

AI in manufacturing

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Overview

■ Process, Product, Equipment

EBI: E-beam inspection
VM: virtual metrology
FDC: Fault detection and classification (FDC)
CV: compute vision
AOI: Automated optical inspection
R2R control: run to run control
PHM: prognostic health management
OES: optical emissions spectroscopy (equipment)
PO: parameter optimization
SPC: statistic process control
DOE: Design of Experiment

Pre-process Step
(feedback to next step)

Post-Process
Step

Spectrum,....

Wafer map/ EBI
Defect detection
Position correction

SPC/ DOE

OES

CV 、 AOI

VM

FDC

PO

PHM (PdM)

R2R control

Processing
Step

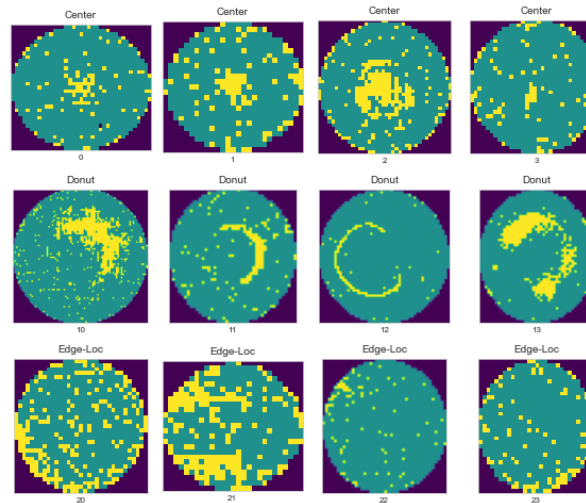
For process or machine

PM schedule



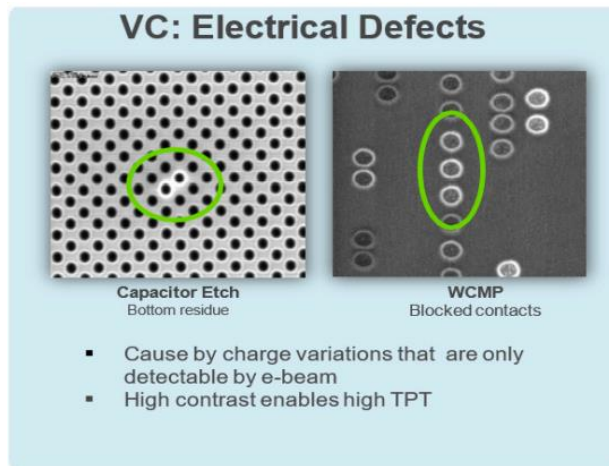
CV Application

- Wafer map

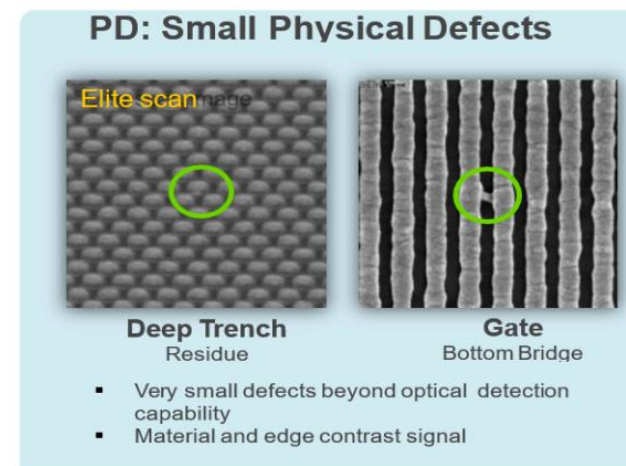


HW2

- Electrons Beam Inspection (EBI)



