Study of Photomask Manufacture Process Based on AI Technology

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DNP

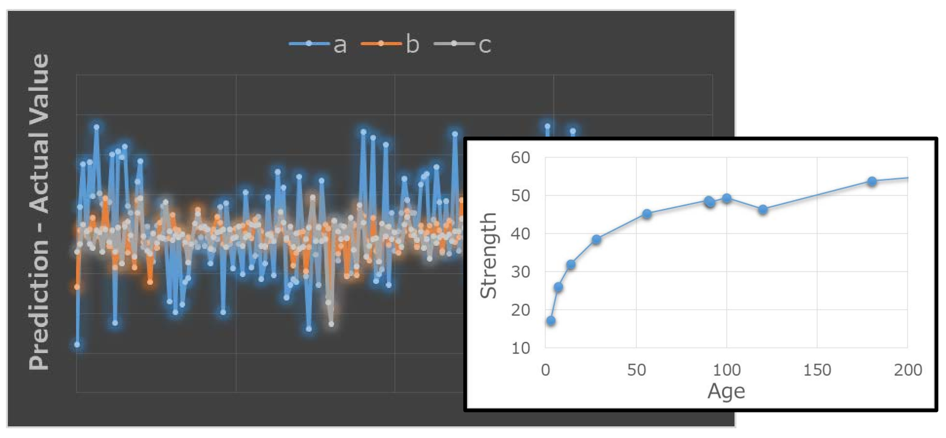
Introduction

■ Motivation

・As a mask merchant, we have wide variety of process. Using these manufacturing data and machine learning, we want to improve our quality.

・XAI(explainable AI) can reach the real root cause.

The example of concrete compressive Strength (dataset ※1) .



	Model	MAE
a	Linear Regression	8.1
b	G.B. Trees (Regression)	3.1
c	-Standardization -Regularization -Light G.B.	2.5

※G.B. : Gradient Boosting
※MAE : Mean Absolute Error

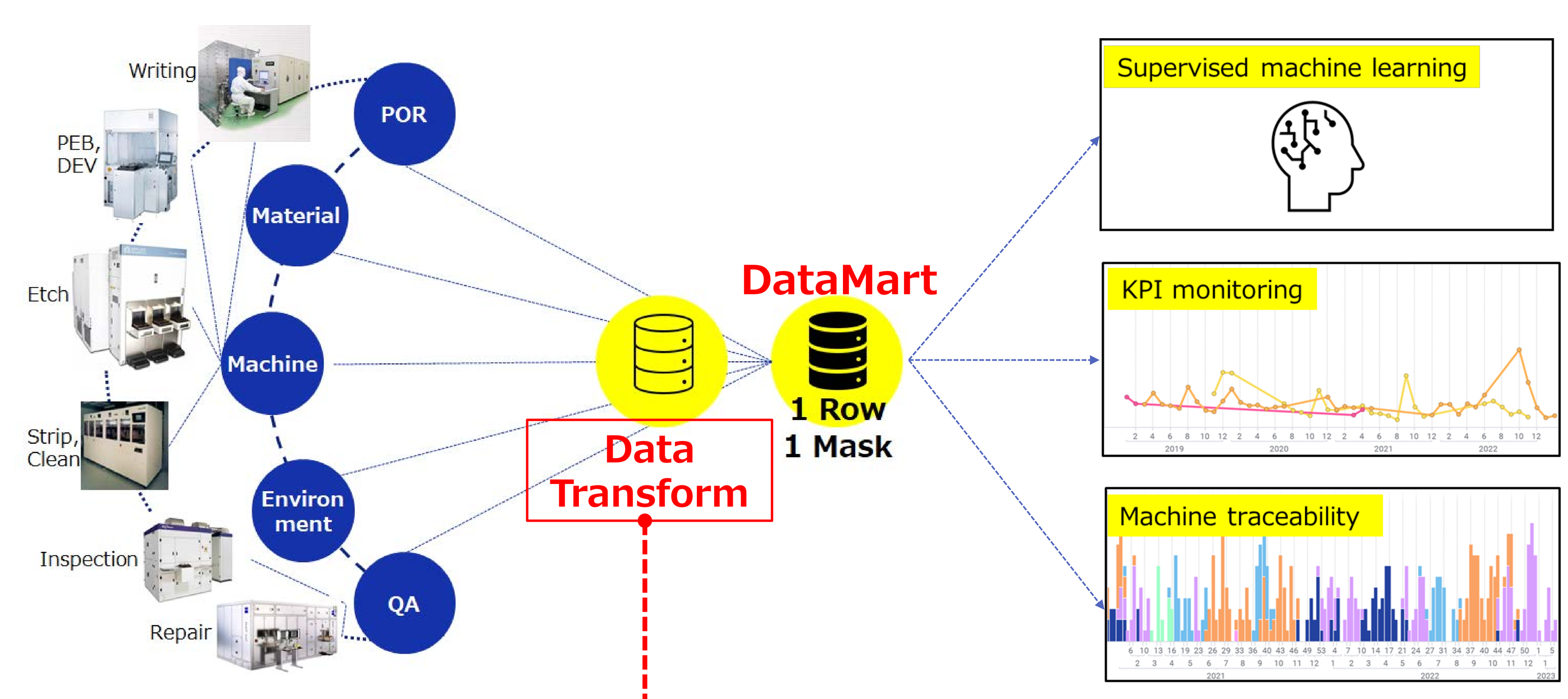
Parameter tuning and machine learning are the keys to mitigating error. Non-linear parameter effects are common in the manufacturing industry.

