

Study on Optimal Design and PHM Methods for New Electrification Systems

Hong Suk Chang¹

¹*Hyundai Motor Company, Hwaseong, 18280, Republic of Korea
paperclock@hyundai.com*

ABSTRACT

This study will describe the development of PHM method for electrified systems in mass-produced vehicles. The results demonstrate that the method is not limited to the research subject but can also be applied to newly developed electrified systems, demonstrating continued applicability even when the target is changed. Next, we will provide an overview of the development of PHM method that can be used universally across electrified systems. In Phase 1, we identified key failure modes that could occur in electrified systems using FMEA, based on data collected from design, analysis, and testing. In Phase 2, we explored appropriate diagnostic methods for each failure mode. For gear failures, we developed rule-based indicators and verified their validity through experiments. For bearing failures, we also developed a rule-based approach to determine the presence of a fault. However, due to limitations in predicting the location of the fault, we re-evaluated the method based on data to confirm its validity. For failure modes, we used CAE analysis models to identify differences between normal and fault signals for eccentricity and demagnetization faults. Similar signal differences were also observed in the test results of the target product. Based on this, we were able to build a robust diagnostic model using only a small amount of experimental data. In Phase 3, we developed a device capable of data collection and edge computing capabilities capable of analyzing and diagnosing signals from actual vehicles, enabling the collection and analysis of the necessary data.

1. INTRODUCTION

Vehicle's health refers to whether the vehicle is in good or bad condition. Each subsystem of a vehicle, such as driving, steering, braking, body structure, suspension, and electric components, has performance or functions that must be maintained while the vehicle is in operation. Therefore, it is necessary to monitor the health status of each system to

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ensure that it is performing its function properly, and to continuously monitor the degradation of performance and to do maintenance in a timely manner to keep the vehicle in good condition.



Figure 1. Wheel motor and Reducer.

PHM[1] (Prognostics & Health Management) technology, which is a health management technology, has been widely used in the aviation, military, and railroad sectors, but it has not been properly utilized in vehicle sector. Because the technology has been developed based on sufficient data for fault diagnosis or prognosis, it has been used in high value-added industries[2] with fewer constraints on the application of necessary sensors. In the vehicle sector, the proportion of vehicles for commercial use rather than personal ownership will increase. This is because with the development of self-driving vehicles, the proportion of companies that provide shared vehicle service platforms and fleet that operate buses and trucks increases. In the case of commercial vehicles, it was judged that it would be advantageous in terms of TCO (total vehicle maintenance cost) if the case of being unable to operate due to a breakdown was minimized. In addition, due to autonomous driving, the driver's direct involvement in vehicle operation and management is absolutely reduced, so research on technology to monitor and manage the health status of the vehicle is necessary. Therefore, in this study, as shown in Figure 1, wheel motors and reducers were conducted in commercial electrification vehicles.

In this study, a large bus wheel motor was performed. Comprehensive research was conducted by measuring sensor signals, analyzing signals to classify failure modes, and identifying health condition to notify the need for vehicle

maintenance to customer. For the electric bus, we explain the approach to find the appropriate PHM method to apply PHM to the vehicle

2. MAIN

2.1. FMEA(failure mode and effect analysis)

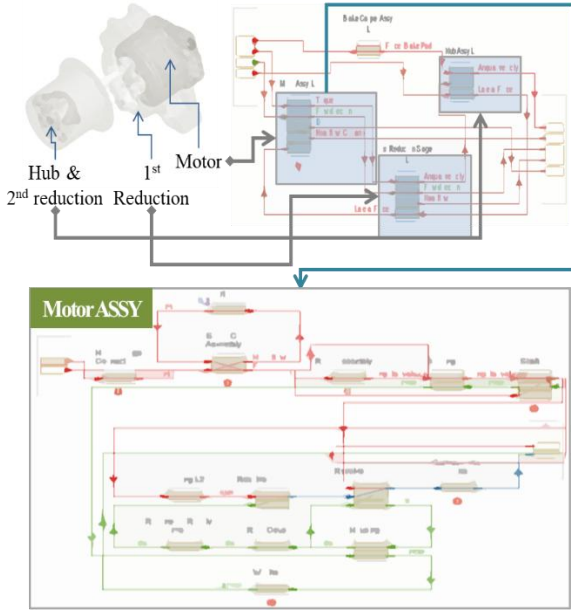


Figure 2. Motor system & Function Modelling.

