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Advancing Durability Testing in Automotive Component through Prognostics and Health Management (PHM) Integration

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ABSTRACT

In automotive Powered Door Systems (PDS), the emergence of grinding and clicking noise over time is a common failure mode. This issue typically arises from design or assembly inconsistencies and intensifies due to wear or increased clearance at its component, becoming noticeable to passengers, and causing discomfort. Numerous automotive manufacturers conduct comprehensive durability tests to tackle such issues during the development. Conventional durability tests, however, rely on the manual effort such as visual and auditory inspection at regular intervals, hence, is subjective and inefficient. This study introduces a novel method by the prognostics and health management (PHM) approach to detect anomaly and assess its severity of the noise during the durability test of the PDS, which may improve the reliability of noise detection and reduces the test time by early termination using prognosis capability. The results demonstrate the potential, paving the way for its broader application across various domains to advance testing processes and reliability.

1. INTRODUCTION

In recent developments in the automotive industry, many components are electrified to enhance the user convenience. Prominent examples include power window, automatic tailgates, and power door systems. These systems, however, often have various forms of wear and joint failures, significantly impacting user satisfaction and perceived vehicle quality.

Most issues with these components stem from design flaws or problems during the assembly process. To address these challenges and improve vehicle durability and reliability, automotive manufacturers conduct durability tests. Conventionally, these tests have relied on manual visual and auditory inspections performed at regular intervals, which are both subjective and inefficient.

Prognostics and Health Management (PHM) technology has gained considerable attention across various industries, including aerospace, smart manufacturing, power plants, and transportation, for its potential to prevent failures, reduce operational costs, and facilitate predictive maintenance.(Choi, 2014; Zio, 2022) The potential of PHM to enhance durability testing is substantial. In this paper, we discuss the application of PHM techniques and frameworks to durability testing, focusing on developing more accurate and automated diagnostic models.

1.1. Power Door System (PDS)

The case study presented in this paper focuses on the Power Door System (PDS), a feature designed to enhance user convenience in high-end vehicles. Figure 1 illustrates a vehicle equipped with the PDS on its rear door, showcasing the application of the PDS. This system automatically closes the door after a passenger enters.

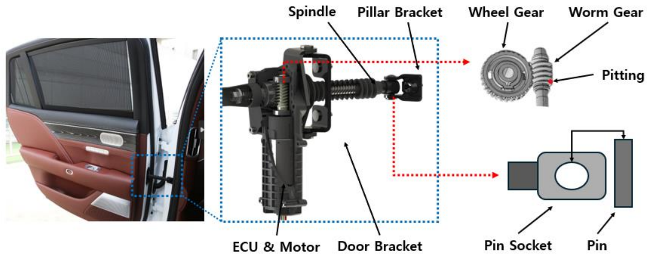


Figure 1. Power door system installed on a vehicle

The PDS is mounted on each door, and as shown in Figure 1, the ends of the spindles are connected into the pillar of vehicle. When the motor rotates, it drives the worm gear to turn the wheel gear. The relative motion then pulls the spindle, closing the door with a mechanism that takes about 3 seconds for the closure operation.

In case of the poor design or manufacturing, the PDS can encounter issues such as a grinding or clicking noises during the door closing, which usually occurs after cycles of door closing. The grinding noise is a continuous rough sound heard throughout the closure. This noise is often caused by small pitting on the drive worm gear, as depicted in upper right corner of Figure 1. On the other hand, the clicking noise is a sharp sound heard at a certain moment during the door closing. It occurs due to clearance, wear or assembly damage between the pin and pin socket connecting to the body's pillar. These noises are characterized as periodic and impulsive, respectively.

In order to determine the occurrence of these noises in the PDS, a durability test is conducted, incorporating both visual and auditory inspections at regular intervals. The method, however, is not reliable nor efficient due to the manual procedure. To overcome this, a diagnostic model is developed, thereby enhancing the reliability and functionality of the PDS.

