한국공학대학교
TECH UNIVERSITY OF KOREA

Anomaly detection of machines and shop floors with AI

ISO/TC 184/SC4 88th meeting conference
Industry Day, Oct. 23rd, 2004

2024. 10. 23

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Contents

01 Introduction

Anomaly detection for machines

Industrial cases

AI-assisted Maintenance

▷ Anomaly detection according to the business application

http://auto.danawa.com/news/?Tab=N1&Work=detail&no=4272873

https://biz.chosun.com/site/data/html_dir/2019/05/14/2019051400488.html

Built-in Sensor
Parameter matching
(Equipment Const.
Recipe Manage.
FDC)+AI

[Discrete Equipment]

https://www.hankyung.com/economy/article/2020032639881

https://www.pumps-africa.com/industrial-pump-maintenance-tips/

Sensor Attachment
CBM/PHM/PdM
(Vibration/Temperature,...
+AI)

[Process Equipment]

Issues for anomaly detection of machines

▷ Challenges of Utilizing Manufacturing Data

- **Data quality or digital data from the controller**
  - ✓ Some controllers are not connected to the Internet nor give digital data as themselves.

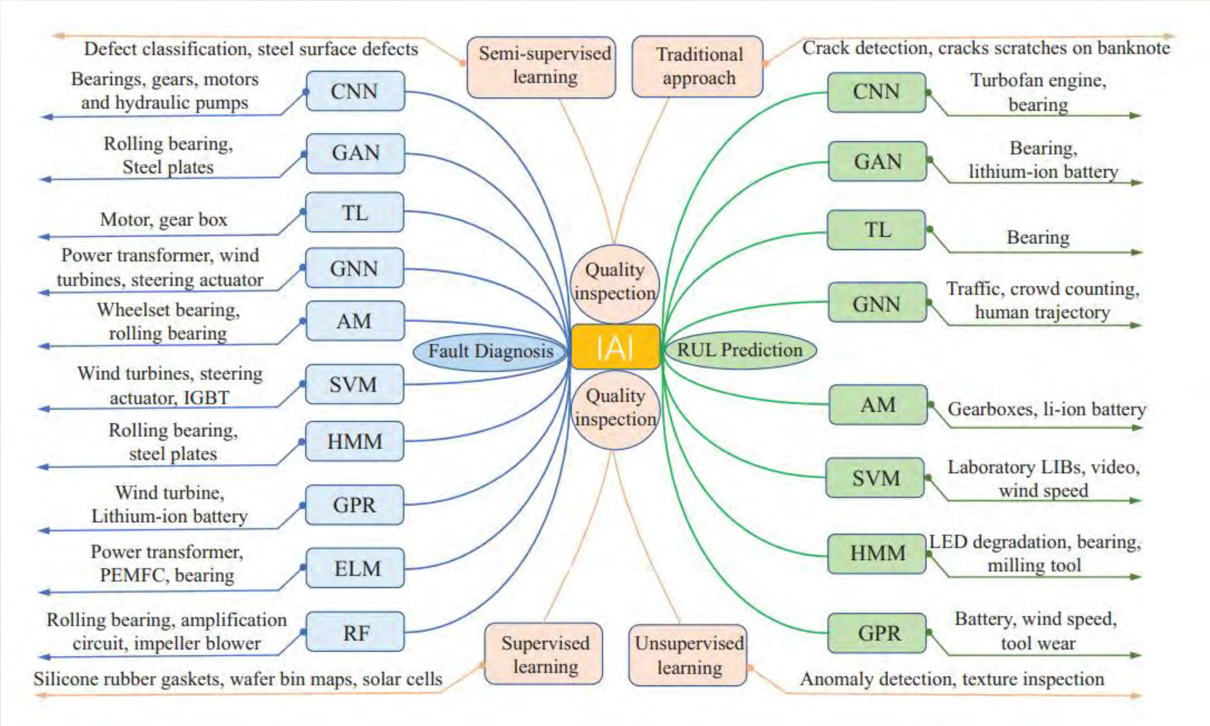
- **Lack of human resources to handle digital data**
  - ✓ Due to the low birth rate and aging population, there is a serious lack of manpower in all industries, and it is difficult to hire highly skilled IT engineers in the manufacturing industry.

Reference: Stratus blog, Stratus Technologies.
https://blog.stratus.com/ko/data-utilization-in-the-manufacturing-industry-four-challenges-and-solutions-explained/

Anomaly detection for machines

AI-assisted anomaly detection

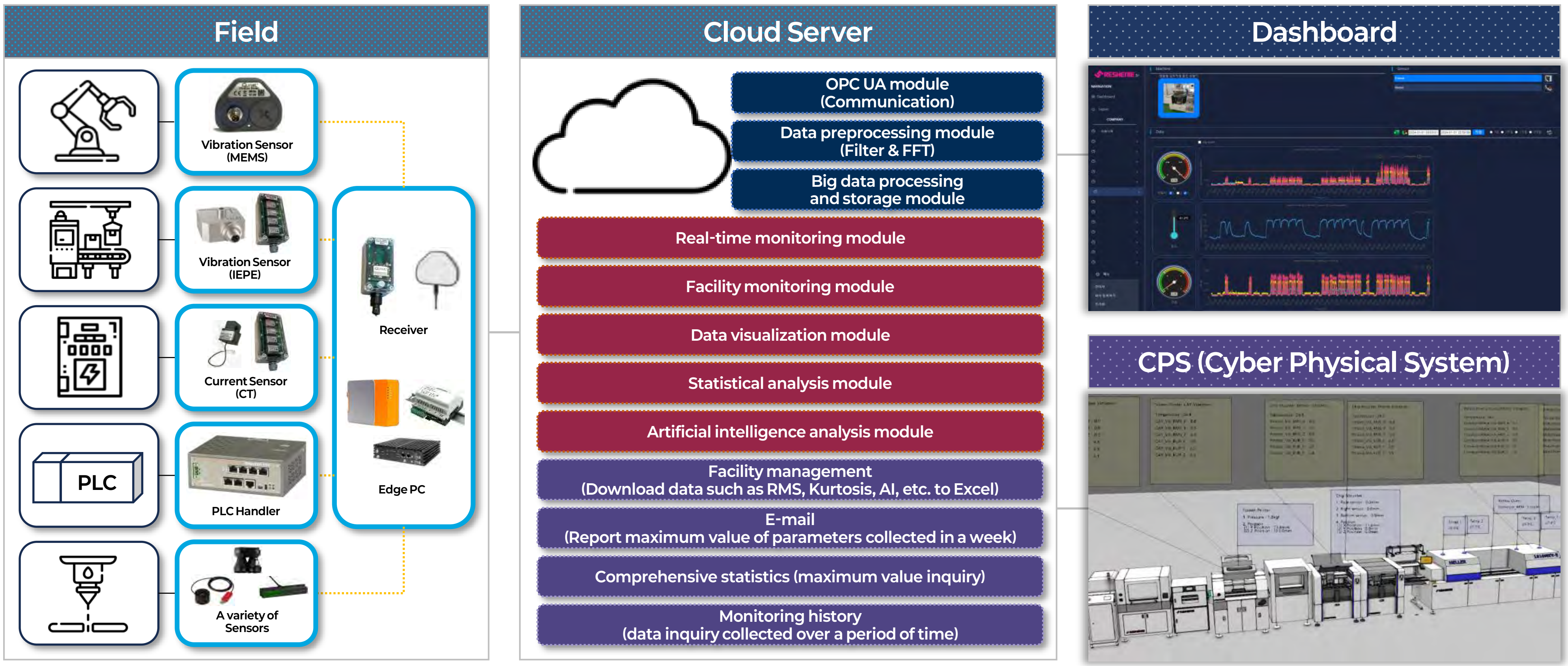
▷ **Artificial intelligence has become the technical core of smart manufacturing.**



Ding, H., Gao, R. X., Isaksson, A. J., Landers, R. G., Parisini, T., & Yuan, Y. (2020). State of AI-based monitoring in smart manufacturing and introduction to focused section. IEEE/ASME transactions on mechatronics, 25(5), 2143-2154.

Hardware and Software strategy

▷ Data acquisition and anomaly detection service for the applications



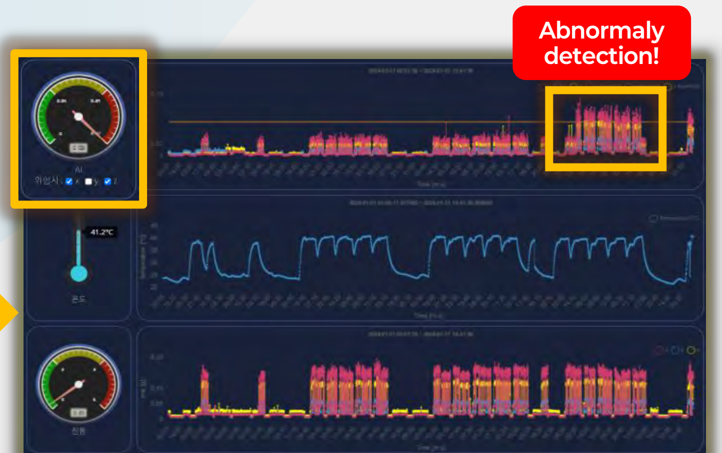
Anomaly detection for machines

Utilities

▷ Utilities without built-in sensors

Utility maintenance

- **Utilities can be managed based on physical data** (vibration, current, etc.) related to the operational status of the facilities
- We can **check the status of all facilities under management anytime, anywhere**, even if not near the facilities
- Condition-based maintenance (CBM) of expensive equipment **enables failure cost risk management**



Realize the prediction for the large fault of rotary system!!

