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Improvement in the prediction performance of subjective evaluation of sound quality for vehicle HVAC system by using SVM algorithm

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ABSTRACT

The reduction of vehicle interior noise has long been the main interest of NVH engineers. Among the various types of vehicle interior noise, HVAC system noise has a great influence on vehicle acoustical comfort and on overall quality perception of a vehicle. In this research, the noise of a vehicle HVAC system was studied using methods and techniques of sound quality engineering. Noise samples were taken from a vehicle as the evaluation objects and subjective evaluation test was carried out with the Paired-comparison method. In addition, multiple regression, back propagation neural network and support vector machine (SVM) models were generated respectively by using four numerical inputs of the objective sound quality metrics, including sound pressure level, loudness, sharpness, and roughness, and one numerical output of subjective response results ("Annoyance"). Results demonstrate that the SVM model predicts the subjective response result "Annoyance" more accurately than traditional methods, and the reliability value is calculated as 0.998 by using statistical analysis. It provides an appropriate method to estimate the sound quality of vehicle HVAC system noise and obviously improve the prediction accuracy. Moreover, it is also found that there is a weak nonlinear relationship between the subjective and objective evaluation results.

Keywords: HVAC system; sound quality; subjective evaluation test; paired comparison; prediction models; SVM algorithm. I-INCE Classification of Subjects Number(s): 51.6, 63.7

1. INTRODUCTION

Recently, the study of sound quality has become a hot topic and attracted an increasing attention from academia and industries. The research of sound quality proposes the objective methods for modern noise control. Meanwhile, the modern noise control not only reduces the sound quality level, but also takes reasonable and effective measures to make the specific products sound quiet and pleasant as much as possible to the ideal situation according to the subjective evaluation (1). With the development of automobile NVH technology, noise transmitted from exterior sources such as the engine, road, tires, and wind, has been decreased dramatically in recent years (2~4). Noise that comes from the interior has become more significant to driver comfort. The major contributor to this interior noise is the HVAC system, which is the focus of this paper. Since people hear sound in a subjective and emotional way, thus, it is difficult to express it in a numerical way. Therefore, a new measure is needed to take the place of current objective measures of noise, such as A-weighted sound quality level.

In the past few years, researchers in home and abroad had carried out a series of studies on the subjective evaluation of sound quality for vehicle HVAC system. H. Silke performed a listening test on seven sound samples of different vehicles in the defrost mode to identify the relevant psychoacoustic parameters for assessing the sound quality of vehicle HVAC system noise, and the correlation between the listeners' preference and additional parameters beside the dominant parameter loudness was analyzed (5). B. Murali obtained the suitable parameters to represent vehicle HVAC system noise by comparing the psychoacoustic parameters calculated objectively with subjective rating by using vehicle HVAC system noise function for the noise samples measured on five different diesel SUVs with different HVAC operating conditions each having variable fan speeds with engine on and off, respectively (6). L. R. Penna studied the perception of annoyance and found that the annoyance caused by the HVAC system noise can be satisfactorily described by Zwicker's stationary loudness model, and a maximum acceptable loudness level for vehicle HVAC system can be determined (7). In these studies, correlations between subjective response and sound quality parameters were calculated and analyzed

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to identify the objective sound quality parameters that contribute more significant to the perception of vehicle HVAC system noise, and linear regression method was mainly employed to establish the prediction model for subjective evaluation of sound quality.

However, human perceptions are very complex and often hard to estimate. Under these conditions, the neural network method and support vector machine (SVM) method are now widely used to establish the prediction models. J. Yoon created the neural network prediction model for a vehicle HVAC system using a regression and neural network model, which improved the reliability of the sound quality index (8). T. Coen classified and compared cars on comfortability using the least squares support vector machine (LS-SVM), which given good prediction results (9). X. M. Shen created the prediction model for vehicle interior noise using multiple linear regression method, BP neural network method and SVM method respectively (10), results show that the SVM model is more accurate than the other two models in the prediction performance, and it also proves that the SVM method is suitable for establishing the prediction model of subjective evaluation index for vehicle interior noise (11). In conclusion, from these literatures mentioned above, it can be found that linear modeling method may not be applicable to establish the subjective evaluation model of sound quality. In other words, the relationships between subjective feeling of hearing and objective psychoacoustic parameters tends to be nonlinear, and more accurately the nonlinear relationship is weaker. Recently, SVM method is widely used for its strong robustness and good generalization ability in the prediction of vehicle interior sound quality, price forecasting, electricity power forecasting, etc. These researches orientation offer useful inspiration for the discussion of the possibility and accuracy of the SVM method in the improvement of prediction performance of subjective evaluation of sound quality.

In this research, the authors firstly carried out the subjective evaluation test of the vehicle HVAC system noise. Then, the sound quality evaluations were performed using both objective and subjective methods, and the sound quality metrics were selected with highly correlated objective and subjective evaluations. After that, the comparisons between the models obtained by current methods (multiple regression, BP neural network) and model obtained by SVM algorithm were focused on and discussed. Results demonstrated that the SVM model is the most highly correlated with subjective evaluation results of the three. Moreover, the SVM algorithm makes it possible for academia and industries to forecast the subjective evaluation results of vehicle HVAC system noise more accurately than ever, through the measured objective psychoacoustic parameters.

2. Subjective evaluation test of sound quality of the HVAC system noise

In this section, the preparations and post-processing for the subjective evaluation test of sound quality of a vehicle HVAC system, including the sound samples collection of a vehicle HVAC system, the selection of the evaluators, subjective evaluation test program, and the analysis of the subjective and objective evaluation of the test results, were stated in detail.

