Development of PHM Algorithm of e-Latch to Prepare for The Era of Autonomous Driving

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Abstract

In self-driving vehicles linked with mobility electrification, system failures that occur suddenly in situations where customers are unaware of signs of failure are directly related to customer injuries. Securing the durability and safety of closure automation system is necessary to increase the customer's safety value so PHM technology makes it possible to predict failures and remaining life in advance during system operation. In addition, since not only various forms of new concept design styling but also innovative new handle designs are applied, it is obviously seen that e-Latch system is widely equipped in the mobility. Thus, in this paper, the study to predict the failure of e-Latch and closure system is implemented via data-driven and physics-driven method, and the algorithm for PHM to estimate remaining life of e-Latch system is also introduced.

1. Introduction

In the era of autonomous driving linked with the electrification of mobility, diverse opening and closing mechanisms are implemented, and the system's electronification becomes common in future mobility. In this context, sudden system failures, which occur without the customer's awareness of fault signs, are directly related to customer injuries. Particularly in cases where the vehicle's owner and user are different, such as PBVs (Purpose Built Vehicles), even if fault signs appear, users may not share these signs with the owners. This leads to a lack of preventive maintenance and increases the risk of customer injuries due to vehicle malfunctions. Therefore, ensuring the durability and safety of closure automation systems is crucial for maximizing customer safety value. Prognostics and Health Management (PHM) technology, which predicts faults and estimates remaining useful life, is considered a key technology for future autonomous driving era closure systems. In the case of B2B shared autonomous vehicles connected with Fleet Management Systems (FMS), the application of this technology is expected to be highly beneficial not only for ensuring customer safety but also for maximizing the durability and minimizing maintenance costs of mobility. Thus, understanding the principles of PHM technology and developing PHM technology optimized for closure systems are essential.

Meanwhile, an appealing exterior is one of the most important values provided to customers, leading to the introduction of various new concept design stylings. The common feature of these new designs is the adoption of diverse opening and closing mechanisms and new handle designs, which are realized by removing mechanical handles, thereby necessitating the application of e-Latch. Previously, e-Latch was directly applied to vehicles without modifications, leading to issues such as dependence on suppliers for new technology due to undisclosed core technologies, difficulties in internalizing technology and improving quality, worsening cost competitiveness, and excessive weight/package issues.

This study aims to examine the e-Latch system, a core and urgent technology for preempting the future mobility paradigm and explore development methods and internalization strategies for this technology. Specifically, the study focuses on developing PHM technology to predict faults and remaining useful life (RUL) of the closure system, targeting the e-Latch system as a key technology in mobility electrification. The objectives include developing test evaluation methods for PHM technology, extracting key fault-related characteristics, diagnosing faults, classifying faults, and predicting remaining useful life. Based on these objectives, the study also aims to establish methodologies for developing PHM technology for electrified parts of closure systems in the future.

Figure 1. Examples of Various Opening and Closing Mechanisms (Application of eLatch)

2. MAIN SUBJECT

2.1. e-Latch PHM Model Development

PHM (Prognostics and Health Management) technology is a system health management technology that monitors the state of mechanical and electrical devices using sensors and other tools, diagnoses the system's condition (normal/fault), and predicts the remaining useful life when signs of faults are detected. This technology consists of four stages: 'performance monitoring,' 'anomaly detection,' 'fault diagnosis/classification,' and 'remaining useful life prediction.'

In the 'performance monitoring' stage, operational data is collected using sensors and preprocessed in various ways to extract fault-related features. During the 'anomaly detection' stage, the extracted features are used to compare the characteristics of the normal state with the monitored state. When signs of faults are detected, a system alarm is triggered. Even if fault signs are detected at this stage, it does not diagnose the condition as a fault.

In the 'fault diagnosis' stage, the detected fault signs are compared with the characteristics of fault types to determine if the monitored state is indeed a fault and to classify the type of fault. Finally, in the 'remaining useful life prediction' stage, the remaining useful life is predicted based on the diagnosed and classified fault types. If necessary, a replacement plan is established and communicated to the user or vehicle owner to prevent sudden failures and maintain the system in a healthy state. As shown in Fig. 2, these stages involve continuous monitoring and fault diagnosis throughout the component's (or vehicle's) lifecycle.

