ISOP-Yield: Yield-Aware Stack-Up Optimization for Advanced Package using Machine Learning

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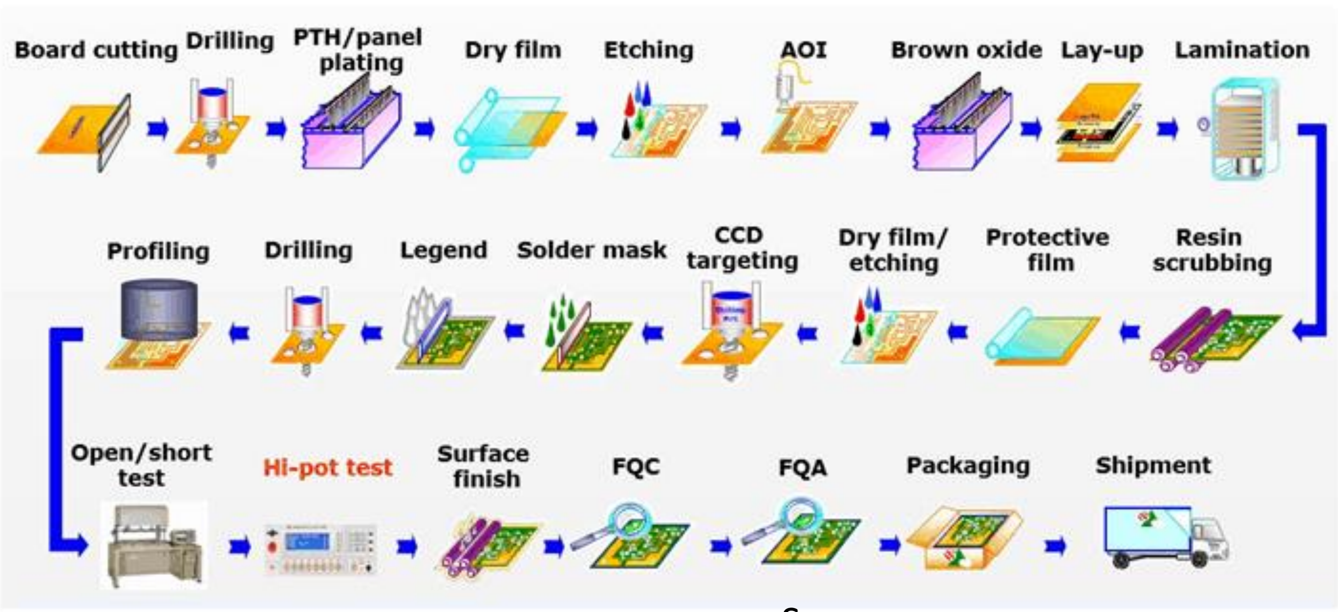
Manufacturing Variations in Advanced Package Design

- Manufacturing variations important in high volume manufacturing
  - E.g., chemical reactions and physical impacts, such as drilling and etching
- Minor environment change can affect QoR
- Need to incorporate them into design process

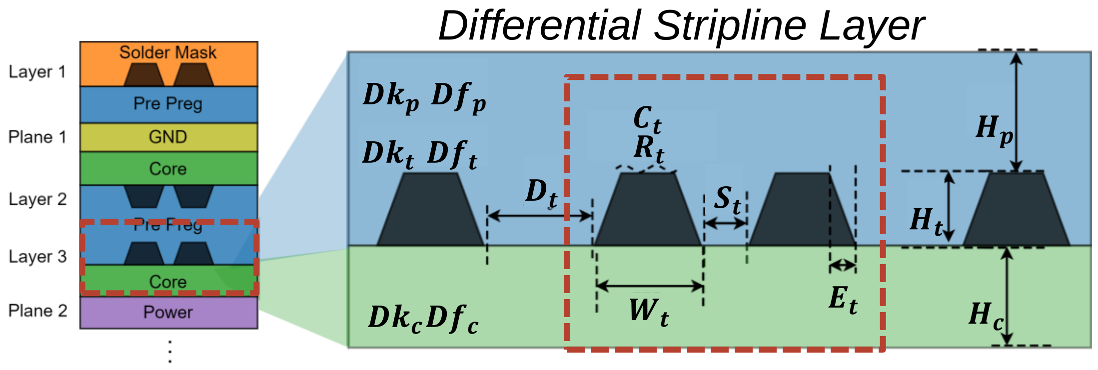


Source:

PCB Stack-Up Design Challenges

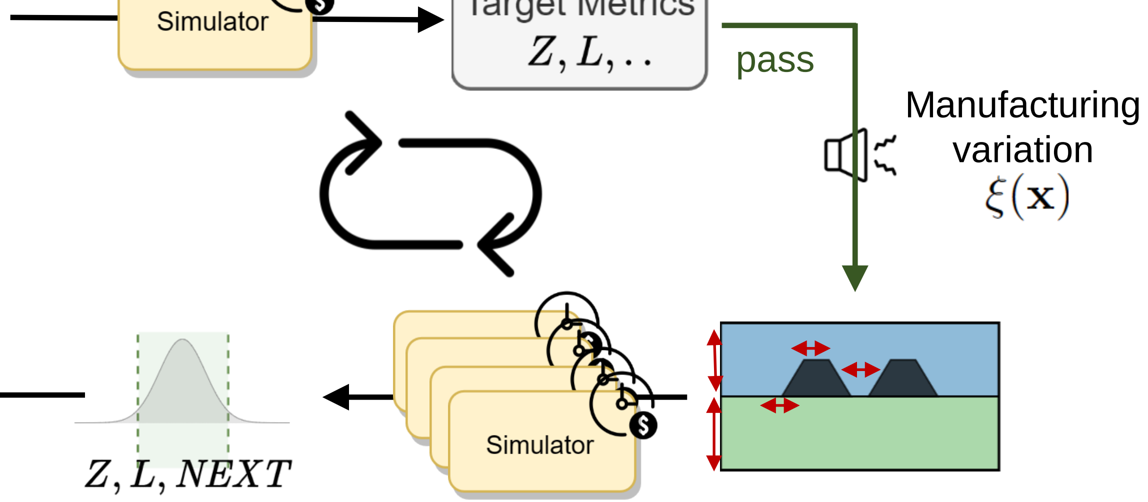
- PCB stack-up design process

Slow
Iterative
Expensive



x	Description
W	Trace width
S	Spacing between differential signals
H	Height
D	Distance between two differential pairs
E	Etch factor

x	Description
R	Surface roughness
Dk	Dielectric constant
Df	Dissipation factor
C	Conductivity



- Multiple design parameters and different performance requirements
- Manufacturing variation effect

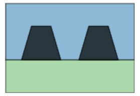
Related Work and Case Study

- Inverse stack-up optimization for advanced package design

- Design Space
- Design Constraints
- Optimization objectives

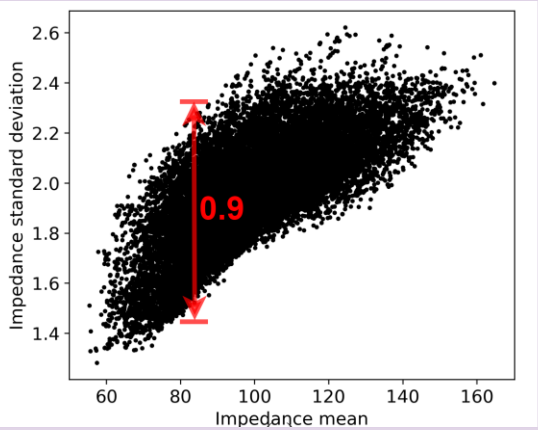
HPO-based framework

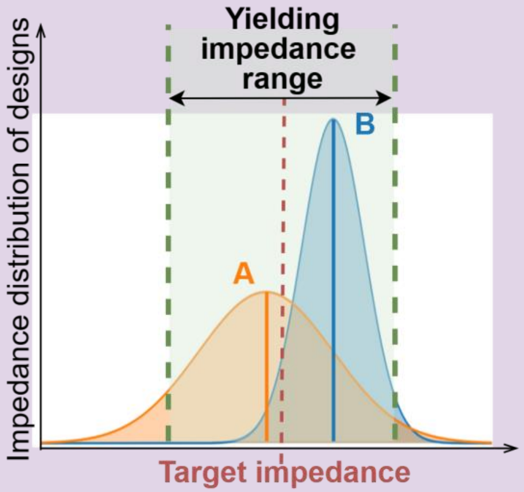
Optimal stack-up design



$W_t, S_t, \ldots, Dk_p$?

