ML based virtual metrology for advanced process control to improved high product mix manufacturing

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Outline

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  - Application: Chemical vapor deposition (CVD)
  - New product introduction (NPI)
- Approach
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  - Calibre® Fab Insight VM modeling
  - VM modeling with and without incorporating design features and FDC data
- Results
  - APC system: R2R control with VM model
  - Control simulation result of APC system
- Conclusion

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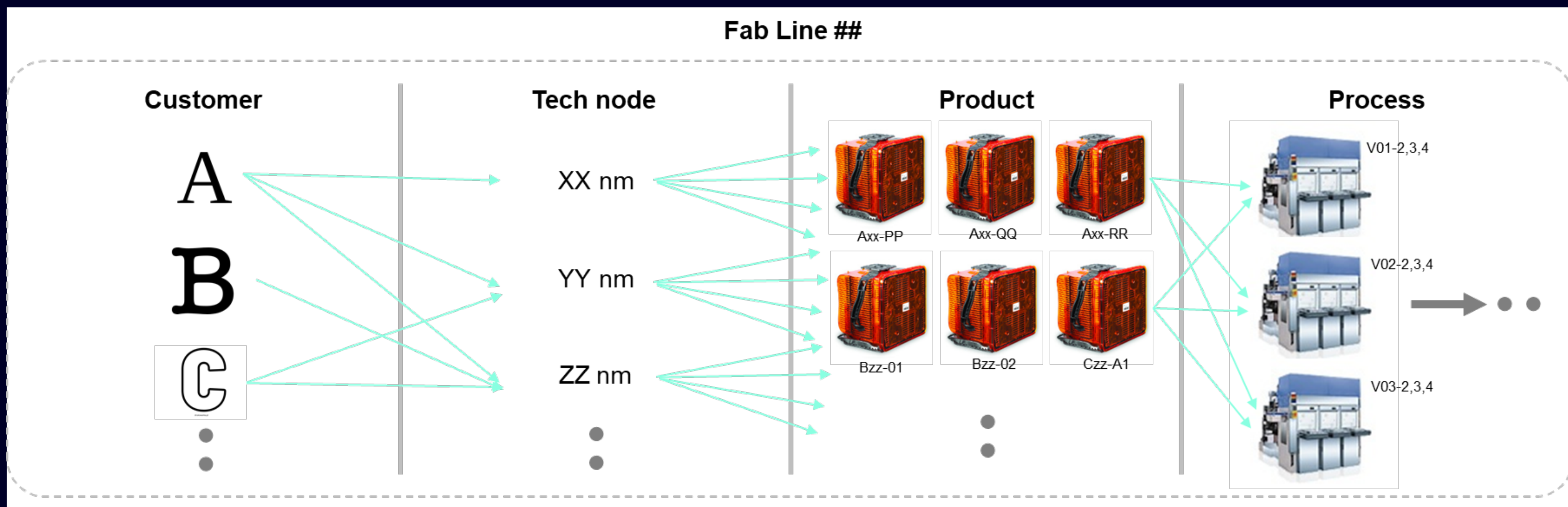
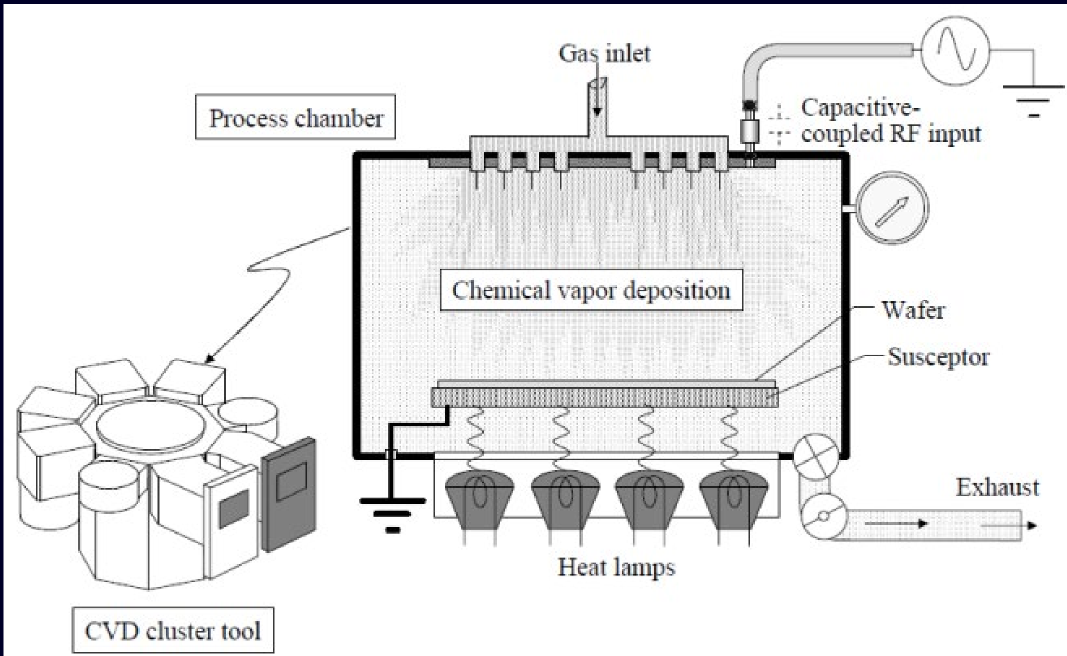
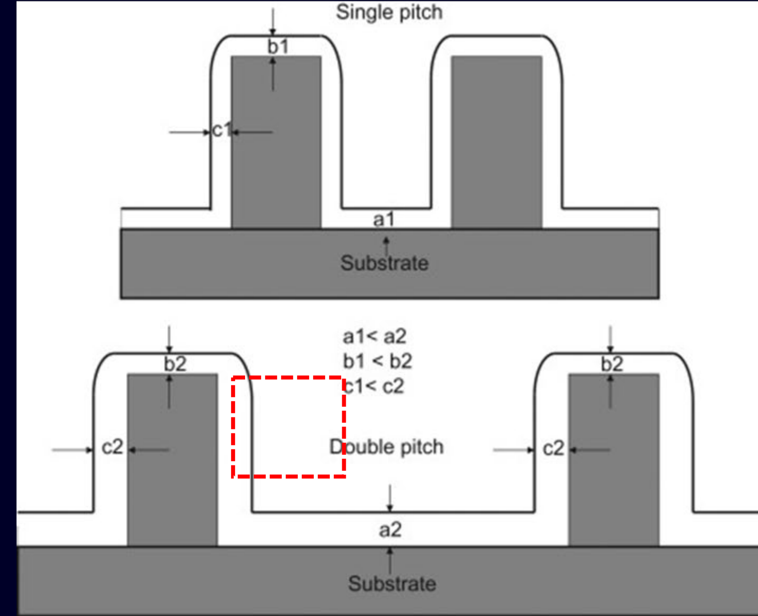
Background: High product mix manufacturing in semiconductor foundry

