Enhancing NextG with ML-Based Multi-User Resource Scheduling

Machine Learning in 5G Challenge Webinar
ITU AI for Good

Presenters:
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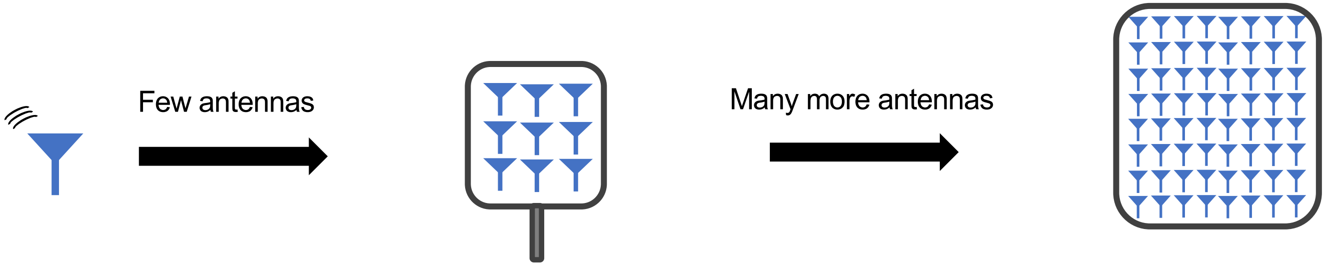
Rice Wireless

Outline

- ❑ Background on Massive MIMO
- ❑ Problem Statement
- ❑ Baseline ML-Based Solution
- ❑ Resources
- ❑ Submission & Evaluation

What is Massive MIMO?



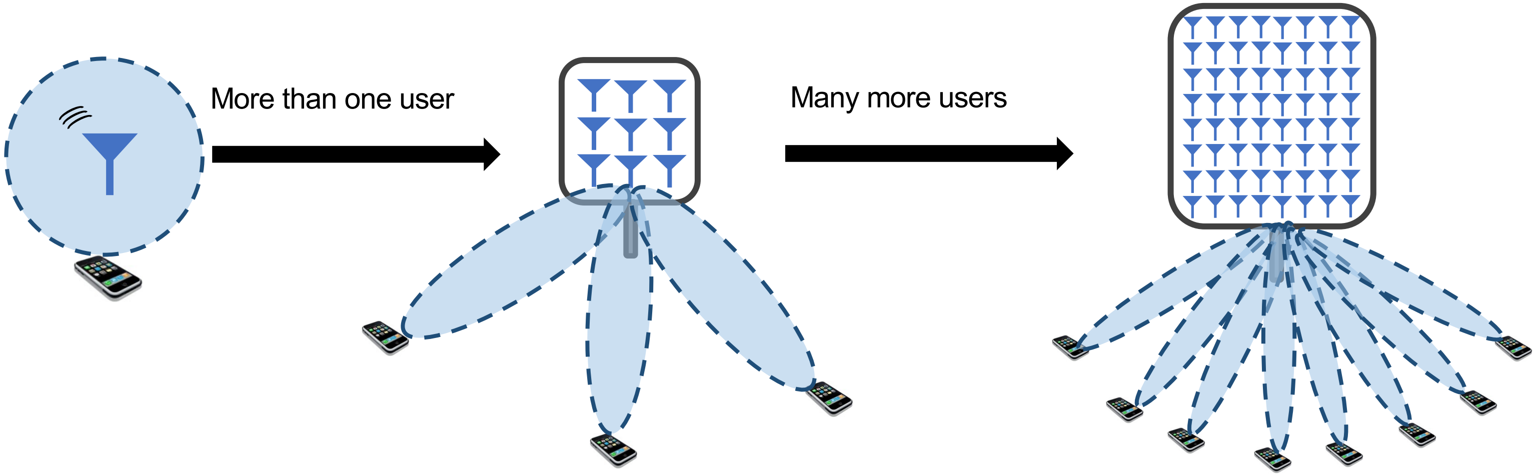
Benefits of MIMO:

- Enhance robustness through diversity in fading channels
- Increase capacity using the same frequency and time resources

T Marzetta, Non-cooperative cellular wireless with unlimited number of base station antennas, IEEE TWC, 2010.

