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Research paper

Data-Driven Identification of Gearbox Housing Structures Using Acoustic Radiation Spectra

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Abstract

The structural design of gearbox housing, such as ribbing and wall thickness, has a significant impact on its noise radiation characteristics, especially in electric vehicle applications where tonal noise is more perceptible. This study presents a novel methodology that uses machine learning and spectral analysis to distinguish between gearbox housing types based solely on their acoustic radiation data. Frequency-domain sound pressure spectra, simulated for multiple design variants, were interpolated and analyzed using Principal Component Analysis (PCA) and K-means clustering. The results reveal that construction types (e.g., fully ribbed, partially ribbed, or without ribs) exhibit distinct acoustic profiles. Furthermore, a Random Forest classifier achieved 88.9% accuracy in predicting structural configuration from the spectra alone. These findings demonstrate that structural design features can be inferred directly from acoustic data, offering a lightweight and geometry-free alternative to traditional NVH simulation workflows. The approach can be integrated as a lightweight plug-in in existing NVH workflows. It ingests acoustic spectra and returns a structural-stiffness label with uncertainty, supporting early-stage screening and late-phase regression checks.

***Keywords**: Gearbox Housing, Acoustic Radiation, Structural Design Classification, Machine Learning, Acoustic Spectra, PCA, K-means, NVH*

1. Introduction

Gearbox housings significantly influence the noise, vibration, and harshness (NVH) behavior of vehicle powertrains—an effect that becomes increasingly critical in electric vehicles (EVs), where tonal gear noise is no longer masked by combustion engine broadband noise (Horváth & Zelei, 2024). Classical approaches to NVH evaluation rely on finite element (FE) or boundary element (BEM) simulations to extract modal characteristics and identify resonant behavior (Rajagopal & Harsha, 2021). These methods are accurate but computationally expensive and difficult to integrate into early-stage design workflows, especially during rapid concept iteration.

To reduce reliance on high-fidelity CAE, machine learning (ML) techniques have been introduced to predict radiated noise or dynamic responses based on geometric or vibration-based input features (Li et al., 2023; Jiang et al., 2022). Surrogate models and digital twin frameworks are gaining traction in this context, enabling fast predictions of NVH performance based on trained data (Ma et al., 2023; Zhao et al., 2022). However, most existing methods either assume access to vibration response fields, geometry-based design parameters, or complete CAE simulation results.

Recent studies have proposed learning-based models to estimate noise levels from vibration–acoustic coupling (Li, Hu, & Wang, 2021), but few have addressed the inverse problem: identifying a component's underlying structural design—such as wall thickness or ribbing concept—purely from its radiated sound spectrum. This classification capability could accelerate early design assessments without requiring geometry files, modal simulations, or physical testing.

This study hypothesizes that gearbox housing structural stiffness levels can be classified from radiated sound spectra using unsupervised and supervised machine learning techniques. Using an open dataset of simulated acoustic responses, we explore the extent to which machine learning models can extract this structural information from frequency-domain data, and evaluate both unsupervised and supervised approaches for doing so.

The industrial relevance of this question lies in the ability to rapidly assess mechanical properties, such as flexibility or rigidity, based solely on sound-pressure data. Typically, generating such spectra requires a CAD model. Our method circumvents this by removing the need for additional finite element (FE) simulations or manual interpretation of structural behavior. This offers a time-saving advantage for early-stage design screening, concept ranking, and surrogate classification in NVH optimization workflows.

Our study aligns with "machine listening," where spectral patterns are embedded (e.g., via PCA) and classified with supervised models to support decision-making. Recent reviews in acoustics document this shift toward data-driven analysis and robust classification in real-world environments (Bianco et al., 2019; Abeßer, 2020).

2. Materials and Methods

2.1 Dataset

We use the “Effect of Lightweight Design on the NVH Behavior of an Electric Vehicle Gearbox Housing” dataset published on the KIT RADAR repository (Farshi Ghodsi et al., 2024). It contains frequency-domain sound-pressure results (100–6000 Hz) for three construction types (Table 1).

