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Evaluating Shenzhen Sound Environment by Using Artificial Neural Networks

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ABSTRACT

Attenuating absolute sound level for urban noise control is not always efficient in which sound meanings has to be included. As evolving from fish-villages with a coastal rural topography, Shenzhen possesses a diversity sound environment containing various ecological sounds. In order to get right knowledge for controlling Shenzhen sound environments, sound meanings have to be measured to give a complete profile. Through a series field studies in Shenzhen, 702 samples covering various sound environments were got. Statistical analyses of heterogeneity of sound environments in Shenzhen were firstly examined. Based on results of subject evaluation of sound level present in a former study, Shenzhen sound environment referring sound levels were investigated. Furthermore, annoyance evaluations to various sounds with a same level 65dB were made using field study data. In order to measure sound meaning attributes influencing sound environment quality, plenty ANN models were developed to predict annoyance evaluations according to sound meaning differences. Finally, combining the results of sound levels and sound meaning, predicting models to a sound environment in Shenzhen were given to provide a feasible tool in measuring and solving Shenzhen noise problems.

Keywords: Subjective evaluation, sound environment, Shenzhen, Artificial Neural Network (ANN)

1. INTRODUCTION

With a constant speeding up urbanization, the city scale of Shenzhen is largely expanding accompanying a series of environmental problems. Amongst them, noise becomes increasingly prominent. According to the bulletins on environmental situation from the Human Settlements and Environment Commission of Shenzhen municipality, the noise complaints reached the first rank in all kinds of environmental complaints and the number is still going up. However, it is not always efficient to subjective noise attenuation just monitoring and controlling sound levels. Plenty authority works have proven that sound levels and sound meanings are main attributes in determining a sound environment quality (1, 2). With a regard of subjective facet, a sound environment could be described by absolute and relative sensations of a person responding to sounds and the occurring environment under listening conditions (3). Therefore, absolute level reduction to certain sound sources may not cause high quality sound environment, because the character of the sound is equally important. Some sounds have a positive impact, whereas others have a negative regardless of their sound levels (4). Schafer defined 'soundscape' as a proper term to note a sound environment with emphasis on the way it is perceived (5). Ever since the concept emerged, researchers have wondered how sound environments would affect peoples' life in a city. Although sound environment is a physical phenomenon, considering its affective effects on human lives, soundscape approach that takes information of a sound environment the same important is more used (6, 7). To measure a sound environment quality, subjective evaluation of various sounds should be taken into account. Most importantly, judging a sound environment should be through human perception. However, it has been less reflected when coping with a sound environmental problems presently in China. It is very

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incorrect specially in some ecological city such as Shenzhen. According to the report of the Shenzhen Environmental Monitoring Station, sound levels often surpass 60dB in many ecological areas in summer time due to bird singing (8). Hence, it is necessary to consider sound sources difference when monitoring a sound environment in Shenzhen for getting right knowledge to improve society well beings.

Although previous studies have acknowledged the importance of taking sound sources in formulating a sound environment quality, quantitative studies of differentiating sound sources are still less, resulting in confusing understanding when measuring sound environment in the environmental monitoring works. This paper addresses a method to evaluate a sound environment regarding sound levels as well as sound sources. Since having successfully predicted subjective evaluations of soundscape and sound preference and sound sources (9,10,11,12,13), ANN models developed to predict sound sources according to subjective evaluations. The study is conducted as giving a practical tool in solving noise monitoring problems brought up by the Shenzhen Environmental Monitoring Station.

2. METHODOLOGY

In order to evaluate quality of various sound environments in Shenzhen, intensive field studies have been carried out ranging very different built environments (14). Based on 702 sound environment samples recorded from field studies, statistical analyses of sound levels to different sound environments have been made. Then, 44 typical sound sources were extracted standing for 702 sound environments. Following this, 25 seconds recording of 44 typical sources were cut used in laboratory experiment to elicit annoyance evaluation due to sound source variation. According to results from the laboratory experiment, ANN models were developed to give annoyance evaluation uniquely from sound source differences. The hypothesis of the study is the successful ANN model can measure annoyance of sound source as complimentary in the current monitoring work of sound environment.

