HYBRID METROLOGY ASSISTED by MACHINE LEARNING at NANOMETER SCALE

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CEA-LETI: FROM LAB TO FAB

A WORLD-LEADING R&D ORGANIZATION

2,000 talent people

~300 industrial partners

>13,700 sq. m. cleanroom space

80 startups created

3,200 patents in portfolio

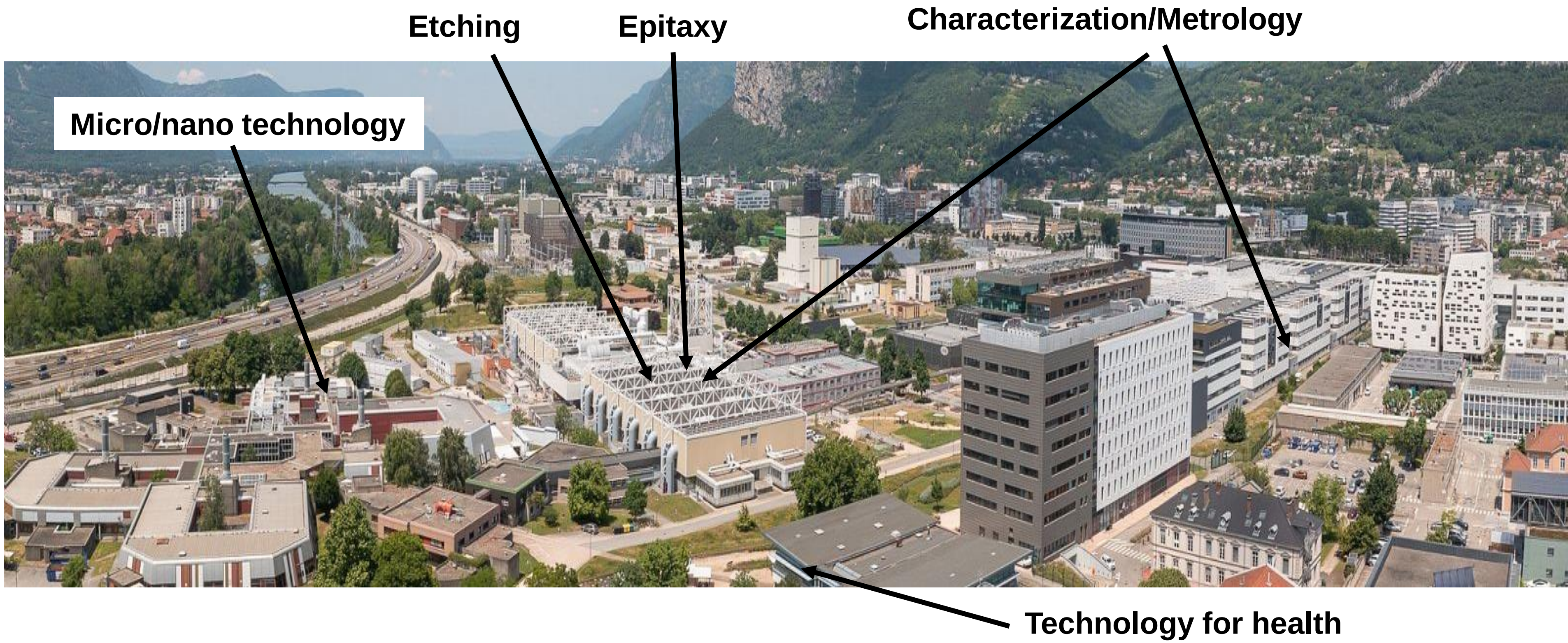
7/24 clean room operation

LTM at a glance

French academic lab:

Creation: 1999

Location:



Expertise domains: Microelectronic, Nano-technologies, Nanomaterials, techno for health

OUTLINE

- ❑ **CONTEXT**

- ❑ METHODOLOGY DESCRIPTION
  - ➢ Sample modeling
  - ➢ Metrology techniques simulations
  - ➢ Neural Network architecture

- ❑ RESULTS

- ❑ CONCLUSIONS

Definition

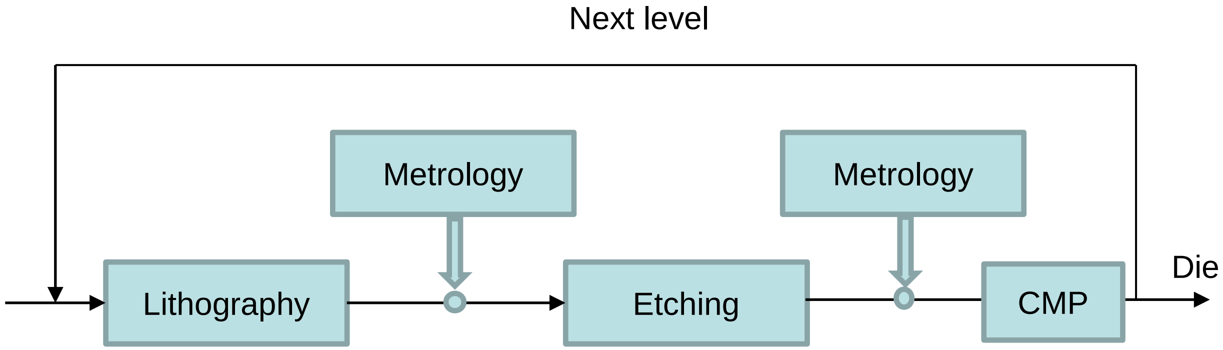
- **Hybrid metrology** refers to a measurement approach that combines several different measurement methods (or techniques) to obtain results that are more accurate, reliable, or comprehensive than those obtained using a single method.

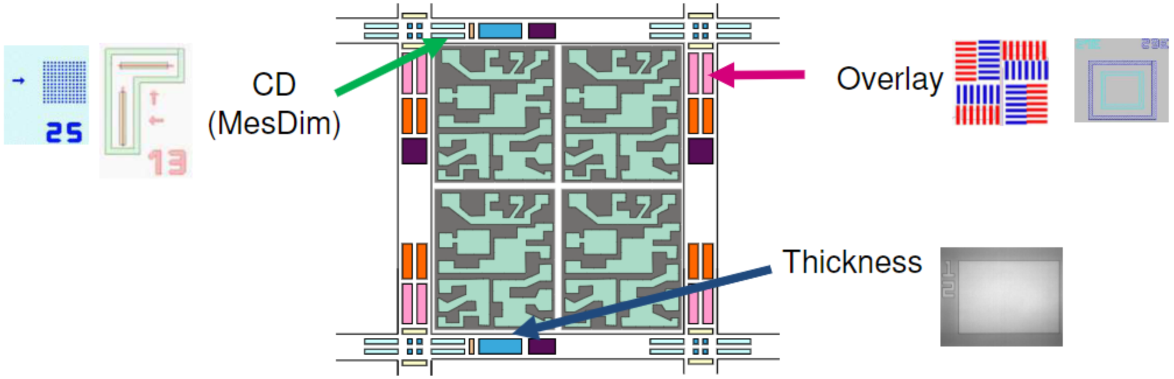
- Using of hybrid metrology:
  - improving measurement accuracy,
  - reduce uncertainties,
  - compensate for the limitations of one technique with another
  - measure quantities that are difficult to access directly.

- The final result is a fusion of the data, which is more robust than each source taken separately.

Specific patterns for dimensional metrology

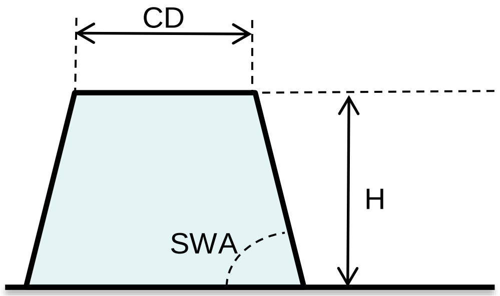
Patterning process





Measurements are not made directly within the die.

Specific metrology patterns in the Cutting paths.

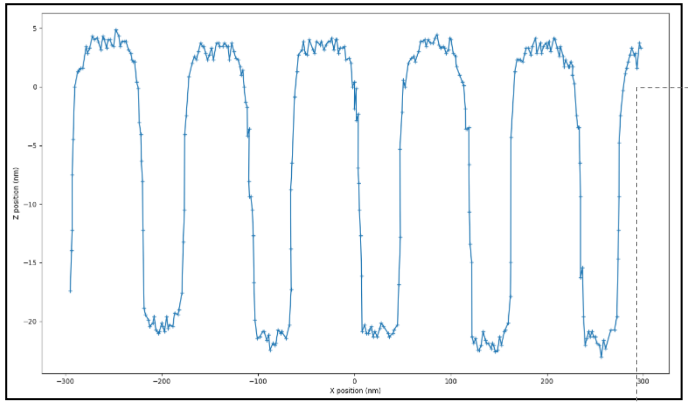


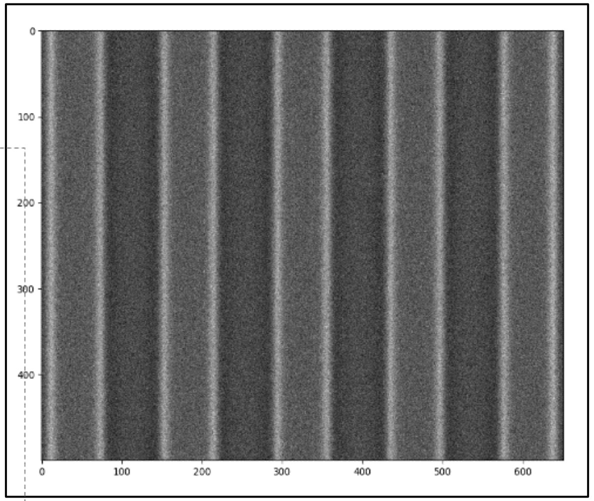
Lines gratings

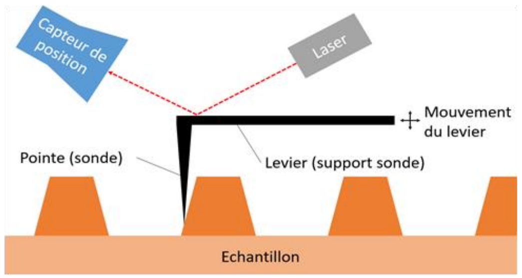
Dimensional parameters:

- Critical Dimension (**CD**)
- Height (**H**)
- Side Wall Angle (**SWA**)

