Deep Learning/Machine Learning Techniques for Vibration Condition Monitoring of Major Facilities in Automobile Assembly/Painting Plants

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ABSTRACT

Since 2013, we have been expanding the vibration monitoring system to prevent malfunctions of rotating equipment in Hyundai/Kia Motors' global factories. In this paper, a secondary analysis model was explored using an existing legacy program containing vibration trend and spectrum data. In the existing case, it goes through the steps of setting the alarm level - raising the vibration - reaching the alarm - alarm - recognizing - analyzing the vibration - drawing the result. An automation program was applied to reduce the steps to vibration increase - derivation of abnormal equipment - result analysis. In addition, we will also cover essential system components for the operation of additional development programs.

Keywords: Condition Monitoring, Sensors, Signal Analysis, Failure Analysis, From PHM and CBM+ considerations to Maintenance, Predictive Maintenance, Deep learning, LSTM, Anomaly detection, Autoencoder, CNN

1. INTRODUCTION

Vibration systems are one of the most effective systems for monitoring equipment condition. It is not only applied to many energy/steel/heavy industry facilities,

It is also used in finished car factories. Because production volume is directly related to money, the consistency of equipment is very important in finished car factories. In order to monitor facility condition vibration, the following elements are essential. Vibration sensor - cable - vibration collection module - server - vibration analysis program. Most of the existing vibration monitoring systems show this type.(Fig.1)

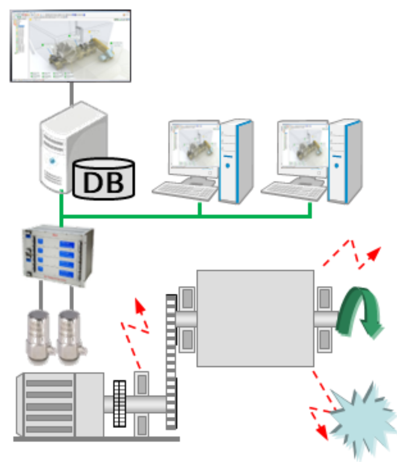


Fig.1 Existing vibration monitoring system

Recently, there are many companies that advertise that vibration condition monitoring can be done automatically. However, these companies have low reliability and lack in-house experience. In order to avoid this, a new system is proposed to the traditional vibration monitoring system companies, but additional system development is almost impossible due to lack of technology and cost issues. Therefore, while utilizing the vibration data of the existing system, we intend to apply a new machine learning/deep learning algorithm. We also try to find the most effective algorithm among them.

2. VIBRATION ANALYSIS

2.1. Background

I worked in Hyundai Motor Company's global monitoring room and managed thousands of vibration points. It has at least 2 sensors per facility and has a point of velocity acceleration (+enveloping) per sensor. It takes a lot of effort to manage thousands of points. Normally, management is performed based on the alarm level set for each facility type, but the alarm system becomes useless for facilities that rise rapidly below the alarm level. In addition, it takes a lot of time to analyze numerous frequency domain graphs. Therefore, an AI that automatically analyzes vibration trends and frequency domain analysis was needed.

2.2. Trend/frequency graph analysis

There are two concepts in vibration analysis. Trend analysis through time series vibration data. Cause analysis through vibration frequency domain data. In the case of the former, the severity of the vibration can be known, whereas in the case of the latter, the cause of the vibration and the type of defect that the equipment has can be known. In the case of the former, it corresponds to 'detection of anomaly' of the facility, and in the case of the latter, it is included in the 'cause of anomaly'. If you ask whether the former or the latter is important, I can say that the former is important. Isn't it important to notice if there is something wrong with our human body, and a detailed examination comes next? However, a system that only cries out that there is an abnormality without telling the cause of the abnormal vibration can become just noisy, annoying and inconvenient. Therefore, to apply a highly reliable vibration system, both vibration trend and frequency analysis are essential. In order to select a vibration trend analysis model and a frequency analysis model, the history of vibration reduction after vibration rise-repair of 947 cases was used. Based on this, time series data analysis techniques such as LSTM, simple average change, ARIMA model, auto gressive, exponential smoothing, and autoencoder were used for an effective trend analysis data model. In addition, the vibration frequency analysis model used image CNN model, numerical-based 1D-CNN model, spectrum band model for each defect using K-Means, and tree-based model.

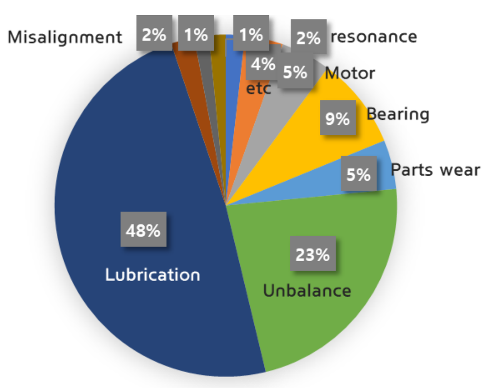


Fig.2 Causes of vibration defects

2.3. Scope and Limitations

The study focuses on Hyundai Motor Company's assembly/painting plants, utilizing vibration data collected from approximately 947 cases of vibration reduction. The analysis is limited to the evaluation of six time series data analysis models and four vibration frequency spectrum analysis models. The research does not account for other factors that may affect vibration, such as environmental conditions or equipment age.

