MADEin4

Metrology Advances for Digitized ECS industry 4.0

Automotive and Semiconductor Domains Analogy

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AEIT

AGENDA

- MADEin4 Project Essentials
- Objective and Industry 4.0 boosters
- Automotive and Semiconductor domains analogy
- Data is the new oil: design, modeling, metrology and ML
  Context creation
- Automotive domain use cases
- Summary and Outlook

AGENDA

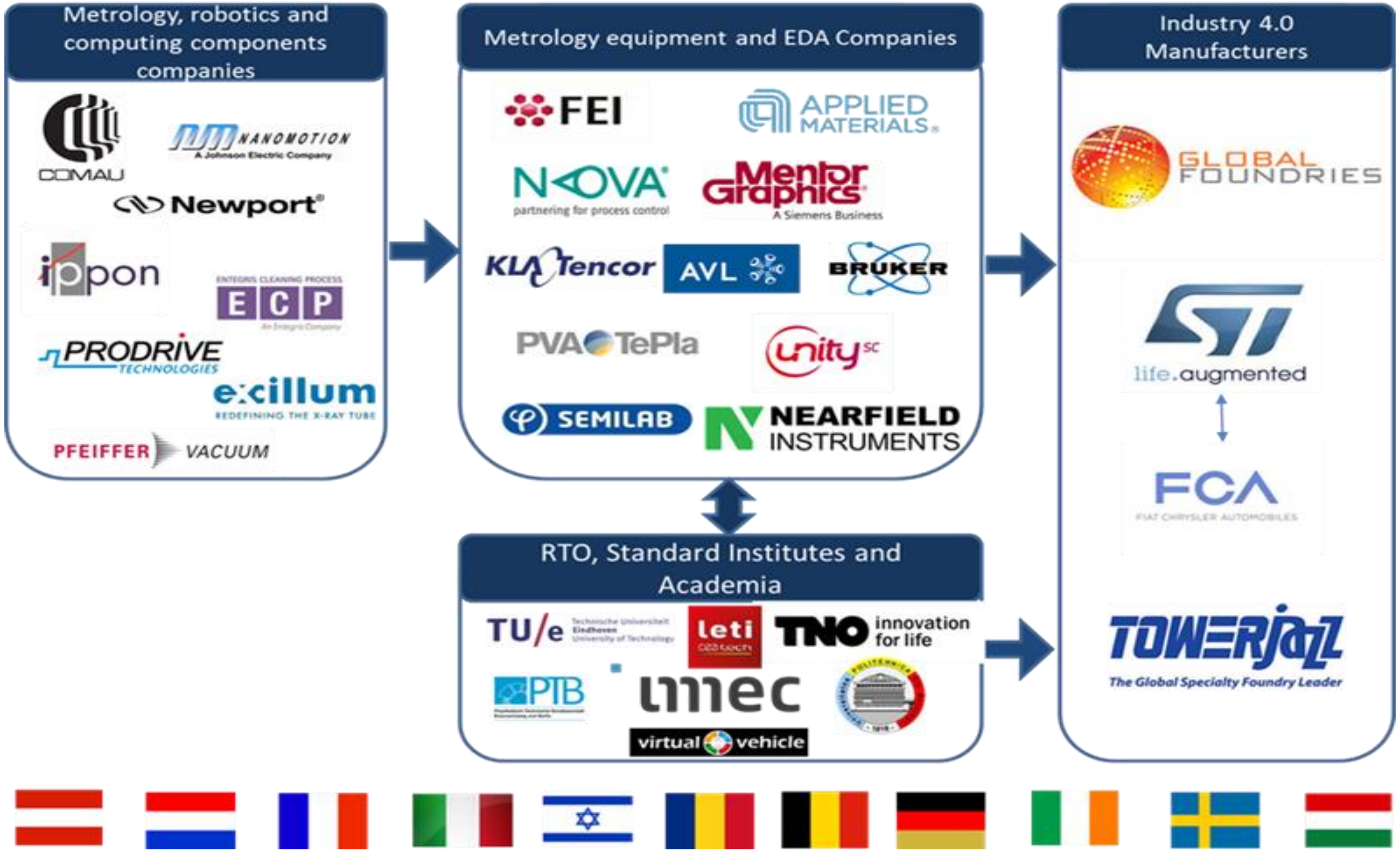
MADEin4 Project Essentials

Objective and Industry 4.0 boosters

MADEIn4 project essentials

- Number of consortium members: 47
- Countries involved: 10
- Start date: April 1, 2019
- Duration: 36 months
- Total effort: person.months: 10,503 (875 person.years)
- Total H2020 eligible costs: € 126,176,472.50

MADEIn4 project essentials



Objective and Industry 4.0 boosters

Develop and qualify new productivity boosters:

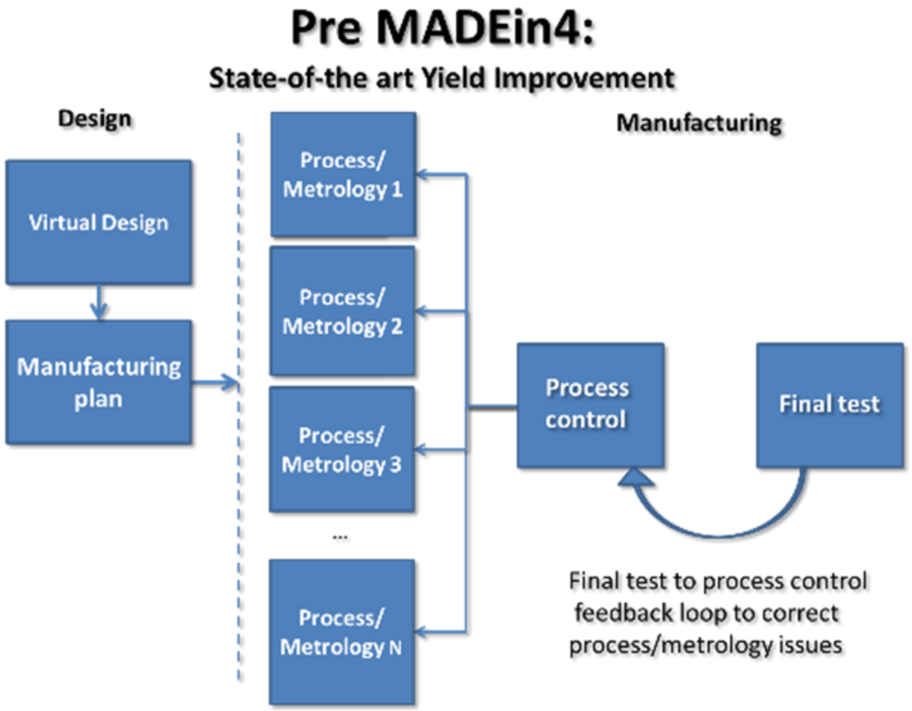
- Booster 1: High-productivity metrology and inspection tools for semiconductor and automotive industry

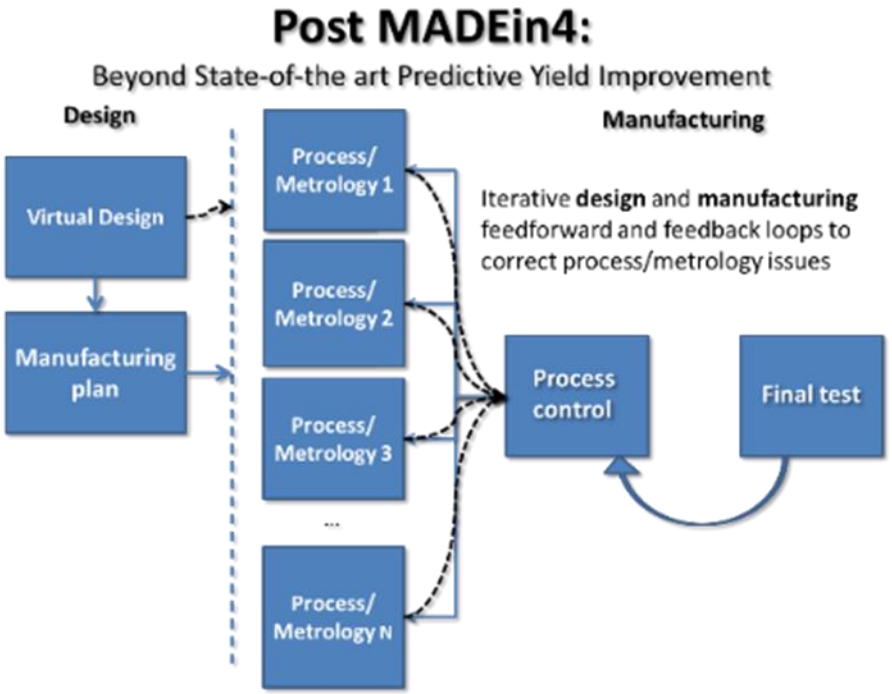
- Booster 2: Ready for “industry 4.0” Cyber Physical Systems (CPS):
  - Higher data rates and smart acquisition and processing
  - Smart use of data to improve the over-all productivity and predictability

