A Graph Convolutional Neural Network approach for throughput prediction in next-generation WLANs

ITU-ML5G-PS-013: Improving the capacity of IEEE 802.11 WLANs through Machine Learning

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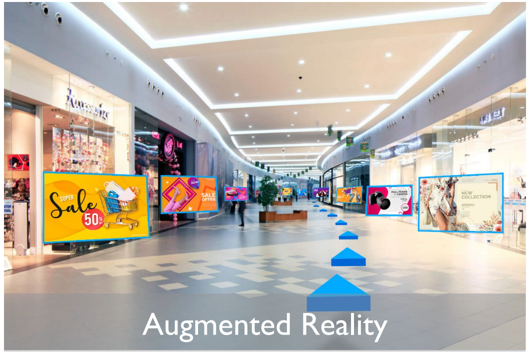
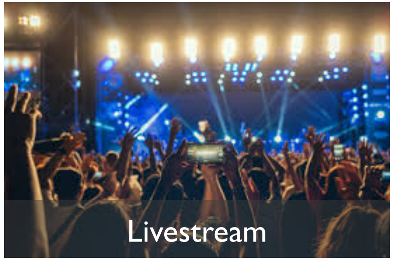
Context

Million connected devices with higher demands in bandwidth





- New services are becoming a reality
  - Higher Bandwidth
  - High availability for high number of users
- Wi-Fi will remain an important technology to support such services
  - Wi-Fi hotspots will fourfold increase by 2023[1]

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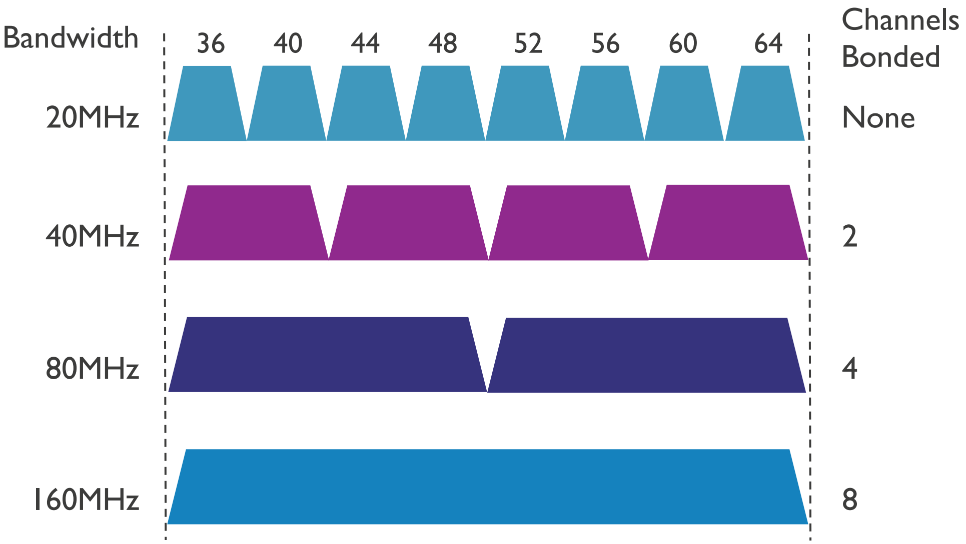
1. Cisco annual internet report (2018–2023) white paper. Available on: http://www.cisco.com/go/vni

