The 38th Annual AAAI Conference on Artificial Intelligence
FEBRUARY 20-27, 2024 | VANCOUVER, CANADA
VANCOUVER CONVENTION CENTRE – WEST BUILDING

Towards Automated RISC-V Microarchitecture Design with Reinforcement Learning

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January 11, 2024

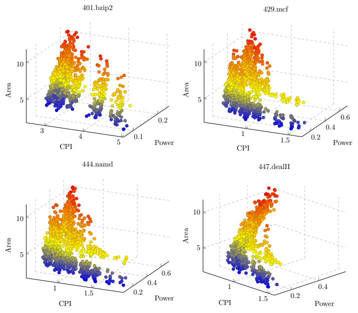
Outline

Introduction

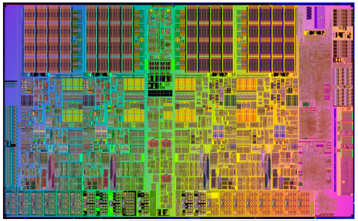
Introduction

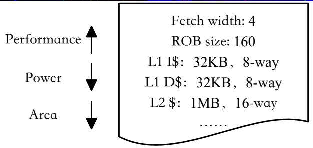
Problem Formulation

Given the microarchitecture design space and target workloads, how do we efficiently search for optimal microarchitectures that can satisfy the pre-determined performance, power, and area (PPA) design targets?



An example microprocessor's design space for SPEC2K6





Fetch width: 4
ROB size: 160
L1 I$: 32KB, 8-way
L1 D$: 32KB, 8-way
L2 $: 1MB, 16-way
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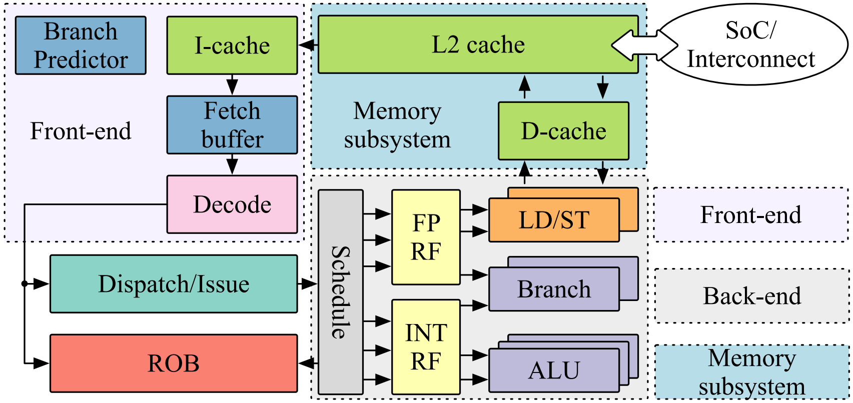
An example of the microarchitecture design space exploration.

Introduction



An overview of the example microprocessor microarchitecture, including different *components*.

Related Work

- Industry: computer architects' expertise.
- Academia:
  - Analytical methodology: interpretable PPA models, explainable search strategy, *etc.*[1][2]
  - Black-box methodology: machine-learning-based PPA modeling and search strategy.[3][4][5]

Limitations:

- Industry solution: architects' personal bias can yield sub-optimal solutions.
- Academic solution: not tightly coupled with expert knowledge & mathematical limitation in the Gaussian process modeling.

[1] Tejas S Karkhanis and James E Smith (2004). "A First-order Superscalar Processor Model". In: *IEEE/ACM International Symposium on Computer Architecture (ISCA)*. IEEE, pp. 338–349.

[2] Tejas S Karkhanis and James E Smith (2007). "Automated design of application specific superscalar processors: an analytical approach". In: *IEEE/ACM International Symposium on Computer Architecture (ISCA)*, pp. 402–411.

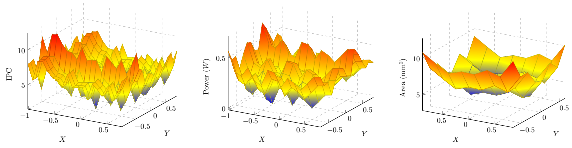
[3] Engin İpek et al. (2006). "Efficiently Exploring Architectural Design Spaces via Predictive Modeling". In: *ACM International Conference on Architectural Support for Programming Languages and Operating Systems (ASPLOS)*, pp. 195–206.

