Summary of Reliability Assessment Practical Examples

The Liaison Council of Three Ministries on Disaster Prevention of Petroleum Complexes
(Ministry of Economy, Trade and Industry; Fire and Disaster Management Agency; and Ministry of Health, Labour and Welfare)

March 2021

* This document summarizes the contents regarding reliability evaluation from the seven AI development cases listed on the Practical Examples of Reliability Assessment (published separately). Details include system overview, relationship to other systems, architecture of machine learning component, and setting of qualities.

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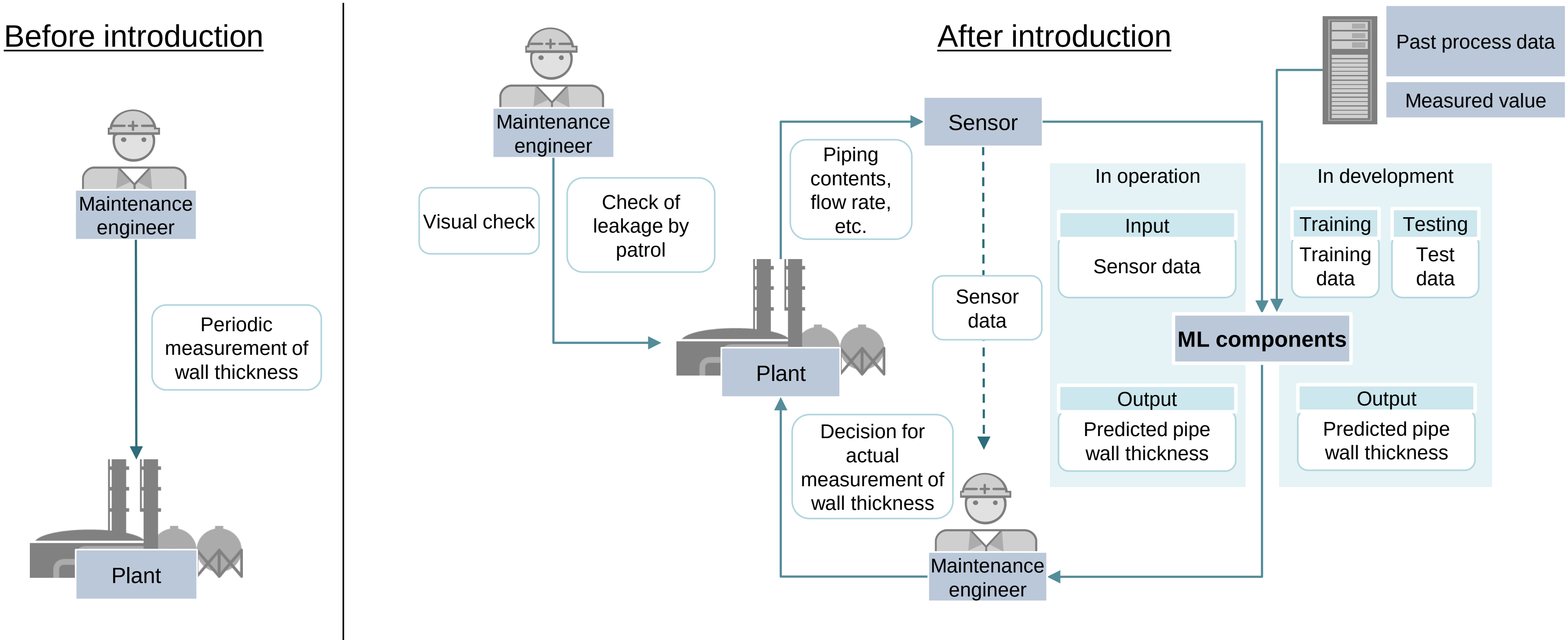
1. Prediction of Pipe Wall Thickness

Yokogawa Electric Corporation

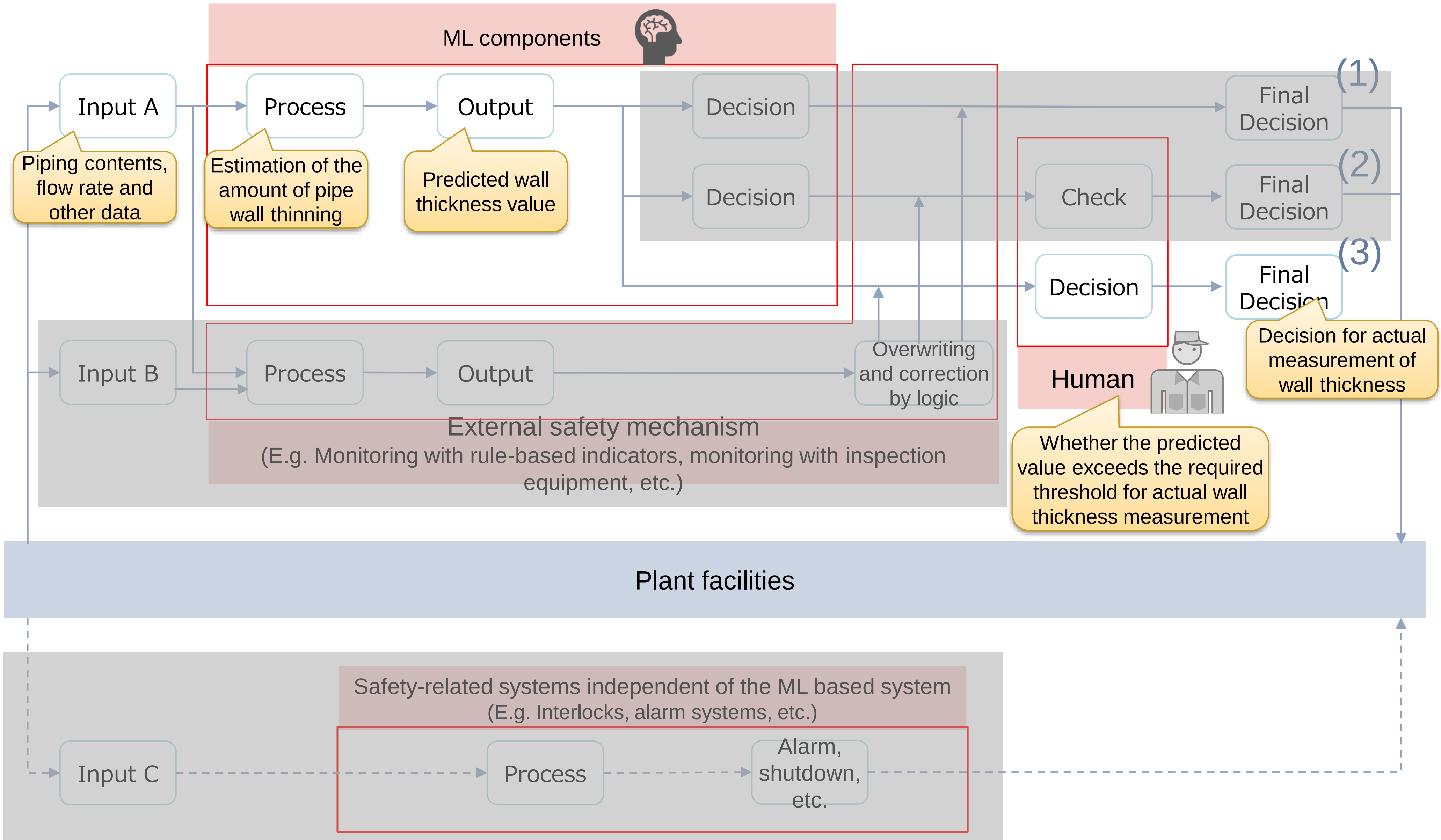
1. Prediction of Pipe Wall Thickness —Case Overview—

- This is an ML based system that predicts the current pipe wall thickness by estimating the amount of wall thinning based on process data, etc. The purpose of this system is to ensure safety by responding to rapid corrosion between periodic inspections, and to improve maintenance efficiency and reduce lost profit by reducing excessive inspection and replacement work.
- The functional requirement set is "Predicting pipe wall thickness by estimating the amount of wall thinning."
- ML components predict the current pipe wall thickness by estimating the amount of wall thinning and output predicted values of wall thickness to maintenance engineers. Maintenance engineers use this output and various pieces of sensor data to determine whether an actual measurement of wall thickness is necessary.



Numbers (1) to (3) indicate "Avoidability by human."
See Figure 2-7 in Guideline item 2.2.3.

1. Prediction of Pipe Wall Thickness —Relationship with Other Systems—



1. Prediction of Pipe Wall Thickness
—Composition of ML Components and Setting the Quality in Use and the External Quality—

<Composition of ML components>

Learning methodology	Supervised regression
Learning model	The relationship between the piping content type, flow rate, flow velocity, pressure, etc., which may affect pipe wall thinning, and the amount of wall thinning is learned.
Input data in operation	Process data (data on contents, flow rate, flow velocity, material and pressure of piping)
Training data in development	Process data (data on contents, flow rate, flow velocity, material and pressure of piping), thickness data (actual measured values)
Test data in development	Process data (data on contents, flow rate, flow velocity, material and pressure of piping), thickness data (actual measured values)

<Setting the quality in use and the external quality>

Quality in Use	External Quality
Risk avoidance	
Do not overlook a state that requires actual measurement of wall thickness by a maintenance engineer.	Keep errors in predicting wall thickness to be thicker than it actually is within certain limits
Performance	
Eliminate unnecessary maintenance	Keep errors in predicting wall thickness to be thinner than it actually is within certain limits

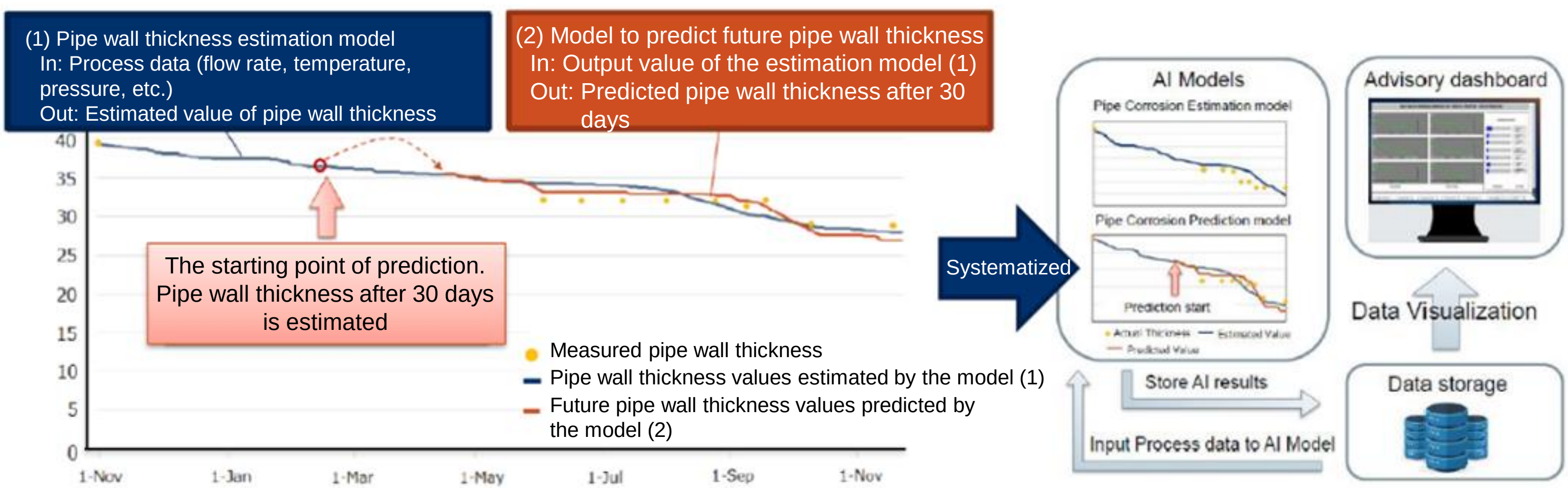
1. Prediction of Pipe Wall Thickness
— Details of Case (Role of AI System and Effects of Its Adoption)—

