

TAFAs: Design Automation of Analog Mixed-Signal FIR Filters Using Time Approximation Architecture

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The Speaker's Biography



Shiyu Su received the B.S. degrees from BUPT and QMUL in 2011, and the M.S. and Ph.D. degrees from USC in 2013 and 2019, all in electrical engineering.

His research interests include data converters, all digital PLL, RF/millimeter-wave transceivers, and analog/mixed-signal design automation, micro-unmanned vehicles.

Dr. Su was the recipient of IEEE SSCS Predoctoral Achievement Award for 2017–2018, IEEE SSCS Student Travel Grant Award for 2019–2020. He is a Ming Hsieh Institute Scholar from 2019 to 2020.

POSH Team at USC





Outline

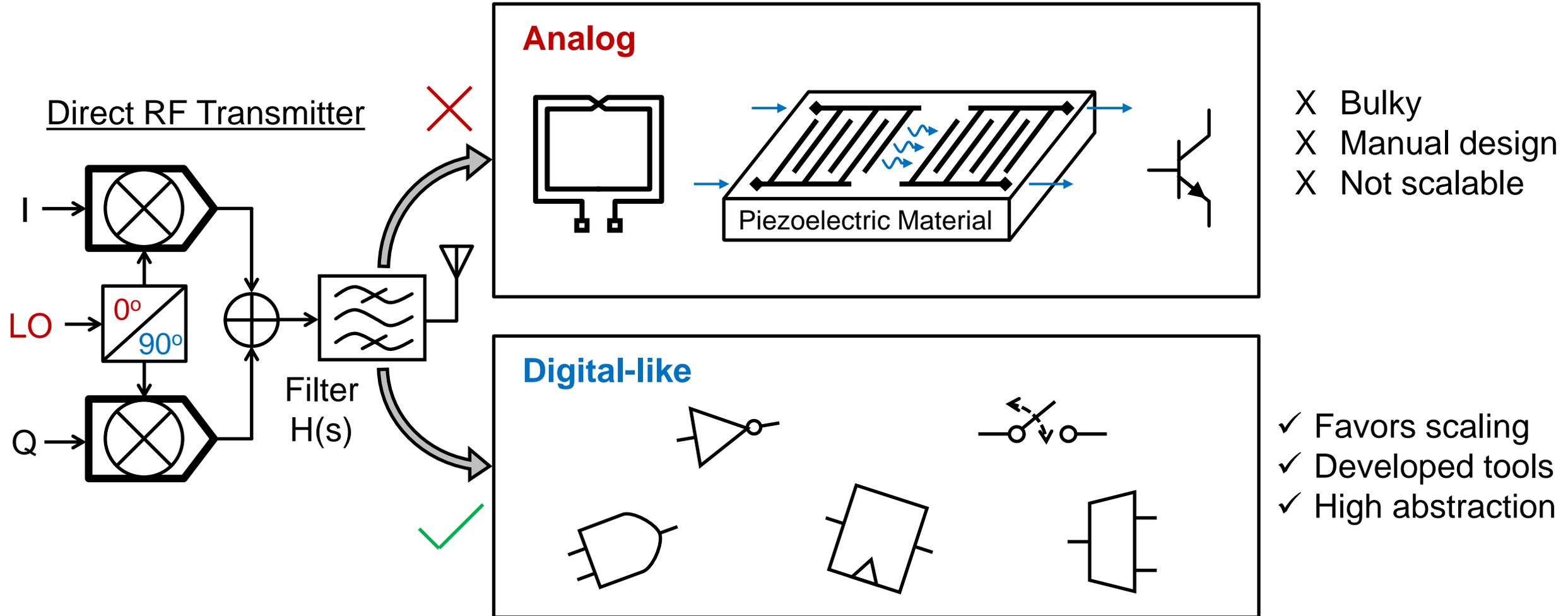
- Introduction
- Proposed AMS filter design flow
 - **Hybrid TAF pattern generation**
 - **NN-based parameter search**
- Experimental results
- Conclusion

AMS: Analog/mixed-signal

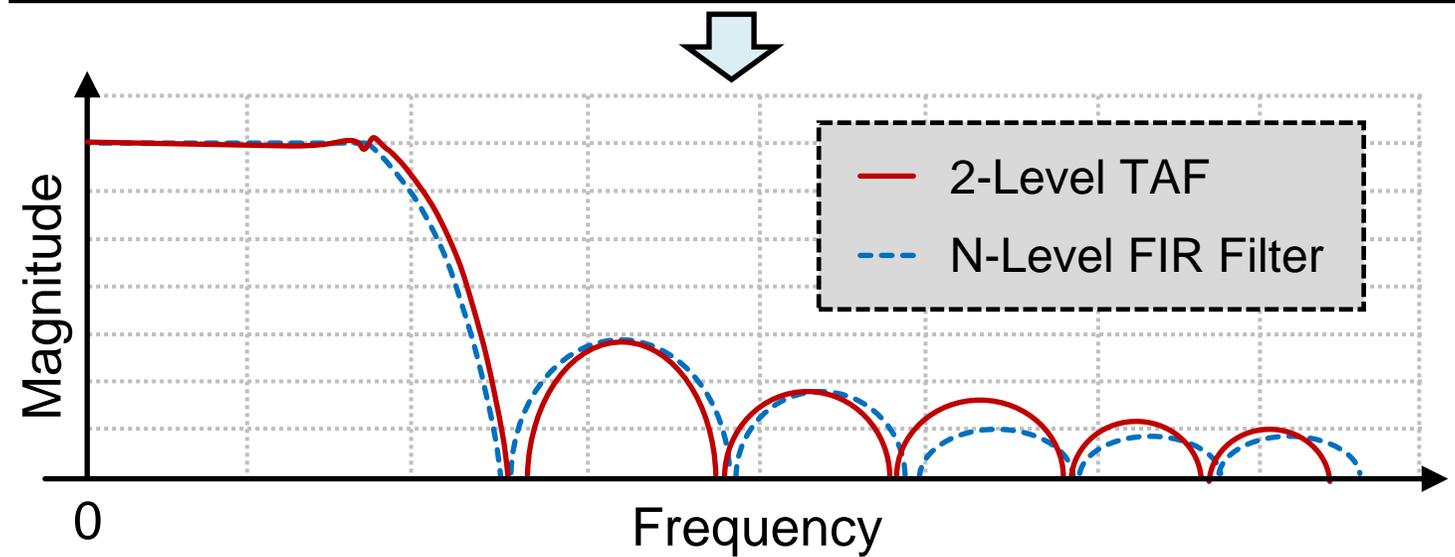
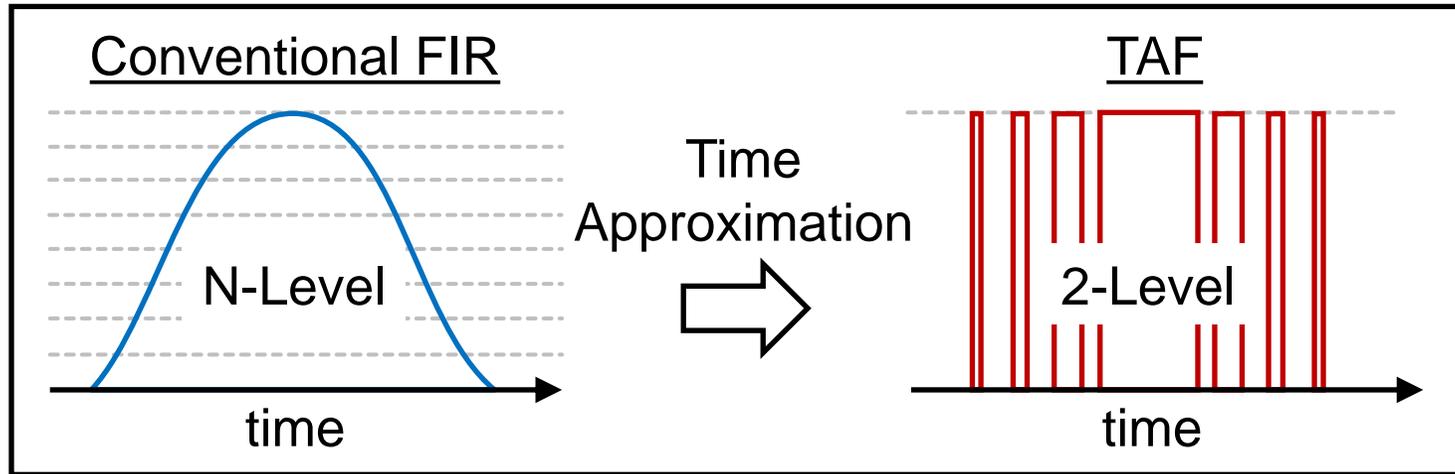
TAF: time-approximation filter

NN: Neural network

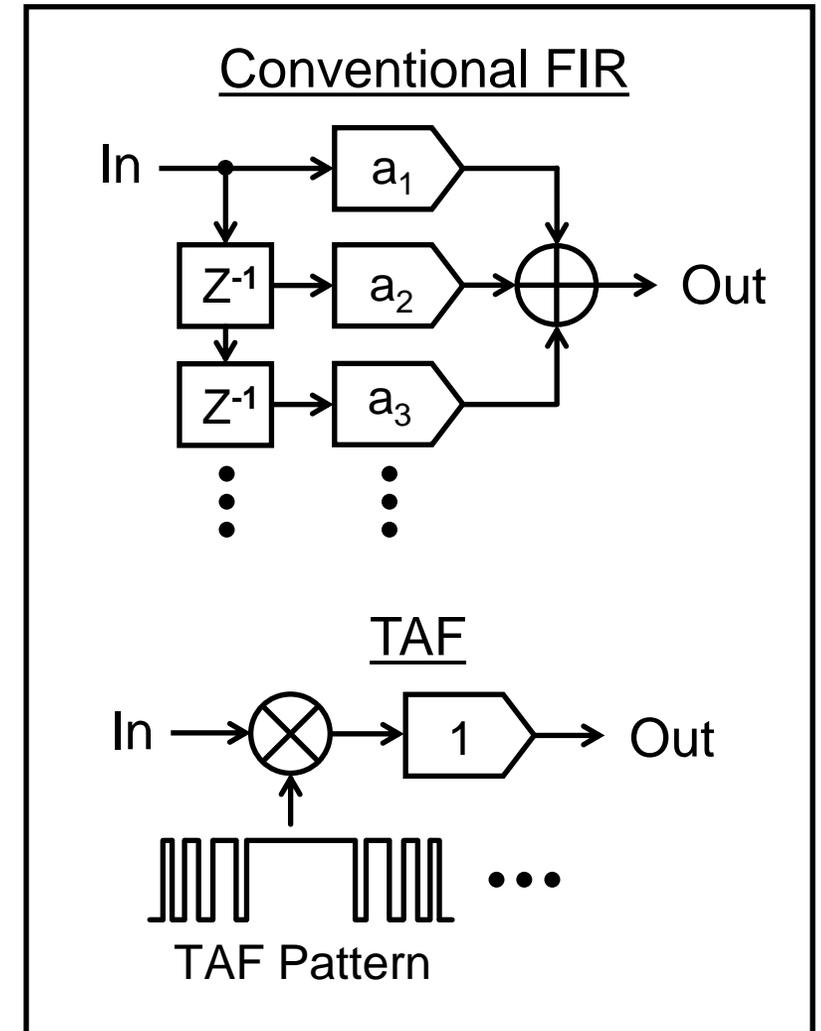
Motivation – Towards “Digital-Like” Design



