ISOP: Machine Learning-Assisted Inverse Stack-Up Optimization for Advanced Package Design

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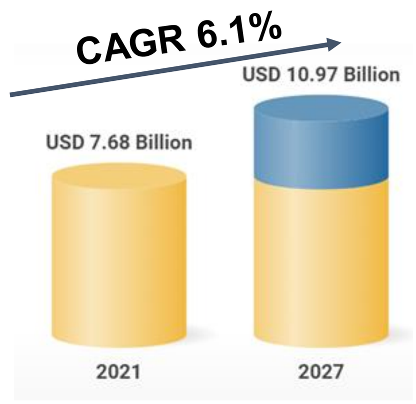
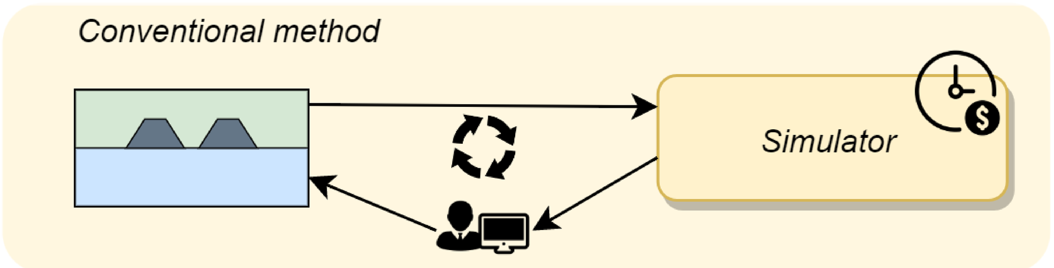
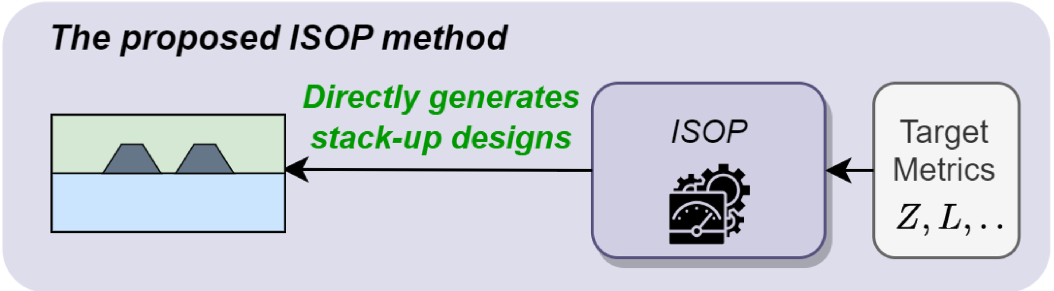
Motivation



- The marking demand is increasing for advanced package design, such as high-density interconnect printed circuit boards (HDI PCBs).
- Regardless of their purpose, the key function of PCB is to ensure component connectivity and communication.
- Stack-up design is critical to a PCB's construction and performance, as it determines the quality of board signals and the performance of transmission lines.



⊖Manual ⊖Slow ⊖Iterative



⊕Automated ⊕Fast ⊕Efficient

- The current manual design process for stack-up is time-consuming, tedious, and sub-optimal.
- An automated solution for stack-up design could save time and improve the quality of PCB designs.

Problem Formulation

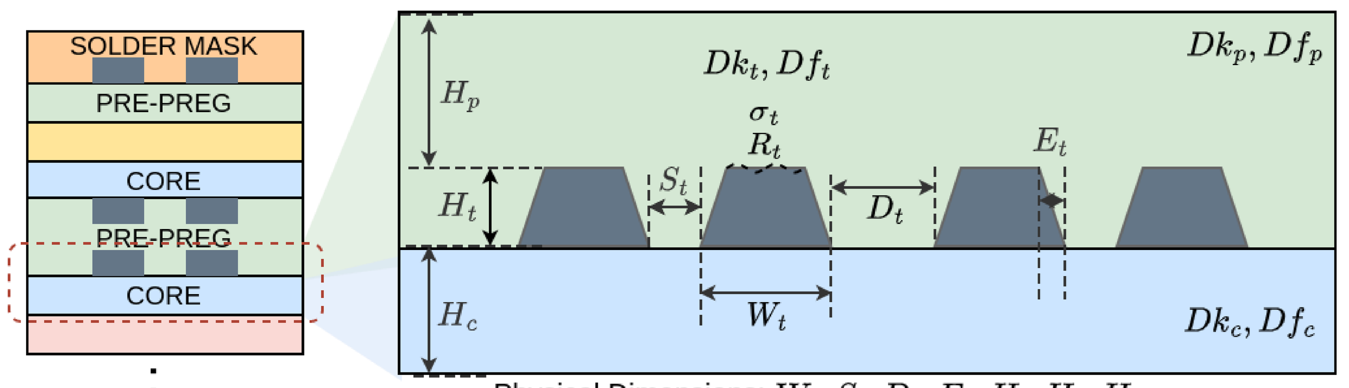
Design Parameters & Ranges (S) | Design Constraints (f^C) | Optimization Objectives (f^{FoM})

