Impedance Response Extrapolation of PDNs using Recurrent Neural Networks

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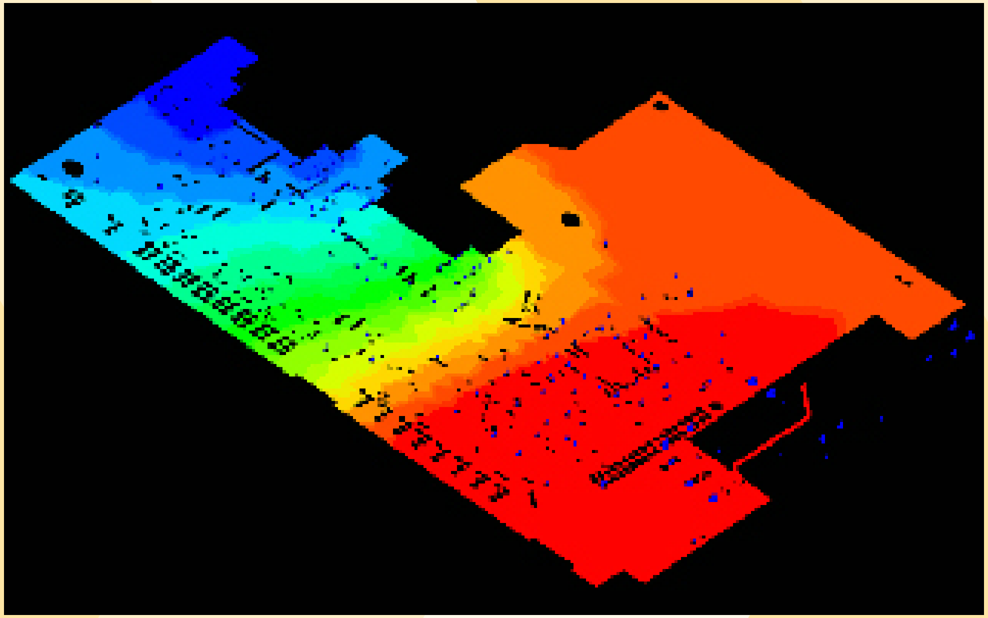
1. Objective

