Sound quality objective evaluation of electric and combustion engine cars

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Abstract

As the consumption change of combustion engine cars (ICEV) to electric cars (EV) continues, there are audible changes perceived inside the car due to engine components alterations. Thus, an objective evaluation of sound quality study is necessary to uncover mentioned audible shift. EV Sound stimuli from Swart et al and an added ICEV sound stimuli is used to evaluate its psychoacoustics values using a MATLAB-based program, PsySound3. Extracted value was investigated with statistical methods to evaluate psychoacoustics characteristics of each sample such as loudness, sharpness, roughness, tau-e, and peak frequency. ANOVA and Tukey test verified that HEV and PEV have smaller values in loudness and tau-e compared to ICEV and generated/enhanced EV. ICEV has higher values in loudness compared to HEV, PEV, and generated/enhanced EV. While generated/enhanced EV has extreme value in all parameters. During the process, probable connection between parameters were established as well. Similar sound stimuli patterns of Tukey test result were found in loudness, tau-e and peak frequency. Comparable trendlines were also discovered between sharpness, roughness, and tau-e.

Keywords: sound quality, psychoacoustics, electric vehicle.

1 Introduction

Electric vehicle (EV) have different components from internal combustion engine vehicle (ICEV). In ICEV, the driving force comes from the combustion of gasoline and air that moves the piston. This process involves various mechanical components and combustion that continue as long as the car is moving. Whereas EV, the driving force is obtained from electricity by the battery, moves through the inverter, causes an electromagnetic process that drives the motor.

The disappearance of ICEV combustion sound and vibration engine on EV, not only causes sound pressure level (SPL) reduction inside the cabin but also leads to disturbing noises due to masking loss which is usually given by combustion engine loud sound [1]. In addition, EV sound consists of more tonal character due to its high-frequency components. As a result, EV sound can be perceived as annoying and unpleasant by the user [2].

The reduction of SPL in EV's cabin makes this parameter no longer appropriate to use in determining EV sound. Psychoacoustic parameters related to sound quality (SQ) are considered better to determine the appropriate EV sound [3]. Research for indoor EV sound using SQ method has been carried out by Swart et al [4], Qian et al [5], and other researchers, but this research will focus on psychoacoustic parameters.

As one of the objective judgements of sound quality, psychoacoustics parameters deemed appropriate to measure noise. These parameters mimics the complex psychoacoustical features of human ear and considers psychological aspects of men [6] to value the subjectivity in perceiving sounds. There are various parameters in psychoacoustics, and numerous models has been proposed [7],[8],[9],[10],[11]. However, all models have

a common idea in their algorithms: they weight and filter the sound as human ears do before calculation. Therefore, the final equation for psychoacoustics parameters usually sums up the calculated value across all banked noise, usually in critical band e.g., Bark scale, Erb scale.
The main purpose in this study is to evaluate the characteristics of EV and ICEV sound stimuli expressed in psychoacoustics parameters. The extracted value of each parameter furthermore becomes the traits of each sound stimuli, allowing comparisons to be done. This comparison was executed with simple statistical analysis, performed generally and by pairs of sound stimuli across the parameters. Through the process, patterns of sound stimuli sequence also emerged, establishing connection between parameters in this study.

2 Methods

2.1 Sound stimuli

This research uses sound recording from data article "Electric vehicle sound stimuli data and enhancements" by Swart et al [12]. Six cabin interior sounds of PEV and HEV were recorded on the freeway with WOT (Wide Open Throttle) acceleration from 0 km/h to 120 km/h in the shortest time possible. Sounds were recorded from the driver's seat using Squadriga I data acquisition system from Head Acoustics and a BHS I binaural headset, using a sample rate of 44.1 kHz. There are 12 interior cabin EV sound recordings in total, including sounds samples that are generated/enhanced. As a comparison from Swart et al, a 2013 Toyota New Avanza ICEV cabin interior sound recording was also taken using phone recorder. ICEV specification and recording condition can be seen on **Table 1**.
Level of all sounds sample was then normalized using Audacity and smoothed at the end of the sample. Format conversion was also done from .mp3 to .wav.