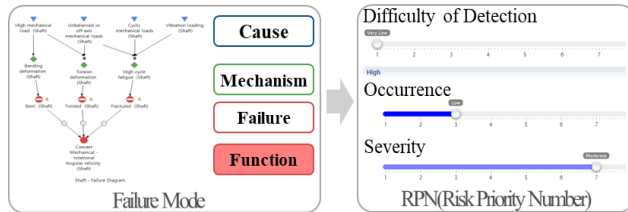


Figure 3. Fault Tree Analysis & RPN calculation.

Hyundai Motor Company has accumulated technology, experience, and a lot of data about internal combustion engines. On the contrary, a lot of effort was put into the electrification system in the development process, but data in the field is still lacking and is being accumulated one by one. Therefore, the first thing to do is what are the failure modes that can occur in the electrification system, and in order to detect the corresponding failure mode, a suitable detection method such as sensor type and location must be reviewed.

As shown in Figure 2, in order to proceed with FMEA[3], functional modeling of the electrification system was performed. When each function does not work properly, it is possible to understand how it affects the entire system, and to analyze the cause of why each function does not work properly. Subsequently, as shown in Figure 3, FTA[4] was

conducted to derive the most critical failure modes considering the difficulty of detection, occurrence, and severity. In addition, through a literature review with experts on the system, additional failure modes that can occur in the electrification system were discovered.

In terms of maintenance for each failure, it can be summarized as in Figure 4. Determine whether to repair regularly like engine oil, repair after a breakdown, or repair according to the health condition, and in case of repair according to the condition, decide whether to notify only the failure or the remaining useful life in advance[5]. In Figure 5, it was selected through the above process, and the failure modes requiring diagnosis is classified into mechanical faults and magnetic faults.

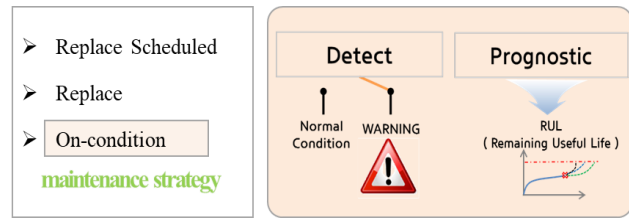


Figure 4. Maintenance strategy.

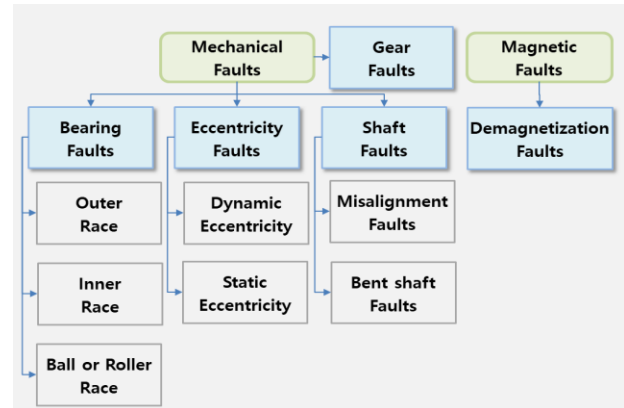


Figure 5. Mechanical and magnetic failure modes.

2.2. PHM(Diagnosis & Prognosis) model development

In this section, the research on the method of detecting the preselected failure mode in the previous section will be explained. The existing method was to collect all the data acquired by using various sensors[6] for the object, and then use the acquired data to classify both normal products and defective products using an artificial intelligence(AI) method. This was the most common approach. However, in order to do so, there must be enough failure data, but if the number of failure data is small, the data bias between normal data and failure data is severe, limiting the application of AI models.