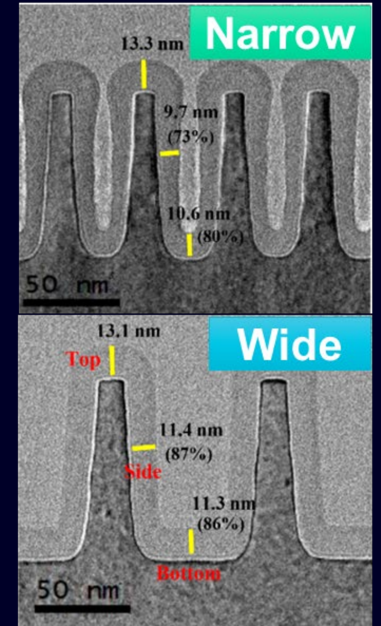


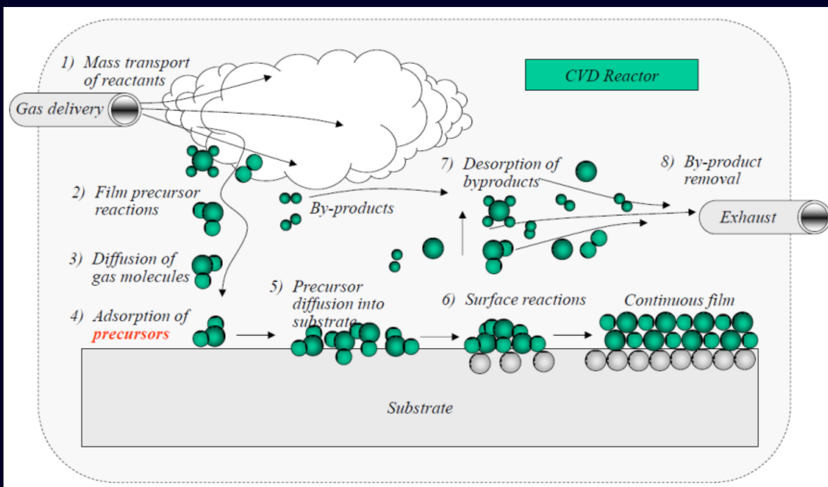
- Growing demand for **custom-designed products** from diverse customers requires increased manufacturing flexibility
- High product mix manufacturing involves coordination of various chambers and processes
- Complex operational challenges results in reduced yields and higher costs, requiring development of effective strategies

Application: Chemical vapor deposition (CVD) - Challenges









Variation in deposition thickness in high product mix environment due to

- Device layout design
- Chamber condition drift

Design Features can influence film thickness by affecting key transistor parameters like threshold voltage and overlap capacitance, that impacts yield

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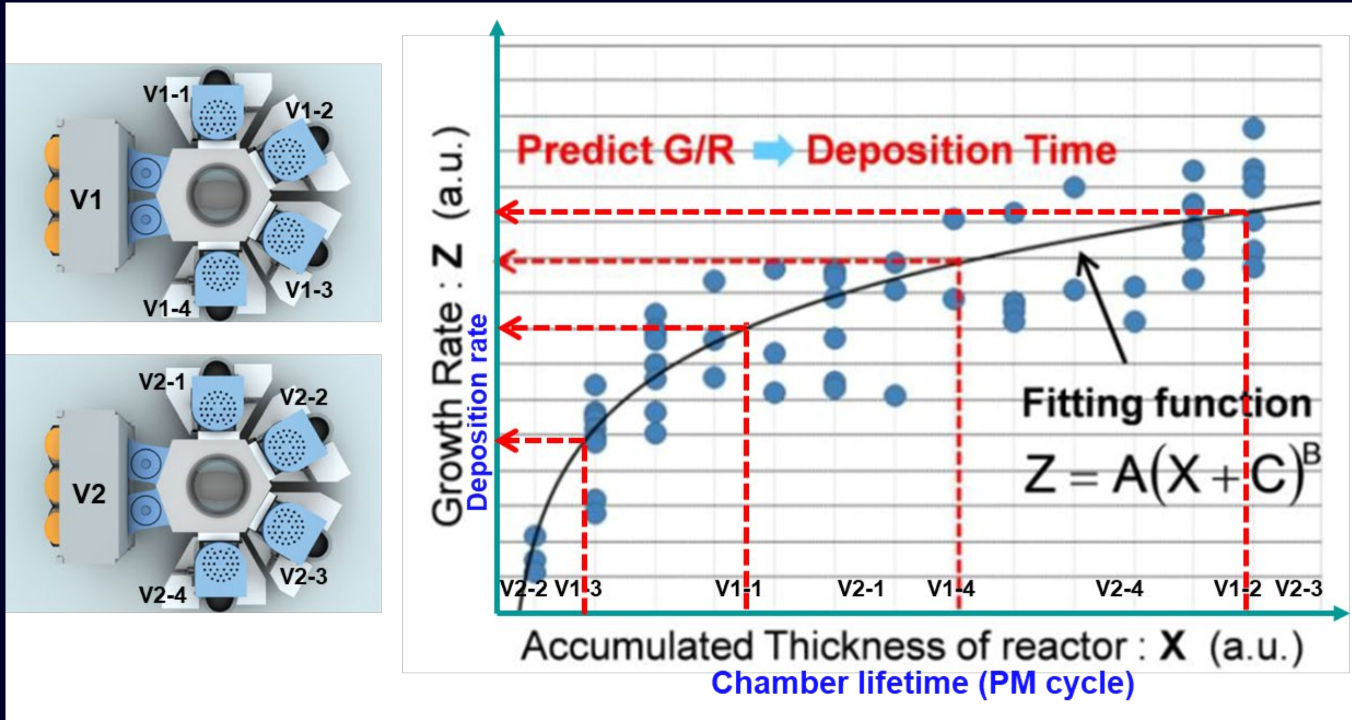
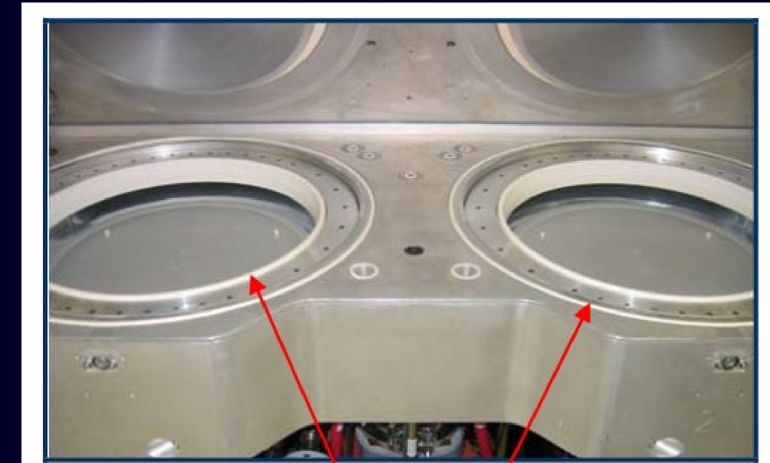
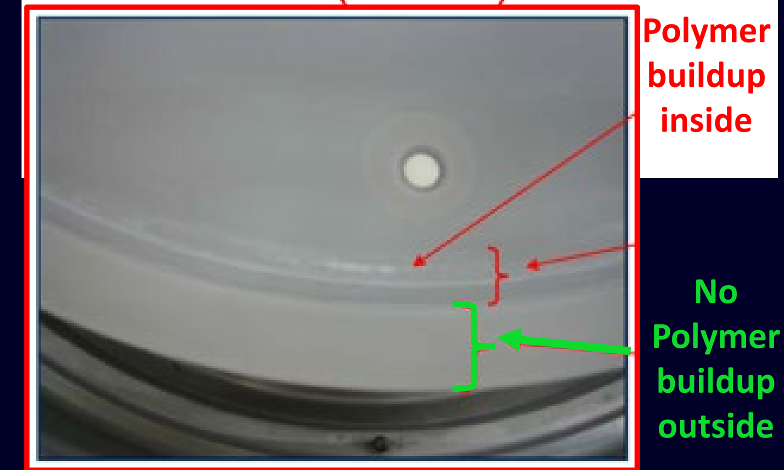
Application: Chemical vapor deposition (CVD) - Challenges







CVD Process variability (Drift in CVD film growth rate) during Preventive Maintenance (PM) cycles and chamber-to-chamber variations

Caused by decreasing surface area and reactive gas consumption within the CVD chamber because of accumulated film thickness

PM cycles: the entire process cycle between PMs

Efficient management of PM cycle variation and chamber matching can help reduce fab line efficiency and throughput loss