AGENDA

Semiconductor and Automotive domains analogy

Semiconductor and Automotive domains analogy





From: reactive manufacturing to predictive manufacturing

Semiconductor and Automotive domains analogy

Semiconductor

Number of measurements per wafer 10^3

Wafers per month 10^5

Number different products $10^2 < x < 10^3$

Highly automated manufacturing

Number of inputs per unit process (features) 10^2

Manufacturing process longevity much less than 10^1 years

Litho/
SEM

Etch/
SEM

…

CMP/
Reflectometry

Automotive

Doors welding/
Optical inspection

Painting/
Optical inspection

…

Engines Assembly/
EOL hot test

Number of measurements per car $>>10^3$

Cars per month 10^5

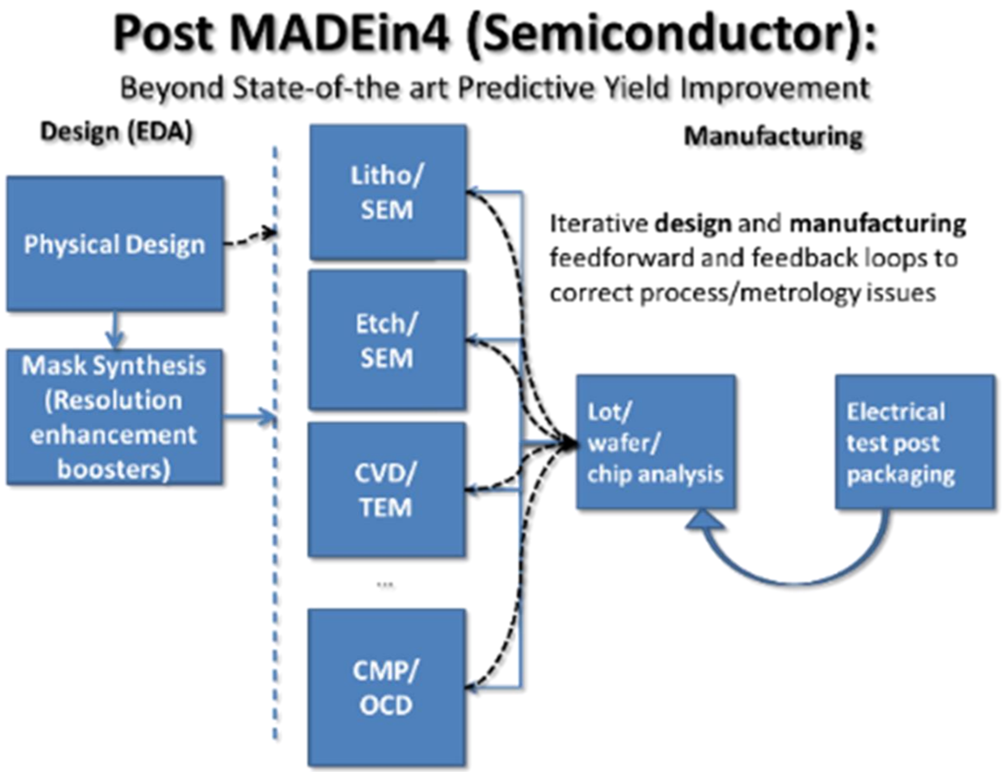
Number of different configurations $10^2 < x < 10^3$

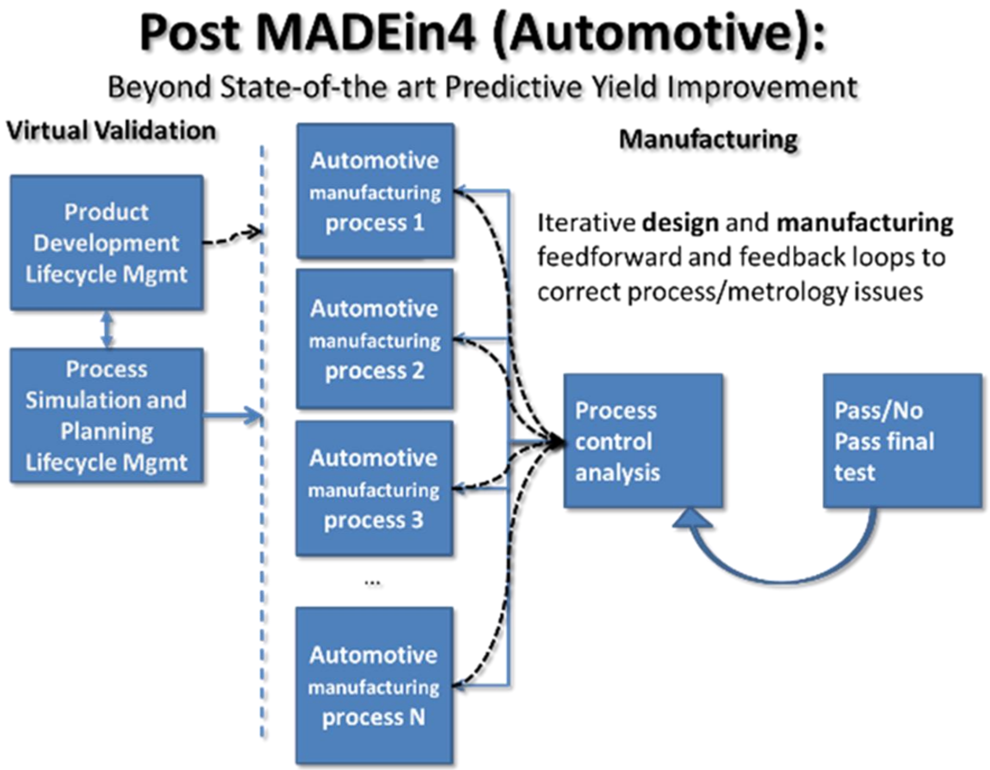
Highly automated manufacturing

Number of inputs per unit process (features) 10^2

Manufacturing process continuously under improvement and changes

Semiconductor and Automotive domains analogy





The Semiconductor and Automotive industries are sharing similar design and manufacturing flows and differ by the content of each of the design and manufacturing modules

This allows to develop innovative shared machine learning based methodologies which will enable the transformation of the manufacturing from reactive to predictive

AGENDA

Data is the new oil: design, modeling, metrology and ML

Context creation

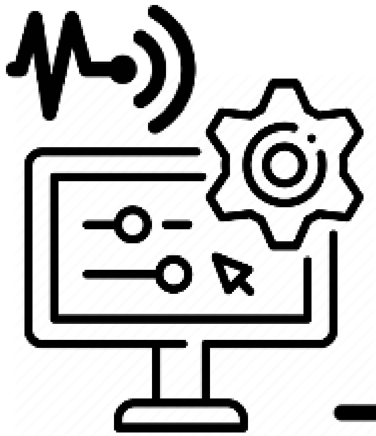
Data is the new oil

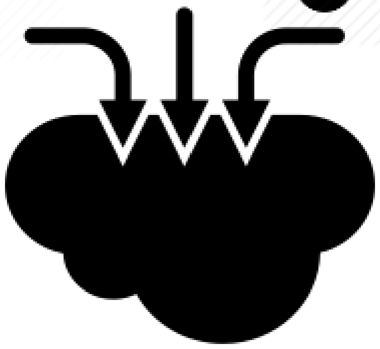
1

Data collected and pushed to the cloud

2

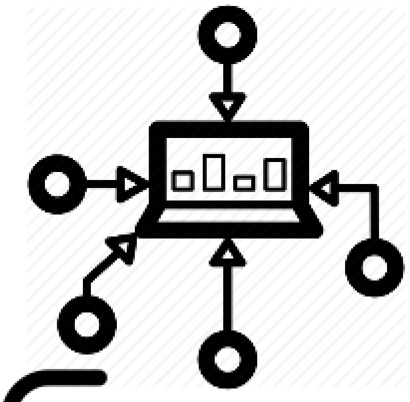
Sensors are added to industrial computers