In order to overcome this, the most important point in this study is to analyze which signal is most dominantly affected in a fault state. For the medium-sized wheel motor object in Fig.6, the failure mode was injected and the target test was conducted to confirm whether the same trend appeared in the actual measured signal.

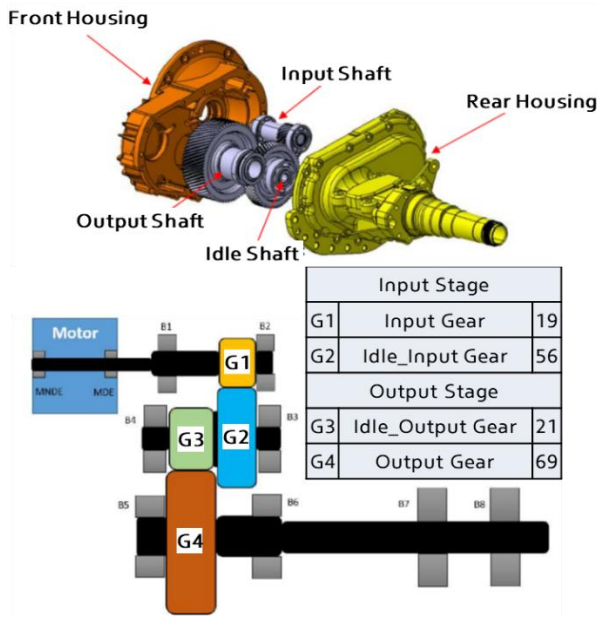


Figure 6. Wheel motor system schematic

2.2.1. Hybrid approach PHM model development

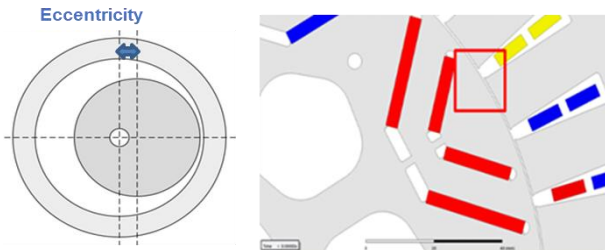


Figure 7. Reflecting Eccentricity in CAE Model

For eccentricity among several failure modes, a hybrid method was applied. Eccentricity refers to the phenomenon of being offset in the axis of rotation of the stator and rotor. If the amount of eccentricity of the shaft fluctuates according to rotation, it is called dynamic eccentricity, and if the amount of eccentricity remains constant even when rotating, it is called static eccentricity. In general motor systems, eccentricity does not occur much, but in the case of wheel motors, there is a problem that eccentricity often occurs due to the load coming from the wheel. As shown in Figure 7, the analysis was conducted by reflecting the eccentricity of the

motor in the analysis model, and it was checked whether there was a signal change in the normal and faulty conditions in the obtained signals (current, counter-electromotive force, magnetic flux, etc.).

As shown in Figure 8, when there is no eccentric, there is no sideband value, and it can be confirmed that the sideband value increases as the eccentricity increases. Looking at the change of the corresponding factor obtained from the test, it was confirmed that the change in the value for the eccentricity in the sideband was the same as in the analysis.

In addition, at the test site, there are many restrictions because test samples must be made to confirm by the test, and the dynamo must be operated even though vibration is greatly generated due to the eccentricity.

Therefore, it was decided to establish a diagnosis model in a hybrid approach by securing an overall tendency according to the amount of eccentricity using an analysis model and merging a small number of test data.