High Spatial Reuse via Multi-User Beamforming

- Large degrees of freedom to beamform to many users



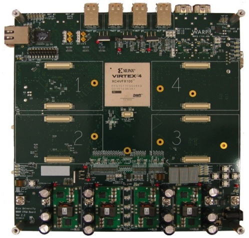
Benefits of massive MIMO:

- Significant increase in capacity
- Simplifies interference management across cells

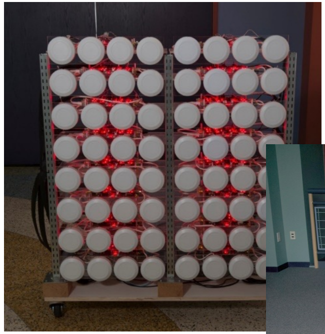
Rice Wireless Platforms

- WARP: Multiple-antenna software-defined radios
    - First-ever software-defined radio with MIMO capability

- Argos: Practical massive MIMO systems
    - First-ever mMIMO base-station design with multi-user beamforming capability



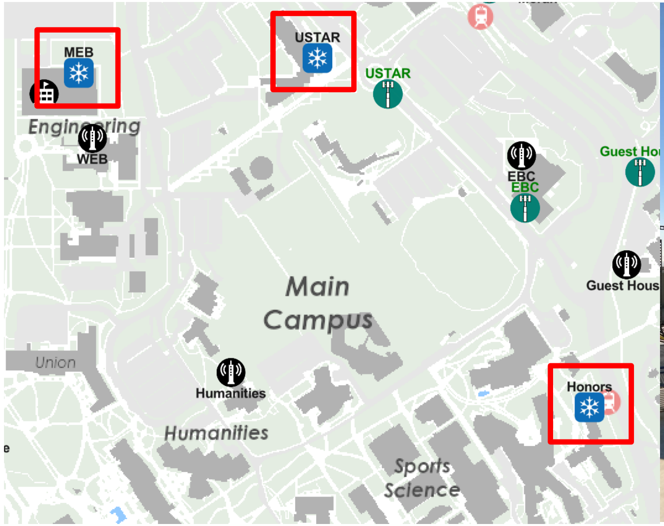
WARP



64 antenna

Argos

Rice RENEW Platform – An NSF PAWR Platform




- World’s first multi-cell testbed for massive MU-MIMO
- Public Deployment at the University of Utah (POWDER)

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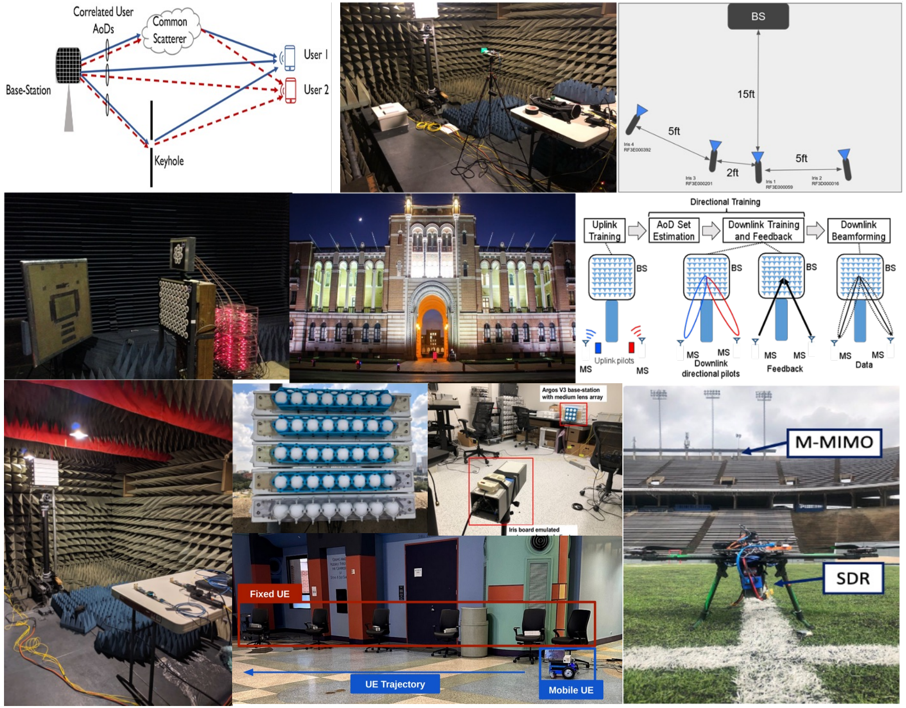
RENEW Open Datasets