Role of AI system

- So far, the amount of pipe wall thinning has been checked by periodic inspections. The amount of pipe wall thinning does not always progress steadily over time, but sometimes rapidly. Therefore, **piping has had to be replaced earlier than originally planned**. Replacing piping sooner than its service life **incurs lost profit**.
- Introducing an AI system to estimate the corrosion state of piping makes it possible to detect rapid wall thinning by knowing the amount of pipe wall thinning in real time, something that has only been checked periodically. This can **optimize the piping replacement timing** and also **prevent lost profit** by replacing piping according to the deterioration state.

Effects

- Because pipe wall thickness, which was traditionally checked by periodical inspections, **can be predicted and detected**, the piping replacement timing is optimized in real time.
- Optimizing the piping replacement timing makes it possible to use piping for a longer period than now, leading to a **reduction in lost profit**.

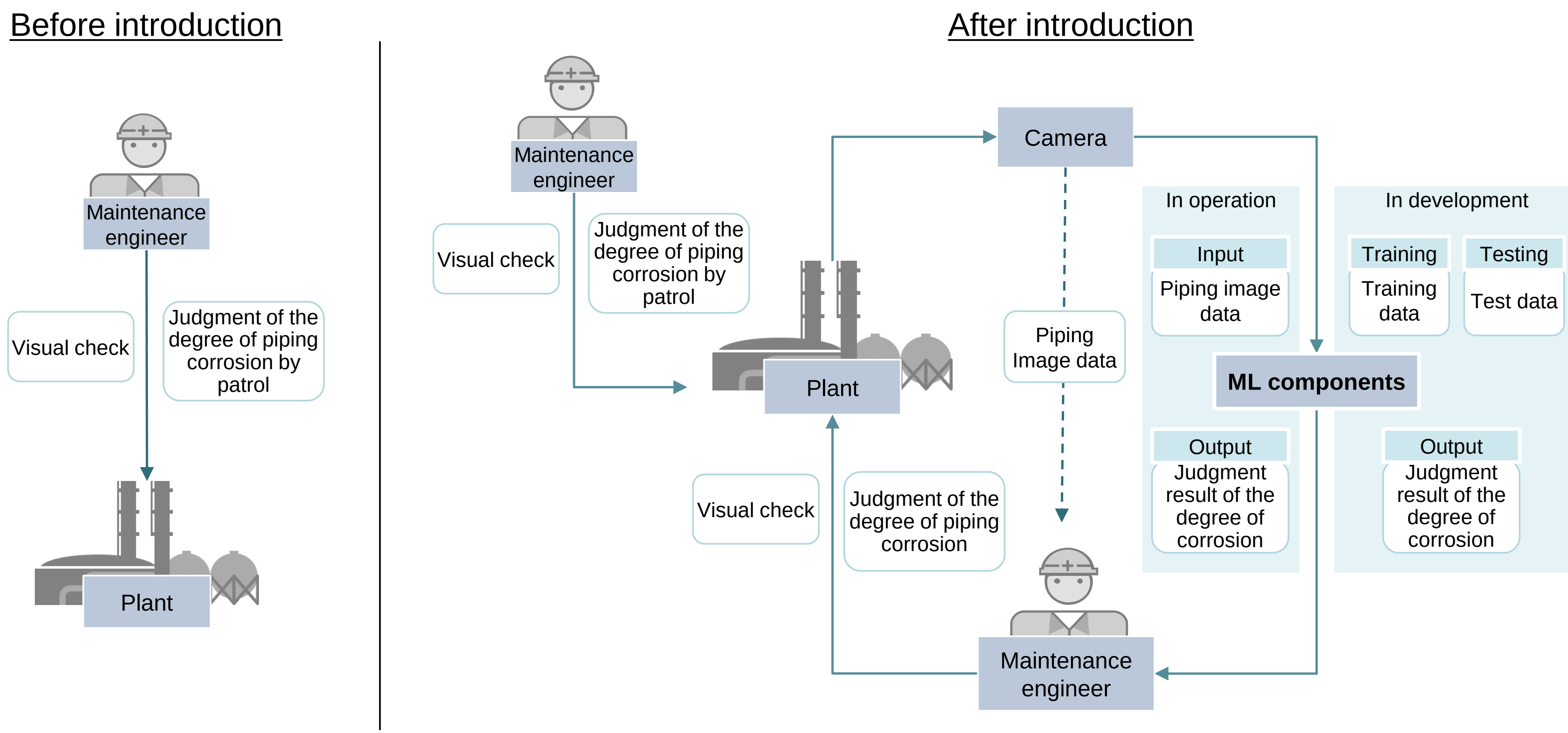


2. Pipeline image diagnosis

Mitsubishi Chemical Corporation/NEC Corporation

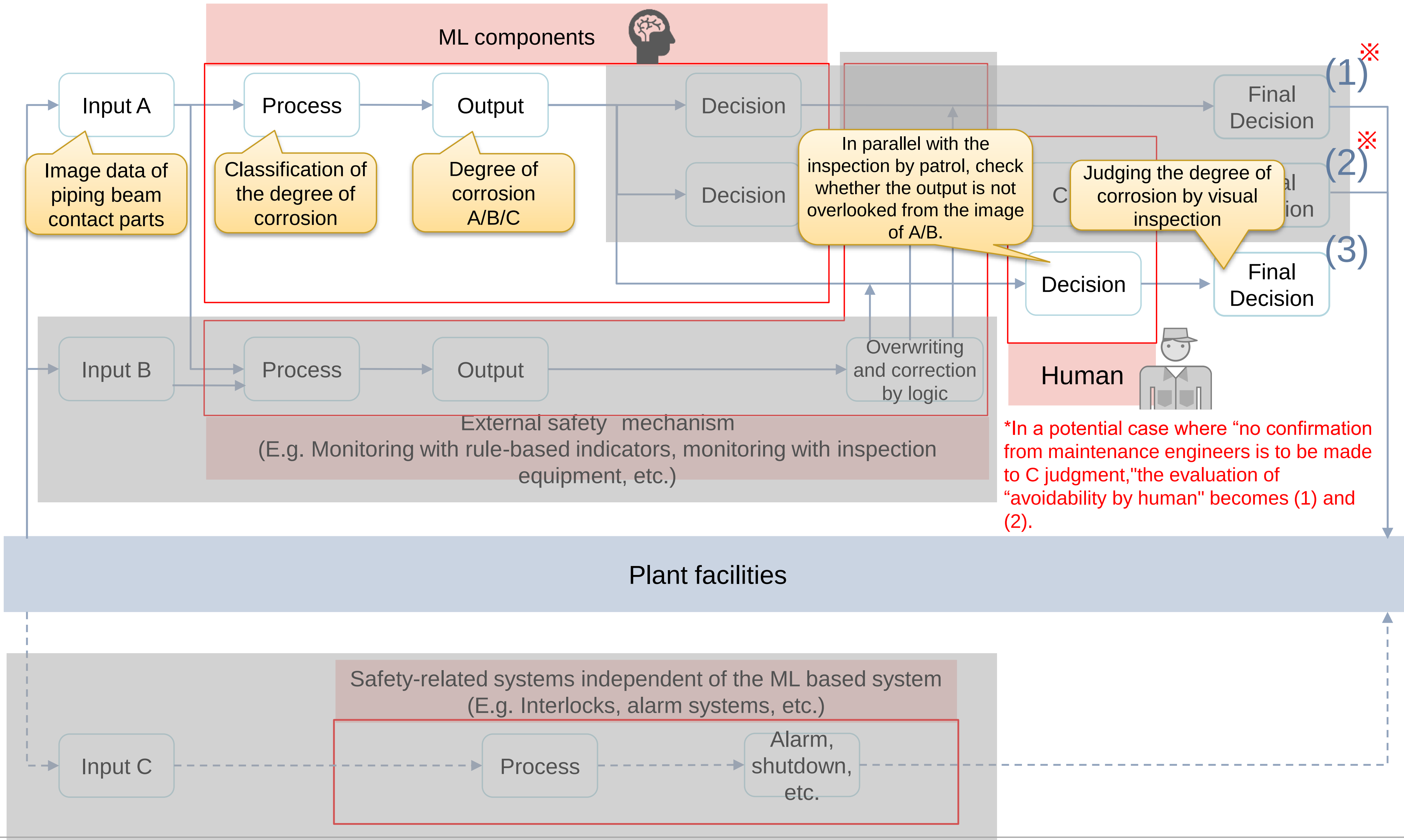
2. Pipeline image diagnosis —Case Overview—

- This is an ML based system for automatically judging the degree of corrosion of piping beam contact parts based on image data in order to prevent overlooking corrosion in a visual inspection.
- The functional requirement set is “Automatically judge the degree of corrosion at piping beam contact parts.”
- Based on images of piping beam contact parts, ML components judge the degree of corrosion on those parts and output the result of the degree of corrosion to the maintenance engineer. The maintenance engineer checks the image data of the parts deemed "corroded" and judges the feasibility of a field visual inspection. This is operated in parallel with corrosion management by patrol to prevent overlooking corrosion.



2. Pipeline image diagnosis
—Relationship with Other Systems—

Numbers (1) to (3) indicate "Avoidability by human."
See Figure 2-7 in Guideline item 2.2.3.