Parameters	LB-UB	Step
W_t	2-5	0.1
S_t	2-10	0.5
…	…	…
Dk_p	0.001-0.02	0.001

$Z_o = 85\,\Omega$
$Z_\pm = 1\,\Omega$

Minimize $|L|$ @ 16GHz

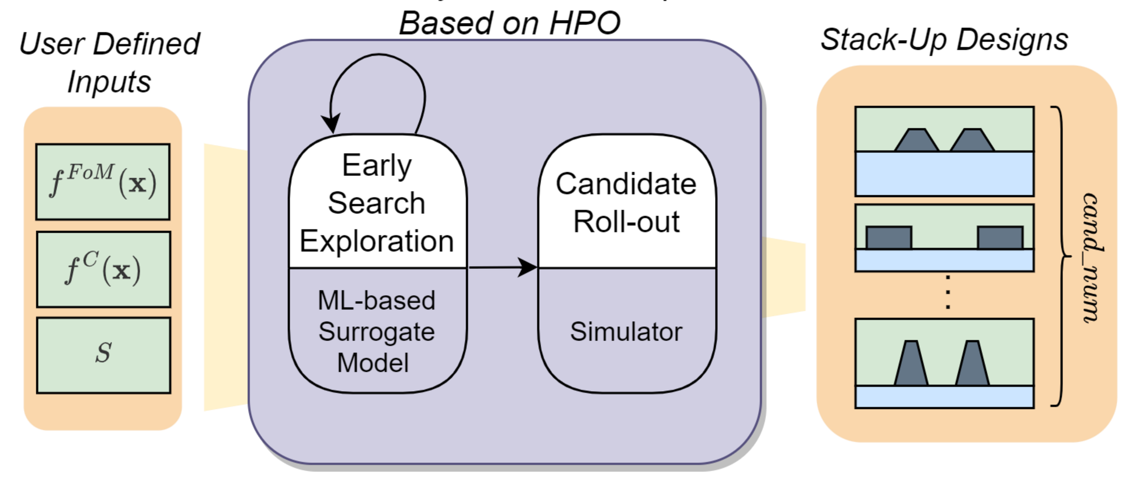
What is the optimal stack-up design?



Physical Dimensions: $W_t, S_t, D_t, E_t, H_t, H_c, H_p$
Material Properties: $Dk_t, Df_t, Rt, \sigma_t, Dk_c, Df_c, Dk_p, Df_p$

ISOP Framework

Non-convex search space ↓ Discrete HPO algorithm (Harmonica)	Runtime overhead ↓ ML surrogate model	Multiple different objectives ↓ Efficient objective function



