IMPROVING NEXT-GENERATION WIRELESS NETWORK PERFORMANCE AND RELIABILITY WITH DEEP LEARNING

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Ph.D. Defense

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VISION FOR 5G COMMUNICATIONS

10 ms • LATENCY
7.2 Exabytes/Month • DATA TRAFFIC
1 Gb/s • PEAK DATA RATES
3 GHz • AVAILABLE SPECTRUM
100,000 Connections/Km² • CONNECTION DENSITY

LATENCY • <1 ms
DATA TRAFFIC • 50 Exabytes/Month (2021)
PEAK DATA RATES • 20 Gb/s
AVAILABLE SPECTRUM • 30 GHz
CONNECTION DENSITY • 1 Million Connections/Km²

NETWORK ANALYTICS • “Network Data Analytics Function” (3gpp)

[https://www.qorvo.com/design-hub/blog/getting-to-5g-comparing-4g-and-5g-system-requirements]
VISION FOR INTELLIGENT WIRELESS NETWORK


Hybrid approach to unleash next-generation wireless “network intelligence”
**Motivation: Deep Learning in Communications**

- Absence of accurate mathematical formulations
  - data-driven approaches using ray-tracing datasets or field-measurements
  [[Zappone19]]
- Incremental changes in radio resource management (RRM) algorithms
  - industry standards still prefer “legacy” algorithms despite successive evolutions
  [[3gpp15]] & [[3gpp18]]
- Desire for fully autonomous self-organizing networks (SON)
  - operators are under constant pressure to reduce operational expenditure without impacting performance
  [[Zappone19]]
CONTRIBUTIONS

- How to improve next-generation wireless networks system performance?
- Disrupt the legacy industry standards to boost reliability and eliminate performance bottlenecks

**Contributions are on the downlink (BS to UE)**

**PHY perspective**

**Contribution 1**

- Joint Beamforming, Power Control, and Interference Coordination

**Contribution 2**

- Intelligent Coordinated Multipoint
- Beamforming, Power Control, and Interference Coordination

**Contribution 3**

- Predictive Band Switching

**RRM perspective**

Improve user rates
Contribution 1

**JOINT BEAMFORMING, POWER CONTROL, AND INTERFERENCE COORDINATION**

Discussed in the PhD Qualifying Exam and Included in the PhD Dissertation

**Related publications:**


**BACKGROUND**

- **Problem**
  - User served by a base station receives interference from neighboring base station
  - Base station serving the user causes interference to other users

- **Goal**
  - Maximize the signal to interference plus noise ratio (SINR) from serving base station to user

- **Parameters**
  - **Beamforming (BF)** to create a virtual sense of a user-specific channel for data
  - **Power Control (PC)** to control the transmit power of the serving BS towards a user
  - **Interference Coordination (IC)** to control the transmit power of the neighboring BSs
  - **User spatial coordinates**

- **Approach**
  - Perform binary encoding of BF, PC, and IC actions to enable joint actions
  - If SINR of all users improve, then reward actions. This resolves the *race condition*
  - Compare proposed solution with optimal solution
**SYSTEM MODEL**

- **Multi-user downlink system**
  - Multi-cell environment with single-antenna users
  - \(L\) total dual-band base stations
  - Uniform linear array (ULA) antennas (\(M\))
  - Power control for all users
  - Codebook analog beamforming for mmWave data
  - More power control commands for sub-6 GHz voice

- **Narrow-band geometric channel model**
  
  \[
  h_{\ell,b} = \sqrt{\frac{M}{\beta_{\ell,b}}} \sum_{p=1}^{N_{\ell,b}} \alpha_{\ell,b}^p \mathbf{a}^* \left( \theta_{\ell,b}^p \right) \]

  - \(\beta_{\ell,b}\) gain
  - \(\alpha_{\ell,b}^p\) path loss for user served by BS \(l\) in area of BS \(b\)
  - \(\theta_{\ell,b}^p\) angle of departure
  - \(\mathbf{a}^*\) array response vector

  - Suitable for both sub-6 and mmWave propagation
  - Smaller number of paths at mmWave (sparse)

- **Beamforming vector**
  
  \[
  f_n := \mathbf{a}(\theta_n), \quad n = \{1, 2, \ldots, L\} \]

- **Signal model for the user served by the \(\ell\)-th BS:**
  
  \[
  y_{\ell} = h_{\ell,\ell}^* f_{\ell} x_{\ell} + \sum_{b \neq \ell} h_{\ell,b}^* f_b x_b + n_{\ell} \]