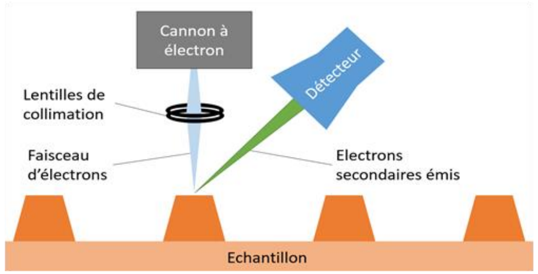
Metrology techniques



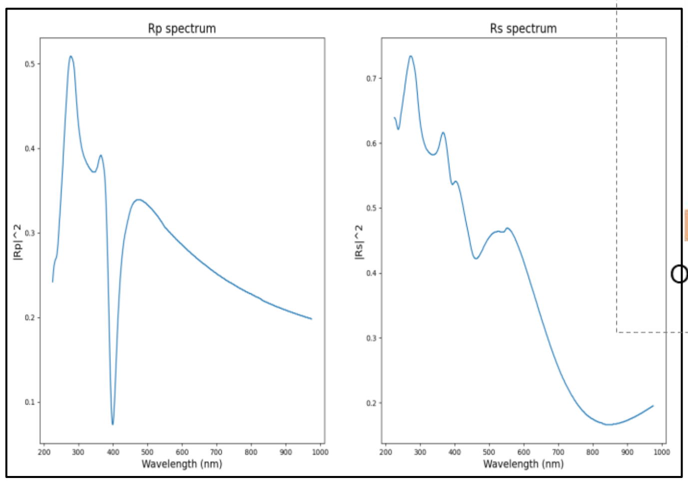


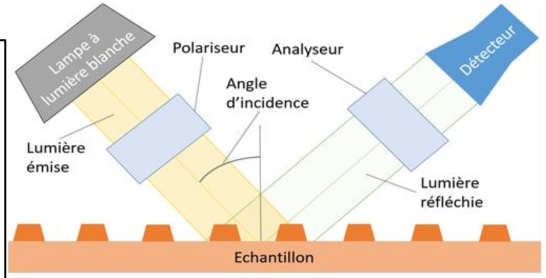


Atomic Force Microscope (**AFM**)



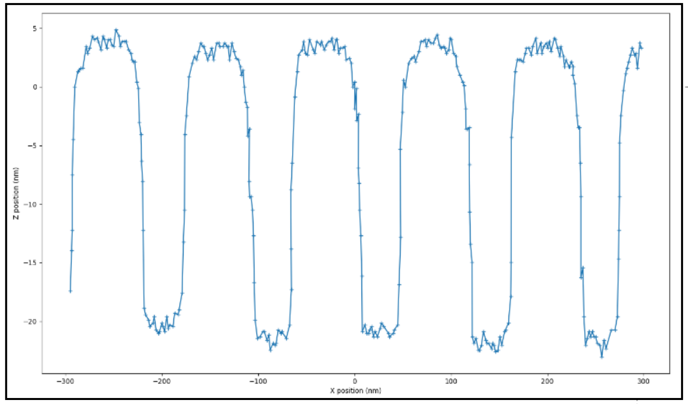
Critical Dimension Scanning Electron Microscope (**CD-SEM**)

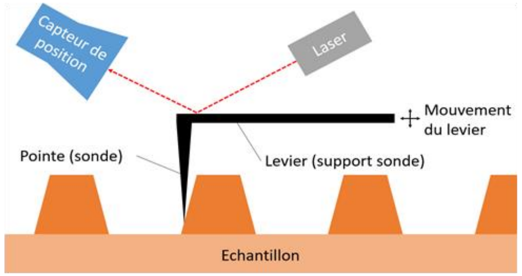




Optical Critical Dimension (Scatterometry) (**OCD**)

Metrology techniques





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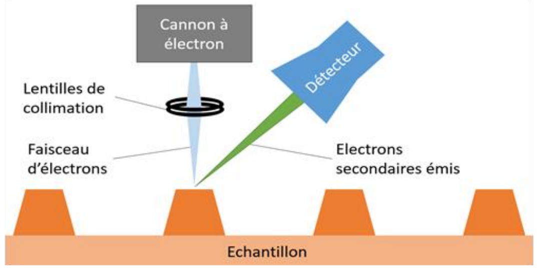
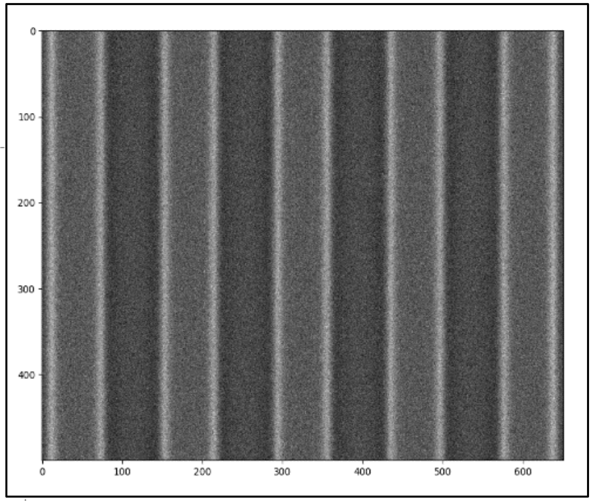
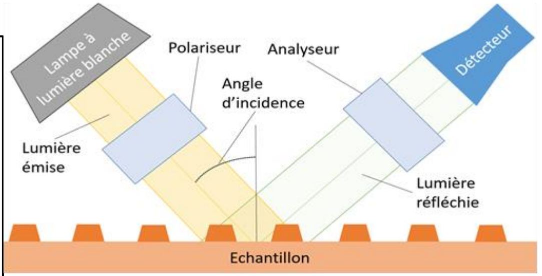


Critical Dimension Scanning Electron Microscope (**CD-SEM**)





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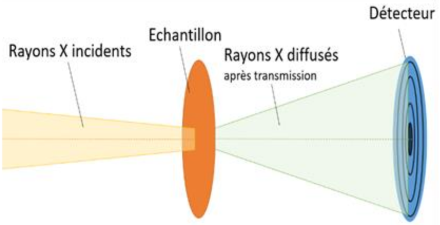
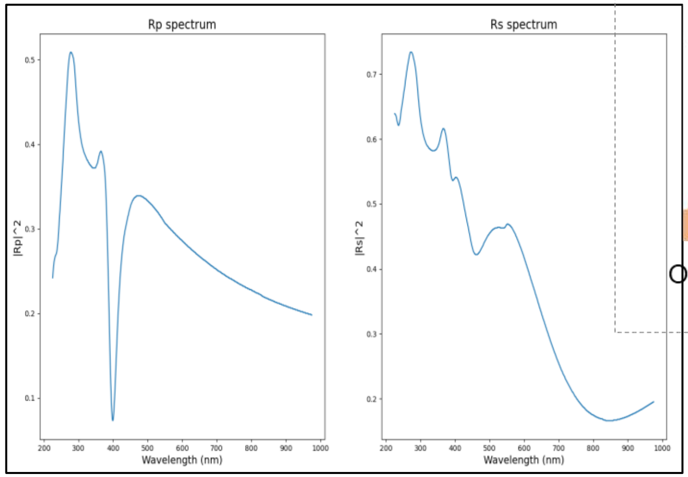
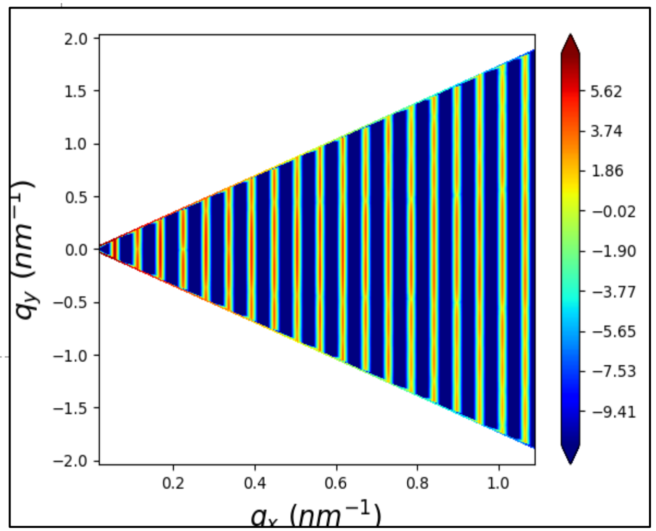


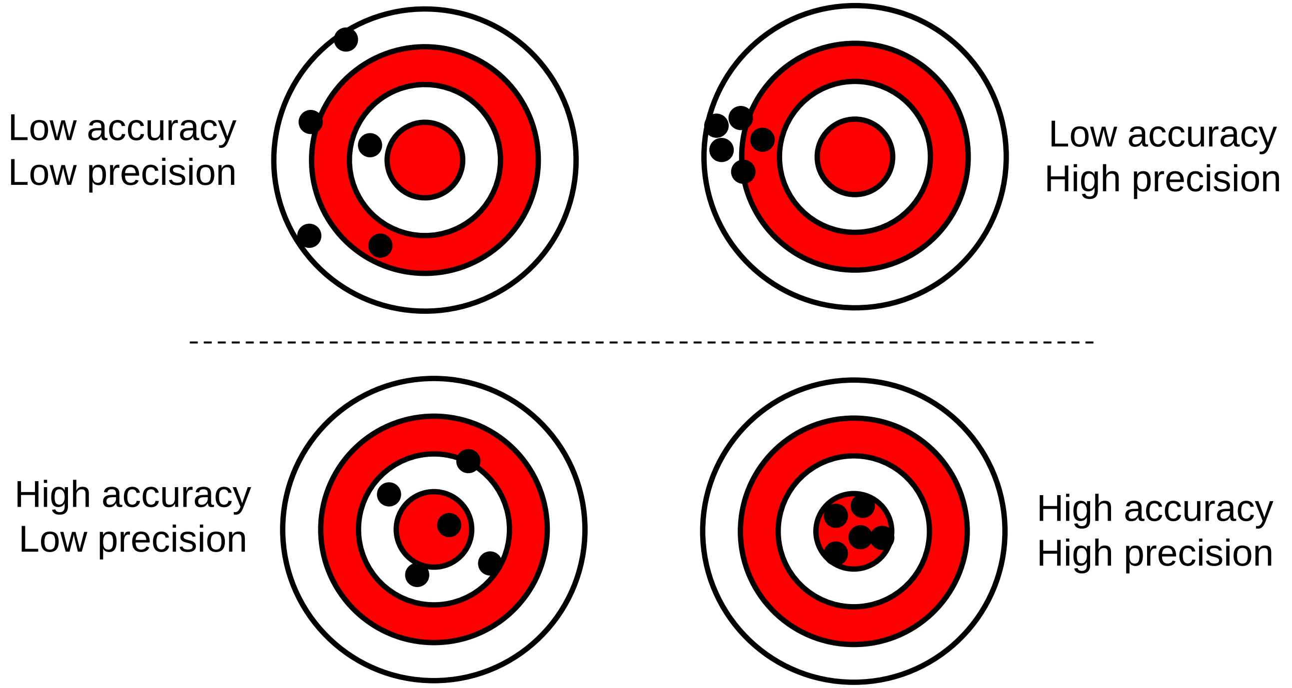
Critical Dimension Small Angle X-ray Scattering (**CD-SAXS**)





Metrology behaviors

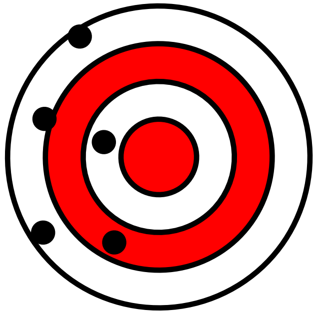
- ❑ Accuracy
- ❑ Precision



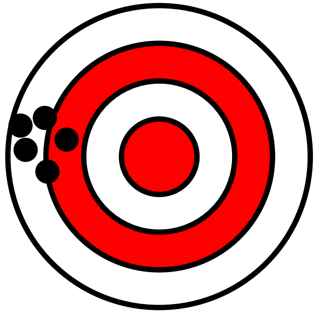
Accuracy : how close a set of measurements is to the true (reference) value

Precision : how close the measurements are to each other.

