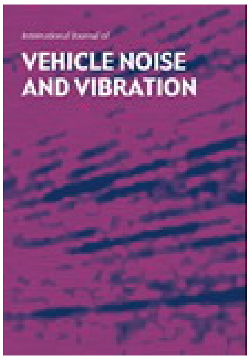

International Journal of Vehicle Noise and Vibration

ISSN online: 1479-148X - ISSN print: 1479-1471
https://www.inderscience.com/ijvnv

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DOI: 10.1504/IJVNV.2022.10053607

Article History:

Received:	16 June 2022
Accepted:	05 December 2022
Published online:	10 April 2023

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Sound quality prediction of unsteady vehicle interior sound

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Abstract: In this paper, the noise samples of pure electric vehicles under unsteady-state are collected. Then, the subjective evaluation test is carried out after pre-processing such as screening and intercepting. The subjective sound quality scores of the noise samples are obtained. Meanwhile, the noise samples are calculated of four conventional psychoacoustic objective parameters such as loudness, sharpness, roughness, and speech intelligibility. Preprocessing by ensemble empirical mode decomposition (EEMD) is performed. Characteristic parameters of noise samples such as time-frequency domain fractal dimension difference and sample entropy of noise samples are obtained based on fractal dimension and sample entropy theory. Finally, the quality prediction model of vehicle interior sound is established based on six characteristic parameters and BP neural network. The results show that the prediction effect is excellent for the subjective scores of sound quality of unsteady interior sound in the vehicle.

Keywords: BP neural network; unsteady state signal; sound quality; ensemble empirical mode decomposition; EEMD.

Reference to this paper should be made as follows: Xie, X. and Wen, Z. (2023) 'Sound quality prediction of unsteady vehicle interior sound', *Int. J. Vehicle Noise and Vibration*, Vol. 19, Nos. 1/2, pp.55–66.

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1 Introduction

Many researchers at home and abroad have done abundant work on the sound quality of conventional fuel vehicles (Qatu, 2012; Qatu and Asadi, 2012; Qatu and Mohamad, 2012). Many novel concepts and research methods are continuously emerging. They have achieved great practical accomplishments after being applied on the practical research and development of vehicles. With the increasing awareness of environmental protection and the consumption of fossil fuels such as petroleum, pure electric vehicles have gradually become the focus of research and development of vehicles. Research on the sound quality of pure electric vehicles interiors has become increasingly active.

Pure electrical vehicles (BEVs) are equipped some devices such as motors and reducers instead of internal combustion engines and gearboxes compared to conventional fuel vehicles. For noise sources in vehicles, pure electrical vehicles lack the low-frequency masking effect of internal combustion engines (Xie, 2005). Passengers of pure electrical vehicles will have more obvious feelings of road noise and wind noise under the same conditions.

Researchers have done abundant work to solve this problem. They analysed the sound quality of electric vehicle and found out the main noise factors that produced the interior noise. They combined with active and passive de-noise technology of NVH to control the vehicle interior noise that obtained good results (Qatu et al., 2009, 2011). In the research of sound quality, Honda Motor Company in Japan put forward more than ten subjective feelings such as loud, roaring, sharp and stable as the evaluation standard of sound quality (Hoeldrich and Pflueger, 1999). At present, the international research on automobile sound quality is still in continuous improvement. Due to the different factors such as nationality, culture, region and economic development level, the sound quality researchers in different countries around the world have different understanding of sound quality, so it is difficult to form a generally applicable sound quality evaluation standard. Therefore, the research on sound quality has the diversity of research methods and the differences of research results. Mitsubishi Motors Corporation found the main noise factors causing the noise of electric vehicle by analysing the sound quality in the vehicle (Nakashinnkiri and Okazaki, 2011). In 2013, Zhu researched sound quality of electric vehicles and proposed de-noise measures. In 2016, Qian deeply researched the evaluation and control technology of sound quality of pure electric vehicles. In 2018, Wang et al. studied and analysed the impact of electromagnetic noise on sound quality of pure electric vehicles. With the emphasis on the development of electric vehicles, different research institutes and R&D teams have begun to pay attention to the research on the interior sound quality of pure electric vehicles. However, there are relatively few studies on the analysis and evaluation of unsteady sound quality.