2. Pipeline image diagnosis
— Composition of ML Components and Setting the Quality in Use and the External Quality—

<Composition of ML components>

Learning methodology	Classification (supervised)
Learning model	Classification model that classifies the degree of corrosion based on the piping image characteristics
Input data in operation	Image data of piping beam contact parts
Training data in development	Image data of piping beam contact parts + Label of the degree of corrosion
Test data in development	Image data of piping beam contact parts + Label of the degree of corrosion

<Setting the quality in use and the external quality>

Quality in Use	External Quality
Risk avoidance	
Judge an appropriate degree of corrosion even in images taken under different photographing conditions so that parts requiring a detailed inspection are not overlooked.	Minimize the rate of false negatives, which judge A (Response required)/B (Follow-up required) as C (No problem) because the judgment of the 3 levels of A/B/C varies in the judgment of corrosion using images taken under different photographing conditions as inputs.
Performance	
Do not judge parts that do not require detailed inspection as requiring inspection	When the degree of corrosion is judged with the 3 levels of A/B/C, keep the false positives that C (No problem) is judged to be A (Response required)/B (Follow-up required) within certain limits.

2. Pipeline image diagnosis —Details of Case (Role of AI System and Effects of Its Adoption)—

Role of AI system

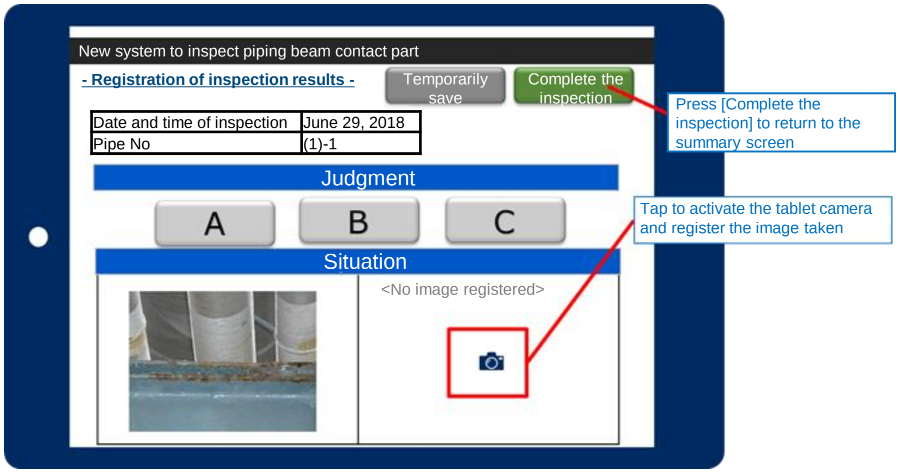
- In conventional corrosion management by patrol, there were concerns of **potential oversights at inspection points** due to the area to inspect being extremely large, and the fact that corrosion is hard to notice. In addition, inspection has **depended on the skills of the inspector** because the corrosion is to be evaluated based on qualitative criteria.
- Introducing an AI system that can automatically determine the degree of corrosion enables **comprehensive primary inspections** (screening of visual inspection objects) over a large area. At the same time, since **a single set of corrosion judgment criteria can be applied universally across inspections**, oversights due to variations in the skills of inspectors can be avoided.

Effects

- By judging the degree of corrosion through image diagnosis, it is possible to **level out the judgment criteria** and prevent oversights due to variations in the skills of inspectors.
- It is no longer necessary to carry out field visual inspections sequentially in large areas, thereby **reducing the workload of the inspectors**.
- By performing conventional corrosion management through patrol at the same time, inspections can be double-checked to **detect human errors**.
- Younger inspectors can view and consult the output of image diagnosis constructed from inspection results of experienced inspectors. In this sense, the system can be used in **passing on know-hows in corrosion inspection**.
- By accumulating image data and information on the judgment results of the degree of corrosion, changes over time can be systematically managed. This leads to enhanced **equipment management by analyzing the corrosion tendency**.

[Example of validation data]

Image A **Image B** **Image C**

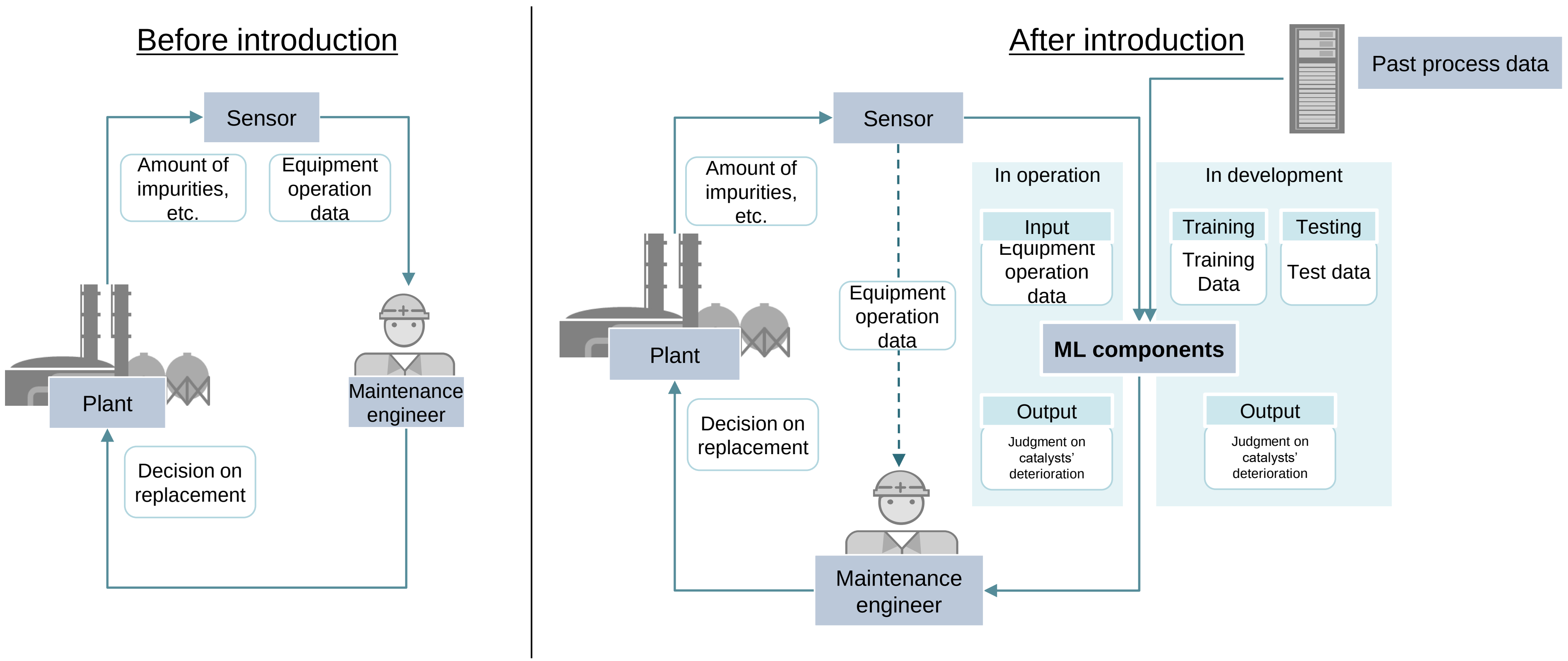


3. Equipment Deterioration Diagnosis

Yokogawa Electric Corporation

3. Equipment Deterioration Diagnosis —Case Overview— *The system currently targets catalysts among equipment.

- This is an ML based system that determines whether catalysts have deteriorated, for the purpose of developing a maintenance plan based on catalysts deterioration patterns and shortening shutdown period.
- The functional requirement set is “Predicting the deterioration of catalysts.”
- The ML components judge whether catalysts have deteriorated, and if judged so, an alert is sent to the maintenance engineer. The maintenance engineer then judges whether catalysts need to be inspected or replaced based on the sent information and the equipment operation data.



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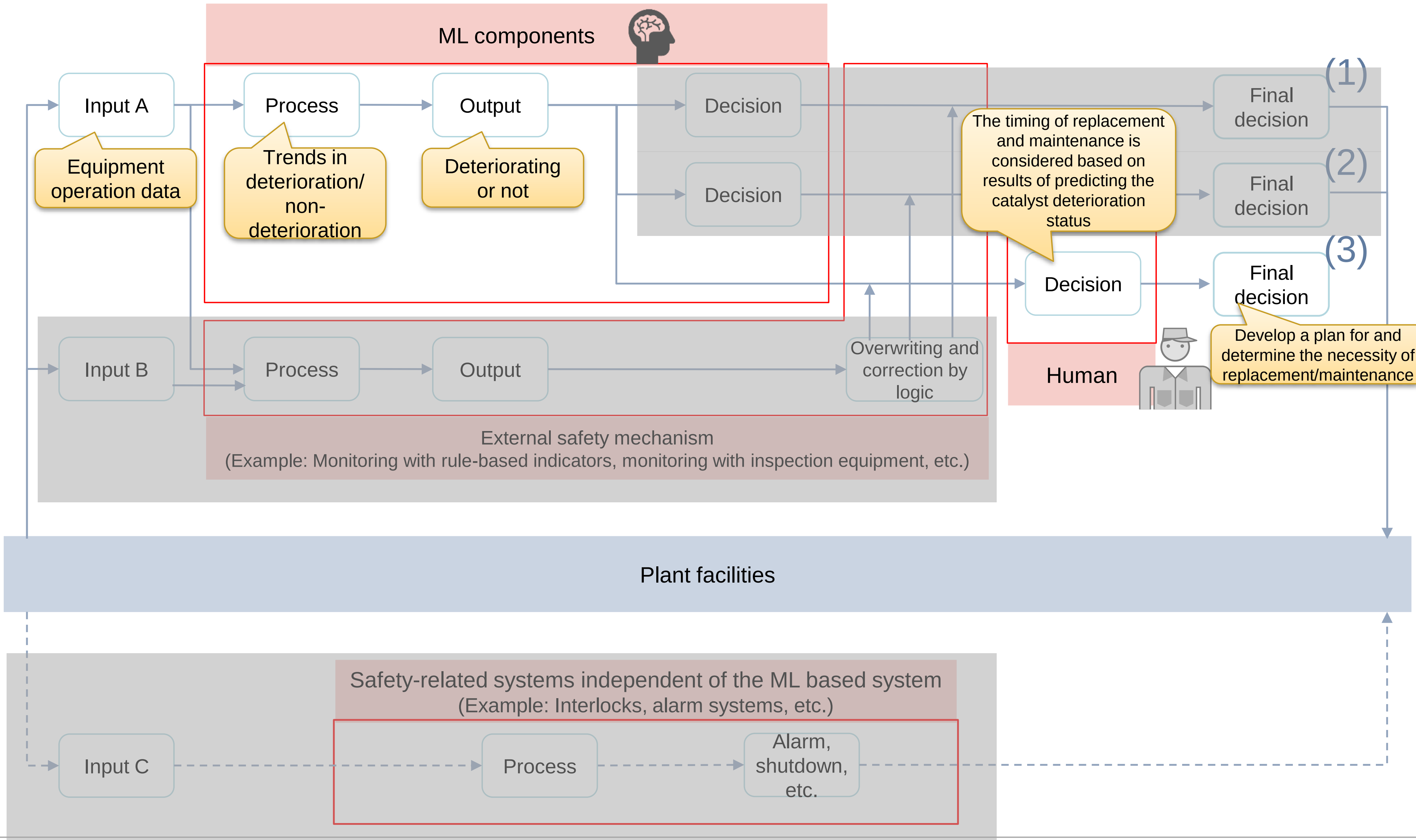
3. Equipment Deterioration Diagnosis —Relationship with Other Systems—



3. Equipment Deterioration Diagnosis
—Composition of ML Components and Setting the Quality in Use and the External Quality—

<Composition of ML components>

Learning methodology	Supervised classification
Learning model	Learns the degree of deterioration of catalysts from process data at the time of deterioration and non-deterioration
Input data in operation	Process data (reactor temperature, pressure, composition of feed, etc.)
Training data in development	Process data (reactor temperature, pressure, composition of feed, etc.), maintenance information
Test data in development	Process data (reactor temperature, pressure, composition of feed, etc.), maintenance information

<Example of setting the quality in use and the external quality>

Quality in Use	External Quality
Risk avoidance	
-	-
Performance	
The state of deterioration should be estimated correctly.	The classification errors between "deterioration" and "no deterioration" are kept to a certain level.
The progress of deterioration is judged early enough to develop a maintenance plan.	The result of judging the change from "no deterioration" to "deterioration" is output before a predetermined time.