(※1) I-Cheng Yeh, "Modeling of strength of high performance concrete using artificial neural networks," *Cement and Concrete Research*, Vol. 28, No. 12, pp. 1797-1808 (1998)

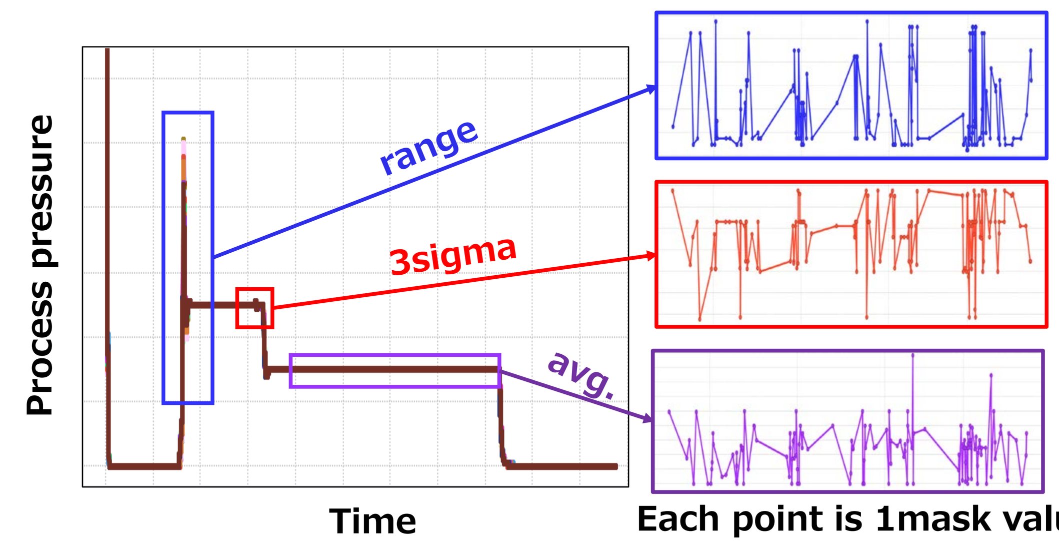
	Item	Objective
1	DataMart build up	✓ Comprehensive data collection
2	Defect improvement by machine learning	✓ how to extract the root cause - to mitigate un-effected parameter impact - XAI ✓ for opaque and isolated defects ✓ for killer defect

DataMart build up

Mutually Exclusive, Collectively Exhaustive

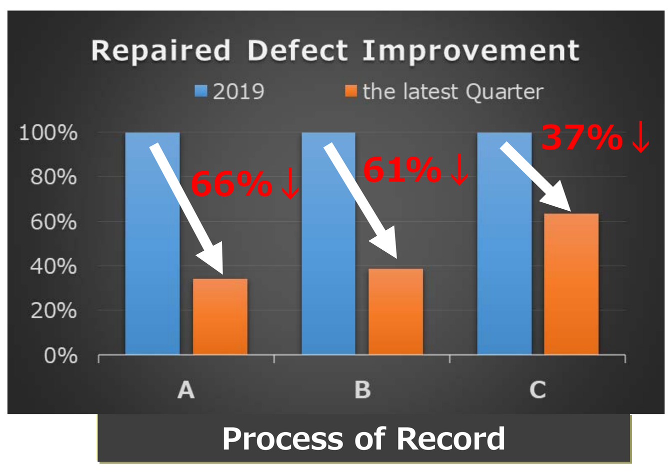


RAW data to feature value - e.g. vacuum equipment process



Extracting the characteristic parts from the raw data and replaced with statistical values for each feature

