

# A Hybrid Machine Learning and Numeric Optimization Approach to Analog Circuit Deobfuscation

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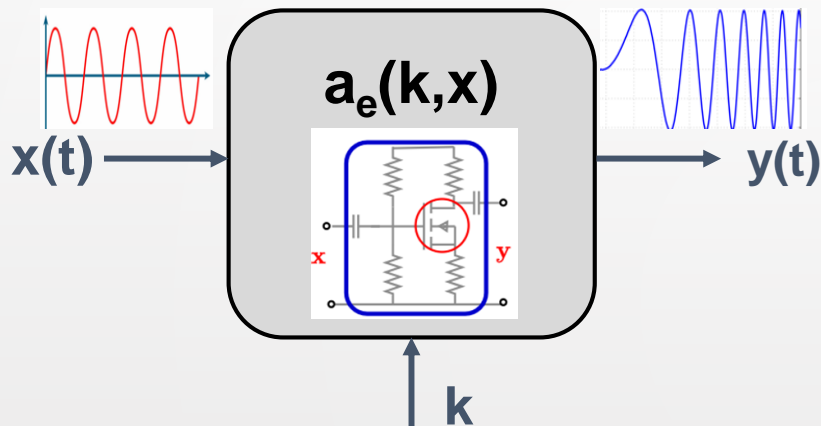
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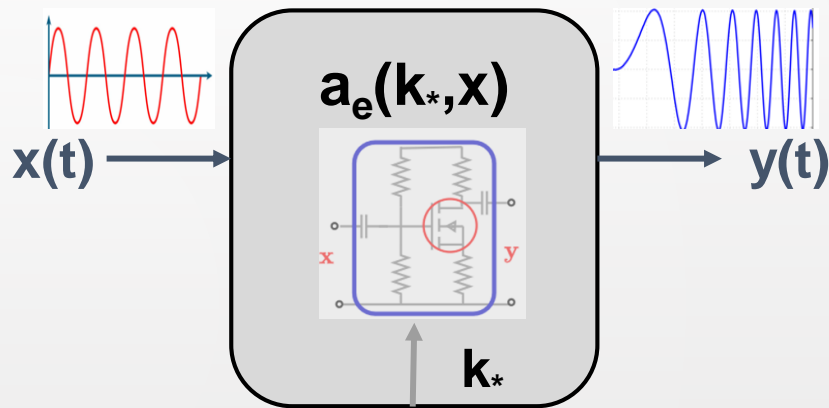
- **Background and Motivation**
- Proposed Method
- Experiments and results
- Discussion
- Conclusion

# Oracle Guided Circuit Learning (OGCL)

Obfuscated (Analog) Circuit



Oracle (Analog) Circuit



where  $k_*$  = unknown analog values  
 $x$  = controllable analog inputs  
 $a_e$  = analog circuit  
 $y$  = output response