2.1 Data analysis

Through field studies, 702 samples representing all different kinds of sound environments in Shenzhen were obtained. Firstly, sound level differences were investigated to all collected sound environment samples. In general, the samples were recorded in Shenzhen six administration districts, named the District I, II, III, IV, V, VI. From the District I to VI, the study site contains less and less natural elements whereas more and more artificial works. In Figure 1, it shows the sound level changes in one day of the six administration districts. Based on in situ observation, Districts I is the place remained many natural components, e.g. mountain topography, natural villages with a rather long coastline. Among the six administration districts, it has the lowest urban development. The District II is the residential, commercial and industrial area, and it has middle development stage with lower construction intensity. The District III is constituted by residential area and industry with low intensity of development. Districts IV is residential, commercial and financial services area with higher development intensity and small natural, and has the higher density of the road network. Districts V is constituted by industry and coastline of the longest region. Districts VI is center of city, constituted by living, commercial office, school, hospital and other service facilities area with the highest development intensity and larger artificial green area. In the Figure 1, it can be found that the administration districts I has the lowest Leq and the highest Leq in districts VI, with a difference of nearly 20dB. Districts II, III, IV have similar Leq, especially districts V and VI. Analyzing the built environment, it is understood that administration districts I has the lowest construction and the largest green area. The construction of districts VI is the most extensive. Among of their Leq (From Districts I to VI), the area with the largest natural distribution has the lowest sound level and the quietest environment. In the meanwhile, the area with more artificial components is found to have higher sound level.

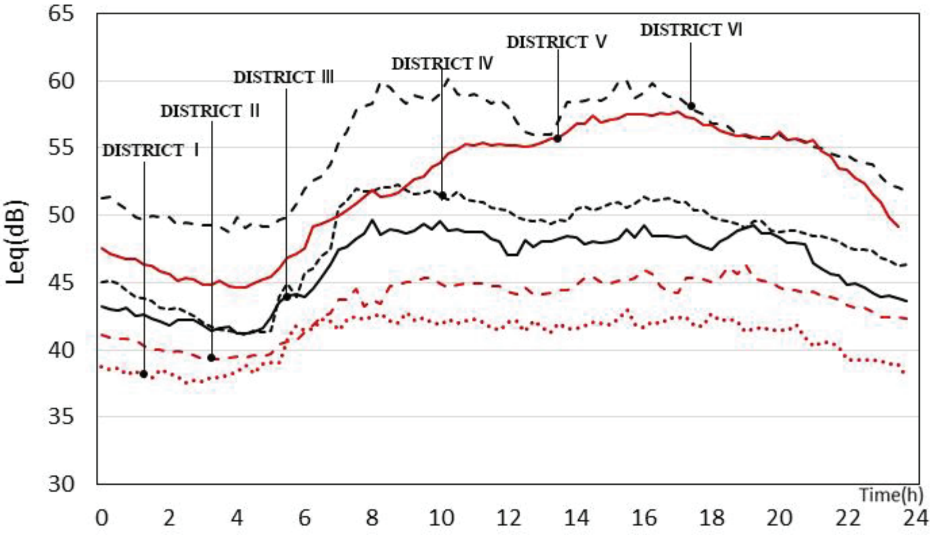

Figure 1– Sound level changes in one day of six administrative districts

To all the 702 sound environment samples, many sound sources included, however, three main kinds of sound types can be classified as many studies pointed (7). They are natural sound sources, urban living sound sources (basically from man's living and activities), and mechanical sound sources. In order to explore relationships between various sounds and their incident environment, sound environment samples were also concluded from three kinds of environments, namely natural sound environment, mix sound environment, and artificial sound environment. Among them, natural sound environments are mainly distributed in the mountain topography areas of District I, III, IV, V, VI. In the same time, it has less mechanical sound. The artificial sound environments are mainly distributed in artificially built environment areas which far away from the natural environment of mountains, parks and water. These areas have obvious sound sources of urban living and machinery. In addition, the mix sound environments are distributed in mountains and water topography areas, especially the mountains of Districts II. While the natural sound sources are obvious, the sound sources of urban living and machinery still exist. Then, in order to quantitatively describe three kinds of sound sources in their incident corresponding environment, the acoustic and psychoacoustic parameters of 702 sound environment samples were calculated.

