The MADEin4 project

LTM-CNRS contribution (collaboration with STMicroelectronics)

New Industry 4.0 metrology approaches driven by predictive in line control requirements :

At the frontier between academic studies and industrial world

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February 16th 2021
Technology Unites Global Summit

LTM

(Laboratoire des Technologies de la Microelectronique)
Grenoble – France

- **CNRS – UGA** (Grenoble Alpes University) **Academic Research lab** benefiting of **industrial clean room access** (hosted in CEA-LETI environment)

- Technological research performed on state of the art 200 and 300mm tools, in **close collaboration with industrials** like ST

- Research lab dedicated to **micro- & nanotechnologies**:
  - Advanced materials, Nanomaterials and Integration
  - Plasma etching processes for nanoelectronics and emerging devices
  - Advanced Lithography
  - Micro - and nanotechnologies for Health

- Around 90 people including ~30 Ph.D. students

STMicroelectronics

- One of the world's largest semiconductor companies
- 2019 revenues of **$9.56B**
- **46,000** employees of which **7,800** in R&D
- Over **80** Sales & marketing offices serving over **100,000** customers across the globe
- **11** Manufacturing sites
- Signatory of the United Nations Global Compact (UNGC), Member of the Responsible Business Alliance (RBA)

As of December 31, 2019

STMicroelectronics @Crolles, France

More than ~10,000 employees in France

3 manufacturing sites

7 R&D sites

2 sales/marketing sites

1st Private **employer** in Isère

Among the 1st **exporters** in the Auvergne Rhône-Alpes area

Created in **1973**

Created in **1992**

~2,000 employees

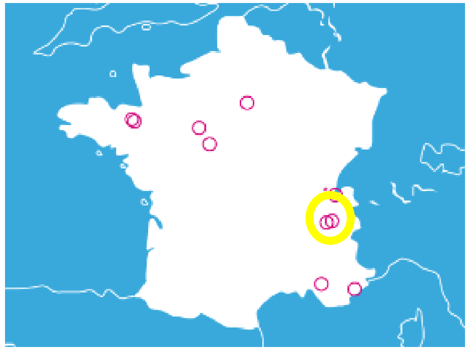
Grenoble
Product Development

Crolles
Technology R&D
Manufacturing

~4,200 employees

Over
€5 billion invested
in infrastructure in Crolles since the site's creation

Local stakeholders
Universities, SME, local ecosystem
CEA/Leti, Soitec…



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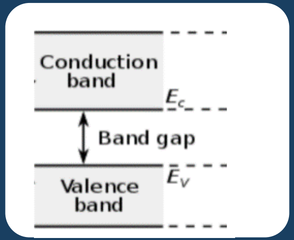
Industry 4.0 context

Advanced technology nodes → Technology Diversification

Key Enabler → Increase productivity

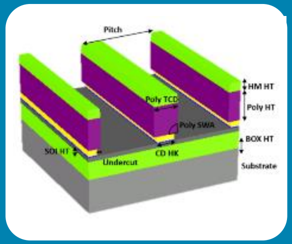
GET MORE out of what we already get from metrology steps

GET MORE



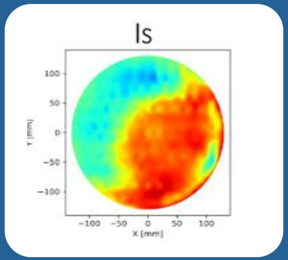
1) **Increase Knowledge (MADEin4 booster 1)** → New parameter

- New materials intoduced in fab to support technology diversification
- New characteristics needed for direct analysis inline
- Mutualise metrology techniques to get new information



2) **Increase Robustness (MADEin4 booster 1)** → New approach for Hybridization

- Benefit from different sources of metrology techniques to get more accurate measurements
- Use proper smart algorithm based on NN to enhance quality from combinaison of inline raw signal and collected data



3) **Go Faster (MADEin4 booster 2)** → New approach for process deviation

- Model based techniques are very time and ressources consuming
- Model less approach is now needed even at R&D phase when structures and materials are not fully defined