2.1 Noise samples collection

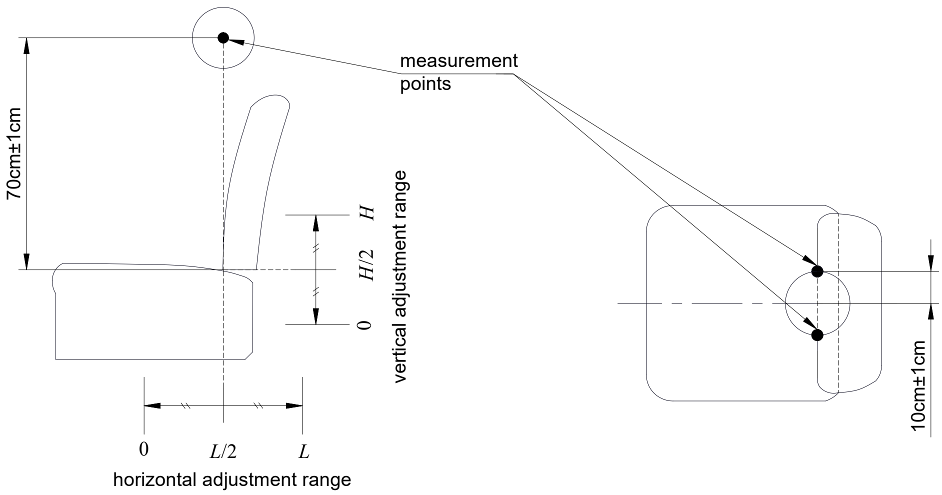
Sound samples were collected in a vehicle manufactured by a Chinese auto company at idle speed in the semi-anechoic room, with five fan speeds and three HVAC modes by using the BEQ-Head (from HEAD acoustics) recording system. The artificial head was placed on the driver's seat and a person was seated in the passenger's seat to control the HVAC system, as shown in Figure 1. Windows and doors were always closed, and the driver seat position was unchanged in all recording process. Moreover, the notebook was placed outside the car to avoid the background noise generated by the hard-drive of the notebook.

(a) Recording system (b) Artificial head placement

Figure 1 – The BEQ - Head based recording system and artificial head placement.

The position of the artificial head referred to the international standard "ISO 5128: 1980-20 Acoustic Car interior noise measurement method" (12), as shown in Figure 2. It is about 10 cm ±1 cm from the measurement points to the seat longitudinal center line, and vertical height is 70 cm ±1 cm away from the seat surface. On top of this, the seat was adjusted to the middle of the height adjustment range and horizontal adjustment range. Before the recording, the diversion rails were also needed to set to the middle range to guarantee the maximum air volume at each outlet.

After all these settings were done, the authors recorded the HVAC system noise three times for each operating condition under the stable working state by using BEQ-Head recording system. Finally, the sound samples were screened and edited to 5 seconds for the subjective evaluation test.



(a) Side view (b) Vertical view

Figure 2 – The position of the artificial head and seat adjustment

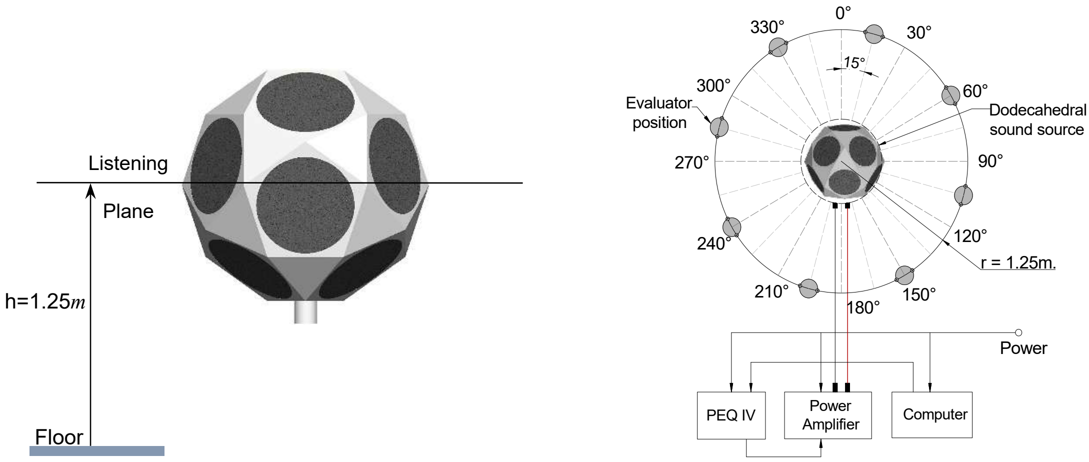
2.2 Evaluator selection

In this study, twenty-four volunteers were invited to take part in the subjective evaluation tests, and all of them are master or doctoral students. Their mean age was about 24.2 years old, and standard deviation was 3.1 years. 66.7% of the volunteers were male and 54.2% worked with acoustics on the projects of the laboratory. Though, this is a limitation, as the jury does not represent reliably all customers of this category of car, all subjects are potential customers of this car. Besides, it was expected that these subjects would be more critical or at least have more ability to express their complaints. However, this does not affect the accuracy of the prediction models established by using different methods.

2.3 Subjective evaluation test

In this research, a novel program for the subjective evaluation test was carried out, and the sounds were presented to them via the dodecahedron sound source for its omnidirectionallity, as shown in Figure 3. This program allows more people to participate in the test carried out in the semi-anechoic room at the same time, thus, it shortened the time cost and settled the problem of non-ideal experimental conditions in the process of subjective evaluation test of sound quality.

