

Spectrum-efficient Beamforming beyond 5G: Model-driven AI Algorithms and SDR Testbed

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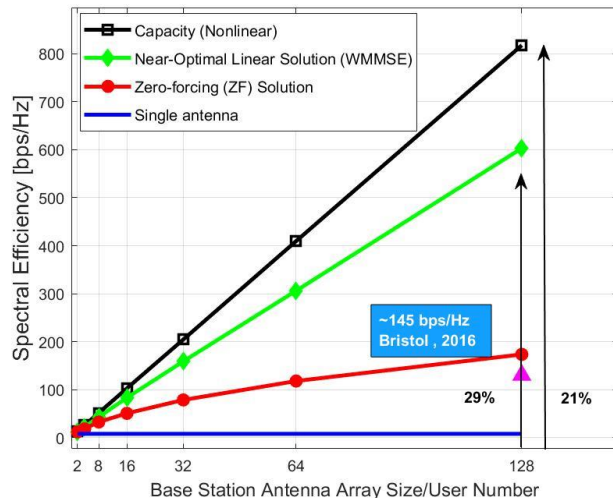


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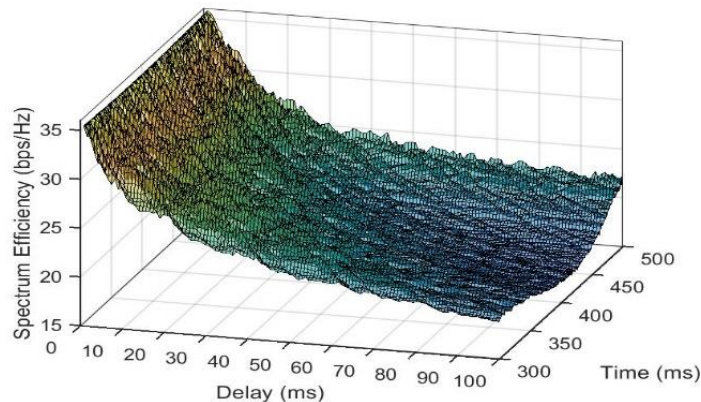
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Spectrum-efficient transmit beamforming

Spectrum efficiency vs antennas



Impact of delay using measured data



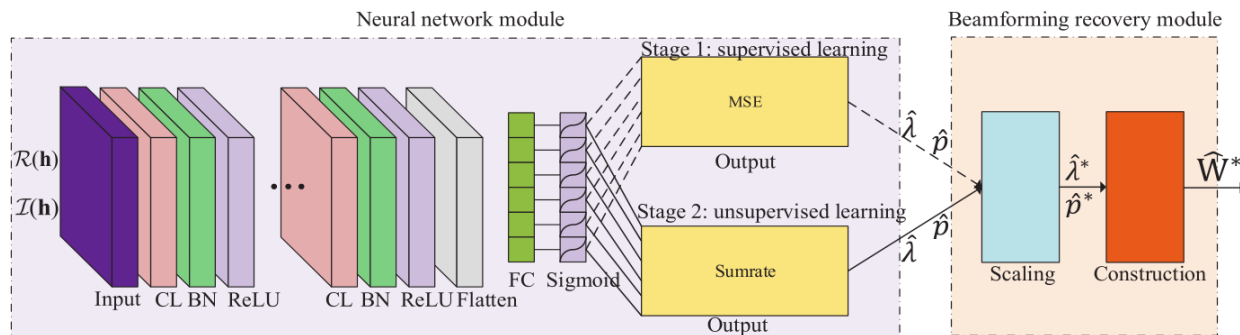
Why not optimal solution? Complexity

- Numerical optimisation
- Channel estimation overhead
- Scalability (>100s to achieve capacity@128 antennas)

Is deep learning the solution?