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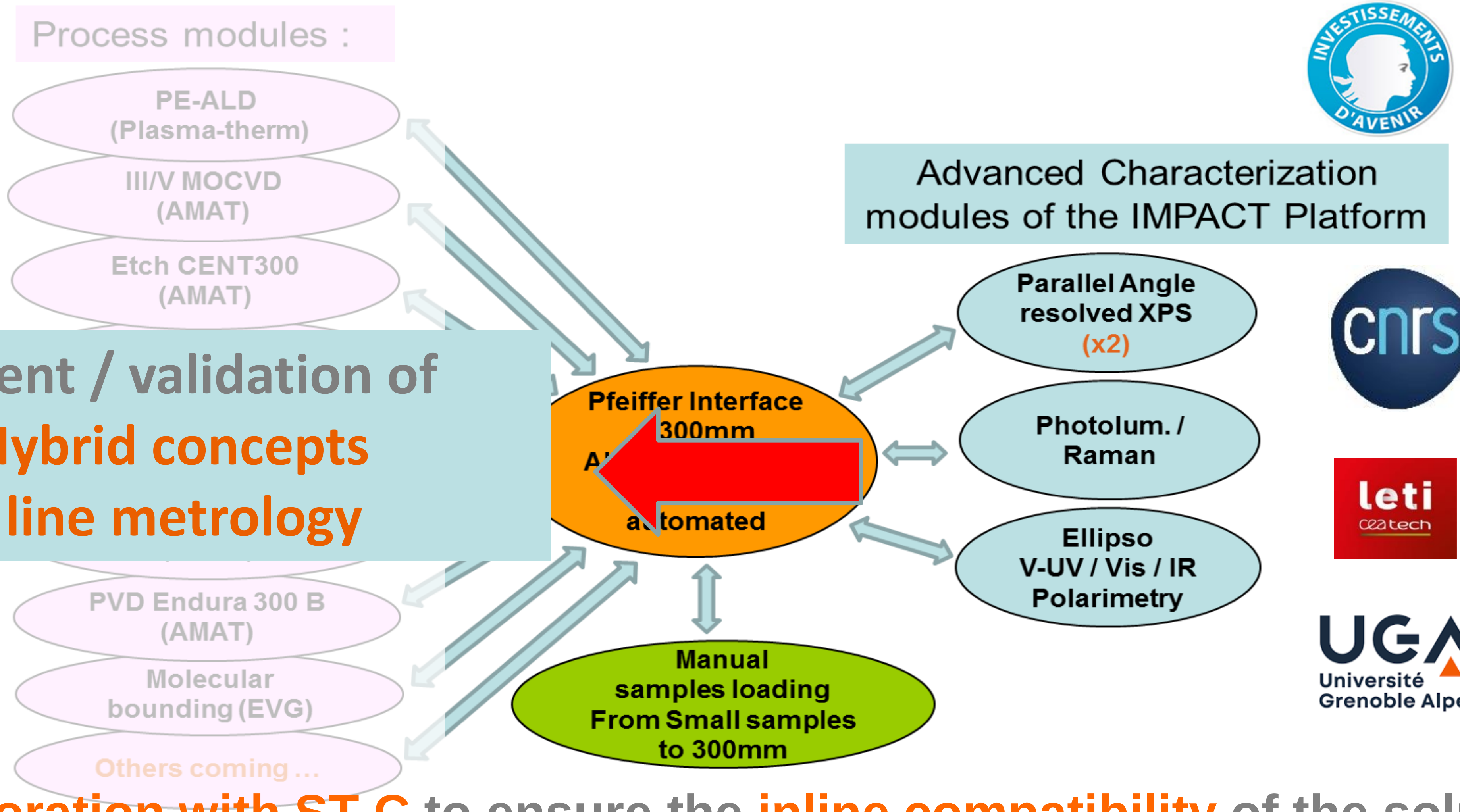
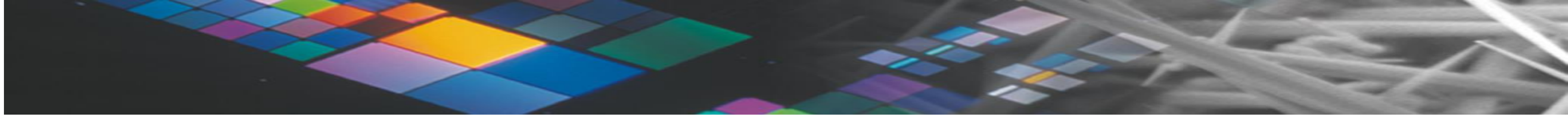
Use of unique metrology tool set based on versatile and powerful Hybrid Lab techniques implemented on an Inline 300mm platform.



Assessment / validation of new Hybrid concepts for in line metrology

Close collaboration with ST-C to ensure the inline compatibility of the solutions

LTM
LABORATOIRE DES TECHNOLOGIES DE LA MICROÉLECTRONIQUE

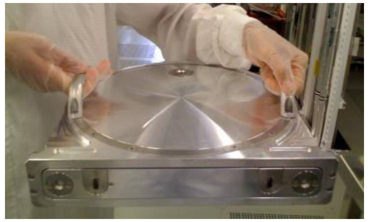


LTM's 'IMPACT' Inline 300mm platform advanced specifications for MadeIn4

- **XPS**
  - ✓ **pAR-XPS** (parallel angle resolved XPS)
  - ✓ Angles from **20° to 80° without sample tilt**
  - ✓ Spot size 20 to 400µm
  - ✓ Ion beam Ar etching for abrasion
- **Ellipsometry**
  - ✓ **IR to V-UV : 12 µm (0,1 eV) to 145 nm (8,55 eV)**
  - ✓ IR **Polarimetry**
  - ✓ Azimutal rotation
  - ✓ **Sample heating (up to 450°C)**
- **Photolum / Raman**
  - ✓ Based on Labram HR (best in class Raman system)
  - ✓ **IR to UV (3 lasers : 355nm / 532nm / 1064 nm)**
  - ✓ Confocal measurements (depth resolution)
  - ✓ Spatial resolution < 3µm