- Self-interference reduction technique for massive MIMO systems
- Comprehensive many-antenna MU-MIMO channel measurement campaign (indoor/outdoor)
- FDD Massive MIMO
- Multi-User MIMO dataset with inter-user channel correlation (AoD)
- Full-Duplex (Self-Interference in mMIMO)
- AoA (mMIMO)
- Uplink Massive MIMO with Coherent and Non-coherent Array
- Experimental Evaluation of AoA Estimation for UAV to Massive MIMO
- LensFD (full-duplex mMIMO)
- Indoor Mobility mMIMO



RENEW has published 11 datasets so far and more on the way
https://renew-wireless.org/datasets.html

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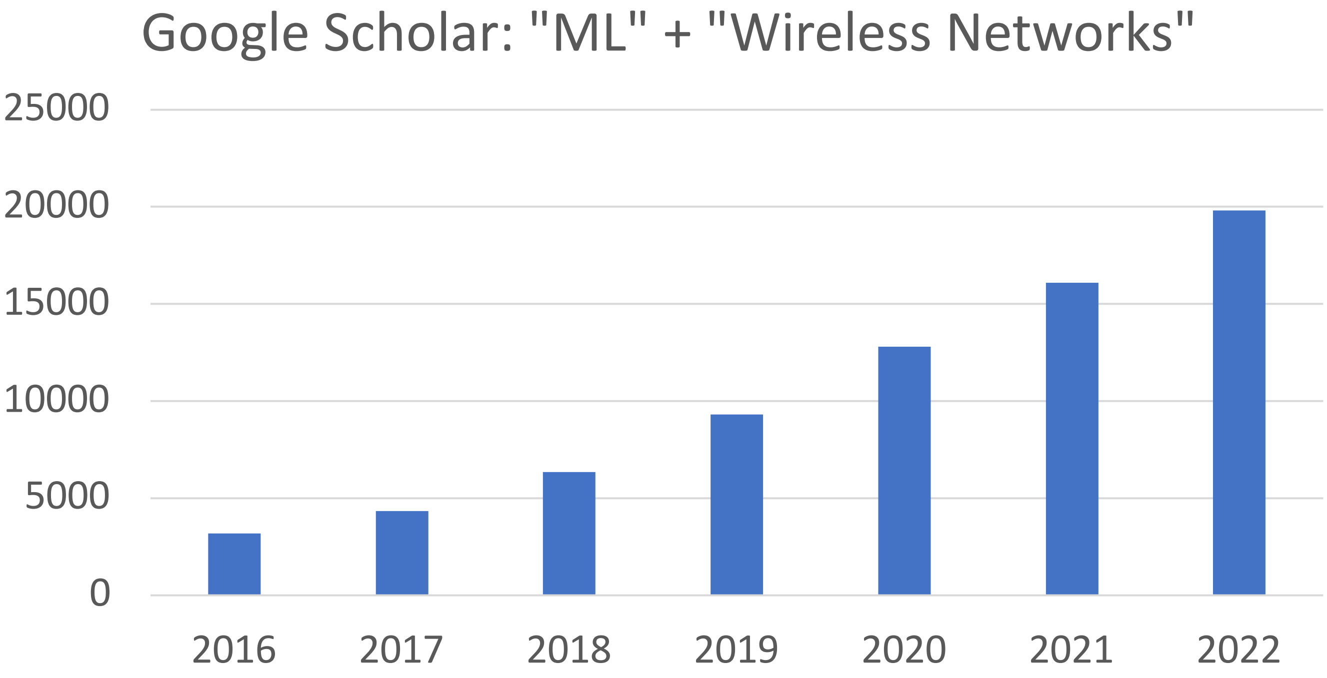
Machine Learning in Wireless