$$a_e(k, x) \equiv a_e(k_*, x)$$

# Applications of OGCL

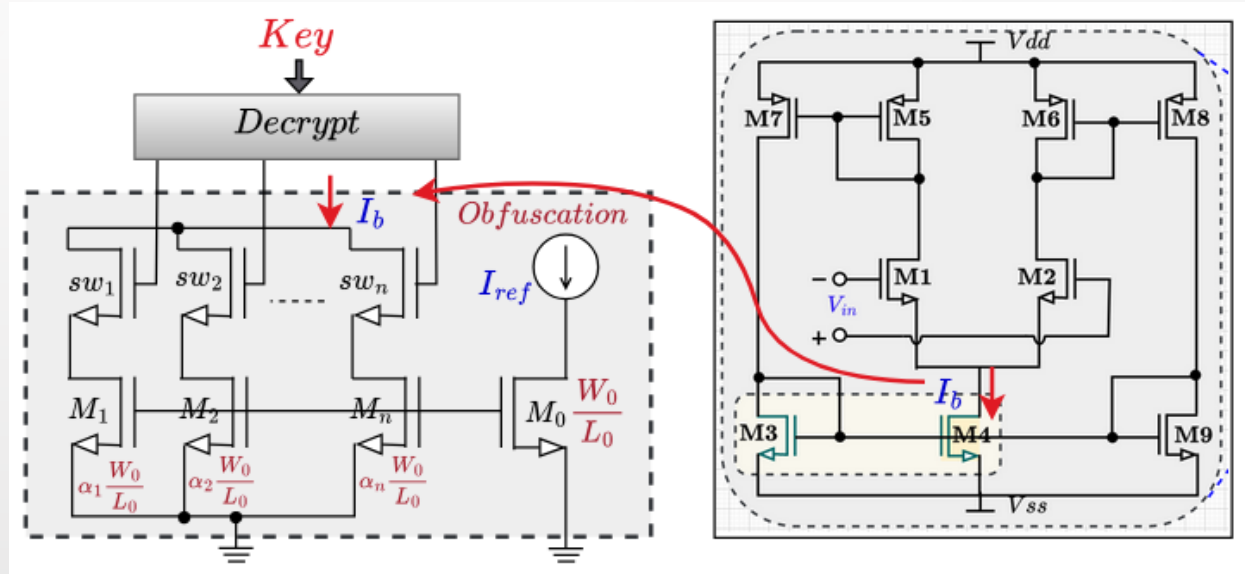
- Security Analysis of circuit obfuscation
- Predicting Unknowns that are obscured in reverse engineering<sup>[1]</sup>
- Trojan Detection <sup>[2]</sup>

[1] Jain, Dipali, Guangwei Zhao, Rajesh Datta, and Kaveh Shamsi. "Towards Machine-Learning-based Oracle-Guided Analog Circuit Deobfuscation." In *2024 IEEE International Test Conference (ITC)*, pp. 323-332. IEEE, 2024.

[2] Datta, Rajesh Kumar, Guangwei Zhao, Dipali Jain, and Kaveh Shamsi. "On Hardware Trojan Detection using Oracle-Guided Circuit Learning." In *Proceedings of the Great Lakes Symposium on VLSI 2024*, pp. 198-203. 2024.

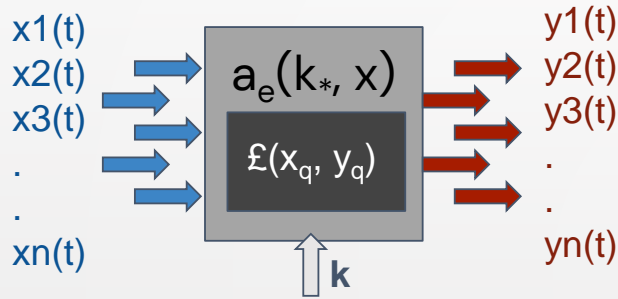
# Analog Circuit Obfuscation.

Obfuscating a current mirror circuit used to bias an amplifier



# Equation (Analytical) Based Approach

## Time-independent analog circuit :



$$f_j(x_n, k_n, s_n) = y_n$$

$x_n$  = query inputs

$k_n$  = unknowns

$s_n$  = intermediate variables

$y_n$  = observables

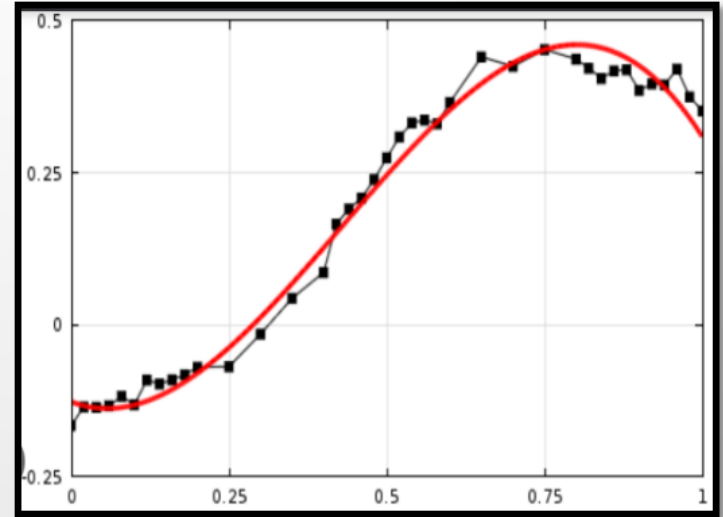
- Static: Nonlinear Programming (NLP)