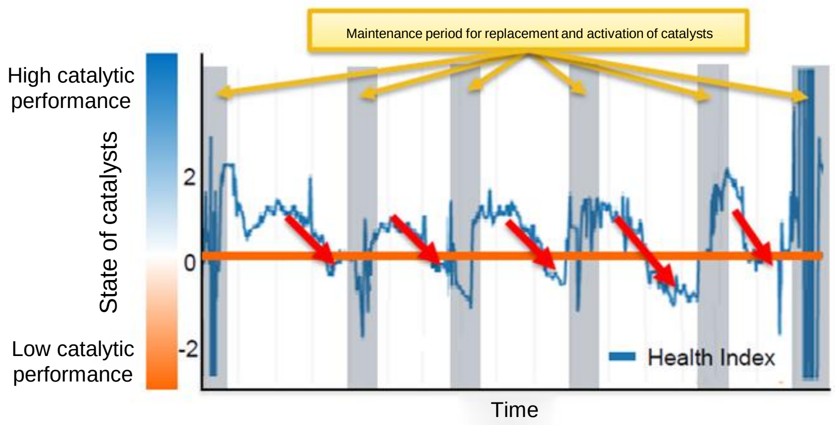
3. Equipment Deterioration Diagnosis
—Details of Case (Role of AI System and Effects of Its Adoption)—

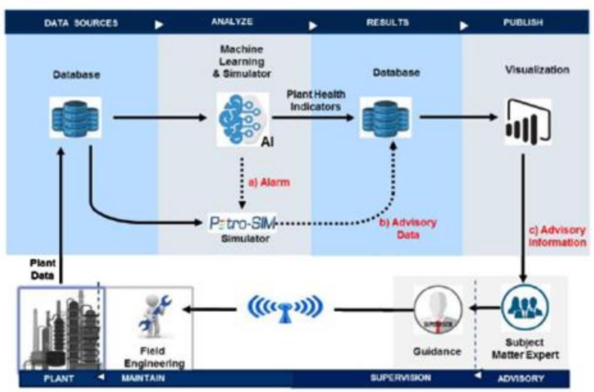
Role of AI system

- Maintenance for replacement and activation of catalysts is determined based on the amount of impurities and experience of maintenance engineers, but **it has been difficult to plan the maintenance timing in advance**. The replacement of catalysts requires a shutdown, during which the plant stands offline. Therefore, **the shutdown period needs to be as brief as possible**. In order to achieve this, it is necessary to make a maintenance plan in advance and implement it systematically, but such measure has not been feasible so far.
- By using plant data to diagnose catalyst deterioration, the replacement timing can be considered based on the deterioration tendency and **a maintenance plan can be made in advance**. Thus, **the shutdown period can be shortened**.

Effects

- By diagnosing the deterioration state of catalysts, **a maintenance plan can be made in advance**.
- By making a maintenance plan in advance, **the shutdown period can be shortened**.
- By using the system to assist inexperienced maintenance engineer, **the judgments criteria between different engineers can be standardized** regardless of experience.





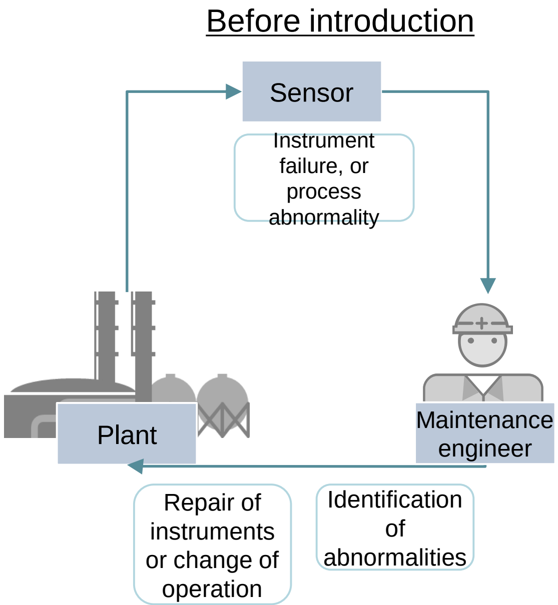
4-1. Prediction and Diagnosis of Abnormality

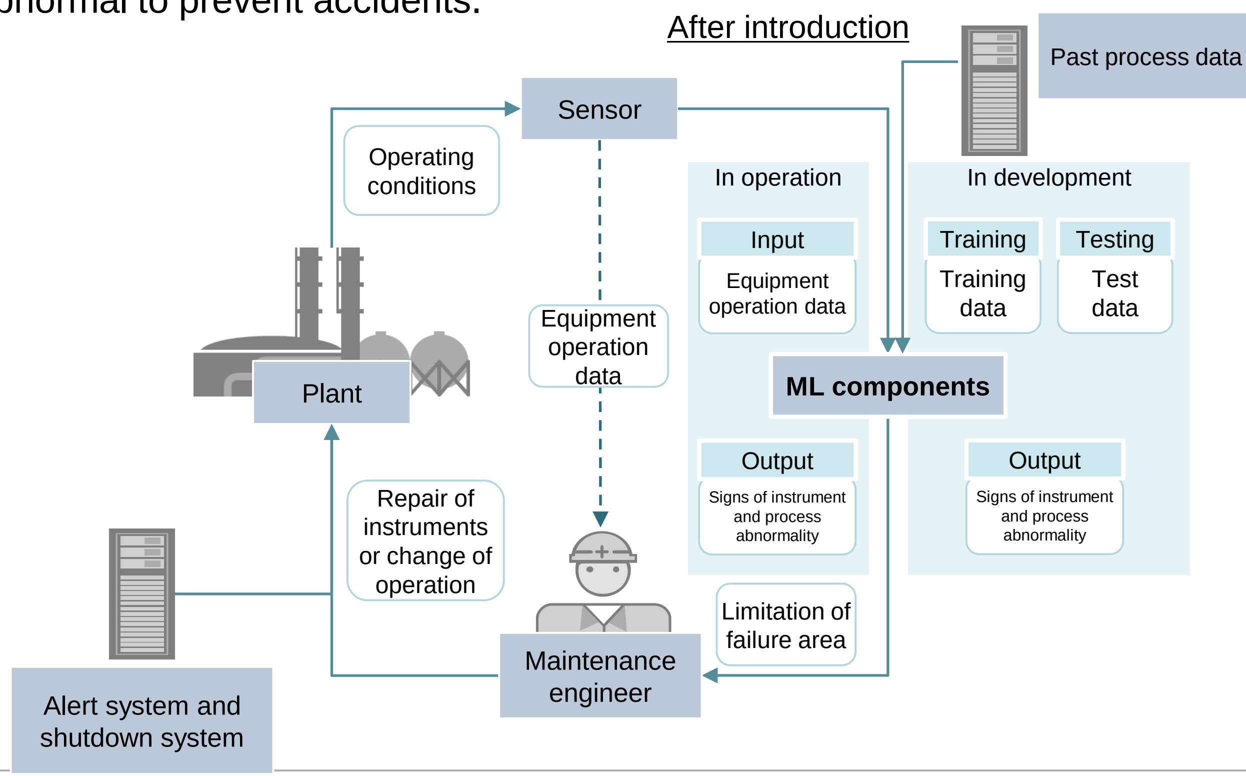
Chiyoda Corporation / Seibu Oil Company Limited

4-1. Prediction and Diagnosis of Abnormality —Case Overview—

<Case overview>

- By analyzing IoT sensors in combination with operational historian data (process data), abnormalities in devices and instruments, as well as operations that could lead to abnormalities, are detected at the predictive stage with high accuracy.
- The functional requirements set are "Detect abnormalities early with high accuracy under various operating conditions" and "Identify the reason for abnormality."
- ML components judge the degree of abnormality based on various operating conditions, and output signs of abnormality to the operator. The components also determine which area and system within the process system is suffering abnormality. In response, the operator judges whether to change the operation or checks and repairs devices and instruments considered abnormal to prevent accidents.