This PHM technology is applicable to safety-critical components that can cause serious injury to customers in case of failure, components that require high durability due to frequent usage, and electrified components (or sensor-enabled components) that allow continuous performance monitoring. In the closure system, the e-Latch (Electric Latch) falls into this category.

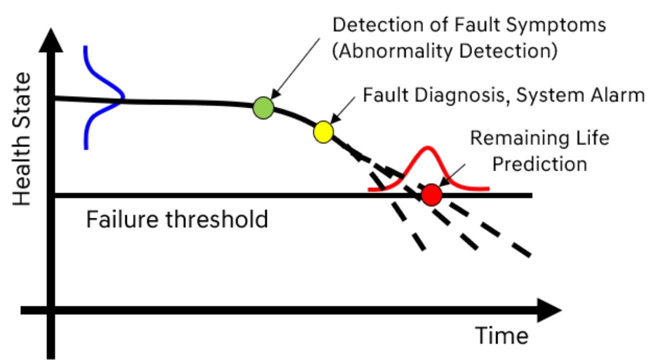


Figure 2. Overview of the PHM Model

The PHM model can be developed through two methods. The first method is the "Physics-of-Failure (POF) PHM Model based on Performance Degradation" (Fig.3). This method assumes that the performance remaining life at a specific point follows an existing physical model of performance degradation and constructs a fault diagnosis and remaining life prediction model. It is applicable when there is a known performance degradation physical model for a system, making it suitable for simple systems or systems where a performance degradation model has been established after development. However, as the e-Latch consists of over 40 components and lacks a developed performance degradation model, the development of a physical model-based PHM model is not feasible.

Therefore, we applied the second PHM model development methodology, the "Data-Driven PHM Model" (Fig.3). This method collects and analyzes test data on performance degradation and faults under various conditions and utilizes machine learning to construct fault diagnosis and remaining life prediction models. Since there is no established performance degradation physical model for the system and it is a complex system, the data-driven approach is suitable, especially for initial development systems. Thus, it is appropriate for developing the e-Latch PHM model.

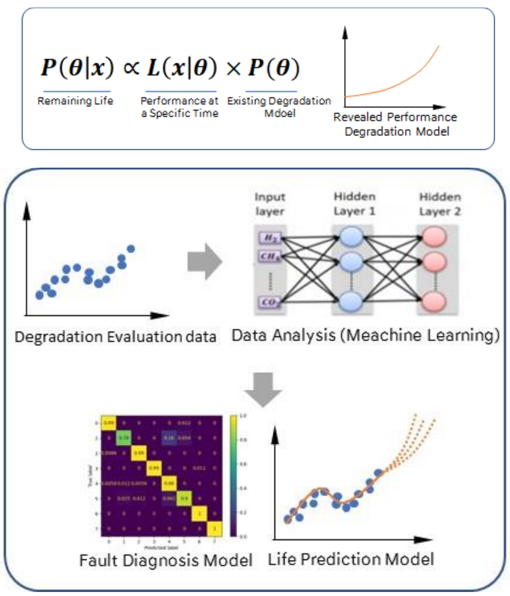


Figure 3. POF PHM / Data Driven PHM

As previously described, the e-Latch system is configured for performance degradation evaluation data collection, as depicted in Fig. 4. The system comprises a handle, controller, and latch. The system operation proceeds in the following sequence: 'Handle: Signal Transmission for Opening' -> 'Controller: Signal Reception & Data Monitoring' -> 'Latch: Execution of Opening and Transmission of Characteristics'. The controller takes an input signal from the exterior handle and, after a 1000ms delay, sends out signals to the e-Latch motor, specifying the voltage, current, and angular position of each switch.

e-Latch faults are defined through potential field claim Fault Tree Analysis, and independent samples are created for each fault. Subsequently, performance degradation evaluations are conducted at the component and vehicle levels, and data are collected. In this context, Fault Tree Analysis (FTA) is a systematic methodology employed to identify and analyze all potential failure modes within a complex system. Specifically for an e-Latch, FTA can be utilized to assess the failure modes of its two primary components: the worm and wheel gear, which may result from degradation or complete failure.