01 Introduction

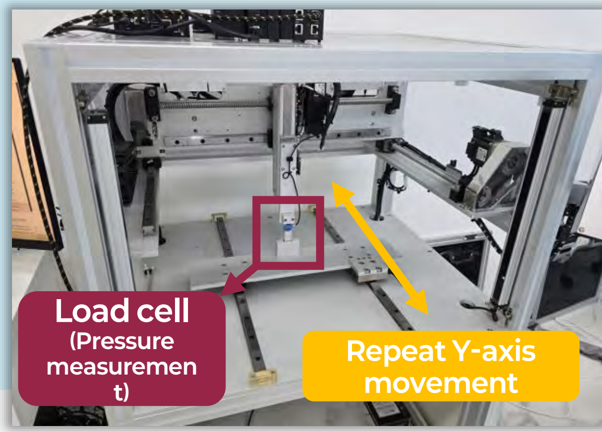
Anomaly detection for machines

Equipment

▷ Equipment with built-in sensors

Process-based equipment maintenance

- **Processes can be managed based on physical data** (pressure, displacement, etc.) associated with core processes
- **We can check the status of all core processes under management anytime, anywhere,** even if not near the facility
- In case of product failure, **process data can be analyzed to infer the cause of failure**



Changes in pressure according to the position of orthogonal robot

Parallelism between the upper rail & the lower rail **is defective !!**

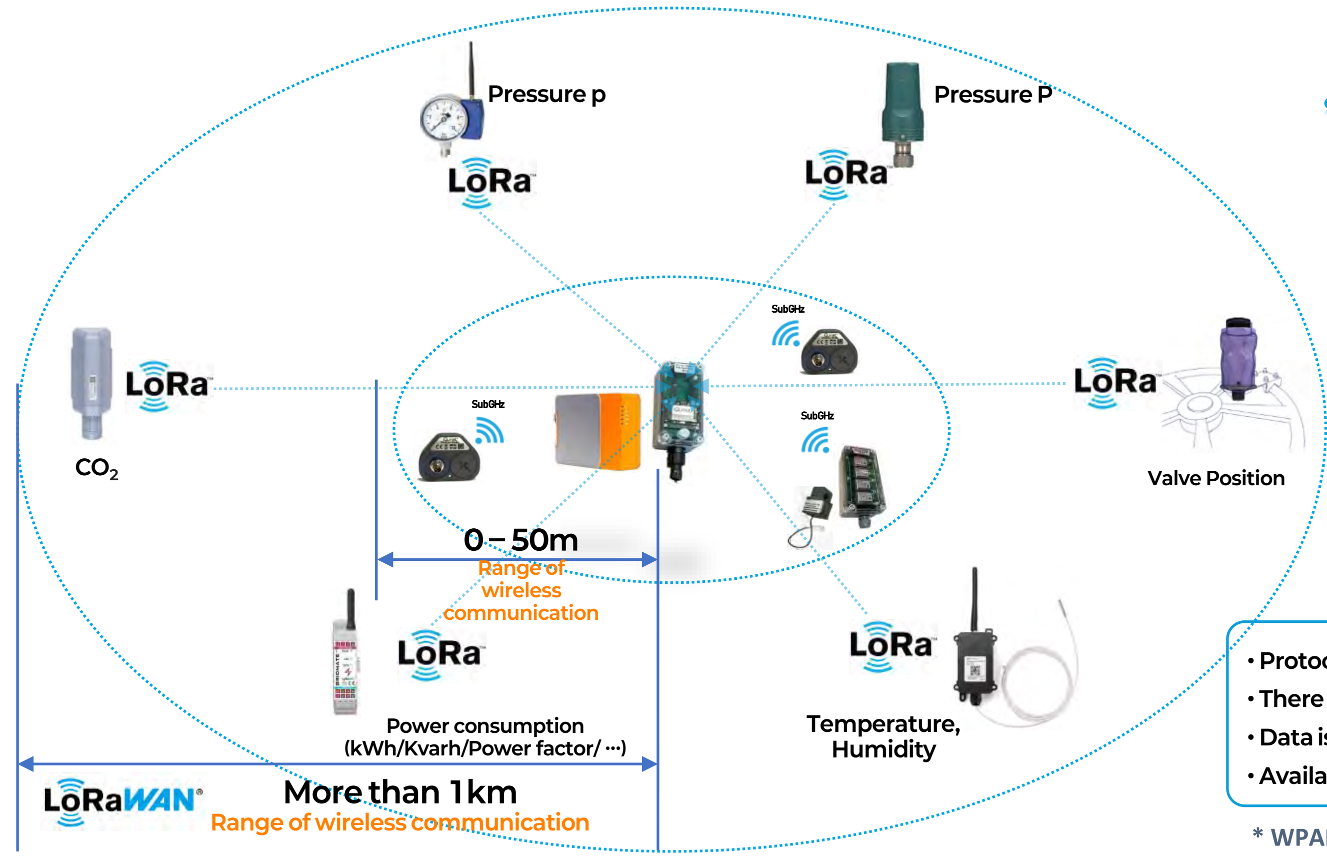
02 Anomaly detection of utilities

02 Anomaly detection

Anomaly detection for utilities

Data acquisition

▷ Rotating machineries and wide factory areas



- Edge Server (Intelligent IIoT Edge)
- LoRa LoRaWAN Sensors in LPWAN
  - Remote asset monitoring sensors in LPWAN
  - Examples : Pressure air&liquid, level, pulse, ···
  - T°/RH/VOC/CO2/H2O/NH3 ···
  - Oil contaminations, valve position ···
- SubGhz Sensors in WPAN
  - Condition monitoring sensors in WPAN
  - Examples : Vibration, current

LoRaWAN

- Protocol sensors have DIRECT local link to the server.
- There is no gateway nor (private) LoRa network access required.
- Data is stored local.
- Available in embedded OPC UA server or embedded MQTT client.

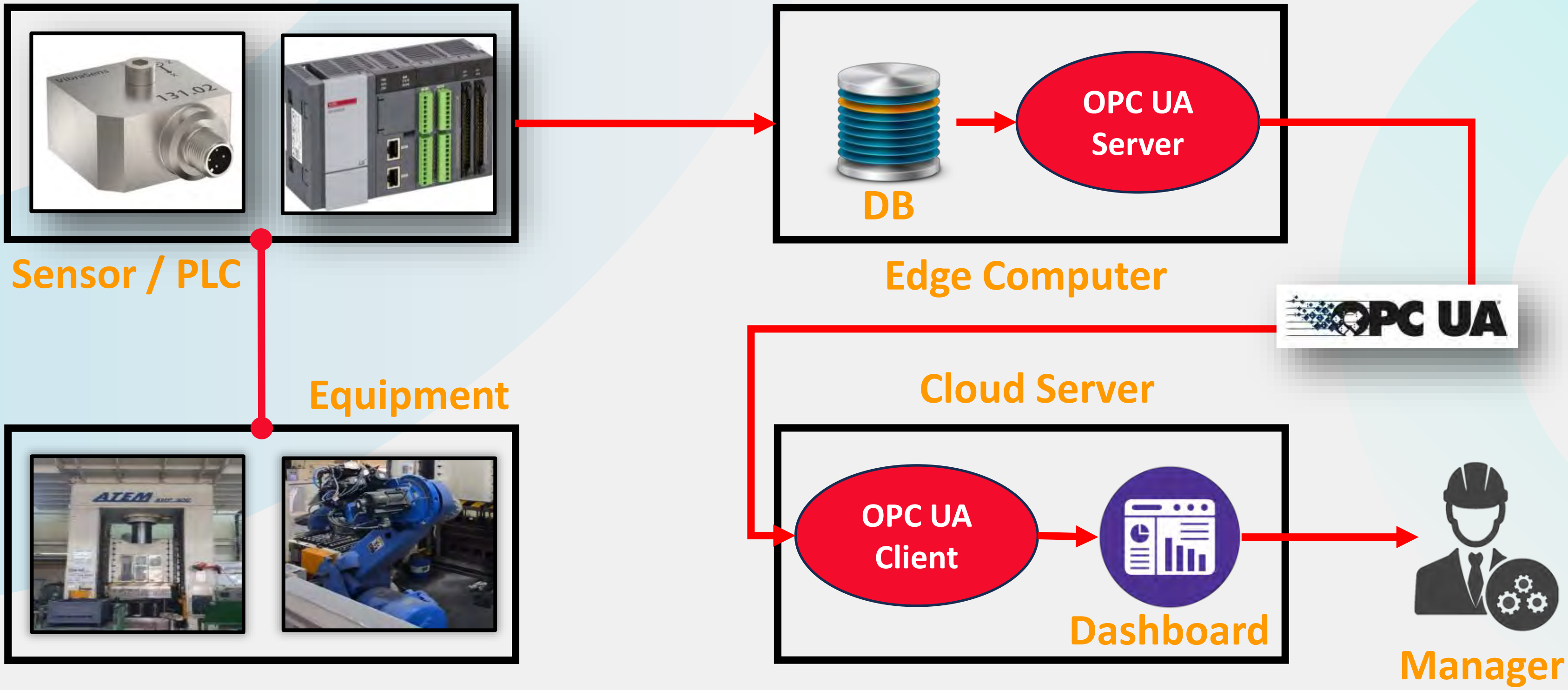
* **WPAN** = Wireless Personal Area Network

* **LPWAN** = Low Power Wide Area Network

Anomaly detection for utilities

Data storage

▷ **Anomaly Detection System for Rotating machineries**
- Storing vibration data for long time (at least several months and years)
- AI Modeling for the designated machine positions
- Continuous decision making for the signals and alarms if necessary

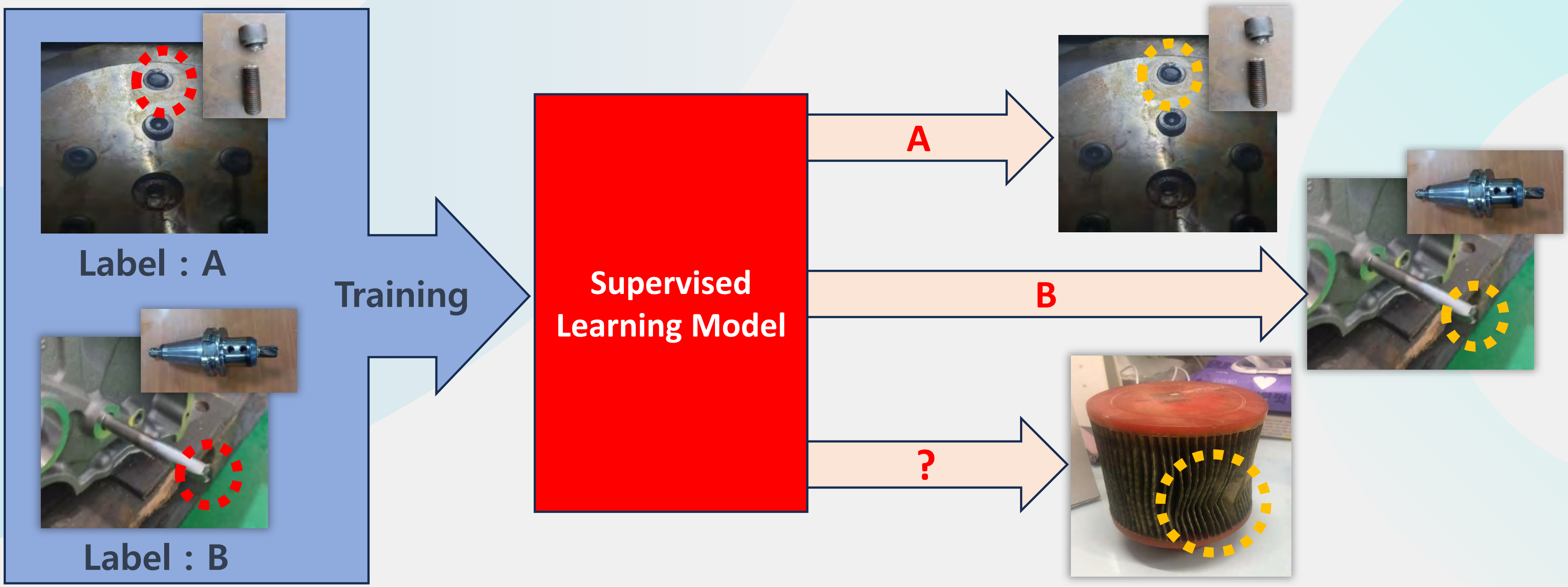


Anomaly detection for utilities

AI application

▷ Unsupervised Learning

Because of **the considerable variety of potential equipment failures,** unsupervised learning models have been employed for anomaly detection in the manufacturing industry.