Digital-Like Time-Approximation Filter (TAF)



[Su VLSI 2019]



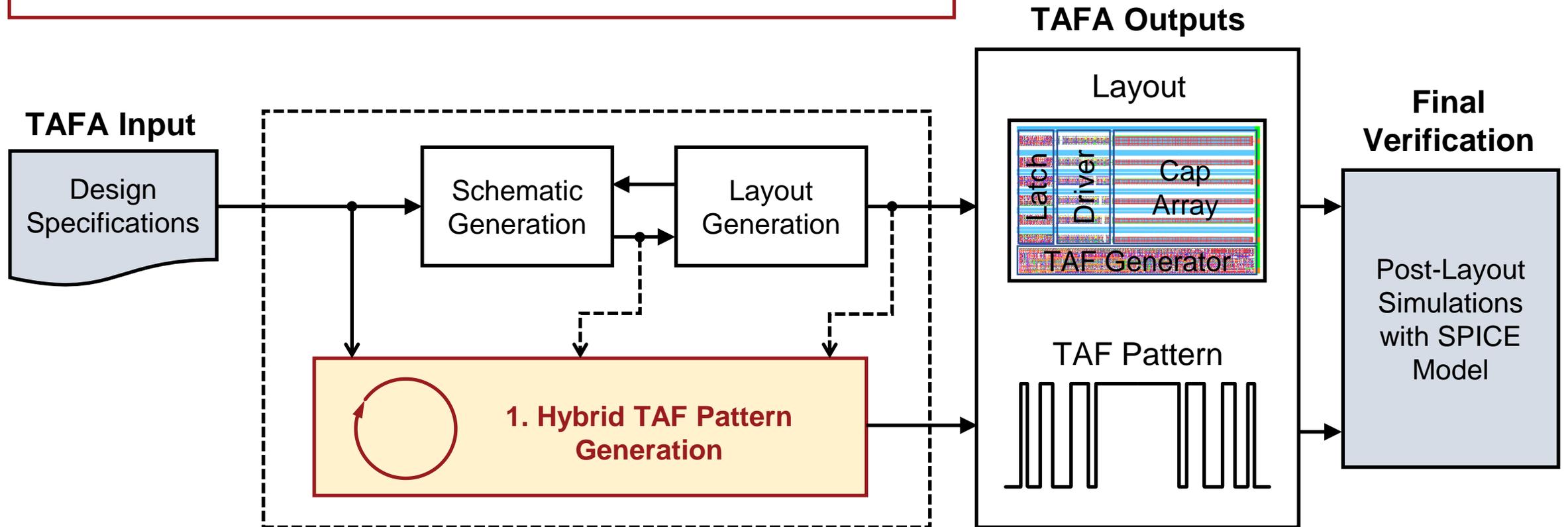
Implementation

Challenges of TAF Design

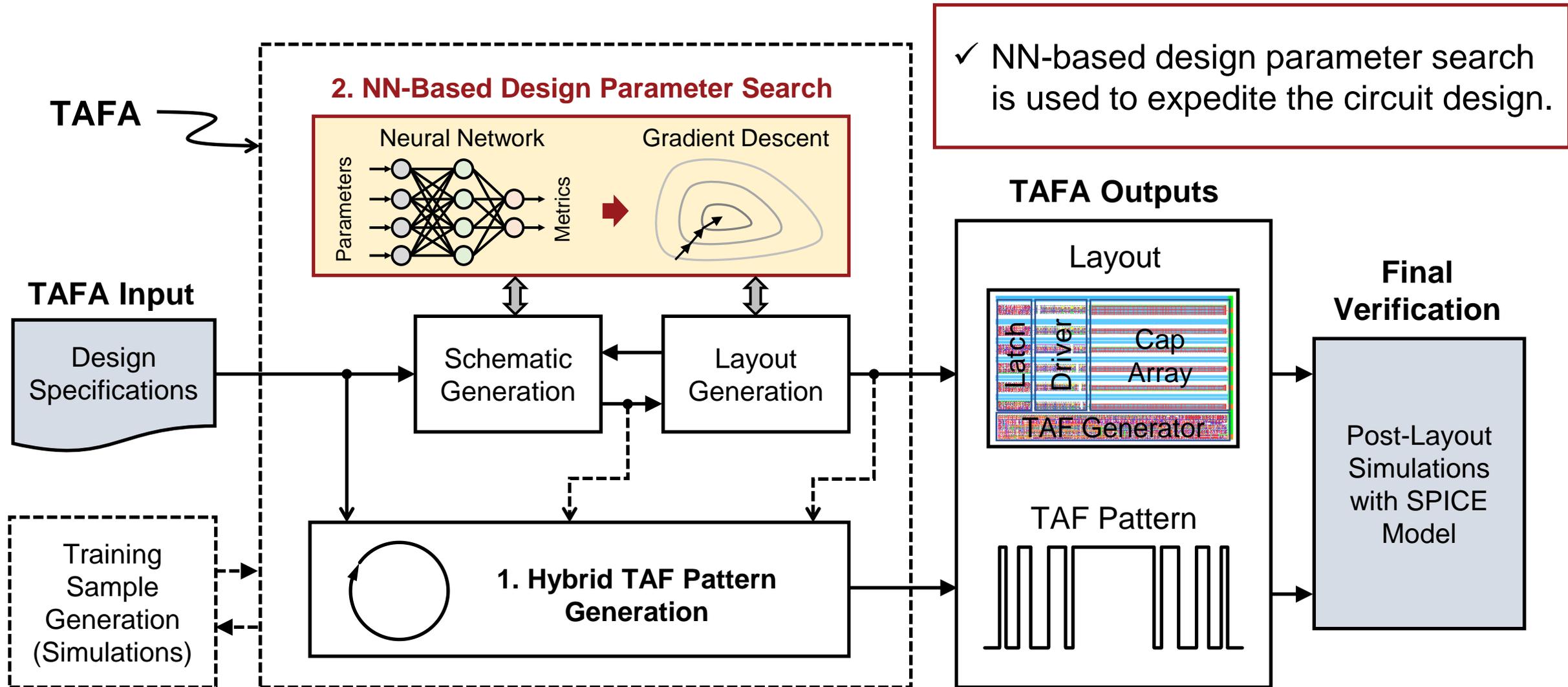
1. The **time resolution** for time approximation is limited by the system clock rate.
2. There are remaining analog circuits that require intensive **hand-crafted design**.

Hybrid TAF Pattern Generation

✓ Hybrid TAF pattern generation is proposed to derive a nearly optimum impulse response for a TAF



NN-Based Design Parameter Search

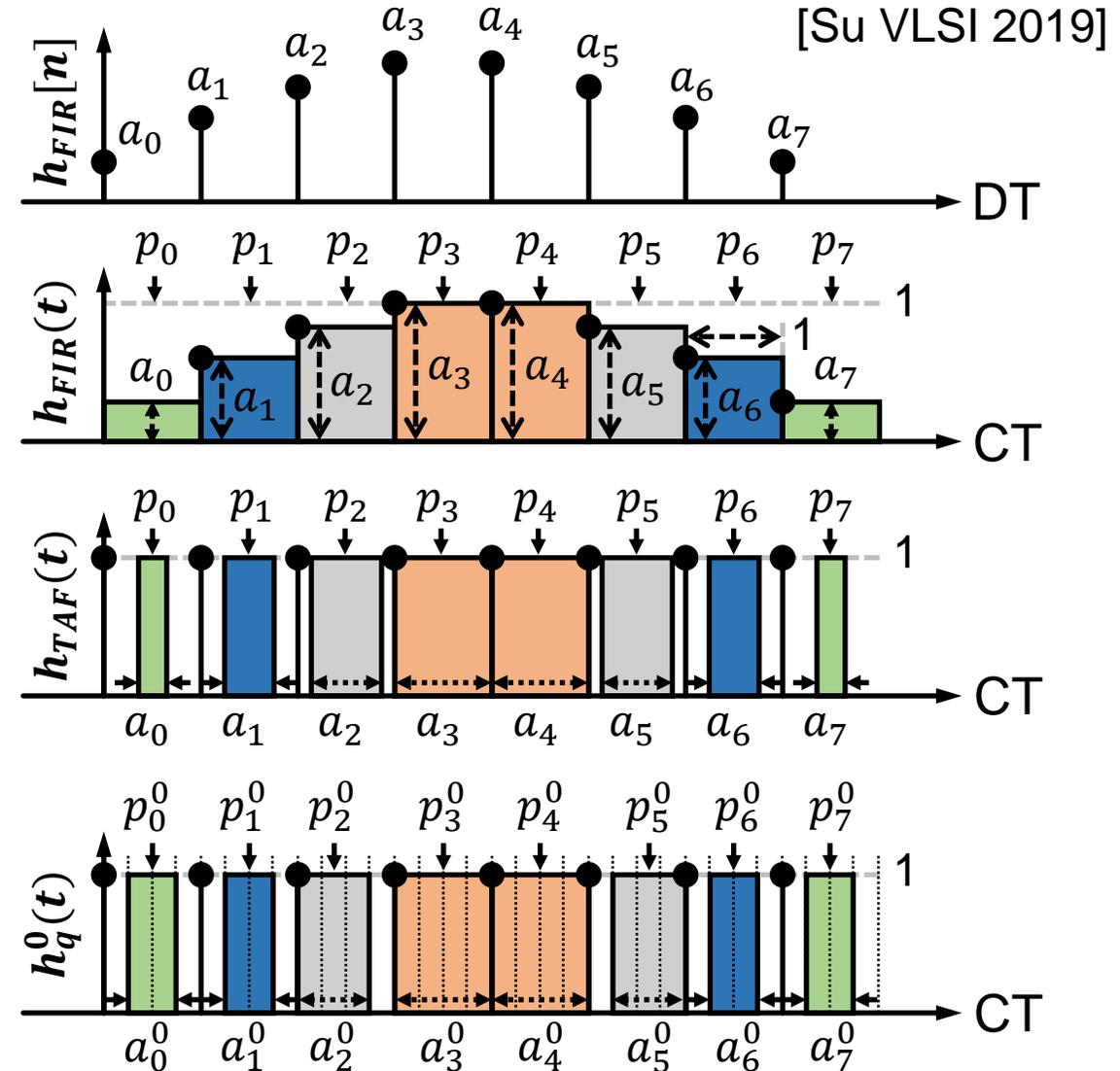
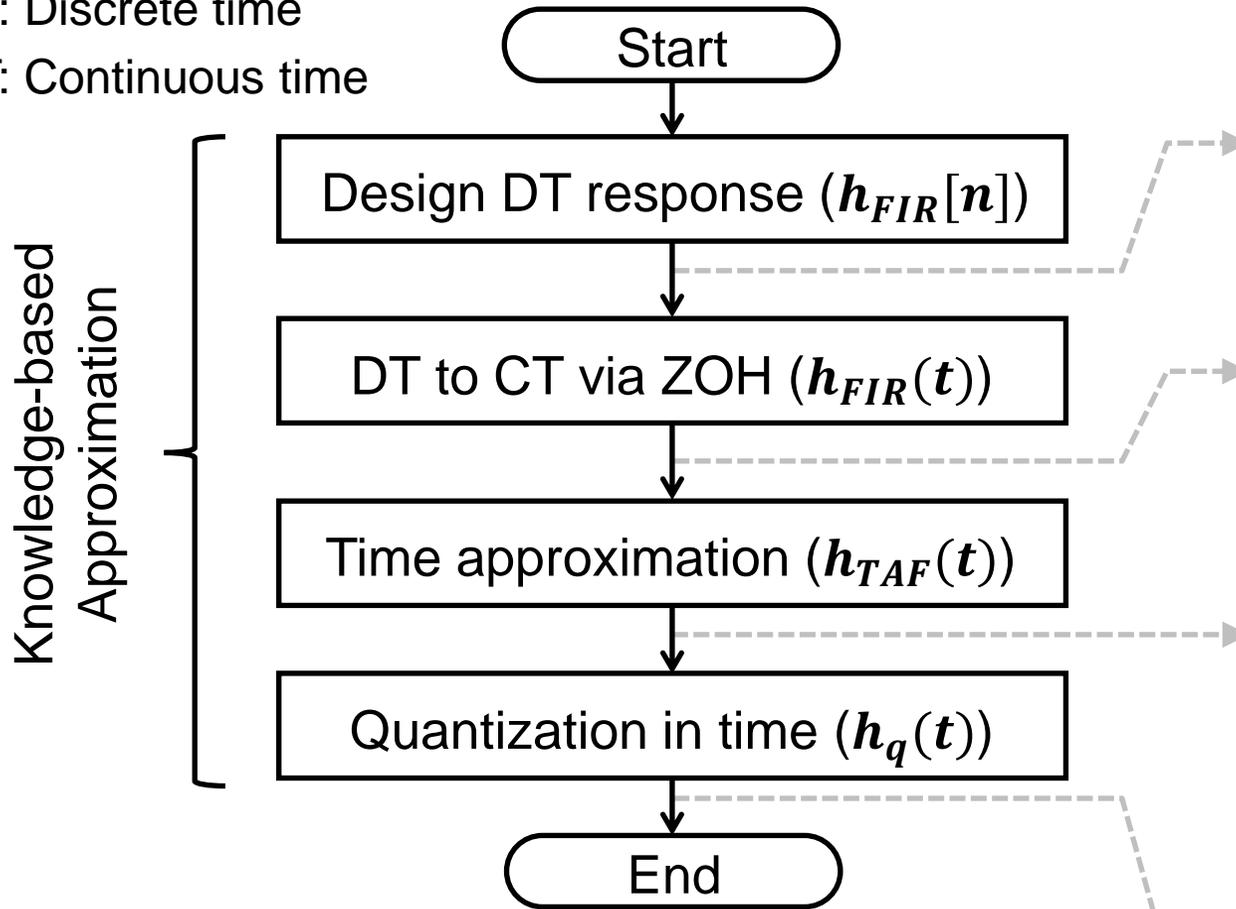