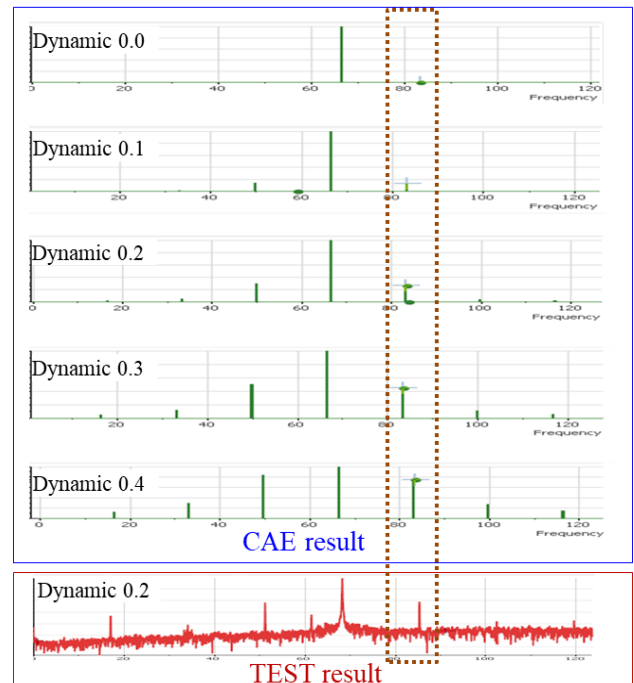


Figure 8. Dominant factors: Same CAE/test results

2.2.2. Rule-based PHM model development

In order to identify faults in gears and bearings, it is known that when gears and bearings are faulty, each fault frequency is modulated with the excitation signal frequency to affect the sidebands, as shown in Figure 9. Therefore, in order to properly separate the corresponding fault frequency, the fault frequency was derived through the Hilbert transform[8], which is a method of demodulation, and the spectrum value

of the fault frequency was used to determine the degree of fault of each failure mode. Thus, a defect index was constructed.

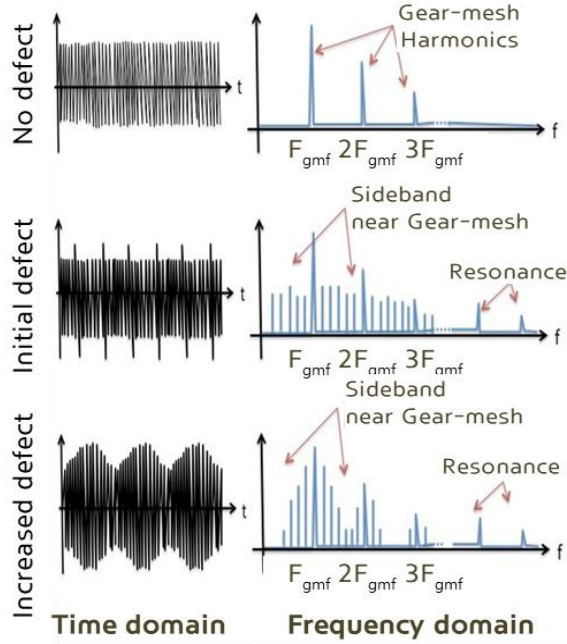


Figure 9. Frequency Amplitude Effect as Deterioration

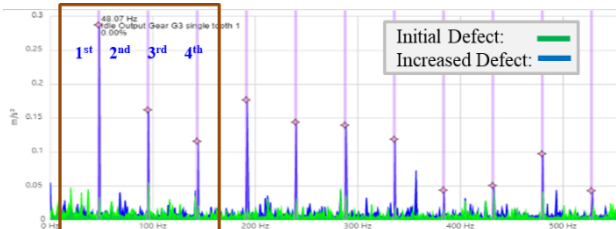


Figure 10. Idle gear defect frequency: increase in amplitude

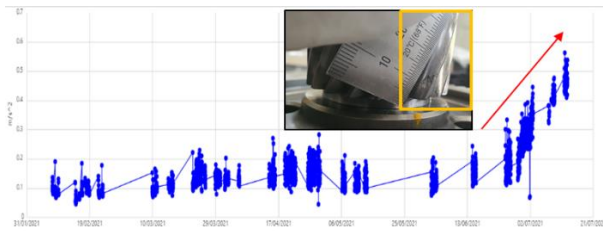


Figure 11. Idle gear (G3) defect (Index trend by date)

An system level durability test was conducted using the driving conditions of the real vehicle. Among the collected data, the Hilbert transform was performed using the acceleration data, and the defect signal hidden in the acceleration signal was extracted as shown in Figure 10. Compared to the beginning of the durability test, it can be seen that the index corresponding to the defective component

increased at the time of completion of the durability test. Figure 11 shows the change trend of the defect component index of the idle gear part in the middle of the durability test. It was confirmed that the index increased rapidly from the point after about 5 months. When disassembling the object that had undergone the durability test, as shown in Figure 11, a defect actually occurred in the gear part. It was confirmed that the increase in the index could be monitored even through the vibration signals collected in the durability test.