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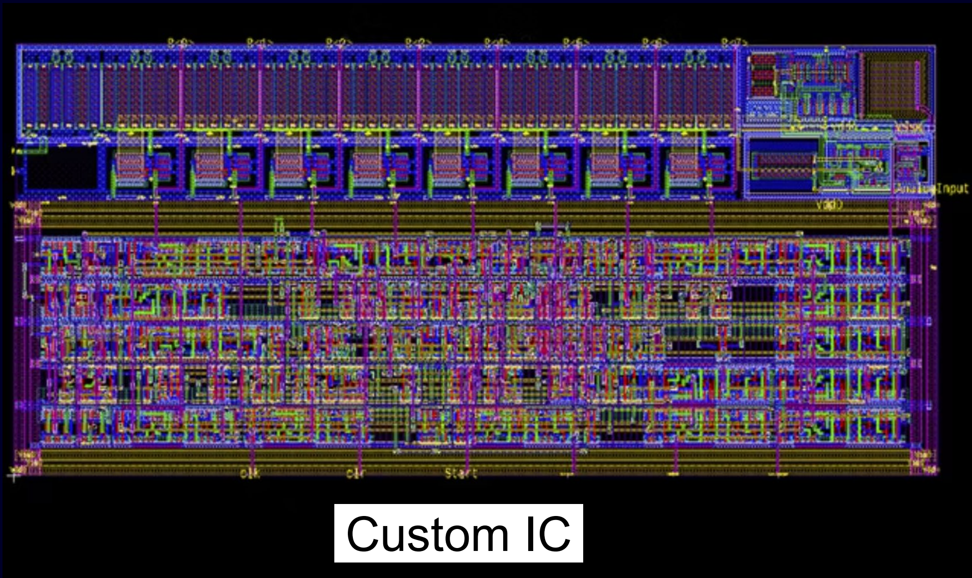
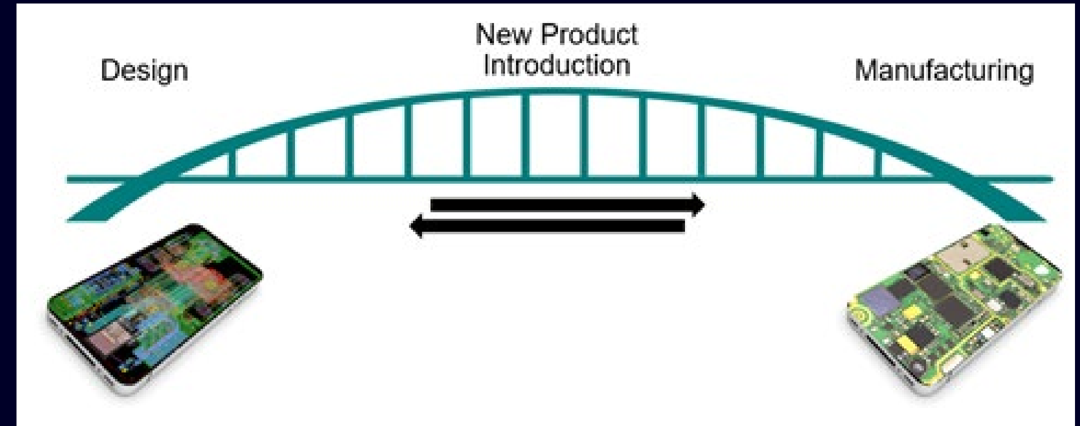
New product introduction (NPI)





High Mix Production → Frequent **New Product Introductions (NPI)**

- Complex setup, time-consuming if not optimized
- Challenges for traditional run-to-run (R2R) advanced process control (APC) methods

Machine learning (ML) based virtual metrology (VM) approach proposed as an effective process control solution

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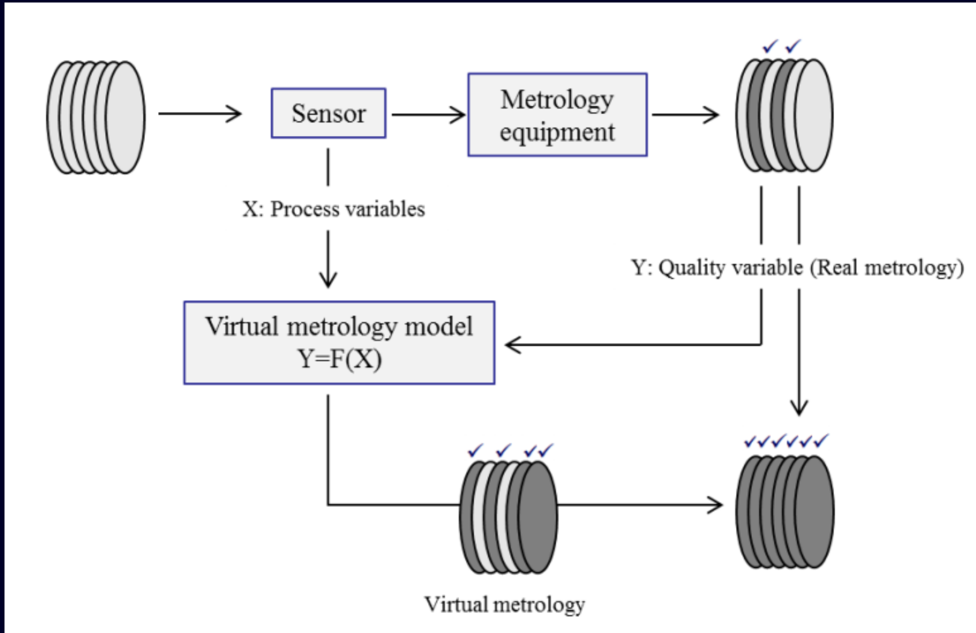
Virtual metrology (VM) development and utilization for control system

Metrology used for monitoring wafers to update control models. Effective metrology systems can help achieve precision during CVD Process.



Reliance on metrology tools can

- Extend processing times
- Raising costs
- Trade-off between cost and quality

Virtual metrology (VM) optimizes control in the CVD process, striking a balance between cost and quality

- Traditional VM uses process chamber data, including fault detection and classification (FDC), to predict metrology results
- VM seamlessly integrates predictions into real-time, high-volume manufacturing control systems, especially in run-to-run (R2R) settings

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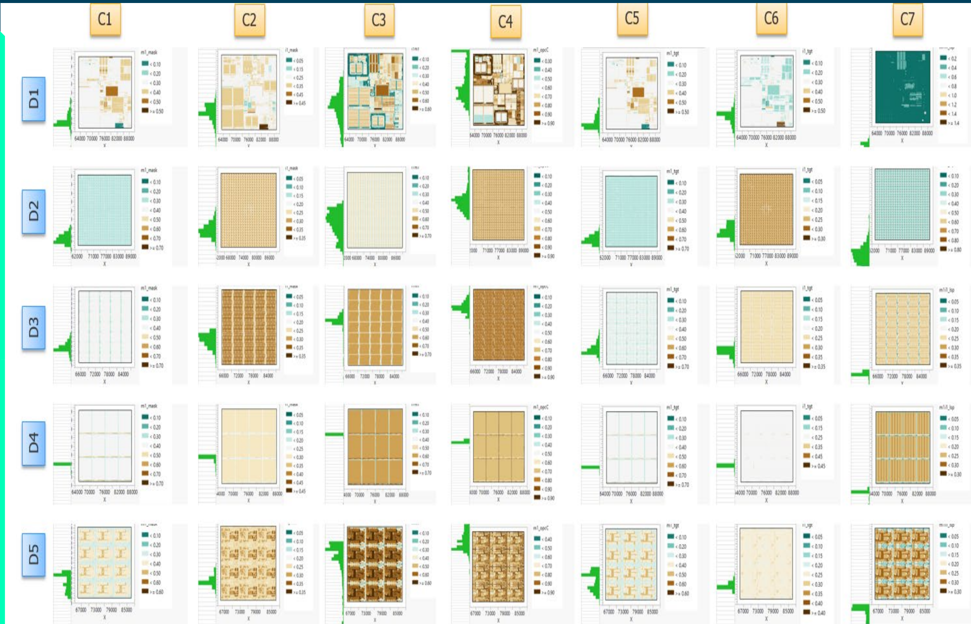
Digital Twin Product: Understanding impact of product design

