 5.14, it is also interesting to note that although frequency of visiting the site and reason for visiting the site are insignificant related to the sound preference evaluation for most sounds, both of them have been found significant related to the evaluation of the sound of construction in two case study sites: site 5- Kritis and site 6- Makedonomahon, which both are in the same city, Thessaloniki, Greece. This might be related with its culture background.

Other behavioural factors, such as wearing earphones, reading/writing, and moving activities, are considered to be less relevant to the sound preference evaluation and then the importance of them for the subjective evaluation of sound preference has not been analysed in this section although their relations with the sound level evaluation were studied in Chapter 4.

***Table 5.14** Relationships between frequency of visiting the site, reason for visiting the site and the sound preference evaluations*

| Site | Natural sounds | | | | | | Human sounds | | | | | | Mechanical sounds | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Bird | | Water | | Insect | | Speech | | Footsteps | | Children playing | | Car passing | | Bus passing | | Vehicle parking | | Construction | |
| | Frequency | Reason | Frequency | Reason | Frequency | Reason | Frequency | Reason | Frequency | Reason | Frequency | Reason | Frequency | Reason | Frequency | Reason | Frequency | Reason | Frequency | Reason |
| 1 | | | 0.12 | -0.04 | | | -0.06 | 0.06 | -0.03 | 0.10 | | | -0.02 | -0.058 | -0.1 | 0.02 | | | | |
| 2 | | | | | | | 0.17(*) | 0.04 | 0.15 | 0.00 | | | -0.06 | 0.00 | | | | | | |
| 3 | | | | | | | 0.11(*) | 0.12(**) | 0.02 | 0.04 | -0.1(**) | 0.10(*) | -0.01 | 0.00 | | | | | | |
| 4 | | | | | | | -0.06 | -0.06 | 0.09(*) | -0.02 | -0.04 | 0.00 | 0.00 | -0.05 | | | | | | |
| 5 | | | | | | | 0.23(**) | -0.07 | | | 0.00 | -0.073 | -0.08(*) | 0.13(**) | -0.04 | 0.07 | | | -0.11(**) | 0.10(**) |
| 6 | | | | | | | | | | | -0.10(**) | -0.06 | -0.11(**) | -0.11(**) | -0.10(**) | -0.12(**) | | | -0.09(**) | -0.14(**) |
| 7 | | | 0.07 | 0.00 | | | 0.11(**) | -0.03 | | | | | 0.06 | 0.04 | 0.07 | -0.01 | | | | |
| 8 | | | | | | | -0.04 | -0.01 | | | 0.01 | -0.02 | 0.07 | -0.09 | | | | | | |
| 9 | 0.04 | -0.02 | | | | | 0.00 | -0.02 | | | 0.05 | 0.01 | -0.04 | -0.03 | | | | | | |
| 10 | | | | | | | 0.00 | -0.06 | 0.04 | -0.01 | | | -0.04 | 0.07 | 0.01 | -0.05 | | | | |
| 11 | 0.18 | 0.00 | | | | | -0.06 | -0.07 | | | | | 0.18(**) | 0.12(*) | 0.21(**) | 0.28(**) | | | | |
| 12 | | | 0.07 | 0.03 | | | 0.06 | 0.17 | 0.11 | 0.11 | | | 0.03 | 0.08 | 0.08 | 0.10 | | | | |
| 13 | | | | | | | -0.02 | -0.08 | 0.01 | -0.03 | | | -0.05 | -0.00 | -0.03 | -0.02 | | | | |
| 14 | | | 0.14(**) | 0.04 | | | 0.11(**) | 0.08 | | | 0.10(*) | 0.03 | 0.07 | 0.06 | 0.06 | 0.04 | 0.09(*) | 0.07 | 0.06 | 0.05 |
| 15 | -0.1 | -0.04 | | | -0.03 | -0.04 | -0.05 | 0.03 | | | | | 0.02 | 0.06 | 0.03 | 0.07 | | | | |
| 16 | | | | | 0.05 | -0.17(**) | -0.02 | -0.02 | 0.02 | 0.00 | | | -0.09 | 0.03 | -0.11 | 0.00 | -0.02 | 0.02 | | |
| 17 | | | | | | | 0.01 | | -0.09 | | | | -0.23 | | -0.14 | | | | | |
| 18 | | | 0.03 | | | | -0.24(*) | | | | | | -0.15 | | -0.06 | | -0.04 | | | |
| 19 | -0.17 | | -0.11 | | -0.20 | | -0.12 | | | | | | -0.09 | | 0.12 | | | | | |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

### 5.4.3 Site preferences

In this section, the effect of a psychological factor, site preferences, on the sound preference evaluations is studied. Table 5.15 shows that the effect of site preferences is insignificant on the preference evaluation of natural sounds, although only a small number of sites are considered. Conversely, for some human or mechanical sounds, especially children playing, car and buses passing, and vehicle parking, the importance of site preferences for the evaluations is significant in a high percentage of sites, at 42-100%, as shown in Table 5.13. A possible reason is that those sounds are distinguishable sounds on the sites, as keynotes or sound marks and also, some sounds are rather loud, such as children playing.

***Table 5.15** Relationships between site preferences and the sound preference evaluations*

| Site | Natural sounds | | Human sounds | | | Mechanical sounds | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Bird | Water | Speech | Footsteps | Children playing | Car passing | Bus passing | Vehicle parking | Construction |
| 1 | | 0.13 | 0.16 | 0.08 | | -0.09 | -0.16 | | |
| 2 | | | 0.02 | 0.13 | | -0.24(**) | | | |
| 3 | | | -0.05 | 0.02 | -0.02 | 0.05 | | | |
| 4 | | | 0.00 | 0.00 | -0.09 | -0.07(*) | | | |
| 5 | | | 0.31(*) | | 0.16(**) | -0.03 | 0.04 | | 0.00 |
| 6 | | | | | 0.26(**) | -0.03 | -0.02 | | -0.07 |
| 7 | | 0.01 | 0.04 | | | -0.24(**) | -0.23(**) | | |
| 8 | | | -0.06 | | -0.06 | -0.20(**) | | | |
| 9 | 0.05 | | 0.01 | | 0.04 | -0.12(**) | | | |
| 10 | | | 0.04 | 0.05 | | -0.26(**) | -0.20(**) | | |
| 11 | -0.1 | | 0.16(*) | | | -0.21(**) | -0.21(**) | | |
| 12 | | 0.04 | -0.1 | -0.33(**) | | -0.15(**) | -0.09 | | |
| 13 | | | 0.14 | 0.16 | | 0.14 | 0.09 | | |
| 14 | | 0.57(**) | 0.54(**) | | 0.36(**) | 0.31(**) | 0.33(**) | 0.28(**) | 0.28(**) |
| 15 | | | | | | | | | |
| 16 | | | | | | | | | |
| 17 | | | | | | | | | |
| 18 | | | | | | | | | |
| 19 | | | | | | | | | |

*Marks * and ** indicate significant correlations, with * representing $p<=0.05$ and ** representing $p<=0.01$*

### 5.4.4 Home sound experience

As discussed in Chapter 4, long-term sound level experience has been found to be an important factor in influencing the sound level evaluation in urban open spaces. The effect of home sound experience on the sound preference evaluation is therefore studied in this section. Table 5.16 shows significant differences for a given sound between the people who hear the sound at home or not hear the sound at home. Five sound types, namely bird, insect, speech, music and traffic were included for the home environment, for the field surveys more detailed classifications were made, including three types of music and four types of traffic sounds.

*Table 5.16 Mean difference in the sound preference evaluations of a given sound between people who hear the sound at home or not (No – Yes)*

| Site | Bird | Insect | Speech | Car passing | Bus passing | Vehicle parking | Construction | Music in street | Music from passing car | Music in shop |
|---|---|---|---|---|---|---|---|---|---|---|
| 15 | 0.10 (*) | -0.09 | 0.16 | -0.06 | 0.01 | -0.084 | -0.11(*) | 0.16 | 0.2 | 0.18 |
| 16 | 0.1 | 0.12 | 0.07 | -0.09 | -0.04 | -0.07 | -0.02 | 0.04 | 0.09 | 0.09 |
| 17 | 0.12 | | 0.16 | 0.19 | 0.13 | 0.2 | 0.03 | -0.15 | -0.01 | 0.19 |
| 18 | 0.16 | | 0.55 | 0.06 | 0.07 | 0.07 | | 0.2 | 0.33 (*) | 0.4 |
| 19 | 0.19 (*) | | 0.09 | 0.04 | 0.1 | 0.13 | 0.19 | 0.21 | -0.47(*) | 0.27 |
| China (all sites) | 0.11(**) | 0.09 | 0.12(*) | -0.04 | 0.02 | -0.02 | -0.02 | 0.09 | 0.12 (*) | 0.20 (**) |

*Marks * and ** indicate significant correlations, with * representing p<=0.05 and ** representing p<=0.01*

In Table 5.16, it can be seen that the differences between the two groups of people are insignificant for most of the sounds, in most of the case study sites, except for birdsongs and music from passing car, for which 3 out of 6 case study sites show significant differences. In other words, the sounds heard at home generally do not affect the sound preference in urban open spaces significantly. A possible reason is that some sounds, such as traffic, are rather common, so that the experience at home is less important in terms of the sound preference. For birdsong, it is interesting to note in Table 5.14 that the mean differences are all positive, suggesting that those people who hear birdsongs often at home may tend to prefer birdsongs in urban open spaces too.

## 5.5 Conclusions

The effect of various factors, including types of sound sources, psychoacoustic parameters: loudness and sharpness, social/demographic characteristics, physical conditions, behavioural/psychological status, and the home sound experience on the sound preference evaluation for three sound types: natural, human and mechanical, has been systematically studied in this chapter.

The effect of sound types on the subjective evaluation of sound preference has been studied in several facets: the sound categories, the sound subcategories and the visual effect. Four subjective evaluations responding to sound effect namely preference, noisiness, comfort, and pleasantness were investigated in the lab experiment although only the preference evaluations has been examined in the field studies. In terms of sound categories, natural sounds (bird, water, insect) are preferred more than mechanical sounds (cars passing, buses passing, vehicle parking and construction), while human sounds are in the middle. Besides the sound categories, the sound subcategories, such as the sound actions or functions have been found also important to affect the sound preference evaluation. For instance, the church bell is more preferred than the clock bell and the music played in a street is more preferred than the music from a store or a passing car. The study also showed the Chinese people are more annoyed by the sound of children playing and buses passing than the EU people.

With regard to the subjective evaluations of preference, noisiness, comfort, and pleasantness, based on the laboratory experiments, the results prove again that people are fond with natural sounds and annoyed by the mechanical sounds. In terms of the visual effect, the result indicates that a positive view can improve the sound preference evaluation whereas negative scenery will reduce the preference feelings of a sound. It is also interesting to note that either the effect of sound categories or the visual effect on the noisiness evaluation is less than on the other three preference evaluations, whilst the relationships between the comfort and pleasantness evaluations are rather close compared to that between the noisiness and the preference evaluations.

The relationship between two psychoacoustic parameters: loudness and sharpness, and the subjective evaluations (including preference, noisiness, comfort, and pleasantness) have been studied. Significant correlation has been found between loudness and the four preference sensation evaluations for single sound. A sound with higher loudness has been found with less preference, especially for the single sounds. However, the effect of loudness on the evaluations of combined sounds is relatively less than single sounds. It is found that loudness has a closer relationship to the noisiness evaluation than other evaluations, which might explain why the noisiness evaluation is less affected by sound categories or visual effect. Again, a close relationship between the comfort and pleasantness evaluations has been found. In relation to the same sound with different sound levels, a negative relationship exists between loudness and the subjective evaluations, as expected. Unlike loudness, within the range of the studied sounds, a sound with a higher sharpness was perceived with a higher preference but this is not true for the combined sounds. In relation to the combined sounds, it is found that a sound is less preferred if sharpness is higher but this was only with five studied sounds.

In terms of social/demographic factors, the results suggest that age and education are two factors which generally correlated with the sound preference significantly, although the correlation may vary with different types of urban open spaces and sounds. It is interesting to note that with increasing age or education level, people tend to prefer natural sounds and are more annoyed by mechanical sounds. It has also been found that the gender, occupation and residence status generally would not be correlated with the sound preference evaluation significantly although gender is relatively more related to birdsongs.

In terms of physical/behavioural/psychological factors, generally speaking, their importance for the sound preference evaluation is insignificant, except for a limited case study sites and certain sound types. Among these factors, reason for visiting the site has the weakest relation with the sound preference evaluation, and site preferences are related most with the sound preference evaluation. The importance of home sound environment for the sound preference has been found to be generally insignificant, except for certain sounds. For example, those people who hear birdsongs often at home may tend to prefer birdsongs in urban open spaces too. In addition to contribute some guidelines for soundscape research or design in urban open spaces, the results are also important in determining the inputs for sound preference prediction models in Chapter 7; with such models the simultaneous effects of various factors can also be taken into account in the soundscape design process.

## Chapter 6

# ANN Models for the Sound Level/Acoustic Comfort Evaluations

Based on the statistic analyses in Chapter 4, this chapter explores the feasibility of using ANN models to predict the sound level and acoustic comfort evaluations. Two kinds of prediction models were developed using Qnet, for sound level and acoustic comfort evaluations, respectively. NeuroSolutions models have then been developed to compare with Qnet models. Moreover, for comparing with ANN models, a conventional statistical technique, ordinal logistic regression (OLR), was explored. Finally, a mapping method is proposed to visually present the models' predictions, to assist urban planners/designers at design stage.

## 6.1 Test of the model performance

Using site 6- the Makedonomahon Square in Thessaloniki as an example, the prediction performance of ANN modeling was examined, considering the sound level evaluation. For making such a model, besides training and test set, a third one has to be assigned for model evaluation, and thus a large number of samples are needed. Site 6-Makedonomahon, Thessaloniki, Greece is whereby selected to develop this model as it has sufficient training samples.

### 6.1.1 The model of sound level evaluations for the Makedonomahon

For building this sound level evaluation model of the Makedonomahon, the 1037 samples were split into three sets, including training, test and evaluation sets, taking 70%, 10% and 20% of the total samples, respectively. The test set was for internally monitoring the network performance, whereas the evaluation set was for externally testing the network performance after it was fixed.

The network of this model was trained and refined through optimizing training process as the previous models. The final optimal network and its prediction result are shown in Table 6.1. It can be seen that the optimal network has 2 hidden layers and 11 hidden nodes. Its prediction performance is acceptable although the correlation coefficient between prediction outputs and desired targets is not absolutely high, which is 0.69 for the training set and 0.44 for the test set. The RMS error for this network is also acceptable, which is 0.11 for training and 0.16 for test.

***Table 6.1** Model for the sound level evaluations based on the site 6- Makedonomahon, Thessaloniki Greece*

| Site | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Input variables | Output variable | Hidden layer | Hidden node | Test sample size | Coefficient | | RMS error | |
| | | | | | | Training | Test | Training | Test |
| 6 - Makedonomahon | Phy1, 2, 8 B2, 5, 6 S1, 2, 3, 4 Psy1, 2, 6, 7 | Subjective evaluations of sound level | 2 | 11 | 120 | 0.69 | 0.44 | 0.11 | 0.16 |

*Phy1-Season, Phy2-Time of day, Phy8-Sound pressure level; B2-Whether reading or writing, B5-Frequency of visiting the site, B6-Reason for visiting the site; S1-Age, S2-Gender, S3-Occupation, S4-Education; Psy1-Site preference, Psy2-View assessment, Psy6-Brightness evaluations, Psy7-Overall physical evaluations*

### 6.1.2 Results and discussions

After the model was well trained, a recall mode from Qnet is applied for evaluating its performance. In Qnet, the recall mode is for neural network recall, which is the processing of new inputs through a trained network (Vesta, 2000). As mentioned above, the samples used for recalling are 204, which are around 20% of 1037, and all of them have never been presented for the training process. A comparison between the prediction outputs from the model recalling and the real evaluations obtained from the field surveys is made.

The difference and correlation between the outputs and targets was calculated using the Paired-Samples T Test of SPSS. The analysis results are shown in Table 6.2. It can be seen that no significant difference has been found between the network outputs and real targets. Moreover, the mean and standard deviation of the targets and of the outputs are very similar, which is 0.87 (target) and 0.799 (output) for the mean and, 0.903 (target) and 0.727 (output) for the standard deviation. The correlation of these two factors achieved a significance level, and the correlation coefficient is also acceptable, *r*= 0.287, considering the test correlation of the network is only 0.44. The result from the above statistical analysis suggests that the ANN model built for predicting the sound level evaluations of site 6- Makedonomahon Square is reliable.

***Table 6.2** Results of the Paired-Samples T Test between the network predictions and the real targets*

| Number | Differences | | | | Correlation | |
|---|---|---|---|---|---|---|
| | Mean | | Std. Deviation | Sig. difference | Correlation coefficient | Significance |
| 204 | target | 0.870 | 0.903 | 0.322 | 0.287 | 0.00 |
| | output | 0.799 | 0.727 | | | |

While in the case of Makedonomahon the sample size was rather large, and it was thus possible to use 20% of the samples for external testing of the model performance, for other case study sites, where the sample sizes were relatively small, it would be more efficient to use all the samples for model training. Therefore, in the following modeling process, no evaluation set was used.

## 6.2 Qnet models for the sound level evaluations

ANN model of predicting the subjective evaluations of sound level is considered as one sub-model in the whole soundscape modelling system as can be seen in Fig.3.11. Therefore, in this section, using Qnet, three kinds of models for the sound level evaluations are gradually developed, which are general, individual and group models. The input variables for all of these models are derived from physical explicit and social implicit factors as stated in Chapter 3.

### 6.2.1 General models

A general model was firstly explored using the data from all of the 19 case study sites. This model represented a universal situation of urban open spaces. According to the significance levels analysed by combining data from all of the case study sites into one dataset, 16 factors were chosen as input variables, which are physical factors: air-temperature, wind speed, relative humidity and SPL; behavioural factors: whether reading/writing, whether watching somewhere, movement status and grouping; social/demographical factors: age, category, education, residential status and sound level experience at home; and psychological factors: view assessment, and the brightness and overall physical evaluations. A number of models using different hidden layers and nodes were constructed. None of the models, however, converged, suggesting that a general model including all kinds of urban open space is not feasible.

Although the general model developed above failed, efforts were also made for other general models, which explore using the common significant factors for all the 19 case study sites, where a factor was selected as an input variable if it has significant correlation with the sound level evaluations in at least four case study sites. For the five Chinese sites, the data were combined due to the relatively small sample sizes for each case study site. The network architecture for all of studied cases and their prediction results are shown in Table 6.3.

As shown in Table 6.3, the input variables for 14 case study sites are the same; however, for the model developed for all of the Chinese case study sites, the input variables are slightly different. The factors including whether interviewees were under the sun-shade, reasons for visiting the site and the subjects' site preference, are not used in the China model as they were not examined in the field studies in China. Although such differences exist, the models are still comparable as major inputs are the same. The output variable for all of the models is the subjective evaluations of sound level. Again, a number of networks were explored through optimising training and refining processes as described in Section 3.4. In Table 6.1, it can be seen that the correlation coefficient of test set for all of the models is rather varied, ranging from $r$=0.22 to $r$=0.66. This result suggests that such general models used for a universal situation are not feasible yet.

***Table 6.3*** *General models for the sound level evaluations*

| Site | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Input variables | Output variable | Hidden layer | Hidden node | Test sample size | Coefficient | | RMS error | |
| | | | | | | Training | Test | Training | Test |
| 1 | Phy1, 2, 3, 4, 5, 6, 7, 8<br>B3, 5, 6, 7<br>S1, 3, 4, 6<br>Psy1, 2, 3, 4, 6, 7 | Subjective evaluations of sound level | 1 | 3 | 38 | 0.58 | 0.29 | 0.09 | 0.127 |
| 2 | | | 1 | 3 | 40 | 0.63 | 0.22 | 0.114 | 0.140 |
| 3 | | | 1 | 5 | 44 | 0.82 | 0.61 | 0.09 | 0.126 |
| 4 | | | 1 | 4 | 65 | 0.68 | 0.35 | 0.120 | 0.164 |
| 5 | | | 1 | 8 | 76 | 0.68 | 0.46 | 0.114 | 0.144 |
| 6 | | | 1 | 4 | 97 | 0.57 | 0.44 | 0.170 | 0.191 |
| 7 | | | 1 | 4 | 50 | 0.61 | 0.40 | 0.135 | 0.173 |
| 8 | | | 1 | 6 | 52 | 0.76 | 0.66 | 0.102 | 0.147 |
| 9 | | | 2 | 5 | 74 | 0.49 | 0.30 | 0.122 | 0.126 |
| 10 | | | 2 | 6 | 86 | 0.52 | 0.28 | 0.123 | 0.144 |
| 11 | | | 1 | 3 | 25 | 0.86 | 0.55 | 0.08 | 0.146 |
| 12 | | | 1 | 2 | 23 | 0.73 | 0.53 | 0.102 | 0.125 |
| 13 | | | 1 | 2 | 25 | 0.64 | 0.22 | 0.103 | 0.141 |
| 14 | | | 1 | 2 | 25 | 0.79 | 0.47 | 0.103 | 0.157 |
| China | Phy2, 3, 4, 5, 6, 8<br>B3, 5, 7<br>S1, 3, 4, 6<br>Psy2, 3, 4, 6, 7 | | 1 | 5 | 60 | 0.70 | 0.53 | 0.09 | 0.118 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations*

### 6.2.2 Individual models

As general models developed for predicting a universal situation in urban open spaces failed to make a prediction of the sound level evaluations, models were then developed to the individual case study sites. Amongst the 19 case study sites, four were randomly selected for developing individual models, including site 2- the Kassel Florentiner Square, site 3- Athens Karaiskaki Square, site 13- Sheffield Barkers Pool, and site 14- Sheffield Peace Gardens. Table 6.4 shows the network architecture of these 4 models and their prediction results. The networks shown in Table 6.4 are the final optimal ones based on optimizing training processes. The input variables for each individual model are shown in Table 6.4. The output is the subjective evaluations of sound level. For all of the individual models, only 1 or 2 hidden layers were set and less than 7 hidden nodes were chosen, whilst around 10%of the samples were selected as test set for each model.

