Techniques for CAD Tool Parameter Auto-tuning in Physical Synthesis: A Survey

Hao Geng¹, Tinghuan Chen¹, Qi Sun¹, Bei Yu¹
¹The Chinese University of Hong Kong
{heng, thchen, qsun, byu}@cse.cuhk.edu.hk

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Hao GENG
The Chinese University of Hong Kong (CUHK)
hgeng@cse.cuhk.edu.hk

Hao is a postdoctoral researcher at the Department of Computer Science and Engineering, the Chinese University of Hong Kong. Prior to that, he pursued his Ph.D. degree under the supervision of Prof. Bei YU in the same university. His research interests include design space exploration, machine learning, deep learning and the optimization methods with applications in VLSI CAD. He has received one best paper award nomination from ASPDAC 2019.
1. EDA tools have been developed to aid and speed the closure of IC design.
2. Numerous tunable parameters with different data types are exposed as hints for human and impact the QoR of the tool outcome.
3. How to find optimal parameter configurations?
What is Physical Design Tool Parameter Tuning?

The overview of the parameter tuning of a physical design tool
1. Oceans of values of design parameters need to be determined or tuned
2. Multiple quality-of-result (QoR) metrics (e.g., area, power, and delay) to be optimized
3. "Black-box" parameter-to-performance mappings: no explicit function expressions
4. Time-consuming EDA tool evaluation
5. Existing methods: Heuristic Method-based, Machine Learning-based
The framework of the SynTunSys.

Heuristic-based Work: SynTunSys (STS)

Parameters | Primitives | Scenarios
---|---|---
Area reduction param 1 | | |
Area reduction param 2 | area_he | area_he
Area reduction param 3 | | |
Set native VT to RVT | | |
Allow 10% LVT | rvt_lvt10 | rvt_lvt10, restruct_a
Restructuring for area | restruct_a | restruct_a
Restructuring for timing | restruct_t | rvt_lvt10, restruct_t

The illustration of the interaction of parameters, primitives, and scenarios in the SynTunSys.
The learning decision algorithm of the SynTunSys.

Heuristic-based Work: SynTunSys (STS)
Iterative Tuning Run 1
Parallel LSPD Flow Runs
QoR cost analysis
QoR statistics
Macro Data
Cost Function
Iterative Feedback

Iterative Tuning Run 2
Parallel LSPD Flow Runs
QoR cost analysis
QoR statistics
Macro Data
Cost Function
Iterative Feedback

Archive populated from many iterative DSE runs of parameter tuning

Archived QoR results are reused for training the recommender system

The Recommender System-based Tuning Flow

- Archive data filter
- Hyper-parameters

Training (offline)

- Macro
- Cost function

Trained Model

Recommendation (online)

Recommended Scenarios

The associated tuning framework in DAC’19.

Deep reinforcement learning-based parameter tuning of a placement tool\textsuperscript{1}.

\textsuperscript{1}A. Agnesina et al., “VLSI placement parameter optimization using deep reinforcement learning,” ICCAD, 2020.
The diagram of the workflow proposed in MLCAD’19.

Y. Ma et al., “CAD tool design space exploration via Bayesian optimization,” MLCAD, 2019.
More Important Features
Other Features

1. Model-less Sampling

Quality variation vector: 9 7 5 3 2 1
Important features indicator: 0 0 1 1 1 0

2. Model-guided Sampling (Exploration)

Samples in one cluster
○ Unselected Samples
○ Selected Samples (max 1 sample each cluster)
○ Selected Samples (no longer limited to cluster)

3. Model-guided Sampling (Exploitation)

An example of sampling by clustering in ASPDAC’20.  

• A survey of recent line of arts in tool parameter tuning
• Parameter space auto-pruning
• Rethinking Gaussian process in iterative refinement tuning frameworks like Bayesian optimization
• Collectively considering parameter auto-tuning of multiple tools exploited in the whole design flow
• ... ...
THANK YOU!