Visualizing impact of product design features on the model using SHAP analysis



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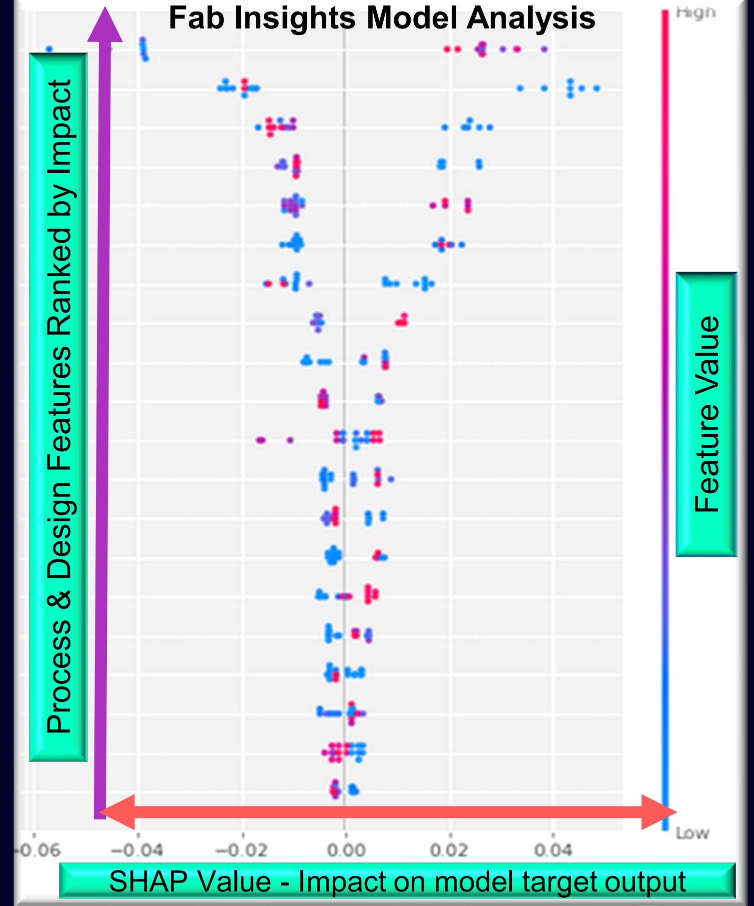
Process Characterization

Process

Metrology



Design, simulate, and verify products digitally

Leverage physical design understanding to capture sensitive product characteristics

- VM can utilize specific design features extracted for better predictions across various layouts and technologies

  Extended VM model for enhancing control performance especially high product mix manufacturing

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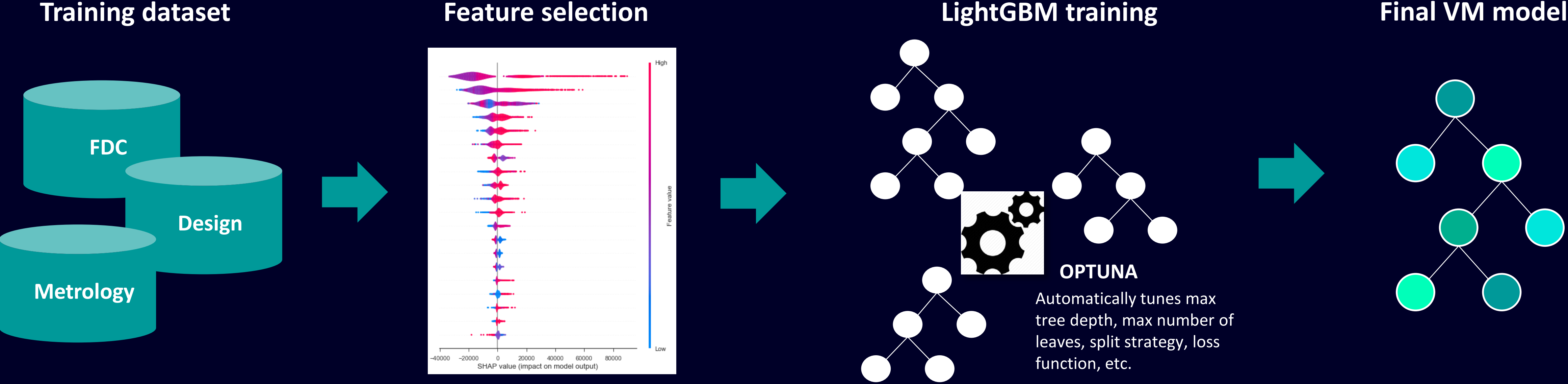
Calibre® Fab Insights - VM model overview



Based on Shapley analysis, select subset of input features (top N important features) for training to prevent model from overfitting

Using OPTUNA's hyperparameter optimization, train LightGBM model based on best set of hyperparameters.

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ML Model for VM

- Known to be very fast (GBM→XGBoost→LightGBM), while requiring low memory when training on large dataset – ideal for FAB data

3
Features
Float data
Convert
Features
Bin data
Construct histogram
Features
Bins
Decision tree
Histogram: = minus

Training set
1
2
DT_1
DT_2
DT_n
Residual
Residual
$f_1(x)$
$f_2(x)$
$f_n(x)$
Leaf-wise tree growth
$\sum_{i=1}^{n} f_i(x)$

(2022)

1

Being an ensemble model, a trained LightGBM consists of **multiple sub-models**, called "weak learners". Each weak learner focuses on part of dataset that was poorly predicted by other weak learners. Final prediction made by LightGBM is an aggregation of predictions made by individual weak learners.

2

Each weak learner is a **decision tree model consisting of nodes and leaves**. Therefore, it requires decisions about which feature and value to split on at each node. The tree grows leaf-wise, meaning that it only splits on nodes that leads to poor prediction.

