Physics-Informed Data Driven Plasma Equipment/Process Control Technologies for Plasma Applications

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Make Your Plasma Equipment Smart

Plasma Equipment Intelligent Research & Experimental Platform

PEI 플라즈마장비지능화연구단

Data-Driven Plasma Equipment Intelligent Research Platform

Make Your Plasma Equipment Smart

Season1

D. B. Graves - J. Phys. D: Appl. Phys. 52, 30LT02 (2019)

Letters

IOP Publishing Journal of Physics D: Applied Physics

J. Phys. D: Appl. Phys. 52 (2019) 30LT02 (9pp) https://doi.org/10.1088/1361-6463/ab1f3f

Letter

Machine learning for modeling, diagnostics, and control of non-equilibrium plasmas

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Abstract

Machine learning (ML) is a set of computational tools that can analyze and utilize large amounts of data for many different purposes. Recent breakthroughs in ML and artificial intelligence largely enabled by advances in computing power and parallel computing present cross-disciplinary research opportunities to exploit some of these techniques in the field of non-equilibrium plasma (NEP) studies. This paper presents our perspectives on how ML can potentially transform modeling and simulation, real-time monitoring, and control of NEP.

Keywords: non-equilibrium plasma, machine learning, artificial intelligence

(Some figures may appear in colour only in the online journal)

Table 1. An overview of potential applications of ML for modeling, diagnostics, and control of NEPs.

	Supervised learning (e.g. regression, neural networks, kriging, support vector machines)	Unsupervised learning (e.g. clustering, dimension reduction)	Reinforcement learning
Predictive modeling	Learning nonlinear mappings for plasma-surface interactions [4, 22], learning inexpensive surrogate models from theoretical simulation data [7], plasma dose quantification	Selection of relevant input features for building simpler models from data [5]	
Diagnostics	Inference of plasma and surface properties from spectral data [6, 10, 32],	Extraction of latent information from measurements [46–48],	
	Detection of abnormal drifts and variabilities [6]		
Process control	Learning multivariable input–output mappings of process dynamics for model-based control [45, 56, 57]		Learning-based control

S. Park, J. Seong, G.-H. Kim, et al., Plasma Information based Virtual Metrology in **2022 Review of Data Driven Plasma Science**, Physics of Plasmas

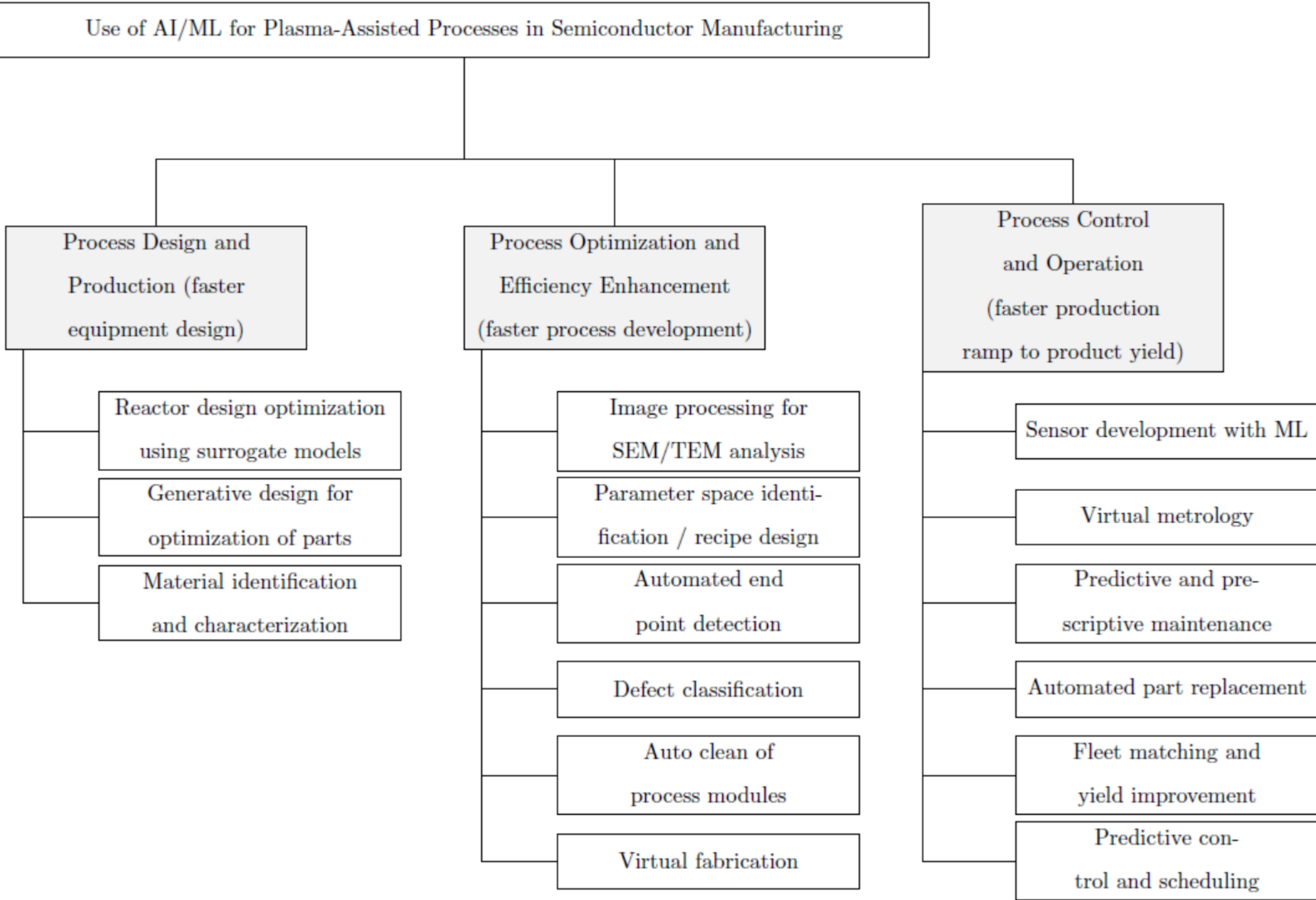


FIG. 30: An overview of the applications of AI/ML for the design, development, and operation of plasma-assisted processes for semiconductor manufacturing, towards accelerating the time-to-market of new processes and products for the consumer electronics industry via smart manufacturing practices.

Lam Research

Article

Human–machine collaboration for improving semiconductor process development

Nature | Vol 616 | 27 April 2023 | 707

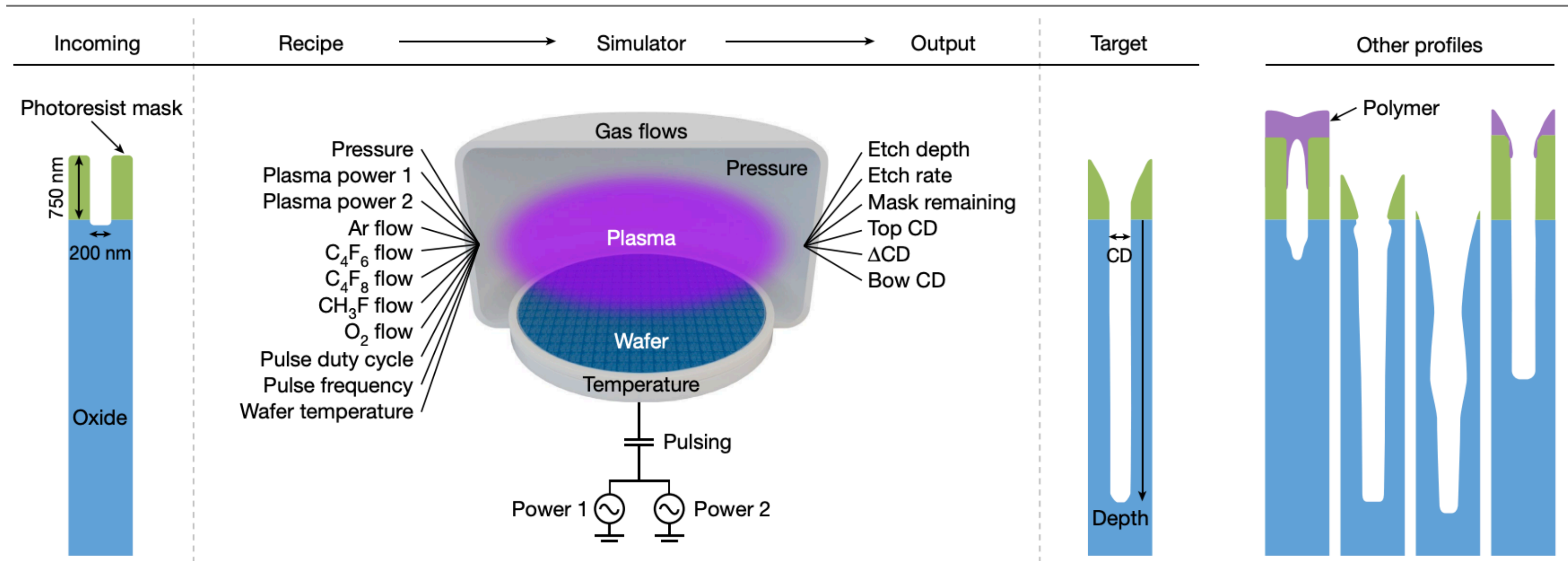


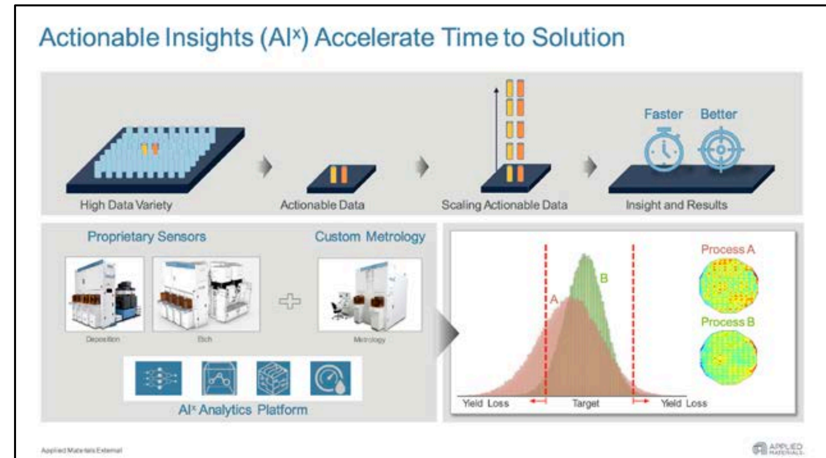
Fig. 1 | Schematic of the virtual process used in the game. The input of the virtual process is a 'recipe' that controls the plasma interactions with a silicon wafer. For a given recipe, the simulator outputs metrics along with a cross-sectional image of a profile on the wafer. The target profile is shown along with examples of other profiles that do not meet target. The goal of the game is to find a suitable recipe at the lowest cost-to-target. CD, critical dimension.