  - Inter-cellular interference
  - Gaussian noise

  \[
  \mathbb{E}[|x_{\ell}|^2] = P_{TX,\ell} \]

  \[
  n_{\ell} \sim \text{Normal}(0, \sigma_n^2) \]

- **Received SINR for the user served by the \(\ell\)-th BS:**
  
  \[
  \gamma_{\ell}[t] = \frac{P_{TX,\ell}[t]|h_{\ell,\ell}^*[t]f_{\ell}[t]|^2}{\sigma_n^2 + \sum_{b \neq \ell} P_{TX,b}[t]|h_{\ell,b}^*[t]f_b[t]|^2} \]
**Motivation and Problem Formulation**

- Improve SINR through joint power control, interference coordination, beam selection

\[
\text{maximize} \quad \prod_{j \in \{1, 2, \ldots, L\}} \gamma_j[t] \\
\text{subject to} \quad P_{TX,j}[t] \in \mathcal{P}, \quad \forall j, \\
\quad f_j[t] \in \mathcal{F}, \quad \forall j, \\
\quad \gamma_j[t] \geq \gamma_{\text{target}}
\]

- Baseline solution for voice is obtained from fixed power allocation with adaptive coding
- Optimal solution (upper bound) for data is found through a brute force over all
  - beam patterns
  - power commands for the BSs

- Run-time complexity of $O(M^L)$ for $M$ antennas and $L$ base stations.

How can we reduce the complexity?
SOLUTION

- **Deep Reinforcement Learning**
  1. Create an environment from the system model
  2. Create a joint reward \( r_{s,s',a}[t; q] \)
  3. Reward the agent for every time the SINR improves.

- **Use deep Q-network (DQN) as an estimator for state-action value function \( Q_\pi(\cdot) \)**
  1. Greedy policy \( \pi \)
  2. Train the DQN using minibatch samples to minimize the loss function:

\[
\min_{\theta_t} L_t(\theta_t) := \mathbb{E}_{s,a} \left[ (y_t - Q_\pi(s, a; \theta_t))^2 \right]
\]

\( y_t := \mathbb{E}_{s'}[r_{s,s',a} + \gamma \max_{a'} Q_\pi(s', a'; \theta_{t-1}) | s_t, a_t] \)

**Can an \( \varepsilon \)-greedy policy do better?**
**Solution (L = 2)**

- **Joint beamforming, power control, and interference coordination (JB-PCIC) encoding**

  - **Bearer selector**
    - \( q = 0: \)
      - \( \begin{array}{c|c}
          2 & IC_e[t] \\
          2 & PC_b[t]
        \end{array} \)
    - \( q = 1: \)
      - \( \begin{array}{c|c}
          1 & IC_e[t] \\
          1 & PC_b[t]
        \end{array} \)

  - \( P = \{-3, -1, 1, 3\} \Rightarrow p(00) = -3, p(01) = -1, p(10) = 1, p(11) = 3 \)

  - Enables up to 16 simultaneous actions for voice and 16 for data

- **Reward function**

  \[
  r_{s,s',a}[t; q] := \begin{cases} 
  p(0) = -3, & p(1) = -1, & p(2) = 1, & p(3) = 3 \\
  r_{\min} & \text{if any constraint in problem formulation becomes inactive.} \\
  r_{s,s',a}[t; q] + r_{\max} & \text{if the target SINR is achieved.}
  \end{cases}
  \]

- **States**

  \[
  (s_t^0, s_t^1) := UE_\ell(x[t], y[t]), \quad (s_t^2, s_t^3) := UE_b(x[t], y[t]), \\
  s_t^4 := P_{TX,\ell}[t], \quad s_t^5 := P_{TX,b}[t], \\
  s_t^6 := f_\ell[t], \quad s_t^7 := f_b[t],
  \]