## Time-dependent analog circuit :

- Dynamic: Differential-Algebraic Equations (DAEs), with time derivatives of  $x(t)$ ,  $y(t)$ ,  $s(t)$

# Optimal Control Approach

- Finding the optimal value of the set of unknown parameters  $k$ ,
- Solutions to DAEs are sufficiently close to a set of desired curves.
- Larger systems involve performing numeric integration with new  $k_n$  created at every time point
- Using NLP to solve expanded system of equations optimize for the desired fitness function



# Deobfuscation Via ML and Optimization

## Motivation

- Eliminate the need for manual derivation of circuit equations
- Published SMT-based attack:
  - equations are extracted by hand that relate unknowns to specific observations
- Emerging trend in analog EDA domain:
  - use of end-to-end and graph-based machine learning to replace tasks like:
    - SPICE simulation
    - Parameter optimization

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# Overall Flow

## Dataset Generation

### Training

**Obfuscated circuit ( $a_e(k,x)$ )**

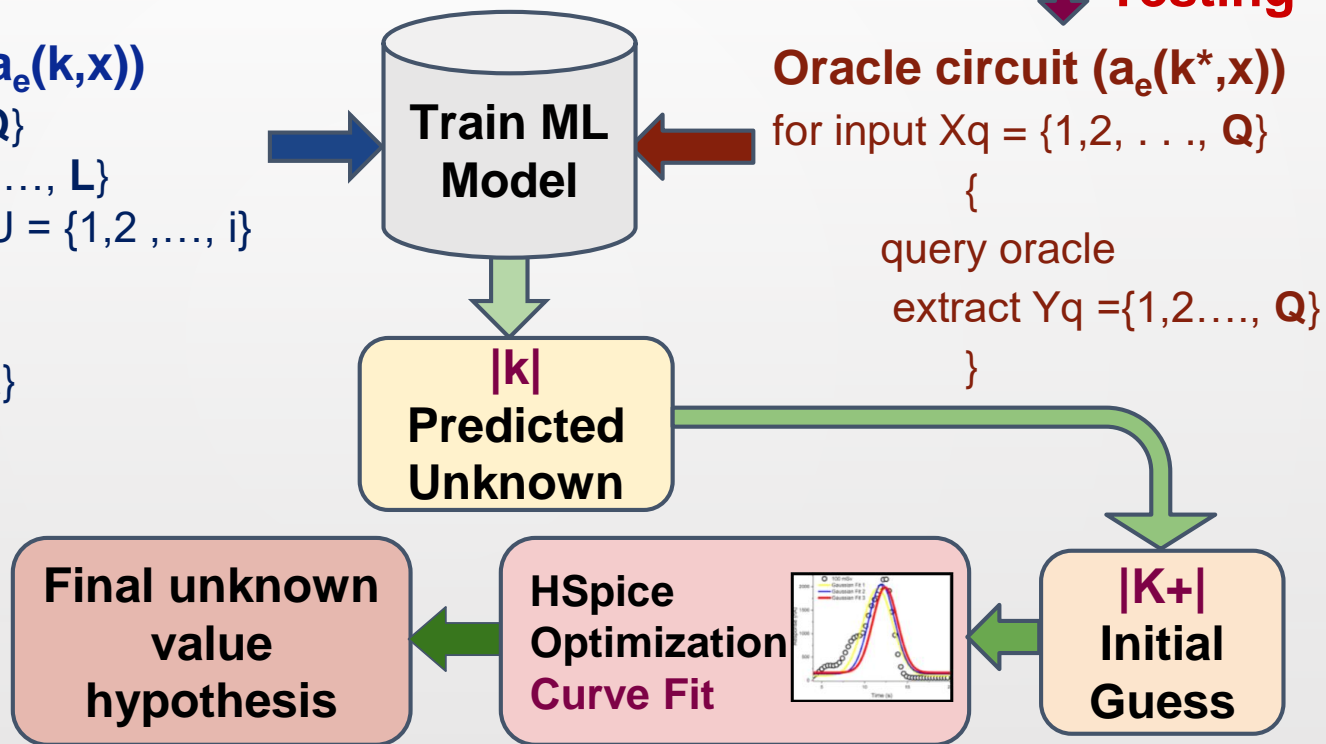
for input  $X_q = \{1, 2, \dots, Q\}$   
for unknown  $K = \{1, 2, \dots, L\}$   
for random choice  $U = \{1, 2, \dots, i\}$   
{  
perform simulation  
extract  $Y_q = \{1, 2, \dots, Q\}$   
}  
+

