Learning Optimal Sniffer Channel Assignment for Small Cell Cognitive Radio Networks

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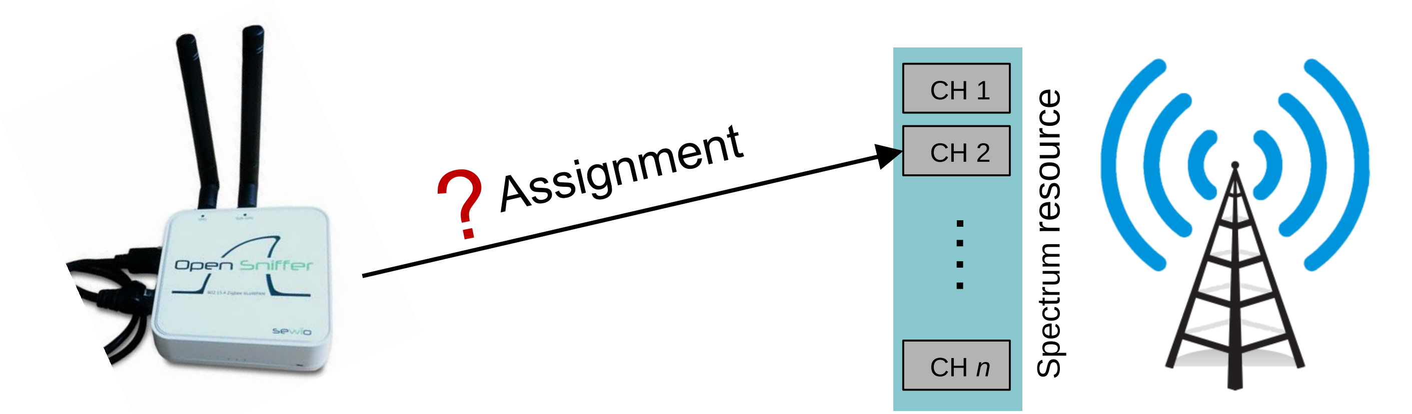
Introduction

- Passive Monitoring in Wireless Networks
  - Capture network traffic to analyze the network conditions and performance.
  - Network operations: resource management, network configuration, fault diagnosis, network intrusion detection
- Sniffer Channel Assignment (SCA)



Sniffer
(*Limited bandwidth*)

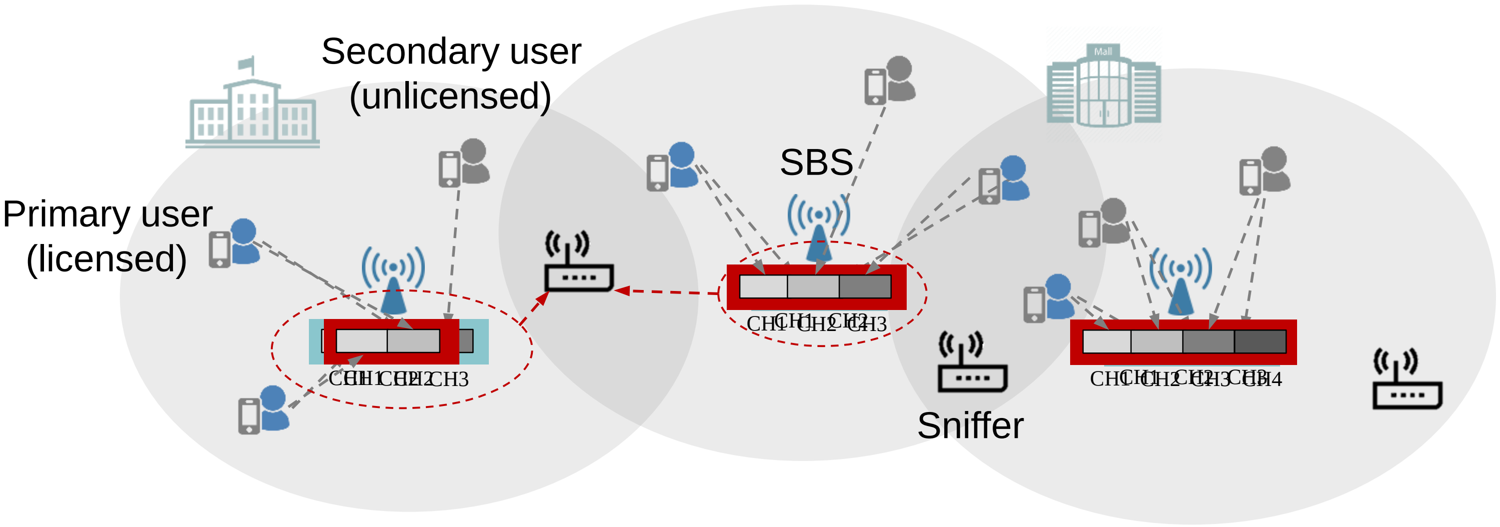
Base Station
(*Multi-Channels*)