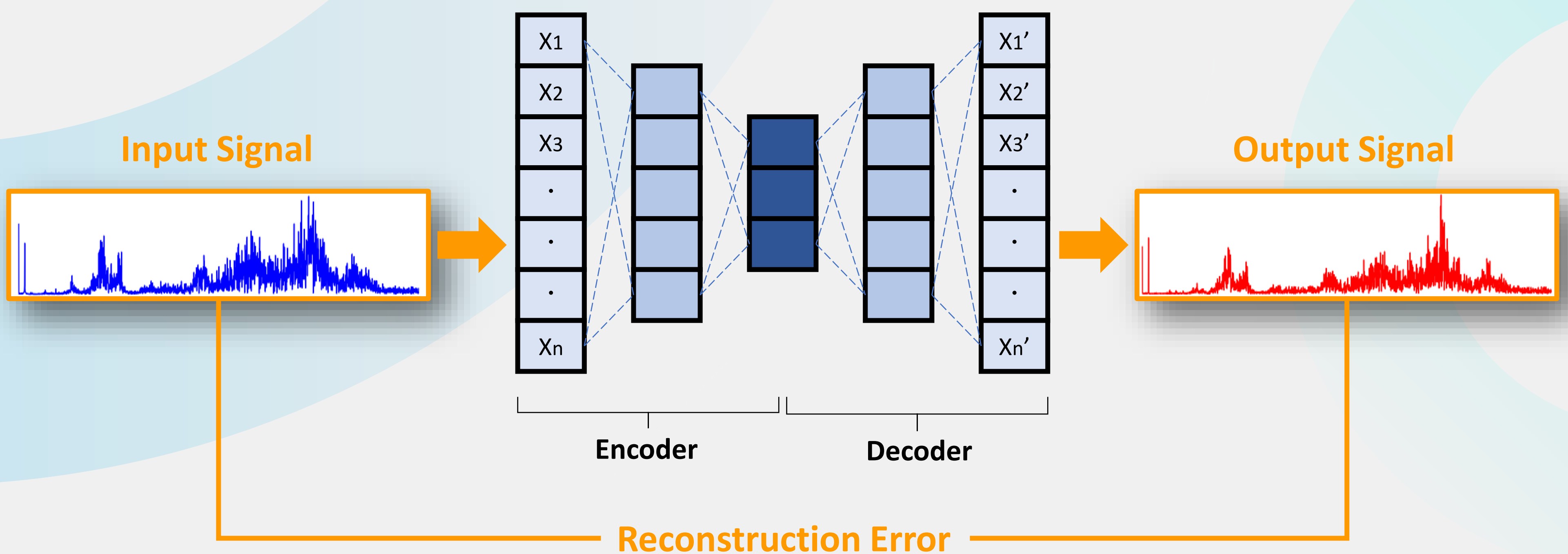


Anomaly detection for utilities

AI application

▷ Autoencoder Model for Anomaly Detection

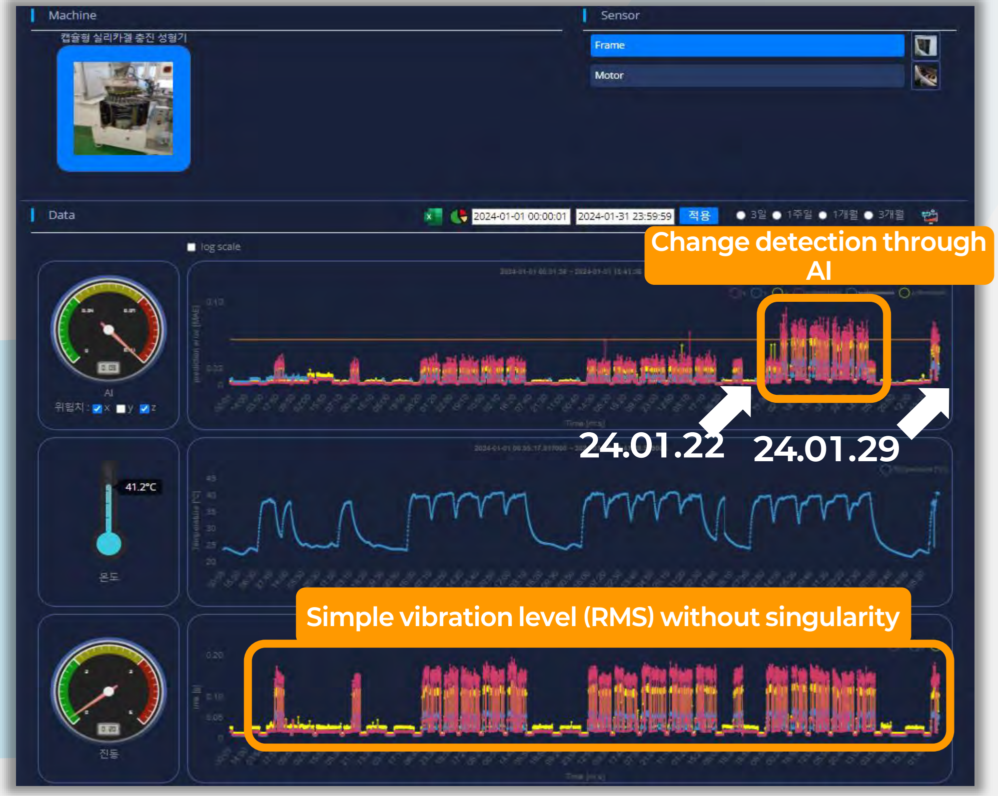
- Autoencoder model learns how to produce output data as close to the input signal without data labels.
- Using a difference between the input and the output signal detects anomalies.

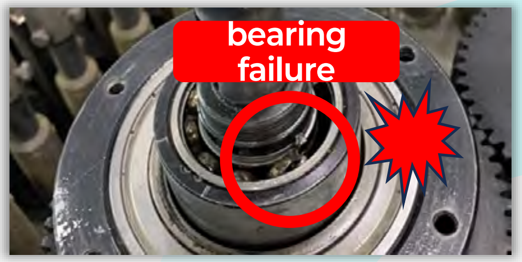


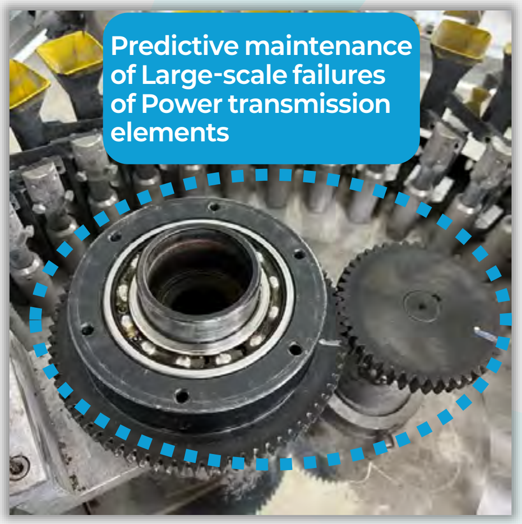
Anomaly detection for utilities

Use cases 1

- ▷ Around January 2024, a bearing failure connected to the main motor of the high-speed packaging equipment was detected and the bearing was replaced at an appropriate time.





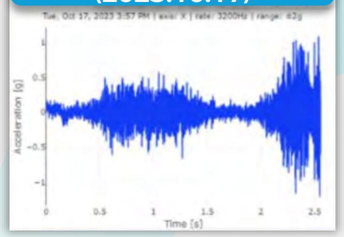


Anomaly detection for utilities

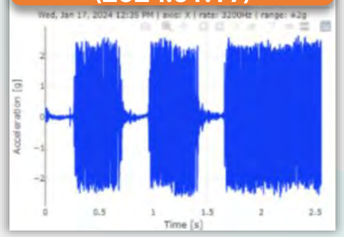
Use cases 2

- Between October 2023 and January 2024, detected failures in joint motors of large transport robots and replaced the motors at the appropriate time.

Motor normal signal (2023.10.17)



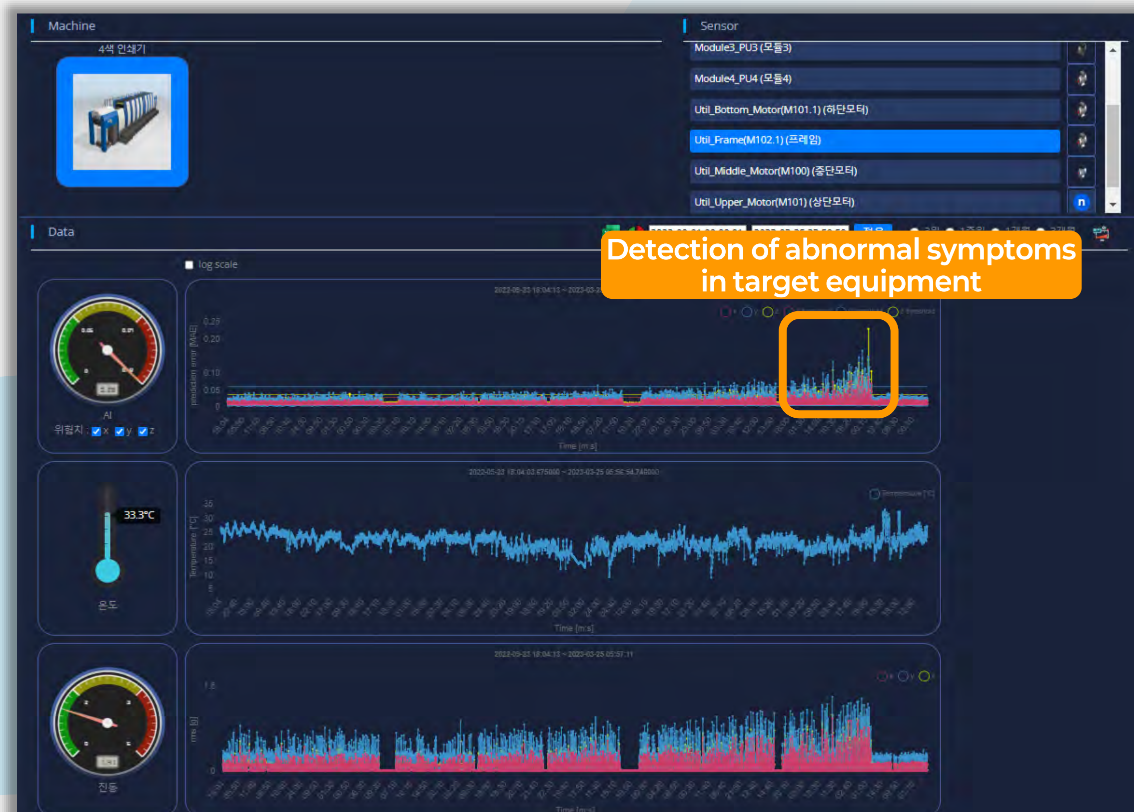
Motor failure signal (2024.01.17)



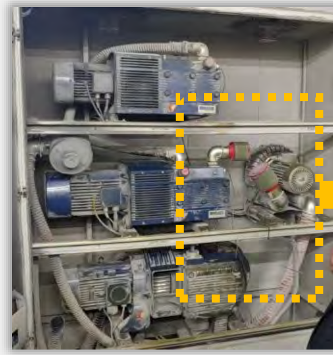
Anomaly detection for utilities

Use cases 3

- Around March 2023, abnormal signals were detected in the bearings of a large printing press.