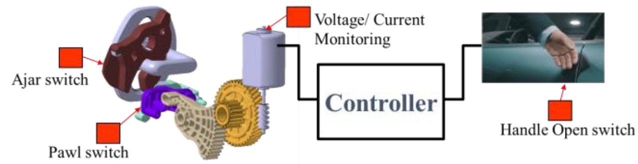


Figure 4. e-Latch System Configuration and Data Visualization

The overview of the PHM model development performed based on the collected data is depicted in Fig. 5. The collected data undergo preprocessing tasks such as signal segmentation to extract features. These extracted features are then used for machine learning to diagnose faults and classify fault types. The classified faults estimate the performance degradation status for each type, and based on this, predict the remaining useful life to complete the PHM model development.

2.2. Implementation and tests

Data collection for fault diagnosis and classification was conducted by evaluating both components and real vehicle conditions for each fault type. For remaining useful life prediction data collection, evaluations were performed at four severity levels (normal, 50% degradation, 75% degradation, 99% degradation) in component RIG-mounted conditions, with the remaining levels calculated using linear interpolation. At least 100 data samples were collected by combining each condition and severity level for analysis.

During evaluations, the e-Latch controller recorded motor current/voltage and switch signals when the e-Latch was released. The controller activates the motor based on the received I/S or O/S switch signal and operates the pole attached to the motor to release the latch. During this process, the lever connected to the pole switch and the AZA switch rotates sequentially, and the controller supplies power to the motor for approximately 600ms from the initial switch point if the switch signals are confirmed to operate correctly in order.

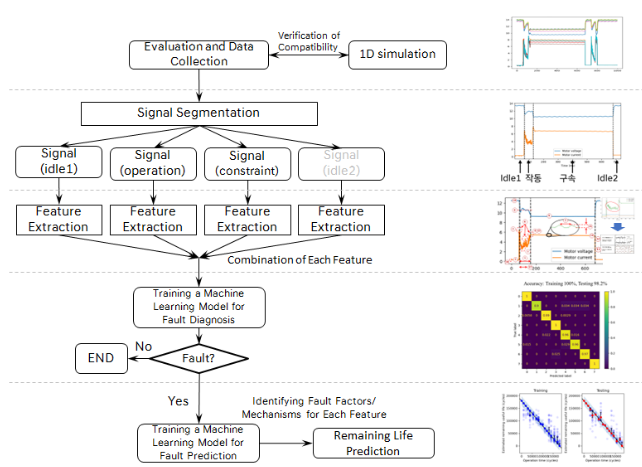


Figure 5. Overview of PHM Model Development

Signal segmentation was performed based on motor current/voltage signals. The operation state of the latch is divided into four sections: Idle1, Operation, Constrained, and Idle2. The peak value of the motor current is used as a landmark to determine the latch state. The division between the Idle1 and Operation sections is defined by the first current peak point (1). The division between the Constrained and Idle2 sections is defined as the point where the current returns to the Idle1 level after the first peak point (1).

Before performing machine learning, the collected data undergoes an evaluation data integrity check. This involves analyzing the e-Latch mechanism layout to confirm the theoretical operating resistance (represented here by simplified formulas and diagrams). To account for variations due to tolerances in the theoretically calculated normal values, Python code was developed to verify the latch operating resistance at different motor rotation angles under normal and tolerance conditions (Fig. 6). The verification of operating resistance is based on the results of internalizing the proprietary e-Latch design technology.

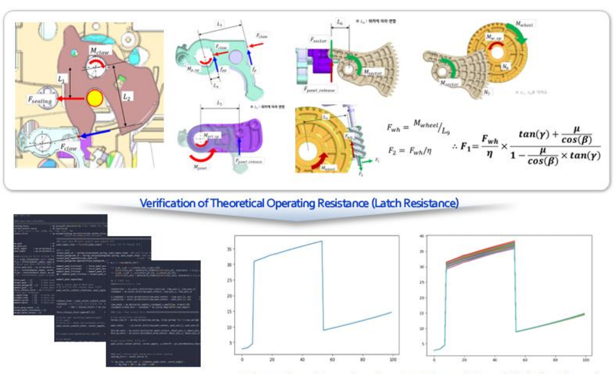


Figure 6. e-Latch Operating Resistance

Next, the performance of the motor is implemented through mathematical modeling, as shown below (Fig. 7).

