FACULTY OF ENGINEERING
AND ARCHITECTURE

DEPARTMENT OF INFORMATION TECHNOLOGY
RESEARCH GROUP ELECTROMAGNETICS

A NOVEL METHODOLOGY TO CREATE GENERATIVE STATISTICAL MODELS OF INTERCONNECTS

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OUTLINE

- Current Issues
- Proposed model
- Applications
  - Multiconductor Transmission Line
  - Connector footprint
  - Cascade of components
  - Time domain
- Conclusion

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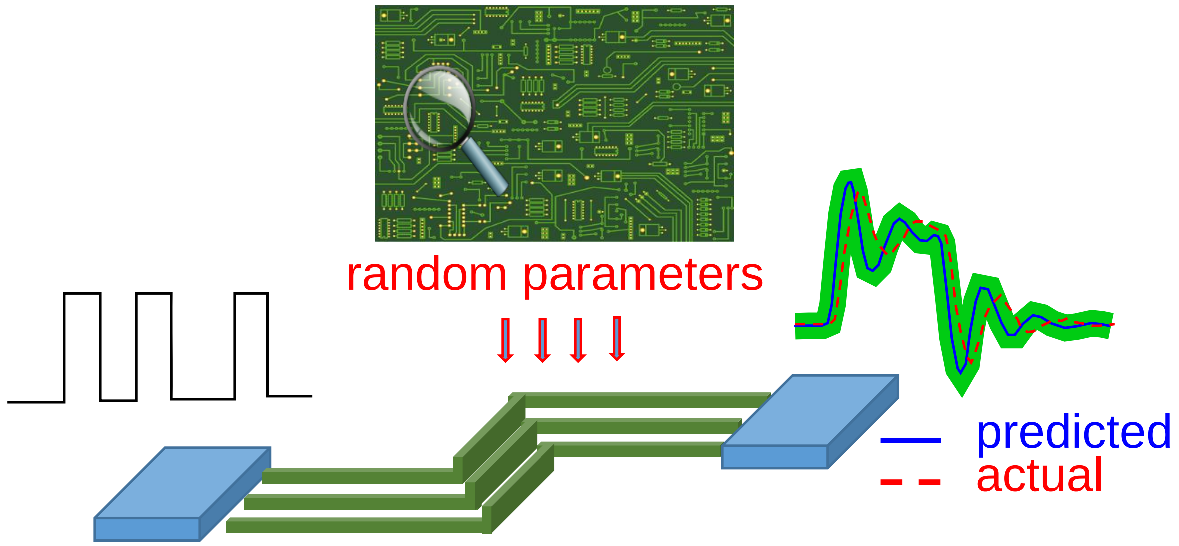
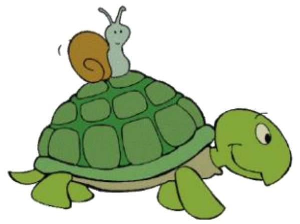
CURRENT ISSUES



- **Variability** is introduced by the manufacturing process



- **Monte Carlo** analysis (measurement/simulation) can be slow to impossible

- **Source of variability** is often unknown or difficult to determine

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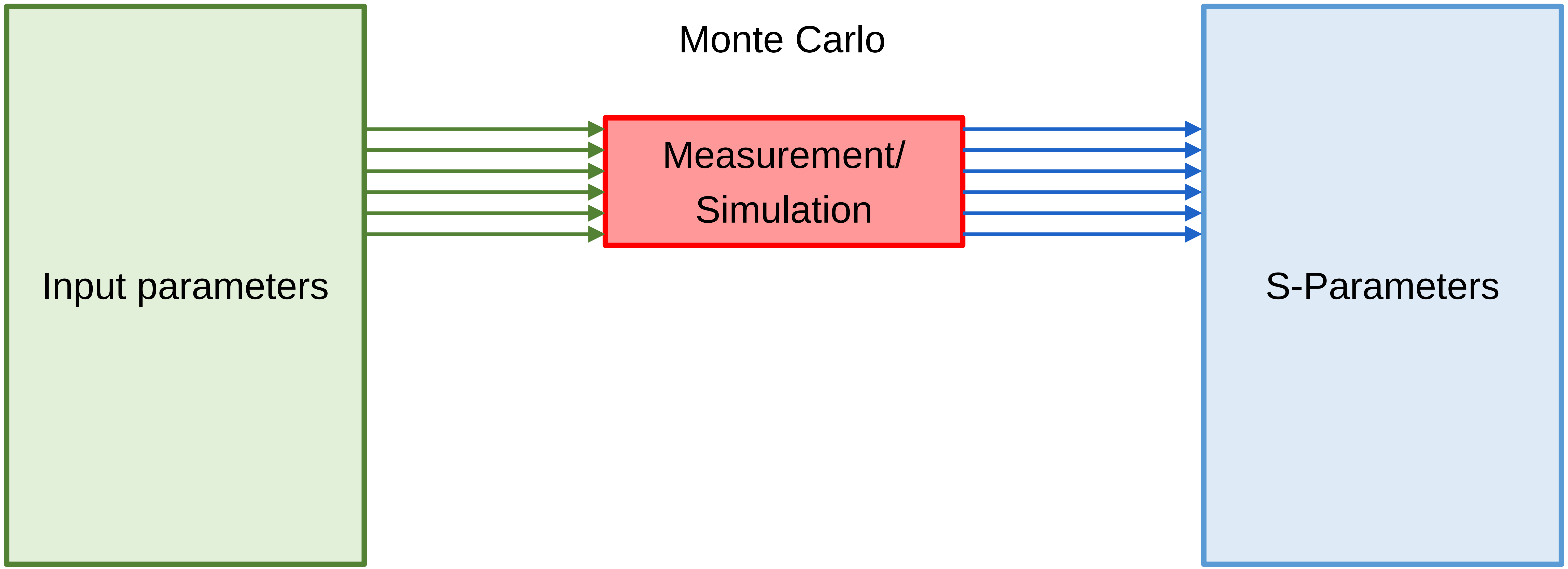
CURRENT SOLUTIONS



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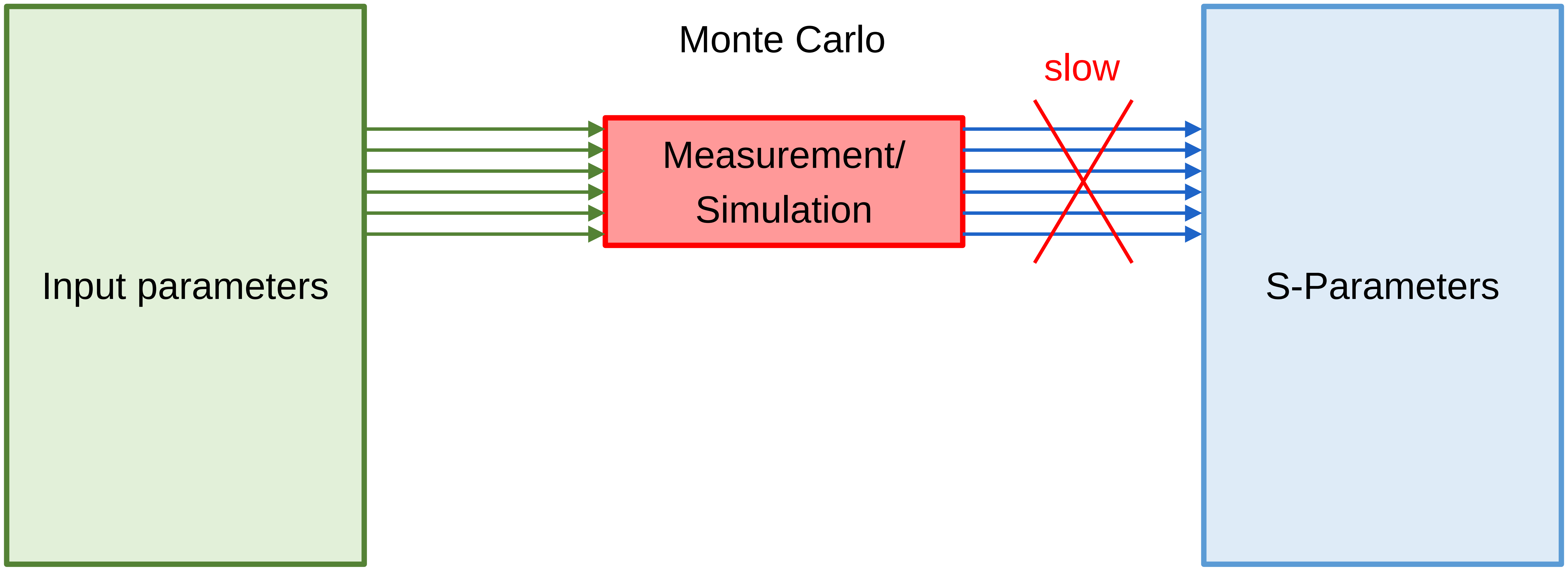
CURRENT SOLUTIONS



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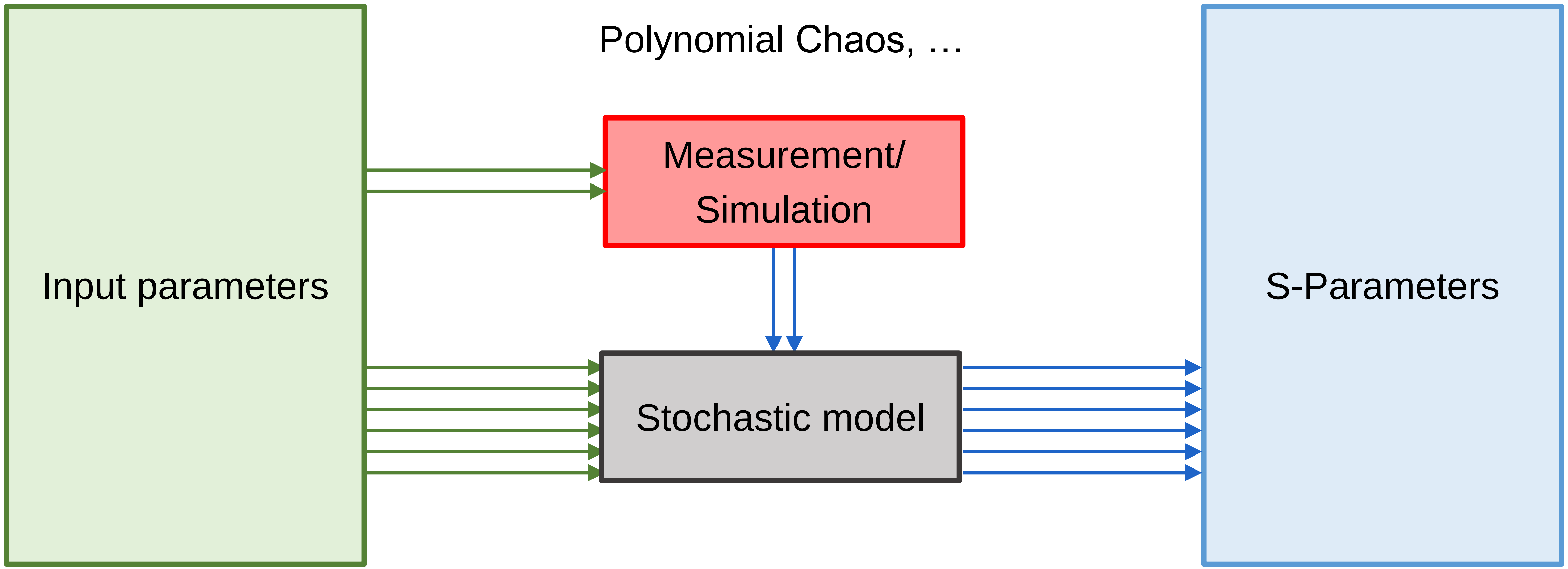

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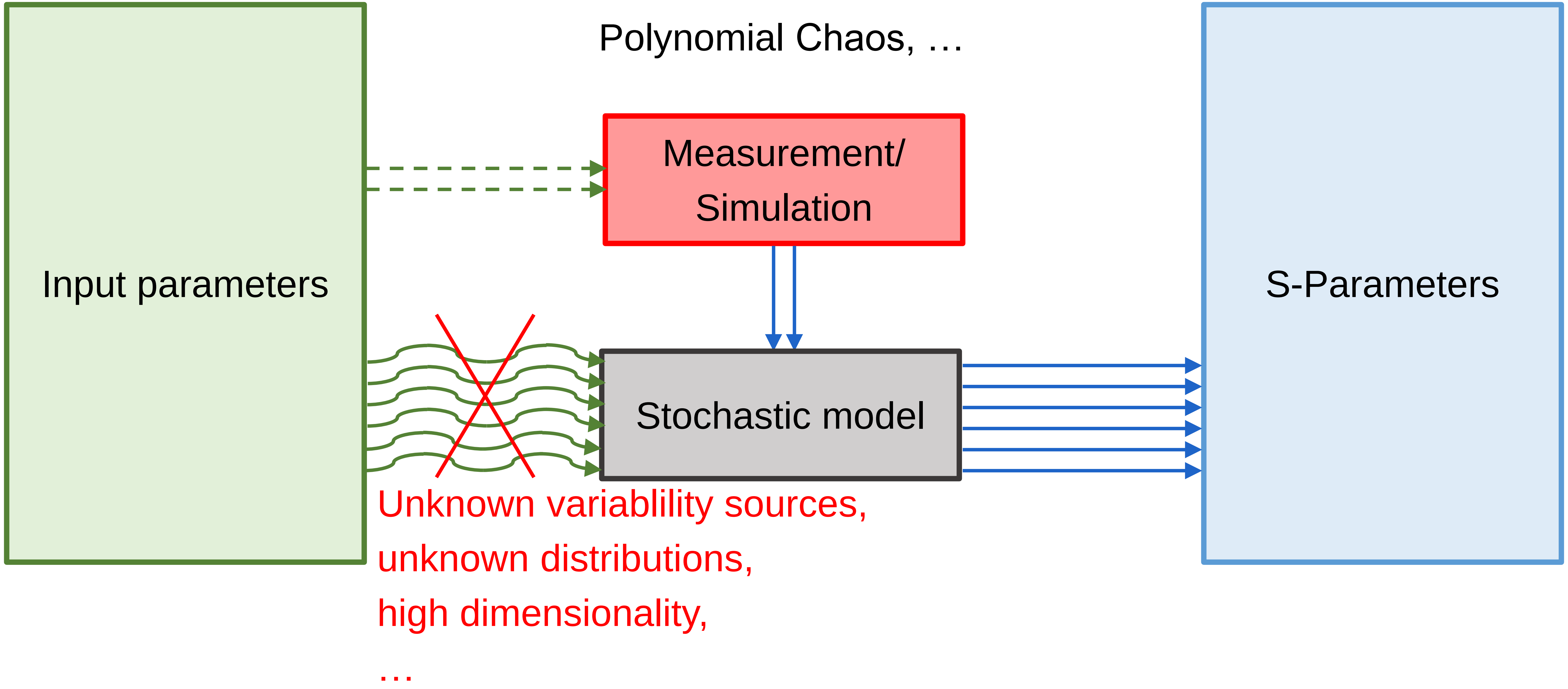
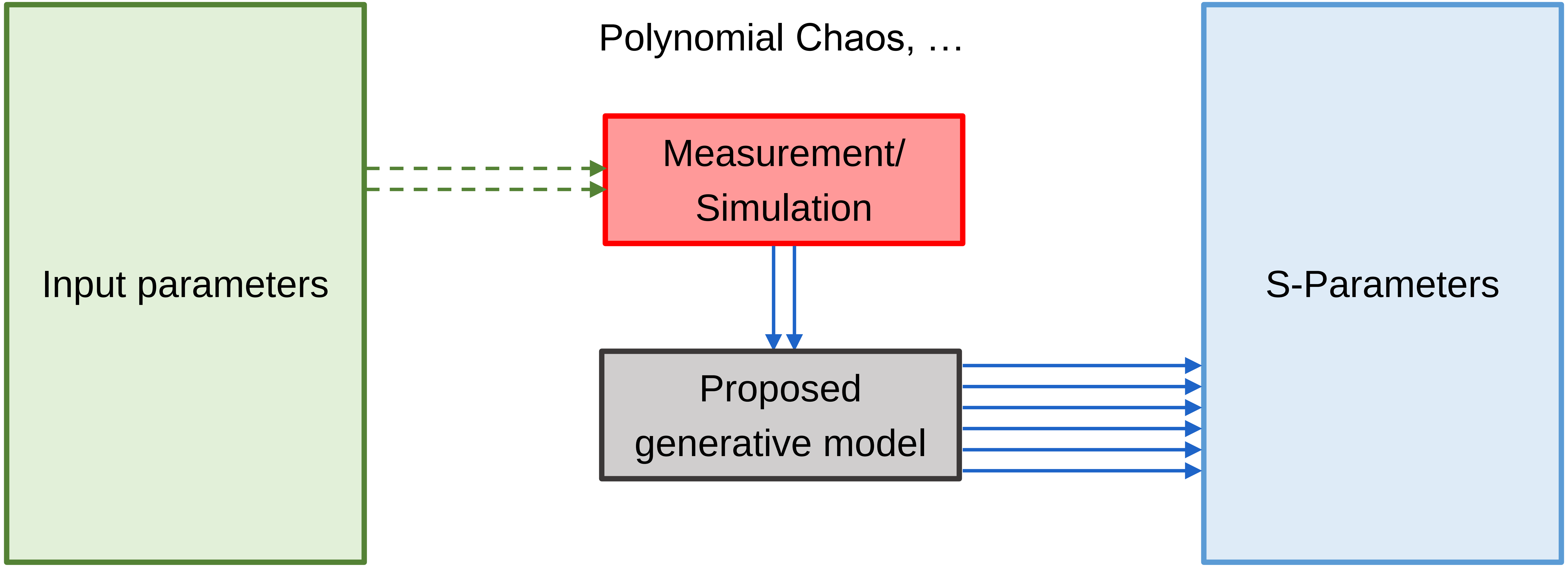


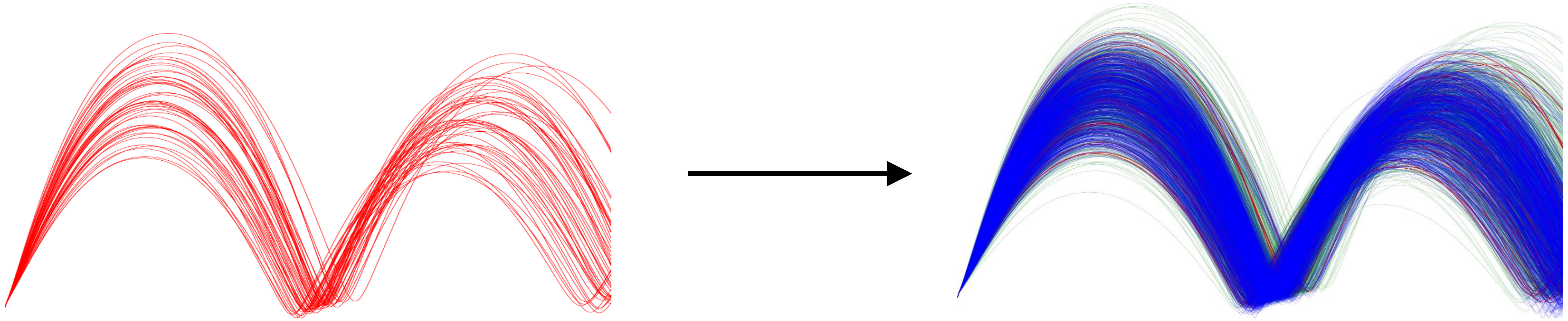
CURRENT SOLUTIONS



PROPOSED SOLUTION

To overcome these issues, we propose the following modeling method:

small set of **expensive** training samples | **large** set of **cheap** generated samples



Three-step model:

- **Vector Fitting** (VF)
- **Principal Component Analysis** (PCA)
- **Kernel Density Estimate** (KDE)

Selection of **passive samples** in post-processing

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PROPOSED MODEL

➢ **Vector Fitting [1,2]:**

Expand S-parameters of training samples into partial fractions:

$$\bar{\bar{S}} \approx \sum_{k=1}^{N} \frac{\overline{\overline{R_k}}}{s - a_k}$$

with **stable**, complex conjugate pole pairs a_k, and common poles for all training samples

➔ Set of N residue matrices $\overline{\overline{R_k}}$ for each training sample (frequency-independent)

