Deep Learning for THz Channel Estimation and Beamforming Prediction via Sub-6GHz Channel



MODERN
WIRELESS
NETWORKS
GROUP

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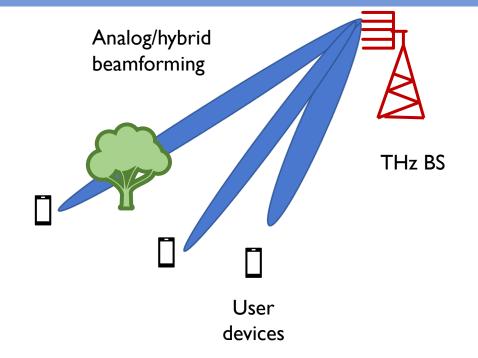
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Communications at Terahertz (THz) Frequencies

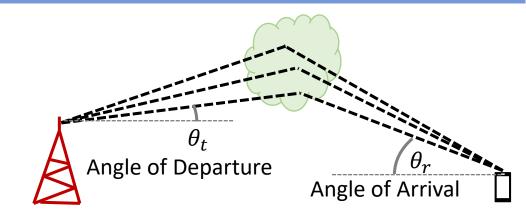
- Emerging wireless applications
 - Augmented reality, ultra-low latency video conferencing.
- Requiring data rates in Tb/s.
- Even mmWave assisted 5G may fall short of requirement.
- Use of THz spectrum is inevitable.
- Challenges of THz signals
 - Exponential pathloss decay due to atmospheric attenuation,
 - High blockage and penetration losses.
- Implications
 - Ultra dense base station (BS) deployment
 - Large antenna arrays with analog/hybrid beamforming.



THz Channel Estimation

- Real-time and reasonably accurate THz channel estimation is required.
- Conventional channel estimation methods, e.g. least square (LS) or linear minimum mean squared (LMMS) estimation, require large number of uplink pilot signals due to large antenna array at THz
 - Significant overhead considering real-time applications.
 - Not viable.
- Sub-6GHz channel, on the other hand, can be estimated with a smaller number of uplink pilots
 - Relatively low overhead.

Can we estimate THz channel from Sub-6GHz channel values?