(1) $v(t) = R * i(t) + L * \frac{di(t)}{dt} + v_e(t)$

(2) $\tau_m(t) = K_T * i(t)$

(3) $J * \frac{d\omega(t)}{dt} + b * \omega(t) = \tau_m(t) - \tau_l(t)$

(4) $v_e(t) = K_e * \omega(t)$

This can be transformed using the Laplace transform as follows.

(5) V(s) - $V_e(s) = R * I(s) + L * s * I(s)$

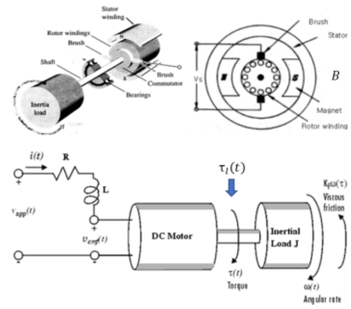
➔ I(s) = $\frac{V(s) - V_e(s)}{L*S+R}$ …(5.1)

(6) T_m(s) = $K_T * I(s)$

(7) J*s* $\omega(s)$ + b*$\omega(s) = T_m(s) - T_l(s)$

➔ ω(s) = $\frac{T_m(s) - T_l(s)}{J*S+B}$

(8) $V_e(s) = K_e * \omega(s)$



J : Motor's Moment of inertia
L : Inductance
b : Motor's viscous friction coefficient
T_m : Motor torque
T_l : Load torque (Latch Torque)
K_T : Torque Constant
K_e : Back EMF constant (Generally same as K_T)
v_e : Back EMF (=B*l*v(자속밀도 x 도선길이 x 속도))

Figure 7. e-Latch Operating Resistance

Finally, the motor performance curve applied to the e-Latch, with the calculated parameters, is shown below.

(1) Max. Torque at Max. Efficiency

$$T_N = T_s \frac{\sqrt{i_0 i_s} - i_0}{i_s - i_0} (unit: \text{N.m}) = 3.9955 \text{ (mN.m)}$$

(2) Nominal Voltage

$$V_N = input\ V (unit: \text{N.m}) = 12.5 \text{ (V)}$$

(3) Angular Velocity

$$v(t) = R * i(t) + L * \frac{di(t)}{dt} + v_e(t)$$

$V = R * i + V_e$ (∵ Generally, L ≒ 0)

$$V = R * i + K\omega \ (\because V_e = K_e\omega \ , \ K_e = K_t = K)$$

$$V = \frac{T}{K} R + K\omega \ (\because \tau_m(t) = K_T i, \ K_e = K_t = K)$$

$$\therefore \omega = -\frac{R}{K^2} T + \frac{V}{K} = \text{aT} + \text{b (a = Slope, b} = y_0)$$

(4) Find the K & R

$$\omega = -\frac{R}{K^2} T + \frac{V}{K} (@\ \omega_0,\ V_N,\ T_0 = 0,\ \&\ @\ T_s,\ \omega_s = 0)$$

➔ K = 0.00765 (V/(rad/s))

➔ R = 2.1862 (Ω)

(5) Nominal Angular Velocity (ω_N @T_N, K, R, V_N)

$$\omega_N = -\frac{R}{K^2} T_N + \frac{V_N}{K} = 1484.4367 \text{ (rad/s)}$$

(6) Nominal Current (i_N)

$$i_N = \frac{V_N - K * \omega_N}{R} = 0.522\ (A)$$

Based on the latch resistance simulation and the motor's mathematical modeling, a physical model is created to simulate the actual operating components of the e-Latch. This physical model, known as a 1D simulation model, demonstrates the latch's operation in response to a single input value. The simulation results are compared with the actual evaluation data to verify that the evaluation data is normal and usable.