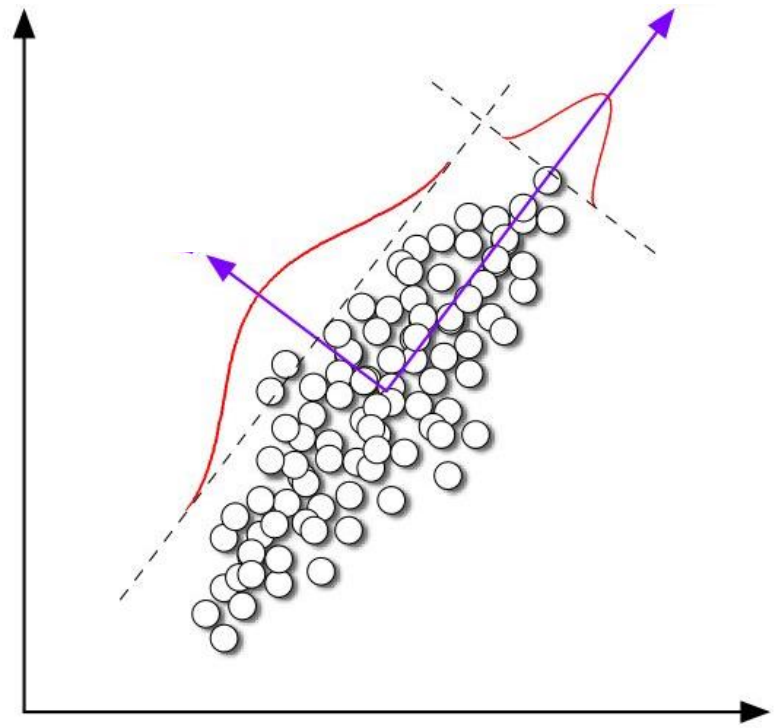
[1] B. Gustavsen and A. Semlyen, IEEE Transactions on Power Delivery, vol. 14, pp. 1052-1061 (1999)
[2] D. Deschrijver et al., IEEE Microwave and Wireless Components Letters, vol. 18, pp. 383–385 (2008)

PROPOSED MODEL

➢ **Principal Component Analysis (PCA) [3,4]:**

N $(N_p \times N_p)$ complex symmetric matrices $\overline{\overline{R_k}}$ → $NN_p(N_p+1)$ real variables

➔ Apply PCA to reduce dimensionality and remove linear correlations



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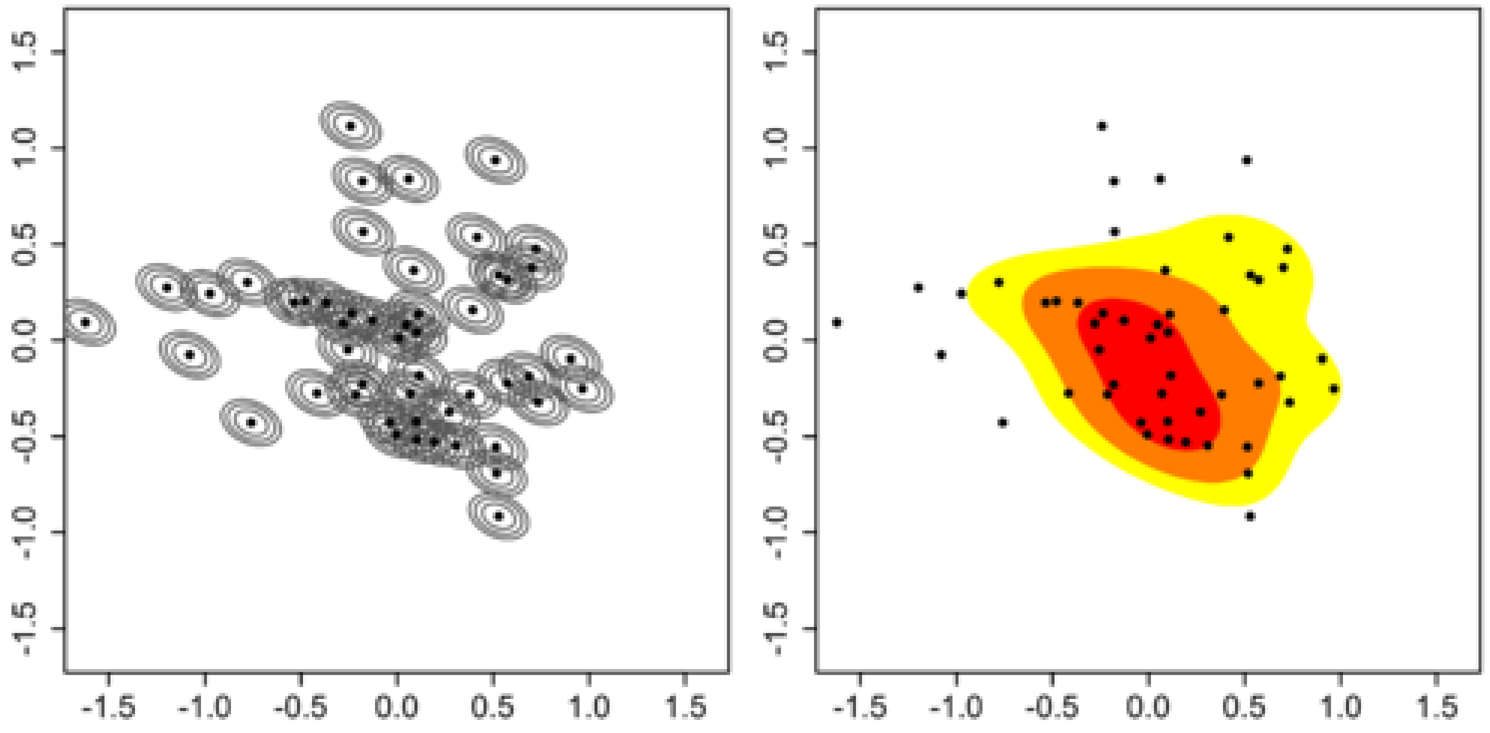
[3] H. Hotelling, Journal of Educational Psychology, vol. 24, pp. 417–441 (1933)
[4] H. Abdi and L. J. Williams, Wiley Interdisciplinary Reviews: Computational Statistics, vol. 2, pp. 433-459 (2010)

PROPOSED MODEL

➢ **Kernel Density Estimation (KDE) [5]:**

- Estimates a distribution by placing a multivariate 'kernel' (e.g. Gaussian) on each training point. The estimated PDF is a normalized sum of the kernels.
- models nonlinear correlations



[5] M. Kristan et al., Pattern Recognition, vol. 44, pp. 2630–2642 (2011)

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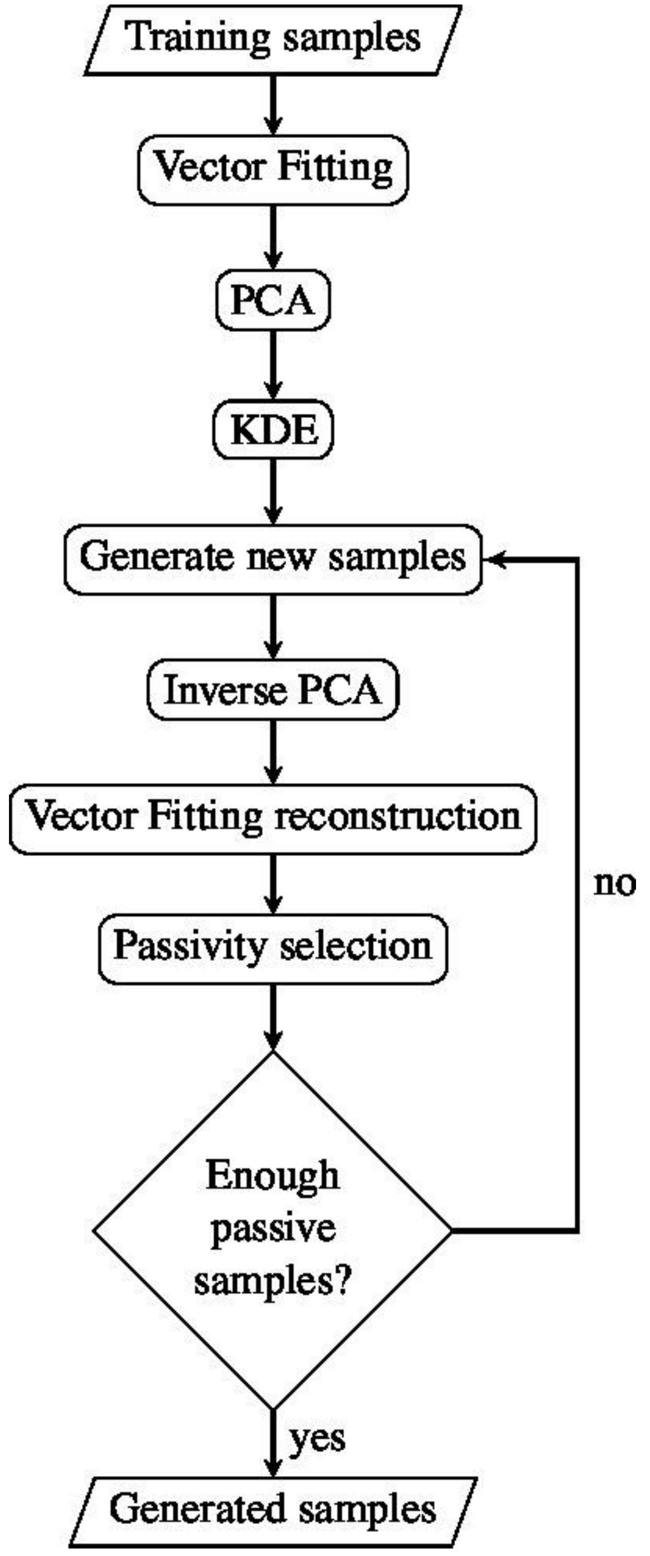
PROPOSED MODEL

Generative model:

- Generate new samples from KDE
- After inverse PCA, build S-parameters using common poles
- **Passivity selection** in post-processing:
  - Nonpassive samples are rejected (no bias)
  - New samples are generated until goal is reached



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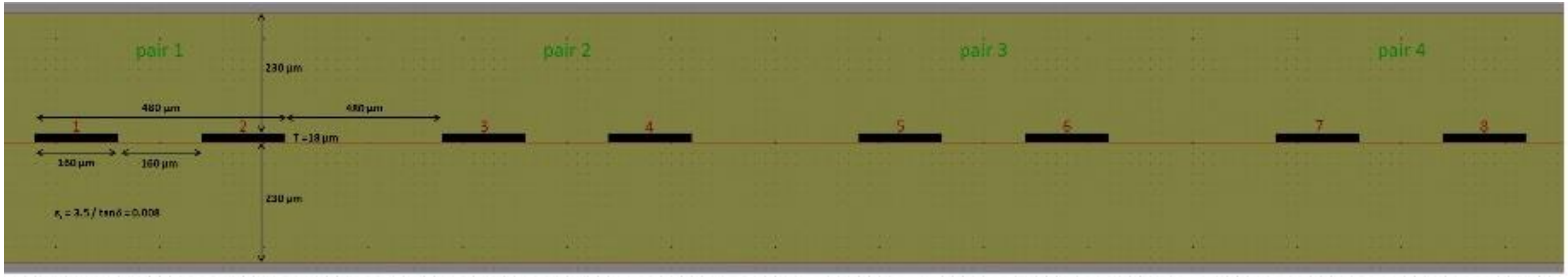
APPLICATION 1: STRIPLINE

Stripline MTL:

- 4 pairs of lines
- 16 ports
- Differential signaling
- Varying ε_r

- Modeled through RLGC-parameters
- Length: 10.0 cm
- 1000 simulated RLGC-parameters
- 50 training samples



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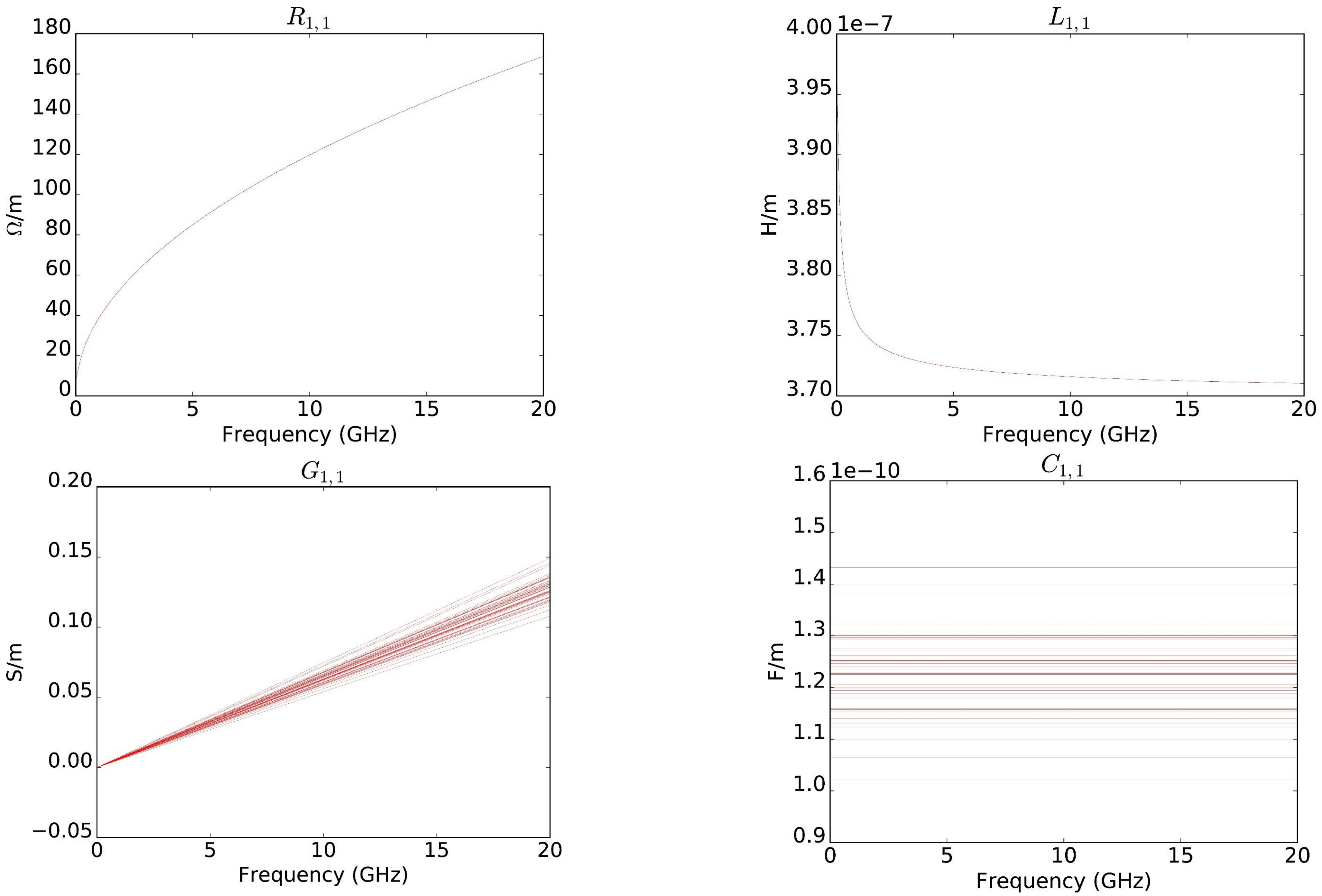
50 Training samples



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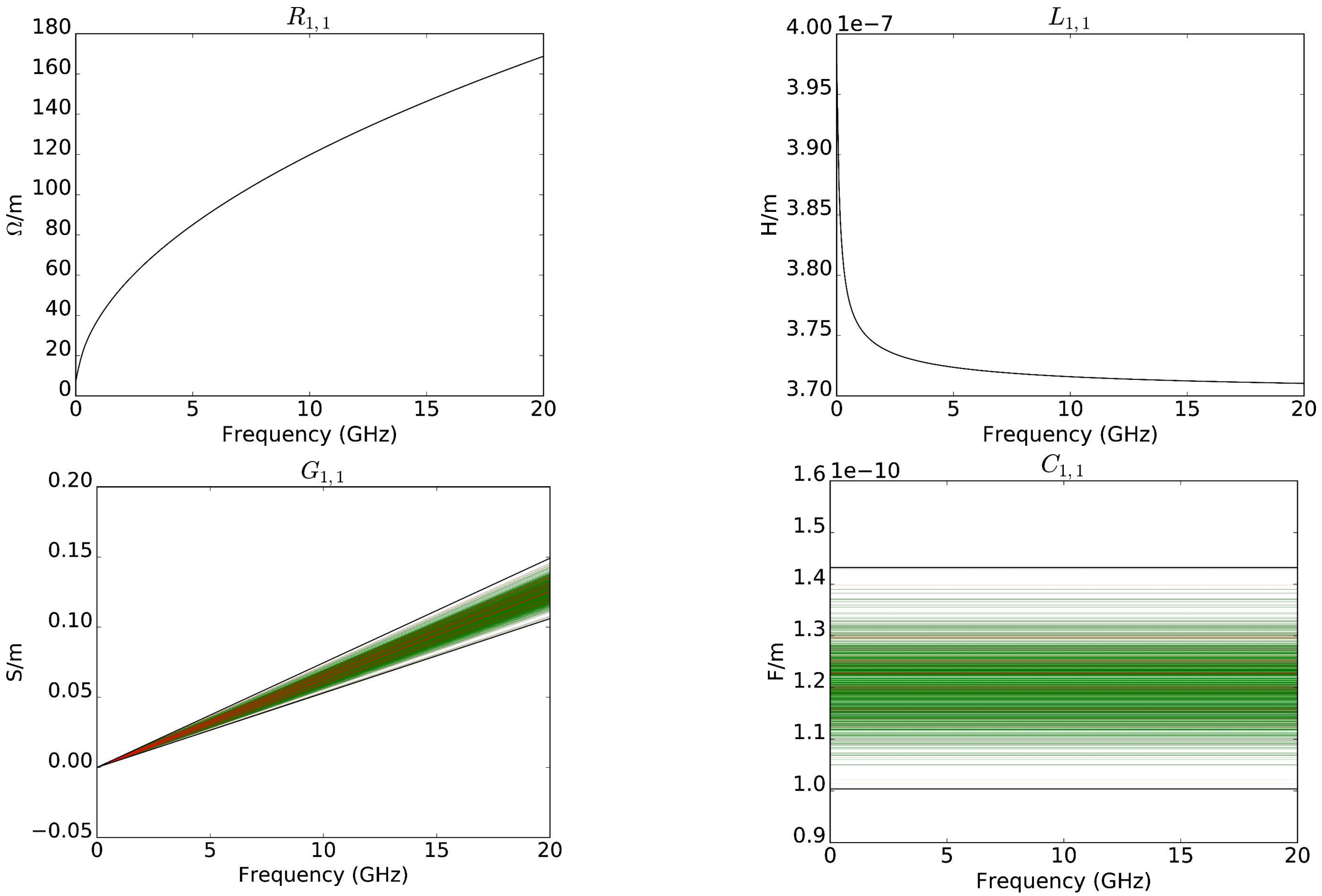

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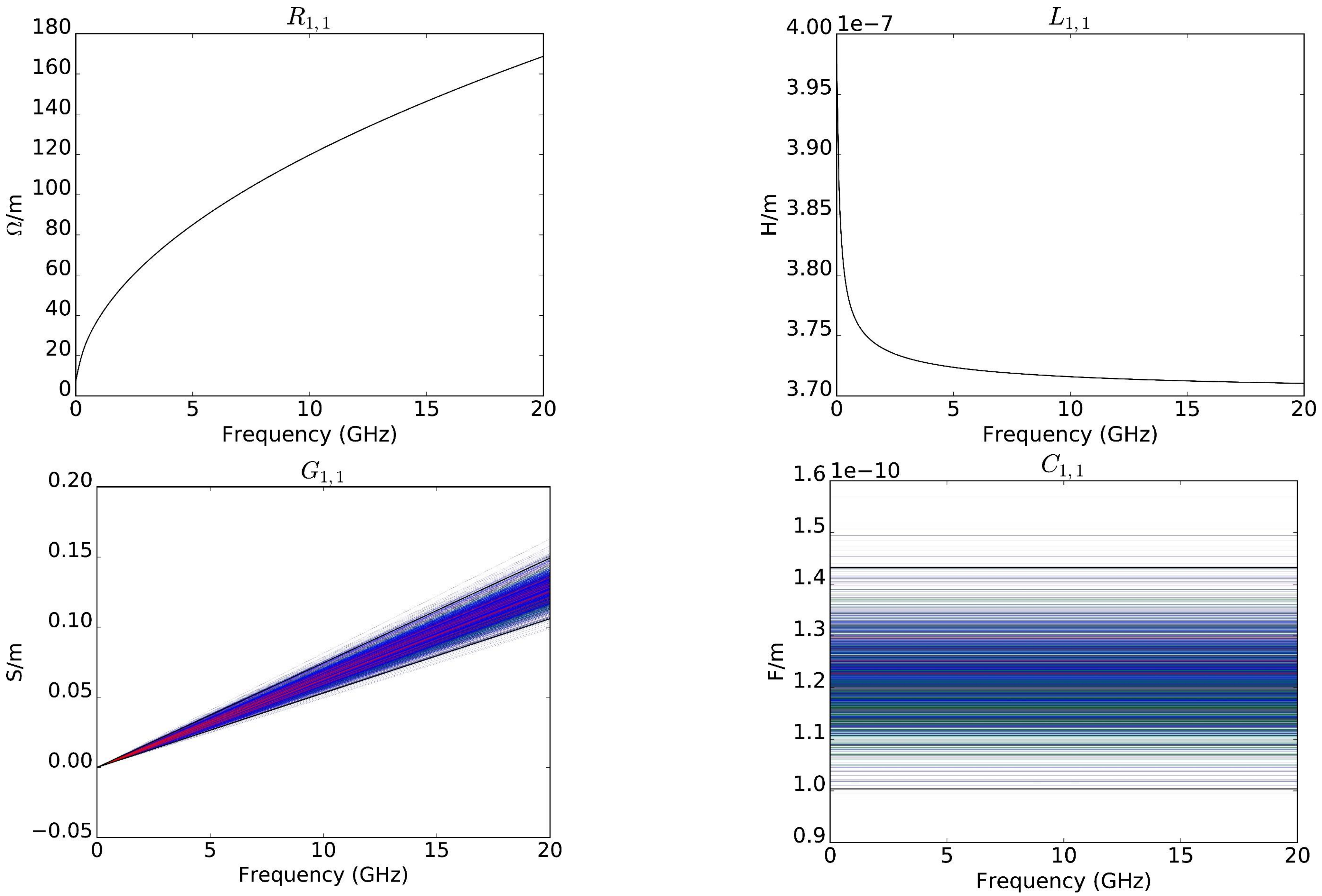