Although the dodecahedron sound source is widely used in the architecture acoustics measurement for its omnidirectionallity, this property is limited to the frequency and distance. Specifically, the directivity deviation becomes more obvious with the increasing of sound frequencies, as well as shorten of the distance between the measuring point and the dodecahedron sound source center (13~15). Therefore, it is necessary to determine evaluators' positions in the subjective evaluation test. A set of measurements of the directivity deviation at 500 Hz, 1 kHz, 2 kHz and 4 kHz were carried out. And in the process of analysis of directivity deviation results, a maximum directivity deviation at ±1.5dB was taken into consideration to guarantee the accuracy and reliability of subjective evaluation test program. Besides, subjective evaluation tests were carried out via the dodecahedron sound source and headphones respectively, and results show that the subjective evaluation results obtained via dodecahedron sound source basically agree with those obtained via headphone. The experimental program used in this paper was verified with high reliability and



(a) Side view of horizontal measurement plane (b) Setup of subjective evaluation test

Figure 3 – Setup for subjective evaluation test via dodecahedron sound source

accuracy in another study (16). Thus, no more words are to state more than necessary in this paper.

Before the test, artificial head was employed to calibrate the experimental A-weighted SPL value of the positions according to the sample's actual SPL value by adjusting the power amplifier. Subjective responses on the scale were converted to corresponding numerical values between "1" and "10", as shown in Figure 4. The value "1" means that the subject marked the ''Very annoying" anchor and the value "10" means the ''Not annoying" anchor. In the proceeding of the sound quality test, paired comparison method was employed, which facilitated the process of evaluators' response on converting the scale to numerical values. After the test, mean values of the subjective response were calculated for each sound sample.

	1	2	3	4	5	6	7	8	9	10	
Annoyance	□	□	□	□	□	□	□	□	□	□	Not annoyance

Figure 4 – Ten step scale anchored at the bipolar adjectives for subjective evaluation test

2.4 Subjective and objective evaluation for sound quality metrics

The subjective evaluation scores given by volunteers in the test were firstly checked with error data test based on the principle of triangular cycle, and three persons' evaluation data were excluded. Then, the Kendall's $\boldsymbol{W}$ (also known as Kendall's coefficient of concordance) (17-19) was introduced to validate the consistency of the remaining data. It is a normalization of the statistic of the Friedman test, and it can be used for assessing agreement among raters. Kendall's $\boldsymbol{W}$ ranges from 0 (no agreement) to 1 (complete agreement). The calculation formula of Kendall's $\boldsymbol{W}$ is shown as Eq.(1),

$$\boldsymbol{W} = \frac{12S}{m^2\left(n^3 - n\right)} \tag{1}$$

where, object i is given the rank $r_{i,j}$ by judge number j, and there are in total n objects and m judges. R_i is the total rank given to object i, $\overline{R}$ is mean value of these total ranks, and S is sum of squared deviations, a shown in Eq.(2).

$$R_i = \sum_{j=1}^{m} r_{i,j}, \quad \overline{R} = \frac{1}{n}\sum_{i=1}^{n} R_i, \quad S = \sum_{i=1}^{n}\left(R_i - \overline{R}\right)^2 \tag{2}$$

If the test statistic $\boldsymbol{W}$ is 1, then all the judges or survey respondents have been unanimous, and each judge or respondent has assigned the same order to the list of objects or concerns. If $\boldsymbol{W}$ is 0, then there is no overall trend of agreement among the respondents, and their responses may be regarded as essentially random. Intermediate values of W indicate a greater or lesser degree of unanimity among the various judges or respondents (20~22).

Based on the calculation formula, the Kendall's W is 0.335 with χ^2 of 131.77. Therefore, 99.5% of confidence probability for the cases can be suggested that the evaluation data was of high consistency, in another word, the subjective evaluation test data was reliable and effective. Eventually, the mean scores of the subjective evaluation test via dodecahedron sound source were obtained, as shown in Table 1.

Table 1 – Mean scores of the subjective evaluation test

Mode	Fan speed	Mean score	Mode	Fan speed	Mean score	Mode	Fan speed	Mean score
Front with cooling	1	6.944	Foot with heating	1	7.653	Window with heating	1	7.713
	2	5.958		2	6.528		2	6.235
	3	4.625		3	5.236		3	4.855
	4	2.778		4	3.556		4	3.224
	5	1.347		5	1.819		5	1.499

In this paper, five objective sound quality metrics (loudness, sharpness, roughness, fluctuation strength and tonality) were calculated by ArtemiS software from the recorded data. The results of the objective evaluation were widely distributed. The range of loudness was 3.75~31.00 *sone*, sharpness was 0.71~2.52 *acum*, roughness was 0.81~3.15 *asper*, fluctuation strength was 0.0064~0.0175 *vacil*, tonality was 0.0314~0.0365 *tu*, and A-weighted sound pressure level was 45.1~71.3 dB(A).

3. Results analysis and modeling

In order to identify the sound quality parameters that contribute more significantly to the perception of vehicle HVAC system noise, correlations between subjective response and sound quality parameters were calculated using SPSS software, as shown in Table 2. It is obvious that four parameters, including A-weighted SPL, loudness, sharpness and roughness, are of high correlation coefficients with the subjective evaluation results. Thus, these four parameters were chosen to construct the prediction models of subjective evaluation of sound quality for the vehicle HVAC system.

Table 2 – Correlation coefficients between subjective responses and objective parameters

Parameters	A-SPL	Loudness	Sharpness	Roughness	Fluctuation Strength	Tonality
Coefficients	-0.995	-0.970	-0.993	-0.984	-0.842	-0.474

3.1 Analysis of sound quality evaluation by multiple linear regression model

Multiple linear regression algorithm is a means of determining relationships between sets of observations which we will refer to as variables (23, 25). It attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. The "multiple" refers to multiple independent variables. The simplest case of such relationships is the single independent variable case and it seems sensible to use this special case to define the procedure and terms and then generalize to the multi independent variable case.