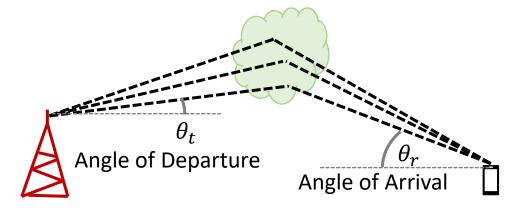


THz Channel Estimation

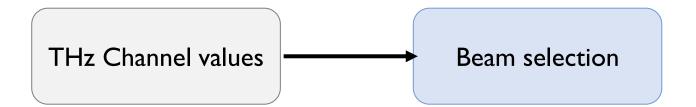
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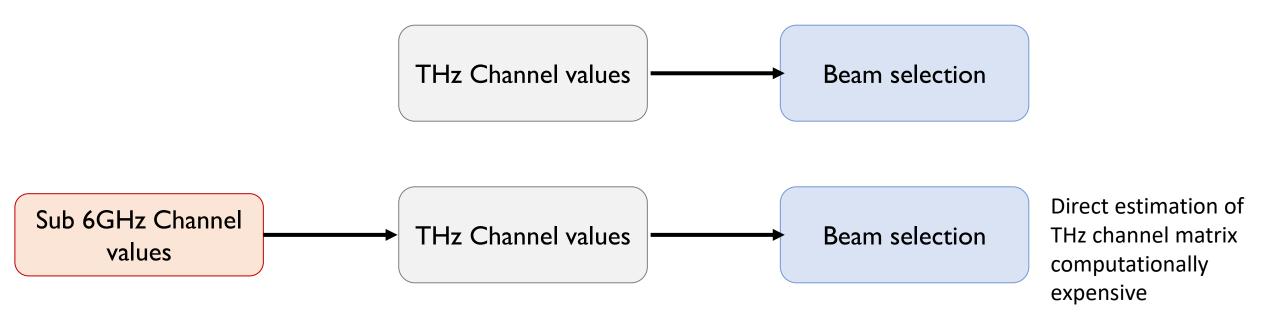
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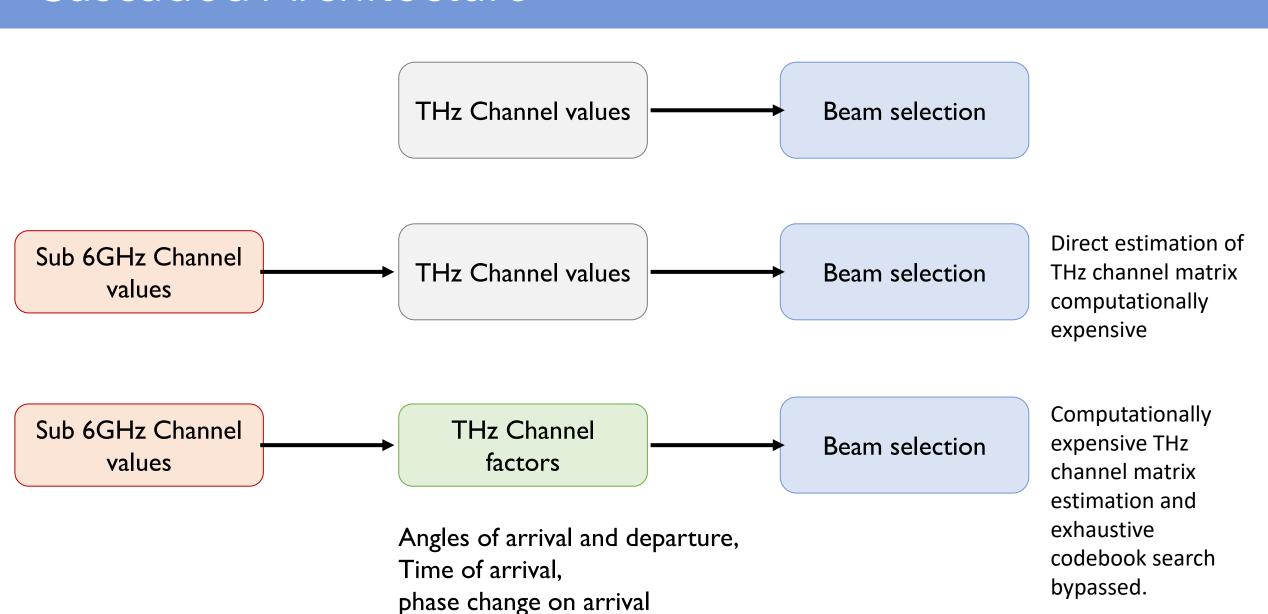
Can we take transmitter side decision from Sub-6GHz channel values?



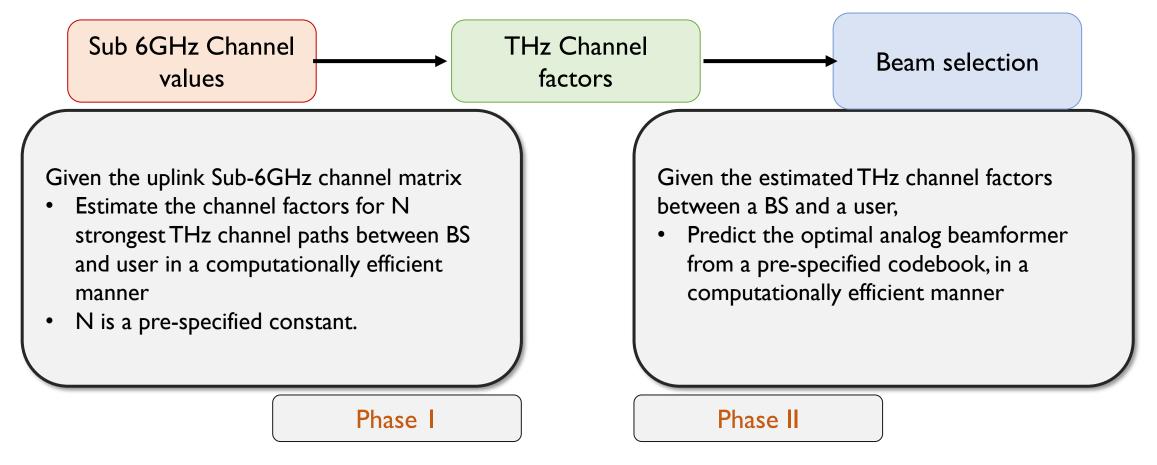
Beam selection
BS selection
Blockage prediction