In this paper, the unsteady-state noise samples of pure electric vehicle are taken. The acquisition and subjective evaluation test of the vehicle noise samples are introduced. Four psychoacoustic objective parameters, such as loudness, sharpness, roughness and speech intelligibility, are calculated after screening and intercepting the noise samples. At the same time, pre-processing of the ensemble empirical mode decomposition (EEMD) on the noise samples is performed. The fractal dimension difference and sample entropy in time-frequency domain are obtained based on fractal dimension and sample entropy. Finally, the six-dimensional input eigenvector is established according to the extracted characteristic parameters. The vehicle interior sound quality prediction model based on

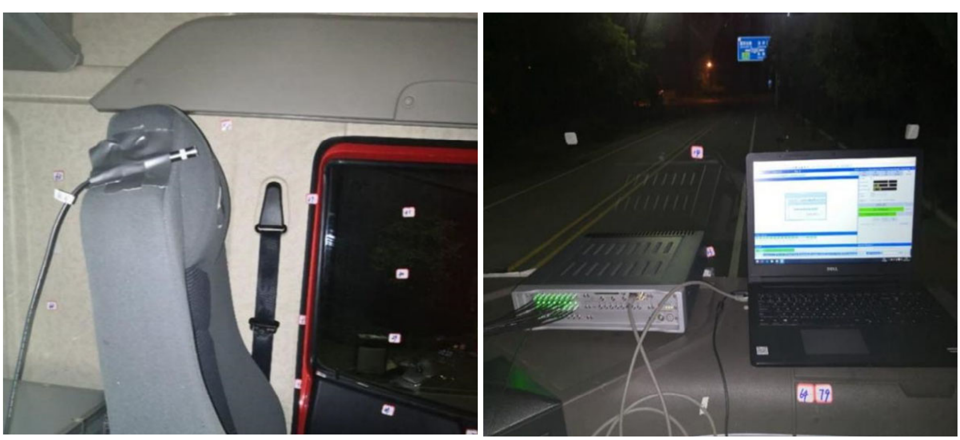
BP neural network is established, and the predicted results are compared with subjective grading scores.

2 The vehicle interior noise acquisition and the calculation of subjective and objective parameters

2.1 The vehicle interior noise acquisition

There should be no large interference objects within 20 m around the road during test following the requirements of the acoustic test environment specified in GB/T 18697-2002 'Acoustics-measurement of noise inside motor vehicles'. LMS SCM205 data acquisition front-end, PCB 378B02 free field microphone and LMS Test.Lab 17A data acquisition and processing software are used to collect the interior noise samples in the vehicle. The microphones are fixed on the driver's right ear. The test system is visible in Figure 1. The sampling frequency of data acquisition is 44.1 kHz and the frequency resolution is 1 Hz. The noise samples of three working conditions are obtained from two different BEVs such as starting, acceleration and sliding conditions. Three tests were performed under each working condition. Except for meeting the requirements of the test environmental conditions, the doors and windows of vehicles must be closed during the acquisition progress of samples. Other factors that may affect the test results should be minimised.

Figure 1 Sound test system, (a) main driver's right ear measuring point (b) LMS SCM205 system (see online version for colours)



(a) (b)

2.2 Acoustic parameters calculation

The noise samples are screened and intercepted after completing the samples acquisition. Every signal was intercepted by every 5S as an effective research sample. Finally, 168 effective noise samples are obtained and numbered according to S1~S168. The 168 unsteady noise samples are calculated by LMS Test.Lab 17A software. Then four acoustic objective parameters such as loudness, sharpness, roughness and speech intelligibility are obtained. The results are shown in Table 1.