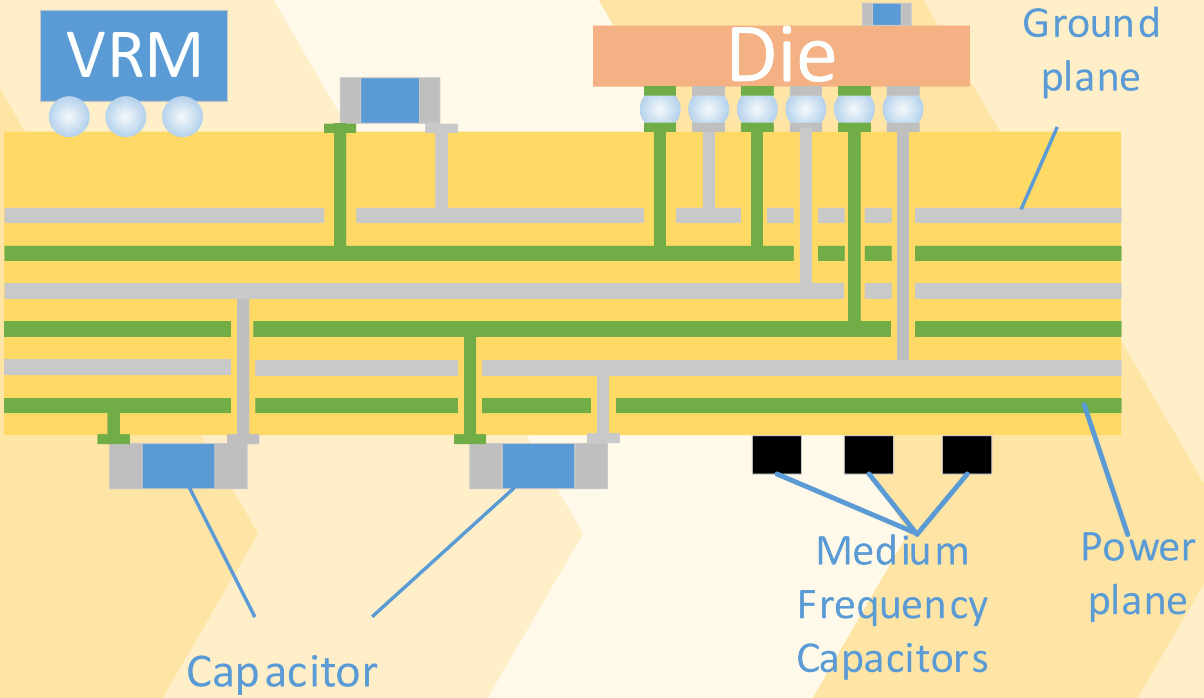


ANSYS SIwave-DC for Power Integrity Analysis

- Tracking impedance response is crucial to the design of a power delivery network
- Extrapolation in frequency means to accurately predict the response beyond the simulated frequency range
- Designers carry out simulations to determine if response is lower than target impedance
- **Our goal:** Can a surrogate model be used to predict a response outside the range of training data? That saves *memory and computation time*

2. Prior Work

2.1 PDN Stack up

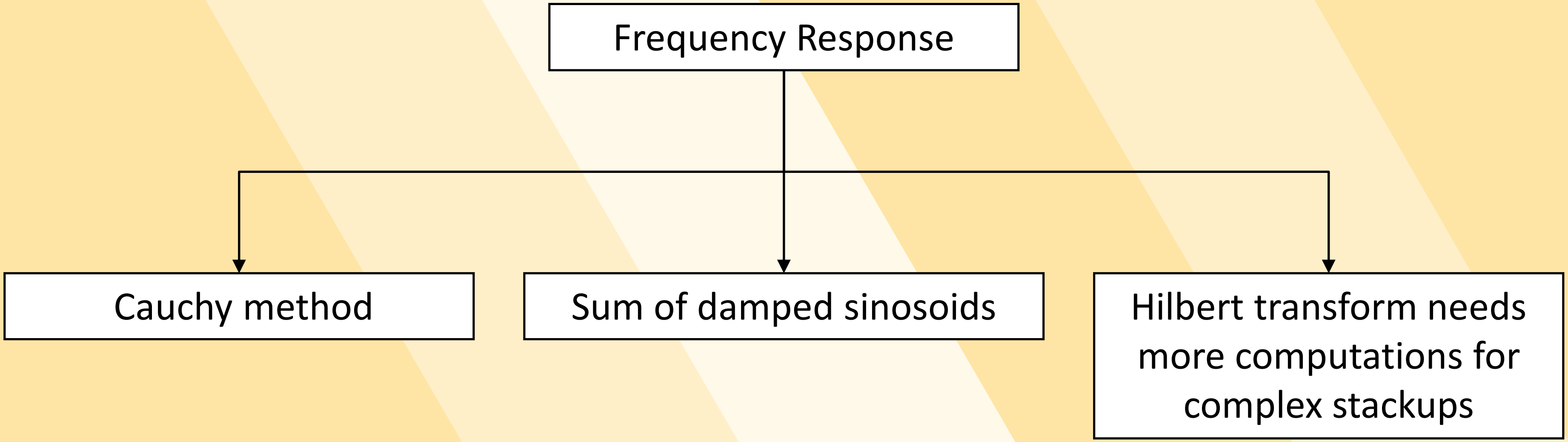


- ☐ PDN Stack up:
  - ☐ Voltage Regulator Module
  - ☐ Interposer P/G grid
  - ☐ C4 / μ-bump array
  - ☐ Through silicon vias array

Physical parameters		Min value	Max Value
Conductivity	σ_{Si}	$1 \times 10^7\ S/m$	$1 \times 10^7\ S/m$
Metal height	t_{metal}	0.5μm	1μm
Grid width	W_{grid}	10μm	30μm
Grid spacing	w_{grid}	100μm	300 μm
TSV radius	r_{TSV}	5 μm	25 μm
TSV pitch	p_{TSV}	15 μm	75 μm
C4 bump radius	r_{C4}	50μm	250 μm
C4 bump pitch	p_{C4}	150 μm	750 μm
Substrate thickness	h_{imd}	0.7μm	1 μm
μ-bump radius	r_{μ}	10μm	20μm
Si-dielectric	ϵ_{si}	11.9ϵ_o	
Poly dielectric	ϵ_{poly}	3.9ϵ_o	