Table 1 – ICEV specification and recording condition

Sound Sample	Model	Year	Propulsion	Drive System	Tyre type	Capacity	Recording condition
A	Toyota New Avanza	2013	ICEV	Gear box with multiple stages	Bridgestone B250	1296 cc	Cloudy, moist

Table 2 – Selected sound stimuli

Sound	Source	Type	Description
R	Renault ZOE	PEV	WOT interior sound signature[a]
V	Volkswagen e-Up! interior	PEV	WOT interior sound signature[a]
P	Porsche Panamera Hybrid interior	HEV	WOT interior sound signature[a]
B	BMW i3 sound concept	Generated/enhanced EV	Enhanced sound signature concept[a]
E	Motor orders	Generated/enhanced EV	Generated stimulus using data orders[a]
S	Shepard's Tone	Generated/enhanced EV	Shepard-Risset Glissando with 110 Hz fundamental frequency[a]
A	Toyota New Avanza	ICEV	WOT interior sound signature

[a] refer to Swart data article [12] for full details

2.2 Characteristics analysis

The sound samples' psychoacoustics parameters were extracted using an open-source, MATLAB-based program called Psysound3 [13]. The program provides analysis of sound files in different formats, using broad selection of audio analysers modules. Calibration after input used a 1 kHz sine wave generated in Audacity, since gain sensitivity is important and influences the output psychoacoustics parameter values. The main output formats of the analysers are time-series, spectrum objects, and time-spectrum objects [14]. All formats output data can be extracted to .csv for further analysis.
Five psychoacoustics parameters are observed to discover the characteristics difference between sound stimuli: loudness, sharpness, roughness, τ_e, and peak frequency. Three former parameters are selected based on their common use in identifying car interior and automobile noise. Two others, τ_e and peak frequency are the uncommon ones but useful in identifying pitch and related preferred condition for the temporal factors of a sound field[15]. Furthermore, these five selected parameters are frequently used to calculate sensory pleasantness, rating of preference, and annoyance metric [4], [16], [17], [9]. Each parameter is calculated using provided algorithm. Loudness of each sound stimuli is calculated using Glasberg and Moore's time-varying loudness model [18], meanwhile sharpness is based on Zwicker's calculation method [7], and roughness is based on Daniel dan Weber's model [19]. Both τ_e and peak frequency are the independent factors extracted from each time frame of auto-correlation function (ACF), with their definitions provided by Ando [20], [21].
The elimination of existing sound stimuli was done subsequently to reduce the number of samples. The process is done by selecting sound stimuli with maximum and minimum value of each psychoacoustics parameters. Following this manner, the process eliminated half of the sound samples, and the other selected half were used for further statistics analysis. The selected few are listed in Error! Reference source not found..

3 Result and Discussion

3.1 ANOVA Test

Psychoacoustic results on loudness, sharpness, roughness, tau-e, and peak frequency were tested by ANOVA to determine whether there are differences on each sound sample character in each psychoacoustic parameter. P-value of ANOVA test can be seen in **Table 3**.
ANOVA p-value for all psychoacoustic parameters is lower than 0.05, so there is a statistically significant difference between at least a pair of sound stimuli for each psychoacoustic parameter.

Table 3 – P-value for ANOVA test of psychoacoustic parameter

Psychoacoustic Parameter	P-value
Loudness	0.000
Roughness	0.000
Sharpness	0.000
Tau-e	0.000
Peak frequency	0.000

3.2 Discussion for Each Psychoacoustic Parameter

3.2.1 Loudness

Sound samples in the same colour box on error bar are sound pairs that are statistically insignificant in Tukey test. For loudness in **Figure 1**, it can be said that each sound sample has a different loudness character. This is indicated by the absence of sound samples that are in the same colour box.

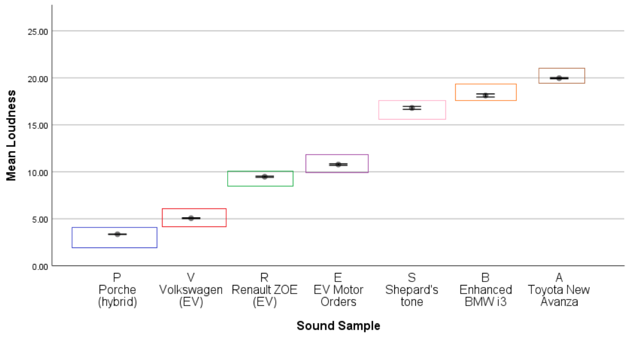


Figure 1 – Mean loudness for each sound sample

The sound sample with the highest loudness is ICEV (sound sample A). The reason is expected to be the dominant combustion engine components that were heard. Thus, an electric car that does not have a combustion engine component automatically has a lower loudness level. Sample P, which is an HEV car having the lowest loudness value, followed by two PEV car sound samples. Although HEV has a combustion motor component, HEV has a lower loudness level. This can happen because the HEV sound sample is a plug-in hybrid electric car, so the combustion engine component was not active during the sample measurement.

