Wireless Optimisation via Convex Bandits

Unlicensed LTE/WiFi Coexistence

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Unlicensed LTE/WiFi Coexistence

Unlicensed LTE

- Mobile traffic demands are exponentially increasing.
- General consensus:
  - Aggregate data rate needs to increase by 1000x!
- This increase may be achieved mainly through gains in:[1]
  - Densification (small cells).
  - Advances in MIMO.
  - Wide spectrum: mmWave and the **unlicensed 5GHz band**.
    - Offloading using other technologies vs. **LTE access**.

[1] Andrews, Jeffrey G., et al. *What will 5G be?. IEEE Journal on Selected Areas in Communications, Special Issue on 5G Communication Systems, Editorial/Tutorial Paper, September 2014.*

Coexistence of Unlicensed LTE and WiFi

- LTE and WiFi channel accesses are very different in nature:
  - LTE uses a scheduled-based approach.
  - WiFi abides to polite rules (random access).
- Along with unmodified LTE **WiFi networks can starve**.
- **Concerns** have been raised from the WiFi Alliance and FCC.
- Coexistence mechanisms are required.

Fair Sharing

Fairness guarantees

- How to divide resources to be fair to both networks?
- What does fairness even mean?
- We take a **proportional fair** approach:[2]
  - Intuitively, give more resources to more efficient devices...
  - ...as far as no other is too penalised from that.
  - Popular due to its analytical tractability as well.

[2] C. Cano and D. J. Leith, *Unlicensed LTE/WiFi Coexistence: Is LBT Inherently Fairer Than CSAT?* in IEEE International Conference on Communication (ICC), 2016.

Proportional fair allocation

- Convex optimisation problem:

$$\max_{\tilde{s}_{\mathrm{wifi},j},\tilde{s}_{\mathrm{LTE}},\tilde{z}} \tilde{s}_{\mathrm{LTE}} + \sum_{j=1}^{n} \tilde{s}_{\mathrm{wifi},j}$$

$$\begin{aligned} s.t. \quad & \tilde{s}_{\mathrm{wifi},j} - \log s_j - \tilde{z} + \log(T_{\mathrm{on}} + c_1 + e^{\tilde{z}}) \leq 0, \;\; j = 1, \ldots, n \\ & \tilde{s}_{\mathrm{LTE}} - \log q + \log(T_{\mathrm{on}} + c_1 + e^{\tilde{z}}) \leq 0, \end{aligned}$$

where $z = \bar{T}_{\mathrm{off}} - c_1$, $q := r(T_{\mathrm{on}} - c_2)$ and c_1 and c_2 are constants that capture the heterogeneity cost.

Applying Bandits

Change of traditional paradigm

- Move from **characterising** the network behaviour.
  - Which requires assumptions and inferring parameters.
- To **learn** the fair configuration by **interacting** with the environment.
- Can we benefit from the problem being **convex**?
  - Many wireless optimisation problems are formulated as convex.

Bandit convex optimisation

- General idea:
  - Repeated game in which the adversary is constrained to select **convex cost functions**.
  - Interested in guaranteeing that the cumulative sum of the incurred losses is as small as possible (low regret).
- Benefits:
  - Intrinsically handles **network dynamics**.
  - Only the **variable to optimize** is needed as input.

BCO State-of-the-art

- Algorithms use gradient descent **without a gradient**:
  - Feed gradient descent with an estimation of the gradient.
  - Pioneered by Flaxman.[3]
  - Followed by many refined versions.[4]
- None of these are practical:
  - Single-point estimations have **high variance** in practice.
  - Multi-point estimations require sampling the function **multiple times per round**.

[3] A. Flaxman, A. Kalai, and B. McMahan, *Online convex optimization in the bandit setting: Gradient descent without a gradient* in Proceedings of the Sixteenth Annual ACM-SIAM Symposium on Discrete Algorithms (SODA), 2005, pp. 385-394.

[4] X. Hu, L. Prashanth, A. Gyrgy, and C. Szepesvri, *(bandit) convex optimization with biased noisy gradient oracles,* in Artificial Intelligence and Statistics, 2016, pp. 819828.

Sequential BCO

- We use multi-point estimation ideas by Agarwal.[5]
  - But combine queries from **two consecutive rounds**.
- Results:
  - If the functions change arbitrarily:
    - Matches best single-point known results: $O\left(T^{3/4}\right)$.
  - If the function changes *infrequently*:[6]
    - Same regret bound as Agarwal: $O\left(\sqrt{T}\right)$.