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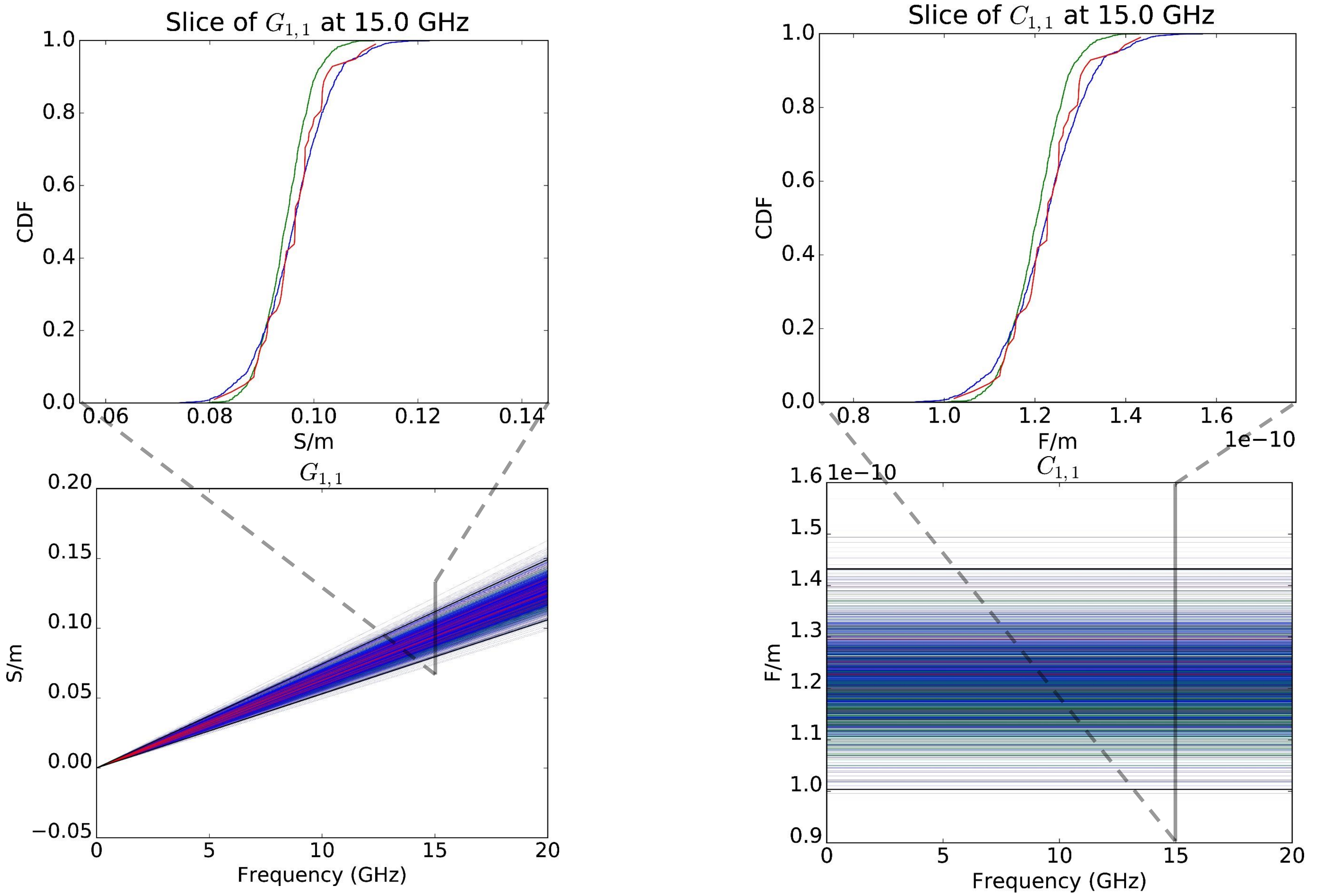

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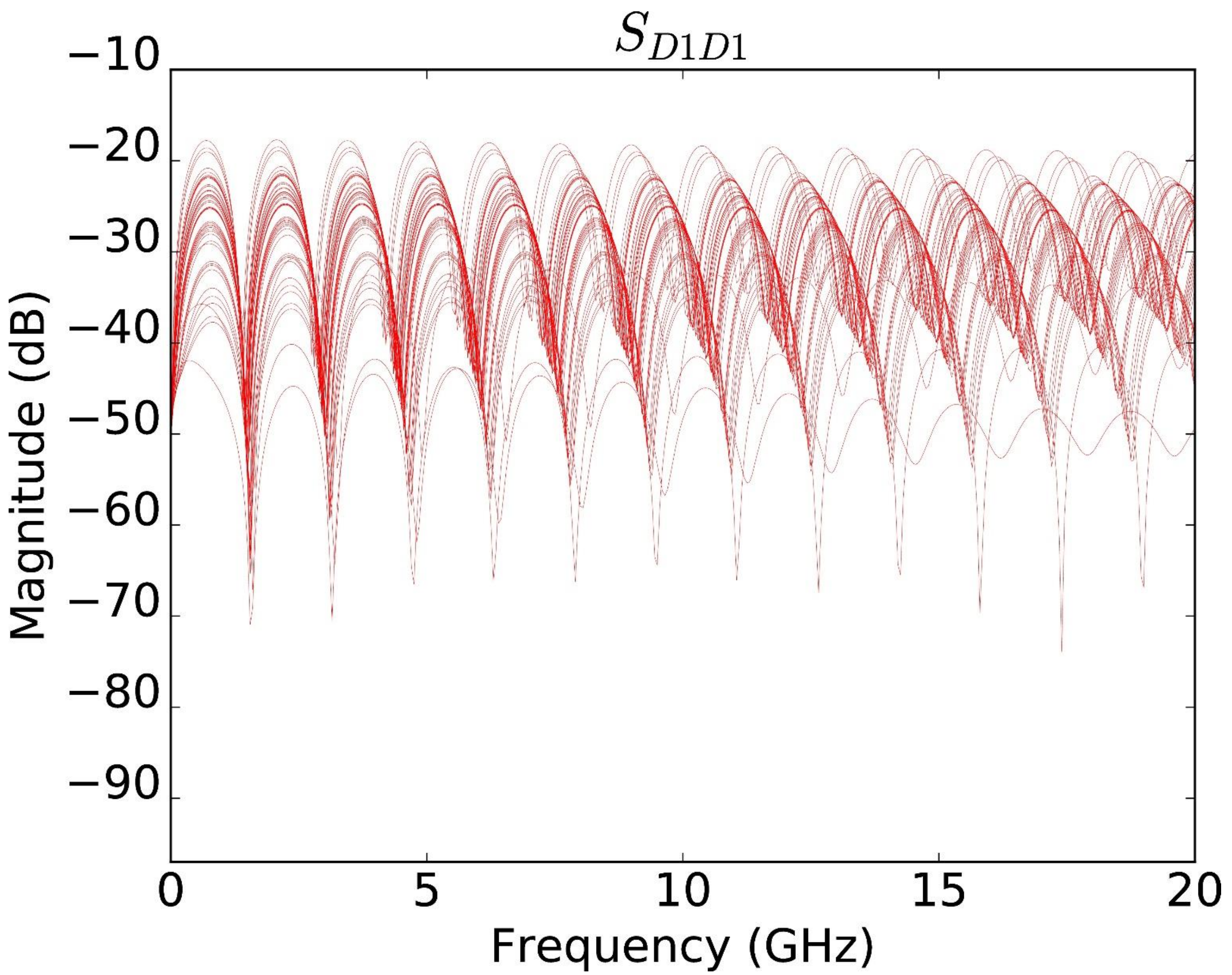

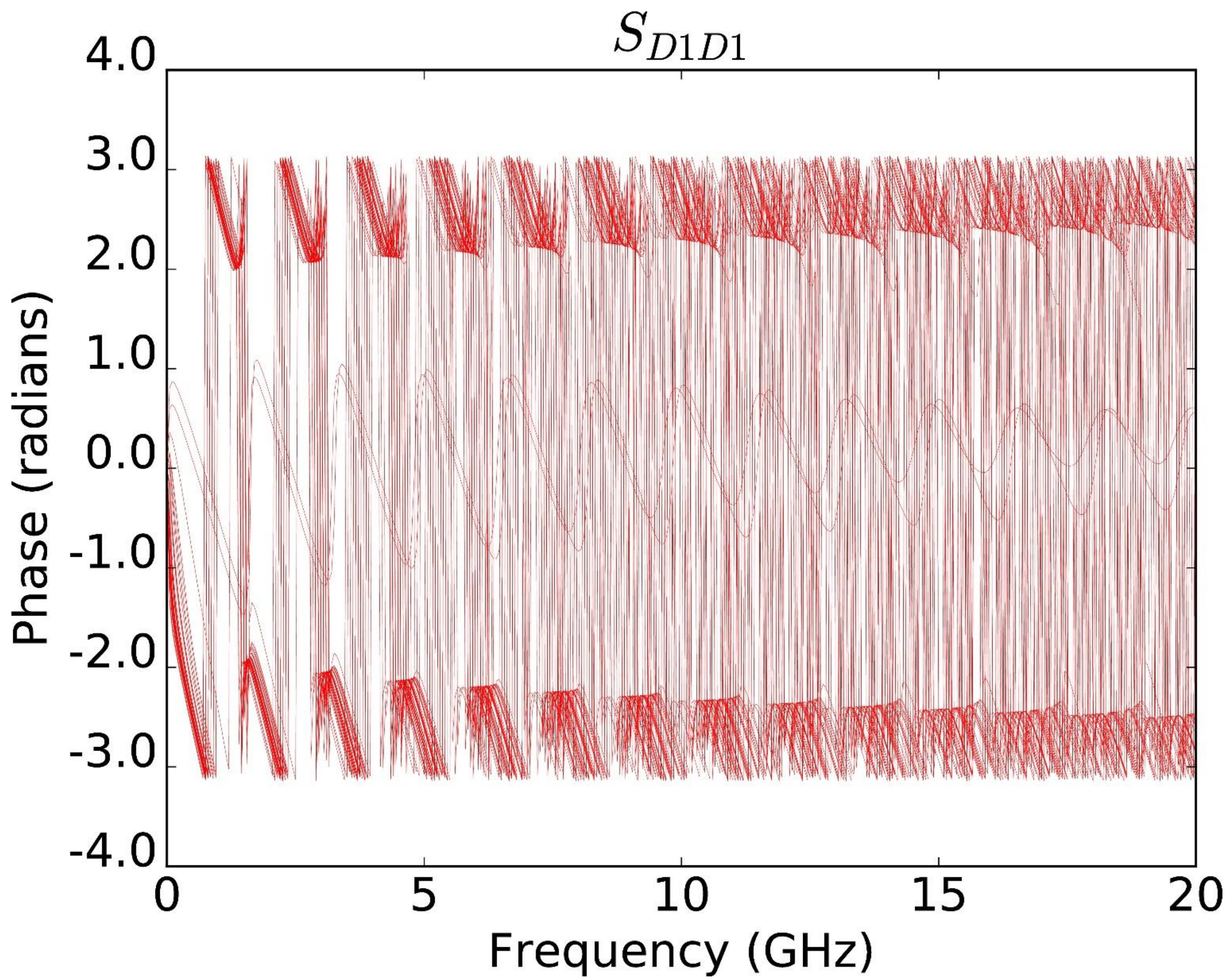

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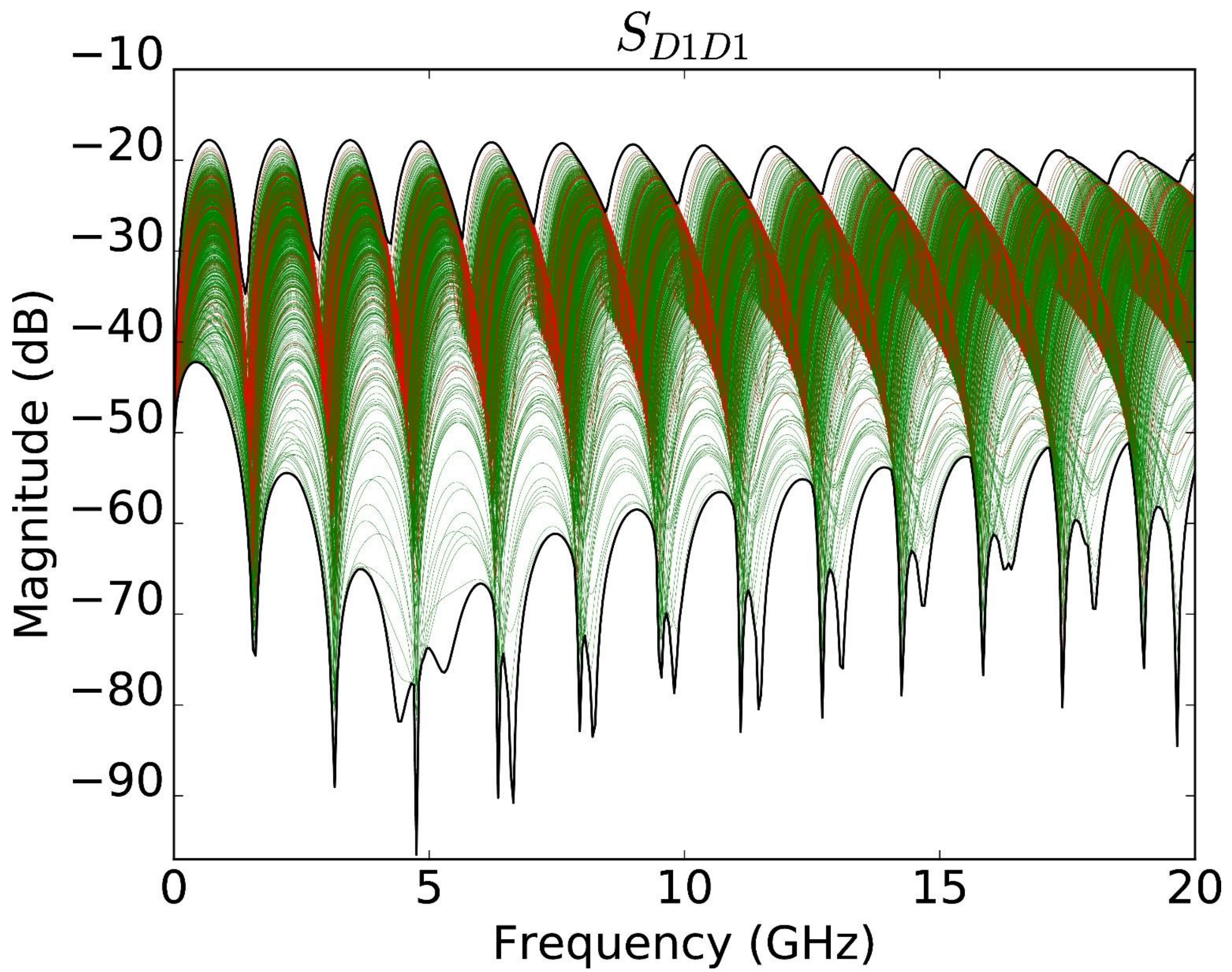

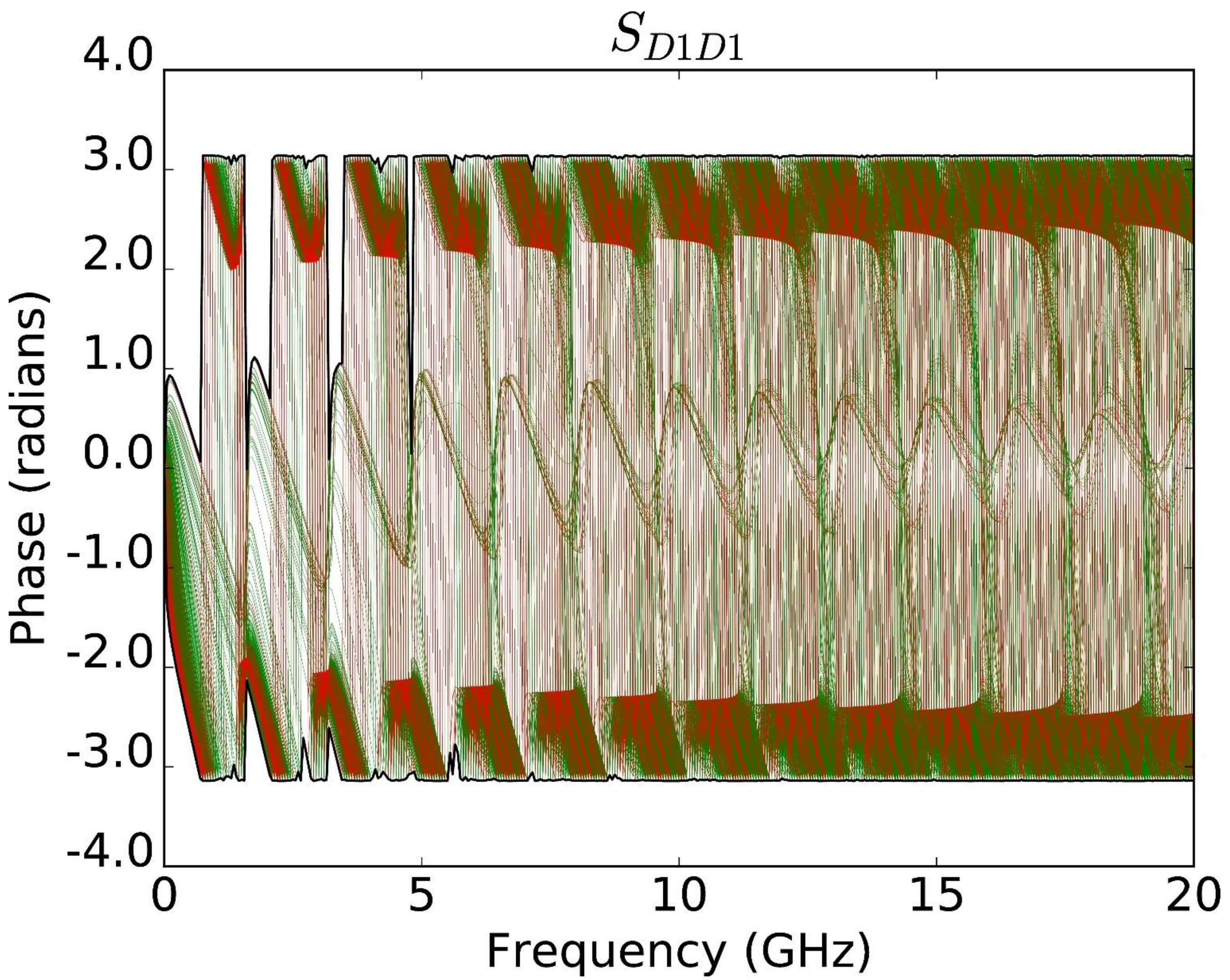

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APPLICATION 1: STRIPLINE

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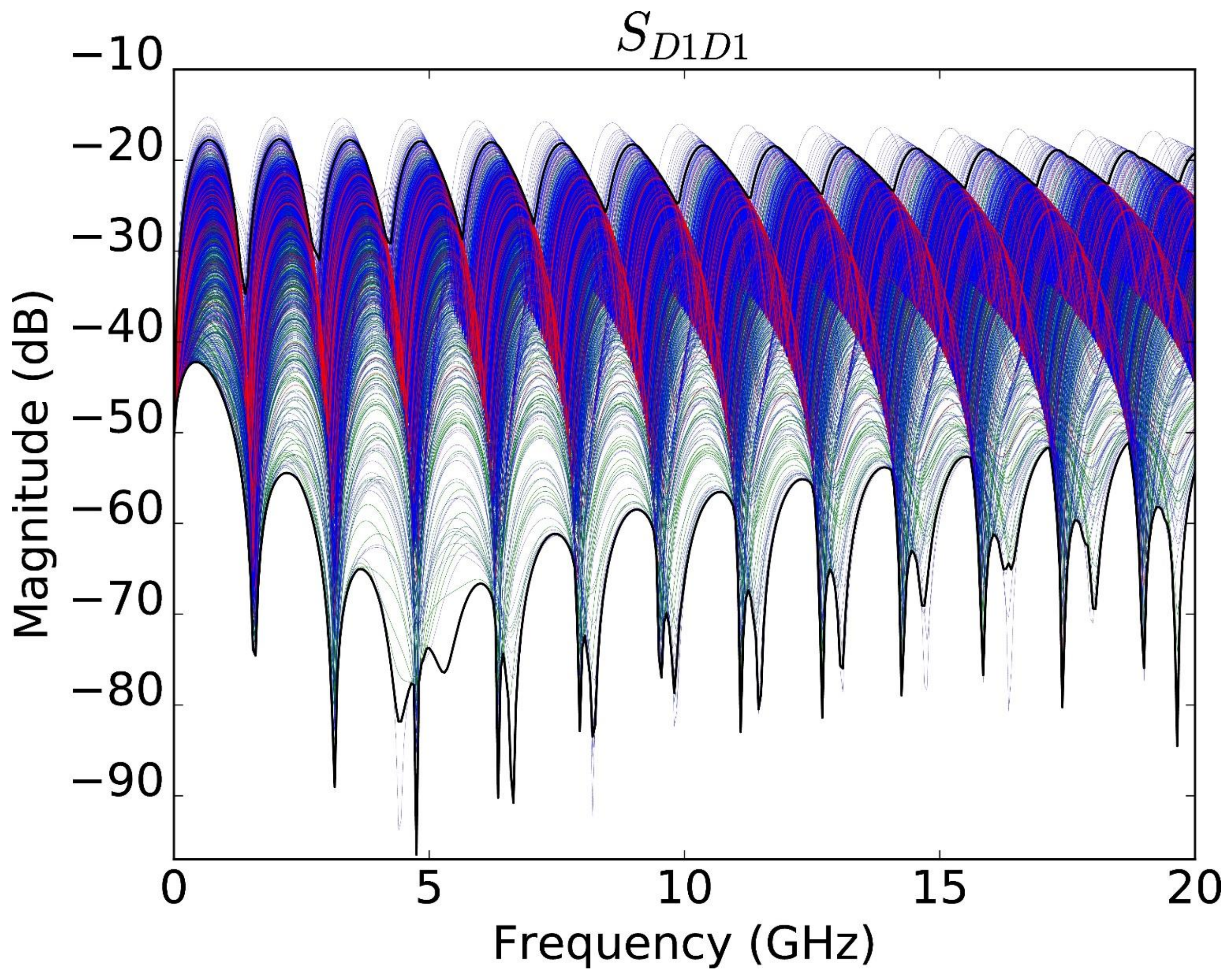