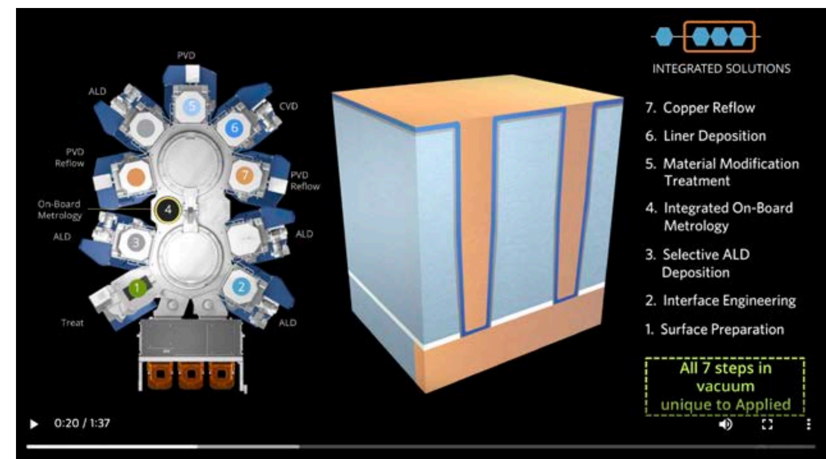
Applied Materials

@Applied Materials

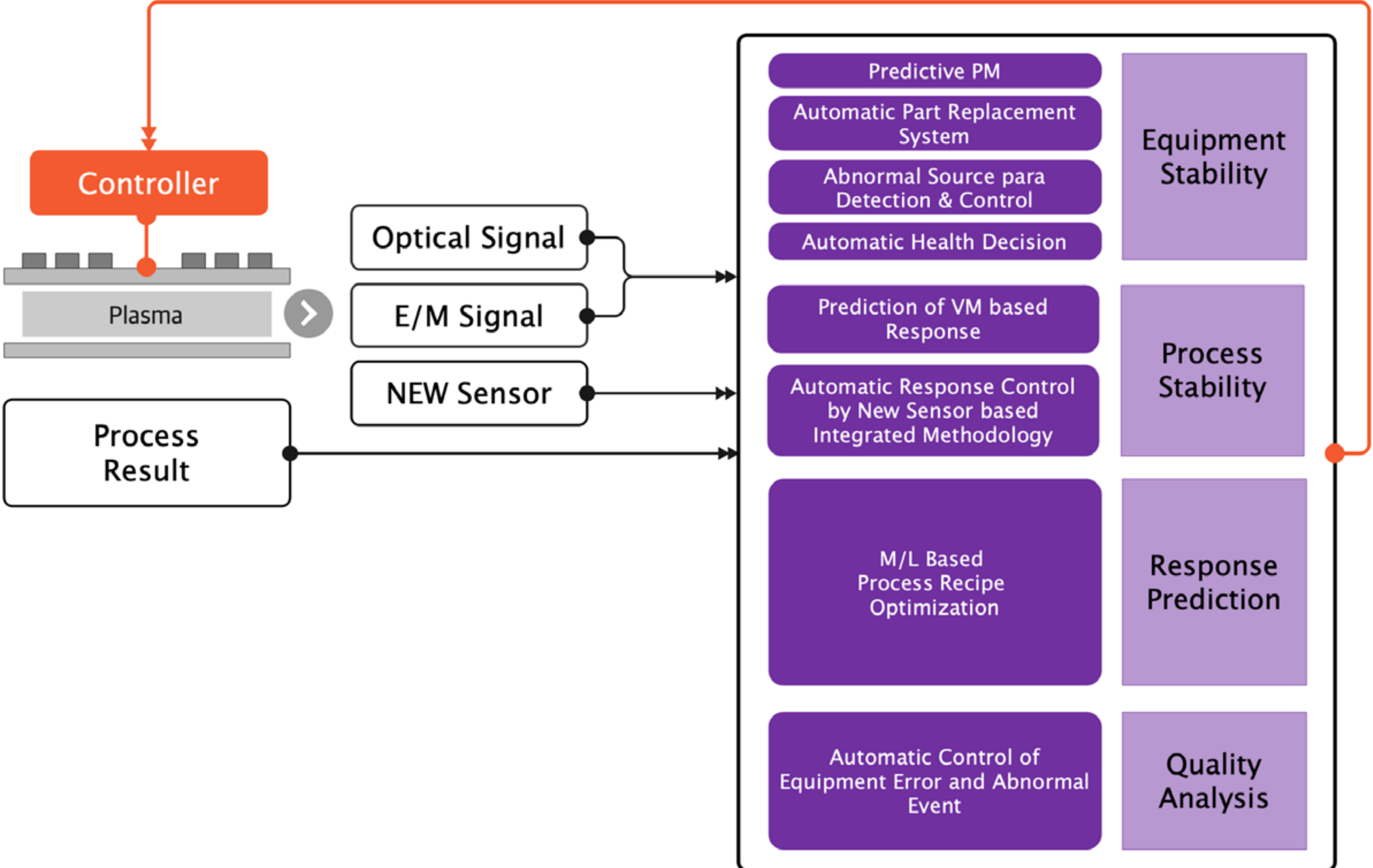
The AI^X platform includes:

- ChamberAI®: New sensors and machine learning algorithms for Applied Materials process chambers with real-time analytics of variables
- On-board metrology: Unique in-vacuum metrology that enables new films to be measured as they are being deposited, with angstrom-level precision
- Inline metrology: Unique algorithms based on Applied eBeam metrology which can provide a 100-fold increase in measurement speed with 50 percent higher resolution
- AppliedPRO®: Process Recipe Optimizer generates digital process maps that accelerate materials and recipe development, reduce variability, and widen process windows
- Digital twins: The AI^X platform includes digital twin models of select Applied Materials chambers and systems that enable virtual experiments as well as on-demand energy and chemical consumption of semiconductor manufacturing equipment through our EcoTwin efficiency software
- Computing: The AI^X platform includes the computing resources needed to store and analyze massive data using machine learning and AI algorithms





Make Your Plasma Equipment Smart



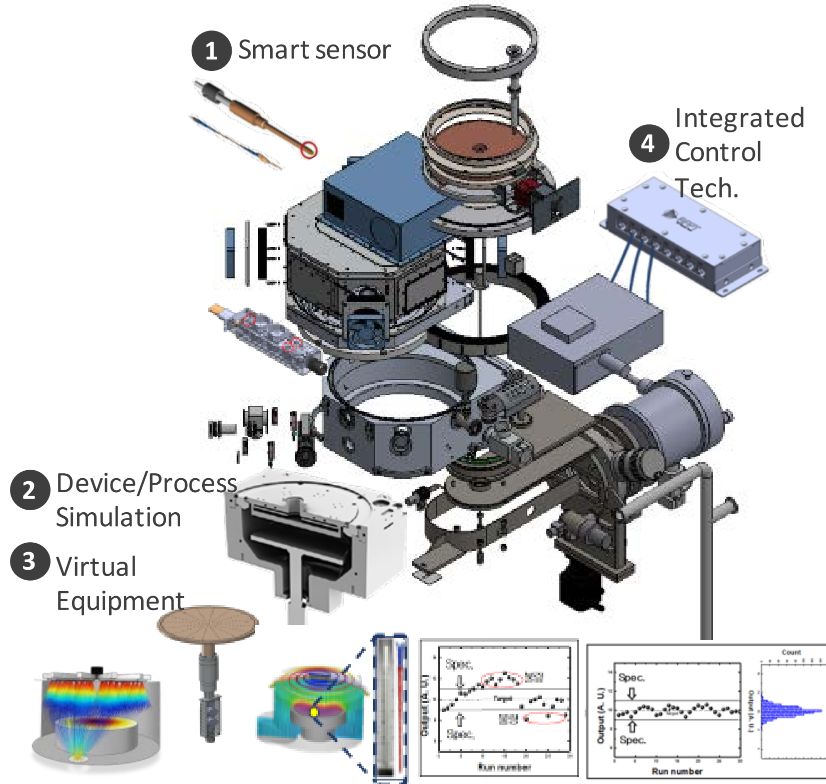
Plasma E. I. Convergence Research Center (2020.11.1)

Advanced Process/Equipment Control Module

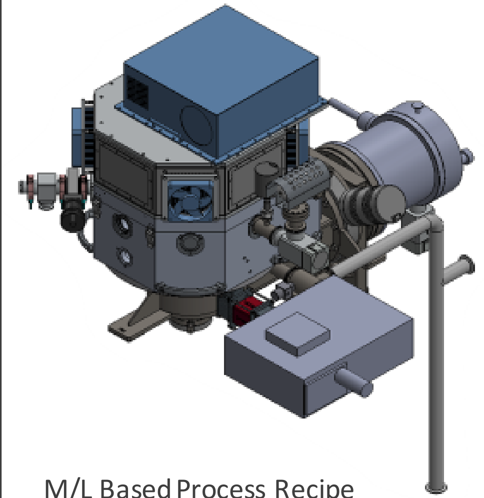
4 National Institutes and 14 Universities with device making industries

Core Tech.