Based on the characteristics of HVAC system noise, prediction model was obtained by using the multiple linear regression method to describe the relationship between the subjective response and objective psychoacoustics parameters (3, 23, 24), as shown in Eq. (3):

$$\{y_m\} = d_0 + \sum_{i=1}^{n} d_i \{f_i(x_1, x_2, x_3, \ldots, x_m)\} + \{\varepsilon_m\} \tag{3}$$

where, ym is the subjective response value of sample m; di(i=1, 2, 3… n) are the regression coefficients; xi(i=1, 2, 3… m) are the objective psychoacoustics parameters; fi(g) is the psychoacoustics parameters calculation function; εm is the calculation error. The matrix expression form of Eq.(3) is shown in Eq.(4),

$$\boldsymbol{y} = \boldsymbol{Bd} + \boldsymbol{\varepsilon} \tag{4}$$

where, ***B*** is a column matrices, and its column vectors are the values of the objective psychoacoustics parameters obtained by the $f_i(\cdot)$ function. And ***y***, ***d***, ***ε*** are shown as below.

$$\begin{cases} \boldsymbol{y} = \left(y_1, y_2, y_3, ..., y_m\right)^T \\ \boldsymbol{d} = \left(d_0, d_2, d_3, ..., d_n\right)^T \\ \boldsymbol{\varepsilon} = \left(\varepsilon_1, \varepsilon_2, \varepsilon_3, ..., \varepsilon_m\right)^T \end{cases} \tag{5}$$

The regression coefficients $\boldsymbol{d}_i$ can be obtained by solving the following equation,

$$\boldsymbol{B}^T \boldsymbol{y} = \left[\boldsymbol{B}^T \boldsymbol{B}\right] \boldsymbol{d} \tag{6}$$

Then, choose the parameters with the higher correlation between the objective sound quality metrics and subjective response values to take into the Eq.(6).Besides, the values fit by the Eq.(3) are denoted $\hat{y}_i$, and the residuals ε_i are equal to $y_i - \hat{y}_i$, the difference between the observed and fitted values. The sum of the residuals is equal to zero. The variance σ^2 may be estimated by Eq.(7), also known as the mean-squared error (or MSE), and the estimate of the standard error $\boldsymbol{s}$ is the square root of the MSE. In addition, the calculation formula of $\boldsymbol{s}$ is given in the Eq.(8),

$$s^2 = \frac{\sum \varepsilon_i^2}{m-n-1} \tag{7}$$

The least-squares estimates $\boldsymbol{d}_i$ is usually computed by statistical software. In this paper, the multiple regression software used is **SPSS**, a professional statistics program. Firstly, the stepwise procedure was used for the multiple regression model, in which parameters with the higher correlation between the objective sound quality metrics and subjective sound quality value was reflected in the analysis. Then, a multiple regression model was generated with four objective numerical inputs (SPL, loudness, sharpness, and roughness) of the sound quality metrics and one subjective output (“***Annoyance***”). The result of this multiple regression analysis is shown in Eq.(8),

$$\boldsymbol{Annoyance} = 15.037 - 0.158\boldsymbol{L_A} - 0.0012\boldsymbol{L_d} - 1.223\boldsymbol{S_p} + 0.204\boldsymbol{C_r} \tag{8}$$

where, $\boldsymbol{L_A}$ is A-weighted sound pressure level, $\boldsymbol{L_d}$ is the loudness value, $\boldsymbol{S_p}$ is the sharpness value and $\boldsymbol{C_r}$ is the roughness value and the correlation coefficient of the regression model reaches 0.985 with a standard error of 0.237, which is of high accuracy.

In order to validate the statistical reliability of the regression model, a common statistical method, Analysis of Variance (ANOVA), was used to accomplish this, which tests the significance of the regression (23). As shown in Table 3, the model F value is 295.471, and the significant level of automatic inspection is 0.000, which indicates that there is no significant difference between the objective psychoacoustics parameters and subjective response values.

Table 3 – ANOVA of the multiple regression model

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	66.818	4	16.704	295.471	0.000

3.2 Analysis of sound quality evaluation by BP neural network model

Back propagation (BP) neural network is one kind of artificial neural networks (ANN), a prediction algorithm that is the most extensive in various neural network models and it has recently come into a wide range of applications (26). It consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. BP neural network is an adaptive system and non-linear statistical data modeling tool, which could exactly reflect the operation states and characteristics of a system.

BP neural network is a multi-layer network model of a one-way communication, including the input layer, hidden layer and output layer. There are full internet connections between the upper layer and lower layer, and no connections among neurons in the same layer. Connection weights of each layer can be adjusted by learning. When the network obtains a learning sample, neural activation values are transmitted from the input layer to the output layer through the intermediate layer, and the input response of the network is received in the output layer. If the network cannot obtain the target output in the output layer, it will enter the back propagation stage which error of the output signal return back to the input layer along the original connection pathway. By modifying the layers of the weight, the error signal will be reduced. With the back-propagation of the error is repeated, the correct response rate is rising in the output layer (27-29).

In the input layer, every node represents an input variable. In this study, the input variables that they represent are the psychoacoustics parameters (A-weighted SPL, loudness, sharpness, and roughness). The hidden layer is the backbone of the entire network system. The prediction accuracy is closely related to the settings of the hidden layer. In order to simplify the design, there is only one hidden layer in this BP neural network. The improvement of the error accuracy is obtained by increasing the number of nodes in the hidden layer. The number of hidden layer nodes is determined by Eq.(8) (27,30),

$$\boldsymbol{m} = \sqrt{\boldsymbol{n} + \boldsymbol{l}} + \boldsymbol{\alpha} \tag{8}$$

where, $\boldsymbol{m}$ is the number of hidden layer nodes, $\boldsymbol{n}$ is the number of input layer nodes, $\boldsymbol{l}$ is the number of output layer nodes, $\boldsymbol{\alpha}$ is an adjustment constant, ranges from 1 to 10. In this study, the number of the hidden layer was set to be six by using trial and error method.