- Very dynamic field: Lots of new papers being published



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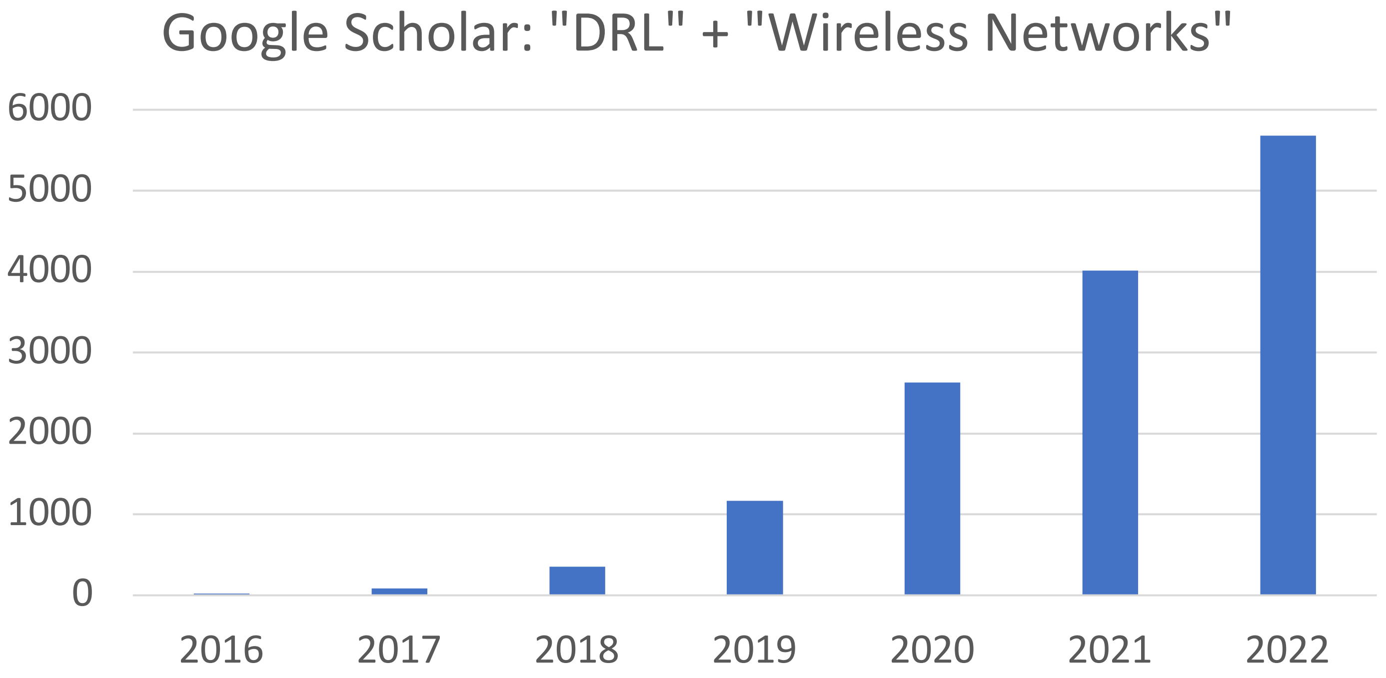
Machine Learning in Wireless

- Very dynamic field: New trends



Machine Learning in Wireless

- Wide application across different layers
  - Power allocation and beamforming
  - Spectrum sharing
  - Cache management
  - Link scheduling
  - User association
  - BS switching
  - Routing
  - Mobility management
  - Localization
  - and many more!