**Data Augmentation  
with PV:  $U(LQ)$**

### Testing

**Oracle circuit ( $a_e(k^*,x)$ )**

for input  $X_q = \{1, 2, \dots, Q\}$   
{  
query oracle  
extract  $Y_q = \{1, 2, \dots, Q\}$   
}



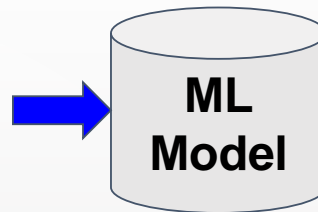
# ML Feature Vector

$Xq \rightarrow$  set of  $Q$  input queries,

$Yq \rightarrow$  output observations

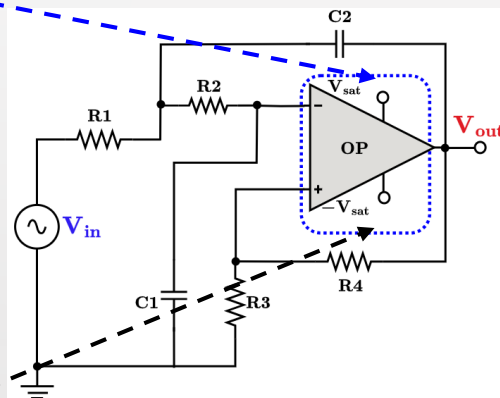
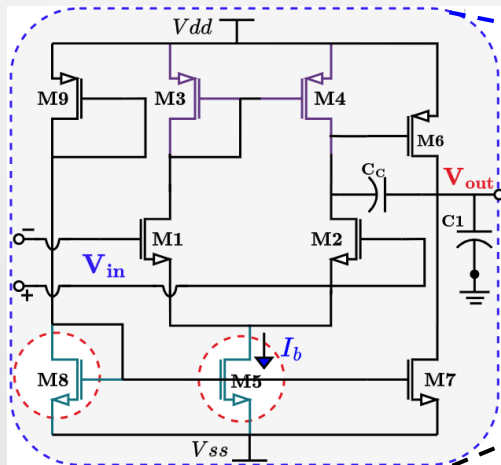
$ae \rightarrow$  obfuscated circuit

$[ae(Xq) \rightarrow Yq]$



$k+$   
hypothesis key

## Second-Order Low Pass Filter



**Fin** :  $[ V_{ac} , V_{dc} , G_o(f_1), \dots G_o(f_{25}), f_c, K, R_1, R_2, C_1, W_1/L_1, W_2/L_2, W_3/L_3, dev\_count, num\_cap, num\_resi, num\_trans ]$

**Target Unknown:**  $Wk_5/Lk_5, Ck_2.$

# Hybrid Approach

## Benefits:

- **Convergence.**

- Better convergence with the ML-produced initial guess.