After the determination of the number of hidden nodes $\boldsymbol{m}$, the last thing to do is to choose the activation function that fits the BP neural network model best. Normally, the most commonly used is the sigmoid activation function, as shown in Eq.(9), and so it was in this paper.

$$f(x) = \frac{1}{1+e^{-x}} \tag{9}$$

Therefore, a 4-6-1 structure for BP neural network model was determined. And the detail BP feed forward neural network configuration for the subjective evaluation index of sound quality is shown in **Figure 5**. In this newly designed model, there are three layers, i.e., input layer, hidden layer, and output layer. The objective sound quality metrics of SPL, loudness, sharpness, and roughness was established as the input variables, and the mean value of "***Annoyance***" was defined as the output variable. On top of this, the transfer function is a sigmoid function from the input layer to the hidden layer, and a linear function from the hidden layer to the output layer.

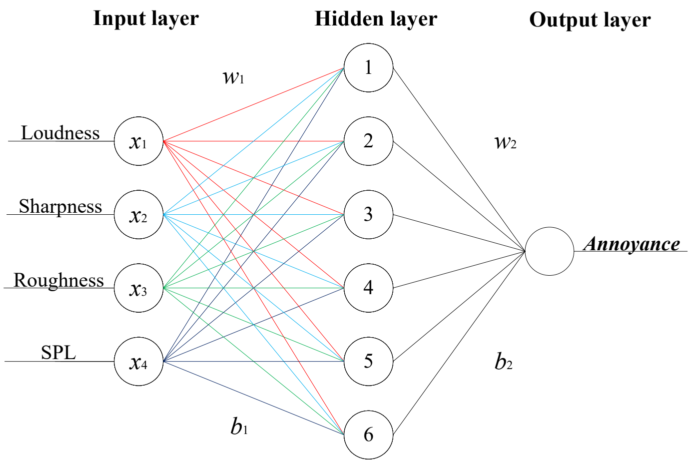


Figure 5 – Structure of BP neural network model.

In this research, Matlab toolbox was employed to establish a BP neural network model for vehicle HVAC system noise. In the process of modeling, parameters were set as following, the neural

Table 4 – The BP neural network model for subjective evaluation index of sound quality.

Content	Hidden unit weights w_1				Output unit weight	Hidden unit bias	Output unit bias
Metrics	Loudness	Sharpness	Roughness	SPL	w_2	b_1	b_2
Value	2.07	-1.46	3.01	1.92	0.36	-4.38	0.41
	2.89	0.33	-0.10	3.27	0.52	-2.63	
	-2.40	2.95	1.93	1.00	0.49	0.88	
	2.12	2.38	-1.84	-2.38	-0.22	0.88	
	1.13	-2.93	-0.67	2.98	0.31	2.63	
	-2.04	2.39	2.11	2.20	-0.66	-4.38	

network model yielded a learning rate of 0.05 and a momentum coefficient of 0.9. Moreover, learning was performed until either the number of repetitions reached 100,000 or the error (RMSE) reached 0.01. The calculated subjective evaluation index of sound quality is shown in Eq.(10)[8],

$$\boldsymbol{Annoyance} = \boldsymbol{f}_2\left(\boldsymbol{w}_2\boldsymbol{f}_1\left(\boldsymbol{w}_1\boldsymbol{x}+\boldsymbol{b}_1\right)\right)+\boldsymbol{b}_2 \tag{10}$$

where, w is the weight matrix, b is the bias, x is the input variable, f1 is the tan-sigmoid function of “logsig”, and f2 is the linear function of “purelin”. The values of BP neural network model are shown in Table 4.

3.3 Analysis of sound quality evaluation by the support vector machine model

In machine learning, support vector machines (SVM, also support vector networks) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis (31). Its basic idea is to transform the signal to a higher dimensional feature space first, and then find an optimal hyper plane to maximize the classification margin (32).

Similar to the neural network based techniques, the SVM based modeling also involves training and testing of data instances such that the training set comprise of target outcome variable(s) by mapping several predictor variables. The advantages of SVM include strong inference capacity, generalization ability, fast learning capacity, and ability for accurate predictions. For example, the generalization ability of SVM learning mainly depends on the capacity and basic reliance on space dimensionality and other parameters such as upper bound and kernel parameters (33, 34). However, the performance of BP neural network relies on several controlling parameters such as the number of hidden layers, the number of hidden nodes, the learning rate, the momentum term, epochs, transfer functions and weights initialization. Moreover, balancing an optimal combination of those parameters for good neural network predictions is a challenging task in several settings.

Following section provides some useful collated synopsis on SVM principles e.g. from literatures (33~36). Suggest that a training set is considered such that,

$$D_{training} = \left\{x_i, y_i\right\}_{i=1}^{n} \tag{11}$$

where, x_i represents a set of input vectors and ‘y_i’ refers to target labels of ‘−1’ for class 1 or ‘+1’ for class 2.