***Table 6.4** Models for the sound level evaluations based on individual sites*

| Site | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Input variables | Output variable | Hidden layer | Hidden node | Test sample size | Coefficient | | RMS error | |
| | | | | | | Training | Test | Training | Test |
| 2 | Phy3, 5, 8<br>B4, 6<br>Psy4 | Subjective evaluations of sound level | 2 | 6 | 40 | 0.41 | 0.31 | 0.131 | 0.130 |
| 3 | Phy1, 2, 3, 4, 5, 6, 8<br>B3<br>S3<br>Psy1, 3, 4, 5, 6 | | 1 | 7 | 50 | 0.76 | 0.68 | 0.096 | 0.129 |
| 13 | Phy8<br>S6<br>Psy2 | | 2 | 4 | 50 | 0.45 | 0.41 | 0.123 | 0.142 |
| 14 | Phy1, 2, 8<br>B2, 3, 7<br>S1, 3, 4, 6<br>Psy1 | | 2 | 7 | 50 | 0.72 | 0.61 | 0.109 | 0.138 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations*

The results in Table 6.4 show that the predictions of two individual models are successful, which are the Karaiski model and the Peace Gardens model, but the predictions of the others are not. It can be seen that for the Karaiskaki and Peace Gardens models, their predictions are rather good, with a correlation coefficient for test set over 0.6; for the Barkers Pool model, its prediction is also acceptable although the correlation coefficient for the test set is only 0.41. In contrast, for the Florentiner model, the prediction performance is weak, with *r* only 0.31 for the test set. The unsuccessful prediction might be caused by poor input data which were less related to the output. Hence a refined study with detail investigations is necessary. In terms of RMS error, it is found that all of these four individual models were terminated at a similar test error, which was around 0.12. This means that their trainings had reached an acceptable level. Comparing with the general models, more successful predictions were made by the individual models.

### 6.2.3 Group models

Although the individual models can make considerably better predictions than the general model, they are specifically developed for a certain urban open space and there is a lack of practicality. Therefore, efforts were also made to develop models for urban open spaces with similar characteristics. Based on the classification of the 19 case study sites, four kinds of urban open spaces were classified according to their locations/functions. These are city centres, residential areas, tourist spots, and the vicinity of railway stations. Corresponding to these four kinds of urban open spaces, four types of group models were established; namely models of city centres, models of residential areas, models of tourist spots, and models of railway stations. For each type of group model, samples of some case study sites were grouped according to their city/country/continent. For each model, the input variables were selected according to the significance levels of relevant factors in the case study sites in the group.

#### 6.2.3.1 Models for city centres

With regard to city centres, three models are developed. As shown in Table 3.1, seven case study sites are located in city centers. Six were paired, according to the same locations, in developing group models of city centres, which can possibly represent a typical urban open space in a certain area's city centres. In total, three models for city centres in Sheffield (a city of UK, which includes two case study sites, site13- Barkers Pool and site14- Peace Gardens), Greece (including site3- Karaiskaki, Athens and site6- Makedonomahon, Thessaloniki) and China (including site16- Xi Dan Square, Beijing and site18- Nanjing road Square, Shanghai) were developed. After optimizing training process, the network architecture and prediction results for the final optimal models are shown in Table 6.5.

The input variables were chosen based on the significance levels derived from the analyses of combined field studies data. The selected variables for all of the developed city centre models are shown in Table 6.5. Table 6.5 also shows the network architecture of each model. A simple network was established for the optimal models with only 1 or 2 hidden layers and several hidden nodes. In Table 6.3, it is also found that an acceptable prediction has been achieved for all of the models. The correlation coefficient of the test set for the Sheffield city centres model is 0.52, for the Greece city centres model is 0.48, and for the China city centres model is 0.45. The RMS error for all of these models is above 0.13, which is higher than the individual models.

***Table 6.5** Models for the sound level evaluations in terms of the city centres*

| Location | | Site | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Input variables | Output variable | Hidden layer | Hidden node | Test sample size | Coefficient | | RMS error | |
| | | | | | | | | Training | Test | Training | Test |
| City centres | Sheffield | 13<br>14- | Phy1, 2, 3, 4, 5, 6, 7, 8<br>B3, 4, 5, 6, 7<br>S1, 2, 3, 4, 5, 6<br>Psy1, 2 | Subjective evaluations of sound level | 2 | 10 | 110 | 0.58 | 0.52 | 0.145 | 0.164 |
| | Greece | 3<br>6 | Phy1, 2, 6, 7, 8<br>B7<br>S3<br>Psy1, 2 | | 1 | 3 | 80 | 0.60 | 0.48 | 0.121 | 0.130 |
| | China | 16<br>18 | Phy2, 3, 4, 6, 8<br>B2, 3, 4, 5<br>S4<br>Psy2 | | 1 | 4 | 60 | 0.58 | 0.45 | 0.101 | 0.130 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations*

### 6.2.3.2 Models for residential areas

For residential areas, two group models were developed based on the locations of case study sites. Amongst the 19 case study sites, five are located in residential areas, which can be grouped into two areas, one is the EU and the other is China. The model of the EU includes the case study sites, 5- Kritis of Thessaloniki, Greece, 8- Piazza Petazzi of Milan, Italy, and 9- Jardin de Perolles of Fribourg, Switzerland. The China model includes two case study sites, 15- Chang Chun Yuan Square of Beijing and 19- Xu Jia Hui Park of Shanghai, China.

Again, with the optimizing training process, the optimal networks were obtained. The network architecture of these two models and their prediction results are also shown in Table 6.6. It can be seen that the predictions of these two models are poor with a low correlation coefficient of the test set, which is 0.34 for the EU residential model, and 0.38 for the China residential model. For both models, the RMS error is rather high; it shows again that the prediction performance of these two models is not good. The poor performance might be caused by the large areas covered by the model predictions, as the input data are rather varied.

***Table 6.6** Models for the sound level evaluations in terms of the residential areas*

| Location | | Site | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Input variables | Output variable | Hidden layer | Hidden node | Test sample size | Coefficient | | RMS error | |
| | | | | | | | | Training | Test | Training | Test |
| Residential | EU | 5, 8, 9 | Phy1, 3, 4, 6, 7, 8<br>B3<br>S1, 3, 4, 5, 6<br>Psy1, 2 | Subjective evaluations of sound level | 1 | 5 | 180 | 0.42 | 0.34 | 0.138 | 0.146 |
| | China | 15, 19 | Phy4, 5, 8<br>B5<br>S6<br>Psy2, 3, 5, 7 | | 1 | 7 | 30 | 0.74 | 0.38 | 0.075 | 0.173 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations*

### 6.2.3.3 Models for tourist spots

The results from the previous group models show that a better prediction model is the one which is made using data from a relatively small area, such as a city, rather than a relatively large area, such as a number of cities across the EU. Hence, two models were developed for tourist spots in order to compare the prediction performance made by a model for a small area and a model for a large area. For the tourist spots, two models were then developed; one was based on the case study sites from one city, Cambridge, and the other was based on the case study sites both from the EU and China. In terms of the multiple training and refining, the optimal network for both models was obtained. The network architecture and their prediction performance are shown in Table 6.7.

*Table 6.7 Models for the sound level evaluations in terms of the tourist areas*

<table>
<tr><th colspan="2" rowspan="3">Location</th><th rowspan="3">Site</th><th colspan="5">Network architecture</th><th colspan="4">Results</th></tr>
<tr><th rowspan="2">Input variables</th><th rowspan="2">Output variable</th><th rowspan="2">Hidden layer</th><th rowspan="2">Hidden node</th><th rowspan="2">Test sample size</th><th colspan="2">Coefficient</th><th colspan="2">RMS error</th></tr>
<tr><th>Training</th><th>Test</th><th>Training</th><th>Test</th></tr>
<tr><td rowspan="2">Tourist</td><td>Cambridge</td><td>11<br>12</td><td>Phy3, 5, 7, 8<br>B2, 3, 4<br>S1, 3, 4, 5<br>Psy1</td><td rowspan="2">Subjective evaluations of sound level</td><td>1</td><td>7</td><td>90</td><td>0.73</td><td>0.60</td><td>0.111</td><td>0.126</td></tr>
<tr><td>EU + China</td><td>2<br>4<br>11<br>12<br>17</td><td>Phy2, 3, 5, 8<br>B2, 3, 4<br>S1, 3, 5<br>Psy2</td><td>1</td><td>9</td><td>208</td><td>0.49</td><td>0.31</td><td>0.135</td><td>0.150</td></tr>
</table>

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations*

In Table 6.7, the optimal models for tourist spots were found to be a simple network with 1 hidden layer and less than 10 hidden nodes. The inputs and output are shown in Table 6.7 as well. It is evident that predictions of the Cambridge model are much better than predictions of the EU + China model. For the Cambridge model, the correlation coefficient for the test set is 0.6, whereas it is only 0.31 for the EU + China model. Whistle the RMS error is 0.111 (training set) and 0.126 (test set) for the Cambridge model, and 0.135 (training set) and 0.150 (test set) for the EU + China model. These results suggest that the more specific the position of group models to be learned from, the better the models are at making predictions for a new urban open space.

#### 6.2.3.4 A model for railway stations

There are only two case study sites located in the vicinity of railway stations. They are site 1- Bahnhofsplatz of Kassel, Germany and site 10- Place de la Gare of Fribourg, Switzerland. Thus one group model was developed for the railway stations, using a combination of these two case study sites. The optimal network for this model is shown in Table 6.8, as well as its performance results.

***Table 6.8*** *Models for the sound level evaluations in terms of vicinity of railway stations*

| Location | Site | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Input variables | Output variable | Hidden layer | Hidden node | Test sample size | Coefficient | | RMS error | |
| | | | | | | | Training | Test | Training | Test |
| Railway | 1<br>10 | Phy4, 5, 8<br>B3, 4, 6, 7<br>S2, 4<br>Psy1, 2 | Subjective evaluations of sound level | 2 | 11 | 110 | 0.48 | 0.35 | 0.118 | 0.132 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations*

The optimal network for this model is slightly complex which has 2 hidden layers with 11 hidden nodes. Table 6.8 shows that poor predictions were made by this model. The correlation coefficient for the test set is only 0.35. The RMS error is 0.118 for the training set and 0.132 for the test set. This may be related to the variation of the physical conditions contained within the two case study sites used for model development. The Bahnhofsplatz Square is situated on a sloping area with a level of height difference of nine meters, whilst the Place de la Gare Square is sited on high ground which overlooks the old town (Yang, 2005).

#### 6.2.3.5 Summary and discussions

Overall, the above results on modeling the subjective evaluations of sound level in urban open spaces suggest that a general model for all of the case study sites is not feasible due to the complex physical and social variations in urban open spaces. Models based on individual case study sites perform well but their application range is limited. Group models for certain types of location/function, however, may be reliable and also practical. Nevertheless, the accuracy and reliability of a group model depend on a situation it is learned from, the more specific a situation the group model builds for, the better the predictions it makes.

## 6.3 Qnet models for the acoustic comfort evaluations

As detailed in Section 3.4.1, the ANN model for predicting the subjective evaluations of acoustic comfort is an overall model for the soundscape evaluations. Chapter 4 discussed that many factors may affect the subjective evaluations of acoustic comfort. Amongst them, the subjective evaluations of sound level and the evaluations of physical comfort to other environments are more significant, which need to be included in the models for the acoustic comfort evaluations. However, all of these subjective evaluations are not available to be known at the design stage, which is why sub-models were proposed for overall soundscape evaluations (namely acoustic comfort evaluations in this study). As all of these subjective evaluations have already been obtained in the social surveys, they could be directly used in building the prediction models of acoustic comfort evaluations for the existing situations in this study.

Like the models for the sound level evaluations, 3 kinds of models including general, individual and group models are developed step by step using Qnet in this section. The input variables selected for all of the models are based on the significance levels derived from Chapter 4.

### 6.3.1 General models

The models for predicting the acoustic comfort evaluations are made for seven case study sites as only these case study sites have examined the acoustic comfort evaluations. Two are located in Sheffield, UK, and five are situated in China.

According to input selections, two approaches were applied to build the general models for predicting the acoustic comfort evaluations. General model 1 combined all of the seven case study sites as one dataset. Factors were selected to be the input variables if they reached the significance level. However, in general model 2, factors were selected as the input variables if a significance level has been achieved in at least two case study sites. Several models were thus developed for the general model 2, one for each case study site except the sites in Shanghai, where a model was made combining all of the sites, due to their small sample size. In addition, in general model 2, a model combining all of the seven case study sites has also been made in comparing with other models established for the general model 2. The optimal networks for all of the models, through optimizing training processes, have then been obtained. The results are shown in Table 6.9.

For the general model 1, the optimal network has 2 hidden layers and 6 hidden nodes with 100 samples for the test set (approximately 10% of total amount). For the general model 2, as it contains many models, the optimal networks are varied in terms of different models. Generally speaking, there are 1 or 2 hidden layers with less than 7 hidden nodes in the optimal networks. The input variables for all of the models contained in the general model 2 are the physical factors: humidity and SPL; the behavioural factor: grouping; the social factor: sound level experience at home; and the psychological factors: view assessment, heat, brightness, overall physical and sound level evaluations.

In Table 6.9, it can be seen that an acceptable prediction has been achieved by the general model 1 as the correlation coefficient for the test set between outputs and targets is satisfactory with $r$=0.56. For the general model 2, the prediction performance of the models established based on the different studied cases is rather varied. Some predictions are successful, such as the model for site 13- Barkers Pool of Sheffield, UK, which has a correlation coefficient 0.63 for the test set. But, some are unsuccessful, such as the model for site 16- Xi Dan of Beijing, China, with a low correlation coefficient for the test set $r$=0.37. The result indicates that a general model with the same input variables for a universal situation is not reliable. In Table 6.7, it can also be seen that the RMS errors for all of the general models is around 0.1, which is acceptable although not entirely satisfactory.

***Table 6.9** Overall models for the acoustic comfort evaluations*

| | Site | Network architecture | | | | Results | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Input variables | Output variable | Hidden layer | Hidden node | Test pattern | Coefficient | | RMS | |
| | | | | | | | Train | Test | Train | Test |
| Model 1 | 13 | Phy3, 4, 5, 8 B4, 7 S1, 4, 5, 6 Psy2, 4,5,6,7, 8 | Subjective evaluations of acoustic comfort | 2 | 6 | 100 | 0.60 | 0.56 | 0.119 | 0.121 |
| | 14 | | | | | | | | | |
| | 15 | | | | | | | | | |
| | 16- | | | | | | | | | |
| | 17 | | | | | | | | | |
| | 18 | | | | | | | | | |
| | 19 | | | | | | | | | |
| Model 2 | 13 | Phy5, 8 B7 S6 Psy2, 3, 6,7, 8 | | 1 | 4 | 24 | 0.80 | 0.63 | 0.089 | 0.117 |
| | 14 | | | 1 | 3 | 25 | 0.76 | 0.58 | 0.010 | 0.125 |
| | 15 | | | 1 | 4 | 30 | 0.71 | 0.59 | 0.082 | 0.124 |
| | 16 | | | 2 | 5 | 27 | 0.64 | 0.37 | 0.107 | 0.109 |
| | Shanghai | | | 1 | 2 | 15 | 0.71 | 0.35 | 0.085 | 0.136 |
| | All 7 sites | | | 2 | 7 | 110 | 0.59 | 0.59 | 0.118 | 0.124 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations, Psy8-Sound level evaluations*

### 6.3.2 Individual models

Although the performance of the general models is acceptable, efforts have also been made for individual models based on individual case study sites in order to consistent with the models of sound level evaluations. In this section, two typical case study sites were chosen for developing individual models of predicting the acoustic comfort evaluations; one is site 14- Peace Gardens of Sheffield, UK, and the other is site 16- Xi Dan Square of Beijing, China.

The optimal networks of individual models were achieved through optimizing training process as described in Chapter 3. The networks and their prediction results are shown in Table 6.10. The network for the Peace Gardens model of acoustic comfort evaluation has 2 hidden layers and 7 hidden nodes, and the network for the Xi Dan model of acoustic comfort evaluation also has 2 hidden layer but with 5 hidden nodes. The results show that good predictions were made by both models, especially for the Peace Gardens model ($r$=0.79). Compared to the general models, the prediction performance of the individual models is generally better. The RMS errors for both models are acceptable although the values are not low, which is 0.07 (training) and 0.103 (test) for the Peace Gardens model, and 0.09 (training) and 0.122 (test) for the Xi Dan model.

***Table 6.10 Models for the acoustic comfort evaluations based on individual sites***

| Site | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Input variables | Output variable | Hidden layer | Hidden node | Test sample size | Coefficient | | RMS error | |
| | | | | | | Train | Test | Train | Test |
| 14 | Phy1, 2, 4, 5, 8<br>B7<br>S6<br>Psy2, 3, 4, 6, 7, 8 | Subjective evaluations of acoustic comfort | 2 | 7 | 30 | 0.90 | 0.79 | 0.07 | 0.103 |
| 16 | Phy3, 5<br>S3, 4<br>Psy2, 3, 6, 7, 8 | | 2 | 5 | 25 | 0.74 | 0.59 | 0.09 | 0.122 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations, Psy8-Sound level evaluations*

### 6.3.3 Group models

Using the similar procedure as building the group models of the sound level evaluations, two group models of the acoustic comfort evaluations have also been developed. The both models are for the city centres, one includes two case study sites in Sheffield, namely the Sheffield model, and the other contains two case study sites in China, called the China model. The optimal networks of these two models and their prediction results are shown in Table 6.11.

*Table 6.11 Models for the acoustic comfort evaluations in terms of locations/functions*

| Location | | Site | Network architecture: Input variables | Output variable | Hidden layer | Hidden node | Test sample size | Results: Coefficient Train | Coefficient Test | RMS error Train | RMS error Test |
|---|---|---|---|---|---|---|---|---|---|---|---|
| City Centre | Sheffield | 13, 14 | Phy1, 2, 5, 8<br>B7<br>S6<br>Psy2, 3, 5 6, 7, 8 | Subjective evaluations of acoustic comfort | 2 | 7 | 50 | 0.74 | 0.68 | 0.104 | 0.105 |
| City Centre | China | 16, 18 | Phy8<br>B4<br>S3, 4<br>Psy2, 3, 4, 6, 7, 8 | Subjective evaluations of acoustic comfort | 2 | 5 | 30 | 0.66 | 0.59 | 0.102 | 0.122 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations, Psy8-Sound level evaluations*

In Table 6.11, it can be seen that the optimal network for the Sheffield model is the one which has 2 hidden layers with 7 hidden nodes. The optimal one for the China has 2 hidden layers with 5 hidden nodes. Both optimal networks were obtained again based on optimizing training process described in Section 3.4. The prediction performance of these two group models is rather good. They are better than the general models but slightly worse than the individual ones. In spite of the Chinese individual model making similar predictions as the Chinese group model, the former produced better predictions for the soundscape evaluations compared to the latter.

### 6.3.4 Summary and discussions

Similar to the models developed for the sound level evaluations, three kinds of models, namely general, individual and group, were developed for the acoustic comfort evaluations in this section. It is found that individual models made the best predictions, whereas the general ones made the worst. The group models are rather successful, whose prediction performance is just slightly worse than the individuals'. It is also found that the prediction performance of the acoustic comfort models is considerably better than that of the sound level evaluation models. This might be mainly caused by the role of influencing factors. Based on the analyses of Chapter 4, it is well known that some psychological factors are closely related to the acoustic comfort evaluations, whereas on the other hand, none factors except SPL has that strong relation with the sound level evaluations.

## 6.4 NeuroSolutions models for the sound level evaluations

In addition to Qnet models, ANN models using NeuroSolutions were developed to predict the sound level evaluations. They were also established at three levels, where a general model was firstly tried, followed by an individual model, and then a group model was developed. Finally, based on the same case study sites, a comparison between the NeuroSolutions models and the Qnet models is made.

In order to compare the NeuroSolutions models with the Qnet models, the input variables used to the former were also used to the latter for the same studied cases. The network developed by NeuroSolutions may differ from that developed by Qnet due to their different architecture constructions. Despite of this difference, their prediction results can still be compared because of the use of the same inputs and output.

### 6.4.1 A general model

Using NeuroSolutions, a combining dataset for 19 case study sites were used to develop a general model, which is similar to the Qnet general model 1. The same input variables as the Qnet model were chosen based on the significance levels for the combining dataset. They are physical factors, air-temperature, wind speed, relative humidity and SPL; behavioural factors, whether reading/writing, whether watching somewhere, movement status and grouping; social/demographical factors, age, category, education, residential status and sound level experience at home; and psychological factors, view assessment, and the brightness and overall physical evaluations. After reducing missing and noise data, the efficient samples are 9051 which can be used for model developing. Unlike the Qnet model, 20% of these data, named cross validation (CV) set, has to be used for testing the training as discussed in Section 3.4.

The optimal network was obtained based on the optimising training and refining process. The network architecture and its prediction results are shown in Table 6.12. It can be seen that for the well-built NeuroSolutions general model, it has a network of 3 hidden layers with 62 hidden processing elements (PEs). A poor prediction performance was found for this model as its correlation coefficient between the outputs and the targets is only 0.20 for the training set and 0.13 for the CV set. The MSE is 0.03 for the training set and 0.04 for the CV set. Prior to the Qnet general model 1, the NeuroSolutions general model has converged but its predictions are considerably poor.

*Table 6.12 NeuroSolutions models for predicting the sound level evaluations*

| Model | Network architecture | | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Input variables | Output variables | Hidden layer | Hidden PEs | CV sample | Coefficient | | MSE | |
| | | | | | | Train | CV. | Train | CV. |
| General | Phy3, 4, 5, 8<br>B2, 3, 4, 7<br>S1, 3, 4, 5, 6<br>Psy2, 6, 7 | Subjective evaluations of sound level | 3 | 62 | 1810 | 0.20 | 0.13 | 0.03 | 0.04 |
| 3-Karaiskaki | Phy1, 2, 3, 4, 5, 6, 8<br>B3<br>S3<br>Psy1, 3, 4, 5, 6 | | 1 | 7 | 103 | 0.50 | 0.24 | 0.03 | 0.04 |
| Cambridge | Phy3, 5, 7, 8<br>B2, 3, 4<br>S1, 3, 4, 5<br>Psy1 | | 1 | 7 | 176 | 0.43 | 0.35 | 0.03 | 0.03 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations*

### 6.4.2 An individual model

Using NeuroSolutions, an individual model for the sound level evaluations was developed for site 3- Karaiskaki, Athens, Greece, because the prediction performance of the Karaiskaki model by Qnet is the best amongst all of the developed individual models.

Table 6.12 also shows the optimal network of the Karaiskaki model and its prediction results. It can be seen that 1 hidden layer with 7 hidden PEs were set for the optimal one. A rather poor prediction performance was found for this model as the correlation coefficient for the CV set is only 0.24. Nevertheless it has a poor prediction performance, this model is better than the general model developed in Section 6.4.1.

It is interesting to note that the Karaiskaki model by NeuroSolutions performed much worse than the Karaiskaki model by Qnet, where the correlation coefficient of the CV set for the former is 0.24 and that of the test set for the latter is 0.68. This might be caused by a poor training of the NeuroSolutions model because its correlation coefficient for the training set is only 0.50, whereas for the Qnet model this is 0.76 as shown in Table 6.2. This may be due to NeuroSolutions needing more training samples than Qnet. Also, the samples used for the NeuroSolutions training are smaller than Qnet, as 20% of the samples have to be used internally to monitor the training process in NeuroSolutions, whereas only 10% of the samples are needed in Qnet.

