A Failure Prognostic Method for Advanced Complex Systems

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With today's increasingly complex and large-scale systems such as transportation equipment and power generation plants, unexpected situations may occur that are impossible to foresee based solely on the characteristics of individual system elements, and minute changes in one area may have a significant impact on the entire system. Many such systems must be available most of the time and a system failure or a stoppage can pose a threat to human lives. Therefore, Mitsubishi Heavy Industries, Ltd. (MHI) has developed a method to detect failure-prone areas in complex, large-scale systems. A variety of simulated failures in scale models of aircraft hydraulic and air-conditioning systems have been successfully detected using this method.

1. Introduction

Recently, mechanical systems such as transportation equipment, industrial machinery, robots and nuclear power generators have been growing in complexity. These systems require complex interactions between multiple elements of a diverse nature. Unexpected situations may occur that are impossible to foresee based solely on the characteristics of individual system elements, and minute changes in one area may have a significant impact on the entire system.

As such, there is a growing need for technology that can accurately identify and detect fault areas, particularly in mission critical systems where a failure or stoppage of the system can pose a threat to human life and safety. However, the following issues exist in the application of such technology:

(1) Space limitations make it difficult to add failure detection sensors to cover every area of the system.

(2) Data from existing sensors cannot be used as parameters to explicitly detect a failure event, thus making it difficult to establish a detection system with a threshold value for each data item and a formula to accurately identify a system failure.

(3) Non-stationarity effects resulting from changes in the flight environment and operating conditions mean that the same parameter can indicate either normal or abnormal operation of an aircraft depending on the particular circumstances. As such, stationary state data cannot be uniformly applied to determine a failure.

To solve these three issues, using the example of an aircraft as a particularly complex, large-scale mechanical system, Mitsubishi Heavy Industries, Ltd. (MHI) has developed a method to detect areas of predictive failure. Of the numerous systems required in aircraft operation, this study focuses on the hydraulic and air-conditioning systems. A scale model test piece for each system (enabling partial simulation of the system as a whole) was developed to generate data to verify the ability of this method to detect multiple failures of various types.

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2. Algorithm

Methods of detecting a predictive failure event and its location generally fall into two categories. To estimate the subject's status, the first group uses a model that reflects physical phenomena and probabilistic perturbation, while the second analyzes sensor data patterns. As mentioned in Section 1, this study focuses on aircraft hydraulic and air-conditioning systems. In addition to their high complexity, the characteristics of these systems also vary depending on age, making the first method difficult to apply. Thus, the pattern recognition method is employed in this study.

In detecting predictive failure through pattern recognition, a detection system first needs to learn data patterns while the system is in operation. This method is called machine learning. In machine learning, pattern recognition is performed by establishing a decision boundary in the data space and observing on which side of the boundary the given data lay, as shown in **Figure 1**. In this study, the detection of predictive failure can be approached by determining how to draw a discriminative line that properly separates data during normal operation (normal data) from data while predictive failure is occurring during system operation (failure data).