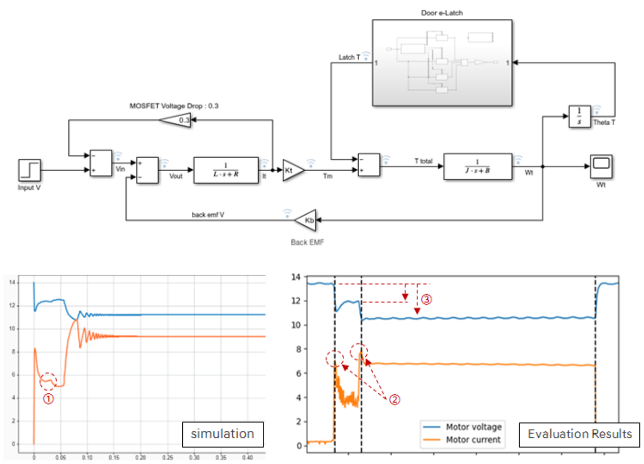


Figure 8. Simulation and Data Integrity Check

When comparing the simulation results graph and the measured evaluation data, several patterns were observed in both: the occurrence of peak currents during operation (w-shaped pattern) (①), the initial peak patterns during the beginning of operation and the onset of constraint (②), and the overall pattern of the current waveform. Additionally, the voltage drop patterns during operation and constraint were observed in both the simulation and evaluation results (③). Although there were slight differences in the detailed values of current and voltage, these are estimated to be due to environmental factors (e.g., wire resistance) during the actual evaluation. Therefore, the integrity of the evaluation data is confirmed, making it possible to develop the PHM model through data analysis and feature extraction.

For the development of the PHM model, the current (voltage) fluctuation patterns were first used to classify the signal intervals into three stages based on the statistical characteristics of the DC motor: (1) Idle interval: from receiving the handle operation signal to just before the motor's actual operation, (2) Operation interval: from motor operation to latch release, and (3) Constraint interval: maintaining state after latch release, and continuing motor overload state. This classification is shown in Fig. 9.

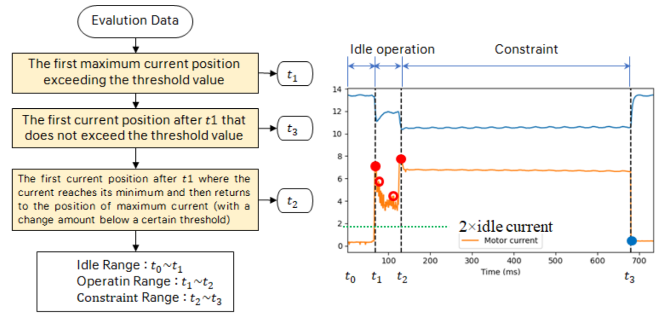


Figure 9. Signal Segmentation

Next, after verifying data integrity, 20 features were extracted from each signal data. This is shown in Fig. 10. It is assumed that the characteristics of the motor signals will change with the degradation of the latch. The features extracted from the motor signals reflect the characteristics of the signals, and the machine learning model can find patterns in these features to distinguish between faulty and normal latches. The physical meaning of each feature and its correlation with the e-Latch system were examined to select the final fault-related features.

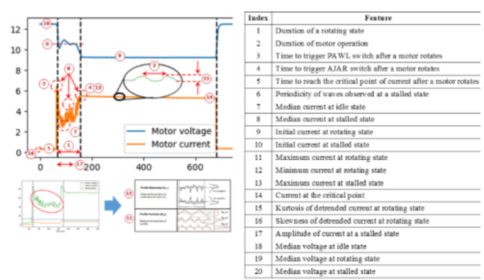
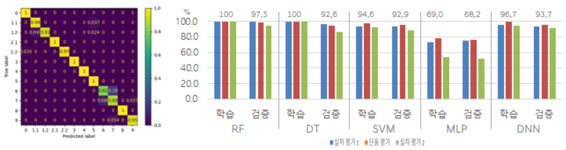


Figure 10. Fault-Related Features

The machine learning for developing the fault diagnosis model was performed using the extracted fault-related features. This process proceeded in the following steps: data partitioning, extraction of fault-related features, machine learning model training, and machine learning model validation. For the evaluation of single-unit degradation, only normal data and data from evaluations at 99% degradation were utilized for fault classification. This procedure was also followed for future residual life prediction. The machine learning training results showed that fault diagnosis and classification were generally achievable with high accuracy, averaging above 90% for most applied algorithms. The algorithms used included Random Forest, Decision Tree, Support Vector Machine, Multi-Layer Perceptron, and Deep Neural Network. The prediction accuracy of the machine learning algorithms was observed to be in the following order: Random Forest > DNN > Decision Tree > SVM > MLP. While there were no issues with the analysis speed for diagnosing faults in a single data point across all algorithms, Random Forest demonstrated superior performance in terms of overall accuracy and speed. (Fig. 11)