3.2.2 Sharpness

In **Figure 2**, sound S has the highest mean sharpness, and sound E has the lowest mean sharpness. Sharpness represents the ratio of high and low-frequency components in a signal, and sharpness can be reduced if there are additional low-frequency components. It can be seen **Figure 3**, sound E is a sound generated by MATLAB, as an approach to the sound of motor with gas input on combustion engine. Therefore, there is some addition of low-frequency components as shown in **Figure 3(a)**, which results in a lower mean sharpness. Meanwhile, the presence of high-frequency components that consistently increase over time (**Figure 3(b)**) on sound S causes a higher sharpness.

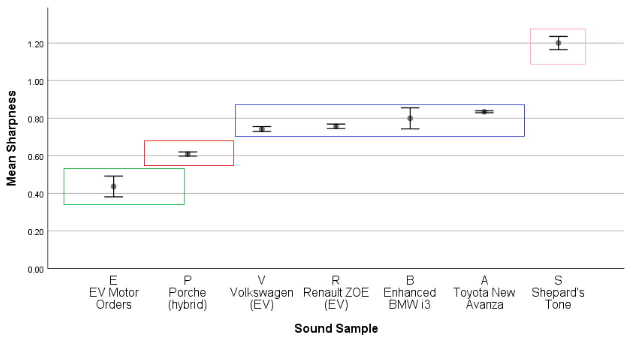
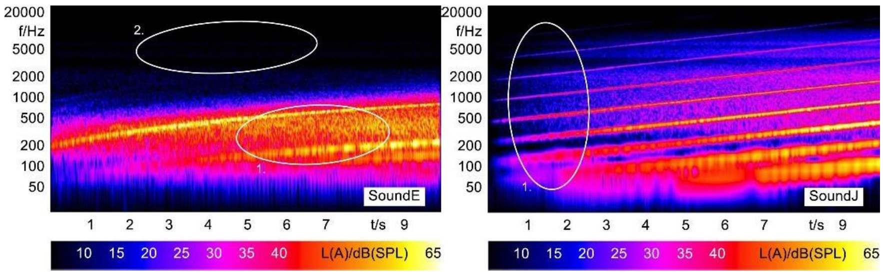


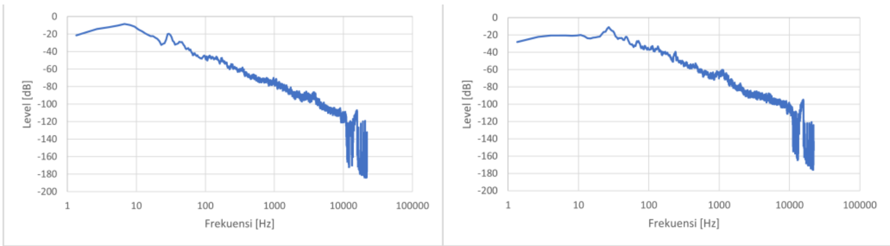
Figure 2 – Mean sharpness for each sound sample



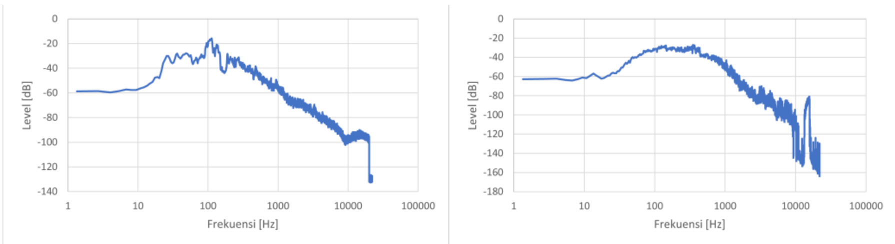
(a) (b)

Figure 3 – Spectrogram of (a) EV Motor Orders and (b) Shepard's Tone [12]

Sound samples inside the blue box (**Figure 2**) that is V, R, A, and B are statistically insignificant. V and R sound samples has the same position. This can be further analyzed using frequency component of each sample in **Figure 4 (a)-(d)**, which can be obtained through the spectrum plot in Audacity. It can be seen that these four samples have approximately the same high and low-frequency components, especially sound V (Volkswagen) and R (Renault) because both stimuli are PEV sound samples.