### 6.4.3 A model for tourist spots

With NeuroSolutions, a group model was also developed for the two tourist sites in Cambridge, because the model for those two sites using Qnet showed a good prediction performance. Similar to the development of previous NeuroSolutions models, the input variables for this model are the same as the Cambridge model by Qnet. An optimal network in the Cambridge NeuroSolutions model has also been obtained by optimising the network with a large number of possible networks structures, resulting in good prediction results.

It can be seen that the optimal network has 1 hidden layer with 7 hidden PEs. The prediction performance of this model was rather poor, where a correlation coefficient of 0.35 has been found for the CV set. However, comparing to the Karaiskaki model, the prediction performance of Cambridge model is better. Nevertheless, the predictions made by the NeuroSolutions model for Cambridge are inferior to those made by the Qnet model for Cambridge, as can be seen in Table 6.5. A possible reason for this may be similar as that for the Karaiskaki model, which is limited by the sample size.

### 6.4.4 Summary and discussions

Using NeuroSolutions, three models were developed in this section; (1) general model, (2) individual model for Karaiskaki, and, (3) group model, for Cambridge. Overall, the predictions of all three models were not successful, although the Cambridge model made the best predictions and the general model made the worst. It is interesting to find that whilst the NeuroSolutions model for Cambridge is better than the NeuroSolutions model for Karaiskaki, the opposite situation is seen for the Qnet models. The reason for this might be related to strict requirement of samples size by NeuroSolutions when coping with a complex network, such as the network made for the Cambridge model and the Karaiskaki model because many input variables were included. Besides, NeuroSolutions needs 20% of overall samples to monitor a training process, whereas Qnet just needs 10%, which means that more samples can be used for training in Qnet.

On the contrary, it is found that NeuroSolutions has a stronger capability to deal with a larger amount of data than Qnet does, as it was able to reach a convergence for all of the combined data from the 19 case study sites, whereas it was not for Qnet. Another advantage of NeuroSolutions over Qnet is that it can translate a nominal variable into several inputs corresponding to the categories which the variable has. NeuroSolutions are therefore, mainly used to develop the sound preference models in Chapter 7, as in Chapter 5, few factors have been found closely related with the sound preference evaluations.

## 6.5 Ordinal logistic regression (OLR) models

In order to compare ANN models with conventional statistical models, ordinal logistic regression (OLR) were introduced and employed. The ordinal logistic regression (OLR) is nonlinear statistical modelling technique. It is processed with logistic functions to yield a probability of a single output (Fahrmeir & Tutz, 1994). The OLR programme used the maximum likelihood method to derive coefficients. The programme is written by Dr. Harrison in the University of Sheffield. Based on a typical case study site, 14 - Peace Gardens of Sheffield, UK, one model was developed for the sound level evaluations, and another was built for the acoustic comfort evaluations. Subsequently, a comparison between the OLR models and Qnet models was made.

### 6.5.1 OLR models for the sound level evaluations

Using the same inputs as the Qnet model, the OLR model for the sound level evaluations of the Peace Gardens was established. The input variables are the physical factors, season, time of day and SPL; the behavioural factors, whether reading/writing, whether watching somewhere and grouping; the social/demographical factors, age, category, education and sound level experience at home; and the psychological factor, the site preference, which has also been shown in Table 6.4. The prediction results of this OLR model are shown in Table 6.13. The columns of the table present the prediction outputs from the OLR model; the rows illustrate the true targets.

***Table 6.13** The prediction result of the Peace Gardens' OLR model for sound level evaluations*

| | PREDICTION | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Very quiet | Quiet | Neutral | Noisy | Very noisy | Total | Percentage (%) |
| TURE | Very quiet | **0** | 1 | 2 | 4 | 0 | 7 | 0 |
| | Quiet | 0 | **27** | 47 | 13 | 0 | 87 | 31 |
| | Neutral | 0 | 11 | **87** | 60 | 0 | 158 | 55 |
| | Noisy | 0 | 4 | 55 | **139** | 10 | 208 | 67 |
| | Very noisy | 0 | 0 | 0 | 32 | **15** | 47 | 32 |
| | Total | 0 | 43 | 191 | 248 | 25 | 507 | 53 |

Five outputs were obtained corresponding to the five evaluation scales. The average prediction accuracy was 53% for this OLR model. While such accuracy levels are acceptable, with ANN models better predictions were obtained, with a test correlation coefficient of 0.61 for the sound level evaluation and 0.79 for the acoustic comfort evaluation, as can be seen in Table 6.4.

### 6.5.2 OLR models for the acoustic comfort evaluations

For the acoustic comfort evaluations of the Peace Gardens, the input variables for the OLR model are also the same as the Qnet model, which are the physical factors, season, time of day, wind speed, relative humidity and SPL; the behavioural factor, grouping; the social factor, sound level experience at home; and the psychological factors, view assessment, and the evaluations of heat, brightness, overall physical comfort.

The prediction results of the OLR model are shown in Table 6.14. It can be seen that successful predictions were made by this model. Its average accuracy of predictions is 61%, which is higher than the OLR model for the sound level evaluations. Comparing the Qnet model developed for the acoustic comfort evaluations of the Peace Gardens, however, a better prediction was obtained by the Qnet model, as shown in the Table 6.10, where the correlation coefficient for the test set is 0.79.

*Table 6.14 The prediction result of the Peace Gardens' OLR model for acoustic comfort evaluations*

| | | PREDICTION | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Very Un-com. | Un-com. | Neutral | Com. | Very Com. | Total | Percentage (%) |
| TURE | Very Un-com. | **0** | 1 | 0 | 2 | 0 | 3 | 0 |
| | Un-com. | 0 | **10** | 14 | 12 | 0 | 36 | 28 |
| | Neutral | 0 | 8 | **27** | 28 | 0 | 63 | 43 |
| | Com. | 0 | 10 | 6 | **114** | 0 | 130 | 88 |
| | Very Com. | 0 | 1 | 1 | 15 | **2** | 19 | 11 |
| | Total | 0 | 30 | 48 | 171 | 2 | 251 | 61 |

### 6.5.3 Summary and discussions

In this section, OLR models were built for predicting the subjective evaluations of sound level as well as acoustic comfort, using the data derived from the case study of the Peace Gardens, Sheffield, UK. The prediction performance of both OLR models is generally acceptable. Comparing with the Qnet models developed for the same studied case, it is found that the prediction performance of OLR models is worse, which indicates that ANN has more power in coping with the problems of predicting the subjective evaluations of soundscape. A main reason is that ANN has the capability to learn the different relationships between various data, whereas OLR is rather limited within the ordinal data, which is not the case for some of the data in this study. Another advantage of ANN over OLR may be found in its flexible learning structure which is made by a multilayer network trained with back propagation error, which cannot be reached by a conventional statistical model. A similar result has also been obtained by a comparison study of logistic regression and ANNs in the medical area (Kennedy, Harrison & Marshall, 1994).

## 6.6 Maps of the sound level/acoustic comfort evaluations

There is no doubt that ANN can predict the subjective evaluations of soundscape in urban open spaces based on the models developed in previous sections. The direct results from ANN models, however, are difficult for urban planners/designers to use. Accordingly, a mapping method is proposed in order to visually present the predictions of soundscape evaluations made by ANN models, which may be more "user friendly" at the planning/designing stage. Therefore, following the models established above, soundscape quality mapping techniques were developed for the sound level evaluations as well as for the acoustic comfort evaluations.

While it is evident that a universal ANN model for all kinds of urban open space is not appropriate/feasible and models based on the data of individual case study sites are too specific, it is proposed that urban open spaces should be classified into certain types, taking into account the functions and locations of the urban open spaces, and for each type an ANN model for soundscape quality mapping can be developed and applied in practice. In this section, however, for the sake of convenience, the ANN models based on site-14, Peace Gardens in Sheffield is used below as an example to demonstrate the mapping technique, although the model actually should be used to produce soundscape quality maps for other urban open spaces with similar locations/functions as the case study site used in developing the model.

Four sets of maps are produced for the following social factors: age (younger, 13-18 years VS older, >65 years) (for the sound level and the acoustic comfort evaluations), education (lower, secondary education vs. higher, high education level) (for the sound level evaluations), sound level experience at home (quieter vs. noisier) (for the acoustic comfort evaluations).

### 6.6.1 Maps for the age groups

The well-performed Peace Gardens model for the sound level evaluations was recalled in Qnet without supervision. With the same inputs of other variables and new inputs of age, the predictions of sound level evaluations were made by the recall model. Using the outputs of the recalled model, two maps were drawn presenting the two potential age groups' evaluations of sound level as shown in Fig. 6.1 (a) & (b). Following the same procedure, two maps presenting the acoustic comfort evaluations were made as shown in Fig. 6.1 (c) & (d).The SPL value marked on each grid area was obtained using software Cadna (Data Kustik, 2006) in another project (Wang, Kang, & Zhou, 2007). The maps are coloured according to the degree of the sound level/acoustic comfort evaluations with regard to two age groups in terms of various SPL in the site.

With the colour from purple to red, the subjective evaluation is from very quiet (for sound level)/very uncomfortable (for acoustic comfort) to very noisy/very comfortable.

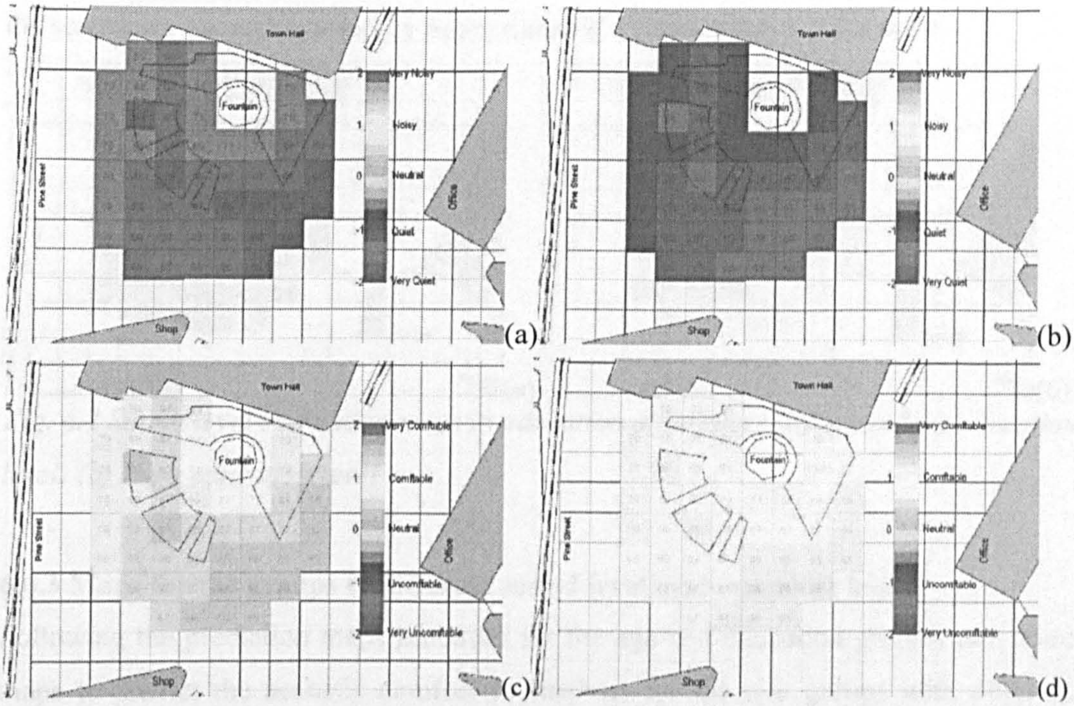



***Fig. 6.1** Sound level/acoustic comfort evaluation maps for age difference: (a) 13-18 yrs for sound level evaluations; (b) >65 yrs for sound level evaluations; (c) 13-18 yrs for acoustic comfort evaluations; (d) >65 yrs for acoustic comfort evaluations.*

In Fig. 6.1 (a) & (b), it can be seen that the age group 13-18 will generally feel quieter than the >65 age group, whereas in terms of acoustic comfort, the difference between the two age groups becomes much less, as shown in Fig.6.1 (c) & (d). Observing the evaluations around the fountain area, it is also interesting to note that the age group 13-18 would feel slightly quieter with a higher water sound level.

### 6.6.2 Maps for the education groups

Besides age, prediction maps have also been made to two education groups, one is the group of the people having a secondary education level, and the other is the group of the people having a higher education level than a high school. Using the same drawing approach as mentioned in Section 6.6.1, the prediction maps for the education group were produced and illustrated in the Fig. 6.2 (a) & (b). Fig. 6.2 (a) presents the predictions of the sound level evaluations by the group of secondary education level, and Fig. 6.2 (b) shows the predictions by the group of the high education level. The result suggests that people at the high education level would feel noisier than people at the secondary education level, by approximately 1 point at the 5-point scale.

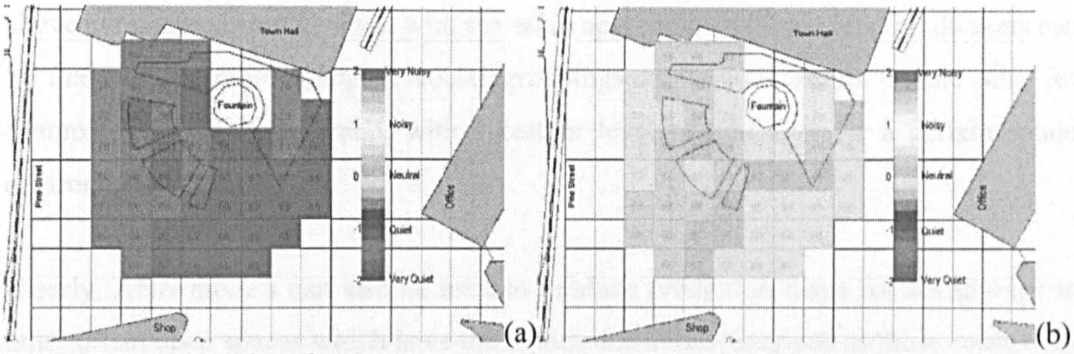



*Fig. 6.2 Sound level evaluation maps in education differences (a) Secondary education level; (b) High education level*

### 6.6.3 Maps for the groups of different sound level evaluations at home

Following the prediction maps produced for the age and education groups, two more maps to predict the acoustic comfort evaluations for the two groups with different sound level experience at home are created and shown in Fig 6.3 (a) & (b). Fig. 6.3 (a) illustrates a map for predicting the acoustic comfort evaluations for the people from noisy places. Fig. 6.3 (b) shows the predictions for the acoustic comfort evaluations for the people from quiet places. The differences can be seen in the figure between the two groups, which have been discussed in Section 4.2.4.

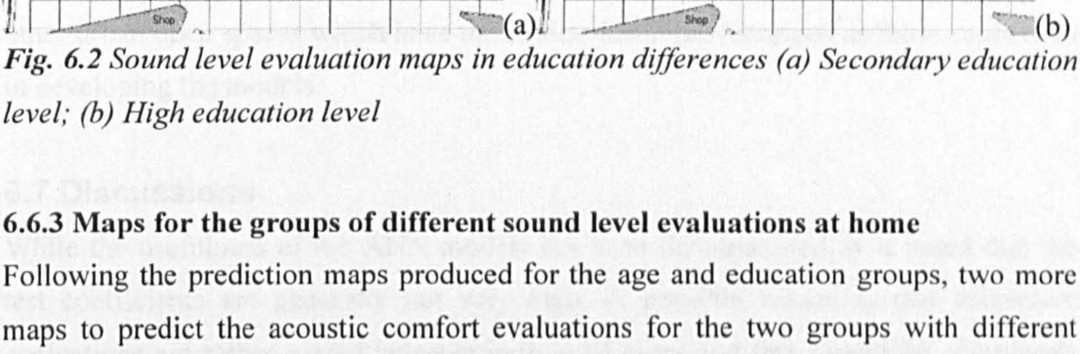



*Fig. 6.3 Acoustic comfort evaluation map for different sound level experience (a) People from noisier home; (b) People from quieter home*

### 6.6.4 Summary and discussions

The above maps are some examples to show how the prediction maps derived from

ANN models could present the potential users' evaluations of soundscape in a certain urban open space no matter whether it was built. These maps have only been made for one varied variable with the same other variables. However, it is noted that whilst the above comparisons are generic, with the same approach, ANN models' predictions can be mapped for more complex social groupings, at various zones on the site, for example, a certain age group, with a certain level of education or a certain sound environment at home.

Clearly, ANN models can also be used to produce prediction maps for soundscape to other urban open spaces which have the similar locations/functions as those cases used in developing the models.

## 6.7 Discussions

While the usefulness of the ANN models has been demonstrated, it is noted that the test coefficients are generally not very high. A possible reason is that subjective evaluations are rather varied between individual users and this cannot be completely represented by computer models. In addition, the environments of the field studies in this research have not been controlled to meet research purpose. Further improvements could be made if controlled field studies can be carried out. Nevertheless there is no ideal environment for field studies, laboratory experiments have to be employed to provide complementary information for building ANN models.

Furthermore, some inputs, such as the subjective evaluations of various physical conditions, e. g. sound level, thermal, lighting, cannot be gained at a design stage because either these physical conditions or the social users do not really exist. Therefore, the prediction outputs of the sub-models are important in providing the inputs for models of overall soundscape evaluations at the design stage. In this study, as examples, the models of the overall soundscape evaluations, acoustic comfort evaluations, are developed for the existing urban open spaces used in the case study sites rather than from virtual urban open spaces developed at the design stage. Hence, all of the inputs used in building the acoustic comfort models, overall soundscape models, are from the real evaluations obtained in the field surveys instead of the sub-models' predictions. However, improvements could be made by establishing a number of sub-models, including the evaluation of sound level (background sound), sound preference (noticed sounds, foreground sounds or soundmarks) and the evaluation of other physical factors, such as satisfaction of thermal, lighting, view and overall physical environment. For this further carefully designed field studies would be useful (Yu & Kang, 2009b).

## 6.8 Conclusions

Using the data from the 19 case study sites, ANN models for predicting the subjective evaluations of sound level and acoustic comfort were gradually developed in this chapter. In Section 6.1 and 6.2, using Qnet programme, models were developed at three levels from a general situation to a typical condition. They are referred to as general model, individual model and group models respectively. It has been found that for both sound level and acoustic comfort evaluations, general models are less feasible that the other models for all the case study sites due to the complex physical and social environments in urban open spaces. The models based on individual case study sites performed well, but their application is limited, whereas the models based on certain types of locations/functions appeared to be more reliable and practical. It has also been found that the acoustic comfort models are more successful than the sound level models, primarily due to the relative importance of various influencing factors on the acoustic comfort evaluations.

In order to validate the model's accuracy, an example was made for the sound level evaluation model of Makedonomahon in Section 6.3. A well trained model was recalled and its prediction outputs compared with the real targets. The result showed that no significant difference existed between the modelling outputs and the real targets. Moreover, the correlation coefficient of the outputs and targets is acceptable high, suggesting that the model's predictions are close to the real on-site evaluations.

NeuroSolutions was also employed in developing ANN models for predicting the sound level evaluations. In Section 6.4, three NeuroSolutions models were established: the general model, the individual model for Karaiskaki, and the group model for

Cambridge. Overall, the general model made the worst prediction and the group Cambridge model made the best. In terms of NeuroSolutions, it is also found that the general model is unfeasible in making a universal prediction. Using NeuroSolutions, the individual Karaiskaki model made a poorer prediction than the group Cambridge model did, which is different from the Qnet models. This may be due to the different model constructions used by NeuroSolutions and Qnet. NeuroSolutions is more sensitive to the sample size for training than Qnet, as NeuroSolutions uses more data in the training process for a complex network than Qnet. Also, Qnet just needs 10% of the data for internally guiding a training process whereas NeuroSolutions needs 20% of the data.

A further comparison with conventional non-linear statistical models was made in this chapter as well. Ordinal logistic regression (OLR) models were developed in Section 6.5 in order to compare with the ANN models built by Qnet. The OLR models were established for predicting the subjective evaluations of sound level as well as acoustic comfort to the case study site 14- Peace Gardens in Sheffield, UK. The result showed that the predictions of the OLR models were acceptable although when compared to the Qnet models, their prediction performance was relatively worse.

In Section 6.6, based on the well-trained models developed by Qnet to a typical case study site 14- the Peace Gardens, Sheffield, UK, several prediction maps were drawn to present the subjective evaluations of sound level/acoustic comfort for potential users. The study introduces some models to demonstrate how the prediction maps work for urban open spaces' planning/designing. Based on the success of these maps, further work may wish to explore soundscape evaluations in more complex social groupings at various zones on the site. In the meanwhile, the predictions of ANN models could also be expected to be integrated into GIS system, which may greatly benefit the urban development in achieving social well-beings.

Chapter 7

# ANN Models for the Sound Preference Evaluations

Followed by the development of ANN models for predicting the sound level and acoustic comfort evaluations in Chapter 6, Chapter 7 explores the possibility of using ANN to predict the sound preference evaluations. NeuroSolutions models are mainly developed in this chapter, whilst a comparison with the Qnet models is also made.

The sound preference models are also sub-models in the modelling framework for predicting the evaluations of soundscape (see Fig. 3.11). It is more sophisticated than the sound-level or the acoustic comfort models since various sound sources exist. Based on the findings in Chapter 5, it has been known that the subjective evaluations of sound preference vary significantly according to 3 sound types, natural, human and mechanical. In this chapter, therefore, ANN models are made for three sounds, birdsong, children shouting, and cars passing, which stand for the above three sound types respectively.

In relation to predicting the subjective evaluation of the above three sounds, four types of NeuroSolutions models were developed. For each kind of model, several models have been explored. The first type of model was developed for predicting the combined evaluations of all of the three sounds. In sequent, two models were investigated, one was based on the laboratory experiments and the other was based on the 19 field studies and the laboratory experiments. The second kind of model was made for predicting the subjective evaluations of birdsong at four levels, namely general, individual, group, and lab. The third kind of model was developed for the predictions of children shouting also at four levels. Following the development of modelling the subjective evaluations of birdsong and children shouting, the fourth kind of model was studied for the sound of cars passing, again at four levels.

In order to compare with the NeuroSolutions models, Qnet models are also made in this chapter for predicting the subjective evaluations of birdsong. Finally, a mapping method is proposed and examined in order to feasibly aid urban planners/designers with regard to the sound preference; and a summary of the whole chapter is also drawn.