Additionally, to confirm the reliability of the rule-based PHM method, it was checked whether there was a change in the defect index when a defect was intentionally injected into the gear as shown in Figure 12. For reference, this location was the location where the index did not change during the durability test. When a defect is injected, as shown in Figure 13, it was confirmed that there was a clear change in the index. As a result, it was proved that diagnosis of gears and gear shafts can be made based on rules.

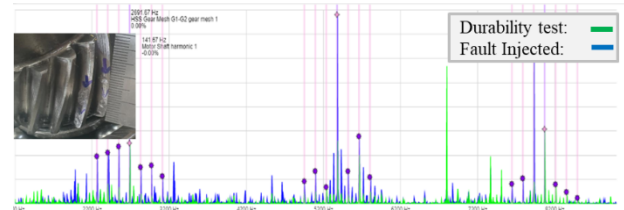


Figure 12. Vibration signal FFT analysis(spectrum)

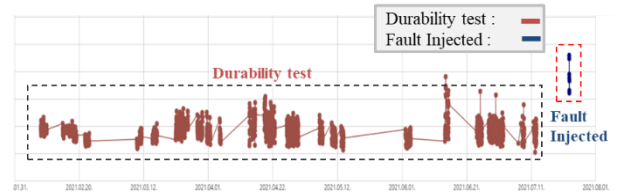


Figure 13. Index comparison(Durability/ Fault Injected)

2.2.3. Data-based PHM model development

The AI learning method was used to predict the temperature near the motor windings or bearings. When the winding of the motor is deteriorated or the bearing is severely worn, the temperature increases rapidly compared to normal. This was reviewed as a virtual sensor using an thermal analysis model, but the actual temperature sensor is not a very expensive, and it is possible to install all temperature sensors in the location where temperature measurement is required. So we took the method of collecting the temperature in real time under all operating conditions. Therefore, it was decided to build a temperature prediction model when the vehicle driven in a normal condition. As shown in Figure 14, various learning models were conducted, and the Decision Tree model was the most accurate, but it was not robust because there was a section where the temperature trend changed rapidly. When

the gradient boosted random forest method was used, both accuracy and reliability were secured, and the temperature prediction model was built by selecting the corresponding method. A prediction model[9] was constructed with the inverter and motor bearing temperatures, and it was confirmed that it was an approximate model with the accuracy of Table 1.

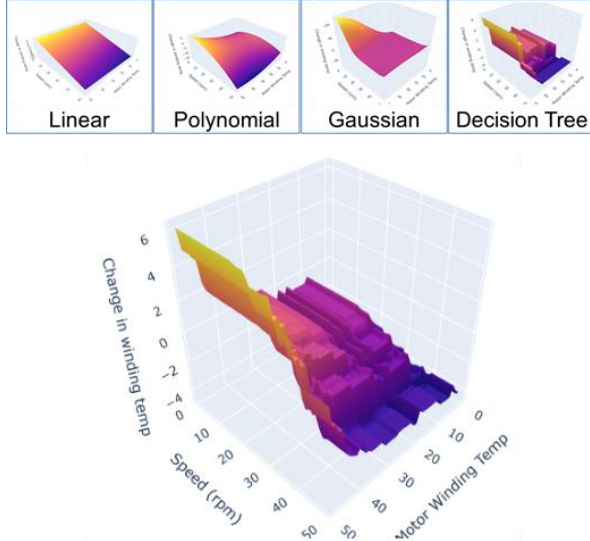


Figure 14. Idle gear (G3) defect (Index trend by date)

Table 1. RMSE of Inverter & motor bearing model.