3

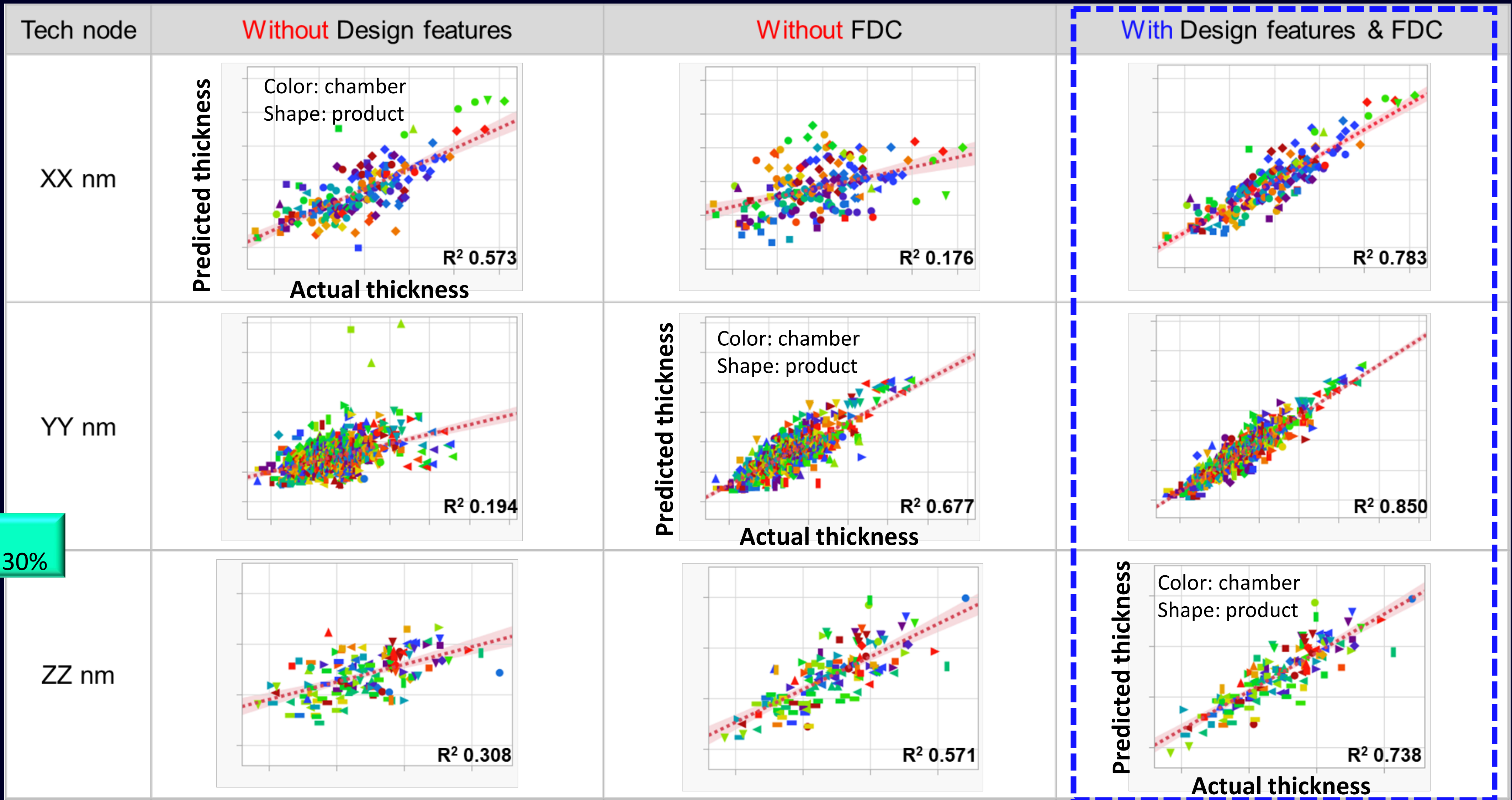
Splitting strategy for LightGBM's decision tree is determined by **histograms constructed for each feature**. By using histograms instead of raw data, computational/memory efficiency is improved.

Due to the way LightGBM is structured, as shown above, LightGBM is associated with many hyperparameters such as max tree depth, max number of leaves, max number of bins for histogram, etc. **These were tuned automatically using the OPTUNA library**.

VM modeling with and without incorporating design features and FDC data

Data for modeling
- Tech nodes: 3
- Product: 70
- Chambers: 15
  5 equipment units
  Each with 3 chambers

VM modeling: -
Training: 70% - Testing: 30%



※ Specific thickness targets for each technology node have been omitted due to confidentiality concerns

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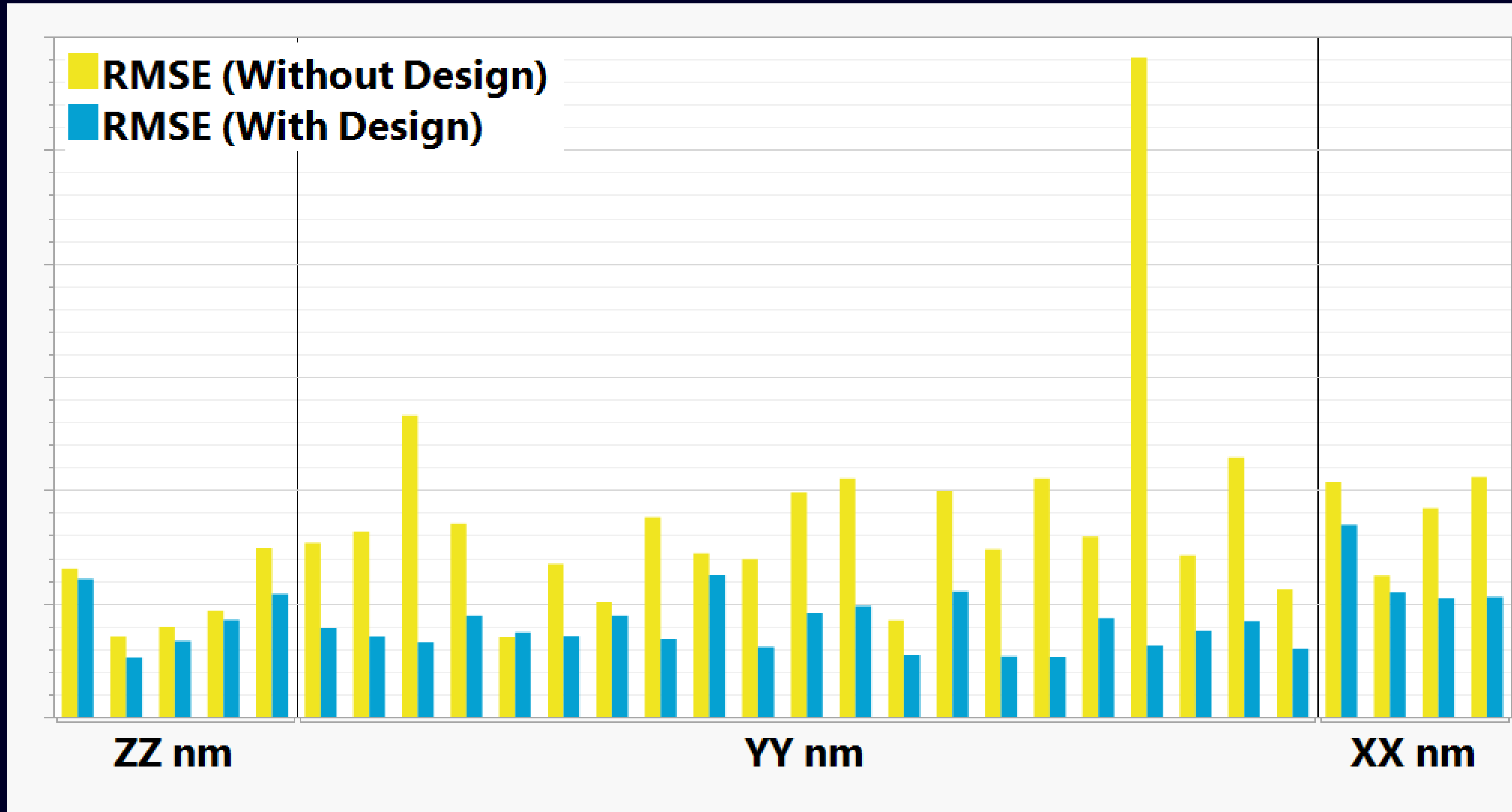
VM modeling with and without incorporating design features by product



VM model incorporates design features consistently exhibits significantly better performance

