Development of Anomaly Detection Technology Applicable to Various Equipment Groups in Smart Factory

Kiwon Park[1], Myoung Gyo Lee[2], Sung Yong Cho[3], Yoon Jang[4], Young Tae Choi[5]

[1, 2, 5] Hyundai Motor Company, 37, Cheoldobangmulgwan-ro, Uiwang-si, Gyeonggi-do, Republic of Korea
king521dom@hyundai.com, hesse667@hyundai.com, 9562768@hyundai.com
[3, 4] Kia Motors, 37, Cheoldobangmulgwan-ro, Uiwang-si, Gyeonggi-do, Republic of Korea
sungyongcho@kia.com, yunifree@kia.com

ABSTRACT

This study delves into the creation of anomaly detection technology applicable to a range of equipment groups within smart factories. This advanced technology uses high-performance MEMS vibration sensors, edge CMS devices, and PHM platforms to tackle issues such as data imbalance, learning model limitations, complex equipment operating patterns, and real-time processing. It also addresses central server concentration, data cycling problem, various equipment classification, and algorithm operation problems that can arise when implementing systems in the field. Using AI-based vibration detection algorithms, data can be collected at high sampling rates and analyzed in real-time through edge computing, minimizing latency and mitigating server capacity issues compared to cloud-based analytics. The system continually monitors and learns standard performance data from equipment to provide practical solutions that minimize equipment failures and downtimes. The results of this study are impressive, as it has successfully developed anomaly detection framework and PHM systems that are expected to enhance the efficiency and sustainability of smart factories. Furthermore, the study aims to showcase and improve the effectiveness of predictive maintenance in both domestic and international automotive factory production lines. This revolutionary technology will be a key component in smart and software-defined factories and help companies achieve intelligent automation.

1. INTRODUCTION

The rise of smart factories has recently led to an increase in production line automation equipment. As a result, maintenance activities have become crucial, and the need for predictive maintenance technology that can foresee equipment failures has emerged. Many companies are exploring ways to perform predictive maintenance, from installing additional sensors to analyzing controller data. Currently, predictive maintenance technology is limited to equipment that moves at a constant speed, like large turbines and fan motors.

We have developed a PHM (Prognostics and Health Management) system and an AI-based vibration detection algorithm capable of predicting anomalies in constant and variable-speed equipment to meet this need. Our technology stands out as it can collect vibration data at a high sampling rate, perform AI learning, and make decisions at the edge.

The PHM system consists of two primary components: the CMS (Condition Monitoring System) module and the PHM platform. The CMS module is a device equipped with edge computing functions, data collection capabilities, and decision-making algorithms. The PHM platform, on the other hand, monitors mining data from the CMS module, manages its operations, and deploys registered algorithms as a service for each CMS. Additionally, the platform is responsible for deploying the optimal algorithm as a module. The algorithm used in the PHM platform is developed through deep learning AI modeling and is registered and deployed as a CMS module [1].

Four-stage research was undertaken to create an AI-powered anomaly detection algorithm that relies on vibration data. Initially, a PoC (Proof of Concept) scenario was devised that focused on identifying the target equipment (robot reducer, automation equipment drive motor, etc.), the operating type (constant/variable speed, part/finished product), and the target defect type (robot reducer defect, motor bearing damage, etc.). Next, data was collected based on specific criteria for data type (vibration, current, speed, etc.) and collection method (CMS module, PLC, Cloud, etc.). In the third stage, signal feature extraction methods were defined through feature-based analysis, which uses domain knowledge to determine data analysis. An anomaly detection method was also developed to check abnormal scores by learning the normal group to suit the data imbalance situation where it is challenging to secure abnormal data compared to normal. The AI model used an Auto-Encoder structure and an unsupervised learning method, and an optimal model was developed through hyper-parameter adjustment to define the anomaly score [2]. The algorithm was verified through PoC activities by matching the score of the normal/abnormal state of equipment with the actual motor defect phenomenon.

The PHM system and AI anomaly detection algorithm operate within the production line to learn and monitor the equipment's standard performance data. An alarm prompts maintenance activities when a score falls outside the normal range [3]. This approach minimizes equipment failure and ultimately aims to reduce non-operation rates. By leveraging data analysis to inform condition-based maintenance activities, our system establishes highly efficient maintenance and production plans that surpass traditional time and usage-based approaches. As a result, we can lower costs associated with non-operation rates within the production line [4].

2. Background

Current predictive maintenance systems have typically utilized centralized models to analyze and predict facility-level data gathered from a central server. This approach has allowed rule-based algorithms to successfully extract key characteristics and implement predictive maintenance, even in low data sample rate environments where the facility operates at a constant speed.

However, operation patterns have become more complex with the rise of smart factories and diverse automation equipment. As the number of transmission equipment containing acceleration and deceleration patterns increases and the data types become more varied, data quality and accuracy have become increasingly important. A high data sample rate is required to analyze these transmission facilities effectively, and the utilization of AI algorithms has become crucial.

As a solution, we have developed a cutting-edge PHM system that seamlessly integrates an edge device and platform. With the power of edge computing technology, this system can efficiently process data near the facility, thereby reducing the volume of data transmitted to the central server. This not only lessens network load but also alleviates server burden. Furthermore, the system's real-time processing capabilities have been enhanced, resulting in a faster response time for our predictive maintenance system.

A framework for detecting anomalies that utilize advanced AI algorithms has been crafted to manage high data sample rates and identify significant features for precise anomaly detection. This framework has been customized for different kinds of facilities and effectively fulfills the requirements of smart factories.

Adopting smart manufacturing has necessitated a departure from conventional, centralized PHM systems towards decentralized, intelligent, and adaptive solutions. Incorporating edge computing and robust AI analytics is a forward-looking measure that promotes operational efficiency and dependability in contemporary automated facilities. Such innovations react to the evolving industrial landscape and a deliberate strategy to harness sophisticated technologies for more accurate fault prediction and prevention.

3. Challenges

3.1. Challenges with PHM system developments

3.1.1. Data imbalance

Smart factories primarily collect steady-state data, which poses a challenge in detecting anomalies. The lack of abnormal data makes developing effective anomaly detection models difficult, as supervised learning models require sufficient labeled abnormal data. However, intentionally creating abnormal states in real environments is not feasible [5]. As a solution, an experimental test bench can be created to simulate normal and abnormal conditions to ensure a continuous supply of abnormal data. This data can be used to perform PoC verification. By conducting PoC, we can collect normal/abnormal data based on test conditions and create labeled data for each facility. This enables the use of highly accurate supervised learning models.

Unsupervised or semi-supervised learning methods are commonly used to solve the data imbalance in in-line. Unsupervised learning uncovers hidden patterns without labels, while semi-supervised learning enhances model performance by utilizing limited labeled data. This approach leverages smart factory inline data, primarily normal data, to establish normal distribution benchmarks for monitoring status. We can monitor anomaly score set up the lines divided warning and fault. By configuring and implementing the system on the production line, we can effectively address issues related to data imbalances.