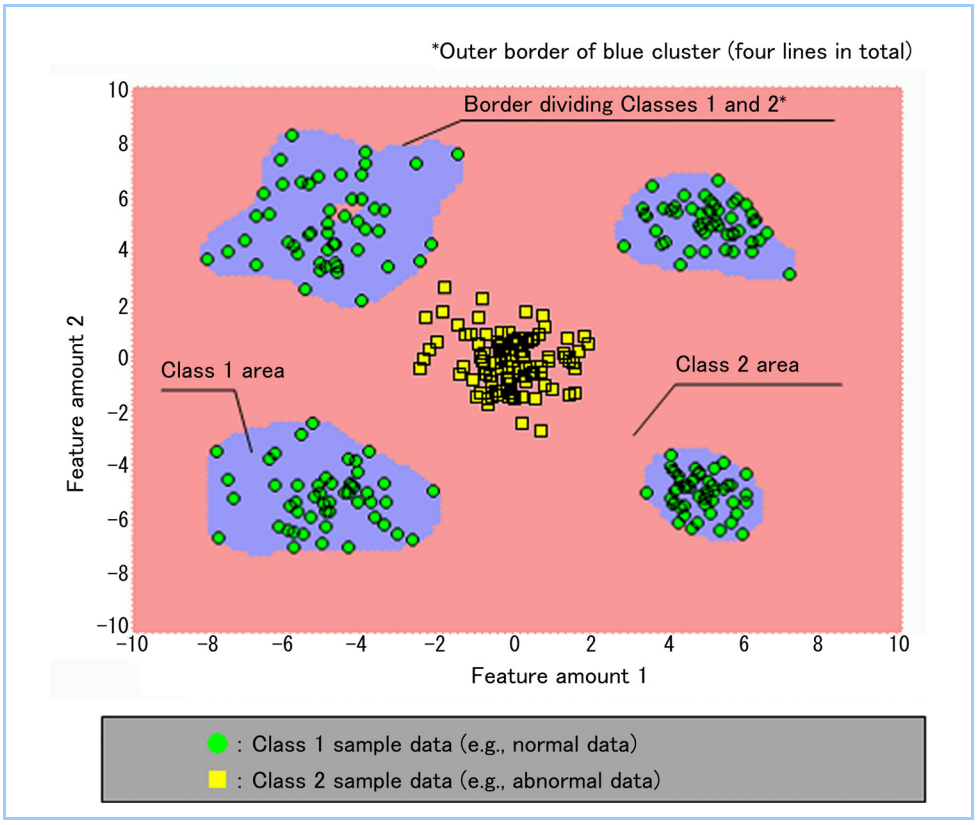

Figure 1 Example of pattern recognition in machine learning (artificial 2-D data)

Three factors in this study, however, cause the shape of the boundary line to become extremely complex. These factors are as follows: the high complexity of hydraulic and air-conditioning systems, the fact that usable data is obtained only from existing sensors and the existence of non-stationarity effects due to changes in operating conditions. To address this issue, a support vector machine (SVM) is used[1]. An SVM alone produces a straight-line boundary that separates data. When combined with the kernel method, however, a boundary with a complex shape such as illustrated in Figure 1 can be drawn[2]. In applying an SVM in the detection of predictive failure, while both normal and failure patters need to be learned, it is often the case that existing data samples include significantly more normal data than failure data. With such a major disparity between the two types of data, recognition accuracy using an SVM is known to decrease substantially. Meanwhile, another SVM approach is a technique called one-class SVM (OC-SVM) that uses only one type of data as the training set[3]. In this study, the failure detection system determines whether something is normal or abnormal based on the OC-SVM method, using normal data patterns as the training data. In detecting fault areas, another machine learning method known

as a self-organizing map (SOM) is applied[4]. Failure data samples of multiple types are used in SOM training. Based on the assumption that data behaviors vary depending on fault areas, area-specific data classification using SOM is also considered.

Figure 2 illustrates the flow of the method that MHI has developed. The detection of predictive failure is first performed. Subsequent detection of fault area is only performed on data falling into the failure category. For high-accuracy detection of predictive failure, MHI has developed an original kernel function (proposed kernel) based on the OC-SVM method. In addition, to capture temporal variations of data, data sets are pre-processed by segmenting into blocks (i.e., patterns include instantaneous values and past data). Furthermore, a method for automatic adjustment of kernel parameters has been developed (i.e., optimization of kernel parameters using assessment functions).