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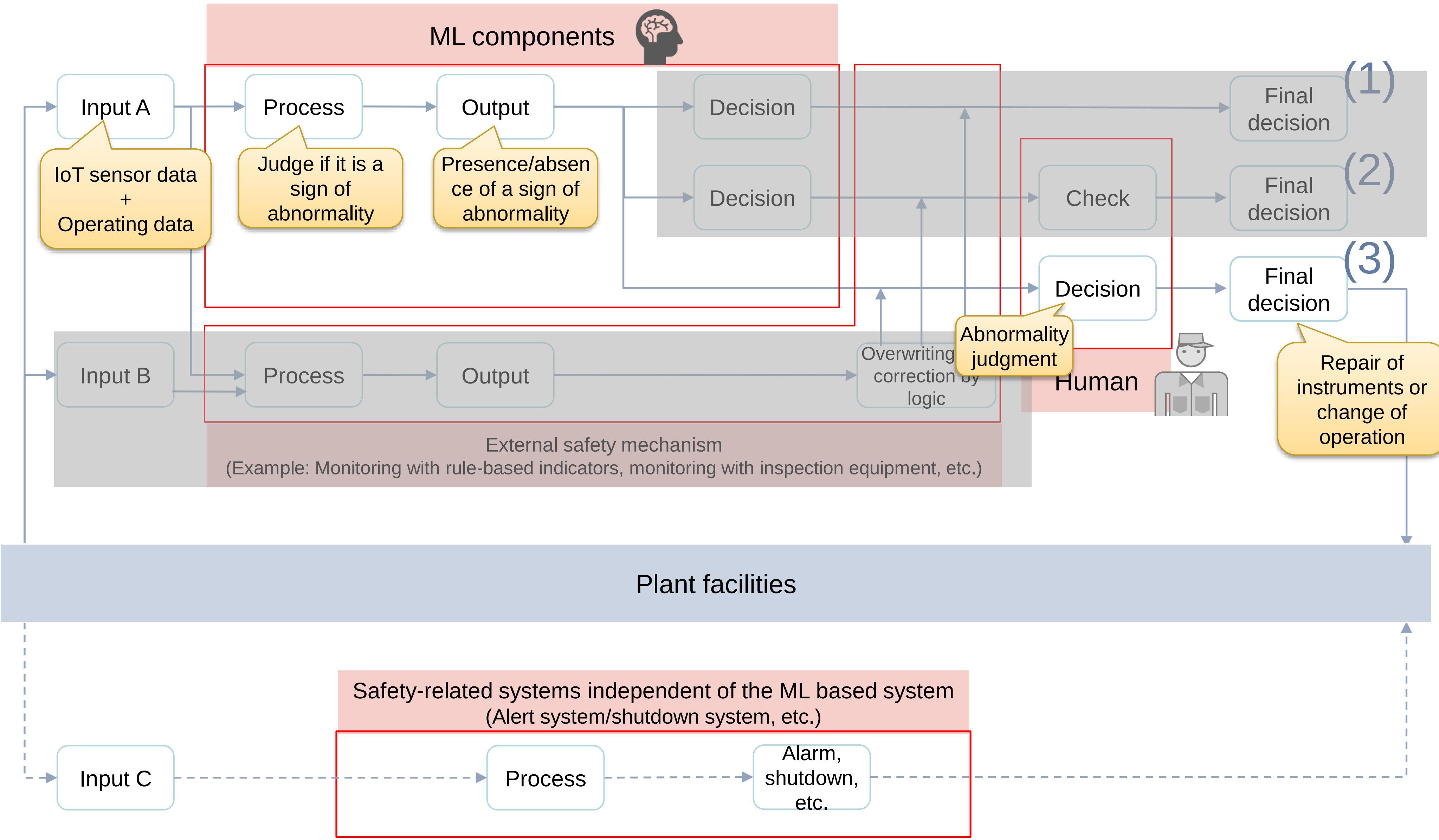
4-1. Prediction and Diagnosis of Abnormality —Relationship with Other Systems—



4-1. Prediction and Diagnosis of Abnormality —Composition of ML Components and Setting the Quality in Use and the External Quality—

<Composition of ML components>

Learning methodology	Supervised regression
Learning model	Predict the value of the target sensor from the operation data and sensor data
Input data in operation	Maintenance data (vibration value and valve opening), operating data (pressure, temperature, flow rate, properties, physical calculation values, etc.)
Training data in development	Maintenance data (vibration value and valve opening), operating data (pressure, temperature, flow rate, properties, physical calculation values, etc.)
Test data in development	Maintenance data (vibration value and valve opening), operating data (pressure, temperature, flow rate, properties, physical calculation values, etc.)

<Example of setting the quality in use and the external quality>

Quality in Use	External Quality
Risk avoidance	
Abnormalities are detected early and correctly under various operating conditions	Minimize false negatives where abnormal cases are classified as normal.
Performance	
Minimize false alarms and the workload of operators and inspectors	Maintain false positives where normal cases are classified as abnormal under certain threshold.
A deterioration tendency is predicted early enough to respond to abnormalities.	Abnormality detection results are output before a predetermined time.
The cause of abnormality can be narrowed down and reduce down time.	Maintain accurate prediction rates of the cause above certain threshold.

4-1. Prediction and Diagnosis of Abnormality
—Details of Case (Role of AI System and Effects of Its Adoption)—

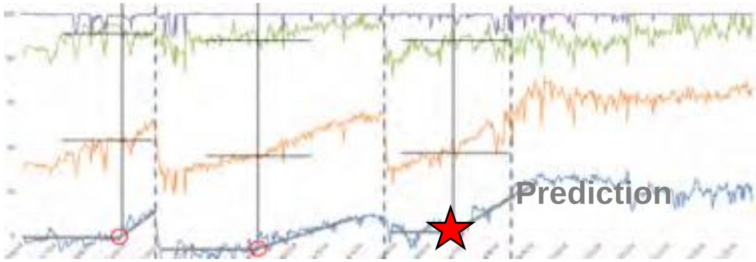
Role of AI system

- When an abnormality alarm is raised, determining the cause of the alarm remains difficult; as such, identifying the cause of the alarm and determining the response relies **heavily on experienced operators**. The existing diagnostic tools can **hardly detect abnormalities** until occurrence of failure (the initial stage of failure), and a certain amount of **false detection** exists.
- By introducing an AI system that learned operation data and safety data, and that quickly detects abnormalities under various operating conditions, **abnormality prediction in advance** before initial signs of abnormality, can be achieved. This **reduces risks of failure and loss of production opportunity** more than ever. The AI system allows extensive overview of safety data and operation data combined and enables **cause identification, determining the response, and early actions without relying on experienced operators**.

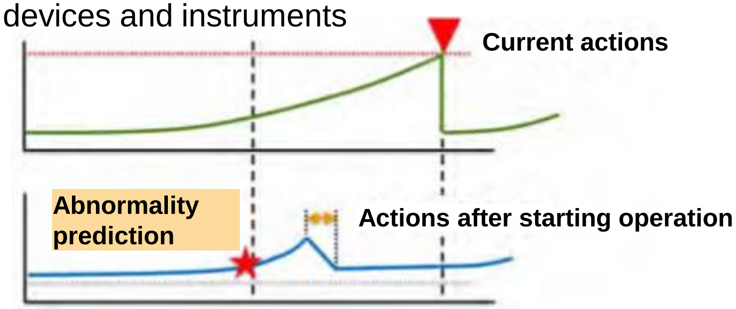
Effects

- The whole system process abnormality monitoring and safety assessment AI makes it possible to find not only failure of devices and instruments, but also abnormal behavior of the whole process equipment, resulting in **improved accuracy in locating abnormalities** (the cause of abnormality can be narrowed down) and **early response**.
- In addition, the system enables real-time monitoring of the status of devices and instruments in the same system, **reducing the frequency of operator patrol** and **field workloads**.
- By monitoring and assessing the impacts of process fluctuations on devices and instruments, **incidence of device failures can be reduced** without reducing productivity, and this in turn **reduces risks of failure and opportunity costs**.
- When an alarm is raised, the judgment of whether it is a process abnormality or device/instrument abnormality has been dependent on experienced operators. However, the AI allows inexperienced operators to take accurate and early actions.

Detection and prediction of process abnormality (process imbalance)



Early detection and prediction of abnormalities of devices and instruments



4.2 Prediction and Diagnosis of Abnormality

JGC Japan Corporation

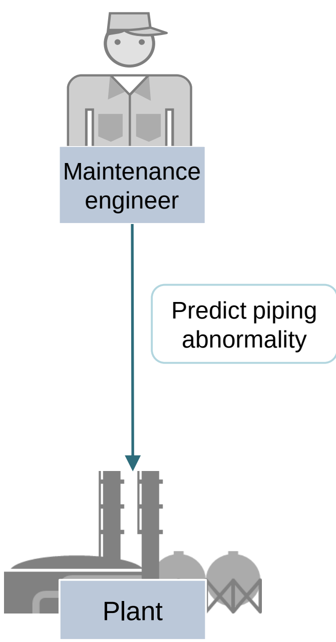
*This practical example has the features of use cases of not only "prediction and diagnosis of abnormality" but also "prediction of pipe wall thickness," and the reliability assessment is carried out by referring to both use cases.

4-2. Prediction and Diagnosis of Abnormality —Case Overview—

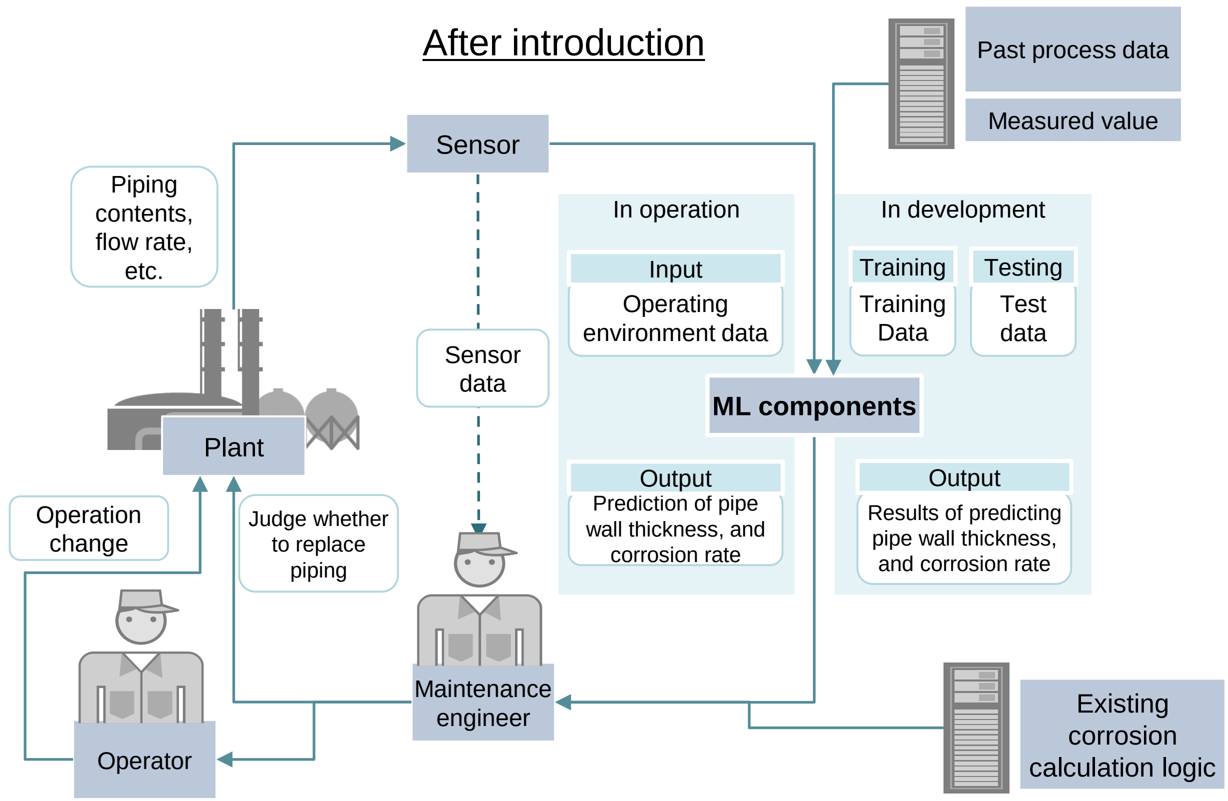
<Case overview>

- This is an ML based system that detects signs of abnormality in piping from operation data and environmental changes in order to avoid trouble caused by piping abnormality.
- The functional requirements set are “Clarify a corrosion point and send an alarm when an abnormal sign is detected” and “Output the variables and numerical values that caused the abnormality prediction.”
- ML components judge the corrosion rate from operation data and environmental changes, and provide the result to maintenance engineers. The maintenance engineers promptly take measures to prevent trouble in response to the result (incl. changing the operation in coordination with operators). The system also allows maintenance based on prediction, preventing accidents in advance.