INVESTISSEMENTS D'AVENIR

Specific 300mm vacuum carrier with Industrial compatible design



LTM actions in MadeIn4
In line with **Booster 1 & Booster 2**

1) **Hybridation** between **XPS** and several optical techniques (**Ellipsometry, Raman, …**) for ultra-thin film metrology

2) **Robustness improvement** of metrology standards accuracy through **CD-SAXS measurements** in partnership with LETI
AI based approach

3) Ellipsometry / Polarimetry for fast critical errors detections in **large surfaces 3D patterns**
Very fast model less approach

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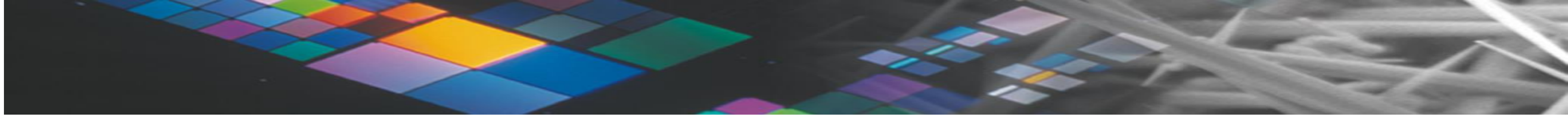
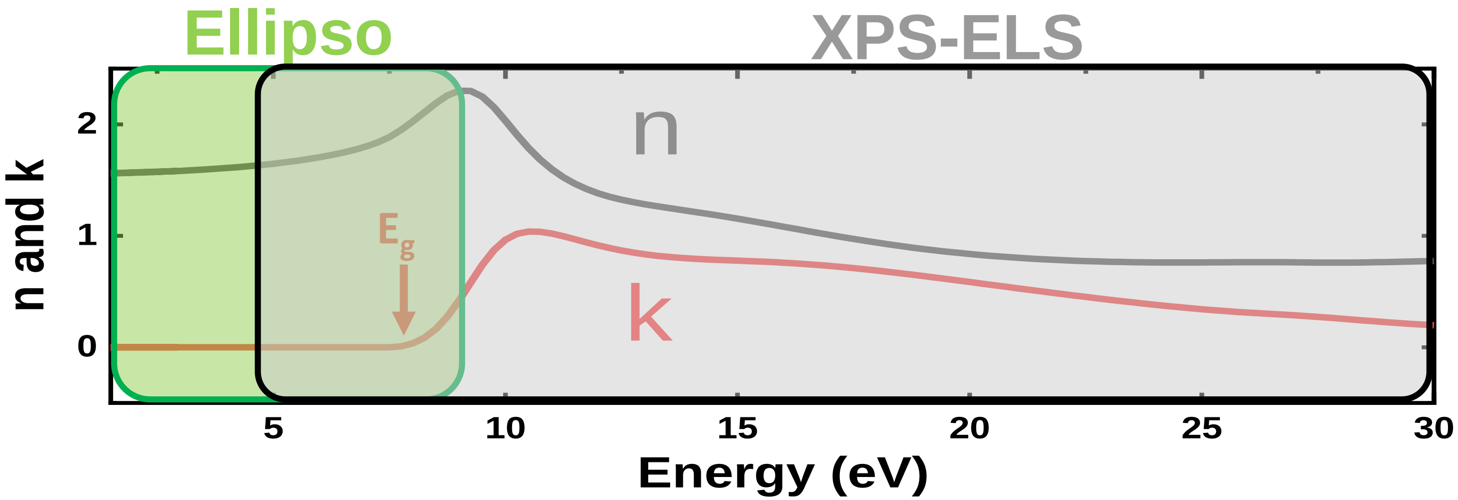
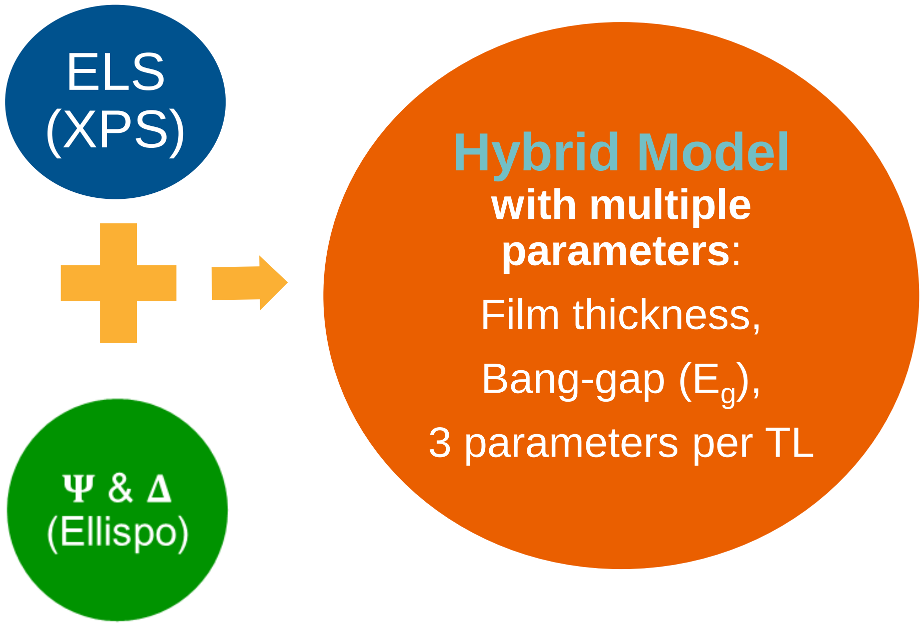


