Foresighted Resource Scheduling in Software-Defined Radio Access Networks

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Outline

Global Mobile Data Traffic

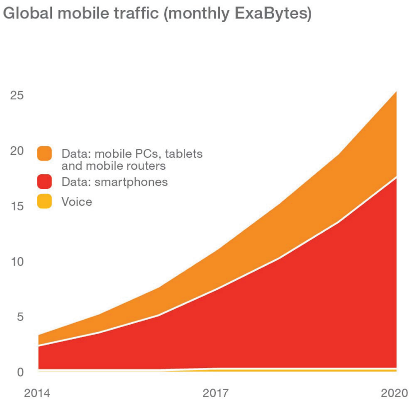

Figure 1: Global mobile data traffic (Source: Ericsson Mobility Report, Feb. 2015.).

- Compound annual growth rate: $\sim 40\%$.

Cellular Network Capacity

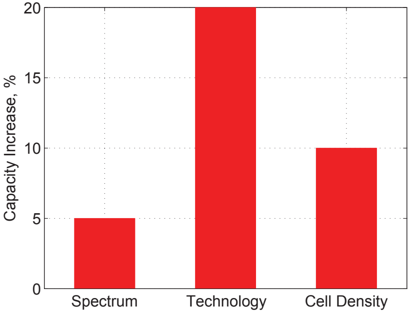

Figure 2: Expected capacity increase in cellular networks in the future based off Ericsson (Source: New network topologies.).

- Expected future capacity growth rate: $105\% \times 120\% \times 110\% - 100\% = 38.6\%$.

Approaches to Meet the Increasing Mobile Traffic

- Acquiring new spectrum bands;
- Developing novel spectrum sharing techniques;
- Implementing more cell sites;
- Scheduling delay-tolerant mobile data traffic;
- Performing traffic offloading;
- ...

Software-defined Radio Access Networks (SoftRANs)

- Basic idea:
  - abstracting all base stations as a logical centralized network controller (CNC);
  - simplifying network management by decoupling the control plane from the data plane.

Resource Scheduling in SoftRANs

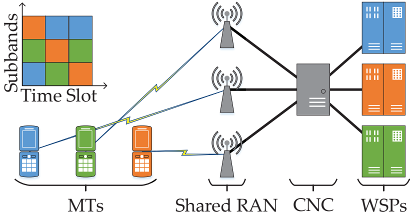

Figure 3: An illustration example of resource scheduling in an SoftRAN. The wireless service providers (WSPs) provide diverse wireless services to the mobile terminals (MTs) over a common physical infrastructure managed by an CNC.

Challenges

- In an SoftRAN, the dynamics originate from time-varying channel conditions experienced by MTs, WSPs' competing behaviors and bursty traffic.
- Resource scheduling schemes need to be designed scalable for large networks.

System Model (1/2)

- Each WSP $k \in \mathcal{K}$ serves a set $\mathcal{N}_k$ of N_k MTs.
- At the beginning of each time slot,
  - the WSPs bid for subband access by announcing value functions according to their bidding policies Ω_k, $\forall k \in \mathcal{K}$; and
  - the CNC allocates a set of $\mathcal{J}$ of subbands to MTs according to a Vickrey-Clarke-Groves (VCG) pricing mechanism.
- During time slot t, the subband allocation $\mathbf{y}_n^t = [\{y_{n,j}^t | j \in \mathcal{J}\}]^{\mathrm{T}}$ of MT $n \in \mathcal{N} \triangleq \cup_{k \in \mathcal{K}} \mathcal{N}_k$ satisfies $\sum_{n \in \mathcal{N}} y_{n,j}^t \leq 1, \forall j \in \mathcal{J}$ and $\sum_{j \in \mathcal{J}} y_{n,j}^t \leq 1$, where $y_{n,j}^t \in \{0, 1\}$ indicates the allocation of subband j to MT n.

System Model (2/2)

- Over time slots $t = 1, 2, \cdots$, the network dynamics $\mathbf{x}^t$ include
  - the queue dynamics for each MT $n \in \mathcal{N}$: $b_n^{t+1} = \min\{b_n^t - D_n^t + A_n^t, L_b\}$, where the packet departures D_n^t are determined by the achieved data rate; and
  - the channel state information (CSI) $h_{n,j}^t$ experienced by each MT n over each subband $j \in \mathcal{J}$, which is modelled by a discrete-time Markov chain.
- Given $\Omega = (\Omega_k, \Omega_{-k})$, the $\{\mathbf{x}^t | t = 1, 2, \cdots\}$ is Markovian.

Objective

- By designing an optimal bidding policy Ω_k, each WSP $k \in \mathcal{K}$ aims to maximize the long-term expected payoff.

Stochastic Game

- A stochastic game formulation,
  - Players: the set $\mathcal{K}$ of WSPs;
  - Action: the value functions $[\{\theta_n(\mathbf{x}^t, \mathbf{y}_n^t) | n \in \mathcal{N}_k\}]$ at each time slot t for each WSP $k \in \mathcal{K}$;
  - Payoff: the utility accumulated over all its MTs minus the payment to the CNC $\sum_{n \in \mathcal{N}_k} \beta_n f(b_n^t, \mathbf{y}_n^t) - \zeta_k^t$ at time t for each WSP k;
  - State Transition: after performing the actions, $\mathbf{x}^t \rightarrow \mathbf{x}^{t+1}$.
- Formally, for any WSP $k \in K$,

$$\max_{\Omega_k} G_k(\mathbf{x}, \Omega)$$
$$= \mathbb{E}^{\Omega} \left\{ (1-\gamma) \sum_{m=t}^{\infty} \gamma^{m-t} \left(\sum_{n \in \mathcal{N}_k} \beta_n f(b_n^m, \mathbf{y}_n^m) - \zeta_k^m \right) \middle| \mathbf{x} = \mathbf{x}^t \right\}.$$