- **More than One-Shot.**

- There is no feedback or adjustment over the solution in ML.

- **Dealing with High Dimensionality.**

- ML approach as a standalone additionally suffers from the curse of dimensionality when the number of unknowns is large.

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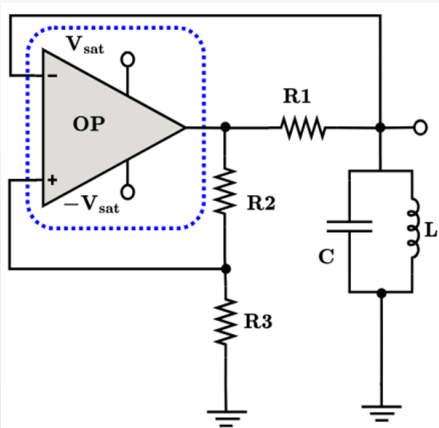
# Experiments and Results

- ML Model:
  - RF
  - Figure of merit (PE):  $(y_p - y_t)/y_t \times 100$
- Star-HSpice optimization.
  - curve-fitting optimization: 20 points from transient simulations.
  - goal-based optimization: user-defined variables to hit certain targets (settling time, rise time, etc.)
    - requires providing a data file with the target values, an input netlist file, optimization parameters, component limits, and (critical to our hybrid scheme) an initial guess

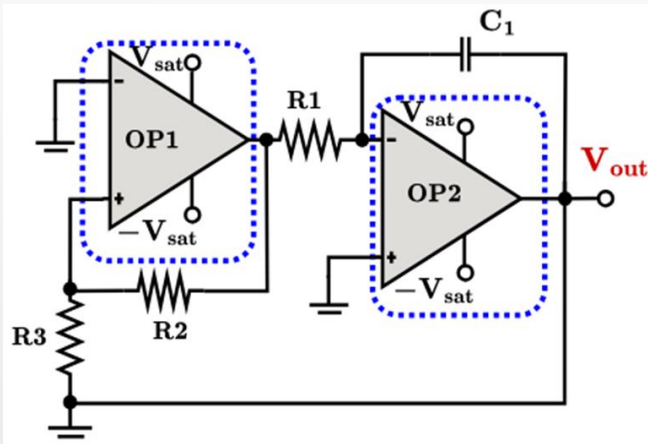
# Benchmark Circuits

## Oscillators

LCO



TWG



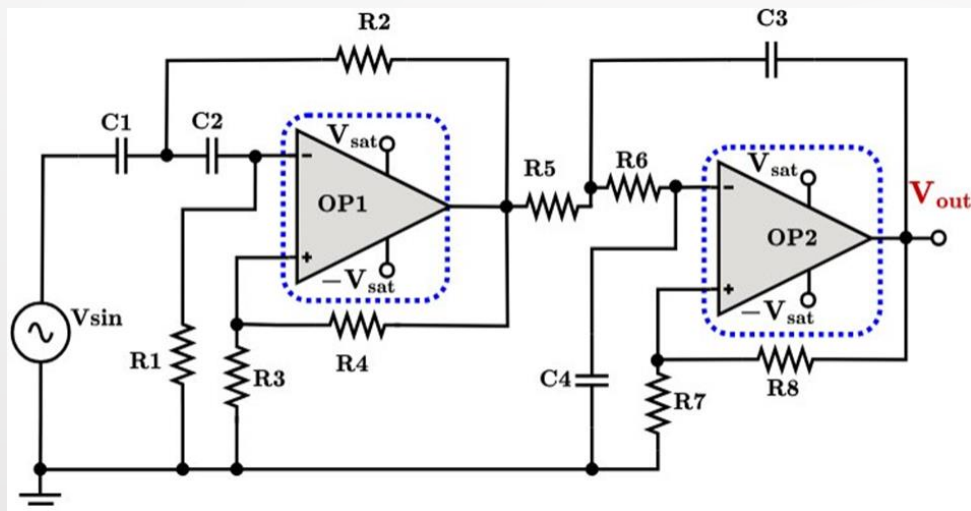
# samples 10000 in 103.6  
seconds for 2 unknowns