Booster 1 - Hybrid Model 1 :
Robust bandgap & wide range optical constants n,k determination

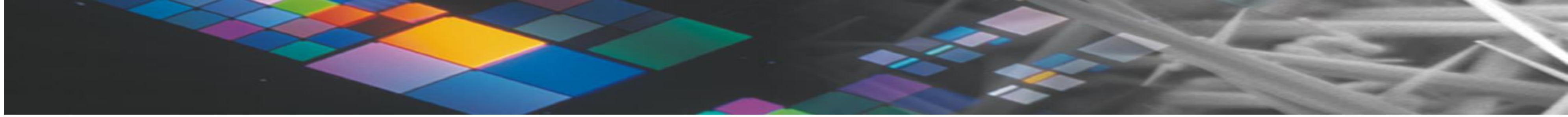
- **Actual limitations:**
  - **Ellipsometry:** Small energy range and E_g value is dependent on the model used
  - **XPS-ELS:** Lack of precision in baseline leading to an overestimation of E_g the value

GOAL: Combine XPS-ELS and Ellipsometry for a **robust and wide-energy range (up to 30eV) optical characterization method**

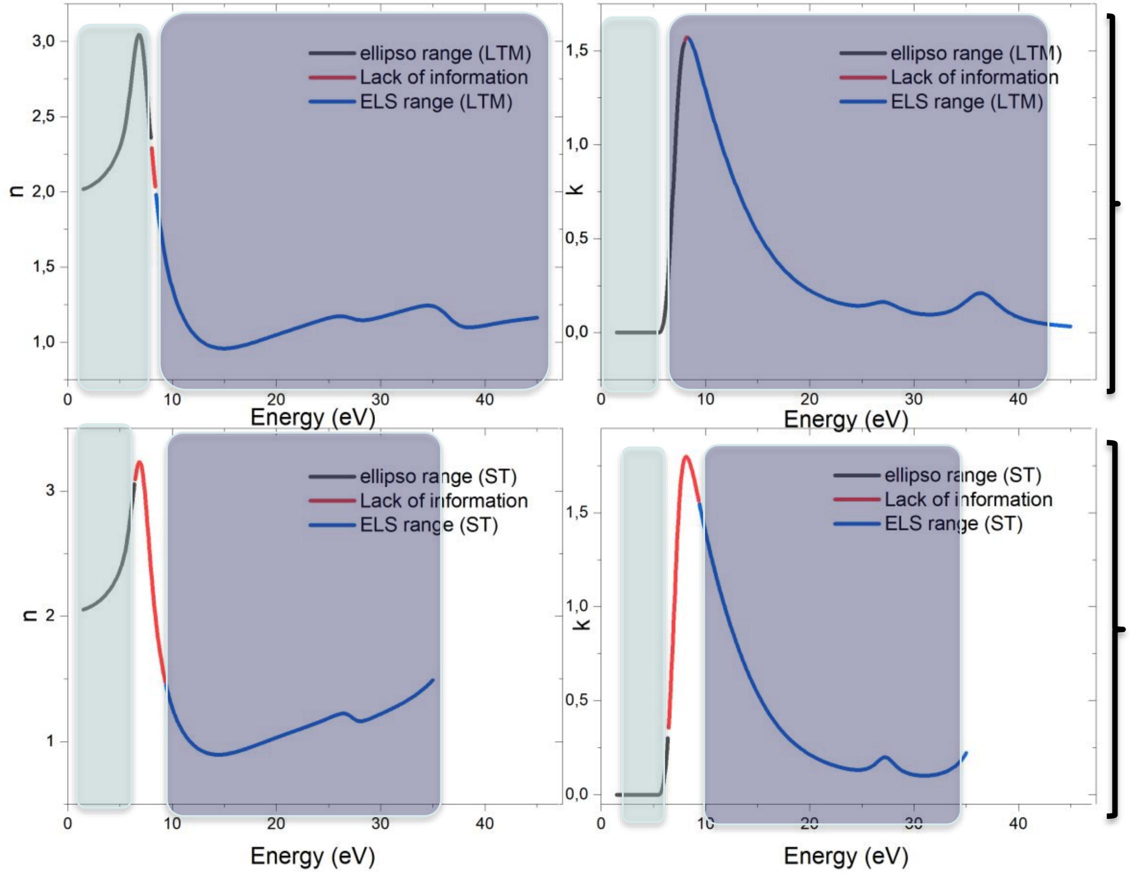




Hybridization of ellipsometry and energy loss spectra from XPS for bandgap and optical constants determination in SiON thin films