2. Prior Work

2.2 Literature Survey



Frequency Response

Cauchy method

Sum of damped sinosoids

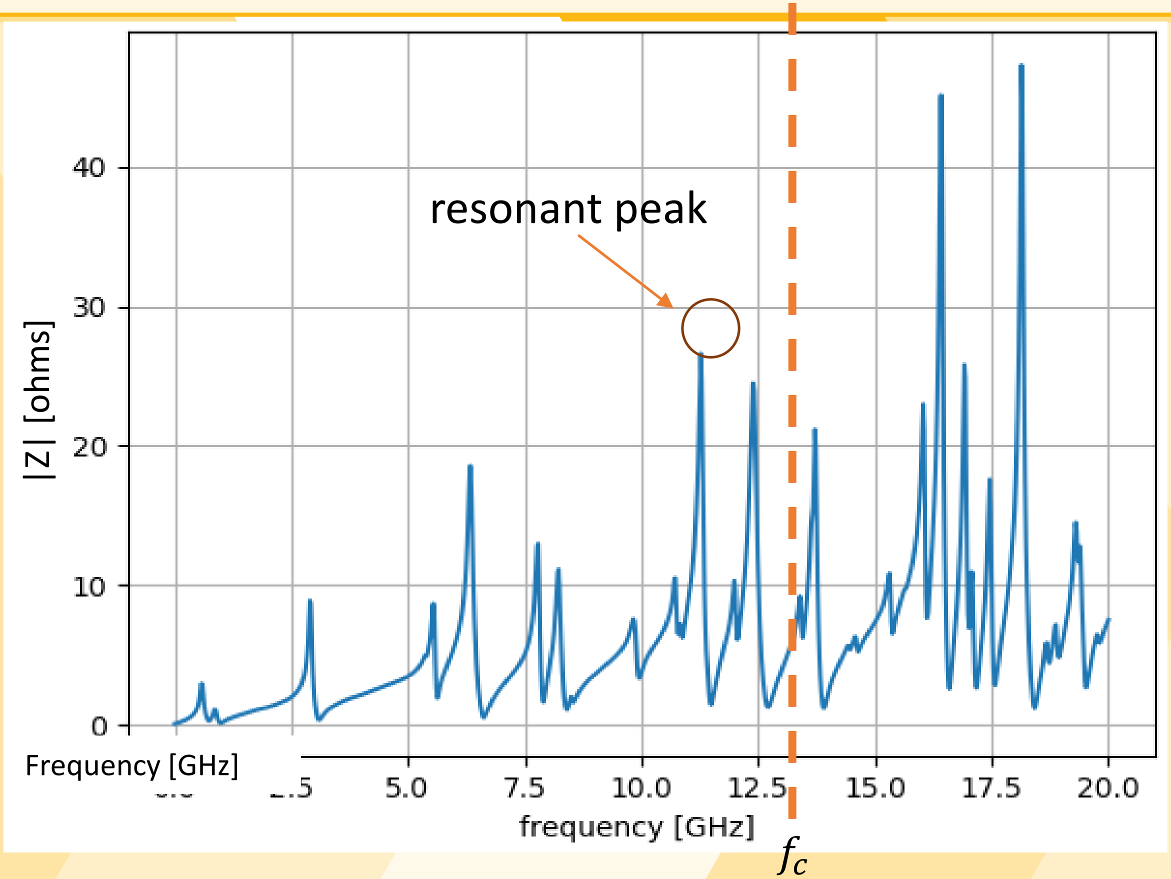
Hilbert transform needs more computations for complex stackups

- Interpolation and extrapolation using iterative Hilbert Transform → computationally inefficient
- Frequency response as a sum of damped sinusoids → less frequency range and simple stackup
- Cauchy method → narrowband responses only

[1] J. M. Frye and A. Q. Martin, ”Extrapolation of Time and Frequency Responses of Resonant Antennas Using Damped Sinusoids and Orthogonal Polynomials,” in IEEE Transactions on Antennas and Propagation, vol. 56, no. 4, pp. 933-943, April 2008
[2] S. M. Narayana et al., ”Interpolation/extrapolation of frequency domain responses using the Hilbert transform,”in IEEE Transactionson Microwave Theory and Techniques, vol. 44, no. 10, pp. 1621-1627, Oct. 1996.
[3] R. S. Adve, T. K. Sarkar, S. M. Rao, E. K. Miller and D. R. Pflug, ”Application of the Cauchy method for extrapolating/interpolating narrowband system responses,” in IEEE Transactions on Microwave Theory and Techniques, vol. 45, no. 5, pp. 837-845, May 1997.