2.2 Laboratory experiments

In order to explore how a sound environment to influence a community only with a regard of sound meaning differences, laboratory experiment in order to elicit annoyance evaluations of the different sound sources with a certain sound level (say 65 dB) was constructed. In all, 44 typical sound sources were extracted from 702 sound environment samples by comparing acoustic and psychoacoustic parameters, which can represent typical sound environment in Shenzhen. In order to get correct responds from subjects, the replaying time in the laboratory is controlled to be 25 seconds that is long enough to give aural perception to a sound environment. At the same time, The L_{eq} of each signal was fixed to 65 dBA by adjusting the amplitude of the signal and the volume of the amplifier. The experiment lasted about 45 minutes, with a 1-minute break in the middle. Experiment place is located in the listening room, and the background noise is below 40 dB.

In order to the subject evaluation of sound source, the content of the questionnaire mainly includes two parts: personal background information and subjective perception of sound source. The subjective evaluation is divided into 1-9 levels (Indicators of quietness, comfort, loudness, annoyance and pleasure). The lower number show the bad evaluation, and the higher number show the good evaluation. In total 328 people were interviewed. According to the 44 sound source representative samples, a total of 14,432 questionnaires were collected. Alternatively, the study deleted 11 questionnaires with errors. Finally, 14,421 valid questionnaires were obtained.

2.3 Categorizing sound source

According to subjective evaluations, the 44 laboratory study sounds can be assembled into 5-scale category by using cluster analysis. The result is shown in Figure 2. It can be seen that according to subjective evaluation of the quietness only according to sound source difference 5 categories could be obtained, the quietness evaluation category from 1 to 5: Category 1 is very quiet, which is mainly the natural sound type, including wave, water, bird and insect sound and their mixed sound. Category 2 is quiet, which is mainly the mixed sound with obvious natural sound and the clear man’s living and activities sound. The evaluation of this kind of sound source is also relatively high, mainly between 4-5. Category 3 is general, which is mainly composed of mixed sound with more living sound. Although the natural sound is involved, its influence is weak. The evaluation of this kind of sound source is mainly between 3.5-4. Category 4 is noise, which is mostly mixed sound and commercial noise involving mechanical sound. Influenced by the mechanical sound such as automobile and aircraft, it has a low annoyance evaluation, and its value is mainly between 3.1 and 3.5. Category 5 is very noisy, which is mainly mechanical sound and the mechanical sound. Thus, the subjective annoyance evaluation results of the sound source be obtained, and in order to identify the category of the sound source, 5 categories were selected to train ANN models.