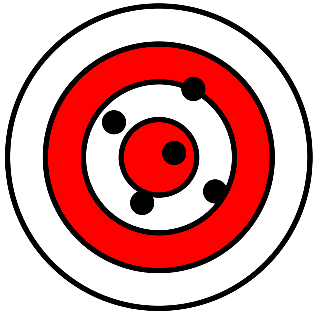
Metrology behaviors



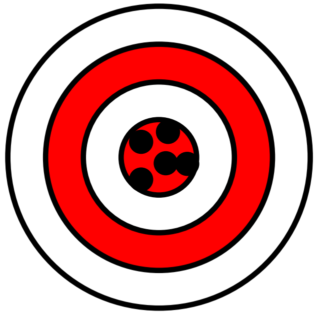
Low accuracy
Low precision



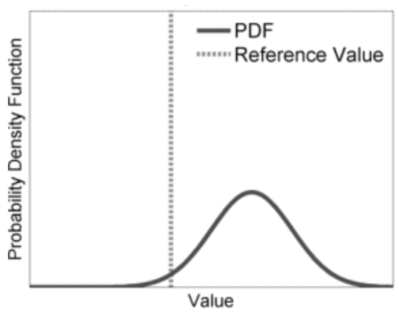
Low accuracy
High precision

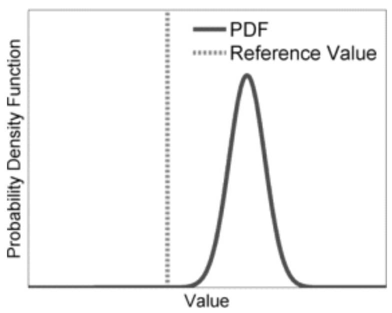


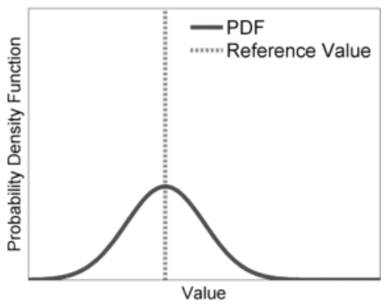
High accuracy
Low precision

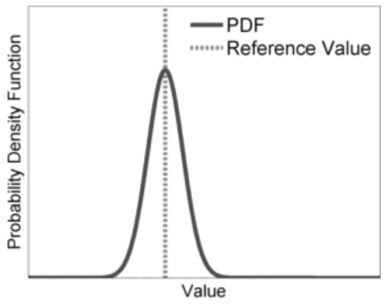


High accuracy
High precision





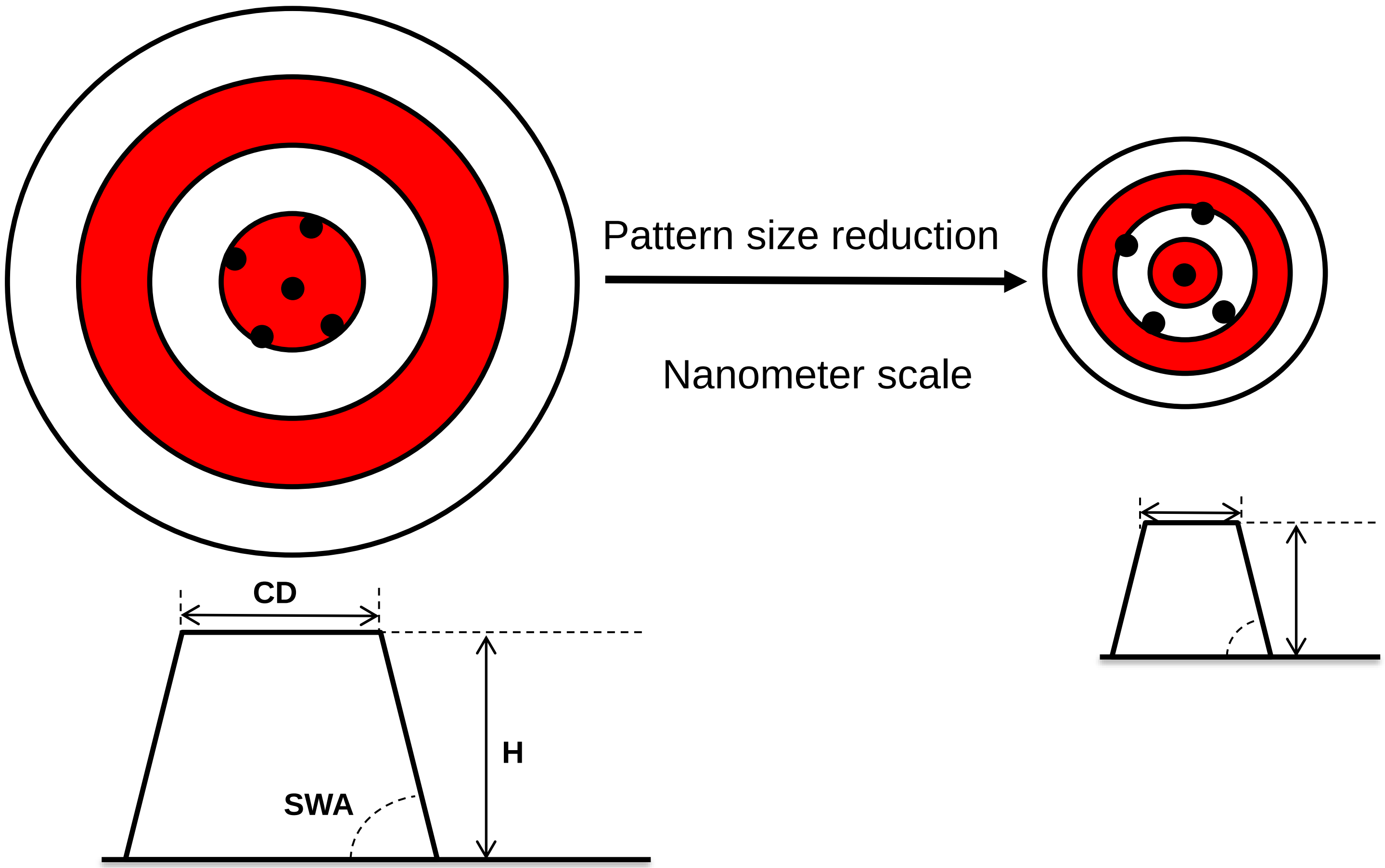




Mean Value & Standard Deviation

Metrology behaviors

- The accuracy
- The precision



These behaviors are relative to the pattern size

Metrology challenges

Metrology requirements are driven by :

- advanced lithography and multi-patterning processes
- new materials, and beyond CMOS materials
- new device architectures

Smaller dimensions (sub-5nm)

Complex patterns (3D structures)

Ability to provide robust and accurate measurements

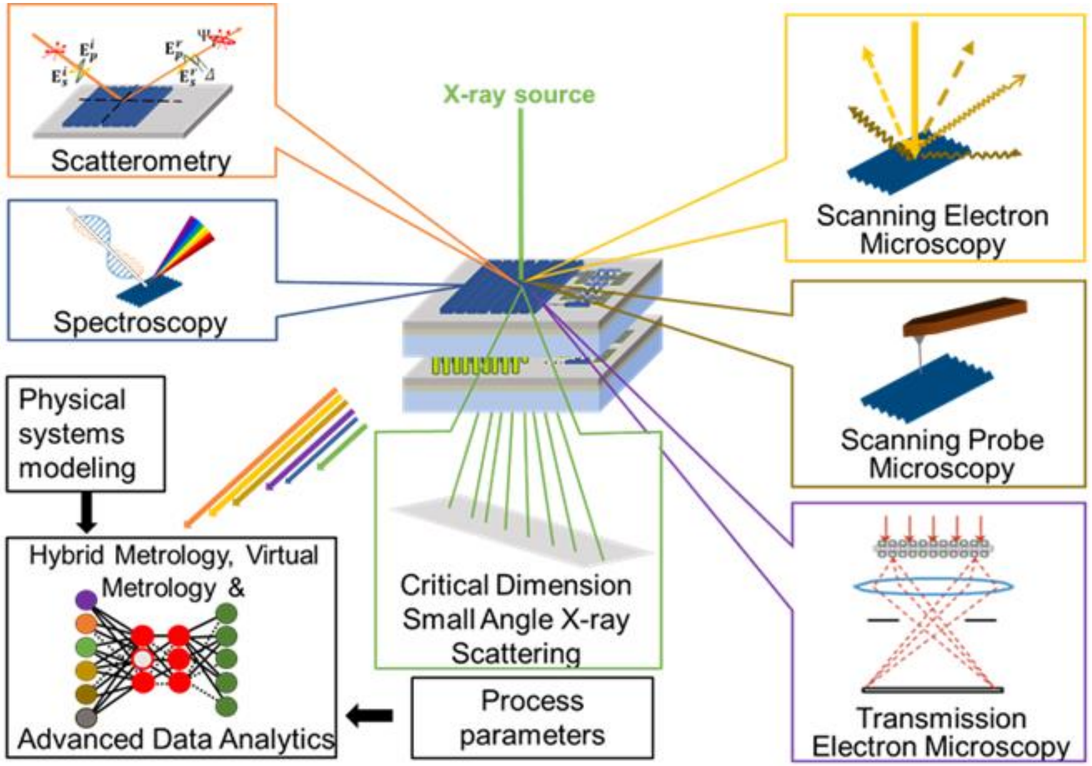
Fast and non-destructive (production, high throughput).

Can the introduction of **machine learning** improve the performance of the dimensional metrology in microelectronic with an **hyrid approach** ?