Broadband multi-channel wireless networks

Macrocell networks

Sniffer Channel Assignment in Small-cell Cognitive Radio

- Small-cell Network Towards 5G



- New Challenges
  - Multi-cell scenario and SCA subjects to physical constraints
  - Time-varying spectrum resource at small-cell base station (SBSs)
  - Imperfect monitoring, unreliability of mmWave propagation

Contributions

- Sniffer Channel Assignment in Small-cell Cognitive Radio
  - Multi-cell scenario with assignment constraints
  - Time-varying spectrum resource
  - Imperfect monitoring
  - Redundant assignment
- Optimization-based Solution
  - With statistical knowledge about imperfect monitoring
- Online Sniffer Channel Assignment using Bandit Learning
  - Learn the knowledge about imperfect monitoring
  - Contextual Combinatorial Multi-armed bandit

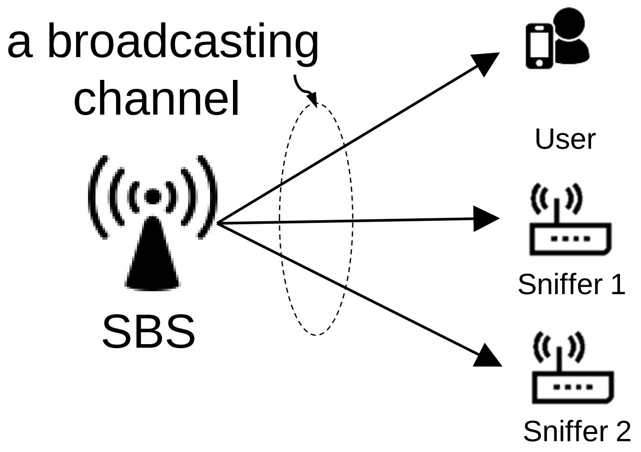
SCA Problem Formulation

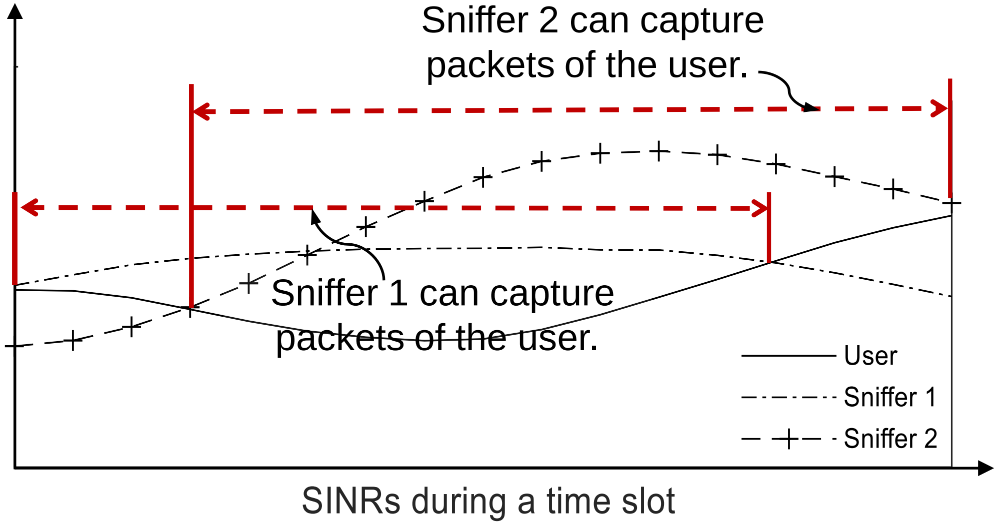
- Sniffer Channel Assignment
  - Assign a set of sniffers $\mathcal{S} = \{1,2,\dots,S\}$ to a set of channels $\mathcal{H}^t$
  - Assignment decision $\boldsymbol{a}^t \coloneqq \{a_s^t\}_{s\in\mathcal{S}}$, $a_s^t \in \mathcal{C}_s^t \subseteq \mathcal{H}^t$
- Utility Maximization
  - Objective
    - Utility maximization: $u^t(\boldsymbol{a}^t;\boldsymbol{p}^t) = \sum_{k\in\mathcal{H}^t} \underline{w_k}\,\underline{\theta_k^t(\boldsymbol{a}^t;\boldsymbol{p}^t)}$
  - Importance of channel $w_k, k \in \mathcal{H}^t$
    - Amount of traffics on the channel
    - Time occupied by licensed users and unlicensed users
  - Packet capture probability $\theta_k^t(\boldsymbol{a}^t;\boldsymbol{p}^t)$
    - Assignment decision $\boldsymbol{a}^t$: number of sniffers assigned to channel k
    - $\boldsymbol{p}^t = \{p_{s,k}^t\}_{s\in\mathcal{S},k\in\mathcal{H}^t}$ denotes the performance of sniffer s on channel k