3. Technical Approach

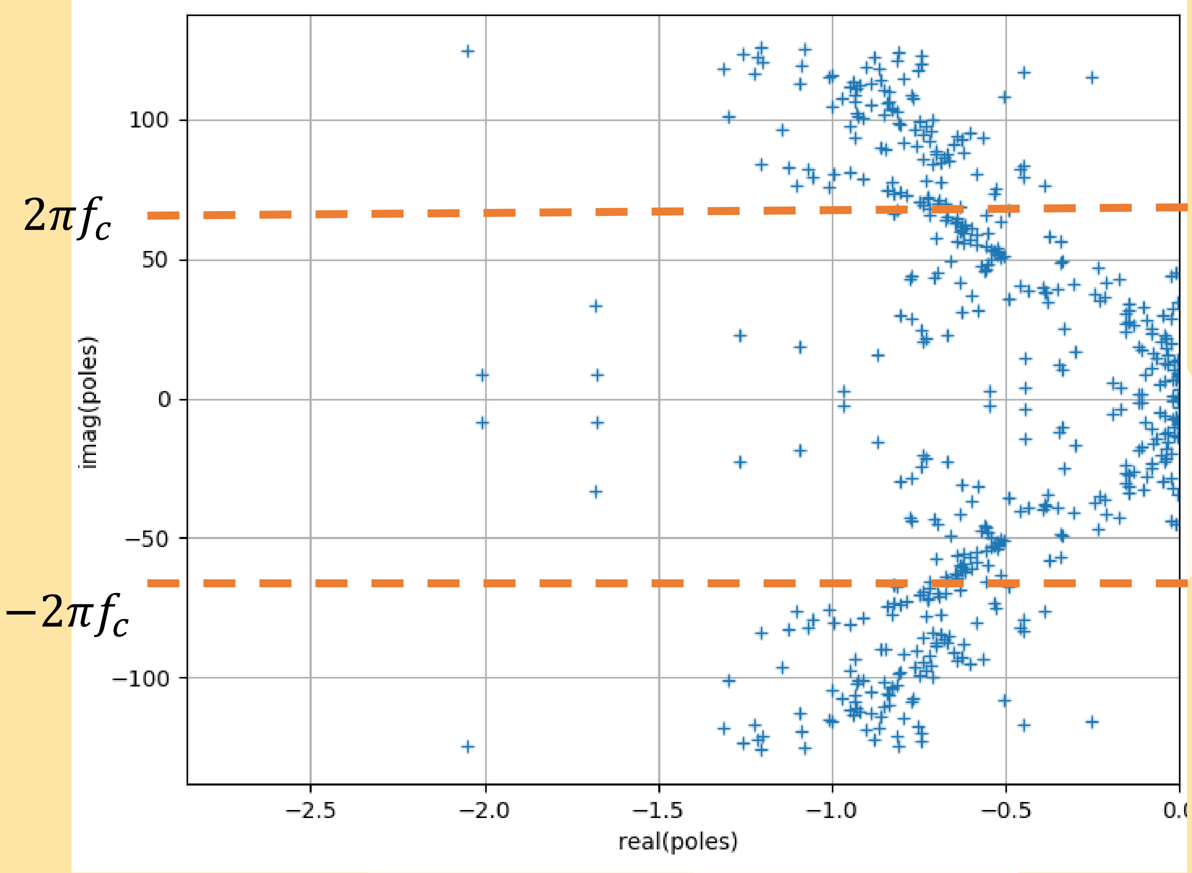
3.1 Impedance Response of a PDN



- How does one go about extrapolation with band-limited response?

- How do you determine the maximum extrapolation frequency for which the pole and zero trained model is accurate?