Voltage contrast electrical defects

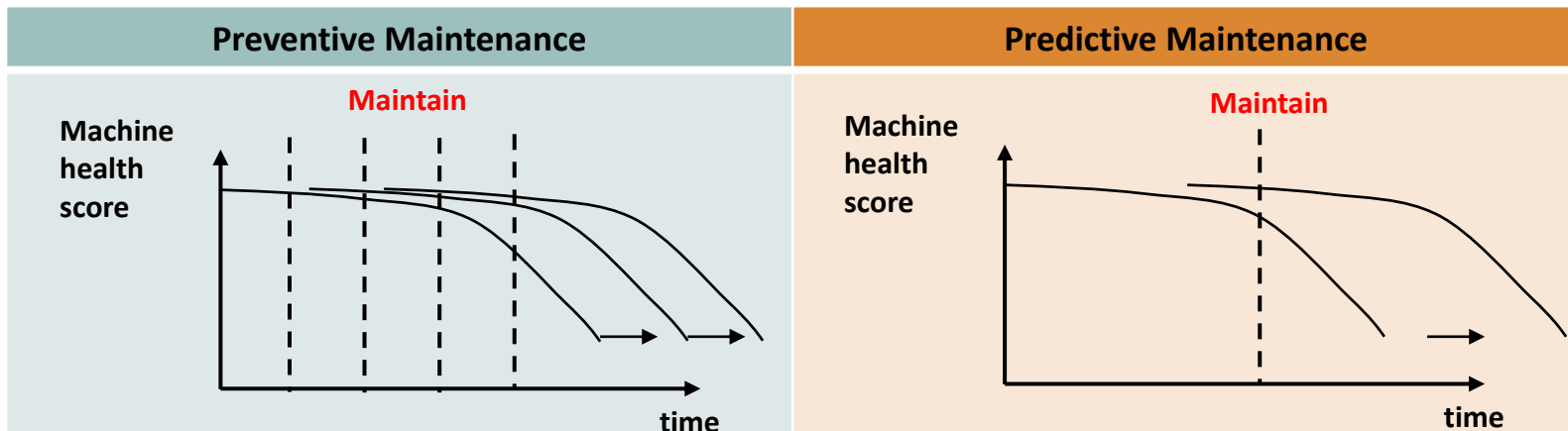
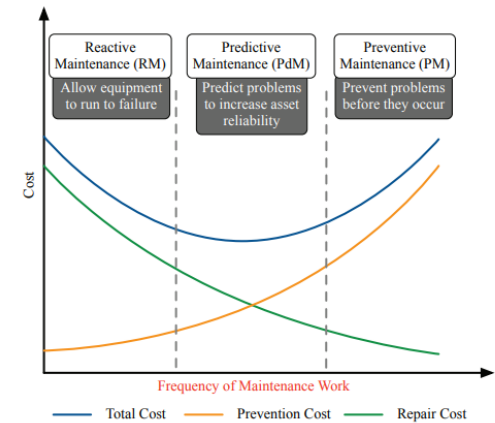


Physical defects



Maintenance Strategy

- Run-to-Failure (R2F) or Corrective maintenance
 - Only happens when an equipment stops working
 - Require to stop the production and repair the part
- Preventive Maintenance (PvM)
 - Time-based maintenance/ Scheduled maintenance: periodically maintain usually based on time or process iteration
 - Generally effective to avoid failure but increase unnecessary corrective action
- Predictive Maintenance (PdM)
 - Use predictive tools to determine when maintenance action need to be taken
 - Based on continuous monitor (e.g. sensor data from machine, process, ...)



PHM

■ Prognostic and health management (PHM)

- Detection + Diagnostics + Prognostics (Predictive maintenance is one of Prognostics target)
- Utilize sensory signals to monitor the health condition, detect anomalies, diagnose the faults, and predict the remaining useful life (RUL)

	Stage 1	Stage 2	Stage 3
	Fault Detection	Fault Type Classification	Remaining Useful Life
Problem type	Binary classification problem	Multi- classification problem	Regression problem
Example	Normal vs. Abnormal	Defect type e.g. Scratch, broken,...	When will the tools malfunction