SCA Problem Formulation

- Theory of Secrecy Channel Capacity

$$p_{s,k}^{t} = \Pr\{\mathrm{SINR}_{\mathrm{sniffer},k}^{t} \geq \mathrm{SINR}_{\mathrm{user},k}^{t}\}$$ **(Non-outage probability)**





- Redundant Sniffer Assignment

Sniffers assigned to channel k

Packet capture probability: $$\theta_k^t(a^t; p^t) = \begin{cases} 1 - \prod_{s \in \mathcal{S}_k(\boldsymbol{a}^t)} \left(1 - p_{s,k}^t\right), & if \;\; \mathcal{S}_k(\boldsymbol{a}^t) \neq \emptyset \\ 0, & if \;\; \mathcal{S}_k(\boldsymbol{a}^t) = \emptyset \end{cases}$$

Sniffer Channel with Oracle Information

- Oracle Solution
  - Assuming the packet capture probability is known
    - Solve in each time slot *t* :

$$\mathcal{P}1: \quad \max_{\boldsymbol{a}^t} \; u^t(\boldsymbol{a}^t;\boldsymbol{p}^t) = \sum_{k\in\mathcal{H}^t} w_k \theta_k^t(\boldsymbol{a}^t;\boldsymbol{p}^t), \qquad \mathrm{s.t.}\; a_s^t \in \mathcal{C}_s^t \cup \{null\}$$

  - Result
    - $\mathcal{P}1$ is a Matroid-constrained Submodular Maximization (MCSM) problem.
    - Greedy algorithm solves MCSM problem with ½ - approximation.

$$u^t(\underbrace{\boldsymbol{a}^{*,t}}_{\text{Action obtained by greedy algorithm}};\boldsymbol{p}^t) \geq \frac{1}{2} u^t(\underbrace{\boldsymbol{a}^{\mathrm{opt},t}}_{\text{Optimal actions}};\boldsymbol{p}^t)$$

Sniffer Channel Assignment via Online Learning

- Necessity of learning
  - Non-outage probability $\boldsymbol{p}^t$ is **unknown** in practice
  - Algorithm: Online Sniffer Channel Assignment (OSA)
    - Solve a long-term problem in a time horizon $1,2,..,T$:

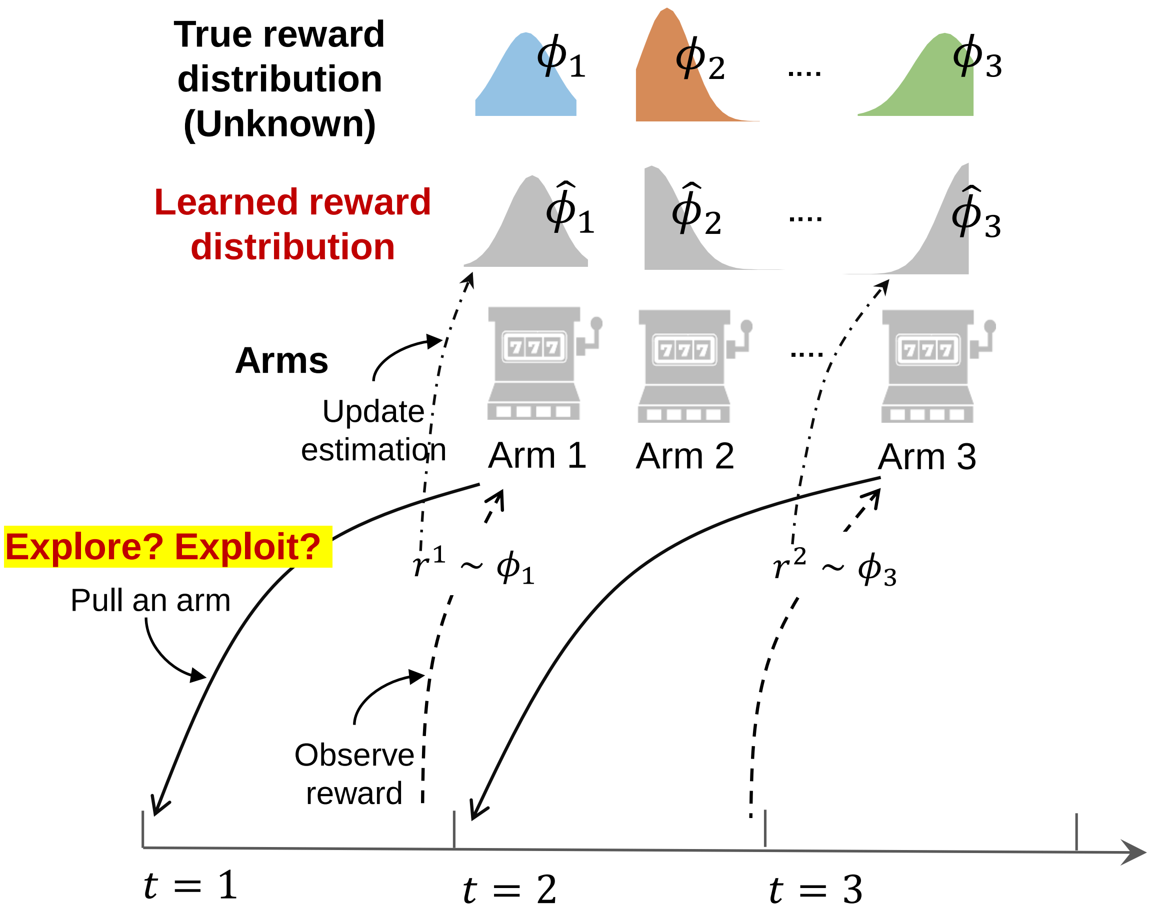
$$\max_{\boldsymbol{a}^1,\boldsymbol{a}^2,\dots\boldsymbol{a}^T} \sum_{t=1}^{T} \sum_{k\in\mathcal{H}^t} w_k \theta_k^t(\boldsymbol{a}^t;\widehat{\boldsymbol{p}}^t),$$

$$\text{s.t. } a_s^t \in \mathcal{C}_s^t \cup \{null\}, \forall t$$

  - Learning while optimizing
    - **Task1**: Learning the non-outage probabilities $\widehat{\boldsymbol{p}}^t$ over time
    - **Task2:** Maximize the utility based on the learned knowledge
    - Trade-off between two purposes, balanced by Multi-armed bandit

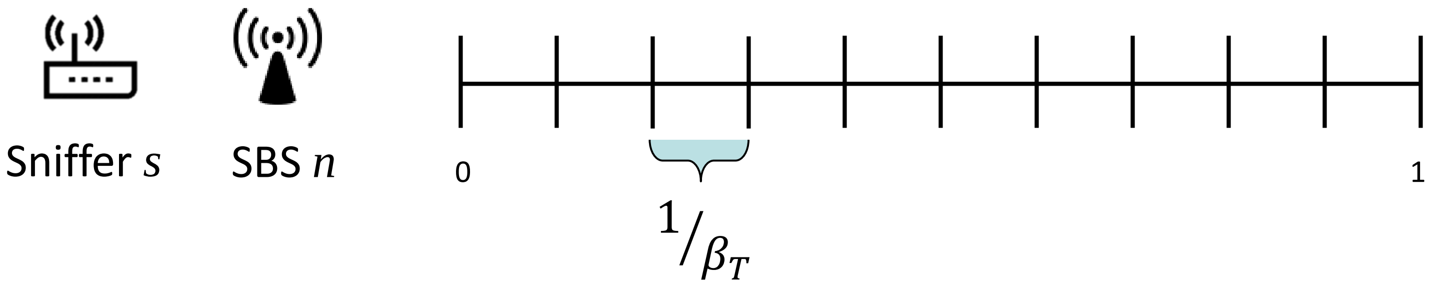
Online Learning via Multi-armed Bandit

- Multi-armed Bandit Problem (MAB)
  - Learn the reward of arms
    - *- Arm/Action: sniffer-channel pairs*
    - *- Rewards to be learned: non-outage probability*
  - Objective
    - *- Maximize the collected rewards*
  - Exploration-Exploitation Tradeoff
    - *- Exploration: pull an arm to learn the its reward*
    - *- Exploitation: pull an arm that yielded highest reward according to past experience*
- Limitations
  - Pull one arm each time slot
    - *- Assign one sniffer at a time*
  - Learn general rewards
    - *- Not aware of available side-information (context)*