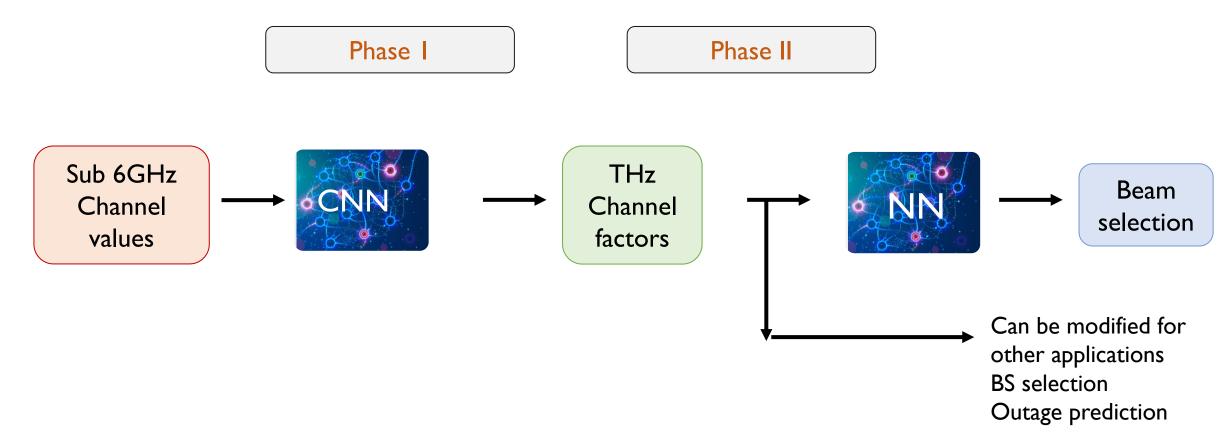






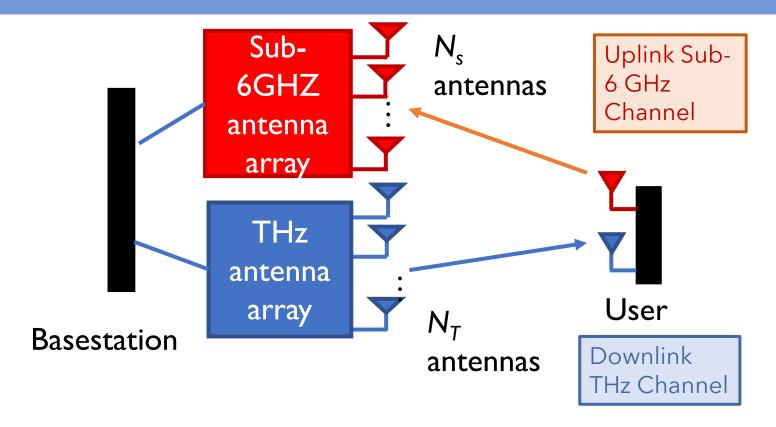


- Deep Learning algorithms efficiently map otherwise intractable functions, using training data.
- Convolutional Neural Networks (CNN) suitable for extracting spatial/temporal features directly from raw data.

