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RankTuner: When Design Tool Parameter Tuning Meets Preference Bayesian Optimization

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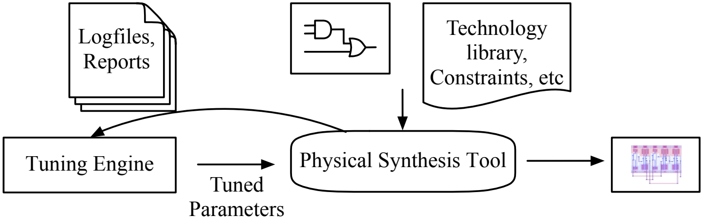
Outline

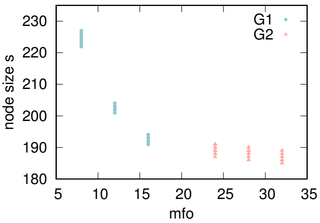
1. Introduction
2. Algorithm
3. Experiments
4. Conclusion

Introduction

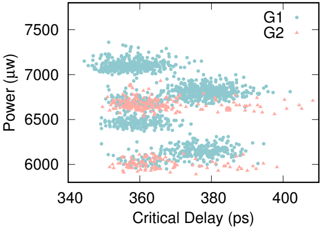
Starting from EDA Tool Parameter Tuning



(a) EDA tool parameter tuning

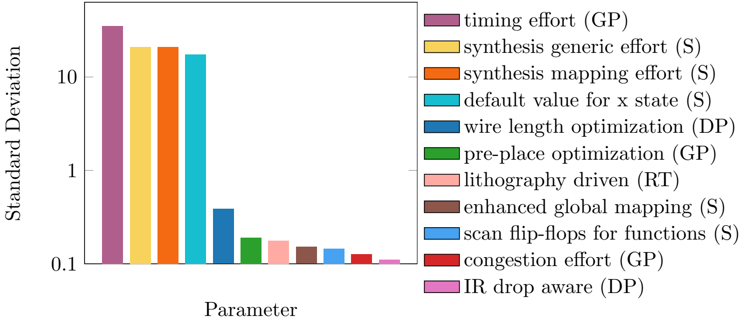


(b) Front-End Perspective



(c) Back-End Perspective

High-dimensional Black-box Optimization



- **High-dimensional**: A lot of values of design parameters need to be determined or tuned ($n_{\text{Params}} \geq 150$)
- Multiple quality-of-result (QoR) metrics (e.g., area, power, and delay) to be optimized
- **"Black-box"** parameter-to-performance mappings: no explicit function expressions
- **Time-consuming** EDA tool evaluation, i.e., expensive data annotation

EDA Tool Parameter Tuning

- EDA tools provide effective and complex optimization options
- Efficient Tool Parameter Tuning
  - XGBoost[1]
  - Neural Networks (NN)[2]
  - Gaussian process (GP)[3]
- These approaches typically view tool parameter tuning as a regression task!

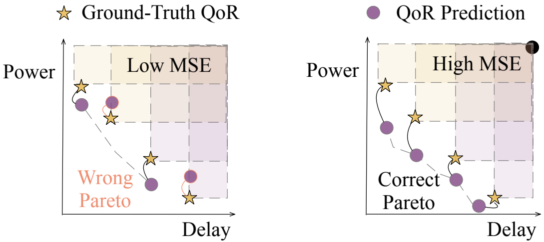
[1] E. Ustun et al. (2019). "LAMDA: Learning-Assisted Multi-stage Autotuning for FPGA Design Closure". In: *Proc. FCCM*, pp. 74–77.

[2] Jihye Kwon, Matthew M. Ziegler, and Luca P. Carloni (2019). "A Learning-Based Recommender System for Autotuning Design Flows of Industrial High-Performance Processors". In: *Proc. DAC*.

[3] Hao Geng et al. (2022). "PTPT: physical design tool parameter tuning via multi-objective Bayesian optimization". In: *IEEE TCAD* 42.1, pp. 178–189.