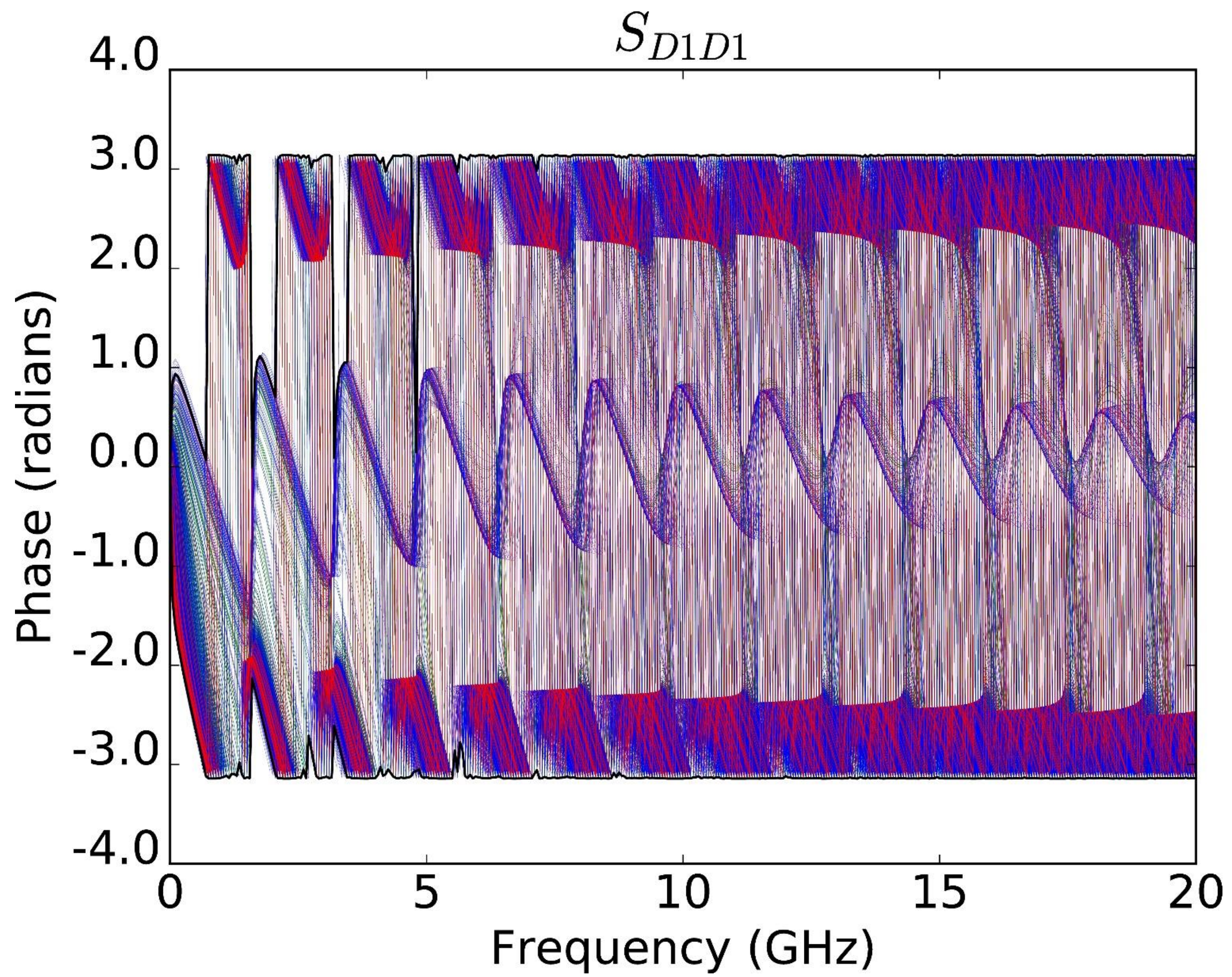

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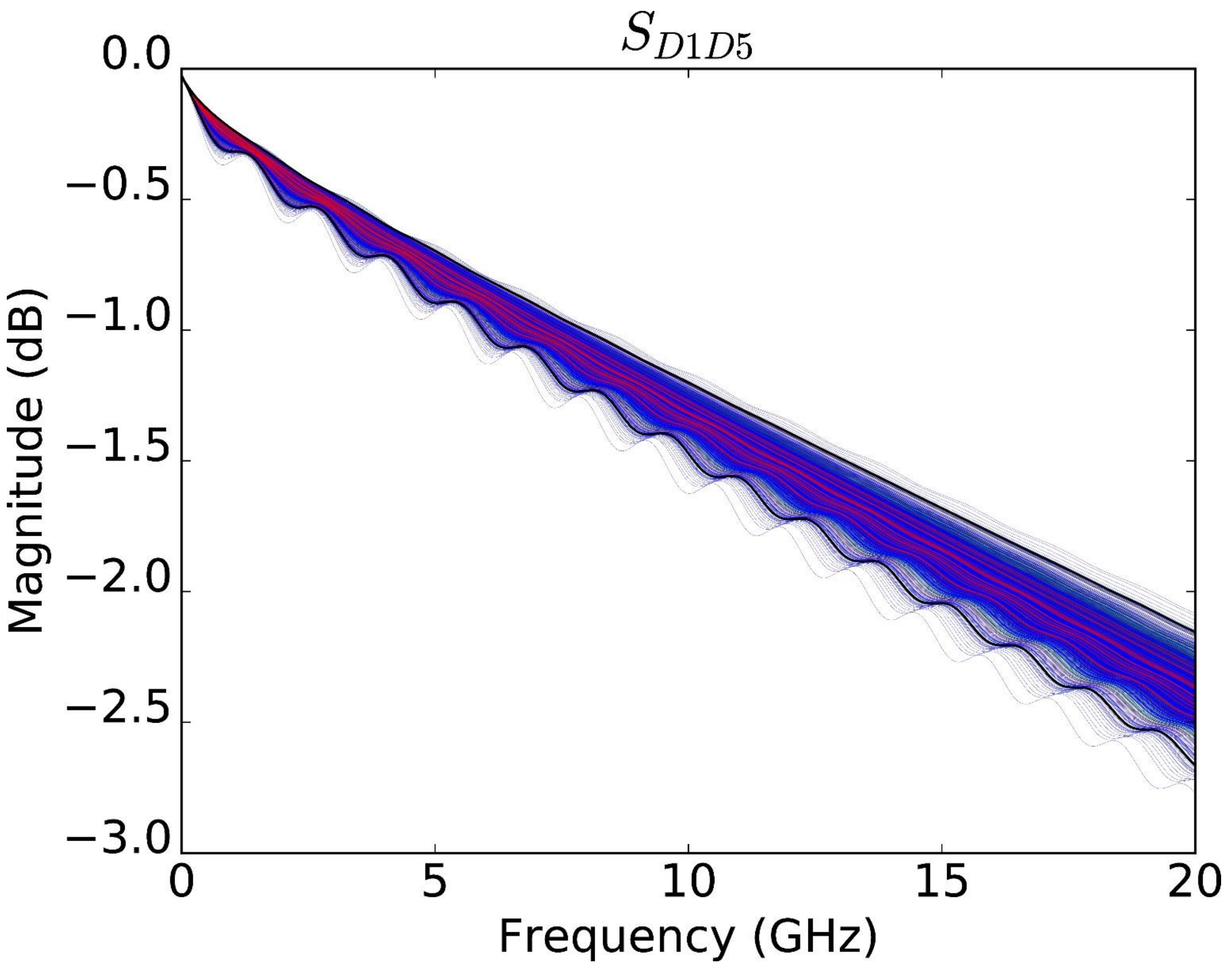

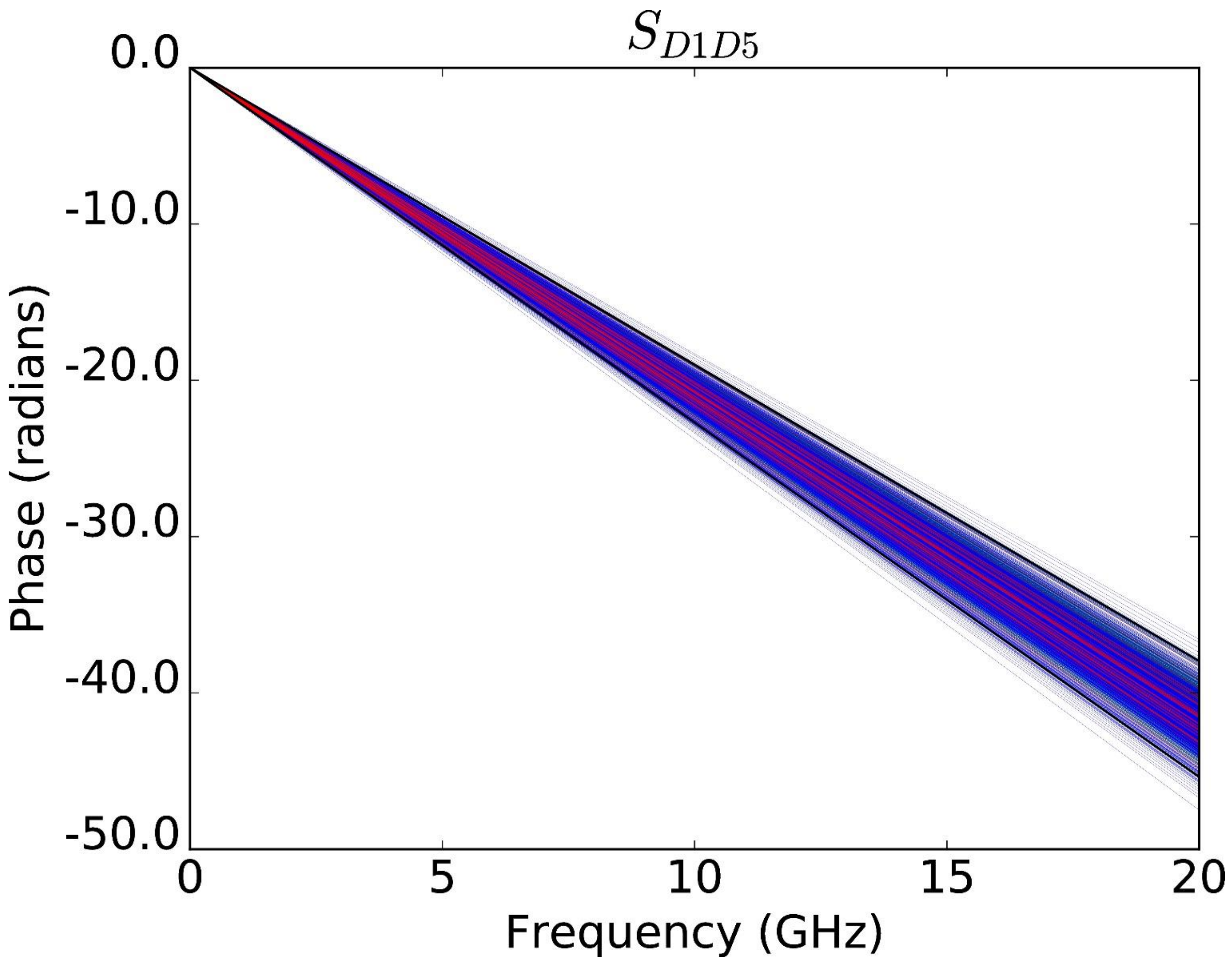

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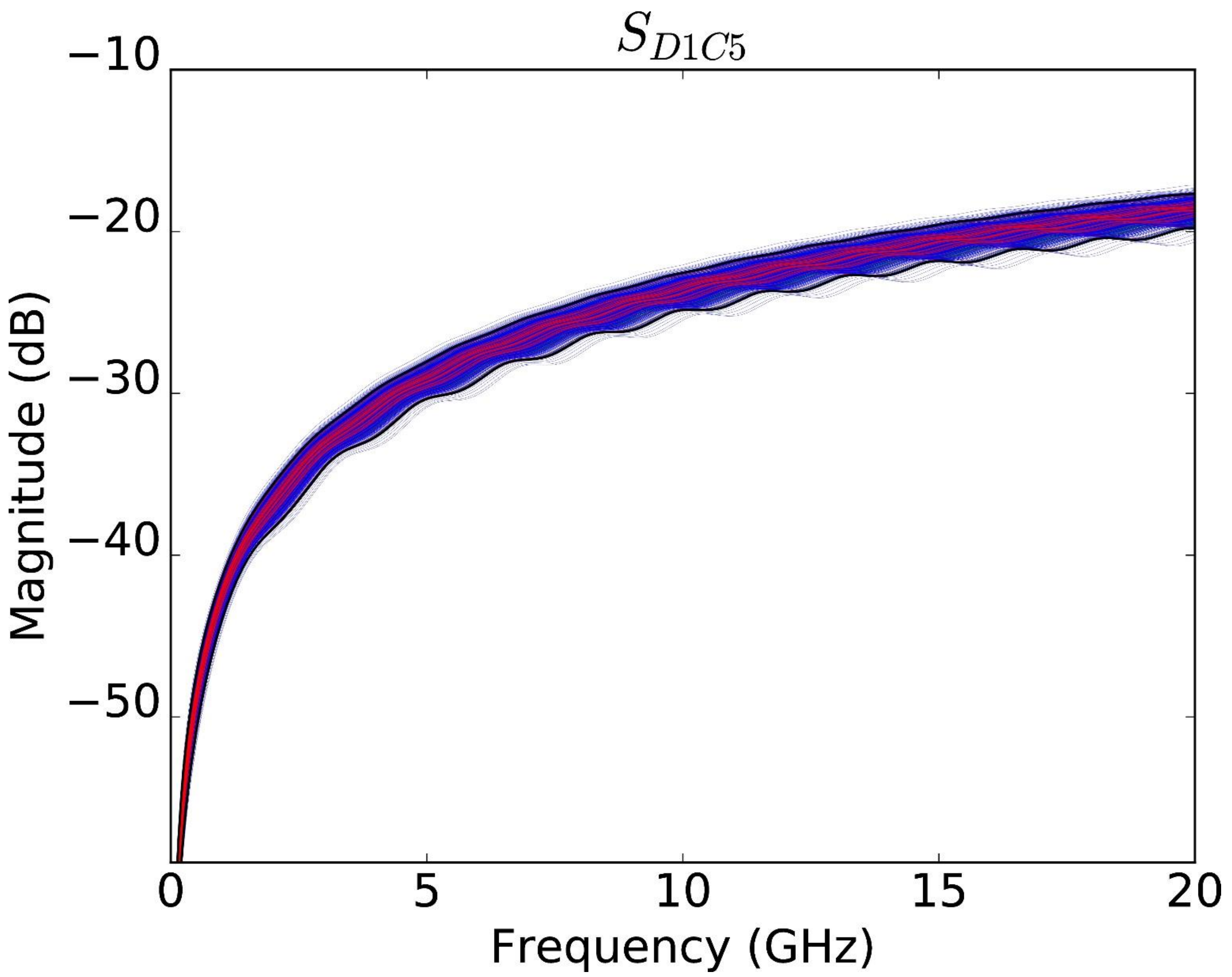