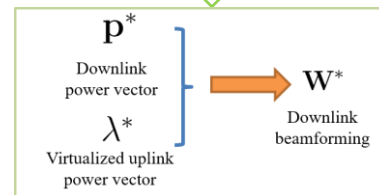
- Large data
- No performance guarantee
- Data-driven, ignore model information

Neural network + Model information via Signal processing



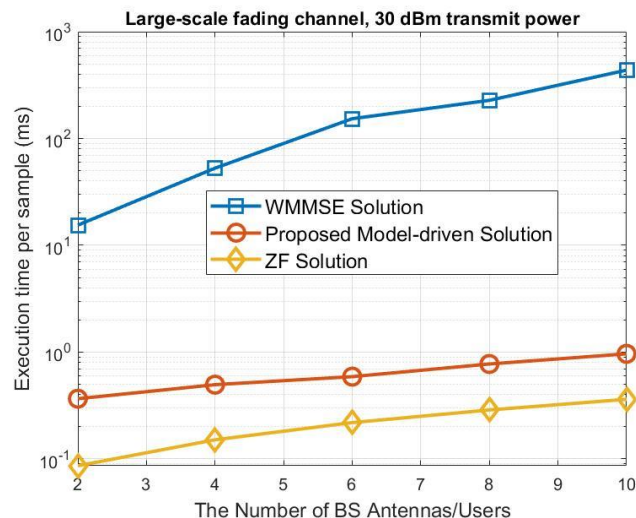
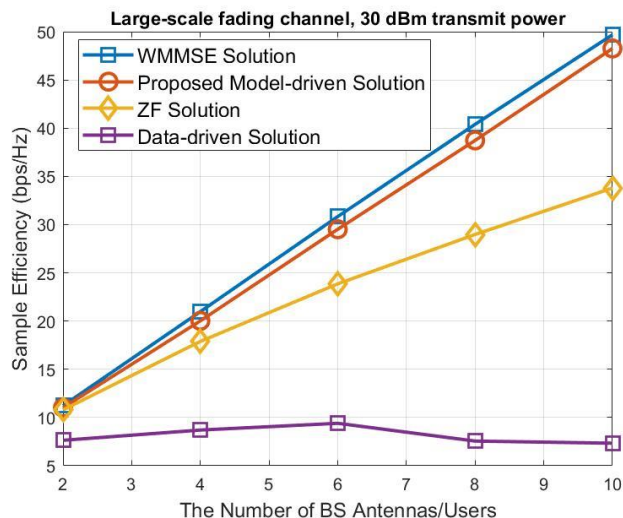
Model information: solution structure, sum rate

$$\mathbf{w}_k^* = \sqrt{p_k} \frac{(\mathbf{I}_N + \sum_{k=1}^K \frac{\lambda_k}{\sigma^2} \mathbf{h}_k \mathbf{h}_k^H)^{-1} \mathbf{h}_k}{\|(\mathbf{I}_N + \sum_{k=1}^K \frac{\lambda_k}{\sigma^2} \mathbf{h}_k \mathbf{h}_k^H)^{-1} \mathbf{h}_k\|_2}$$



Sum Spectrum Efficiency Results

Model-driven BNN achieves the best tradeoff between performance and complexity.

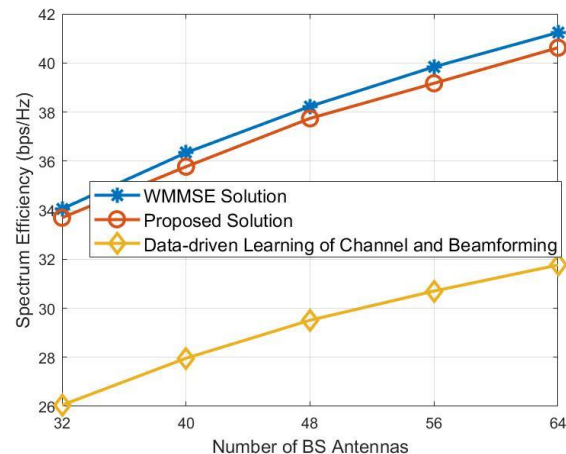
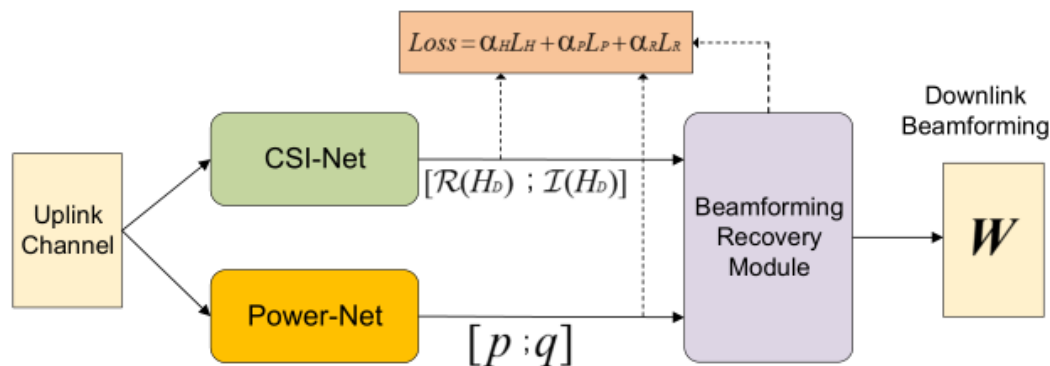