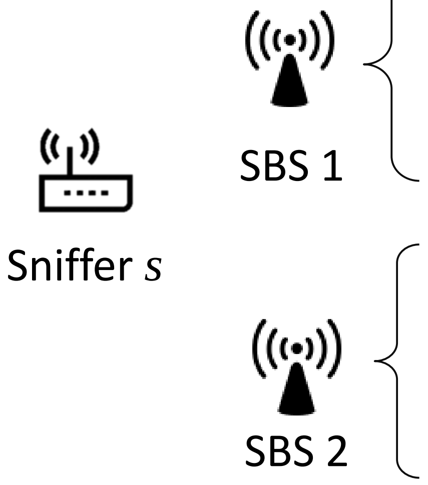
Contextual Combinatorial MAB (CCMAB)

- Utilize Context Information
  - Context: SINR of Sniffers
    - Recall $p_{s,k}^{t} = \Pr\{SINR_{s,k}^{t} \geq SINR_{u,k}^{t}\}$
    - $SINR_{u,k}^{t}$ of users is unknown yet $SINR_{\mathrm{s,k}}^{\mathrm{t}}$ of sniffers is observable (denoted by $\phi_{s,k}^{t} \in \Phi$)
  - Context-parameterized non-outage probability
    - $p_{s,k}^{t} \sim p_{s,n}(\phi_{s,k}^{t})$ from unknown distribution parameterized by $\phi_{s,k}^{t}$
    - $\mu_{s,n}(\phi_{s,k}^{t}) \coloneqq \mathbb{E}[p_{s,n}(\phi_{s,k}^{t})]$
  - Estimation of non-outage probability
    - Collect historical data for each context $\mathcal{E} \sim p_{s,n}(\phi_{s,k}^{t})$
    - Estimate the expected value $\mathcal{E} \rightarrow \hat{\mu}_{s,n}(\phi_{s,k}^{t})$
  - Context partitioning
    - Continuous context $\Phi \coloneqq [0,1] \rightarrow$ discrete context intervals $\mathcal{L}_T$
    - Similarity assumption: *Similar context* $\rightarrow$ *Similar non-outage probability*