Case Study With Manufacturing Variations





- Distinct design solutions with standard deviation varying significantly
- **Design A** has better nominal performance, but **B** has higher yield

→ **Need method to consider both performance and yield**

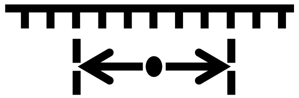
PCB Stack-Up Yield Optimization

- Yield-aware stack-up optimization task

Design Space (S)

Param	LB-UB	Step
W_t	2-5	0.1
S_t	2-10	0.5
…	…	…

Design Constraints (f^C)



$Z_o = 85\ \Omega$
$Z_{\pm} = 1\ \Omega$

Optimization Objectives (f^{FoM})

Minimize
|L| @ 16GHz
Minimize
|NEXT|

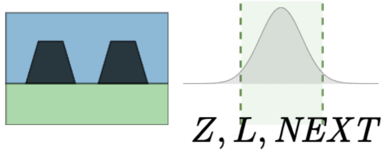
Yield Requirement

$\mathcal{Y}(\mathbf{x} \diamond \xi,\ \Delta YR) \geq p$

- Yield function $\mathcal{Y}$
- Manufacturing variation ξ
- Yielding range ΔYR
- Target yield rate p

ISOP-Yield: HPO with noisy input

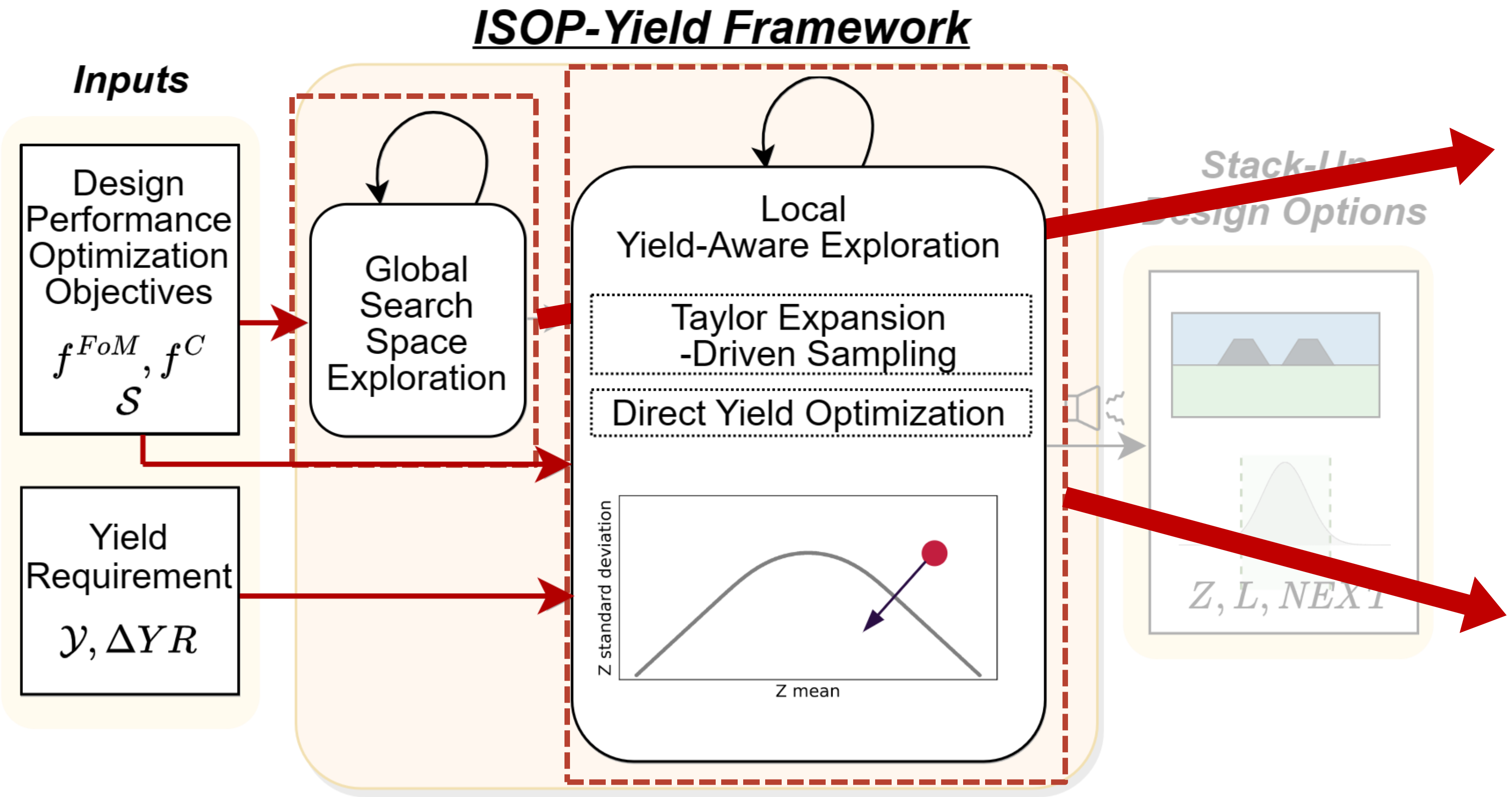
Manufacturing yield-aware stack-up design