Accuracy of Machine Learning Algorithm		actual vehicle evaluation 1 (Data : 2819ea)	Component Evaluation (Data : 1294ea)	actual vehicle evaluation 2 (Data : 3288ea)	average
Random Forest (RF)	Training (%)	100.0	100.0	100.0	100.0
	Test (%)	99.5	98.4	94.6	97.5
Decision Tree (DT)	Training (%)	100.0	100.0	100.0	100.0
	Test (%)	96.2	94.9	86.8	92.6
Support Vector Machine (SVM)	Training (%)	93.7	98.0	92.2	94.6
	Test (%)	93.8	96.0	89.0	92.9
Multi-Layer Perceptron (MLP)	Training (%)	73.5	78.9	54.5	69.0
	Test (%)	75.7	76.4	52.4	68.2
Deep Neural Network (DNN)	Training (%)	95.6	99.7	94.9	96.7
	Test (%)	93.4	96.0	91.7	93.7

Figure 11. Accuracy by Algorithm

Next, residual life prediction was performed. Outliers due to human error, experimental setup error, measurement error, etc., were identified in the major features. As these outliers could affect the training and testing of the machine learning model, they were identified and removed. Outliers related to human error and experimental setup error were defined as errors using rules based on the programmed logic of the e-Latch controller. Feature sets extracted from data that did not adhere to the rules were removed. The removal rules included "motor operation time less than 600ms", "motor operation time greater than or equal to 650ms", "AJAR switch on time less than PAWL switch on time", and "no detected peak current during rotation state".

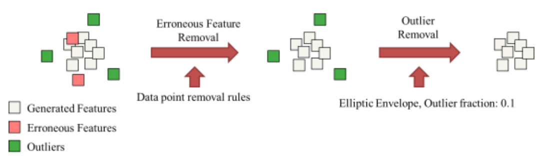


Figure 12. Feature preprocessing procedure

The extracted features were verified for redundancy, monotonicity, effectiveness, and efficiency, with each having a crucial role in determining the fault modes of the e-Latch system. As different fault modes may exhibit different behaviors, the features characterizing their operation may vary as well. The process involves characterizing each feature and filtering out some features based on threshold values. This is necessary as not all features used in fault diagnosis have equal importance for each fault category. The process includes:

ⓐ Redundancy Removal: Identification and removal of features representing the same signal characteristics.

ⓑ Monotonicity Verification: Confirmation of features exhibiting monotonic behavior (increase or decrease) with fault degradation.

ⓒ Efficiency Validation: Identification of features with high impact on classifying degradation levels among those exhibiting monotonic behavior.

ⓓ Feature Elimination: Determination of the minimum/optimal number of features suitable for classifying degradation levels.

Following the selection of final features, machine learning is employed to predict the remaining useful life. This process follows a similar outline as the one used for fault diagnosis and classification. The algorithms used in this phase are identified, and their respective accuracies are verified. (Fig.13 & Fig.14)

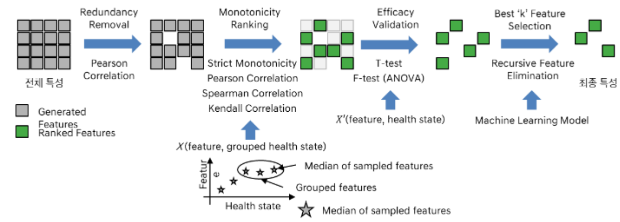


Figure 13. Feature Selection

Types of Algorithms	Accuracy (Margin of Error < 5%)		Accuracy (Margin of Error < 10%)		Accuracy (RMSE*)	
	Training	Validation	Training	Validation	Training	Validation
Linear regression	35.5%	31.7%	64.2%	58.9%	3292.94	3401.92
Linear regression (Lasso)	18.1%	18.5%	36.7%	36.2%	3293.47	3402.18
Linear regression (Elastic)	16.5%	16.5%	30.5%	30.2%	3691.83	3725.53
K-nearest neighbor (KNN)	88.3%	78.4%	94.5%	86.7%	1508.77	2082.28
Classification and regression trees (CART)	99.5%	84.3%	99.9%	86.9%	0.12	3105.49
Gradient boosted trees, GBM	95.1%	73.9%	98.8%	83.3%	1149.84	2224.11
Gradient boosted trees, XGB	99.5%	77.5%	99.9%	83.6%	29.07	2250.56