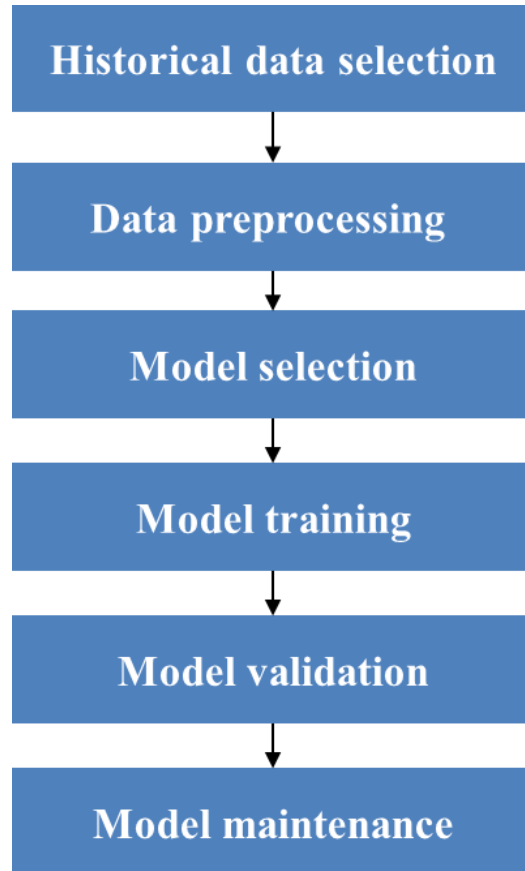


Supervised learning/
Anomaly detection

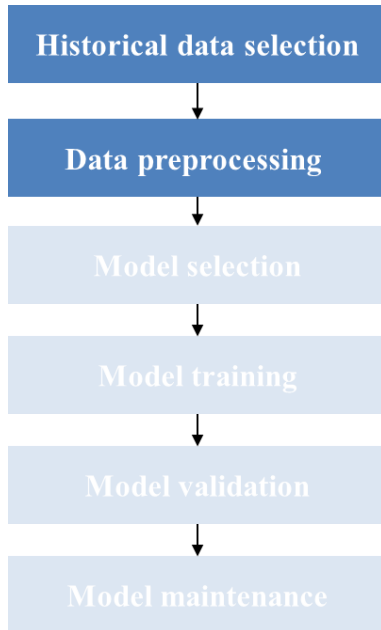
Challenge: imbalance class, unlabeled data, insufficient data, concept drift, real time prediction...



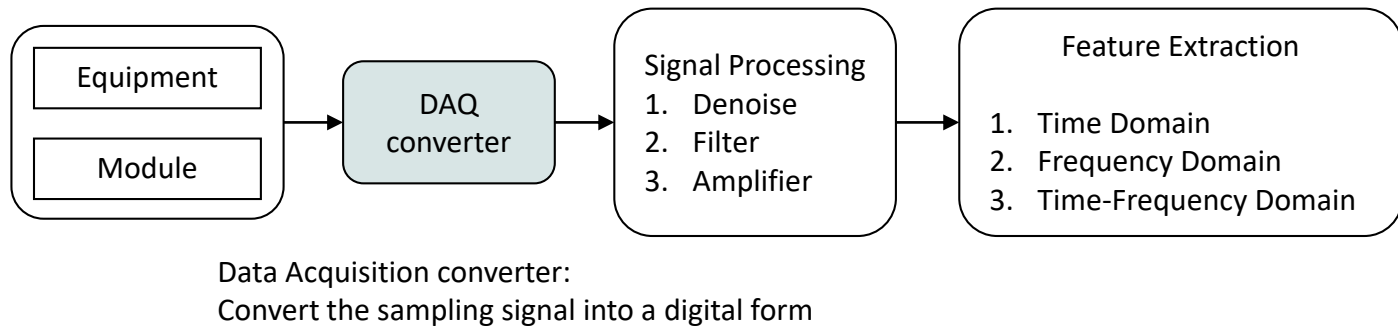
Procedure



Procedure



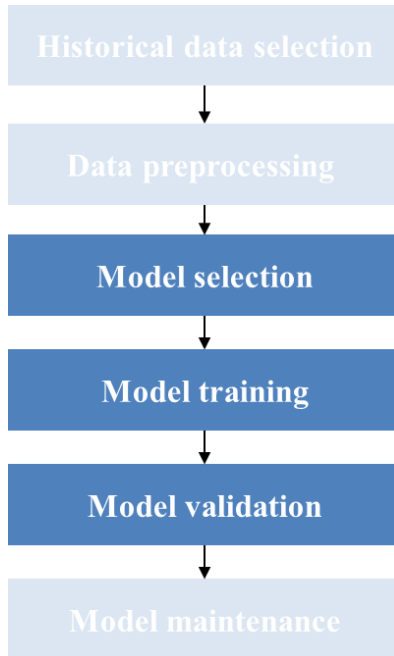
- Data acquisition step: sensory data (vibration, accelerometers, thermometer, acoustic, etc)
- Feature extraction
- Data cleaning, transformation, reduction, outlier detection...