Table 1 Psychoacoustic objective parameters of samples

Number	*Loudness (sone)*	*Sharpness (acum)*	*Roughness (asper)*	*Speech intelligibility (AI)*
S1	8.63574	1.17088	0.19584	96.54603
S2	11.73765	0.91790	0.16399	92.74586
S3	17.11755	0.86283	0.17780	79.57755
S4	20.61245	0.85023	0.18180	70.07233
S5	25.02789	0.86004	0.19146	59.58890
S6	23.46342	0.84330	0.22102	62.57755
…	…	…	…	…
S168	7.27750	0.93388	0.11562	96.78094

2.3 Subjective evaluation

The subjective evaluation of vehicles sound quality needs to be based on human beings and their subjective feelings (Yan, 2009). The subjective evaluation results of the noise samples under different working conditions are obtained through evaluation tests. The essence of subjective evaluation test is to numerically quantify or to rank the sound quality of the noise samples. In this paper, the grading method is adopted as the evaluation method. The subjective evaluation index is the degree of pleasure, which is a parameter that reflects people's subjective acceptance of noise signals. A jury with 21 participants are composed of students, teachers and drivers, including 15 males and 6 females, which is selected for the evaluation. The participants were briefly trained before evaluation to meet the requirements of the subjective evaluation test. For these participants, the basis requirements are good hearing condition, a certain understanding of vehicle interior sound quality and normal emotion during the subjective evaluation. Table 2 displays the subjective evaluation results.

Table 2 Subjective scores of the noise samples

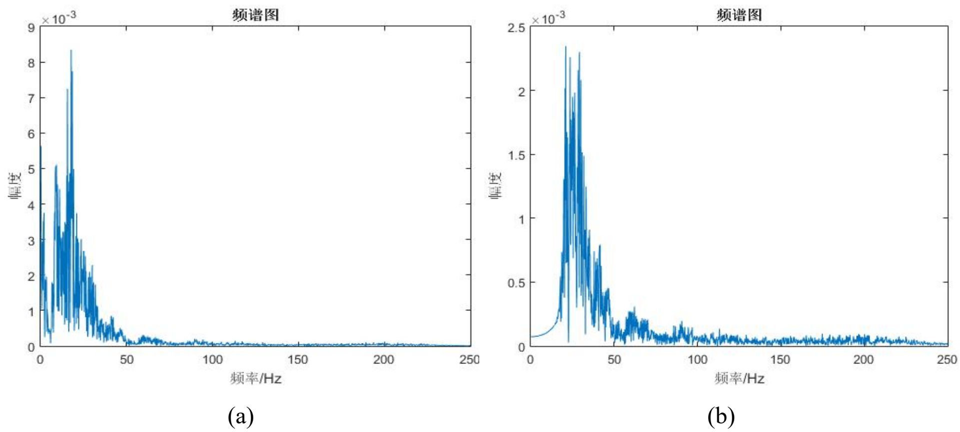
Number	*Score*	*Number*	*Score*
S1	7.0	S85	6.8
S2	6.5	S86	7.0
S3	6.0	S87	8.0
S4	5.0	S88	7.9
S5	4.9	S89	7.8
S6	4.7	S90	7.2
…	…	…	…
S84	6.5	S168	8.0

3 Time-frequency characteristic parameter extraction

3.1 Pre-processing

The spectrum diagrams are obtained by Fourier transform of the samples. The results show that the main frequency part of the samples is concentrated in the low frequency, and the high frequency has little influence. The auditory frequency range of the human ear is concentrated in the range of 20 Hz to 20 kHz. In order to highlight the main influencing factors, the samples are resampled and high-pass filtered to filter out low-frequency components below 20 Hz, as shown in Figure 2.