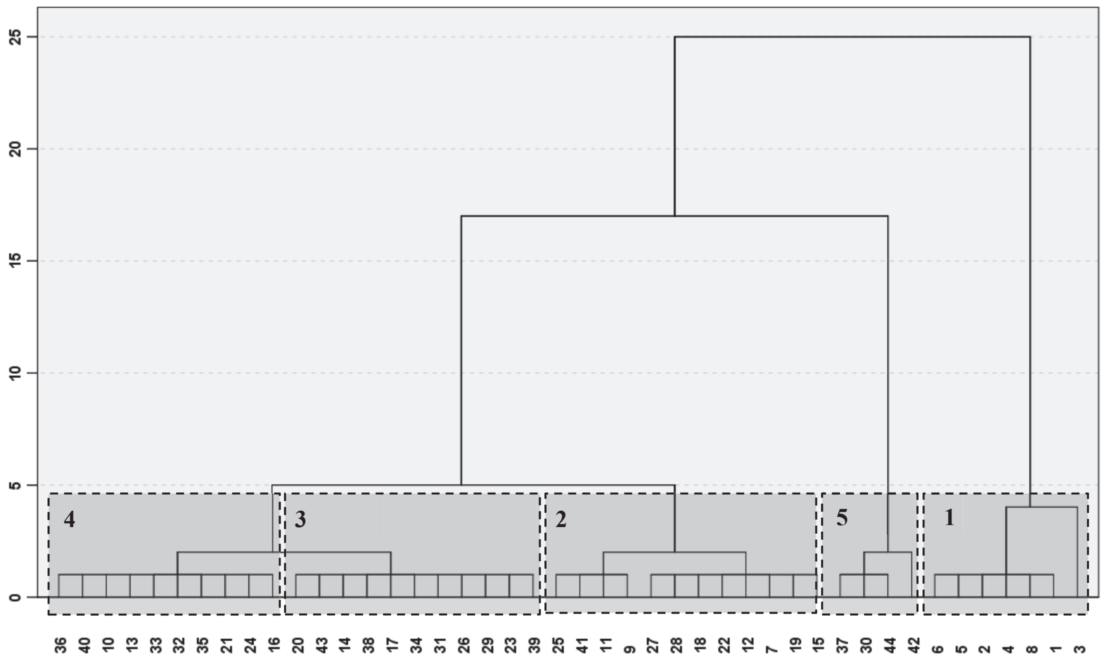

Figure 2–Category of subject of evaluation

2.4 ANN modeling

In order to evaluate a sound environment regarding sound sources difference, ANN models were employed to give quantitative results of annoy affect from sound source. This is because annoyance evaluation from sound source facet is not able to be measured. In the study, a 5-scale category of sound source was used to show annoy affection from very quiet to very noisy.

As a close relationship is quite important to ANN models’ prediction (13), relationships of various factors from acoustic and psychoacoustic parameters to subjective annoyance evaluation of a sound were explored, in which person correlation was used. According to the relationship of subjective evaluation and factors from sound amplitude domain (L_{eq}, L_{10}, L_{90}, loudness(L)), frequency domain(roughness(R), sharpness(S) and tonality (Ton)), and time domain (fluctuation strength (Fls)) have been calculated by Artemis. Totally, 8 significant correlation factors were chosen to be input in ANN models. In the meanwhile, 5-sound source categories got from section 2.3 were assigned as the outputs in the ANN model.

Figure 3. shows detailed information for the networks, including input variables and network structures. The number of input layer nodes of each model is equal to the number of input characteristics, the output layer node number is 5-sound source categories. The activation function of each hidden layer is linear rectifier function (Relu), used to increase the nonlinear neural network, the activation function of output layer uses the softmax function, is used to predict the probability of each category, loss function was Cross Entropy, optimization algorithm was root back propagation optimization algorithm(RMSProp), each of the models is iterated 1000 times. Finally, the best artificial neural network is used to predict the evaluation of sound source in Shenzhen.