## 7.1 Modelling the subjective evaluations for multiple single sounds

In this section, two models are developed for predicting the combined subjective evaluations of three sounds: birdsong, children shouting and cars passing. One model is made using the samples obtained from Part II of the laboratory experiments, which is called the Lab model; the other is made with the data collected from a typical case study site, 9- Jardin de Perolles in Frobourg, Switzerland, as all the three sounds were examined. It is named the JdP model. These two models differ in the output from others which are developed later in this chapter.

### 7.1.1 Data issues

For the Lab model, based on the analyses in Chapter 5, factors relevant to the sound preference evaluation have been chosen as input variables. They are age, gender, loudness, sharpness, and the sound category. Average loudness and sharpness calculated for the birdsong, children shouting and sound of cars passing obtained in Part II of the laboratory experiment are used in model constructions. As mentioned in Chapter 3, the basic neuron in NeuroSolutions network is called perceptron elements (PEs). The totals PEs in the input layer of this model are eight, as gender was translated into two and the sound category into three. The outputs are the subjective evaluations of multiple single sounds, which are birdsong, children shouting and sound of cars passing. The total outputs are four in terms of four evaluation attributes, namely preference, noisiness, comfort, and pleasantness, as examined in Part II of the laboratory experiments. As one participant responded to three sounds, the responses from 56 participants were 148. After reducing the missing and noise data, the total efficient samples for the Lab model became 143.

For the JdP model, the input variables are age, occupation, education, and the sound category, also selected based on the significant levels examined in Chapter 5. In this model, unlike the Lab model, loudness and sharpness are excluded as they were not available in the social surveys. Similar to the Lab model, the sound categories are extended into three inputs; and the total PEs are therefore six in the input layer of the JdP model. Differing from the Lab model, however, the output for the JdP model is only one, which is the subjective preference evaluation of all three sounds. Again, as one subject responded to three sounds, correspondingly, the total samples for the JdP model were 2260 after reducing the missing and noise data.

### 7.1.2 Network construction

Following the same optimizing procedure of network selections as mentioned in Chapter 3, the optimal networks for the Lab and JdP models are obtained and shown in Table 7.1. It can be seen that two hide layers are made for both models. For the Lab model, 4 hide PEs are set for each hide layer, whereas for the JdP model, 9 hide PEs are set for the hide layer 1 and 5 for the hide layer 2. As in NeuroSolutions, usually 20% of the overall samples have to be used internally testing ANN models. Hence, the CV sets for these 2 models are 28 for the Lab and 452 for the JdP.

*Table 7.1 The universal models for predicting the sound preference evaluations*

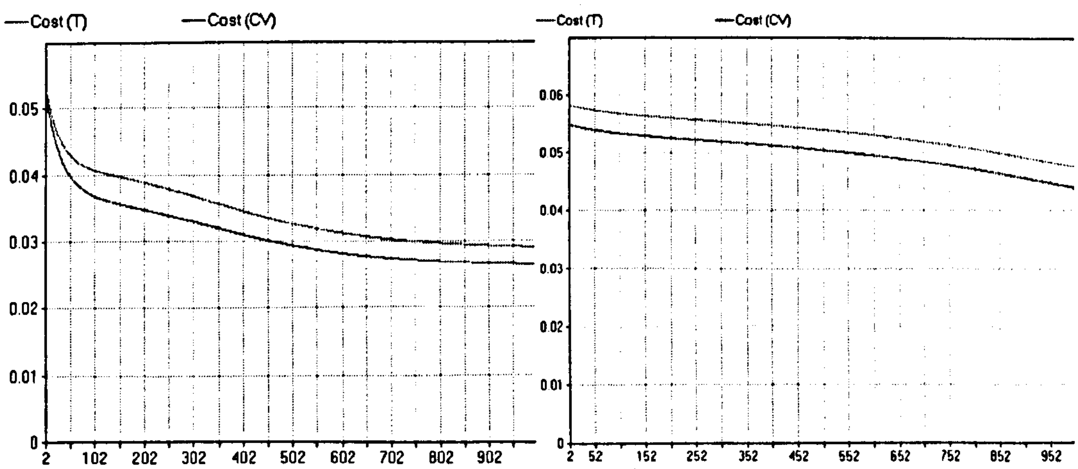
| Model | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Input variables | Output variables | Hide layer | Hide PEs | CV sample | Coefficient | | MSE | |
| | | | | | | Train | CV. | Train | CV. |
| Lab | S1, 2, Loudness, sharpness The sound category | Preference, noisiness, comfort, pleasantness evaluation | 2 | 4; 4 | 28 | 0.53 | 0.52 | 0.08 | 0.05 |
| Site 9-JdP | S1, 3, 4 The sound category | Preference evaluation | 2 | 9; 5 | 904 | 0.71 | 0.67 | 0.06 | 0.06 |

*S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations*

### 7.1.3 Model performance

The results of correlation coefficient and MSE for the Lab and JdP models are also shown in the Table 7.1. It can be seen that for both models, an acceptable prediction has been achieved. The correlation coefficient between the network outputs and the desired targets for the Lab model is 0.53 (training set) and 0.52 for (CV set), whilst for the JdP model, it is 0.71 (training set) and 0.69 (CV set). In terms of MSE for both models, it is 0.08 (training set) and 0.05 (CV set) for the Lab model, and 0.06 for both of training and CV set for the JdP model. These results indicate that more accurate prediction has been achieved by the JdP model. This could be due to two reasons: one is that the number of samples used for constructing the Lab model is much less than those used for constructing the JdP model, and the other is that more output variables are included in the Lab model.

The learning curves for the Lab and the JdP model are illustrated in Fig. 7.1 (a) and (b). A good convergence has been obtained by both models. The result shows that the CV curve decreased with the training curve and both reached their minimum error at around 1000 epochs.




(a) (b)

*Fig. 7.1 MSE DataGraph (a) the Lab model; (b) the JdP model*

## 7.2 Modelling the subjective evaluations for birdsong

In terms of predicting the subjective evaluations of birdsong, four kinds of models are developed in this section, namely general, individual, group, and lab model. A general model is made based on the data combining all of the case study sites where a preference of birdsong was questioned. An individual model is developed also for the case study site 9- Jardin de Perolles, Frobourg, Switzerland, so that a comparison could be made with the JdP model which was developed in Section 7.1, two group models are constructed for the case study sites of the EU and China respectively where the birdsong was evaluated. Furthermore, a lab model is also made based on Part II of the laboratory experiments, in which the subjective evaluations of birdsong have been examined through presenting an audio record.

### 7.2.1 A general model

A general model is developed in terms of a general circumstance covering various situations. Samples collected from all of the case study sites as well as the laboratory experiments, where the birdsong was evaluated, are used to develop a general model. The included studied cases were obtained from nine sites (site 9, 11, 13-19) and Part I experiments. In total, 2448 samples were used in constructing a general model.

Based on the statistical analyses in Chapter 5, the selected variables for the inputs are age, gender, occupation, and education. The output is the subjective preference evaluation of birdsong, which is also the output for the individual and group models. The total PEs are five in the input layer as gender has been translated into two. The final optimal network is obtained after the same optimizing training process as mentioned in Section 3.4. The network and its prediction results are shown in Table 7.2. It can be seen that the network includes 2 hide layers with 12 hide PEs in the layer 1, and 8 in the layer 2. The samples for CV are 489, approximately 20% of the overall samples.

In Table 7.2, a poor prediction performance has been found for the general model of birdsong. The correlation coefficient between the outputs and the targets is rather low which is less than 0.20 either for the training or for the CV set. The MSE is 0.04 for both the training and CV set. The results indicate that the general model of birdsong is not successful as its prediction performance is unacceptable. Comparing this model with above two models, it is found that the former is much worse. A possible reason for this is that the distribution of the target for the birdsong evaluations is rather concentrated, mostly located around -1 as shown in Fig 7.2. A fine scale category, such as a 5- point scale, may be needed in improving the accuracy of modelling prediction.

***Table 7.2 Models for predicting the subjective evaluations of birdsong***

| | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Input variables | Output variables | Hide layer | Hide PEs | CV sample | Coefficient | | MSE | |
| | | | | | | Train | CV. | Train | CV. |
| General | S1, 2, 3, 4 | The preference evaluation of birdsong | 2 | 12; 8 | 489 | 0.18 | 0.11 | 0.04 | 0.04 |
| Site 9- Jardin de Perolles | S1, 3, 4 Phy2 | | 2 | 11; 5 | 146 | 0.34 | 0.23 | 0.03 | 0.03 |
| EU | S1, 2, 3, 4 | | 2 | 22; 11 | 331 | 0.27 | 0.23 | 0.03 | 0.04 |
| China | S1, 4 | | 2 | 17; 8 | 159 | 0.20 | 0.10 | 0.00 | 0.02 |
| Lab | S1, 2 Loudness, Sharpness | | 1 | 4; | 32 | 0.71 | 0.60 | 0.08 | 0.08 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations*

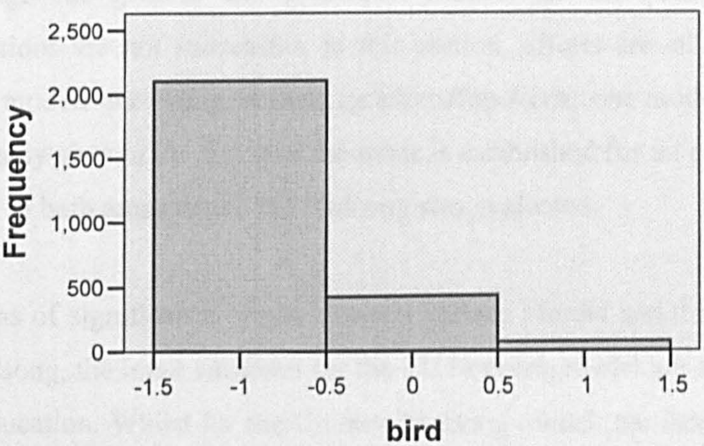



*Fig. 7.2 The distribution of subjective evaluations of birdsong*

### 7.2.2 An individual model

In comparison with the general model of birdsong, an individual model for birdsong is investigated in making a prediction for a specific location. In order to compare with the JdP model which was developed in Section 7.1, site 9- Jardin de Perolles is chosen to build an individual model of birdsong as well as of children shouting and the sound of cars passing.

In terms of significance level obtained in Chapter 5, the input variables for the individual model of birdsong are age, occupation, education and time of day. The total inputs are four as no nominal variable included. The efficient samples for the model construction are 732, and 146 are used for CV. The optimal network for the individual model of birdsong is also shown in Table 7.2 as well as its prediction results. It shows that the optimal network has 2 hide layers with 11 PEs in layer 1 and 5 PEs in layer 2.

The prediction performance of this individual model is not satisfactory, as it is shown in Table 7.2 that the correlation coefficient between the outputs and the targets is rather low although it is higher than that of the general birdsong model. It is also found that the MSR is 0.03 for both the training and CV set, indicating that this model was terminated at a lower minimum error than the general model of birdsong.

### 7.2.3 Group models

Although the general and individual models for the prediction of the birdsong evaluations are not successful, in this section, efforts are still made to develop two group models according to their locations/functions; one model is built for all of the case study sites in the EU, and the other is established for all of the case study sites in China, in both areas where the birdsong was evaluated.

In terms of significance levels between various factors and the subjective evaluations of birdsong, the input variables for the EU birdsong model are age, gender, occupation, and education. Whilst for the Chinese birdsong model, the input variables are age and education. The total inputs are five for the EU birdsong model as gender has been extended into two inputs, and the total inputs for the Chinese birdsong model are two. The efficient samples which could be used for building the EU birdsong model are 1659, and those of the Chinese birdsong model are 799. Meanwhile, approximately 20% of the samples are set for cross validation (CV) for both group models.

The optimal networks for these 2 models have been achieved by the same optimizing training process as the previous one did. The results are also shown in Table 7.2. It can be seen that the EU birdsong model has 2 hide layers with 22 hide PEs in the layer 1 and 11 in the layer 2, whilst the Chinese birdsong model also has 2 hide layers but with 17 hide PEs in the layer 1 and 8 in the layer2. In the Table 7.2, the prediction results of these two group models are shown as well. It is found that inaccurate predictions were made by both models, as a low correlation coefficient for the CV set is obtained, which is 0.27 (training set) and 0.23 (CV set) to the EU birdsong model, and 0.20 (training set) and 0.18 (CV set) to the Chinese birdsong model. The MSE of the EU birdsong model is 0.03 (training) and 0.04 (CV), and that of the Chinese birdsong model is 0.00 (training) and 0.02 (CV). The results show that a slightly better prediction has been made by the EU birdsong model compared to the general birdsong model, whereas the prediction performance of the Chinese birdsong model is the same as that of the general birdsong model.

### 7.2.4 A lab model

In addition to the general, individual, and group birdsong models, a lab model has also been developed for predicting the subjective evaluations of birdsong. The samples in constructing this model are derived from Part II of the laboratory experiment where an audio record of birdsong has been presented and evaluated. Based on the statistical analyses in Chapter 5, the input variables for this lab model are age, gender, loudness, and sharpness. The total PEs in the input layer are six with gender having been translated into two inputs. In contrast to the models developed for birdsong in the previous sections, 4 rather than 1 output are predicted by this model because four subjective evaluations were examined in Part II of the laboratory experiments. They are the evaluations of preference, noisiness, comfort and pleasantness. Since 3 birdsongs with different loud level were examined, for each participant, there are 3 responses, and for 56 participants, there are 168 responses in total. After eliminating the missing and noise data, the total samples could be used for training the lab model are 162. Amongst them, 32 samples were selected to be CV set.

The optimal network for the lab model of birdsong and its prediction results are also shown in Table 7.2. The well-performed network is the one which has 1 hide layer with 4 hide PEs. Table 7.2 shows that comparing to the other birdsong models developed before a much better prediction performance has been obtained by the lab model. A rather high correlation coefficient between the outputs and the targets has been achieved both for the training and CV set with a value of 0.71 and 0.60 respectively, indicating a good prediction has been made by the lab birdsong model. The MSR value is 0.08 for the training as well as CV set, which is higher than the other birdsong models. This might be caused by a small number of samples which were used to train the network.

### 7.2.5 Summary

In Section 7.2, a general model, an individual model, two group models, and a lab model for predicting the subjective evaluations of birdsong have been explored. The results show that except the lab model, all of the others have a poor prediction performance. Unlike the models for the sound level and acoustic comfort evaluations, in terms of the models for the sound preference evaluations, not much improvement was found from the general to the individual model, whereas a significant improvement was made by the lab model. This may be due to the psychoacoustic parameters, loudness and sharpness, were input to the lab model as other models did not include these two factors. The result suggests that loudness and sharpness could play an important role in determining the sound preference evaluations especially loudness, as it is more important because of relating to the sound level changes, and this finding also corresponds to the results obtained in Chapter 5.

## 7.3 Modelling the subjective evaluations for children shouting

While the birdsong models based on field surveys do not perform well, efforts are made to examine the situations with different sound types, by establishing models for predicting the subjective evaluations of children shouting (this section) and cars passing (Section 7.4). In this section, a general, an individual and two group models are developed for children shouting, whereas a lab model is not developed as it is not available.

### 7.3.1 A general model

Data collected from all of the case study sites as and the laboratory experiments, where the children shouting were evaluated, are used in constructing the general model of children shouting. In total, 5868 samples could be used to develop this general model. Amongst them, approximately 20% of the overall samples, 1173 were chosen to be the CV set for internally monitoring the training. The input variables for this model are age, occupation and education, selecting based on the significant levels between various factors and the evaluations of children shouting obtained from Chapter 5. The output is the preference evaluation of children shouting; it is also the output for the individual and group models. Using the same optimizing training process as shown before, the optimal network was obtained. The network is shown in Table 7.3 as well as its prediction results.

***Table 7.3** Models for predicting the subjective evaluations of children shouting*

| | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Input variables | Output variables | Hide layer | Hide PEs | CV sample | Coefficient | | MSE | |
| | | | | | | Train | CV. | Train | CV. |
| General | S1, 3, 4 | The preference evaluation of birdsong | 3 | 25; 12; 5 | 1173 | 0.13 | 0.12 | 0.11 | 0.11 |
| Site 9- Jardin de Perolles | S1, 3, 4 Psy2 | | 2 | 11; 5 | 149 | 0.32 | 0.15 | 0.07 | 0.09 |
| EU | S1, 3 | | 2 | 30; 20 | 1035 | 0.10 | 0.09 | 0.11 | 0.11 |
| China | S1, 2 | | 2 | 16; 8 | 161 | 0.17 | 0.16 | 0.10 | 0.11 |

*S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations*

Table 7.3 shows that the optimal network for the general model of children shouting has 3 hide layers with 25 PEs in layer 1 and 12 PEs in layer 2 and 5 PEs in layer 3. The prediction performance of this model is poor as it can be seen that the correlation coefficient is 0.13 for the training set and 0.12 for the CV set, which is rather low. Table 7.3 also shows that the MSE of this model is 0.11 for both the training and CV set; comparing the MSEs of the birdsong models, it is relatively higher.

### 7.3.2 An individual model

With the same reason as the individual model for birdsong, site 9- Jardin de Perolles in Frobourg, Switzerland is chose to be used in developing the individual model for children shouting. Based on the relationships between various factors and the subjective evaluations of children shouting, age, occupation, education, and time of day have been chosen as input variables for the individual model of children shouting. The efficient samples which could be used to this model are 746. The optimal network and its prediction results are also shown in Table 7.3. It can be seen that the optimal network of the individual model for children shouting is formed by 2 hide layers with 11 PEs in layer 1 and 5 in layer 2. The prediction performance of this model is also poor, with a correlation coefficient for CV set $r$=0.15, although this is slightly better than the general model of children shouting.

### 7.3.3 Group models

In this section, two group models are developed for predicting the evaluations of children shouting regarding the locations/functions. These two models are also made for the case study sites of the EU and China, which are similar to the group models of birdsong. After reducing the missing and noise data, the total efficient samples are 5179 for the EU model and 809 for the Chinese model. In terms of CV set, 20% of the samples have been chosen for internally testing the networks' predictions. Based on the significant levels examined in Chapter 5, the input variables for the EU model are age and occupation, and for the Chinese model are age and gender. The optimal networks of these two models are also obtained based on the optimizing training process as mentioned in Section 3.4. The final well-trained networks and their prediction results are shown in Table 7.3 as well.

Table 7.3 shows that the optimal network for the EU model is the one which has 2 hide layers with 30 PEs in layer 1 and 20 in layer 2, and the optimal one for the Chinese model has 2 hide layers with 16 PEs in layer 1 and 8 in layer 2. The prediction results show that both models made inaccurate predictions, which has rather poor correlation coefficients for the CV set. It can be seen that for the EU model, the correlation coefficient of training set is 0.10 (training) and 0.09 (CV), and for the Chinese model, it is 0.17 (training) and 0.16 (CV) which is slightly better than the EU model. Table 7.3 also shows that the MSE of the EU model is 0.11 for both the training and CV set, and that of the Chinese model is 0.10 and 0.11 for the training and CV set respectively, which are higher than that of the group birdsong models, indicating the group models of children shouting are worse.

### 7.3.4 Summary

In Section 7.3, a general model, an individual model and two group models are developed for predicting the subjective evaluations of children shouting. The results showed that all of these models are not successful as their correlation coefficients between the outputs and the targets are low, with the highest less than 0.2. A slightly better prediction has been made by the individual model than the others. Compared to the birdsong models developed in Section 7.2, the prediction performance of the children shouting models are worse, as the MSE of the children shouting models is usually higher than that of the birdsong models. Unlike the birdsong, a lab model is not available for the children shouting, as different levels of children shouting were not examined in Part II experiments.

## 7.4 Modelling the subjective evaluations for cars passing

From this section, models for predicting the subjective evaluations of a mechanical sound, sound of cars passing, are studied. Again, four types of models are developed to predict the subjective evaluations of cars passing. These were one general, one individual model, two groups, and one lab model.

### 7.4.1 A general model

As sound of cars passing was evaluated in all of the 19 case study sites, the samples which are used for the general model of cars passing are much more than the general model of birdsong/children shouting. Therefore, the selection of the input variables for this model is different from the other models to some extent. It is based on the significant levels derived from the statistical analyses not only for the data combining all of the case study sites but also for the data of each case study site. Eventually, five factors are chosen as input variables, which are season, age, gender, education, and residence status. Hence, the total inputs are seven, as gender and residence status were translated into four inputs. The output is the subjective preference evaluation of the sound of cars passing, which is also the output for the individual and group models of cars passing. In total, 8489 samples are efficient to build this general model, where 1697 of them are randomly set for the CV use. The optimal network and its prediction results are shown in Table 7.4.

*Table 7.4 Models for predicting the subjective evaluations of cars passing*

| | Network architecture | | | | | Results | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Input variables | Output variables | Hide layer | Hide PEs | CV sample | Coefficient | | MSE | |
| | | | | | | Train | CV. | Train | CV. |
| General | Phy1<br>S1, 2, 4, 5 | The preference evaluation of birdsong | 3 | 40; 20; 10 | 1697 | 0.16 | 0.06 | 0.07 | 0.07 |
| Site 9- Jardin de Perolles | Phy2<br>S1, 3, 4<br>Psy1 | | 2 | 9; 4 | 160 | 0.19 | 0.11 | 0.05 | 0.05 |
| EU | Phy1<br>S1, 4<br>B5<br>Psy1 | | 2 | 40; 20 | 1485 | 0.14 | 0.11 | 0.06 | 0.08 |
| China | S1, 4 | | 1 | 21 | 159 | 0.34 | 0.23 | 0.06 | 0.06 |
| Lab | S1, 2<br>Loudness<br>sharpness | | 2 | 4; 4 | 32 | 0.64 | 0.46 | 0.06 | 0.07 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; B1-Whether wearing earphones, B2-Whether reading or writing, B3-Whether watching somewhere, B4-Movement status, B5-Frequency of visiting the site, B6-Reason for visiting the site, B7-Grouping; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations; Psy1-Site preference, Psy2-View assessment, Psy3-Heat evaluations, Psy4-Wind evaluations, Psy5-Humidity evaluations, Psy6-Brightness evaluations, Psy7-Overall physical evaluations.*

The optimal network was obtained based on the optimizing training process. It is the one which has 3 hide layers with 40 PEs in layer 1, 20 PEs in layer 2 and 10 PEs in layer 3. In Table 7.4, it can be seen that a poor prediction performance was achieved by this model as its correlation coefficient is only 0.06 for the CV set. The MSE is not low yet, which is 0.07 both for the training and CV set. The result indicates again that the prediction made by the general model of cars passing is inaccurate.

### 7.4.2 An individual model

Site 9- Jardin de Perolles, Frobourg Switzerland is selected again to build the individual model of cars passing in consistent with the individual model of birdsong/children shouting. Based on the significant levels obtained in Chapter 5, the input variables for this model are time of day, age, occupation, education, and the site preference. The total inputs are six because the site preference, as to be a nominal variable, has been translated into two inputs. In total, 802 samples can be used to build the individual model of cars passing, and 20% of them are used to be a CV set.