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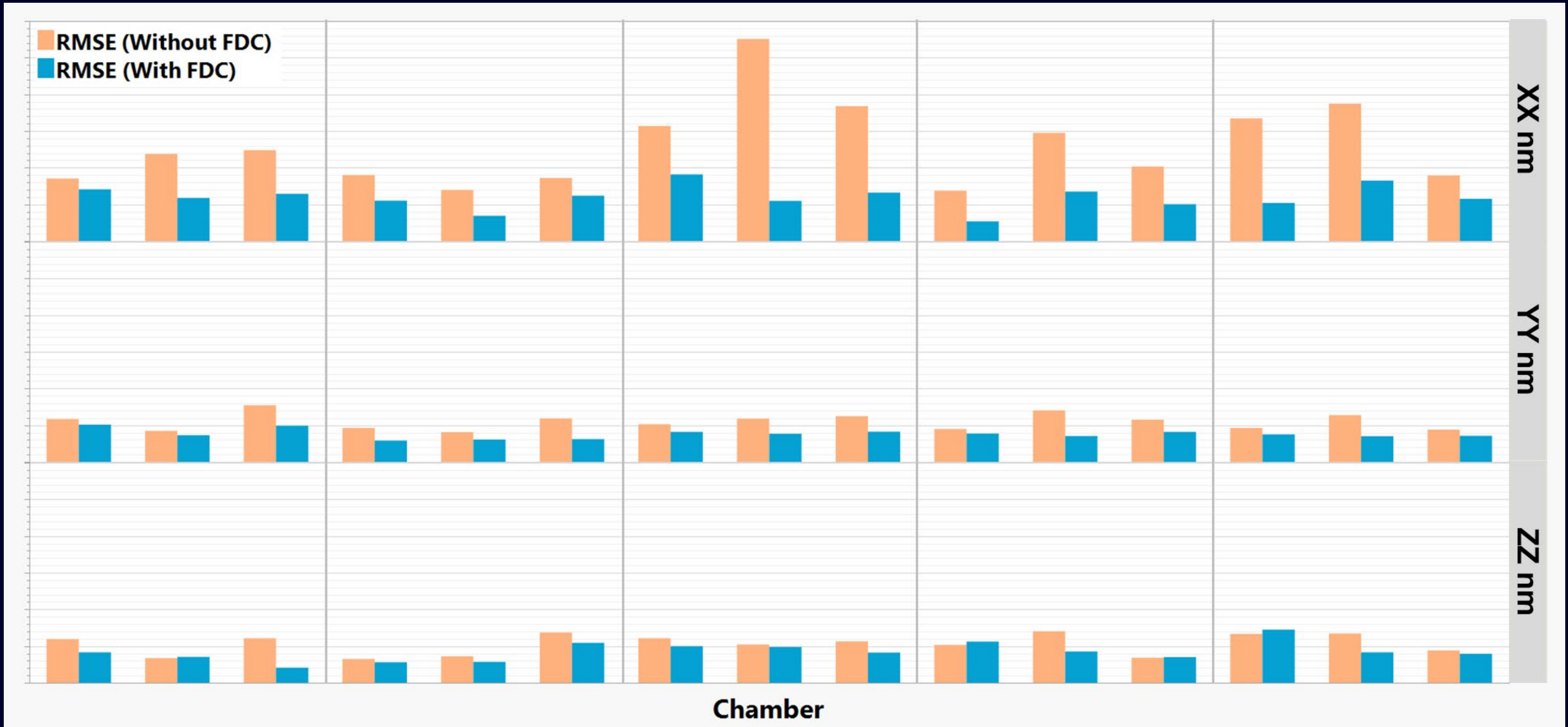
VM modeling with and without incorporating FDC data by chamber



VM model incorporates FDC data exhibits better performance across the majority of segmented cases

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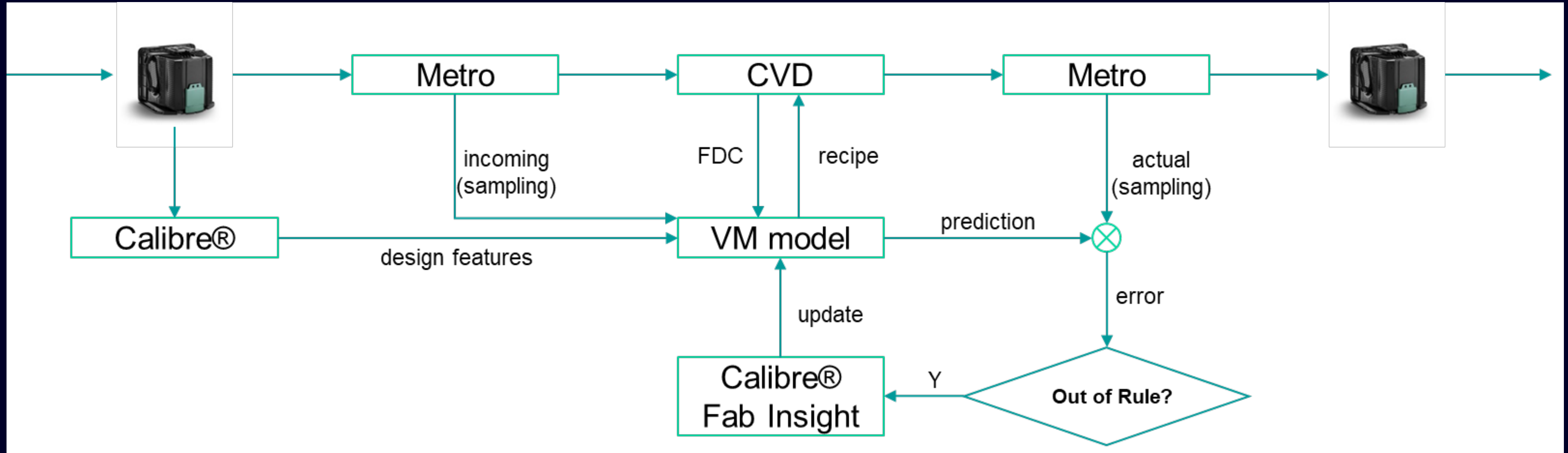
APC system: R2R control with VM model



Advanced process control (APC) system, utilizing the VM model for run-to-run (R2R) control

- CVD process recipe is derived from the VM model, which integrates design features, fault detection and classification (FDC), and incoming measurements to achieve the target thickness
- After post-measurement, the prediction error calculated by comparing the predicted thickness with the actual thickness after processing
- If the error surpasses predefined rules, such as specifications or a 20% threshold, the VM model is triggered to update, incorporating additional data within a predefined time frame