Table 1: Construction types labeled with SSI.

Construction type	Description	Files (n)	Label (= SSI)
Type 0	No ribs (flexible)	4	0
Type 1	Partial ribbing	4	1
Type 2	Full ribbing (rigid)	4	2

The integer label is termed the Structural Stiffness Index (SSI) and is used throughout the analysis.
Figure 1 illustrates the broadband SPL behaviour: the fully ribbed housing consistently exhibits lower spectral peaks than the non-ribbed variant, confirming the damping effect of structural stiffening.

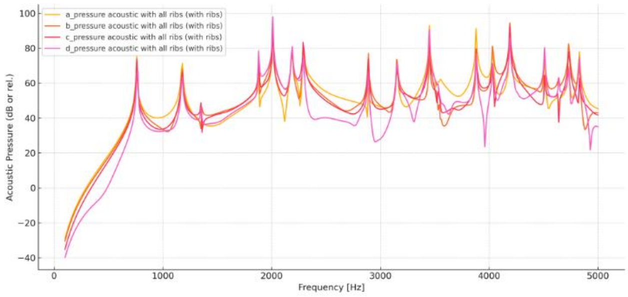

Fig. 1: Broadband acoustic pressure spectra for gearbox housings with and without ribs, showing how increased structural stiffness (full ribbing) leads to reduced spectral peaks in the critical NVH frequency range.

2.2 Workflow

(1) Export acoustic radiation spectra from test or CAE. (2) Interpolate to a common frequency grid and standardize. (3) Compute a PCA embedding for drift/novelty checks. (4) Cluster with K-means to expose structure (ARI for evaluation). (5) Train a Random Forest classifier on labeled data and report accuracy with cross-validation. (6) Provide class probabilities and flag out-of-distribution samples based on PCA distance and probability entropy.

2.3 Spectral Pre-processing

The resulting matrix X, consisting of 9 samples with 100 frequency-domain pressure features each, and the corresponding label vector y (SSI) were saved for reproducibility.

2.4 Dimensionality Reduction and Clustering

Principal Component Analysis (PCA; Jolliffe, 2016) compressed the spectra to two principal components (PCs). K-means clustering (MacQueen, 1967) with $k = 3$ was then applied in PC-space. Cluster quality was quantified using the Adjusted Rand Index (ARI).

2.5 Classification

A Random-Forest (RF) classifier (Breiman, 2001) with 100 trees was trained to predict SSI from the 100-point spectra. Performance was evaluated with a 3-fold cross-validation.

2.6 Frequency-Specific Features

To highlight dominant tonal contributions, pressure amplitudes were extracted at five characteristic NVH frequencies (1560, 1980, 2010, 2300, 2900 Hz). These features were compared across SSI levels.
The five frequencies (1560, 1980, 2010, 2300, and 2900 Hz) were chosen based on their prominence in the simulated spectra and their alignment with known gearbox tonal noise sources, such as gear meshing harmonics and structural resonance modes identified in prior NVH studies. These frequencies are typically most sensitive to changes in housing stiffness and ribbing configuration.
We have also noted in the Discussion section that a broader frequency analysis could be considered in future work.

3. Results

3.1 Spectral Separation in PCA Space

Figure 2a shows the PCA projection coloured by SSI. The three housing concepts occupy distinct regions, indicating that global spectral shape encodes structural stiffness.

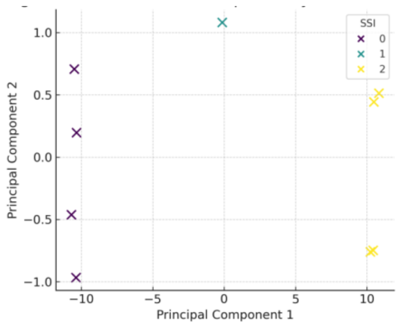

Fig.2a: PCA projection of acoustic spectra, where PC1 and PC2 capture variance in spectral shape driven primarily by structural stiffness (SSI). Distinct clustering reflects differences in ribbing configuration.