  A total of 8 states
SIMULATION

Communication System Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base station (BS) maximum transmit power $P_{\text{BS}}^\text{max}$</td>
<td>46 dBm</td>
</tr>
<tr>
<td>Cellular geometry</td>
<td>circular</td>
</tr>
<tr>
<td>Propagation model (voice, h')</td>
<td>(COST231, 63)</td>
</tr>
<tr>
<td>Antenna gain $(G_{\text{TX}}^\text{out}, G_{\text{TX}}^\text{in})$</td>
<td>(11, 3) dBi</td>
</tr>
<tr>
<td>Max. number of UEs per BS $N_{\text{max}}$</td>
<td>10</td>
</tr>
<tr>
<td>Probability of LOS $P_{\text{LOS}, \text{PL}^\text{LOS}}$</td>
<td>(0.9, 0.8)</td>
</tr>
<tr>
<td>Number of transmit antennas $M_{\text{voice}, M_{\text{bf}}}$</td>
<td>(1, 4, 8, 16, 32, 64)</td>
</tr>
<tr>
<td>Downlink frequency band</td>
<td>(2100 MHz, 28 GHz)</td>
</tr>
<tr>
<td>Cell radius $r$</td>
<td>(350, 150) m</td>
</tr>
<tr>
<td>User equipment (UE) antenna gain $(G_{\text{TX}}^\text{out}, G_{\text{TX}}^\text{in})$</td>
<td>0 dBi</td>
</tr>
<tr>
<td>Inter-site distance $R$</td>
<td>(525, 225) m</td>
</tr>
<tr>
<td>Number of multipaths $N_p$</td>
<td>(15, 4)</td>
</tr>
<tr>
<td>UE average movement speed $v$</td>
<td>(5, 2) km/h</td>
</tr>
<tr>
<td>Radio frame duration $T_{\text{voice}}, T_{\text{bf}}$</td>
<td>(20, 10) ms</td>
</tr>
</tbody>
</table>

Deep Reinforcement Learning Hyperparameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount factor $\gamma$</td>
<td>0.995</td>
</tr>
<tr>
<td>Exploration rate decay $\alpha$</td>
<td>0.9995</td>
</tr>
<tr>
<td>Initial exploration rate $\epsilon$</td>
<td>1.000</td>
</tr>
<tr>
<td>Minimum exploration rate $(\epsilon_{\min}^1, \epsilon_{\min}^2)$</td>
<td>(0.15, 0.10)</td>
</tr>
<tr>
<td>Number of states $</td>
<td>S</td>
</tr>
<tr>
<td>Number of actions $</td>
<td>A</td>
</tr>
<tr>
<td>Deep Q-Network width $H$</td>
<td>24</td>
</tr>
<tr>
<td>Deep Q-Network depth</td>
<td>2</td>
</tr>
</tbody>
</table>

JB-PCIC algorithm achieves upper bound on performance but without exhaustive search in action space
SUMMARY

Optimize users’ received SINR

I. Voice bearers
   • Perform power control for the serving cell
   • Coordinate transmit power for the other cells
   • Voice uses adaptive coding

II. Data bearers
   • Perform power control for the serving cell
   • Coordinate transmit power for the other cells

CONTRIBUTION 1: JOINT BEAMFORMING AND POWER CONTROL

Optimal
   • Exponential in number of base stations
   • Uses brute force

Proposed
   • Uses deep reinforcement learning
   • Encoding to facilitate joint actions
   • Avoids exhaustive search in the action space
Contribution 2

**IMPROVED DOWNLINK COORDINATED MULTIPoint PERFORMANCE**

**Related publications:**


BACKGROUND

- Problem
  - Industry implementations trigger coordinated multipoint (CoMP) based on user SINR
  - This yields low user throughput

- Goal
  - Develop triggering function to improve the user throughput

- Parameters
  - Block Error Rate (BLER) target for codeword reception error
  - Channel State Information (CSI) to help derive transmission rank

- Approach
  - Train a classifier to learn the relationship between the reported measurements and the BLER
  - If a user is predicted to have a BLER lower than the target, configure rank-2 transmission
  - Compare with SINR-based trigger
SYSTEM MODEL

- Multi-user downlink system
  - Multi-cell environment with multiple-antenna users
  - Small cells scattered in the service area
  - Macro cells and small cells can form a distributed MIMO channel with \( n_t \) transmit antennas
  - Zero-Forcing (ZF) receiver at the user end

- Signal model for the \( i \)-th user (narrowband):
  \[ r_i = \sqrt{\frac{E_{s,i}}{n_t}} H_i s_i + v_i \]  
  - Gaussian noise
  - Distributed MIMO channel (both large- and small-scale gain)

- The received SNR for the \( i \)-th user at the \( j \)-th antenna
  \[ \gamma_j^{(i)} = \frac{P_{BS}^{(i)}}{n_t \sigma_v^2} [H_i^* H_i]_{j,j}^{-1}, \quad j = 1, \ldots, n_s \]
  - ZF receiver enhanced noise power
  - Number of receive antennas

- The received power for the \( i \)-th user at the \( j \)-th antenna:
  \[ P_{UE,j}^{(i)} := \sigma_v^2 (i)_j = \frac{P_{BS}^{(i)}}{n_t} [H_i^* H_i]_{j,j}^{-1}, \quad j = 1, \ldots, n_s \]

- The received reference symbol power (RSRP) for the \( i \)-th user:
  \[ P_{RS}^{(i)} = P_{UE,j=1}^{(i)} / \left( N_{SC} N_{PRB} \right) \]
  - Number of resource blocks
  - Number of subcarriers in a resource block
  - UE received power measured at the first antenna