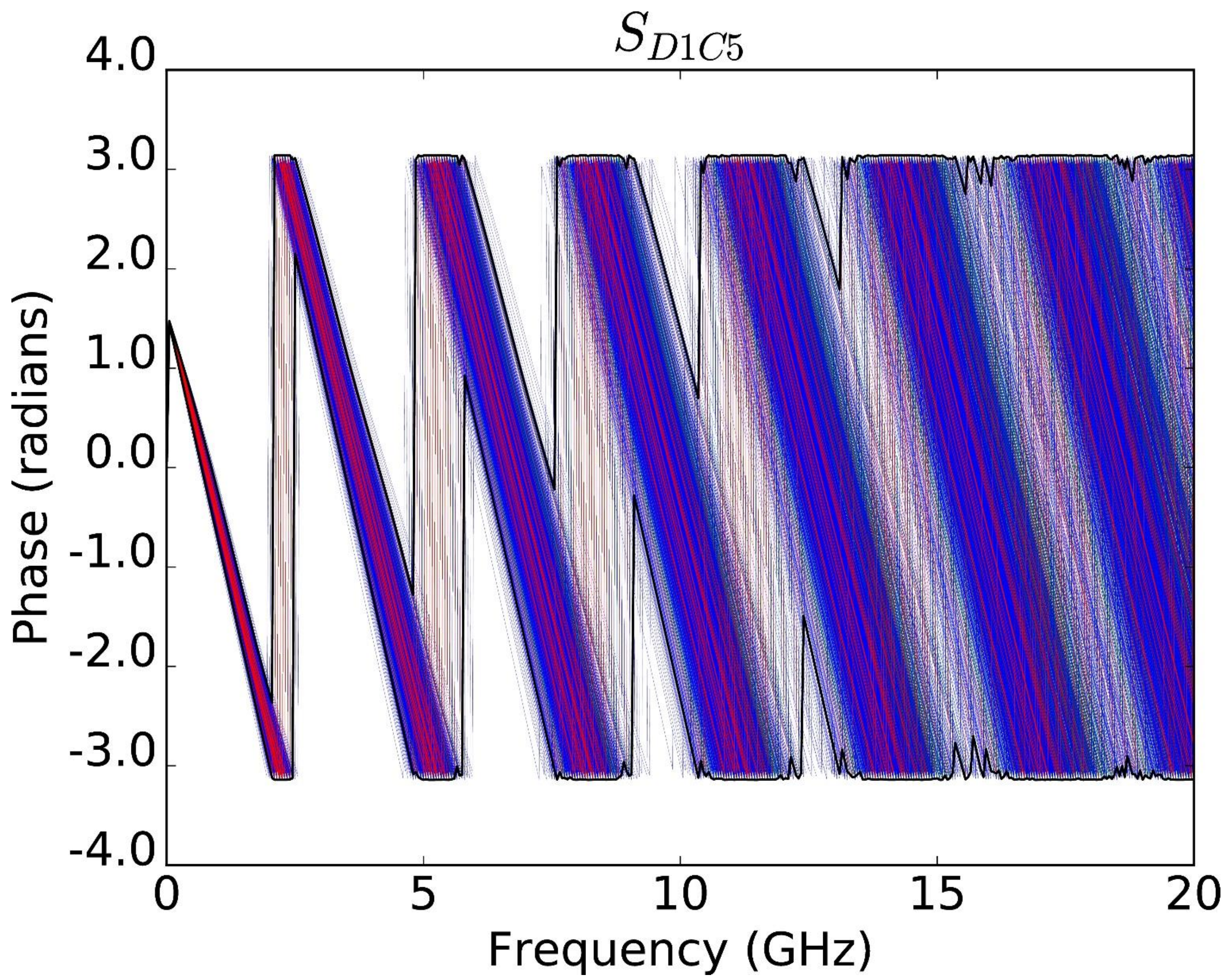

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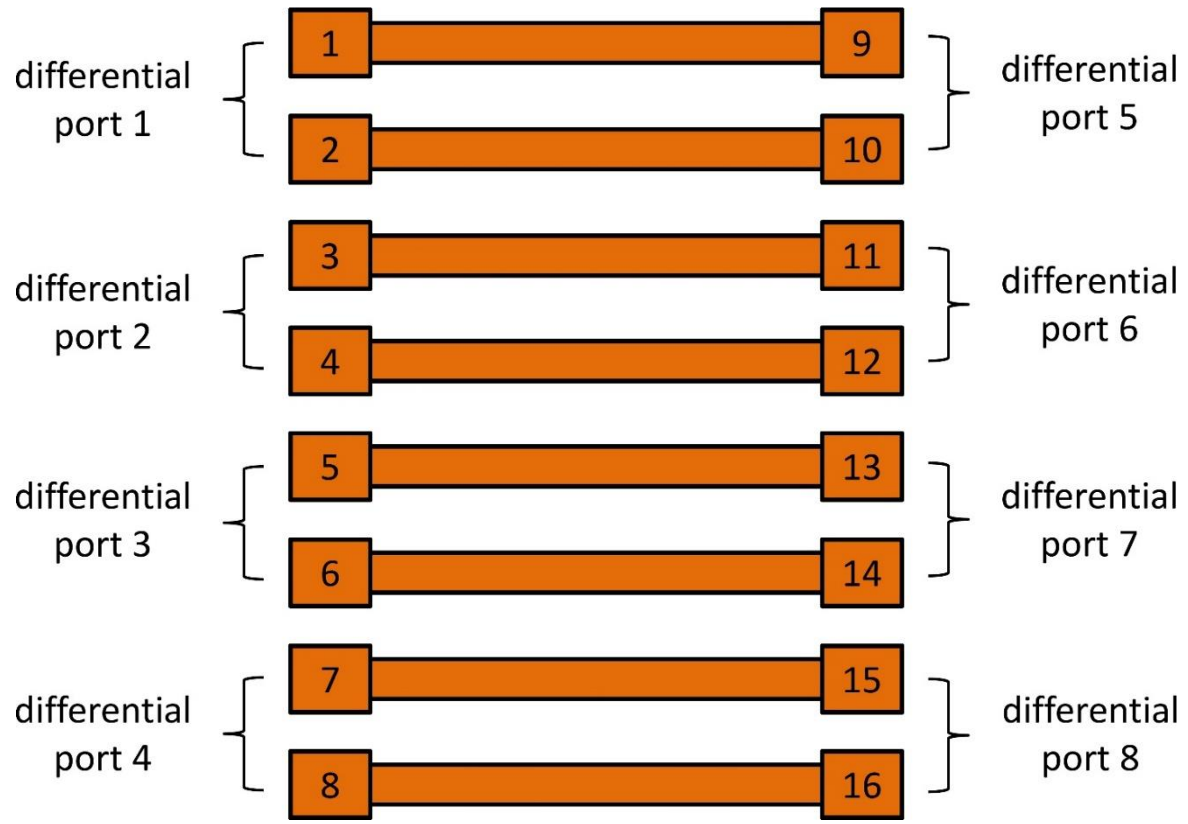
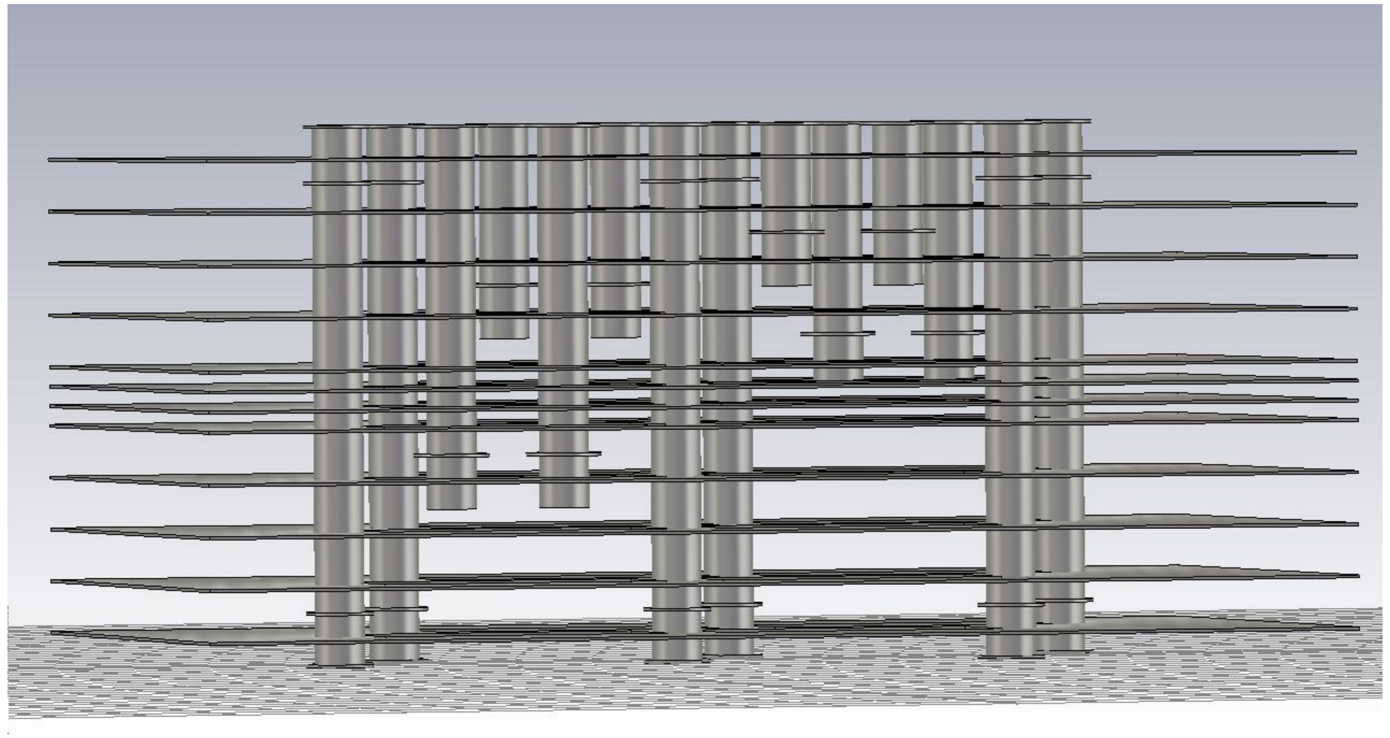
APPLICATION 2: FOOTPRINT

Connector footprint:

- 4 pairs of lines
- 16 ports
- Differential signaling
- **40 varying input parameters** (uniform)
- 450 **simulated** S-parameters
- 50 training samples





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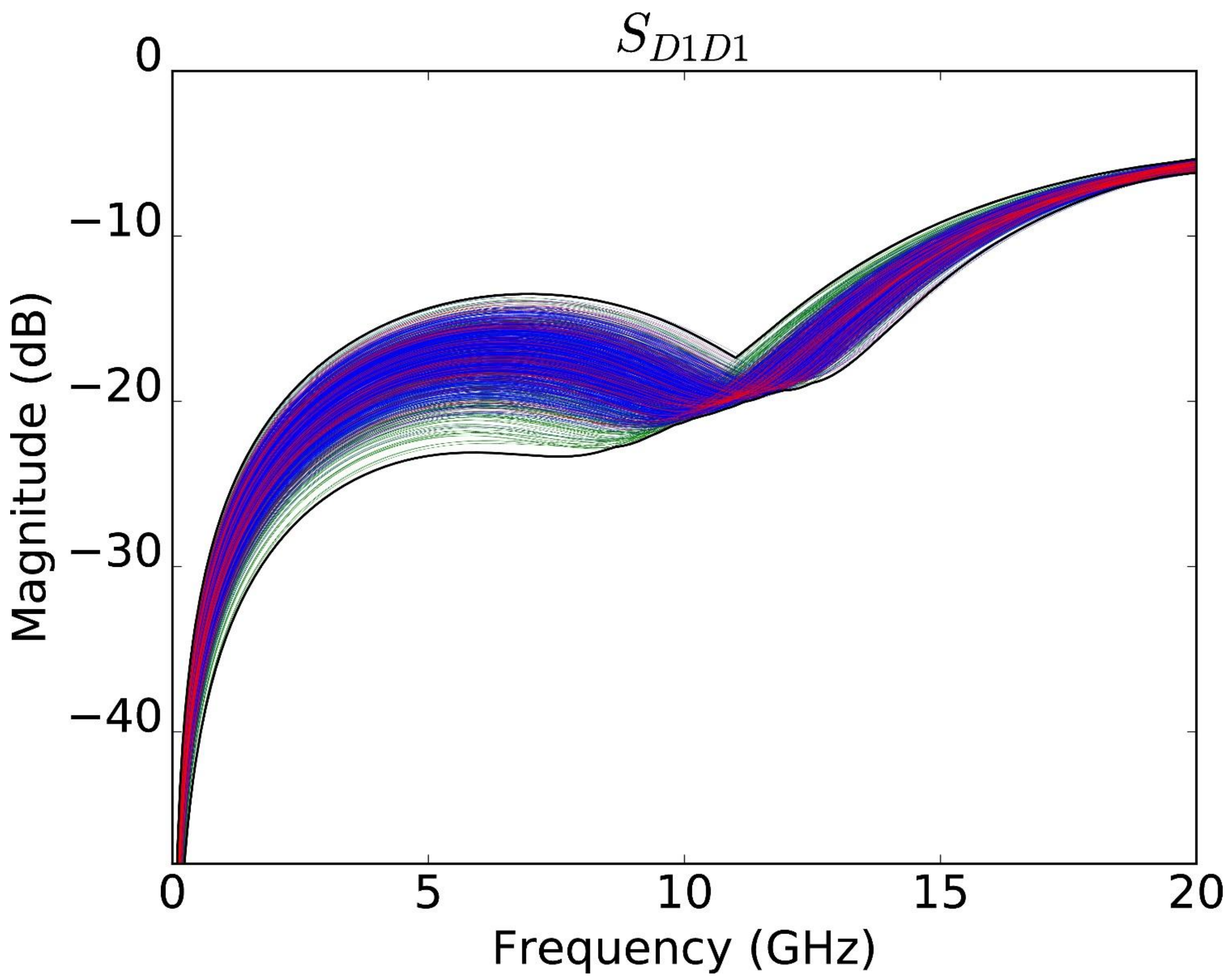
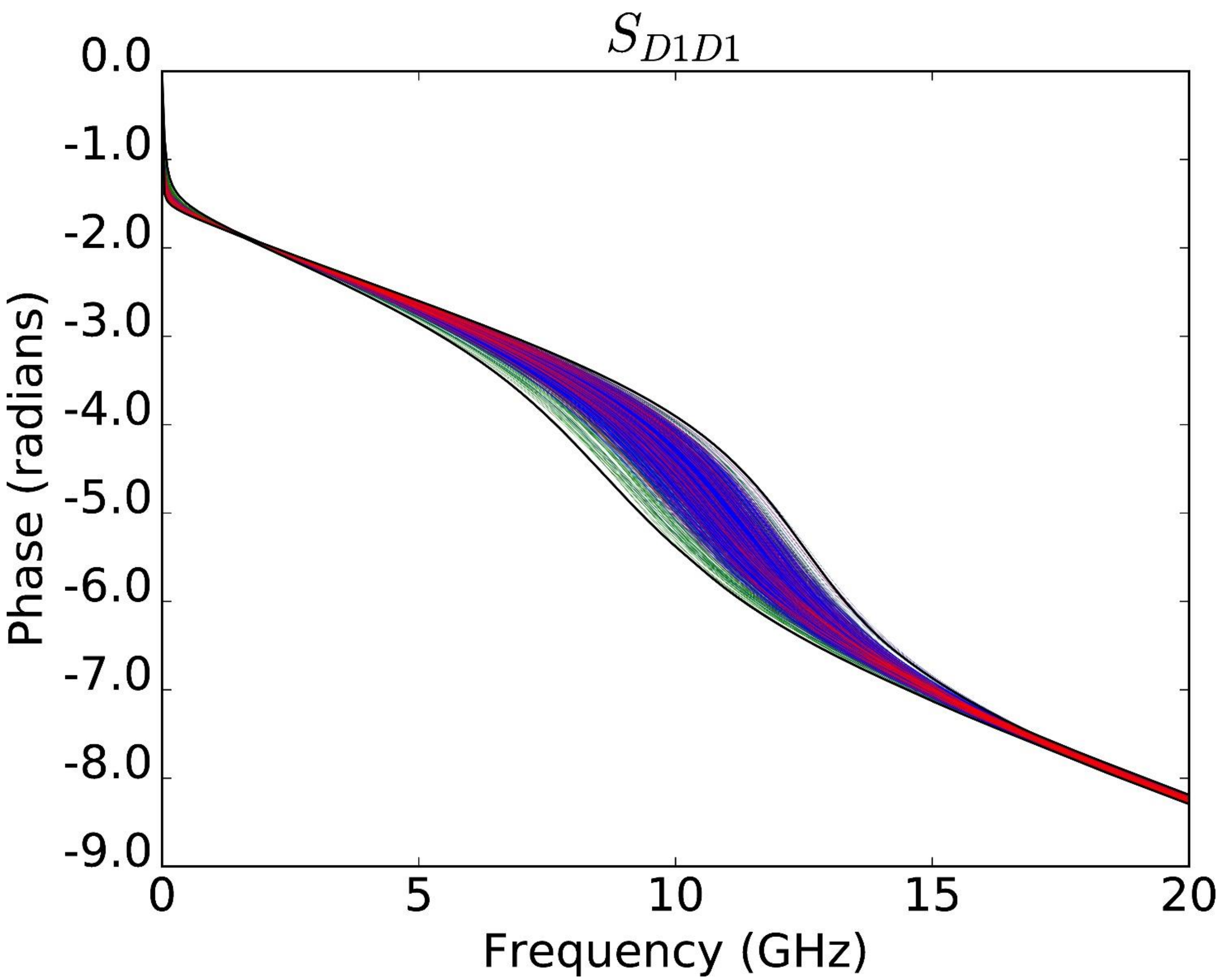
APPLICATION 2: FOOTPRINT

50 Training samples   400 Simulated validation samples   450 Generated samples





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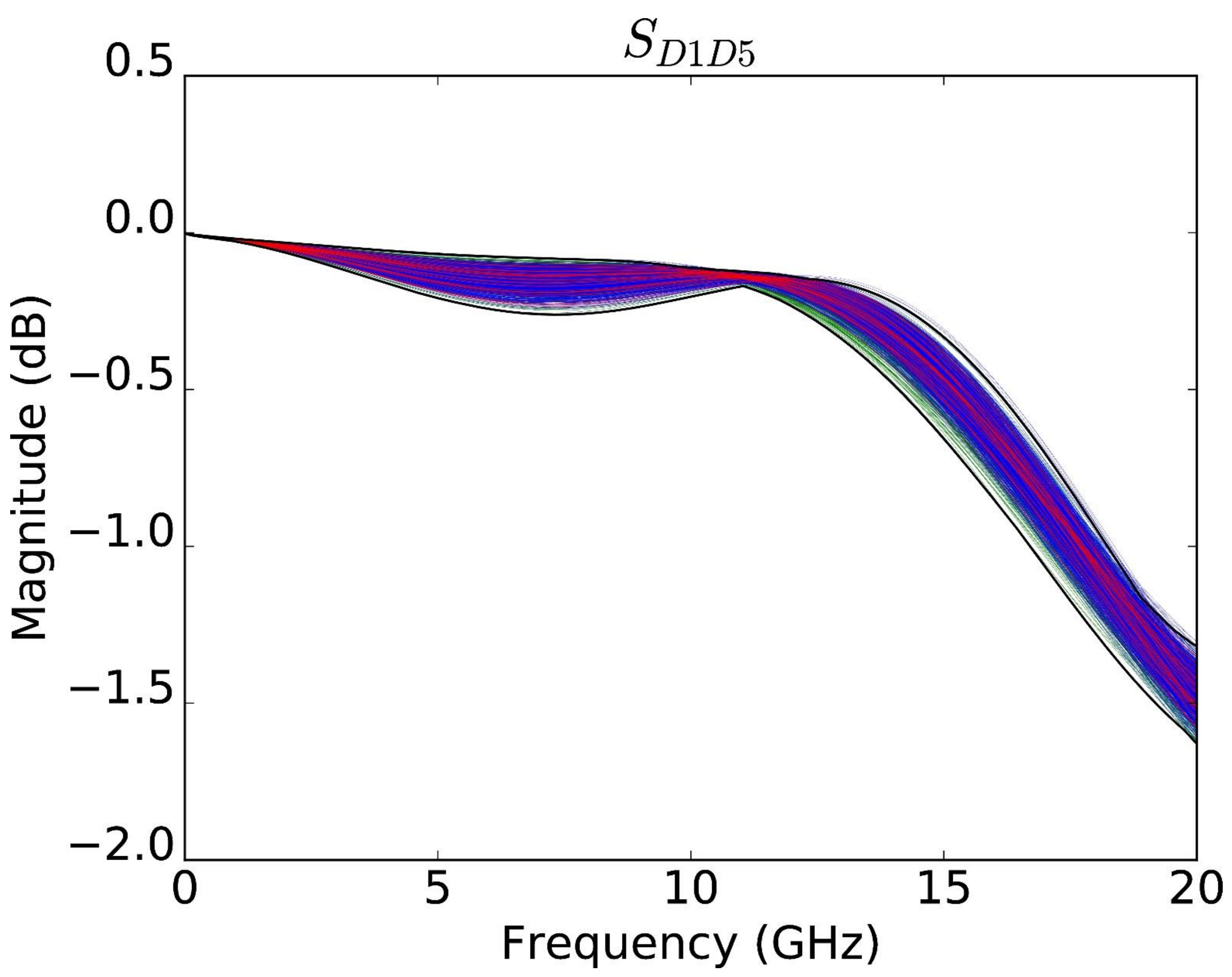