(a) (b)



(c) (d)

Figure 4 – Frequency components of sound stimuli (a) Volkswagen e-Up! (b) Renault ZOE (c) Toyota New Avanza (d) Enhanced BMW i3

3.2.3 Tau-e

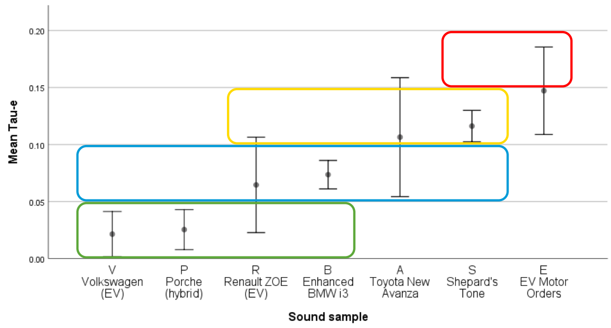


Figure 5 – Mean tau-e of selected sound samples

There are different patterns of insignificant different for τ_e compared to the other parameters discussed above. This difference between sound samples can be divided into four parts, as the coloured boxes suggest in **Figure 5**. This visual data representation of τ_e for each sound sample includes four coloured boxes which indicate the Tukey test results. It is important to note that the presented error bar is not of high accuracy to represent insignificance, resulting in inconsistencies between the graph and boxes, and thus is utilized only as data view assistance.

The green box, indicates the insignificant difference between sample V, P, R, and B. This data shows that PEV and HEV sound samples have broad bandwidth, since small value of τ_e represent noise with similar characteristics to white noise. This characteristic is the immediate effect to aerodynamics noise dominance in PEV and HEV. On the contrary, even though aerodynamic noise is undeniably present, combustion engine noise of ICEV sound sample is more prominent. Therefore, as indicated in yellow box, sample A, S, P, and B has statistically insignificant difference. Furthermore, it is evident that both sample R and B has a wide range of τ_e value, as shown in blue box. This implies both wideband noise and tonal noise is present in samples mentioned. Regardless, sample S and E have the most tonal characteristics of all samples, as shown in red box. In [21], Ando states that τ_e as a correlation feature partially predicts loudness percept. This statement is also proven with comparing **Figure 1** and **Figure 5**. Upon comparison, both data gives the same trendline, with PEV and HEV sound samples having lower value than ICEV and generated/enhanced EV sound samples in both parameters: loudness and τ_e. Therefore, in this study, τ_e and loudness relates unidirectionally.

Another connection is also evident by comparing sharpness and τ_e Tukey test results. From sample V to S, both parameters give a unidirectional tendency, except sample E. Additional analysis uncovers that tonality characteristic of noise defines sharpness. This increasing value of sharpness is detected in noises with bandwidth smaller than a critical band [7]. In this study, the high frequency tonal component is becoming more evident from sample V to S. Meanwhile, sample E as a generated sound sample has lower order addition, meaning the sample also generates a low frequency tonal noise. This addition therefore fathomed to be the reason of sample E’s small sharpness value.