samples 10000 in 119.3  
seconds for 3 unknowns

	LCO		TWG		
	U1	U2	U1	U2	U3
ML	0.4	1.3	0.1	1.6	1.8
ML(PV)	4.15	6.87	9.4	12.6	14.8
Spice	1.1	4.7	5.26	6.14	6.32
ML+ Spice	0.01	0.12	0.01	0.25	0.72

# Benchmark Circuits

## Fourth order Butterworth Sallen Key Band Pass Filter

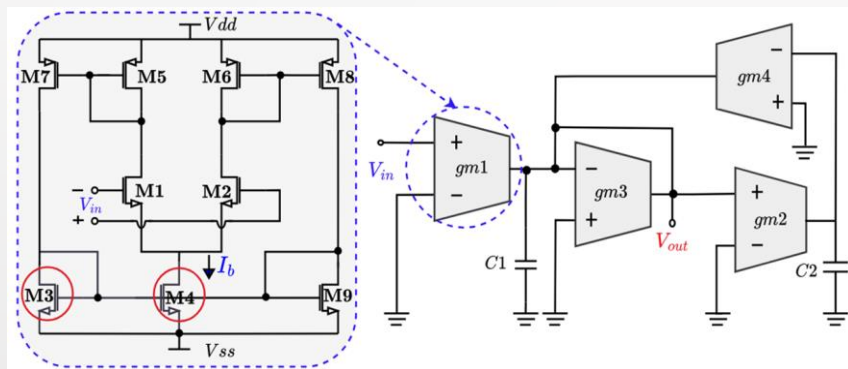


# samples 32400 in 535.4 seconds for 4 unknowns

	FOSKBPF			
	U1	U2	U3	U4
ML	3.92	2.83	3.45	4.34
ML(PV)	14.7	20.1	20.0	23.3
Spice	6.49	2.71	4.66	1.24
ML+ Spice	1.33	1.21	1.68	1.91

# Benchmark Circuits

## Second order Gm-C Band Pass Filter using OTA with CCM supplying the bias current [3]



# samples 1500 in 103.6 seconds for 6 unknowns

	GmC-BPF					
	U1	U2	U3	U4	U5	U6
ML	3.4	3.7	4.8	5.9	5.8	6.6
ML(PV)	9.2	10.0	12.5	13.8	14.6	16.0
Spice	2.09	1.24	4.55	5.22	9.18	2.89
ML+ Spice	1.8	1.07	1.32	1.66	1.21	1.01

[3] N. G. Jayasankaran et al, "Breaking Analog Locking Techniques via Satisfiability Modulo Theories," 2019 IEEE International Test Conference (ITC), Washington, DC, USA, 2019, pp. 1-10, doi: 10.1109/ITC44170.2019.9000113.

