Faculty of Engineering, Built Environment and Information Technology

Fakulteit Ingenieurswese, Bou-omgewing en Inligtingtegnologie / Lefapha la Boetšenere, Tikologo ya Kago le Theknolotši ya Tshedimošo

Machine Learning-based Base Station Association for Resource Allocation in 5G Heterogeneous Cognitive Networks

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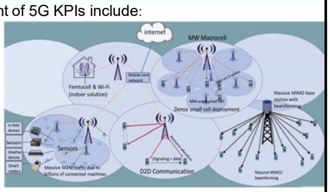
Presentation Outline

- Overview of 5G networks
- Modelling for devices in 5G networks
- Machine learning
- System model & problem formulation
- Q-learning-based BS association for CRN
- Simulation results

5G Networks Overview

- 5G aims to support connection of the internet of people and internet of things, while providing high data rates and reduced latency for communication
- Technologies that enable achievement of 5G KPIs include:
  - Cognitive radio (CR) terminals/networks
  - Massive MIMO & mmWave
  - Heterogeneous networks (HetNets)
  - Device-to-device (D2D) communication
  - Energy harvesting
  - Smart grids



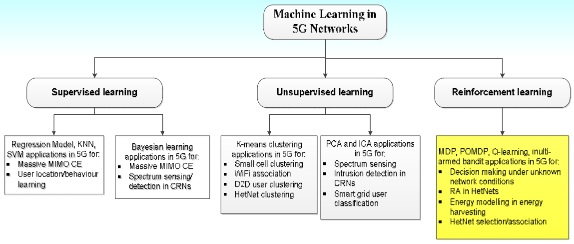
Modelling for Optimizing 5G Networks

- Smart devices for 5G networks are capable of jointly using many different frequency bands and communication technologies.
- Analysis of network characteristics such as user association, resource allocation and data routing using SINR as the base metric for resource allocation is indequate.
- There is need for integrating multiple parameters in the optimization of 5G networks.
- Consider context-aware models for cognitive user terminals, which enable interference management and avoidance in multi-tier 5G networks

Machine Learning (ML)

- A modelling technique that has found applications in
  - Gaming
  - Data mining
  - Telecommunications
  - Bio-sciences
  - Control automation
- An artificial intelligence tool that is being conceived to support smart CR terminals
- Basically explained, a machine learns the execution of a particular task with the goal of maintaining a specific performance metric, based on a particular experience.

Machine Learning in 5G



System Model

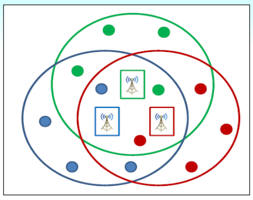


Fig. 1. System model showing an overlay deployment of three small cell clusters in a macrocell

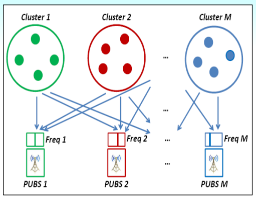


Fig. 2. Illustration of clustering in BS association

Problem Formulation

The optimization problem for resource allocation is formulated as

$$U = \max \sum_{i \in N} x_{i,m} \cdot f^{(m)}, \qquad (1)$$

subject to

$$\textstyle\sum_{i \in N} \lambda_s^i \leq C, \qquad (2)$$

$$\psi_{i,m} \geq \psi_{min}, \qquad \forall i \in N, \qquad (3)$$

where $x_{i,m} = \left(\frac{b_m}{\sum_{i \in N} \lambda_s^i}\right) \log(1 + \psi_{i,m})$ is the throughput for user i, provided by BS m,

C is the capacity of each PUBS (no. of SU transmissions that it can accommodate)

ψ_{min} is the minimum QoS requirement for all SUs

$f^{(m)}$ is a classification rule that maps previous BS load and cluster states to a future network state

Q-learning

- A reinforcement learning technique that does not require the exact transition formulation of the system
- Maintain a Q-table consisting of Q values that represent a reward resulting from taking an action a when in state s
- An agent is trained such that its actions should interact with the environment to maximize the cumulative reward resulting from the interactions

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Q-learning Based BS Association in CRN

- The objective in this scenario is to minimize the infinite horizon discounted power cost, subject to a constraint on the infinite horizon discounted delay
- The expected discounted power cost and expected discounted delay are then defined as

$$\bar{P}^{\pi}(s) = \mathbb{E}\left[\sum_{i=0}^{\infty} \gamma^i \rho\left(s^i, \pi(s^i)\right) | s^0 = s\right] \text{ and}$$

$$\bar{D}^{\pi}(s) = \mathbb{E}\left[\sum_{i=0}^{\infty} \gamma^i g\left(s^i, \pi(s^i)\right) | s^0 = s\right],$$

respectively. The formal objective is then stated as

$$\text{minimize } \bar{P}^{\pi}(s),$$

$$\text{subject to } \bar{D}^{\pi}(s) \le \delta,$$

where δ is the discounted buffer cost constraint.

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Q-learning Algorithm for a CRN Context

Algorithm 1: Proposed Approximate Q-Learning Algorithm for Base Station Association in a CRN

Input: x_0, θ, α
Output: Trained SUs
01: Initialize x_0 and θ
02: **For** each learning episode **do**
03: Arbitrarily initialize $Q(s, a)$
04: Initialize s_t
05: **For** each step t **do**
06: Choose a from $\mathcal{A}$ using derived ϵ-greedy
07: Take action a_t, observe r, s_{t+1}
08: $Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_{t+1} + \gamma \max_a Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)]$
09: Measure x_{t+1}, receive r_{t+1}
10: $\theta \leftarrow \theta + \alpha_t[r_{t+1} + \max_{\alpha_{t+1}} Q(x_a^{t+1}, a_{t+1}; \theta) - Q(x_t, a_t; \theta)] \frac{\partial \hat{Q}(x_t, a_t; \theta)}{\partial \theta}$
11: **End for**
12: $s_t \leftarrow s_{t+1}$
13: **End for**

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Simulation Results

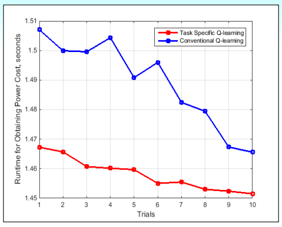

Fig. 3. Comparison of runtime for gathering power cost for the proposed task specific Q-learning and conventional Q-learning

Parameter	Value
Bandwidth	8 MHz
Downlink center frequency	2.1 GHz
Channel model type	Jakes
Scheduling algorithm	Proportional fair
Inter-site distance	20 m
Propagation environment	Urban
BS maximum transmit power	46 dBm
Shadow fading margin standard dev	8 dB
Noise power density	-174 dBm/Hz
Neural network hidden layer dimension	24, 24
One episode duration	50 TTIs
Discount factor, γ	0.950
Learning rate, α	0.001

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Conclusion

- A machine learning-based user association policy for SUs in a cluster-based CRN was presented.
- The proposed task specific Q-learning technique gave better runtime convergence compared to the conventional Q-learning technique in obtaining the cost of transmitting at a certain power.
- The proposed approach is more favorable for application in wireless networks where there are not enough computational resources to smartly learn more than one aspect at every time slot.

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