- For time series data (Two ways to model)
 1. Traditional time series approach: $X_t = \beta_0 + \beta_1 X_{t-1} + \beta_2 X_{t-2}$
 2. View as a common regression/ classification problem
 - Sliding Window determination
 - Time domain: kurtosis, min, max, std, mean, range,...
 - Frequency domain: spectral, envelop
 - Time Frequency domain: STFT, WPT, HHT...



Procedure



- For time series data (Two ways to model)
 1. Traditional time series approach
 - ARIMA, SARIMA
 - Holt-Winter exponential smoothing
 - Kalman filter, Particle filter
 - RNN, LSTM, GRU
 2. View as a common regression/ classification problem
 - LR, Ridge, Lasso
 - SVR
 - RF, XGB
 - ANN, CNN, TCN

Feature selection: PCA, LDA, KPCA, SVD, MF, AE, filter-based, wrapper-based

It's important to have previous R2F and PvM strategies to generate historical data of maintenance



Methodology review

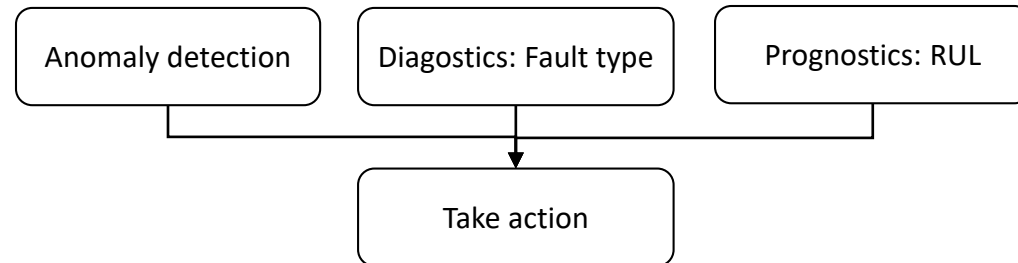
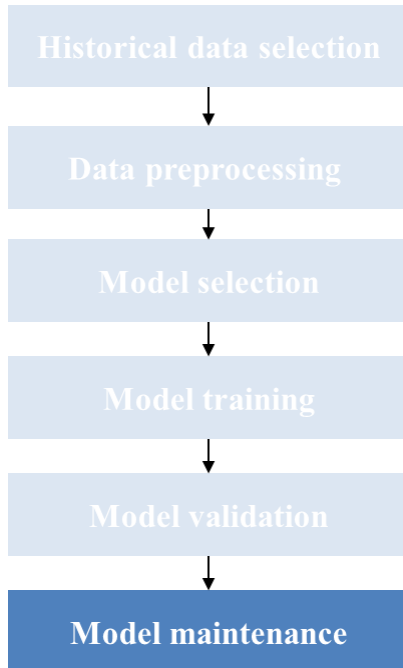
Table 3
A summary of the most recent papers for predictive maintenance.