Figure 2 (a) Before high-pass filtering (b) After high-pass filtering (see online version for colours)



3.2 Time-frequency domain fractal dimension difference based on EEMD

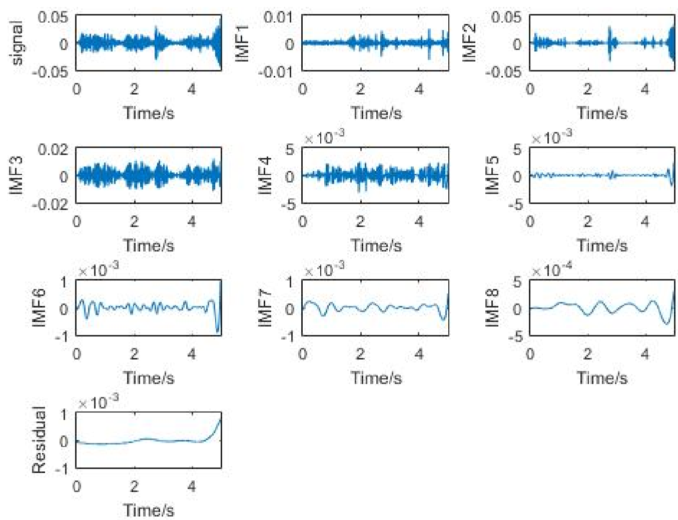
The time domain and frequency domain waveform diagrams of the noise samples show the noise amplitudes changing with time and frequency. There are different expressions of the essential properties of the signals from different angles. To get the more comprehensive description of sound quality, Liu et al. (2018) have researched from the perspective of time domain and frequency domain waveforms based on fractal theory. They proposed a parameter based on time-frequency domain fractal dimension difference was used to objectively describe the sound quality. The conclusion is that the smaller the time-frequency domain fractal dimension difference, the better the sound quality; the higher the dimensional difference, the worse the sound quality.

The relative knowledge of EEMD method is innovatively introduced on the basis of time-frequency domain fractal dimension difference (Cai et al., 2019). In this section, an improved method of extracting sound quality evaluation parameters based on EEMD time-frequency domain fractal box dimension difference (EEMD-DFDTF) is proposed. The pre-processed samples are disposed by EEMD to obtain a series of IMF components reflecting different frequency segments of the noise samples. The IMF components are selected, and the invalid components are eliminated. The remaining feature-sensitive components are reconstructed to obtain reconstructed samples that can better reflect the essential characteristics of the noise samples. The time-frequency domain fractal dimension difference of the reconstructed samples is calculated as objective parameters of sound quality.

3.2.1 The EEMD method

Wu and Huang proposed the EEMD based on the empirical mode decomposition (EMD) method. They solved the modal aliasing problem existing in the EMD method by uniformly adding white noise in the time domain during the decomposition process (Meng, 2013).

Figure 3 Ensemble empirical mode decomposition (see online version for colours)



The processes of noise samples decomposition by EEMD are as follows:

1 Add white noise to the original noise samples.

2 Decompose the samples after adding white noise and obtain n IMF components $c_i(t)$, $i = 1, \ldots, n$.

3 Repeat the above steps 1 and 2 N times, the amplitude of white noise added each time is the same, and the frequency, phase, etc. are different.

4 The IMF components obtained by decomposing N times are collectively averaged according to the same number. Finally, the i^{th} IMF component can be expressed as:

$$c_i(t) = \frac{1}{N}\sum_{j=1}^{N} c_{ij}(t) \tag{1}$$

When N is large enough, the noise residual in the corresponding IMF mean can be ignored.

EEMD needs to set the screening times, the aggregation iterations times, and the amplitude of white noise added during samples decomposition. Wu and Huang proposed the screening stop criterion of the fixed screening times to set the screening times.

Generally speaking, when the screening times is 10, the upper and lower envelopes of all IMF components can meet the requirements of zero-axis symmetry. For the setting of aggregation iterations times and white noise additions times, the empirical rules for reference are as follow:

$$\varepsilon_n = \frac{\varepsilon}{\sqrt{N}} \tag{2}$$

where N is the times of white noise added. ε is the amplitude of white noise. ε_n is the average influence degree of white noise.