[4] Tianshi Chen et al. (2014). "Archranker: A ranking approach to design space exploration". In: *IEEE/ACM International Symposium on Computer Architecture (ISCA)*, pp. 1–12.

[5] Dandan Li et al. (2016). "Efficient design space exploration via statistical sampling and AdaBoost learning". In: *ACM/IEEE Design Automation Conference (DAC)*, pp. 1–6.

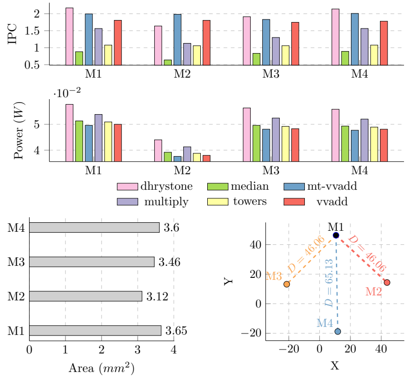
Limitation of Gaussian Process Modeling[6]

The kernel function of the Gaussian process mathematically attributes the PPA differences between two microarchitectures to the microarchitecture embedding distances.



(a) Performance (b) Power (c) Area

A visualization of the design space for 458.sjeng.



An example of different BOOM microarchitectures to demonstrate the claim.

[6] Chen Bai et al. (2021). "BOOM-Explorer: RISC-V BOOM Microarchitecture Design Space Exploration Framework". In: *IEEE/ACM International Conference on Computer-Aided Design (ICCAD)*, pp. 1–9.

Introduction

Highlights of our new black-box methodology:

- Remove mathematical limitation in the Gaussian process modeling (*i.e.*, free of unrealistic assumptions).
- Tightly coupled with expert knowledge: *microarchitecture scaling graph*.
- PPA design preference-driven exploration.
- Lightweight agent training environment design to accelerate the learning process.

Preliminaries

RISC-V Microarchitecture Design Space

Table 1: RISC-V Microarchitecture Design Space

Design	Component	Parameters	Candidate
Rocket	Branch predictor	RAS	0 : 12 : 3 [+]
		BTB.nEntries	0 : 56 : 14
		BHT.nEntries	0 : 1024 : 256
	I-cache	nWays	1, 2, 4
		nTLBWays	4 : 32 : 4
	Functional unit	FPU	1, 2
		mulDiv	1, 2, 3
		VM	1, 2
	D-cache	nSets	32, 64
		nWays	1, 2, 4
		nTLBWays	4 : 32 : 4
		nMSHRs	1, 2, 3
Small/Medium Large/Mega Giga SonicBOOM	Branch predictor	Type	1, 2, 3
		maxBrCount	4 : 22 : 2
	IFU	numFetchBufferEntries	6 : 46 : 2
		fetchWidth	4, 8
		ftq.nEntries	12 : 64 : 4
	pipelineWidth		1 : 5 : 1
	ROB		24 : 160 : 4
	PRF	numIntPhysRegisters	40 : 176 : 8
		numFpPRF	34 : 132 : 6
	ISU	numFpPhysRegisters	1 : 5 : 1
		numEntries	6 : 52 : 2
		dispatchWidth	1 : 5 : 1
	LSU	LDQ	6 : 32 : 2
		STQ	6 : 36 : 2
	I-cache	nWays	4, 8
		nSets	32, 64
	D-cache	nWays	4, 8
		nSets	64, 128
		nMSHRs	2 : 10 : 2

[*] The values are start number:end number:stride, e.g., 0 : 12 : 3 denotes the entries of RAS can be 0, 3, 6, etc., until 12.

Microarchitecture PPA Modeling

- Pre-RTL PPA modeling infrastructure:
  - GEM5[7][8] , McPAT[9], *etc.*
- RTL PPA modeling infrastructure:
  - Synopsys VCS[10], Synopsys PrimeTime PX[11], *etc.*

[7]Nathan Binkert, Bradford Beckmann, Gabriel Black, et al. (2011). "The Gem5 Simulator". In: *SIGARCH Comput. Archit. News* 39.2, pp. 1–7.