R&D Platform



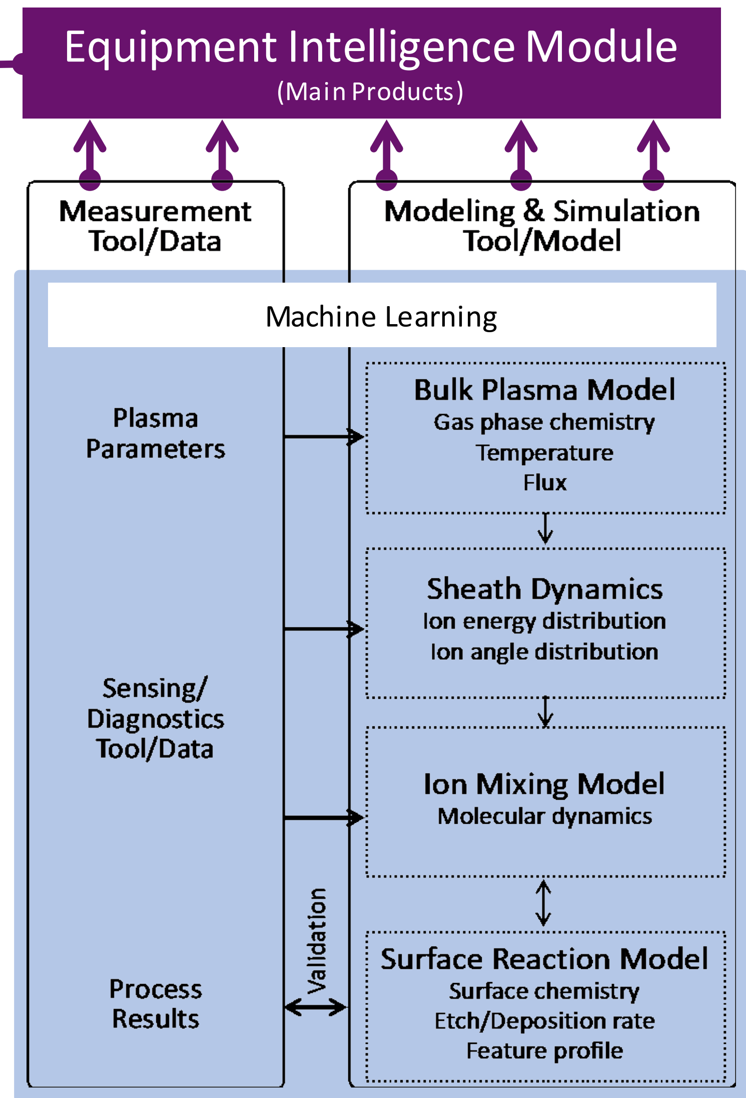
Demonstration with Industry



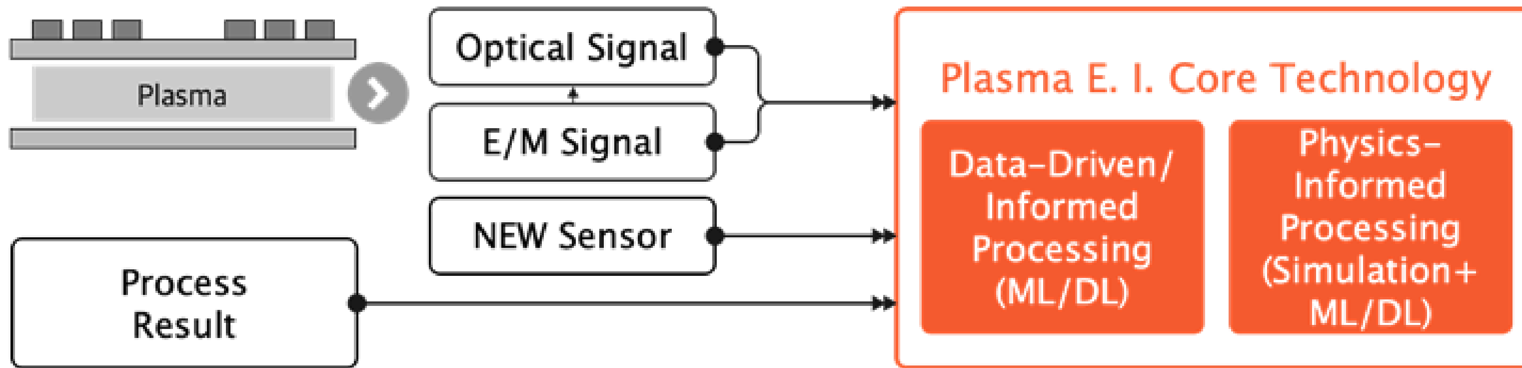
M/L Based Process Recipe Optimization

Automatic Response Control by New Sensor based Integrated Methodology

Automatic Control of Equipment Error and Abnormal Event

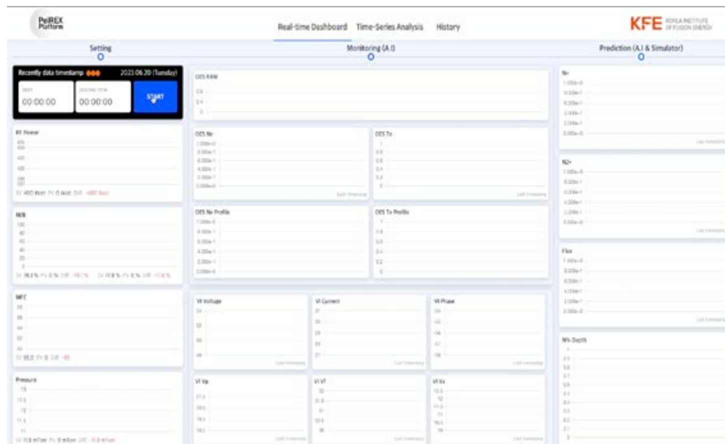


Process/Device Control
(Tuning Knobs → to system)
Equipment Intelligence Module
(Main Products)
Measurement Tool/Data
Modeling & Simulation Tool/Model
Machine Learning
Plasma Parameters
Sensing/ Diagnostics Tool/Data
Process Results
Validation
Bulk Plasma Model
Gas phase chemistry
Temperature
Flux
Sheath Dynamics
Ion energy distribution
Ion angle distribution
Ion Mixing Model
Molecular dynamics
Surface Reaction Model
Surface chemistry
Etch/Deposition rate
Feature profile
meter scale
millimeter scale
nanometer scale
Deposition on wall
Incoming gas
Redeposition
Electron impact reactions
Dissociation
Gas inlet
Incoming gas
Plasma
Pump out
Gaseous products
Gas phase reaction
Transport to surface
Chamber wall
Sheath
Gaseous reactions
Ion bombardment
Transport byproducts from plasma to surface
Transport Gaseous products from plasma to surface
Adsorbed on the surface
Surface Reaction
Deposition product on surface
Wafer surface



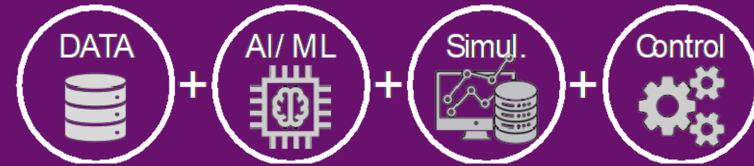
Providing solutions for process engineers

Prediction of VM based response



M/L based process optimization

PeiREX® Platform
everywhere of us



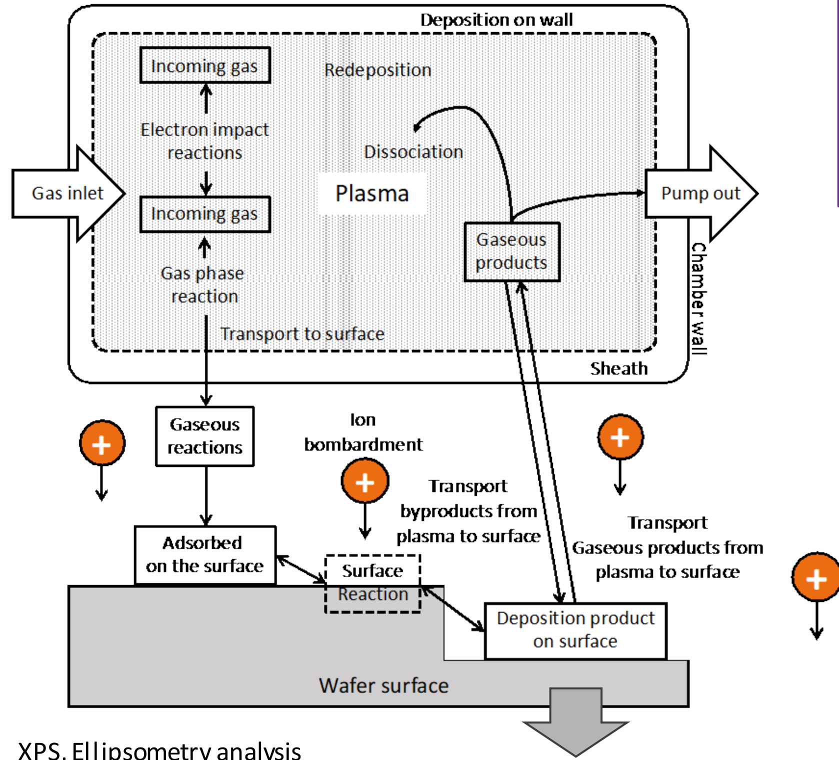
Best Practices : Plasma Nitridation Equipment/Process

① Parameter monitoring Tech. for SiON thin film characteristics
→ plasma uniformity, electron temperature & density, ion flux …

② N doping concentration control for SiON
→ Power, Gas Pressure, …

③ Device reliability
→ Process Management, R&D-Demonstration Gap, …

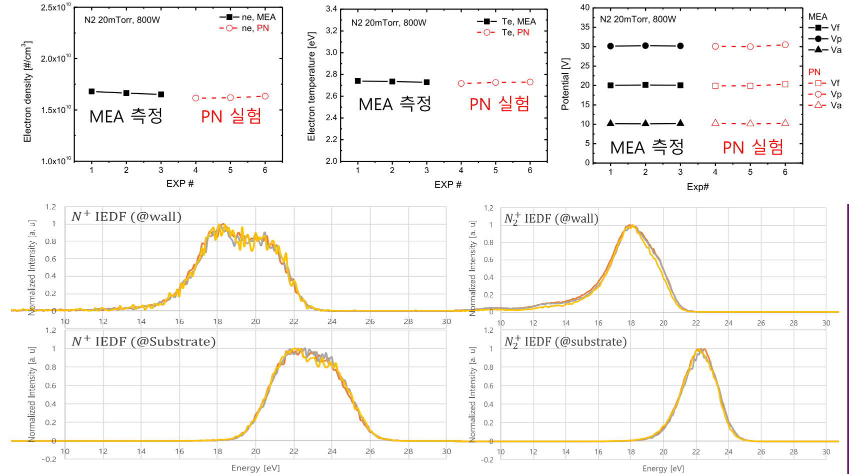
Data-Driven Process Analysis



Plasma Parameters & Monitoring Data

- n_e(CP), T_e, V_f, V_p, I_{isat}(LP), N^+, N_2^+(Ion species mass & energy @MEA1, MEA2)
- Monitoring data : OES (λ $(= 200\sim1,100\ \mathrm{nm})$, R $\geq 0.5\ \mathrm{nm}$)
- VI Probe (VI1(@antenna), VI2(@sub.)) : 15th harmonic components (voltage, current, phase, phase harmonics)

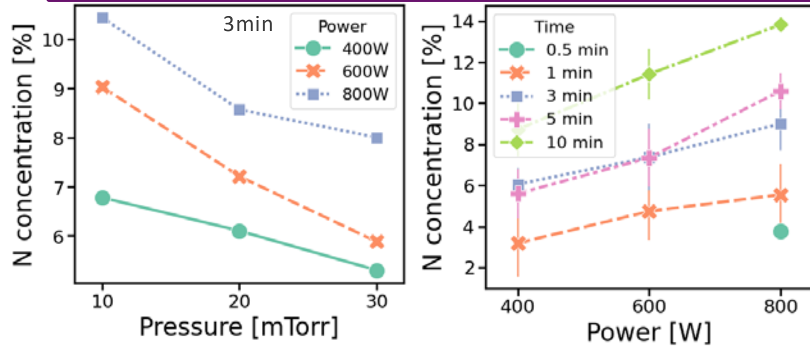
- Measured plasma parameter = PN process

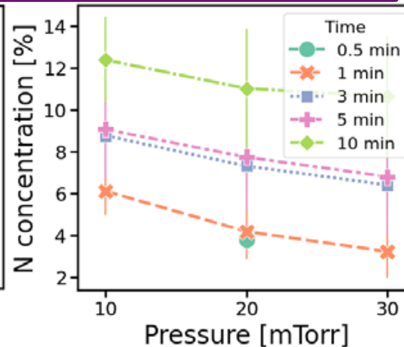


Bulk to Substrate

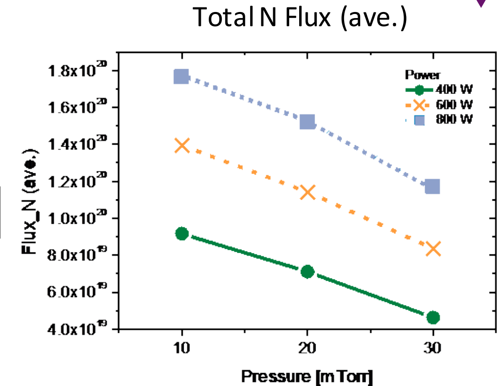
XPS, Ellipsometry analysis

Nitridation process data @ wafer surface



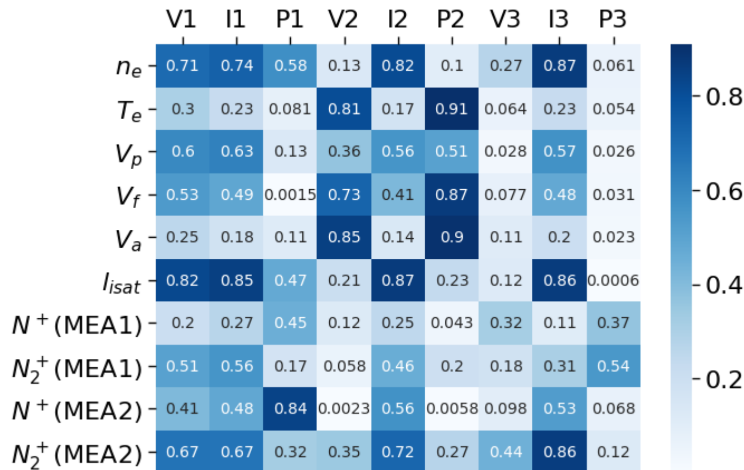


Total N Flux (ave.)