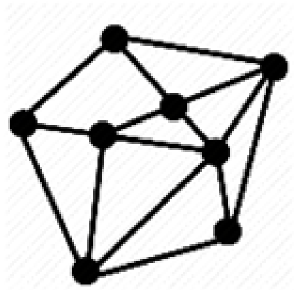
3

Constant data collection for future possible usage

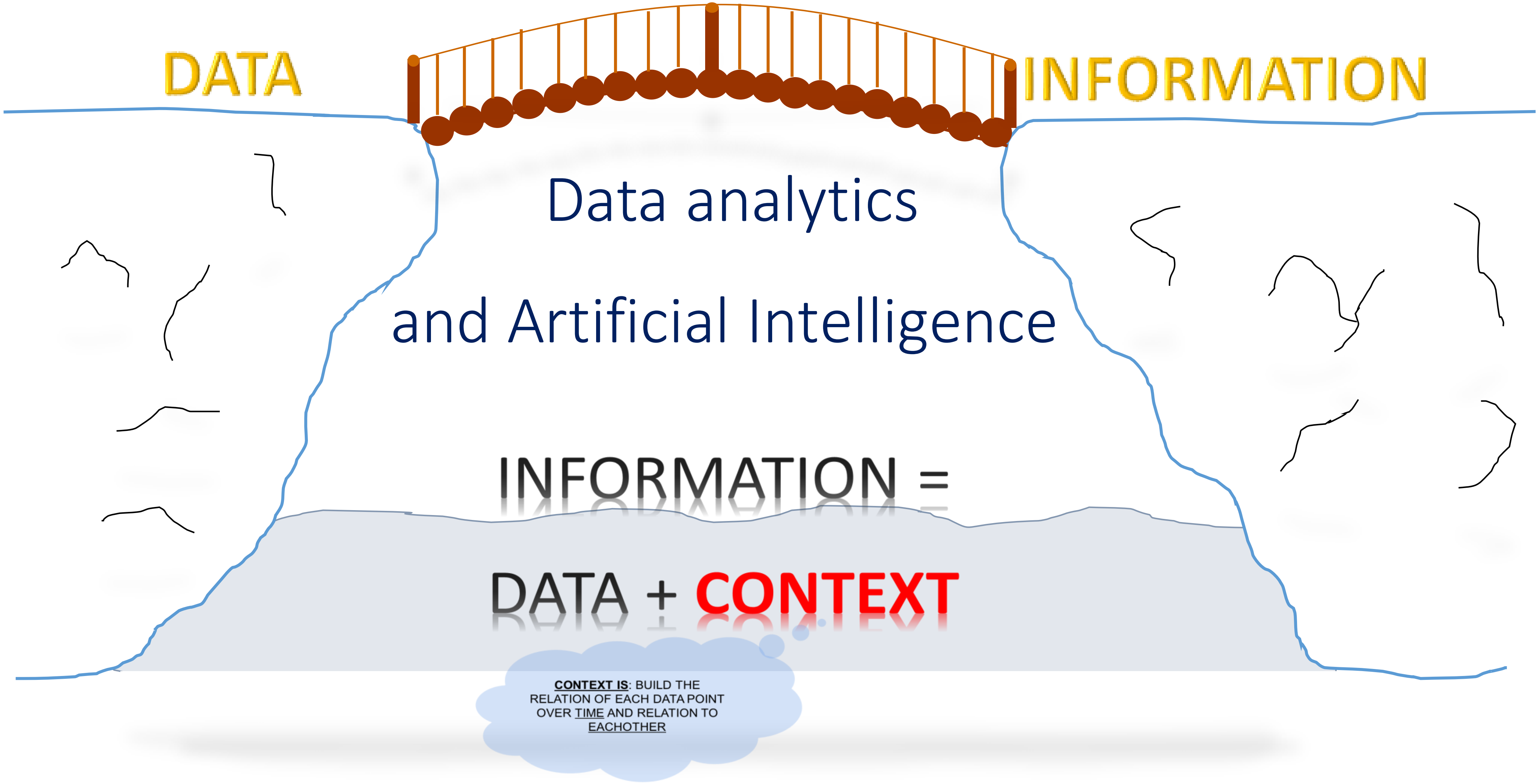


4

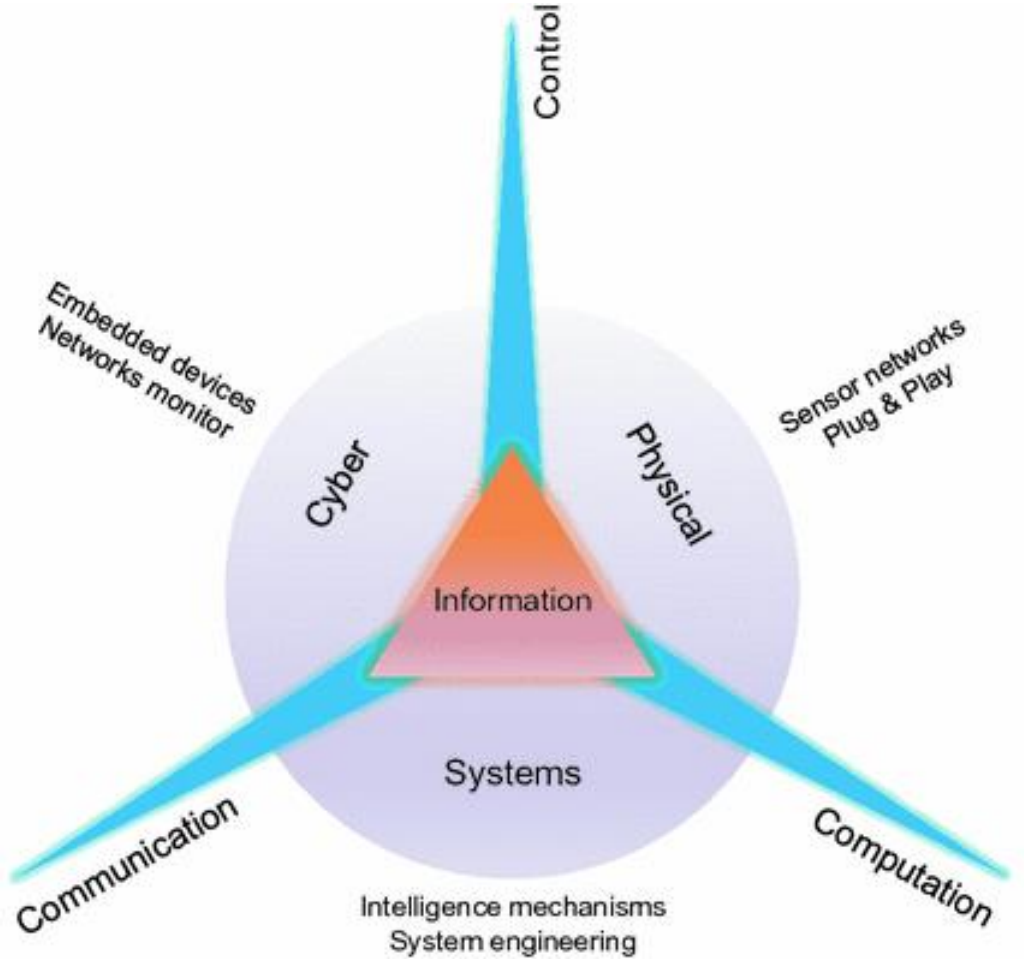
Data analysis by tailor-made algorithms



CONTEXT (crossing) the chasm

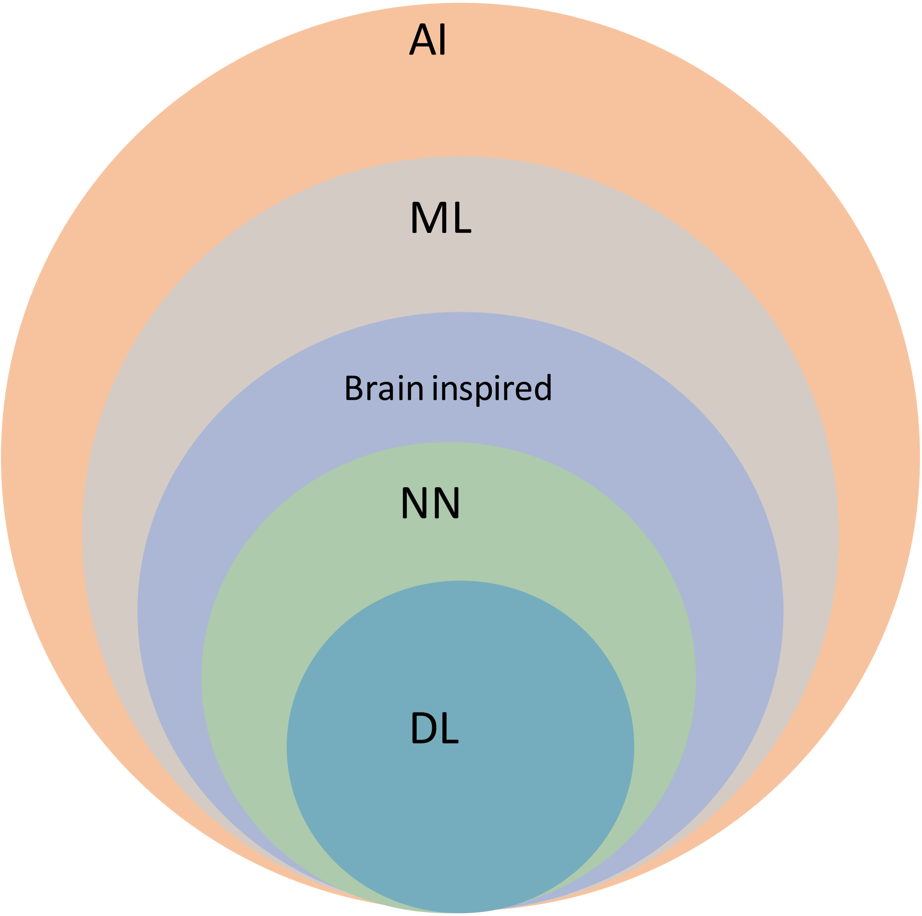


Cyber-physical Systems (CPS) for Information Creation



The interaction of physical and computing, including embedded intelligence at all levels

Artificial Intelligence (AI)

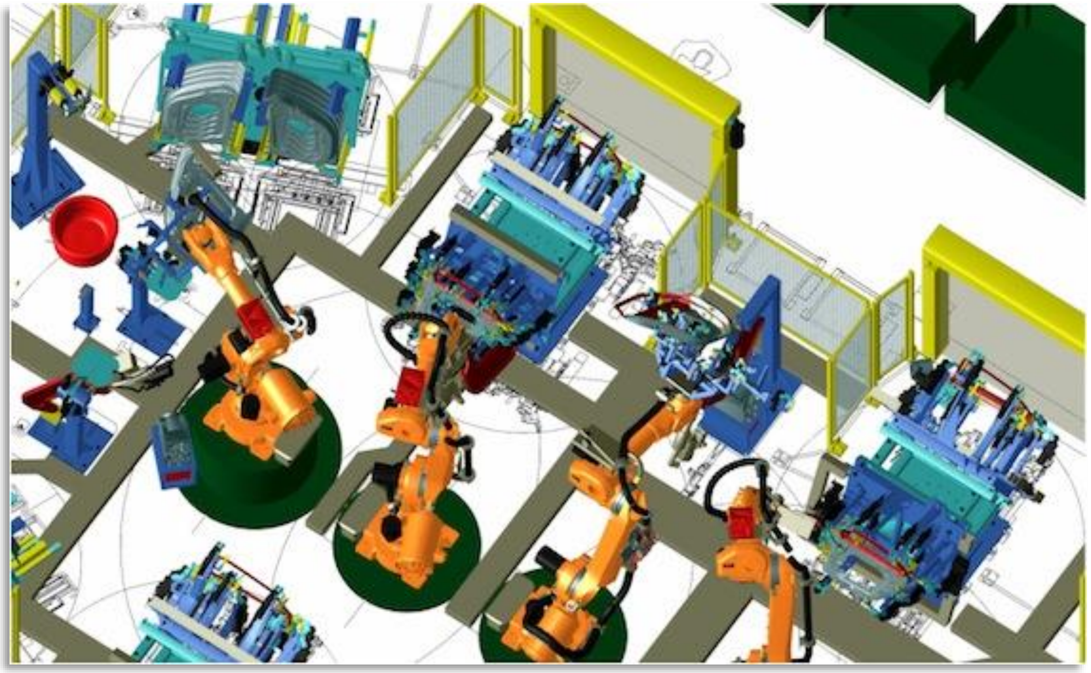


- AI: Artificial intelligence making decisions about a system
- ML: Machine learning modeling the behavior of a system
- NN: Neural networks are one implementation of machine learning
- DL: Deep learning is one implementation of Neural networks

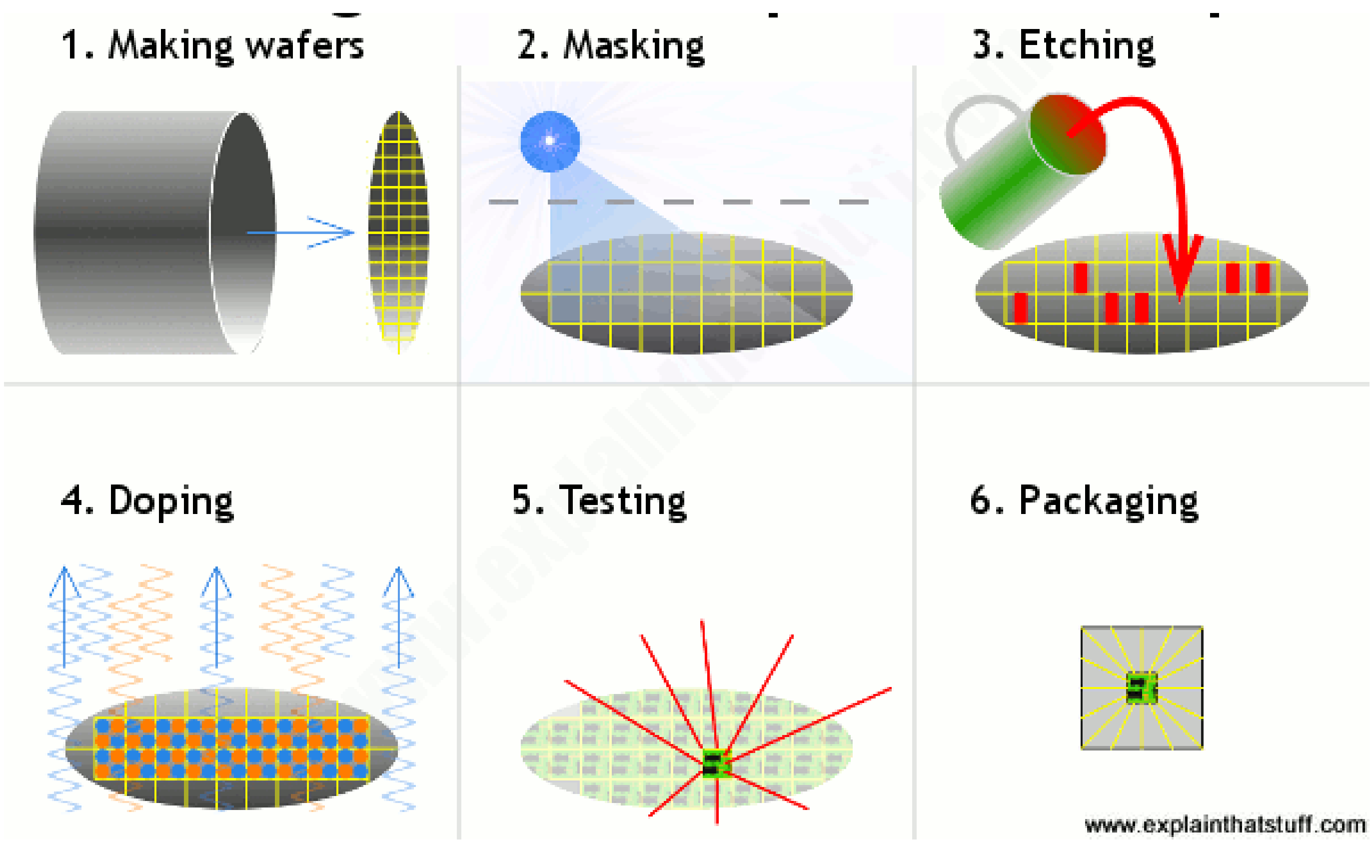
Digital twinning: Creating a virtual Representation of the Production Process