Target	Model Features	RMSE (°C) (Train Data)	RMSE (°C) (Test Data)
Change in Inverter Temp.	Current, Coolant system temperature, Torque, Speed	0.170	0.171
Change in Motor front Bearing Temp.	Current, Speed, Coolant system temperature	0.087	0.083

Using this temperature AI model, the gap (residual) between the predicted value and the actual measured value is checked like as shown in Figure 15, and it is used as an index to detect abnormal temperature changes. Figure 16 shows the temperature change during the actual durability test, and it was confirmed that the temperature change of the motor was below the reference line (red line) and there was no specific temperature change, and there was no deterioration of the corresponding part after the durability test.

When constructing a PHM model for bearings, as shown in Figure 17, the frequency corresponding to bearing defects is well known, so a rule-based PHM model was created. As a result of confirming the suitability of this method, it was confirmed that it was well over 99% to determine whether or not there was a failure in the bearing. On the other hand, it was confirmed that it was less than 70% accurate to classify

where the defect was located among the inner ring, outer ring, ball, and cage of the bear.

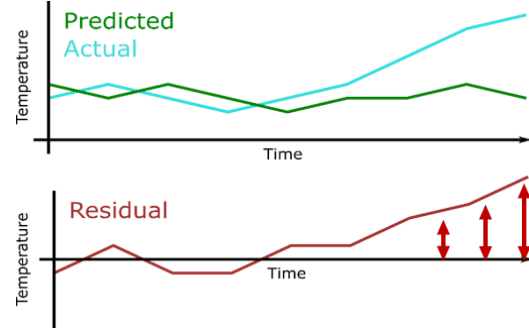


Figure 15. Idle gear (G3) defect (Index trend by date)

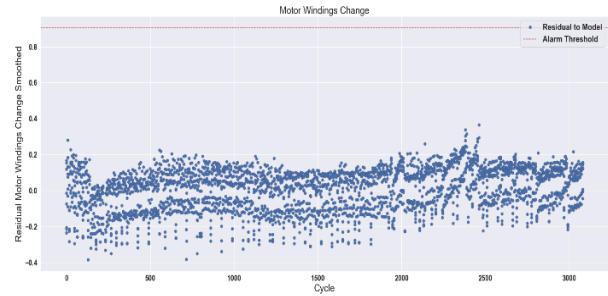


Figure 16. Idle gear (G3) defect (Index trend by date)

$$P_D = \frac{D_1 + D_2}{2}$$

$$N_B = \text{Number of balls}$$

$$\beta = \text{Contact angle}$$

$$BPFO = \text{RPM} \frac{N_B}{2} \left(1 - \frac{B_D}{P_D} \cos(\beta) \right)$$

$$BPFI = \text{RPM} \frac{N_B}{2} \left(1 + \frac{B_D}{P_D} \cos(\beta) \right)$$

$$BSF = \text{RPM} \frac{P_D}{B_D} \left[1 - \left(\frac{B_D}{P_D} \cos(\beta) \right)^2 \right]$$

$$FTF = \text{RPM} \frac{1}{2} \left(1 - \frac{B_D}{P_D} \cos(\beta) \right)$$

Figure 17. Idle gear (G3) defect (Index trend by date)

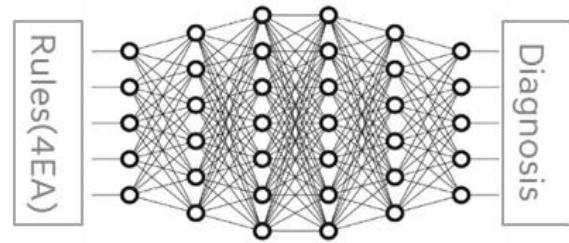


Figure 18. Idle gear (G3) defect (Index trend by date)

In order to build a diagnostic model based on data, in most cases, statistics from time series data and data extracted from frequency data are used for learning. Whereas in this study, to improve the accuracy, we proceeded with only the four indices corresponding to the rules in the bearing presented above as inputs. Since the number of types is infinite depending on the learning method, the DNN method shown in Figure 18 was used to make learning as simple as possible and consistent, and the accuracy was found to be over 99%. It was confirmed that a sufficient PHM model could be created with this approach.

