An Approach to Create Trench Depth Prediction Model -Xueting Wang

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1.Introduction

In power MOSFET manufacturing, in order to detect the abnormality of the equipment in real time, we created a prediction model from multiple equipment process parameters (PPC)[1) -2)] (Fig. 1). Two years ago, we reported the method to monitor the condition of equipment by the cross-sectional trench area prediction model. But this area was calculated roughly from the trench depth and width, so it became clear that the abnormality detection sensitivity was insufficient if we only use this model. Therefore, we decided to examine a predictive model for trench depth and width. In this paper, we will describe the problems and solutions to create the trench depth prediction that is especially challenging.

2. Problems and Solutions

(1) Problems

The trench we describe in this report is formed by multiple steps of the RIE (Reactive Ion Etching) process (Fig. 2). There are approximately 400 parameters in RIE equipment logs which may affect the trench depth. Since these parameters are composed of multiple steps, each parameter is entangled intricately with one another. Furthermore, as trench depth model is likely a non-linear model, we tried to use GBDT (Gradient Boosting Decision Tree), which is one of the ensemble learning method using decision tree, to create the trench depth model.

We used the same method as previously reported to do the data preprocessing (screening of outliers, removal of constant value factors, etc.), followed by the creation of the prediction model using GBDT. The obtained training accuracy of the model is very high (R^2=0.99), while the verification accuracy is low (R^2=0.39) (Fig. 3). The difference between the training accuracy and the verification accuracy is too large. So first we checked the learning curve (Fig. 4). It shows that even when the number of the training data increases, the training score remains as 1, whilst the verification score remains low. Thus, we speculated that over-fitting may had occurred during the modeling process.

(2) Approach and Results

In order to investigate the cause of the large difference between the training accuracy and the verification accuracy, we compared the time-series trends of the actual value and the predicted value in both training and verification. As a result, the actual value and the predicted value showed almost same trend in training. But on the other hand, the difference between the actual value and the predicted value is sometimes large in the verification (Fig. 5). At those periods, the actual value changed greatly, but the predicted value did not change so much. After looking into the equipment log parameters, we know that some parameters changed greatly during the same time periods. After we confirmed with our equipment technician, it was found that an event (equipment maintenance) had been performed during those periods.

So we tried to create a model excluding the data for a certain period after equipment maintenance. The learning curve shows that as the number of samples increased, the training and verification scores tended to gradually approach each other (Fig. 7), the verification accuracy was also improved by about 0.2 (Fig. 8). From this result, it was confirmed that the decrease in accuracy is due to over-fitting, and that the accuracy can be improved by excluding the data for a certain extent after events.

3. Conclusions

We attempted to create a trench depth model with GBDT. Although the accuracy of the model was not good at the beginning, during cause investigation, we found out that the equipment condition changes after equipment events (maintenance, etc.). Over-fitting occurred due to abnormal data after the equipment event. So over-fitting can be suppressed by excluding the data when the equipment condition changed. In the equipment abnormality detection, there was no problem even if the equipment event data was excluded. And excluding the abnormal data can lead to the improvement of the accuracy of the equipment control prediction model.

4. References

1) Xueting Wang, Yasuhisa Oomuro, Kazutaka Nagashima, "RIE Equipment Control by Cross-sectional Trench Area Prediction," Proceedings of AEC/APC Symposium Asia 2019, TDA-014.

2) M. Kano, "Data-based Process Modeling" Journal of the Society of Instrument and Control Engineers, vol. 49(2), pp 101-106, 2010.