Hybrid metrology

"It seems ***inevitable to use more than one type of measurement***, tool, and method, and take advantage of the rich, multifaceted set of data by ***combining the most reliable information gained from each source***. This combined (complementary, **hybrid) metrology** would be necessary for **sub-10 nm dimensional metrology**. Hybrid metrology has shown promising advantages **in significantly reducing the overall uncertainties**, i.e., augmenting the confidence in the results, and in the optimization of various complementary measurement methods for cost."

Text & picture : *IEEE International Roadmap for Devices and Systems, "Metrology." Institute of Electrical and Electronics Engineers, 2023, doi: 10.60627/FF6X-D213.*



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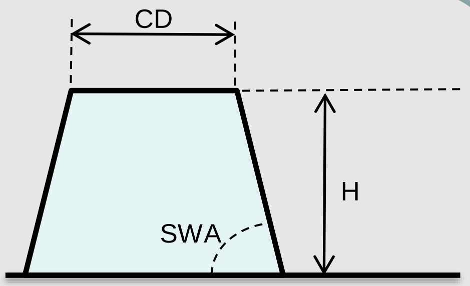
- **METHODOLOGY DESCRIPTION**
  - **Sample modeling**
  - **Metrology techniques simulations**
  - **Neural Network architecture**
- RESULTS
- CONCLUSIONS

Methodology description



Line gratings on Si wafers

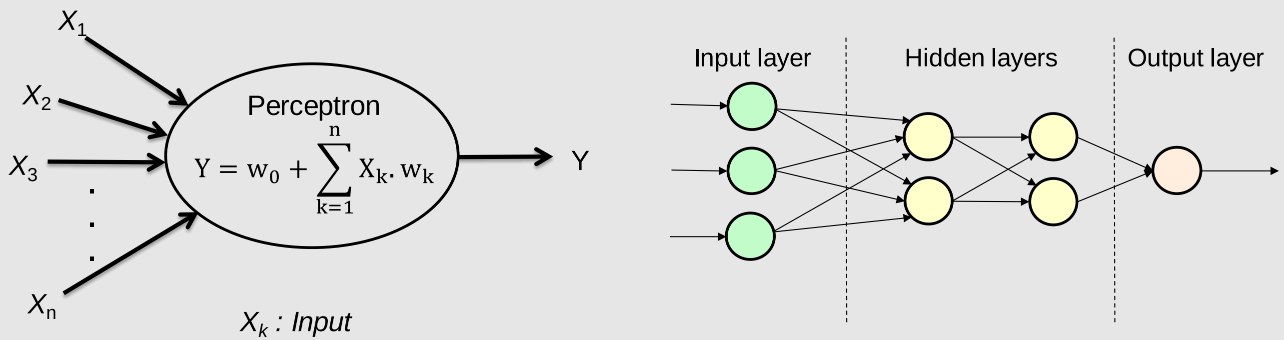
Fixed pitch: 112nm

$$\begin{cases} 30\text{ nm} \leq \text{CD} \leq 65\text{ nm} \\ 20\text{ nm} \leq \text{H} \leq 100\text{ nm} \\ 80° \leq \text{SWA} \leq 90° \end{cases}$$

Techniques available:

- Atomic Force Microscope (**AFM**)
- Critical Dimension Scanning Electron Microscope (**CD-SEM**)
- Optical Critical Dimension (Scatterometry) (**OCD**)
- Critical Dimension Small Angle X-ray Scattering (**CD-SAXS**)

Artificial Neural Network (**ANN**).



X_k : Input
Y : Output
w_k : Weight of X_k
w_0 : Bias

MAIN ISSUE

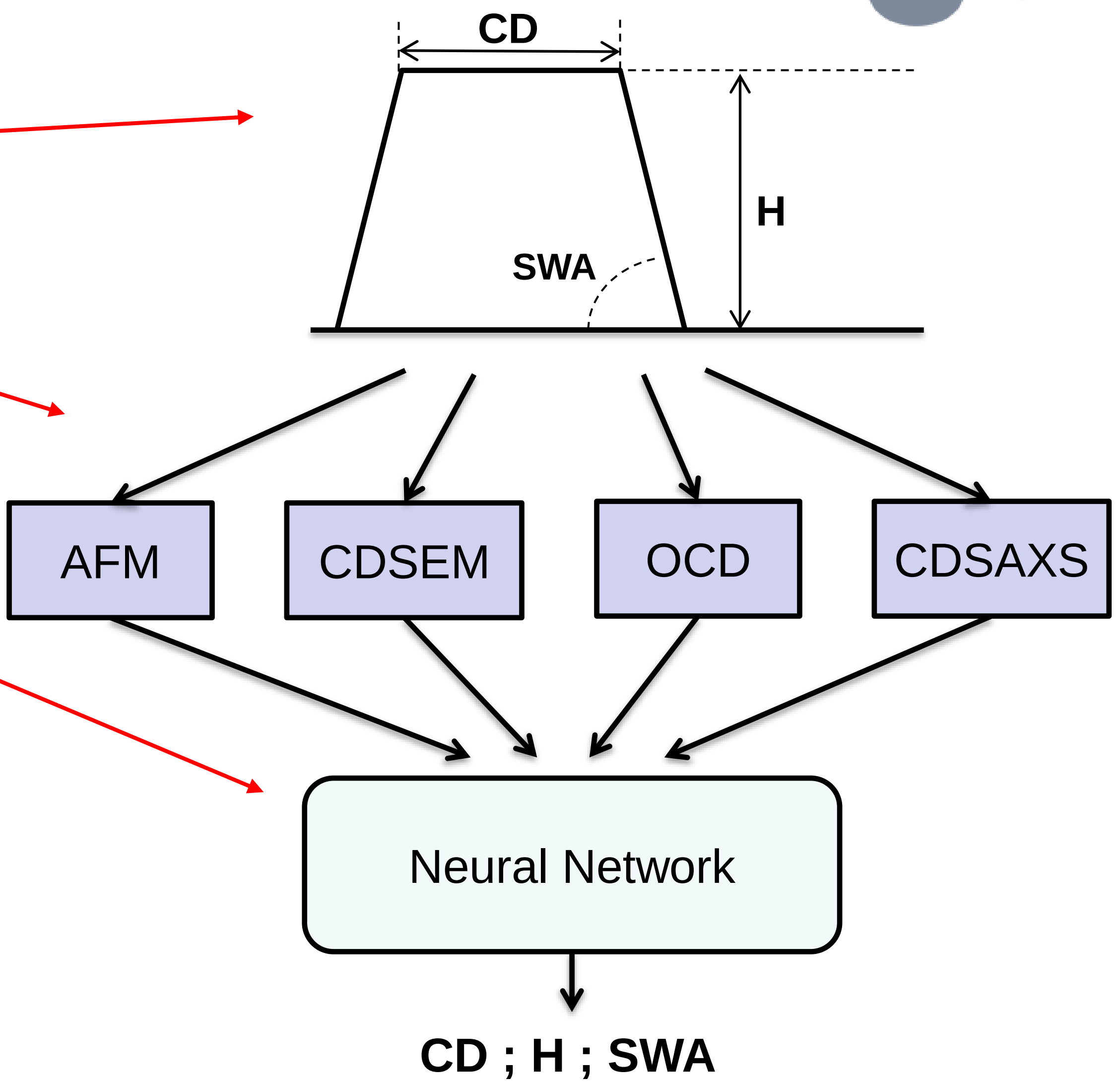
Data set for Network Training and validation

Limitation: low set of experimental data from techniques

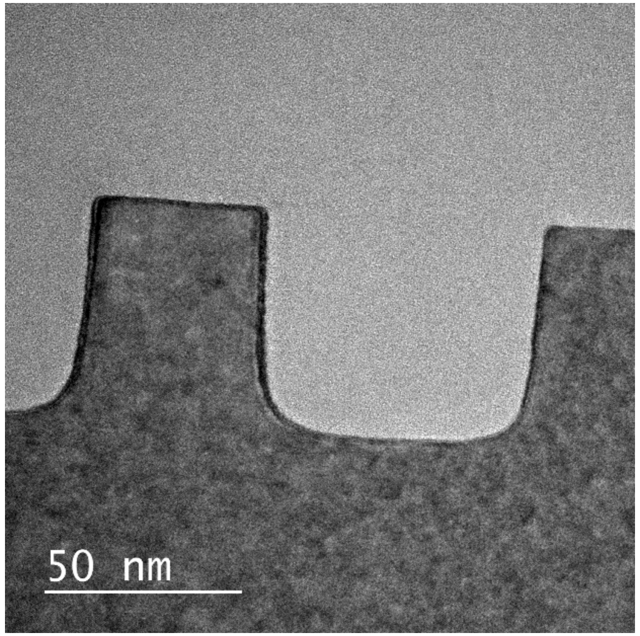
Modeling and simulation approach

Methodology description

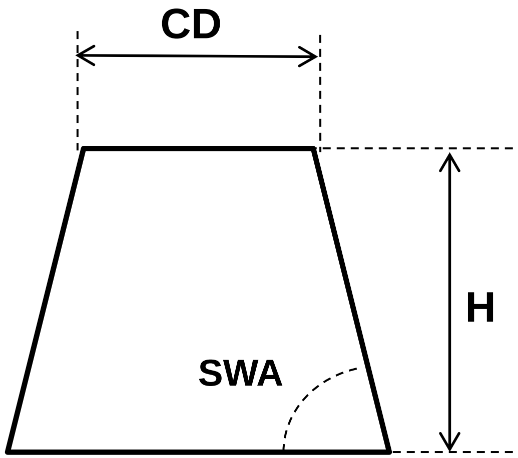
- ❑ Sample modeling
- ❑ Metrology techniques simulations
- ❑ Neural Network Archtitecture