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Traditional TAF Pattern Generation

DT: Discrete time
CT: Continuous time

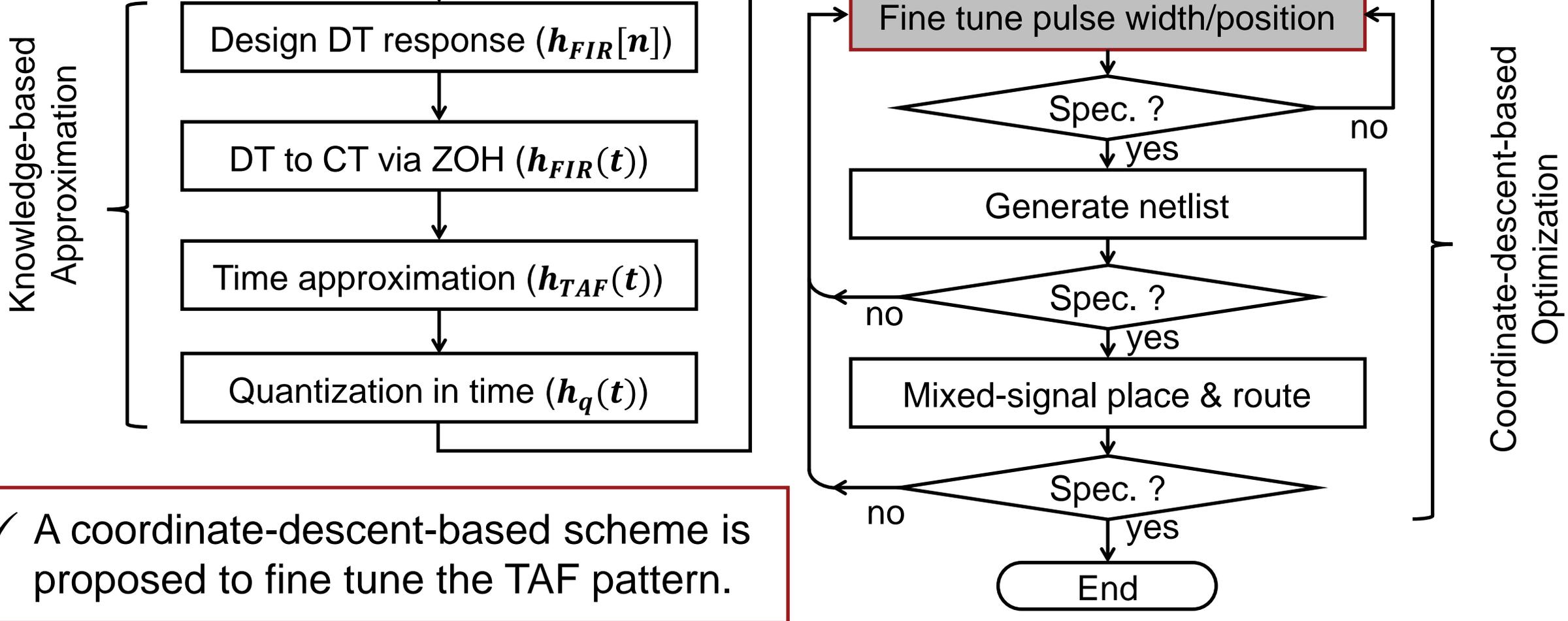


- Time quantization error limits the time approximation accuracy.

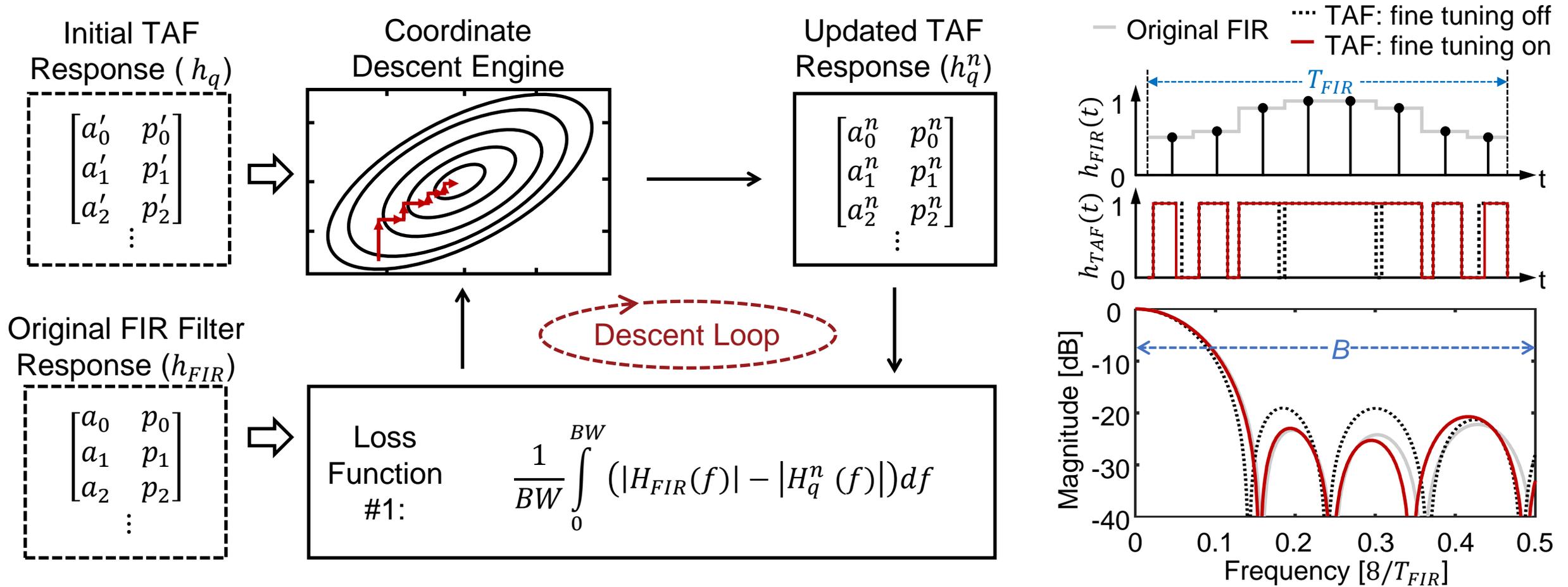
Hybrid TAF Pattern Generation Flow

DT: Discrete time

CT: Continuous time



Fine Tuning with Custom Loss Functions



✓ Fine tune the width (a) and position (p) of each pulse in the TAF pattern using different loss functions. For example, loss function # 1 is used to **better approximate the original or target FIR filter response.**

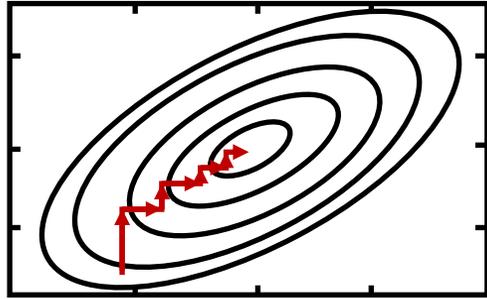
Fine Tuning with Custom Loss Functions

Initial TAF Response (h_q)

$$\begin{bmatrix} a'_0 & p'_0 \\ a'_1 & p'_1 \\ a'_2 & p'_2 \\ \vdots & \vdots \end{bmatrix}$$