3.1.2. Challenges with learning models

While unsupervised or semi-supervised learning methods can effectively identify anomalies, they do have a drawback because it can be challenging to pinpoint the exact cause of the anomaly. For instance, if a model detects an abnormality, it does not necessarily reveal whether the sensor responsible for the anomaly is faulty. To address this issue, it is necessary to conduct a thorough re-analysis of the facility's data after an anomaly is detected. Data from sensors must be separated and examined individually for each moving part or component location in the equipment, and specific patterns or characteristics contributing to the anomalies must be identified. To accurately determine the characteristic frequency based on the rotational speed of each component and identify any unusual fluctuations, we utilize domain knowledge to collect statistical data on gear frequency bands prior to the learning process. This stored information can be easily accessed through our platform for thorough analysis. This approach can be incredibly helpful in taking practical measures to resolve the issue.

3.1.3. Equipment challenges with complex patterns of robots

Sophisticated machinery, such as robots, can be challenging to monitor for irregularities due to their frequent acceleration, deceleration, and complex patterns. Additionally, the lengthy cycle times and diverse movements of robots make it difficult to identify patterns using traditional methods. However, advanced algorithms, including cycling techniques and signal processing methods such as time-frequency transformation (STFT) [6], can be applied to more accurately detect abnormal changes. These techniques make it possible to detect abnormalities with a higher degree of accuracy, even in facilities with complex patterns.

3.2. Challenges when applying PHM in the field

3.2.1. Challenges with the central server concentration method

In a cutting-edge factory setting, copious amounts of data are produced from diverse facilities. Specifically, intricate automation facilities generate significant quantities of data, including high sample rate vibration data. However, the conventional approach of transmitting this data to a central server for processing results in heightened network load and latency [7]. A practical solution to this challenge is to create an 'edge + platform system' leveraging edge computing technology to analyze data in real-time near the facility, extract critical information, and transmit it to the central server. This approach can expedite data processing while minimizing communication costs and central server storage management cost.

3.2.2. Challenges with cycling

In order to analyze data, it is necessary to cycle the data for a certain period, and PLC data is often used for this purpose. PLC typically utilizes line start/end process signals to timestamp data accurately. While low sample rate data is easily timestamped, high sample rate data like vibration presents a challenge. While the existing method to set timestamps was straightforward given the low data sample rate, more intricate equipment necessitates using high-sample rate vibration data to prevent information loss through down-sampling. However, this presents a challenge when attempting to set timestamps with PLC due to its limitation of about ten samples per second to avoid taxing the controller. As vibration sample rates can reach up to 16 k Samples/second, the resulting difference of approximately 1600 times is sufficient for information loss. A cycling or robust delay learning method is needed to address this issue.

3.2.3. Challenges with algorithm operation

Given the dynamic nature of smart factory environments, ensuring that AI algorithms remain up-to-date is crucial. To achieve this, an MLOps must be implemented, enabling periodic retraining and redeployment of algorithms [8]. Moreover, a collaborative approach between operating departments and maintenance organizations must be established to adapt swiftly and effectively, with a mechanism in place for rapid feedback and adaptation.

The upkeep and enhancement of AI algorithms demand consistent attention and a well-structured approach. To achieve this, the operations, conservation, and AI development departments must collaborate closely. Through monitoring data, identifying areas that require retraining, and leveraging real-time operational feedback, they can optimize the predictive conservation system's performance, leading to heightened efficiency.

3.2.4. Challenges with directing maintenance workers

In the early stage of system implementation, maintenance workers may face challenges in responding promptly to fault alarms. To enhance their response effectiveness, it is imperative to set up a system that showcases the blueprint of each facility on the platform and highlights the precise location of the alarm. The platform clearly presents the factory layout, indicating the location of all facilities. Every moving part of the facility has sensors and edge devices placed in precise locations, making it easy for maintenance workers to identify maintenance work locations through alarms displayed on the screen. Achieving this level of efficiency should be effortless. This approach will significantly boost the speed and precision of maintenance work.

4. METHODS

4.1. PHM System

4.1.1. Vibration sensor

Smart factory transmission equipment requires more precise and accurate data analysis. For this purpose, we used a vibration sensor with a sensitivity of 160 mV/g and a sampling rate of more than 8 k Samples/second to obtain high-quality data. These high-performance wired vibration sensors have the disadvantage of incurring additional installation costs. Still, applying a cost-effective, inexpensive vibration sensor of the MEMS type has compensated for this disadvantage. This makes it possible to collect high-quality vibration data economically.

Table 1. Vibration sensor

Vibration Sensor	Type	MEMS
	Axis	Z (mono)
	Sensitivity	160mV/g

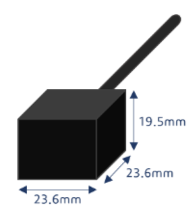

Figure 1. Vibration sensor

4.1.2. Edge CMS (Continuous Monitoring System)

As the amount of data increases exponentially, concentrating data on a central server for analysis becomes difficult due to storage capacity management and data latency issues. In particular, high sampling rate data processing is essential in facilities with complex patterns, which makes centralized analysis more difficult. To respond to this, we developed Edge CMS with edge computing capabilities, processing high-sample rate vibration data in real-time at the edge, extracting features, and calculating AI scores. The system supports 24-bit resolution and a sampling rate of 16kS/s, allowing processing without data loss. AI algorithms are mounted on these Edge CMSs and can make decisions immediately near the facility.

Table 2. Edge CMS module

CMS Module	Max. Sampling Rate	16 k sample/sec
	Channel	8 channel
	Bit Resolution	24 bit

Figure 2. Edge CMS module

4.1.3. PHM Platform

The PHM platform is located on the central server and manages each Edge CMS device applied to each facility. The AI algorithm is registered in the platform as learned and then distributed to the CMS, which requires updates when necessary to optimize and manage abnormality detection. For example, if the line situation changes and the operating pattern teaching is modified, two weeks' worth of raw data is relearned, and the learned model is redistributed to the CMS located in the relevant process facility for operational management. In other words, the MLOps cycle that allows re-learning/re-distribution was implemented. Key features and AI scores calculated from the CMS located at each facility are transmitted to the platform and displayed to check trends by date. If the appropriate standard value is exceeded, a warning and fault alarm is given to notify the operator, and it displays which equipment and location on the layout shows signs of abnormality, helping to instruct maintenance workers on maintenance work. The platform layout was modeled after each factory line, and the web screen was designed so that if an error occurs, the area is marked in red to be visually checked immediately.