Using the same optimizing training process as mentioned in Section 3.4, the optimal network is gained and also shown in Table 7.4 as well as its prediction output. The network is constructed by 2 hide layers which has 9 hide PEs are in layer 1 and 4 in layer 2. A poor prediction performance is also found to be made by this model, although its performance is slightly better than the general model of cars passing. The correlation coefficient between the outputs and the targets is 0.19 for the training set and 0.11 for the CV set. It also has a low MSE, which is 0.05 for both the training and CV set. Generally speaking, the prediction made by this model is inaccurate and unacceptable.

### 7.4.3 Group models

The individual model of cars passing is followed by two group models developed for predicting the subjective evaluations of sound of cars passing. Like the group models of birdsong/children shouting, the samples used to build the group models of cars passing are also from the case study sites of the EU and China where the sound of cars passing was evaluated.

In terms of significant levels between various factors and the subjective evaluations of sound of cars passing, the input variables are selected to be factors: season, age, education, frequency of using the site and the site preference, for the EU model, and, age and education for the Chinese model. For the EU cars passing model, the total PEs in the input layer are 7 as the site preference has been translated into 2 inputs. For the Chinese cars passing model, the total inputs are 2. Total samples which can be used in the EU model are 7,429, and in the Chinese model are 796, whilst 20% of them are assigned to be the CV set.

The optimal networks of these two group models are shown in Table 7.4. It can be seen that the network for the EU cars passing model has 2 hide layers with 40 PEs in layer 1 and 20 in layer 2, and for the Chinese cars passing model has 1 hide layer with 21 hide PEs. Also in Table 7.4, the prediction results of these two models are shown. It is found that both model's prediction performance is not successful, although a slightly better performance was made by the Chinese model. It is also found that amongst all of the cars passing models, the Chinese one made the best despite its correlation coefficient between the outputs and the targets is still low, which is 0.34 (training set) and 0.23 (CV set). Both group models have been found terminated at a similar minimum error. The MSE is 0.06 and 0.08 for the training and CV set of the EU cars passing model, whilst it is 0.06 for the training and CV set of the Chinese cars passing model.

### 7.4.4 A lab model

In terms of the subjective evaluations of the sound of cars passing, a lab model is available to be developed which is similar as the lab model of birdsong. Regarding the analyses results obtained in Chapter 5, the input variables for the lab model of cars passing are age, gender, loudness, and sharpness. Like the lab model of birdsong, 56 participants gave 168 responses to the sound of cars passing as three loud levels of cars passing were examined in the laboratory experiments. After reducing the missing and noise data, the final efficient samples are 162 in total. Amongst them, 32 samples were chosen to be a CV set.

Table 7.4 also shows that the optimal network of the lab model for cars passing and its prediction results. The network contains 2 hide layers with 4 hide PEs in each layer. The prediction performance of this model is much better than that of all of the models for the cars passing. Its correlation coefficient is 0.64 for the training and 0.46 for the CV set, suggesting the model's prediction is acceptable. A reason might be similar to that for the lab model of birdsong, this being the closer relationship between the inputs, loudness and sharpness, and the output, the subjective evaluations of sound preference. However, the MSE did not reach a low value, which is 0.06 and 0.07 for the training and CV set respectively.

### 7.4.5 Summary

In Section 7.4, 4 types of models: a general, an individual, two groups and a lab model, are developed to predict the subjective evaluations of cars passing. The results showed that the lab model was the most successful and made the best predictions in all of the models. The possible reason is related to the input variables, as the psychoacoustic parameters, loudness and sharpness were able to be inputted onto the lab model, and these two factors were proven to be important in determining the subjective evaluation of sound preference in Chapter 5.

Overall, the other models are not successful and unacceptable, although the individual and group models are slightly better than the general model. The best one amongst them is the Chinese cars passing model despite its correlation coefficient is still low. This might be due to a relationship between education and the subjective evaluations of cars passing, which is found to be closely related. A significance level exists in 4 out of 5 case study sites in China. In these sites, a correlation coefficient of at least $r$>0.19 was found.

## 7.5 Qnet models for predicting the subjective evaluations of birdsong

In this section, the models are developed using Qnet to predict the birdsong evaluations as an example to compare the performance made between NeuroSolutions and Qnet. Hence, 4 types of models are developed, which are a general, an individual, a group, and a lab model. The input variables and samples used for building these Qnet models are the same as those for building the NeuroSolutions models as can be seen in Section 7.2. While 20% of the samples have to be used for internally testing the network predictions in NeuroSolutions, only 10% of the samples are used to be test set in Qnet. The learning function used for the Qnet models is sigmoid that is the similar algorithm as SigmoidAxon in NeuroSolutions. A difference between Qnet and

NeuroSolutions is the genetic algorithm (GA) technique, which was applied to the NeuroSolutions models but was not available for the Qnet models.

### 7.5.1 A general model

The input variables which are set for the general Qnet model of birdsong are the same as those for the general NeuroSolutions model, which are age, gender, occupation, and education. The total inputs are four as shown in Table 7.5, and the output is the subjective preference evaluations of birdsong. The optimal network of this model is also obtained through the optimizing training process. The network and its prediction results are shown in Table 7.5.

*Table 7.5 Qnet models for predicting the subjective evaluations of birdsong*

| | Network architecture: Input variables | Output variables | Hide layer | Hide nodes | Test sample | Results: Coefficient Train | Coefficient Test. | RMS error Train | RMS error Test |
|---|---|---|---|---|---|---|---|---|---|
| General | S1, 2, 3, 4 | The preference evaluation of birdsong | 2 | 3, 2 | 250 | 0.29 | 0.08 | 0.16 | 0.16 |
| Site 9- Jardin de Perolles | S1, 3, 4 Phy2 | | 2 | 2, 1 | 75 | 0.33 | 0.21 | 0.11 | 0.13 |
| EU | S1, 2, 3, 4 | | 2 | 4, 1 | 170 | 0.30 | 0.24 | 0.16 | 0.16 |
| Lab | S1, 2, 4 Loudness, Sharpness | | 1 | 4 | 16 | 0.71 | 0.67 | 0.20 | 0.20 |

*Phy1-Season, Phy2-Time of day, Phy3-Air temperature, Phy4-Wind speed, Phy5-Relative humidity, Phy6-Horizontal luminance, Phy7-Sun shade, Phy8-Sound pressure level; S1-Age, S2-Gender, S3-Occupation, S4-Education, S5-Residential status, S6-Home sound level evaluations*

Table 7.5 shows that the optimal network is the one which has 2 hide layers with 3 hide nodes in layer 1 and 2 in layer 2. After reducing the noise and the missing samples, all of the efficient ones collected from the case study sites where the birdsong was evaluated are used to train the network. Amongst them, 250 samples approximately 10% of the total are set for use in the test. The results show that the prediction made by this network is rather poor as a low correlation coefficient between the outputs and the targets was obtained. It is 0.08 for the test set and 0.29 for the training set. The RMS error is 0.16 for the training as well as the test set. Comparing the Qnet general model with the NeuroSolutions general model (see Table 7.2), it is found that the predictions of both models are poor although the NeuroSolutions model has a slightly higher correlation coefficient of the test set, which is $r$=0.11. It is interesting to note that both models were terminated at the same minimum error, as the RMS error of the Qnet model is 0.16 (training and test) and the MSE of the NeuroSolutions model is 0.04 (training and test).

### 7.5.2 An individual model

The individual model developed by Qnet is using the same case study site as the individual model developed by NeuroSolutions, which is site 9- Jardin de Perolles, Frobourg Switzerland. Using the same inputs and samples as the NeuroSolutions model, the Qnet model is established with 10% of the total samples for the test set and the optimal network is obtained through the same optimizing training process. The network and the prediction results are shown in Table 7.5.

In Table 7.5, it can be seen that the optimal network is the one which has 2 hide layers with 2 hide nodes in layer 1 and 1 in layer 2. The prediction performance of this model is not successful yet as the correlation coefficient between the outputs and targets is low as $r$=0.33 for the training set and 0.21 for the test set. However, comparing the general model made by Qnet also shown in Table 7.5, it is found that this model made better predictions. Comparing this model with the individual Neurosolutions model of birdsong, a tiny difference between both models has been found where a slightly higher correlation coefficient was achieved by the Neurosolutions model as can be seen in Table 7.2. It is also interesting to note that the trainings of both models stopped at a similar minimum error as the RMS error of the individual Qnet model is 0.11 (training set) and 0.13 (test set) and the MSE of the individual Neurosolutions model is 0.03 (both training and CV set).

### 7.5.3 A group model

A group model for birdsong developed by Qnet is also made for comparing with the group model developed by Neurosolutions. This model is established using the same samples and input variables as the EUNeurosolutions model of birdsong. The total samples are 1659 and the input variables are age, gender, occupation, and education. In order to test the network internally, 10% of the samples are used for the test set. The optimal network is obtained through the optimizing training process. The optimal network and its prediction results are also shown in Table 7.5. It can be seen that the optimal network is the one which has 2 hide layers with 4 hide nodes in layer 1 and 1 in layer 2.

The prediction results from the group Qnet model are very similar as those from the individual Qnet model, in which it can be seen that the correlation coefficient between the outputs and the targets is 0.30 for the training set and 0.24 for the test set. Comparing the EU Qnet model with the EU NeuroSolutions model, it is found that the prediction performance of both models is not successful, although there is a tiny difference which the correlation coefficient is slightly lower for the NeuroSolutions model as can be seen in Table 7.2. Both models were terminated at a similar minimum error, which for the Qnet model, the RMS error is 0.16 for both training and test set, and for the NeuroSolutions model, the MSE is 0.03 for the training set and 0.04 for the CV set.

### 7.5.4 A lab model

A lab model is also developed with Qnet. It is based on Part II laboratory experiments, which is the same as the lab model developed by NeuroSolutions as stated in Section 7.2.4. With the same input variables and the samples used in the NeuroSolutions lab model, the Qnet lab model for birdsong is established and shown in Table 7.5. It can be seen that the input variables of the Qnet lab model are age, gender and education. The optimal network is the one which has 1 hide layer with 4 hide nodes.

Table 7.5 shows that the correlation coefficient of the lab Qnet model for birdsong is rather high, which is 0.71 and 0.60 for the training and test set respectively. This result suggests that a good prediction performance has been achieved by this model. Its predictions are more accurate than those made by the other Qnet models as also shown in Table 7.5. In Table 7.5, it also shows that the RMS error of this model is not low yet, which is 0.20 for both training and test set. The reason for this could be that the number of samples used in the lab model is limited, which might cause unreliable learning. Comparing the Qnet lab model (see Table 7.5) with the NeuroSolutions lab model (see Table 7.2), both built for birdsong, a similar prediction performance has been found, because the correlation coefficient of both models are closer and both were terminated at a similar minimum error, which is 0.20 for the Qnet model (RMS error for both training and test) vs. 0.08 for the NeuroSolutions model (MSE for both training and test).

### 7.5.5 Summary

In order to compare NeuroSolutions with Qnet, four types of models were developed in this section for predicting the subjective evaluations of birdsong using Qnet. These are a general, individual, group and lab model. With the same inputs and samples as those of the NeuroSolutions models, the four Qnet models were established and compared with the corresponding NeuroSolutions models in terms of their prediction performance.

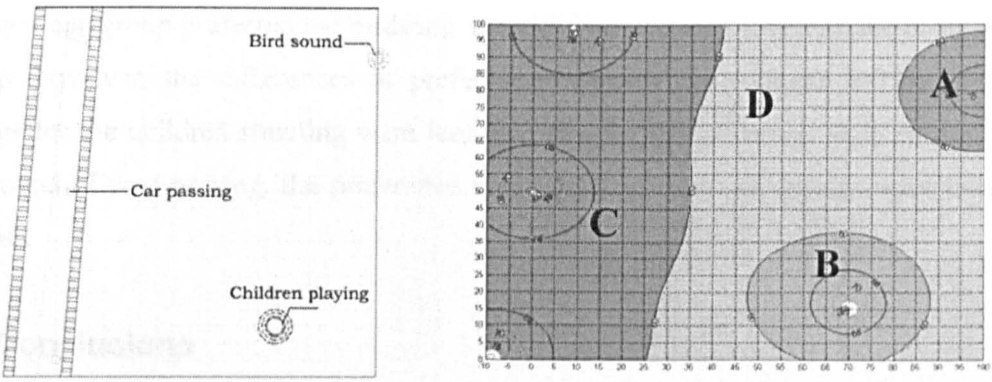
The results showed that the best predictions for the subjective evaluations of birdsong were made by the lab model, whereas the predications made by the other models were much worse. Comparing the results derived from the Qnet models with those from the NeuroSolutions models, it is interesting to note that the prediction performance made by both models is very similar. Only a small difference has been found to show that, in general a slightly better prediction was made by the NeuroSolutions models. It is also interesting to note that both Qnet and the NeuroSolutions models were terminated at a similar minimum error, implying that a global minimum error was reached by both models.

## 7.6 Development of sound preference maps

A mapping method is proposed in this section to present the subjective evaluations of sound preference for the potential users in a hypothetical urban open space. This is a parallel study to the study of mapping the subjective evaluations for the sound level and acoustic comfort as demonstrated in Chapter 6.

The successfully developed JdP model, as shown in Table 7.1, is used to make predictions and then a set of maps are created to present the evaluations of potential users. Although the JdP model was made based on a typical case study site, it would be appropriate to use for universal situations. One reason is that the determining factors are sound meanings which are less dependent on the site differences. The findings of the previous sections showed that only a tiny difference exists between the predictions of various models (the general, individual and group model) with respect to their location differences.

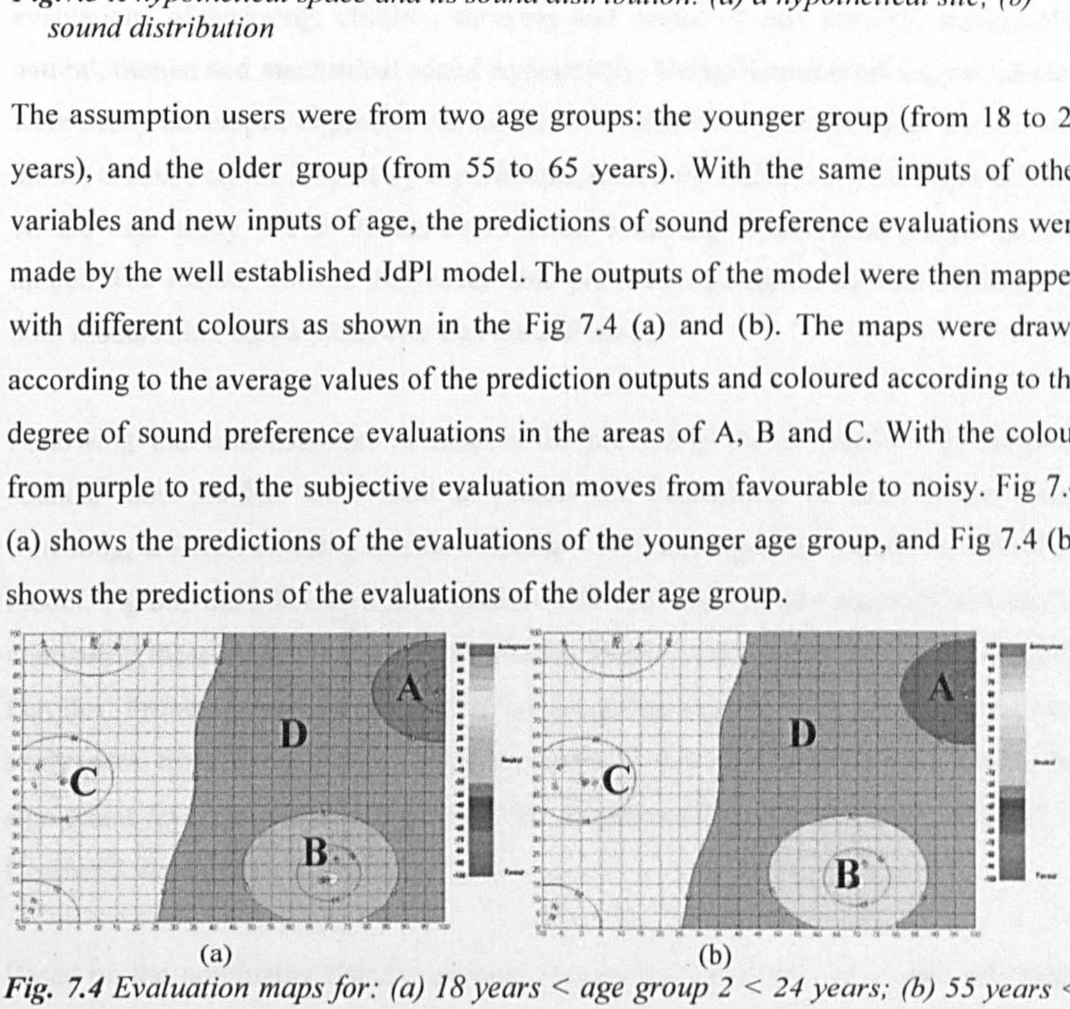
In this study, a hypothetic urban open space was designed, where three sounds, birdsong, children shouting and cars passing were assumed to exist as shown in Fig.7.3 (a). This urban open space was supposed to be a space situated in an urban park, where a busy two-way road is nearby. The area was assumed to be dominated by the sound of birdsong, children shouting, and cars passing in three separate areas. More than 100 metres distance was assigned between each sound, because with such distance, the sound level would approximately reduce over 20 dB and the effect of other single sounds could be ignored. In terms of the sound levels, the areas were marked based on sound notability; which were A (birdsong), B (children shouting), C (cars passing), and D (combined sounds) which are marked with different colours as shown in Fig. 7.3 (b). In the area of A, B or C, one of above three sounds dominated, whereas the effects of others were ignored because they were rather weak. However, in the area of D, the dominated sound was combined with more than 2 out of 3 sounds being mixed. As the subjective evaluation of combined sounds is rather complicated and has not been included in this study, the maps produced below are only for the evaluations of the single sounds of birdsong, children shouting and cars passing.




(a) (b)

*Fig.7.3 A hypothetical space and its sound distribution: (a) a hypothetical site; (b) sound distribution*

The assumption users were from two age groups: the younger group (from 18 to 24 years), and the older group (from 55 to 65 years). With the same inputs of other variables and new inputs of age, the predictions of sound preference evaluations were made by the well established JdPl model. The outputs of the model were then mapped with different colours as shown in the Fig 7.4 (a) and (b). The maps were drawn according to the average values of the prediction outputs and coloured according to the degree of sound preference evaluations in the areas of A, B and C. With the colour from purple to red, the subjective evaluation moves from favourable to noisy. Fig 7.4 (a) shows the predictions of the evaluations of the younger age group, and Fig 7.4 (b) shows the predictions of the evaluations of the older age group.




(a) (b)

*Fig. 7.4 Evaluation maps for: (a) 18 years < age group 2 < 24 years; (b) 55 years < age group 7 < 64 years*

By comparing Fig. 7.4 (a) with Fig. 7.4 (b), it is interesting to note that: (1) different colour is presented in area A and B; (2) a similar colour is shown in area C; (3) a significant colour difference is presented in area A. This result suggests that the younger age group preferred the birdsong and children shouting less than the older age group; however, the differences of preference between the younger and the older groups for the children shouting were less than that for the birdsong. With respect to the sound of cars passing, the preference evaluations of both age groups were rather similar.

## 7.7 Conclusions

In this chapter, ANN models have been developed for predicting the subjective evaluations of birdsong, children shouting and sound of cars passing, representing natural, human and mechanical sound respectively. Using NeuroSolutions, two models were firstly developed to predict the subjective evaluations of above three sounds. One model is based on the laboratory experiments, called the Lab model; the other is based on the case study site 9- Jardin de Perolles, Frobourg Switzerland, called the JdP model. The results showed that acceptable prediction performance was achieved by both models although a better one was the JdP model.

Following the establishment of models for predicting the evaluations of all three sounds, more models were built to predict the evaluations of each single sound (birdsong, children shouting and cars passing). They are a general model, an individual model, 2 group models, and a lab model (not for the sound of cars passing). In order to comparing these models, all of the individual models were made for site 9- Jardin de Perolles, Frobourg Switzerland and all of the group models were made for the case study sites from the EU and China. In terms of selecting the input variables, the significant levels of various factors on the sound preference evaluations obtained in Chapter 5 were used.

Based on the optimizing training process, the optimal networks were obtained. Their prediction result showed that there is no difference between the general, individual and group models for predicting the preference evaluations of the 3 aforementioned sounds. This result is rather different from the result obtained from the sound level and acoustic comfort models, where the individual models made much better predictions than those made by the general models. Regarding the sound preference evaluation models, all of the general, individual and groups presented a poor prediction performance, with a less than 0.3 low correlation coefficient for the test set. This result implied that the location differences are not important in determining the subjective evaluations of sound preference. This might be because the studied factors are less directly related to the sound preference evaluations.

Although there is not much difference amongst the general, individual and group models, a distinct difference has been found between the lab models and the other models for birdsong and sound of cars passing. On comparing the models developed for the two studied sounds, namely birdsong and cars passing, it is interesting to note that considerably better predictions were made by the lab models in which psychoacoustic parameters, loudness and sharpness have been input. A possible reason for this is due to the introduction of loudness and sharpness, which have a close relationship with the sound preference evaluations, showing again that the subjective evaluations of sound preference are more related to the sound itself rather than the sites where it was heard. However, further study is still needed to follow this up, considering more psychoacoustic parameters, sounds and situations.

A similar prediction performance has been achieved by both the Qnet and the NeuroSolutions models corresponding to the same cases study sites. It is also interesting to note that both the Qnet and the NeuroSolutions models were terminated at a similar minimal error, implying that the trainings of both models were reached their global minimums.

Based on a successful model, prediction maps have been developed to provide a feasible approach to connect the decision-makers and the space users at the design/planning stage.

In this chapter, it is interesting to note that the models developed for predicting the evaluations of all three sounds could make much better predictions than the models developed only for predicting the evaluations of one sound. The possible reason for this is that sound category is an input variable for the models in predicting the evaluations of all three sounds, which were found to be significantly related to the subjective evaluations of sound preference; however, this variable cannot be used to the models for predicting the evaluations of one single sound. Nevertheless, all of the models developed in this chapter were for prediction of the single sounds. For the combined sounds, however, according to their complicated compositions, the prediction models might be sophisticated and rather different from the single sound's models, for which further detailed studies are required.