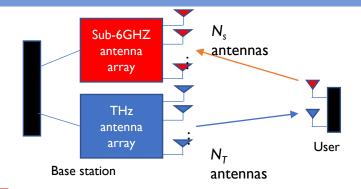


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System Model



Channel Model



Uplink Sub-6 GHz Channel

$$y_{\rm S}[k] = h_{\rm S}[k] \ x_{\rm S}[k] + n_{\rm S}[k]$$
 received sub-6 input received uplink channel symbol noise sub-6 symbol from UE to vector BS $_{\mathbb{C}^{Ns \times 1}}$

- OFDM with K subcarriers
- Let $k \in \{1, 2, ..., K\}$ be the OFDM subcarrier index.
- N_s small enough for fully digital beamforming.

Downlink THz Channel

$$y_{\mathrm{T}}[k] = h_{\mathrm{T}}^{H}[k] \ p \ x_{\mathrm{T}}[k] + n_{\mathrm{T}}[k]$$
 downlink received channel beam symbol symbol at THz from from P BS to UE v_{T}

- Fully analog beamforming adopted for THz scenario, single RF chain with N_T quantized phase shifters.
- Pre-suppled codebook P comprises all candidate beamformers.

Channel Model

Geometric channel model (both Sub-6GHz and THz)

Sub-6GHz channel:

$$h_{S}[k] = \sum_{m=0}^{M-1} \lambda_{m} \, \alpha_{r,m}(\phi_{r,m}, \theta_{r,m}) \, \alpha_{t,m}^{*}(\phi_{t,m}\theta_{t,m})$$

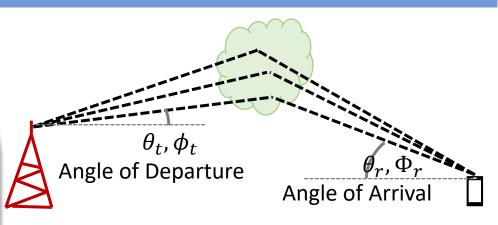
k = OFDM subcarrier index

M = number of channel paths

 λ_m = path gain

 $\phi_{r,m}$ and $\theta_{r,m}$ = azimuth and elevation angles of arrival

 $\phi_{t,m}$ and $\theta_{t,m}$ = azimuth and elevation angles of departure



for *M*th channel path

Channel Model for THz

- Significant molecular absorption, exponentially dependent on the link distance r: $\delta(r)$
- THz path gain contains additional absorption term.

$$p_{\rm rx} = p_{\rm tx} \, \ell'(r) \, \delta(r)$$

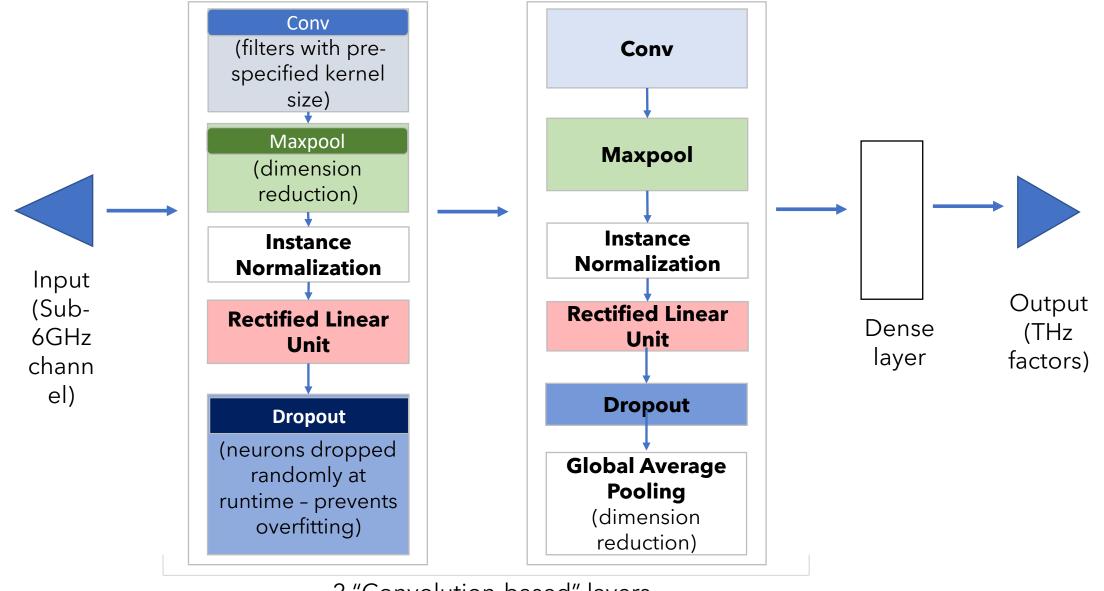
where r is the distance between receiver and transmitter, $\ell'(r)$ is the power law path gain