Vector-fitted pole diagram



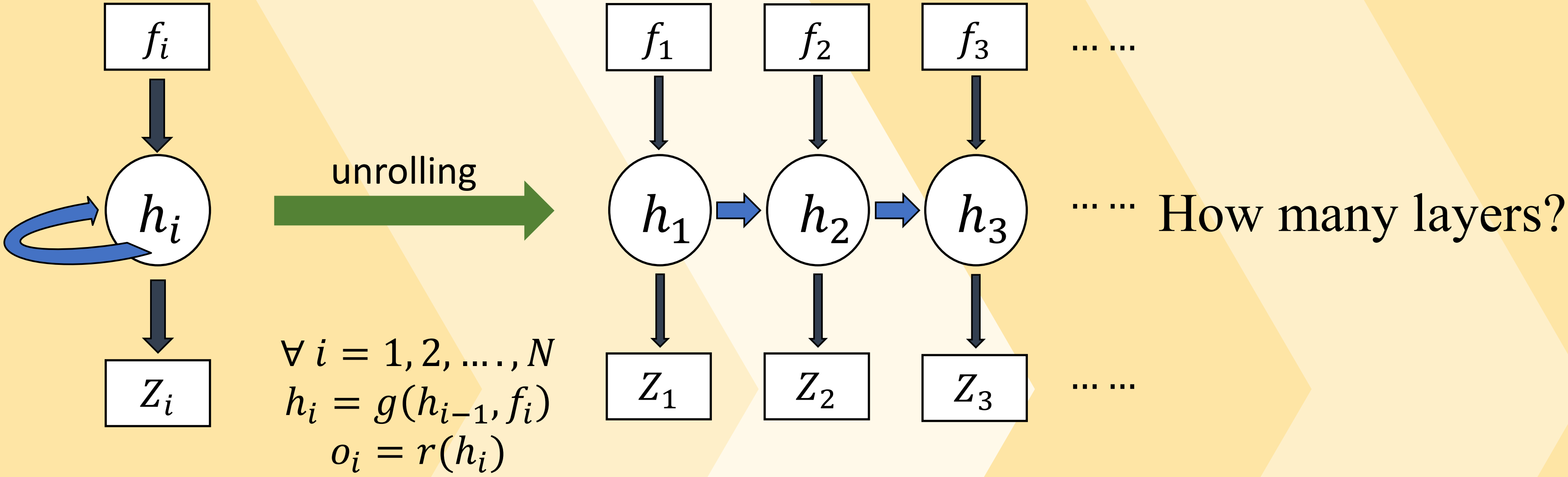
Illustrative vector-fitted pole representation of impedance response