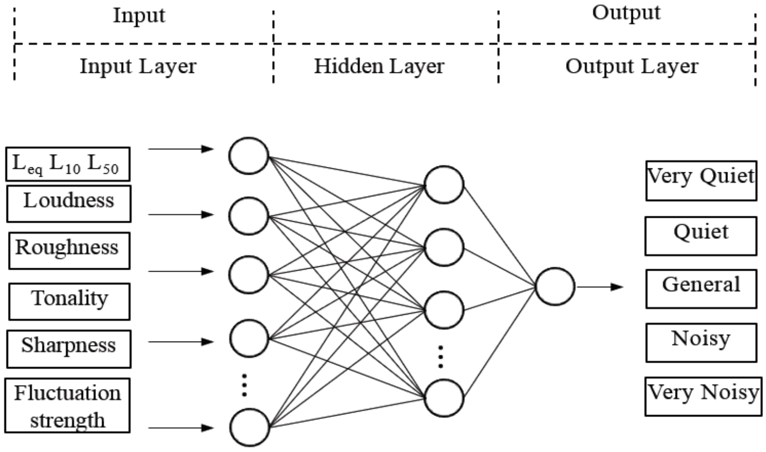

Figure 3 –Structure of ANN model

3 RESULTS

It is well understanding that sound level is key factor to affect annoyance perception of a sound environment. However, sound sources also take an important role to a person's calm assessment to certain sounds when the sound level is not very high (say 65dB). Using sound environment samples from field studies, the study explored annoyance evaluations of various sound environments in Shenzhen in order to give a correct understanding of noise annoyance in such an ecological city. Sound level and sound sources are two aspects key determinants in a sound environment that have been studied respectively. To annoyance evaluation from sound level facet, an evaluation model was proposed based on reviewed previous studies. To annoyance evaluation from sound source facet, ANN models was employed based on categorized sound sources according to subjective evaluations in laboratory experiments.

3.1 Evaluating sound environment in terms of sound levels.

Literature reviews showed that sound level directly affects subjective evaluations of a sound environment. Study has been done to subject's noisy responding to sound level used ANN model prediction (16). A former study pointed that although sound level is the key factor to determine noisy evaluations, factors from social/demographic aspects have also some influence regarding sound level differences (17).

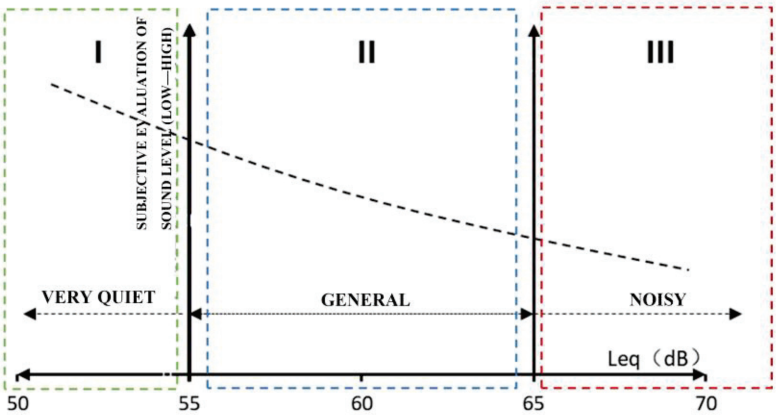

Figure 4 –Sound level evaluation model regarding subjective facets

Based on results of previous studies (16-17), annoyance evaluation of a sound environment regarding sound level was studied, a result of annoyance evaluation to sound level was given in the Figure 4. It shows that the subjective annoyance evaluation deteriorates as the sound level increases. However, the subjective annoyance evaluation is similar in a range of sound level. Thus, the annoyance evaluation can be graded into 3 ranks, from rank I to III. The sound level of rank I is below 55 dB. The subjective annoyance evaluation is relatively quiet. Rank II is between 55 dB and 65 dB and subjective evaluation in general. Rank III is greater than 65 dB, sound evaluation is accounted for noisy. Then, in order to get results of the sound level annoyance evaluation in various sound environment, it can be directly judged according to the sound level.

Based on sound level evaluation model as shown in Figure 4, annoyance evaluation of sound level to the Shenzhen was studied. Annoyance evaluation of sound level to different sound environment was analyzed as shown in Figure 5. It can be seen that the natural sound environment is mainly constituted of very quiet and general, the proportion of noisy is relatively small, so the sound level is basically below 65 dB, and a large part is below 55 dB. The mixed sound environment is general. It is indicated that the sound level is mainly between 55 dB and 65 dB. The artificial sound environment has a rating below general evaluation, especially noisy evaluation, while very quiet evaluation is very less, indicating that the sound level is basically 55 dB, and mostly above 65 dB. Therefore, from the evaluation results of the three type of sound environment, the natural sound environment is the quietest, the mixed sound environment in general, and the artificial sound environment is the noisiest.