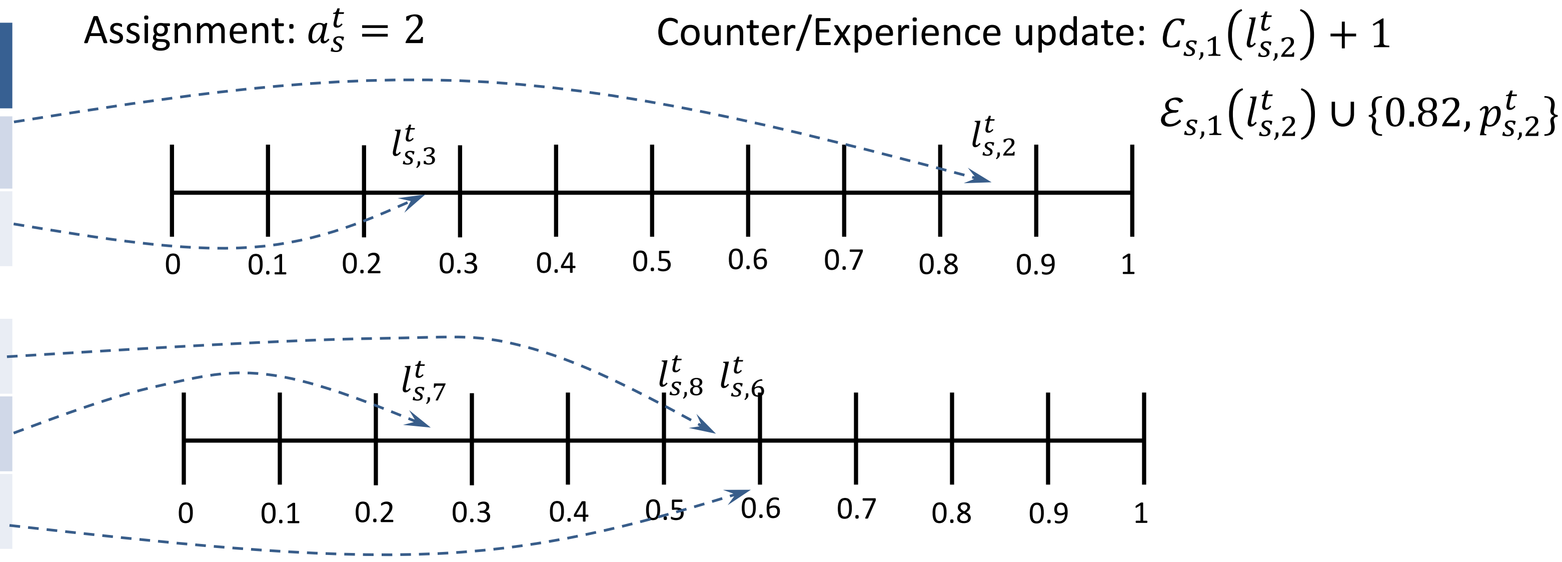


Online Learning via Multi-armed Bandit

- Counter and Experience
  - Counter $C_{s,n}(l)$ and Experience $\mathcal{E}_{s,n}(l)$
    - Counter $C_{s,n}(l)$ records amount of collected data
    - $\mathcal{E}_{s,n}(l)$ stores the observed non-outage probabilities
    - Estimated non-outage probability $\hat{\mu}^t_{s,n}(l) = \frac{1}{C^t_{s,n}(l)} \sum_{p\in\mathcal{E}_{s,n}(l)} p$



Channel Index k	Normalized SINR
2	0.82
3	0.26
6	0.58
7	0.27
8	0.51



Online Learning via Multi-armed Bandit

- Online Sniffer Channel Assignment with CCMAB
  - Context observation
    - Each sniffer s senses SINRs $\phi_{s,k}^t$ on accessible channels $k \in \mathcal{C}_s$,
    - Find $l_{s,k}^t$ such that $\phi_{s,k}^t \in l_{s,k}^t$
    - **Under-explored channels** for sniffer s $\mathcal{C}_{\mathrm{s}}^{\mathrm{ue},t} := \{k \in \mathcal{C}_s^t \mid C_{s,n}(l_{s,k}^t) < Q(t)\}$

Determine whether the estimation is accurate

  - Exploration
    - $\mathcal{S}^{\mathrm{ue},t} = \{s \in \mathcal{S} \mid \mathcal{C}_{\mathrm{s}}^{ue,t} \neq \emptyset\}$, randomly assign sniffer $s \in \mathcal{S}^{\mathrm{ue},t}$ to a channel in $\mathcal{C}_{\mathrm{s}}^{\mathrm{ue},t}$
  - Exploitation
    - $\mathcal{S}^{\mathrm{ed},t} = \{s \in \mathcal{S} \mid \mathcal{C}_{\mathrm{s}}^{ue,t} = \emptyset\}$

$$\max_{\boldsymbol{a}^t} \sum_{k \in \mathcal{H}^t} w_k \theta_k^t(\boldsymbol{a}^t; \widehat{\boldsymbol{p}}^t)$$

$$\text{s.t.} \quad a_s^t \in \mathcal{C}_s^t \cup \{null\}, \forall s \in \mathcal{S}^{\mathrm{ed},t}$$

$$a_s^t = null, \forall s \in \mathcal{S}^{\mathrm{ue},t}$$

Online Learning via Multi-armed Bandit

- Performance Analysis
  - Regret

Optimal actions Decision of OSA

$$R(T) = \sum_{t=1}^{T} u(\boxed{\boldsymbol{a}^{\text{opt},t}}; \boldsymbol{p}^t) - \sum_{t=1}^{T} u(\boxed{\boldsymbol{a}^t}; \boldsymbol{p}^t)$$

  - Regret Upper Bound

Theorem. Let $\mathrm{Q}(t) = t^{\frac{2\alpha}{3\alpha+1}} \log(t)$ and $\beta_T = \left\lceil T^{\frac{1}{3\alpha+1}} \right\rceil$, the upper bound of $\mathbb{E}[R(T)]$ is
$$O(NS^2 w^{max} T^{\frac{2\alpha+1}{3\alpha+1}} \log T)$$

- The regret upper bound is sublinear ⇒ Asymptotically optimal

Simulations

- Setup
  - 8 SBSs (blue tringles) in 1200m×1200m area
  - 25 sniffers (red squares) with grid layout
  - Randomly deployed Users (yellow dots)
  - Background color is the user density
- Factors affects SINR
  - Pathloss (distance and random shadowing)
  - Interferences (# of nearby users)