Detection of abnormal symptoms in target equipment



Abnormality detection sensor

After detecting abnormal signs of bearing, replace the motor.

02 Anomaly detection

Anomaly detection for utilities

Use case 4

▷ **By August 2023, equipment predictive maintenance was realized through replacement of air filters in large-scale printing machines.**

Anomaly detection for utilities

Use case 5

▷ **September 2024, Predictive maintenance of equipment was realized through detection of broken hose in large printing machine utility motor**

broken hose

Replacement hose

03 Anomaly detection of equipment

Anomaly detection for equipment

Process parameter management

- Key process parameters of the facility process are monitored through analog gauges (Figure 1) or digital panel meters (Figure 2).

- Only the condition values at the time of observation can be checked, and systematic history management is difficult.

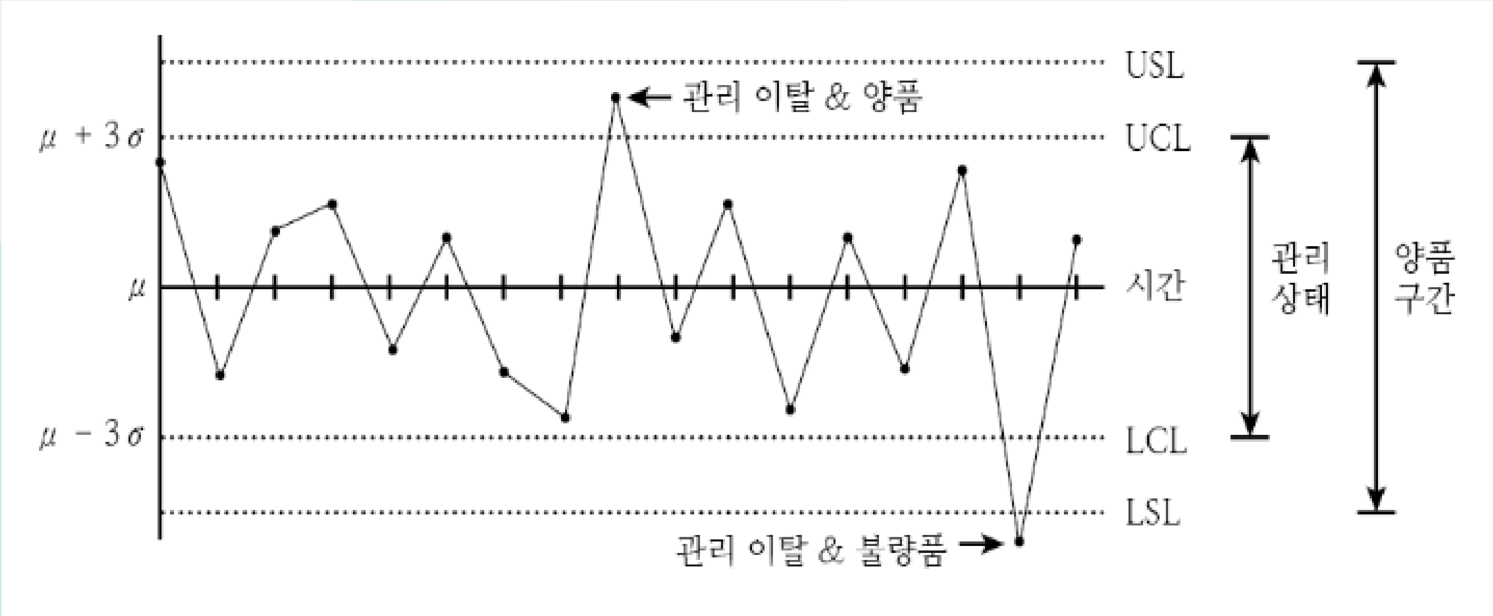
<Figure 1> Example of analog gauge

<Figure 2> Example of digital panel meter

03 Anomaly detection
Anomaly detection for equipment

Management using control charts

- **The control chart consists of time (Figure 3, X-axis), parameter values (Figure 3, Y-axis), upper control limit (UCL), lower control limit (LCL), upper specification limit (USL), and lower specification limit (LSL).**

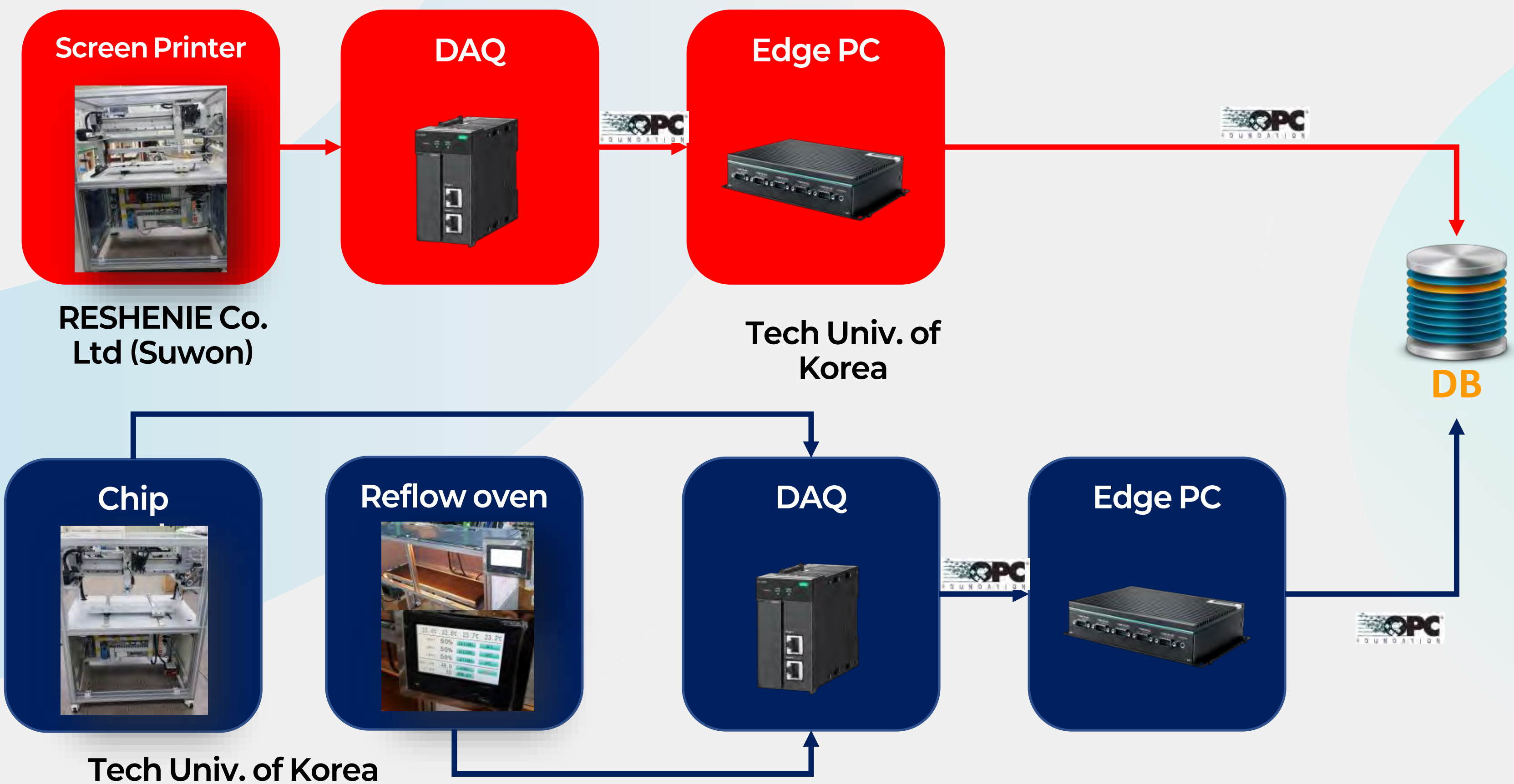


<Figure 3> Control Chart

Anomaly detection for equipment

Data Acquisition

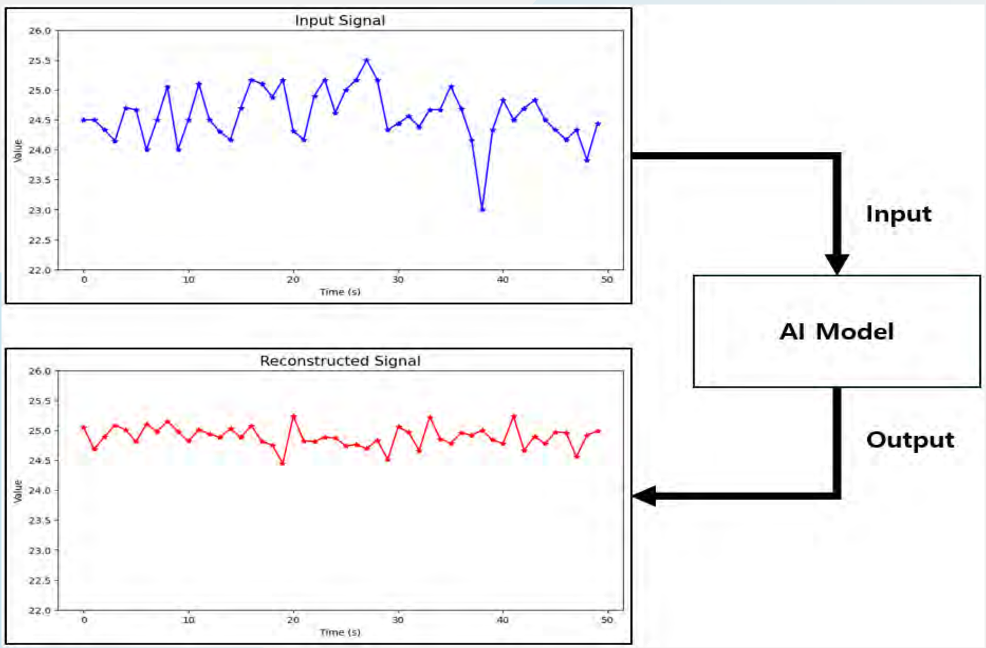
▷ Edge and AAS-based CPS digital twin implementation (distributed data collection architecture)