Channel Bonding

Provide a higher channel capacity

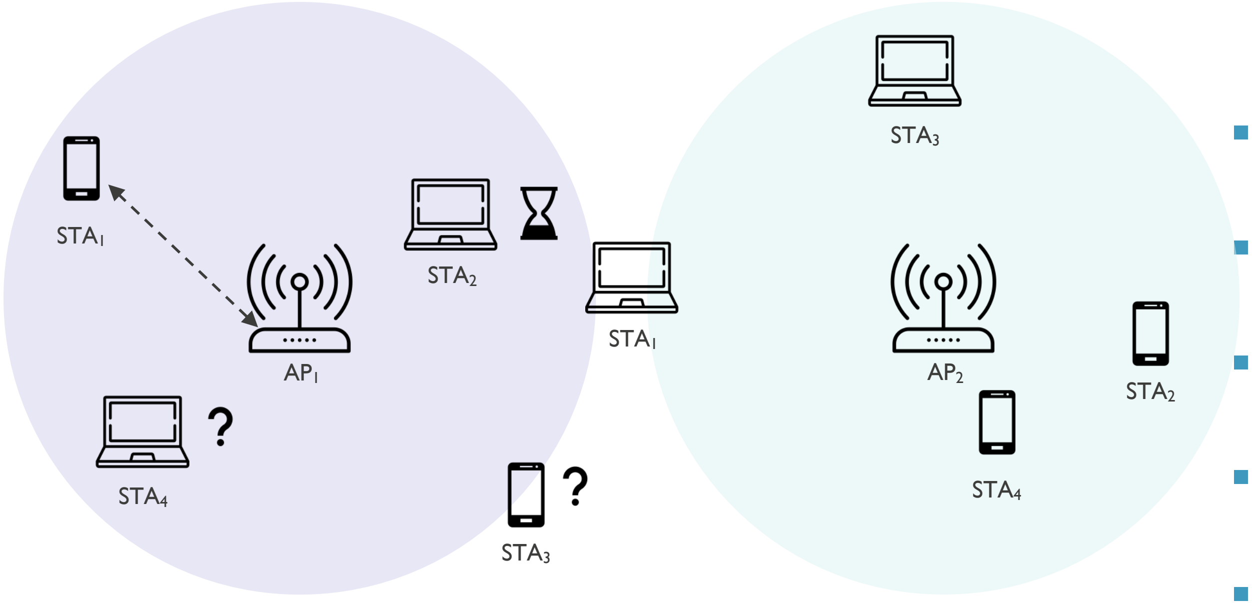
- Introduced in 802.11n[2] (2009).
- Two adjacent channels are bonded.
  - Recent versions (802.11ac/ax) allow more channels to be bonded.



2. IEEE, "Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications Amendment 5 : Enhancements for Higher Throughput", Standard, 2009.

Channel Bonding Problems

OBSS interactions



- Stochastics interactions based on the CSMA algorithm.
- Transmission over the full/sub set of channels.
- High data rate = high packet error.
- Inter STA – Inter WLAN interference.
- Hidden or exposed nodes.
- Starvation.

Previous Solutions

- Analytical models[3]
- Markov Chains[4]
- Simulations

- Assumptions that do not hold.
- Complexity increases with the number of devices.

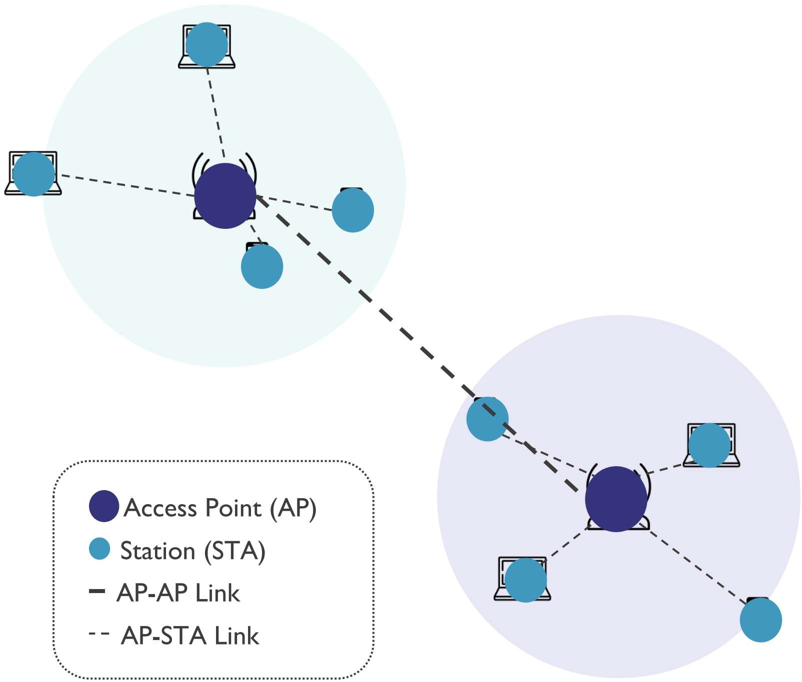
- Machine Learning / Artificial Intelligence[5]
  - Reinforcement Learning to select CB Policy[6]

3. L. Deek et al, “Intelligent channel bonding in 802.11n wlans,” IEEE Transactions on Mobile Computing, vol. 13, no. 6, pp. 1242–1255, 2013
4. S. Barrachina-Muñoz, F. Wilhelmi, and B. Bellalta, “Dynamic channel bonding in spatially distributed high-density wlans,” IEEE Transactions on Mobile Computing, vol. 19, no. 4, pp. 821–835, 2019.
5. ITU-T Y.3170-series - Machine learning in future networks including IMT-2020: use cases,” ITU-T, Specification, 2019. [Online]. Available: https://www.itu.int/rec/T-REC-Y.Sup55-201910-I/en4
6. Y. Luo and K.-W. Chin, “Learning to bond in dense wlans with random traffic demands,” IEEE Transactions on Vehicular Technology, vol. 69, no. 10, pp. 11 868–11 879, 2020.