Defect Factor extraction by machine learning



In addition to traditional method (e.g. split test), we took advantage of

・Mask traceability data and

・Machine Learning

Variable	Item	Target and Example	Parameter count
Target	Defect count	Over / Under threshold = Posi./ Nega.	1
Explanatory	Material	Material, Glass coverage	≒ 1000
	Machine	Log	
	Method	Process path, Recipe	
	Traceability	Process Delay	
	Environment	Airborne Molecular Contamination	

Too many explanatory parameter ⇒ must reduce

"Permutation Importance(PI)" can measure the variable importance (※2).

$$error = Loss\ Function(target, model(X))$$

We choose one(a) variable, sort it randomly and get new vector(X_a^p).

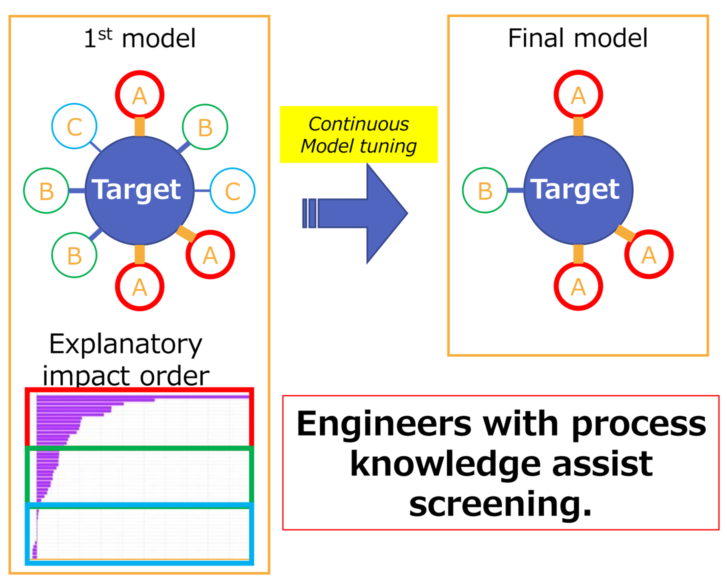
$$error^p = Loss\ Function\left(target, model(X_a^p)\right)$$

$$Permutation\ Importance(a) = \frac{error^p}{error}$$

If PI value is big, this variable has big effect.

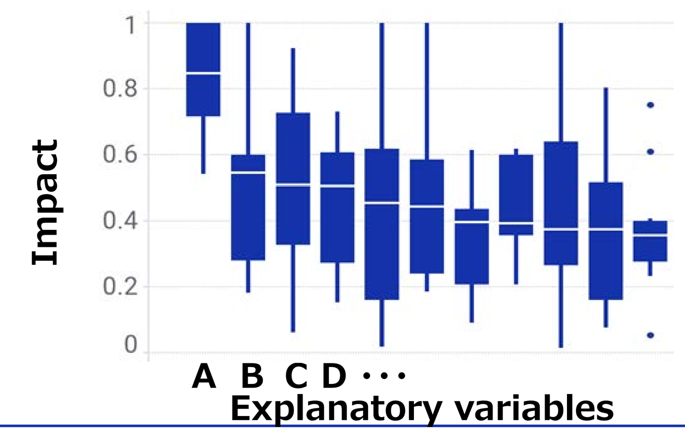
(※2) Aaron Fisher, Cynthia Rudin, Francesca Dominici, "All Models are Wrong, but Many are Useful: Learning a Variable's Importance by Studying an Entire Class of Prediction Models Simultaneously, *Journal of Machine Learning Research 20 (177), 1-81, (2019)*