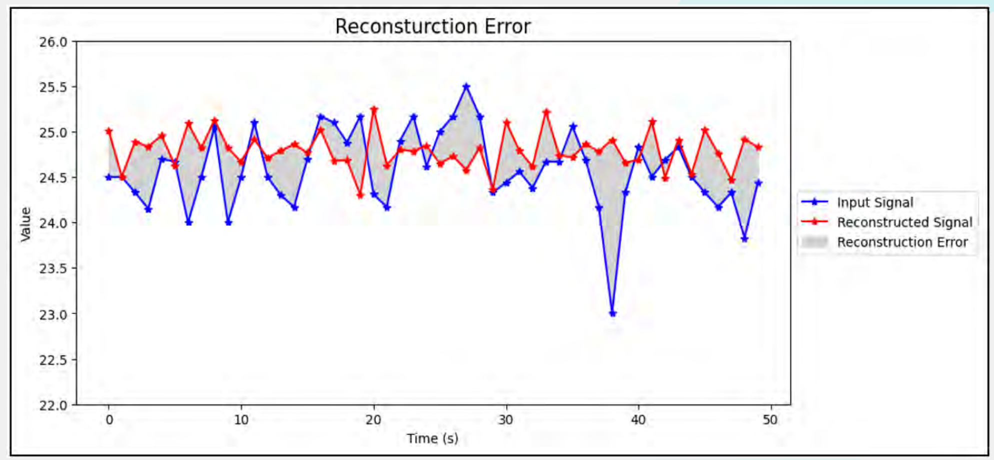


Anomaly detection for equipment

Reconstruction Error

- Utilizing AI models that restore (reconstruct) input signals (Fig. 4,5) by applying artificial intelligence technologies such as machine learning and deep learning to large amounts of process data collected under normal process conditions





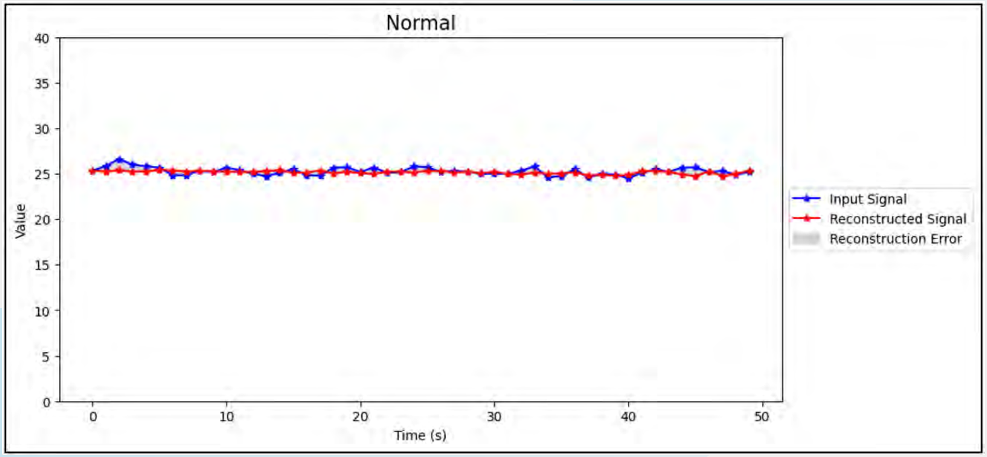
<Figure 5> Reconstruction error

<Figure 4> AI model that reconstructs input signals

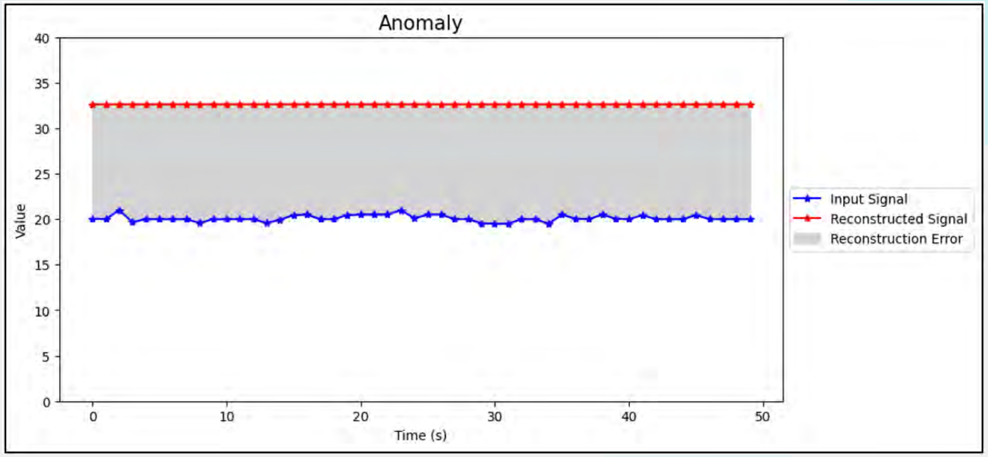
Anomaly detection for equipment

Data Acquisition

▷ **Process abnormalities are determined using the reconstruction error, which is the difference between the input signal entered into the AI model and the output reconstructed signal.**



<Figure 6> Reconstruction error of normal signal

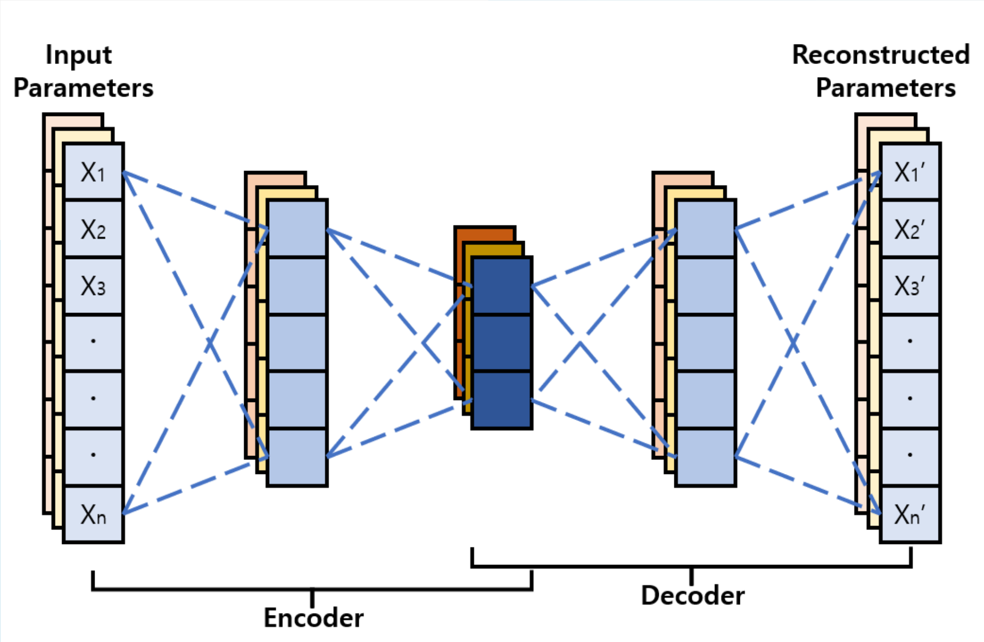


<Figure 7> Reconstruction error of abnormal signal

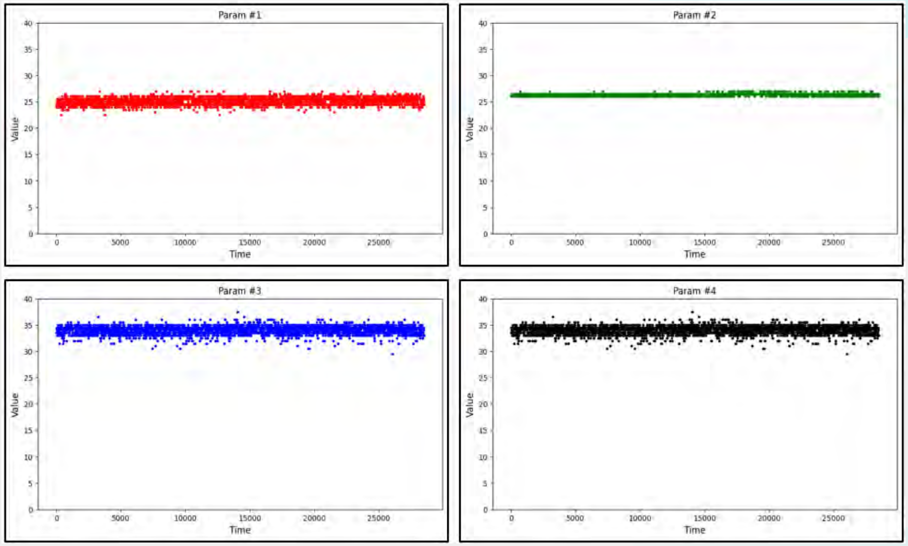
Anomaly detection for equipment

Data Learning

▷ **The artificial intelligence model can apply unsupervised learning and deep learning models such as autoencoders, stacked autoencoders, long short-term memory autoencoders, and convolutional autoencoders.**