[5] A. Agarwal, O. Dekel, and L. Xiao, *Optimal Algorithms for Online Convex Optimization with Multi-Point Bandit Feedback.* in COLT, 2010, pp. 2840.

[6] At most N times in T with $N << T$.

Formulation of our Example as a BCO Problem

Repeated Game

- In each round $t = 1, 2, \ldots, T$:
  - The player chooses a point $\tilde{z}_t \in \mathcal{K}$.
  - The adversary independently chooses $f_t \in \mathcal{F}$.
  - The player observes $f_t(\tilde{z}_t)$.
- The decision set $\mathcal{K}$ is convex.
- All functions in $\mathcal{F}$ are convex in $\tilde{z}_t$.

Experimental Results

Convergence and sensitivity to learning parameters

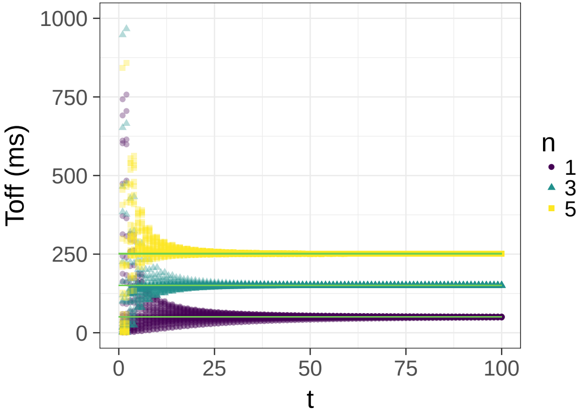


Figure: $\omega = 0.01$.

Convergence and sensitivity to learning parameters

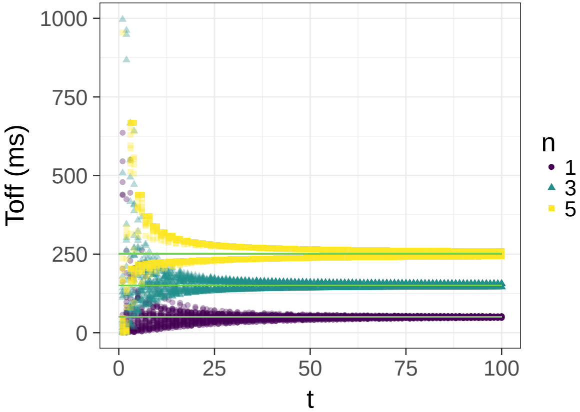


Figure: $\omega = 1$.

Adaptability to network dynamics

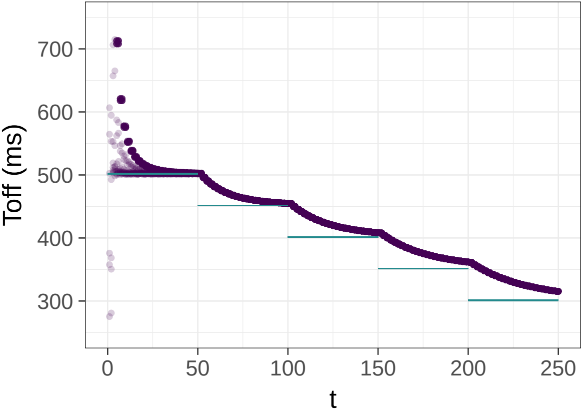
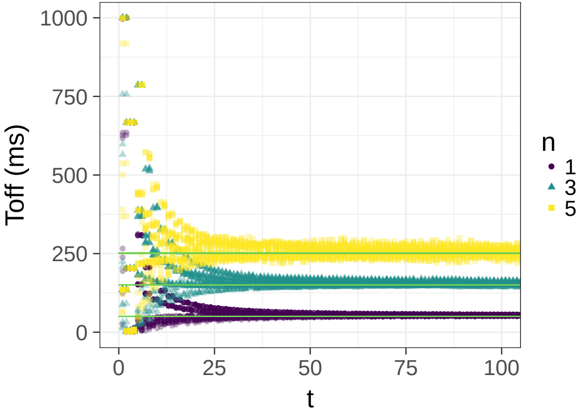


Figure: n increases in 1.

Noisy estimates

- Cost function vs. simulator evaluations.



Final Remarks

- Many network problems are **formulated as convex**.
- Bandit Convex Optimisation can **ease implementation**.
  - Only the variable to optimise is needed as input.
  - Handles network dynamics intrinsically.
- Still much research **ahead**.
  - Explore single-point estimation further.
  - Methods to deal with noisy estimates.
  - Higher dimension problems.


lte
WiFi n