## Chapter 8

# Conclusions and Future Works

The main motivation behind this thesis is to present the state-of-the-art development of simulating subjective evaluations of soundscape in urban open spaces in order to aid urban designers/planners. Based on the fundamentals of Environmental Psychology, a large number of field surveys have been conducted by the research groups as well as by the author in 19 typical urban open spaces and followed by indoor experiments. Statistical analyses have then been qualitatively made for the collected data from the case study sites and laboratory experiments. Various factors from acoustic, physical, social/demographical, behavioural and psychological aspects have been explored as to their influence on the subjective evaluations of soundscape in urban open spaces. Based on the significant levels of these factors on the soundscape evaluations, ANN models have then been developed to predict the soundscape evaluations of potential users in a developing urban open space. In summary, the components of this study can be distinguished into five parts.

## 8.1 Contributions

### 8.1.1 Application of ANNs in soundscape study

In this study, ANN technique has been systematically explored in soundscape research. Previous studies by various authors have provided crucial information in soundscape research; however, they are not specifically efficient in taking all potential factors into account at one time; furthermore, a feasible tool is lacking to transfer the research achievements into common practices, e.g. soundscape planning/designing. As soundscape takes sounds as positive and active elements instead of negative ones, understanding the subjective evaluations is essential in creating a good soundscape quality. This includes the evaluations of sound level, acoustic comfort and sound preference. Conventional statistical analyses cannot reach such a goal since the subjective evaluations of soundscape are rather complicated, relating to various disciplines from the study of acoustics to environmental psychology. This study has then employed a critical methodology, ANNs, to predict the subjective evaluations of soundscape, considering all potential influences of various factors. Most importantly, this study proposes a useful method to connect soundscape research to soundscape design with regard to improving the sonic environment of urban open spaces.

### 8.1.2 Factors related to the sound level/acoustic comfort evaluations

The influences of various factors on the sound level and acoustic comfort evaluations have been qualitatively analysed. The research suggests that there is a varied effect of different factors on the subjective evaluations of sound level and acoustic comfort in terms of the diversity of the case study sites.

Generally speaking, the social/demographical factors are insignificantly in relation to the sound level evaluations, although occupation and education, as two associated factors, carry a much greater importance. The sound level experience at home, however, is an important social factor here. Some physical factors have more influence on the sound level evaluations than the social/demographical factors do. Amongst them, SPL has been found to be the most crucial. The effects of many behavioural factors, on the other hand, are insignificant to the sound level evaluations. However, the watching behaviour is highly related, again indicating visual/aural interactions. The behavioural factor, reason for visiting the site, also carries some importance. The effects of many psychological factors on the sound level evaluations cannot be ignored, whereas the psychological factor, the humidity evaluations, has limited importance.

The influence of most physical factors studied in this research on the acoustic comfort evaluation is not significant, although the influence of SPL is still relatively significant. The importance of social/demographical factors on the acoustic comfort evaluation is also limited; however, the influence of the psychological factors, including the view assessment, the subjective evaluations of brightness, sound level and overall physical comfort, are considerably significant. As with the social/demographical factors, the behavioural factors have also been found to be insignificantly related to the acoustic comfort evaluation.

Besides giving useful guidelines, the results of the above mentioned statistical analyses also provide crucial information for selecting the input variables for ANN models, which are important in reducing their complexity and then making efficient predictions.

### 8.1.3 Factors related to the sound preference evaluations

The study of factors influencing the sound preference evaluations demonstrates that the effect of various factors on the sound preference evaluations varied corresponding to the sound sources, including nature, human or mechanical sounds. The general sound preference evaluation has been particularly studied in the field studies and the Part I laboratory experiment, whilst more personal sensations/attributes, including the sound preference, noisiness, comfort, and pleasantness, were explored in Part II & III laboratory experiments.

The results show that the important factors related to the sound preference evaluation include sound category, sub-category and visual effect. Two psychoacoustic parameters, loudness and sharpness, have also been found to have a close relationship with the sound preference evaluations, especially the effect of loudness on the subjective evaluation of noisiness, and the effect of sharpness on the subjective evaluation of pleasantness and comfort. Other psychoacoustic parameters were not examined due to the limitation of the software. With regard to the social/demographical factors, age affects more on natural sounds, whereas education has a greater influence on mechanical sounds. In terms of physical/behavioural/psychological factors, generally speaking, their influence on the sound preference evaluations is insignificant, except in a limited case study sites and certain sound sources. These results are also important in determining the input variables for ANN models to predict the subjective evaluations of sound preference.

### 8.1.4 ANN models for predicting the sound level and acoustic comfort evaluations

Given the complicated relationships between various factors and the soundscape evaluations, ANN models have then been developed based on the information provided by the statistical analyses in Chapter 4 & 5. The models have been established at three levels, for a general situation, an individual site, and specific locations for practical use by urban designers/planners respectively. It has been found that for both sound level and acoustic comfort evaluation, a general model for all the case study sites is less feasible due to the complex physical and social environments in urban open spaces; models based on individual case study sites perform well but the application is limited; whereas specific models for certain types of location/function would be reliable and practical. The performance of acoustic comfort models is considerably better than that of sound level models, mainly due to the relative importance of various input variables for the ANN models. With ANN models soundscape quality prediction maps can be produced, as demonstrated through an example.

In addition, the NeuroSolutions models have been developed in comparison with the Qnet models. Differences have been found for the individual and practical models for certain types of spaces between the NeuroSolutions and the Qnet. With NeuroSolutions, better predictions have been made by the practical models, whereas for Qnet, better ones have been made by the individual models. Moreover, the Qnet models generally made more successful predictions than the NeuroSolutions models. Furthermore, the feasibility of using OLR models for predicting the subjective evaluation of soundscape has also been explored. The results showed that OLR models could make acceptable predictions, but their prediction performance is relatively worse compared to that of Qnet models.

### 8.1.5 ANN models for predicting the subjective evaluations of sound

Using NeuroSolutions, ANN models for predicting the subjective evaluations of sounds have been made. Three sounds have been explored, which are birdsong, children shouting and cars passing. For evaluations of combining all three sounds, two models were developed, and the results showed that successful predictions have been made by both models.

For the subjective evaluations of an individual sound, four kinds of models have been built, namely general, individual, group, and lab model. The results showed that very good predictions have been made by all the lab models no matter whether they had been developed for birdsong, children shouting, or cars passing. For the other models, the performance is not satisfactory. No significant differences of predictions have been found among them, although individual models generally made slightly better predictions. This result indicates that the location difference may not have much impact on the subjective evaluations of sound preference.

A similar prediction performance has been achieved by the Qnet models as has by the NeuroSolutions models for the evaluations of the birdsong. This result contrasts with the rather different result made by these two models for the sound level/acoustic comfort evaluations, where the predication performance of the Qnet models is different from the NeuroSolutions model. The reason might be that the data used for training the NeuroSolutions model for the evaluations of birdsong are relatively more sufficient than the data used for training the NeuroSolutions models for the sound level/acoustic comfort evaluations, because far fewer variables are used as inputs in the former than the latter.

## 8.2 Future works

It is noted that to all the models developed for predicting the soundscape evaluations, their test coefficients between outputs and targets are generally not very high, all less than 0.8. A possible reason is that subjective evaluations are rather varied between individual users and this cannot be completely represented by computer models. On the other hand, further improvements could be made by establishing a more efficient model. There are two ways that could improve ANN predictions. The first is to use efficient data in model predictions. The data employed in this study were gained from a wide range of field surveys, which are of value for exploring a universal situation but not specific position. Controlled field surveys are considered useful in improving the model predictions.

On the other hand, further improvements could be made by establishing a more complex model structure, where a number of sub-models can be developed, including the evaluation of sound level (background sound), sound preference (noticed sounds, foreground sounds or soundmarks) and the evaluation of other physical factors, such as satisfaction of thermal, lighting, view and overall physical environment. The outputs of the sub-models can then be used as the input of an overall model for the acoustic comfort evaluation. For this further carefully designed field studies would be useful.

Due to the software limitations, only loudness and sharpness were studied and input to the models for the purpose of predicting the sound preference evaluations. Other psychoacoustic parameter such as roughness was not included. Hence, it is expected that a further improvement could be made for the sound preference evaluation models if the use of more psychoacoustic parameters were available.

This study provides a useful method to integrate soundscape research into acoustic designs in urban open spaces. With this method, the study offers an example of how to connect the views of users and those of designers/planners at the design stage. Such a method could be extended into the other environmental research areas, and used for transforming public assessments into a design process (Yu & Kang, 2008b). Contemporary designers take 'people' as the main subject in their designs. Around this 'subject', various physical environments should be taken into account as a whole. Such holistic approach requires understanding of the relationships between various physical environments and their social users. As ANN models have been proven to be useful to predict such relationships, further ways of using them to predict the subjective evaluations of other physical environments are necessary in improving the environmental qualities of a designed space. Moreover, further works of refining ANN models are indispensable, and integrating the model predictions into GIS is expectable.

# References

01dB-Stell. (2001). *Symphonie measurement system - Getting started manual.* Limonest: 01dB-Stell.

Aasen, B. (2002). *Urban squares.* Mu̇nich; Basel: Callwey Georg D.W. GmbH.

Moivre, A. De (1756). *Doctrine of chances: or, a method of calculating the probabilities of events in play* (3rd ed.). London: A. Millar.

Ackley, D. H., Hinton, G. E., & Sejnowski, T. J. (1985). A Learning algorithm for boltzmann machines. *Cognitive Science*, 9, 147-69.

Adrain, R. (1808). *The analyst, or, mathematical museum.* Philadelphia: William P. Farrand and Co.

Alais, D., Burr, D., & Carlile, S. (2007). Audiovisual interactions in the perception of space and time. *Proceedings of 19th International Congress on Acoustics (ICA)*, Madrid.

Anderson, D., & McNeill, G. (1992). *Artificial neural networks technology: A DACS state-of-art report.* New York: Kaman Sciences Corporation.

Badran, F., & Thiria, S. (1991). Wind ambiguity removal by the use of neural network techniques. *Journal of Geophysical Research*, 96, 20521-20529.

Ballas, J. A. (1993). Common factors in the identification of an assortment of brief everyday sounds. *Journal of Experimental Psychology: Human Perception and Performance*, 19, 250-67.

Baum, A., Singer, J. E., & Baum, C. S. (1982). Stress and environment. In C.W. Evans (Ed.), *Environmental stress* (pp.15-44). Cambridge: Cambridge University Press.

Bedwell, C. H. (1972). The eye, vision, and visual discomfort. *Lighting Research and Technology*, 4(3), 151-155.

Bell, G., & Tyrwhitt, J. (Eds.). (1972). *Human identity in the urban environment.* Harmondsworth: Penguin.

Beltran, R., Wang, L., & Wang, X. (2004). Predicting worsted spinning performance with an artificial neural network model. *Textile Res. J.*, 74(9), 757–763.

Bennett, C. A. (1977). The demographic variables of discomfort glare. *Lighting Design and Application*, 7(1), 22-32.

Berglund, B., Lindvall, T., & Schwela, D. H. (1999). Guidelines for community noise. *World Health Organization Report* (pp.94). Geneva: OMS.

Berglund, B., Nilssona, M. E., & Pekalab, P. (2004). Towards certification of indoor and outdoor soundscapes. *Proceedings of Inter-Noise 2004*, Prague, Czech Republic.

Berglund, B., & Nilsson, M. E. (2006). On a tool for measuring soundscape quality in urban residential areas. *Acta Acustica United with Acustica*, 92, 938-944.

Bernoulli, D. (1954). Exposition of a new theory on the measurement of risk. *Econometrica*, 22(1), 23-36.

Bertoni, D., Franchini, A., Magnoni, M., Tartoni, P., & Vallet, M. (1993). Reaction of people to urban traffic noise in Modena, Italy. *Proceedings of the 6th Congress on Noise as a Public Health Problem, Noise, and Man*, Nice, France.

Bishop, C. M. (1995). *Neural networks for pattern recognition*. Oxford: Clarendon Press.

Bjork, E. A. (1985). The perceived quality of natural sounds. *Acustica*, 57, 185-188.

Boser, B., Guyon, I., & Vapnik, V. N. (1992). A training algorithm for optimal margin classifier. *Fifth Annual Workshop on Computational Learning Theory*, San Mateo, CA.

Botteldooren, D., & Coensel, B. D. (2006). Quality assessment of quiet areas: A multi-criteria approach. *Proceedings of the $6^{th}$ European Conference on Noise Control*, Tampere, Finland.

Boubekri, M., Yin, Z., & Guy, R. (1997). A neural network solution to an architectural design problem: Design of a light shelf. *Architectural Science Review*, 40, 17-21.

Boznar, M., Lesjak, M., & Mlakar, P. (1993). A neural network-based method for the short-term predictions of ambient $SO_2$ concentrations in highly polluted industrial areas of complex terrain. *Atmospheric Environment*, 27(2), 221-230.

Brambilla, G., & Maffei, L. (2006). Responses to noise in urban parks and in rural quiet areas. *Acta Acustica United with Acustica*, 92, 881-886.

Brown, A. L., & Muhar, A. (2004). An approach to the acoustic design of outdoor space. *Journal of Environmental Planning and Management*, *47*(6), 827-842.

Carles, J. L., Barrio, I. L., & Delucio, J. V. (1999). Sound influence on landscape values. *Landscape and Urban Planning*, 43, 191-200.

Carles, J. L., Bernaldez, F. G., & Delucio, J. V. (1992). Audiovisual interactions and soundscape preferences. *Landscape Research*, 17, 52-56.

Chao, L-C., & Skibniewski, M. J. (1994). Estimating construction productivity: neural-network-based approach. *J. Comput. Civil Engng.*, 8, 234-51.

Chase, S. B., & Aktan, A. E. (Eds.). (2001). *Health monitoring and management of civil infrastructure systems*. Bellingham, Washington: SPIE.

Cheng, L., & Adams, D. L. (1995). Yarn strength prediction using neural networks, *Textile Res. J.* 65(9), 495-500.

Coensel, B. D., & Botteldooren, D. (2006). The quiet rural soundscape and how to characterize it. *Acta Acustica United with Acustica*, 92, 887-897.

Cohen, S. (1978). Environmental load and the allocation of attention. In A. Baum, J. E. Singer & S. Valins (Eds.), *Advances in environmental psychology*. Hillsdale, New Jersey: Lawrence Erlbaum Associates.

Cohen, M. A., & Grossberg, S. (1983). Absolute stability of global pattern formation and parallel memory storage by competitive neural networks. *IEEE Transactions on Systems, Man and Cybernetics*, 13, 815-26.

Cohen, S., & Weinstein, N. (1982). Nonauditory effects of noise on behaviour and health. In C.W. Evans (Ed.), *Environmental stress*. Cambridge: Cambridge University Press.

Coolican, H. (1996). *Introduction to research methods and statistics in psychology* (2nd ed.). UK: Hodder & Stoughton.

Cortes, C., & Vapnik, V. (1995). Support vector networks. *Machine Learning*, 20, 273-297.

Cotes, R., & Matsko, J. M. (1768). *Aestimatio errorum in mixta mathesi: per variationes partium trianguli plani et sphaerici*. Lemgouiae: Typis Meyerianis.

Data Kustik (2006). *Cadna/A for windows - user manual*. Munich: Kustik.

Davis, G. E. (1975). *Attitudinal mediation of annoyance to transportation noise*. Unpublished Manuscript.

Dubois, D., Guastavino, C., & Raimbault, M. (2006). A cognitive approach to urban soundscape: Using verbal data to access everyday life auditory categories. *Acta Acustica United with Acustica*, 92, 945-951.

Egan, M. D. (1988). *Architectural acoustics*. New York: McGraw-Hill, Inc.

Elkordy, M. F., Chang, K. C., & Lee, G. (1994). A structural damage neural network monitoring system. *Microcomp. Civil Engng.*, 9, 83-96.

Fahrmeir, L., & Tutz, G. (1994). *Multivariate statistical modelling based on generalized linear models*. New York; London: Springer-Verlag.

Farooq, A., & Cherif, C. (2008). Use of artificial neural networks for determining the leveling action point at the auto-leveling draw frame. *Textile Res. J.*, 78(6), 502-509.

Fields, J. M. (1993). Effect of personal and situational variables on noise annoyance in residential areas. *J. Acoust. Soc. Am.*, 93, 2753-2763.

Fiedler, J. (1978). *Field research: a manual for logistics and management of scientific studies in natural settings*. San Francisco; London: Jossey-Bass.

Fisher-Gewirtzman, D., Burt, M., & Tzamir, Y. (2003). A 3-D visual method for comparative evaluation of dense built-up environments. *Environment and Planning B: Planning and Design*, 30, 575-587.

Fisher, J. D., Bell P. A., & Baum, A. (1990). *Environmental psychology* (4th ed.). London; New York: Holt, Rinehart and Winston.

Freeman, W. J. (1995). *Societies of brains*. Hillsdale, New Jersey: Lawrence-Erblaum.

Fricke, F. R. (1999). Neural network analysis applied to architectural design. *Proceedings of ANZAScA Annual Conference*, Sydney.

Fujiwara, M. (2006). Audio-visual interaction in the image evaluation of the environment: An on-site investigation. *Proceedings of Internoise2006*, Honolulu, USA.

Gärling, T., & Golledge, R. G. (Eds.) (1993). *Behaviour and environment: psychological and geographical approaches*. Amsterdam; London: North-Holland.

Gauss, C. F. (1809). *Theoria motus corporum coelestium*. Hamburg: Perthes. Translation reprinted (1963), *Theory of the motions of the heavenly bodies moving about the sun in conic sections*. New York: Dover.

Gaver, W. (1993). What in the world do we hear? An ecological approach to auditory event perception. *Ecological Psychology*, 5, 1-29.

Ge, J., & Hokao, K. (2004). Research on the sound environment of urban open space from the viewpoint of soundscape: A case study of Saga forest park, Japan. *Acta Acustica United with Acustica.*, 90, 555-563.

Gehl, J. (1987). *Life between buildings: Using public spaces*. New York: Van Nostrand Reinhold.

Gibson, J. J. (1986). *The ecological approach to visual perception*. New Jersey; London: Lawrence Erlbaum Associates.

Gifford, R. (2002). *Environmental psychology: principles and practice* (3rd ed.). Colville, Washington: Optimal Books.

Girardet, H. (1996). *The gaia atlas of cities: New directions for sustainable urban living*. UN-HABITAT.

Glass, D. C., & Singer, J. E. (1972). *Urban stress: Experiments on noise and social stressors*. New York: Academic Press.

Gold, S. M. (1980). *Recreation planning and development*. New York: McGraw-Hill.

Goldstein, J. (1979). Descriptors of auditory magnitude and methods of rating community noise. In R. J. Peppin & C. W. Rodman (Eds.), *Community noise* (pp. 38-72). Philadelphia: American Society for Testing and Materials.

Greenhalgh, L. (1996). People, parks & cities: A guide to current good practice in urban parks. In *A report for the department of the environment*. London: HMSO.

Guastavino, C. (2006). The ideal urban soundscape: investigating the sound quality of French cities. *Acta Acustica United with Acustica*, 92, 945-951.

Häußermann, H., & Siebel, W. (1987). *Neue urbanität, suhrkamp*. Frankfurt: Main.

Haykin, S. S. (1994). *Neural networks: A comprehensive foundation*. New York; Oxford: Maxwell Macmillan.

Hebb, D. O. (1949). *The organization of behaviour: A neuropsychological theory*. New York: Wiley.

Hecht – Nielsen, R. (1990). *Neurocomputing*. Reading, Massachusetts: Addison-Wesley.

Hedfors, P. & Grahn, P. (1998). Soundscapes in urban and rural planning and design. In R. M. Schafer & H. Järviluoma (Eds.) *Northern soundscapes: Yearbook of soundscape studies* (pp. 67–82). Tampere: Department of Folk Tradition Publication.

Heimstra, N. W., & McFarling, L. H. (1974). *Environmental psychology*. Monterey, California: Brooks/Cole.

Hinton, P. R. (2004). *Statistics explained* (2nd ed.). London: Routledge.

Hiramatus, K. (2006). A review of soundscape studies in Japan. *Acta Acustica United with Acustica*, 92, 857-864.

Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the Natural Academy of Science*, 79, 2554-2558.

Howard, D. M., & Angus, J. (2001). *Acoustics and psychoacoustics*. Oxford: Focal Press.

Huntingdon, J. E. (2003). *Forecasting colour at water Treatment works using artificial neural networks* (PhD dissertation). Sheffield: University of Sheffield.

Jayasundara, C. C. (2002). *Use of genetic algorithm, artificial neural networks and standard statistical techniques to predict psychological outcomes of patients admitted to accident and emergency departments* (MSc dissertation). Sheffield: University of Sheffield.

Jones, D., & Franklin, S. P. (1990). Choosing a network: matching the architecture to the application. In A. Maren, C. Harston & R. Pap (Eds.) *Handbook of neural computing applications* (pp. 221). San Diego, California: Academic.

Judith, F. (1978). *Field research: A manual for logistics and management of scientific studies in natural settings*. London; San Francisco: Jossey-Bass.

Kang, J. (2000). Sound propagation in street canyons: Comparison between diffusely and geometrically reflecting boundaries. *J. Acoust. Soc. Am.*, 107, 1394-1404.

Kang, J. (2001). Sound propagation in interconnected urban streets: A parametric study. *Environment and Planning B: Planning and Design*, 28, 281-294.

Kang, J. (2002). Comparison of sound fields in regularly-shaped, long and flat enclosures with diffusely reflecting boundaries. *International Journal of Acoustics and Vibration*, 7, 165-171.

Kang, J. (2004). Application of radiosity method in acoustic simulation. *Proceddings of the 18th International Congress on Acoustics (ICA)*, Kyoto, Japan.

Kang, J. (2006a). *Urban sound environment*. London: Taylor & Francis incorporating Spon.

Kang, J. (2006b). Aural-visual interactions: In the built environment. *The second Annual Meeting EPSRC Network for Comfort and Energy use in Buildings (NCEUB)*, Sheffield.

Kang, J., Yang, W., & Zhang, M. (2004). Sound environment and acoustic comfort in urban spaces. In M. Nikolopoulou (Ed.), *Design open spaces in the urban environment: A bioclimatic approach* (pp. 32-36). Greece: CRES, Attiki.

Kang, J., & Zhang, M. (2002). Semantic differential analysis on the soundscape of urban open public spaces. *J. Acoust. Soc. Am.*, 112(5), 2435

Karunanithi, N., Grenney, W. J., Witley, D., & Bovee, K. (1994). Neural networks for river flow predictions. *J. Comput. Civil Engng.*, 8(2), 201-220.

Kennedy, R. L., Harrison, R. F., & Marshall, S. J. (1994). A comparison of logistic regression and artificial neural network models for the early diagnosis of acute myocardial infarction (AMI). *The University of Sheffield, Department of Automatic Control and Systems Engineering, Research Report*, 539.

Kernohan, D., Gray, J., & Daish, J. (1992). *User participation in building design and management: a generic approach to building evaluation.* UK: Butterworth Architecture.

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science*, 220, 671-680.