In this paper, the times of EEMD aggregation iterations is set to 100. Because there is no guiding principle to choose the amplitude coefficient of white Gaussian noise, the general selection range is 0.01~0.4. Combined with the above equation and relevant experience, the amplitude of white noise is set to 0.4.

According to the above, a series of IMF components arranged in descending order of frequency are obtained by using EEMD to decompose samples.

3.2.2 IMF component selection and reconstruction

There may be meaningless components in the IMF components obtained after EEMD decomposition of noise samples. These meaningless false natural modal components in low frequency components are very common, especially the last few-order IMF components obtained by decomposition. If you do not pay attention to rejection in the actual analysis, the subsequent analysis will be interfered.

In this paper, the correlation coefficient rejection method is taken as the false IMF components rejection method (Chen et al., 2012). That is, the correlation values between each IMF component and the noise samples before decomposition is calculated. Generally, the threshold value is set to 1/10 of the maximum of all correlation coefficients. The IMF component whose correlation value is less than the threshold value will be regarded as a meaningless component, which should be rejected in the actual analysis. The correlation value of the two samples X and Y are calculated as follows:

$$\rho_{X,Y} = \frac{\sum (X-\bar{X})(Y-\bar{Y})}{\sqrt{\sum (X-\bar{X})^2 \sum (Y-\bar{Y})^2}} \tag{3}$$

where $\rho_{X,Y}$ is the Pearson correlation coefficient between the samples X and Y.

After the invalid components are rejected, the remaining IMF components are considered to be sensitive modal components, which retain more original samples information. These IMF components are selected for reconstruction to obtain noise samples reconstructed, which can reflect original samples characteristic information (Xie et al., 2020).

The noise samples S1~S168 are pre-processed by screening and resampling, and then decomposed by EEMD. The samples obtained by reconstructing after rejecting the invalid IMF components are used as input. The multi-scale box dimension difference in the time-frequency domain is calculated as the objective evaluation parameters of vehicle interior sound quality. As shown in Table 3, where T_i is the time domain fractal dimension. P_i is the frequency domain fractal dimension. C_i is the time-frequency domain fractal dimension difference.

Table 3 Time-frequency domain fractal dimension difference of noise samples

Sample	S_i	P_i	C_i	*Sample*	S_i	P_i	C_i
S1	1.5632	1.5239	0.0393	S85	1.5553	1.5000	0.0553
S2	1.5239	1.4589	0.0650	S86	1.5676	1.4829	0.0847
S3	1.5314	1.5182	0.0132	S87	1.5262	1.4893	0.0369
…	…	…	…	…	…	…	…
S84	1.5771	1.4909	0.0862	S168	1.5426	1.4933	0.0493

3.3 Sample entropy feature extraction based on EEMD

3.3.1 Sample entropy theory

Entropy value was first used to describe the complexity of the physical systems. Later, with the widespread application, entropy theory was also applied to the field of signal processing. Firstly, the approximate entropy is applied to accurately classify the samples according to the deterministic and random samples, which has low requirements on data points. Therefore, it is often used to describe the characteristics of the samples. Although the approximate entropy is widely used, it also has a lot of congenital defects. For example, the own data will be compared in the actual operation process, resulting in significant deviation of the calculation results. For the low-complexity samples, the entropy values cannot be distinguished. In the view of the shortcomings of approximate entropy, sample entropy theory has been gradually developed. The sample entropy is developed based on the improvement of the approximate entropy theory. It has the advantages of anti-interference, anti-noise, good consistency and few data points requirement (Huang et al., 2017).

According to the sample entropy theory, the sample entropy of noise samples reconstructed by EEMD is calculated. The calculated results are used as an objective evaluation parameter of vehicle interior sound quality, as shown in Table 4.

