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GAN-based Massive MIMO Channel Model Trained on Measured Data

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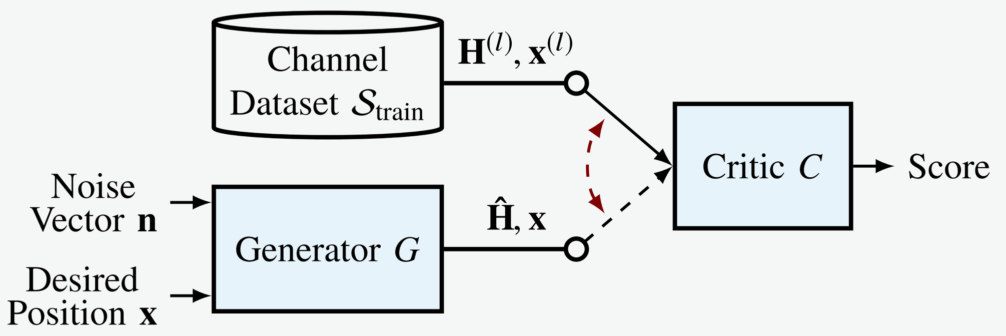
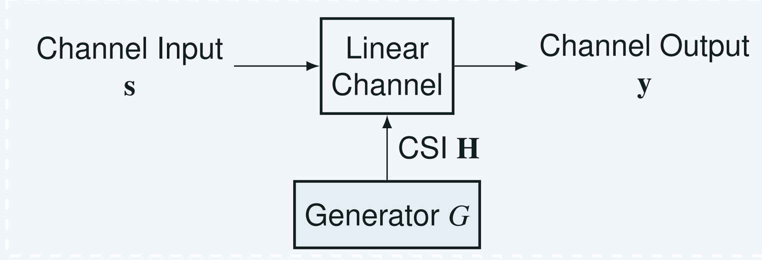
Abstract

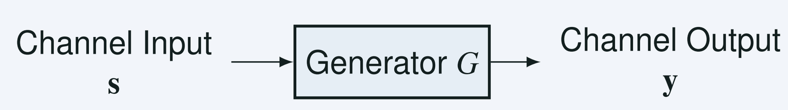


Wireless channel models are a commonly used tool for the development of wireless telecommunication systems and standards. The currently prevailing geometry-based stochastic channel models (GSCMs) were manually specified for certain environments in a manual process requiring extensive domain knowledge, on the basis of channel measurement campaigns. Instead of this manual process, a generative machine learning model like a generative adversarial network (GAN) may be used to automatically learn the distribution of channel statistics. Subsequently, the GAN's generator may be viewed as a channel model that can replace conventional stochastic or raytracer-based models. We propose a GAN architecture for a massive MIMO channel model, and train it on measurement data produced by a distributed massive MIMO channel sounder.

Literature Review / Contributions



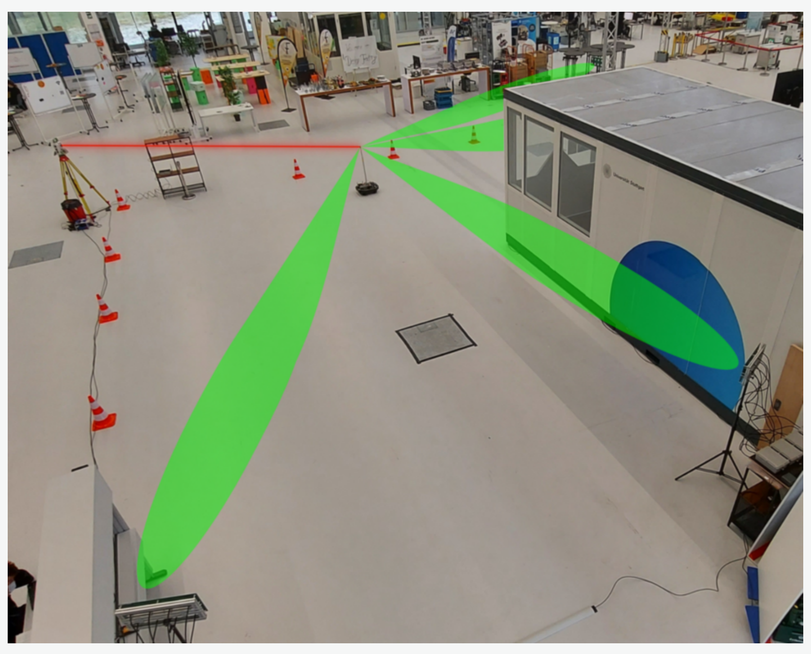
(a) Linear: Generator produces CSI [1, 2, 3, 4, 5, 6]