Stochastic Learning Approach (1/2)

- Focusing on the bidding policy Ω_k that $G_k(\mathbf{x}, (\Omega_k, \Omega_{-k})) = G_k(\mathbf{b}_k, \Omega_k)$, $\forall k \in \mathcal{K}$.
- Approximating $G_k\left(\mathbf{b}_k, \Omega_k\right) \approx \sum_{n \in \mathcal{N}_k} V_n\left(b_n, \Omega_k\right)$, where

$$V_n\left(b_n, \Omega_k\right) = \max_{\mathbf{y}_n} \left\{ \begin{array}{c} (1-\gamma)\left(\beta_n f\left(b_n, \mathbf{y}_n\right) - \bar{\zeta}_n\left(b_n\right)\right) + \\ \gamma \sum_{b_n'} \Pr\left\{b_n' | b_n, \mathbf{y}_n\right\} V_n\left(b_n', \Omega_k\right) \end{array} \right\},$$

  and $\bar{\zeta}_n(b_n)$ is the shard payment of MT n.
- Defining the value function for MT n as

$$\theta_n\left(b_n, \mathbf{y}_n\right) = \beta_n f\left(b_n, \mathbf{y}_n\right) + \frac{\gamma}{1-\gamma} \sum_{b_n'} \Pr\left\{b_n' \middle| b_n, \mathbf{y}_n\right\} V_n\left(b_n', \Omega_k^*\right).$$

Stochastic Learning Approach (2/2)

- Defining an Q-factor as

$$Q_n^*(b_n, \mathbf{y}_n) = (1-\gamma)\left(\beta_n f\left(b_n, \mathbf{y}_n\right) - \bar{\zeta}_n\left(b_n\right)\right) \\ + \gamma \sum_{b_n'} \Pr\left\{b_n' | b_n, \mathbf{y}_n\right\} V_n\left(b_n', \Omega_k^*\right),$$

  which can be learned using traditional Q-learning rule.

- Finally, the value function of MT n at time t,

$$\theta_n\left(b_n^t, \mathbf{y}_n^t\right) = \frac{1}{1-\gamma}\left(\max_{\mathbf{y}_n} Q_n^t\left(b_n^t, \mathbf{y}_n\right) + \bar{\zeta}_n^t\left(b_n^t\right)\right).$$

Numerical Results (1/2)

There are 5 WSPs and 80 subbands with the same bandwidth 500KHz. Packets arrive into each MT n's buffer according to an independent Poisson arrival process with average arrival rate $\lambda_n$packets/second, and the packet sizes are exponentially distributed with average packet size 10^5bits/packet.

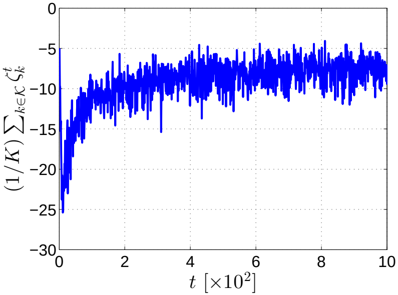

Figure 4: Trajectory of the average payment $(1/K)\sum_{k\in\mathcal{K}}\zeta_k^t$ paid by the WSPs to the CNC. The number of MTs subscribed to WSP k is $N_k = 20$, $\forall k \in \mathcal{K}$. The packet arrival rate of each MT n is $\lambda_n = 2$ packets/second, $\forall n \in \mathcal{N}$.

Numerical Results (2/2)

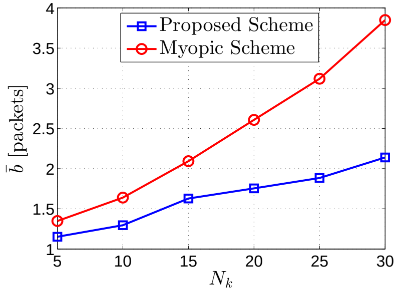

Figure 5: Average number of packets in MTs' queues $\bar{b}$ versus the number of MTs per WSP N_k. N_k is set to be the same for all WSPs $k \in \mathcal{K}$ in each simulation. The packet arrival rate of each MT n is $\lambda_n = 2$ packets/second, $\forall n \in \mathcal{N}$.

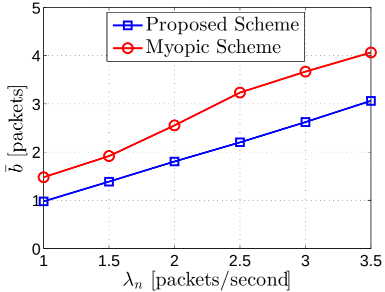

Figure 6: Average number of packets in MTs' queues $\bar{b}$ versus the packet arrival rate of each MT λ_n. The number of MTs subscribed to WSP k is $N_k = 20$, $\forall k \in \mathcal{K}$. The λ_n is same for all MTs $n \in \mathcal{N}$ in each simulation.

- The proposed algorithm converges fast and achieves significant performance gain.

Conclusions

(1) This work investigates the problem of resource scheduling in an SoftRAN, where multiple WSPs compete subbands for serving their MTs.

(2) A stochastic learning approach is proposed to approximate the optimal resource scheduling policy.

(3) Numerical results validate that the proposed algorithm outperforms the myopic scheme.

Thanks for your patience!

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