Traditional modeling: Physical models requiring little data but deep understanding of the process.

ML-based modeling: “black box” models requiring feature engineering coupled with sensor data.



CPS SENSORS: From Silicon wafer to IC Processes and Metrology



700 to 1500 operations for an average CMOS process

- **2-3 months** manufacturing time
- **22-50** lithography layers
- **20** Diffusion Ops.
- **23-40** implants Ops.
- **13** DRY Etch Ops
- **78** WET Etch Ops
- **21** Thin-Film (metal) Ops.
- **7** CMP (Chemical-Mechanical-Polish) Ops.
- **240 Metrology** Ops.
- **240 Yield** Ops.

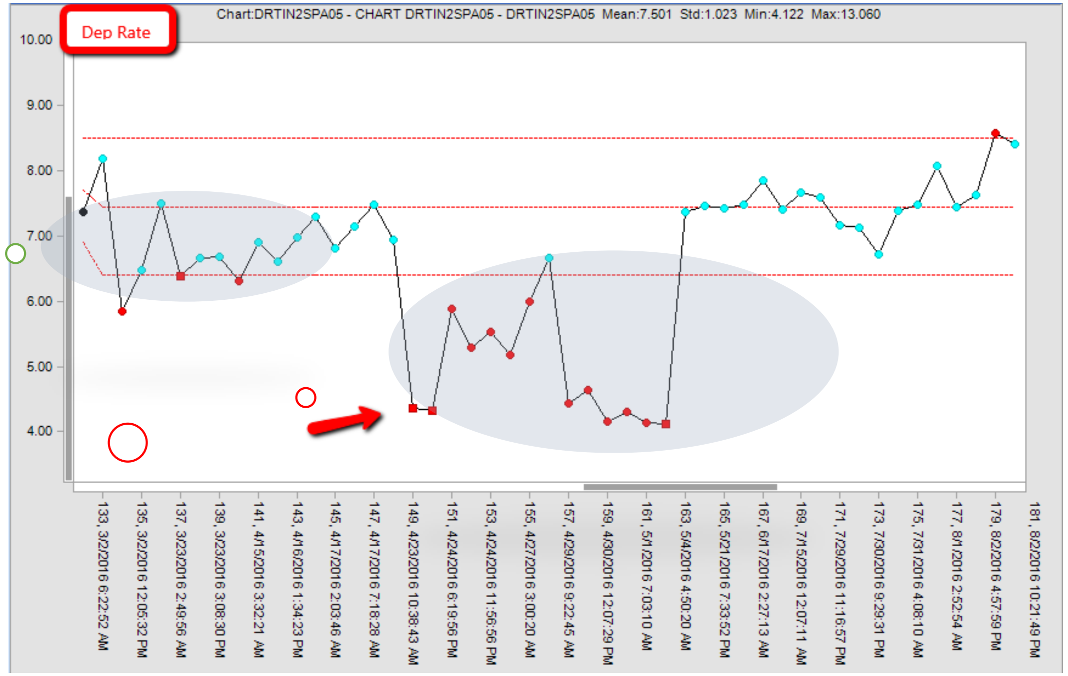
Source: TOWER

CPS Sensor Pre-Warn

Metrology use case - Metal deposition rate

Early indications of problems?

Tool is down for service!



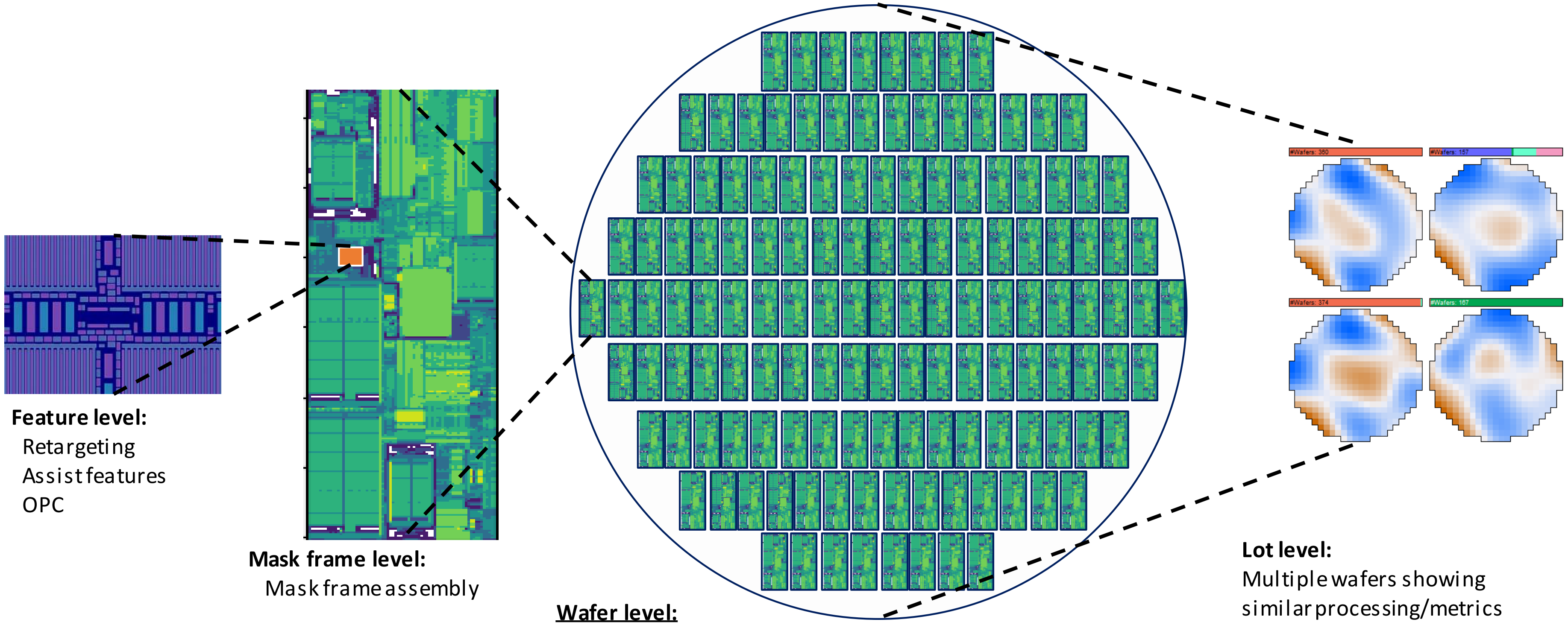
AI to pre-warn about process issues

Source: TOWER

Predictive Yield: Feature Engineering

From Feature to Lot level

Different processes require their own level of abstraction to capture specific process behavior

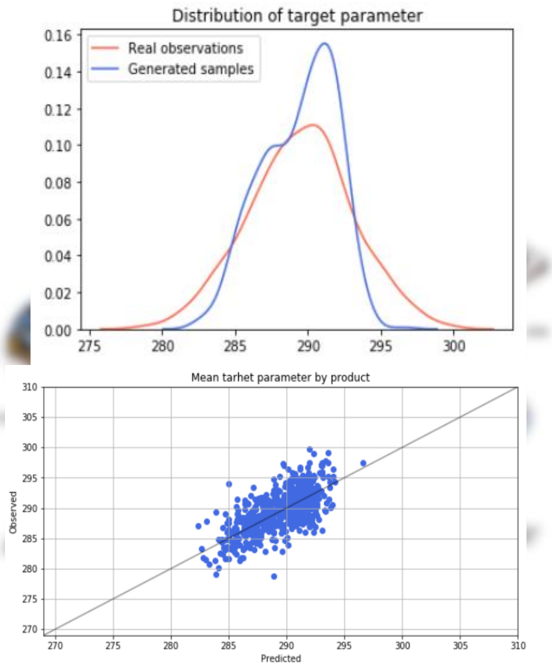


Source: MENTOR

Predictive Yield

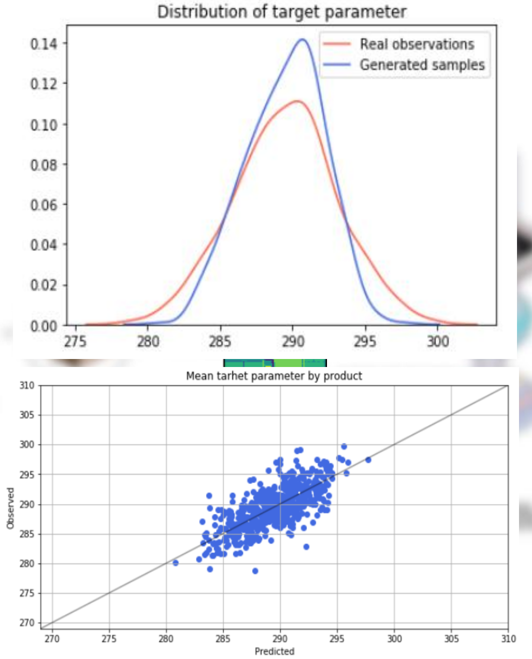
Full process sequence characterization

Input:
Process



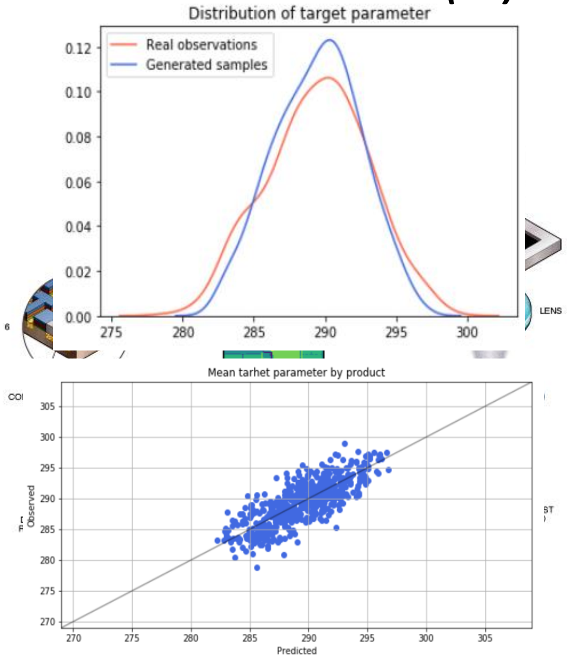
0.47 R-squared score for predicted vs observed
2.09 MAE (Mean absolute Error) score