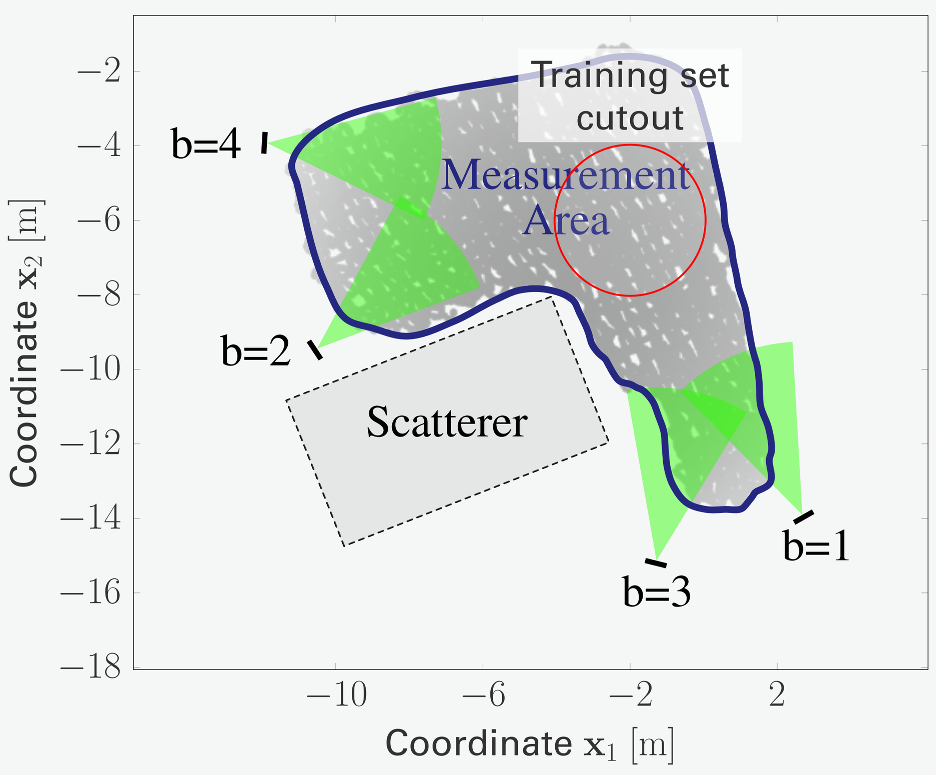
(b) Nonlinear: Generator conditioned on input [7, 8]

- **GAN-based channel models** have been proposed previously, especially as a more automated alternative to geometry-based stochastic channel models (GSCMs)
- This work focuses on the **linear** GAN-based channel model type, which generates channel state information (CSI)
- **Contribution**: GAN tested on real-world dataset for the first time, conditioning on UE locations $\mathbf{x} \in \mathbb{R}^2$