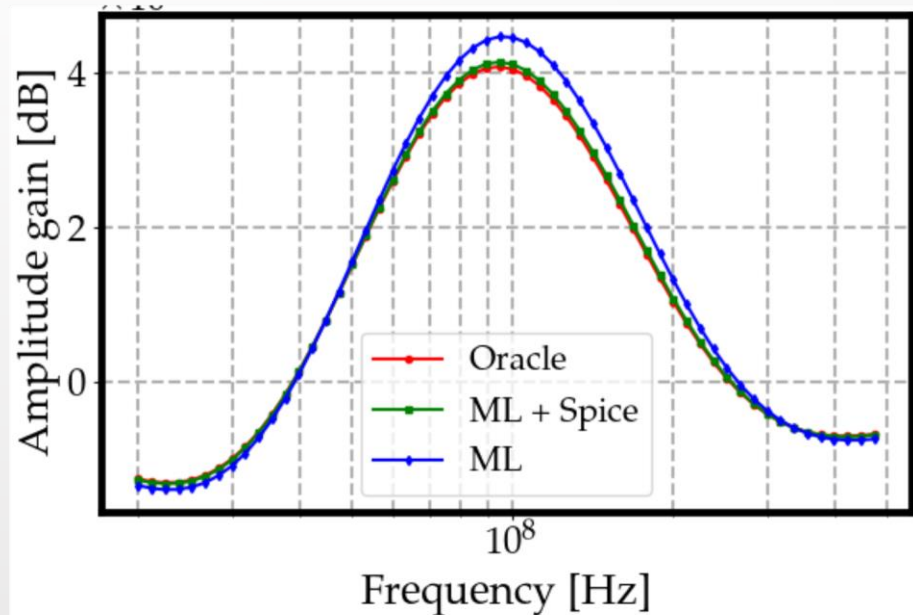
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# Discussion

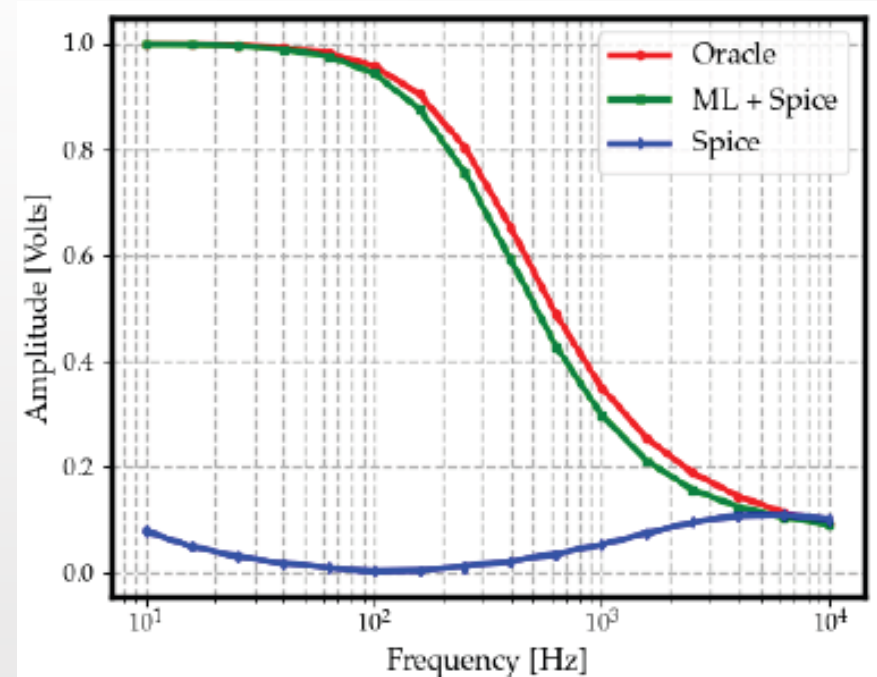
**FOGmBPF** simulation for Oracle circuit, by substituting

- values of unknowns predicted by ML model
- values of unknowns predicted using a hybrid ML+Spice approach



# Discussion

Spice optimizer solution for the **Second Order LPF** when plugged into the circuit diverges from the oracle at lower frequencies indicating a local optima trap. The ML+Spice flow however avoids this.



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# Conclusion

- First use of a hybrid machine learning and optimization approach to automated generic analog circuit deobfuscation
- Does not rely on manual equation extraction and analysis by an expert.
- The automated flow based on using an ML-produced guess as an initial value in a subsequent Newton method optimization loop
- Demonstrated superior accuracy and runtime compared to either method as a standalone, especially in the presence of process variation.

# Acknowledgement

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Thank you

Questions?