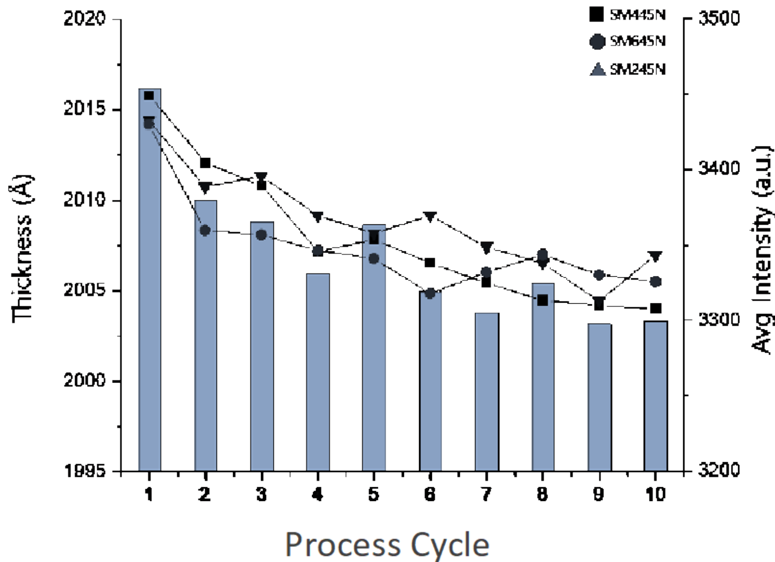
Data-Informed Results

VI probe Data vs. Plasma Parameters

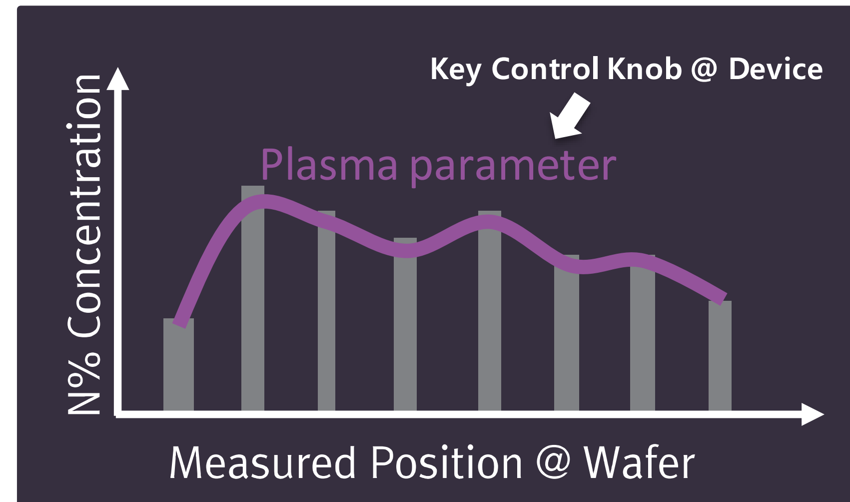


OES Data vs. Plasma Parameters

System	Wavelength (nm)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	(MEA1)	(MEA1)	(MEA2)	(MEA2)
First Negative System (FNS) (□) Second Positive System (SPS) (□)	295.55	0.85	0.49	0.71	0.74	0.41	0.38	1.00	0.44	0.96
	315.98	0.76	0.61	0.81	0.77	0.53	0.28	1.00	0.32	0.96
	337.15	0.67	0.71	0.86	0.77	0.62	0.21	0.98	0.24	0.92
	357.49	0.72	0.67	0.83	0.77	0.58	0.25	0.98	0.29	0.94
	370.93	0.79	0.56	0.77	0.76	0.49	0.32	1.00	0.37	0.96
	375.40	0.74	0.62	0.81	0.77	0.55	0.27	0.98	0.30	0.96
	380.14	0.71	0.67	0.85	0.77	0.59	0.23	0.98	0.26	0.94
	389.34	0.92	0.36	0.59	0.67	0.29	0.50	0.96	0.58	0.94
	394.07	0.79	0.58	0.77	0.76	0.50	0.31	1.00	0.36	0.96
	399.59	0.72	0.64	0.83	0.77	0.56	0.25	0.98	0.29	0.94
First Positive System (FPS) (□)	582.71	0.86	0.01	0.13	0.31	0.00	0.81	0.52	0.98	0.56
	589.39	0.86	0.01	0.12	0.30	0.00	0.81	0.49	0.98	0.55
	645.18	0.83	0.00	0.09	0.27	0.00	0.81	0.45	0.98	0.49
	652.83	0.83	0.00	0.09	0.27	0.00	0.81	0.45	0.98	0.49
	660.73	0.83	0.00	0.10	0.27	0.00	0.81	0.46	0.98	0.50
	668.87	0.77	0.00	0.06	0.22	0.01	0.83	0.38	1.00	0.44
	675.23	0.76	0.00	0.05	0.21	0.01	0.83	0.37	0.98	0.41
	746.09	0.77	0.00	0.06	0.21	0.01	0.83	0.38	1.00	0.42
	760.69	0.72	0.01	0.03	0.18	0.03	0.83	0.32	0.98	0.37
	770.74	0.64	0.03	0.01	0.12	0.07	0.81	0.24	0.96	0.28

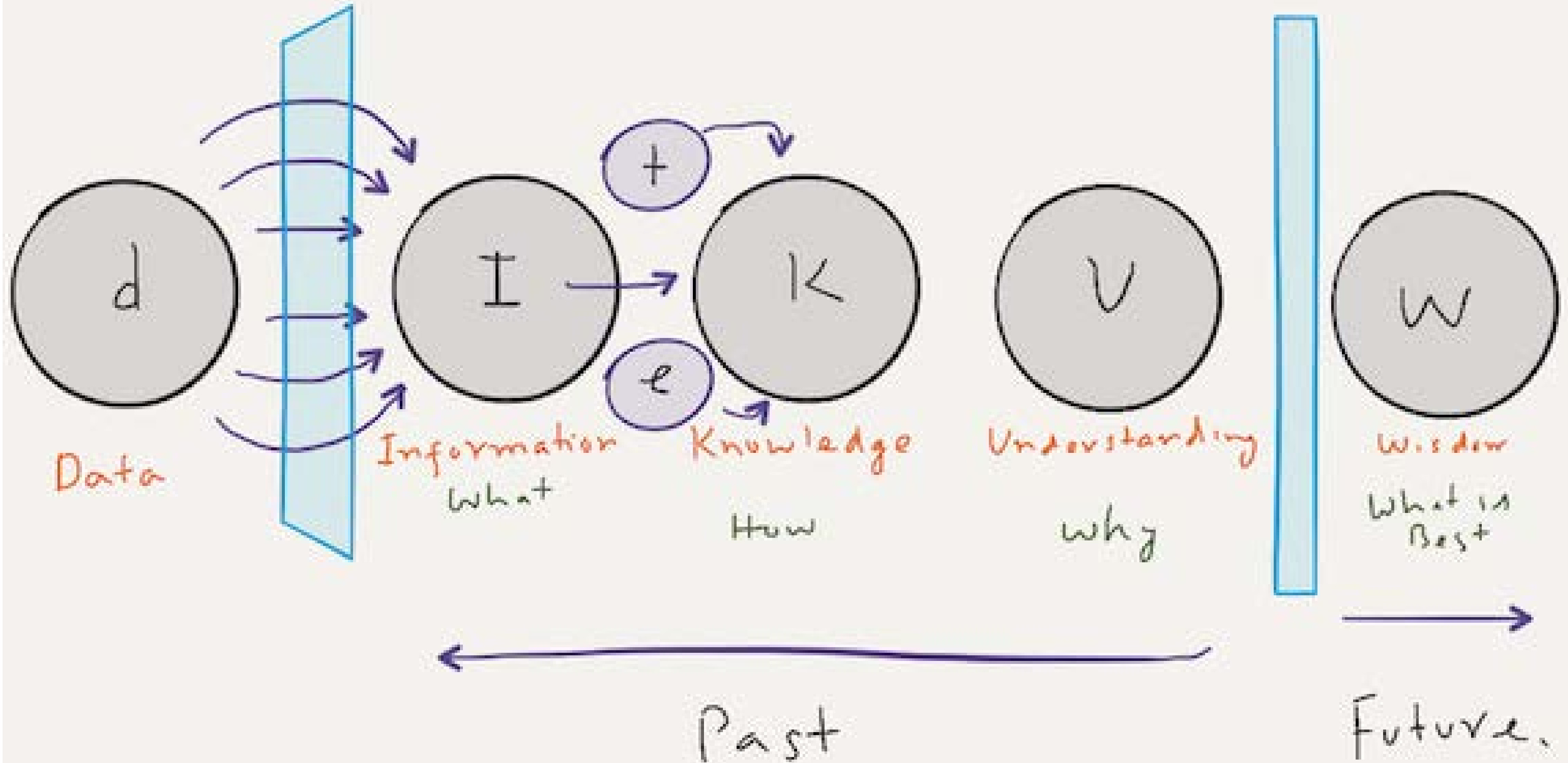


OES Data vs. THK Data (Process Results)



Plasma para. Vs. N% (Process Results)

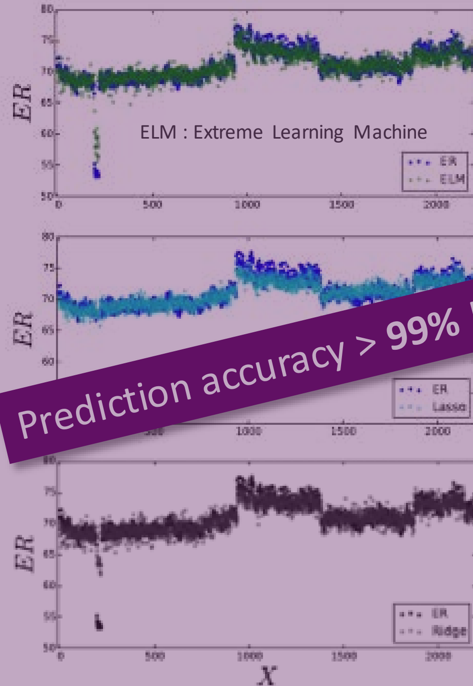
Data Science.COM



Data-Driven ➔ Data-Informed ➔ Data-Inspired

It is Difficult by AI Alone !