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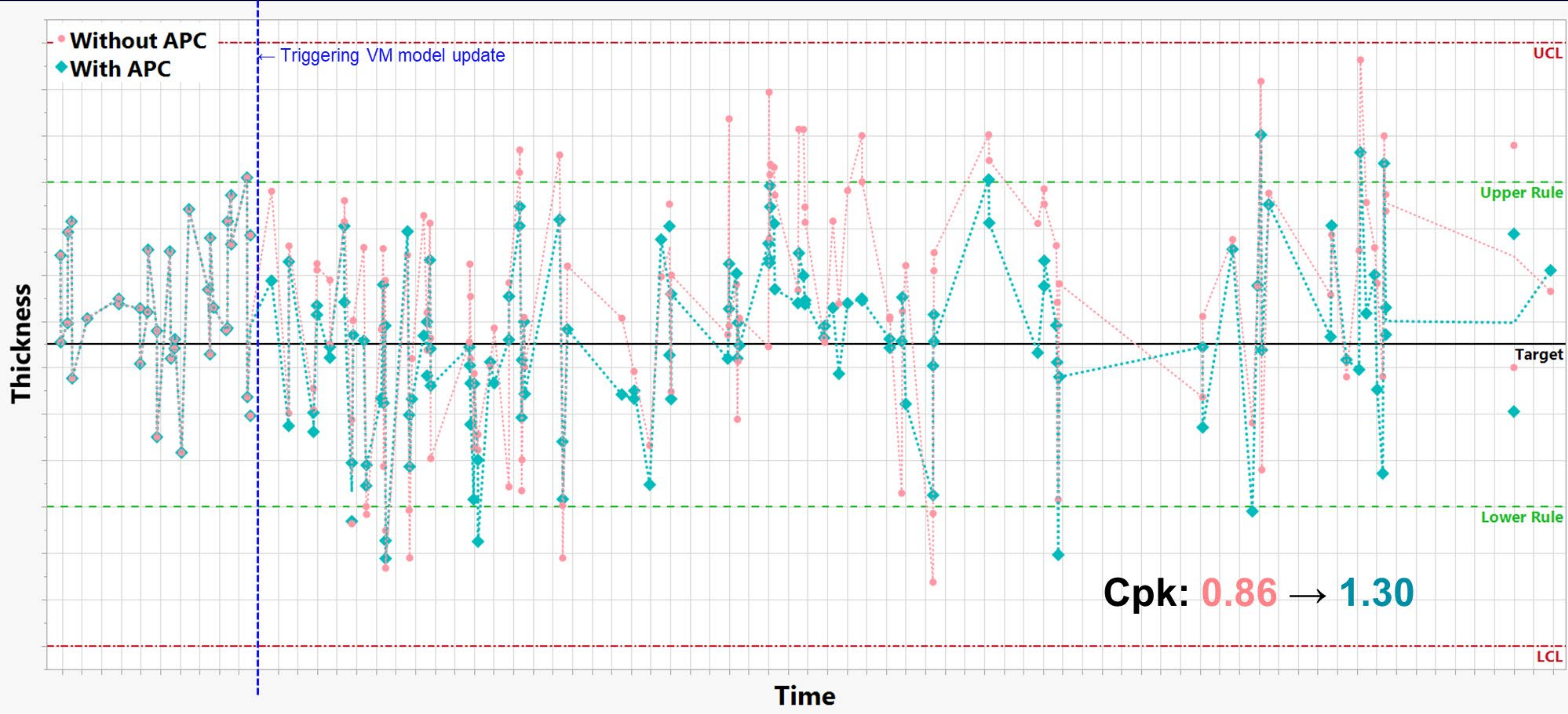
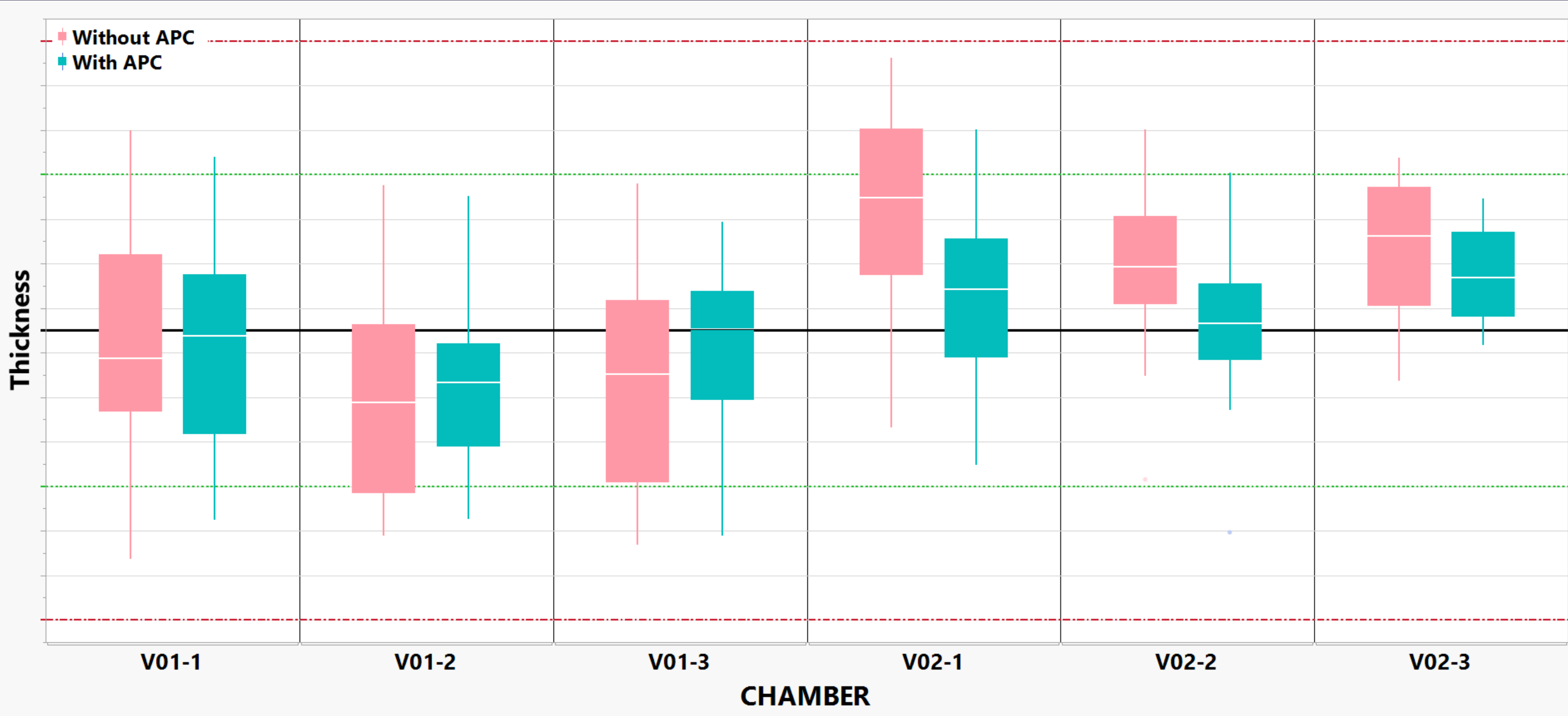
Control simulation result of APC system



The system effectively mitigates variations in the R2R deposition film thickness and accurately adjusts the thickness to the desired target value

※ Due to the limited size of the dataset, the control simulation primarily focuses on a single technology node (YY nm)

Control simulation result of APC system by chamber



Improvement in chamber-to-chamber thickness variation with the implementation of the APC system

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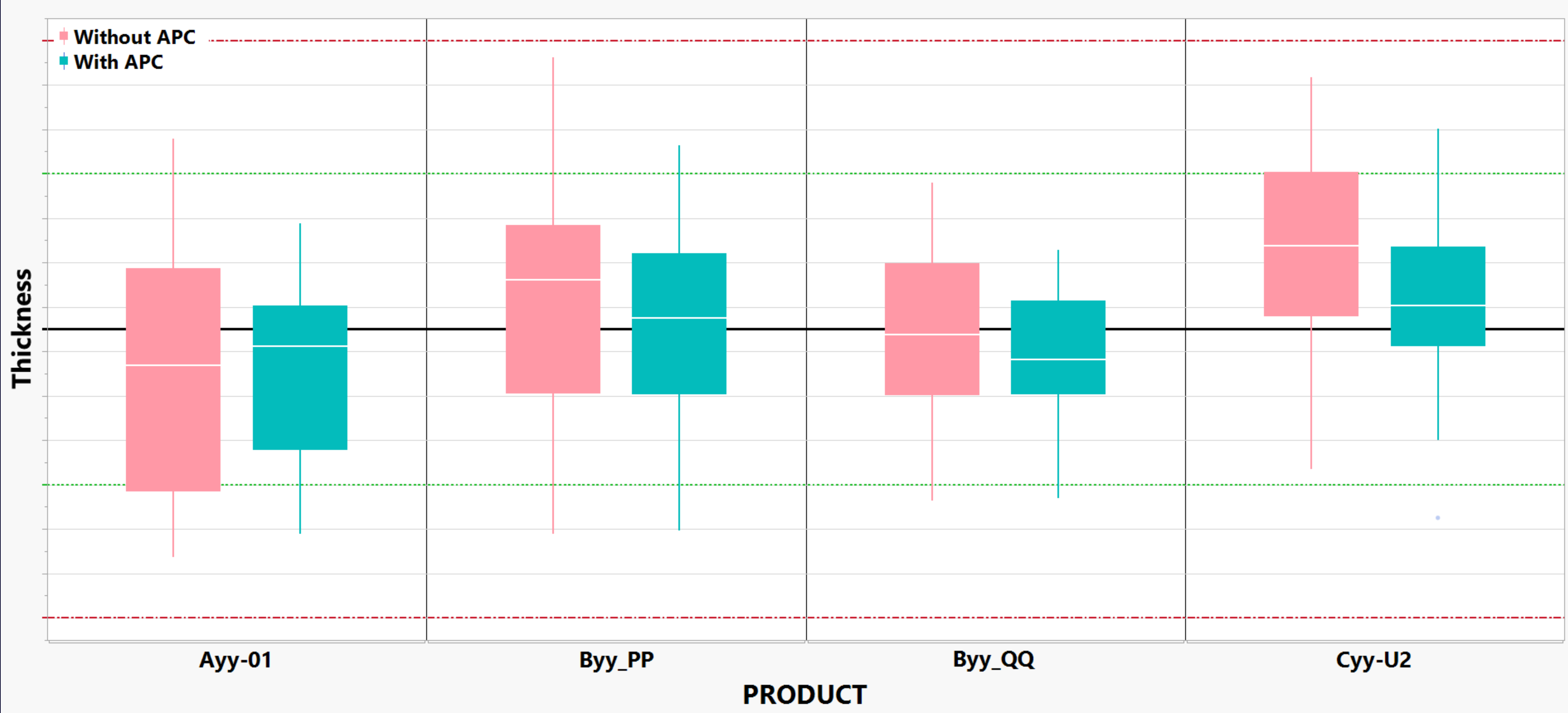
Control simulation result of APC system by product