Coordinate Descent Engine



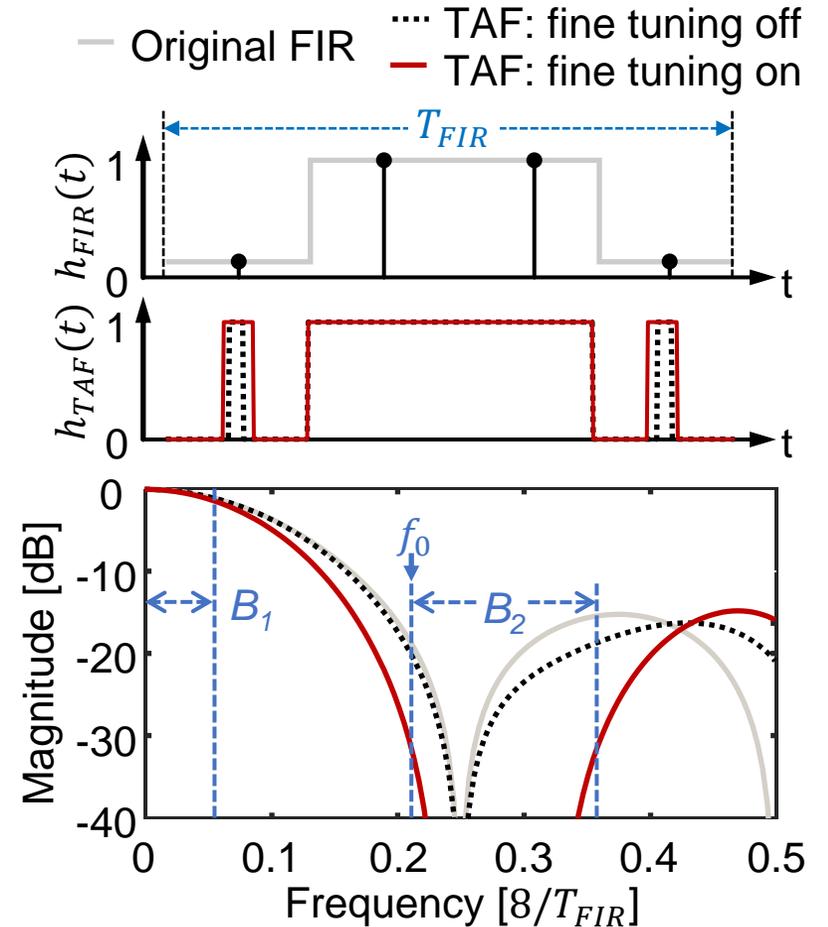
Updated TAF Response (h_q^n)

$$\begin{bmatrix} a_0^n & p_0^n \\ a_1^n & p_1^n \\ a_2^n & p_2^n \\ \vdots & \vdots \end{bmatrix}$$

Descent Loop

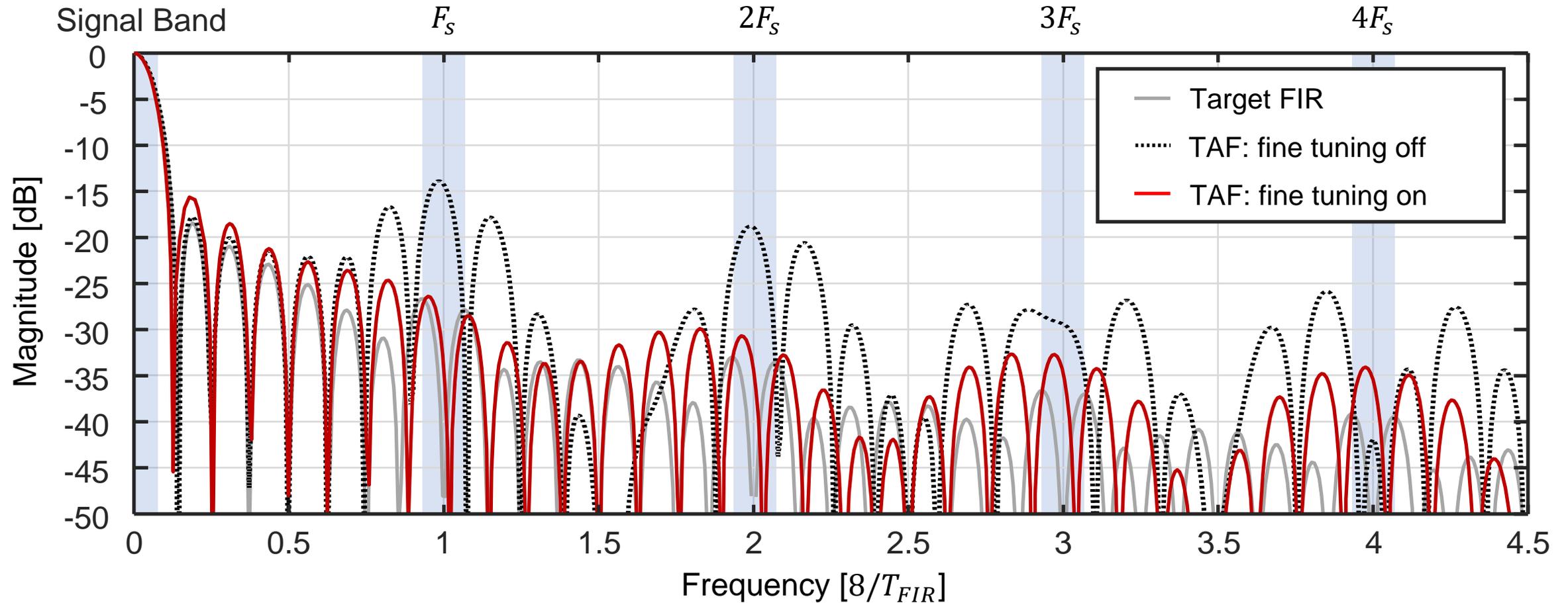
Loss Function #2:

$$\int_0^{BW_1} \left(\frac{|H_q^n(f)|}{BW_1} \right) df - \int_{f_0}^{f_0+BW_2} \left(\frac{|H_q^n(f)|}{BW_2} \right) df$$



- ✓ Starting from the original FIR filter response, loss function # 2 is used to **enhance the filter attenuation at specific band of interest** instead of approaching to the original FIR filter response.

Fine Tuning with Custom Loss Functions



- ✓ In addition, loss function # 2 can be also used to **optimize the far-out spectrum**, avoiding unwanted peaks at high frequencies.

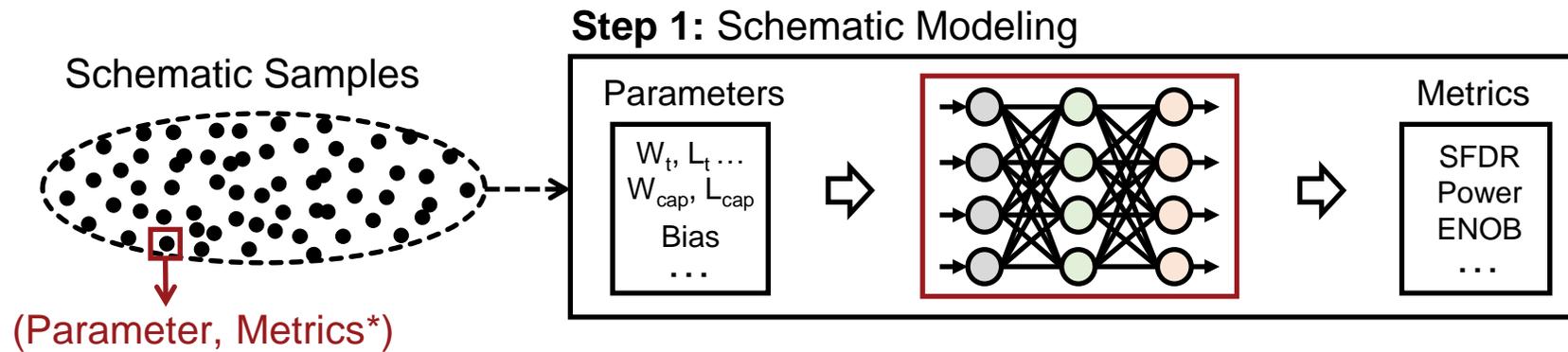
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NN-Based Surrogate Model for AMS Circuits



Human in Loop (Developer)



Pros:

1. Well-developed
2. Fast inference
3. Reusable
4. Low computational cost

Con:

Required sufficient training data. (Post-layout simulations of AMS circuits using SPICE model can be extremely expensive!)



Given a target model accuracy, how to reduce the required training data?

✓ An NN-based Surrogate model is used to imitate the parameters-to-metrics (P2M) relationship of the AMS circuit.

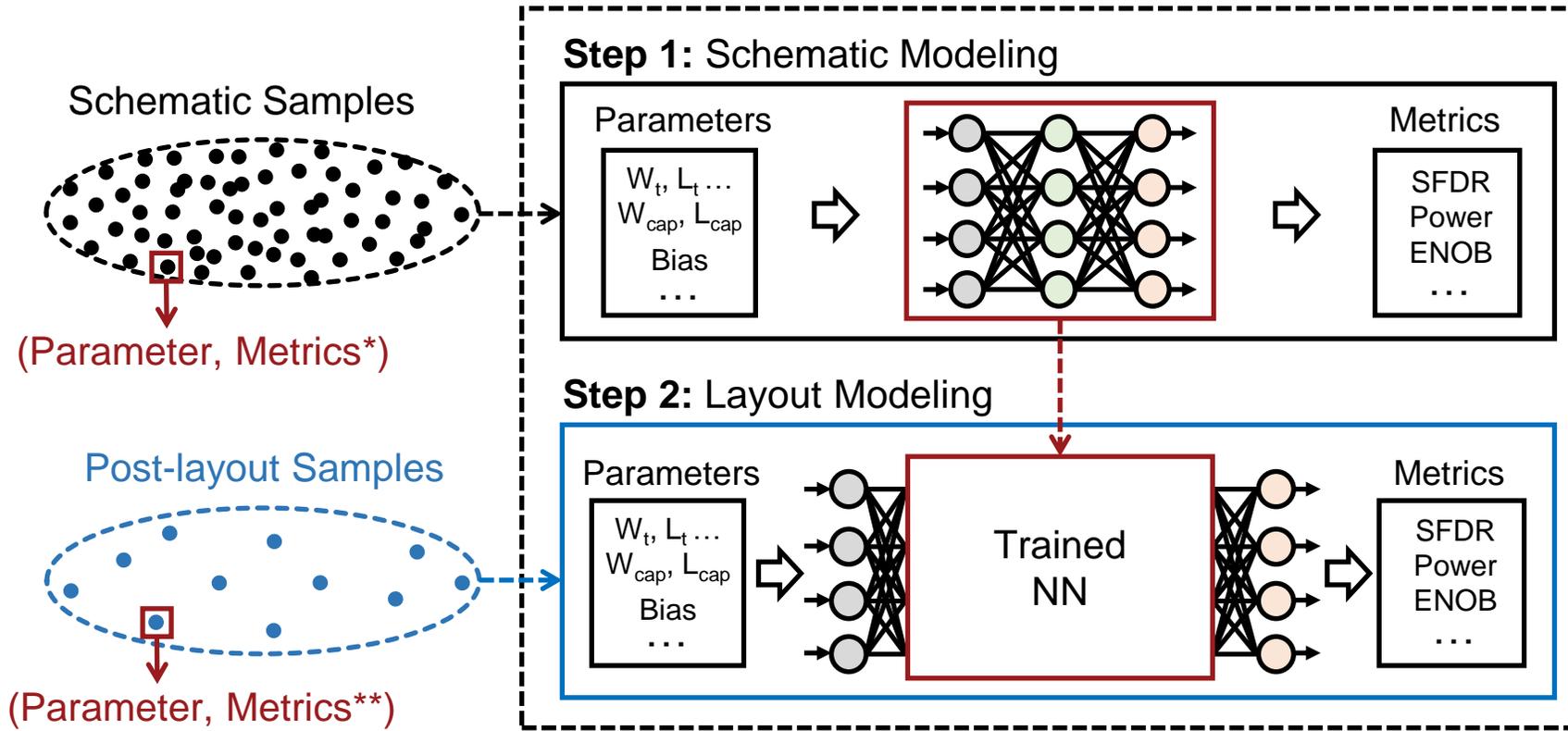
* Obtained from schematic simulations; ** Obtained from post-layout simulations;

Layout-Aware Model Using Transfer Learning



Human in Loop (Developer)

NN-Based Layout-Aware Modeling



- ✓ Leverage the knowledge learned from schematic simulations via transfer learning.
- ✓ Note that the model training including the training sample generation only needs to be done **once**.