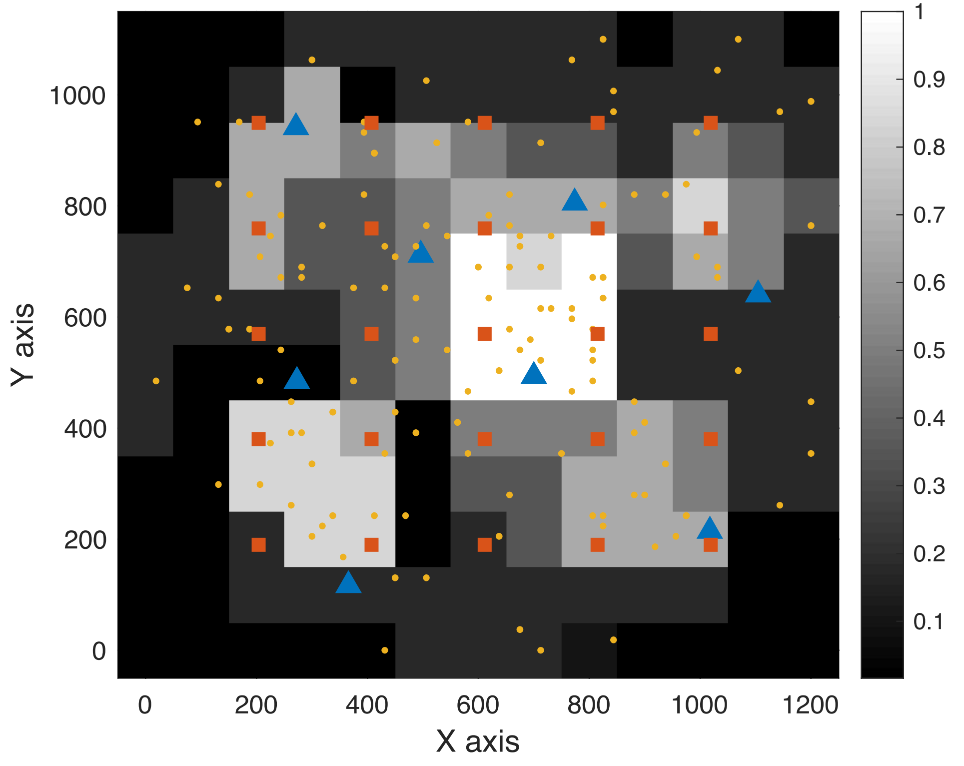


Fig. Simulation model

Simulations

- Benchmarks
  - **Oracle**: knowns the non-outage probability when making the SCA decision
  - **UCB**: a classic MAB algorithm, non-contextual and non-combinatorial
  - **LinUCB**: a variant of UCB and assumes the reward is a linear function of context
  - **Random**: takes random assignment decisions
- Cumulative rewards
  - OSA achieves close-to-oracle performance
- Regret
  - OSA achieves sublinear regret