1.2. Sensor Selection

To choose a sensor that can reveal useful features for the diagnosis, four sensors are considered for the potential candidates: motor current, motor rotation (hall sensor), and accelerometer attached to the PDS and to the body side. The current and hall sensor data are collected at a rate of 4 kHz, while the accelerometer data at 25.6 kHz.

Figure 2 illustrates the signals captured by these sensors during the operation of PDS. Each graph within the figure represents the data from different sensors, plotted over time to show the dynamic changes in sensor readings as the door progresses through 3 repetitions of open and close motions.

Upon comparison of these signals in terms of efficacy of diagnostic, consistency, strength and the convenience of installation, the accelerometer signals perpendicular to the body side is found appropriate for the study. Consequently, all the signals discussed in this paper are measured from this sensor.

The rest of the paper is outlined as follows: Section 2 introduces the PHM framework, Section 3 and 4 detail the process of developing diagnostic models for grinding noise and clicking noise, respectively. Lastly, conclusions are presented in Section 5.

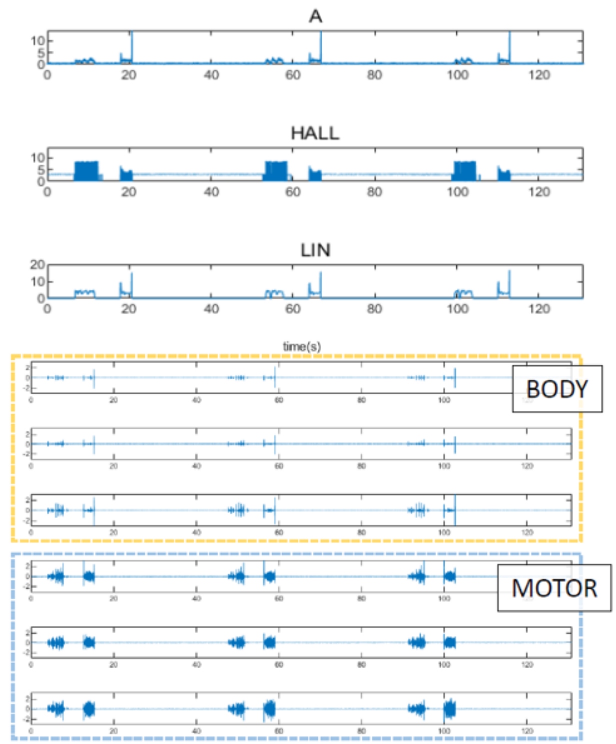


Figure 2. Various sensor signals of the PDS motion

2. PHM FRAMEWORK

In this section, the development procedure of diagnostic model and its application to test data are addressed. Figure 3 illustrates the overall flowchart of the PHM process. It has two major phases: construction of the diagnostic model and its application.

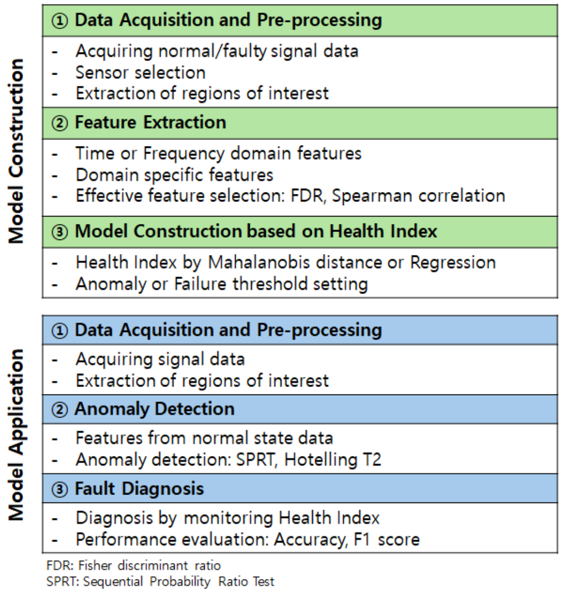


Figure 3. Flowchart of PHM framework

In the construction phase, the first step is the collection of sensor signals and pre-processing. Two types of signal data are collected in the test: first is the discrete data for normal and faulty conditions. second is the continuous data from the normal to the failure. In a single set of signal data, not the whole period is exploited but only a segment is taken for a better feature extraction. This varies depending on the considered noise, which accounts for the symptoms and causes of failures as well as the operational mechanisms of the system.