4.2. Anomaly detection framework

4.2.1. Cycling Techniques

'Cycling' is 'Extracting one cycle in operating data patterns of equipment'. Our data must be 'cut off' in the equipment operation cycle. Usually, cutting is done with PLC signals, but down-sampling is necessary to match the start / end signal timestamps to the data. However, the simple down-sampling method may be ineffective when collecting vibration ineffective when collecting vibration data at 8kS/s

Figure 3. PHM platform monitoring screen composition

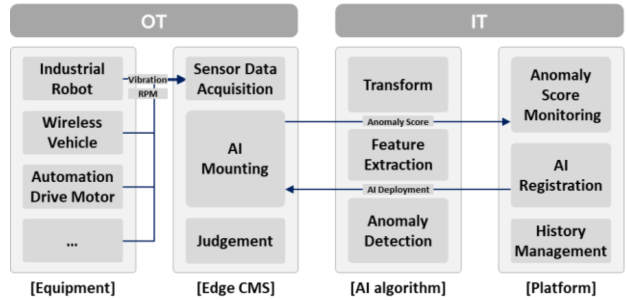

Figure 4. A configuration block diagram of the PHM platform and Edge CMS module connection with AI algorithm in the OT/IT range

to analyze transmission equipment that repeats acceleration/deceleration. To overcome this, we utilized an auto-cycling technique to divide the acceleration, constant speed, and deceleration sections. We obtained the specific frequency by determining the rotational frequency based on the equipment motor's RPM. We then counted the peaks of the acceleration/deceleration in both time and frequency and set a vibration magnitude threshold to divide the acceleration/constant speed/deceleration sections. This technique can be applied to various equipment motors, including lifts, conveyors, and stackers/destackers for transporting logistics boxes or vehicles. Regardless of the distance traveled, the acceleration/constant speed/deceleration types can be learned and utilized separately.

Advanced gear-shifting equipment, such as robots, faces a challenge when splitting acceleration and deceleration using auto-cycling techniques. As a result, the entire one cycle must be used for learning. The process signals receive start and end bits, which are then used to set the cycling point. To ensure robust learning despite delays caused by different sample rates, features are imaged at a later point. The frequency distortion caused by converting the entire cycle is resolved through STFT conversion, allowing for the utilization of all time-frequency information.

4.2.2. Preprocessing and Conversion

Data value can vary depending on the unique conditions of each facility. To refine normal data, checking its distribution, applying DC offset, and filtering where necessary is essential. Since most equipment comprises motors and gears, confirming rotation frequency in the frequency spectrum based on speed is possible. Features are extracted to ensure accurate expression of rotational frequency and harmonic components based on gear mesh theory [9], and window size is set to perform FFT spectrum conversion up to the 4kHz band [10], [11]. After conversion, RMS statistics are calculated for each harmonic frequency band and basic statistics like Min, Max, Average, Kurtosis, and Skewness [12]. This data is stored on a server to enable detailed analysis and monitoring. The magnitude of the FFT spectrum converted to a 1D shape is fed into the AI algorithm for further study. The spectrum is transformed with a window size of 3 seconds, and data is extracted through window sliding with a duration of 0.25 seconds [13]. In the slow-speed equipment, the spectrum is reduced to 1.5 kHz, and the conversion values for each channel are concatenated and studied in the form of a wave set. This process has led to the development of an optimized anomaly detection framework that applies different conversion techniques to suit the specific characteristics of each facility.

Robots utilize STFT transformation to extract features, which involves cycling in the manner described above. The output of STFT is a 2D shape from a colormap image, which serves as input to the AI algorithm. When features are extracted using 1D Conv, some degree of conversion freedom allows for flattening and use within the algorithm. The STFT value is also stored separately and used for detailed feature analysis. The robot stores features in separate channels for each axis to allow for more accurate analysis. This approach enables the identification of any anomaly score increase in a specific channel, which can then be used to issue maintenance instructions for the affected axis. The FFT spectrum is re-extracted for the robot's statistics, using a window size of 3 seconds within one cycle. The extracted features are stored similarly to the driving motor of general equipment and are not separately learned by the AI model. They are stored on the server for monitoring during detailed analysis.

4.2.3. AI algorithm

The most effective method for confirming data classification is Dimensional Reduction Visualization. This involves reducing the extracted features' dimensions and representing them on a 2D graph's x and y axes. Doing so can ascertain how the feature distribution is formed by date and whether it is clustered. LDA (Linear Discriminant Analysis) is utilized for dimensionality reduction [14]. The average feature value for each date is represented as a single point, and each month is color-coded to show how the features change visually from one month to the next.

Supervised learning struggles to classify typical smart factory data due to the difficulty of obtaining abnormal data. However, clear labeling can ensure the accuracy of this method. To address this issue, we developed an algorithm to collect abnormal data and classify the collected abnormal data so that it can be distinguished from normal data in various scenarios, such as motor misalignment, bearing failure, bearing cage damage, robot reducer failure, and lubricant shortage. We utilized deep learning, specifically a convolution method, to capture features easily using spatial information of image data. The 1D CNN layer consisted of 3 layers, utilizing the relu activation function [15], a model was created to classify into normal/abnormal through the dense layer. After verification, over 97% of the classifications were confirmed. The classification model was saved in the system, and data on diverse types of defects were collected and attributed to the system for future classification purposes.

In cases where there is insufficiently abnormal data, Anomaly Detection can be achieved by establishing a baseline of what constitutes "normal" data and monitoring any deviations from that baseline through a scoring system. An AI algorithm utilizing an auto-encoder structure must be introduced to employ this method [16]. Before training the model, extracted features are inputted as the model's input values. When dealing with robots, input values take the form of images, for which a convolution layer is created to facilitate image analysis. This layer consists of three layers with a relu activation function, and instead of pooling, it utilizes the stride technique to employ all pixel information [17]. The decoder comprises three Conv2DTranspose layers reconstructing the extracted features. Learning uses the Adam optimizer, mae loss, and appropriate batch_size and learning_rate parameters. The trained model predicts new data with the same feature shape, calculates the loss difference from the normal group learning value, and generates an anomaly score. Anomaly detection is achieved by monitoring this score over time and checking the platform display for gradual increases.

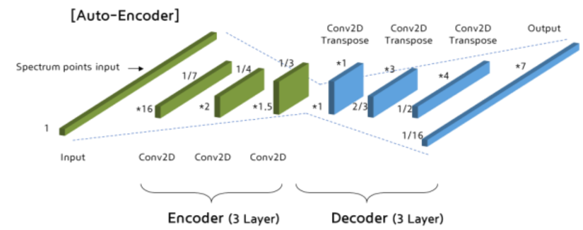

Figure 5. Configuration of vibration-based AI model (Auto-Encoder) for Anomaly detection

5. Verification

5.1 Verification of PoC

5.1.1 Construction of Test-bench and data collection environment through PoC

We set up an external test bench and conducted a PoC test to gather information on the target equipment. In the case of industrial robots, we installed vibration sensors on each axis of the reducer part for manufacturers such as Hyundai, ABB, Yaskawa, and Kawasaki. We repeatedly drove the machine by teaching it a complex, 6-axis movement that could withstand heavy use. To collect vibration data from the reducer part, we used a motor with the same capacity as the logistics line conveyor and lift equipment and connected a load system to apply a constant speed drive. We monitored and verified the target type by selecting equipment with a high non-operation rate in-line, such as when replacing a reducer due to mechanical defects.