Machine Learning in Wireless

Networking Layers

	Problem	New capabilities
Network layer	Routing	• **3x** decrease in **delay** • Same computation time IEEE ICASSP 2023
Data Link layer	Link scheduling	• **50%** increase in **throughput** • Same computation time IEEE TWC 2022, IEEE ICASSP 2022
Physical layer	Beamforming	• **40%** increase in **achievable rate** • **20x** decrease in **computation time** IEEE MILCOM 2021, IEEE TWC 2023

Efficient and higher-performing networks by **compounding benefits across layers**

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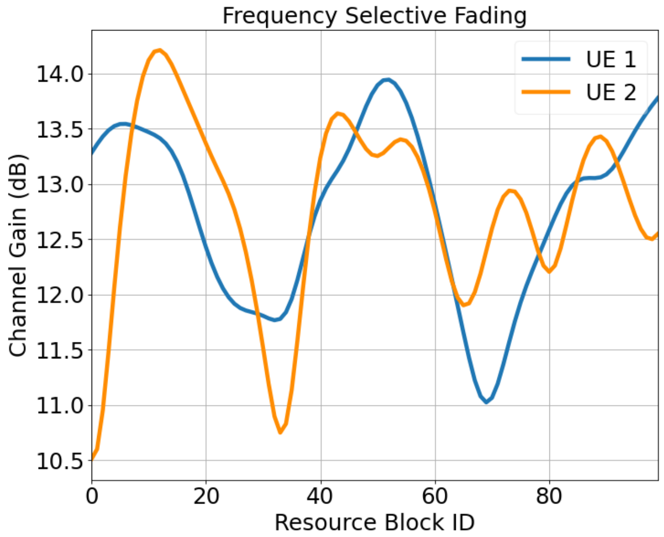
Beamforming Process

- Considering uplink signal model: $\mathbf{y} = \mathbf{Hx} + \mathbf{n}$ — $\mathbf{H}_{\mathrm{M}\times\mathrm{K}}$: channel matrix
- Zero-Forcing beamformer: $\mathbf{W} = \widehat{\mathbf{H}}(\widehat{\mathbf{H}}^{\mathbf{H}}\widehat{\mathbf{H}})^{-1}$ — $\widehat{\mathbf{H}}$: estimated channel matrix
- Estimate transmitted symbols $\hat{\mathbf{x}} = \mathbf{Wy}$
- Achievable rate: $\mathbf{R} = \log(1 + \mathbf{SINR}), \quad \mathbf{SINR} = \mathbf{f}(\hat{\mathbf{x}}, \mathbf{x})$

Channel Correlation Challenge

- **H** will be ill-conditioned when channels are correlated leading to high inter-user interference (low SINR)



$$\mathbf{W} = \hat{\mathbf{H}}(\hat{\mathbf{H}}^{\mathbf{H}}\hat{\mathbf{H}})^{-1} \qquad \hat{\mathbf{x}} = \mathbf{W}\mathbf{y} \qquad \boldsymbol{\gamma} = \mathbf{log}(\mathbf{1} + \mathbf{SINR})$$

Need for careful user scheduling

Resource Scheduling in Massive MIMO Networks

- **Scheduling Problem Statement**: Schedule *time*, *frequency* and *spatial* resources to users to maximize rate and fairness