Next is the feature extraction and selection. Various features are extracted, including time domain, frequency domain, and domain-specific features.(Sim et al., 2020) Effective feature selection involves choosing the features with higher value of Fisher Discriminant Ratio (FDR) that can better distinguish the normal and faulty conditions in case of discrete data and the features with a higher Spearman correlation in case of the continuous data.

Based on the selected features, a health index (HI) is constructed in the next step. While there are several approaches for this, Mahalanobis distance is employed in this study, which is useful when there are the normal features only. Thresholds for anomaly and failure are established for the HI, respectively, to effectively distinguish between the normal, warning and failure states.

In the application phase, data from the test subjects are collected. Following the procedures defined in the diagnostic model, the HI is calculated and monitored to perform anomaly or fault detection. This systematic approach allows for precise and proactive management of system health.

3. DIAGNOSIS MODEL FOR GRINDING NOISE

To develop the diagnostic model for grinding noise, normal and faulty data sets are collected from three specific cases. Among these, case A involves less severe noise occurrence, while the cases B and C involve relatively severe noise occurrences.

Table 1. grinding noise datasets

Vehicle / Placement	Class	Features	Case
Vehicle1 / Front	Normal	-	A
	Faulty	Small grinding noise	
Vehicle1 / Rear	Normal	-	B
	Faulty	Loud grinding noise	
Vehicle2 / Rear	Normal	-	C
	Faulty	Loud grinding noise	

As described in Section 2, for the development of the diagnostic model, accelerometer which attached to the vehicle's body is utilized. Figure 4 presents simultaneous recordings of the motor's relative rotational speed and vibration signals. It can be observed that the motor operates in three phases of acceleration, constant speed, and deceleration.

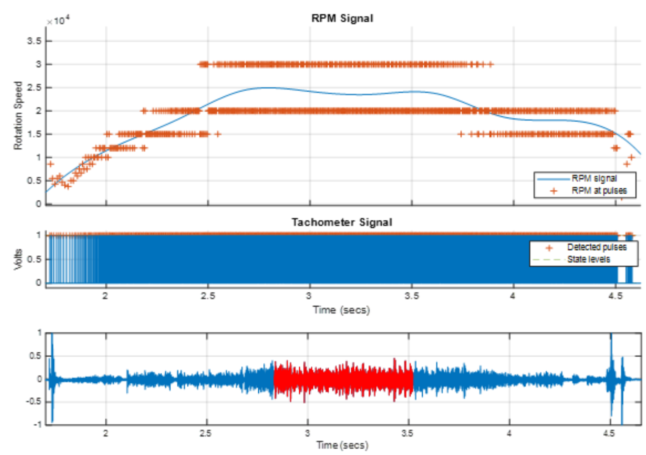


Figure 4. Motor speed and accelerometer signal while closing

Since the grinding noise occurs continuously during the closing operation, the signal over the whole period can be responsible for the noise. However, only a part with constant speed is chosen for the efficacy of feature extraction.

Using the signal in constant speed, numerous candidate features are extracted as shown in Figure 5, in which the blue o and red x denote the normal and fault respectively. Note that all the features are normalized by Gaussian distribution. Among these, more significant features are selected that can distinguish the two classes more clearly. For this purpose, Fisher discriminant ratio (FDR) is calculated, defined as follows.