Measurement Dataset



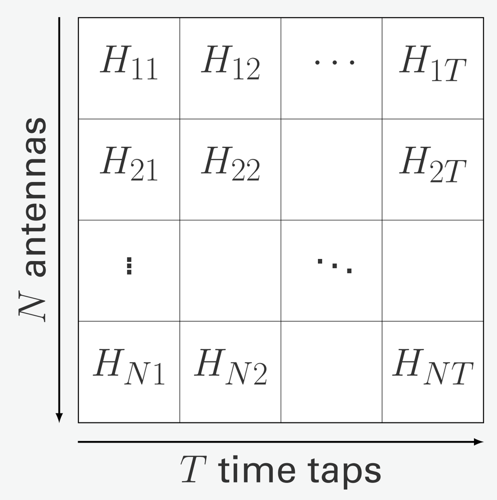
Top View Map



The dataset was measured by DICHASUS (`https://dichasus.inue.uni-stuttgart.de`), our "big data" distributed massive MIMO channel sounder [9].

Carrier Frequency	$1.272\,\mathrm{GHz}$
Bandwidth	$50\,\mathrm{MHz}$
Antennas	4 arrays, 2×4 antennas
Dataset Size	$\lvert\mathcal{S}_{\text{train}}\rvert = 17857$, $\lvert\mathcal{S}_{\text{test}}\rvert = 20973$

CSI Format, Neural Network, Training Procedure



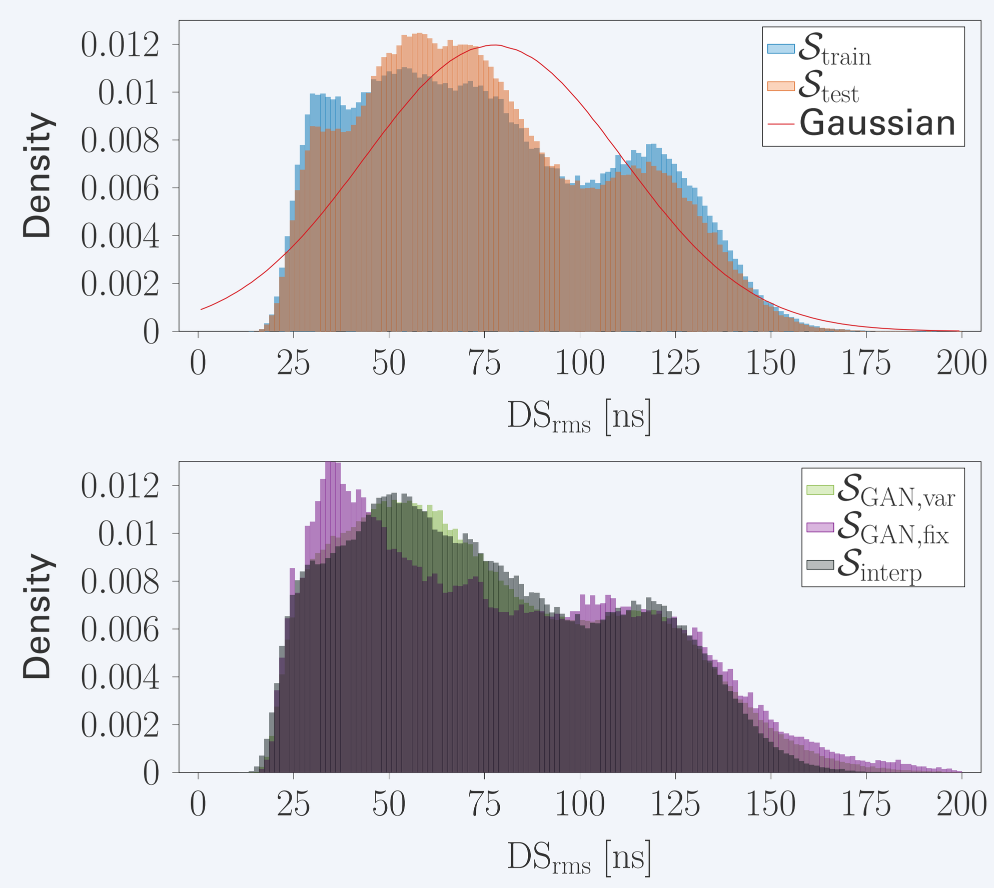
- CSI representation: Time-domain channel impulse responses, complex-valued
- Single UE, multi-antenna BS
- $T = 40$ taps, $N = 32$ antennas
- Wasserstein GAN (WGAN) with Gradient Penalty (GP)
- Simple fully connected network, ReLU activation

Training / test set are disjoint, but from same environment.