5.1.2 Development of Motor PHM diagnosis algorithm and Verification in Test-bench

A dynamometer was installed on the motor and reducer (manufactured by SEW) to confirm the PoC, which drives the automation equipment utilized in actual mass production. A load was applied, and critical parts were equipped with a vibration sensor to collect data. The system was run at a constant speed of 1800rpm with load currents ranging from 2.5 to 0.1A.

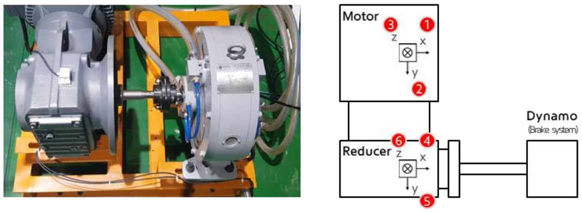

Figure 6. Real and dynamometer configuration diagram of Motor and Reducer

In our analysis, we compared normal and abnormal data. Specifically, we examined changes in vibration magnitude on the time axis and alterations in specific frequency values, band ranges, and harmonics of the rotating body on the frequency axis. Using this information, we conducted a date-wise assessment to determine if there was a gradual change.

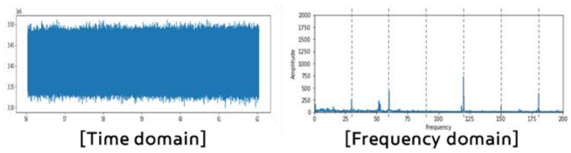

Figure 7. Normal data pattern by time/frequency domain

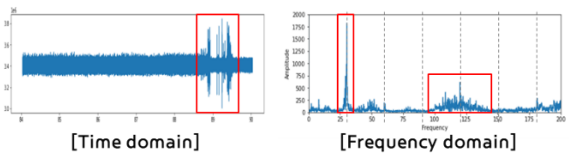

Figure 8. Abnormal data pattern by time/frequency domain

Our process involves extracting feature vectors from acquired data using FFT spectral transformation. These vectors are then input into an autoencoder model, which returns an output vector. The model first learns the vector of the normal group, compares it with the vector of new data, and returns the error value as the final score using MAE. To test this, we selected ten days of motor operation data with the same conditions and the occurrence time of an abnormality. We trained the model using the first three days and predicted the next seven days. Finally, we analyzed the predictions to identify any changes in the data.

Figure 9 displays vibration RMS values over time, indicating that the RMS only increased at the time of failure, making it challenging to predict through rule-based measurement value monitoring. However, in Figure 10, the Anomaly score gradually increases over time. Figure 11 displays the average value per date, revealing an increasing score from January 28th. As the anomaly score rises, data that differs from the standard norm is being collected, making it feasible to operate a PHM system that anticipates failure and notifies the time of failure via an anomaly score baseline of 0.2 to 0.3.

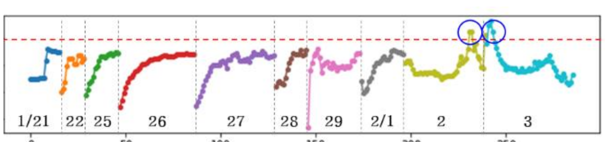

Figure 9. Comparison of vibration RMS values by date

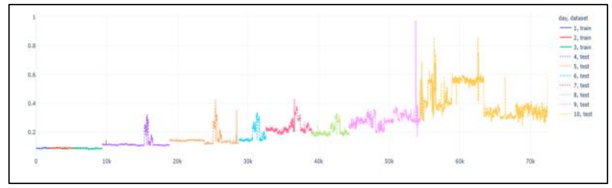

Figure 10. Comparison of Anomaly scores by date

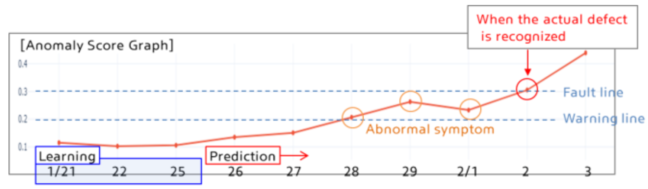

Figure 11. Comparison of Anomaly scores average

After the actual abnormal data was acquired, the operation stopped due to motor failure after continued operation for two months, and a motor disassembly analysis was performed to confirm the phenomenon.

The cause is damage to the reducer and internal bearing due to dynamometer misalignment. Damage to the bearing cage and excessive tooth surface wear can be seen in Figure 12. As a result, a prediction model for motor failure was developed, and it was confirmed that the algorithm could be applied and operated by matching the failure phenomenon.

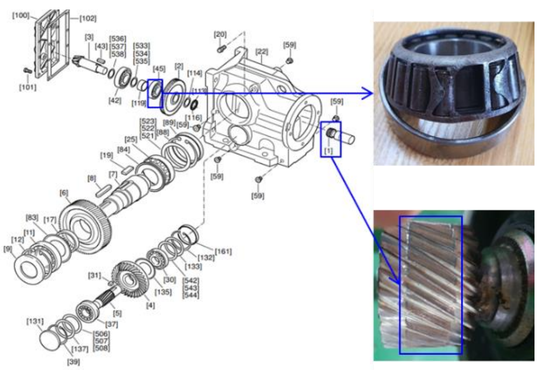

Figure 12. Result of disassembling bearing of faulty reducer

5.2 Verification of Production factory in-line

5.2.1 Inline data analysis process

An aging robot was selected from the in-line welding robots used for car body production to verify the development algorithm. A vibration sensor was installed, and data was collected. The robot was significantly aged after operating for 11 years without a reducer replacement. Upon analysis of the iron concentration in the reducer grease, it was found to be approaching the replacement criterion. The data was monitored for an additional four months, and the reducer was replaced with a new product. The change in Anomaly score was checked to verify the replacement. This verification process aims to determine whether the aging pattern is distinguishable from normal, even if it is not a failure, and whether the score can increase gradually and eventually lead to a failure.

Figure 13. Appearance of aging robot reducer in-line

The anomaly detection process utilized the Auto-Encoder model through AI technology. Upon replacement, the data was swiftly learned and compared to the data not learned before replacement using the AE model for score evaluation by date. Below is the comprehensive data analysis procedure that is verified based on what is described in Chapter 4.