Reference	ML method(s)	Equipment	Description of the data applied for predictive maintenance	Data type ^a
(Onanena et al., 2009)	LR	Fuel cell	Electrochemical impedance spectroscopy measurements	RD
(Hong and Zhou, 2012)	GPR	Bearing	Vibration data	RD
(Susto et al., 2012)	Linear regularization and Ridge regression	–	Ion Beam Etching process	RD
(Schopka et al., 2013)	LR, RF and BN	Filament	Process data, equipment data and logistic data of breakdown in an implanter ion source	RD
(Susto et al., 2013)	SVM	Tungsten filament	Historical maintenance cycles	RD
(Li et al., 2014)	SVM	Rail network	Historical detector data, failure data, maintenance action data, inspection schedule data, train type data and weather data	RD
(Praveenkumar et al., 2014)	SVM	Automobile gearbox	Vibration signals	RD
(Abu-Samah et al., 2015)	BN	–	Event driven maintenance	RD
(Garg et al., 2015)	MGGP	Metal lathe	Vibration and acoustic signals	RD
(Prytz et al., 2015)	RF	Air compressors in trucks and buses	Data collected on-board the vehicles and service records collected from equipment manufacturers	RD
(Biswal and Sabareesh, 2015)	ANN	Wind turbine	Accelerometer data	RD
(Machado and Mota, 2015)	ANN and SVM	Electrical power systems	Electrical signals	SD
(Susto et al., 2015)	SVM and k-NN	Tungsten filament	Benchmark of semiconductor manufacturing maintenance	RD
(Durbhaka and Selvaraj, 2016)	k-NN, SVM, k-means	Bearing	Vibration signal	RD
(Susto and Beghi, 2016)	SAFE	Semiconductor manufacturing	Maintenance cycle data	RD
(Aydin and Guldamlasioglu, 2017)	LSTM	Engine	Operational and sensor measurements data	RD
(Canizo et al., 2017)	RF	Wind turbine	Status data (alarms activations and deactivations) and operational data from the performance of wind turbines	RD
(Santos et al., 2017)	RF	Squirrel-cage induction motors	Current and voltage waveforms	SD
(Eke et al., 2017)	k-means	Oil immersed power transformer	Dissolved gases concentrations	RD
(Kanawaday and Sane, 2017)	ARIMA	Slitting machine	Sensor data from a slitting machine	RD
(Mathew et al., 2017)	SVM	–	Time-series sensor measurements	SD
(Mathew et al., 2017)	LR, DT, SVM, RF, k-NN, k-means, Gradient Boost, AdaBoost, Deep learning and ANOVA	Turbofan engine	Turbo fan engine data from a prognostics data repository of NASA	RD
(Pan et al., 2017)	CNN	–	Non-intuitive and unstructured acoustic sensor data	RD
(Kumar et al., 2018)	FURIA	Gas turbine	Big data set generated from a gas turbine propulsion plant simulator	SD
(Lasisi and Attah-Okine, 2018)	LDA, SVM and RF	Sample mile track	Track geometry data	RD
(Su and Huang, 2018)	RF	Hard disk drive	Historical data (vibration, temperature, and other variables)	RD
(Uhlmann et al., 2018)	k-means	Laser melting	Machine tool sensor data	RD
(Amihai et al., 2018)	Deep learning	–	Vibration data	RD
(Amihai et al., 2018)	RF	Industrial pumps	Vibration data	RD
(Amruthnath and Gupta, 2018)	PCA, Hierarchical clustering, k-means, Fuzzy C-means and model-based clustering	Exhaust fan	Vibration data	RD
(Butte et al., 2018)	GLM, RF, gradient boosting and deep learning	Semiconductor	Process sensors, process recipe parameters and wafer count on a critical equipment component	RD
(Huuhtanen and Jung, 2018)	CNN	Photovoltaic panels	Daily electrical power signal	RD
(Kolokas et al., 2018)	DT, RF, NB-G, NB-B and ANN	Industrial equipment for anode production	Process sensor data from operation periods	RD
(Kulkarni et al., 2018)	RF	Supermarket refrigeration systems	Temperature sensor and defrost state	RD
(Paolanti et al., 2018)	RF	–	Data from sensors, PLCs and communication protocols	RD
(Luo et al., 2018)	Deep learning	Computer numerical control machine	Vibration signal	RD

Carvalho, T. P., Soares, F. A., Vita, R., Francisco, R. d. P., Basto, J. P., and Alcalá, S. G. (2019), "A systematic literature review of machine learning methods applied to predictive maintenance," *Computers & Industrial Engineering*, Vol. 137, pp. 106024.



Procedure



- How to take action?
 1. Rule-based or Domain Expert
 2. Mathematical programming
 3. Markov decision process
 4. Reinforcement Learning
- Performance metrics:
 - Diagnostics: Accuracy, Error rate, F1 score, ROC
 - Prognostics (RUL): MAE, RMSE, MAPE, Confidence Interval, Prognostic accuracy criterion (PAC)...
 - Prognostics (R2F): mean prediction error and std, overall average bias, variability
- Monitoring:
 - when to retrain? Maintain model performance
 - Control Chart...