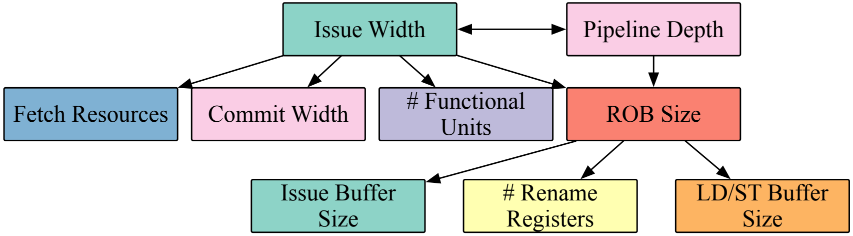
[8]Jason Lowe-Power et al. (2020). "The GEM5 Simulator: Version 20.0+". In: *arXiv preprint arXiv:2007.03152*.

[9]Sheng Li et al. (2009). "McPAT: An integrated power, area, and timing modeling framework for multicore and manycore architectures". In: *IEEE/ACM International Symposium on Microarchitecture (MICRO)*, pp. 469–480.

[10]*Synopsys VCS* (2023). https://www.synopsys.com/verification/simulation/vcs.html.

[11]*Synopsys PrimeTime PX Power Analysis* (2023). https://news.synopsys.com/index.php?s=20295&item=123041.

Microarchitecture Scaling Graph



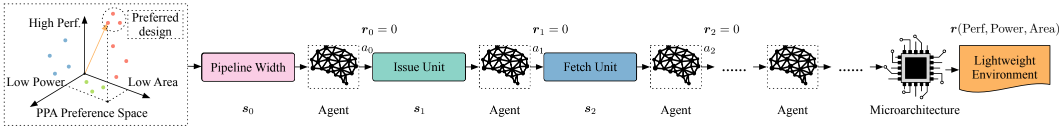
A microarchitecture scaling graph of an example out-of-order microprocessor.

- The microarchitecture scaling graph is a directed graph. Nodes are *components*. Edges are components' decision precedences[12].
- The graph is derived from the interval analysis. And the conclusion from the graph is general for Von Neumann architecture.

[12] Stijn Eyerman et al. (2009). "A Mechanistic Performance Model for Superscalar Out-of-order Processors". In: *Transactions on Computer Systems* 27.2, pp. 1–37.

Reinforcement Learning Methodology

Reinforcement Learning (RL) Methodology



An overview of our reinforcement learning methodology.

- The state space is the microarchitecture design space.
- The action space is the candidate set of components' types of corresponding hardware resources.
- The state transition is defined based on the microarchitecture scaling graph.
- Embed the architect's PPA design preference in the methodology.

PPA Design Preference

Reward scalarization:

$$r = \boldsymbol{r}(\text{Perf}, \text{Power}, \text{Area}) \cdot (\alpha, \beta, \gamma)^{\top} \tag{1}$$[13]

α, β, and γ are weights controlling the PPA trade-off.
Simplex constraints for PPA design preference $\boldsymbol{\phi}$:

$$\begin{gathered} r = \boldsymbol{r}(\text{Perf}, \text{Power}, \text{Area}) \cdot \boldsymbol{\phi}^{\top} \\ \forall i,\ \phi_i \geq 0,\ \sum_i \phi_i = 1 \end{gathered} \tag{2}$$

[13] Perf, Power, Area are normalized values.

Embed PPA Preference Space into RL

Generalized Bellman optimality equality:

$$\begin{aligned}&\boldsymbol{Q}(\boldsymbol{s},a,\boldsymbol{\phi}) = \\ &\boldsymbol{r}(\boldsymbol{s},a) + \zeta\mathbb{E}_{\boldsymbol{s}'\sim\mathcal{P}(\cdot|\boldsymbol{s},a)}\mathcal{T}(\boldsymbol{Q}(\boldsymbol{s}',a,\boldsymbol{\phi})), \\ &\mathcal{T}(\boldsymbol{Q}(\boldsymbol{s}',a,\boldsymbol{\phi})) = \underset{\boldsymbol{Q}}{arg}\ \underset{a'\in A,\boldsymbol{\phi}'\in\Phi}{max}\ \boldsymbol{Q}(\boldsymbol{s}',a',\boldsymbol{\phi}')\boldsymbol{\phi}^\top,\end{aligned} \tag{3}$$

ζ is the discount factor, $\boldsymbol{Q}(\boldsymbol{s},a,\boldsymbol{\phi})$ is the state-action vector, and $\boldsymbol{\phi}$ is the PPA design preference.