Using raw vibration data, we extracted one-cycle data by analyzing the similarity or the on/off signals of a PLC. The data collected includes six channels and spans 51 seconds, with sensors installed on each axis of a 6-axis robot. However, the window size was too large to analyze one-cycle data in the frequency spectrum. To address this, we used partial data corresponding 1~3 seconds to transform to FFT spectrum or performed an STFT transformation using total cycled data to extract features in both time and frequency bands. This is a key method for extracting features based on the equipment and operation pattern. The converted STFT was then shaped into an image with the following input dimensions.

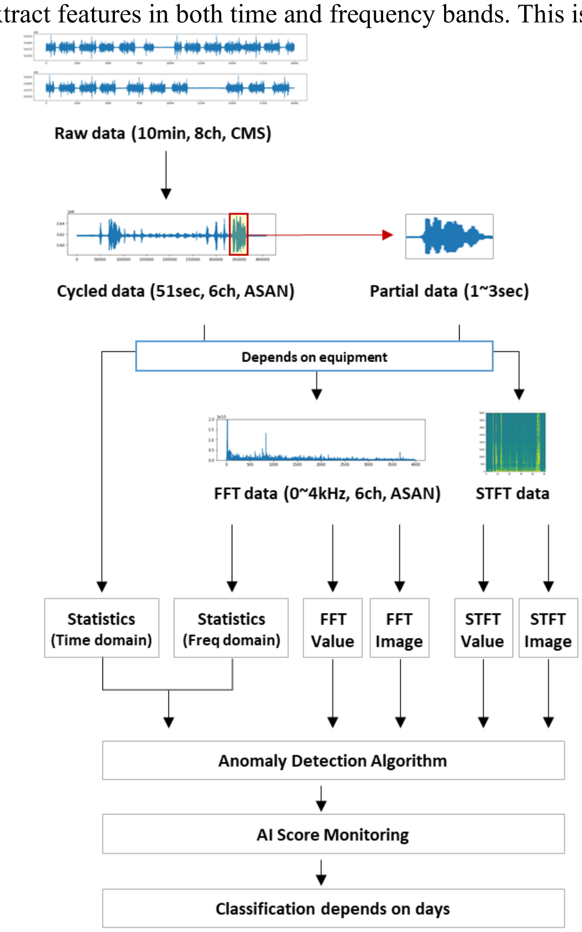

Figure 14. In-line data analysis process

Abnormal dataset: (580, 385, 387, 3)
Normal dataset: (185, 385, 387, 3)

To ensure accurate and reliable results, we split 60% of the data set into a training dataset of 459 samples and a test dataset of 306 samples. This allowed us to effectively organize and analyze the data before proceeding with the learning process.

5.2.2 Visualization of data distribution

To visually represent the distribution of data, we employed dimensionality reduction using the LDA (Linear Discriminant Analysis) technique. This involved breaking it down into two-dimensional components and displaying it on a 2D graph. M5 to M10 in the graph represent months. After the reducer was replaced, October was expressed in brown, and the months from May to September before the replacement were expressed in a different color. Upon observation, we concluded that the data's distribution clusters were formed differently before and after the reducer replacement.

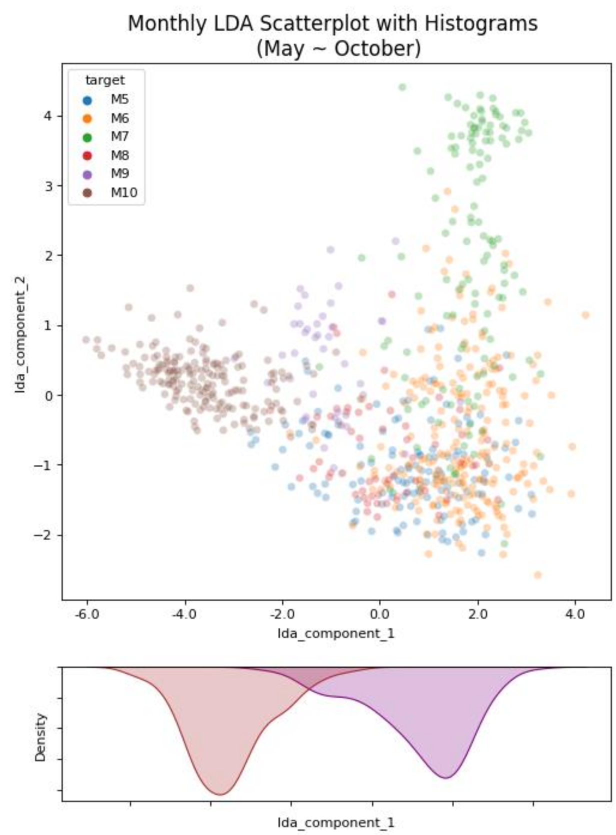

Figure 15. Monthly scatter plots and histograms were separated using Linear Discriminant Analysis – Abnormal (M5~9_purple) and Normal (M10_brown).

5.2.3 Results of Anomaly Detection Analysis

We use STFT colormap image as the characteristic feature. Utilizing colormap images demonstrated superior feature extraction through a convolution layer [18]. This led to a highly effective anomaly detection model, which relied on an Auto-Encoder structure as its foundation. Specifically, we constructed an encoder consisting of three convolutio and a decoder featuring a convolution transpose layer.

50% of the normal dataset was used for learning, and the remaining abnormal and normal datasets were used as a test set to check the anomaly score.

A discernible visual difference was observed in the scatter plot after comparing the reconstruction error before and after replacement with a new product. The distribution graph distinguishes the abnormal state in orange color and normal state in blue color before and after the replacement time point. (Figure 17). Subsequently, upon setting the error threshold, the distinction in distribution between the normal state, which is represented in dark blue and the abnormal state, which is represented in orange, was confirmed through the histogram. These findings suggest that the replacement product had a significant impact on the reconstruction error and, thus, could enhance the overall performance of the system. (Figure 18)

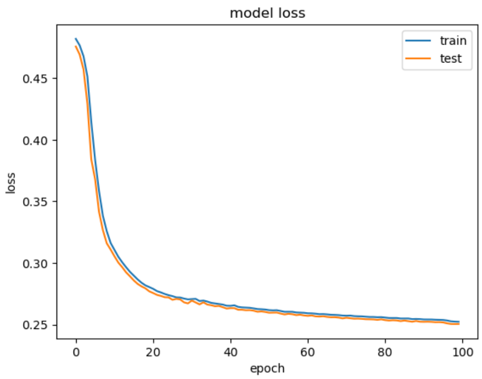

Figure 16. Auto-Encoder Model learning loss graph

Learning was performed by repeating epochs to minimize loss.