Figure 14. Accuracy by Algorithm

To reduce the error in residual life prediction, a Median Filter was applied. This filter helps mitigate the influence of outlier data by reducing the impact of abnormal data (outlier data) when mixed with normal data. Ultimately, the predicted residual life achieved approximately 95.3% accuracy on the training data and around 89.4% accuracy on the test data.

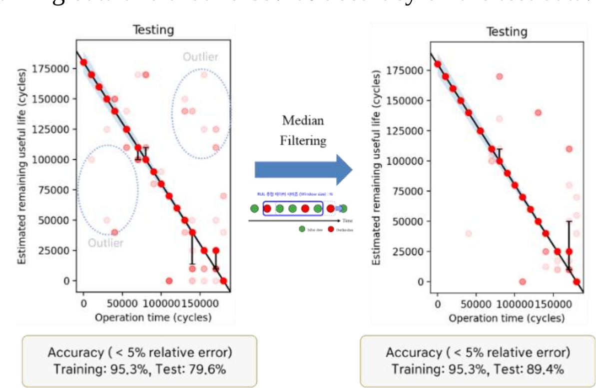


Figure 15. Residual Life Prediction Results

Additionally, when developing the initial fault diagnosis model, fault classification was conducted using normal data and data evaluated at a 99% performance degradation state. Subsequently, the model was updated to include intermediate performance degradation states (50%, 75%) by adding corresponding evaluation data. As the differences in characteristics between intermediate performance degradation states and normal states may not be as distinct as those between a 99% performance degradation state and a normal state, a logistic model was trained after grouping the features and labeling the normal and fault models. In some cases, intermittent classification as normal was observed in the evaluation of certain performance degradation states after fault diagnosis. To address this, the "k out of N rule" was applied. The complexity of the system, which requires a comprehensive judgment based on various features rather than relying on representative and intuitive features for fault diagnosis, contributed to this decision.

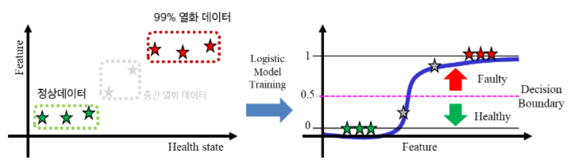
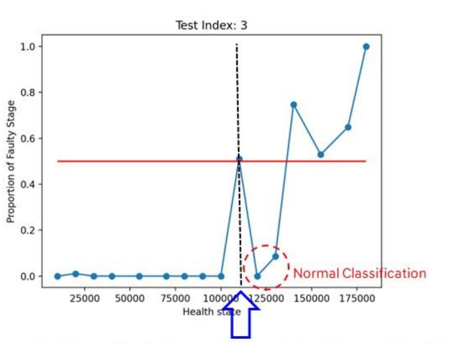


Figure 16. The labeling of fault data and the logistic model.

The "k out of N rule" involves:

1. Determining the size of N consecutive data points for fault diagnosis (Size: N)
2. Checking the number of fault data points classified as faults within the consecutive N data points
3. Considering the occurrence time as the fault occurrence time if the number of fault data points measured as faults is equal to or greater than k
4. Considering the fault data points as outliers if the number of fault data points measured as faults is less than k
5. Moving the fault diagnosis data size sequentially by one each time the next data point comes in, and performing steps ② to ④

By applying this method, the accuracy of fault diagnosis can be improved.