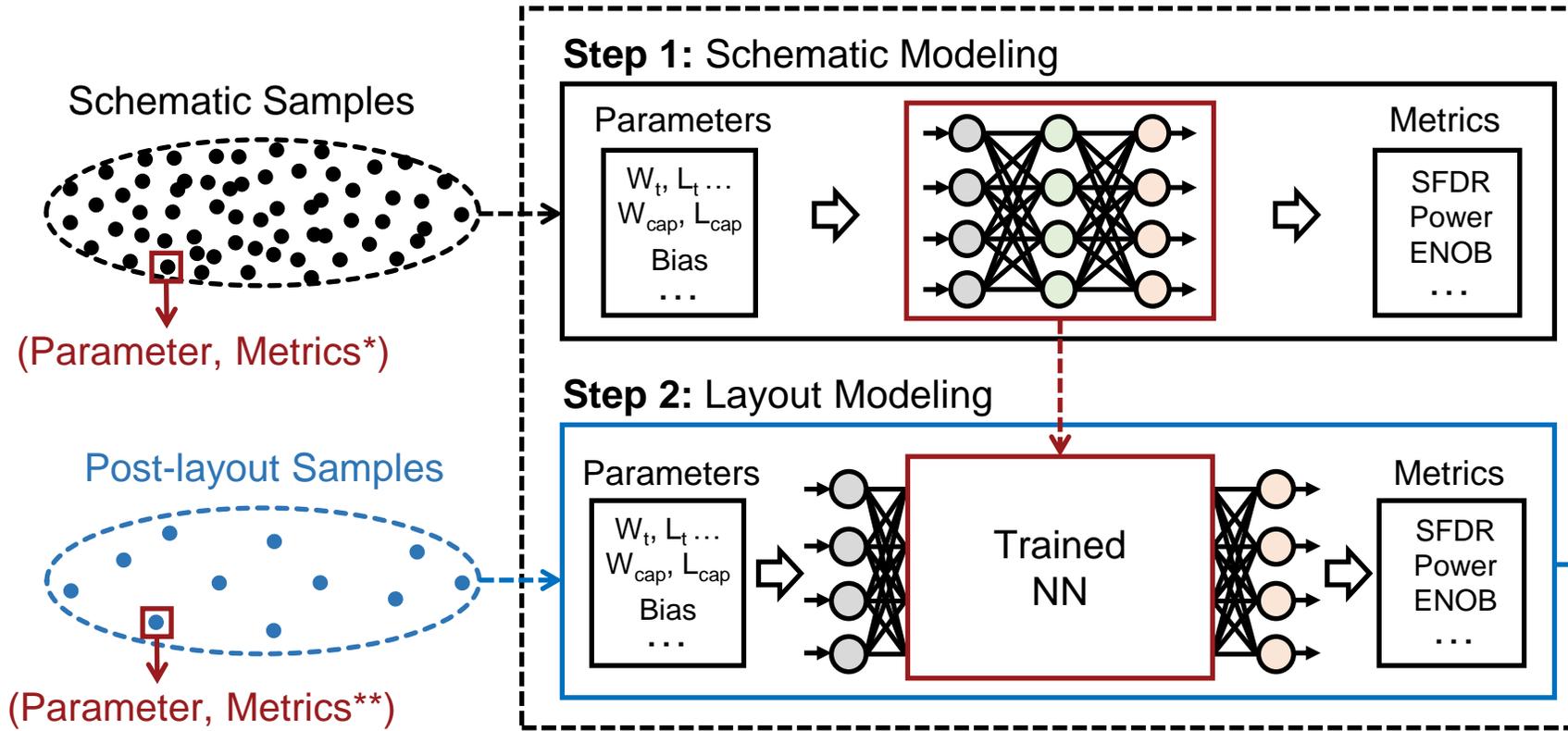
* Obtained from schematic simulations; ** Obtained from post-layout simulations;

Rapid Design Parameter Search



Human in Loop (Developer)

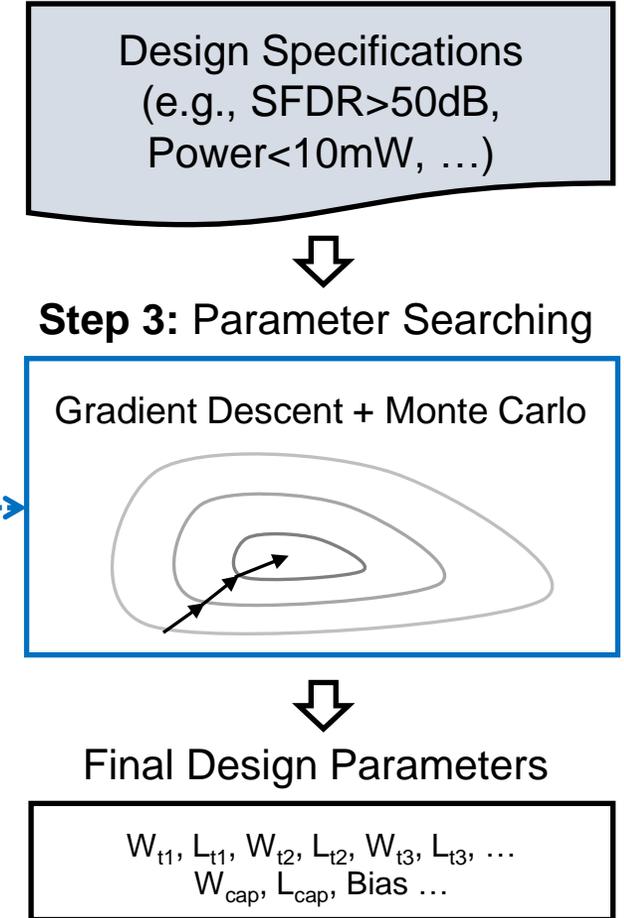
NN-Based Layout-Aware Modeling



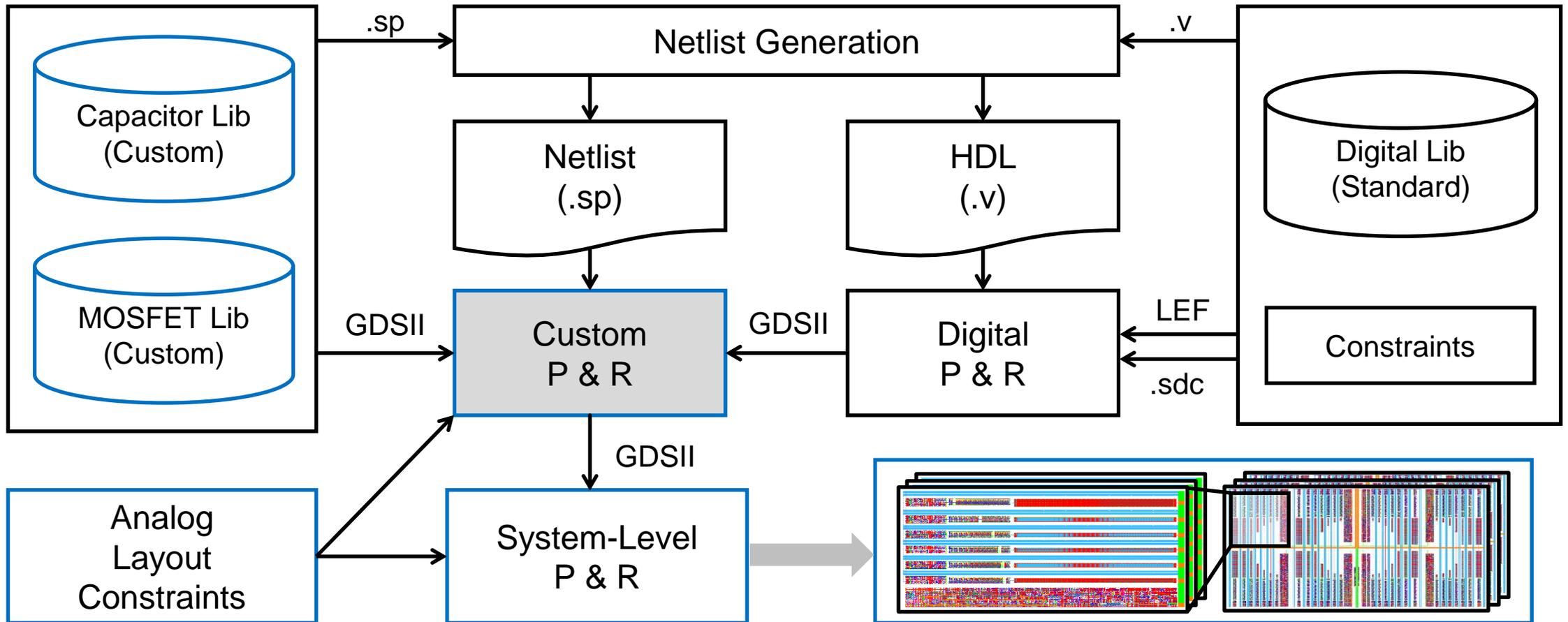
* Obtained from schematic simulations; ** Obtained from post-layout simulations;



Automated (User)