Proposed Solution: Graph Neural Networks – GNN[7]

DL do not exploit graph-like structured data

- A graph is 2-tuple G=(V, E) where V are the nodes and E are the links.
- Each node has its own set of features.
  - Node type
  - SINR
  - Channels used
  - Airtime
- Each link has its own set of features
  - Distance
  - RSSI
  - Interference



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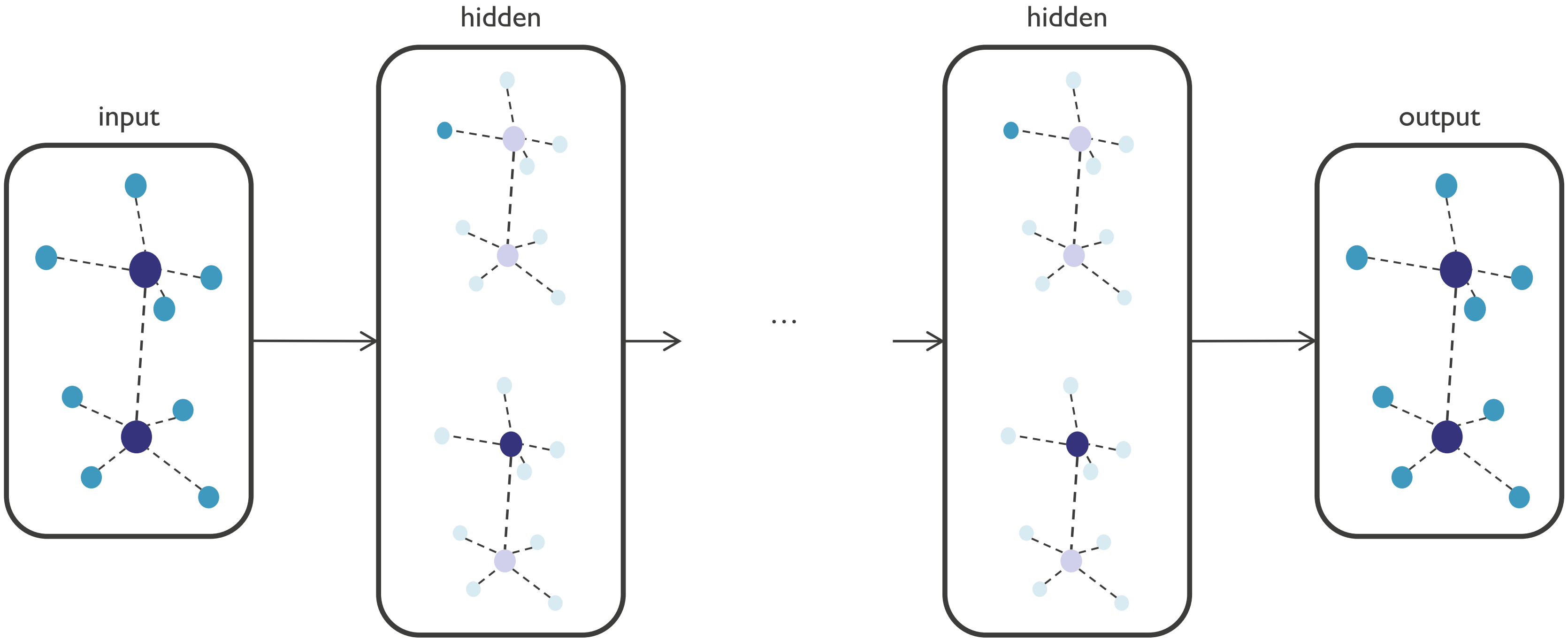
7. F. Scarselli, et al, "The graph neural network model," IEEE Transactions on Neural Networks, vol. 20, no. 1, pp. 61–80, 2008.