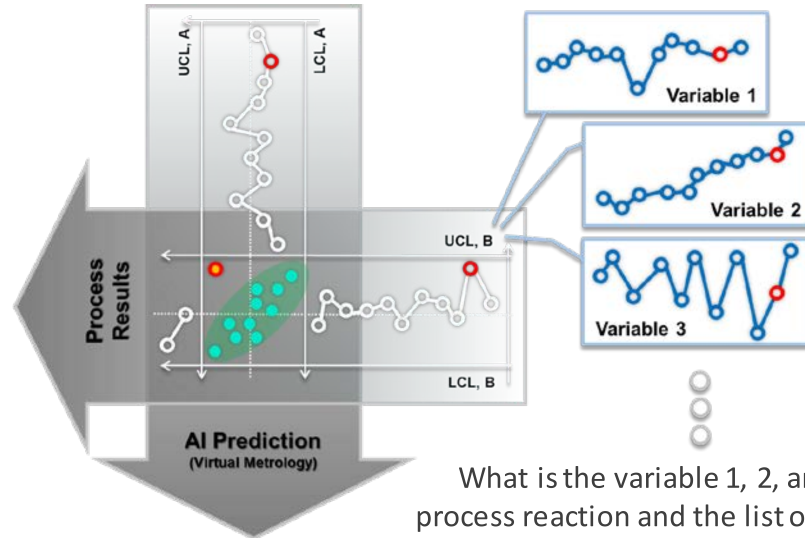
VM performance based on the various AI models



L Puggini *et al.*, EAAI 67 (2018) 126-135.

And, AI DOES NOT give us the answers to this question !

✓ But, AI alone can not give us the answers, especially for the plasma-assisted processes.



What is the variable 1, 2, and 3 in the process reaction and the list of root causes?

To control the process reaction rates, we have to deal :

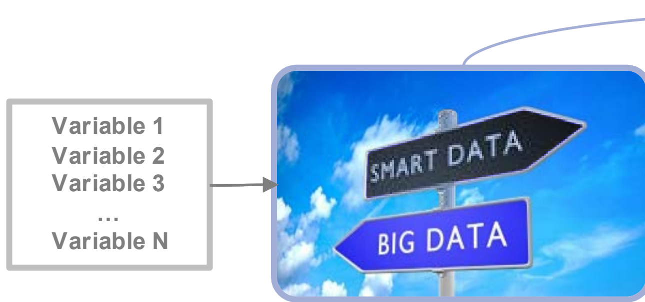
$$R_{proc} = n_{target}\left(\pm \sum_j k_j s_j D_j \nabla N_j + \sum_l \kappa_l \Gamma_l \right)$$

$$\left\langle n_j n_e \int_{E_{thr}}^{\infty} \sigma_{ej}(\varepsilon)\sqrt{\varepsilon/2m_e}\, f_e(\varepsilon)\, d\varepsilon \right\rangle_t$$

And to solve the problem during the processes, we have to find the root cause :

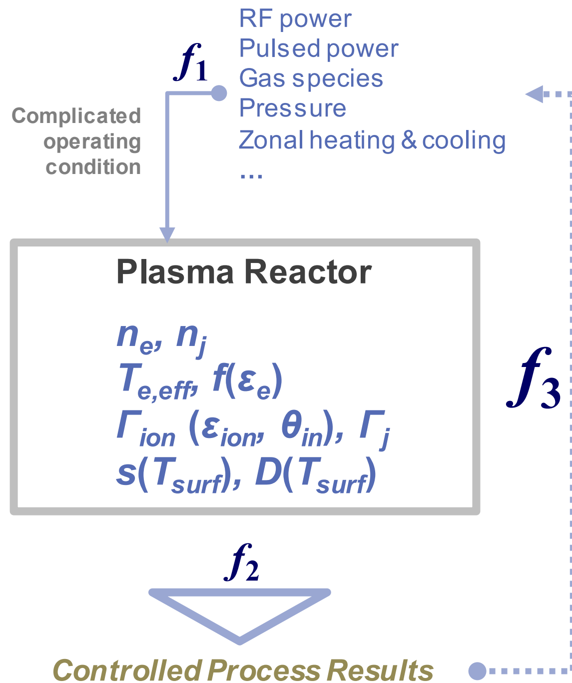
- Power absorption
- Gas mixing ratio
- Vacuum and exhaustion
- Wall contamination
- ESC aging

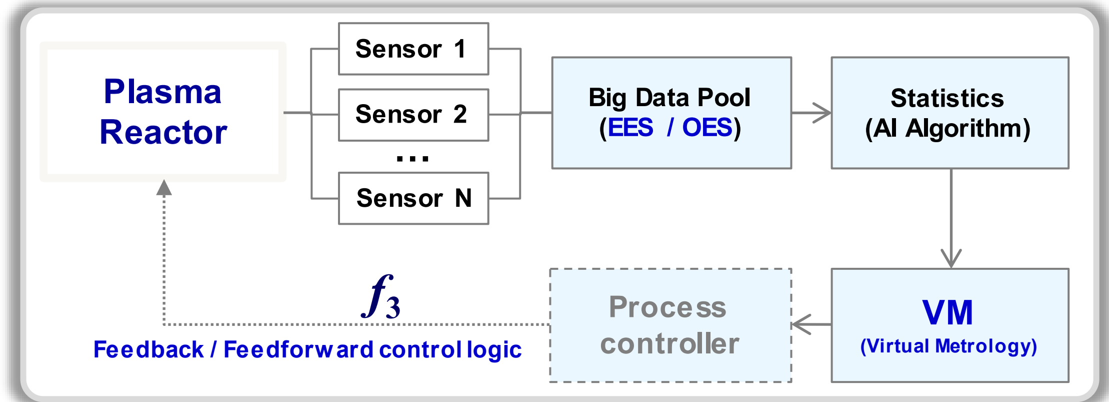
WHO can give us the answers?



?

How to Translate the BIG DATA to the Plasma Processing Engineers?





And, How to make f_3, the process control logic based on the analyzed root causes of the each problmes?

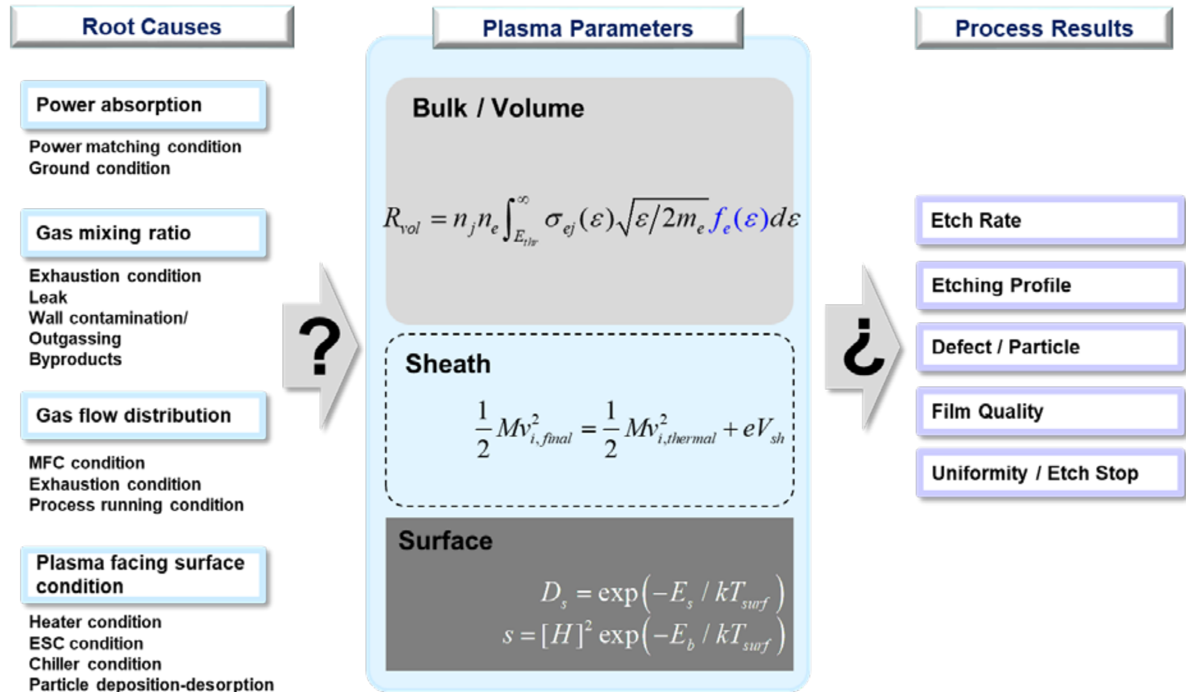
Plasma Physics should do :

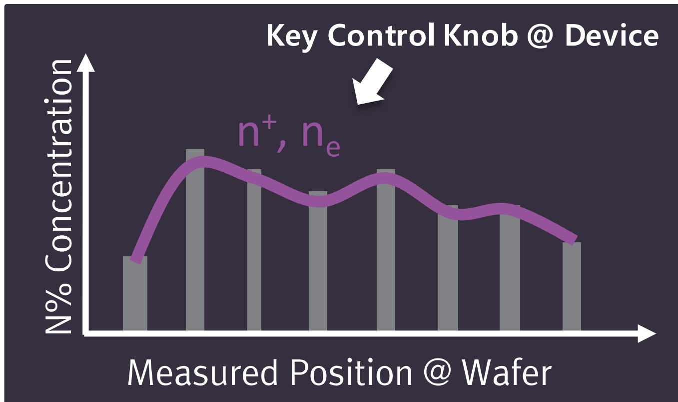
(1) Define of the problem
(2) Approach to the solution

WHAT we have to do?

Translation of the BIG DATA to the Plasma Processing Engineers

Make Smart Index from the BIG DATA pool which includes information about the plasmas!





Various Strategies of the Translation for Plasma Processing Engineers

G-H Kim, J Shinagawa et al., 2022 Review of Data-Driven Plasma Science

Equipment Data :
Pressure / Flow / RF /
Exhaustion / Cooling / etc.

Domain knowledge 1

What is required?

Plasma
- Chemistry
- Ion & neutral flux

Glass (or wafer)

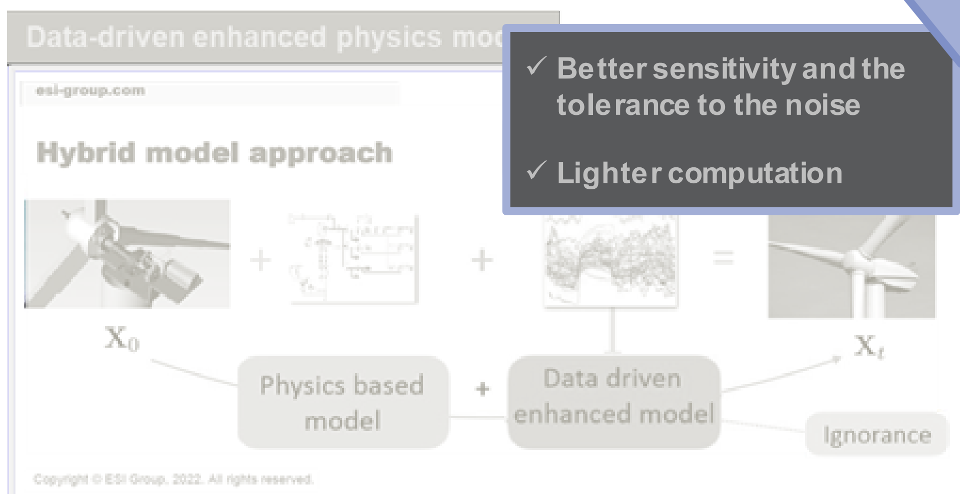
Domain knowledge 2

How to obtain?