Joao Resende & al., Materials Chemistry and Physics Volume 259, 1 February 2021, 124000



Extended range of use of the Hybrid model

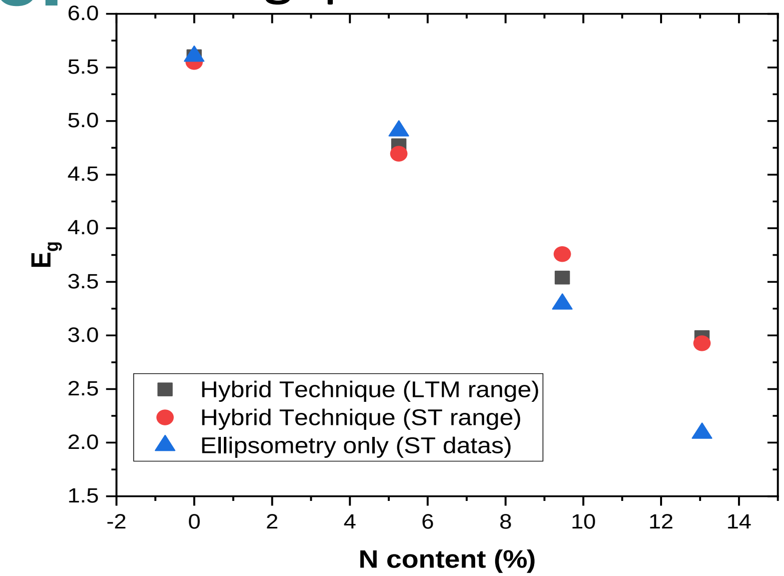


LTM measurements (ellipso 0.6-**8eV**)

ST measurements (ellipso 0.6-**6eV**)

Robust technique, still valid with a bandgap **outside** the range of ellipsometry or XPS only

Bandgap determination



Good agreement for **bandgap**, **n** and **k** determination **even with the lack of data**

Validated on:

- ✓ SiON
- ✓ SnO2
- ✓ HfON
- ✓ SiGe

Materials under investigation:

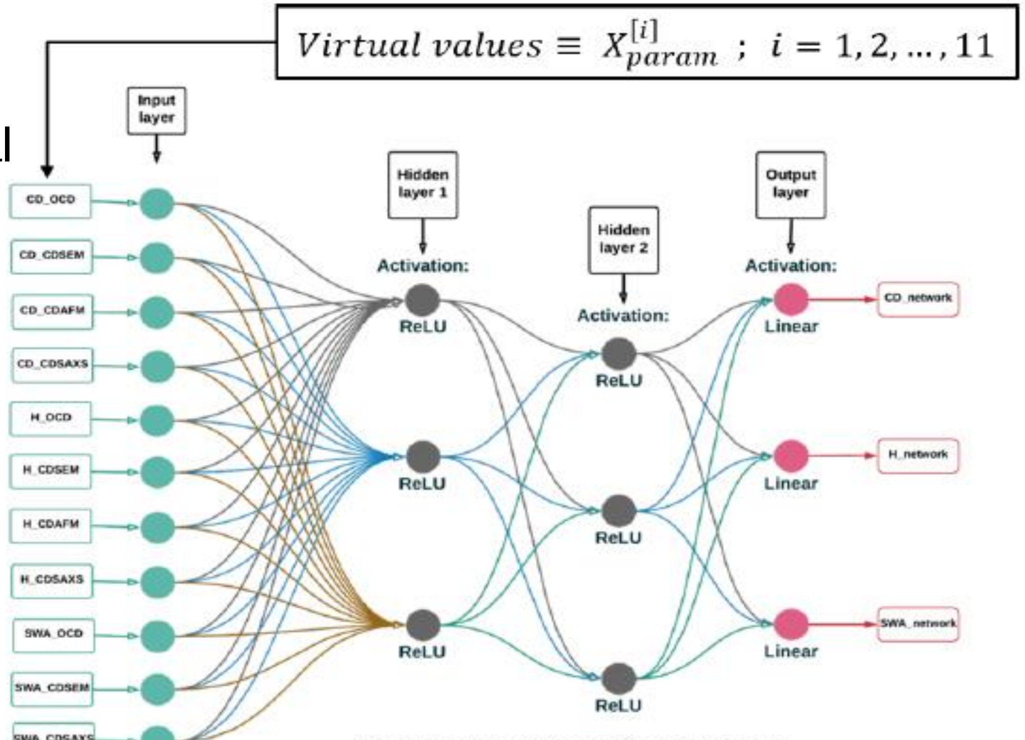
- ❑ GST
- ❑ MoOx
- ❑ AZO

Booster 1 - Hybrid model 2 :