Motivation

- Existing methods focus on predicting the **exact** QoR values
  - The enormous options make it difficult to train an accurate model[4]
  - A lack of uncertainty modeling leads to inaccurate Pareto relationship[5]
- What do we need? Ranking-based tuning framework!
  - Preference Bayesian Optimization $\rightarrow$ Pairwise GP + Duel-Thompson Sampling

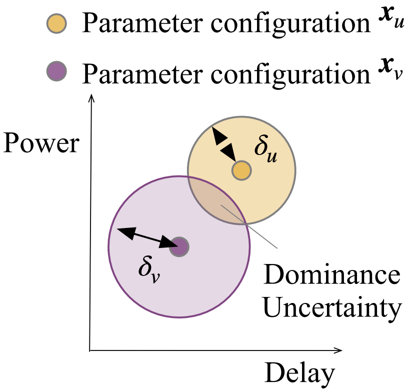


[4]Hao Geng et al. (2022). "PTPT: physical design tool parameter tuning via multi-objective Bayesian optimization". In: *IEEE TCAD* 42.1, pp. 178–189.

[5]Qi Sun et al. (2022). "Correlated multi-objective multi-fidelity optimization for HLS directives design". In: *ACM Transactions on Design Automation of Electronic Systems (TODAES)* 27.4, pp. 1–27.

Algorithm

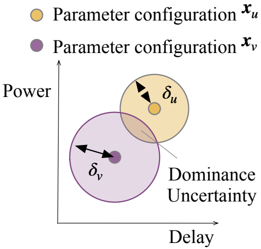
The Pairwise Gaussian Process



A pairwise likelihood function is defined as:

$$p_{\text{ideal}}(\boldsymbol{x}_v \succeq \boldsymbol{x}_u | f(\boldsymbol{x}_v), f(\boldsymbol{x}_u)) = \begin{cases} 1 & \text{if } f(\boldsymbol{x}_v) \geq f(\boldsymbol{x}_u) \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The Dominating Uncertainty Region

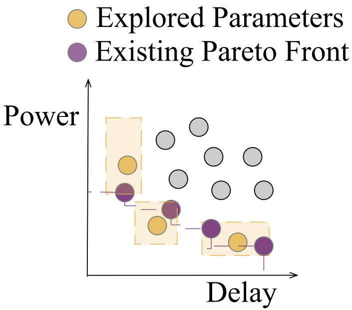


Using a Gaussian noise to model the dominance uncertainty, the pairwise likelihood function could be formulated as:

$$
\begin{aligned}
\Phi(z_k) = & p\left(\boldsymbol{x}_v \succeq \boldsymbol{x}_u \mid f\left(\boldsymbol{x}_v\right), f\left(\boldsymbol{x}_u\right)\right), \\
& = \iint p_{\text{ideal}}\left(\boldsymbol{x}_v \succeq \boldsymbol{x}_k \mid f\left(\boldsymbol{x}_v\right) + \delta_v, f\left(\boldsymbol{x}_u\right) + \delta_u\right) \\
& \mathcal{N}\left(\delta_v; 0, \sigma^2\right) \mathcal{N}\left(\delta_u; 0, \sigma^2\right) \mathrm{d}\delta_v \mathrm{d}\delta_u,
\end{aligned}
\tag{2}
$$

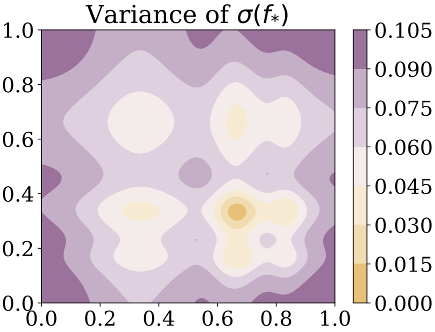
where $z_k = \frac{f(\boldsymbol{x}_u) - f(\boldsymbol{x}_u)}{\sqrt{2}\sigma}$ and $\Phi(z) = \int_{-\infty}^{2} N(\gamma; 0, 1) \mathrm{d}\gamma$.