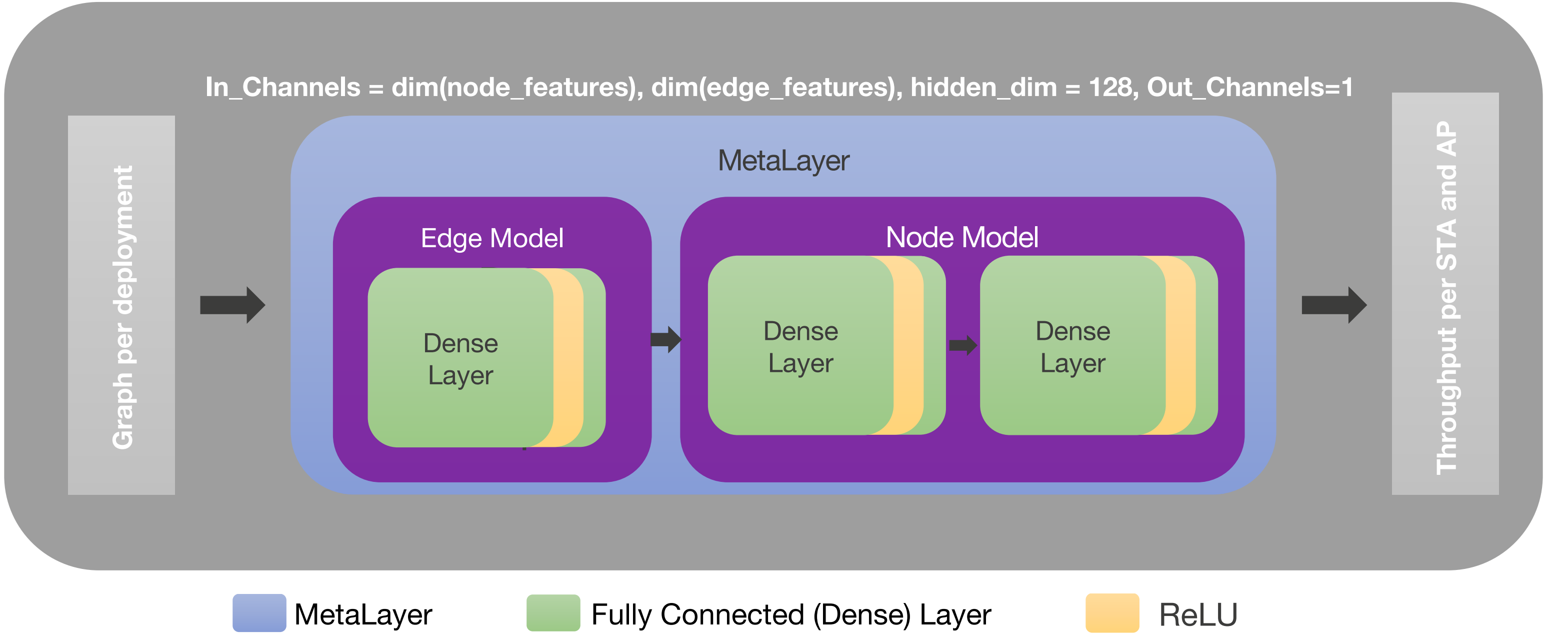
Graph processing

Follows a traditional multilayer approach of (Deep) Neural Networks



Model - MetaNet

Each layer is designed to find patterns in the graph-like structured data[8]



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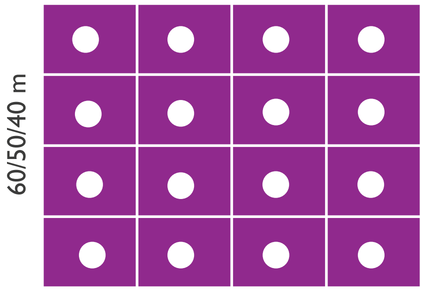
8. P. W. Battaglia et al., "Relational inductive biases, deep learning, and graph networks,", arXiv preprint arXiv:1806.01261, 2018

Training Dataset

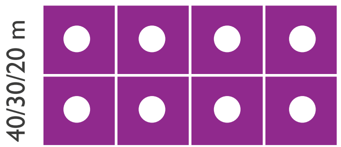
Characteristics

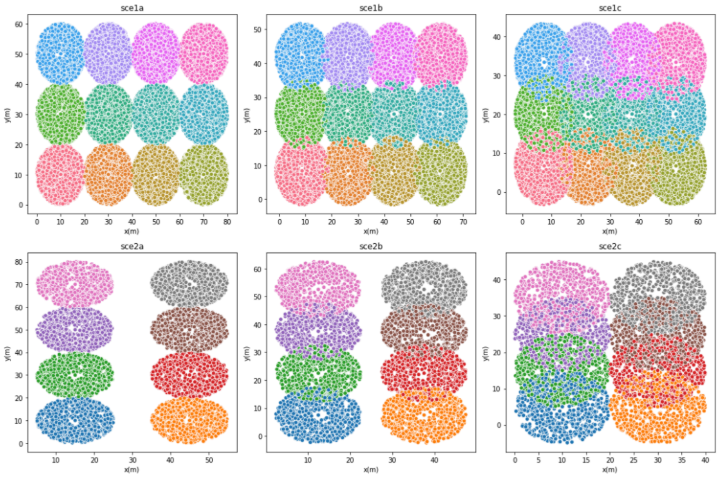
- Two scenarios with modifications on user density per m^2
- 3 map sizes per scenario.
- 100 deployments per scenario.
- Each scenario introduce more interference than the other.
- Different channel configurations.
- 80% Training – 480 Graphs.
- 20% Validation – 120 Graphs.