$W_t, S_t, \ldots, Dk_p$?

ISOP-Yield Framework

- Overall Flow



- Global search:
  Based on ISOP algorithm, focus on finding **high performance** design candidates

- Local search:
  Based on GD, focus mainly on optimizing for **yield** using smooth ML model

Taylor Expansion-Driven Design Sampling Method

- Taylor expansion-driven method instead of typical MC sampling
- Taylor expansion:

$$\boxed{M_i(\mathbf{x}+\xi(\mathbf{x}))} = \boxed{M_i(\mathbf{x})} + \boxed{\xi(\mathbf{x})^T} \cdot \boxed{\nabla M_i(\mathbf{x})}$$

Evaluation of $\mathbf{x}$ under manufacturing variation $\xi(\mathbf{x})$

Evaluating [N] samples

Evaluation of $\mathbf{x}$

Manufacturing variation at $\mathbf{x}$

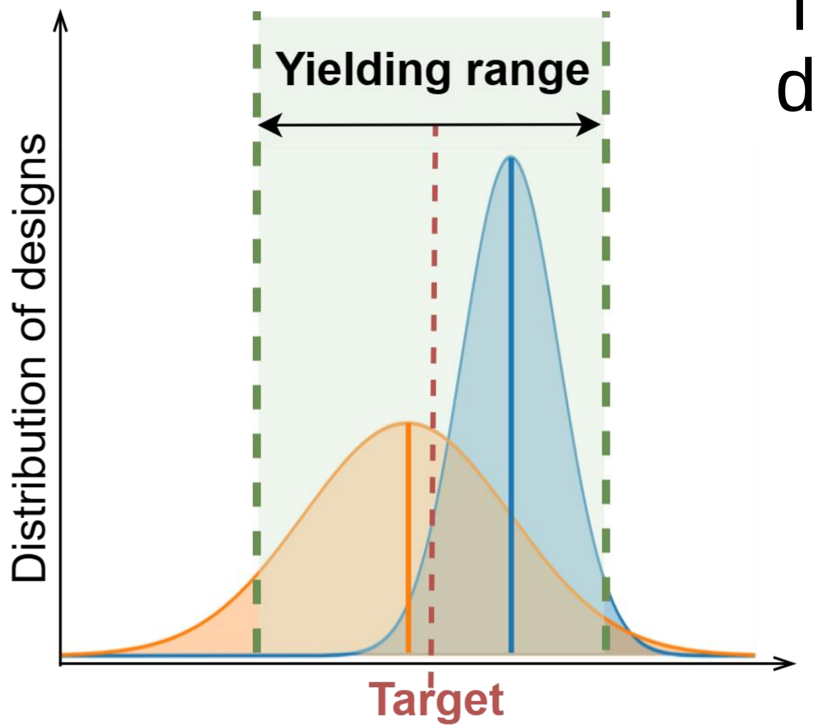
Gradient of ML model at $\mathbf{x}$

Evaluating [1] sample

→ Accelerates yield analysis

Direct Yield Optimization

- For flexibility in balancing design quality and yield



1) We observe the output's underlying distribution

→Most similar to the normal distribution

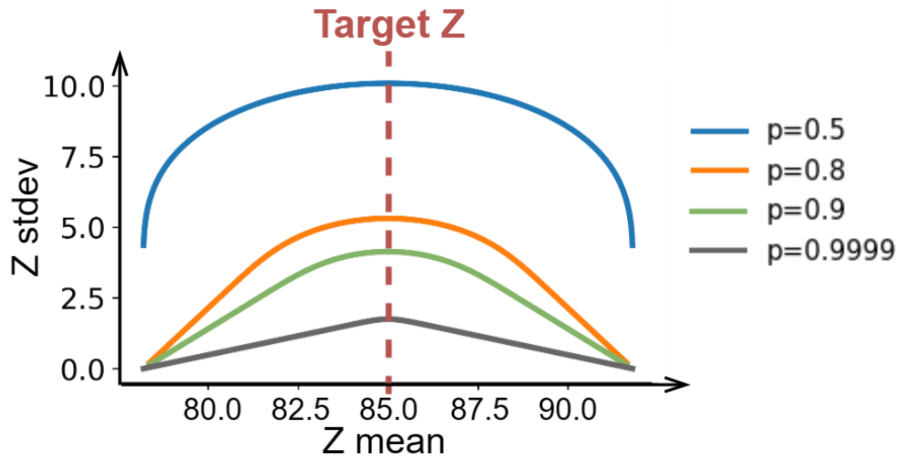
→A straightforward approach will be to make the distribution mean close to target and as tight as possible

→ This approach lacks precise control over the target yield