Evaluation Procedure

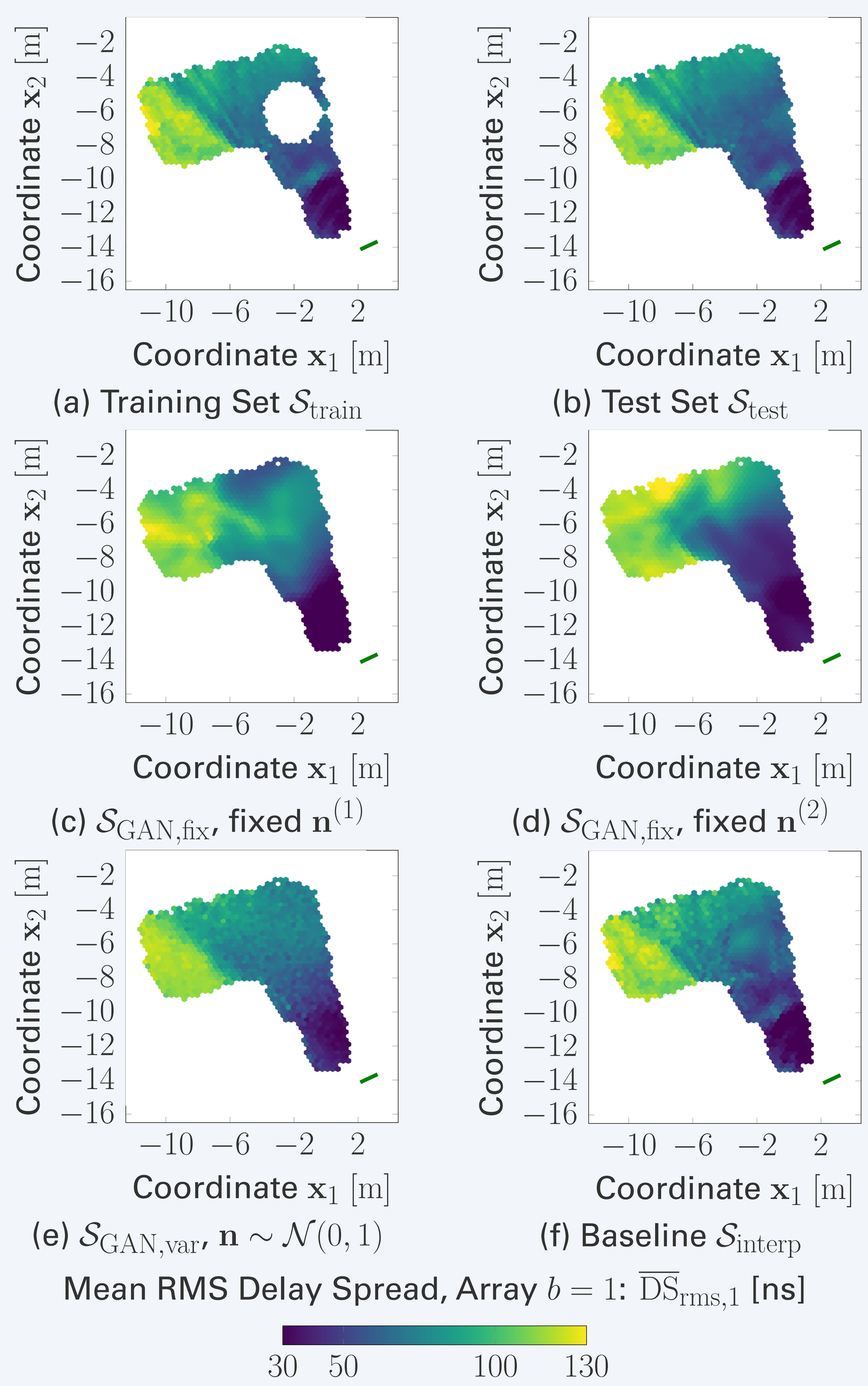
- Challenge: CSI is hard to interpret by humans
- Solution: Analyze derived statistics, such as RMS delay spread, azimuth angle of arrival
- Two evaluation methods:
  - Constant generator noise input $\mathbf{n}$: CSI $\mathcal{S}_{\text{GAN,fix}}$
  - Variable generator noise input $\mathbf{n}$: CSI $\mathcal{S}_{\text{GAN,var}}$
- Baseline: Linear CSI interpolation, $\mathcal{S}_{\text{interp}}$