Artificial Neural Networks (NN) for dimensional metrology

Maxime Besacier (LTM) – Jerôme Reche & Patrice Gergaud (LETI)

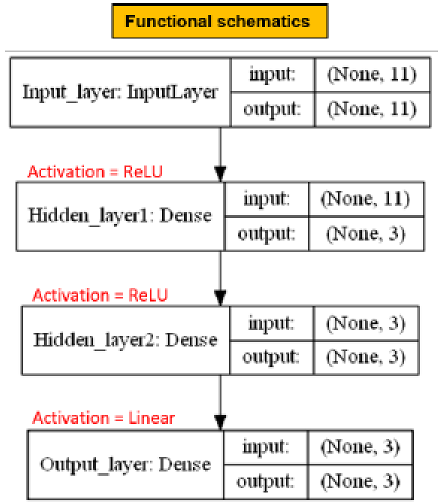
- Based on different metrology tools: OCD, CDSEM, CD-AFM, CDSAXS with samples from LETI
- Goal: improve the robustness of results, reduce the measurement uncertainties
- Methodology steps:
  - Create a simulated data base depending on the experimental uncertainties of metrology techniques to train and validate the NN.
  - Design a NN with input, hidden and output layers.
  - Analysis of the NN model performances.
  - Convergence tests of the NN model
  - Optimization of model architectures

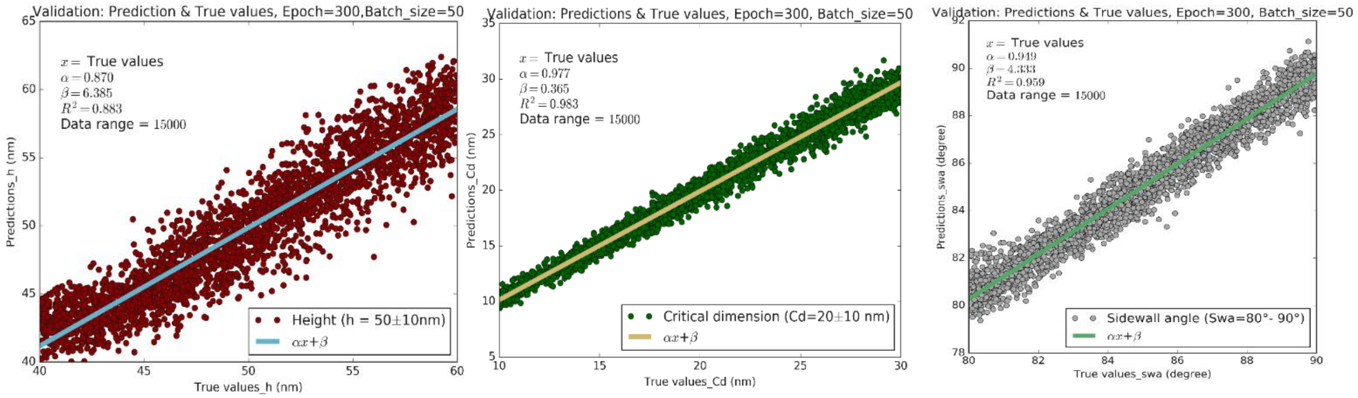


CD: Critical Dimensions ; H: Height ; SWA: Sidewalls Angle

Artificial Neural Networks (NN) for dimensional metrology

- Virtual samples: lines (H = 50nm, CD = 20nm, SWA = 90°)
- Data base for training and validation steps: 14x15000 data
  - 14 = 11 virtual values & 3 « true » values: virtual values are built such as:
    - $data_{virtual} = data_{true} + data_{true} \times rand() \times uncertainty_{technique}$