ISOP could be extended to other scenarios of interconnect optimization

1) HPO process -> Harmonica algorithm

Discrete domain HPO + Parallelized design parameter sampling

→ avoid explorations with invalid design parameters

→ fast and efficient batched evaluation of samples

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1: Encode x and S
2: search space T(x) ← S
3: for i ← 1 to iter_num do
4:     Take q random sample x^q from T(x)
5:     T(x) ← update_space(T(x), x^q, ĝ(M̂(·)))
6: end for
```

2) ML surrogate model

Fast query of evaluation metrics

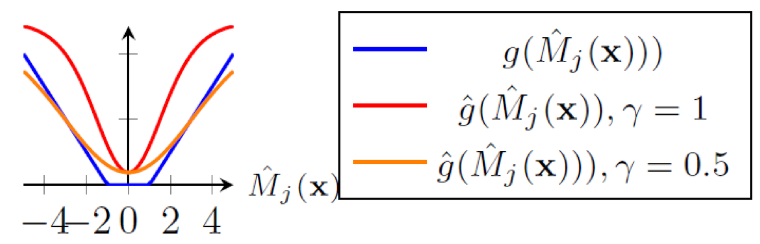
→ observe more samples in large search space with reduced runtime

Regression problem with tabular features

90k unique stack-up designs, preprocessing, MAPE/sMAPE

3) Efficient objective function

$$\mathbf{x}^* = \underset{\mathbf{x}\in X}{\operatorname{argmin}}\ \boxed{g(\mathbf{x})}$$



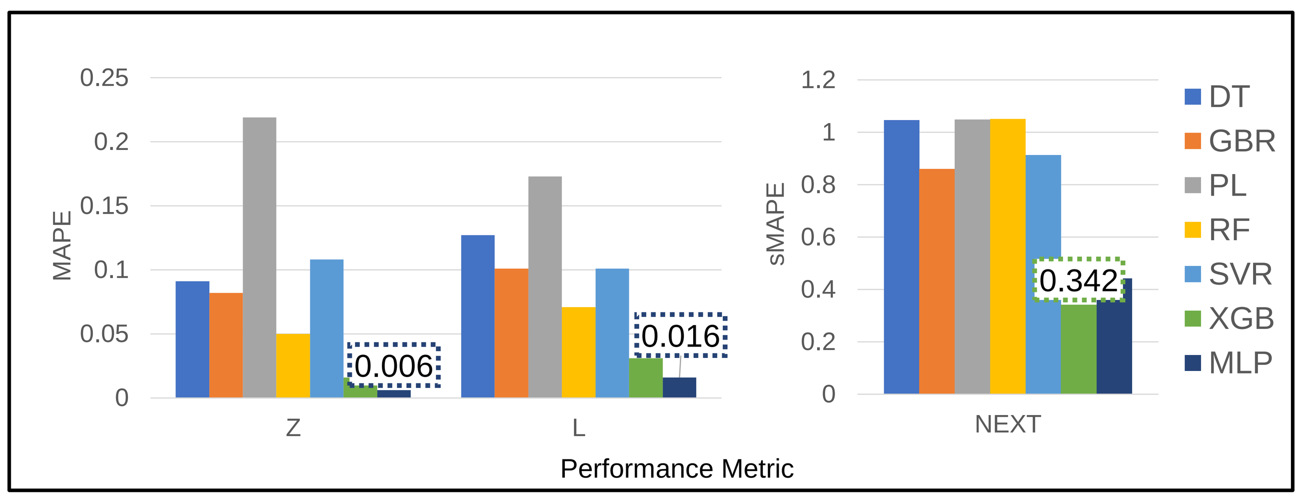
$g(\mathbf{x})$	$\hat{g}(\mathbf{x})$
$\sum_i w_i^{FoM}\cdot f_i^{FoM}(\mathbf{x}) + \sum_j w_j^C\cdot f_j^C(\mathbf{x})$ $f_j^C(\mathbf{x}) = \max(M_j(\mathbf{x}) - f_{j\pm}, 0)$	$\sum_i w_i^{FoM}\cdot f_i^{FoM}(\mathbf{x}) + \sum_j w_j^C\cdot \hat{f}_j^C(\mathbf{x})$ $\hat{f}_j^C(\mathbf{x}) = S(\gamma\cdot \widehat{M_j}(\mathbf{x}) - f_{j\pm}) + S(-\gamma\cdot \widehat{M_j}(\mathbf{x}) - f_{j\pm})$