3.2.4 Peak frequency

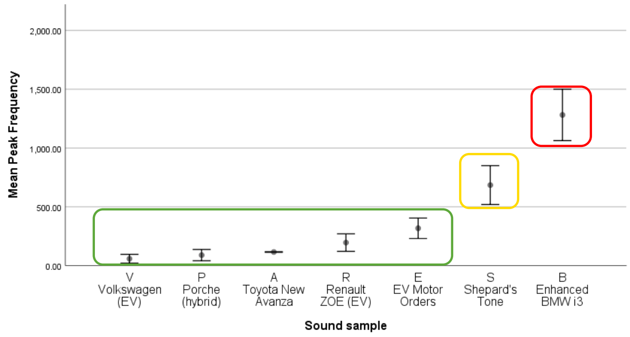


Figure 6 – Mean peak frequency of selected sound samples

Based on **Figure 6**, peak frequency value of each sample has conspicuous difference, particularly sample S and B, as yellow and red boxes suggest. Sample S - Shepard's glissando tone – naturally consisted of high frequencies. Sample B, as an enhanced BMW i3 cabin sound signature, underwent the addition of E^{7th} harmony as part of its enhanced process. This addition may be the reason of its high peak frequency value. Nevertheless, the other samples are proven in having statistically insignificant difference while also possess low peak frequency component, as indicated in the green box. It is also evident that PEV, HEV, and ICEV sound stimuli are found to have similarities in peak frequency value. ICEV low frequency components are explicitly from its combustion engine. For HEV and PEV, [12] suggests tire and wind noises as its source.
Upon comparison with other parameters, similar patterns of sound stimuli sequence were found between loudness and peak frequency. Sample V, P, and R as HEV and PEV sound stimuli have small values in general, while sample S and B inhibited higher values. The contradictory in this pattern is sample A, which should have a lower value in loudness based on its value in peak frequency. After going through some supplementary analysis, researchers contend to the level domain of sound stimuli. A noise loudness value is affected by two components: its level and frequency contents [7]. Speaking in frequency domain, sample S and B should have higher loudness value than sample A, since both samples inhibited higher and more sensitive region of frequency to human ear. But in level domain, since normalization in Audacity only applies to highest amplitude peak in each sound stimuli, overall level of sample A is higher than sample S and B due to the whirring and booming sound of combustion engine in WOT state.

3.2.5 Roughness

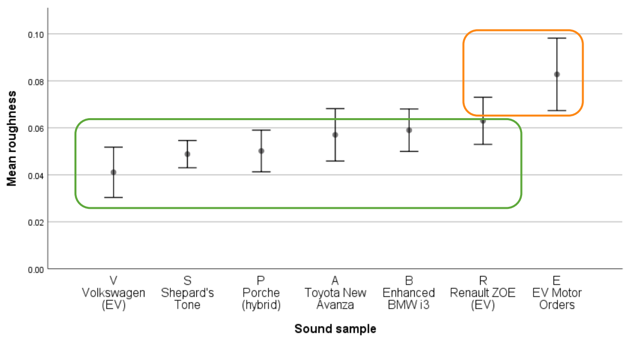


Figure 7 – Mean roughness of selected sound samples

In case of roughness, all selected sound samples are divided into two groups, shown in **Figure 7**. All samples – except sample E – are members of the first group (green box) which have statistically insignificant difference in mean roughness value with each other, proven with Tukey test. That is, with lower roughness value than sample E, which constructs the second group along with sample R in yellow box. The result shows sample E has the highest and distinguished roughness value, while PEV and HEV sound samples has statistically equal roughness value with ICEV sound samples, even though their drive components are different. These outcomes are congruent with research by Swart [22], which states that sample E is characterized by initial roughness value, attributed to the addition of frequency modulation. It is also important to note that in his research, Swart mentions that there is a possible counteraction between roughness and sharpness. In this study, the mentioned possibility evinces in sample E, but is elusive in other samples. Comparison between roughness and τ_e is also worth to point out, since sample E and sample V both have maximum and minimum value respectively in mentioned parameters. This outcome denotes probable connection, that tonality increases roughness value. Yet not all results correspond to this probability, since modulation in amplitude, frequency, or both is also needed to take account of.

4 Conclusions

Seven cabin sound stimuli of EV and ICEV were evaluated objectively using five psychoacoustic parameters. The time-series data of each parameter then analysed statistically using ANOVA test and Tukey test. The former test revealed there were statistically significant difference between at least two sound stimuli in each parameter. The latter, however, showed different insignificant combination across the parameters. HEV and PEV sound stimuli were found to have smaller values in loudness and tau-e parameters compared to other sound stimuli. ICEV sound sample had notable high value in loudness due to its combustion components. Meanwhile, generated/enhanced EV sound stimuli had extreme values all over the parameters. Additional discovery was also found regarding the probable connection of parameters. Loudness was found to have connections with tau-e and peak frequency, while sharpness, tau-e, and roughness have probable connection between them. Similar studies of psychoacoustics parameters reveal corresponding results. However, even though some of these connections had been established, some others are not yet resolute. Further analysis is needed alongside subjective evaluation with more scrutiny to obtain promising results.

Acknowledgements

We would like to thank Institut Teknologi Bandung on their PPMI program which has funded our research.

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