<Figure 8> AI learning model

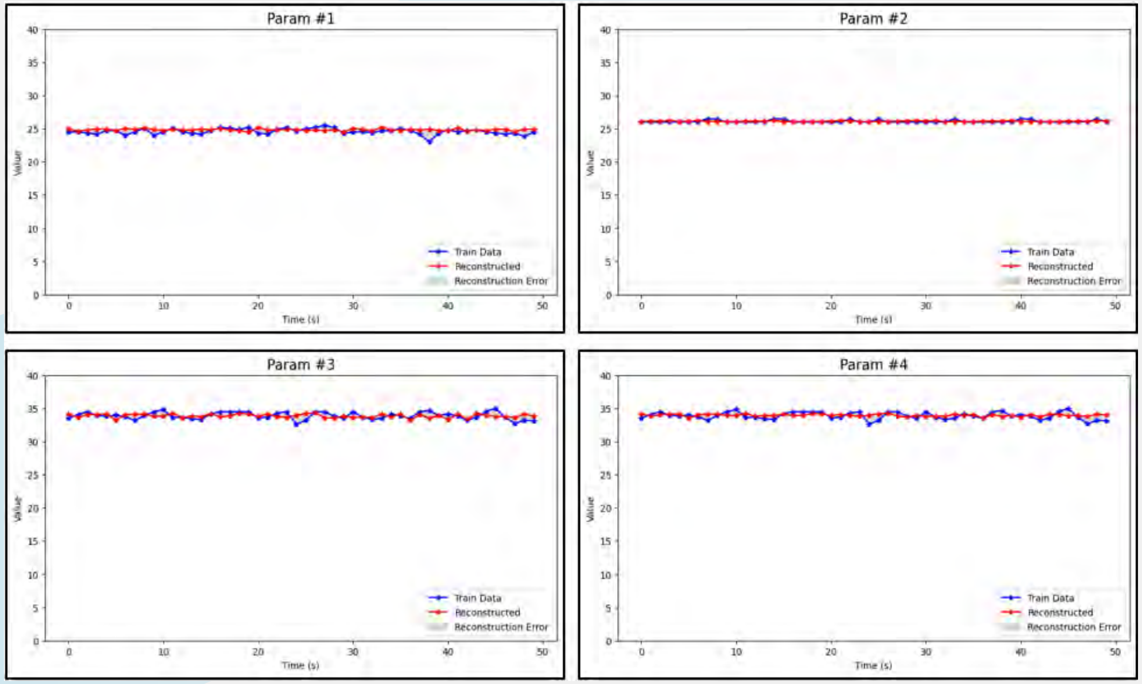


<Figure 9> Example of learning data

Anomaly detection for equipment

Calculating the error in reconstructing learning data

▷ **Compute the reconstruction error of all process data used in learning.**



<Figure 10> Calculation of reconstruction error by process data

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |X_i - X_i'|$$

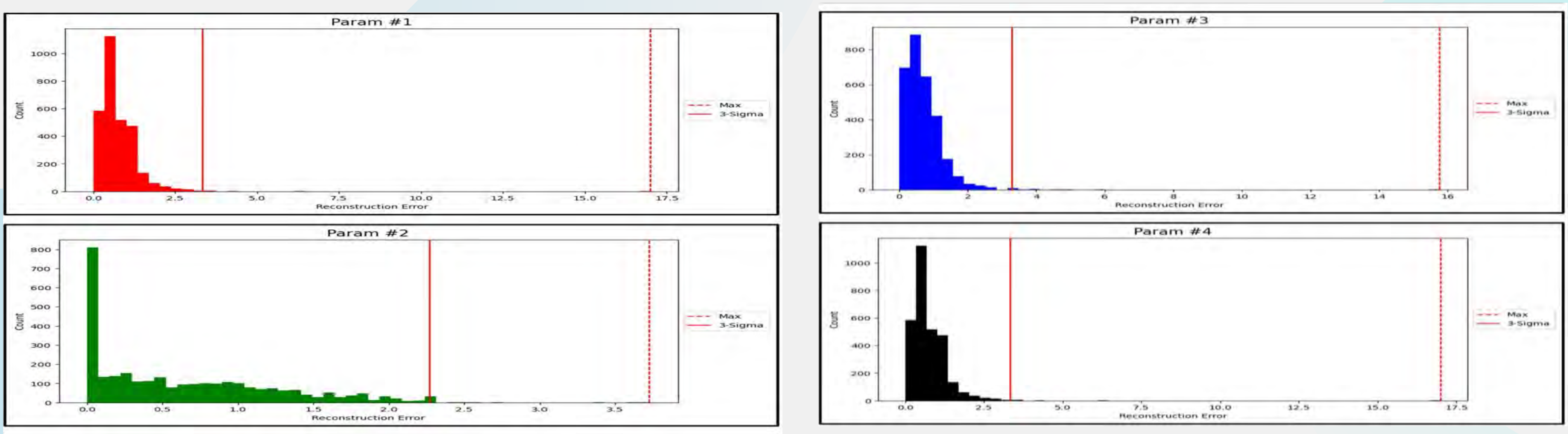
$$MSE = \frac{1}{n}\sum_{i=1}^{n} (X_i - X_i')^2$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{\sum_{i=1}^{n}(X_i - X_i')^2}{n}}$$

Anomaly detection for equipment

Setting the threshold

▷ **The threshold can be determined by applying the maximum value (Max) of the reconstruction error value of the learning data or the 3 sigma rule (99.7%), and can be determined differently depending on the characteristics of the process data.**

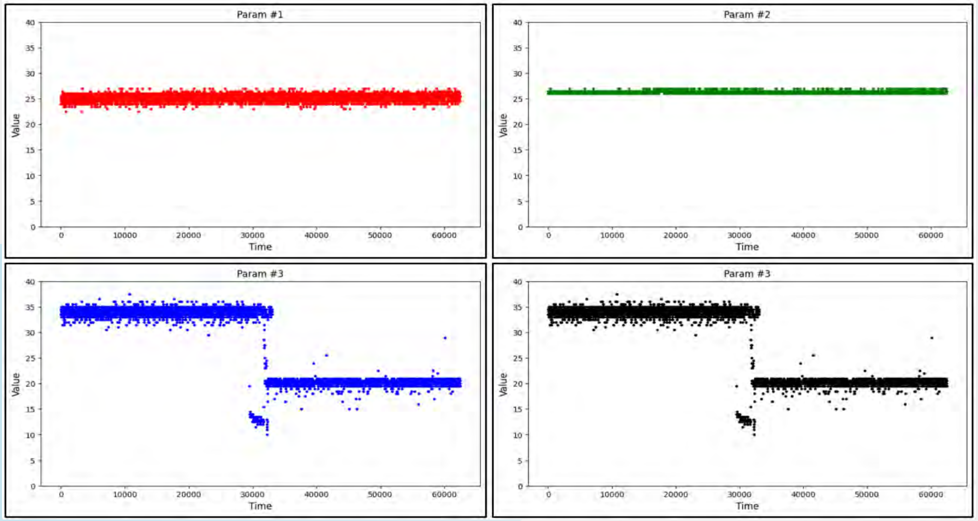


<Figure 11> Distribution of reconstruction errors by process data

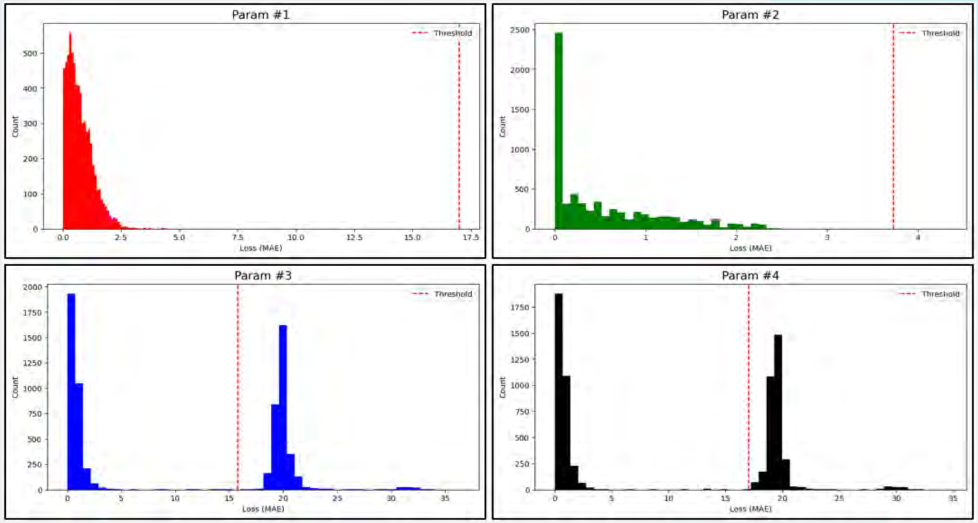
Anomaly detection for equipment

Calculating the error in reconstruction of evaluation data

▷ **The reconstruction error of the evaluation data is calculated through the same process as (step 4).**



<Figure 12> Evaluation data for each process parameter



<Figure 13> Distribution of reconstruction error and threshold of evaluation data

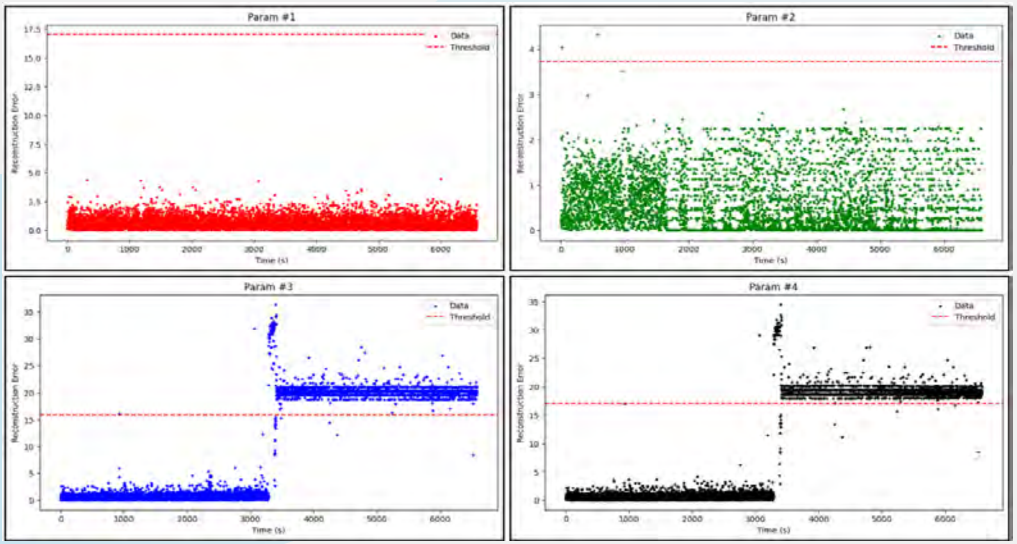
Anomaly detection for equipment

Anomaly Detection

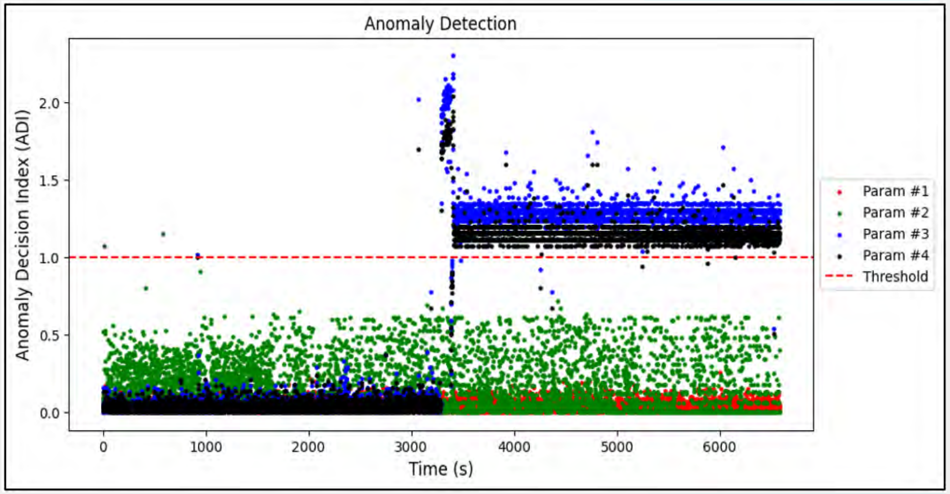
- ▹ **Anomaly determination using reconstruction error and threshold for each process data**
- ▹ **Using the reconstruction error value and threshold ratio for each process data, the Anomaly Decision Index, which can be determined as normal or abnormal for each process parameter based on value 1, is defined as follows.**

$$Anomaly\ Decision\ Index(ADI) = \frac{Reconstruction\ Error}{Threshold}$$

$$\begin{cases} ADI \geq 1 : Anomaly \\ ADI < 1 : Normal \end{cases}$$



<Figure 14> Anomaly detection results for test data by process data



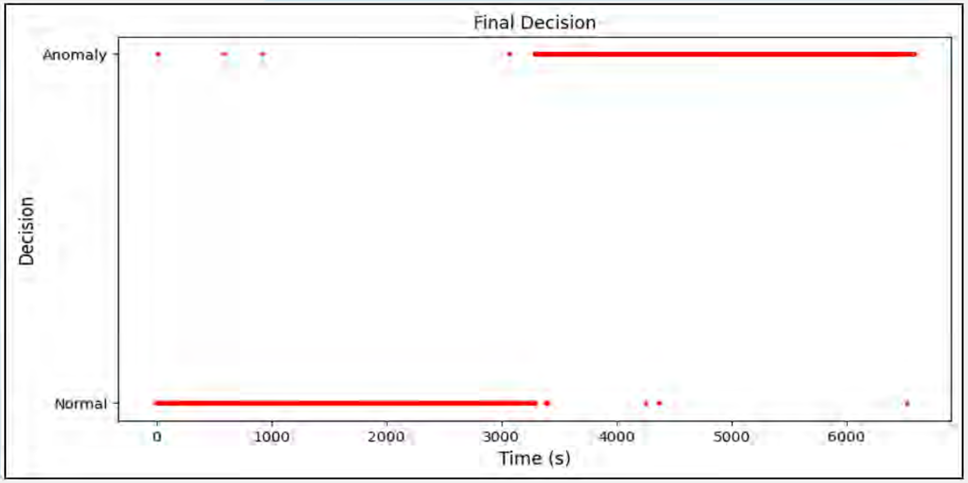
<Figure 15> Results of overall process parameter abnormality judgment using ADI