Input:
Process & Layout



0.51 R-squared score for predicted vs observed
1.96 MAE (Mean absolute Error) score

Input:
Process & Layout & Previous Measurements (all)

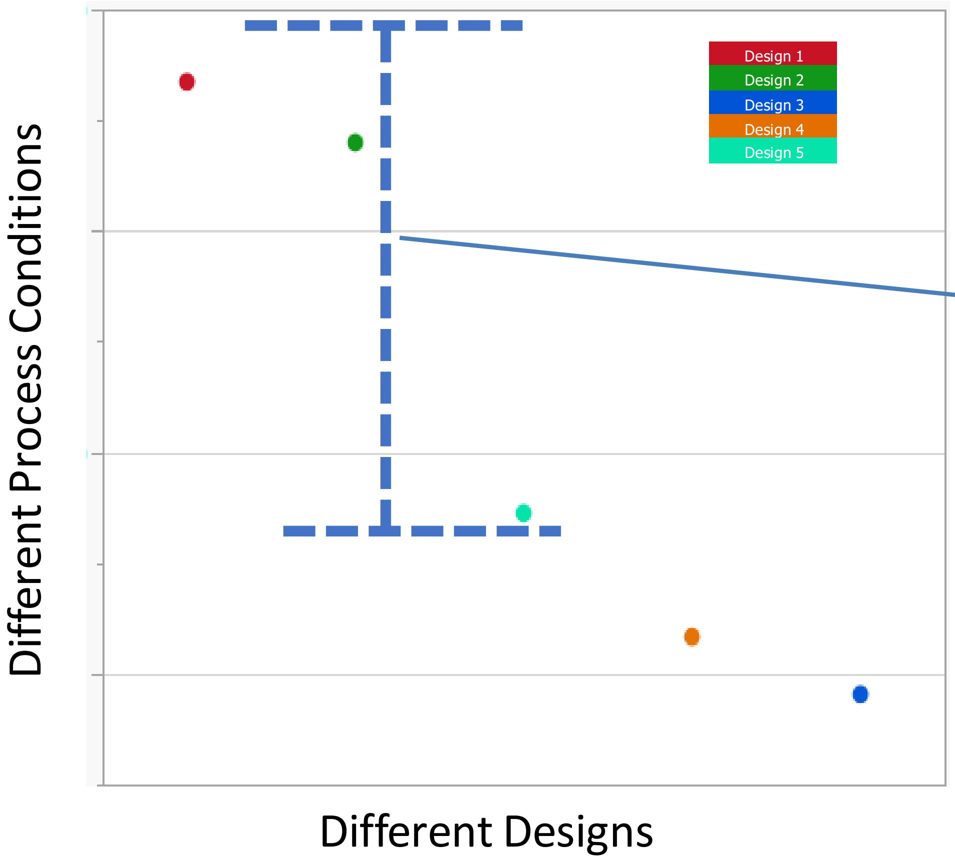


0.62 R-squared score for predicted vs observed
1.74 MAE (Mean absolute Error) score

Source: MENTOR

Predictive Yield

Digital Twin - Process characterization modeling & optimization



Different designs respond differently to process conditions

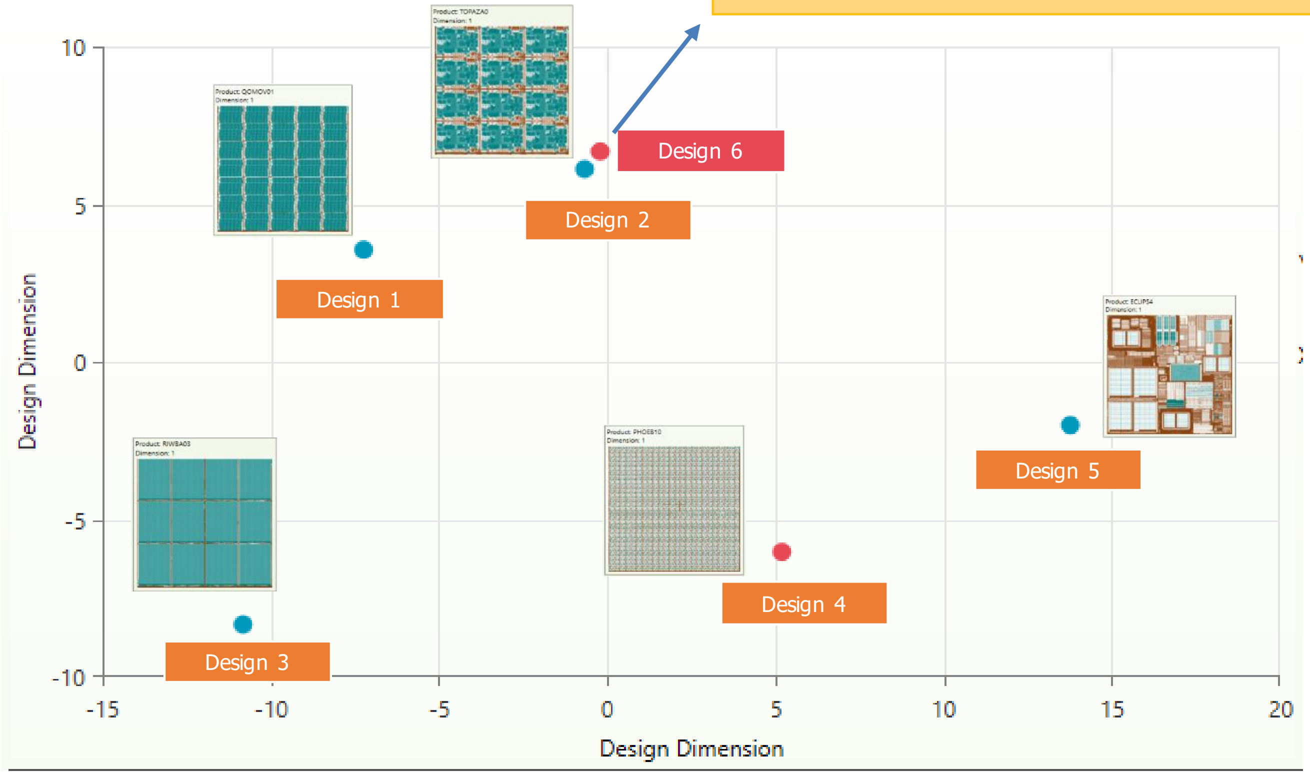
They are manually optimized in a time consuming and expensive fashion

Source: MENTOR

Predictive Yield

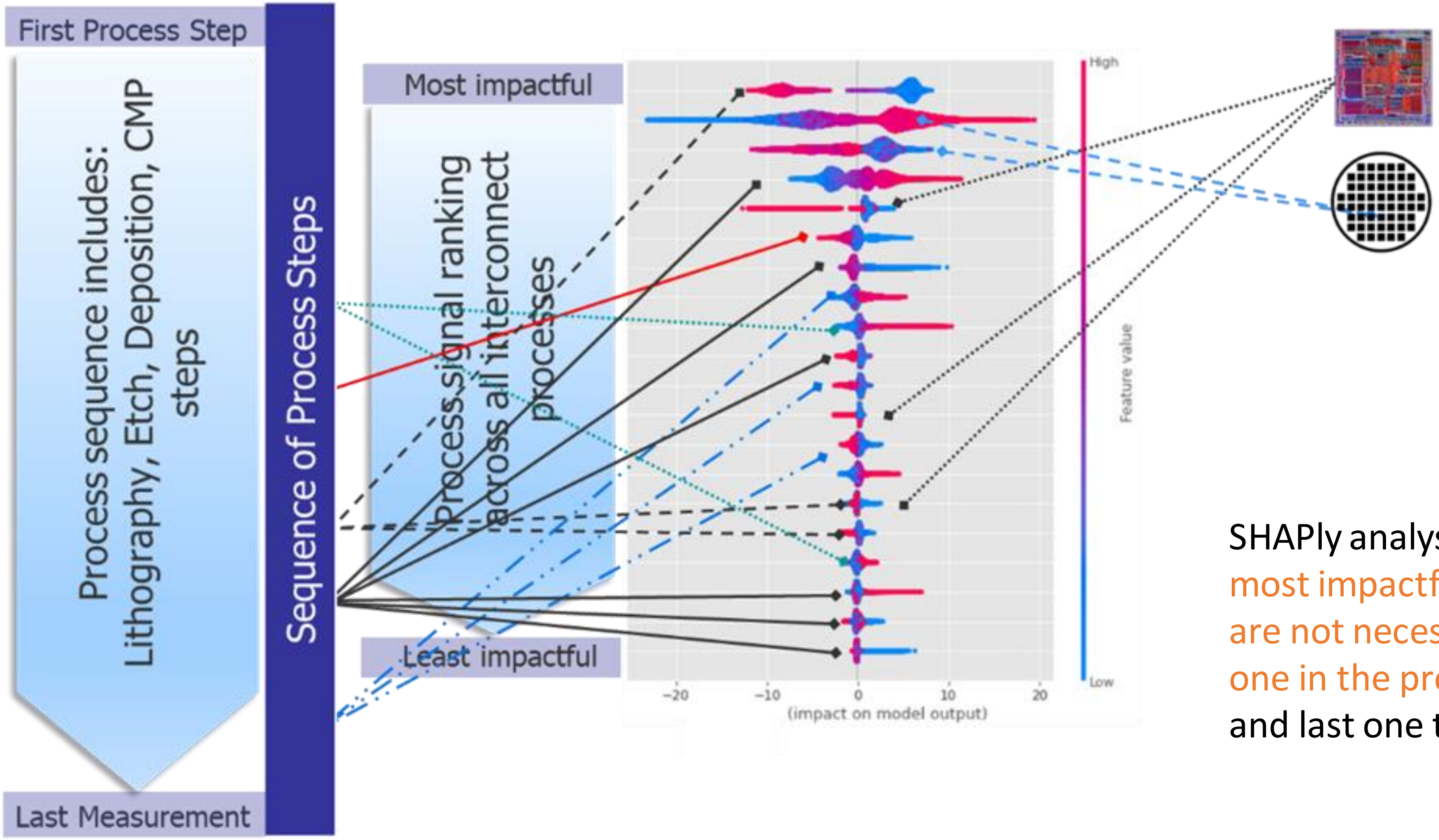
Digital Twin - Design-aware process optimization