Custom AMS Layout Flow

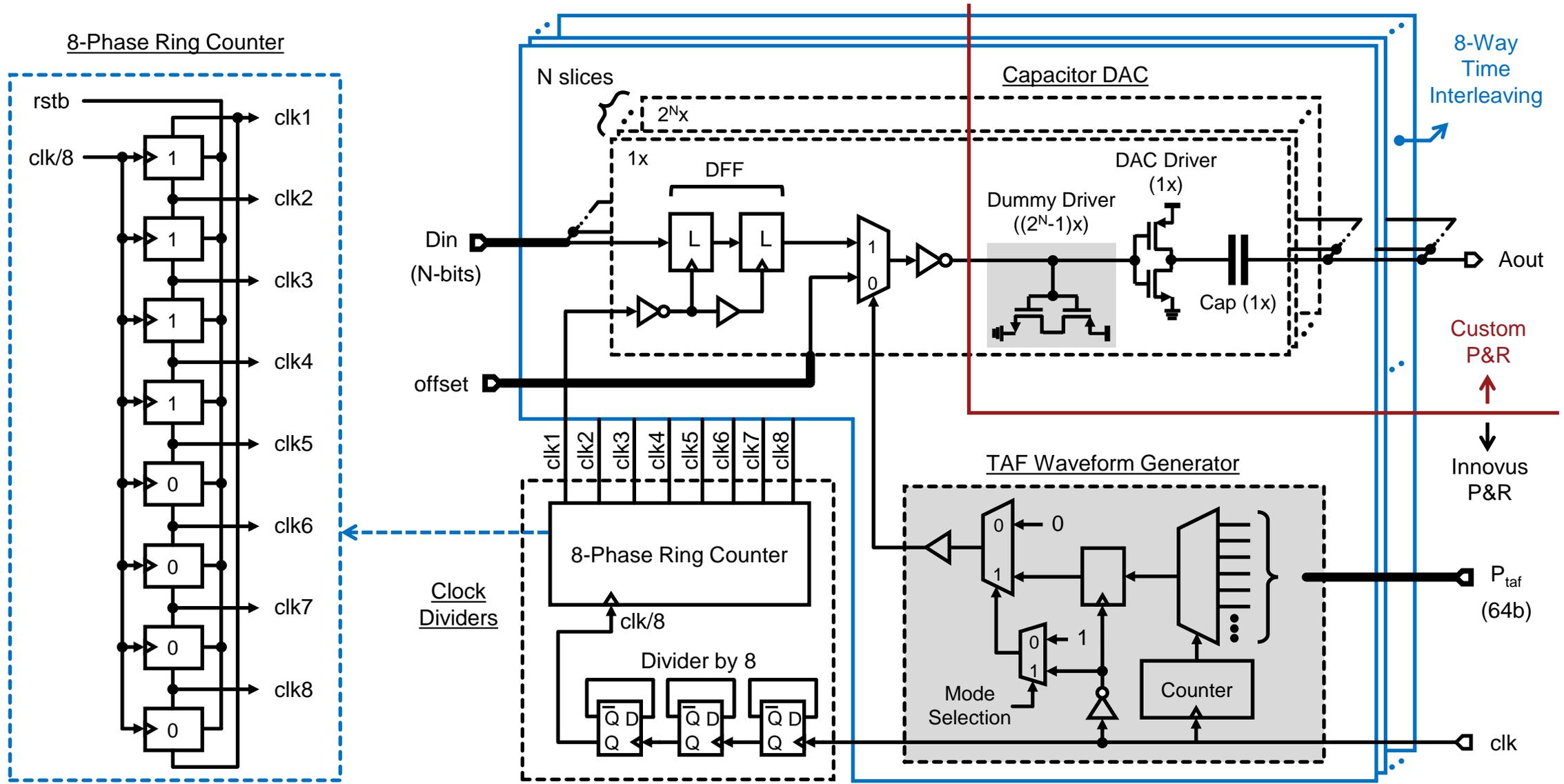


✓ Customize the P&R for performance-sensitive blocks and top-level integration while maximally leverage standard digital flow.

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 - Neural-network-based parameter search
-  • **Experimental results**
- Conclusion

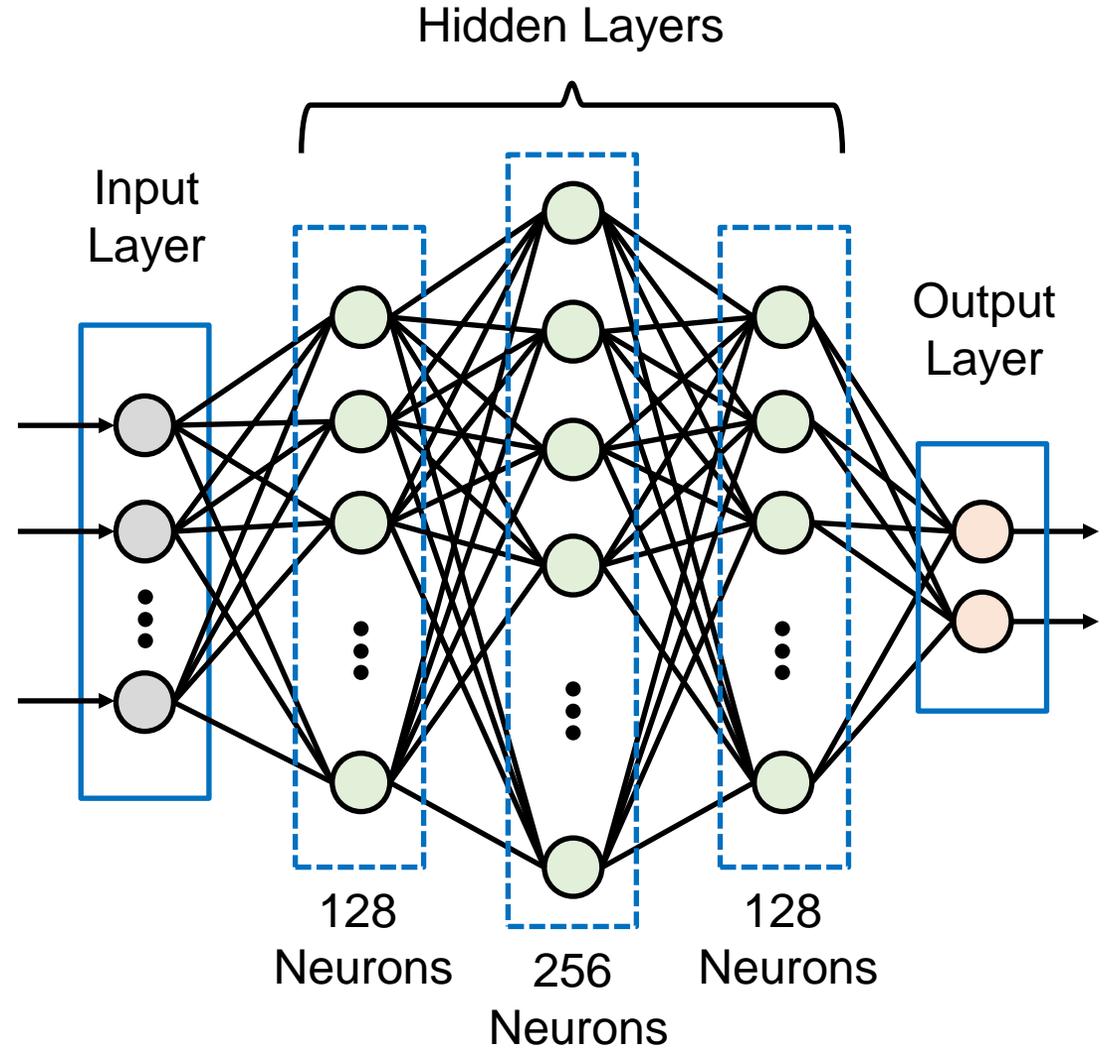
Fully Synthesizable Circuit Implementation



Design Parameters & Performance Metrics

Input

Design Parameters (Size)
Data latch (stage 1)
Data latch (stage 2)
Mixing MUX
Driver of the Mixing MUX
Clock driver
DFF for the ring counter
PMOS of the DAC driver
NMOS of the DAC driver
Capacitor



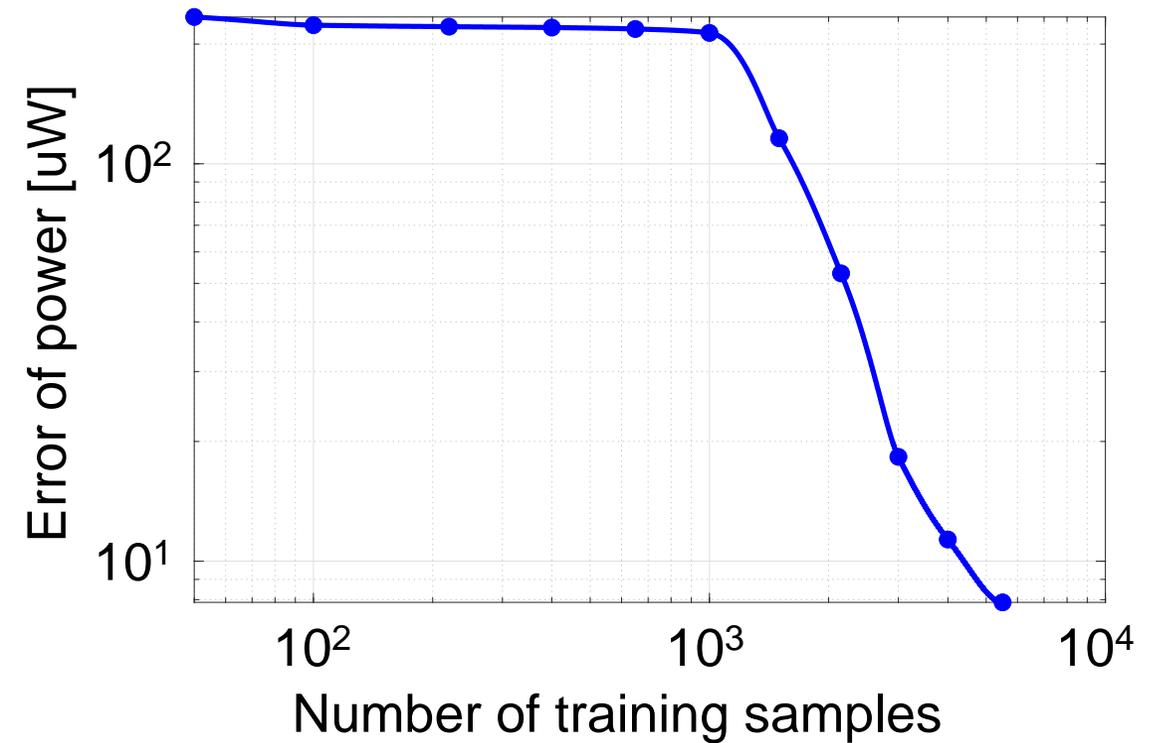
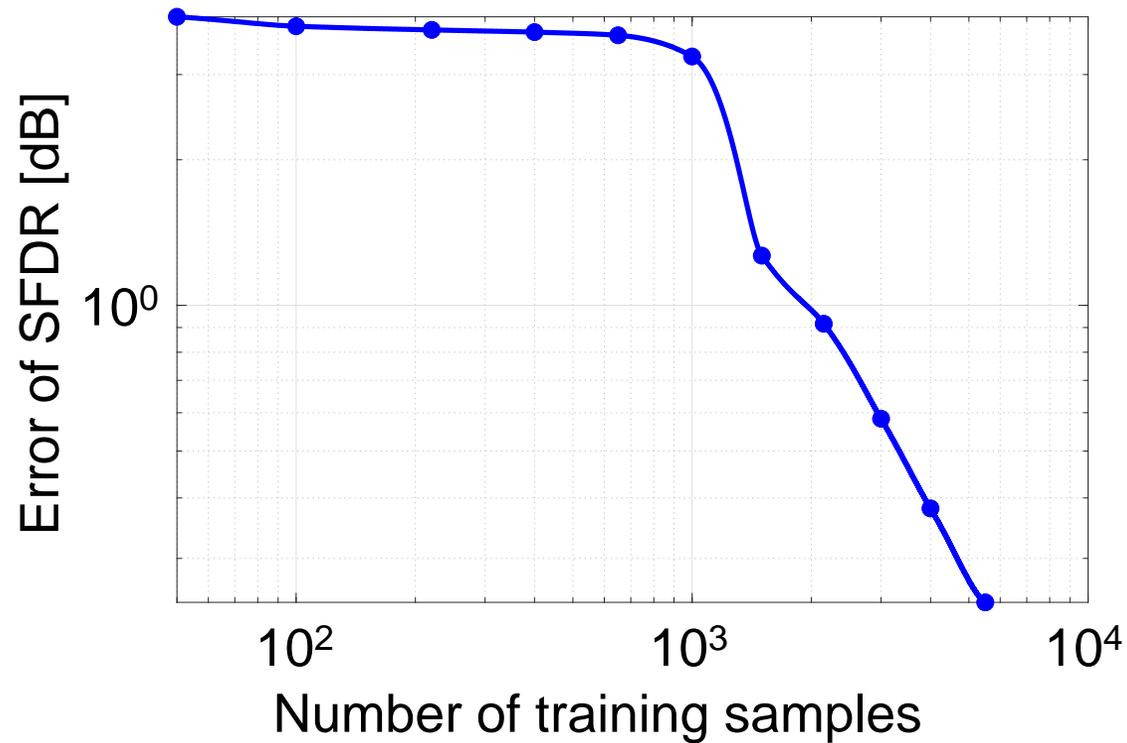
Output