And in this,

$$\boldsymbol{x}_i = \left(x_i^1, x_i^2, \ldots x_i^n\right) \in R^n \tag{12}$$

$$y = \begin{cases} 1 & if\ \boldsymbol{x}_i\ in\,class\ 1 \\ -1 & if\ \boldsymbol{x}_i\ in\,class\ 2 \end{cases} \tag{13}$$

As per binary classification case,

$$y_i\left(\boldsymbol{w}^T\phi\left(\boldsymbol{x}_i\right)+b \geq 1\right) \quad i=1,2,\ldots,n \tag{14}$$

where, ‘b’ represents the bias element and ‘$\boldsymbol{w}$’ refers the weight vector such that,

$$\boldsymbol{w}\cdot x+b \begin{cases} \geq 1 & if\ \ y_i = 1 \\ \leq -1 & if\ \ y_i = -1 \end{cases} \tag{15}$$

If the hyper-plane is represented by $y=\boldsymbol{w}^Tx+b$, then the distance between ($\boldsymbol{w}\cdot x+b=1$) and ($\boldsymbol{w}\cdot x+b=-1$) is shown in Eq.(16).

$$\frac{2}{\left\|\boldsymbol{w}\right\|} = \frac{2}{\left\|\boldsymbol{w}^T\cdot\boldsymbol{w}\right\|} \tag{16}$$

With Lagrange transformation considerations, the objective function can be represented as $\min f\left(\alpha\right)$,

$$f\left(\alpha\right) = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j x_i x_j \tag{17}$$

where, $f(\alpha)$ subject to Eq.(18), and α is the non-negative Lagrange multiplier and

$$\sum_{i=1}^{n}\alpha_i y_i = 0, \quad \alpha_i \geq 0, \quad i=1,2,\ldots,n \tag{18}$$

As most of the classification problems are linearly non-separable instances, a slack variable (also known as relaxation variable) ξ_i is introduced such that the optimization problem is changed as follows:

$$\underset{w,b,\xi}{Min} = \left[\frac{\boldsymbol{w}^T \boldsymbol{w}}{2} + C\sum_{i=1}^{n} \xi_i \right] \tag{19}$$

where, C is the penalty parameter of the error term; $y_i\left(w^T \cdot x_i\right) + b \geq 1 - \xi_i$; i=1,...,n and $\xi_i \geq 0$. For easing the computations, kernel functions are introduced and the nonlinear classifier function for non-separable cases can be determined using the following Eq.(19):

$$y(x) = \mathrm{sgn}\left(\sum_{i=1}^{n} y_i \alpha_i k\left(x_i, x_j\right) + b \right) \tag{20}$$

Moreover, it is interesting to know that for conventional neural network, and the architecture and neuron number must be properly designed to achieve high classification accuracy. But for the SVM classifier, the key is to choose a proper kernel function. In general, linear function, polynomial function, radial basis function (RBF), sigmoid function, etc., can be adopted as the kernel function (36-38). In this paper, RBF function was used in the designed SVM classifier as it has excellent performance in many applications. The function can be given as below:

$$k\left(x_i, x\right) = \exp\left[-\frac{\left\| x_i - x \right\|}{2\sigma^2} \right] \tag{21}$$

where x_i are the four input variables, to achieve high classification accuracy, the parameter σ and constraint C should be tuned and optimized by using the cross-validation method.

In this study, a newly developed structure of support vector machines model is shown in **Figure 6**, in which s denotes the number of support vectors. It consists of four input variables (x_1~x_4: loudness, sharpness, roughness and A-weighted SPL) from the scaled residuals, and one output which indicates whether the current state belongs to the corresponding normal or faulty condition or not.

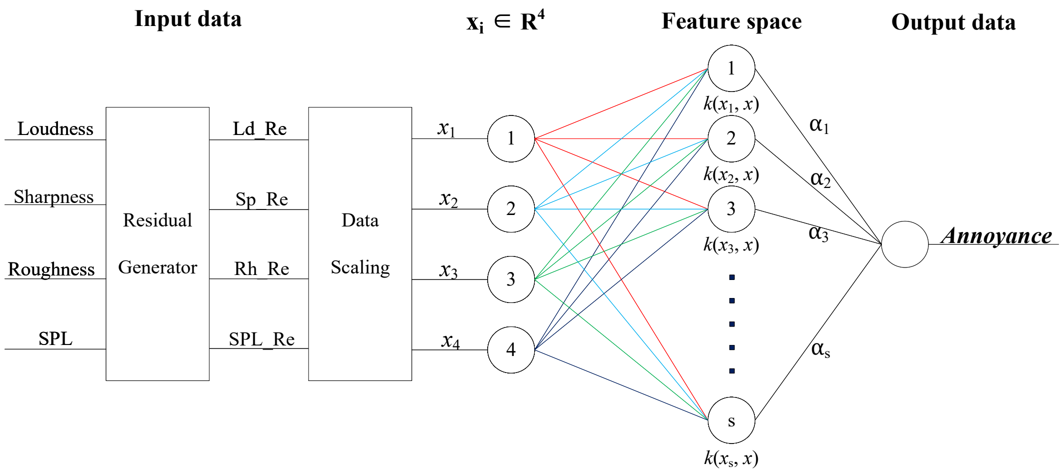


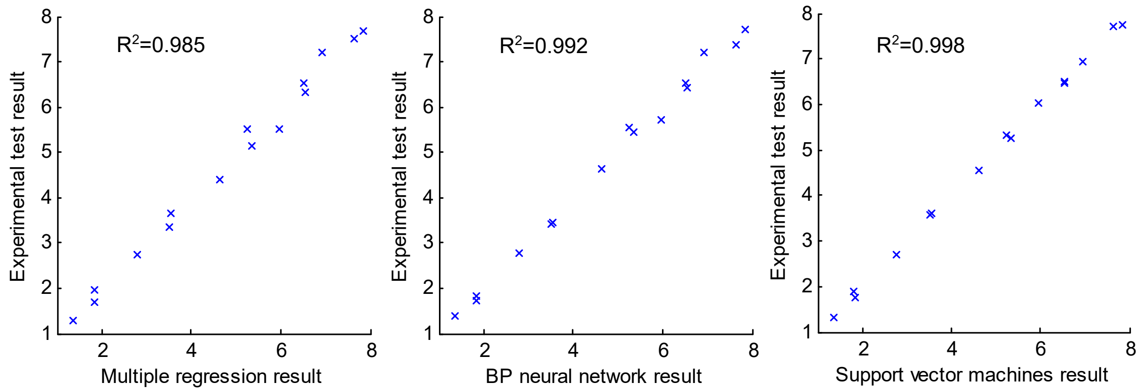
Figure 6 – Structure of support vector machines model

