Intelligent motor valve with failure prediction feature - Hiroyuki Kawazato[1]

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1. Introduction

In the dry etching process, wafer temperature control is extremely important because the critical dimension (CD) strongly depends on the wafer temperature [1]. Wafer temperature is maintained constant by the chiller connected to the etching system. In the chiller, motor valves play important role to control the fluids such as coolant and cooling water (Fig.1). Once the motor valves fail, not only will the yield drop, but in the worst case, the production itself will stop. Therefore, it is very important to predict the failure in advance. The semiconductor smart factories introduce intelligent tools that can predict the failures based on self-diagnose technology [2]. From now on, the edge modules like valves will also need to be intelligent.

For creating a failure prediction model, genetic algorithm [3] or deep learning [4] is commonly used. However, the models created with these technologies are not suitable for inclusion in the motor valve, because they require hardware with extensive computational power. This paper presents a newly developed compact failure prediction algorithm that can be installed in the edge modules with limited computational power, which enables the motor valve to be intelligent.

2. Experimental

A control block diagram for the motor valve is shown in Fig.2. The manipulated variable (MV) output from the controller rotates the actuator inside the motor valve so that the set value (SV) and the process variable (PV) are equal. The amount of rotation of the actuator is measured by the rotary encoder and fed back to the controller as PV. We have created the prediction model using machine learning based on 60,969 sets of data of PV and MV of non-failed motor valves, and developed a prediction algorithm suitable for edge modules. The validity of the algorithm was verified using normal and worn valves.

3. Results and Discussion

Figure 3 shows the PV, MV and difference between PV and MV (PV−MV) as a function of time. There is no clear difference in PV−MV between normal and abnormal. This may be due to a few seconds delay of actuator rotation. Therefore PV−MV cannot be used as a feature value to predict abnormality. Then, we calculated the predicted value of PV (Pred PV) after actuator rotation using prediction model. Figure 4 shows the PV, MV and difference between PV and Pred PV (PV−Pred PV) as a function of time. The peak-to-peak value of PV−Pred PV is 1.7% for normal and 3.1% for abnormal. Normal and abnormal is clearly distinguished. Therefore, we decided to use PV−Pred PV as a feature value to predict abnormality.

Prediction accuracy was calculated by multiple regression analysis (OLS, Lasso) and decision tree analysis (LGBM, RF), using short-term data. The results are shown in Table 1 together with the required computing power. Decision tree analysis has higher prediction accuracy. For instance, prediction accuracy of LGBM is 93.98 % for normal and 68.60 % for abnormal. However, the memory size and number of steps are very large at $1.2x10^3$ kB and $3.28x10^6$ steps, respectively. The prediction accuracy by OLS is 87.60% for normal and 66.43% for abnormal, which are lower than those of LGBM. However, the memory size and number of steps are very small at 0.6 kB and 150 steps, respectively. There was no difference in failure prediction results even with the OLS which has inferior prediction accuracy. Based on the above results, OLS was selected as a machine learning method for calculating prediction accuracy.

Figure 5 shows the calculation flow to reduce the probability of misjudgment by calculating the match rate between measured PV and Pred PV multiple times. Figure 6 shows the results of long-term match rate analysis. The average match rate is 87.60% for normal motor valves and 66.40% for abnormal ones, showing a clear difference. This result shows that it is possible to determine the abnormality of motor valves by failure prediction algorithm using OLS.

4. Conclusion

We have developed a compact failure prediction algorithm using multiple regression analysis OLS. This algorithm can be installed in motor valves because it needs only 150 steps for calculation. This technology will enable the motor valves to be intelligent.

References

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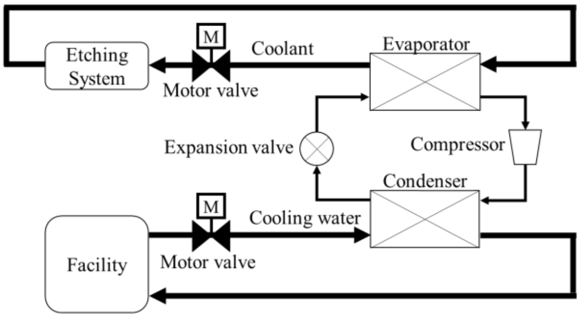

Fig.1. Schematic diagram of chiller system.

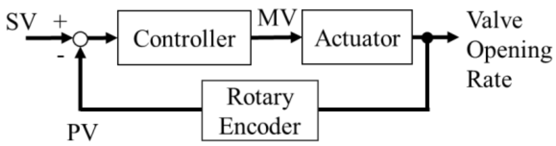

Fig.2. Control block diagram for motor valve.