Acquisition Function for Pareto-dominance Comparison



- **Exploration and Exploitation of Comparisons**
  - Searching across the entire search space of parameter tuning requires an effective balance between **exploration and exploitation**
  - The key aspect is to select informative parameter pairs for comparison

Pareto-Dominace Thompson Sampling



1. **Selecting $\boldsymbol{x}$** The first element of the new comparison, $\boldsymbol{x}_{\text{next}}$, is selected as:

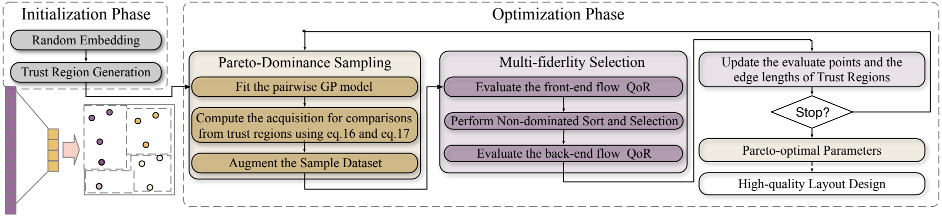
$$\boldsymbol{x}_{\text{next}} = \arg\max_{\boldsymbol{x} \in \mathcal{X}} \int_{\mathcal{X}} \pi_{\tilde{f}}\left([\boldsymbol{x}, \boldsymbol{x}']\right) \mathrm{d}\boldsymbol{x}'. \tag{3}$$

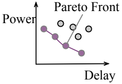
2. **Selecting $\boldsymbol{x}'$**: The second element is selected as the parameter configuration that maximizes the variance of $\sigma\left(f_\star\right)$ in the direction of $\boldsymbol{x}_{\text{next}}$,

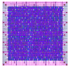
$$\boldsymbol{x}'_{\text{next}} = \arg\max_{\boldsymbol{x}'_\star \in \mathcal{X}} \mathbb{V}\left[\sigma\left(f_\star\right) \mid \left[\boldsymbol{x}_\star, \boldsymbol{x}'_\star\right], \boldsymbol{x}_\star = \boldsymbol{x}_{\text{next}}\right]. \tag{4}$$

The Overall Flow of Our RankTuner Framework

1. Random Embedding Generation
2. Trust-region Initialization
3. Informative Comparision Selection between Regions
4. Multi-fidelity Evaluation and Update







Experiments

Experimental Setup

- Benchmarks: RISC-V processors (`RISCV32I`[6] and `Rocket`[7]), and `BlackParrot`[8] processors (`BP`).
- The QoR-related metrics are used to compare the parameter tuning methods as in[9]:
  - Hypervolume (HV)
  - Maximum performance improvement (MPI1), Maximum power improvement (MPI2), Maximum area improvement (MAI).
  - Maximum performance-power improvement (MPPI), and Maximum performance-area improvement (MPAI)

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[6] James E. Stine, Ryan Ridley, and Teodor-Dumitru Ene (2021). *OSU Datapath/Control RV32 Single-Cycle and Pipelined Architecture in SV*.

[7] Krste Asanovic et al. (2016). "The rocket chip generator". In: *EECS Department, University of California, Berkeley, Tech. Rep. UCB/EECS-2016-17* 4.

[8] Daniel Petrisko et al. (2020). "BlackParrot: An Agile Open-Source RISC-V Multicore for Accelerator SoCs". In: *Proc. MICRO* 40.4, pp. 93–102.

[9] Su Zheng et al. (2023). "Boosting VLSI Design Flow Parameter Tuning with Random Embedding and Multi-objective Trust-region Bayesian Optimization". In: 28.5, pp. 1–23.

Comparison Between Ours and Previous Methods

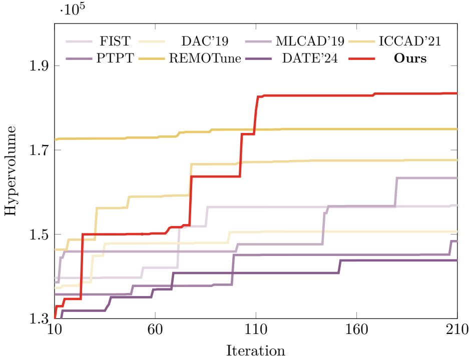
Table: Comparison of Parameter Tuning Methods on `RISCV32I` Benchmark.