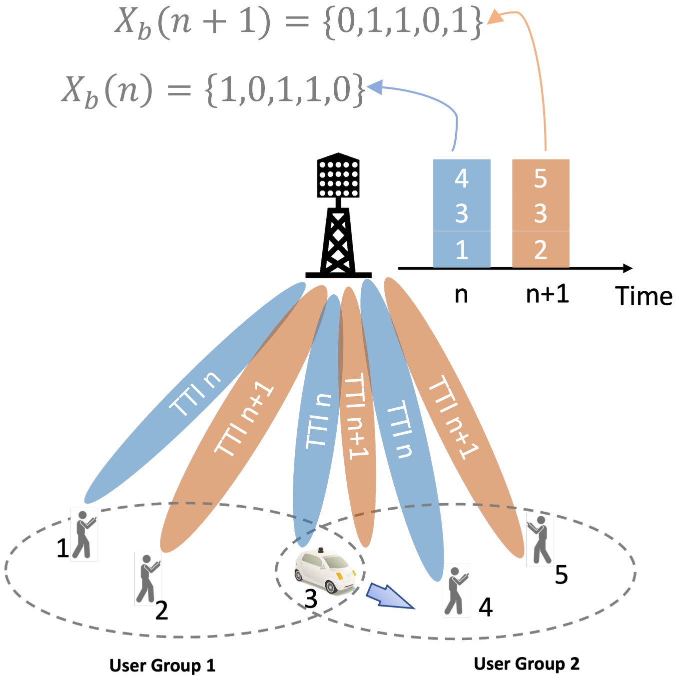
$$\arg\max_{X=\{x_{b,l}\}} \sum_{b}^{B} \sum_{l}^{L} U_{b,l}(t) x_{b,l}(t)$$

$$x_{b,l}(t) \in \{0,1\}$$

Scheduling decision for user l at RB b

$$U_{b,l}(t) = \frac{R_{b,l}(t)}{\sum_{v<t} x_{b,l}(v) R_{b,l}(v)}$$

Proportional-fair rate for user l



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Design Metrics

- Sum Rate
- Fairness
- Computational Complexity

Opt. Sum Rate (MR)

$$\underset{\mathcal{L}}{\operatorname{argmax}} \sum_{l \in \mathcal{L}} R_l(t),$$

Opt. Proportionally Fair Rate (PF)

$$\underset{\mathcal{L}}{\operatorname{argmax}} \sum_{l \in \mathcal{L}} \frac{R_l(t)}{\sum_{p<t} R_l(p)},$$

Optimal solutions have high computational complexity (NP-hard)

Approximate PF

(Kuchi et al., 2022)

PF weight sort + User Grouping

RR-UG

(Yang et al., 2019)

User Grouping + Round Robin

Heuristic suboptimal in sum rate, fairness or both

Can we hit all goals through machine learning?

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SMART Scheduler

- Deep Reinforcement Learning (DRL) Solution
  - Based on Soft Actor-Critic Model
  - Good exploration property
  - Scalable to large networks

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A Deep Reinforcement Learning-Based Resource Scheduler for Massive MIMO Networks

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Modeling with Deep Reinforcement Learning (DRL)

- Reward Function
  - Normalized rate and fairness

$$Reward_t = \boxed{\beta} R_t^{total} + (1-\beta) F_t$$

Weight

Normalized

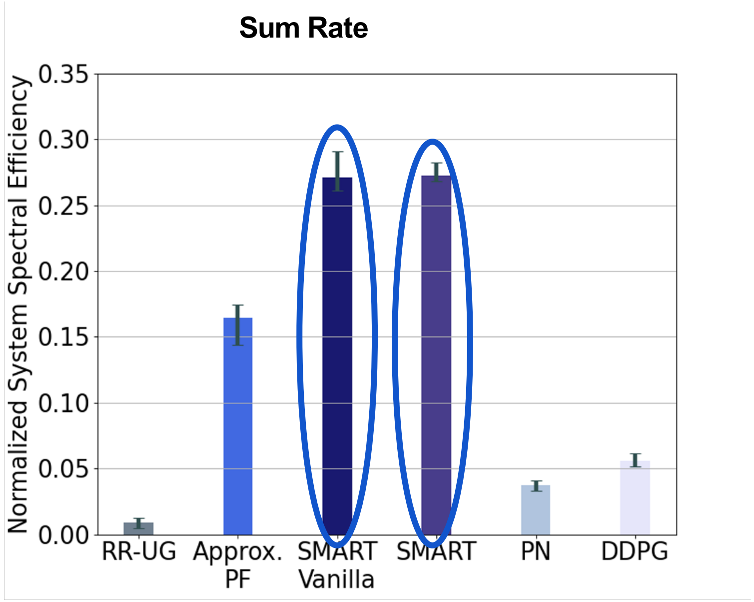
$$\boxed{R_t^{total}} = \sum_b^B \sum_l^L R_{b,l}(t) x_{b,l}(t)$$