2.3. Device development for collection and analysis

As shown in Figure 19, very expensive measuring equipment must be used to acquire sensor data such as acceleration, current, and temperature at once. In order to apply it to several vehicles and see its usability, it was necessary to develop a dedicated device, so it was manufactured as shown in Figure 20. More than 10 collection devices (Figure 20 (left)) could be manufactured with the price of one commercial measuring equipment. In addition, since it is necessary to extract the previously created index as soon as the sensor data is acquired from the vehicle, a device (Figure 20 (right)) with an edge computing module capable of processing and analyzing signals based on Linux was developed. A storage device for storing data was additionally manufactured as a module.

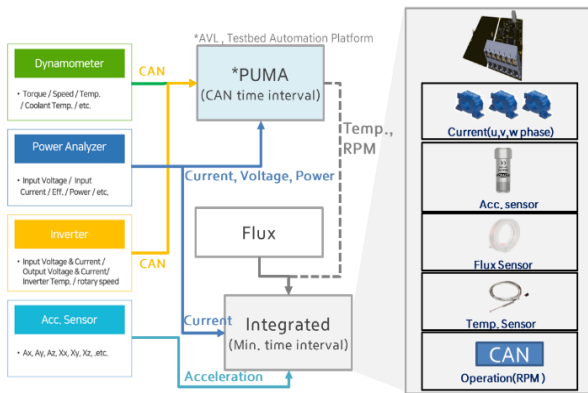


Figure 19. Multi-Sensor Data Acquisition Module.

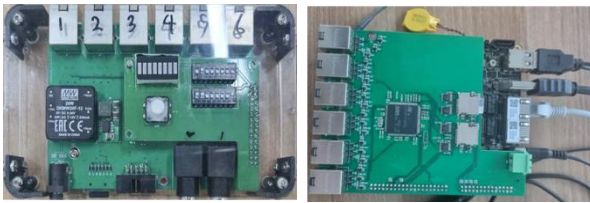


Figure 20. Collection (left), collection and analysis (right).

2.4. Monitoring Platform

As shown in Figure 21, the collected data was stored in the server and a monitoring environment was built to analyze the data. When the collected data is saved, an analysis is performed on the index developed to check system condition, and the change trend of the index over time can be checked while driving the vehicle. Even if the index improves, you can set up a new index to see the trend. In the future, when the preemptively developed index and systematically stored data accumulate, it is also necessary to build an environment in which the existing index for system condition check can be improved by using additional AI methods. Figure 22 is a graph obtained by observing the daily index change during the durability test from the actual test. And when each point is selected, the defect obtained through the demodulation process that was used to create the index can be confirmed, and a platform is built to enable an in-depth understanding of where the defect occurred.

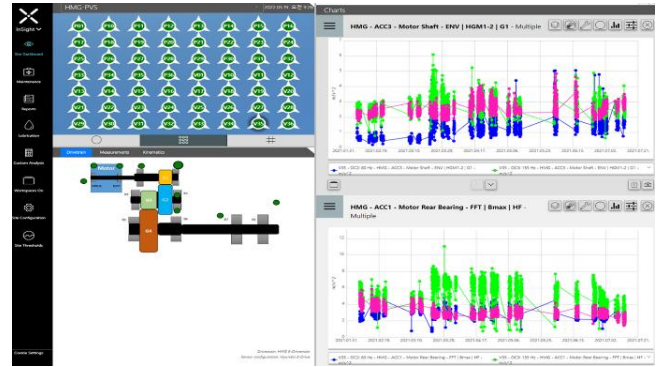


Figure 21. Monitoring Platform

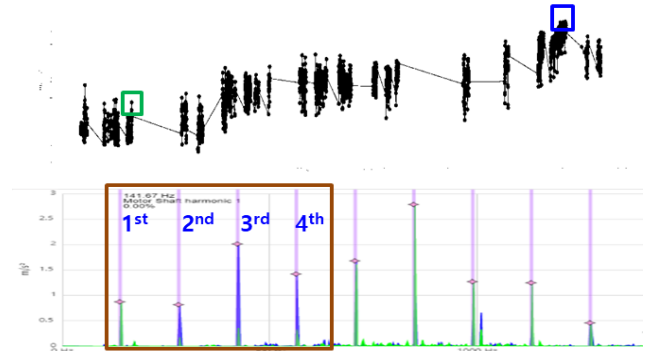


Figure 22. Monitor the vehicle System's condition

Author, A. A., (Year). *Title of dissertation*. Doctoral dissertation. Name of Institution, Location. URL