3.2 Unsupervised Pattern Discovery

K-means reproduced this separation (Figure 2b). The clustering achieved ARI = 0.77, demonstrating strong agreement with the ground-truth labels.

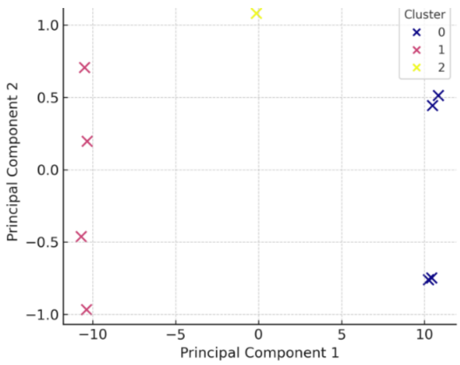

Fig. 2b: K-means Clustering in PCA Space.

3.3 Supervised Classification

The RF model predicted SSI with 88.9 % ± 0.0 % accuracy, confirming that spectra alone suffice for reliable identification (Table 2).

3.4 Frequency-Domain Feature Analysis

Figure 3 compares pressure amplitudes at key NVH-relevant frequencies using boxplots. At both 2010 Hz and 2900 Hz, the fully ribbed housing (SSI = 2) exhibits the lowest median sound pressure levels, while the flexible design (SSI = 0) shows consistently higher peaks. This trend supports the theoretical expectation that increased structural stiffness shifts resonance modes to higher frequencies and reduces acoustic radiation at these critical points.

Table 2: Performance of the models.

Model performance summary	Value
K-means ARI	0.77
RF accuracy (3-fold CV)	88.90%

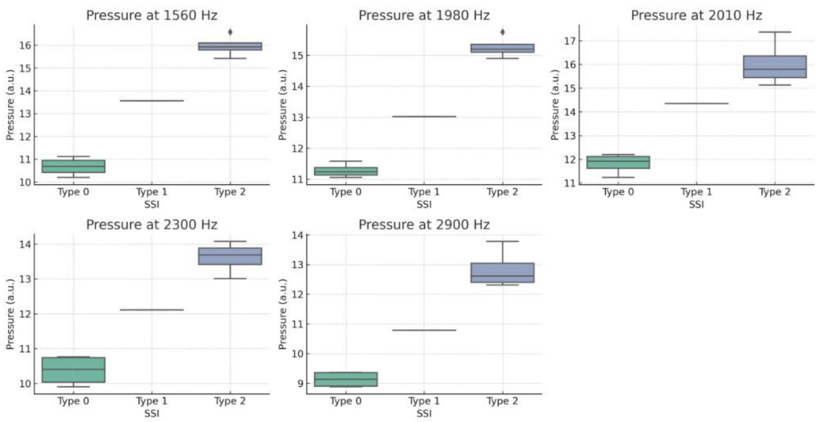

Fig.3: Acoustic Pressure at Key Frequencies by Structural Stiffness Index.

An ARI of 0.77 indicates strong agreement between the unsupervised clusters and the structural-stiffness labels, suggesting that the spectral patterns carry sufficient information to separate housing variants without geometry.

4. Discussion

The findings of this study highlight the potential of data-driven techniques to extract meaningful structural insights from acoustic radiation spectra. Traditionally, predicting the impact of structural design—such as ribbing or wall thickness—on radiated noise required detailed modal analysis or physical prototyping. Here, we demonstrate that acoustic frequency-domain data alone can serve as a proxy for such structural characteristics.

The clear clustering observed in the PCA space confirms that the acoustic response is systematically influenced by the mechanical stiffness of the gearbox housing. K-means clustering achieved a high Adjusted Rand Index (ARI) of 0.77, despite having no access to structural labels during training. This indicates that the spectral profile naturally encodes physical properties such as stiffness and resonance behavior.