Ultimate objective function (non-differentiable)	Smooth objective function Enables more searches at the border
Used for later roll-out stage, with actual simulation	Used for search stage, with ML surrogate model

Experimental Results

- Experiment setting
  - 15 Design parameters,
  - ML training dataset space $> 10^{29}$
  - Experiment search space $> 10^{19}$
  - 4 Different tasks

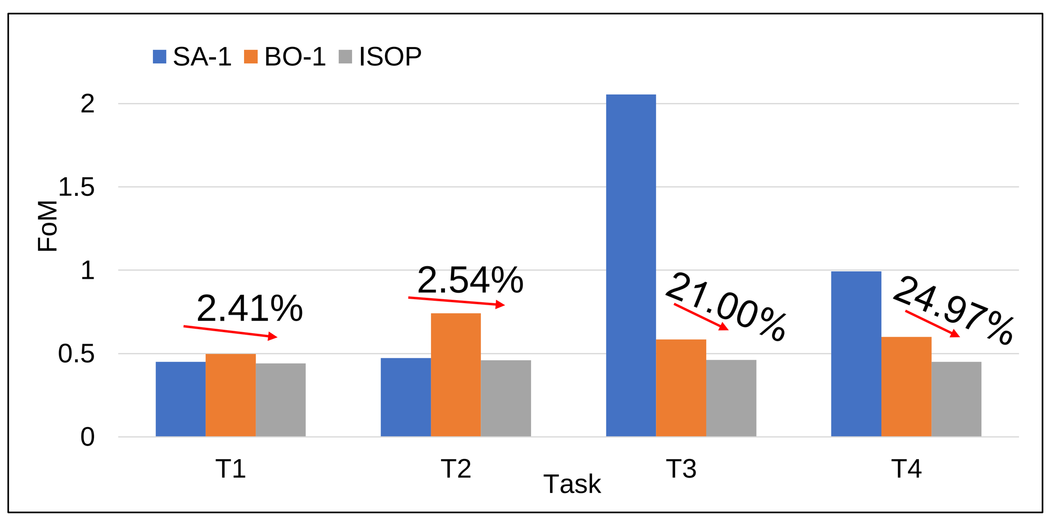
Tasks	f^{FoM}	f^C	$Z_o, Z_\pm$ [Ω]	$NEXT_o, NEXT_\pm$ [mV]
T1	L	Z	85, 1	-
T2	L	Z	100, 2	-
T3	L	$Z, NEXT$	85, 1	0, 0.05
T4	$L + 2\cdot NEXT$	Z	85, 1	0

- Evaluation of trained models



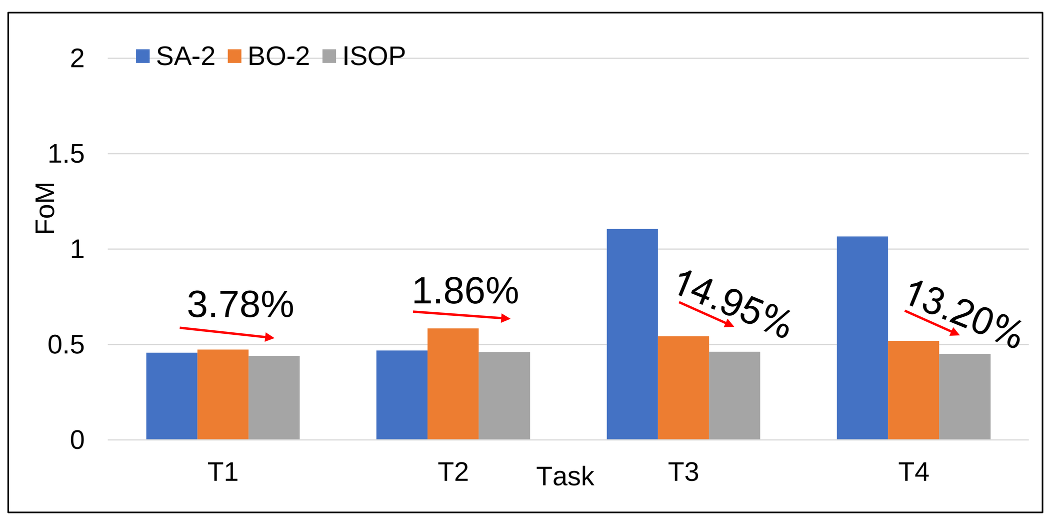
- Result under similar runtime

Success Rate (%)	T1	T2	T3	T4
SA-1	1	1	0.1	0.1
BO-1	1	1	1	1
ISOP	1	1	1	1



- Result under similar number of samples seen

Success Rate (%)	T1	T2	T3	T4
SA-2	1	1	0.2	0.1
BO-2	1	1	1	1
ISOP	1	1	1	1



Conclusion

- ISOP is a novel framework for automated stack-up design in advanced package design, leveraging HPO and ML-based surrogate models.
- Experimental results show excellent design solutions in minutes.
- ISOP can be extended to other interconnect optimization scenarios, and the advantages of our flexible framework will continue to expand to enable global optimization over different performance metrics.

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