- $\ell(r) = \ell'(r)\delta(r)$ is the effective path gain for THz channel.
- THz channel model can be obtained from the Sub-6GHz channel equation by replacing corresponding terms with their THz channel counterparts.
- Channel factors for a channel path: (effective) pathloss, azimuth and elevation angles of arrival and departure, time of arrival, and phase difference on arrival.
- Given the channel factors for M channel paths, the channel can be determined completely.

Phase I: THz Channel Factors Estimation

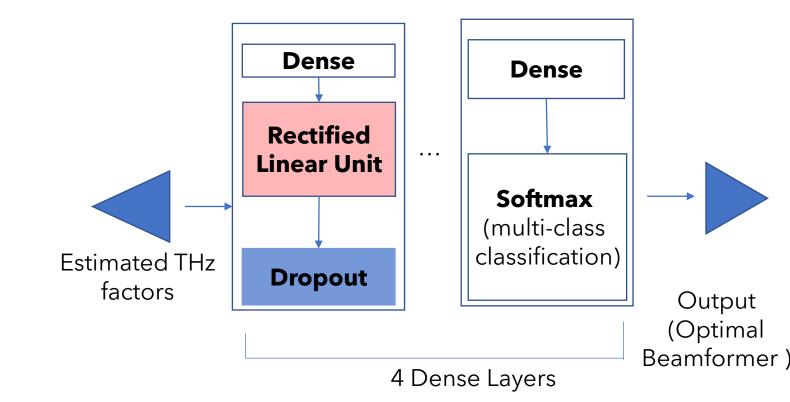
- Input : Sub-6GHz channel matrix $h_S \in \mathbb{C}^{K \times N_S}$ estimated using uplink pilot signals. Each element of h_S is separated into magnitude and phase angle - resulting in a 3D matrix $h_S' \in \mathbb{C}^{K \times N_S \times 2}$
- Output :THz channel factors for the first (strongest) N channel paths, where N is a pre-specified hyperparameter $-S_T \in \mathbb{R}^{N \times 7}$
- CNN based model to estimate THz channel factors.
- Training Phase :
 - Raytracing data obtained for both Sub-6GHz and THz channels, from multiple users training samples (h'_S, S_T)
- Deployment Phase :
 - Sub-6GHz channel matrix estimated from uplink signals used by model to estimate THz channel factors.
 - We considered the ray trace data for sub-6GHz channel as the input.

Phase I: Proposed Learning Network's Architecture



Phase II: Optimal Analog Beamformer Prediction

- Input : S_T Estimated THz channel factors from CNN model
- Output : Optimal beamformer index
- Deep neural network to directly predict the optimal beamformer index from the estimated THz factors.



Phase II: Optimal Analog Beamformer Prediction

Training Phase:

- THz raytracing data (S_T) obtained for multiple users
 - Used to compute THz channel matrix h_T .
- Exhaustive beam search is conducted from entire codebook P
 - Optimal beamformer index \hat{p} , providing the highest spectral efficiency is selected.

$$\hat{p} = \underset{p \in P}{\operatorname{argmax}} \left(\sum_{k=1}^{K} \log_2 \left(1 + \operatorname{SNR} \left| h_T^H[k] \ p \right|^2 \right) \right)$$

• Neural network input samples are (S_T, p_{ind}) , where p_{ind} is the categorical variable representing index of \hat{p} in P.