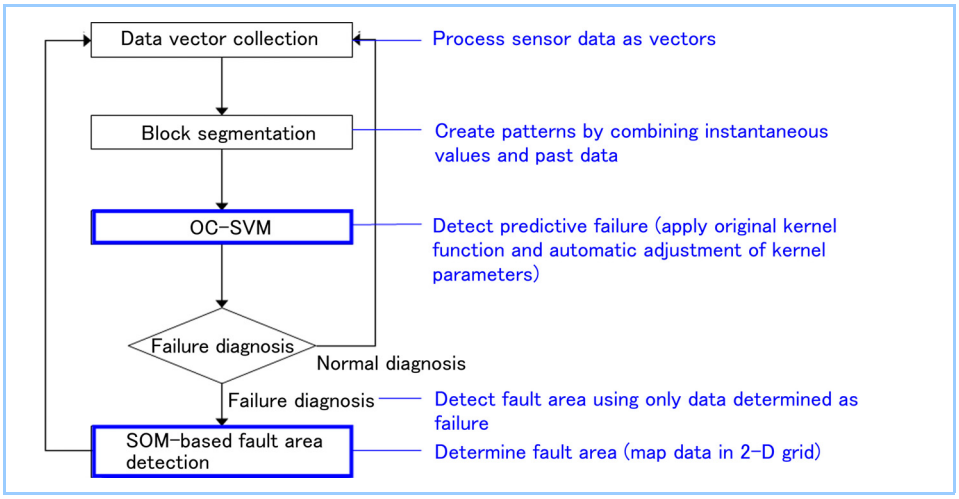

Figure 2 Flow of detection method of predictive failure and corresponding area

3. Scale models

Parts of an aircraft's wings (e.g., aileron, ground spoiler, multifunction spoiler) are powered by oil pressure. Ailerons, for example, are used to control rolling of the aircraft, whereas ground spoilers are used to slow the aircraft upon landing. Failures in the hydraulic system, therefore, lead to serious problems such as inability to maneuver the aircraft's position or runway overrun upon landing.

Meanwhile, the aircraft air-conditioning system processes high-temperature air drawn from the engine intakes and uses it in cooling/heating units. When the engine starts immediately before takeoff, the load on the system increases drastically. This sometimes causes malfunctioning of the intake area and flight suspension.

As failures in the above systems can have dire consequences for an aircraft, early fault detection is crucial. In this study, scale models simulating parts of the two systems were developed in order to assess the accuracy level of the detection method.

3.1 Hydraulic system

The configuration and images of the scale model are shown in **Figure 3**. As illustrated, the actuator for various control surface elements such as the ailerons is powered by the oil discharged from the engine pump. A failure mode and effect analysis (FMEA) on the hydraulic system has found abnormalities that occur in engine pumps, control valves and actuators to be particularly serious. Therefore, actual devices are used for these components, whereas simulated models are used for the control system and the airframe control, based on a simulation technique known as the hardware-in-the-loop system (HILS).

Taking into account the result of the FMEA analysis, a drop in volume efficiency of the engine pump and internal leaks in the control valves (ailerons and multifunction spoilers) are chosen as failure events simulated using the scale model in Figure 3. In this model, both events are recreated by opening the valves, which are equipped with a mechanism that creates leaks.

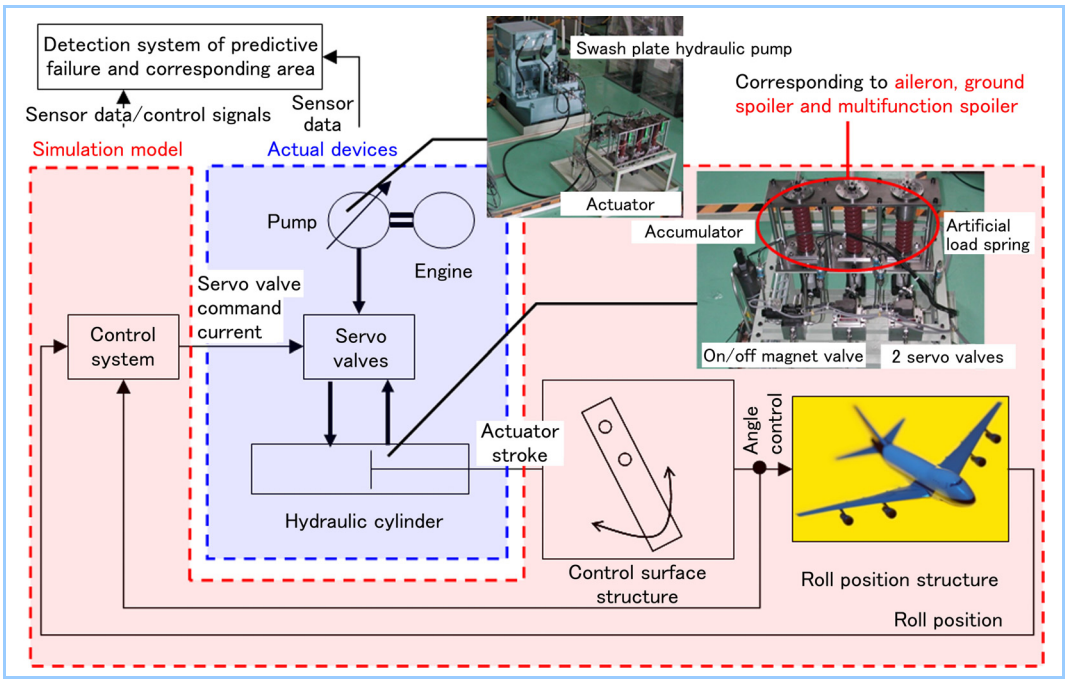

Figure 3 Configuration and images of hydraulic scale model (HILS)