The time of fault diagnosis through logistic model training

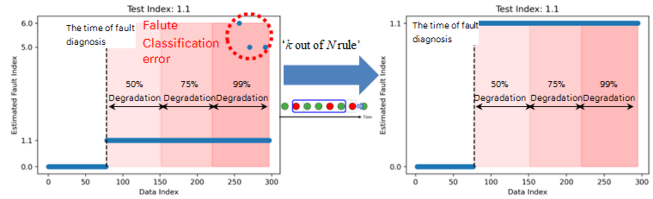


Figure 17. Improving Fault Diagnosis Model Accuracy.

3. CONCLUSION

In this study, we examined the e-Latch system, which is considered a key technology for seizing the future mobility paradigm and one of the most urgent technologies. We explored methodologies for developing this system and internalizing the technological capabilities necessary for its development, as well as for developing PHM (Prognostics and Health Management) technology to predict the failure and remaining useful lifecycle (RUL) of closure systems such as e-Latch, which are essential for mobility electrification. Through this research, we obtained the following results: ① Securing competitiveness in terms of technology and cost/weight aspects through the development of our unique e-Latch mechanism; ② Technological leadership through patent acquisition; ③ Establishment of methodologies for developing PHM models based on evaluation data for parts (e.g., e-Latch) using vehicles, and methods for predicting remaining useful life; ④ Confirmation of initial performance prediction through the development of structure/tolerance-reflected e-Latch 1D simulations; ⑤ Development of fault diagnosis models reflecting performance degradation conditions and acquisition of expertise; ⑥ Establishment of robust fault diagnosis models through the application of the 'k out of N rule' to be resilient to outliers; ⑦ Development of big data preprocessing and major feature selection methodologies. The content presented in this paper has significant advantages from the perspective of customers, enabling the acquisition of future-oriented technological capabilities in terms of technology and design aspects necessary for closure components in the era of autonomous driving. By proactively securing technology that is not yet scheduled for application by other companies, we can enhance brand image and seize the future technology market. In particular, having proprietary e-Latch technology enables the development of standardized e-Latch components centered on our existing patents, leading to increased product competitiveness and cost savings. Furthermore, since PHM technology was developed without the need for additional fault measurement sensors, but only using the voltage/current of the motor and the timing of switch signals, there is no additional cost associated with applying new technology, thus expecting considerable enhancement in product competitiveness. Additionally, it is easy to apply the PHM model to other closure components using motors, allowing for horizontal expansion in various directions in the future.

For these reasons, it is necessary to expand the application of such design methodologies to entire vehicle systems in order to respond to the rapidly changing automotive competition environment.

REFERENCES

Seokju, Ham., (2019). *1. A Comparative Study of Fault Diagnosis for Train Door System*.

Muniyappa Amarnath (2012), 2. Experimental investigations Of surface wear assessment of spur gear teeth. September 21, Journal of Vibration and Control. Vol 18. Issue 7

Xiang-Qun Liu. (2000). 3. Fault Detection and Diagnosis of Permanent-Magnet DC Motor Based on Parameter Estimation and Neural Network, vol. 47, pp. 1021-1030. November 2000. IEEE Transactions on industrial Electronics.

Hyungjun Park, (2021). Machine Health Assessment Based on an Anomaly Indicator Using a Generative Adversarial Network. International Journal of Precision Engineering and Manufacturing 22.6 1113-1124.

Seokgoo Kim (2020). Information Value-based Fault Diagnosis of Train Door System Under Multiple Operating Conditions. *Sensors 20.14 (2020): 3952.*

Randall, R. B., Antoni, J. (2011). *Rolling Element Bearing Diagnostics—A Tutorial." Mechanical systems and signal processing*25(2) (2011): 485-520.

Antoni, J., and Randall, R. B. (2006). *The Spectral Kurtosis: application to the vibratory surveillance and diagnostics of rotating machines Mechanical systems and signal processing, 20(2) (2006): 308-331*.

Pedregosa, Fabian, et al. (2011). *Scikit-learn: Machine Learning in Python." Journal of Machine Learning Research, 12 (2011): 2825–2830.*

Rousseeuw, P.J., and Van Driessen, K. (1999) *A Fast Algorithm for The Minimum Covariance Determinant Estimator.* Technometrics, 41(3), 212 (1999)

Guyon, I., et al. (2002 Gene Selection for Cancer Classification Using Support VectorMachines., *Machine Learning, 46 (1) (2002): 389–422*