- The codeword block error rate (BLER) for the \( i \)-th user:
  \[ \beta_i := 1 - \prod_{j=1}^{n_s} (1 - \beta_{j,i}) \]
  - BLER for the codeword transmitted to the \( j \)-th antenna
MOTIVATION AND PROBLEM FORMULATION

- Industry approach is to use the users’ reported CSI to determine proper transmission rank
- BLER increases as the transmission rank increases
  - Throughput decreases as BLER increases
  - Throughput increases as transmission rank increases, assuming decorrelated transmission streams

\[ R_{\text{eff}} = \sum_{i} R_{i}^{\text{eff}} := (1 - \beta_i)n_sB\log_2(1 + \gamma_i) \]

- How to optimize this group of conflicting variables?
- Answer: main idea:
  - When the BLER is low, try to increase the transmission rank, if the second spatially decorrelated stream (i.e., rank-2) is possible.
  - Otherwise, default to a rank-1 transmission.

Users report a “quantized” SNR value known as the channel quality indicator (CQI)

CSI: Channel State Information
BLER: Block Error Rate

Can a dynamic data-driven approach help?
**Solution**

- **Simplify the problem to rank-2 MIMO channel and build a binary classifier**
- **For the binary classifier:**
  - **Labels** are a function of the BLER meeting the standard threshold
  - Use standard-compliant CSI as **learning features** that help define the transmission rank
- **Invalidate the learned model after the channel coherence time passes.**

- **Coordinated Multipoint (CoMP) trigger function:**

  \[ D[t] = \arg \max_y f_y(y[t]) \]

  CoMP trigger (MIMO), based on the majority of votes

  a frequency function: percentage of \( y=0 \) and \( y=1 \) samples (i.e., an empirical probability):

  \[ f_y(y_i) := \frac{\#(y = y_i)}{M}, y \in \{0, 1\}^M \]

- Standards-Compliant

  \[ y_i[t] = \mathbb{1}[\gamma^{(i)}[t] \geq \gamma_{\text{CoMP}}] \]

  uses SINR as a measure of decorrelation

- Proposed

  \[ \hat{y}_i[t] := \text{surrogate}(x_i[t]) \]

  CSI reported by the \( i \)-th user

  a machine learning function
Construct the surrogate function from:

- fully connected deep neural network (DNN)
- support vector machine (SVM)

Define the classification label based on the BLER being within target $y_i[t] := 1[\beta_i \leq \beta_{\text{target}}]$

Train classifiers to minimize loss objective

\[
\begin{align*}
\min_{\Theta} & \quad L(y, \hat{y}; \Theta) := -\sum_k y_k \log \hat{y}_k + (1 - y_k) \log(1 - \hat{y}_k) & \text{binary cross-entropy for DNN} \\
\min_{\mathbf{w}} & \quad \frac{1}{M} \sum_{i=1}^{M} \max(0, 1 - y_i(w^T \mathbf{x}_i - b)) + \alpha \|\mathbf{w}\|^2 & \text{hinge loss and regularization for SVM}
\end{align*}
\]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_0$</td>
<td>Bias term</td>
<td>Float</td>
</tr>
<tr>
<td>$x_1$</td>
<td>CSI-RSRP</td>
<td>Float</td>
</tr>
<tr>
<td>$x_2$</td>
<td>CQI</td>
<td>Integer</td>
</tr>
<tr>
<td>$x_3$</td>
<td>Rank</td>
<td>Integer</td>
</tr>
</tbody>
</table>
**SIMULATION**

<table>
<thead>
<tr>
<th>DNN Hyperparameter</th>
<th>Search range</th>
<th>SVM Hyperparameter</th>
<th>Search range</th>
</tr>
</thead>
<tbody>
<tr>
<td>DNN depth $d$</td>
<td>${1,3,5}$</td>
<td>Kernel</td>
<td>${\text{gaussian, polynomial}}$</td>
</tr>
<tr>
<td>DNN width $w$</td>
<td>${1,3,10}$</td>
<td>Box constraint $C_{Box}$</td>
<td>${0.01,1,10}$</td>
</tr>
<tr>
<td>Optimizer</td>
<td>Stochastic Gradient Descent</td>
<td>Kernel scale $\gamma$</td>
<td>auto [73]</td>
</tr>
</tbody>
</table>