Process for new designs can be virtually optimized



Source: MENTOR

Predictive Yield
Process Impact Analysis

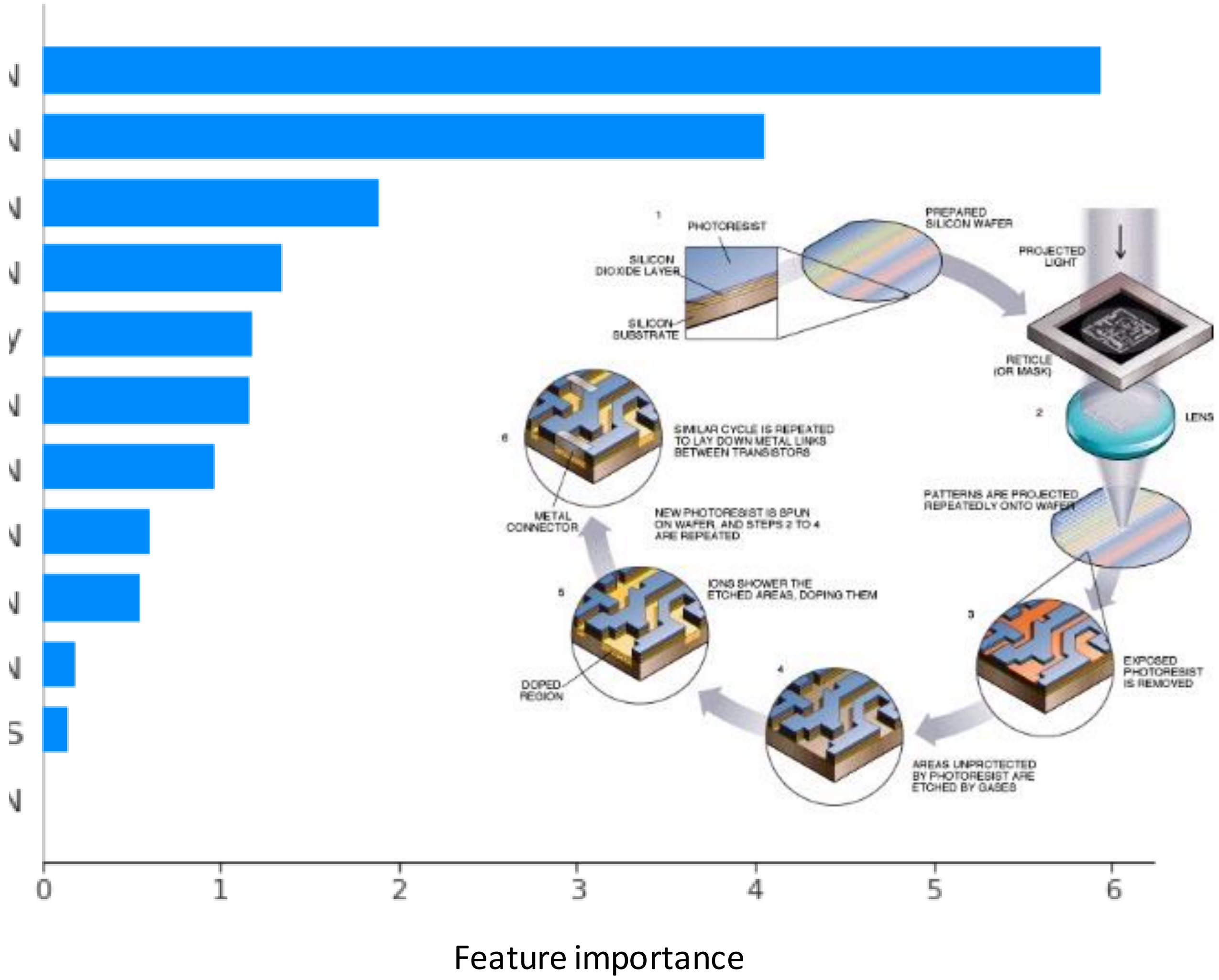


SHAPly analysis show the most impactful process steps are not necessarily the last one in the process sequence and last one to be measured

Source: MENTOR

Predictive Yield

Digital Twin Feature Based Yield Prediction



Feature importance assessment to guide correction or define optimal operation

Source: MENTOR

AGENDA

Automotive domain use cases

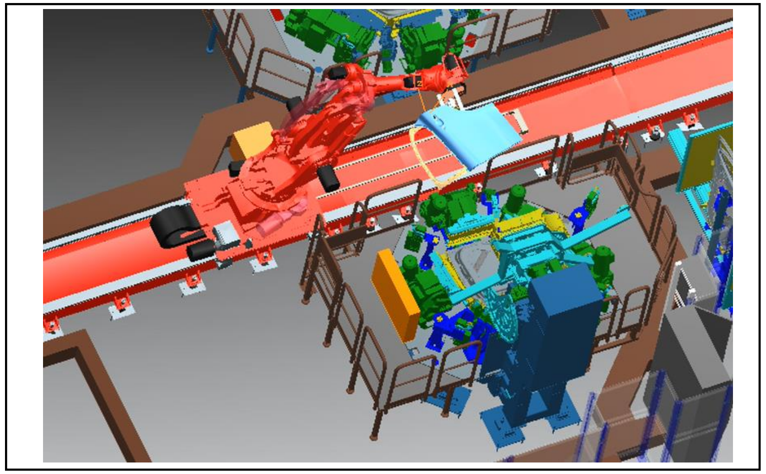
Use Case 1: Cars body line digitization with Pre-Warn scenarios

FCA, NANOMOTION, TOWER, TU DELFT, POLITO

Problem statement: door welding defects rarity

Solution: development of an inline doors inspection **A**utomated **D**efects **C**lassification (**ADC)**

Weldspots with LED illumination



3D Process simulation

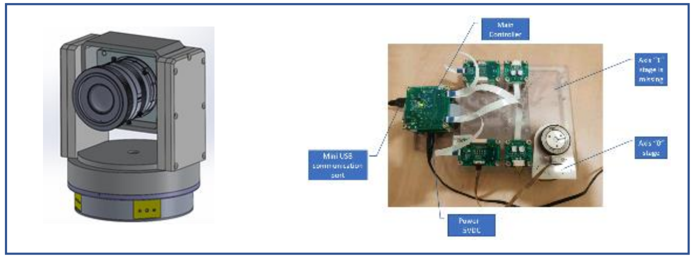
Partners test field

Use Case 1: Cars body line digitization with Pre-Warn scenarios

Welding doors inspection and ADC flow

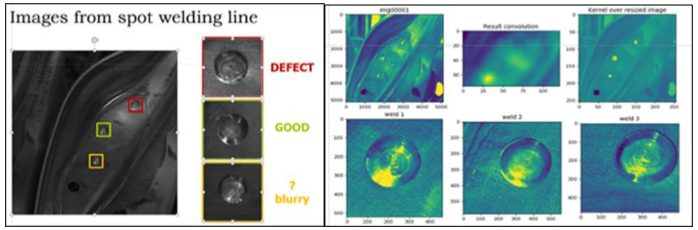
FCA

Design of innovative solution and integration

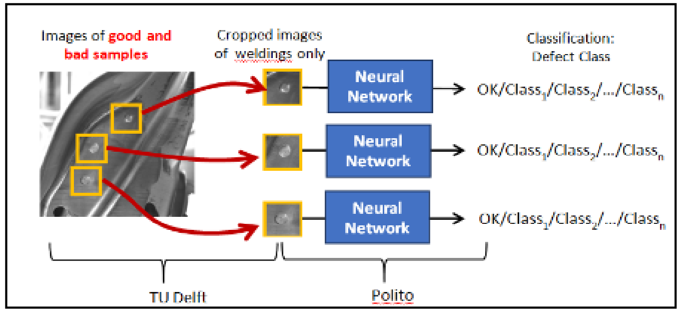


Nanomotion: Camera stabilized gimbal

TOWER: sensor and camera



TUD: Image conditioning



POLITO: Auto Defect classification (**ADC**)

Use Case 1: Cars body line digitization with Pre-Warn scenarios

Automatic Defects Classification in the Semiconductor domain

- ADC is a central server used for Recipe Creation, Runtime Classification & Monitoring in semiconductor manufacturing

- ADC is developed in the Semiconductor domain to:
  - Help semiconductor manufacturers to increase and maintain IC chip yields
  - Monitor whether the process is under control
  - Provide high availability (uptime 99.99%)

Where is my DOI* ?