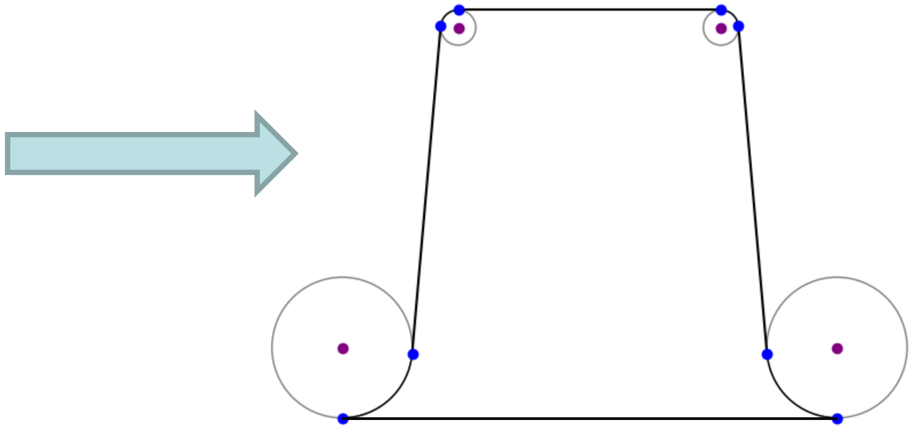


Sample modeling



TEM observation of experimental Si grating lines



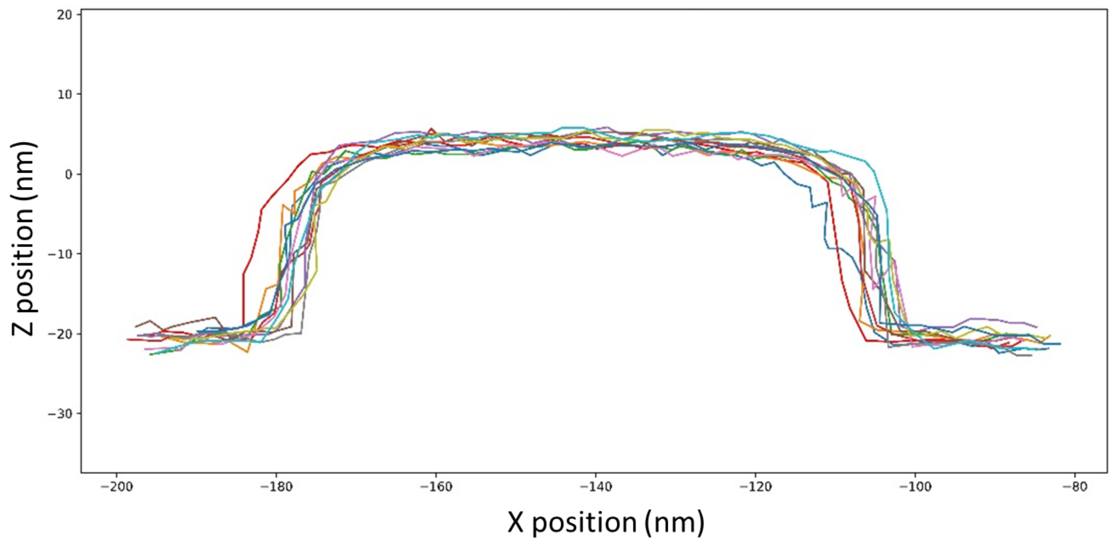


Corner rounding consideration:

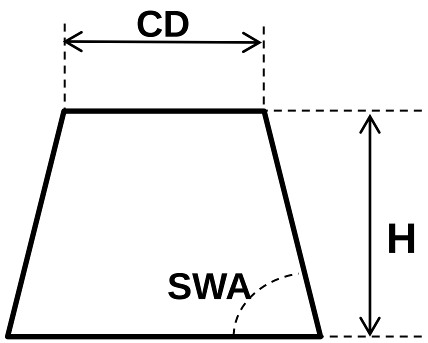
fixed parameter in the model

Top CR radius: 2.5nm – Bottom CR radius: 10.5nm

Sample modeling



AFM measurements on a same experimental Si grating lines



Target values:

CD: 65nm

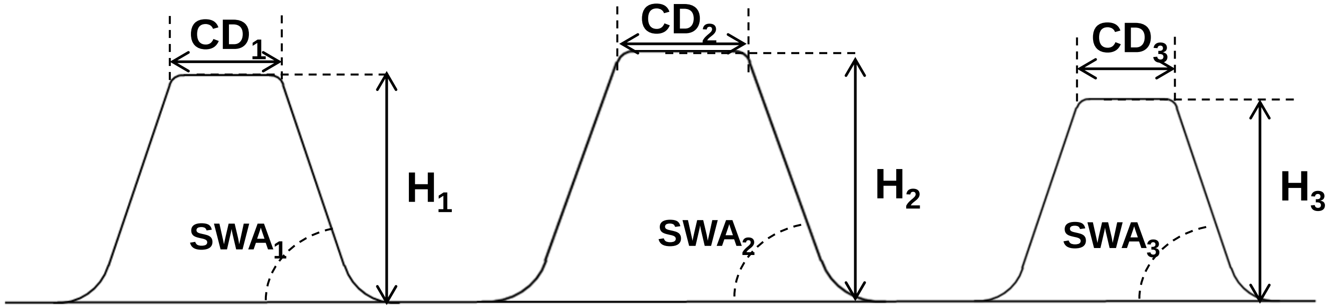
H: 20nm

SWA: 85°

Inter-line variability on the same sample

Shape parameter	**CD**	**H**	**SWA**
variability Std Dev.	1,9nm	0,99nm	3,8°

Multi-lines sample model.



Multi-line modeling approach inspired by research on **modeling variability** between lines for OCD simulations.

Allows the variations observed to be implemented directly in the geometric models, thereby impacting the raw data obtained after simulation.

$$\begin{cases} CD_k = Random_{gauss}(\mu = CD_{target}, \sigma = 1{,}9) \\ H_k = Random_{gauss}(\mu = H_{target}, \sigma = 0{,}99) \\ SWA_k = Random_{gauss}(\mu = SWA_{target}, \sigma = 3{,}8°) \end{cases}$$

A model with 3 lines allows for a certain diversity in variability with a small number of lines.

Metrology techniques simulations

- AFM : ***Home made***
  - Include probe shape influence
- OCD : ***Home made***
  - RCWA algorithm
- CDSAXS : ***Home made***
  - Analytic Fourier Transform
- CDSEM : ***Nebula (TU Delft)***
  - Monte Carlo Electron-Matter interaction

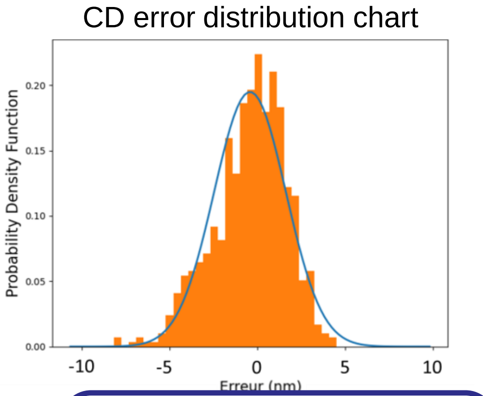
Dataset of 700 samples models inserted in simulators

↓

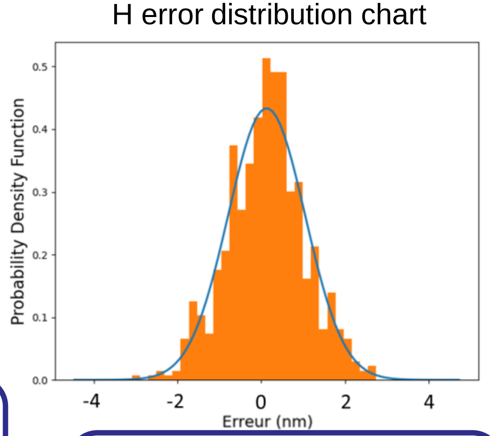
Dimensional parameters extraction and error distribution representation

Metrology techniques simulations

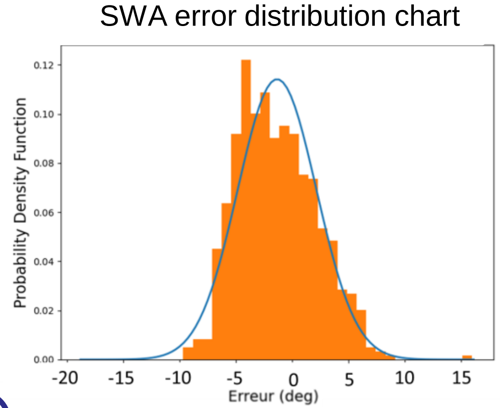
- OCD : ***Home made***
  - RCWA algorithm



Mean = -0,41nm
Std dev. = 2,05 nm

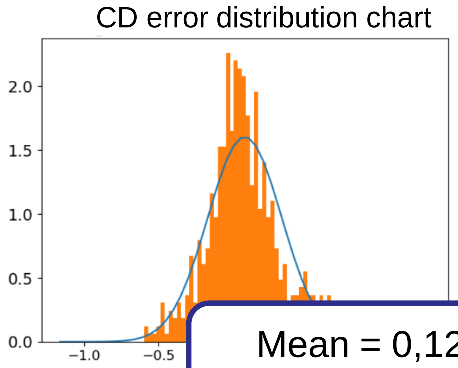


Mean = 0,13 nm
Std dev. = 0,92 nm

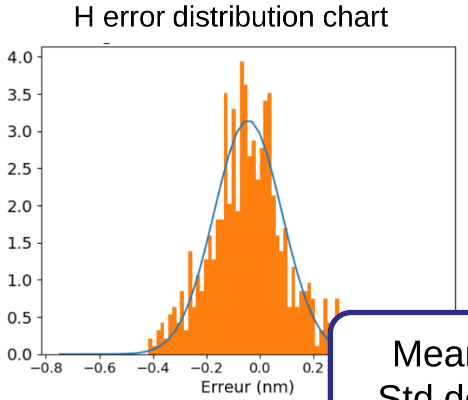


Mean = -1,32 °
Std dev. = 3,49 °

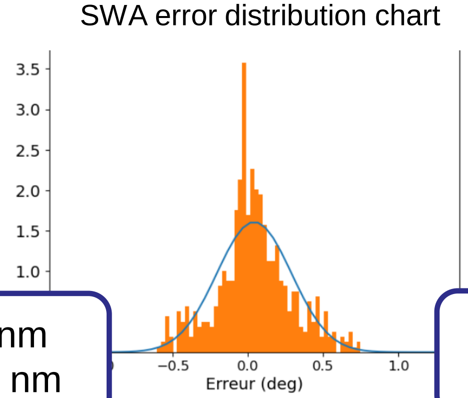
- CDSAXS : ***Home made***
  - Analytic Fourier Transform



Mean = 0,12 nm
Std dev. = 0,54 nm



Mean = -0,05 nm
Std dev. = 0,26 nm

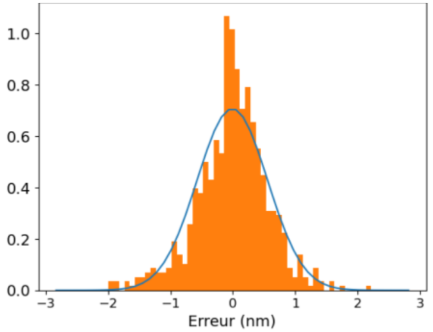


Mean = 0,08 °
Std dev. = 0,67 °

Metrology techniques simulations

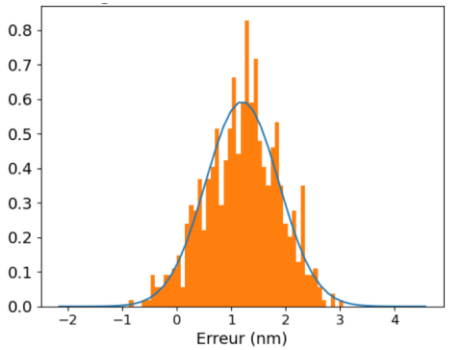
- ❑ AFM : ***Home made***
  - ➢ Include probe shape influence