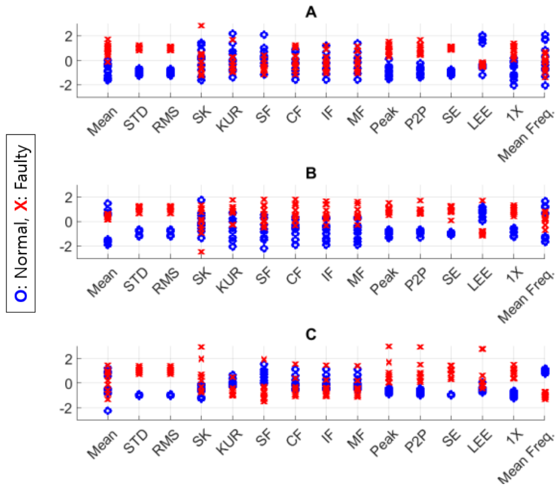


Figure 5. Features from each signal of four datasets

$$FDR = \frac{(\mu_1 - \mu_2)^2}{\sigma_1^2 + \sigma_2^2} \quad (1)$$

where μ_i is mean value of feature, and σ_i is standard deviation of feature for i-th class. As a result, the root mean square (RMS) and Shannon entropy (SE) are recognized as the most important features.

Using these selected features, an HI based on the Mahalanobis distance is constructed from the normal data as defined in the following equation.

$$HI = (\mathbf{x} - \mu_n)'\mathbf{S}_n^{-1}(\mathbf{x} - \mu_n) \quad (2)$$

where $\mathbf{x}$ is feature vector of input data, μ_n is mean of feature vector for normal data and $\mathbf{S}_n$ is covariance matrix of feature for normal data. The results as shown in Figure 6, demonstrate a clear distinction between the normal and faulty data across all cases. Based on the HI values of the collected normal and faulty data, thresholds for anomaly and failure are established as the dotted blue and magenta lines, which are the normal HI at upper 95% confidence and fault HI at lower 95% confidence levels, respectively. This diagnostic model can be utilized in the future tests to determine whether the product yields the grinding noise during the cycles of operation.

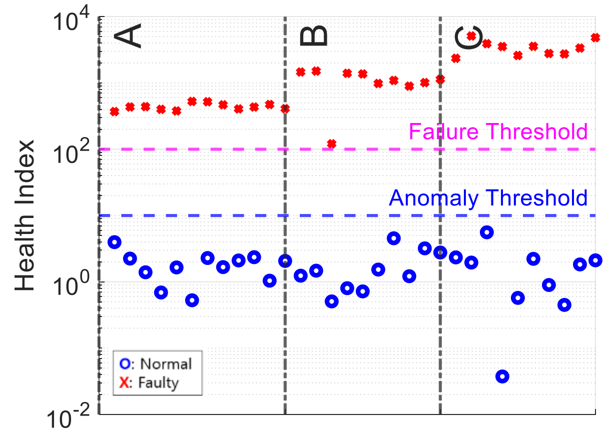


Figure 6. Health index for three cases

4. Diagnosis Model for Clicking Noise

To develop the diagnostic model for clicking noise, datasets are collected from both the front and rear doors of vehicles. The collected datasets are given in Table 2. Front door datasets include four discrete states: two normals and two faults, each collected from different PDS installed on two vehicles. In the table, Normal 1 and Normal 2 indicate no clicking noise. However, Normal 2 is with a subtle grinding noise. And Fault 1 indicates a small clicking noise, while Fault 2 indicates a significantly loud clicking noise. For the rear door, run-to-failure data are collected for up to 38,000 cycles, from which the normal and fault are defined by those less than 10,000 and over 23,000 cycles based on the experts' opinion.

Table 2. Clicking noise datasets

<table>
<tr><th>Vehicle / Placement</th><th>Class</th><th>Feature</th><th>Case</th></tr>
<tr><td>Vehicle1 / Front</td><td>Normal1</td><td>-</td><td rowspan="4">Front</td></tr>
<tr><td>Vehicle1 / Front</td><td>Normal2</td><td>Small grinding noise from motor</td></tr>
<tr><td>Vehicle2 / Front</td><td>Faulty1</td><td>Small clicking noise</td></tr>
<tr><td>Vehicle1 / Front</td><td>Faulty2</td><td>Loud clicking noise</td></tr>
<tr><td rowspan="2">Vehicle2 / Rear</td><td>Normal</td><td>-
(Cycle 0 ~ 10000)</td><td rowspan="2">Rear</td></tr>
<tr><td>Warning</td><td>Tiny clicking noise
(Cycle 10000 ~ 23000)</td></tr>
</table>