Table 4 Sample entropy of noise samples

Number	*Sample entropy*	*Number*	*Sample entropy*	*Number*	*Sample entropy*	*Number*	*Sample entropy*
S1	0.91904	S43	0.95361	S85	0.97402	S127	0.38875
S2	0.80040	S44	0.96856	S86	1.05465	S128	0.83218
S3	0.83754	S45	1.09016	S87	0.90350	S129	1.20130
…	…	…	…	…	…	…	…
S42	0.94564	S84	1.00646	S126	0.0.87537	S168	0.87890

4 Sound quality prediction model construction

According to the noise samples characteristic parameters and subjective evaluation scores extracted in the previous chapters, the sound quality prediction model is established based on BP neural network. The prediction accuracy of prediction model is verified.

4.1 Characteristic parameters pre-processing

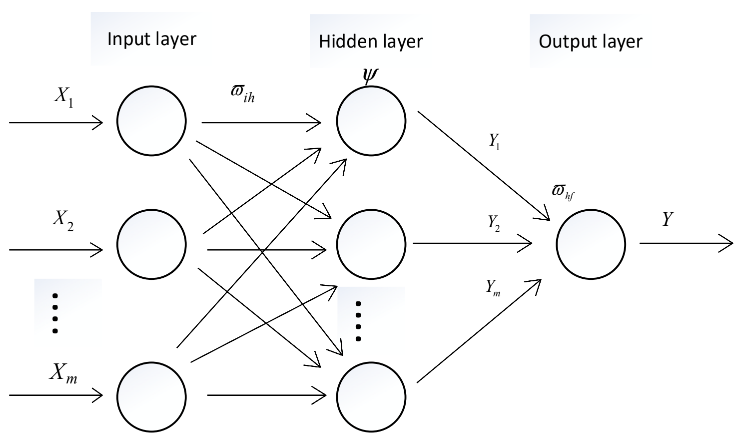
In the previous chapters, the psychoacoustic objective parameters, the EEMD-based domain fractal dimension difference in the time-frequency domain and the sample entropy based on EEMD reconstruction of noise samples are extracted. The values of the above characteristic parameters are quite different, and as input parameters of neural network, the prediction accuracy of neural network will be decrease. The parameters need to be normalised before being used as input (Tang, 2017). In this section, these parameters are normalised to [–1, 1].The equation is as follows:

$$\bar{x} = \frac{x_{\max} + x_{\min}}{2} \tag{4}$$

$$x_i = \frac{2\left(x_i - \bar{x}\right)}{x_{\max} - x_{\min}} \tag{5}$$

where $x_{\max}$ is the maximum of each type of characteristic parameters. $x_{\min}$ is the minimum of each type of characteristic parameters. x_i is the normalised value.

Figure 4 BP network composition



4.2 Prediction of model structure parameters

Back propagation network is also called back propagation neural network. It is a neural network model widely used in data prediction that mainly composed of input layer, hidden layer and output layer, as shown in Figure 4. The determination of the number of hidden layer nodes in BP neural network has a great influence on the accuracy and convergence rate of the neural network. Insufficient number of hidden layer nodes will lead to neural network learning ability declined, insufficient information processing capability. For too many nodes, BP neural network will increase network complexity, make the training time longer, and easily get trapped in local minima. There is no good method to determine the number of hidden layer nodes. The commonly used methods are the trial and error method and the empirical formula method. In this paper, equation (6) is used to determine the number of hidden layer nodes.

$$n_e = \sqrt{(m+n)} + a \tag{6}$$

where m and n are the number of input and output layer nodes respectively. The value of a is generally between 1 to 10 and larger than m. If $(m + n)$ increase, a should be increased synchronously to ensure that the system has sufficient resources for calculation.

The 168 noise samples obtained in previous section are sorted in ascending order of the subjective scores. SX21, SX42, SX63, SX84, …, SX168 are selected as test samples in turn. Those samples are renumbered as SX1~SX168. The rest of the samples are used as training samples.