* Degrees $p \in \{1,2,3,4\}$.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Asymptotic run-time</th>
<th>Number of features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static</td>
<td>$O(1)$</td>
<td>$O(1)$</td>
</tr>
<tr>
<td>SVM CoMP</td>
<td>$O(M^3)$</td>
<td>$O(p)$</td>
</tr>
<tr>
<td>DNN CoMP</td>
<td>$O(Mw^d)$</td>
<td>$O(w^d)$</td>
</tr>
</tbody>
</table>

Parameter | Value |
---|---|
Bandwidth $B$ | 10 MHz |
Downlink center frequency $f_c$ | 2100 MHz |
Downlink user scheduler | Proportional Fair |
Macro BS maximum power | 46 dBm |
Small cell BS maximum power | 37 dBm |
Maximum number of streams $n_s$ | 2 |
Number of PRBs $N_{PRB}$ | 50 |

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>User Throughput [Mbps]</th>
<th>BLER $\beta$</th>
<th>Streams $n_s$</th>
<th>CQI</th>
<th>CSI-RSRP [dBm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static</td>
<td>1.02</td>
<td>-</td>
<td>-</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>SVM CoMP</td>
<td>1.10</td>
<td>7.15%</td>
<td>1.59</td>
<td>3</td>
<td>-58.17</td>
</tr>
<tr>
<td>DNN CoMP</td>
<td>1.16</td>
<td>3.76%</td>
<td>1.55</td>
<td>3</td>
<td>-58.17</td>
</tr>
</tbody>
</table>

*1 Quantities not reported in the published version.

Because CoMP decision is an “imbalanced” classification, DNN does better.
## Summary

### Optimize users' achievable rate

- Achievable rate depends on a group of features, some of which have opposing effects on the rate.
- The use of a data-driven approach to find an improved achievable rate is possible.
- Higher transmission rank does not always lead to better achievable rates.

<table>
<thead>
<tr>
<th>Static</th>
<th>Dynamic</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Triggers rank-2 based on reported SINR (absolute cutoff).</td>
<td>• Triggers rank-2 based on a surrogate function based on deep learning.</td>
</tr>
<tr>
<td></td>
<td>• The surrogate function is relearned every time the channel coherence time passes.</td>
</tr>
</tbody>
</table>

More features and more complicated models lead to better performance.
Contribution 3

Deep Learning Predictive Band Switching in Wireless Networks

Discussed in the PhD Qualifying Exam and Included in the PhD Dissertation

Related publications:


BACKGROUND

- **Problem**
  - Users want to switch to a different frequency band if they expect to get higher throughput
  - Switching between frequency bands requires a “measurement gap” which reduces user throughput

- **Goal**
  - Improve user throughput by exploiting the spatial correlation to eliminate the measurement gap

- **Parameters**
  - Band switch *request* threshold which defines the rate below which UE requests a band switch
  - Band switch *grant* threshold which defines the rate above which the UE request is granted
  - Percentage of users in sub-6 GHz or mmWave vs total users
  - User spatial coordinates

- **Approach**
  - Employ a data-driven approach using a ray-tracing dataset
  - Use deep learning to rank the downlink channel quality based on the users’ coordinates
  - Grant a band switch if *predicted* to improve the user throughput (no need for the gap)
The received **instantaneous** rate for the $i$-th user at the $j$-th frequency band:

$$R^{(i,j)}[t] = B^{(j)} \log_2(1 + \gamma^{(i,j)}[t])$$

- **bandwidth**
- **received SINR**

The received **effective** achievable rate for the $i$-th user at the $j$-th frequency band:

$$R_E^{(i,j,k)}[t] = \left(1 - \frac{T_B^{(j)}}{T_C^{(j)}} + \frac{T_H^{(k)}}{T_C^{(j)}} \right) R^{(i,j)}[t]$$

- **beam training time**
- **band switching overhead**
- **channel coherence time**

Here, $k$ is the band switching algorithm.
MOTIVATION AND PROBLEM FORMULATION

- Next-generation wireless networks will use more frequency bands.

- The band selection problem becomes more complicated:
  - How does user choose a band to improve their rate?

- Problem: [3gpp18]
  - Measurement gap reduces users' effective achievable rates
  - Blindly switching user eliminates need for gap but risks rates

- Solution:
  - Main idea: rank bands based on their quality
  - Grant switch to band with the highest rank if requested.