Deployment Phase:

• CNN estimated THz channel factors provided as input - output is p_{ind} .

Performance Evaluation

Baseline Algorithm:

- I. THz channel matrix, computed from raytracing, passed into a deep learning model to output optimal beamformer index.
- 2. Model comprises a convolutional layer, followed by GAP, ReLU, and 4 dense layers, each followed by ReLU and dropout layers. Softmax function at the end outputs beamformer index.

Upper Bound:

- Exhaustive codebook search using raytracing derived THz channel matrix to find the optimal beamformer by brute force.
- Computationally prohibitive for real-time applications

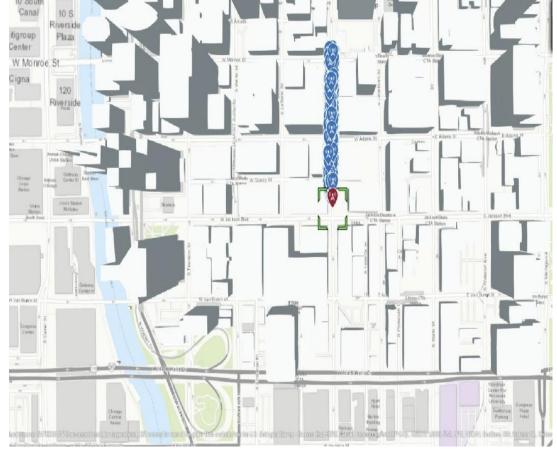
Neural Network Hyperparameters

• The neural network hyperparameters for the CNN based THz factors estimation, and the beamformer prediction models are the following:

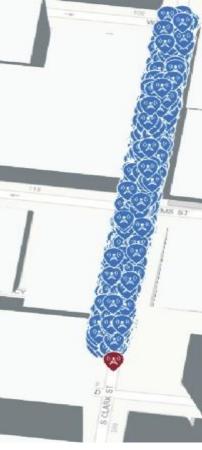
Hyperparameter	THz Estimation	Beamformer Prediction
Conv kernel size	(2,2)	-
Conv no. of filters	64	-
Maxpool kernel size	(2,2)	-
Maxpool stride length	2	-
Dense layer dimension	-	64
No. of training samples	80,000	80,000
No. of test samples	20,000	20,000
No. of epochs	100	100
Task objective	Regression	Classification
Optimizer	Stochastic gradient descent	Adam
Initial learning rate (LR)	10-3	10-2
LR decay factor	0.1	-
LR decay schedule	80 epochs	-
Momentum	0.8	-
Dropout	0.2	0.2

Simulation

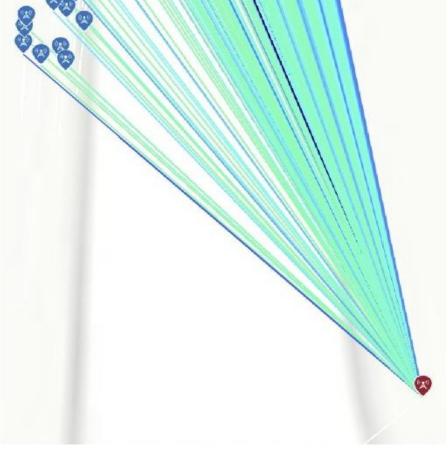
- Raytracing Scenario is generated using MATLAB raytrace function from Communications Toolbox.
- Outdoor environment, rectangular block of dimensions $(400m \times 30m)$ in S Clarke St., Chicago downtown area.
- BS at one corner of rectangular block, user locations randomly generated inside block raytracing data gathered.



Location of BS (red) and users (blue) in Chicago



Zoomed in scenario - S Clarke St.