CD error distribution chart



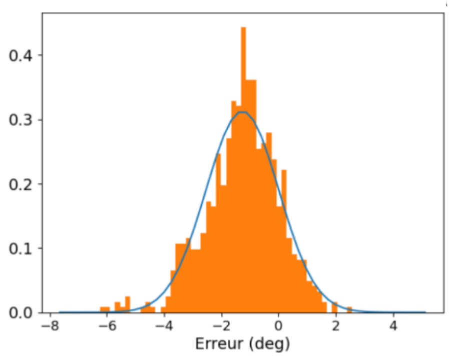
Mean = -0,05 nm
Std dev. = 0,65 nm

H error distribution chart



Mean = 1,19 nm
Std dev. = 0,68 nm

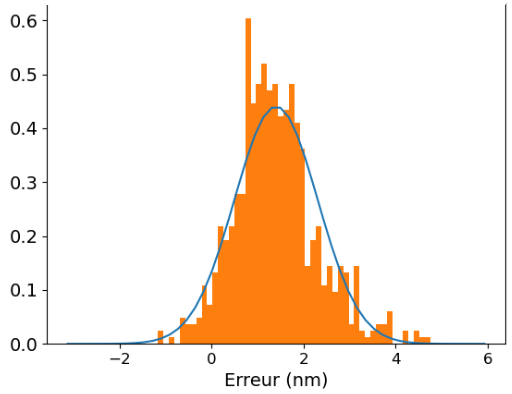
SWA error distribution chart



Mean = -1,29 °
Std dev. = 1,29 °

- ❑ CDSEM : ***Nebula (TU Delft)***
  - ➢ Monte Carlo Electron-Matter interaction

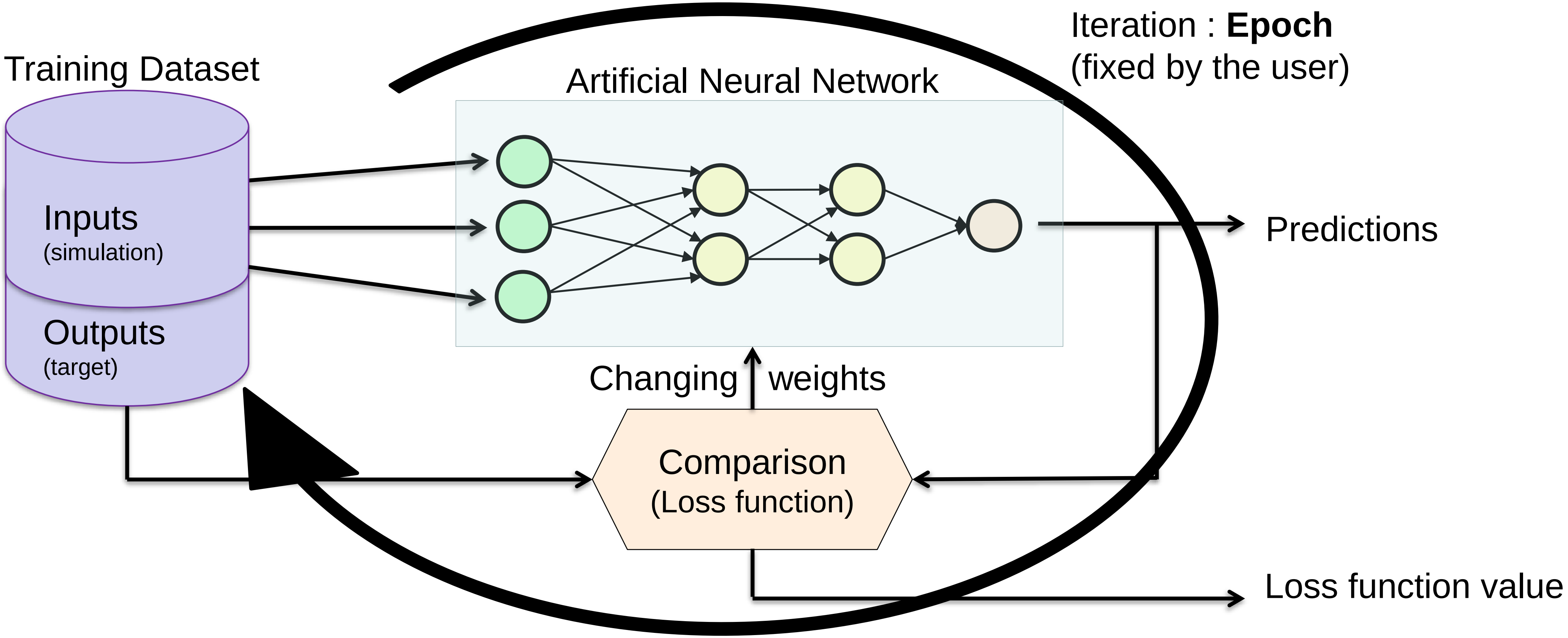
CD error distribution chart



Mean = 1,40 nm
Std dev. = 0,91 nm

Neural Network architecture

Principle:



Repeat the process

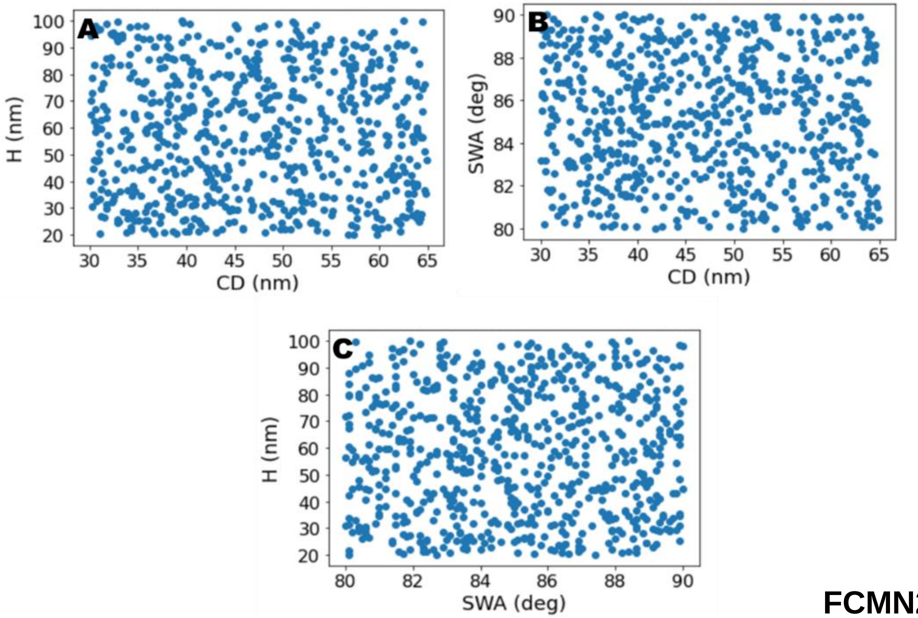
Iteration : **Epoch**
(fixed by the user)

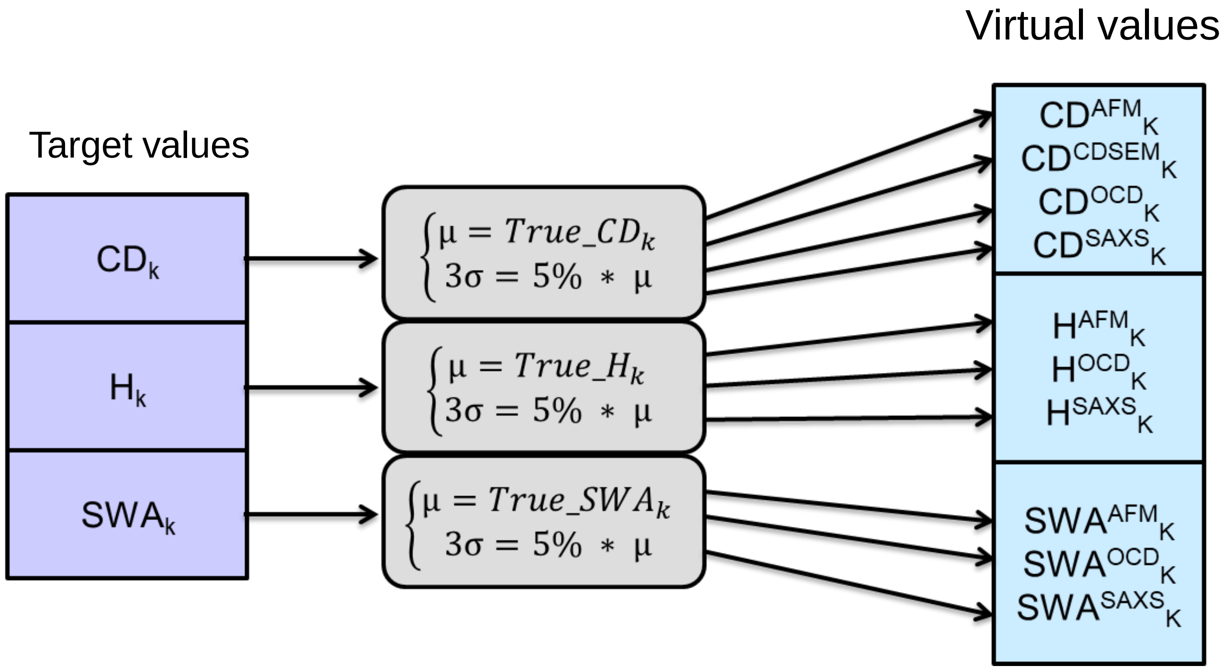
Training dataset for architecture determination

Target value determination with uniform random functions :