Before introduction



After introduction



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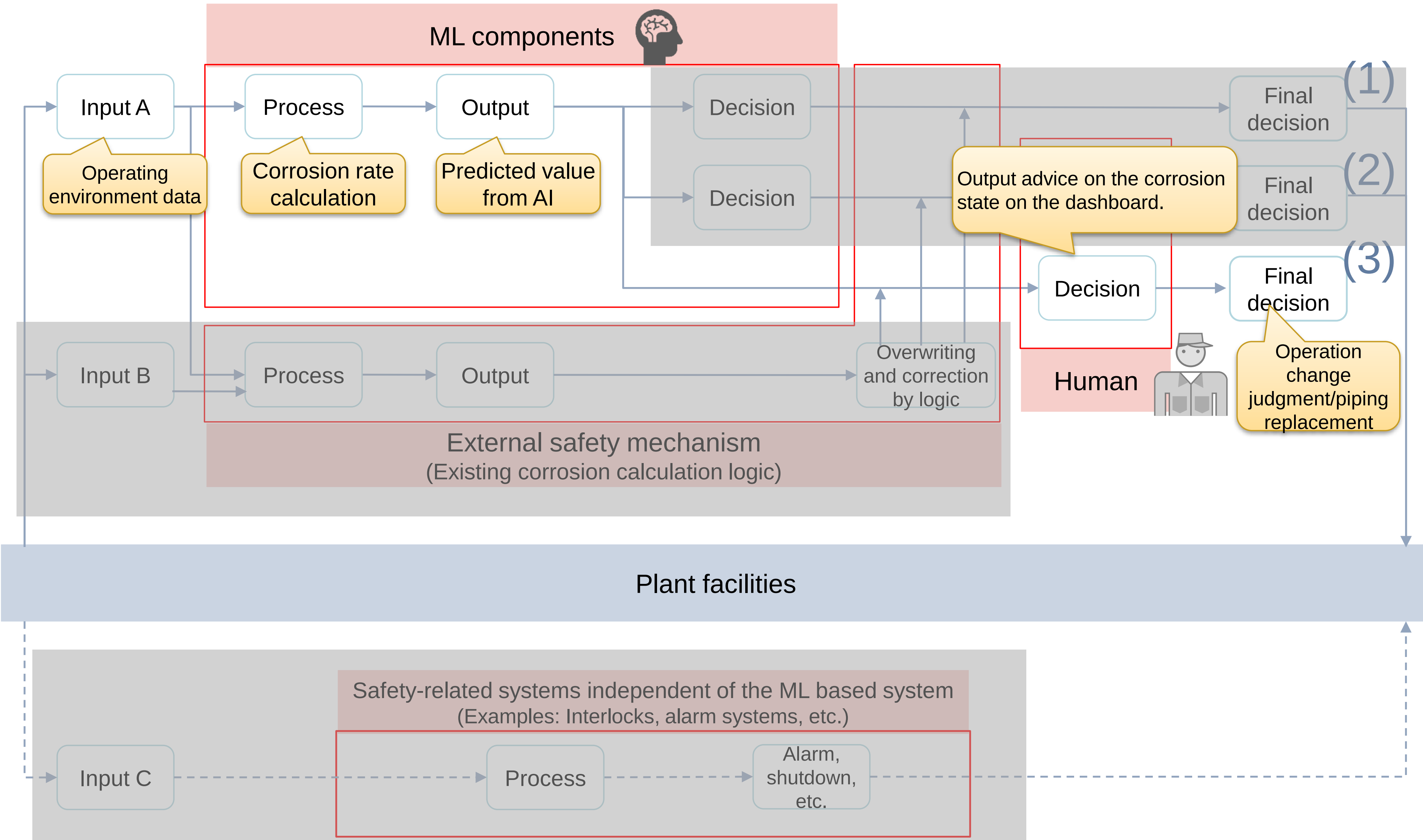
4-2. Prediction and Diagnosis of Abnormality —Relationship with Other Systems—



4-2. Prediction and Diagnosis of Abnormality
—Composition of ML components, Quality in use and Setting the external quality—

<Composition of ML components>

Learning methodology	Regression (supervised learning) *To predict continuous values of wall thickness
Learning model	Actual measurements of corrosion rate in the past rate in the past are set as an objective variable, and piping specifications and process data as explanatory variables.
Input data in operation	Process data (contents, flow rate, flow velocity, pressure, temperature, pH, etc. of piping)
Training data in development	Process data (contents, flow rate, flow velocity, pressure, temperature, pH, etc. of piping) Records of thickness measurement
Test data in development	Process data (contents, flow rate, flow velocity, pressure, temperature, pH, etc. of piping) Records of thickness measurement

<Examples of setting quality in use and external quality>

Quality in Use	External Quality
Risk avoidance	
Not to make a prediction on the hazard side with actually measured C.R. larger than predicted C.R. (C.R: Corrosion Rate)	To minimize errors of predicting a thickness value larger than the actual value.
The variables that have affected the prediction value are suggested so that the cause of the abnormality prediction can be identified.	To minimize errors that erroneously outputs variables that affected a prediction value.
When an abnormal sign is detected, the timing of the alarm will be set to ensure safety in such a way as to prevent a serious incident from occurring.	Alarm is issued within a set time (○ hours in advance).
Performance	
Set the alert frequency to a reasonable level that operators and inspectors do not need to spend too much time resource in checking the contents of alerts.	Keep errors in predicting wall thickness to be thinner than it actually is below certain limits.

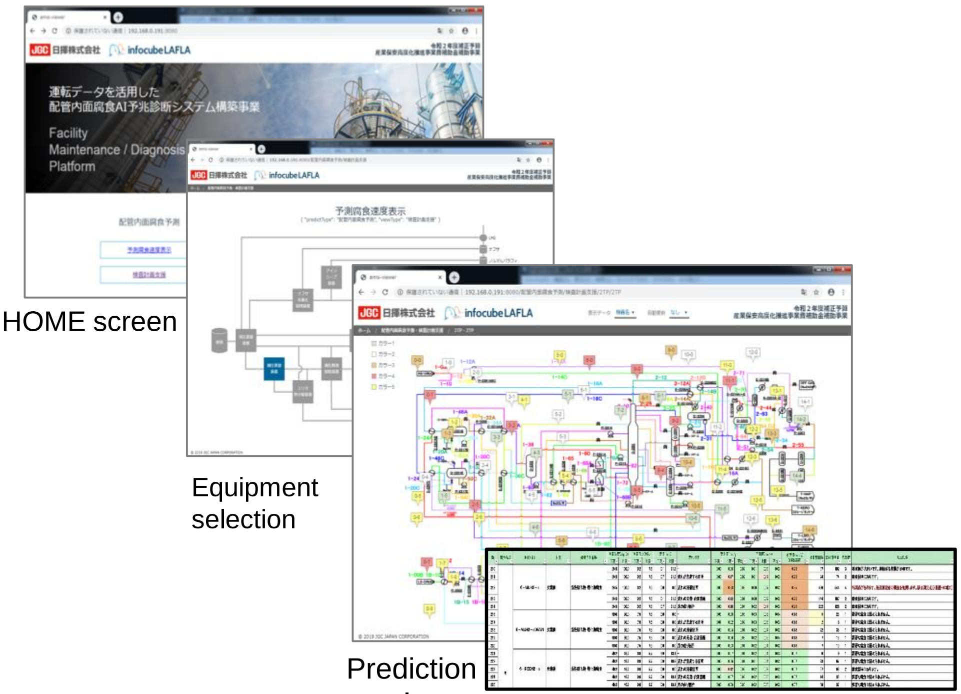
4-2. Prediction and Diagnosis of Abnormality
—Details of Case (Role of AI System and Effects of its Adoption)—

Role of AI system

- Traditionally, control items and values in operation conditions were set based on data such as analysis from simulators. However, from a plant-extensive point of view, the issue remained that **the progression of corrosion was unclear**, due to lack of knowledge on the relationship between fluctuations in real operation data and corrosivity.
- By introducing an AI system that can predict the progression of piping corrosion, **condition-based predictions** remain available even when corrosivity increases due to changes in the environment, allowing for **more reliable decisions** at all times. If sudden corrosion is predicted, maintenance engineers and operators can respond accordingly to prevent problems.

Effects

- By conducting analysis using AI, control items and criteria for operation can be set after clarifying the correlation between process fluctuations and corrosion. This not only **improves operation efficiency** but also **reduces the frequency of issues**.
- **Early warning** can be made possible by clarifying operating conditions in normal and non-normal states, and conducting predictive diagnosis for pipe corrosion.
- **Decisions of high accuracy** becomes possible at all times, with automatic data collection not relying on human labor and condition-based predictions.
- By providing support using AI, even young maintenance engineers can make **highly accurate decisions** at all times.
- Decisions of experienced maintenance engineers will be fed into the AI, allowing for the **passing down of their expertise and techniques**.