Data-driven approach to eliminate the “measurement gap”
SOLUTION

- Optimal solution (upper bound)

\[ R_E^{\star(i)}[t] = \max_{j \in \{\text{sub-6, mmWave}\}} \left( 1 - \frac{T_B^{(j)}}{T_C^{(j)}} \right) R^{(i,j)}[t] \]

- Proposed solution
  - Exploit the spatial correlation between frequency bands based on the location of the user
  - Define the band switch request and the band switch grant decision as follows:

\[ x_{\text{br}}^{(i)}[t] = \mathbb{1}\left( (R^{(i,j)}[t] < \text{threshold}) \right) \]

\[ y^{(i)}[t] = \mathbb{1}\left( (\hat{R}^{(i,j)}[t] > R^{(i,j)}[t]) \right), \quad \forall i \]

- Train a machine learning algorithm using the following features

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(x_0)</td>
<td>Bias term</td>
<td>Integer</td>
</tr>
<tr>
<td>(x_1)</td>
<td>Effective rate at sub-6</td>
<td>Float</td>
</tr>
<tr>
<td>(x_2)</td>
<td>Effective rate at mmWave</td>
<td>Float</td>
</tr>
<tr>
<td>(x_3)</td>
<td>Source technology</td>
<td>Boolean</td>
</tr>
<tr>
<td>(x_4, x_5, x_6)</td>
<td>Coordinates</td>
<td>Float</td>
</tr>
<tr>
<td>(x_7)</td>
<td>Band switch requested</td>
<td>Boolean</td>
</tr>
<tr>
<td>(y)</td>
<td>Band switch decision</td>
<td>Boolean</td>
</tr>
</tbody>
</table>

*Use DeepMIMO ray-tracing dataset and engineer more features* [Alkhateeb19]
SIMULATION

- Scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Users at Start</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>100% sub-6 GHz</td>
</tr>
<tr>
<td>B</td>
<td>100% mmWave</td>
</tr>
<tr>
<td>C</td>
<td>70% sub-6 GHz and 30% mmWave</td>
</tr>
</tbody>
</table>

- Parameters (DNN: deep neural networks, XGBoost: Extreme Gradient Boosting)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of rows in feature matrix</td>
<td>n log n</td>
<td>Complexity control term γ</td>
<td>0.02, 0.04</td>
</tr>
</tbody>
</table>
SIMULATION

- Impact of the band switching threshold on the performance

<table>
<thead>
<tr>
<th>Threshold</th>
<th>Normalized mean effective throughput $R_T$ [Mbps]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Legacy</td>
</tr>
<tr>
<td>Scenario A</td>
<td></td>
</tr>
<tr>
<td>1.72</td>
<td>0.55</td>
</tr>
<tr>
<td>2.00</td>
<td>0.46</td>
</tr>
<tr>
<td>2.60</td>
<td>0.34</td>
</tr>
<tr>
<td>Scenario B</td>
<td></td>
</tr>
<tr>
<td>2.00</td>
<td>0.43</td>
</tr>
<tr>
<td>12.50</td>
<td>0.33</td>
</tr>
</tbody>
</table>

Higher band switching thresholds cause the legacy approach performance to do worse.

Higher band switching thresholds enable my proposed algorithm to do even better.

Legacy approach performs better than blind in low throughput regime.

CONTRIBUTION 3: DEEP LEARNING PREDICTIVE BAND SWITCHING

- Absence of measurement gap in optimal
- ... and near perfect DNN classification decisions

Scenario A: 100% users sub-6 GHz
Scenario B: 100% users mmWave
Scenario C: 30%-70% users
SUMMARY

Optimize users’ achievable rate

- Band switching grows in importance with successive evolutions of wireless technology
- The use of a data-driven approach to rank channels by their estimated quality is possible.
- Using measurement gaps for the band switching procedure is a “performance overkill.”

<table>
<thead>
<tr>
<th>Industry</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Use a gap to measure the candidate frequency band.</td>
<td>Does not require a measurement gap.</td>
</tr>
<tr>
<td>Blindly switch to a different band.</td>
<td>Exploits the spatial and spectral correlation of frequency bands at a given location.</td>
</tr>
<tr>
<td>Legacy</td>
<td>Blind</td>
</tr>
</tbody>
</table>

I disrupt the need to use a measurement gap in band switching
Next-generation wireless networks will require intelligent predictive and prescriptive abilities

- boost reliability and eliminate performance bottlenecks
- disrupt reactive legacy standards

**PHY Layer Perspective**

**Beamforming, Power Control and Interference Coordination**

**Intelligent Coordinated Multipoint**

**RRM Layer Perspective**

**Predictive Band Switching**
FUTURE WORK IN DEEP LEARNING FOR COMMUNICATIONS

- Optimal hybrid beamforming
  - I used simple DFT-based analog beamforming, but digital beamforming generates more patterns
    - at mmWave, a disjoint solution exists, but may not be optimal.
    - Exploit powers of two in the number of antennas

- Improved Cell-Free Massive MIMO
  - Use coordinated BS capabilities with massive MIMO to improve joint-beamforming capabilities

- Generalized multi-band predictive handoff
  - Introduce mobility over multiple base stations and build a multi-class classifier
PUBLICATIONS

Journal articles


Conference papers


SOFTWARE RELEASES

Available at https://github.com/farismismar

  Builds on top of the 3.5 GHz and 28 GHz ray tracing dataset from ASU.