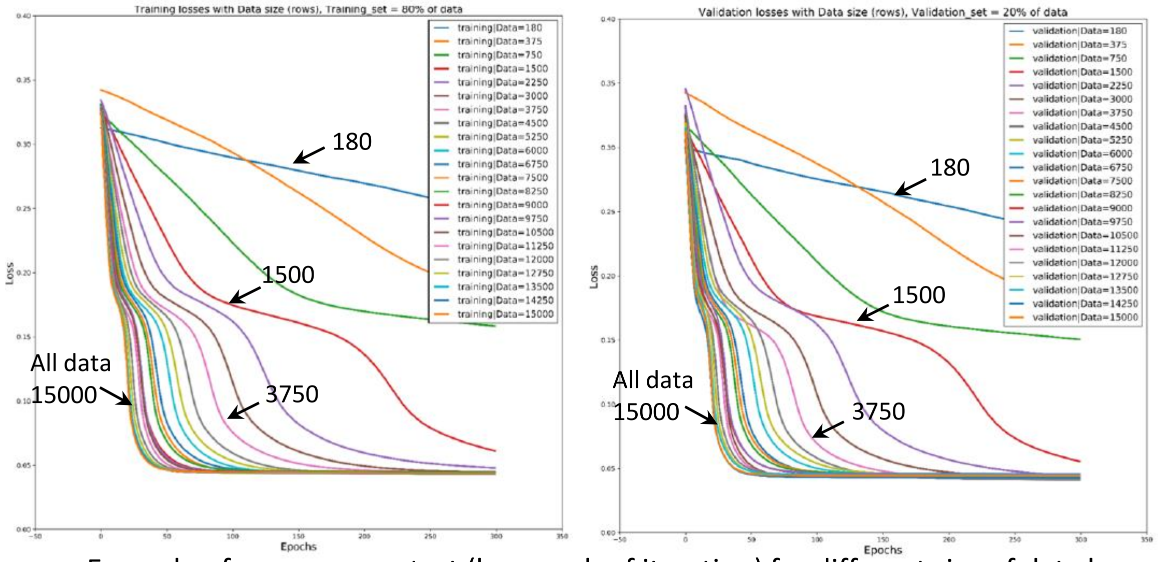




Comparison of the predicted values of H, Cd and Swa by the network vs their true values. The validation set was 20 % of overall data set.

Next steps:

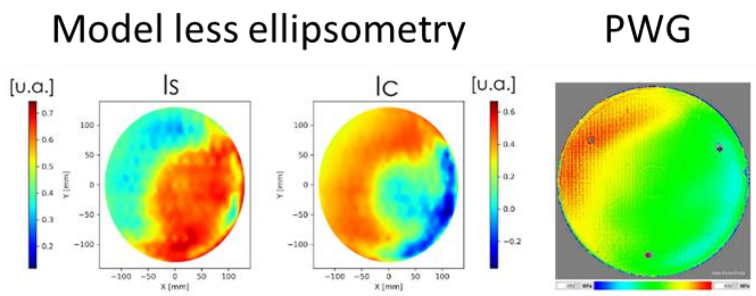
- virtual data coming from modeling of experimental responses
- analysis of data from measurements already carried out
- using of optimized NN model to address sample measurements



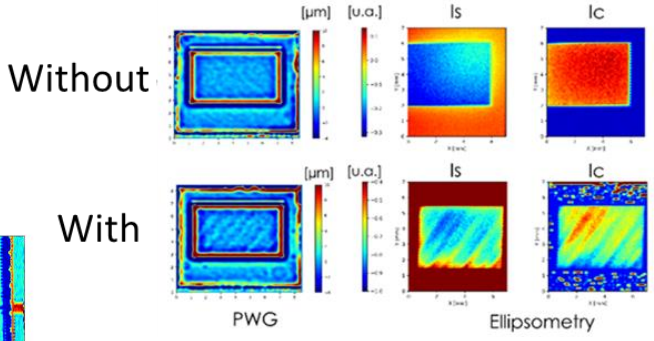
Example of convergence test (loss vs nb of iteration) for different size of data base

Booster 2 : Predictive Fast in-line process deviation characterization and compensation using optical techniques

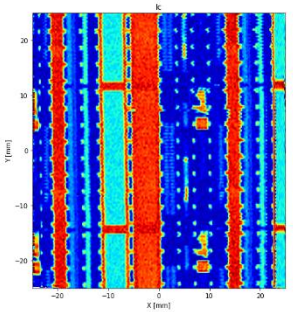
- **Step and repeat measurements scenario for ellipsometry acquisition**
  - Mapping of the whole wafer
    - Using raw data of Ellipsometry acquisition
    - Generation of Ellipsometry images by interpolation
  - Detection of the inhomogeneous stress of SiN layers on **product** wafer
    - Sensitivity demonstrated
    - Validation using PWG cartography
  - Detection of striation of colored resists at the **die** level
    - Sensitivity and validation demonstrated
  - Implementation of Raster mode
    - Once aberration corrected, fast scanning
  - **Machine Learning** for prediction of errors
    - **Prediction efficiency of 96%**