Direct Yield Optimization

2) Calculate the yield boundary points by querying B_{Z_μ} across ΔYR and solve for B_{Z_σ}

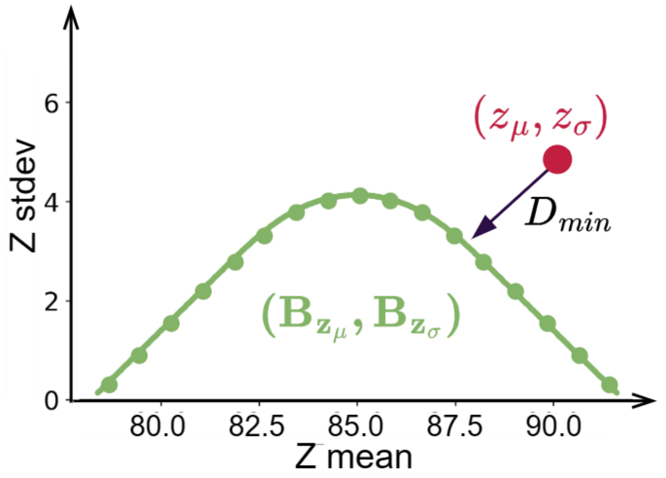
$$\left(cdf\left(\frac{YRL - B_{z_{\mu i}}}{B_{z_{\sigma i}}}\right) - cdf\left(\frac{YRH - B_{z_{\mu i}}}{B_{z_{\sigma i}}}\right) - p \right) = 0$$



3) Include the distance D_{min} in the optimization target for gradient descent

$$loss\_fn = \sum_i w_i^{FoM} \cdot f_i^{FoM} + \sum_j w_j^C \cdot f_j^C + w_y \cdot D_{min}$$

$$D_{min} = \mathtt{YBFlag}(z_\mu, z_\sigma) \times \min\left(\|(\mathbf{B}_{\mathbf{z}_\mu}, \mathbf{B}_{\mathbf{z}_\sigma}) - (z_\mu, z_\sigma)\|_2^2 \right)$$



→ Can meet specific yield target while optimizing performance

Smooth ML Model Training

- Smoothness is particularly important in our framework
  - Gradient descent based local search
  - Our Taylor expansion-driven approach requires infinitely differentiable model

- Use Lipschitz constant: $||M_i(\mathbf{u}) - M_i(\mathbf{v})|| \leq K_L ||\mathbf{u} - \mathbf{v}||$ for all $\mathbf{u}, \mathbf{v} \in S$
- Model training techniques:
  - L2 Weight regularization
  - Early stopping
  - Dropout
  - Lower learning rate
  - Activation function $\mathbf{tanh}$