Sensor A
Sensor B
...
Sensor N

Pre-process

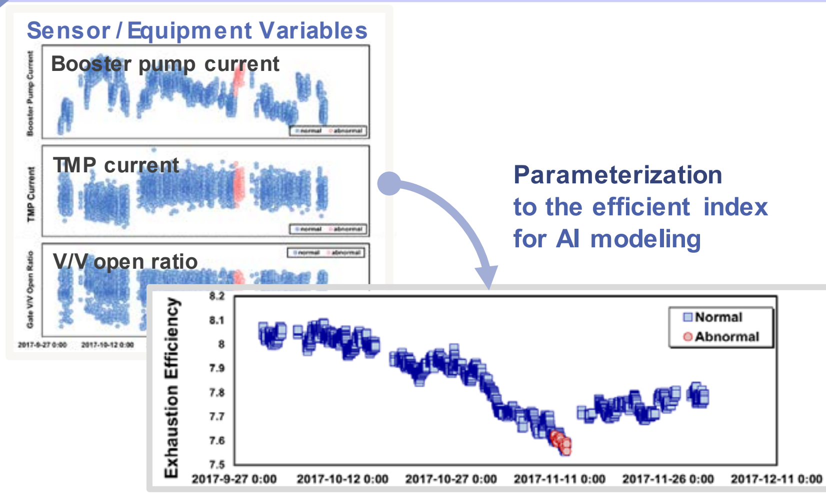
VM or Classification model building data flow



✓ Better sensitivity and the tolerance to the noise

✓ Lighter computation

Physics-based data-driven analysis model



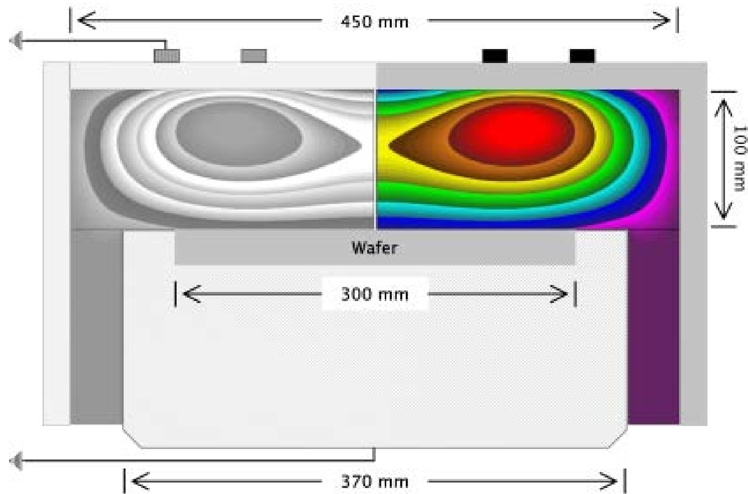
Parameterization to the efficient index for AI modeling

Model Adjusted

(Physics Based Data Driven Analysis Model)

Model Bound
(Purely Theory Based)

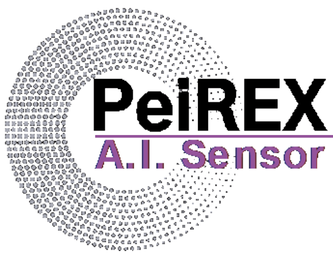
Model Free
(Purely Data Based)



	n_e	T_e	V_p	V_f	V_a	I_{isat}	N^+	N_2^+	N^+	N_2^+
n_e	1	0.041	0.37	0.22	0.036	0.79	0.073	0.11	0.8	0.87
T_e	0.041	1	0.4	0.81	0.97	0.17	0.019	0.24	0.035	0.15
V_p	0.37	0.4	1	0.81	0.32	0.44	0.06	0.48	0.14	0.49
V_f	0.22	0.81	0.81	1	0.76	0.36	0.0009	0.4	0.012	0.4
V_a	0.036	0.97	0.32	0.76	1	0.14	0.05	0.16	0.049	0.16
I_{isat}	0.79	0.17	0.44	0.36	0.14	1	0.14	0.32	0.57	0.76
N^+(MEA1)	0.073	0.019	0.06	0.0009	0.05	0.14	1	0.51	0.18	0.007
N_2^+(MEA1)	0.11	0.24	0.48	0.4	0.16	0.32	0.51	1	0.046	0.085
N^+(MEA2)	0.8	0.035	0.14	0.012	0.049	0.57	0.18	0.046	1	0.54
N_2^+(MEA2)	0.87	0.15	0.49	0.4	0.16	0.76	0.007	0.085	0.54	1

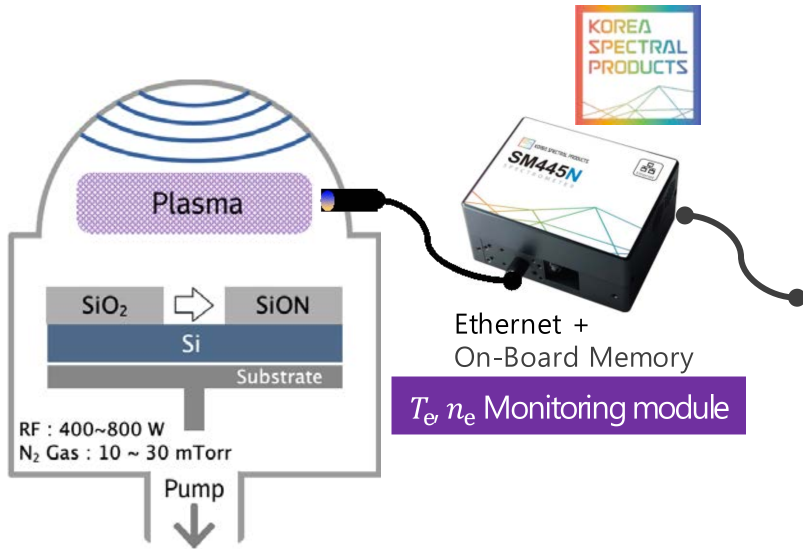
Take advantage of data science + Includes physical understanding/constraints

Allowing for data driven understanding of complex plasma equipment/process system



AI-OES Sensor

Real time plasma parameter (T_e, n_e) monitoring sensor for plasma nitridation process equipment → Plasma parameter analysis algorithms are embedded in H/W



- ICP : 450mm × 100mm (Single & Dual zone antenna)
- RF(13.56 MHz) : 400~800 W
- Gas: N_2, 10~30mTorr

Plasma Electron Temperature (T_e) Monitoring

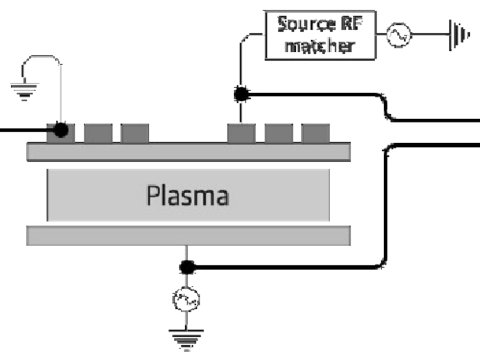
Electron Temperature [eV]

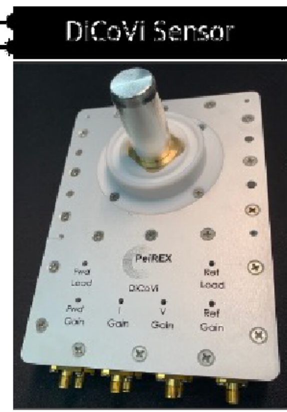
Plasma Electron Density(n_e) Monitoring

Electron Density [cm^{-3}]

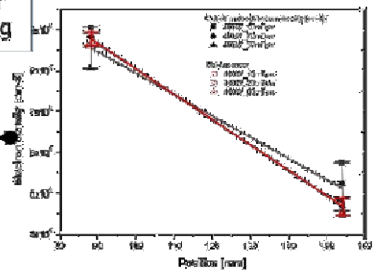
Non- Contact Plasma Property Monitoring Sensor