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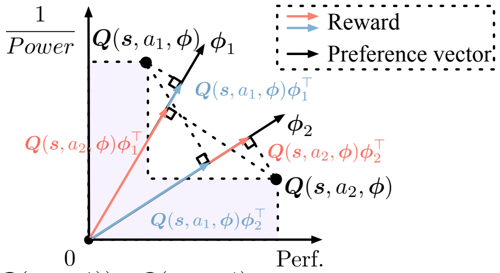


$\frac{1}{Power}$
$\boldsymbol{Q}(\boldsymbol{s},a_1,\boldsymbol{\phi})$
$\boldsymbol{\phi}_1$
Reward
Preference vector
$\boldsymbol{Q}(\boldsymbol{s},a_1,\boldsymbol{\phi})\boldsymbol{\phi}_1^\top$
$\boldsymbol{\phi}_2$
$\boldsymbol{Q}(\boldsymbol{s},a_2,\boldsymbol{\phi})\boldsymbol{\phi}_1^\top$
$\boldsymbol{Q}(\boldsymbol{s},a_2,\boldsymbol{\phi})\boldsymbol{\phi}_2^\top$
$\boldsymbol{Q}(\boldsymbol{s},a_2,\boldsymbol{\phi})$
$\boldsymbol{Q}(\boldsymbol{s},a_1,\boldsymbol{\phi})\boldsymbol{\phi}_2^\top$
0
Perf.

$$\mathcal{T}(\boldsymbol{Q}(\boldsymbol{s},a,\boldsymbol{\phi})) = \boldsymbol{Q}(\boldsymbol{s},a_2,\boldsymbol{\phi}) = \underset{\boldsymbol{Q}}{argmax}\begin{Bmatrix}\boldsymbol{Q}(\boldsymbol{s},a_1,\boldsymbol{\phi})\boldsymbol{\phi}_1^\top, \boldsymbol{Q}(\boldsymbol{s},a_1,\boldsymbol{\phi})\boldsymbol{\phi}_2^\top \\ \boldsymbol{Q}(\boldsymbol{s},a_2,\boldsymbol{\phi})\boldsymbol{\phi}_1^\top, \boldsymbol{Q}(\boldsymbol{s},a_2,\boldsymbol{\phi})\boldsymbol{\phi}_2^\top\end{Bmatrix}$$

Optimization procedure with the generalized Bellman optimality equality.

[14] Axel Abels et al. (2019). "Dynamic Weights In Multi-objective Deep Reinforcement Learning". In: *International Conference on Machine Learning (ICML)*. PMLR, pp. 11–20.

Reinforcement Learning (RL) Methodology

- We adopt the asynchronous advantage actor-critic (A3C)[15].
- We utilize the conditioned neural network design[16].

Gradients of the actor weights $\boldsymbol{\theta}_a$:

$$\begin{aligned}\nabla\boldsymbol{\theta}_a =& \kappa \nabla_{\boldsymbol{\theta}_a} H(\pi(\boldsymbol{s}_t;\boldsymbol{\theta}_a))+ \\ & \mathbb{E}_{\xi\sim\pi}[\sum_{t=0}^{\infty} \nabla_{\boldsymbol{\theta}_a} \log \pi_{\boldsymbol{\theta}_a}(a_t \mid \boldsymbol{s}_t) A(\boldsymbol{s}_t, a_t, \boldsymbol{\phi}')\boldsymbol{\phi}^\top],\end{aligned} \tag{4}$$