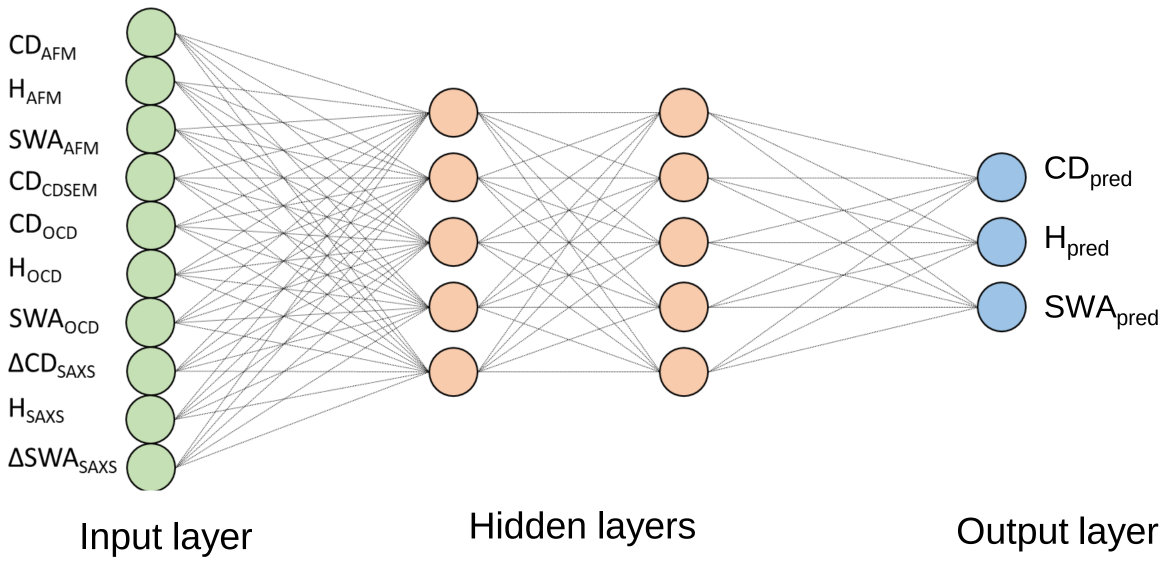
$$\begin{cases} CD = Random_{uniform}(min = 30, max = 65) \\ H = Random_{uniform}(min = 20, max = 100) \\ SWA = Random_{uniform}(min = 80, max = 90) \end{cases}$$

Parameters crossed distribution

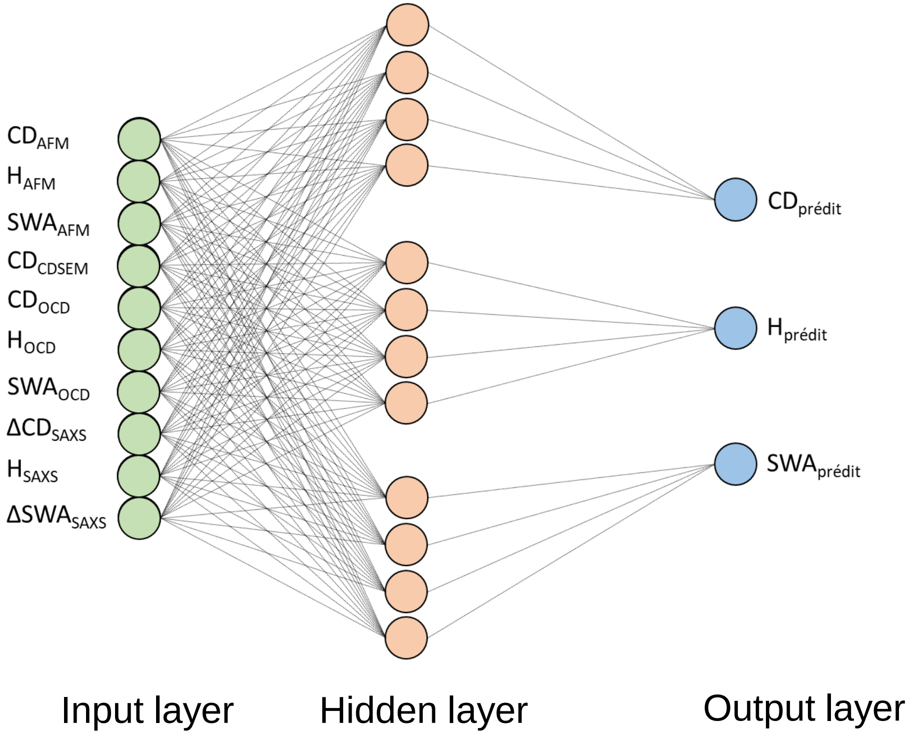




Classic vs multibranch comparison

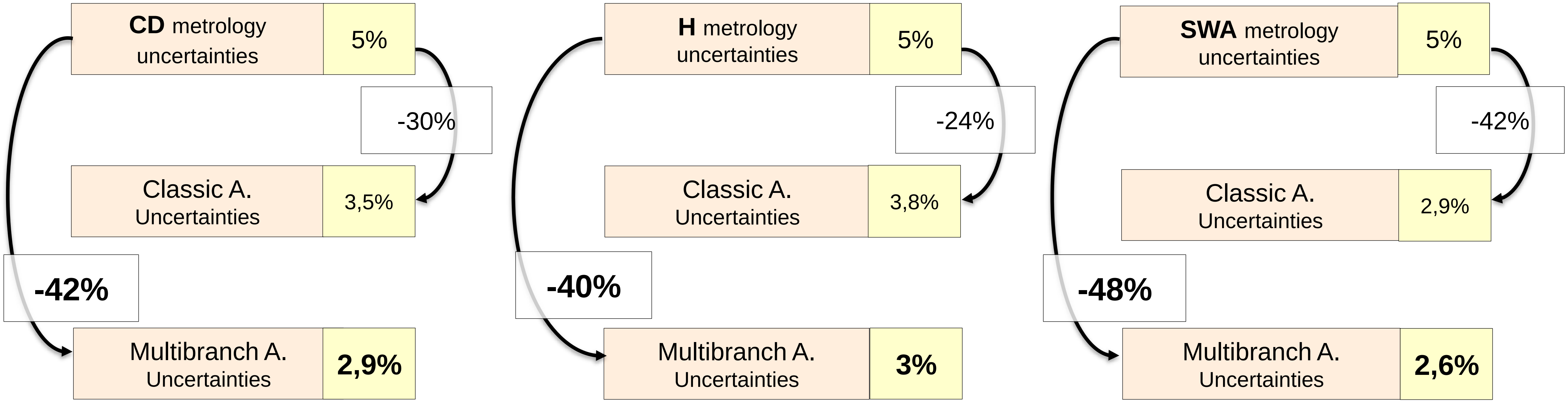


relative error	3σ
CD	3,5%
H	3,8%
SWA	2,9%



Relative error	3σ
CD	2,9%
H	3,0%
SWA	2,6%

Classic vs multibranch comparison



Multi-branch neural network provides the best results.

This architecture will be used

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- **RESULTS of hybridization**
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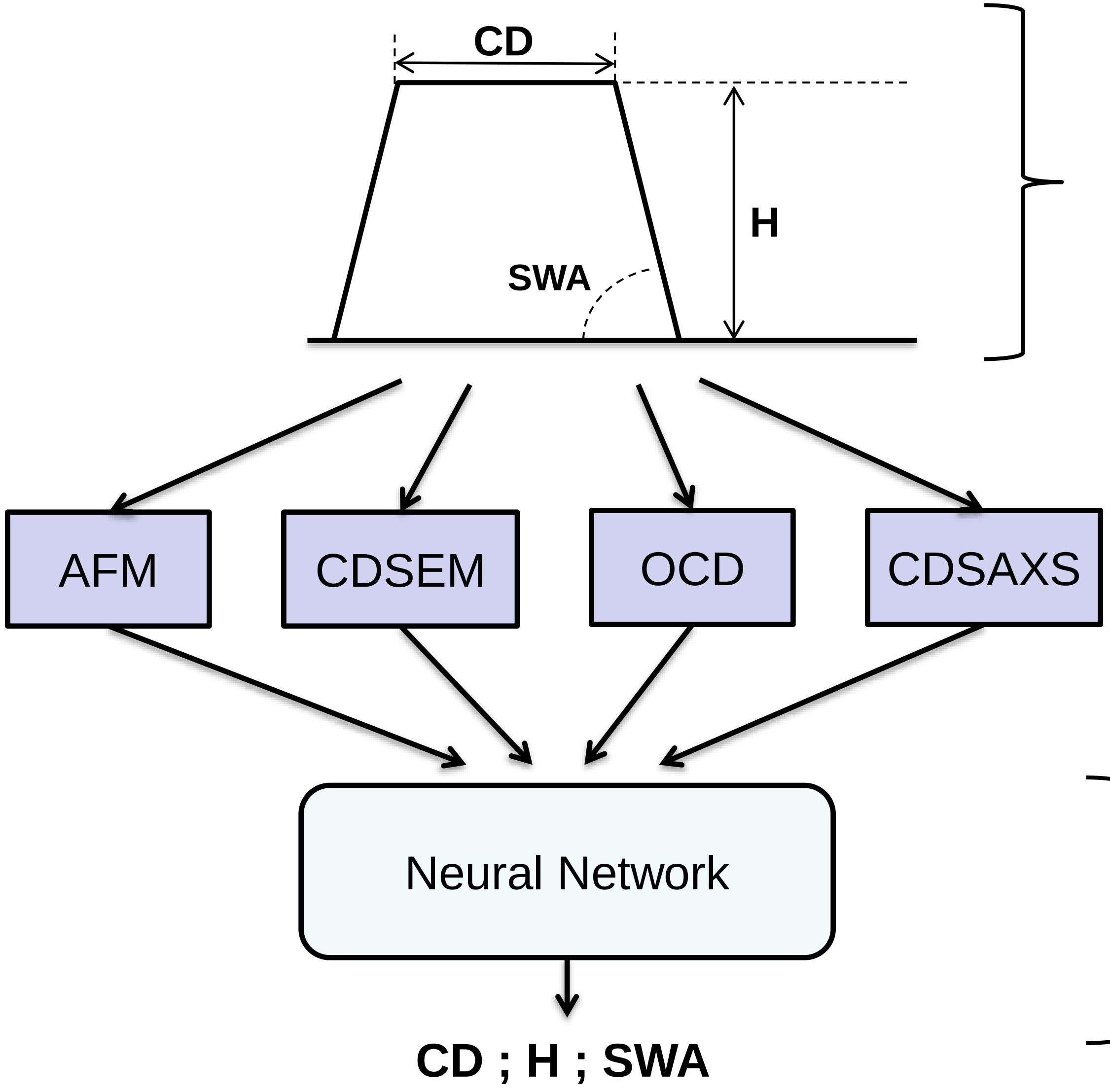
Results of hybridization



Sample Model :

Close to the physical pattern shape

Pattern variability included

Metrology techniques simulators:

Measurement uncertainties included

Output: CD, H & SWA

Neural Network:

Multi-branch Architecture

Results of hybridization

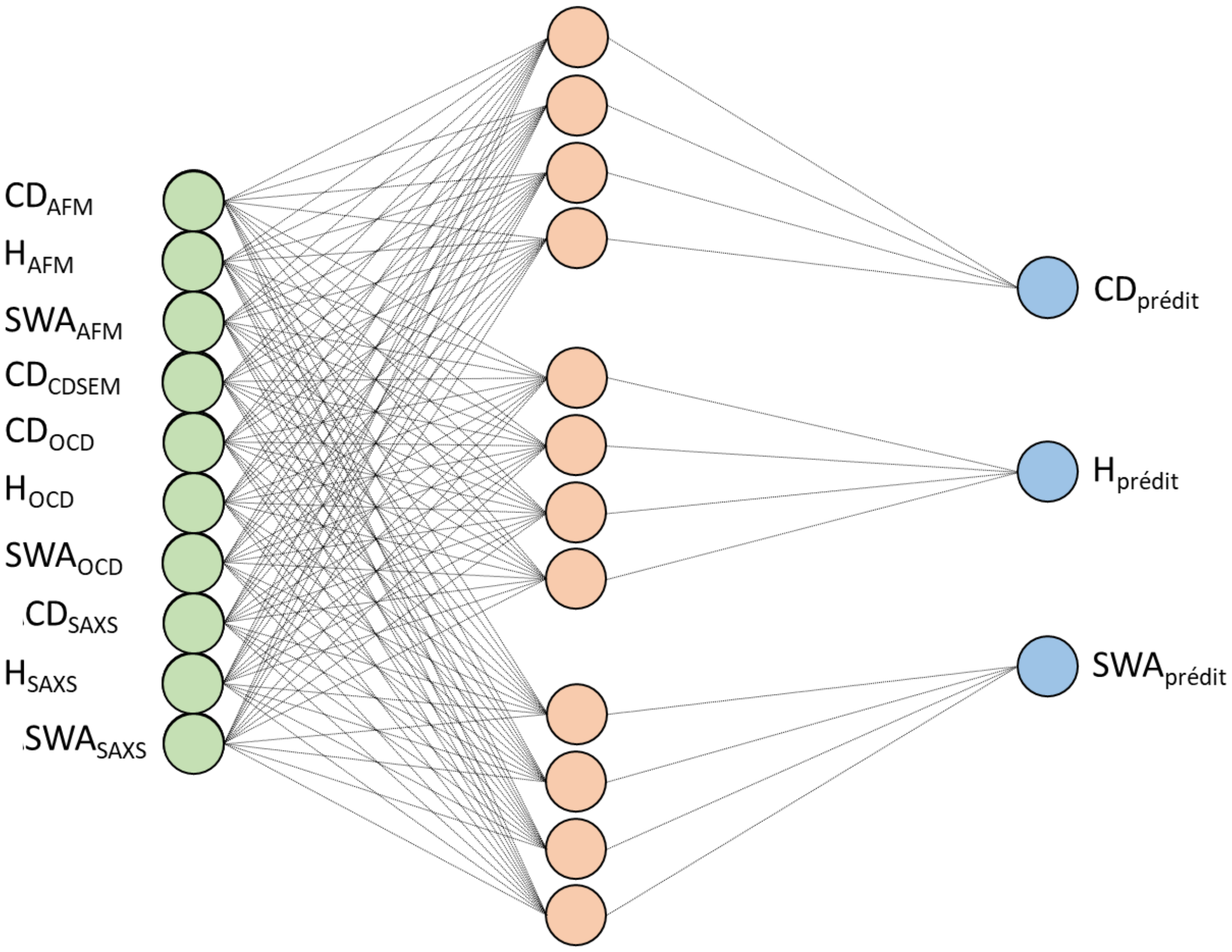
Error standard dev.

AFM
CD = 0,65 nm
H = 0,68 nm
SWA = 1,29 °

CDSEM
CD = 0,91 nm

OCD
CD = 2,05 nm
H = 0,92 nm
SWA = 3,49 °

SAXS
CD = 0,54 nm
H = 0,26 nm
SWA = 0,67 °

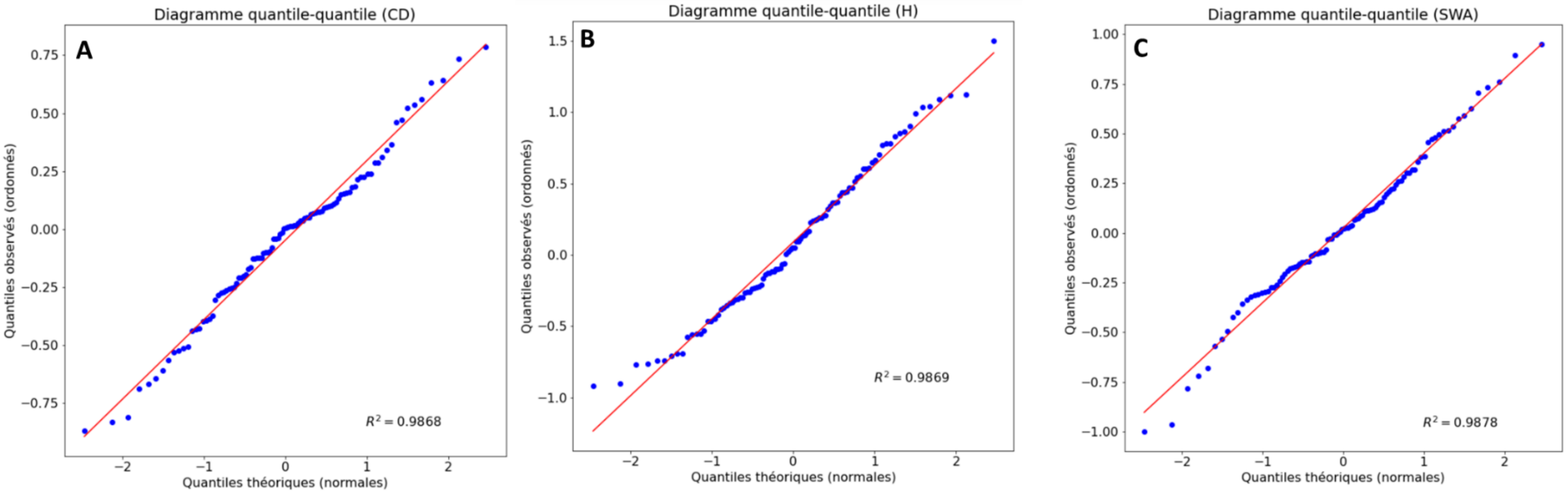


CD_{hybr}
Mean val. = -0,05 nm
Std Dev. = 0,35 nm

H_{hybr}
Mean val = 0,01 nm
Std Dev. = 0,47 nm

SWA_{hybr}
Mean val = 0,01 °
Std Dev. = 0,43 °

Results of hybridization



Quantile-quantile plot (Q-Q Plot) between a theoretical normal distribution and the parameter error distributions: (A) CD, (B) H, and (C) SWA

Conclusions

- Realistic data generation
  - Sample model construction
  - Simulation tools development

- Hybridization by Neural Network
  - Network architecture optimization
  - Predicted results have better accuracy and precision

Hybrid Metrology using Neural Network trained with realistic simulated data can improve the precision & the accuracy of dimensionnal measurements

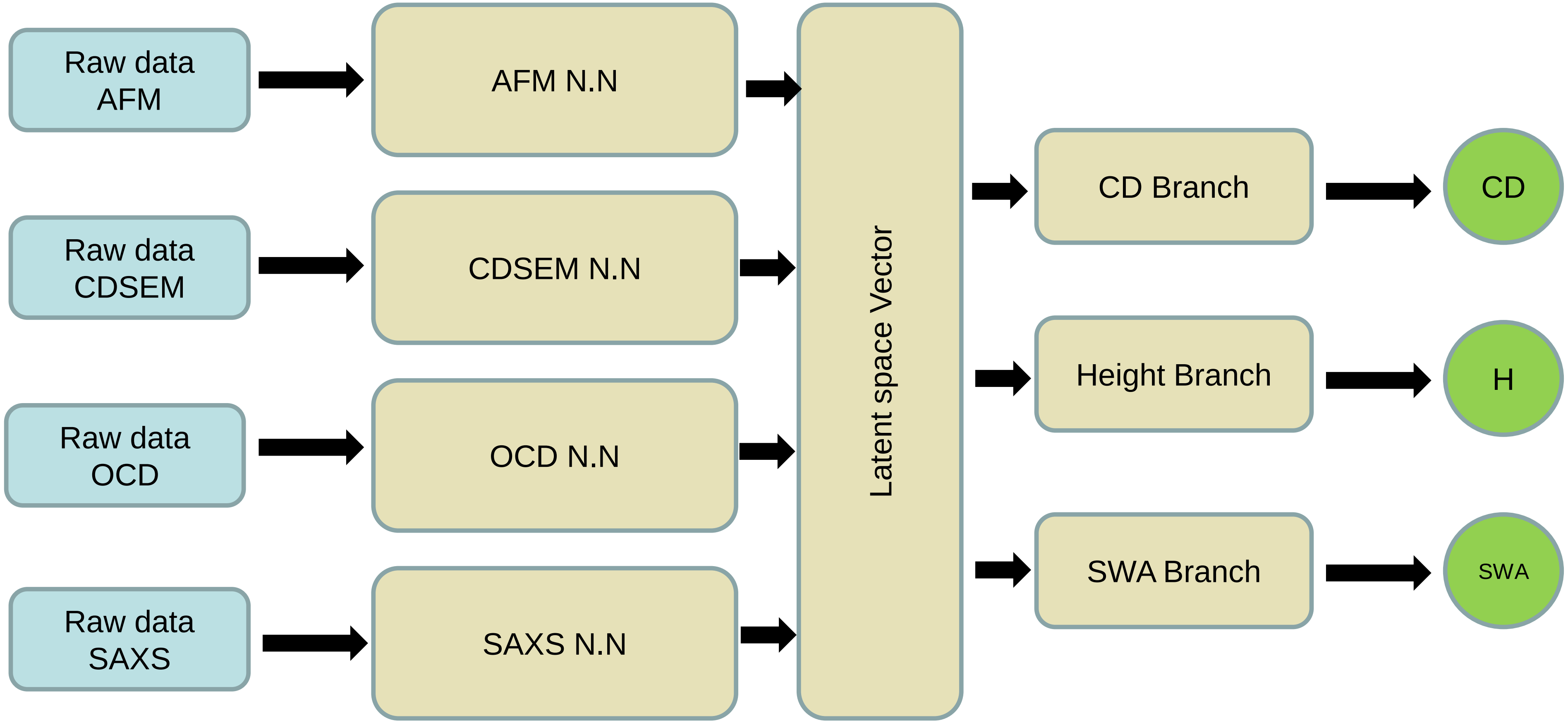
Perspectives

- Introduce experimental data in the training dataset based on physical samples

- **Hybridization with raw data in Neural Network Inputs**

  - **Reduction of information losses before hybridization**
  - **More complex architecture of Neural Network**

Perspectives



To be continued….

THANK YOU