3.2 Air-conditioning system

The scale model of the air-conditioning system represents the portion of an engine intake where high-temperature air flows as shown in **Figure 4**. Furthermore, **Figure 5** shows the configuration of a simulation model that includes a low-temperature air intake system and a heat exchanger developed for this study. The model simulates temperature control of air exiting from the heat exchanger by adjusting low-temperature air flow. In addition, data obtained from the scale model are used in the simulation model to determine validity. Based on the configuration shown in Figure 5, the air-conditioning system model recreates failure events such as heat exchanger leaks, blockage of flow control valves and pressure gauge malfunction.

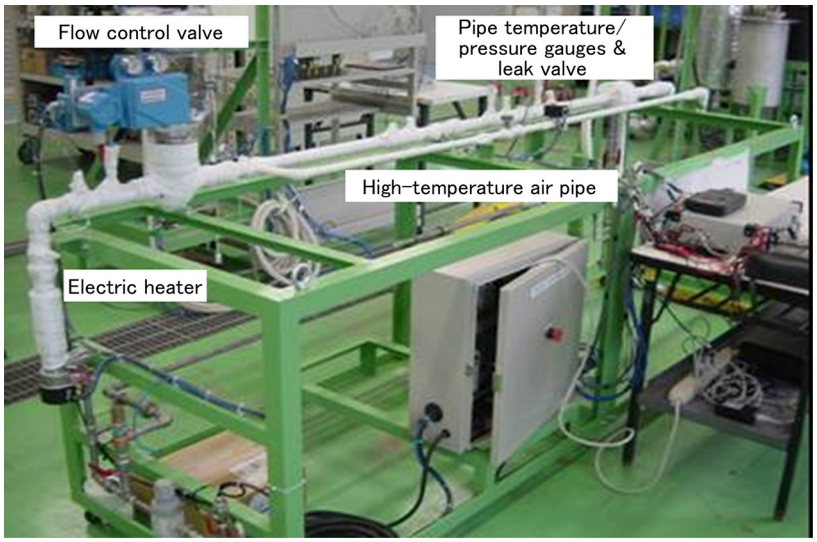

Figure 4 Scale model of air-conditioning system

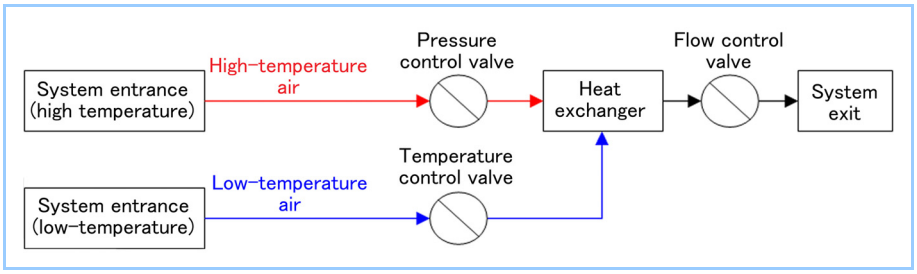

Figure 5 Configuration of simulation model of air-conditioning system

4. Verification program

In an attempt to evaluate the algorithm described in Section 2 and the practical applicability of the method, an on-line verification program that operates and controls the scale model and performs the detection of predictive failure and corresponding area has been developed for the hydraulic system. As shown in **Figure 6**, the program can display OC-SVM-based abnormality detection results and SOM-based fault area detection results, as well as some data observed from the scale model.