1st stage methodology : Explanatory data screening

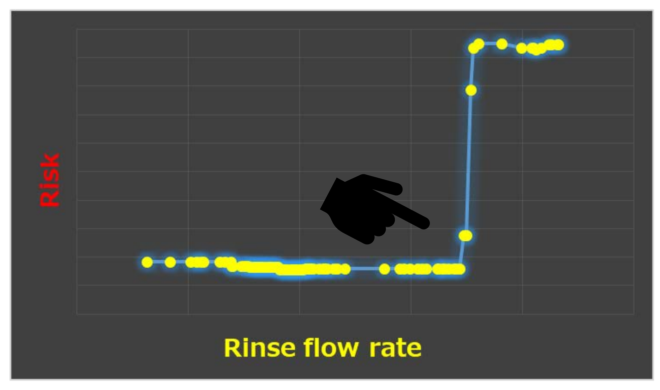


2nd stage methodology : key parameter extracting

1. Using random seed, try to reduce model noise
2. Impact were sorted in descending order using median.

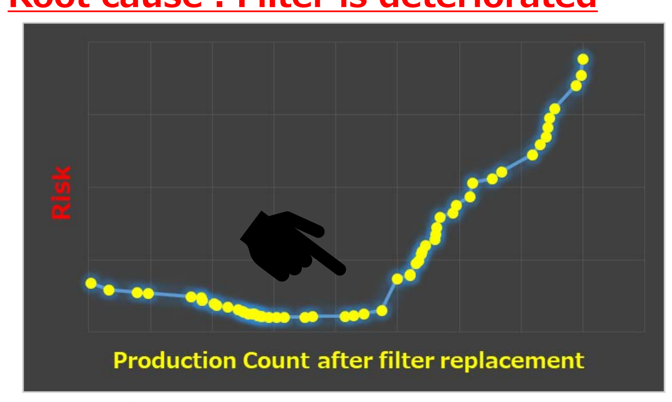


Root cause : Rinse flow rate is effective



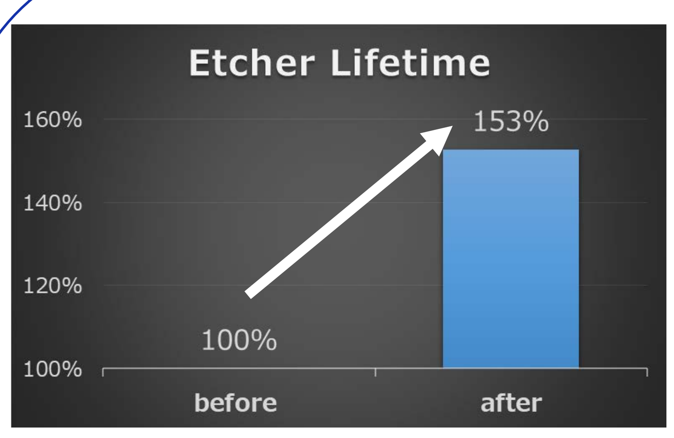
We assume that resist is scattered by rinse flow rate above the certain level.

Root cause : Filter is deteriorated



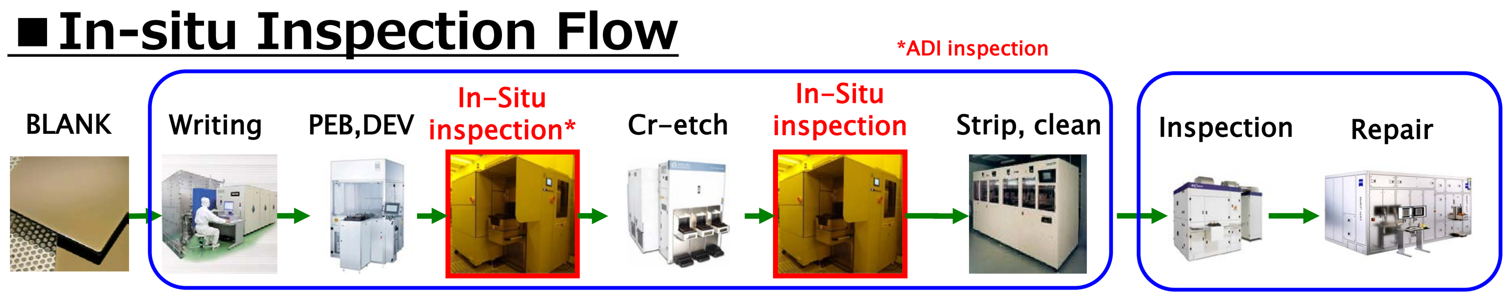
Even if tool particle check's normal, this model tell us the timing of filter replacement.

In-Situ Inspection tool and machine learning



In addition to traditional method, we took advantage of "in-situ inspection tool(JDNP5000)" and Machine Learning

■ In-situ Inspection Flow



Our In-Situ Inspection tool "JDNP5000" (reported at PMJ2017※3) can judge killer defect early, and contribute to improve TAT. In addition, we can narrow down the killer defect(≒ particle) factor in our etching process.