W. Xia, G. Zheng, Y. Zhu, J. Zhang, J. Wang and A. P. Petropulu, "A Deep Learning Framework for Optimization of MISO Downlink Beamforming," IEEE TCOM, Mar. 2020.



Joint Channel Estimation and Beamforming Optimisation

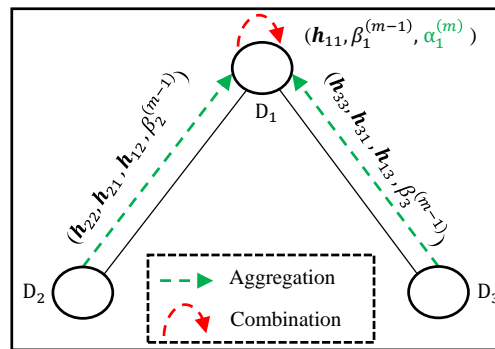
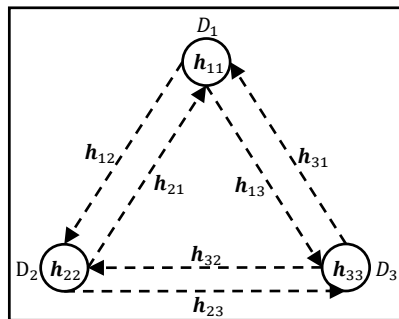
- High overhead in obtaining the downlink channel-> **Learning from uplink**
- Traditional two-stage process: channel estimation, then beamforming optimisation
- Good channel estimation does not guarantee good **end performance**
- ❖ Model-driven learning: **joint downlink channel estimation and rate maximization**
- ❖ Model information: solution structure, objective function



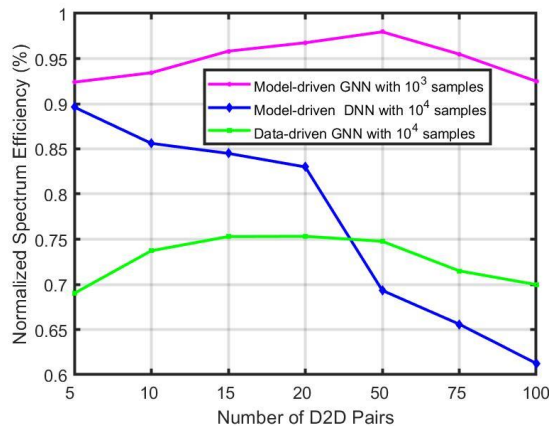
Multi-cell FDD Massive MIMO: Joint and model-driven learning is key to guarantee the **end performance**.



Scalability: Model-driven Graph Neural Network (GNN)



$\alpha_1^{(m)}$: aggregated feature
 $\beta_1^{(m-1)}$: embedding feature



- **Model information: solution structure and network topology**
- **Model-driven GNN improves both scalability and sample efficiency.**

T. Chen, M. You, G. Zheng, and S. Lambotharan, "Graph Neural Network based Beamforming in D2D Wireless Networks," in the 25th International ITG Workshop on Smart Antennas (WSA), Nov.2021, EURECOM.