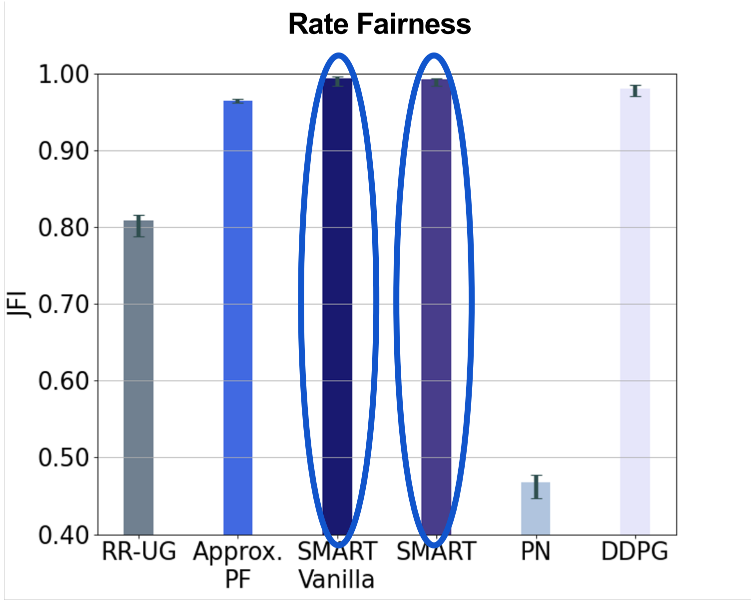
Total amount of transmitted data by user l up to time t

$$F_t = \frac{\left(\sum_{l=1}^{L} \boxed{f_l^t}\right)^2}{L \sum_{l=1}^{L} (f_l^t)^2}$$

Jain's Fairness Index (JFI)

Baseline Results





- **3GPP UMi Channel, 64-antennas, 64 users**
  - SMART performs roughly 2x better than PF (Approx.) in highly mobile scenarios

Computational Complexity

- Execution time (in second) on single CPU core

System Configuration	Scheduler							
	Opt-MR	Opt-PF	Approx-PF	RR-UG	DDPG	PN	SMART-Vanilla	SMART
16×16	0.15	0.21	-	0.0013	0.034	0.059	0.036	0.024
64×64	-	-	0.604	0.0043	0.058	0.235	0.057	0.030
128×128	-	-	-	-	-	-	-	0.071