Experiment Settings

- Manufacturing variation of the design parameters

Type	Parameter	Bounds	Sigma (σ) Equation
Physical Property	W_t	[2, 5]	$0.02 \times W_t$
	S_t	[2, 10]	$0.02 \times S_t$
	$H_{c/p}$	[2, 8]	$0.03 \times H_{c/p}$
	H_t	[0.6, 1.5]	$0.03 \times H_t$
	D_t	[30, 40]	$0.1 \times \min(H_c, H_p)$
	E_t	[0.25]	0.04
Material Property	R_t	[-12.5, 12]	0.4
	$Dk_{t/c/p}$	[2.5, 4.3]	$0.01 \times Dk_{t/c/p}$
	$Df_{t/c/p}$	[0.001, 0.03]	$0.03 \times Df_{t/c/p}$
	C_t	[5.6e+7]	4e+5

- Experiment tasks

Tasks	f^{FoM}	f^{C}	Z_o (Ω)	$Z_{\pm}$ (Ω)	$NEXT_o$ (mV)	$NEXT_{\pm}$ (mV)
T1	$\{L\}$	$\{Z\}$	85	1	-	-
T2	$\{L\}$	$\{Z\}$	100	2	-	-
T3	$\{L\}$	$\{Z,\ NEXT\}$	85	1	0	0.05
T4	$\{L + 2 \cdot NEXT\}$	$\{Z\}$	85	1	-	-

- Each tasks are run in 3 different yielding range (ΔYR):
  - $Z_o \pm 1\%$, $Z_o \pm 5\%$, $Z_o \pm 8\%$

Evaluation of Taylor Expansion Driven Sampling

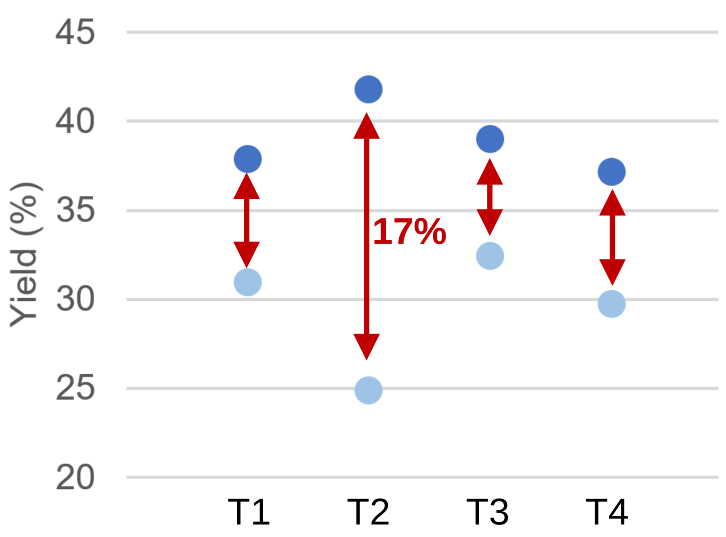
- Comparison of quasi-MC sampling and proposed TE sampling for Z distribution with manufacturing variation

N	Noise of Z_mean ($\times 10^{-5}$)		Noise of Z_stdev ($\times 10^{-5}$)		Run time (sec)		Forward pass cnt	
	QMC	TE	QMC	TE	QMC	TE	QMC	TE
500	204.32	**201.53**	774.92	**730.99**	0.20	**0.05**	500	**1**
1k	66.96	**58.92**	341.74	**324.18**	0.24	**0.06**	1k	**1**
10k	**7.02**	7.53	66.05	**63.42**	0.58	**0.09**	10k	**1**
100k	0.58	**0.46**	8.82	**7.75**	2.63	**0.12**	100k	**1**
1M	0.32	**0.00**	0.62	**0.56**	25.40	**0.78**	1M	**1**