Data-driven GNN: Y. Shen, Y. Shi, J. Zhang and K. B. Letaief, "Graph neural networks for scalable radio resource management: architecture design and theoretical analysis", IEEE J. Select. Areas Commun, Jan. 2021.

❑ Adaptive Resource Optimisation in Dynamic Environments (Model mismatch challenge)

- Y. Yuan, G. Zheng, K. K. Wong, and K. B. Letaief, “Meta-Reinforcement Learning Based Resource Allocation for Dynamic V2X Communications,” to appear in IEEE Trans. Veh. Technol.
- J. Zhang, Y. Yuan, G. Zheng, I. Krikidis and K. K. Wong, “Embedding Model Based Fast Meta Learning for Downlink Beamforming Adaptation,” to appear in IEEE Trans. Wireless Commun.
- Y. Yuan, G. Zheng, K. K. Wong, B. Ottersten, and Z.-Q. Luo, “Transfer learning and meta learning based fast downlink beamforming adaptation,” IEEE Trans. Wireless Commun., Mar. 2021.
- X. Zhang, G. Zheng, and S. Lambotharan, “Trajectory Design for UAV-Assisted Emergency Communications: A Transfer Learning Approach” IEEE GLOBECOM 7-11 December 2020, Taipei, Taiwan.

❑ Robust Radio Signal Classification against Smart Adversarial Attacks

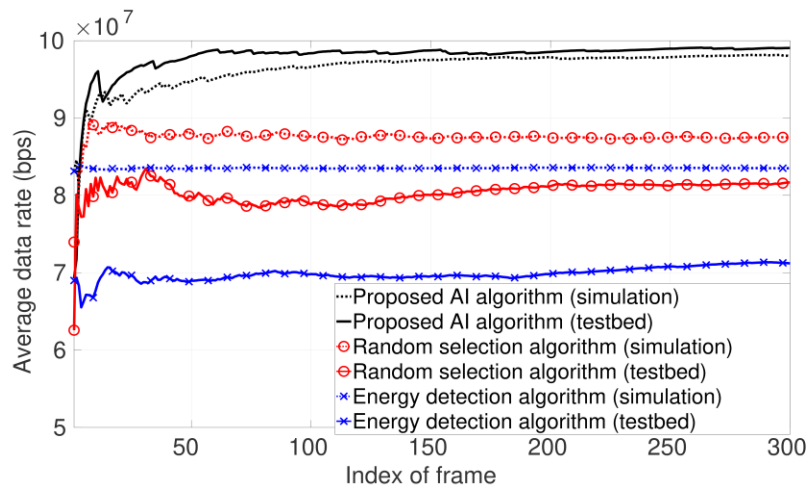
- L. Zhang, S. Lambotharan, G. Zheng, B. AsSadhan and F. Roli, “ Countermeasures Against Adversarial Examples in Radio Signal Classification, ” IEEE WCL, Aug. 2021.
- L. Zhang, S. Lambotharan, G. Zheng, F. Roli, “A Neural Rejection System Against Universal Adversarial Perturbations in Radio Signal Classification,” IEEE GLOBECOM, December 2021, Madrid, Spain.



- **Two secondary users dynamically select one of four primary channels**
- **Allow dynamic spectrum sharing to support vertical applications**

M. You, X. Zhang, G. Zheng, J. Jiang, and H. Sun, "A versatile software defined smart grid testbed: Artificial intelligence enhanced real-time co-evaluation of ICT systems and power systems," IEEE Access, vol. 8, 2020.