2.4. Facility type

The types of facilities are as follows. Supply and exhaust fans and pumps mainly used in the paint process. Lifts and conveyors are mainly used in the assembly process.(Fig.3)

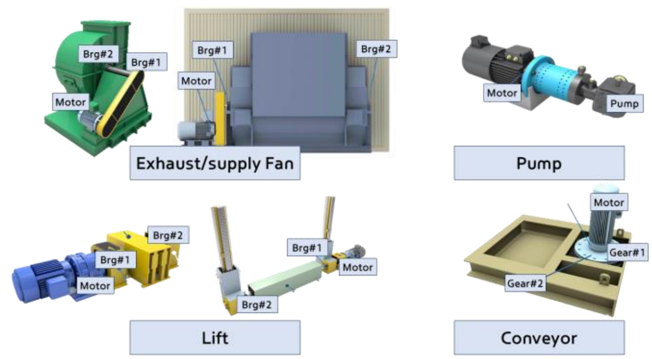


Fig.3 Facility type

All facilities except lifts are constant speed facilities. In order to accurately analyze the vibration of the lift equipment, the following process was performed.

① Measure rotational speed of equipment through speed sensor → ②Measure timewave when certain speed and speed change conditions are satisfied → ③Extract FFT and RMS values

2.5. Datasets

The units of time-series vibration data are acceleration and velocity values. Time series data consists of one vibration value (mm/s rms, g rms) per minute.

In addition, the frequency range and number of lines of data used for FFT spectrum analysis are as follows.

Velocity - Fmax: 500Hz, window: hanning, No. of lines: 1600, spectrum low freq. cutoff: 2Hz

Acceleration - Fmax: 5kHz, window: hanning, No. of lines: 3200, spectrum low freq. Cutoff: 1Hz

3. ANALYSIS MODEL

3.1. Vibration Analysis in the Automotive Industry

Various studies have been conducted on vibration analysis and its applications in the automotive industry. These studies have explored different techniques for detecting defects in machinery, monitoring equipment health, and improving maintenance strategies. Researchers have investigated both traditional methods, such as statistical analysis and spectrum analysis, as well as advanced techniques involving machine learning and deep learning.

3.2. Time Series Analysis Models

Time series analysis has emerged as a popular approach for modeling and forecasting temporal data. Numerous models have been proposed for this purpose, including Long Short-Term Memory (LSTM), Average Analysis, ARIMA model, Auto Regressive, Exponential Smoothing, and Autoencoder. Each of these models offers distinct advantages and drawbacks, with varying levels of success in predicting and diagnosing equipment issues.

3.3. Vibration Frequency Spectrum Analysis Models

Vibration frequency spectrum analysis is another common approach for monitoring equipment health. Image Classification CNN, 1D-CNN, spectrum Band Model for each defect using K-Means, and Tree Analysis Model are some of the most widely-used models for this purpose. These models aim to identify patterns in frequency-domain data, allowing for more effective detection of equipment faults.(Fig.4)

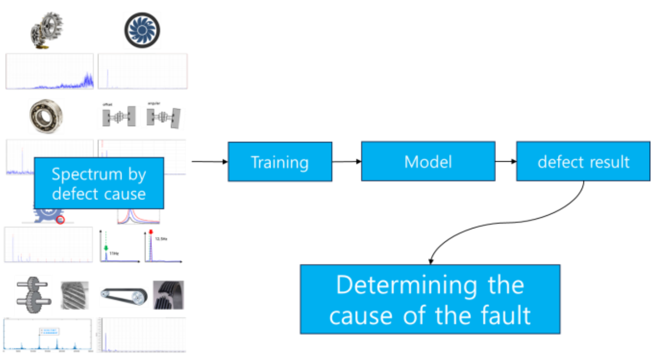


Fig.4.Spectral data analysis model

4. METHODOLOGY

4.1 Data Collection and Preprocessing

Vibration data was collected using a vibration sensor and a DAQ server. The dataset consists of approximately 947 cases of vibration reduction, representing a variety of equipment types and fault conditions. The data was preprocessed to remove noise and anomalies, followed by normalization and feature extraction.

4.2 Time Series Analysis Models

Each of the six time series analysis models (LSTM, Average Analysis, ARIMA, Auto Regressive, Exponential Smoothing, and Autoencoder) was implemented and trained using the preprocessed dataset. Model performance was evaluated using standard metrics such as mean absolute error (MAE) and root mean squared error (RMSE).