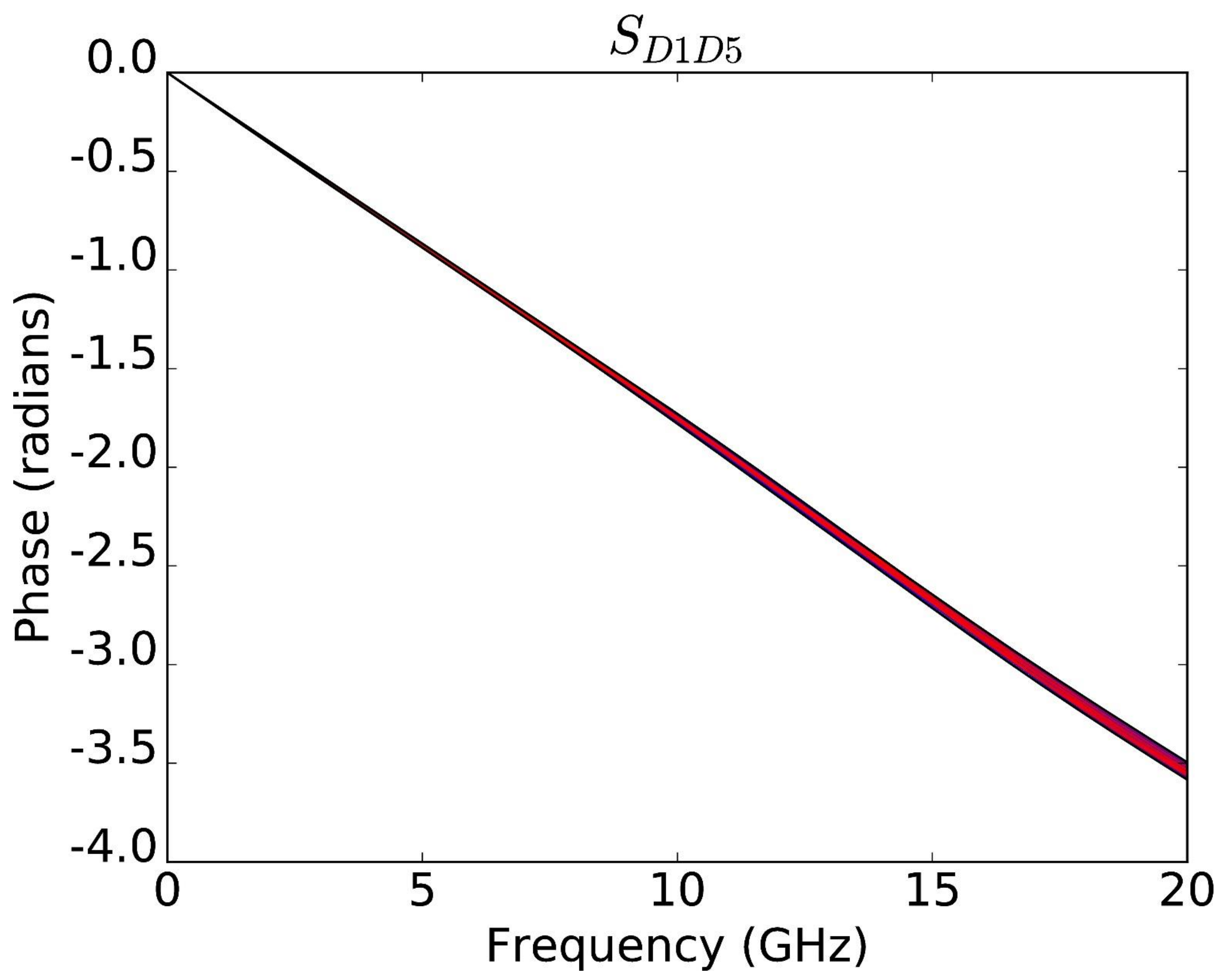

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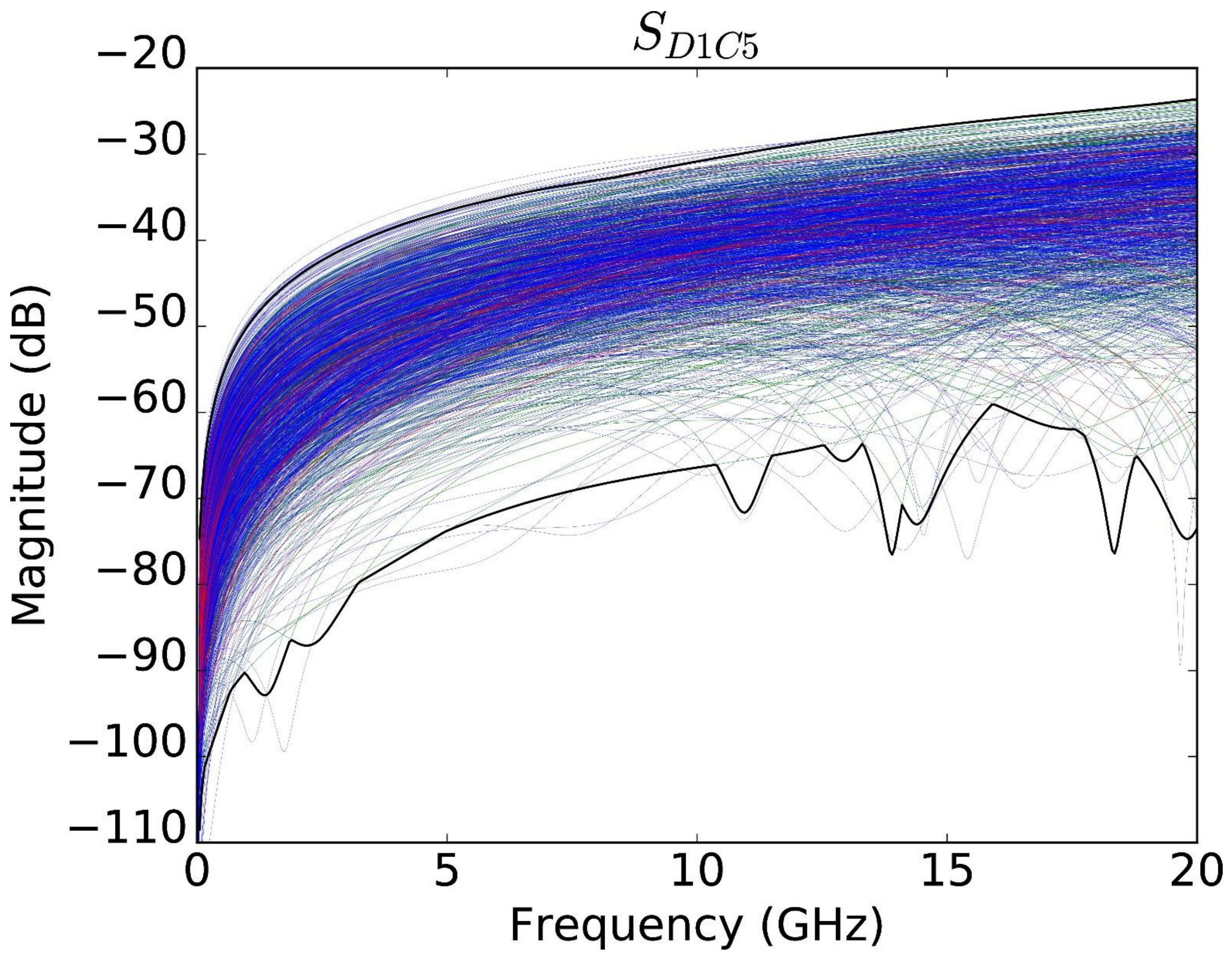

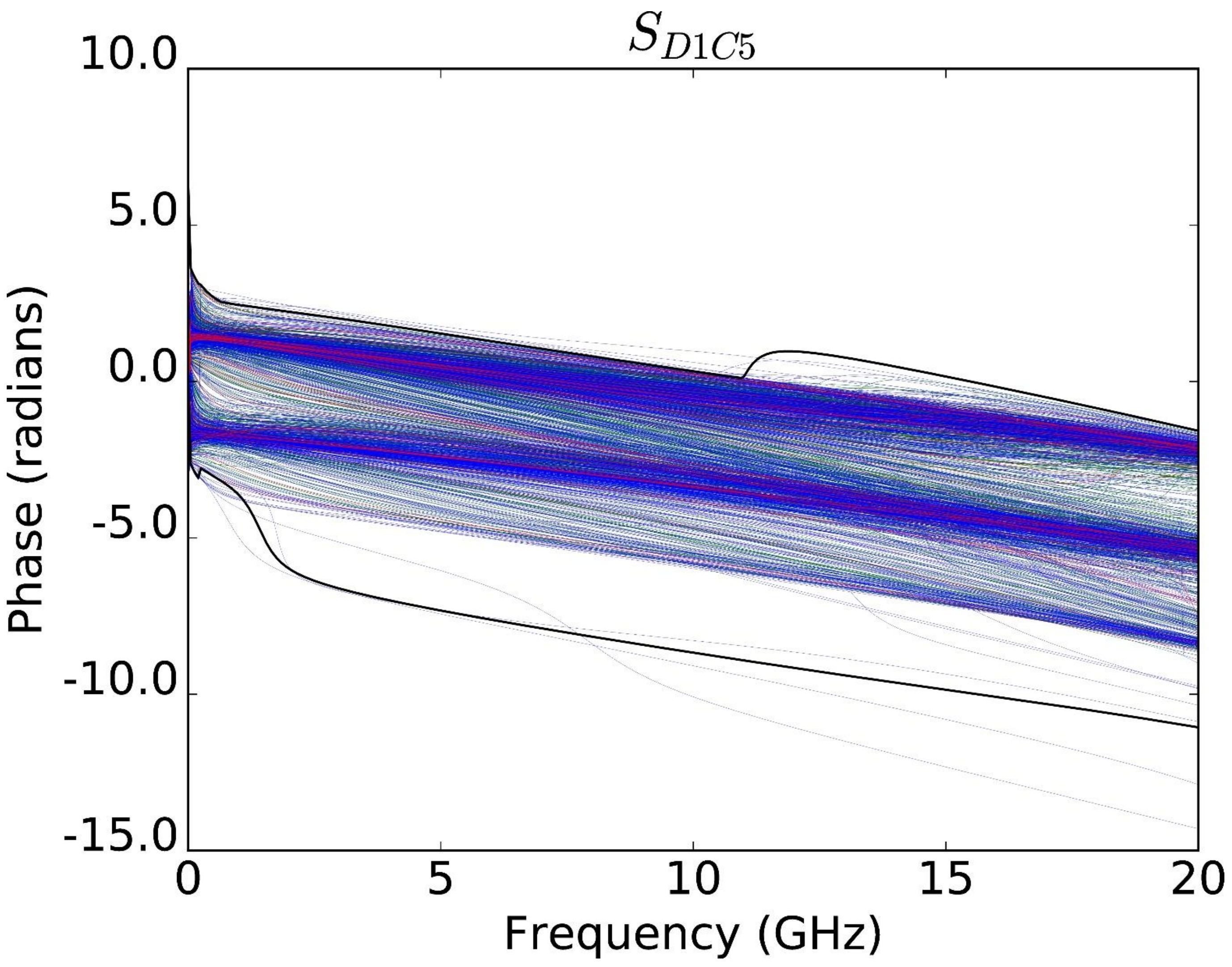

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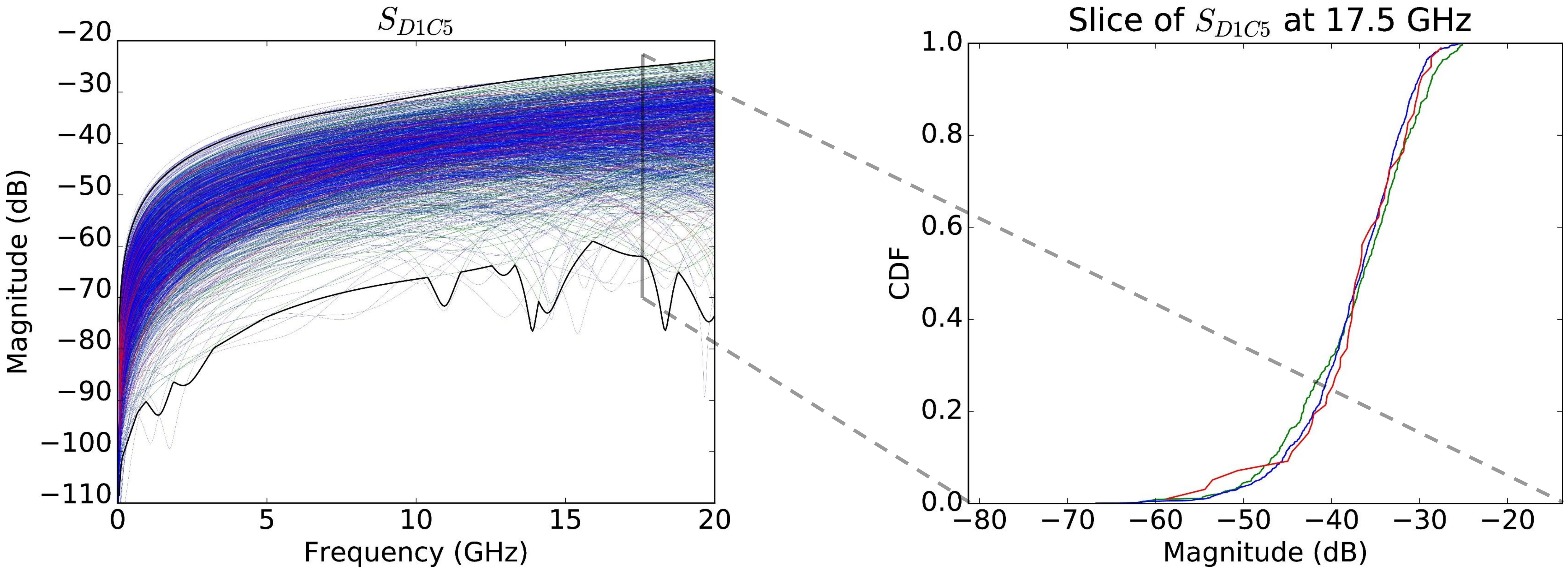

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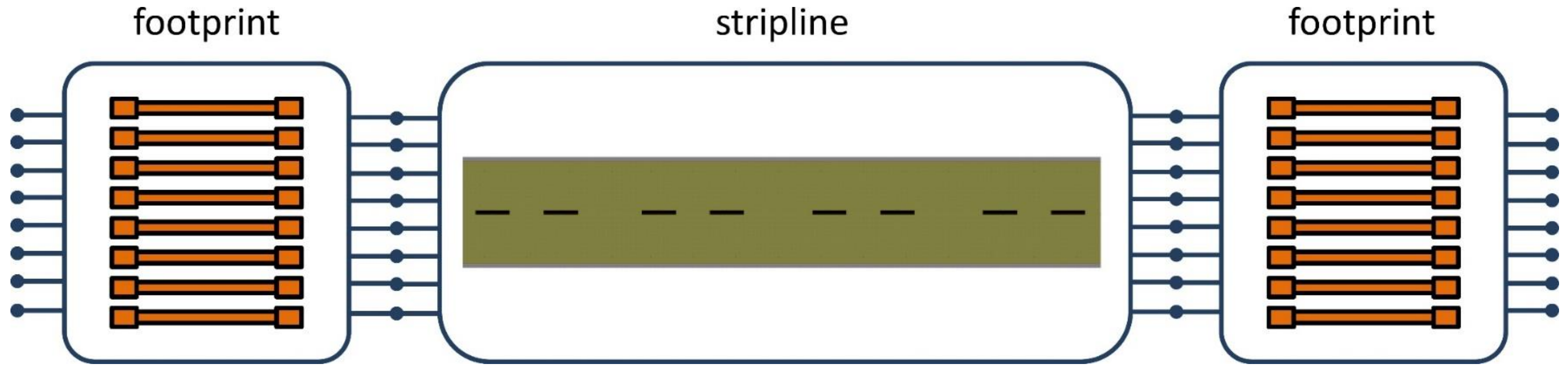
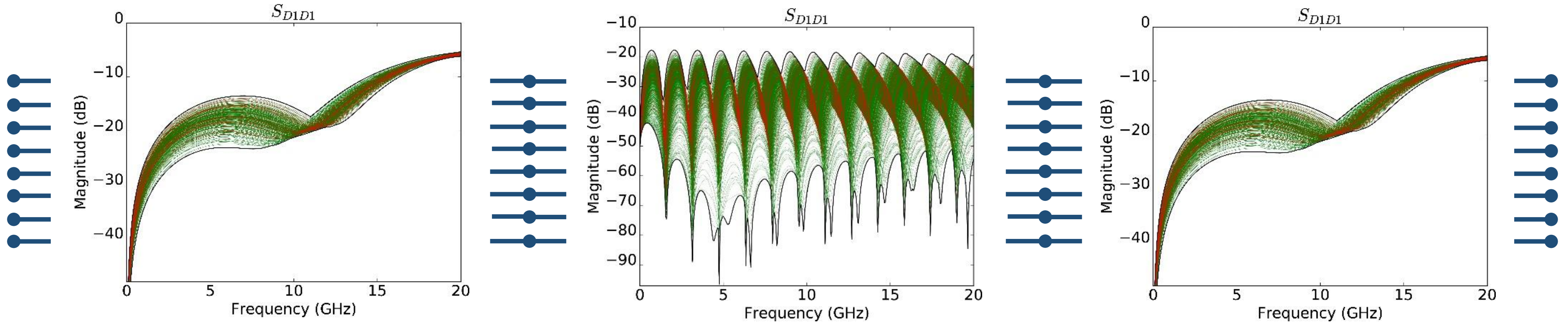
APPLICATION 3: CASCADE

Cascade footprint – stripline - footprint:

– 3 sets of generated and simulated S-parameters

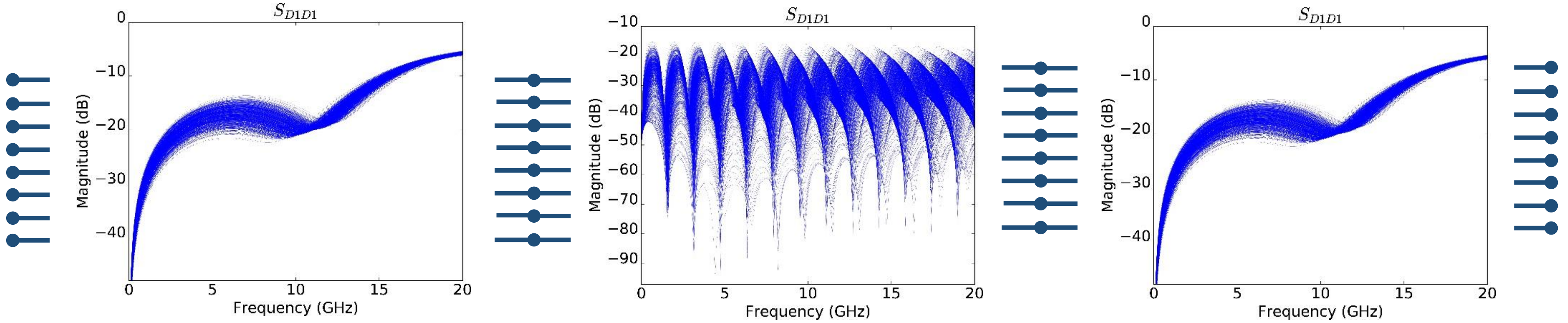




50 Training samples

950 Simulated validation samples

vs



1000 Generated samples

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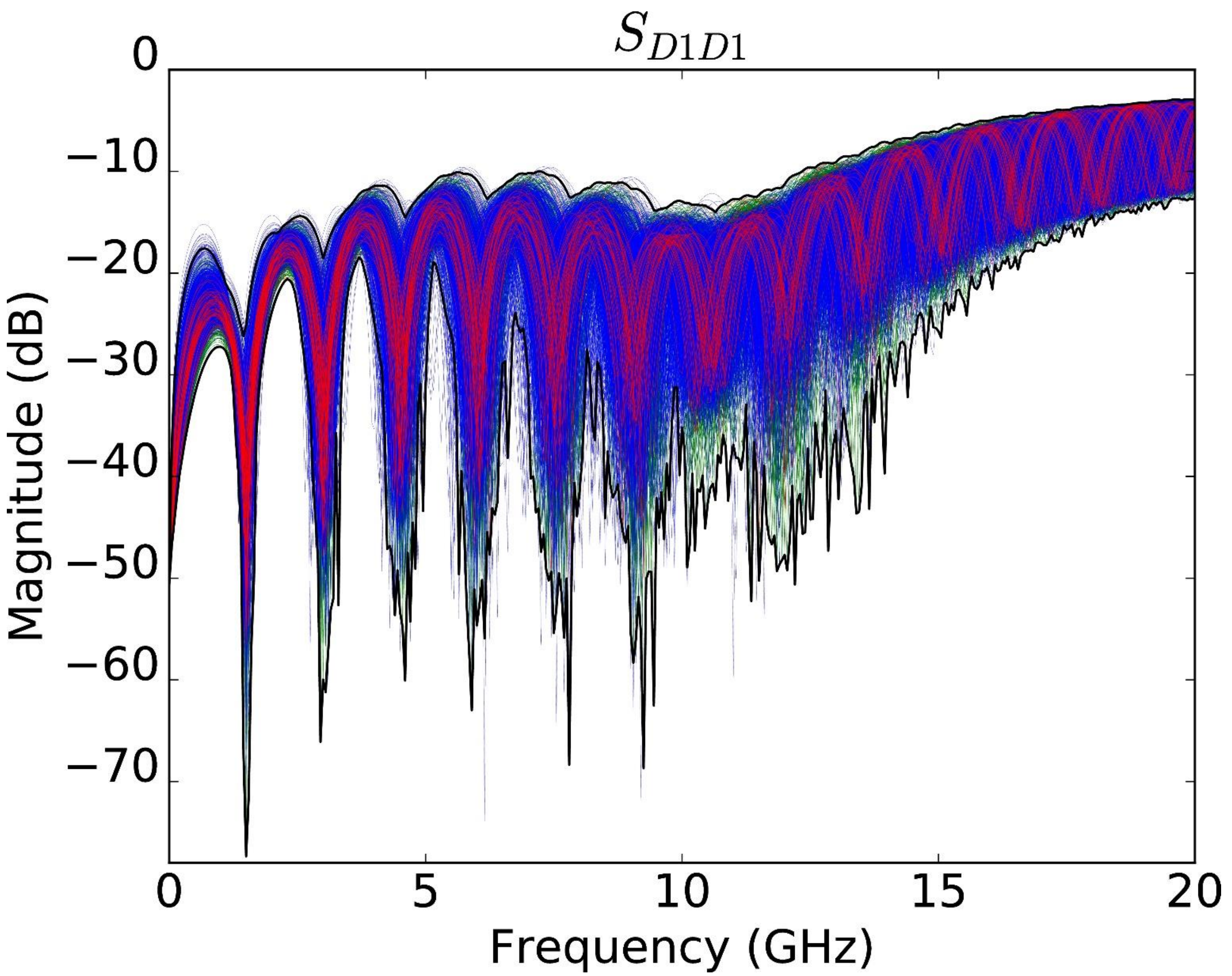
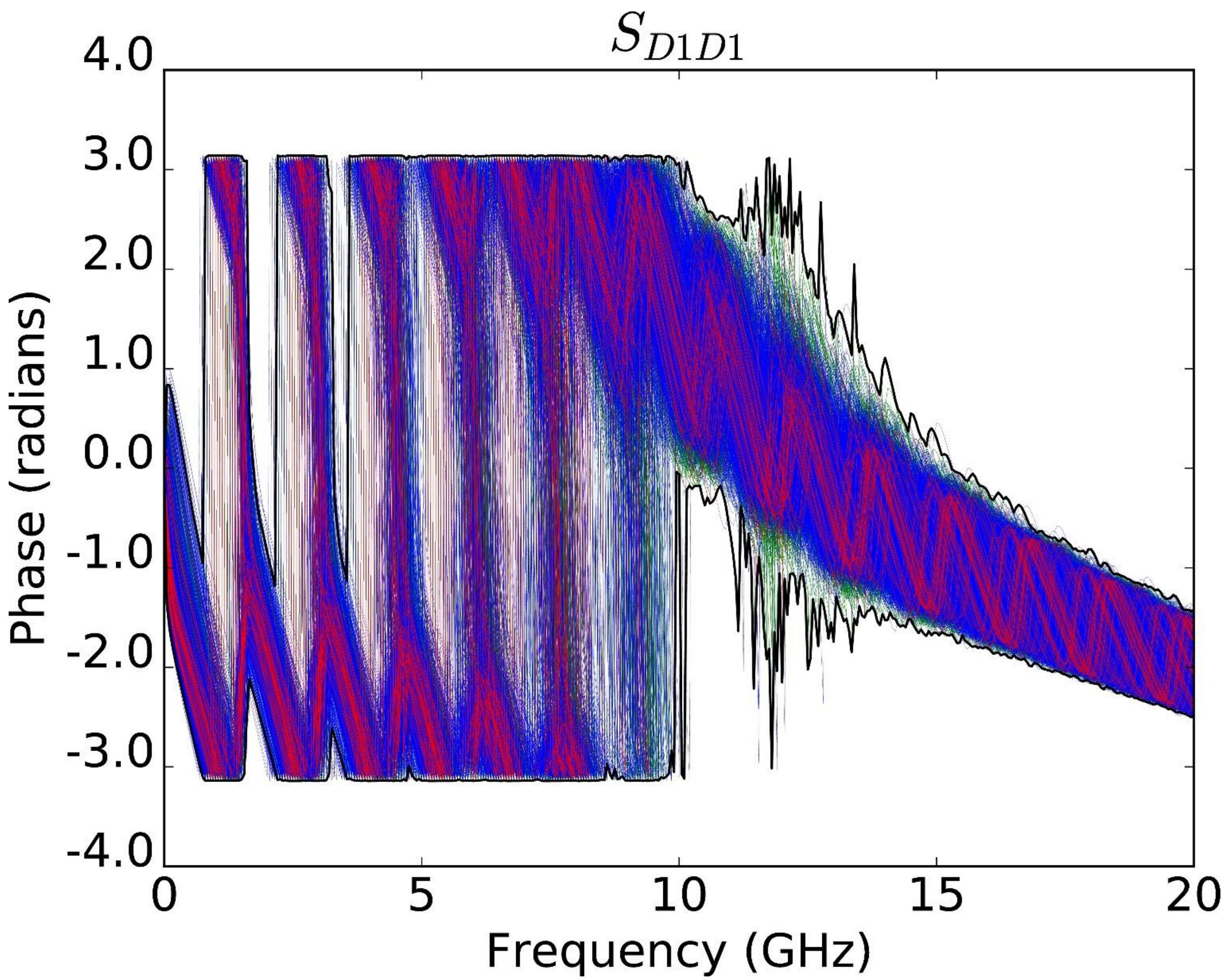
APPLICATION 3: CASCADE