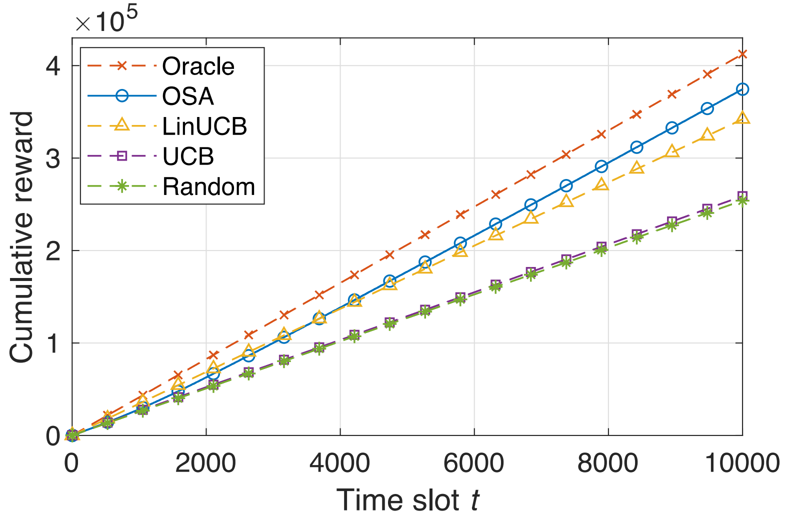


Fig. Comparison of cumulative rewards

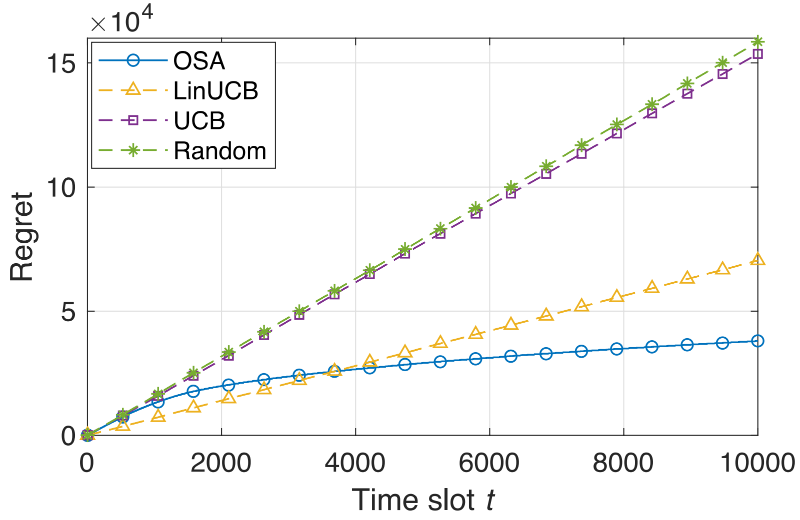
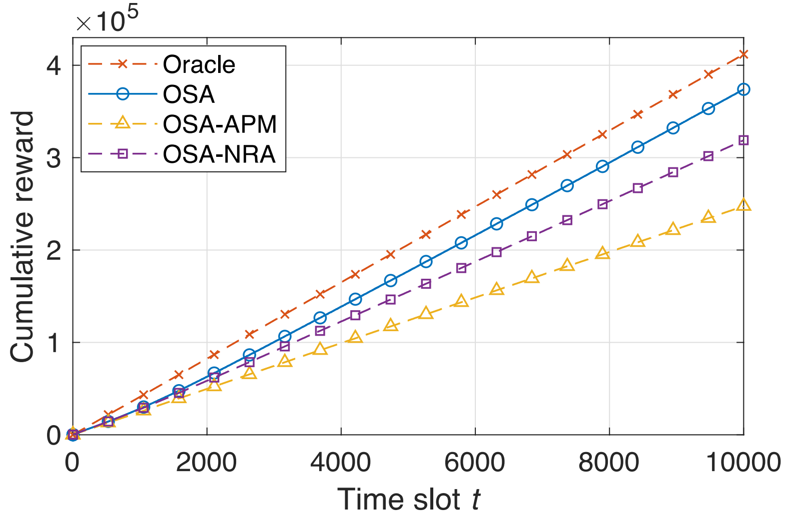


Fig. Comparison of regrets

Simulations

- OSA Variants
  - OSA with Assumed Perfect Monitoring (OSA-APM)
  - OSA with Non-Redundant Assignments (OSA-NRA)
- Rewards and Regret
  - Considering imperfect monitoring and redundant assignment is beneficial
  - Considering redundant assignment provides greater improvement



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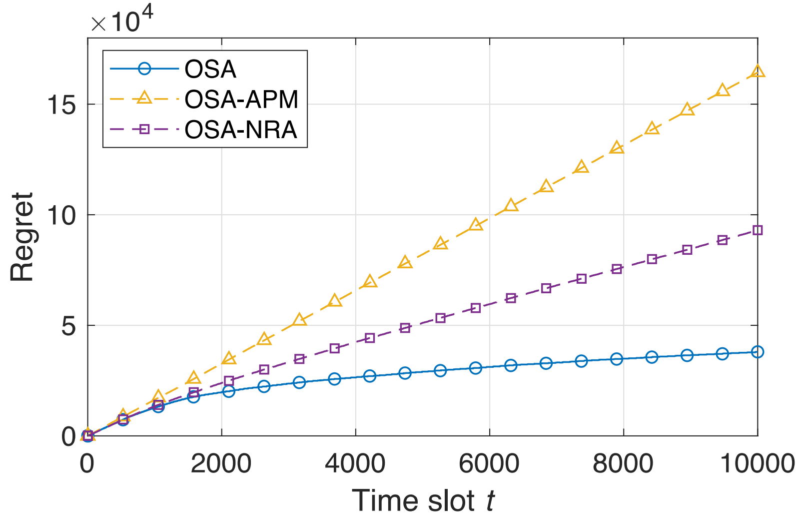

Fig. Comparison of regret

Thank You!

Questions?

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