Anomaly detection for equipment

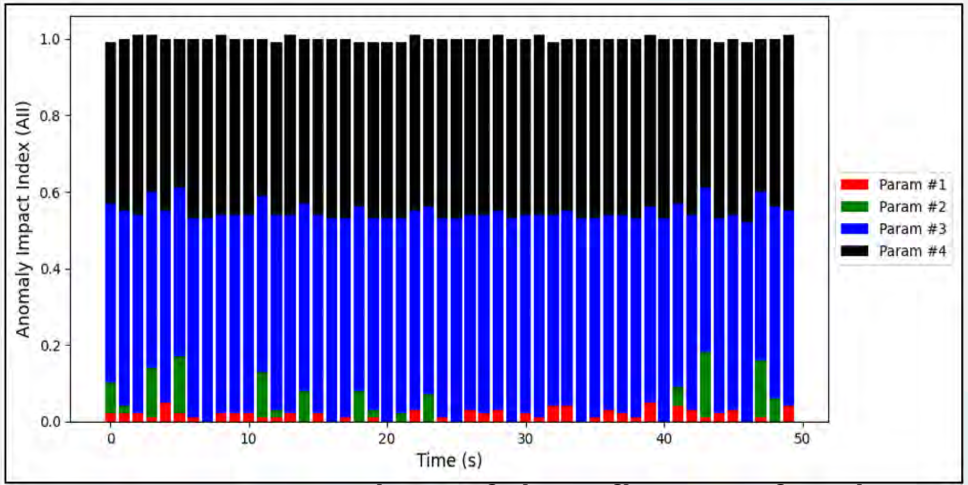
Anomaly Detection

- If any of the process parameters analyzed by the model has an abnormality judgment index greater than 1, it is ultimately diagnosed as a process abnormality
- The Anomaly Impact Index is calculated as the ratio of the sum of the abnormality judgment indices of all process parameters and the abnormality judgment indices of individual process parameters and is used to compare the influence of each parameter when a process abnormality occurs.

$$Anomaly\ Impact\ Index_i\,(AII_i) = \frac{ADI_i}{\sum_{param=1}^{N} ADI_{param}}$$



<Figure 16> Final prediction result of process abnormality



<Figure 17> Analysis of the influence of each process parameter using AII when a process abnormality occurs

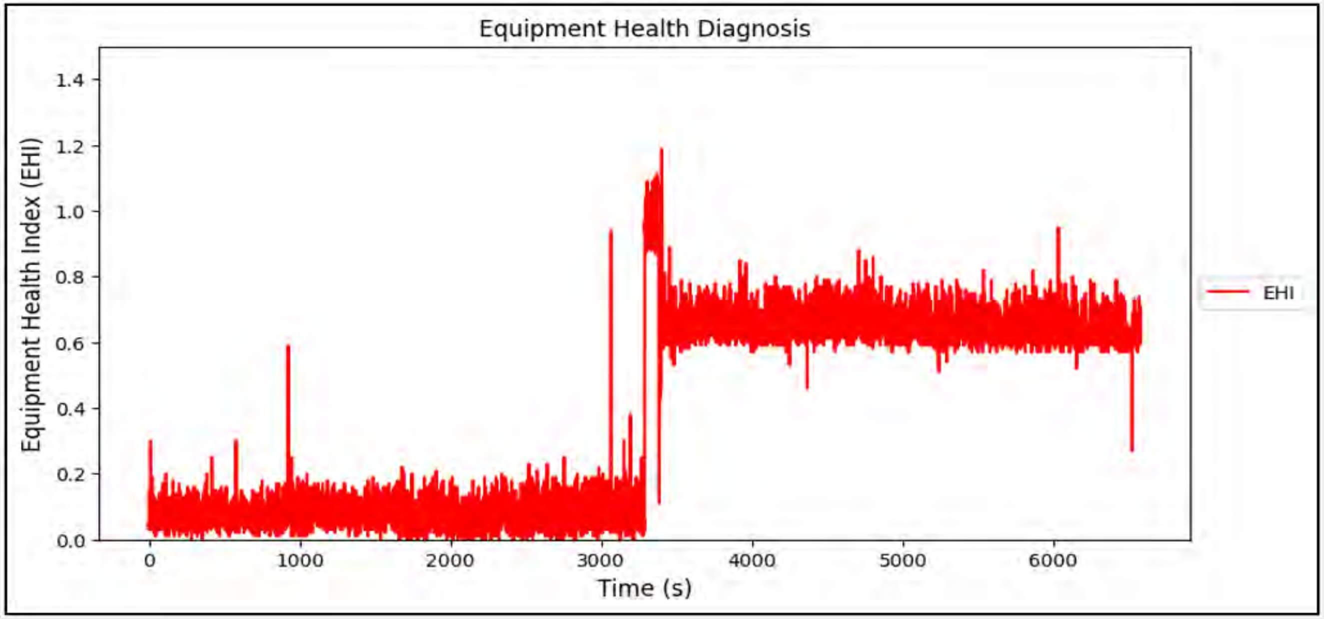
Anomaly detection for equipment

Equipment Health Index

- The equipment health index is defined as the product of the abnormality judgment index of each process parameter and the weight as follows.
- Through the equipment health index, the comprehensive equipment health change considering each process parameter can be identified in real time.

$$Equipment\ Health\ Index\,(EHI) = \sum_{param=1}^{N} (ADI_{param} \times Weight_{param})$$

$$, \sum_{param=1}^{N} Weight_{param} = 1$$



<Figure 18> Diagnosis of facility health using EHI

04 Anomaly detection for workers

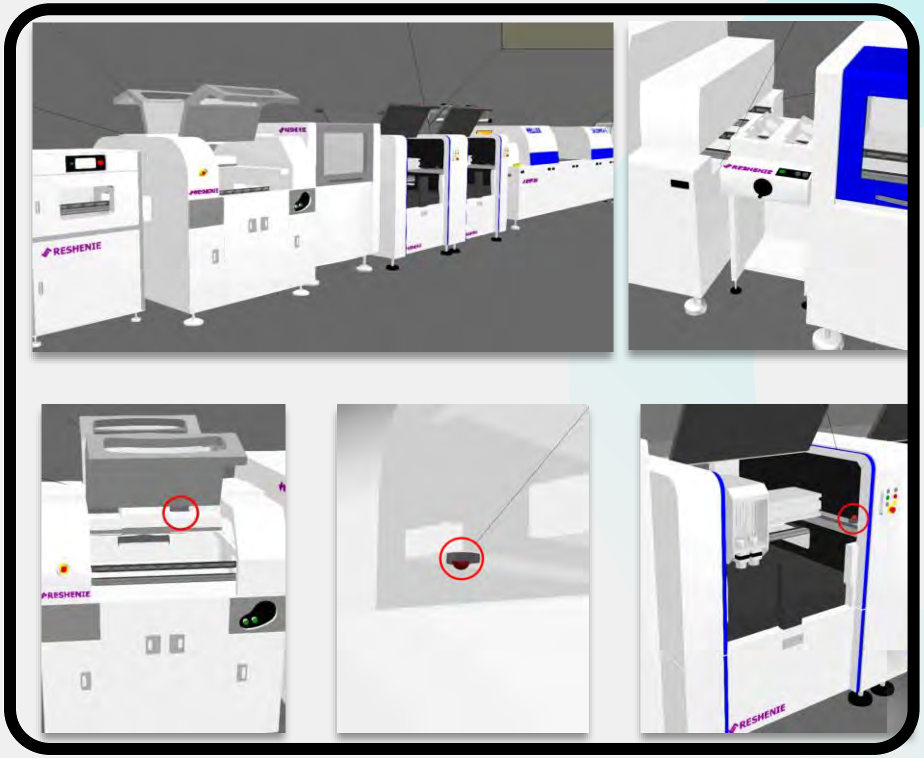
Use case

Digital Twin & CPS for anomaly detection

▷ Edge and AAS-based CPS digital twin implementation

- Acquiring AAS & CPS implementation technology through PLC-Edge computer interface