$$f(s) = \sum_{i=1}^{N} \frac{r_i}{s - p_i} + sd + e$$

Where
r_i are the residues
p_i are the poles
d is the proportional factor

3. Technical Approach

3.2 Recurrent Structure of frequency samples

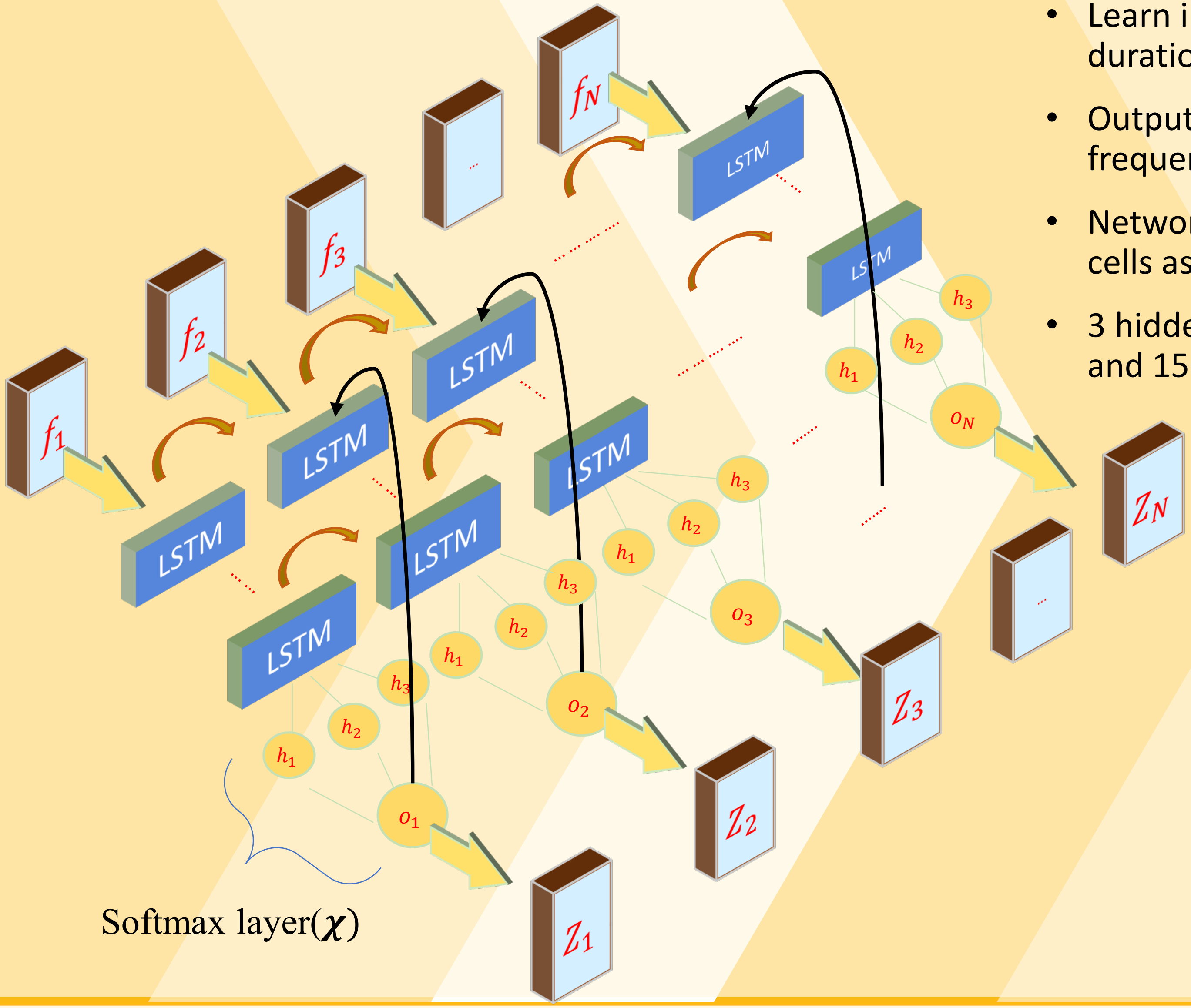


$$\forall\, i = 1, 2, \ldots., N$$
$$h_i = g(h_{i-1}, f_i)$$
$$o_i = r(h_i)$$

- Frequency samples are corelated in frequency space
- Information embedded in band-limited space, one can predict out-of-band values
- Recurrent neural networks form connections among inputs at different indices to predict the future sample value
- Hidden states store essential features from data necessary for construction of the next value