4.3 Prediction effect analysis of prediction model

For comparing the results, the following three cases are analysed.

1 Taking the EEMD-based time-frequency domain fractal dimension difference and sample entropy based on EEMD reconstruction as input parameters. Then a two-dimensional input eigenvector is constructed. So $m = 4$ and $n = 1$, set $a = 4.268$, get $n_e = 6$ according to equation (6). The two-dimensional feature vector is taken as the input parameters. The subjective scores of the noise samples are taken as the output. The sound quality prediction model is established based on BP neural network, with a structure of 2-6-1. The prediction results are shown in Table 5.

Table 5 Comparison of prediction results of 2-6-1 BP model

Number	*Actual result*	*Prediction result*	*Error (%)*	*Number*	*Actual result*	*Prediction result*	*Error (%)*
SX1	5.2	5.4	3.85	SX5	7.0	7.0	0
SX2	6.0	6.7	11.67	SX6	7.3	6.9	5.48
SX3	6.3	6.9	9.52	SX7	7.8	6.9	11.54
SX4	6.6	6.4	3.03	SX8	8.3	6.7	19.28

2 Take four psychoacoustic objective parameters loudness, sharpness, roughness, and speech intelligibility as the input parameters. Then a four-dimensional input eigenvector is constructed. So $m = 4$ and $n = 1$, set $a = 6.764$, get $n_e = 9$ according to equation (6). The four-dimensional feature vector is taken as the input parameters. The subjective scores of the noise samples are taken as the output. The sound quality prediction model is established based on BP neural network, with a structure of 4-9-1. The prediction results are shown in Table 6.

3 The six objective parameters as the EEMD-based time-frequency domain fractal dimension difference, sample entropy based on EEMD reconstruction. The four psychoacoustic objective parameters as loudness, sharpness, roughness, and speech intelligibility are obtained. A six-dimensional eigenvector is taken as the input. The subjective scores of the noise samples are taken as the output. So $m = 6$ and $n = 1$, set $a = 8.354$, get $n_e = 11$ according to equation (6). The sound quality prediction model is established based on BP neural network, with a structure of 6-11-1. The prediction results are shown in Table 7.

Table 6 Comparison of prediction results of 4-9-1 BP model

Number	*Actual result*	*Prediction result*	*Error (%)*	*Number*	*Actual result*	*Prediction result*	*Error (%)*
SX1	5.2	5.1	1.92	SX5	7.0	7.3	4.29
SX2	6.0	7.0	16.67	SX6	7.3	7.3	0
SX3	6.3	5.9	6.35	SX7	7.8	7.3	6.41
SX4	6.6	7.0	6.06	SX8	8.3	7.0	15.66

Table 7 Comparison of prediction results of 6-11-1 BP model

Number	*Actual result*	*Prediction result*	*Error (%)*	*Number*	*Actual result*	*Prediction result*	*Error (%)*
SX1	5.2	5.3	1.92	SX5	7.0	7.0	0
SX2	6.0	6.7	11.67	SX6	7.3	7.2	1.37
SX3	6.3	5.5	12.70	SX7	7.8	7.1	8.97
SX4	6.6	7.2	9.09	SX8	8.3	7.2	13.25

From the prediction results, the actual scores and theoretical values of most prediction samples fit well, and the prediction effect is good. The following is a further comparative analysis of the above three prediction models from the perspectives of maximum error, mean absolute error (MAE) and mean square error (MSE). As shown in Table 8.

Table 8 Comparison of three prediction model

	Model 1	*Model 2*	*Model 3*
Maximum error (%)	19.28	16.67	13.25
MAE	0.60	0.50	0.50
MSE	0.56	0.42	0.40

From the perspective of maximum error, model 3 has the best effect. From the perspective of MAE, the three models are close. The errors of model 2 and model 3 are consistent, slightly better than model 1. From the perspective of MSE, model 3 is the best and most stable. To sum up, the effect of model 3 in the three prediction models is relatively good. The prediction results are more accurate.