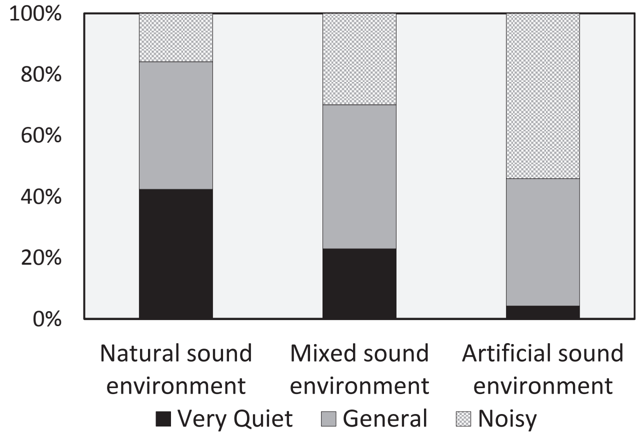

Figure 5 – Difference in sound level evaluation between sound environment

3.2 Prediction sound source by ANN

Besides sound level, sound source is another key factor in evaluating a sound environment referring to annoying perception (6). However, it is difficult to measure annoyance evaluation of a sound source due to involving plenty factors from acoustic and non-acoustic characters. Therefore, laboratory experiment was conducted to get annoyance evaluation of a sound source using data collected from field studies. Finally, sound sources that representing various sound environment in Shenzhen were clustered into a 5-scale categories according subjective evaluation. In building an ANN model, the 5-scale categories of sound sources were used as outputs. And, all possible output variables which including acoustic and psychoacoustic parameters to subjective annoyance evaluation of a sound were used as inputs, e.g. L_{eq}, L_{10}, L_{90}, loudness(L), roughness(R), sharpness(S), tonality (Ton)), and fluctuation strength (Fls). The highest accuracy results of prediction showed that the ANN model which has category 1-3 and 4-5 output variables are the best. And, in the best ANN model, the number of hidden layers is 2, the nodes of the first layer are the twice the number of inputs, and the nodes of the second layer is 32.

Table 1 –Comparison of different input variables in ANN

Model	Output	Input	Layer number	Note (1/2Layer)	Iterations	Maximum accuracy	Average accuracy
1	Category (1, 2, 3)	L_{eq}, L_{10}, L_{50}, L_{90}, L, R, S and Fls	2	16/32	1000	0.86	0.73
2		L_{eq}, L_{10}, L_{50}, L_{90}, L, Ton, S and Fls	2	16/32	1000	0.80	0.69
3		L_{eq}, L_{10}, L_{50}, L_{90}, L, S and Fls	2	14/32	1000	0.85	0.72
4	Category (4, 5)	L_{eq}, L_{10}, L_{50}, L_{90}, L, R, S, Fls , Ton	2	18/32	1000	0.90	0.80
5		L_{eq}, L_{10}, L_{50}, L_{90}, L, Ton, S and R	2	16/32	1000	0.90	0.83

The study compared prediction results for different input characteristics in the grouping ANN models. By comparing prediction results in Table 1, it can be seen the average accuracy of the model 1,2,3 is basically above 0.7, and the maximum accuracy is above 0.8. Meanwhile, the average accuracy of the model 4 and 5 is above 0.8, and the highest accuracy is 0.9. It is indicated that this kind of grouping model can better predict the sound source evaluation. Model 3 has the best results, with an average accuracy of 0.73, a maximum accuracy of 0.89. Therefore, in ANN, using the input variables of L_{eq}, L_{10}, L_{50}, L_{90}, loudness(L), roughness(R), sharpness(S) and fluctuation strength (Fls) of model 3 can accurately predict sound sources of category 1, 2 and 3. Comparing model 4 and 5, it can be found that Model 5 has the best prediction results, with an average accuracy of 0.83, a maximum accuracy of 0.9. Thus, input variables of L_{eq}, L_{10}, L_{50}, L_{90}, loudness (Ton), roughness(R), fluctuation strength (Fls) and tonality (Ton) of Model 5 can make an accurate prediction to sound sources to Category 4 and 5 sound sources.