real RF power measurement VI sensor for non- 50 Ohm load condition

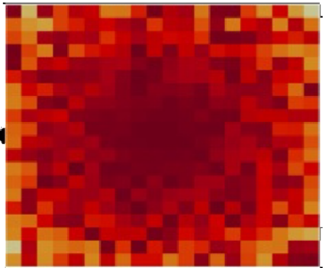




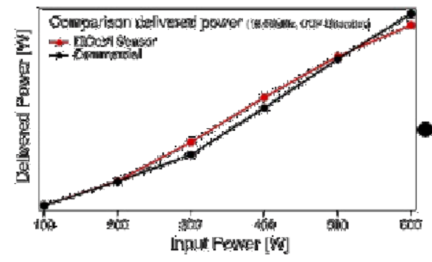
Plasma parameter monitoring



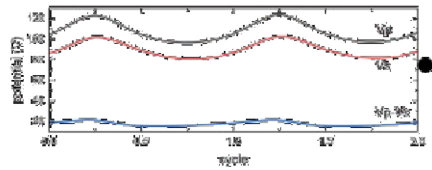
Plasma uniformity, N% monitoring

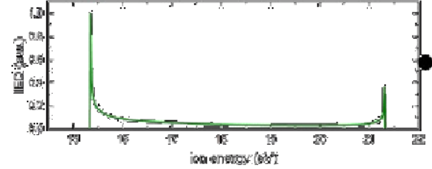


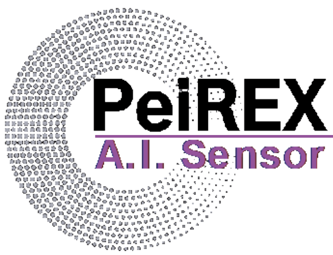
REAL RF Power Measurement



Parameter Monitoring I-V, IEDF, THK, DR, etc





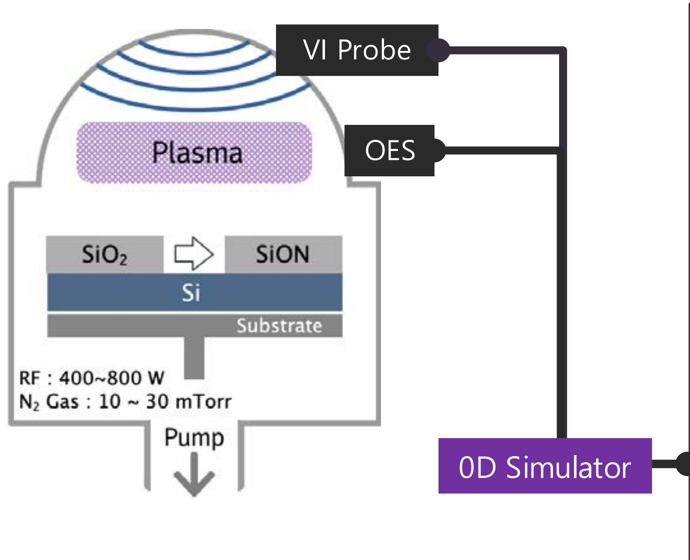


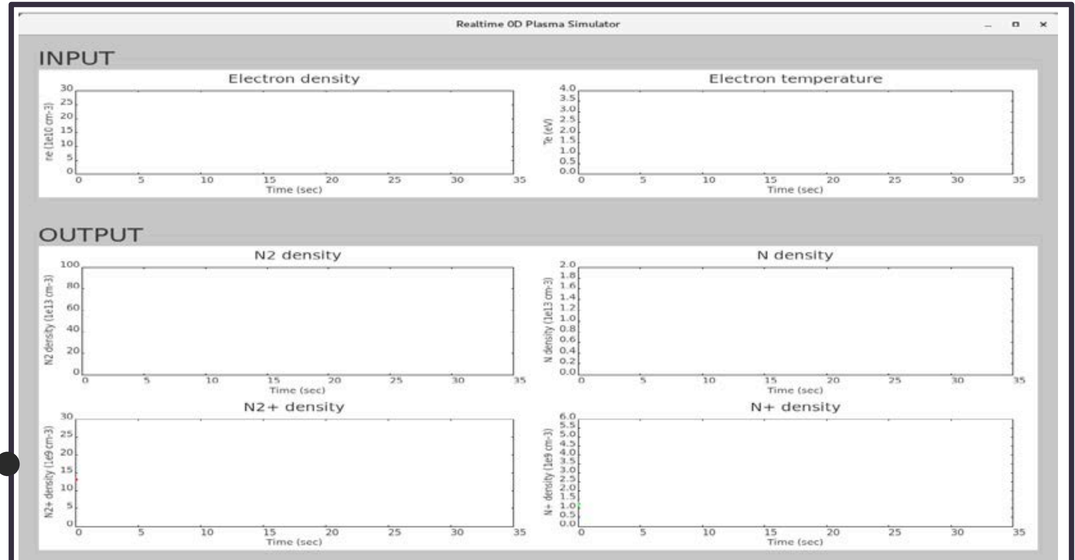
N-ion & Radical VM(Virtual Metrology) Module

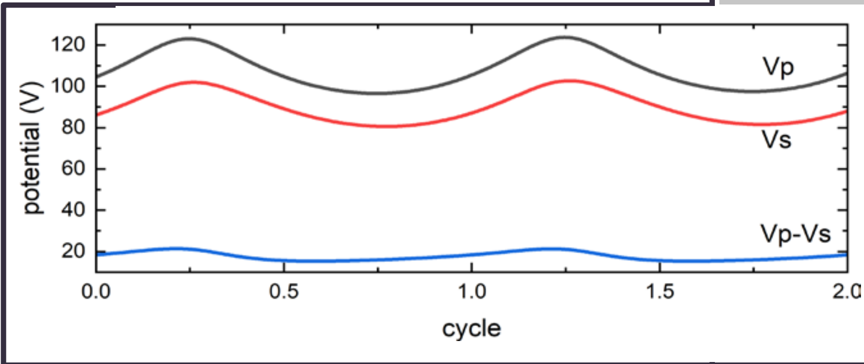
Real time monitoring module for plasma parameters ($N_2^+, N^+, N_2, N_2^*, N(2D), N(2P)$)

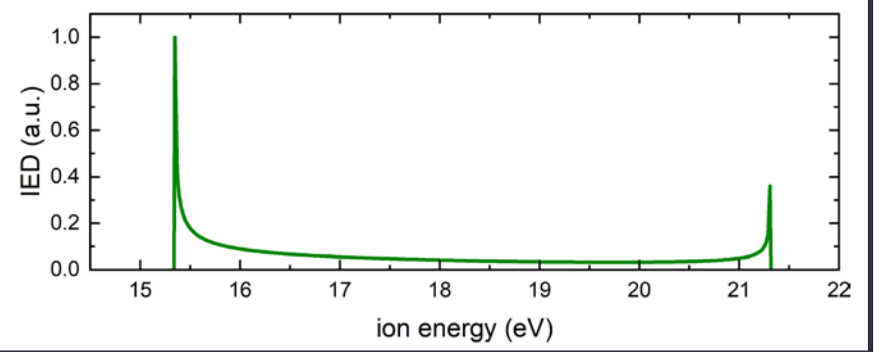
→ based on 0D Simulator (Uncertainty < 1%, Calculation time <1 sec)

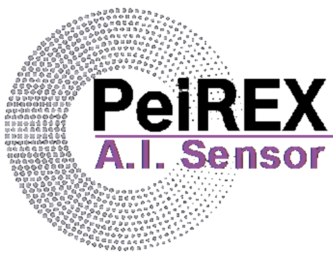
→ plasma potential & Ion Energy Distribution Function(IEDF) monitoring





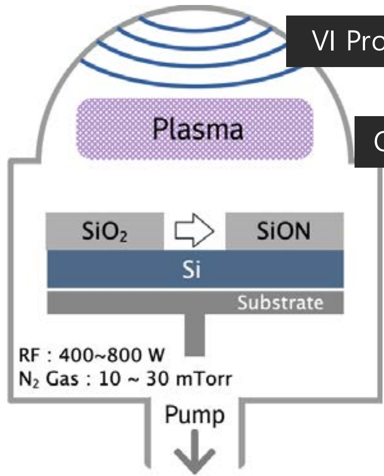


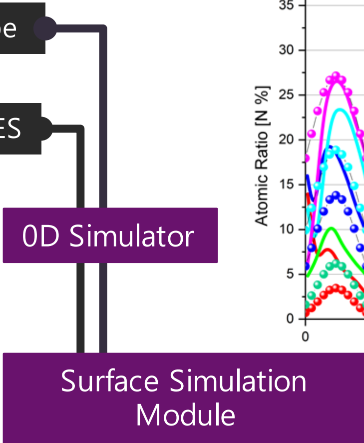


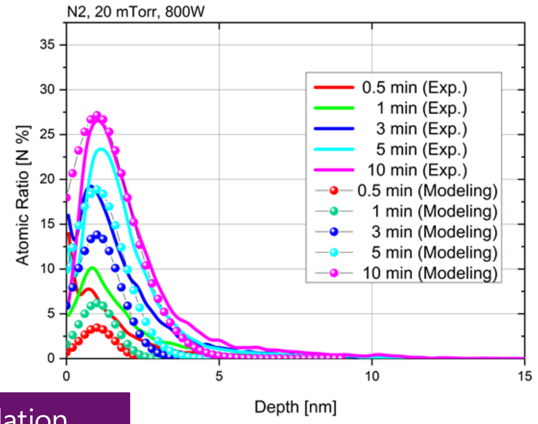


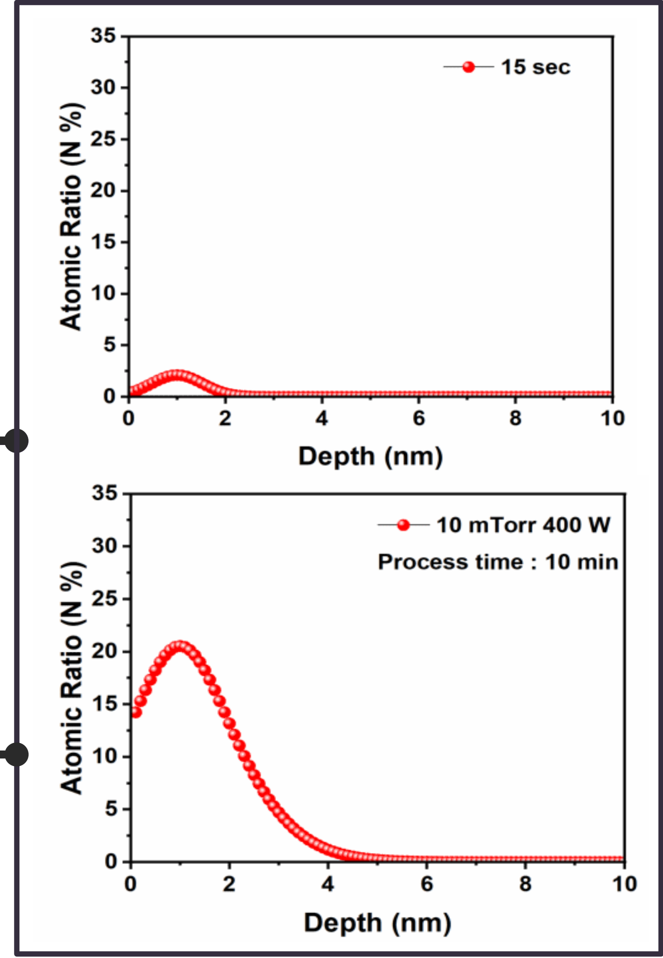
N% VM(Virtual Metrology) Module

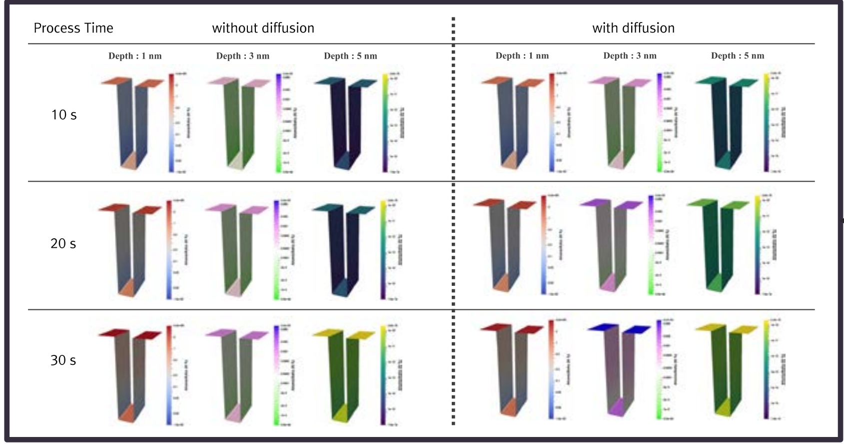
Near real time (<10sec) monitoring module of N % concentration as a oxide position and process time (Uncertainty < 24%) → near real time N% map

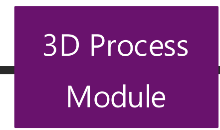




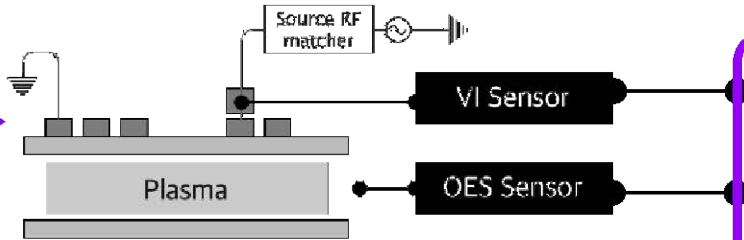








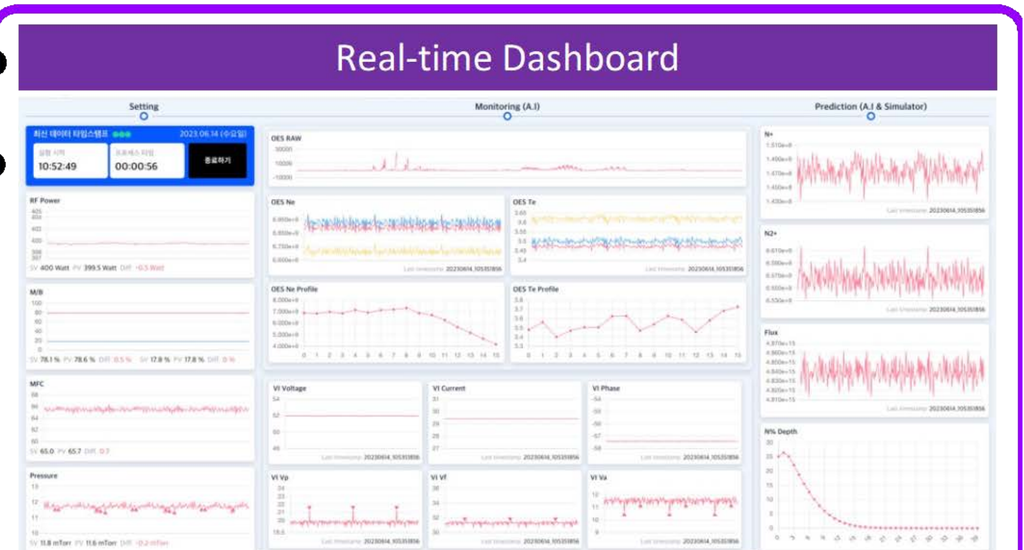
IDAS(Integrated Data Analysis System)