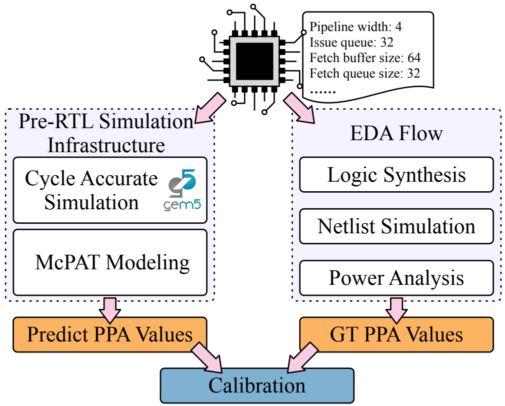
Loss function of the critic:

$$\begin{aligned}L_c =& \rho\|(\boldsymbol{Q}^* - \boldsymbol{Q}(\boldsymbol{s}, a, \boldsymbol{\phi}'; \boldsymbol{\theta}_c))\boldsymbol{\phi}^\top\|_2^2 + \\ & (1-\rho)\|\boldsymbol{Q}^* - \boldsymbol{Q}(\boldsymbol{s}, a, \boldsymbol{\phi}'; \boldsymbol{\theta}_c)\|_2^2,\end{aligned} \tag{5}$$

[15] Volodymyr Mnih, Adria Puigdomenech Badia, et al. (2016). "Asynchronous Methods for Deep Reinforcement Learning". In: *International Conference on Machine Learning (ICML)*. vol. 48, pp. 1928–1937.

[16] Axel Abels et al. (2019). "Dynamic Weights In Multi-objective Deep Reinforcement Learning". In: *International Conference on Machine Learning (ICML)*. PMLR, pp. 11–20.

Accelerate Learning via Lightweight Environment



An overview of the PPA calibration.

- PPA models calibration flow[17].
- PPA models update policy.

[17] Jianwang Zhai et al. (2021). "McPAT-Calib: A Microarchitecture Power Modeling Framework for Modern CPUs". In: *IEEE/ACM International Conference on Computer-Aided Design (ICCAD)*. IEEE, pp. 1–9.

Experiments

Experiments Environment

- RTL implementation: Rocket & BOOM[18][19].
- Technology node: 7-nm ASAP7 PDK[20].
- EDA tools: Cadence Genus 18.12-e012_1, Synopsys VCS M-2017.03, PrimeTime PX R-2020.09-SP1, *etc.*
- Server: 80 $\times$ Intel(R) Xeon(R) CPU e7-4803 v2 @ 2.20GHz, 1TB main memory.

Baselines

- ISCA'14: ArchRanker[21]
- DAC'16: AdaBoost[22]
- ICCAD'21: BOOM-Explorer[23]

[18] Krste Asanović, Rimas Avizienis, Jonathan Bachrach, et al. (2016). *The Rocket Chip Generator*. Tech. rep. University of California, Berkeley.

[19] Jerry Zhao et al. (2020). "SonicBOOM: The 3rd Generation Berkeley Out-of-order Machine". In: *Workshop on Computer Architecture Research with RISC-V (CARRV)*.

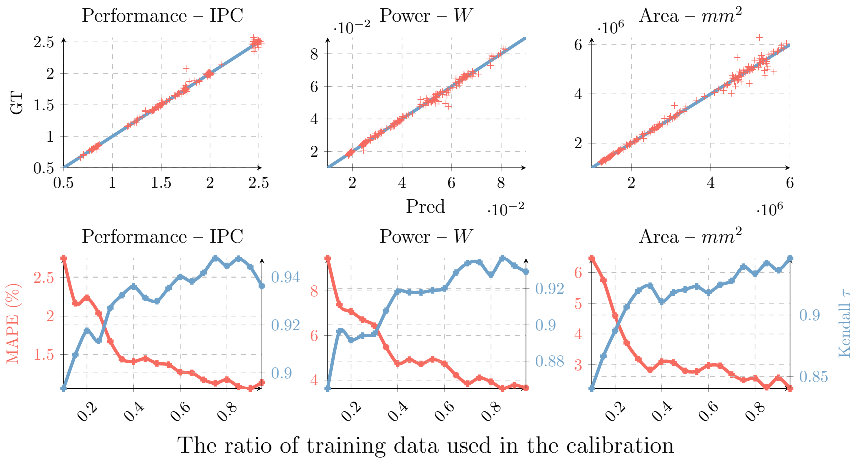
[20] Lawrence T Clark et al. (2016). "ASAP7: A 7-nm FinFET Predictive Process Design Kit". In: *Microelectronics Journal* 53, pp. 105–115.

[21] Tianshi Chen et al. (2014). "Archranker: A ranking approach to design space exploration". In: *IEEE/ACM International Symposium on Computer Architecture (ISCA)*, pp. 1–12.