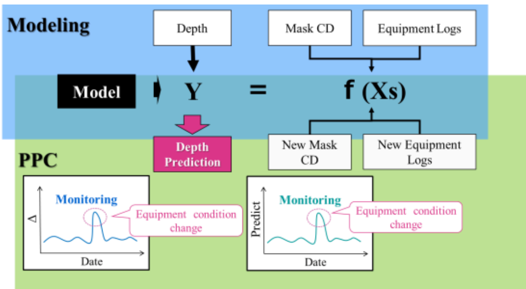


Fig. 1 The Outline of PPC

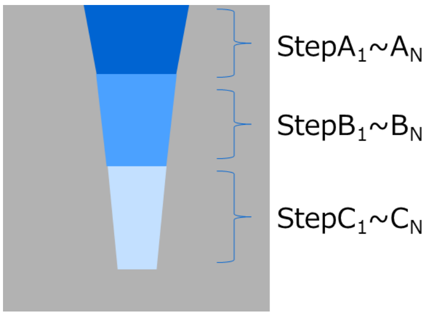
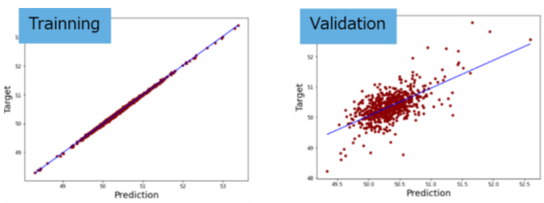


Fig. 2 Image of Trench



(a) training accuracy (b) verification accuracy

Fig. 3 Model Accuracy

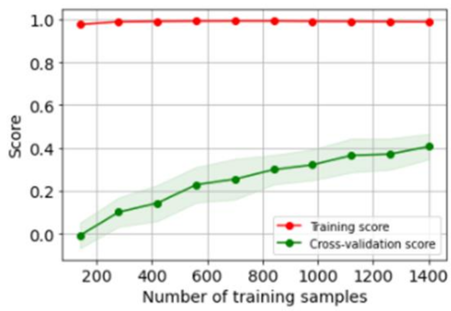
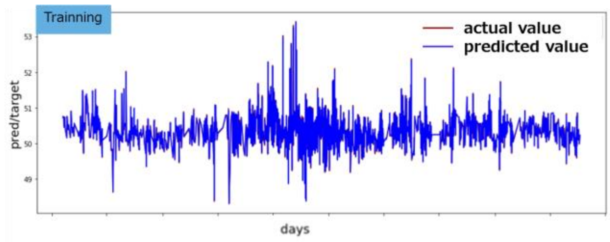
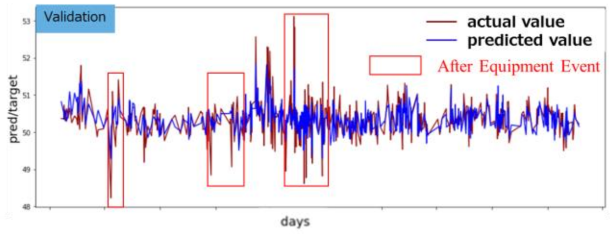


Fig. 4 The Learning Curve



(a) Actual value vs Predicted value of Training data



(b) Actual value vs Predicted value of Verification data

Fig. 5 Comparison of Actual value and Predicted value in Time-series Data

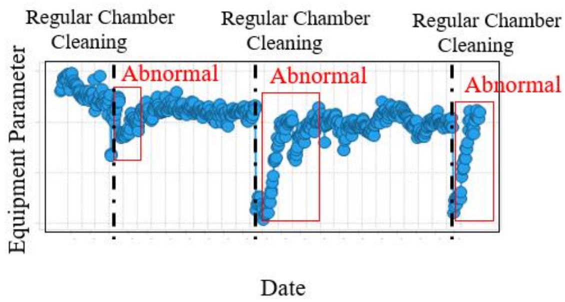
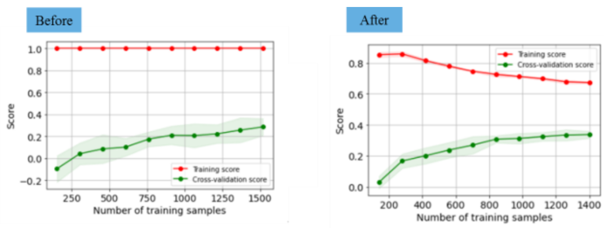


Fig. 6 Time-series data of Equipment Parameter



(a) Including the data after equipment maintenance (b) Excluding the data after equipment maintenance

Fig. 7 Comparison of Learning Curve

Before

	index	Scores
0	R2	0.391680
1	MSE	0.115374

(a) Including the data after equipment maintenance

After

	index	Scores
0	R2	0.647603
1	MSE	0.065921

(b) Excluding the data after equipment maintenance

Fig. 8 Comparison of Model Accuracy