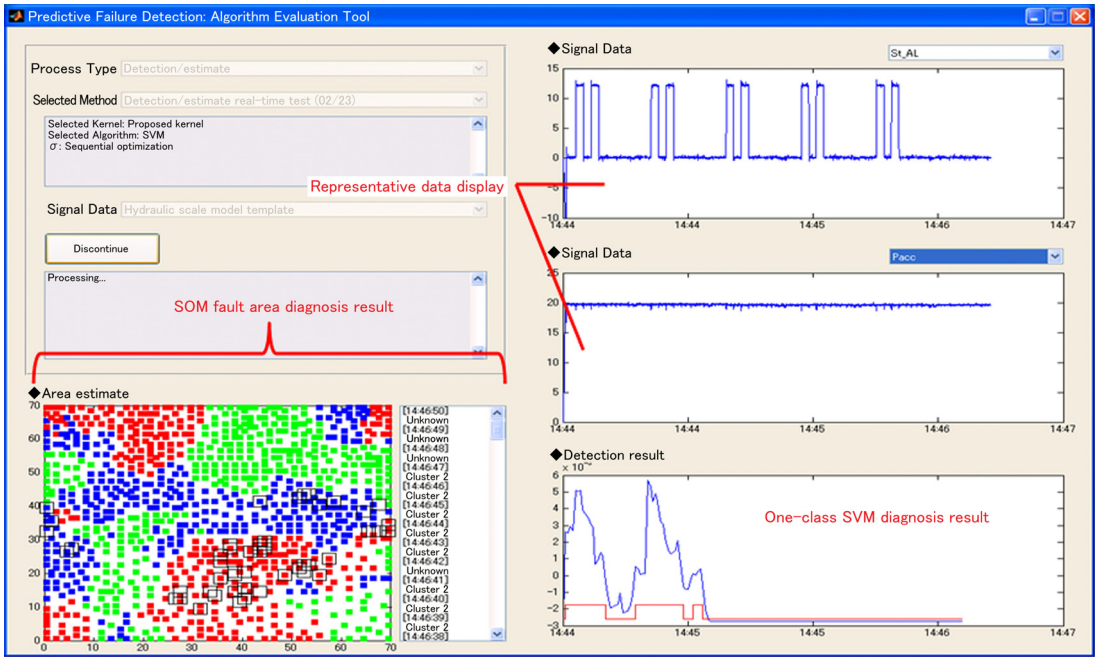

Figure 6 On-line verification program for detection of predictive failure and corresponding area

5. Verification test

This section describes the result of the algorithm evaluation using the scale models. Changes in the altitude of an aircraft cause fluctuations in oil temperature in the hydraulic system and pressure in the air-conditioning system. The scale models developed for this study are used to obtain data by simulating conditions that occur in non-stationary operation during actual flight. As all data input to the algorithm are obtainable from standard sensors on an aircraft, no additional sensors are installed to detect predictive failure and corresponding area.

Figure 7 shows examples of longitudinal data in the hydraulic system with the horizontal axis representing time. The data above indicate behaviors at low oil temperature and the data below at high oil temperature. The blue and red lines represent normal and failure (i.e., drop in volume efficiency) values, respectively. At the same temperature, changes in the ejection pressure of the pump are observed between normal and failure data. However, the pressure also changes when various control surface elements such as ailerons are powered or when oil temperature changes. Therefore, whether the changes observed are due to failure events or an aircraft's non-stationarity effects, such as oil temperature changes, needs to be correctly evaluated.

As described in Section 2, normal data alone are used as the training set in the OC-SVM. The SOM, however, uses failure data from events such as decreased volume efficiency of the pump and malfunction of the servo valves (aileron and multifunction spoiler). Therefore, failure data samples used to identify fault areas need to be obtained in advance. **Figure 8** and **9** show the verification results of the predictive failure detection system in Figure 2. The degree of abnormality in Figure 8 is the OC-SVM classifier output, with non-negative representing normal and negative abnormal. The graph demonstrates that normal data are correctly classified. In addition, it also shows that the original kernel function developed for this study produces a higher accuracy in detecting predictive failure than a conventional Gaussian kernel.