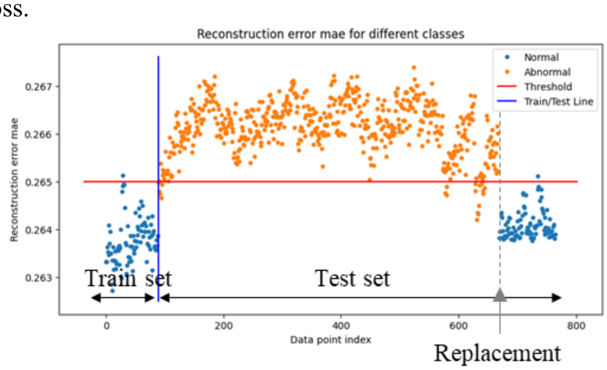

Figure 17. Reconstruction error scatter plot by Train/Test set

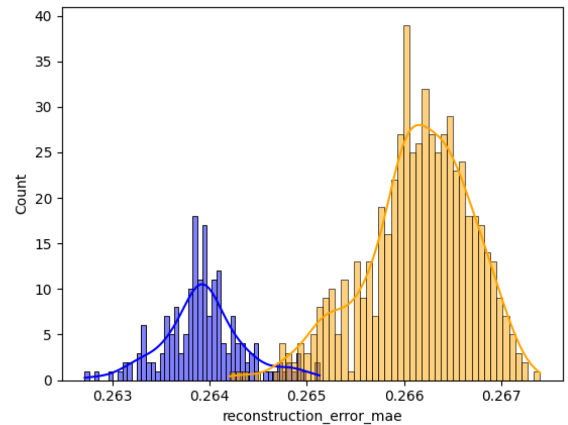

Figure 18. Reconstruction error distribution histogram

It was determined through predictive analysis of the test dataset that significant differences in reconstruction error exist between the normal and abnormal datasets. The formation of distinct clusters in the reconstruction error distribution further confirmed these differences. By setting the appropriate threshold value and checking the classification accuracy, it was ascertained that the classification was highly accurate, exceeding 97%. Additionally, by monitoring the anomaly score through unsupervised learning, variations in data patterns in aging equipment were identified as indicative of potential breakdowns.

Table 3. Test set classification results depending on metrics

Accuracy	Precision	Recall	F1	ROC_AUC
97.04%	99.82%	96.72%	98.25%	97.84%

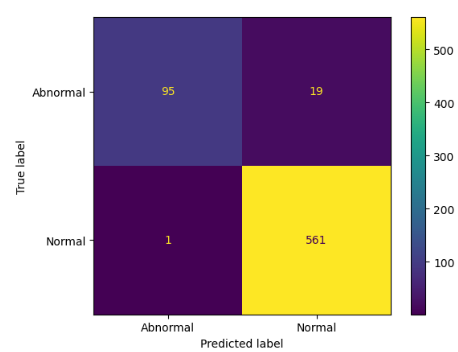

Figure 19. Ab/Normal state confusion matrix of the Test set

6. Smart Factory Application

Our new smart factory's assembly and logistics lines currently utilize the PHM system. It's applied to both constant-speed equipment like fan motors and variable-speed equipment like robots, lifters, and wireless mobile vehicles. Through our research and development, we've been able to internalize our technology and significantly reduce construction investment costs compared to external products. Moving forward, we plan to constantly monitor data and enhance our algorithm by identifying and addressing specific facility defects. Our ultimate goal is to expand horizontally, proving and verifying the effectiveness of predictive maintenance on domestic and overseas automobile production line facilities.

6.1. Classification of Smart Factory Equipment Group

6.1.1 Constant speed equipment

When it comes to equipment that operates at a consistent speed, the relevant data values are monitored and analyzed, or specific window sizes are set to monitor the score obtained from learning features within the frequency spectrum. This applies to equipment like painting fan motors, supply/exhaust fans, and air blow pumps.

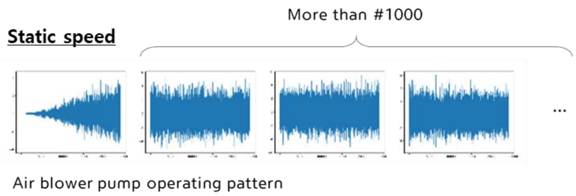

Figure 20. Operation pattern of constant speed equipment

6.1.2 Monotonic acceleration/deceleration pattern equipment

Regarding in-line equipment, movement automation equipment may follow a repetitive pattern of acceleration, deceleration, and constant speed. This is evident in stacker/de-stacker equipment that moves BIW between floors in an automobile manufacturing line and conveyor belt drives for movement between processes. Despite having variable-speed capabilities, the acceleration/constant speed/deceleration pattern remains constant, allowing for the extraction and utilization of features across the frequency spectrum by dividing the pattern accordingly.

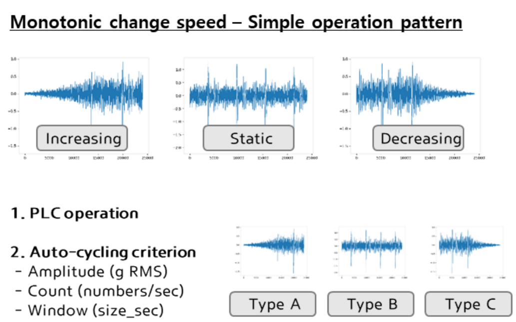

Figure 21. Operation pattern of acceleration/deceleration equipment

6.1.3 Monotonic acceleration/deceleration and various pattern equipment

In logistics box warehouses, repetitive acceleration and deceleration patterns are common, but the locations of the logistics boxes can vary greatly. This is particularly true with equipment such as the MSC (Multi Stacker Crane) and the SC (Stacker Crane). Given the vast number of possible box positions, it is not practical to learn the patterns of each position individually. Instead, the deceleration, constant speed, and acceleration patterns are divided, and learning is conducted by selecting features through the frequency spectrum.

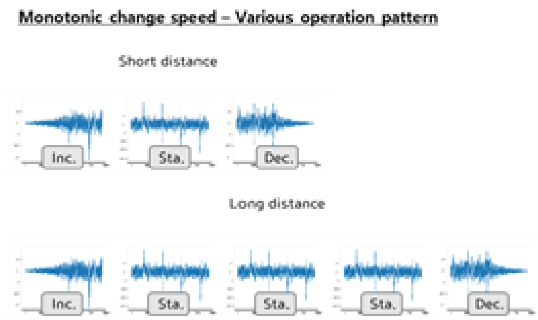

Figure 22. Operation pattern of wireless mobile device

6.1.4 Complex acceleration/deceleration pattern equipment

With the rise of smart factories, 6-axis industrial robots have become the primary choice for automation. However, due to the complexity of their multi-jointed structure, obtaining features for each movement can be challenging. To overcome this, the one-cycle pattern for each process is cropped and transformed into STFT to extract features using both time and frequency. The resulting colormap image is then learned and configured to predict one pattern for a new cycle.