  Builds on top of Vienna University of Technology (TU Wien) Vienna LTE-A Downlink System Level Simulator v1.9.

  Builds on top of Vienna University of Technology (TU Wien) Vienna LTE-A Downlink System Level Simulator v1.9.
REFERENCES


ACRONYMS AND ABBREVIATIONS

3GPP 3rd Generation Partnership Project
BLER Block Error Rate
BS Base Station
CDF Cumulative Distribution Function
CoMP Coordinated Multipoint
CQI Channel Quality Indicator
CSI Channel State Information
DFT Discrete Fourier Transform
DNN Deep Neural Network
DQN Deep Q-Network
DRL Deep Reinforcement Learning
FDD Frequency Division Duplex
FPA Fixed Power Allocation
JBPCIC Joint Beamforming Power Control and Interference Coordination
LOS Line of Sight
LTE(-A) Long Term Evolution (-Advanced)
MAC Medium Access Control
MIMO Multiple Input Multiple Output
ML Machine Learning
NLOS Non-Line of Sight
NR New Radio
O-RAN Open Radio Access Network
OFDM Orthogonal Frequency Division Multiplexing
PHY Physical Layer
PRB Physical Resource Block
QoE Quality of Experience
RAN Radio Access Network
RL Reinforcement Learning
ROC Receiver Operating Characteristic
RRM Radio Resource Management
RSRP Reference Symbol Received Power
SGD Stochastic Gradient Descent
SINR Signal to Interference plus Noise Ratio
SNR Signal to Noise Ratio
SON Self-Organizing Networks
SVM Support Vector Machine
TTI Transmit Time Interval
UE User Equipment
ULA Uniform Linear Array
UPA Uniform Planar Array
VoLTE Voice over Long Term Evolution
ZF Zero-Forcing
## DISSERTATION CONTRIBUTIONS

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dissertation Chapter</strong></td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td><strong>Reference</strong></td>
<td>[Mismar&amp;Evans20a]</td>
<td>[Mismar&amp;Evans19a]</td>
<td>[Mismar&amp;Evans20b]</td>
</tr>
<tr>
<td><strong>Frequency band</strong></td>
<td>mmWave and sub-6 GHz</td>
<td>sub-6 GHz</td>
<td>mmWave and sub-6 GHz</td>
</tr>
<tr>
<td><strong>Stack layer</strong></td>
<td>PHY</td>
<td>PHY</td>
<td>RRM</td>
</tr>
<tr>
<td><strong>Algorithm</strong></td>
<td>DRL</td>
<td>DNN and SVM</td>
<td>DNN and XGBoost</td>
</tr>
<tr>
<td><strong>Direction</strong></td>
<td></td>
<td></td>
<td>Downlink</td>
</tr>
<tr>
<td><strong>Users</strong></td>
<td></td>
<td></td>
<td>Multi-User</td>
</tr>
</tbody>
</table>

**CONTRIBUTION 2: IMPROVED DOWNLINK COORDINATED MULTIPPOINT**

CoMP (Coordinated Multipoint) decisions are "imbalanced" and DNN does better.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Asymptotic run-time</th>
<th>Number of features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static</td>
<td>$O(1)$</td>
<td>$O(1)$</td>
</tr>
<tr>
<td>SVM CoMP</td>
<td>$O(M^3)$</td>
<td>$O(p)$</td>
</tr>
<tr>
<td>DNN CoMP</td>
<td>$O(Mw^d)$</td>
<td>$O(w^d)$</td>
</tr>
</tbody>
</table>

**Simulation**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth $B$</td>
<td>10 MHz</td>
</tr>
<tr>
<td>Downlink center frequency $f_c$</td>
<td>2100 MHz</td>
</tr>
<tr>
<td>Downlink user scheduler</td>
<td>Proportional Fair</td>
</tr>
<tr>
<td>Macro BS maximum power</td>
<td>46 dBm</td>
</tr>
<tr>
<td>Small cell BS maximum power</td>
<td>37 dBm</td>
</tr>
<tr>
<td>Maximum number of streams $n_s$</td>
<td>2</td>
</tr>
<tr>
<td>Number of PRBs $N_{PRB}$</td>
<td>50</td>
</tr>
</tbody>
</table>