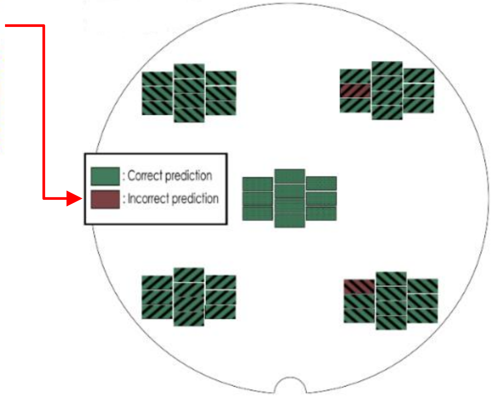
Full wafer



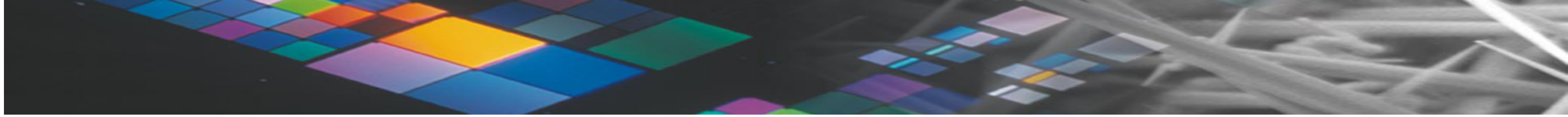
Die level



Imaging using raster mode



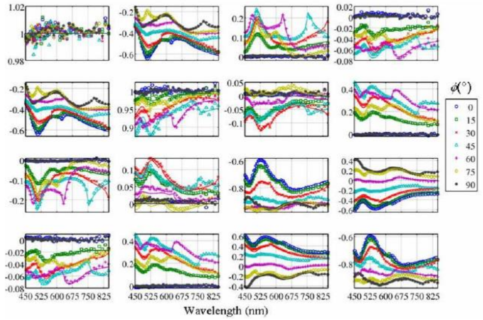
AI automatic detection 96% of efficiency



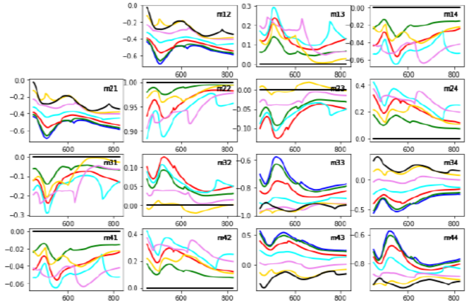
Machine Learning method for the detection of faults from Mueller ellipsometry

- **Rigorous modeling using RCWA scatterometry codes**
  - LTM algorithms upgraded to 3D conical
    - Capable to handle various azimuthal angles
    - Validity code verified using published data

De Martino A, Foldyna M, Novikova T, Cattelan D, Barritault P, Licitra C, Hazart J, Foucher J, Bogeat F (2008) Proc SPIE 6922:69221P. doi:10.1117/12.772 721

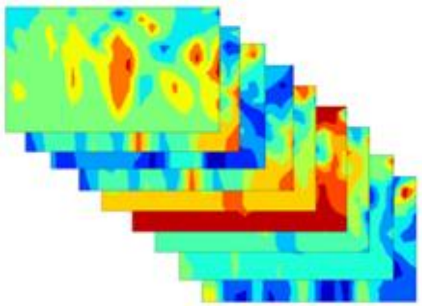


Published results (Martino and al)



LTM results using same data

- **Machine Learning method**



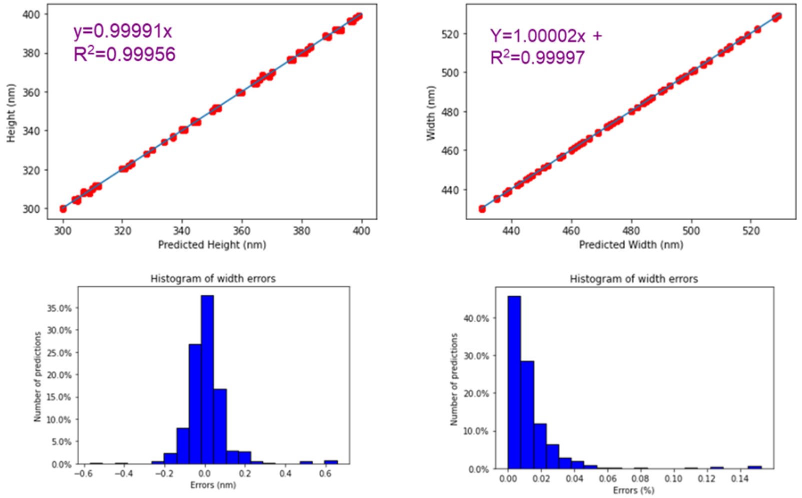
Synthetic data

Stacking of Mueller data

Training set (60%), Validation (20%), Test (10%)

CNN

Prediction



Demonstrated for synthetic case
Next: real case

Prediction results by the CNN and error histogram

MADEin4

Thank You For Your Attention

This project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 826589. The JU receives support from the European Union’s Horizon 2020 research and innovation programme and Netherlands, Belgium, Germany, France, Italy, Austria, Hungary, Romania, Sweden and Israel