In this study, Matlab toolbox (LibSVM) was employed to establish a SVM model for vehicle HVAC system. In the process of modeling, three sets of tests were conducted systematically. The first test was designed to investigate the SVM classifier performance. The steady-state variable data were used to build the SVM classifier. Then, the second test was set to determine the key parameters: σ and C. In this paper, the best constraint C is 1, and the best σ is 1.929. Finally, the third test was designed to evaluate the effect of the training samples. Results show that mean squared error reached at 0.00429, and squared correlation coefficient of 0.95037 (SVM regression), indicated that the support vector machines model established was of good prediction accuracy.

4. Prediction validation and comparison

In order to validate and evaluate the sound quality models obtained using the multiple regression, BP neural network and support vector machines methods, test data were applied and the results were examined.

Figure 7 shows the correlations between sound quality model outputs and subjective test results for "***Annoyance***". As shown in Figure 7, the correlations were 98.5%, 99.2%, and 99.8% for the multiple regression model, BP neural network model and support vector machines model, respectively. Despite each sound quality model showing a difference in correlation, there is not obvious difference after all, the high correlation values indicate their meaningful applicability. So, it can be suggested that the correlation relationship between the subjective evaluation index and objective psychoacoustics parameters of vehicle HVAC system noise is of strong linear, but not that absolutely linear. To be more accurately, it is a weak nonlinear relationship between the subjective and objective evaluation results. Maybe it is the reason that the vehicle HVAC system noise trends to be wide band aerodynamic noise, without extraordinary noise like harsh noise or booming noise, etc.



(a)Multiple regression method (b) BP neural network method (c) SVM method

Figure 7 – Correlations between sound quality outputs and subjective test results for "***Annoyance***"

Table 5 shows the errors of the multiple regression model, BP neural network model and support vector machines model. As shown in Table 5, the SVM model is much more precise than the BP neural network model and multiple regression model, no matter in the aspects of mean square error, relative average error and maximum relative error. Since, there is nonlinear relationship between subjective feelings and the objective evaluation, so the prediction error is larger by using multiple (linear) regression. Even though the BP neural network and support vector machines can realize the nonlinear mapping between the subjective and objective evaluation, the BP neural network prediction method has the disadvantage of slow convergence speed and it is easy to fall into local extremum. The SVM algorithm has the advantages of fast speed and high precision, the effect is better.

Table 5 – Errors of the three prediction models

Prediction model	Multiple regression	BP neural network	Support vector machines
Mean square error /10-2	4.161	2.538	0.429
Relative average error /%	4.115	2.663	1.728
Maximum Relative error /%	8.587	6.522	3.804

In conclusion, the support vector machines model provides a meaningful and more accurate tool for estimating values of the subjective sound quality of the HVAC system noise. Moreover, this SVM algorithm could also be used to build useful grades of products, making it a meaningful tool for making product decisions in terms of quality and price.

5. Conclusion

In this study, the noise of a vehicle HVAC system was studied using methods and techniques of sound quality engineering. Noise samples were taken from a vehicle as the evaluation objects. Subjective evaluation test was carried out with the paired comparison method. Meanwhile, prediction models of subjective evaluation of sound quality for a vehicle HVAC system were generated with the multiple regression method, BP neural network method and SVM method, respectively. Then, test data were applied and the results were examined to validate and evaluate the sound quality models by comparing the correlations and errors with each other.

Results demonstrated that, the SVM model is most highly correlated with subjective evaluation results of "***Annoyance***", which led to determination of suggested methods for sound quality metrics prediction for vehicle HVAC system. Moreover, the correlation relationship between the subjective evaluation index and objective psychoacoustics parameters of vehicle HVAC system noise is of strong linear. Being more accurately, it is a weak nonlinear relationship between the subjective and objective evaluation results. What's more, the multiple linear regression is a good choice if it is not required for the precise prediction, otherwise, the SVM algorithm is a better choice.