The high classification accuracy (88.9%) achieved using Random Forest further confirms that the construction type can be inferred reliably from spectral features. Importantly, this was done without any input from CAD geometry or structural simulations, demonstrating a lightweight evaluation method.

The frequency-domain feature analysis further validated these results. Boxplots of pressure amplitudes at key NVH frequencies (1560–2900 Hz) revealed a consistent relationship between structural stiffness and sound pressure level. This is in line with vibroacoustic theory, where stiffer structures typically exhibit higher modal frequencies and lower amplitudes at resonance.

These results demonstrate that acoustic spectra can assess radiated noise and infer structural design decisions. This opens new pathways for AI-assisted NVH optimization, surrogate modeling, and early-stage design verification. Importantly, this can be done without full-scale simulation or test infrastructure.

A notable limitation of the present study is the relatively small dataset size, comprising only nine simulated spectra. While the results demonstrate clear spectral separation and high classification accuracy, such findings may not fully generalize to broader design variations or real-world conditions. Future work should focus on validating the approach with larger datasets, ideally combining both simulated and experimentally measured acoustic spectra. Incorporating physical prototype testing would help account for manufacturing tolerances, material variability, and environmental influences, thereby strengthening the robustness and industrial applicability of the method

We envision deployment as a thin, tool-agnostic plug-in that ingests acoustic spectra exported from existing NVH toolchains (test benches or CAE post-processing) and returns a Structural Stiffness Index (SSI) with uncertainty. A typical loop is: (1) export spectra. (2) interpolate and standardize. (3) embed with PCA for drift/novelty checks. (4) Classify with a trained Random Forest and log feature attributions. (5) flag out-of-distribution samples for engineer review. This sits naturally after order analysis and before full vibro-acoustic CAE, enabling early screening during concept selection and late-phase regression checks.

Two integration modes are straightforward: (i) batch mode within CI/CD pipelines for digital twin updates, where each new concept is auto-scored against historical spectra; and (ii) interactive dashboards that visualize PCA maps, class probabilities, and frequency-band boxplots. This reduces reliance on heavy FE/BEM runs while maintaining traceability from spectra to verdicts.

5. Conclusion

This study presents a novel methodology for distinguishing gearbox housing designs based solely on their acoustic radiation spectra, without relying on geometric or simulation model inputs. By applying Principal Component Analysis (PCA), K-means clustering, and Random Forest classification to simulated acoustic data, we demonstrated that:

- Gearbox housings with different structural stiffness levels produce acoustically distinct spectral profiles;
- These profiles can be clustered unsupervised with a high degree of accuracy (ARI = 0.77);
- Supervised machine learning models can predict the construction type with up to 88.9% accuracy;
- Specific NVH-related frequencies (e.g., 2010 Hz, 2900 Hz) show strong correlation with the structural configuration.

The proposed method enables automatic classification of gearbox housing stiffness based solely on sound-pressure spectra. It does not require mechanical interpretation, modal analysis, or a full NVH post-processing workflow. A CAD model is typically required to generate these spectra through simulation. Our method eliminates the need to re-run or manually assess structural behavior. This reduces turnaround time in early design screening or late-phase design validation.

Future studies could validate these findings using sound pressure data collected from physical gearbox prototypes to ensure real-world applicability and to account for effects such as manufacturing tolerances, assembly variability, and environmental noise conditions

Future research could explore convolutional neural networks and other deep learning architectures to capture complex, non-linear spectral patterns beyond the capabilities of traditional feature-based methods. Additionally, the methodology could be extended to other powertrain components such as motor housings, transmission cases, or structural subframes, enabling a broader application of data-driven NVH diagnostics

Because the method operates on spectra alone, it can be adopted early in design as a geometry-free screening tool and later as a regression check, complementing—not replacing—established NVH simulations.

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