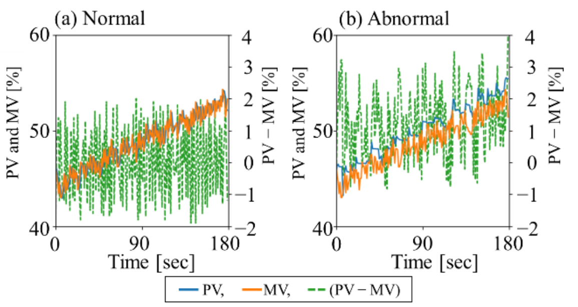

Fig.3. PV, MV and PV−MV as a function of time; (a) normal, (b) abnormal.

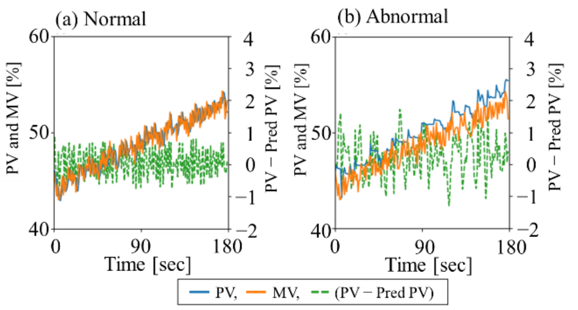

Fig.4. PV, MV and PV− pred PV as a function of time; (a) normal, (b) abnormal.

Table 1. Prediction accuracy calculated by multiple regression analysis and decision tree analysis, using short-term data.

		Multiple regression analysis		Decision tree analysis	
		OLS	Lasso	LGBM	RF
Prediction accuracy [%]	Normal	87.60	67.67	93.98	97.35
	Abnormal	66.43	52.87	68.60	63.24
Memory size [kB]		0.6		1.2×10^3	37.4×10^3
Number of steps [Step]		150		3.28×10^6	31.5×10^6

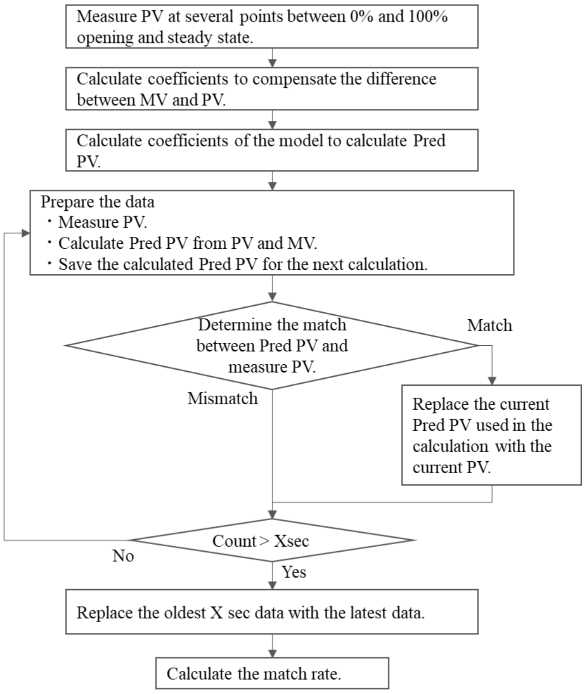

Fig.5. Calculation flow to reduce the probability of misjudgment by calculating the match rate multiple times.

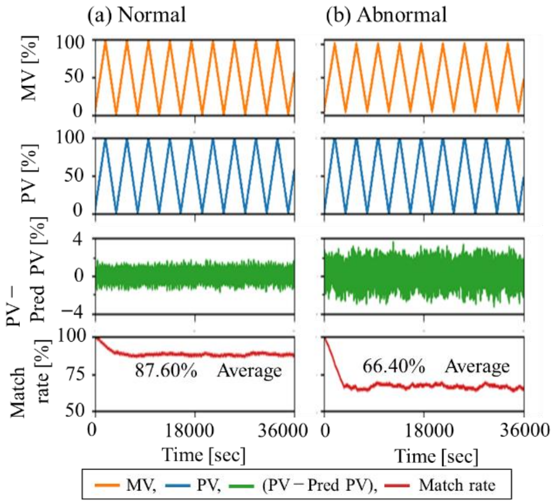

Fig.6. Long-term match rate analysis; (a) normal, (b) abnormal.