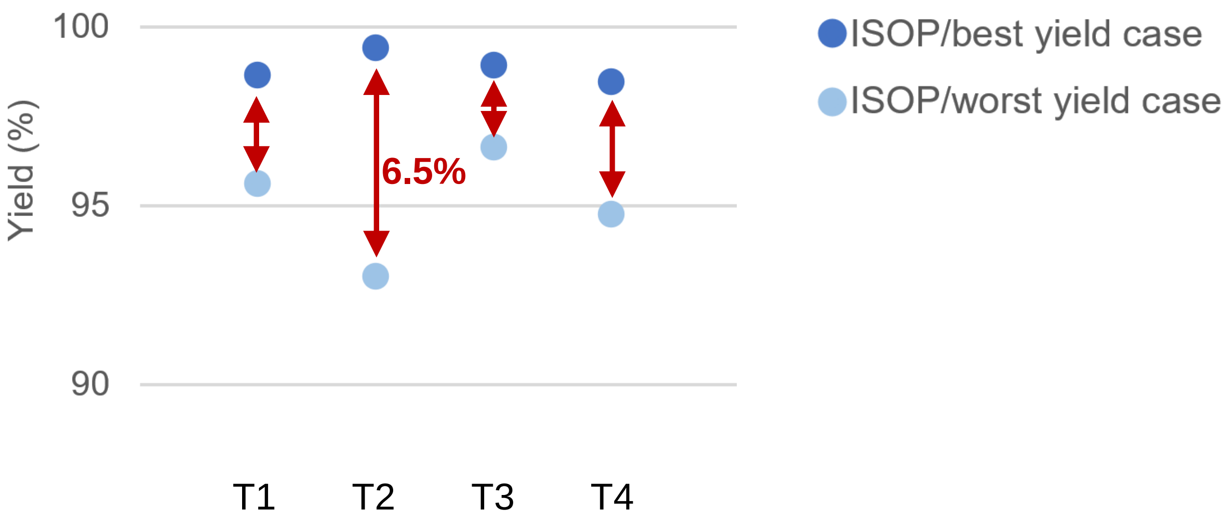
  - Our proposed method (TE) shows smaller noise and low runtime

Evaluation of Yield Optimization

- Baseline ISOP [1] experiment – *does not consider yield*



$\Delta YR = Z_o \pm 1\%$



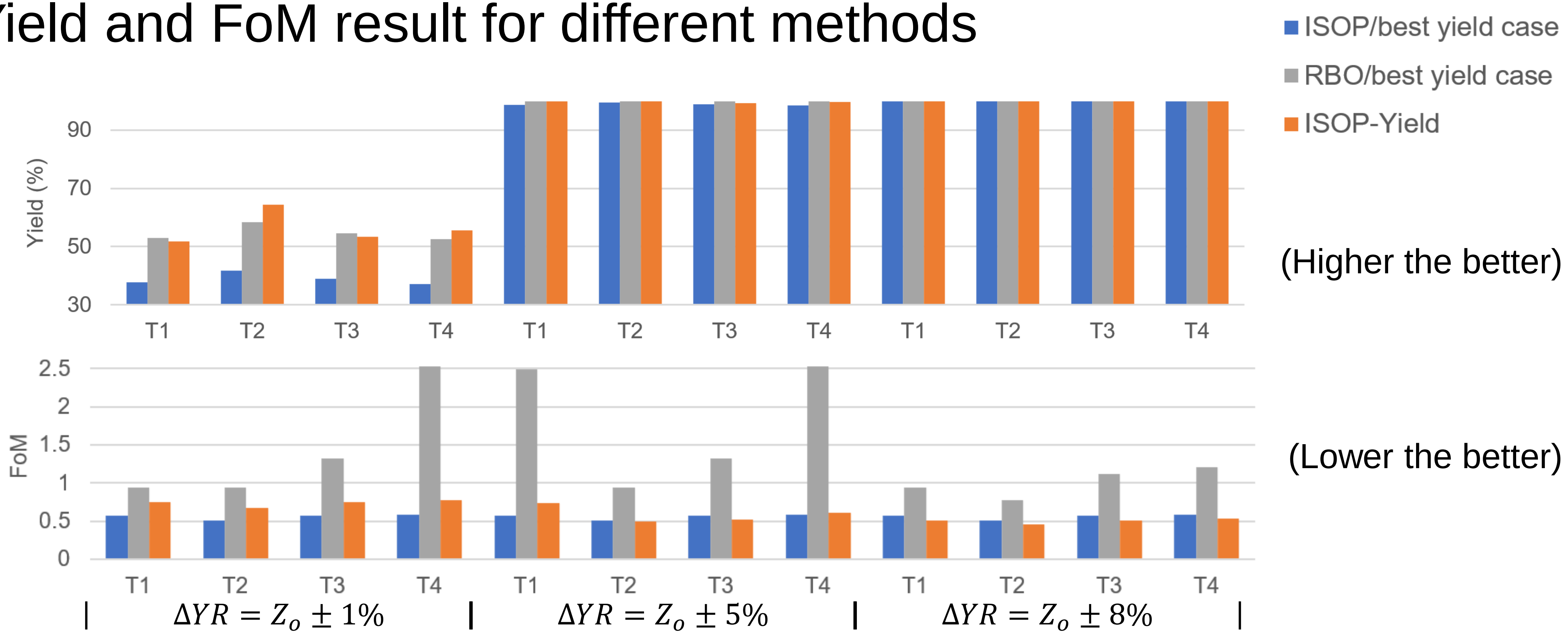
$\Delta YR = Z_o \pm 5\%$

- Yield vary across multiple runs, especially when the yielding range requirement is strict