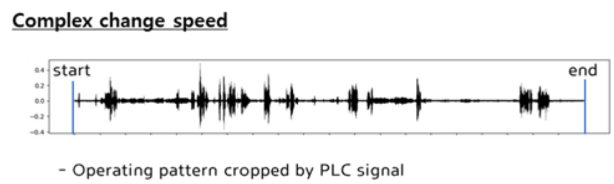

Figure 23. Operation pattern of industrial robot

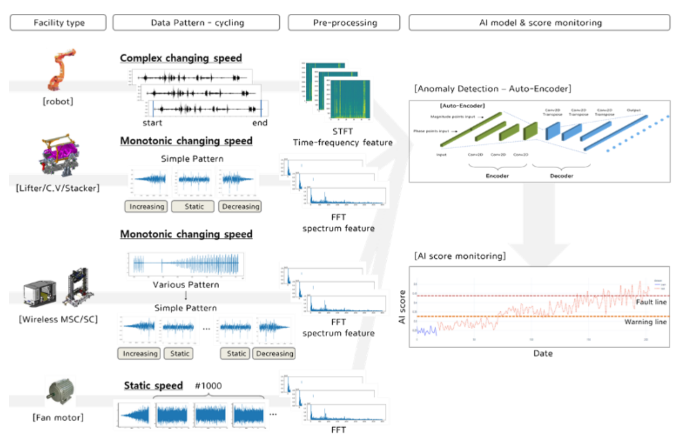

Figure 24. Feature extraction method and anomaly score calculation/monitoring process for various smart factory equipment

The final process is outlined above. When dealing with a fan motor that runs at a constant speed, the frequency spectrum of the continuous speed pattern is used as an input feature. For an engine that drives a stacker/conveyor or wireless mobile device with repetitive acceleration/deceleration, the cycle's acceleration/constant speed/deceleration pattern is separated by the driving part motor and configured through frequency spectrum conversion. For industrial robots with intricate patterns, both time-frequency features are utilized by imaging and organizing STFT features. An auto-encoder structure defines an input shape for each piece of equipment. The model is saved by learning the data of the normal group. When new data is received, the reconstruction error is calculated and compared against the learned features to determine how much it differs. Finally, an anomaly score is calculated, and the smart factory is monitored by date for anomaly detection.

6.2 Smart Factory operation screen

They are displayed below, as Figure 25 shows the smart factory's configuration screen. The process locations that have undergone PHM algorithm application are marked, allowing for confirmation of AI-predicted vibration data anomalies through Anomaly score monitoring. The score's baseline is partitioned into warning and fault lines. Crossing the warning line triggers a yellow alarm while crossing the fault line triggers a red alarm. Workers can observe the red

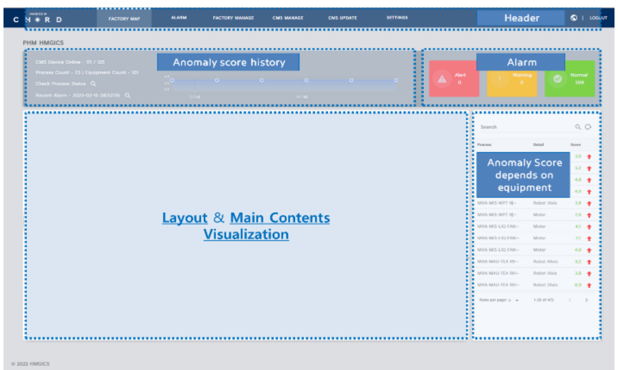

Figure 25. Monitoring screen of the factor layout displayed in the PHM system and each facility's anomaly score

indicator at the factory at the relevant facility location and conduct equipment maintenance activities. The score can be historically tracked by date/time, and a system utilizing MLops has been implemented to enable optimized algorithm re-learning and re-deployment. This system aids in optimizing the anomaly score baseline while operating the factory and conducting intelligent maintenance activities accordingly.

7. Open Problems

Thus far, we have elaborated on developing a PHM system and an abnormality detection framework to effectively address the challenges that may arise when performing predictive maintenance on various facilities within a smart factory. However, there are still some outstanding issues that require attention. Rest assured, we intend to leverage further work to tackle these challenges with precision and efficiency.

7.1. Storage space problem

Despite utilizing edge computing and storing only feature extraction results to address some challenges, many issues still need to be solved. With the emergence of intelligent factories that automate more processes and gather vast amounts of data for analysis, the issue of storage capacity remains a pressing concern.

7.2. The problem of wired sensor installation costs

Vibration data with a high sample rate is ideal for more precise analysis. However, the drawback is that it requires the installation of vibration sensors and the laying of wired cabling. To optimize the return on investment, it is vital to classify equipment based on whether it requires high sample rate data analysis, like vibration.

Installing vibration sensors on every axis would provide valuable data when analyzing robots, but the associated costs would be significant. To mitigate this, it's essential to develop technology that relies on multivariate time series data, such as current, torque, and speed, collected from the robot controller while leveraging multimodal techniques and correlational analysis with vibration to ensure optimal analysis performance without excessive wiring [19], [20].

7.3. Problems classifying various types of defects by line equipment

Efficiently identifying different kinds of defects in manufacturing plants can be challenging. Establishing a seamless collaboration between the operation, analysis, and maintenance departments is crucial. Gathering data on each defect type during factory operations requires meticulous attention to detail and careful feedback collection.

7.4. Problems predicting RUL and lifespan for each line facility

To make precise predictions about facility lifespan [21], data must be collected throughout the entire cycle from the initial operation to the eventual failure. This data can only be obtained once the factory and predictive maintenance system have matured, and the technology can only be developed when the organization and system are well-equipped and consistently engage in seamlessly integrated predictive maintenance activities. With these measures in place, accurate facility lifespan predictions can be confidently made.

7.5. MLOps automation level needs to be increased

The systemization process has been completed; however, users need to re-learn and redistribute the system to utilize its full potential. Once this is done, the system will need further development to enable Continuous Integration and Deployment and subsequently automate MLOps.

7.6. Existing smart factory applications are applied to new facilities.

Due to the implementation of predictive maintenance technology in smart factories, it is anticipated that the emergence of breakdowns caused by aging will be delayed in newly established facilities. As a result, tangible outcomes may take longer to manifest. Given the challenges of collecting defective data in this complex environment, it is imperative to undertake individualized efforts to advance the algorithm.

7.7. Abnormal signal problems, such as simple line failure

In practice, numerous irregular signals may be present alongside the established patterns. These signal include something as basic as a line fault interruption and can be leveraged in detecting abnormalities due to their distinct data format. In instances with misleading performance data, it is crucial to classify it in a manner that recognizes it as one of the typical states rather than categorizing it as an anomaly.

7.8. Types of failure problems that do not tend to increase gradually

Our team oversees an algorithm designed to identify anomalies by monitoring gradual increases in their score compared to a standard value. However, we recognize that certain types of failures may not exhibit gradual increases, requiring a distinct model for prediction. While we can currently diagnose failures that have already occurred, we strive to advance our technology to enable predictive foresight and prevent these failures altogether.