Physical World



Cyber World

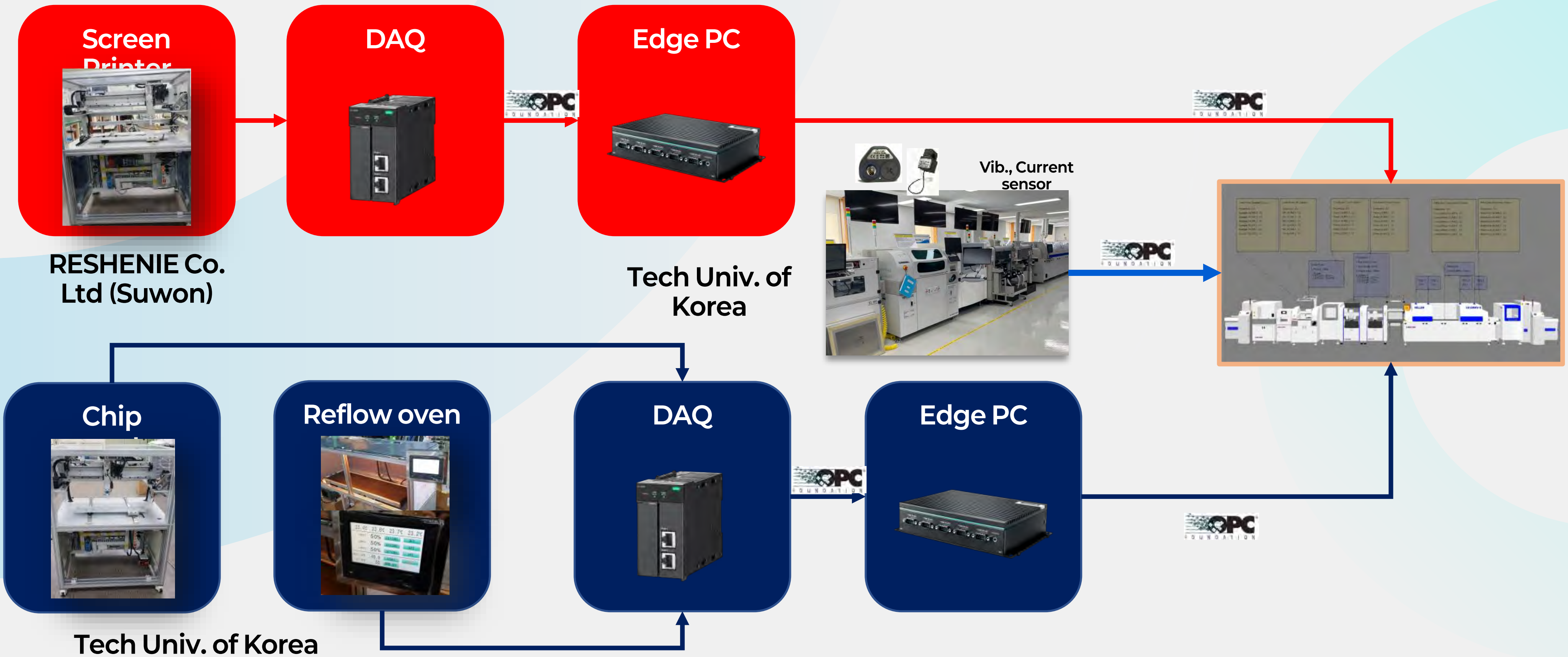
제공: RESHENIE

04 Anomaly detection for workers

Use case

Digital Twin & CPS

▷ Edge and AAS-based CPS digital twin implementation (distributed data collection architecture)



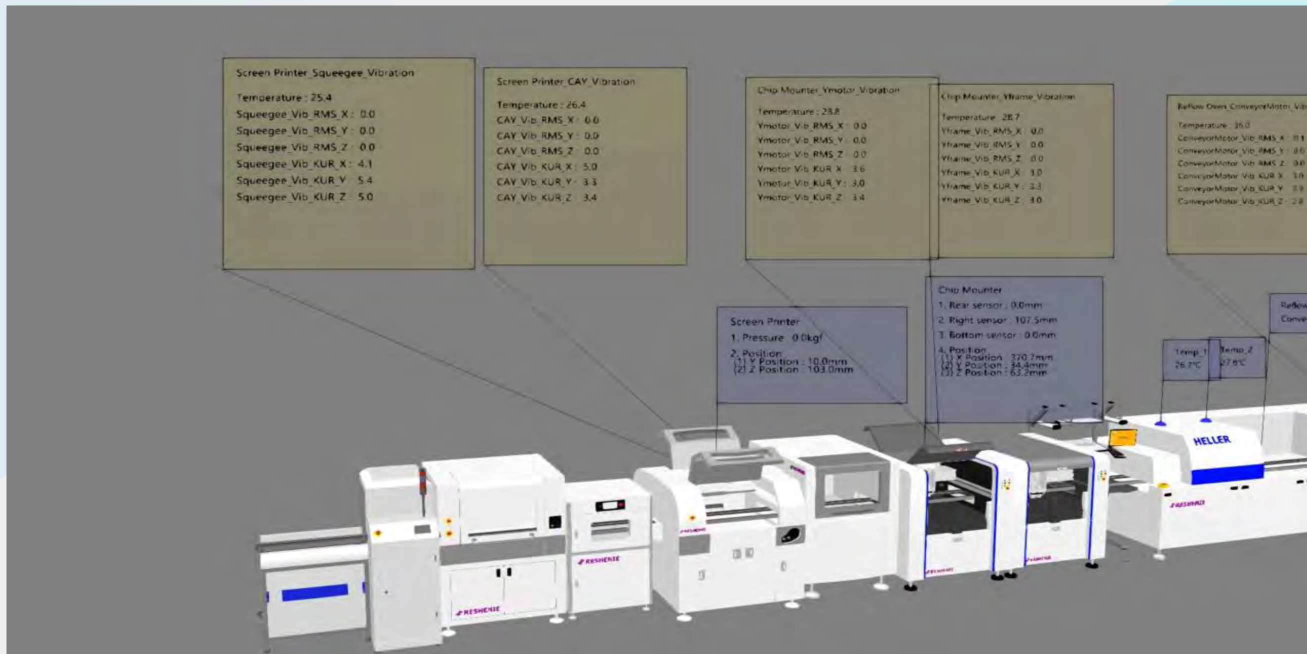
04 Anomaly detection for workers
Use case

Digital Twin & CPS

▷ **Construction of CPS system for core facilities (Screen Printer/Chip Mounter/Reflow) of SMT mounting line**

SMT Line
Cyber System

SMT Line
Physical System

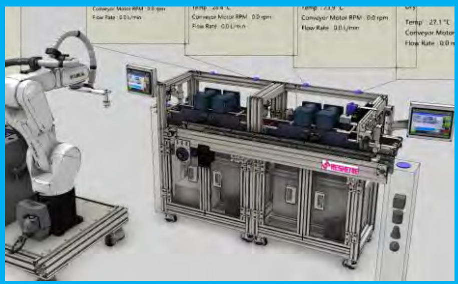


Use case

Digital Twin & CPS

▷ **Construction of a testbed CPS system that simulates core processes(Development/Etching/Strip/Dry) of PCB production line**

DES Line Testbed
Cyber System



DES Line Testbed
Physical System

Web-based parameter monitoring

AI-assisted Maintenance

▷ Condition Monitoring based on PLC equipment

- Web-based real-time process monitoring technology via PLC-Edge computer interface

Squeegee X, Y, Z positions

Squeegee pressure

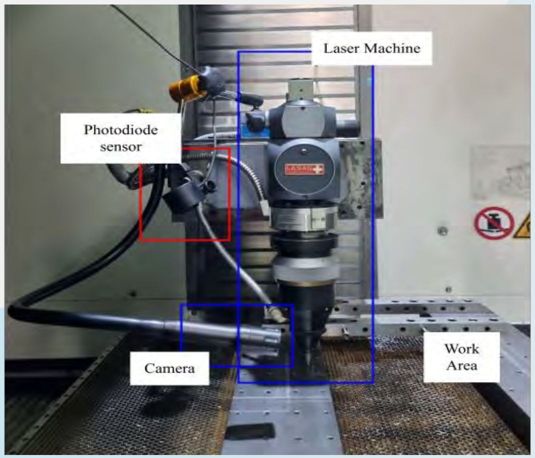
[SMT-Screen Printer Mock-up Target PLC-Edge Real-time Monitoring Screen]

Other types of parameter monitoring

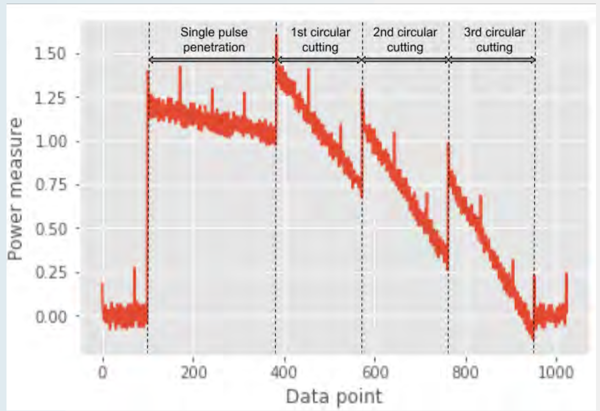
AI-assisted Maintenance

▷ Condition Monitoring Based on Optical Sensors

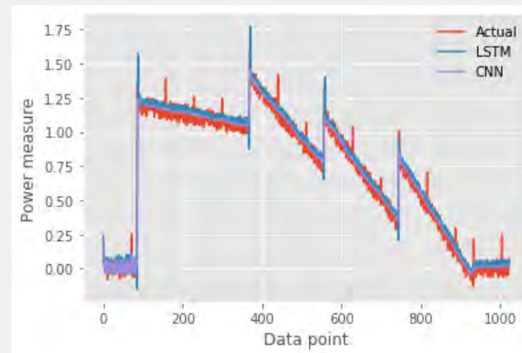
- Development of a real-time process defect detection system for ultra-precision laser processing using optical intensity probe and AI



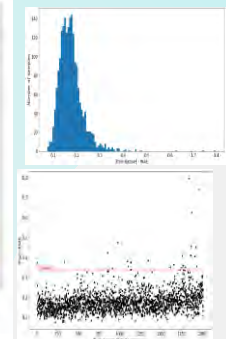
The 1064 nm Nd:YAG Laser : Photo of the experiment set up with Photodiode sensor



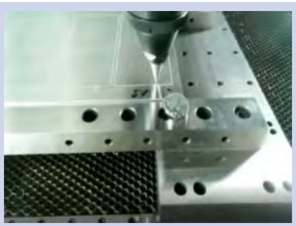
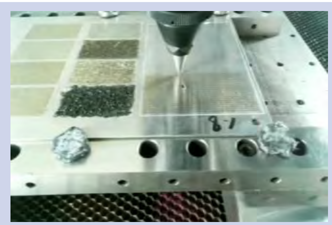
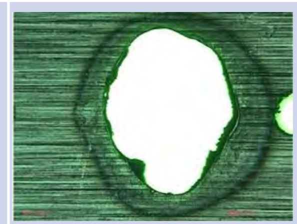
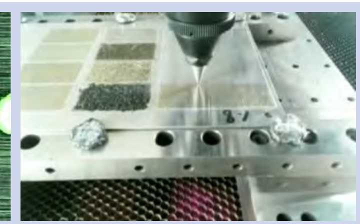
Plot of one period of simulated data of the trepanning method



Actual, and CNN and LSTM reconstruction of one period of simulated data



AI anomaly detection

Proper Drilling	Defect: Incomplete Drilling	Defect: Thermal Explosion
 	 	 

Overall condition monitoring

AI-assisted Maintenance

▷ Digital Twin & Collaborative Condition Monitoring (CCM)

- Both DT and Web-based CCM can give high benefits to the managers and field engineers in terms of factory operation and maintenance

DTw

CCM

(Utilities-Sensor-based, Machines – PLC, HMI, Sensors)

05 Summary

Summary

Anomaly detection for I 4.0

[Anomaly detection for utilities]

1) Strategic approach for the collection of data, storage, signal processing for long-term identification if fields
2) AI with vibration data can be effectively applied for wide areas of machines and factories
3) Unsupervised learning approach shall be useful as the malfunctioning cases are very rare and not much information about machines.

[Anomaly detection for equipment]

1) Process parameters can be used for the anomaly detection of equipment condition for the maintenance and quality control
2) PLC and HMI connection for real time monitoring is necessary for the equipment anomaly detection
3) Digital Twin, CPS and Web-based data monitoring can be used for the workers for the convenience.

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TECH UNIVERSITY OF KOREA

Anomaly detection of machines and shop floors with AI

Thank you

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