[22] Dandan Li et al. (2016). "Efficient design space exploration via statistical sampling and AdaBoost learning". In: *ACM/IEEE Design Automation Conference (DAC)*, pp. 1–6.

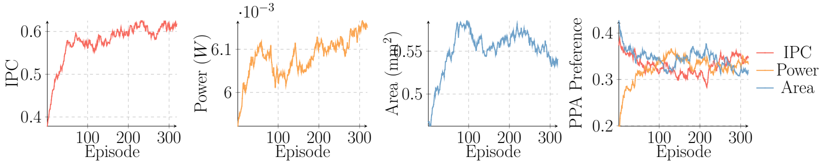
[23] Chen Bai et al. (2021). "BOOM-Explorer: RISC-V BOOM Microarchitecture Design Space Exploration Framework". In: *IEEE/ACM International Conference on Computer-Aided Design (ICCAD)*, pp. 1–9.

Accuracy of Lightweight PPA Models

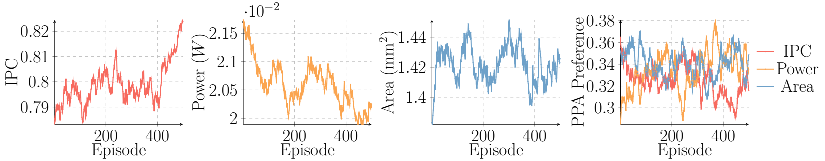


The accuracy of lightweight PPA models, and MAPE and Kendall τ curves *w.r.t.* the calibration data size.