Improvement in product-to-product thickness variation with the implementation of the APC system

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Conclusion

- Growing demand for custom-designed products from diverse customers requires increased manufacturing flexibility and frequent NPI
- ML based VM approach is proposed as an effective process control solution for high product mix manufacturing
  - ➢ Formulate VM model with incorporating design features and FDC data
  - ➢ Employ most advanced and optimized ML methodology to build VM model
  - ➢ Integrate VM model to APC system for R2R control
- Simulation results confirm the remarkable effectiveness of integrating the APC system with the VM model into the CVD process, particularly within a high product mix foundry fab
- Further research and development is actively conducted to enhance the solution and better align it with the demands and requirements of foundry customers

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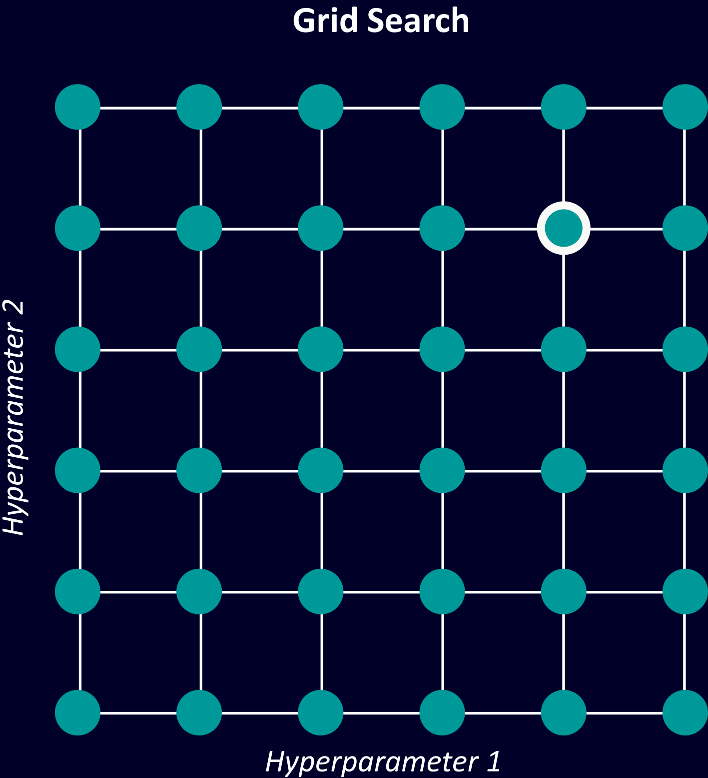
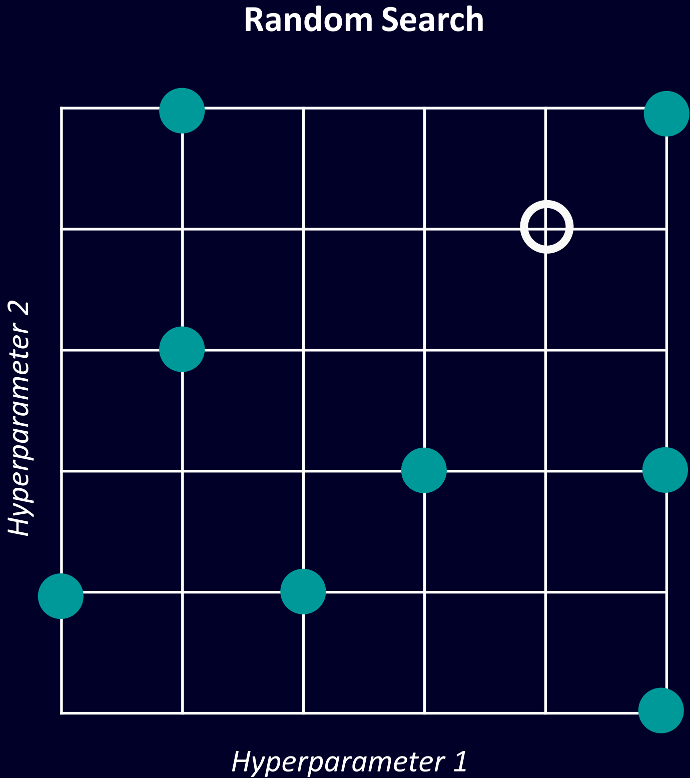
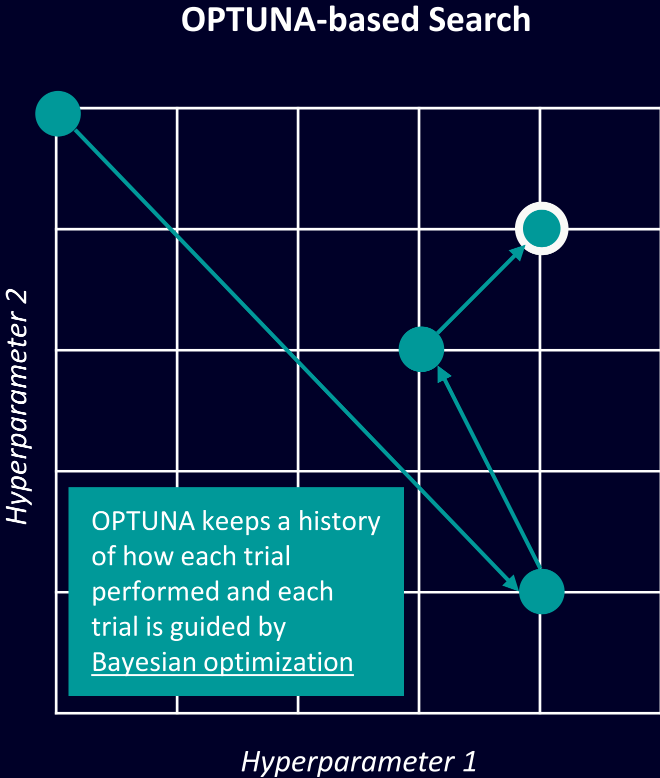
- Hyperparameter tuning requires lots of trial-and-errors if approached naively. OPTUNA can significantly help improve the tuning process



Extremely time consuming



Might completely miss best set



Find best set (or close one) with few trials

○ Best set of hyperparameters (which yields best accuracy)

● Trial for set of hyperparameters

From: 1907.10902.pdf (arxiv.org) (preprint)

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