HOME screen

Equipment selection

Prediction result

Planning support

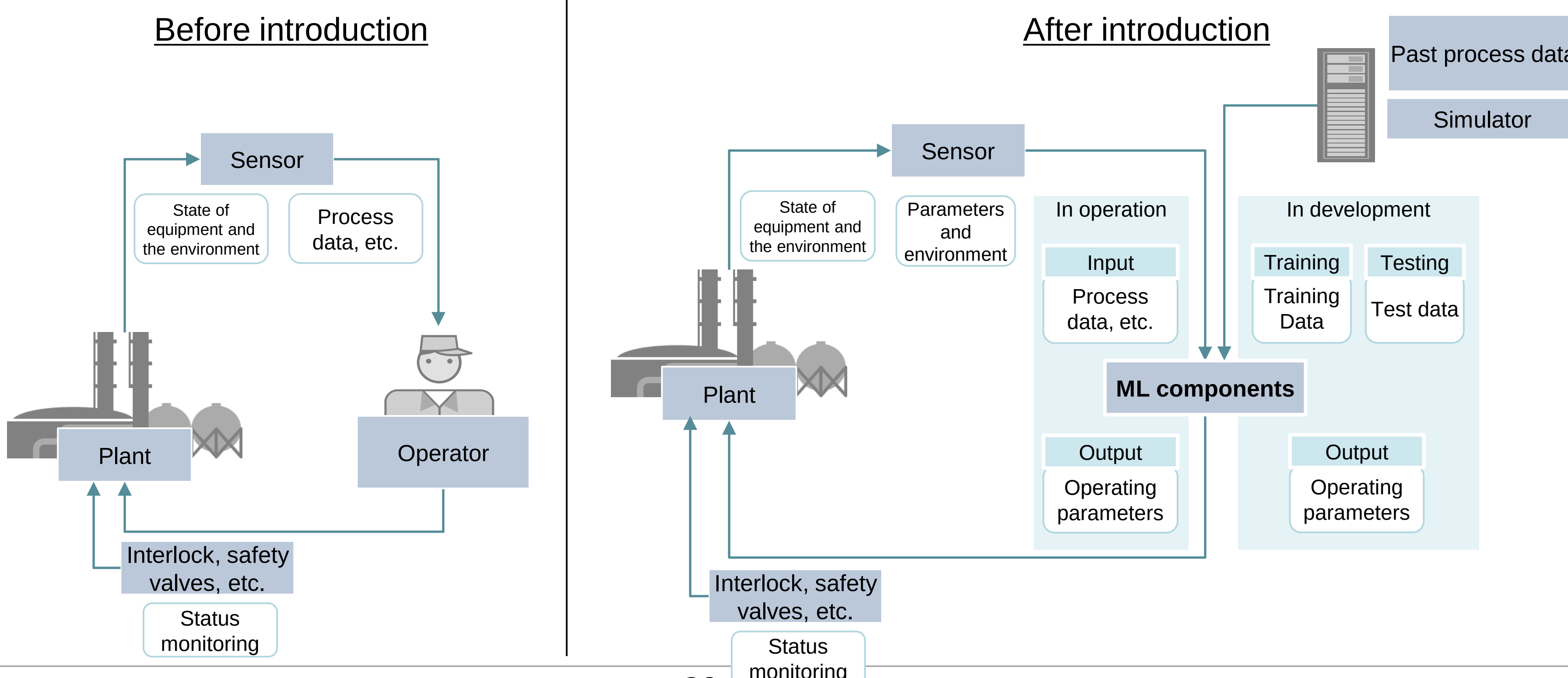
5-1. Optimization of Operation

ENEOS Corporation / Preferred Networks, Inc.

5-1. Optimization of Operation —Case Overview—

<Case overview>

- This is an ML based system that automatically outputs optimum operation parameters from process data for the purpose of realizing automatic operation with production efficiency and energy efficiency equal to or better than operations of experienced operators. This is achieved by stabilizing equipment fluctuations due to disturbances, such as outside air temperature and weather, at all times.
- The functional requirements set are “Operate steadily during equipment fluctuations due to disturbances” and “Operate with optimized production and energy efficiency during normal conditions.”
- From process data, ML components output operation parameters that realizes overall optimization of production efficiency and energy efficiency within a range of allowable safety operation. The output is directly reflected in plant operation.



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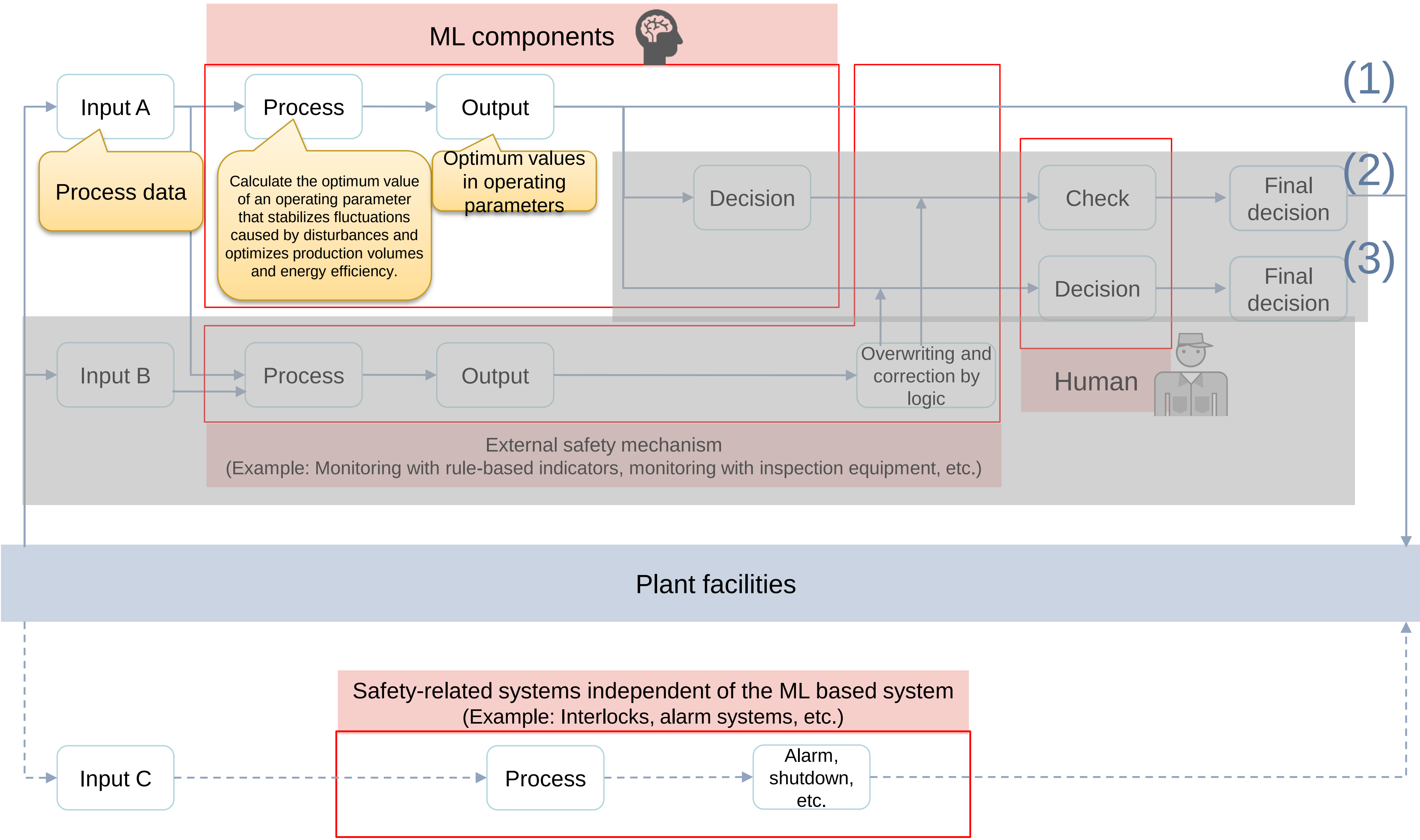
5-1. Optimization of Operation —Relationship with Other Systems—



5-1. Optimization of Operation —Composition of ML components and setting the external quality—

<Composition of ML components>

Learning methodology	Regression (supervised)
Learning model	Learn the relationship between historical process data and future objective functions (product properties, flow rate, etc.)
Input data in operation	Process data (time series data of fluid properties, and the flow rate, temperature, pressure, and liquid level of equipment)
Training data in development	Process data (time series data of fluid properties, and the flow rate, temperature, pressure, and liquid level of equipment)
Test data in development	Process data (time series data of fluid properties, and the flow rate, temperature, pressure, and liquid level of equipment)

<Setting the quality in use and the external quality>

Quality in Use	External Quality
Risk avoidance	
Not to perform an operation that exceeds the equipment design limitation.	To limit the output operation range of AI to a range of allowable safety operation.
To indicate that the present operation zone is within or outside the trained range of AI. (output "this is an unknown field")	To reduce to a certain level the misjudgment rate where the system judges that the operation zone is within trained range when it is actually not.
Performance	
To minimize the number of times the operator responds to alarms.	To take the number of whistle alarm blows of the existing system (DCS) caused by fluctuations due to disturbances to as close to zero as possible.
To realize optimum control in consideration of both production efficiency and energy efficiency when conditions are steady.	To indicate an operation parameter that keeps an indicator, calculated by converting production efficiency and energy efficiency into a monetary value, higher than a certain level.

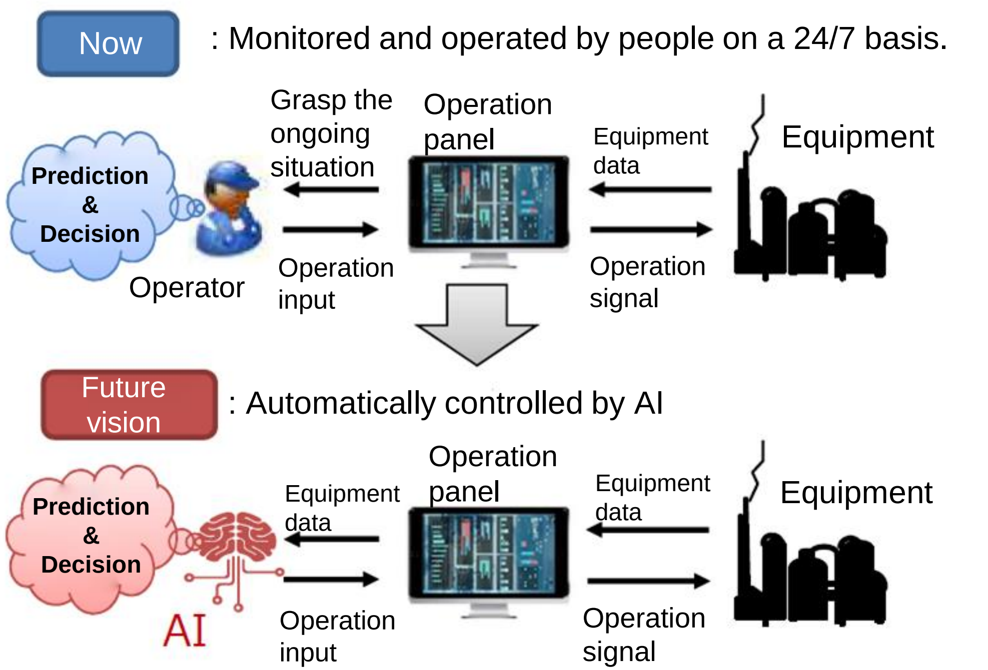
5-1. Optimization of Operation —Details of Case (Role of AI System and Effects of its Adoption)—

Role of AI system

- **The number of fires and leakage accidents** at dangerous facilities in Japan **remain unchanged**, and reducing equipment troubles was an urgent issue to be addressed. In addition to a decline in technical capabilities due to an expected **decrease in the number of experienced operators** in the future, there was a concern that it **securing qualified operators will be difficult** due to a fall in the domestic workforce.
- By using the ML based system for monitoring and operation, **human-factor-based troubles in equipment** (e.g. caused by operation mistakes) **can be reduced**. In addition, by using the ML based system, it will be **possible to maintain optimum operation better than that of experienced operators with minimum human resources**.

Effects

- **Equipment troubles** through human monitoring and operation **can be reduced**.
- By allocating human resources freed up by shift to automation to equipment abnormality detection, **equipment troubles caused by physical factors can also be reduced**.
- It will be possible to maintain **optimized operation in a way that is better than that of experienced operators**.
- Since the plant will be able to operate with a smaller number of people, **continuous operation can be expected even in an emergency** such as when an infectious disease spreads.