3.3 Evaluating sound environment in terms of sound sources

According to the ANN model, this paper predicted the subjective annoyance evaluation of sound source in Shenzhen. Annoyance evaluation of sound sources consists of very quiet, quiet, general, noisy, and very noisy, which is also categorized into 1-5. Through laboratory experiment, Figure 6 presents annoyance evaluation of sound sources to Shenzhen various sound environments.

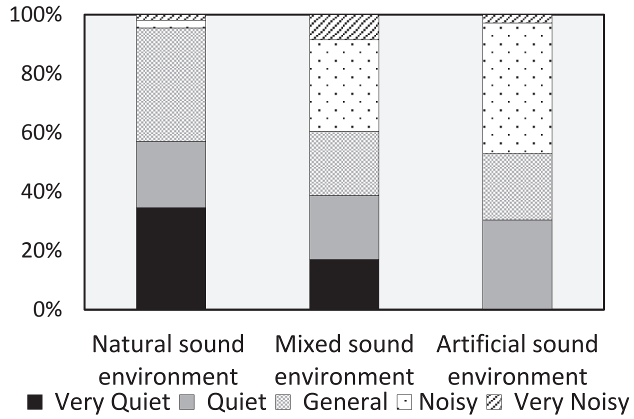

Figure 6 – Difference in sound source evaluation between sound environment

It is found that the natural sound environment is obviously evaluated as the best with more than 50% very quiet and quiet evaluation. The mixed sound environment evaluated as in general with more than 40% very quiet and quiet evaluation, and 40% very noisy and noisy evaluation. However, the artificial sound environment is obviously evaluated as the worst with 0% very quiet , and more than 60% general, noisy and very noisy evaluation. In general, the subjective annoyance evaluation of sound source in the natural sound environment is the quietest, the mixed sound environment in general, and the artificial sound environment is the noisiest. Although the results gave annoyance evaluation of sound source to a sound environment, quantitative study to underpin annoyance evaluation of a certain sound is important in measuring a sound environment regarding sound source. This has been given by using ANN model prediction as can be seen in the section 3.2.

4 CONCLUSIONS

In order to evaluate sound environment in Shenzhen, 44 typical sound sources were extracted from 702 sound environment samples collected through intensive field studies. The studied samples are supposed to stand for all possible sound environment in Shenzhen as already covering spatial and temporal variation of Shenzhen. After analyzing all study samples, three types of sound environments can be classified, namely natural sound environment, mix sound environment, and artificial sound environment. As the sound level and sound sources are key factors to assess annoyance evaluation of a sound environment, they were focused in this study. To sound level, an evaluation model was proposed based on reviewed previous studies, it found although sound level is constantly varied, annoyance evaluation referring to sound level is quite concentrated that can be clustered to very quiet, general and noisy. In Shenzhen, the natural sound environment is found to be quietest, the mixed sound environment is general, and the artificial sound environment is the noisiest. To sound source, the laboratory experiment was conducted to get annoyance evaluation. A 5-scale categories were obtained according to analyze subjective evaluations of sound sources with a certain level (65 dB). It found likely evaluations of sound level, annoyance evaluation of sound source in the natural sound environment is also the quietest, the mixed sound environment is general, and the artificial sound environment is the noisiest. Unlike sound level, it is difficult to measure annoyance perception according to sound source variation. Therefore, ANN models have been employed to give quantitative results of a sound environment with respect of sound source difference. The result shows that ANN models could give relatively accurate prediction of annoyance evaluation if the grouping model with certain sound source categories were used.

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