4.3 Vibration Frequency Spectrum Analysis Models

Similarly, the four vibration frequency spectrum analysis models (Image Classification CNN, 1D-CNN, spectrum Band Model using K-Means, and Tree Analysis Model) were implemented and trained using the preprocessed dataset. Model performance was evaluated using standard metrics such as accuracy, precision, recall, and F1-score.

4.4 Time series analysis model validation method

In order to compare the performance of the time series data model, we learned data from 6 months ago at a certain time and calculated the difference between the predicted value and the actual value of 1 month data after that. The data was normalized to reduce the variation in characteristics by equipment type and size. (Fig.5)

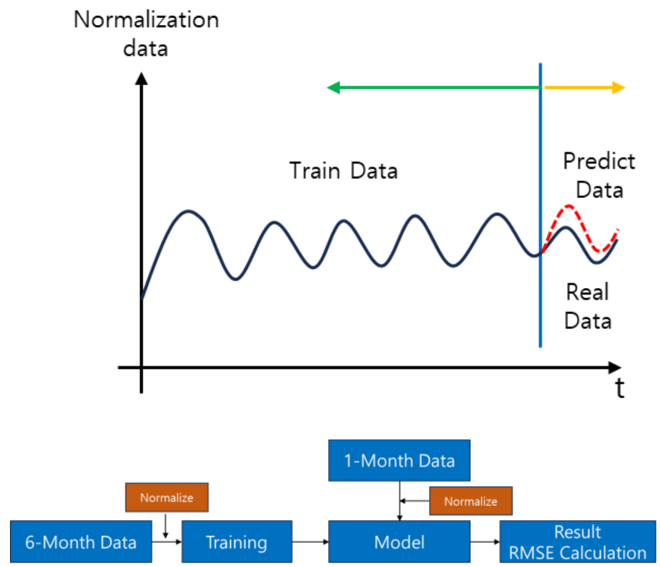


Fig.5 How to validate time series data

4.5 Spectrum Analysis Model Verification Method

The spectrum for each defect such as bearing, imbalance, poor lubrication, misalignment, and resonance was learned in advance. When a new spectrum with defects was added to the learned model, it was judged whether it could find the type of defects well.

The process of collecting spectral FFT and labeling data is as follows.

① An alarm occurs in the vibration monitoring system.

② Maintenance/vibration experts identify the situation

③ If there is an abnormality during vibration analysis, establish a facility maintenance plan and repair it.

④ After repair, check the data and create a repair history record if there is no abnormality in vibration.

5. RESULTS AND ANALYSIS

5.1 Time Series Analysis Model Comparison

The performance of each time series analysis model was compared to determine the best model for predicting and diagnosing equipment issues. The Autoencoder model demonstrated superior performance, achieving the lowest MAE scores among all the models. (Fig.6)

	Autoencoder	LSTM	Average	ARIMA	Auto gressive	Exponential Smoothing
MAE (Mean Absolute Error)	0.020	0.028	0.037	0.031	0.034	0.032

Fig.6 Time series data model performance comparison

5.2 Vibration Frequency Spectrum Analysis Model Comparison

The performance of each vibration frequency spectrum analysis model was compared to identify the most effective model for detecting equipment faults. The 1D-CNN model emerged as the top performer, exhibiting the highest accuracy, precision, recall, and F1-score among all the models. (Fig.7)

	numerical-based 1D-CNN model	image CNN model	K-Means	tree-based model
Precision	0.93	0.85	0.78	0.72
Reccall	0.94	0.86	0.79	0.73
F1 score	0.935	0.855	0.785	0.725

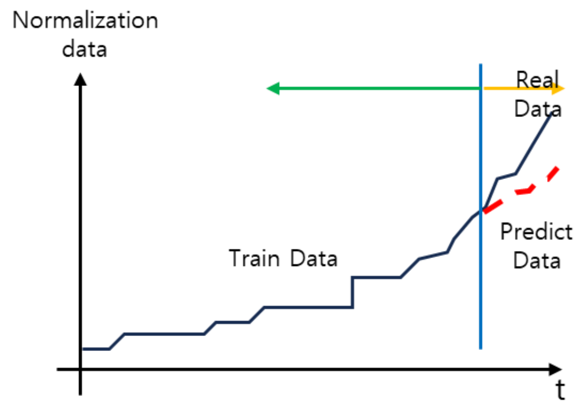
Fig.7 Spectrum data model performance comparison

6. DISCUSSION

6.1 Autoencoder for Time Series Analysis

The superior performance of the Autoencoder model in time series analysis can be attributed to its ability to capture complex patterns and dependencies in the data. Autoencoders are unsupervised neural networks that learn a lower-dimensional representation of the input data, which can be useful for detecting anomalies and predicting future values. The model's success in this application suggests that it may be a promising tool for monitoring the vibration condition of major equipment in Hyundai Motor Company's assembly/painting plants. However, it seems somewhat unreasonable to predict the future of vibration values simply with time series data. Because of the state of the facility, various events, and various variables, 'prediction' seems to be close to impossible, no matter how good the model is used. Therefore, we should not focus on 'prediction', but on 'cognition'. When the difference between the value predicted by the learning model and the actual value widens by more than a certain level, it is necessary for the user to quickly recognize it.