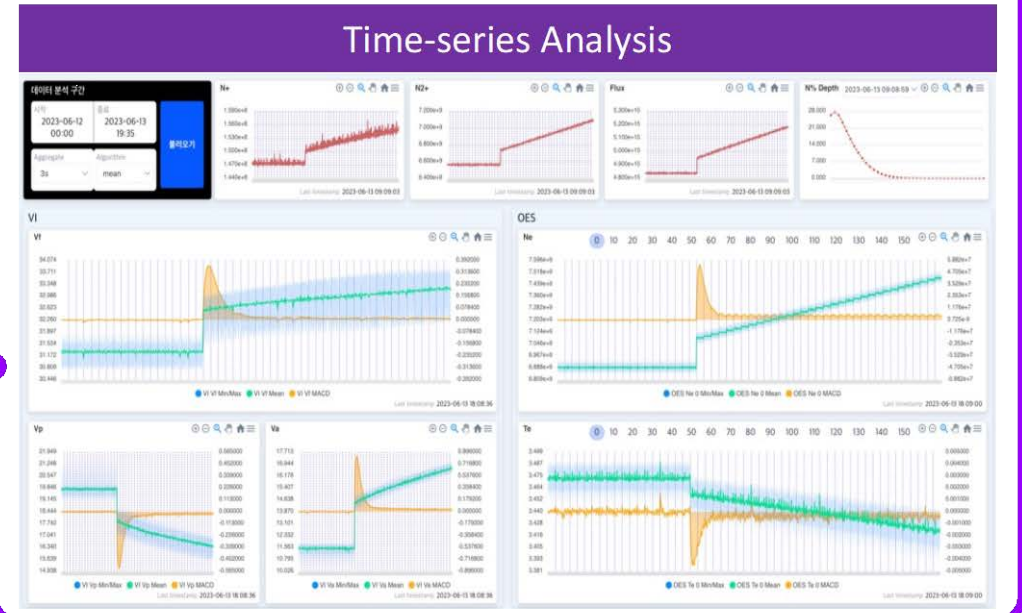


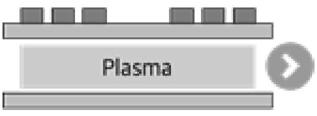
AI-Based Integrated Data Analysis System Optimized for Plasma Nitridation Equipment

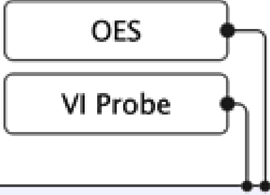
Provides an analysis loop that leads to plasma process equipment data storage, analysis, and evaluation throughout the process cycle.

Real- time analysis less than 1 second.









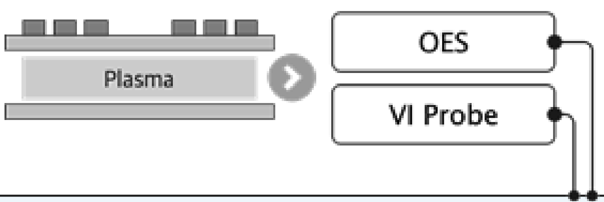
- Sensor data monitoring
- Plasma parameter monitoring
- (Virtual Metrology)
  Plasma parameter & process result

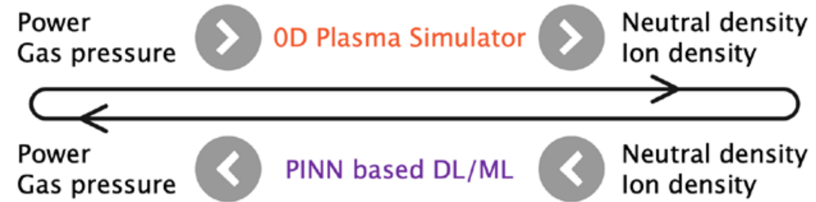
Setting | Monitoring (A.I) | Prediction (A.I & Simulator)

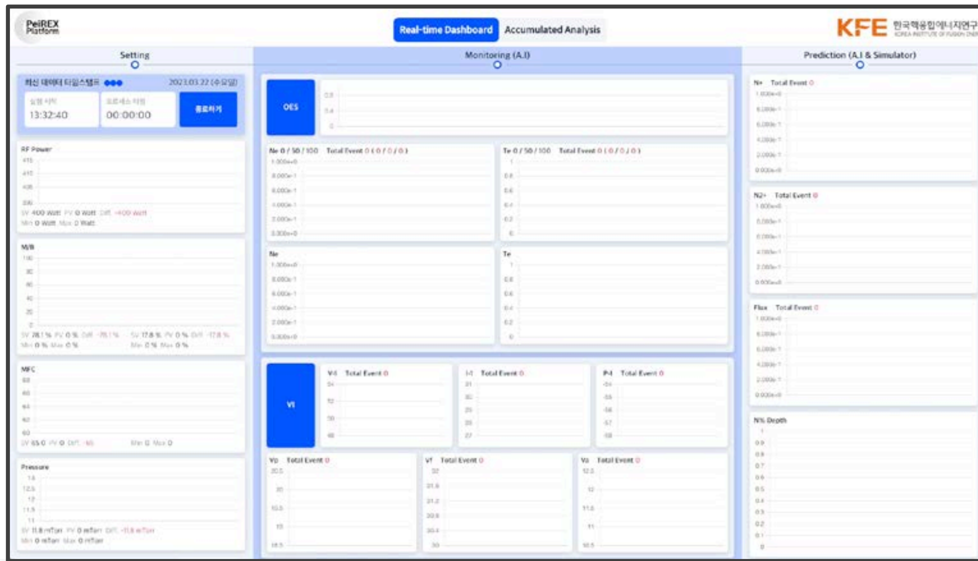
Recently data timestamp 2023.06.20 (Tuesday)

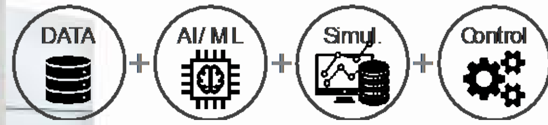
start 00:00:00 | process time 00:00:00 | START

Prediction of VM based response ⇄ M/L based Process Optimization









Predictive PM

Automatic Part Replacement System

Abnormal Source para Detection & Control

Automatic Health Decision

M/L Based Process Recipe Optimization

Automatic Control of Equipment Error and Abnormal Event

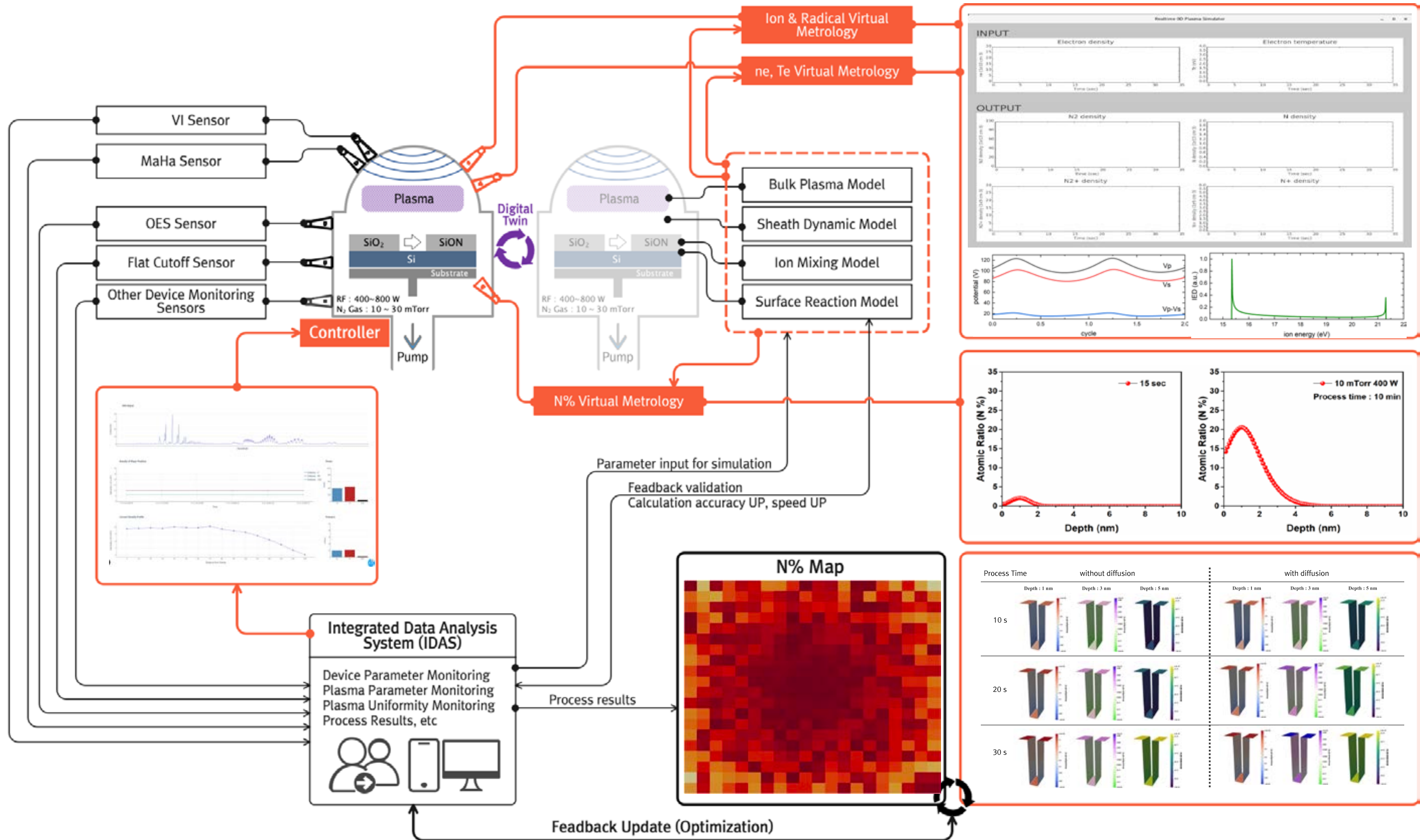
Prediction of VM based Response

Automatic Response Control by New Sensor based Integrated Methodology

R&D Summary

*Make **Smart Index** from the BIG DATA pool which includes **information** about the plasmas!*

Physics-based data-driven approach for plasma equipment



Make Your Plasma Equipment Smart

Plasma Equipment Intelligent Research & Experimental Platform