	Faulty	Small clicking noise (Cycle 23000 ~ 38000)	

As opposed to the grinding noise, clicking noise, characterized as an impulsive signal, typically occurs only at a certain moment during the door closing. To isolate these impulsive events, kurtosis in a short interval with 0.1 second is computed over a sliding time window, which is a widely used feature in vibration analysis for its ability to detect spikes in signals.(Cerrato-Jay et al., 2001; Honarvar & Martin, 1997)

Figure 7 illustrates both the original and its kurtosis for the sound and vibration signal, respectively. In the analysis, signals at the beginning (0-0.3 seconds) and after 2.5 seconds are disregarded as they are those at the start and end of closing, respectively. In the upper two figures, it is observed that the moments when the noise is heard and when its kurtosis shows local peak are the same, as marked by the red explosion symbols. Based on this finding, the vibration signal is processed in the similar manner, which are given in the lower two figures. Interestingly, the moments when the kurtosis shows local peak are the same in the sound and vibration signals. Therefore, the kurtosis is used as the means to identify the moment of clicking noise, and the signal over a small time period of 0.1 second is taken for further processing towards the feature extraction.

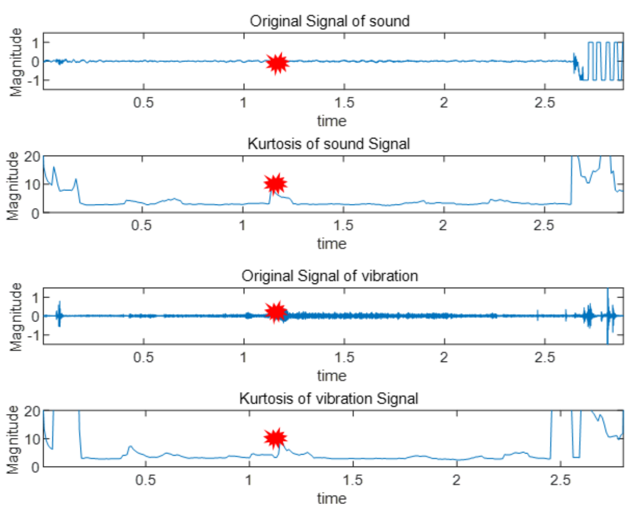
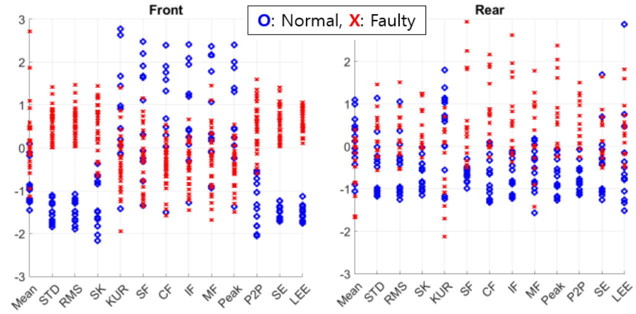


Figure 7. Raw signal and frame kurtosis for sound and vibration signal

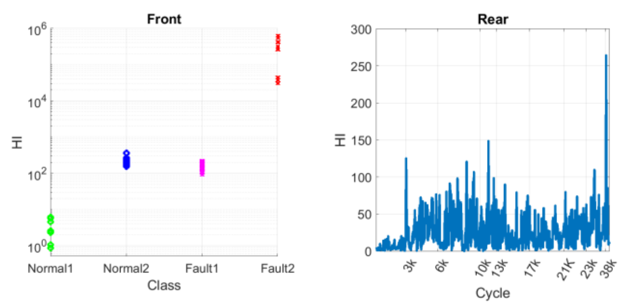
As in the previous section, several candidate features are extracted, from which the most significant ones are sought for. The results are in Figure 8, in which (a) are those for the front (normal 1 and fault 1 only), and (b) are for the rear (normal less than 3,000 cycles and fault over 33,000 cycles) are taken among the run-to-failure data). The blue o and red x denote the normal and fault respectively. In comparison with the grinding noise, the separation between the normal and fault both in the front and rear are less clear.