Kooi, F. L., & Toet, A. (2004). Visual comfort of binocular and 3D displays. *Displays*, 25, 2-3.

Kryter, K. D. (1970). *The effects of noise on man.* New York: Academic Press.

Kull, R. C. (2006). Natural and urban soundscapes: The need for a multi-disciplinary approach. *Acta Acustica United with Acustica*, 92, 898-902.

Lang, J. (1988). Symbolic aesthetics in architecture: Toward a research agenda. In J. L. Nasar (Ed.), *Environmental aesthetics* (pp.11-26). Cambridge: Cambridge University Press.

Lechner, N. (1991). *Heating, cooling, lighting: Design methods for architects.* New York: Wiley.

Lee, J. J., Lee, J. W., Yi, J. H., Yun, C. B., & Jung, H. Y. (2005). Neural networks-based damage detection for bridges considering errors in baseline finite element models. *Journal of Sound and Vibration*, 280(3-5), 555-578.

Legendre, A-M. (1805). *Nouvelles méthodes pour la détermination des orbites des comètes.* Paris: F. Didot.

Lennard, S. H. C. & Lennard, H. L. (1987). *Livable cities: People and places, social and design principles for the future of the city.* Southampton; New York: Gondolier Press.

Ling, F. Y. Y., & Liu, M. (2004). Using neural network to predict performance of design-build projects in Singapore. *Building and Environment*, 39, 1263-1274.

Lozano, E. E. (1974). Visual needs in the urban environment. *Town Planning Review*, 45, 351-374.

Maffiolo, V., David, S., Dubois, D., Vogel, C., Castellengo, M., & Polack, J. D. (1997). Sound characterization of urban environment. *Proceedings of Inter-Noise*, Budapest, Hungary.

Mahoney, M. S. (1973). *The mathematical career of pierre de fermat 1601-1665.* New Jersey: Princeton University Press

Maier, H. R., & Dandy, G. C. (1998). The effect of internal parameters and geometry on the performance of back-propagation neural networks: An empirical study. *Environmental Modelling and Software*, 13, 193-209.

Marcus, C. C., & Francis, C. (1997). *People places* (2nd ed.). London; New York: Van Nostrand Reinhold.

McCormack, B. & Hill, E. (1997). *Conducting a survey: The SPSS workbook.* London: International Thomson.

McCulloch, W. S., & Pitts, W. H. (1943). A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics*, 5, 115-133.

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology.* London: MIT Press.

Mehrotra, K., Mohan, C. K., & Ranka, S. (1996). *Elements of artificial neural networks.* Cambridge, Massachusetts: MIT Press.

Miedema, H. M. E., & Vos, H. (1998). Exposure-response relationships for transportation noise. *J. Acoust. Soc. Am.*, 104, 3432-45.

Minsky, M., & Papert, S. (1969). *Perceptrons.* Cambridge, Massachusetts: MIT Press.

Moore, B. C. J. (1997). *An introduction to the psychology of hearing* (4th ed.). San Diego, California; London: Academic Press.

Nannariello, J., & Fricke, F. R. (1999). The prediction of reverberation time using neural network analysis. *Applied Acoustics*, 58(3), 305-325.

Nannariello, J., & Fricke, F. R. (2001a). The use of neural network analysis to predict the acoustic performance of large rooms: Part I predictions of the parameter G utilizing numerical simulations. *Applied Acoustics*, 62, 917-950.

Nannariello, J., & Fricke, F. R. (2001b). The use of neural network analysis to predict the acoustic performance of large rooms: Part II predictions of the acoustical attributes of concert halls utilizing measured data. *Applied Acoustics*, 62, 951-977.

Nannariello, J., & Fricke, F. R. (2001c). Neural network predictions of speech levels in university classrooms. *Applied Acoustics*, 62, 749-767.

Nannariello, J., & Fricke, F. R. (2002). A neural-computation method of predicting the early inter-aural cross-correlation coefficient (IACCE3) for auditoria. *Applied Acoustics*, 63, 627-641.

Nasar, J. L. (1989). Perception, cognition, and evaluation of urban places. In: I. Altman & E. H. Zube (Eds.), *Public places and spaces* (pp. 31-56). New York: Plenum Press.

NeuroDimension (1995). *NeuroSolutions users manual.* Gainesville, Florida: NeuroDimensions Inc.

Newbold, P. (1991). *Statistics for business and economics* (3rd ed.). Englewood Cliffs, New Jersey: Prentice Hall.

Newman, O. (1972). *Defensible space: people and design in the violent city.* London: Architectural Press.

Nikolopoulou, M. (Ed.) (2004). *Designing open spaces in the urban environment: A bioclimatic approach.* Greece: CRES, Attiki.

Nikolopoulou, M., Lykoudis, S., & Kikira, M. (2004). Thermal comfort models for open urban spaces. In M. Nikolopoulou (Ed.), *Designing open spaces in the urban environment: A bioclimatic approach* (pp. 2-6). Greece: CRES, Attiki.

Nilsson, M. E., & Berglund, B. (2006). Soundscape quality in suburban green areas and city parks. *Acta Acustica United with Acustica*, 92, 857-864.

Maorphet, J. (1994). Parks, open spaces & the future of urban planning. In *Working paper; no.5.* Bournes Green: Comedia & Demos.

Pallant, J. (2005). *SPSS survival manual* (2nd ed.). UK: Open University Press.

Patterson, D. W. (1996). *Artificial neural networks: Theory and applications.* Singapore; London: Prentice-Hall.

Peterson, R. A. (2000). *Constructing effective questionnaires.* London; Thousand Oaks, California: Sage Publications.

Pheasant, R., Horoshenkov, K., & Watts, G. (2008). The acoustic and visual factors influencing the construction of tranquil space in urban and rural environments tranquil spaces-quiet places. *J. Acoust. Soc. Am.*, 123(3), 1446-1457.

Porteous, J. D., & Mastin, J. F. (1985). Soundscape. *Journal of Architectural and Planning Research*, 2, 169-186.

Proshansky, H. M. (1976). Environmental psychology and the real world. *American Psychologist*, 31, 303-310.

Quetelet, A., & Beamish, R. (1839). *Popular instructions on the calculation of probabilities.* London: J. Weale.

Raimbault, M., & Dubois, D. (2005). Urban soundscapes: Experiences and knowledge. *Cities*, 22, 339-350.

Rapoport, A. (1989). *The meaning of the built environment: A nonverbal communication approach.* California: Sage Publications.

Rebaño-Edwards, S. (2007). Modelling perceptions of building quality: A neural network approach. *Building and Environment*, 42, 2762-2777.

Rochester, N., Holland, J., Haibt, L., & Duda, W. (1956). Test on a cell assembly theory of the action of the brain, using a large digital computer. *IRE Transactions on Information Theory*, 2(3), 80-93.

Rosenblatt, F. (1958). The perceptron: A probabilistic model for information storage and organization in the brain. *Psychological Review*, 65, 386-408.

Rumelhart, D. E., Hinton, G. E. & Williams, R. J. (1986). Learning internal representations by error propagation, in parallel distributed processing: Explorations in the microstructures of cognition. In Rumelhart, D. E. & McClelland, J. L. (Eds.), *Vol. 1: Foundations*. Cambridge, Massachusetts: MIT Press.

Russell, J. A., & Snodgrass, J. (1987). Emotion and environment. In D. Stokols & I. Altman (Eds.), *Handbook of environment psychology* (pp. 245-280). New York: Wiley.

Schafer, R. M. (1977). *The tuning of the world.* Toronto: McClelland & Stewart.

Schaudinischky, L. H. (1976). *Sound, man and building.* London: Applied Science.

Schelemay, K. K. (2001). *Soundscape*. New York: Norton.

Schulte-Fortkamp, B. (1996). Combined methods to investigate effects of noise exposure and subjective noise assessment. *Proceedings of Inter-Noise*, Liverpool, UK.

Schulte-Fortkamp, B., & Nitsch, W. (1999). On soundscapes and their meaning regarding noise annoyance measurements. *Proceedings of Inter-Noise*, Fort Lauderdale, Florida, USA.

Schulte-Fortkamp, B. (2002, April-June). The meaning of annoyance in relation to the quality of acoustic environments. *Noise and Health, 4* (15), 13-18.

Schulte-Fortkamp, B. (2006). Soundscape analysis in a residential area: An evaluation of noise and people's mind. *Acta Acustica United with Acustica*, 92, 875-880.

Sejnowski, T. J., & Churchland, P. S. (1992). Silicon brains. *Byte* 17 (10), 131-139.

Sekuler, R., Sekuler, A. B., & Lau, R. (1997). Sound alters visual motion perception. *Nature*, 385, 308.

Selye, H. (1978). *The stress of life*. New York: McGraw-Hill.

Shamey, R., & Hussain, T. (2003). Artificial intelligence in the colour and textile industry. *Rev. Prog. Color*, 33, 33-45.

Shepherd, G. M., & Koch, C. (1990). Dendritic electrotonus and synaptic integration. In G. M. Shepherd (Ed.), *The synaptic organization of the brain*. New York: Oxford University Press.

Shin, Y. G., Ji-Hyeon, J., Chan, K., & Sun-Woo, K. (2007). Evaluation of human emotions depending on variations in audio-visual landscape elements in residential areas. *Proceedings of 19th International Congress on Acoustics (ICA)*, Madrid.

Southworth, M. (1969). The sonic environment of cities. *Environment and Behaviour*, 1, 49–70.

Stokols, D., & Altman, I. (1987). *Handbook of environmental psychology*. New York; Chichester: Wiley.

Swingler, K. (1996). *Applying neural networks: A practical guide*. London: Academic Press.

Szewczyk, Z., & Hajela, P. (1994). Damage detection in structures based on feature-sensitive neural networks. *Journal of Computer Civil Engineering*, 8(2), 163-178.

Tankel, S. (1963). The recreational and aesthetic significance of urban woodland. *Landscape Research*, 7(3), 22-25.

Taylor, L. (1979). *Urban open spaces*. London: Academy Editions.

Templeton, D., & Sacre, P. (1997). *Acoustic in the built environment: Advice for the design team* (2nd ed.). Oxford: Architectural Press.

Thompson, E. A. (2002). *The soundscape of modernity: Architectural acoustics and the culture of listening in America*. Cambridge, Massachusetts; London: MIT Press.

Tipper, J., Beighton, H., Heath, R., Simpson, T., Rollinson, E., Hutton, C., & Gregory, O. (1835). *The ladies' diary: or, woman's almanack, for the year of our lord*. Company of Stationers: J. Wilde. Original: Harvard University.

Tong, Y. Z., & Steven, L. G. P. (2000). Vibration-based model-dependent damage (delamination) identification and health monitoring for composite structures—a review. *Journal of Sound and Vibration*, 230(2), 357-378.

Torigeo, K. (1985). Review of soundscape research and some problems (in Japanese). *Bull. Jpn. Soc. Sci. Des.*, 53, 13-18.

Torigeo, K. (1993). Expansion of the framework of acoustic environment and new dimensions of acoustic design explored by the concept of soundscape. *Proceedings of International Symposium on Design of Amenity*, 232-234.

Tracor, Inc. (1971). Community reactions to airport noise, Vol.1. In *NASA Report CR-1761*. Washington, DC: National Aeronautics and Space Administration.

Truax, B. (1978) (Ed.). *A handbook for acoustic ecology*. Vancouver: ARC Publication.

Truax, B. (1998). Models and strategies for acoustic design. *The Hey Listen! Conference, the Royal Swedish Academy of Music*, Stockholm, Sweden.

Tuaycharoen, N. (2006). *The reduction of discomfort glare from windows by interesting views* (PhD dissertation). Sheffield: University of Sheffield.

United Nations Centre for Human Settlements (UNCHS) (1996). *An urbanizing world: Global report on human settlements*. Oxford: Oxford University Press.

Vanluchene, R. D., & Sun, R. (1990). Neural network in structural engineering. *Microcomp. Civil Engng.*, 5, 109-18.

Vapnik, V. (1998). *Statistical learning theory*. New York: Wiley.

Verzini, A., Frassoni, C., & Oritiz, A. H. (1999). A field study about effects of low frequency noise on man. *Proceedings of the 137th Meeting of the Acoustical Society of America and Forum Acusticum*, Berlin, Germany. Abstract published in *J. Acoust. Soc. Am.*, 105, 942.

Vesta Services Inc. (2000). *Qnet users manual*. Winnetka Illinois, USA.

Walzer, M. (1986). Pleasure and costs of urbanity. *Dissent*, 33(4), 470-475.

Wang, B., Kang, J., & Zhou, J. (2007). Effects of urban morphologic characteristics on the noise mapping: A generic comparison between UK and China. *Proceedings of the 19th International Congress on Acoustics (ICA)*, Madrid, Spain.

Woolley, H. (2003). *Urban open spaces*. London: Spon Press.

Watanabe, K., & Shimojo, S. (2002). When sound affects vision: Effects of auditory grouping on visual motion perception. *Psychological Science*, 12(2), 109-116.

Westerkamp, H. (2000). Sound excursion: Plano pilato, Brasilia. *Soundscape: The Journal of Acoustic Ecology*, 1, 20-21.

Whrightson, K. (2000). An introduction to acoustic ecology. *Soundscape*, 1, 10-13.

Widrow, B., & Hoff, M. E. (1988). *Adaptive switching circuits.* Cambridge, Massachusetts: MIT Press.

Wonnacott, T. H., & Wonnacott, R. J. (1990). *Introductory statistics.* New York: Wiley.

Yamagishi, K., & Yamagishi, M. (1999). *What is soundscape* (in Japanese). Tokyo: NHK Press.

Yang, W. (2005). *An aesthetic approach to the soundscape of urban public open spaces* (PhD dissertation). Sheffield: University of Sheffield.

Yang, W., & Kang, J. (2005a). Soundscape and sound preferences in urban squares: A case study in sheffield. *Urban Design,* 10, 69-88.

Yang, W., & Kang, J. (2005b). Acoustic comfort evaluation in urban open public spaces. *Applied Acoustics,* 66, 1119-1125.

Yu, L. (2003). *Predicting sound field and acoustic comfort in urban open spaces using neural network* (MArch dissertation). Sheffield, University of Sheffield.

Yu, L., & Kang, J. (2005a). Soundscape evaluation in city open spaces using artificial neural network. *Proceedings of UIA – XXII World Congress of Architecture,* Turkey.

Yu, L., & Kang, J. (2005b). Neural network analysis of soundscape in urban open spaces. *The 149th Meeting of the Acoustical Society of America,* Vancouver, Cannada. Abstract also published in *J. Acoust. Soc. Am.*, 117, 2591.

Yu, L., & Kang, J. (2006). Integration of social/demographic factors into the soundscape evaluation of urban open spaces using artificial neural networks. *Proceedings of the 35th Inter-Noise,* Honolulu, USA.

Yu, L., & Kang, J. (2007). Mapping soundscape evaluation in urban open spaces with artificial neural networks and ordinal logistic regression. *Proceedings of 19th International Congress on Acoustics (ICA),* Madrid.

Yu, L., & Kang, J. (2008a). Effects of social, demographical and behavioral factors on the sound level evaluation in urban open spaces. *J. Acoust. Soc. Am.*, 123, 772-783.

Yu, L., & Kang, J. (2008b). Transforming public assessment to soundscape design. *The Proceedings of UIA – XXIII World Congress of Architecture,* Turin, Italy.

Yu, L., & Kang, J. (2009a). Soundscape prediction and design. *The Proceedings of the 40th EDRA Meeting,* Kansas City, USA.

Yu, L., & kang, J. (2009b). Modeling subjective evaluation of soundscape quality in urban open spaces: An artificial neural network approach. *J. Acoust. Soc. Am.*, under review.

Zhang, M., & Kang, J. (2007a).Towards the evaluation, description, and creation of soundscapes in urban open spaces. *Environment and Planning B: Planning and Design*, 34, 68-86.

Zhang, M., & Kang, J. (2007b). Subjective evaluation of urban environment: A case study in Beijing. *International Journal of Environment and Pollution*, Accepted for publication.

Zhang, Q., & Stanley, S. J. (1997). Forecasting raw-water quality parameters for the north Saskatchewan River by neural network modelling. *Water Research*, 31(9), 2340-2350.

Zetzsche, C., Röhrbein, F., Hofbauer, M., & Schill, K. (2002). Audio-visual sensory interactions and the statistical covariance of the natural environment. *Proc. Forum Acousticum 2002, 3rd Conv. Europ. Acoust. Assoc.*, Sevilla, Spain.

Zwicker, E., & Fastl, H. (1999). P*sychoacoustics: Facts and models* (2nd ed.). Berlin; New York: Springer.

# Appendix I:

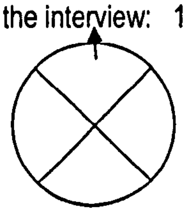
## Questionnaires for the EU surveys

### A. OBSERVATIONS

Description of subject: date - time
location in space (indicate on map)
activity

**Circle where appropriate**

- Age group: (1) child, (2) teenager, (3) 18-24, (4) 25-34, (5) 35-44, (6) 45-54, (7) 55-64, (8) >65
- Sex: (1) Male, (2) Female
- Clothing - T-shirt, (sleeveless/short/long) shirt, (cotton/woollen) jumper, sweatshirt
  - shorts, trousers, jeans, skirt (long, short), dress (short/long, no/short/long sleeves)
  - vest, cardigan, jacket (denim/cotton, wool), raincoat, overcoat, tie
  - umbrella
- 1) Cap/hat 1) Sunglasses *(0) corresponds to absence of it*
- 1) Earphone *(0) corresponds to absence of it*
- Food/drink consumption: a) Cold drink b) Hot drink c) Food
- Interviewee is there: 1) Alone 2) With 1 person 3) With more than 2 persons 4) With a dog
- Interviewee presently stay in sunlight: 1) Yes 2) No
- Person making movements to screen his/her eyes from excessive light (e.g. moving hands above the eyes, rotating or bending the head, blinking) 1) Yes 2) No
- Interviewee performing a reading or writing task just before the interview: 1) Yes 2) No
- Interviewee watching something distant (i.e. >10m away) just before the interview: 1) Yes 2) No
- Which direction sector is the Interviewee presently looking at?



### B. QUESTIONS

- At the moment, do you find it:

| | | | | |
|---|---|---|---|---|
| -2 | -1 | 0 | +1 | +2 |

- What do you think of the **sun** at this moment? *(only asked if sunny)*

| | | |
|---|---|---|
| -1 | 0 | +1 |

- What do you think of the **wind** at this moment?

| | | | | |
|---|---|---|---|---|
| -2 | -1 | 0 | +1 | +2 |

- What do you think of the **humidity** at this moment?

| | | |
|---|---|---|
| -1 | 0 | +1 |

- Are you feeling **comfortable**?

| | |
|---|---|
| 1 | 2 |

- What do you think of the **luminous appearance** of this space?

| | | | | |
|---|---|---|---|---|
| -2 | -1 | 0 | +1 | +2 |

- Do any surfaces appear noticeably **glaring** to you? *(Some answers may not apply for certain cases)*

| | | | | | | |
|---|---|---|---|---|---|---|
| 1 | No | | | | | |
| 2 | Ground or pavement | Surrounding buildings | Vegetation | Water surface | Urban furniture | Canopy or sky |

- Does the **view** from your position affects your appreciation of this site?

| | | |
|---|---|---|
| -1 | 0 | +1 |

- What is your general feeling towards the **sound level** in this space at this moment?

| | | | | |
|---|---|---|---|---|
| -2 | -1 | 0 | +1 | +2 |

- How would you describe the **acoustic** environment at your **home**?

| | | | | |
|---|---|---|---|---|
| -2 | -1 | 0 | +1 | +2 |

- Classify the **4** predominant of the following sounds by ***'annoyance', 'neither favour nor annoyance', 'favour'*** *(Choose 4 sounds only according to the site)*

| | | |
|---|---|---|
| (1) Twittering of birds (A, N, F) | (6) Speaking from surrounding people (A, N, F) | (11) Children's shouting (A, N, F) |
| (2) Bells of church (A, N, F) | (7) Pedestrian crossing (A, N, F) | (12) Passenger cars (A, N, F) |
| (3) Murmurs of water (A, N, F) | (8) Bells or music from clock (A, N, F) | (13) Passenger buses (A, N, F) |
| (4) Music played on street (A, N, F) | (9) Music from passenger cars (A, N, F) | (14) Music from stores (A, N, F) |
| (5) Insects sound (A, N, F) | (10) Vehicle parking (A, N, F) | (15 )Constructions (A, N, F) |

- Why have you come here?
  ..............................................................................................
- Where were you before you came here?
  ..........................................................................
- How frequently do you use the space? 1) per day.... 2) per week.... 3) per month... 4) per year.......
- Is there something you don't like in the area?
  ......................................................................
- What is the use of open space according to your opinion? ....................................................
- Are you local inhabitant? 1) Yes 2) No (Where are you from?...................................... )
- Are you a? 1) pupil/student 2) working person 3) pensioner 4) housekeeper 5) other*...........