3. Technical Approach

3.3 Network Architecture

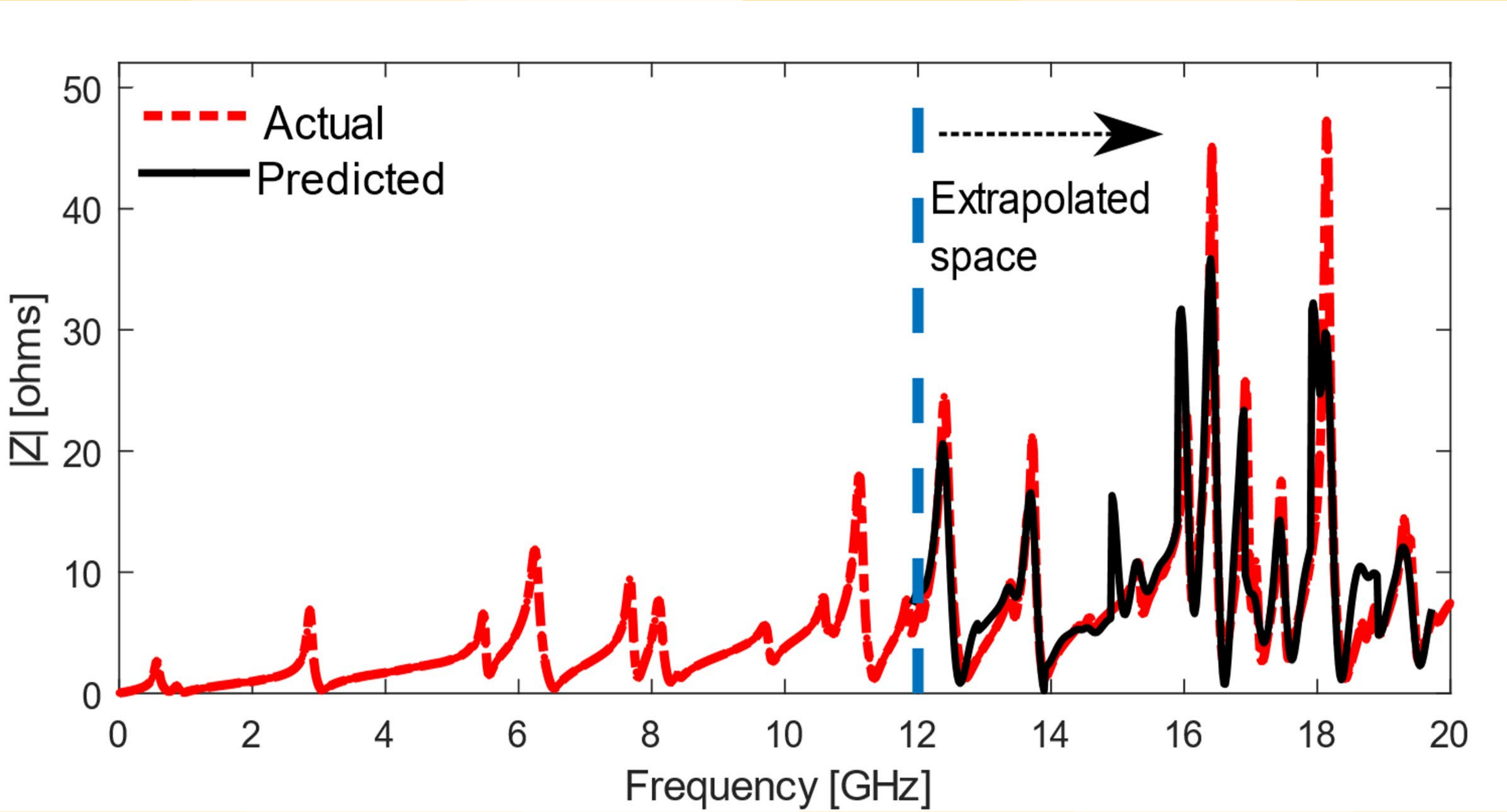


Softmax layer(χ)

- Learn input patterns for longer durations for time
- Output is a function of input frequency & previous outputs
- Network comprised of LSTM cells as hidden layers
- 3 hidden layers having 200, 200 and 150 nodes respectively

5. Results

5.1 Impedance response Extrapolation



$$FOM = (1 - RMSE) * \frac{no.of\ predicted\ poles}{no.of\ actual\ poles} * \frac{no.of\ predicted\ residues}{no.of\ actual\ residues} * 100\% = 78\%$$

5. Results

5.2 PDN sample

- *PDN* has around 60 poles in the training space
- MSE = 0.008 ohms squared

- Together combined with estimated mean and variance of the next batch gives the output impedance