*DOI - Defect Of Interest

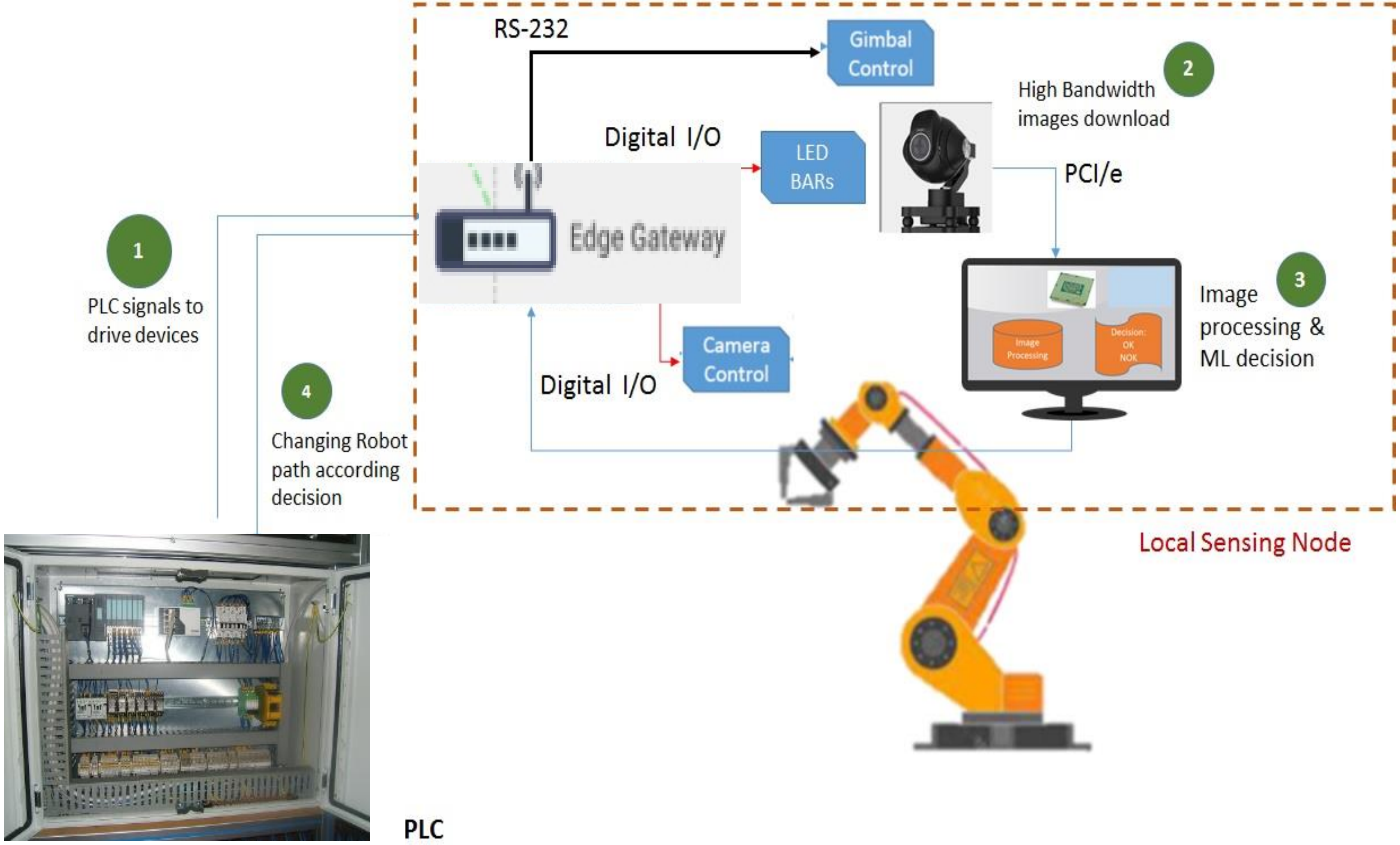
Use Case 1: Cars body line digitization with Pre-Warn scenarios

Automatic Defects Classification in the Semiconductor domain

- As design rule shrinks, defects hide in inspection noise → the amount of manually classified defects is increasing
- Classification can be done faster while taking into account much more attributes than human eyes can
- High consistency can be reached with an Automatic system

Use Case 1: Cars body line digitization with Pre-Warn scenarios

Automotive domain doors inspection and ADC flow overall architecture and processing pipeline

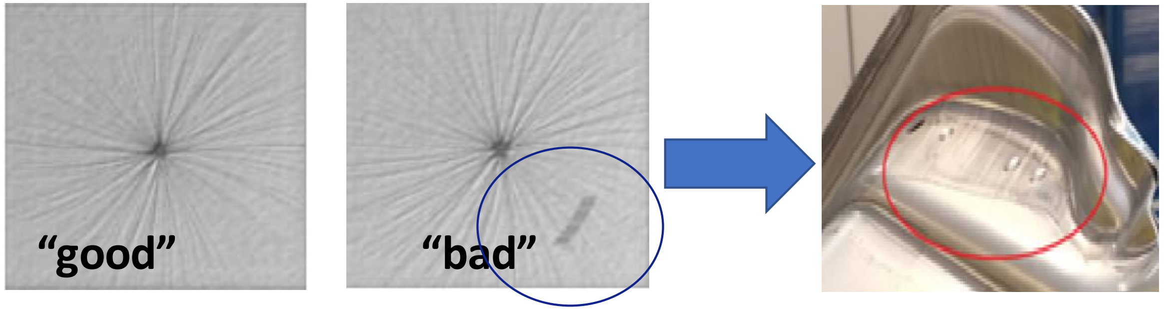


Source: FCA

Use Case 1: Cars body line digitization with Pre-Warn scenarios

Automatic Defects Classification in the Automotive domain

- Preliminary neural networks (NN) tested both on synthetic and real images



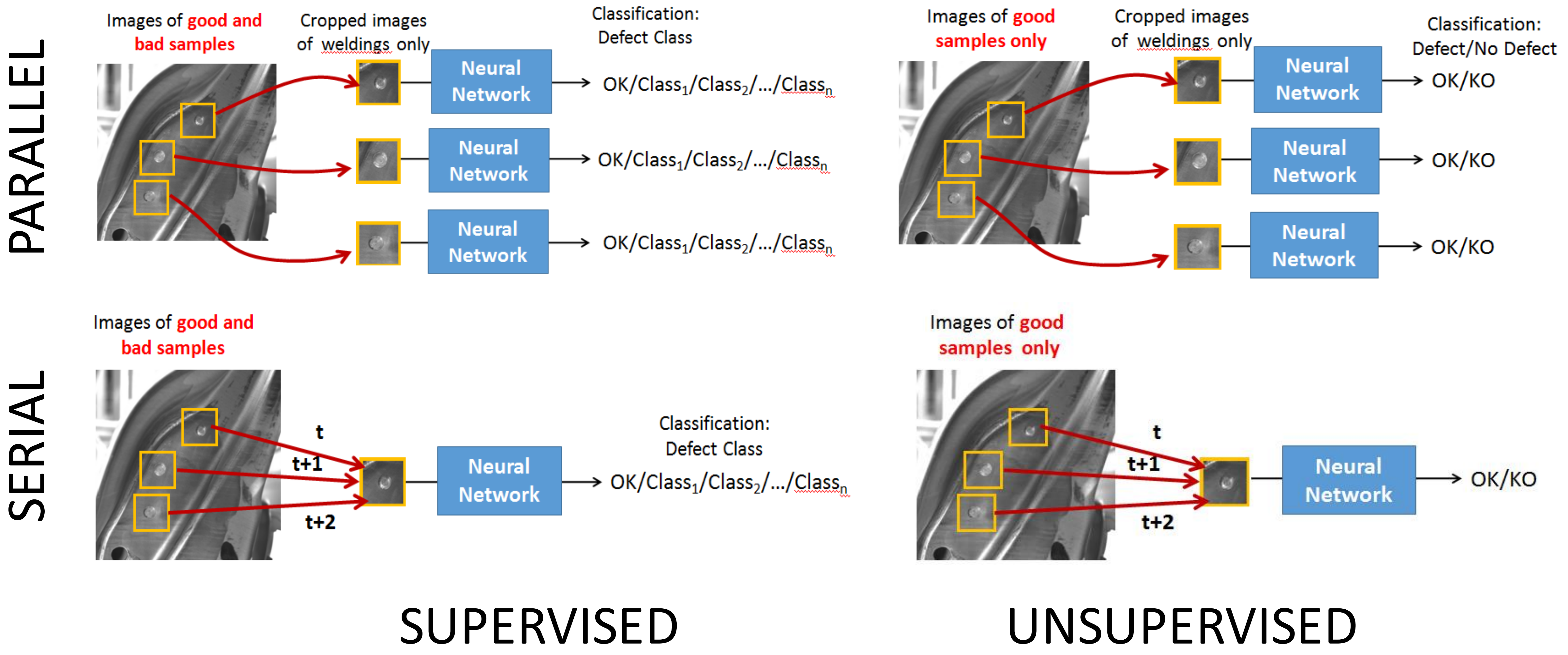
- An independent classification (a distinct network) for each soldering point were used
- Two approaches of NN were compared:
  - **One-class classifiers** (unsupervised)
    - Uses only ``good’’ samples, Classes are OK/KO
  - **Traditional multiclass CNN** (supervised)
    - Classes can be multiple
- Two different architectures of processing options were tested:
  - **Serial**
  - **Parallel**

Choice will depend on the cost (performance) of the overall pipeline of operations (camera, cropping, image processing)

Speed vs. size of the network

Use Case 1: Cars body line digitization with Pre-Warn scenarios

Automatic Defects Classification in the Automotive domain



Use Case 1: Cars body line digitization with Pre-Warn scenarios

Automatic Defects Classification analogy between Automotive and Semiconductor - Outlook

- Exploring 'SEMI – Automotive' ADC potential cross fertilization:
  - **Is there potential value in adapting concepts from SEMI to automotive and vice versa?**

- Objectives
  - Introduction to SEMI and Automotive ADC concepts, challenges and solutions
  - Potential cross fertilization ideas

- Action:
  - Map similarities and differences between SEMI ADC and Automotive ADC: needs, constraints, approaches

Use case 2: End-of-Line Engines Testbenches

AVL, FCA

Problem statement:

End of Line engines tests efficiency:

- Conducting End Of Line engines hot testbench is expensive (time, effort, …)
- Hot EoL tests are conducted for 5-10 % of all engines
- Typically engines are selected randomly, this poses the risk that erroneous engines are overlooked

Solution:

cycle time reduction:

- Reduction of false negatives (healthy engines that are qualified as erroneous) through data-driven selection (correlation of after sale, cold and hot test data)
- Reduction of false positives (erroneous engines that are qualified as healthy) through predictive warning driven from the cold test bench

EoL cold testbeds

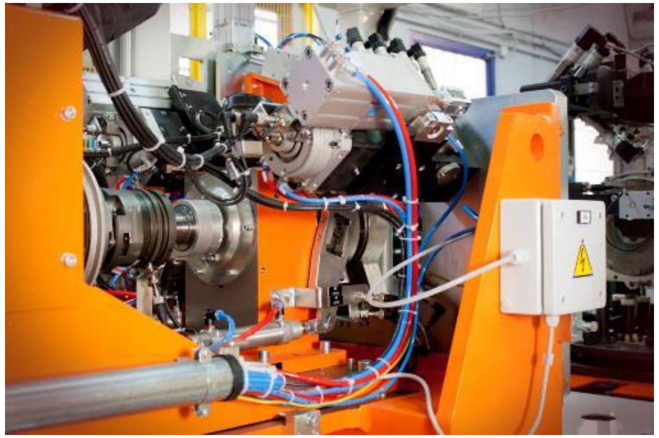
- 30 sec
- In-line

EoL hot testbeds

- ½ h - 3 h
- oil, Electronic Control Unit, fire-up, ..