Scenario 1: 12APs 10-20 STAs



Scenario 2: 8APs 5-10 STAs

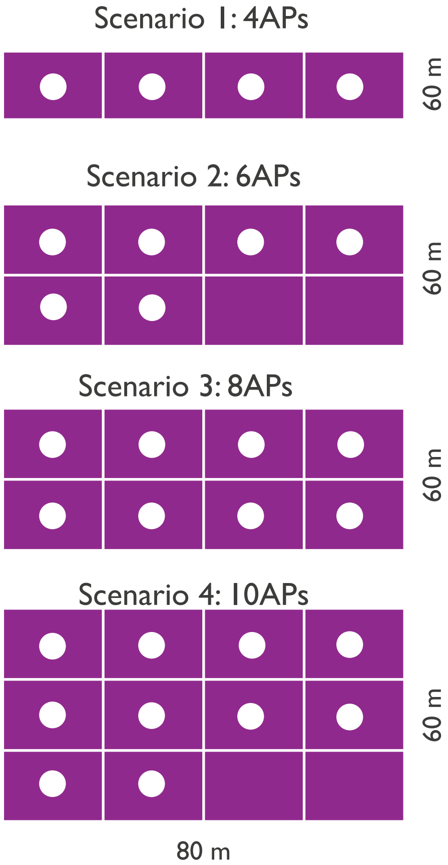




Test Dataset

Characteristics

- Four testing scenarios.
- Different spatial distribution than training.
- 50 random deployments per scenario.

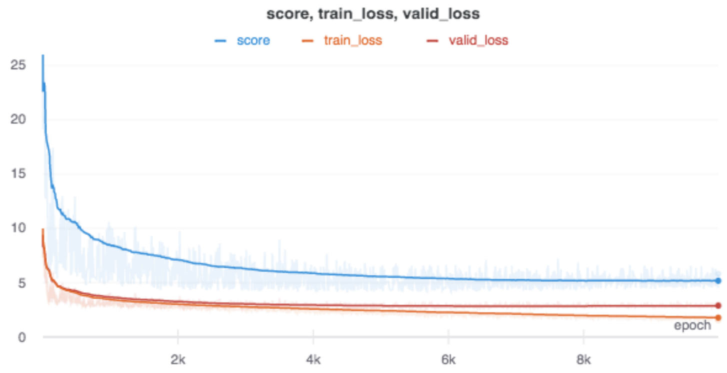


Results

Training

- Training
  - Masked Loss
    - Training loss is designed to learn the STAs' throughput.
    - Throughput AP is computed from predicted STAs throughput.
  - Adam optimizer
  - 10000 epochs
  - 3h of training time.

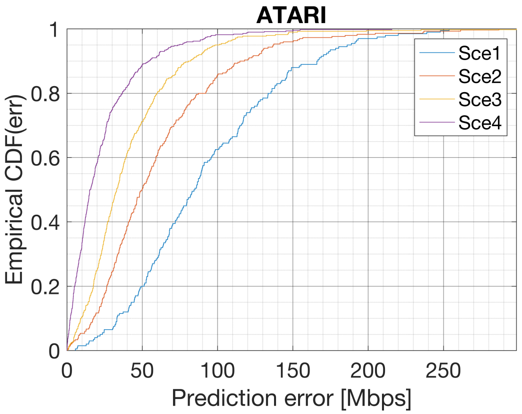
Metric	Loss Value
Train loss (RMSE)	2.057
Validation loss (RMSE)	2.652
Masked Loss (score)	4.197



Results

Testing

- Model is overfitting.
  - Novel architecture for this type of problem.
  - The more similar the test scenario to train scenario, the better the prediction.
  - The amount of data needed to train is big.
- Techniques to avoid overfitting
  - Perform data augmentation.
  - Add regularizers, e.g., dropout.



Scenario	RMSE*
1	26.97
2	18.94
3	12.76
4	8.73

*Over all devices

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Improvements

- Change MetaLayers by Graph Convolutional Layers.
- Implemented a Feed Forward model and a Convolutional model as baseline.
- Next Publication.

Scenario	GCN	FNN	CNN
1	9.384	16.250	16.403
2	8.247	15.562	15.456
3	6.822	11.774	11.485
4	6.481	12.025	11.565

*RMSE over all devices

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