Raytracing - highly zoomed in

Simulation Parameters

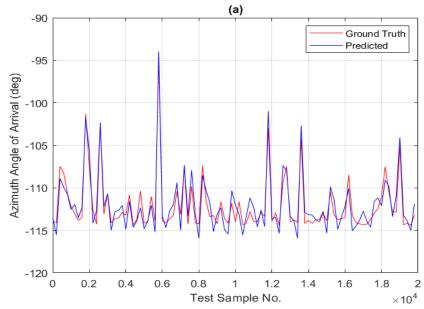
Scenario Parameter	Sub-6GHz	THz
No. of users	100,000	100,000
BS antenna array length	4	128
BS antenna height (m)	8	8
User antenna height (m)	2	2
Center frequency (GHz)	2.4	100
Propagation model	sbr*+gas+cloud	sbr*+gas+cloud
Max no. of channel paths	8	4
Bandwidth (MHz)	20	500
No. of OFDM subcarriers	64	64
Codebook size (X, Y, Z)	$4 \times 64 \times 4$	$4 \times 128 \times 4$

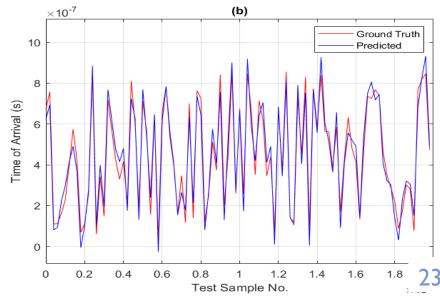
^{* -} sbr = shooting and bouncing rays propagation model

Performance Evaluation: THz Channel Factors Estimation

- Table shows mean and standard deviation absolute errors of proposed algorithm's THz channel factors predictions.
- Error values show high estimation accuracy (<6 degree for AoA, AoD, and Phase Change estimates; and very low errors on ToA and Pathloss as well).
- Figures show the graph of two THz channel factors as examples Azimuth Angle of Arrival and Time of Arrival versus No. of samples.

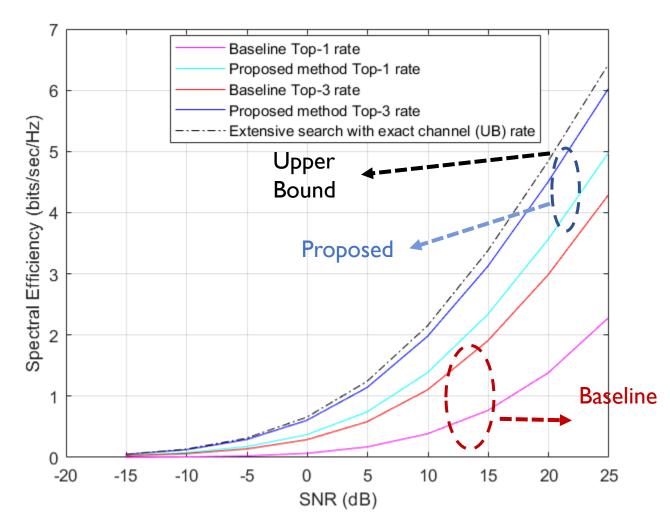
Factors	Average Absolute Error	Standard Deviation
AoD ϕ (deg)	5.67	1.23
AoD θ (deg)	2.36	0.47
AoA ϕ (deg)	2.22	0.63
AoA θ (deg)	4.43	0.91
Phase Change (deg)	5.93	1.08
ToA (10 ⁻¹⁸ s)	3.80	0.67
Pathloss (10 ⁻¹⁹)	5.70	0.35





Performance Evaluation: Beamformer Prediction

- Top-3 rate 3 best beams predicted by model
 Top-1 rate best beam predicted by model
- Wide range of SNR values (-17dB to 25dB) considered.
- Proposed algorithm Top-3 rate approaches computationally prohibitive upper bound spectral efficiency – proving the accuracy of estimated THz channel factors.
- Proposed algorithm Top-1 rate outperforms
 Baseline Top-1 and Top-3 rates validating our
 Sub-6GHz based approach.
- Baseline method inefficient because of THz channel matrix input (high dimensionality).



• Baseline model is **underperforming** compared to our Sub-6GHz based proposed algorithm – because severe THz attenuation renders the THz channel matrix highly noisy; not suitable for deep learning.