To this end, we conducted a model comparison for fast 'cognition'. After learning the time series data for 6 months immediately before the vibration rise, how long it takes until the rmse value of the actual value and the predicted value for one hour after the abnormal vibration occurs differs by more than 0.3. As a result of the experiment, the autoencoder detected abnormal vibration in the first hour. Except for exponential smoothing, other models also recorded fairly good recognition times. (Fig.8)



	Autoencoder	LSTM	Average	ARIMA	Auto gressive	Exponential Smoothing
Time to cognition (Hour)	1	4	3	5	5	25

Fig.8 Recognition time results for each model

6.2 1D-CNN for Vibration Frequency Spectrum Analysis

The 1D-CNN model's outstanding performance in vibration frequency spectrum analysis can be ascribed to its capacity to effectively extract local features from the frequency-domain data. 1D-CNNs are particularly adept at handling sequential data and can capture essential information from the input signal while maintaining a relatively small computational footprint. The success of the 1D-CNN model in this application indicates that it could be a valuable technique for diagnosing equipment faults in Hyundai Motor Company's assembly/painting plants.

6.3 Practical Implications for Hyundai Motor Company

The findings of this study have several practical implications for Hyundai Motor Company. By adopting the Autoencoder and 1D-CNN models for monitoring the vibration condition of their major equipment, the company can enhance its predictive maintenance capabilities and prevent unexpected equipment failures. These models can help identify potential issues before they escalate, allowing for timely interventions and reducing the risk of costly downtime. Furthermore, the integration of these models into the company's existing maintenance systems can lead to improved overall equipment effectiveness (OEE) and increased production efficiency.

7. CONCLUSION

7.1 Summary of Findings

This thesis investigated the application of deep learning and machine learning techniques for monitoring the vibration condition of major equipment in assembly/painting plants of Hyundai Motor Company. The study compared various time series and vibration frequency spectrum analysis models, identifying the Autoencoder and 1D-CNN models as the best performers in their respective domains.

Based on the results of this paper, the following system is proposed for use in real factories. Always monitor time-series vibration data using an autoencoder. If it is determined that abnormal data other than usual comes in, the CNN model analyzes the current spectrum of the facility and notifies the user of the cause of the defect. The user actually checks the equipment condition and checks the condition and vibration value after repair. If it is determined that appropriate repairs have been made, the corresponding data is uploaded to update the time series data analysis model and spectrum analysis model.

These systems offer significant potential for enhancing the company's predictive maintenance capabilities and ensuring the reliability and longevity of its equipment.(Fig.9)

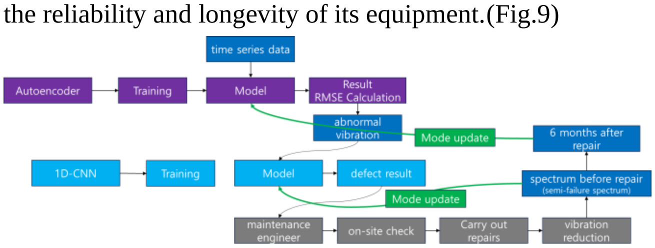


Fig.9 Facility Management Model Proposal

7.2 Future Research Directions

Future research could explore additional deep learning and machine learning techniques for monitoring equipment health, as well as investigate the integration of these models with other data sources, such as temperature, humidity, and acoustic emissions. Additionally, researchers could assess the impact of incorporating these models into Hyundai Motor Company's maintenance systems on key performance indicators (KPIs), such as OEE and production efficiency. Furthermore, the application of these techniques to other industries or equipment types could also be explored to assess their generalizability and utility.

References

"Convolutional Neural Networks for Sentence Classification" by Yoon Kim (2014)

"Time Series Classification from Scratch with Deep Neural Networks: A Strong Baseline" by Zhiguang Wang and Tim Oates (2017)

"Adversarial Autoencoders" by Alireza Makhzani, Jonathon Shlens, Navdeep Jaitly, and Ian Goodfellow (2016):

"Variational Autoencoder for Deep Learning of Images, Labels and Captions" by Yunchen Pu, Zhe Gan, Ricardo Henao, Xin Yuan, Chunyuan Li, Andrew Stevens and Lawrence Carin (2016)

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