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References

1. Zuo YY, Zhou SL and Zhou WF. Subjective analysis and objective evaluation of vehicle sound quality. Advanced Materials Research. 2013;716:674-679.
2. Yoon JH, Yang IH, Jeong JE. Reliability improvement of a sound quality index for a vehicle HVAC system using a regression and neural network model. Applied Acoustics. 2012; 73(11):1099-1103.
3. Zhao T, Lu B, Jiang W, et al. Evaluation for car interior noise quality preference. Journal of Xi'an Jiaotong University. 2012; 46(5):127-131.
4. Park SG, Sim HJ, Yoon JH, et al. Analysis of the HVAC system's sound quality using the design of experiments. Journal of Mechanical Science and Technology. 2009;23(10):2801-2806.
5. Hohls S, Biermeier T, Balschke R, et al. Psychoacoustic analysis of HVAC noise with equal loudness, INTER-NOISE and NOISE-CON Congress and Conference Proceedings; 16-19 November, 2014; Melbourne Australia 2014. p. 1800-1806.
6. Bodla M, Mohammed R, Bhangale R, et al. Identification of sound quality parameters with respect to subjective feel of HVAC noise of diesel SUV's. ASME 2012 Noise Control and Acoustics Division Conference at InterNoise 2012. 19-22 August 2012; New York, USA, 2012. p. 529-536.
7. Leite RP, Paul S, Gerges SNY. A sound quality-based investigation of the HVAC system noise of an automobile model. Applied Acoustics. 2009;70(4):636-645.
8. Yoon JH, Yang IH, Jeong JE. Reliability improvement of a sound quality index for a vehicle HVAC system using a regression and neural network model. Applied Acoustics. 2012; 73(11):1099-1103.
9. Coen T, Jans N, Van de Ponseele P, et al. Modelling the relationship between human perception and Sound Quality parameters using LS-SVMs. Proceeding of the International Conference on Modal Analysis Noise and Vibration Engineering (ISMA 2004), 2004. p. 3749-3763.
10. Shen XM, Zuo SG, et al. Interior sound quality forecast for vehicles based on support vector machine. Journal of vibration and shock. 2010; 29(6):66-68.
11. Shen XM, Zuo SG, Han L, et al. Interior vehicle noise quality prediction using support vector machines. Journal of vibration, measurement & Diagnosis. 2011;31(1):55-58.
12. ISO 5128:1980, Acoustics – measurements of vehicle interior noise, International Organization for Standardization, (1980).
13. Gong M, Xiao Z, Qu T.S. Measurement and analysis of near-field head-related transfer function, Applied Acoustics (in Chinese). 2007;26(6):326-334.
14. Yu GZ. Error of Near-field HRTF measured by using spherical dodecahedral sound source. Journal of South China University of Technology. 2011;39(12):94-99.
15. Yu GZ, Xie BS, Rao D. Near-field head-related transfer functions of an artificial head and its characteristics. ACTA ACUSTCA. 2012;37(4):378-385.
16. Xue F, Sun BB, et al. Investigation on a novel experimental program for subjective evaluation of sound quality. Internoise and noise-con Congress and Conference Proceedings. Institute of Noise Control Engineering 2015; 9-12 August 2015; San Francisco, USA, 2012. p. 4313-4324.

17. Jiang JG. Subjective and objective evaluation of vehicle interior noise sound quality preference and correlation analysis. Automobile Technology. 2012;8(3):6-10.
18. Liang J. Vehicle interior sound quality preference evaluation model based on correlation analysis. Journal of Jilin University. 2009;39(S2):274-278.
19. You JM, Chen TN, He LM. Method for sound quality evaluation of frequency conversion compressor. Journal of Xi'an Jiaotong University. 2008;42(1):13-16.
20. Legendre P. Species associations:The Kendall coefficient of concordance revisited. Journal of agricultural, biological, and environmental statistics. 2005;10(2):226-245.
21. Baumgartner R, Somorjai R, Summers R, et al. Assessment of cluster homogeneity in fMRI data using Kendall's coefficient of concordance. Magnetic Resonance Imaging. 1999;17(10):1525-1532.
22. Kraemer HC. The small sample no null properties of Kendall's coefficient of concordance for normal populations. Journal of the American Statistical Association. 1976;71(355):608-613.
23. Meng XD, Zhang JH, Li LS, et al. Sound quality prediction of diesel engine noise based on regression analysis. Transactions of Csice. 2011;29(6):534-537.
24. Douglas CM. Introduction to linear regression analysis. New York, 2001.
25. Andrews DF. A robust method for multiple linear regression. Technometrics. 1974;16(4):523-531.
26. Yi YQ, Wang Q, Zhao D, et al. BP neural network prediction-based variable-period sampling approach for networked control systems. Applied Mathematics and Computation. 2007;185(2):976-988.
27. Lv SR, Lv S. Applying BP neural network model to forecast peak velocity of blasting ground vibration. Procedia Engineering. 2011;26:257–263.
28. Xie ZH, Zhang Y, Jin C. Prediction of coal spontaneous combustion in goaf based on the BP neural network. Procedia Engineering. 2012;43(7):88–92.
29. Jin GL, Du W, Guo Y. Studies on prediction of separation percent in electro dialysis process via BP neural networks and improved BP algorithms. Desalination. 2012;291(14):78–93.
30. Cheng JC. Spatial prediction of soil nutrition based on BP neural network. Guangdong Agricultural Sciences. 2013;40(7):64-1586.
31. Corinna C, Vapnik V. Support-vector networks. Machine learning. 1995;20(3):273-297.
32. Lam KC, Palaneeswaran E, Yu CY. A support vector machine model for contractor prequalification. Automation in Construction. 2009;18(3):321–329.
33. Ding Y, Song X, et al. Forecasting financial condition of Chinese listed companies based on support vector machine. Expert Systems with Applications. 2008;34(4):3081–3089.
34. Zhao HB. Slope reliability analysis using a support vector machine. Computers and Geotechnics. 2008;35(3):459–467.
35. Navia-Vázquez A, Parrado-Hernández E, Support vector machine interpretation. Neurocomputing. 2006;69(13):1754–1759.
36. An SH, Park UY, Kang KI, et al, Application of support vector machines in assessing conceptual cost estimates. Journal of Computing in Civil Engineering. 2007;21(4):259–264.
37. Liang J. Model-based fault detection and diagnosis of HVAC systems using support vector machine method. International journal of refrigeration. 2007;30(6):1104-1114.
38. Ahmadi MA, Mohammad E, Seyed MH. Prediction breakthrough time of water coning in the fractured reservoirs by implementing low parameter support vector machine approach. Fuel. 2014; 117(1): 579-589.