[1] "ISOP: Machine Learning-Assisted Inverse Stack-Up Optimization for Advanced Package Design," *DATE 2023*.

Evaluation of Yield Optimization

- Yield and FoM result for different methods

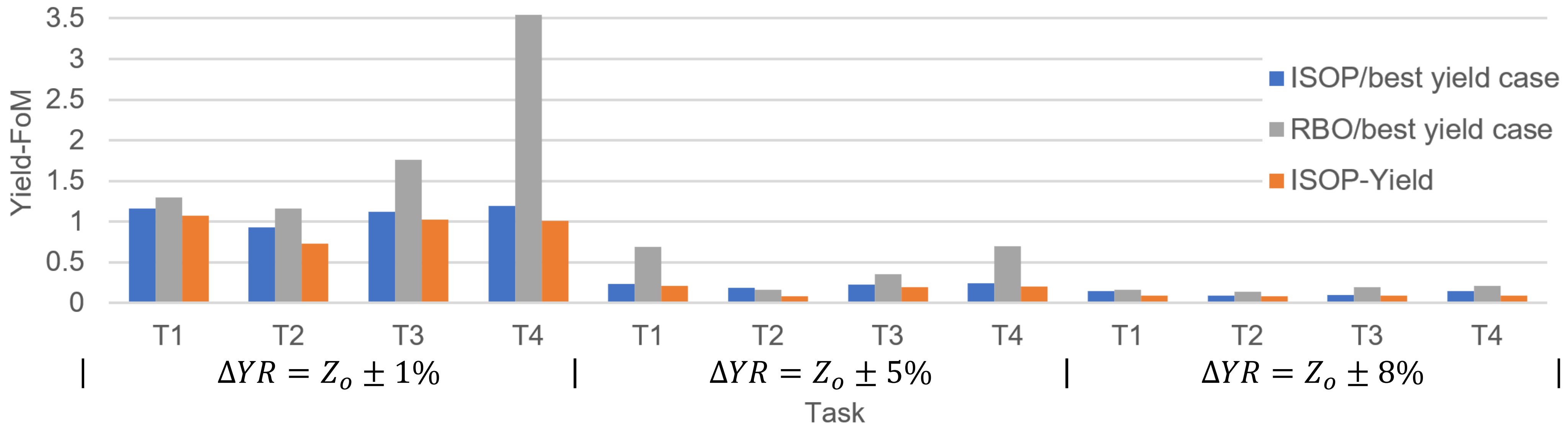


[2] RBO: “Robust Multi-Objective Bayesian Optimization Under Input Noise,” ICML 2022.

Evaluation of Yield Optimization

- Yield-aware FoM (Lower the better)

$$\textbf{Yield-aware FoM} = f^{FoM} / z_{score} \quad \text{for } cdf_s(z_{score}) - cdf_s(\text{-}z_{score}) = \text{Yield}(\%)\ /100$$



- ISOP-Yield outperforms baseline methods in all cases
- ISOP-Yield achieves the user-specified target yield *p* in one minute or less

Evaluation of Yield Optimization

- Different yield target (*p*) for ISOP-Yield ($\Delta YR = Z_o \pm 8\%$)

- ISOP-Yield can consider the trade-off between target yield and FoM

Conclusion

- ISOP-Yield provides a novel framework for optimizing manufacturing yield while preserving design quality by levering three main ideas.
  1) Evaluation of yield requires extensive random sampling of design parameters such as Monte Carlo sampling

     Idea: Propose Taylor Expansion-driven design sampling method
  2) Need for capability to control yield, to balance design performance and yield rate effectively

     Idea: Propose directly yield optimization given target yield rate
  3) ML surrogate model need to be robust and generalized to apply gradient descent and Taylor expansion

     Idea: Utilize smooth and differentiable ML surrogate model

THANK YOU