References

Cai, G.P., Zong, L. and Liu, X. (2019) ‘Ball mill load identification method based on MEEMD-multi-scale fractal box dimension and ELM’, *J. CIESC Journal*, Vol. 70, No. 2, pp.764–771.

Chen, R.X., Tang, B.P. and L, Z.L. (2012) ‘Denoising method of EEMD rotor vibration signal based on correlation coefficient’, *J. Journal of Vibration, Measurement & Diagnosis*, Vol. 32, No. 4, pp.542–546.

Hoeldrich, R. and Pflueger, M. (1999) ‘A parametrized model of psychoacoustical roughness for objective vehicle noise quality evaluation’, *J. Journal of the Acoustical Society of America*, Vol. 105, No. 2, p.1371.

Huang, H.B., Huang, X.R. and Su, R.Q. (2017) 'Prediction of sound quality of transmission system based on EEMD and GA-wavelet neural network', *J. Journal of Vibration and Shock*, Vol. 36, No. 9, pp.130–137.

Liu, H.X., Wu, J.H. and Zhang, J. (2018) 'A new method for sound quality evaluation based on fractal dimension difference in time-frequency domain', *J. Noise and Vibration Control*, Vol. 38, No. S2, pp.526–531.

Meng, F.L. (2013) *Theoretical and Applied Research on Collective Empirical Mode Decomposition*, D. Jiangsu University of Science and Technology.

Nakashinnkiri, H-c. and Okazaki (2011) 'Interior noise evaluation of electric vehicle: noise source contribution analysis', *EVTeC'11; International Electric Vehicle Technology Conference*.

Qatu, M. (2012) 'Recent research on vehicle noise and vibration', *International Journal of Vehicle Noise and Vibration*, Vol. 8, No. 4, pp.289–301.

Qatu, M. and Asadi, E. (2012) 'Vibration of doubly curved shallow shells with arbitrary boundaries', *Applied Acoustics*, Vol. 73, No. 1, pp.21–27.

Qatu, M. and Mohamad, S. (2012) 'Recent research on vehicle noise and vibration', *International Journal of Vehicle Noise and Vibration*, Vol. 8, No. 4, pp.289–301.

Qatu, M., Abdelhamid, M., Jian, P. and Gang, S. (2009) 'Overview of automotive noise and vibration', *International Journal of Vehicle Noise and Vibration*, Vol. 5, Nos. 1–2, pp.1–35.

Qatu, M., King, R., Wheeler, R. and Shubailat, O. (2011) 'Vehicle design for robust driveline NVH due to imbalance and runout using a Monte Carlo process', *SAE International Journal of Passenger Cars – Mechanical Systems*, Vol. 4, No. 2, pp.1033–1038.

Qian, K. (2016) *Research on Sound Quality Evaluation and Control Technology of Electric Vehicles*, D. Jilin University.

Tang, R.Z. (2017) *Data Normalization Method to Improve the Efficiency of SVM Training*, D. Shandong Normal University.

Wang, Y.C., Gu, C.S. and Chen, D.L. (2018) 'Sound quality evaluation and electromagnetic noise analysis of pure electric vehicles', *J. Automobile Applied Technology*, No. 4, pp.3–6.

Xie, X.P., Chen, W.D., Chen, B.G., Cheng, J.S. and Tan, L.G. (2020) 'Comprehensive fatigue estimation and fault diagnosis based on refined generalized multi-scale entropy method of centrifugal fan blades', *J. Measurement*, Vol. 166, p.108224.

Xie, Z.W. (2005) *Research on Psychoacoustic Masking Effect*, D. South China University of Technology.

Yan, L. (2009) *Simulation Study of Human Ear Basement Membrane Filter*, D. Beijing Jiaotong University.

Zhu, Y. (2013) *Analysis and Evaluation of Sound Quality in Pure Electric Vehicles*, D. Jilin University.