8. Conclusion

As the demand for predictive maintenance in automated facilities grows alongside the expansion of smart factories, a new study introduces a necessary PHM (Prognostics and Health Management) system and abnormality detection framework method. The system includes a MEMS vibration sensor, Edge CMS device, and PHM platform, while the anomaly detection framework addresses various challenges such as cycling techniques, preprocessing, and AI algorithm development. This methodology effectively addresses data imbalances, learning model limitations, complex equipment patterns, and real-time processing issues commonly faced in manufacturing plants. It also improves upon the problems that arise when deploying such systems in the field, including central server concentration, cycling, classification of various equipment, and algorithm operation problems.

Cutting-edge anomaly detection technology employs an AI-based vibration detection algorithm to collect data at a high sampling rate. It uses edge computing to analyze this data and make real-time decisions. This approach minimizes latency compared to cloud-based analysis and eliminates server capacity issues. The system monitors standard performance data of equipment, learns from it, and provides practical solutions to mitigate issues, ultimately reducing equipment failure and minimizing downtime.

The study has yielded an impressive outcome with the development of abnormality detection technology and PHM systems that are anticipated to enhance the efficiency and sustainability of smart factories. The new smart factory has already achieved mass production, and the challenge of data imbalance in algorithm development has been overcome through data verification. By replacing the reducer of an aging robot in a domestic factory, the technology has proven to be effective. Additionally, the domestic production of these systems can significantly reduce technology investment costs compared to foreign products while allowing for the internalization of HMG's technology. The technology's potential is not limited to smart factories and can be deployed in new facilities such as wireless logistics carriers.

Moving forward, we aim to demonstrate and enhance the efficiency of predictive maintenance in domestic and international automobile factory production line facilities. This vital technology is the backbone of smart and software-defined factories and is poised to assist numerous companies in their pursuit of intelligent automation. Our strategy involves ongoing data monitoring and algorithmic refinement, paving the way for an optimal production line experience.

References

[1] Niklas Tritschler, Andrew Dugenske, Thomas Kurfess. (2021). An Automated Edge Computing-Based Condition Health Monitoring System: With an Application on Rolling Element Bearings. Journal of Manufacturing Science and Engineering. 143(7): 071006 (8ps)

[2] JK Chow, Z Su, J Wu, PS Tan, X Mao. (2020). Anomaly detection of defects on concrete structures with the convolutional autoencoder. Advanced Engineering Informatics. Elsevier, Volume 45, 101105.

[3] Corbinian Nentwich and Gunther Reinhart. (2021). A Method for Health Indicator Evaluation for Condition Monitoring of Industrial Robot Gears. Robotics 2021, 10(2), 80.

[4] M Pech, J Vrchota, J Bednář. (2021). Predictive maintenance and intelligent sensors in smart factory. Sensors, 2021, 21(4), 1470.

[5] Tareq Tayeh, Abdallah Shami. (2021). Anomaly Detection in Smart Manufacturing with an Application Focus on Robotic Finishing Systems: A Review. arXiv:2107.05053 (cs.RO).

[6] A. Bonci, S. Longhi, G. Nabissi and F. Verdini. (2019). Predictive Maintenance System using motor current signal analysis for Industrial Robot. 2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA), Zaragoza, Spain, pp. 1453-1456.

[7] S. K. Bose, B. Kar, M. Roy, P. K. Gopalakrishnan, and A. Basu. (2019). Adepos: Anomaly detection based power saving for predictive maintenance using edge computing. Proceedings of the 24th Asia and South Pacific Design Automation Conference, pp. 597–602.

[8] Pál Péter Hanzelik, Alex Kummer, János Abonyi. (2022). Edge-Computing and Machine-Learning-Based Framework for Software Sensor Development. Sensors 2022, 22(11), 4268.

[9] Ke Feng, J.C. Ji, Qing Ni, Michael Beer. (2023). A review of vibration-based gear wear monitoring and prediction techniques. Mechanical Systems and Signal Processing Volume 182, 109605.

[10] S. S. Patil and J. A. Gaikwad. (2013). Vibration a

of electrical rotating machines using FFT: A method of predictive maintenance. 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), Tiruchengode, India, pp. 1-6.

[11] George M. Alber and Alan G. Marshall. (1990). Effect of Sampling Rate on Fourier Transform Spectra: Oversampling is Overrated. Appl. Spectrosc. 44, 1111-1116.

[12] Vanraj, Deepam Goyal, Abhineet Saini, S. S. Dhami, B. S. Pabla. (2016). Intelligent predictive maintenance of dynamic systems using condition monitoring and signal processing techniques — A review. 2016 International conference on Advances in Computing, Communication, & Automation (ICACCA) (Spring). Dehradun, India, pp. 1-6.

[13] T. Chen, X. Liu, B. Xia, W. Wang and Y. Lai. (2020). Unsupervised Anomaly Detection of Industrial Robots Using Sliding-Window Convolutional Variational Autoencoder. IEEE Access, vol. 8, pp. 47072-47081.

[14] Dan Li, Guoqiang Hu, Costas J. Spanos. (2016). A data-driven strategy for detection and diagnosis of building chiller faults using linear discriminant analysis. Energy and Buildings Volume 128, Pages 519-529.

[15] Chaity Banerjee, Tathagata Mukherjee, Eduardo Pasiliao. (2019). An Empirical Study on Generalizations of the ReLU Activation Function. ACM SE '19: Proceedings of the 2019 ACM Southeast Conference Pages 164–167.

[16] Yasi Wang, Hongxun Yao, Sicheng Zhao. (2016). Auto-encoder based dimensionality reduction. Neurocomputing, Volume 184, Pages 232-242.

[17] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, Zbigniew Wojna. (2016). Rethinking the Inception Architecture for Computer Vision. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2818-2826.

[18] M. Chen, X. Shi, Y. Zhang, D. Wu and M. Guizani. (2021). Deep Feature Learning for Medical Image Analysis with Convolutional Autoencoder Neural Network. IEEE Transactions on Big Data, vol. 7, no. 4, pp. 750-758.

[19] Unai Izagirre, Imanol Andonegui, Itziar Landa-Torres, Urko Zurutuza. (2022). A practical and synchronized data acquisition network architecture for industrial robot predictive maintenance in manufacturing assembly lines. Robotics and Computer-Integrated Manufacturing Volume 74, 102287.

[20] Athina Tsanousa, Evangelos Bektsis, Constantine Kyriakopoulos, Ana Gómez González, Urko Leturiondo, Ilias Gialampoukidis, Anastasios Karakostas, Stefanos Vrochidis, Ioannis Kompatsiaris. (2022). A Review of Multisensor Data Fusion Solutions in Smart Manufacturing: Systems and Trends. Sensors 2022, 22(5), 1734.

[21] H. Yan, J. Wan, C. Zhang, S. Tang, Q. Hua and Z. Wang. (2018). Industrial Big Data Analytics for Prediction of Remaining Useful Life Based on Deep Learning. IEEE Access, vol. 6, pp. 17190-17197.