Performance Metrics
SFDR
Power

SFDR: Spurious Free Dynamic Range

Training Errors versus Number of Samples

Schematic Model

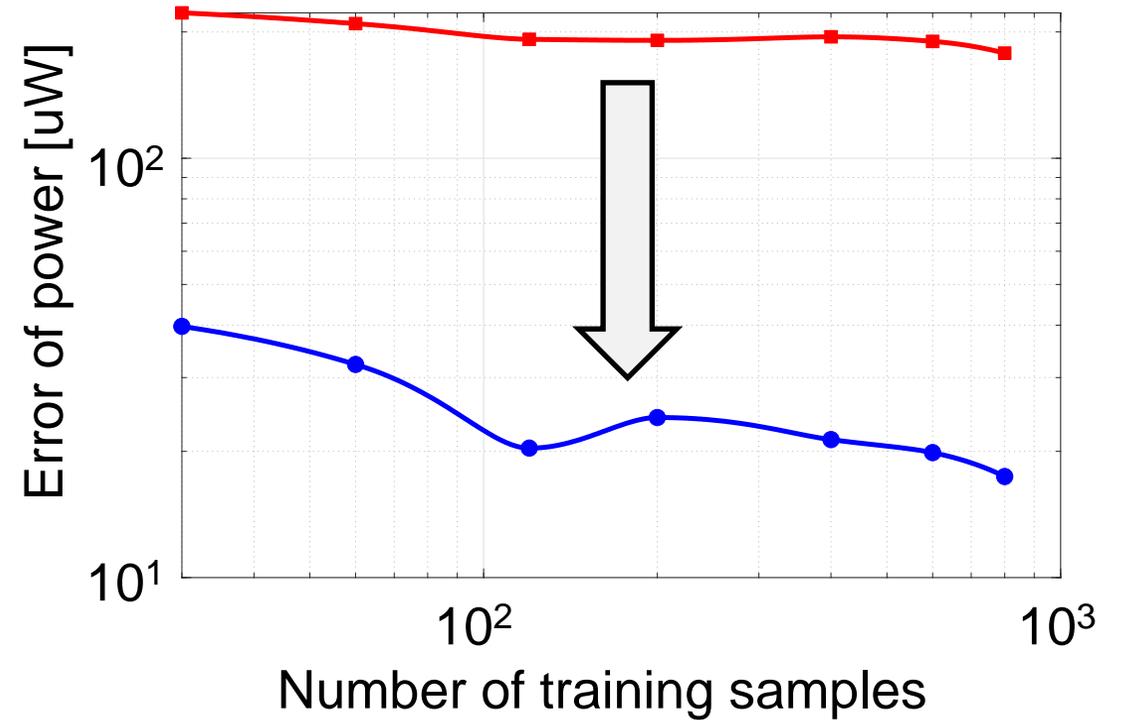
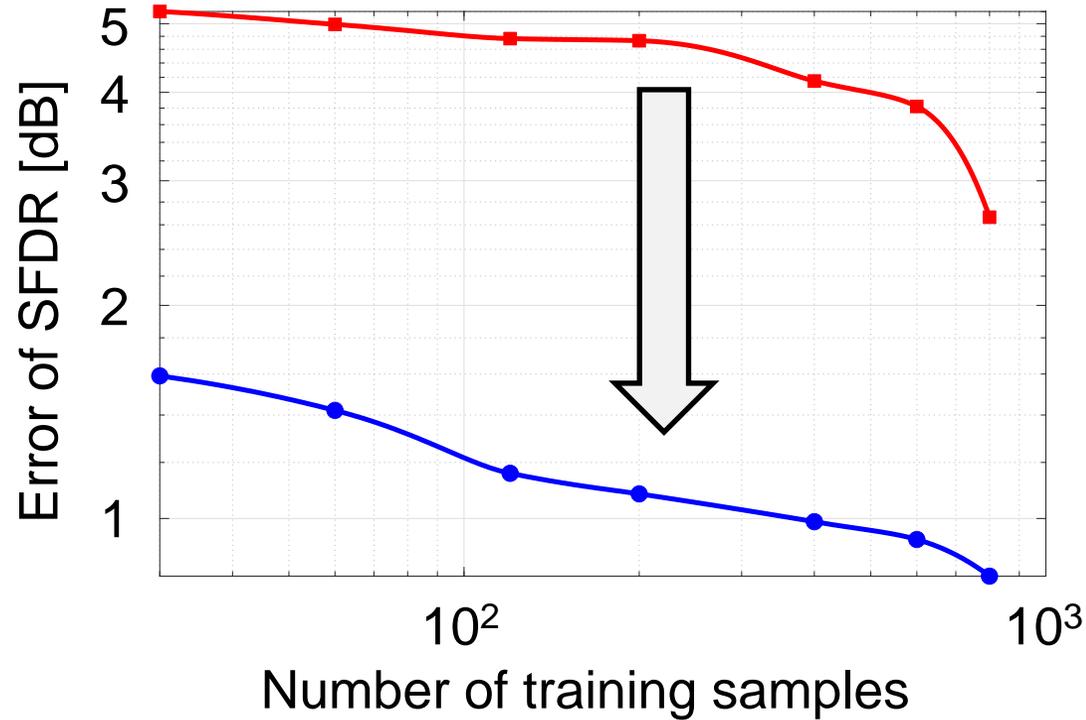


Model Improvement via Transfer Learning

Post-Layout Model

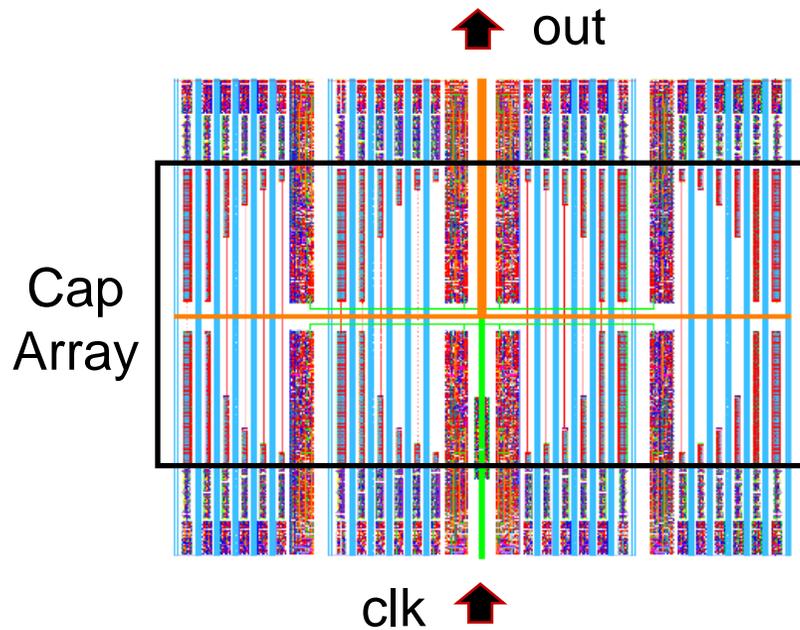
■ Baseline (Trained from Scratch)