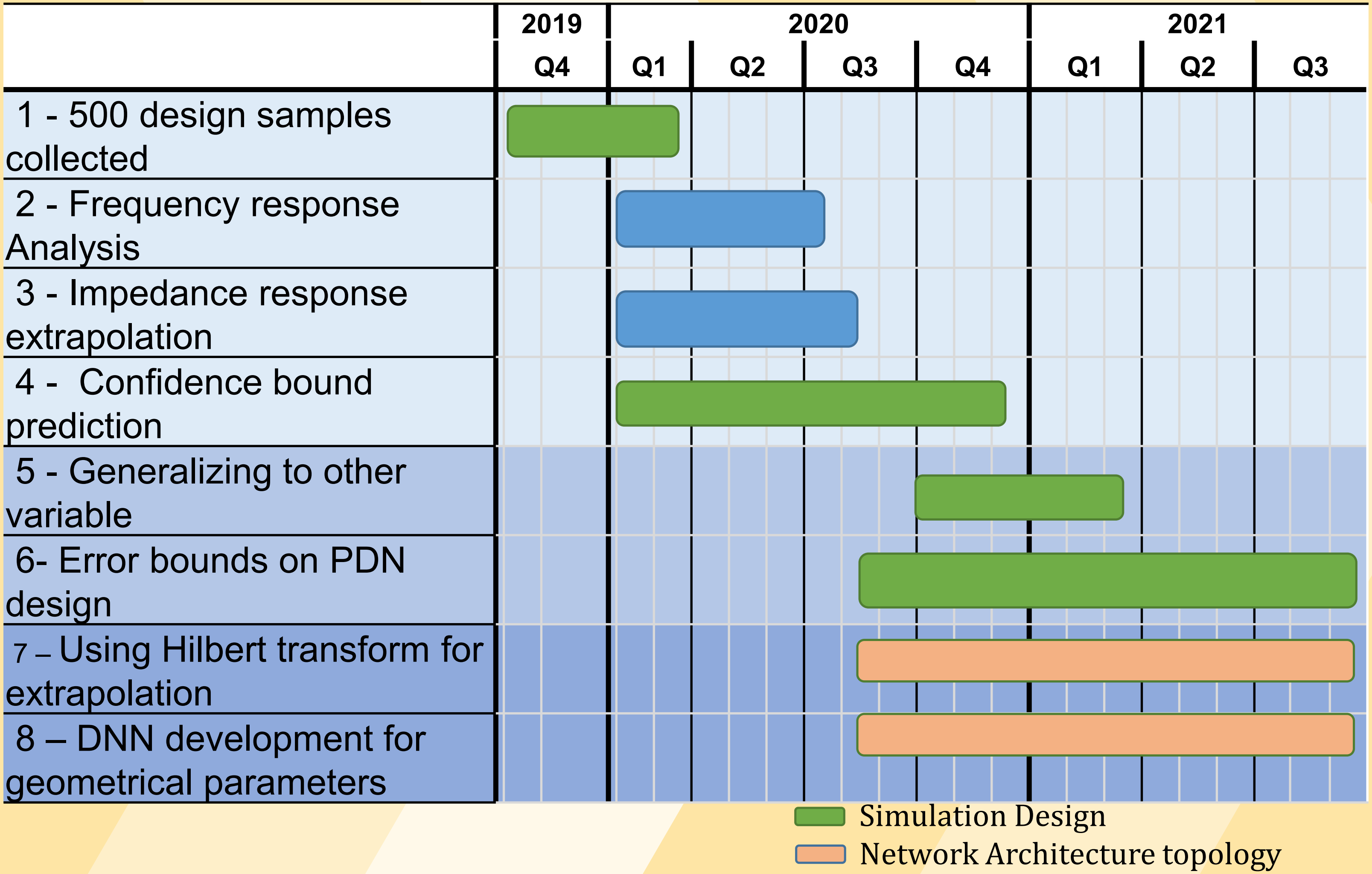
- Dynamic learning rate employed with batch normalization to avoid over-fitting

Physical parameters		**Values**
Conductivity	σ_{Si}	$9.27 * 10^7$ S/m
Metal height	t_{metal}	$0.757\mu m$
Grid width	W_{grid}	$27\mu m$
Grid spacing	w_{grid}	$168\mu m$
TSV radius	r_{TSV}	$7.93\ \mu m$
C4 bump radius	r_{C4}	$240\mu m$
Substrate thickness	h_{imd}	$0.81\mu m$

5. Summary

- ☐ PDN impedance response can be extrapolated using recurrent neural networks with specialized structured nodes called LSTMs
- ☐ The output of the network is a function of operating frequency and previous correlated points in frequency space
- ☐ Extrapolation in frequency saves time and computational resources in comparison to CAD tool avoiding the explicit simulation in out-of-band frequency range
- ☐ This technique is beyond limiting oneself on a certain PDN circuit topology
- ☐ As future work, we are working on providing confidence bounds for our prediction

6. Timeline



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