Carrier Aggregation as a Repeated Game: Learning Algorithms for Efficient Convergence to a Nash Equilibrium

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Motivation

• Extension of current static CA to dynamic CA has been explored recently
• Dynamic CA is possible in a distributed manner
• Few works allow each network to aggregate non-contiguous channels in multiple frequency bands
• Effect of out-of-channel (OOC) interference in adjacent frequency channels is not considered in existing works
What we do

• We model the preference for contiguous channels aggregation (relaxing channel orthogonality)
• We assign a higher cost to the inter-band CA on account of the corresponding physical layer requirements
• We model the problem of dynamic CA as a non-cooperative game
• We propose learning algorithms that converge to a pure NE within a reasonable number of iterations under the conditions of incomplete and imperfect information
Intra-band and inter-band CA

nbands(a) is the number of bands that a node accesses when selecting action a
System model

• $N$ wireless networks
• $B$ available frequency bands, each band has $K_b$ channels
• The cardinality of each network’s action space is:

$$|A_i| = \sum_{n=0}^{M_i} \binom{M}{n}$$

• The reward function of network $i$ is

$$r_i(a) = \begin{cases} 
\frac{1}{M_i} \sum_{c_i \in a_i} \left( 1 - \frac{\gamma_{c_i}}{\gamma_i} \right) \frac{(\text{nbands}(a_i) - 1)\delta}{N_{B_i}} & \text{if } a_i \neq \emptyset \\
0 & \text{if } a_i = \emptyset
\end{cases}$$

• Distributed CA problem as a game denoted by $G = (N, A, r)$
The game

• We prove that
  \[\text{At least one Nash equilibrium in pure strategies exists in CA game } G\]

• Players are not aware of each others actions
• At each stage, each player chooses an action according to the learning algorithm and observes a response from the environment.
• The feedback includes the estimated level of interference in all the available channels
ITEL-BA

\[ E[t_s] = (1 - \epsilon)n_{a_i}T_s + \epsilon MT_s \]

- **Hopeful**
  \[ r_l(\bar{a}_i, a_{-i}) \geq \bar{r}_l \]
  \[ r_l(\bar{a}_i, a_{-i}) > \bar{r}_l \]
  \[ r_l(\bar{a}_i, a_{-i}) > \bar{r}_l \]

- **Content**
  \[ E[t_s] = n_{a_i}T_s \]
  \[ r_l(\bar{a}_i, a_{-i}) = \bar{r}_l \]
  \[ r_l(\bar{a}_i, a_{-i}) = \bar{r}_l \]

- **Watchful**
  \[ E[t_s] = n_{a_i}T_s \]
  \[ r_l(\bar{a}_i, a_{-i}) < \bar{r}_l \]

- **Discontent**
  \[ E[t_s] = MT_s \]
  \[ r_l(\bar{a}_i, a_{-i}) < \bar{r}_l \]

With probability
\[ \phi(r_l(\bar{a}_i, a_{-i}), \bar{r}_l) \]

With probability
\[ 1 - \phi(r_l(\bar{a}_i, a_{-i}), \bar{r}_l) \]
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**ITEL-BA with imperfect information**

• To deal with noisy feedback/sensing, each player computes the received and hypothetical payoffs and then updates $r_{\downarrow i}(k)$ using an $n$-sample weighted moving average.

• In ITEL-BAWII, when a player experiments with new actions either in content or discontent mood, she will select the action that maximizes the average estimated payoff $r_{\downarrow i}(k)$.

• The expected sensing time is TsM for all the states.
Results

Convergence probability of ITEL-BA to an NE for different scenarios
Results

Convergence probability of ITEL-BA and ITEL-BAWII when the observations are not perfect
Conclusions

• We modelled CA problem of autonomous networks operating in shared spectrum as a repeated game
• We proposed learning algorithms that efficiently converge to an NE without the need for complete or even perfect information
• Our results show that the algorithm, which effectively converges to an NE with incomplete information (ITEL-BA), is not efficient in the case of imperfect information
• Our algorithm that effectively deals with imperfect and incomplete information (ITELBAWII) requires additional sensing and computational resources
Thank you
Questions?