● Transfer Learning

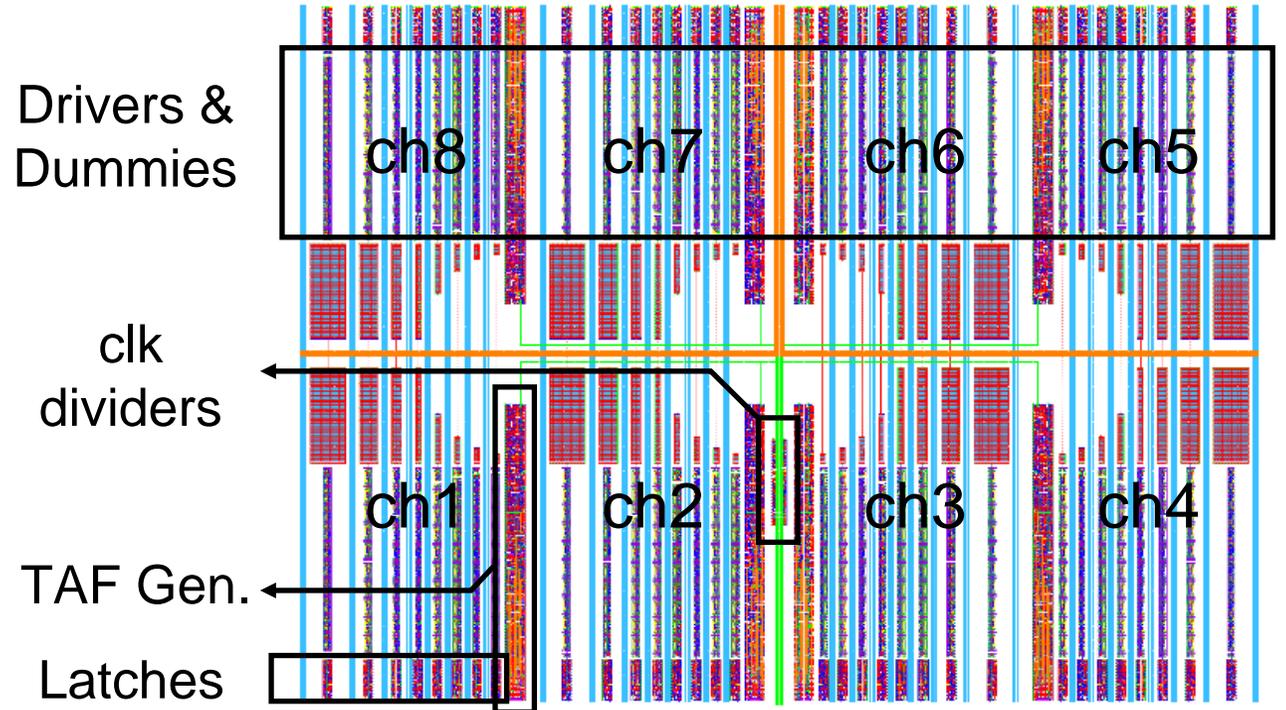


Filter Layout

Design 1: w/ a 6-bit DAC



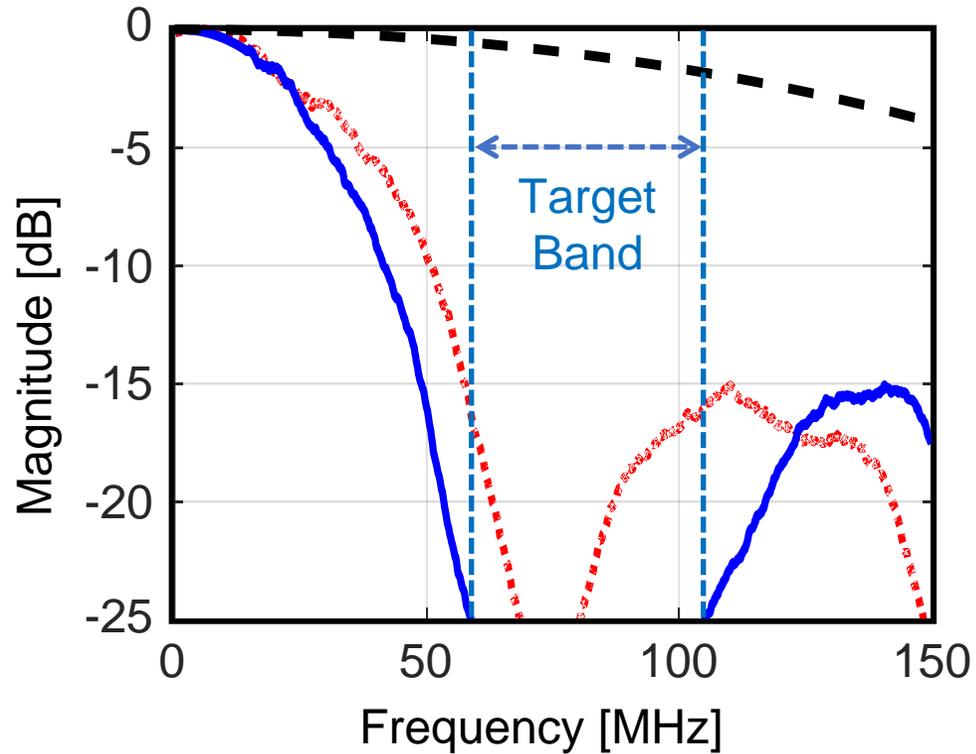
Design 2: w/ an 8-bit DAC



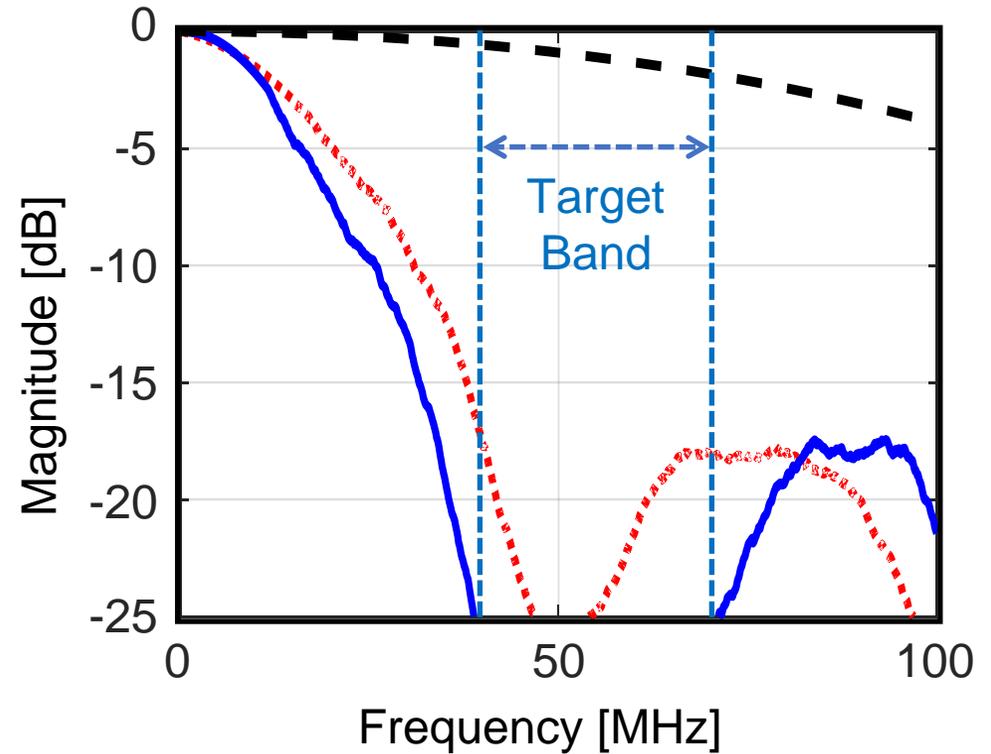
Simulated Filter Responses

— With Hybrid Appr.
 - - - With Knowledge-Based Appr.
 - - - ZOH

Design 1



Design 2



Performance Summary

	DAC Res. [bits]	F_s [MHz]	BW [MHz]	F_{TAF} [GHz]	DAC SFDR [dBc]	Corner Freq.* [dBc]	Atten.** [dB]	Power [mW]	Area [mm ²]
Design 1	6	300	20	2.4	49	21	20	6.9	0.044
Design 2	8	200	10	1.6	51	14	18	5.2	0.089

* Corner frequency of the TAF's frequency response.

** Stop-band attenuation of the TAF.

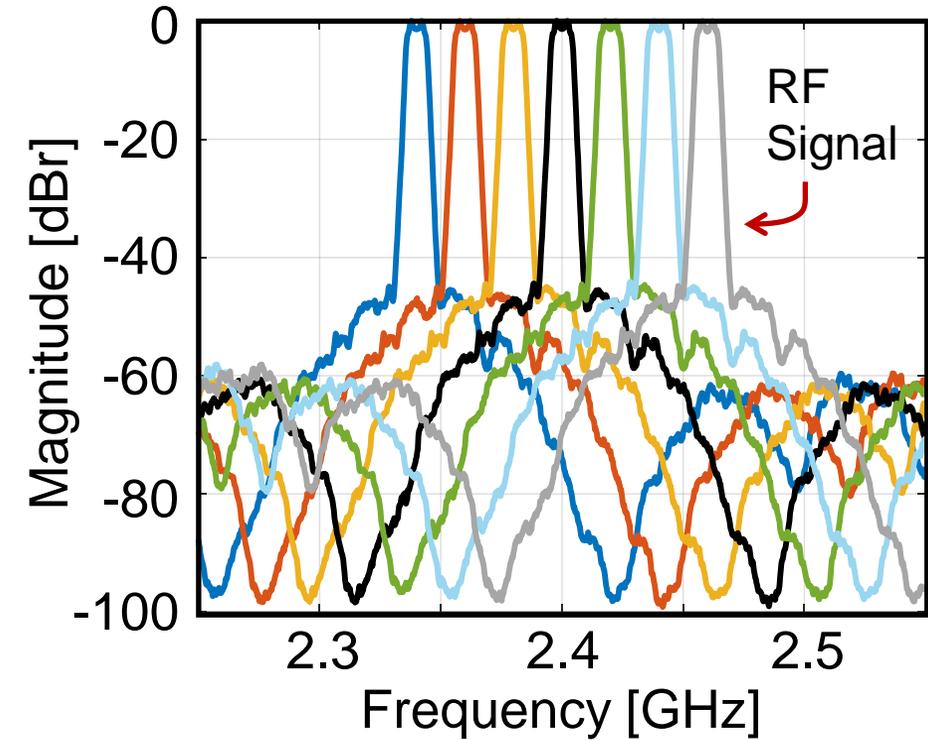
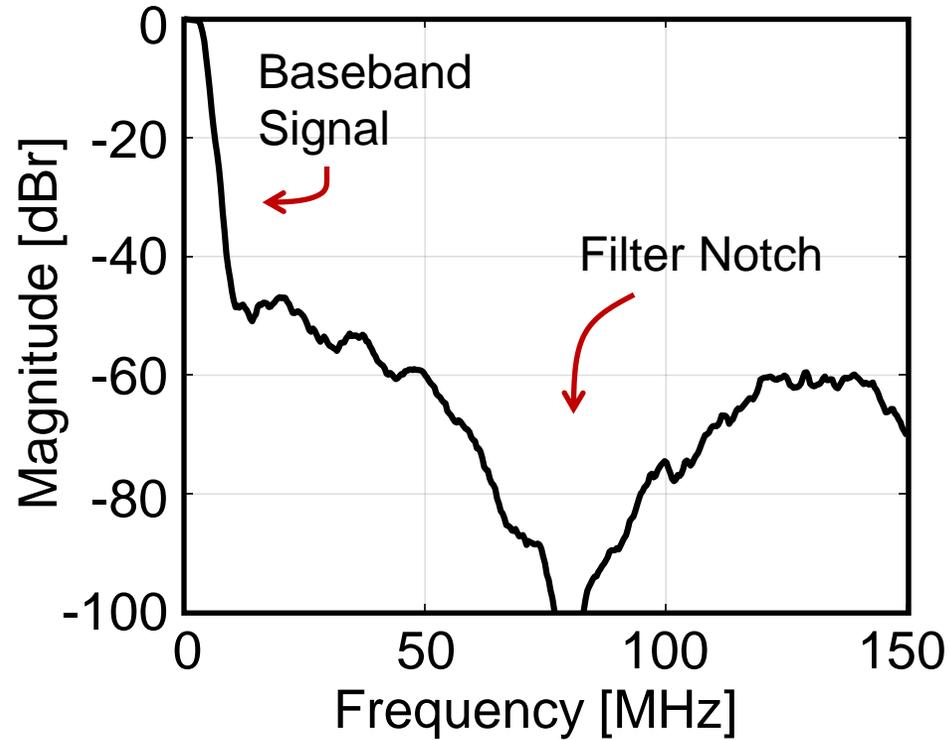
Performance Comparison

	Design 1		Design 2	
	KB**	Hybrid Appr.	KB*	Hybrid Appr.
Attenuation* [dB]	21.3	28.8	21.7	31
BW with >20dB attenuation [MHz]	24.1	63.5	19.7	42.7
BW with >25dB attenuation [MHz]	12	46.58	7.62	32.7

* Average attenuation of the TAF at the target band.

** Knowledge-based time approximation scheme proposed in [Su VLSI 2019].

Bandpass Mode Responses



Conclusion

- TAFA demonstrates a complete design automation flow for FIR AMS filters based on the time-approximation filter (TAF) technique.
- The hybrid pattern generation scheme significantly improves the TAF's performance for various applications.
- The NN-based search algorithm expedites the filter synthesis by orders of magnitude during schematic and layout stages.

Acknowledgement

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