3. APPLICATION OF PHM TECHNOLOGY TO NEW AXLE

Simulation methods were used to conduct preliminary reviews prior to manufacturing a new axle. To accurately replicate the manufacturing process, this study employed state-of-the-art structural analysis methods to reflect contact conditions, press-fit conditions, and bolt-fastening conditions. Topology optimization was performed for structural optimization, and optimization was performed considering the housing processing method, resulting in results that could be manufactured in practice. This study produced a prototype vehicle and performed vibration and strain gauge measurements. As described in the previous section, we have the technology to diagnose failure modes in gears and bearings by analyzing vibration signals to determine the specific part causing the problem. We extracted the collected signals and analyzed them, confirming that they matched the gear mesh frequency of the high-speed shaft. Therefore, we confirmed that damage to the gear section of a high-speed shaft can be identified solely through vibration signals, without disassembly.

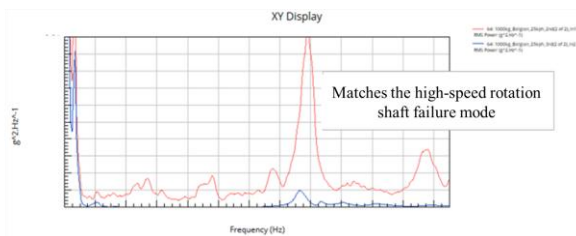


Figure 23. Identifying fault locations by vibration signal



Figure 24. Disassemble and check for faulty parts

A few days after the analysis, the actual noisy target product was disassembled to identify the problematic area, and it was confirmed that the problem occurred in the first-stage high-speed rotation shaft gear section, as predicted.

4. CONCLUSION

In conclusion, the following results can be obtained through the Study on optimal design and PHM methods for new electrification systems' proposed in this study.

(1) By classifying the failure modes that may occur in the motor system and establishing a failure mode detection

method, it can be applied to other industries(wind power generation, AAM, etc.) as well as other motor systems.

(2) In order to identify defects in motors, bearings, and gears and predict temperatures, PHM models suitable for each failure mode were constructed using a hybrid method, data-based, and rule-based approach.

(3) In developing the index necessary to confirm soundness, this study used an CAE model in a unique way. Although there are many constraints in the test in the target test, this hybrid methodology was first presented so that an index can be efficiently developed for other types of motor systems even if failure data is not sufficient.

(4) Based on rule-based experience, it is possible to systematically develop the indexes of gear, bearing, and shaft defects by demodulating the defect frequency for each frequency domain. And it is also possible to build a rule-based PHM model in the new vehicle development stage.

(5) In the case of bearing rule-based diagnosis, it was possible to check whether or not there was a failure, but it was not possible to distinguish the location of the failure. In this study, it was possible to classify up to 99% failure locations by approaching with a DNN method using indexes made based on rules. After the preemptive PHM model was created, as the data accumulated, a methodology to increase the accuracy of the model based on the data could also be established.

(6) Dedicated device with an edge computing module capable of collecting necessary data, analyzing data, and even diagnosing by applying it to the vehicle system was manufactured. In addition to signal analysis in real vehicles, it is possible to analyze even failure modes. As a result, it is possible to build a platform that can continuously collect data and perform fault diagnosis at the vehicle level in a short period of time.

(7) Through database creation and data analysis of the collected data, it is possible to check the trend of the index and analyze the reason for the increase in the index. A monitoring platform that can be used to improve indexes even after the development of PHM models.

(8) The same method was applied to a new motor and reducer combination to verify its effectiveness.

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