(a) (b)

Figure 8. Features from each dataset

Nevertheless, the same procedure is taken to select the most important features, which are RMS (root mean square), P2P (peak-to-peak), and SE (Shannon entropy). The diagnostic performance by the HI made of these features are shown in Figure 9. In Figure 9(a), which is the result of front door, considerable overlap is found between the HI for normal 2 (blue o) and fault 1 (magenta x). Furthermore, in the case of rear door as shown in Figure 9(b), clear increasing trend are not present towards the fault conditions. All these suggest that the selected features are not so effective to use to construct HI.



(a) (b)

Figure 9. Health Index from each dataset

To discover more effective features, another attempt is made, which is the time-frequency analysis. Figure 10 displays a spectrogram of continuous wavelet transformation (CWT), obtained for the instant of 0.1 second centered at the clicking noise. The result reveals that the clicking noise occurs in a very short 10 ms time window at a certain frequency range. In order to quantify this into the feature and use it as the HI, total energy of the impulsive moments within specific time and frequency windows is used. The results are illustrated in Figure 11, in which the Figure 11(a) for the front door shows a better distinction between the normal and fault, and Figure 11(b) for the rear door with run-to-failure presents a better increasing trend in HI, demonstrating the superiority of the CWT based approach over the time-based ones.

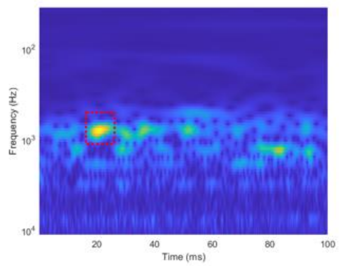
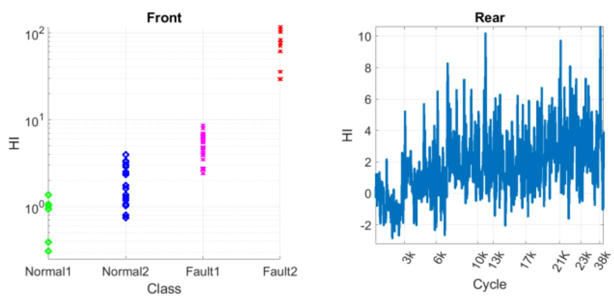


Figure 10. Spectrogram for click noise

Despite these advancements, there remains considerable dispersion in the HI, which makes it still challenging to apply in the field. This variability could stem from various external factors that influence the occurrence of clicking noises. Further signal processing efforts to mitigate these influences or the identification of more effective features will be essential to enhance diagnostic accuracy.



(a) (b)

Figure 11. Health Index from new feature

5. Conclusions

In this study, prognostics and health management (PHM) approach such as the signal processing, feature extraction and selection, and construction of HI, was applied to develop diagnostic models for two representative faults occurring in the power door systems (PDS): grinding and clicking noises. These faults are characterized by a continuous rough sound and a sharp, transient sound during door closure, respectively.

The method has facilitated the development of diagnostic models capable of detecting both types of noises, demonstrating the potential in the real-world applications.

However, much more data are necessary to refine the model and validate its performance, which requires a lot of efforts in time and money. Particularly for the clicking noise model, the HI contains significant uncertainty, highlighting the necessity for exploring diverse approaches and possibly new features to enhance diagnostic accuracy.

By integrating the PHM into the durability tests, we have showcased the potential for automation and quantitative fault assessment. If we can obtain comprehensive run-to-failure (RTF) data, it might also enable us to predict the remaining useful life of components, which could significantly reduce testing time by preemptively forecasting the occurrence of noise issues.

Acknowledgments:

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