We considered this case to be highly compatible with "machine learning".

(※3)Study of in-situ inspection for 10nm lithography mask and beyond, Shingo Yoshikawa, Hideki Inuzuka, Takeshi Kosuge, Masaharu Nishiguchi, Hidemichi Imai, Toshiharu Nishimura, Dai Nippon Printing Co., Ltd. (Japan).

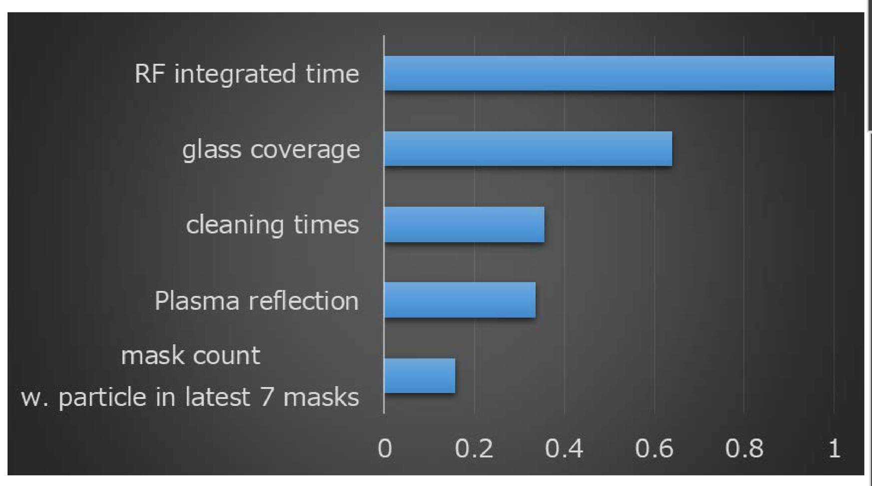
Variable	Item		Parameter count
Target	"No defected" / "defected" Particle = Nega. / Posi.		1
Explanatory	Material	Material, Glass coverage	51
	Machine	Log, Cleaning, RF total time	
	Method	Recipe	

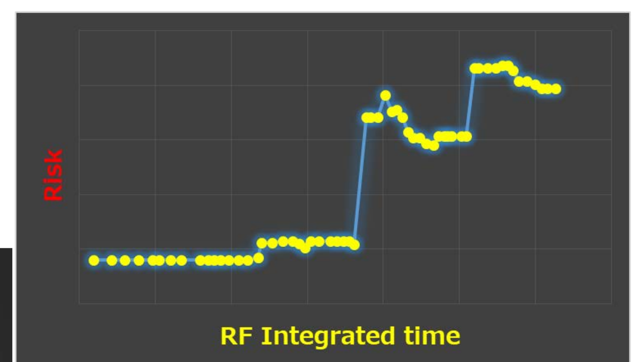
Model : Light Gradient Boosted Trees Classifier

・Cross Validation AUC 0.669

・Recall 0.945

・Precision 0.557





Unstable plasma causes the plasma fluctuation, and trigger to chamber material damage.

$$F = qE - \frac{1}{2}E^2\nabla\varepsilon + \frac{1}{2}\nabla\left(E^2 m\frac{d\varepsilon}{dt}\right)$$ ※4

We improved plasma stability by some ways, then we got good results.

(※4)
・J. A. Stratton, *Electromagnetic Theory.* New York: McGraw-Hill, 1941
・Tsuyoshi Moriya, Hiroyuki Nakayama, Hiroshi Nagaike, Yoshiyuki Kobayashi, Manabu Shimada, and Kikuo Okuyama, "Particle Reduction and Control in Plasma Etching Equipment", *IEEE TRANSACTIONS ON SEMICONDUCTOR MANUFACTURING*, VOL. 18, NO. 4, NOVEMBER, (2005)

Conclusion

■ Machine learning has become very familiar. However, for photomask manufacturers, especially merchant mask makers which have various customers, to take advantage of it, DataMart build up is very important. Because each parameter affecting quality is different by POR.
■ The skills related to data preparation and how to interpret the results are still left to the engineer, and that is where it gets interesting.
■ We are also currently working on guaranteed value prediction and equipment/process anomaly detection using machine learning.

未来のあたりまえをつくる。