\textbf{SOLUTION}

\section*{Why DNN?}

- \textbf{Support Vector Machines}

\[
\max\limits_{\lambda} \sum_{i} \lambda_i - \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \lambda_m \lambda_n y_m y_n K(x_m, x_n) \quad \text{[Cortes95]}
\]

subject to:

\[
\sum_{m=1}^{M} \lambda_m y_m = 0,
\]

\[
0 \leq \lambda_m \leq C_{\text{Box}}, \quad m = 1, \ldots, M
\]

- \textbf{Can be faster than DNN, but suffers from bias towards majority class.}

\[
\#(y = 0) = 1,522 \quad \#(y = 1) = 7,658
\]

\[M = 9,180\]

\textbf{SVM will trigger more rank-2s than DNN, but at the wrong time!}

\section*{Is CoMP triggered in a balanced fashion in a cell?}
DNN achieved ROC AUC = 1.0 with far less training samples than XGBoost.
**SUPPORT VECTOR MACHINES**

- **Primal**

  minimize: \[ \frac{1}{M} \sum_{i=1}^{M} \max(0, 1 - y_i (\mathbf{w}^T \mathbf{x}_i - b)) + \alpha \| \mathbf{w} \|^2 \]

- **Dual**

  maximize: \[ \sum_{i} \lambda_i - \frac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \lambda_m \lambda_n y_m y_n K(\mathbf{x}_m, \mathbf{x}_n) \]

  subject to: \[ \sum_{m=1}^{M} \lambda_m y_m = 0, \]

  \[ 0 \leq \lambda_m \leq C_{\text{Box}}, \quad m = 1, \ldots, M \]

  Computationally more efficient, exploits strong duality, and enables the kernel “trick”
XGBOOST

- A tree-ensemble learning technique, which minimizes this objective function

\[
\text{minimize: } \quad \text{Obj}(\hat{y}) := L(y, \hat{y}) + \alpha \|w\|_1 + \frac{1}{2} \lambda \|w\|_2^2 + \gamma T
\]

- Fast and accurate hence used in many data mining contests

- Uses the sub-gradient (or derivative if differentiable) for the first (gradient) and second order (Hessian) of the objective function

\[
g(t) := \partial \text{Obj}(\hat{y}; t) \\
h(t) := \partial^2 \text{Obj}(\hat{y}; t)
\]

- Logistic loss function:

\[
L(y, y_i) := y_i \log \frac{1}{1 + e^{-\hat{y}_i}} + (1 - y_i) \log \frac{e^{-\hat{y}_i}}{1 + e^{-\hat{y}_i}}
\]

- Using the gradient and Hessian, compute the “gain” for both the right and left subtrees. Choose the direction with the maximum gain.

[Chen16]
Deep neural networks

- **Perceptron**
  
  \[ y := \sigma(x^T \theta + b) \quad x, \theta \in \mathbb{R}^M \]

- **Deeper and wider neural networks**
  - Feed-forward (no loops, adjusts weights \( \theta \))
  - Backpropagation (method of calculating the gradient with respect to the neural network weights)

- **Optimizers**
  - Stochastic Gradient Descent
    \[ \theta := \theta - \eta \nabla L(y, \hat{y}; \theta) \]  
    Uses the gradient and its second moment (i.e., gradient squared). Adapts the learning rate.
  - Adaptive moments “Adam”

- **Slower execution time compared to SVM and XGBoost**
**Deep Q-Learning**

- **Reinforcement learning**
  - Learns through interaction with an environment
  - Seeks to maximize the expected future reward of an agent

- **Policy**: defines a mapping from states to the actions taken
  - Stochastic $\pi_\Theta(a \mid s) : \mathcal{S} \times \mathcal{A} \rightarrow [0, 1]$

- **Experience**
  
  $e_t := (s_t, a_t, r_t, s_{t+1})$

  Stored in a replay buffer

- **Replay**
  - Samples from prior experience (i.e., the replay buffer) to remove potential correlation and improve stability of DQN

- **Bellman**
  
  $Q^*_\pi(s_t, a_t) := \mathbb{E}_{s'} \left[ r_{s, s', a} + \gamma \max_{a'} Q^*_\pi(s', a') \mid s_t, a_t \right]$, \quad [Sutton]

- **Deep Q-Network (DQN)**

  $\lim_{t \rightarrow +\infty} Q^\pi(s, a; \Theta_t) = Q^*_\pi(s, a)$

  Universal approximation theorem

- **Exploration vs exploitation**
  - Select a random action w.p. $\epsilon$
  - Find action that maximizes $Q^*_\pi(s, a)$ w.p. $(1 - \epsilon)$

  $\epsilon$-greedy has linear “regret”

  [Silver]