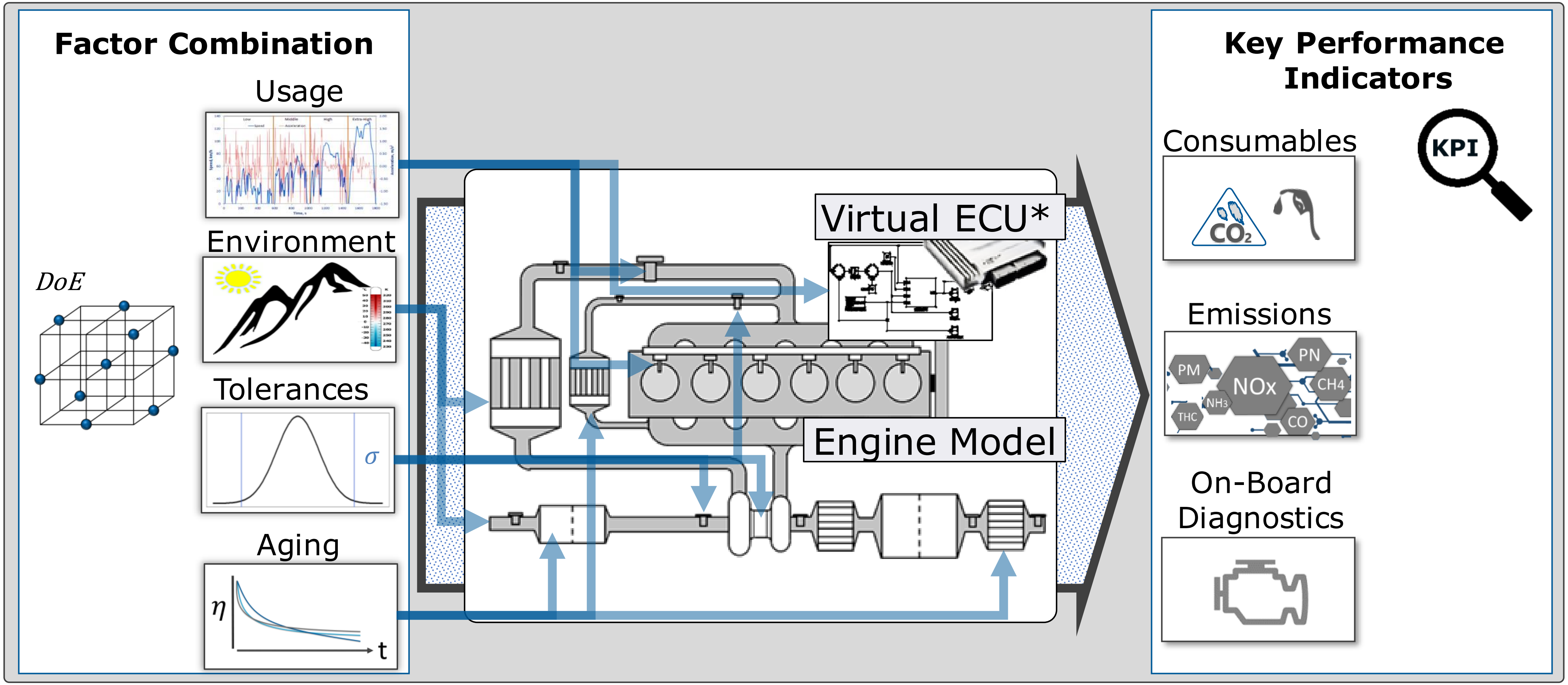
Engine performance testbeds

- 24 – 48 h



Source: AVL List GmbH

Use Case 2: EoL Evaluation of the impact on production tolerances on engine KPIs



*ECU: Electronic Control Unit

Source: AVL List GmbH

Use Case 2: Method EoL Cold/Hot Optimization
(historic data)


Source : AVL List GmbH

EoL cold tests


Source : AVL List GmbH

EoL hot tests

ICE* no.	Ch1 time series	….	Ch [30+] time series
E1	1.2, 1.4, 1.7, ..		1.2, 1.4, 1.7, ..
E2	0.87, 1.2, 1.7, …		0.87, 1.2, 1.7, …
E3	0.27, 0.2, 0.7, …		0.27, 0.2, 0.7, …
..	…		
En	…		

Quality-Indicators / KPIs

Labels (fault modes)

ICE no. (subset of EoL cold test)	Label (test oracle)
E1	healthy
E2	erroneous
E3	healthy
..	
Em	erroneous

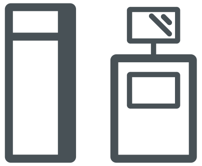
*Internal Combustion Engine

Model learning: e.g., classification model $Y_i = h\left(x_i^{(1)}, x_i^{(2)}, \dots, x_i^{(m)}\right) + E_i$

Use Case 2: Method EoL Cold/Hot Optimization
(live data)

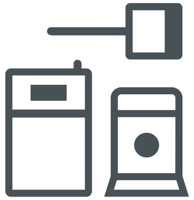
Source : AVL List GmbH

EoL cold tests



Source : AVL List GmbH

EoL hot tests



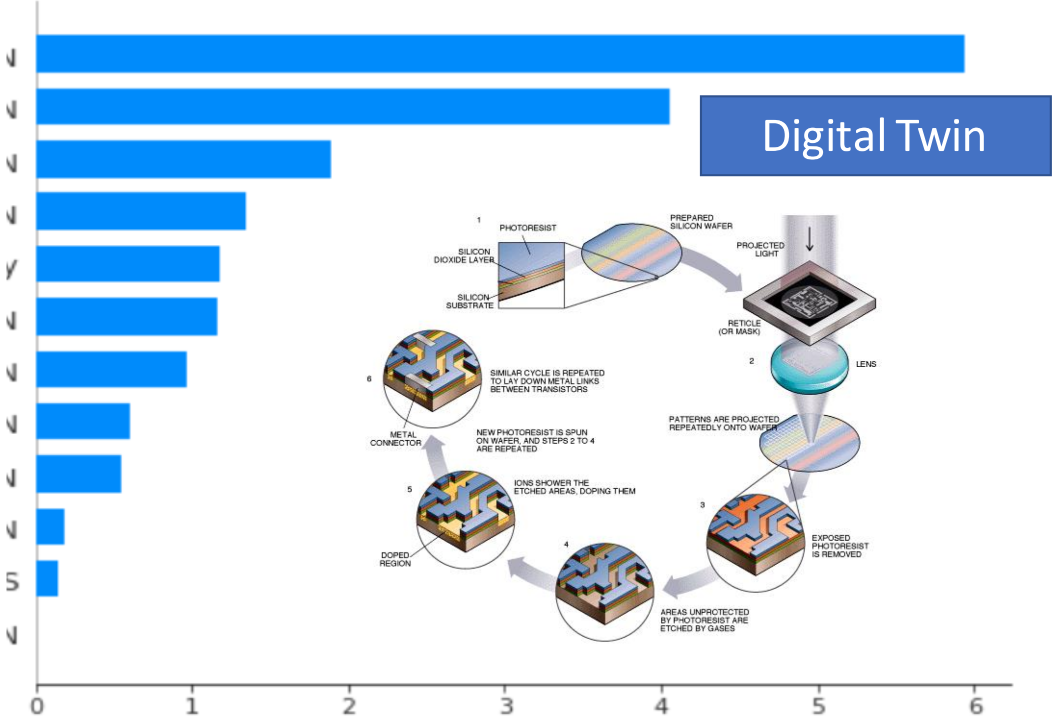
ICE no.	Ch1	….	Ch [30+]
E1	1.2, 1.4, 1.7, ..		1.2, 1.4, 1.7, ..
E2	0.87, 1.2, 1.7, …		0.87, 1.2, 1.7, …
E3	0.27, 0.2, 0.7, …		0.27, 0.2, 0.7, …
..	…		
En	…		

ICE no.	False positive/ False negative
E1	healthy
E2	erroneous engines qualified as healthy
E18	healthy
..	
Em	Healthy engine qualified as erroneous

$$Y_i = h\left(x_i^{(1)}, x_i^{(2)}, \dots, x_i^{(m)}\right) + E_i \rightarrow \text{prediction}$$

Use Case 2: Automotive / Semiconductor Predictive Analysis Analogy

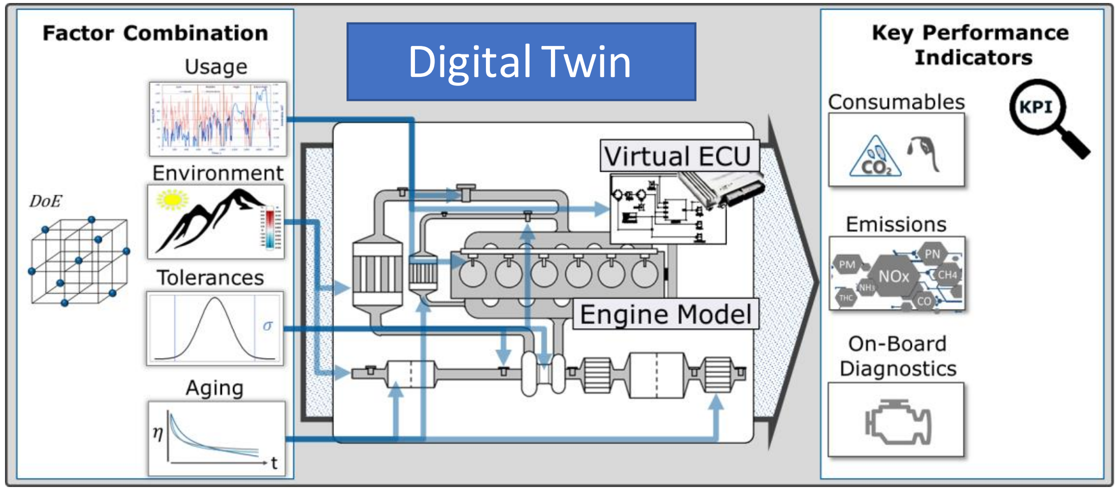
Semiconductors wafers features process prediction



Feature importance

Source: MENTOR

Automotive engines features process prediction



ICE no.	False positive/ False negative
E1	healthy
E2	erroneous engines qualified as healthy
E18	healthy
..	
Em	Healthy engine qualified as erroneous

Source: AVL List GmbH

Summary and Outlook

- Data is the new oil and data analytics with artificial intelligence uses context to produce information

- Analogies between the Semiconductors and Automotive domains could enable cross fertilization between the two

- MADEin4 is expected to make a breakthrough for yield prediction and pre-warn scenarios accuracy and cycle time in both the Semiconductors and Automotive domains by:

  - Enhanced methodologies, algorithms and hardware such the case of automatic defects classification (ADC) in the production line

  - Improved digital twin modeling accuracy with design, process and metrology data from various sources

MADEin4

Thank You For Your Attention

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