  (* ask if tourist and additionally note here)
- What is your educational level? 1) primary school 2) secondary school 3) university

## Appendix II:

### Questionnaires for the Chinese surveys

## 调查员观察表 （调查员填写）

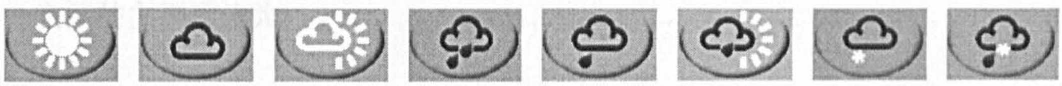
■ 调查地点： 畅春园 调查纪录号：____________

调查员姓名：________________

调查日期： ___/___/___（日/月/年）[星期一 星期二 星期三 星期四 星期五 星期六 星期日 假日]

调查时段： 从________小时(24)______分钟 到________小时(24)______分钟

天气质量：



| 晴 | 阴 | 多云间晴 | 大雨 | 小雨 | 晴间雨 | 雪 | 雨加雪 |
|---|---|---|---|---|---|---|---|
| ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

**1. 被访者性别及行为描述**

性别： ☐男 ☐女

行为：（可以多选）

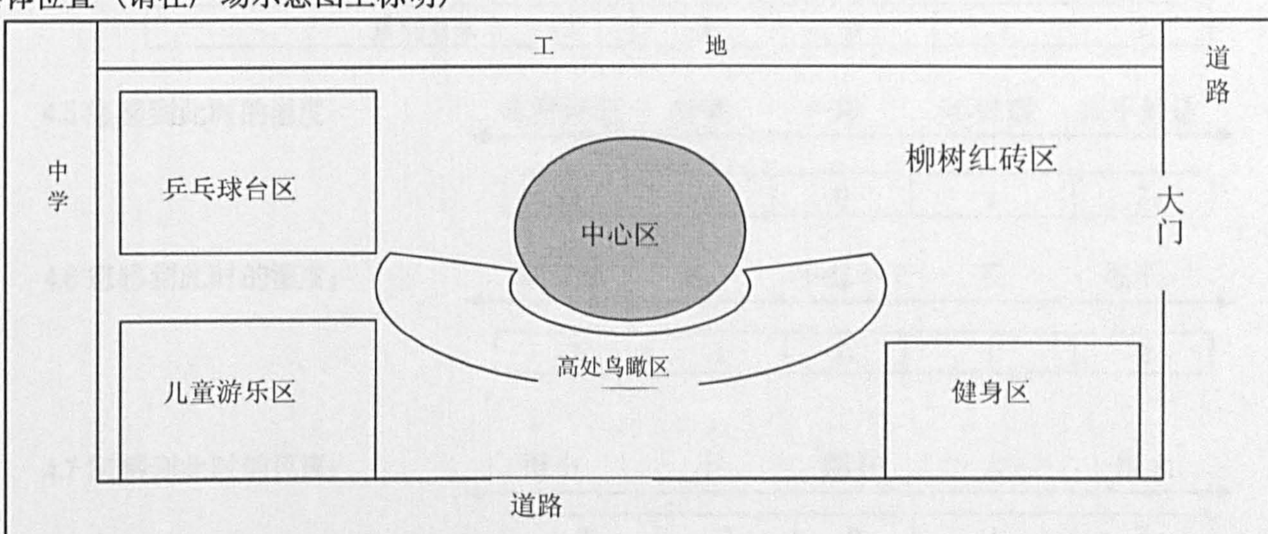
☐ 坐 ☐站 ☐散步 ☐戴耳机听音乐 ☐晒太阳或乘凉 ☐看风景或散步

☐ 读书或看报 ☐眺望 10 米之外的景物 ☐眺望 10 米之内的景物

☐ 与一人以上同行 ☐与宠物同行 ☐体育活动 ☐和孩子(们)一起玩

☐其他 1. ________________（请写出） ☐ 其他 2. ____________________（请写出）

**2.具体位置（请在广场示意图上标明）**




**3. 调查时，使用该空间的人数与正常使用时相比：** ☐很多 ☐多 ☐正常 ☐少 ☐很少

**4. 调查时，该户外空间上有无音乐：** ☐有（请描述为何种音乐）________________ ☐无

**5. 该户外空间周围若有商店及饮 食店时， 则调查营业状况：**

☐全开 ☐多数开 ☐一些开 ☐少数开 ☐全 关

| | | | |
|---|---|---|---|
| 温度：________ | 湿度：________ | 风速：________ | 照度：________ |
| 调查时的声级 ________一分钟 Leq dB(A) | | ［或声级计数据储存号码________________］ | |

## 问卷：（调查员或被调查者填写）

1. 您为什么到这里来？……………………………………………………………………

2. 您经常到这里来吗？

| 几乎每天 | 经常 | 有时 | 偶尔 | 第一次 |
|---|---|---|---|---|
| -2 | -1 | 0 | 1 | 2 |

3. 您认为该户外空间的主要用途为：……………………………………………………

4. 被调查者感受：

4.1 您现在总体感觉舒适吗？　□舒适　　□不舒适

4.2 您　音环境：

| 非常安静 | 安静 | 不静也不吵 | 吵 | 非常吵 |
|---|---|---|---|---|
| -2 | -1 | 0 | 1 | 2 |

4.3 您　回声：

| 非常强 | 强 | 不强也不弱 | 弱 | 非常弱 |
|---|---|---|---|---|
| -2 | -1 | 0 | 1 | 2 |

4.4 请评价以下各项的满意程度：

| | 很不满意 | 不满意 | 一般 | 满意 | 很满意 |
|---|---|---|---|---|---|
| 此户外空间的声音环境 | -2 | -1 | 0 | 1 | 2 |
| 光线效果 | -2 | -1 | 0 | 1 | 2 |
| 视觉效果 | -2 | -1 | 0 | 1 | 2 |
| 景观效果 | -2 | -1 | 0 | 1 | 2 |

4.5 您感到此时的温度：

| 非常舒适 | 舒适 | 一般 | 不舒适 | 很不舒适 |
|---|---|---|---|---|
| -2 | -1 | 0 | 1 | 2 |

4.6 您感到此时的湿度：

| 非常湿 | 湿 | 不湿不干 | 干 | 很干 |
|---|---|---|---|---|
| -2 | -1 | 0 | 1 | 2 |

4.7 您感到此时的风速：

| 很小 | 小 | 温和 | 大 | 很大 |
|---|---|---|---|---|
| -2 | -1 | 0 | 1 | 2 |

5. 您此刻能听到什么声音？

1.……………………………　2.……………………………　3.……………………………

哪种是您最喜欢的（1）……………………………（2）都不喜欢……………………………

您希望在这里听到的声音有哪些 …………………………………………………………

此户外空间内您不想听到的声音有哪些 …………………………………………………

6. 请评价现在的声景(声音环境)(在相应的位置打√)

| | 极度 | 非常 | 有些 | 都不是 | 有些 | 非常 | 极度 | |
|---|---|---|---|---|---|---|---|---|
| 不舒适 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 舒适 |
| 不喜欢 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 喜欢 |
| 吵闹 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 安静 |
| 生硬 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 平缓 |
| 人工化 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 自然的 |
| 慢 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 快 |
| 近 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 远 |
| 软 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 硬 |
| 尖锐 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 平和 |
| 弱 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 强 |
| 直接的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 多方位 |
| 简单 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 复杂 |
| 无回声 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 有回声 |
| 不平稳 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 平稳 |
| 丑恶 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 美丽 |
| 消极的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 积极的 |
| 悲伤 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 高兴 |
| 无聊 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 有趣 |
| 镇静的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 烦恼的 |
| 平滑的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 干涩的 |
| 不友好的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 友好的 |
| 无意义 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 有意义 |

7. 请评价以下二种声音

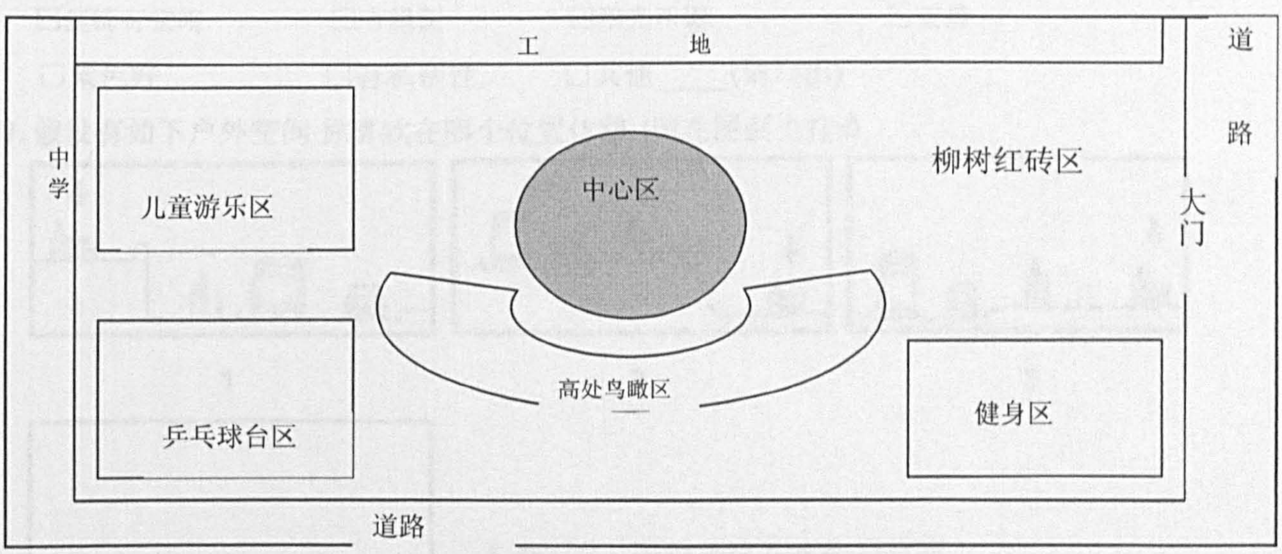
*声音一：汽车行驶声音*

| | 极度 | 非常 | 有些 | 都不是 | 有些 | 非常 | 极度 | |
|---|---|---|---|---|---|---|---|---|
| 不舒适 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 舒适 |
| 不喜欢 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 喜欢 |
| 吵闹 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 安静 |
| 生硬 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 平缓 |
| 人工化 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 自然的 |
| 慢 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 快 |
| 近 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 远 |
| 软 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 硬 |
| 尖锐 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 平和 |
| 弱 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 强 |
| 直接的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 多方位 |
| 简单 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 复杂 |
| 无回声 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 有回声 |
| 不平稳 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 平稳 |
| 丑恶 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 美丽 |
| 消极的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 积极的 |
| 悲伤 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 高兴 |
| 无聊 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 有趣 |
| 镇静的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 烦恼的 |
| 平滑的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 干涩的 |
| 不友好的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 友好的 |
| 无意义 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 有意义 |

*声音二：人声、蝉鸣鸟叫声或音乐声*

| | 极度 | 非常 | 有些 | 都不是 | 有些 | 非常 | 极度 | |
|---|---|---|---|---|---|---|---|---|
| 不舒适 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 舒适 |
| 不喜欢 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 喜欢 |
| 吵闹 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 安静 |
| 生硬 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 平缓 |
| 人工化 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 自然的 |
| 慢 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 快 |
| 近 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 远 |
| 软 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 硬 |
| 尖锐 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 平和 |
| 弱 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 强 |
| 直接的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 多方位 |
| 简单 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 复杂 |
| 无回声 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 有回声 |
| 不平稳 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 平稳 |
| 丑恶 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 美丽 |
| 消极的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 积极的 |
| 悲伤 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 高兴 |
| 无聊 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 有趣 |
| 镇静的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 烦恼的 |
| 平滑的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 干涩的 |
| 不友好的 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 友好的 |
| 无意义 | -3 | -2 | -1 | 0 | 1 | 2 | 3 | 有意义 |

**8. 如果您需要在这里选择一个位置坐下休憩，您会选择（请在图上表示）**




**9. 如果您需要在这里选择一个位置坐下休憩，你是否会选择安静的地点？** □是 □不是

**10. 多数户外空间具有以下一种或多种声音，请根据您的喜好填写：**

（*1*——喜欢； *0*——不闹也不喜欢； *-1*——闹）

| | | | | | |
|---|---|---|---|---|---|
| 鸟叫 | | 周围人们的谈话声 | | 儿童喧闹叫喊声 | |
| 报时钟声 | | 行人走路声 | | 过路小汽车声 | |
| 流水声 | | 音乐声 | | 过路公交车声 | |
| 喷泉声 | | 过路汽车里传出的音乐声 | | 商店的音乐声 | |
| 昆虫鸣叫声 | | 过路汽车停泊的声音 | | 土建工程声 | |

**11.** 你现在住在以下什么区域

☐市区、生活小区　☐工商业聚集区　☐郊区,别墅区　☐其他________(请写出)

**12.** 您喜欢所住地方的声环境吗？　☐喜欢　☐不喜欢

**13.** 你在家中常能听见的声音为哪些 ..........................................................

**14.** 请评价你家(所住的地方)的声环境　非常安静　安静　不静也不吵　吵　非常吵闹

| | | | | |
|---|---|---|---|---|
| -2 | -1 | 0 | 1 | 2 |

**15.** 如果你需要找一个户外空间放松或休憩, 如下哪类声环境的地点你会考虑

☐安静,只有自然声　☐近处有自然声,远处可以有人为声为背景

☐自然声和人为声混合　☐只有人为声

能解释一下为什么吗?

..........................................................................................................................

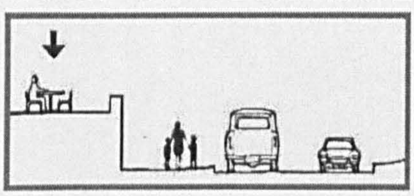
..........................................................................................................................

**16.** 如果你需要在这里选择一个位置坐下休憩, 哪些因素是你会考虑的

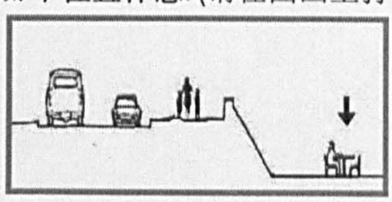
☐座椅有空闲　☐有绿荫　☐阳光明媚　☐安静

☐景色好　☐有私密性　☐其他_____(请写出)

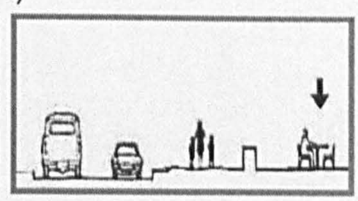
**17.** 假设有如下户外空间 你喜欢在哪个位置休憩: (请在图画上打√)



1



2



3

4 *都不是，请绘出您所喜欢的位置*

**18.** 您认为以下何种因素为 “ 影响城市户外空间舒适度” 的主要因素 (可以多选)

☐声音　☐温度　☐阳光及亮度　☐湿度　☐风速　☐绿地及植物　☐气味

☐固定设施 ( 座椅、长椅、冷热饮等)　☐服务设施 (冷热饮,咖啡等)

☐空气质量　☐安全　☐其他 (请写出) ____________

**19.**请选择下列“城市环境污染”危害性的程度

| | | 非常 | 严重 | 一般 | 不严重 | 极小 |
|---|---|---|---|---|---|---|
| 空气污染 | | | | | | |
| 噪声污染 | | | | | | |
| 水污染 | | | | | | |
| 强光及反光 (光污染) | | | | | | |
| 气味 | | | | | | |
| 化学污染（例：医院，化工厂等） | | | | | | |
| 城市垃圾 | | | | | | |
| 放射性及核污染 | | | | | | |
| 其他 (请写出) | | | | | | |
| 其他 (请写出) | | | | | | |

## 个人信息

***请问您的年龄属于以下哪个年龄段***：☐12 岁以下 ☐13-18 岁 ☐18-24 岁 ☐25-34 岁 ☐35-44 岁 ☐45-54 岁 ☐55-64 岁 ☐65 岁以上

***您的职业是***：______

***您的教育程度***：☐小学 ☐中学(初中,高中) ☐大学及大学以上

***您是***：☐本地居民 ☐暂住人员（来自______省） ☐旅游及探亲访友（来自______省）

***您每月的大致收入是***：☐无固定收入 ☐500 元以下 ☐501-1000 元 ☐1001-2000 元 ☐2001-3000 元 ☐3001-5000 元 ☐5001-10000 元 ☐10000 元以上

# Appendix III:

## Questionnaires for the laboratory experiments

**Instruction:** **There are three parts in the survey. Please answer questions in Part one without hearing. Answer questions in Part two after hearing each sound. Answer questions in Part three after watching each sound video.**

### PART ONE

**1. Please classify the following sounds by ticking "1: annoyance"; "0: neither favour nor annoyance"; "-1: favour"**

| | | | | | |
|---|---|---|---|---|---|
| Twittering of birds | | Speaking from surrounding people | | Traffic | |
| Bells of church/clock | | Children's shouting | | Constructions | |
| Insects sound | | Music played on a square | | Skateboard | |

## PART TWO

### 2. Please answer the below questions according the sounds you have heard

| | Which kind of the sounds have you heard | Classify the sound by "1: annoyance"; "0: neither favour nor annoyance"; "-1: favour" | | | How do you feel of the sound | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | very | fair | neural | fair | very | |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 1** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 2** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 3** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 4** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 5** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 6** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 7** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 8** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 9** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 10** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| | | | | | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| **Sound 11** | | **1** | **0** | **-1** | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |

## PART THREE

### 3. Please answer the below questions according the sounds you have heard

| | Which kind of the sounds have you heard | Classify the sound by "1: annoyance"; "0: neither favour nor annoyance"; "-1: favour" | | | How do you feel of the sound | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | very | fair | neural | fair | very | |
| Sound 12 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| Sound 13 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| Sound 14 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| Sound 15 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| Sound 16 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |

### 4. Please answer the below questions after see videos

| | Which kind of the sounds have you heard | Classify the sound by "1: annoyance"; "0: neither favour nor annoyance"; "-1: favour" | | | How do you feel of the sound | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | very | fair | neural | fair | very | |
| Sound 12 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| Sound 13 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| Sound 14 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| Sound 15 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |
| Sound 16 | | 1 | 0 | -1 | Noisy | 2 | 1 | 0 | -1 | -2 | Quiet |
| | | | | | Discomfort | 2 | 1 | 0 | -1 | -2 | Comfort |
| | | | | | Unpleasant | 2 | 1 | 0 | -1 | -2 | Pleasant |

# Appendix IV:

## Relationships between social/demographical, physical, behavioural, and psychological factors

| Site | Age | | | | Gender | | | | Occupation | | | | Education | | | | Residence | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Season | Time | Frequency | Site Preference | Season | Time | Frequency | Site Preference | Season | Time | Frequency | Site Preference | Season | Time | Frequency | Site Preference | Season | Time | Frequency | Site Preference |
| 1 | 0.06 | -0.02 | 0.05 | 0.02 | -0.10 | -0.10 | 0.03 | -0.06 | 0.30 | 0.06 | -0.19 (**) | -0.01 | 0.01 | 0.12(*) | 0.46 | -0.22(**) | 0.15 | -0.17 | -0.62(**) | 0.05 |
| 2 | 0.01 | 0.07 | 0.07 | 0.50(**) | -0.05 | 0.17(*) | 0.15 | -0.06 | 0.06 | 0.02 | -0.14(**) | 0.22(**) | 0.94 | -0.01 | 0.13 | -0.10 | 0.16 | -0.18(*) | -0.59(**) | 0.04 |
| 3 | 0.00 | 0.19(**) | 0.00 | 0.32(*) | -0.03 | 0.19 | 0.31(**) | -0.06 | 0.00 | 0.12(**) | 0.00 | 0.05 | 0.10 | -0.01 | 0.00 | -0.20(**) | 0.02 | 0.04 | -1.13(**) | -0.09(*) |
| 4 | 0.05 | -0.08(**) | 0.27(**) | 0.13 | 0.06 | -0.09 | 0.09 | 0.05 | 0.04 | -0.01 | 0.21(**) | 0.14(**) | -0.08 | 0.04 | -0.16(**) | -0.21(**) | 0.27(**) | 0.05 | -0.67(**) | 0.02 |
| 5 | 0.00 | -0.12(**) | 0.08(*) | -0.16 | -0.08 | -0.04 | 0.16(**) | 0.02 | 0.00 | -0.07 | 0.07 | -0.03 | -0.02 | 0.05 | -0.21(**) | -0.21(**) | 0.04 | 0.02 | -0.19(**) | -0.05 |
| 6 | 0.11(**) | -0.09(**) | 0.02 | 0.30(*) | -0.18(**) | 0.09 | 0.13(*) | -0.10(**) | 0.11(**) | -0.09(**) | 0.00 | 0.07 | -0.10(**) | 0.01 | -0.06(*) | -0.19(**) | -0.12 | 0.08 | -0.60(**) | -0.01 |
| 7 | 0.02 | -0.16(**) | 0.07 | 0.33(*) | -0.20(*) | -0.12 | 0.09 | -0.09(*) | 0.08 | -0.19(**) | 0.09(*) | 0.17(**) | 0.09(*) | 0.12(**) | -0.08(*) | -0.34(**) | 0.12 | 0.38(**) | -0.52(**) | -0.02 |
| 8 | 0.00 | -0.05 | 0.06 | 0.12 | -0.03 | 0.01 | -0.14 | 0.00 | 0.08(*) | -0.11(**) | 0.09(*) | 0.01 | -0.12(**) | 0.05 | -0.06 | -0.14(**) | -0.24 | 0.33(**) | -0.94(**) | -0.03 |
| 9 | -0.16(**) | -0.17(**) | 0.04 | 0.33(**) | 0.03 | 0.06(**) | 0.01 | -0.11 (**) | -0.11(**) | -0.17(**) | 0.01 | 0.10(*) | -0.03 | -0.06 | -0.14(**) | -0.18(**) | 0.15 | 0.34(**) | -0.72(**) | 0.01 |
| 10 | 0.02 | -0.16(**) | -0.23(**) | -0.19 | -0.14(*) | 0.07 | -0.02 | -0.05 | 0.03 | -0.13(**) | -0.25(**) | 0.00 | -0.03 | -0.04 | 0.04 | -0.13(**) | 0.03 | 0.03 | -0.64(**) | -0.12(**) |
| 11 | 0.20(**) | -0.04 | -0.19(**) | 0.36(*) | 0.07 | -0.17 | 0.10 | 0.00 | 0.05 | 0.03 | -0.12(*) | 0.15(*) | 0.02 | 0.00 | -0.05 | -0.05 | 0.31(**) | 0.11 | -1.17(**) | -0.13(**) |
| 12 | 0.08 | 0.00 | -0.30(**) | 0.27 | 0.02 | -0.15 | 0.09 | 0.08 | -0.11(*) | -0.09(*) | -0.28(**) | 0.05 | 0.00 | -0.07 | 0.08 | -0.16(**) | 0.54(**) | 0.05 | -1.19(**) | -0.08(*) |
| 13 | -0.12(**) | -0.14(*) | -0.22(**) | -0.10 | 0.01 | -0.11 | 0.19(*) | 0.09 | -0.05 | -0.06 | -0.02 | -0.01 | 0.04 | 0.04 | -0.10(*) | -0.09 | -0.01 | 0.23 | -0.23 | -0.12(*) |
| 14 | -0.03 | -0.03 | -0.16(**) | 0.59(*) | -0.22(*) | -2.26(*) | 0.15 | 0.06 | -0.02 | -0.02 | -0.12(**) | 1.94(**) | 0.00 | 0.01 | 0.08 | -0.11(*) | 0.05 | 0.50 | -0.65(**) | -0.01 |
| 15 | | -0.32(**) | 0.31(**) | | | -0.26 | -0.26 | | | 0.10 | -0.07 | | | 0.02 | 0.07 | | | 0.58(**) | -0.68(**) | |
| 16 | | -0.10 | -0.06 | | | 0.21 | -0.03 | | | 0.01 | 0.11 | | | -0.10 | -0.15(**) | | | -0.47 | -0.64(**) | |
| 17 | | 0.02 | -0.17 | | | -0.22 | 0.46 | | | -0.04 | -0.28(*) | | | 0.16 | -0.17 | | | -0.36 | 0.32 | |
| 18 | | | -0.36(**) | | | | -0.01 | | | | -0.19 | | | | -0.30(**) | | | | -1.42(**) | |
| 19 | | -0.28(*) | 0.20 | | | 0.20 | -0.41 | | | -0.13 | 0.15 | | | 0.07 | -0.22 | | | 0.17 | -0.43 | |