Current Status and Future Vision of Plant Operation

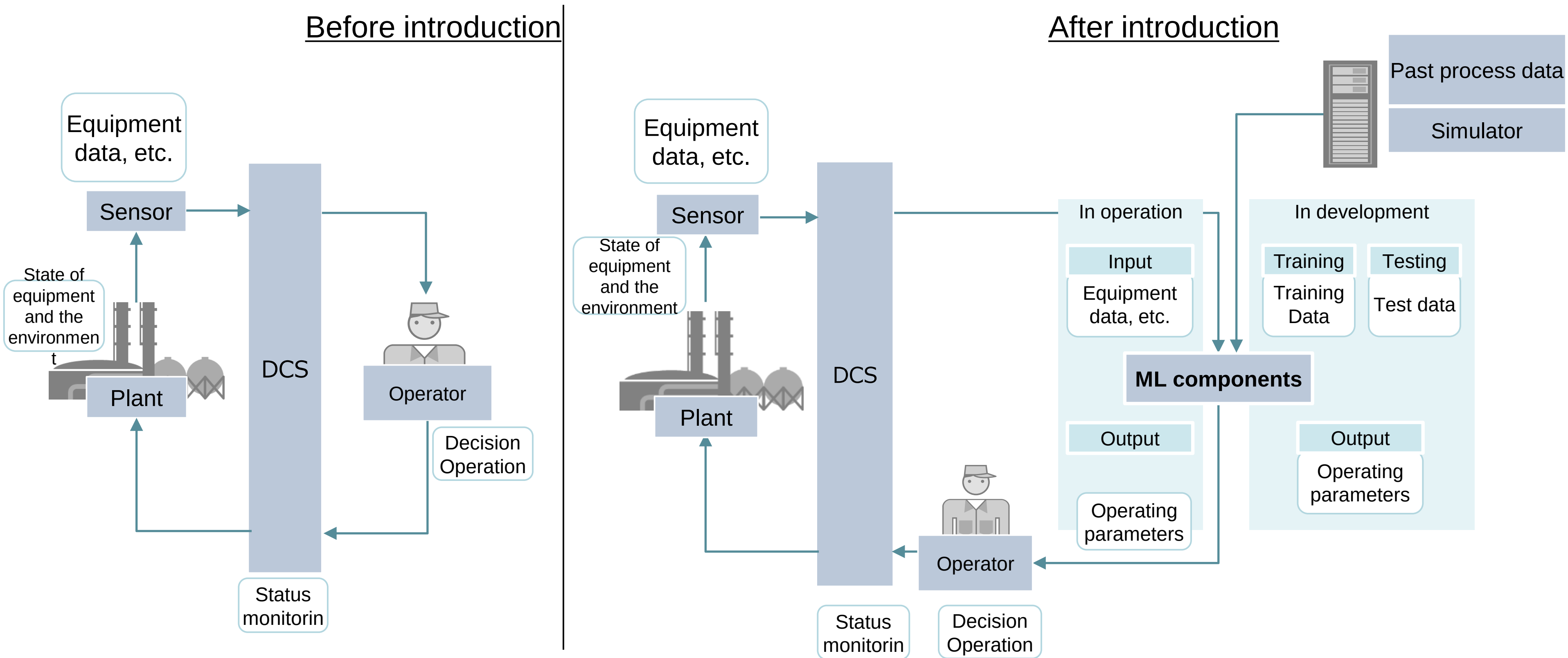
5-2. Optimization of Operation

Yokogawa Electric Corporation / JSR Corporation

5-2. Optimization of Operation —Case Overview—

<Case overview>

- This is an ML based system that automatically outputs optimum operating parameters from process data for the purpose of maintaining quality by detailed operation and achieving higher energy efficiency.
- The functional requirements set are “Use AI control to perform operations equivalent to manual operations” and “Aim for higher energy efficiency while maintaining quality through automatic operation in more detail than the operator’s manual operations.”
- From process data, ML components calculate operating parameters optimum for energy-saving operation within a range corresponding to allowable safety operating specifications, and provide them to the operator. The operator judges whether the output of the ML components is appropriate based on experience and determines the operation of the plant.



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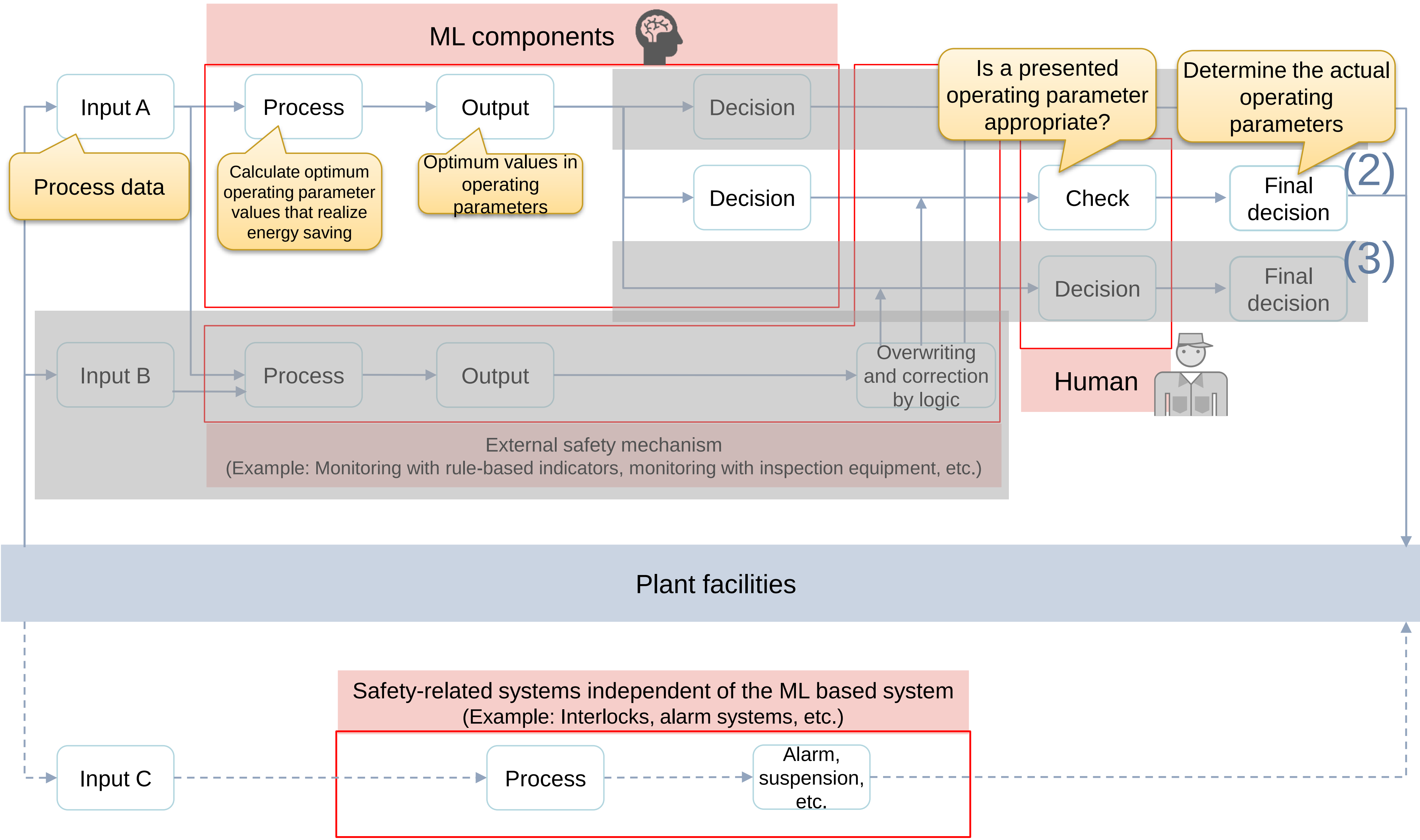
5-2. Optimization of Operation —Relationship with Other Systems—



5-2. Optimization of Operation
—Composition of ML Components and Setting the Quality in Use and the External Quality—

<Composition of ML components>

Learning methodology	Reinforcement learning
Learning model	Learns optimum operating methods for energy efficiency based on process data
Input data in operation	Process data (data of actual equipment, such as the amount of feed to the distillation column, temperature, and the amount of generated materials)
Training data in development	Process data (data of the process simulator)
Test data in development	Process data (data of actual equipment for the past year)

<Example of setting the quality in use and the external quality>

Quality in Use	External Quality
Risk avoidance	
Operating conditions that exceed the allowable safety operating specifications of the equipment are not caused.	The output range is limited to a range corresponding to allowable safety operating specifications.
Output is stable under various conditions.	The prediction accuracy of operating parameters is kept at a certain level or higher.
Performance	
Higher energy efficiency than pre-AI operation is achieved.	Operating parameters that keep energy efficiency indicators above a certain level are presented.

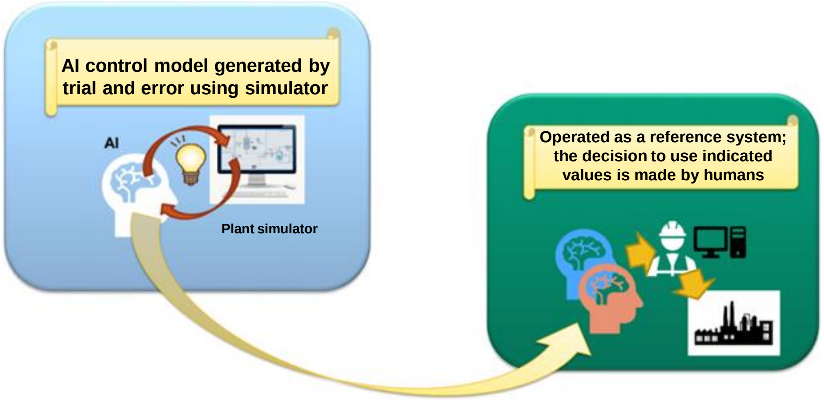
5-2. Optimization of Operation —Details of Case (Role of AI System and Effects of Its Adoption)—

Role of AI system

- In the operation of this plant, PID control and multivariable model predictive control are used for automation and stabilization. However, some processes vulnerable to disturbances require manual control by human operators. This leaves some elements human-dependent.
- If the operation can be automated by using ML components, continued high-quality operation with high energy efficiency can be achieved.

Effects

- It is possible to reduce the number of human resources currently deployed 24 hours a day, thereby **reducing the burden on people**.
- It eliminates factors that depend on individual skills caused by human operation, making it possible to **maintain operation quality**.
- By maintaining high-quality and energy-efficient operation, **the energy consumption rate can be reduced** further, contributing to the society's effort of energy conservation.



Optimization of plant operation
by reinforcement learning AI control algorithm