Method	FIST	DAC'19	MLCAD'19	ICCAD'21	PTPT	REMOTune	DATE'24	**Ours**
HV (10^5)	1.57	1.55	1.63	1.68	1.48	1.75	1.44	**1.84**
$\mathrm{HV}_{0,1}$ (10^3)	2.85	2.72	3.00	2.95	2.70	3.05	2.63	**3.44**
$\mathrm{HV}_{0,2}$ (10^3)	2.94	2.99	3.00	3.07	2.95	3.12	2.84	**3.43**
$\mathrm{HV}_{1,2}$ (10^3)	2.97	2.97	3.00	3.14	2.79	**3.23**	2.77	3.00
MPI1(%)	3.16	2.54	5.00	3.81	3.56	4.38	2.08	**13.64**
MPI2(%)	3.90	2.12	5.12	5.23	0.85	**6.27**	0.68	5.04
MAI(%)	5.47	7.18	4.64	7.10	5.15	**7.45**	4.74	5.12
MPPI(%)	6.94	4.51	9.88	8.83	4.37	10.38	1.30	**13.73**
MPAI (%)	8.46	9.53	9.41	10.63	8.52	11.53	5.43	**12.26**

- RankTuner consistently outperforms them across all benchmarks up to 40.34% improvement of hypervolume.
- RankTuner acquires 4.89% and 3.59% higher hypervolumes than the best baseline method, REMOTuner[10], on `RISCV32I` and `Rocket` benchmarks.

[10] Su Zheng et al. (2023). "Boosting VLSI Design Flow Parameter Tuning with Random Embedding and Multi-objective Trust-region Bayesian Optimization". In: 28.5, pp. 1–23.

The Attained Hypervolume *v.s.* Iteration

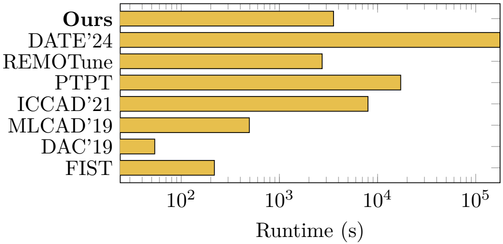


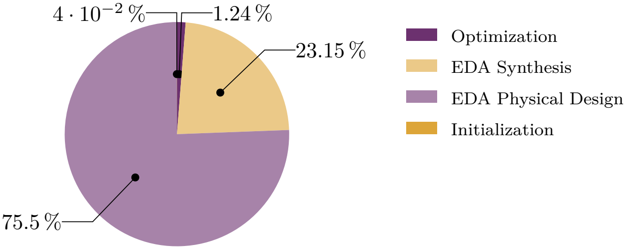
The RankTuner framework also offers a notable advantage in constantly improving the explored Pareto front:

- The RankTuner framework offers a notable advantage in constantly improving the explored Pareto front.
- Although RankTuner has nearly the lowest initial HV value, it continuously improves during the exploration process and eventually surpasses all other methods at around 100 iterations.

The Runtime Comparison & Breakdown

- RankTuner is nearly 4.83× faster than PTPT[11] due to the parallel exploration
- The most consuming part is the EDA Physical Design part, which takes 75.5% of the total runtime. The initialization and optimization time only take about 1.25% in total.





[11] Hao Geng et al. (2022). "PTPT: physical design tool parameter tuning via multi-objective Bayesian optimization". In: *IEEE TCAD* 42.1, pp. 178–189.

Conclusion

Conclusion

- We propose RankTuner, a ranking-based EDA tool parameter tuning framework.
- We introduce a pairwise Gaussian process and a Duel-Thompson sampling to sample informative comparisons.
- RankTuner outperforms state-of-the-art methods in terms of search quality in competitive runtime.

THANK YOU!