- **Multi-armed bandit (MAB) algorithm**
- **Real-time spectrum sensing + past observations**



Title: AIMM (AI-enabled Massive MIMO)

Project Lead: Arman Shojaeifard (InterDigital Europe)

Clusters: UK, Germany, Canada

Duration: 2 years (Oct 2020—Sep 2022)

Budget (total): 3,167.6 K€

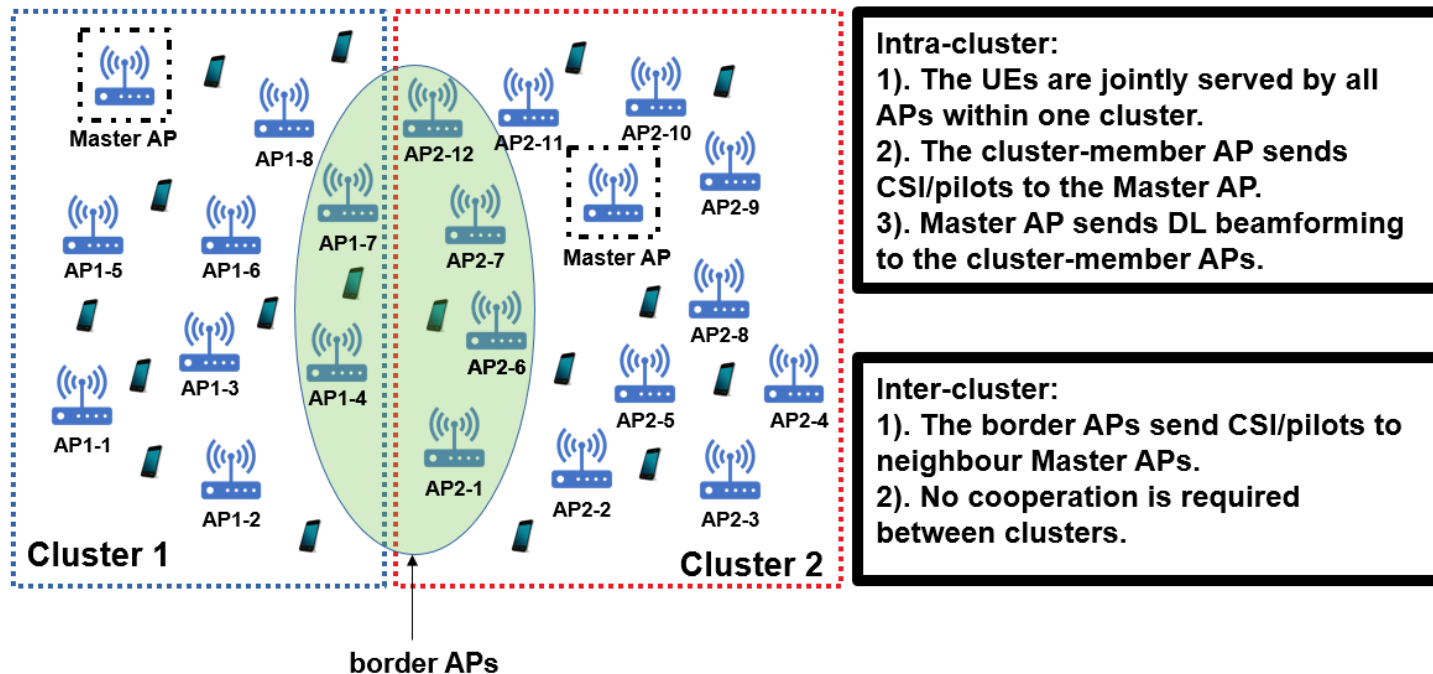
Work-Packages: 6

Website: <https://aimm.celticnext.eu/>

“The AIMM project targets radical performance improvements and efficiency dividends for 5G and beyond Radio Access Network (RAN) through advanced antenna array (Massive MIMO) and Reconfigurable Intelligent Surface (RIS) technologies powered through and managed by the latest advancements in AI.”



Distributed OTA Cell-less MIMO Testbed



Conclusions

What we have done:

- Model-driven AI to improve accuracy, reduce required labelled data
- Focused on complexities: optimisation, channel estimation and scalability

Looking forward:

- Nonlinear precoding, other resource optimisation problems
- From model-driven to knowledge-driven AI
- Make AI an effective, reliable and robust tool for 6G and beyond

Acknowledgement: Signal Processing & Networks Research Group, Collaborators



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