A new anomaly detection method based on deep learning

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1. Introduction

We have developed a new anomaly detection method using Sony's Neural Network Libraries deep learning software. In this report, we show that this method is very useful for EES (Equipment Engineering Systems) and FDC (Fault Detection and Classification) using diverse data from semiconductor manufacturing facilities.

In deep learning, the anomaly detection accuracy is determined according to the number of learning iterations. In other words, the accuracy of anomaly detection is increased by performing repeated deep learning. For example, by performing repeated learning of normal signal value states, it is possible to detect anomalous waveforms whose characteristics differ from the normal state.

In this report, we use deep learning to detect anomalies that are found in a plasma CVD process. The detection method is presented below, and is followed by a detailed discussion of the results. We also discuss the differences between the deep learning method and conventional anomaly detection methods that require human involvement. We will then conclude with a summary.

2. Experimental

2.1 Differences between deep learning and conventional methods

Here, we show the signal waveforms used to detect anomalies, and we discuss the differences between deep learning and conventional methods.

In plasma CVD, electrical signals from the equipment are constantly detected during processing. If an anomaly occurs, then the normal signal changes to an anomalous signal as shown in Fig. 1. In a conventional EES waveform monitoring method that requires human involvement, someone first has to memorize the characteristics of these signal changes. However, with deep learning, these changes are learned automatically so that anomalies can be detected without the need for highly trained human operators. That is, as shown in Fig. 2, when the input consists of numerical waveform data, it can be dimensionally compressed to enable the extraction of waveform features without human intervention. To perform deep learning, we used *Neural Network Libraries*, which is a collection of open-source code produced by Sony.[1)]

2.2 Data Analysis and Fault detection method

This section describes the threshold settings used for detecting plasma electrical signals and for detecting anomalies by deep learning.

First, EES is used to acquire the sensor waveforms. Next, the features of EES waveforms in the normal state are extracted according to the waveform analysis flowchart of Fig. 2. Here, multiple waveforms are input, and their features can be extracted independently.

Next, the normal state is defined based on these extracted features. The normal state is expressed by a score calculation formula in terms of monitoring indices. From the population of normal data, a threshold value is set to define the limit of anomalous states. This threshold value calculation also requires no human intervention. The precision of this threshold value is evaluated as the detection accuracy when classifying normal and anomalous states in the data.

3. Results and Discussion

Here, we describe the monitoring of anomalies in plasma electrical signals. First, Fig. 3 shows the waveform data of a normal state and an anomalous state. To define the normal state shown in Fig. 3, multiple instances of only normal waveform data are extracted from the collected data. Here, we perform normal state feature extraction, define the score extraction formula, and set a score threshold value.

Next, when detecting anomalies, the normal data and anomaly data obtained from the collected data are compared. Scores are calculated, and anomalous

states are detected according to the threshold value. The anomaly detection results are shown in Fig. 4.
The scores shown in Fig. 4 respond sensitively to anomalies in the waveform shapes of all the extracted patterns. Since the scores achieved by the anomaly data all exceed the monitoring threshold, these anomalies are easy to confirm. It is therefore clear that this method facilitates the detection of anomalous data.

4. Conclusion

We have developed a new waveform monitoring method that uses deep learning to define a threshold value to distinguish between normal states and anomalous states. We applied this new method to EES waveform monitoring in semiconductor fabrication equipment, and we showed that anomalies can be detected with high precision from large numbers of waveform patterns. We can conclude that this method is useful for quality stabilization and the prompt detection of equipment anomalies in mass production lines.

References

Neural Network Libraries: https://nnabla.org/

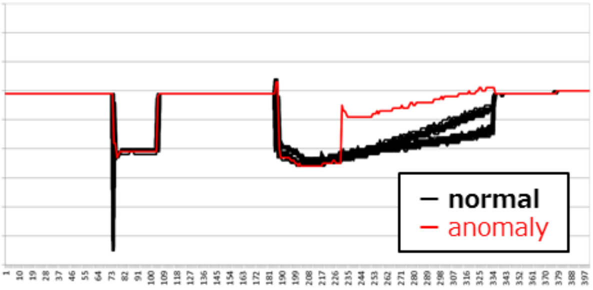

Fig. 1: Normal and anomalous states in plasma electrical signals.

It is difficult to detect anomalous states by conventional methods.

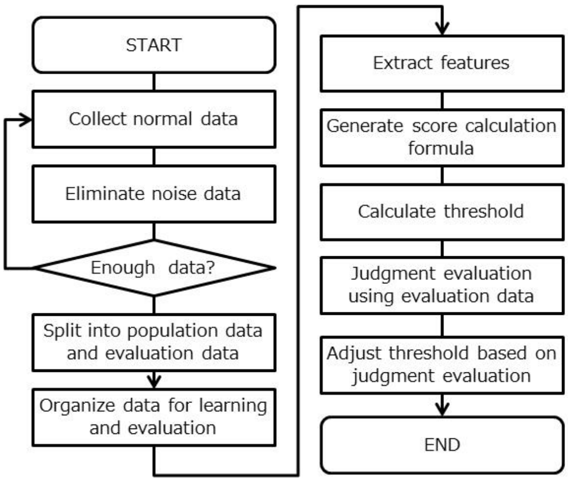

Fig. 2: Flowchart showing how normal data is collected, threshold values are determined, and then waveform analysis is performed to detect anomalies

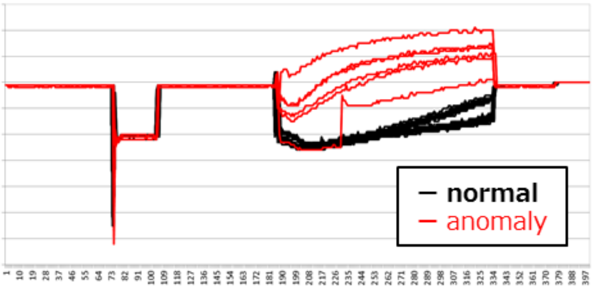

Fig. 3: Normal and anomalous patterns in plasma electrical signals

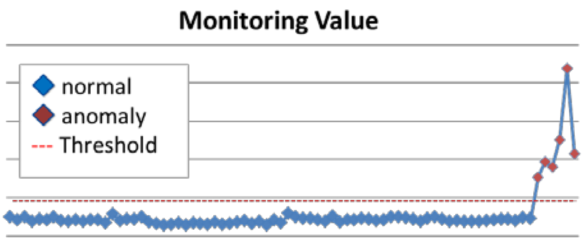

Fig. 4: Detection of anomalies in plasma electrical signals. The red dots towards the right of the figure indicate anomalies. The red line marks the threshold value