50 Training samples 950 Simulated validation samples 1000 Generated samples





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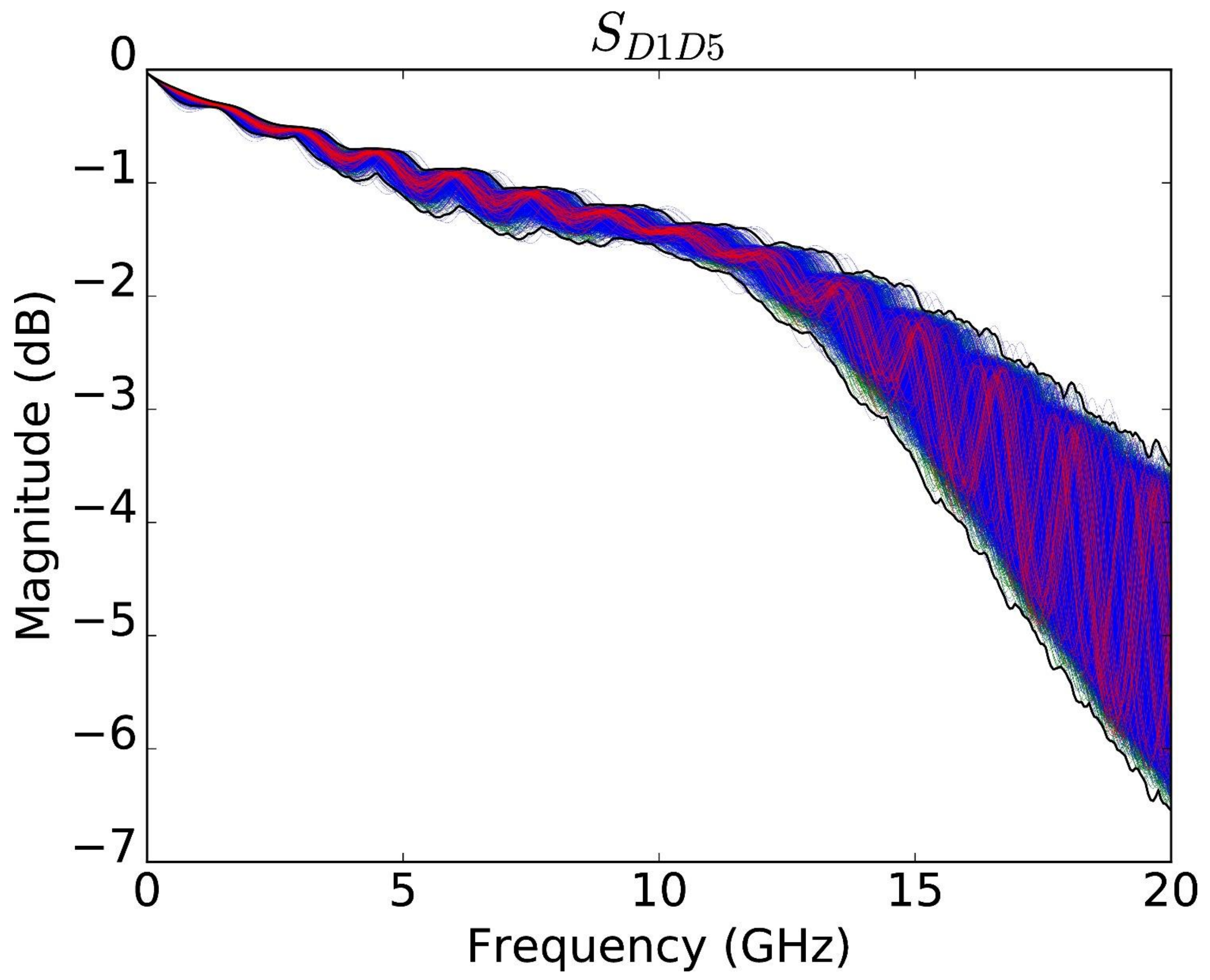

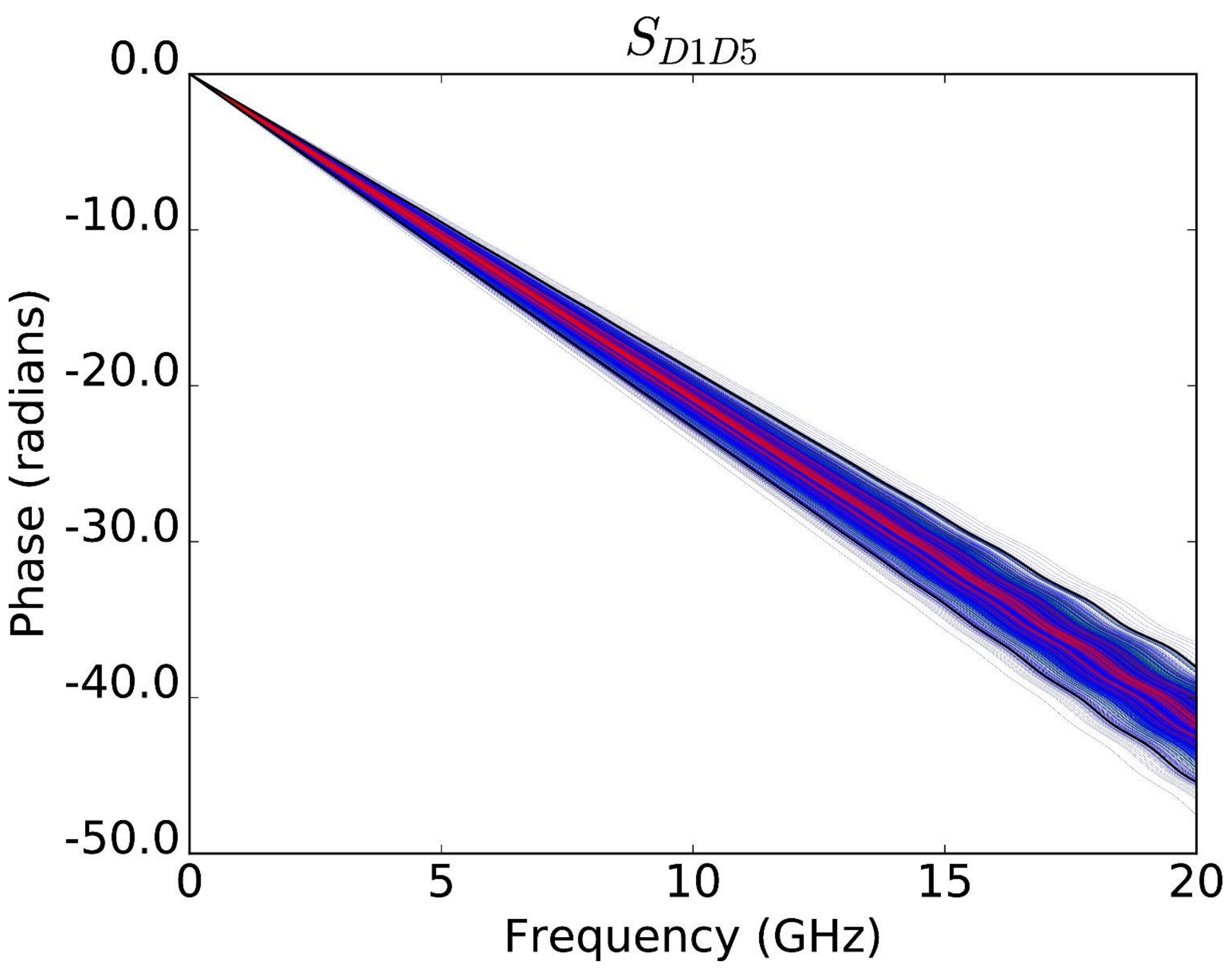

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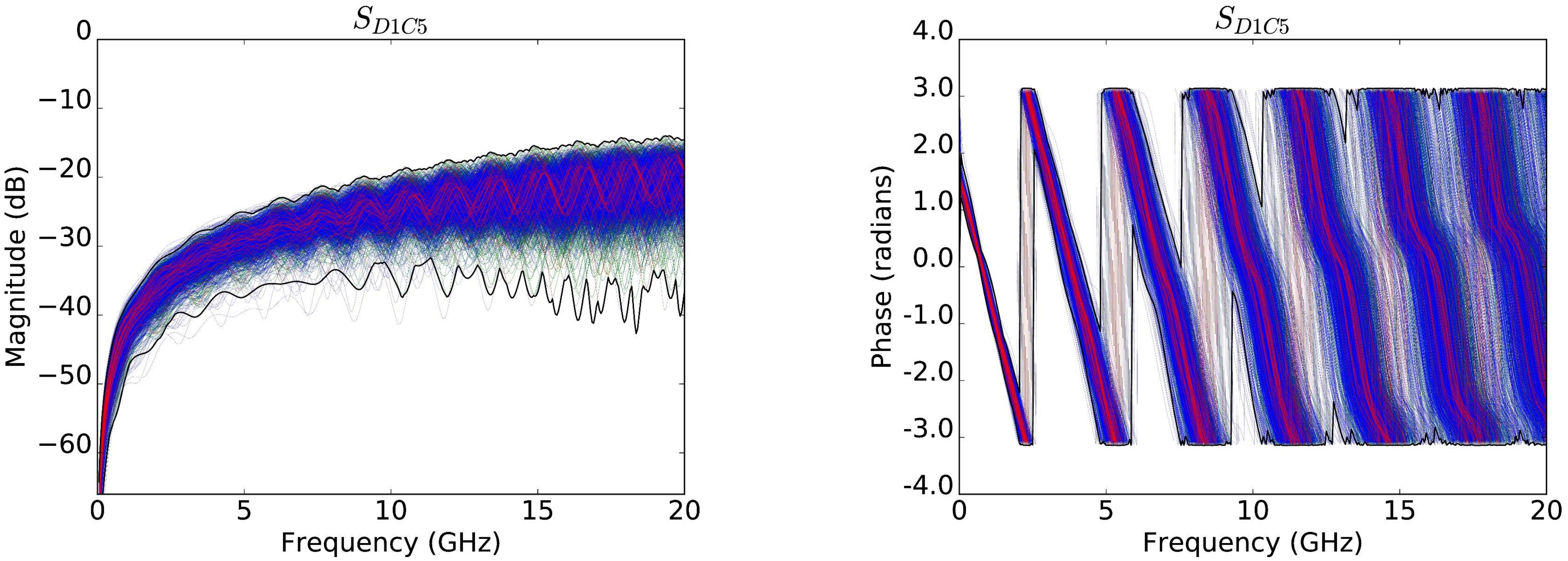

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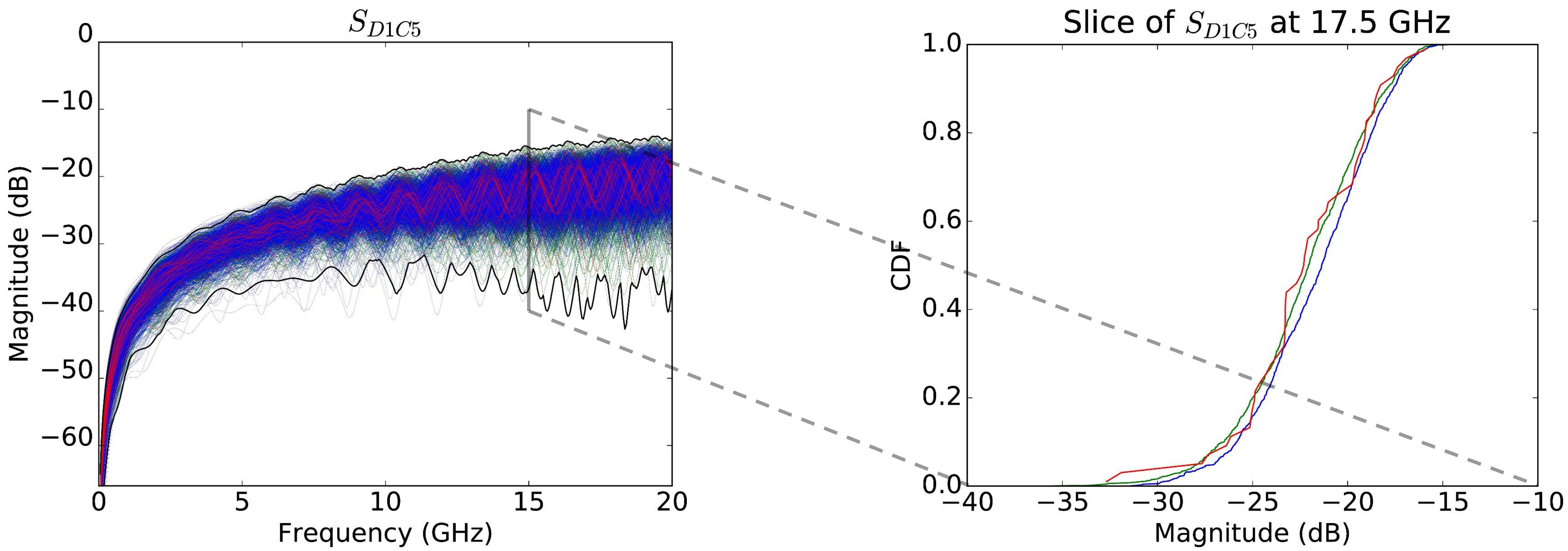
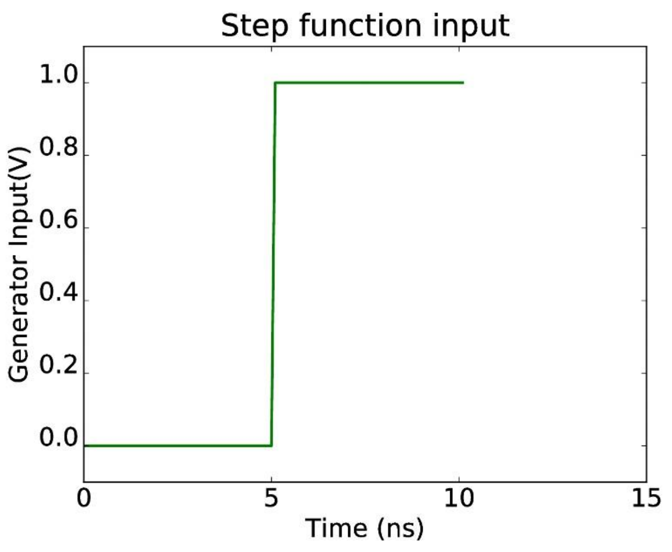
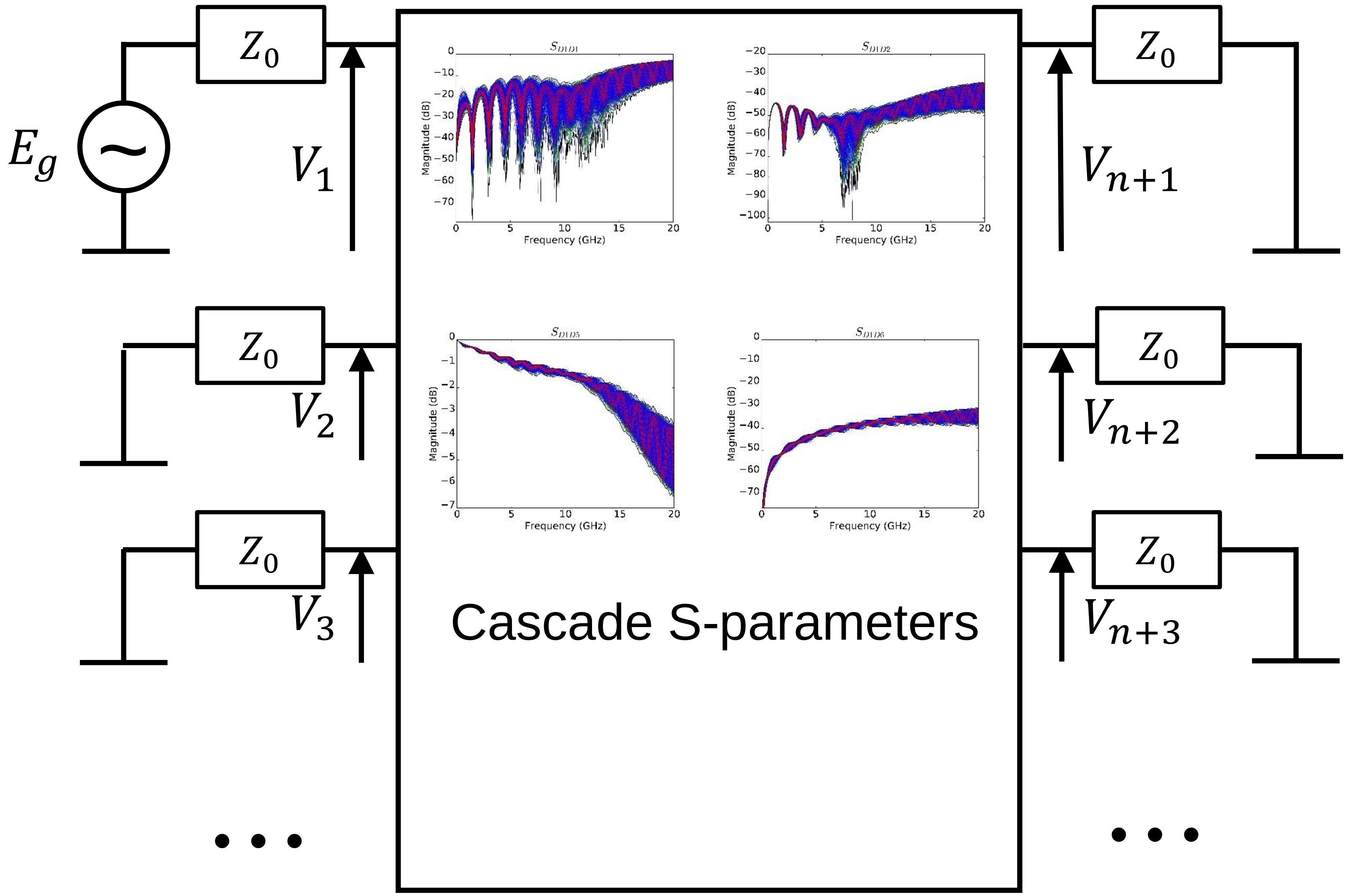