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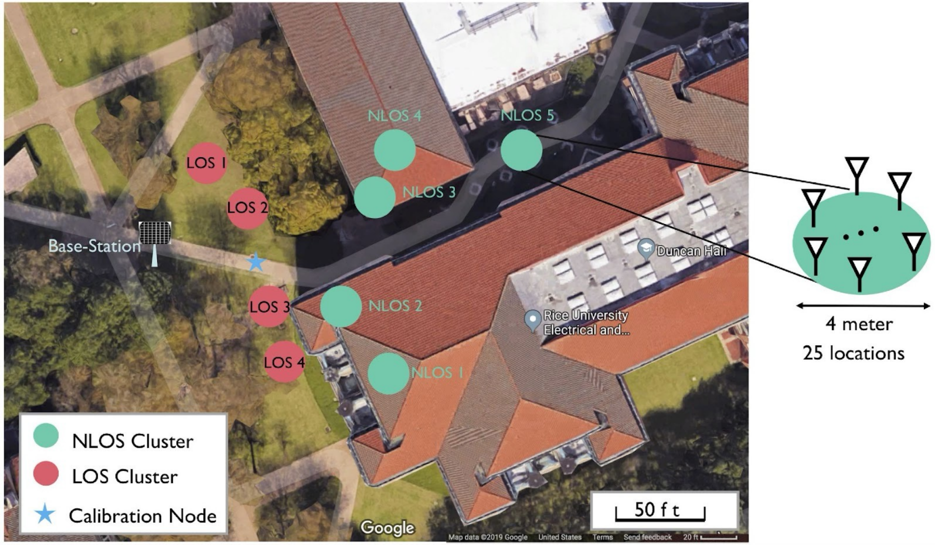
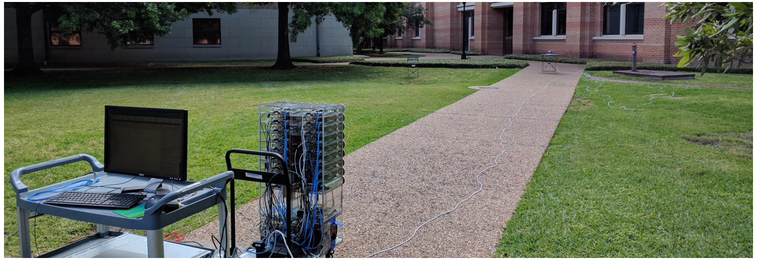
Challenge Dataset: Low Mobility

- Derived from a RENEW dataset
- 64-antenna base station
- 4 LoS and 5 NLoS Clusters
- 64 users with 52 subcarriers
- Movement within clusters
- 500 frames





https://renew-wireless.org/dataset-iuc.html

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Challenge Dataset: High Mobility

- Simulated Channel Dataset
  - Generated with the open-source QuaDRiGa channel simulator
- 3GPP Urban Micro LoS
- 64-antenna base station
- 64 users with 52 subcarriers
- Mobility at random direction 2.8 m/s
- 500 frames

QuaDRiGa: https://quadriga-channel-model.de/

Baseline Code

- https://github.com/3DML-Wireless/SMART-Scheduler
- Python massive MIMO simulator (DRL environment)
- Python/PyTorch Baseline model code for training
- ML Challenge Materials:
    - https://github.com/3DML-Wireless/SMART-Scheduler/ML-Challenge
    - Links to datasets to be used for the challenge
    - Baseline trained model will be posted soon

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Challenge Evaluation Metrics

- Trained models evaluated on 200 frames based on three metrics:

Sum Rate (R)

Fairness (F)

Runtime (T)

$$R = 1/200 \sum_{t=1}^{200} R_t$$

$$F_{200} = \frac{\left(\sum_{l=1}^{L} f_l^{200}\right)^2}{L \sum_{l=1}^{L} \left(f_l^{200}\right)^2}$$

- A variation of provided datasets will be used for evaluation

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Submission Format & Rules

- Provide trained model with code
- Score is calculated as $0.4(R_s/R_b) + 0.2(F_s/F_b) + 0.4(T_b/T_s)$
  - Each parameter is averaged from Low and High Mobility results, e.g.
  - Submitted model should beat the baseline in at least 1 out 6 metric
  - Solutions will be evaluated on DGX A100 GPU server

Model	Low Mobility			High Mobility		
	Sum Rate	Fairness	Runtime	Sum Rate	Fairness	Runtime
Baseline Model (B)	R_B^{LM}	F_B^{LM}	T_B^{LM}	R_B^{HM}	F_B^{HM}	T_B^{HM}
Submitted Model (S)	R_S^{LM}	F_S^{LM}	T_S^{LM}	R_S^{HM}	F_S^{HM}	T_S^{HM}

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Updated baseline numbers will be posted on the challenge repo

Timeline & Prizes

- Start date: May 13, 2024
- End date: Aug 9, 2024
- Ranking Announcements: Aug 16, 2024
- Prizes:
  - 1000 CHF
  - Internship Opportunity at Rice Wireless

Thank you!

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https://renew-wireless.org

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