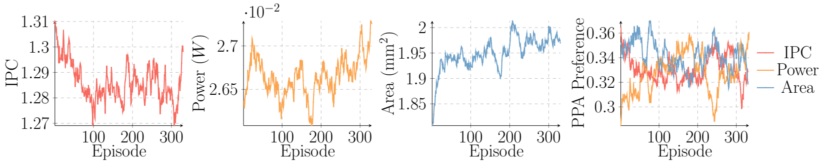
RL Training I



(a) Rocket

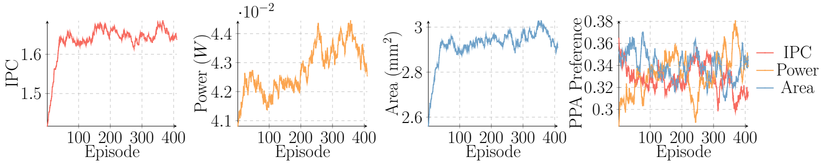


(b) Small-scale BOOM

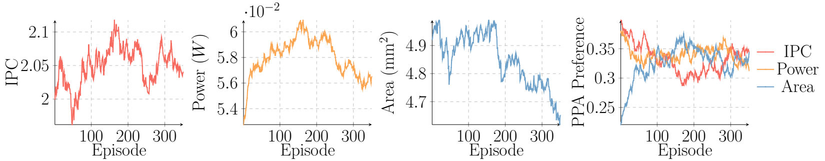


(c) Medium-scale BOOM

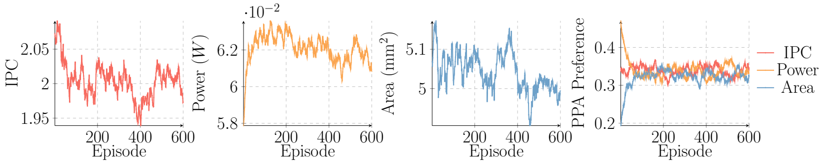
RL Training II



(a) Large-scale BOOM



(b) Mega-scale BOOM



(c) Giga-scale BOOM

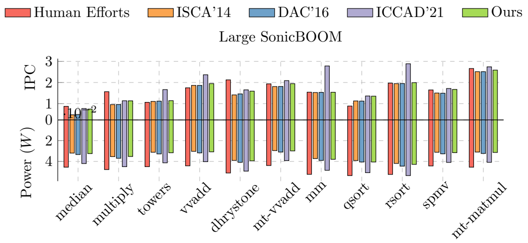
Main Evaluation Results

Table 2: Comparison w. Human Efforts & Prior Arts

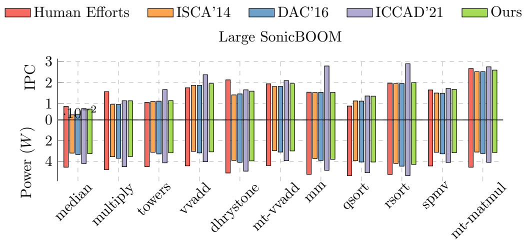
Design	Method	Performance	Power	Area	Perf / Power		Perf / Area		(Perf × Perf) / (Power × Area)		Runtime
		IPC	W	mm^2	Val.	Ratio	Val.	Ratio	Val.	Ratio	
Rocket	Human Efforts	0.7338	0.0027	0.9082	267.4708	–[1]	0.8080	–	216.1090	–	–
	ISCA'14	0.8157	0.0023	0.7943	**359.3222**	**1.3434**×	1.0270	1.2710×	369.0075	1.7075×	8.6111×
	DAC'16	0.5485	0.0018	0.5337	305.3090	1.1415×	1.0278	1.2721×	313.8042	1.4527×	5.8961×
	ICCAD'21	0.7278	0.0021	0.7448	352.7177	1.3187×	0.9771	1.2093×	344.6327	1.5947×	1.5011×
	Ours	0.7278	0.0023	0.5762	313.6958	1.1728×	**1.2631**	**1.5633**×	**396.2335**	**1.8335**×	**1.0000**
Small SonicBOOM	Human Efforts	0.7837	0.0203	1.5048	38.6057	–	0.5209	–	20.1062	–	–
	ISCA'14	0.8197	0.0150	1.2838	54.7692	1.4187×	0.6385	1.2260×	34.9710	1.7393×	5.8033×
	DAC'16	0.8076	0.0147	1.2512	54.8119	1.4198×	0.6454	1.2393×	35.3765	1.7594×	4.7918×
	ICCAD'21	0.8469	0.0200	1.5026	42.3436	1.0968×	0.5636	1.0821×	23.8645	1.1869×	1.3053×
	Ours	0.8403	0.0152	1.2538	**55.2813**	**1.4320**×	**0.6702**	**1.2868**×	**37.0491**	**1.8427**×	**1.0000**
Medium SonicBOOM	Human Efforts	1.1938	0.0256	1.9332	46.6952	–	0.6175	–	28.8363	–	–
	ISCA'14	1.2362	0.0196	1.6242	**62.9622**	**1.3484**×	**0.7611**	**1.2324**×	**47.9192**	**1.6618**×	5.6879×
	DAC'16	1.3757	0.0254	1.9247	54.0894	1.1584×	0.7148	1.1574×	38.6609	1.3407×	4.6966×
	ICCAD'21	1.4454	0.0271	2.1583	53.3342	1.1422×	0.6697	1.0844×	35.7170	1.2386×	1.2793×
	Ours	1.2872	0.0206	1.7351	62.5886	1.3404×	0.7419	1.2014×	46.4339	1.6103×	**1.0000**
Large SonicBOOM	Human Efforts	1.4871	0.0446	3.2055	33.3430	–	0.4639	–	15.4686	–	–
	ISCA'14	1.4900	0.0309	2.5420	48.2184	1.4461×	0.5861	1.2634×	28.2626	1.8271×	5.8920×
	DAC'16	1.4919	0.0324	2.6744	45.9976	1.3795×	0.5578	1.2024×	25.6592	1.6588×	4.8651×
	ICCAD'21	1.9162	0.0409	3.6715	46.8507	1.4051×	0.5219	1.1250×	24.4520	1.5808×	1.3252×
	Ours	1.5882	0.0314	2.5643	**50.6324**	**1.5185**×	**0.6193**	**1.3350**×	**31.3580**	**2.0272**×	**1.0000**
Mega SonicBOOM	Human Efforts	1.9500	0.0578	4.8059	33.7571	–	0.4058	–	13.6972	–	–
	ISCA'14	2.4957	0.0566	5.3676	44.0942	1.3062×	0.4650	1.1459×	20.5020	1.4968×	5.5443×
	DAC'16	2.4995	0.0562	5.3797	44.4483	1.3167×	0.4646	1.1451×	20.6513	1.5077×	4.5780×
	ICCAD'21	2.4823	0.0607	4.7008	40.9170	1.2121×	**0.5281**	**1.3014**×	21.6066	1.5774×	1.2470×
	Ours	2.5232	0.0557	5.2512	**45.3005**	**1.3420**×	0.4805	1.1842×	**21.7674**	**1.5892**×	**1.0000**
Giga SonicBOOM	Human Efforts	1.8717	0.0716	5.0691	26.1538	–	0.3692	–	9.6572	–	–
	ISCA'14	2.2528	0.0622	6.0010	36.2192	1.3849×	0.3754	1.0167×	13.5970	1.4080×	5.6321×
	DAC'16	2.2522	0.0773	5.5995	29.1480	1.1145×	**0.4022**	**1.0893**×	11.7236	1.2140×	4.6505×
	ICCAD'21	2.2650	0.0745	5.8652	30.4162	1.1630×	0.3862	1.0459×	11.7460	1.2163×	1.2668×
	Ours	2.2692	0.0595	5.7459	**38.1587**	**1.4590**×	0.3949	1.0695×	**15.0696**	**1.5605**×	**1.0000**