APPLICATION 4: TIME DOMAIN



Rise time: 250 ps



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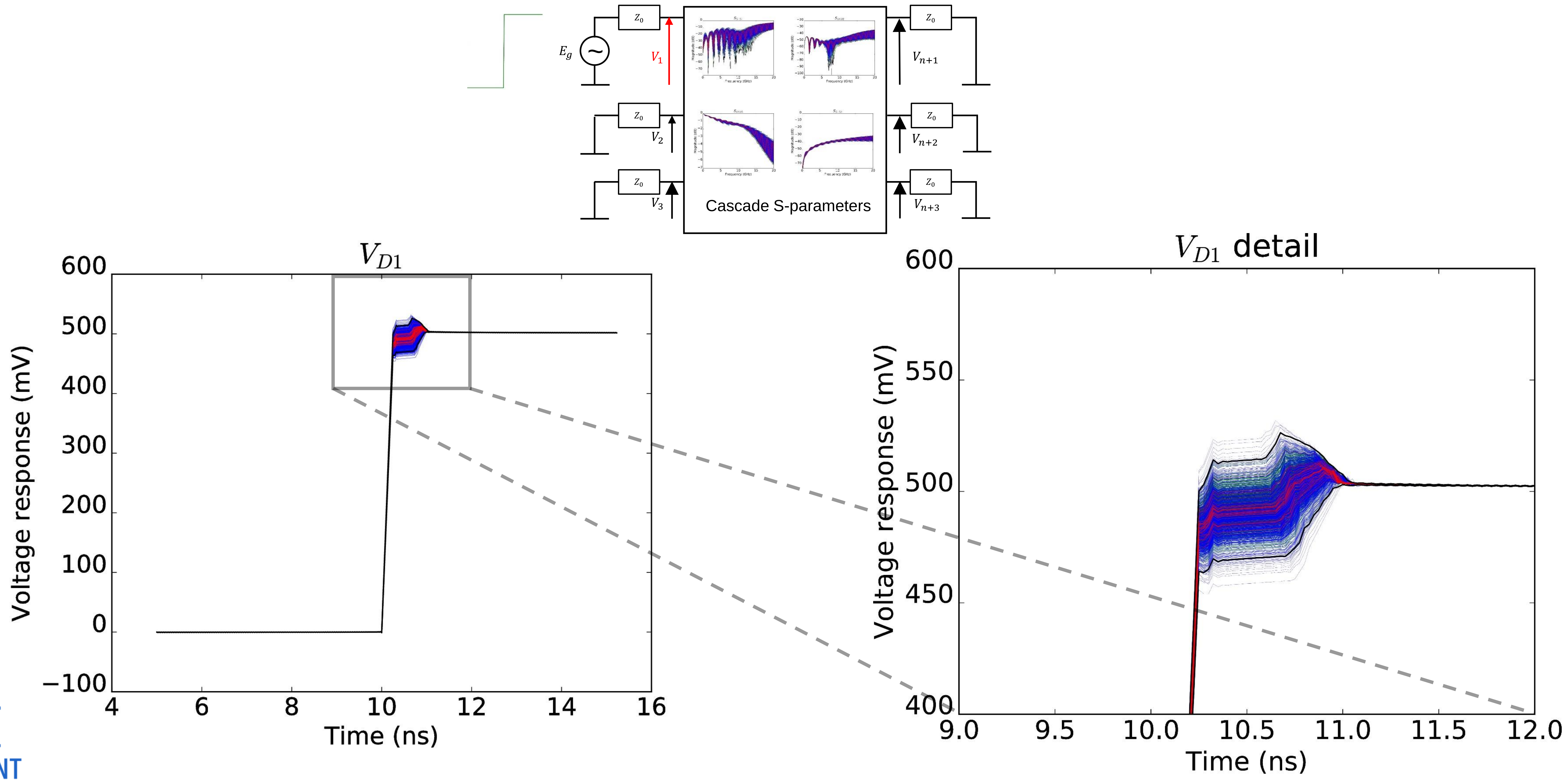
APPLICATION 4: TIME DOMAIN

50 Training samples | 950 Simulated validation samples | 1000 Generated samples



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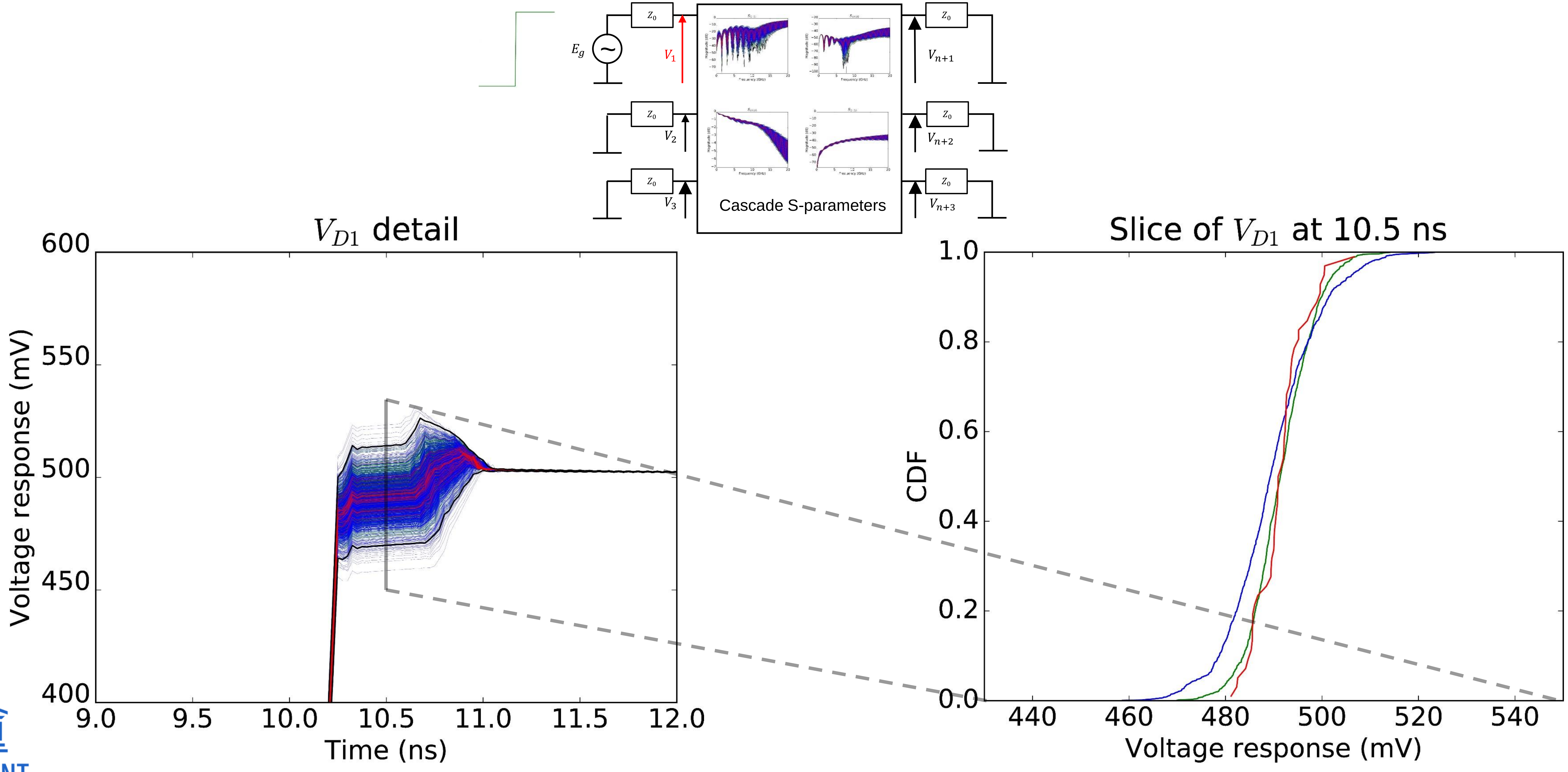

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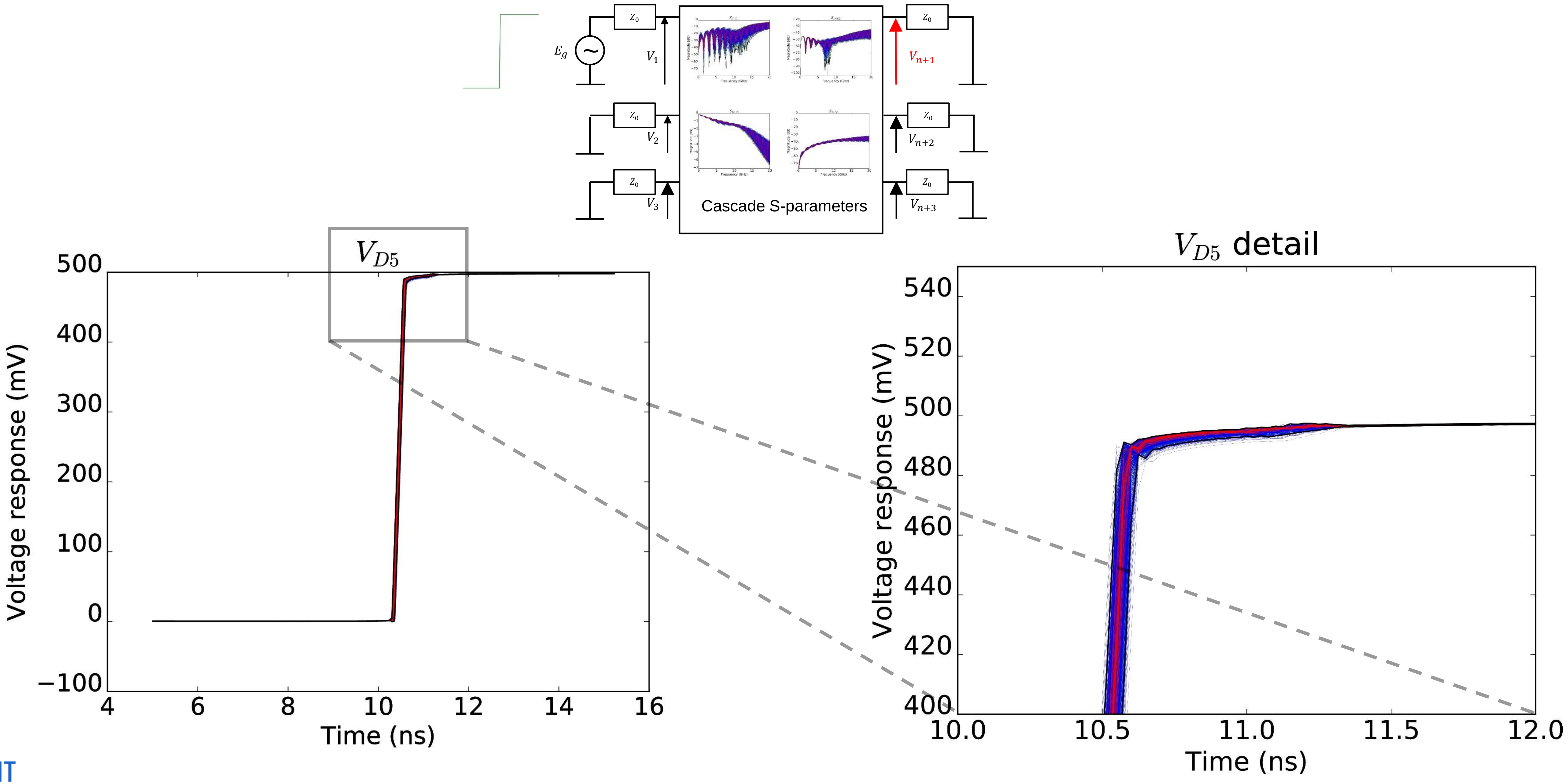

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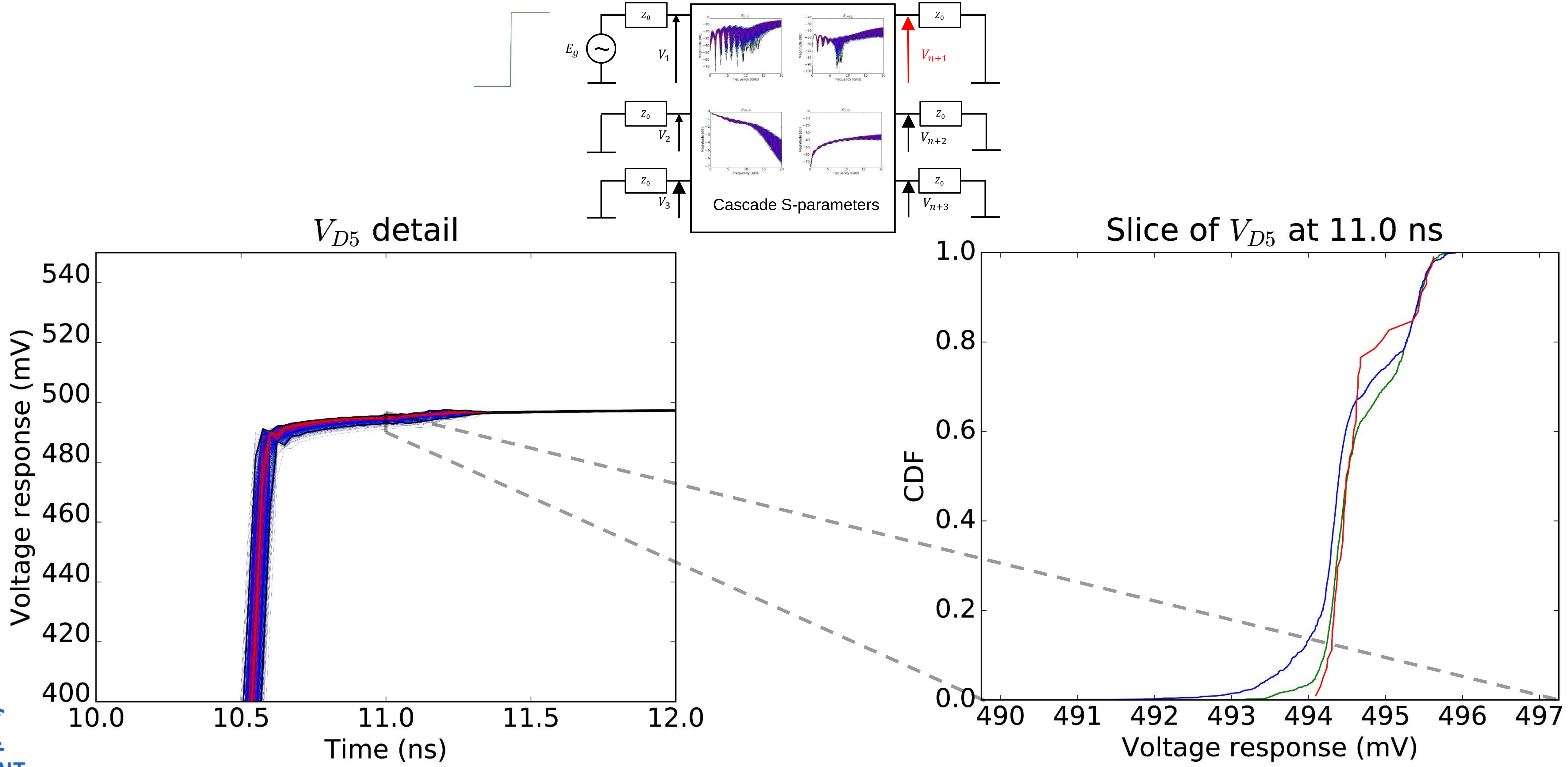

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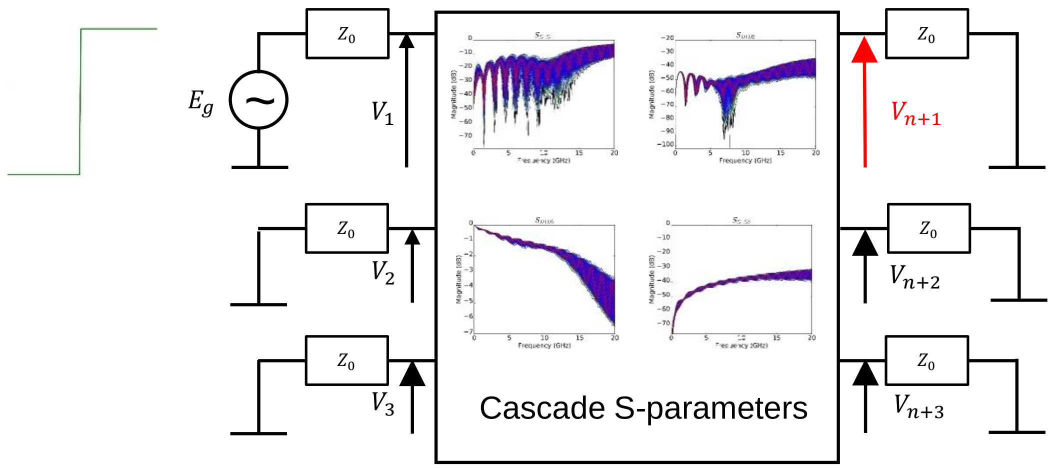

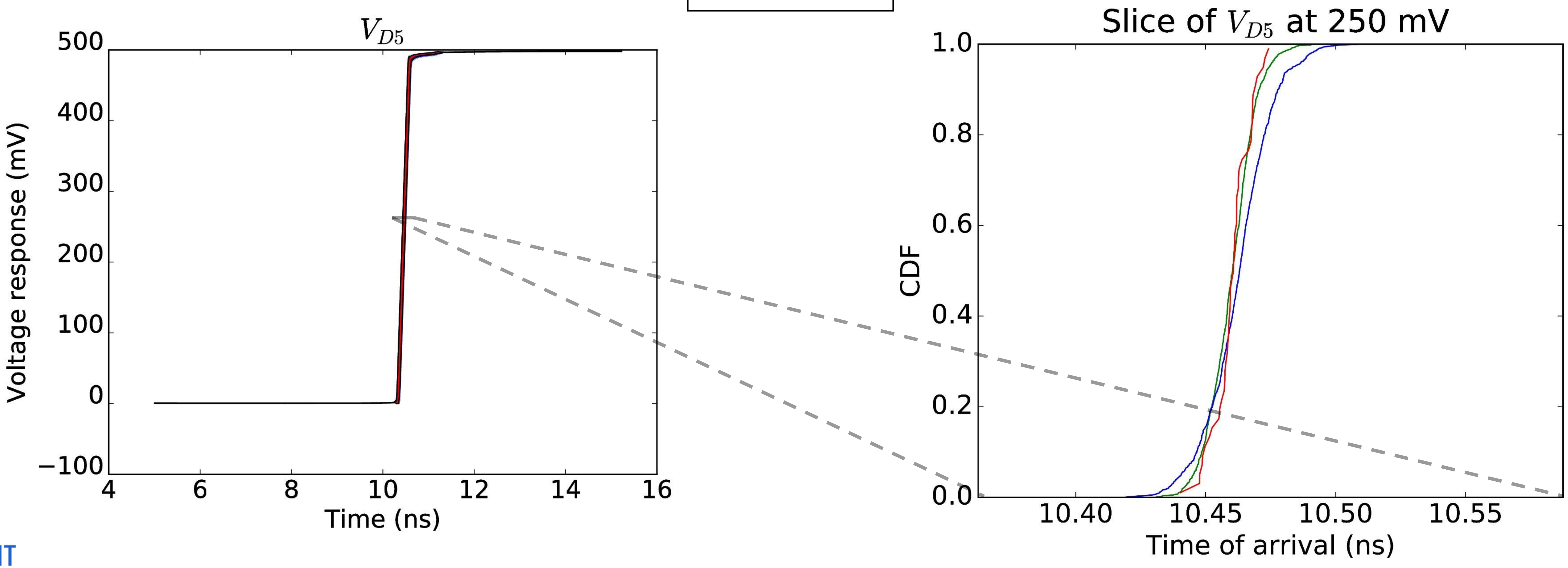

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CONCLUSION

Efficient and accurate stochastic generative modeling technique

- Does not require a-priori knowledge of stochastic distribution of input parameters
- only requires a few (possibly expensive/time-consuming) response samples
- Applicable to both S- & RLGC-parameters
- Modular for use in cascades
- Remains accurate in time domain applications

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