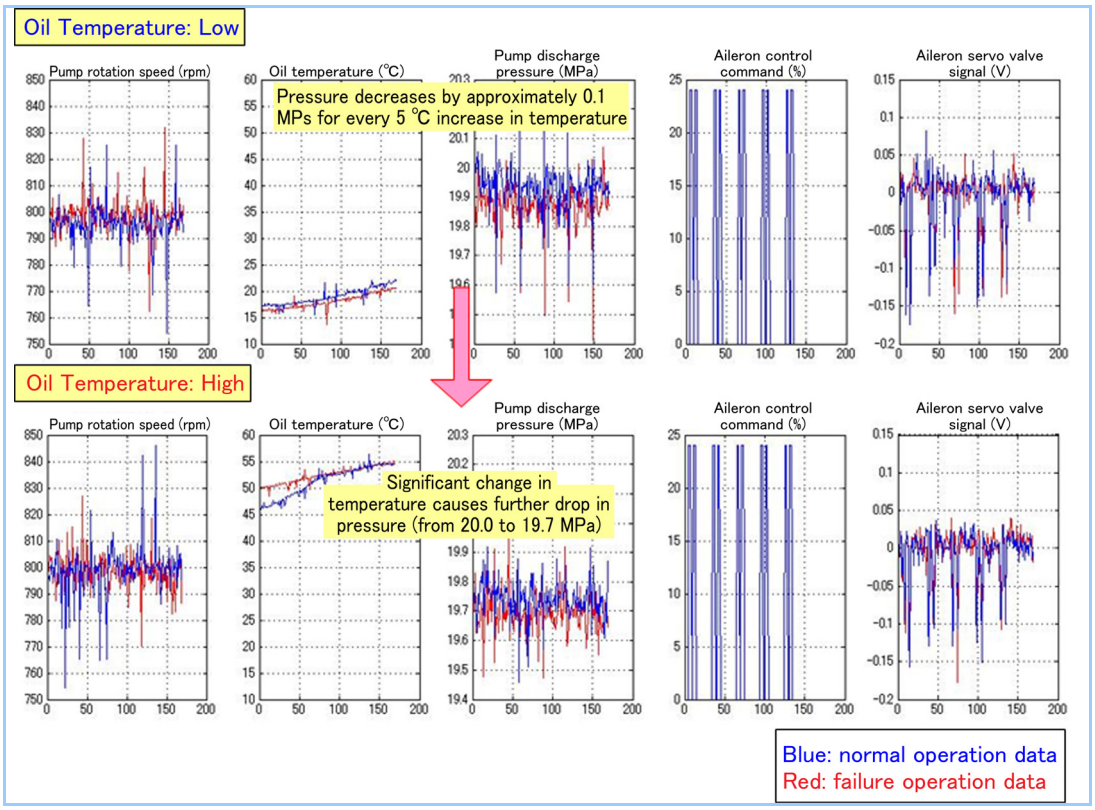

Figure 7 Longitudinal data in hydraulic system

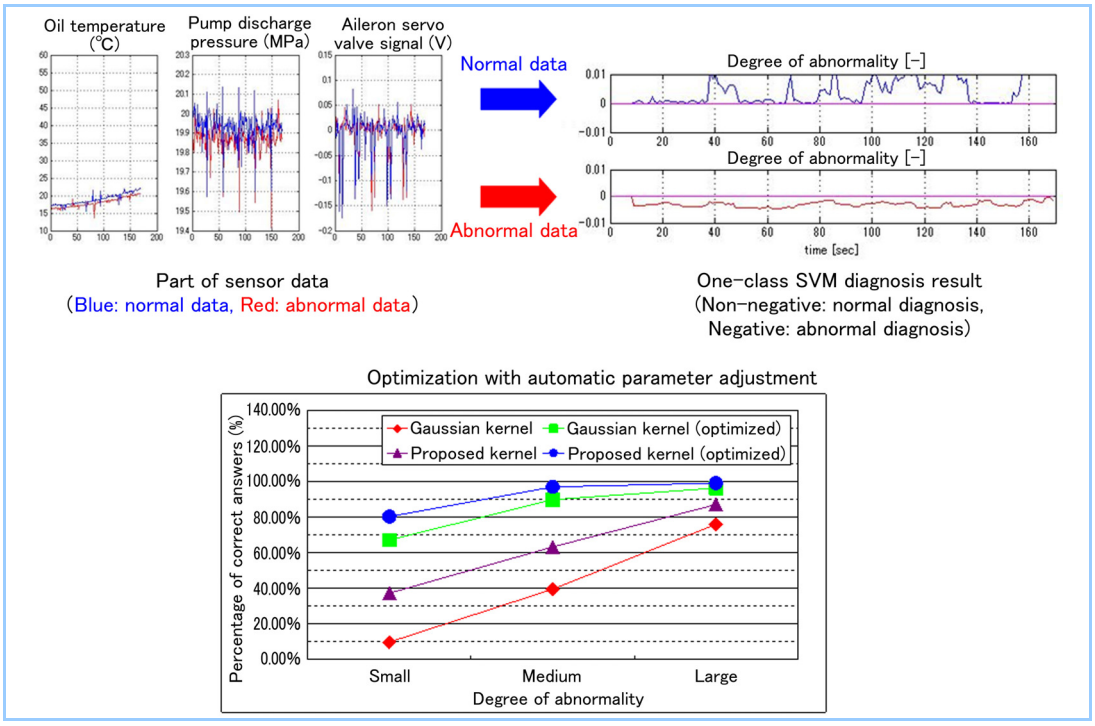

Figure 8 Results of predictive failure detection with One-class SMV

Meanwhile, Figure 9 shows the training results of the SOM, colored in blue, red and green. The vertical and horizontal axes on the map represent coordinates and have no physical reference. The high-dimensional input vectors (sensor data group) in Figure 2 are organized by fault area and mapped onto the two-dimensional grid shown in Figure 9. The tri-colored dots on the grid are the training data in failure events: decreased volume efficiency of the pump (blue) and malfunction of the servo valves (aileron in red and multifunction spoiler in green). As shown, large clusters formed for each failure data group, indicating the training data are properly classified by area. In this example, data from decreased volume efficiency of the pump are presented as the verification result shown with a black square frame. Many black square frames are plotted above the blue dots, indicating the capability of SOM-based fault area detection.

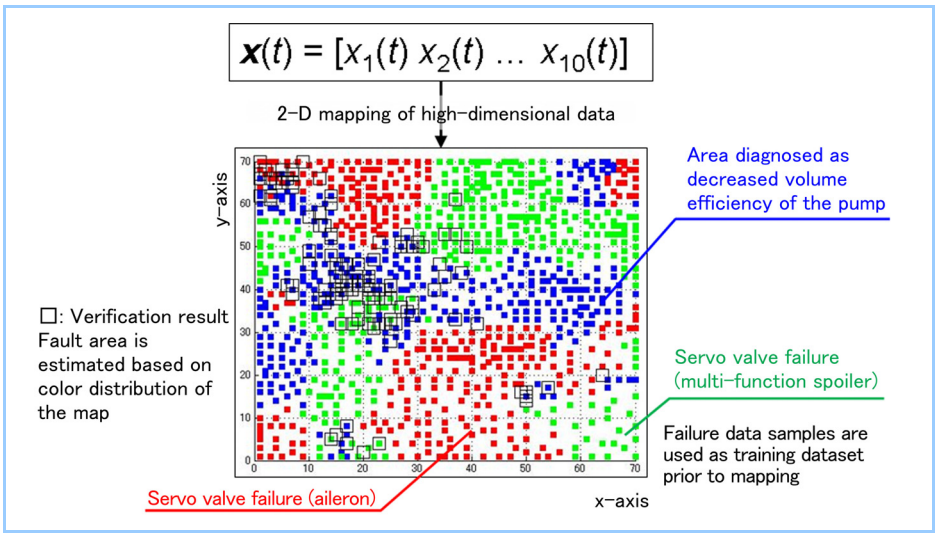

Figure 9 SOM-based fault area detection

6. Conclusion

With today's increasingly complex and large-scale systems such as transportation equipment and power generation plants, unexpected situations may occur that are impossible to foresee based solely on the characteristics of individual system elements, and minute changes in one area may have a significant impact on the entire system. Many such systems are mission critical and a system failure or a stoppage can pose a threat to human lives. Therefore, technology that can detect areas showing signs of failure in advance needs to be implemented. In this study, algorithms for detecting predictive failure are assessed using aircraft as examples of complex large-scale systems. Out of the numerous systems required in aircraft operation, this study focused on hydraulic and air-conditioning systems, where failures cause significant consequences. Data were obtained using scale models for the systems, built partially incorporating actual devices. Furthermore, the validity of the algorithms reviewed in this study was also evaluated using a verification program that performs the algorithms. As a result, different types of simulated failures were successfully detected. MHI will continue to engage in sample data collection and quantitative testing of the method on an ongoing basis. Although this study uses aircraft systems, the application of the developed method is not limited to such systems. As a method based on pattern recognition has potential applications across a wide range of complex systems, MHI will aggressively pursue further development in this area.

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