[1] "–" denotes not applicable.

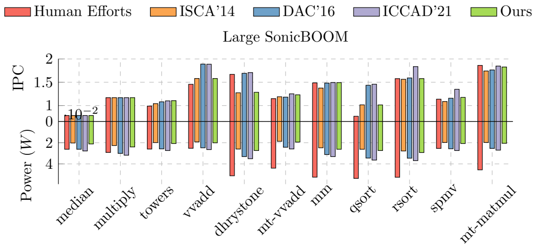
Analysis w. More Workloads



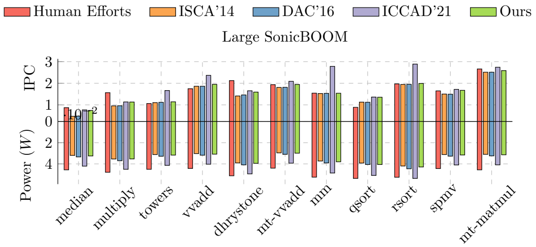
(a) Rocket



(b) Small-scale BOOM

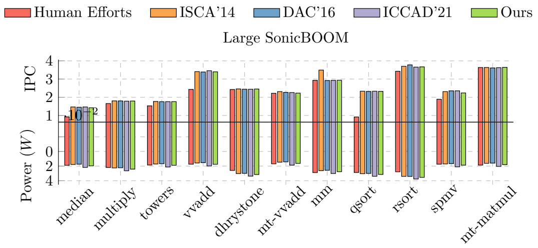


(c) Medium-scale BOOM

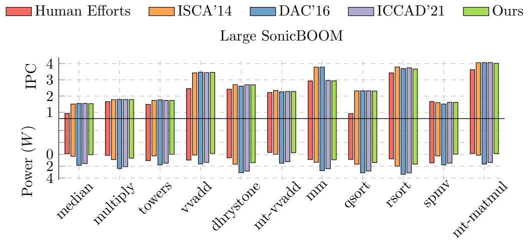


(d) Large-scale BOOM

Analysis w. More Workloads (cont.)



(e) Mega-scale BOOM



(f) Giga-scale BOOM

Summary:

- Our solutions achieve an average of 24.64%, 17.13%, and 6.33% than ICCAD'21, DAC'16, and ISCA'14 in PPA trade-off, respectively with 4.07$\times$ higher efficiency than baselines.
- For large-scale BOOM, compared to human implementations, our solution demonstrates significant improvements in three metrics by factors of 1.35$\times$, 1.23$\times$, and 1.66$\times$, respectively.

Conclusion

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- Remove mathematical limitation in the Gaussian process modeling (*i.e.*, free of unrealistic assumptions).
- Tightly coupled with expert knowledge: *microarchitecture scaling graph*.
- PPA design preference-driven exploration.
- Lightweight agent training environment design to accelerate the learning process.
- Experiments show that our method achieves an average of 16.03% improvement in PPA trade-off with 4.07× higher efficiency than previous state-of-the-art approaches.

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Discussion:

- Why do we choose A3C instead of PPO or SAC?
- Why does our method not perform very well on medium-scale SonicBOOM?
- Is the RL method the sole remedy to resolve the mathematical limitation (unrealistic assumption)?

THANK YOU!