Evaluation: RMS Delay Spread Distribution



The RMS delay spread distribution of the GAN-generated CSI ($\mathcal{S}_{\text{GAN,fix}}$ / $\mathcal{S}_{\text{GAN,var}}$) closely resembles the true distribution ($\mathcal{S}_{\text{train}}$ / $\mathcal{S}_{\text{test}}$). This could also be achieved by linear interpolation ($\mathcal{S}_{\text{interp}}$).

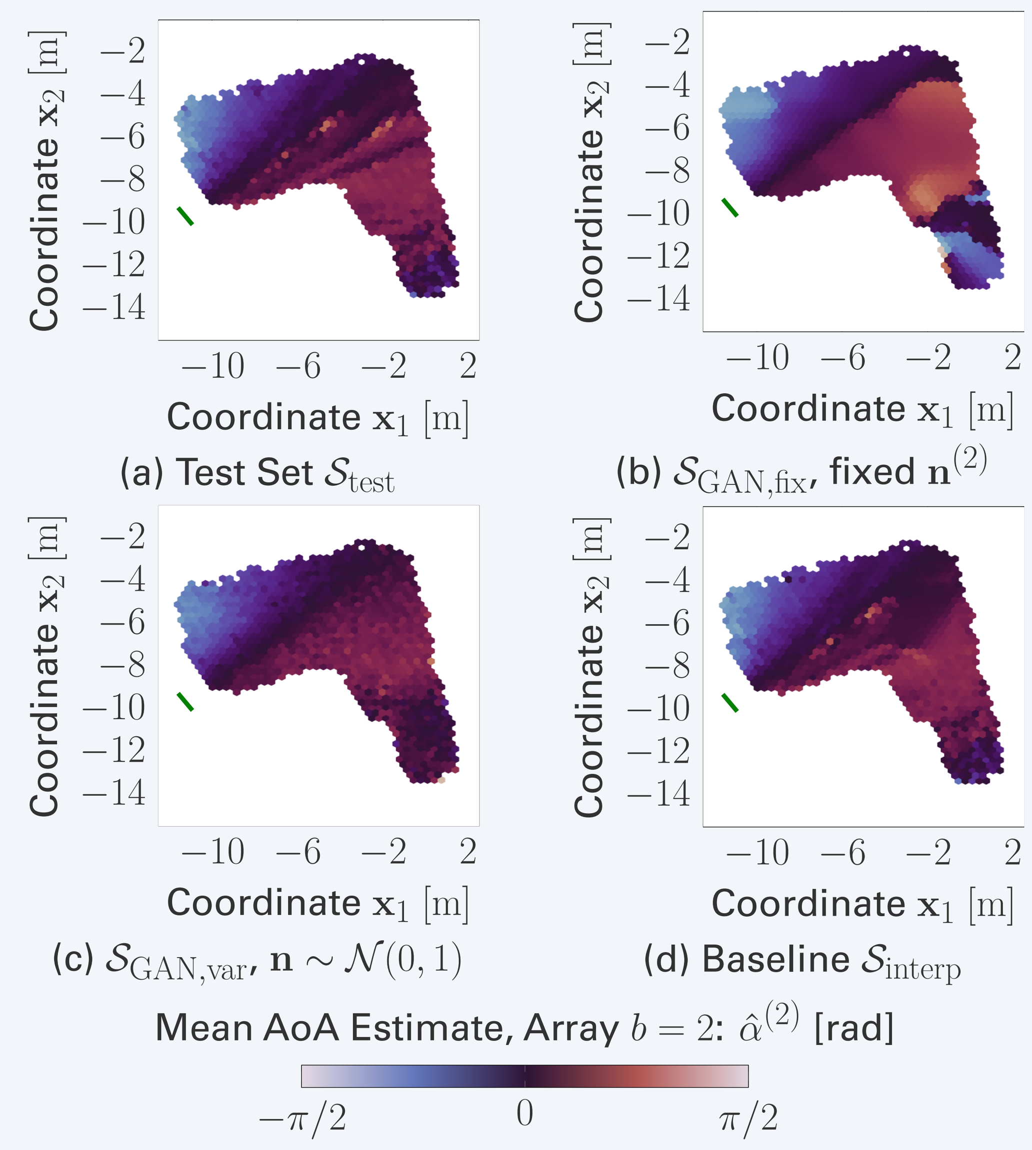
Evaluation: RMS Delay Spread over Space



(a) Training Set $\mathcal{S}_{\text{train}}$ (b) Test Set $\mathcal{S}_{\text{test}}$ (c) $\mathcal{S}_{\text{GAN,fix}}$, fixed $\mathbf{n}^{(1)}$ (d) $\mathcal{S}_{\text{GAN,fix}}$, fixed $\mathbf{n}^{(2)}$ (e) $\mathcal{S}_{\text{GAN,var}}$, $\mathbf{n} \sim \mathcal{N}(0,1)$ (f) Baseline $\mathcal{S}_{\text{interp}}$

Mean RMS Delay Spread, Array $b = 1$: $\overline{\mathrm{DS}}_{\text{rms},1}$ [ns]

Evaluation: Azimuth AoA Estimate (MUSIC) over Space



(a) Test Set $\mathcal{S}_{\text{test}}$ (b) $\mathcal{S}_{\text{GAN,fix}}$, fixed $\mathbf{n}^{(2)}$ (c) $\mathcal{S}_{\text{GAN,var}}$, $\mathbf{n} \sim \mathcal{N}(0,1)$ (d) Baseline $\mathcal{S}_{\text{interp}}$

Mean AoA Estimate, Array $b = 2$: $\hat{\alpha}^{(2)}$ [rad]

Criticism

1. **Lack of spatial consistency**: The GAN-based channel model fails to take spatial autocorrelation / large-scale effects into account. This may be mitigated with an enhanced architecture.
2. **Lack of generalizability**: Environment, carrier frequency, bandwidth and antenna deployment are determined by the underlying training dataset and cannot be changed.
3. **Lack of interpretability**: Properties of the channel model cannot be influenced and their impact on system performance is hard to study: The system just works, or it does not.
4. **Availability of a dataset**: A CSI dataset of the desired environment and system parameters is required for training. Why not just use the dataset as the model? Data augmentation or interpolation may be required, but are easy to implement.

Conclusion and Outlook

- GAN-based channel models work on **real data**.
- GANs are *good random generators*, but *bad interpolators*
- Need to answer some crucial questions and address issues:
  - What is the purpose of GANs in channel modeling?
  - Improve consistency, generalizability, interpretability
- Criticism also applies to other generative models
- Alternative approaches: GAN + Raytracer?

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