PhD Final Oral Defense

Machine Learning Approaches for Wireless Spectrum and Energy Intelligence

Keyu Wu

Department of Electrical and Computer Engineering
University of Alberta, Edmonton, Alberta T6G 1H9, Canada

September, 2018

Outlines:

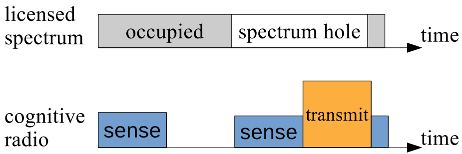
Outline

Spectrum and Energy Consideration of Wireless Communications

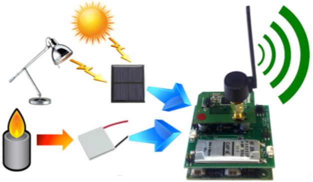
With the increase of data volume, service types and devices, wireless communication face

- Spectrum scarcity
  - Limited spectrum for wireless applications (33% for all commercial applications in 225 to 3700 MHz);
  - Spectrum reallocation is expensive and slow (70 MHz band costs 19.8 billion dollars).
- Energy issue
  - Huge energy consumption without careful design (communication industry may use 51% of global electricity in 2030);
  - Difficult for powering massive amount of IoT devices.

Cognitive Radio and Energy Harvesting



Cognitive radio



Energy harvesting

ML for wireless spectrum & energy intelligence

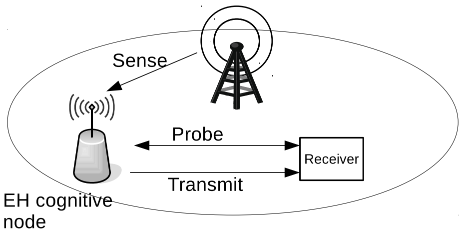
Machine learning, a data-driven methodology, is promising for handling relevant spectrum and energy management problems.

With ML as a primary tool, three research contributions are made

- Joint sensing-probing-transmitting control for EH CR
- Optimal transmission for an EH sensor with data priority consideration
- Cooperative spectrum sensing under spectrum heterogeneity

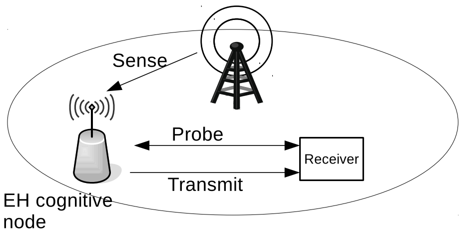
Outline

Sensing-probing-transmitting



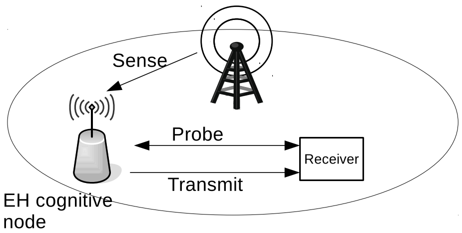
- Harvest: energy package arrives each time slot (uncontrollable)

Sensing-probing-transmitting



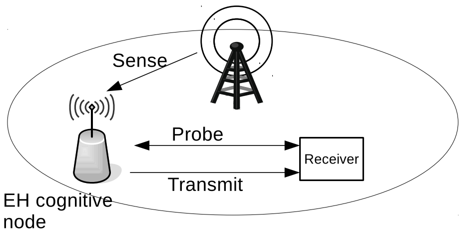
- Harvest: energy package arrives each time slot (uncontrollable)
- Sense: measure channel output to detect and track PU activity

Sensing-probing-transmitting



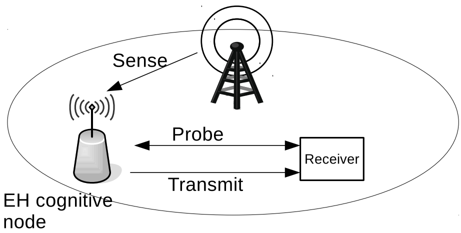
- Harvest: energy package arrives each time slot (uncontrollable)
- Sense: measure channel output to detect and track PU activity
- Probe: estimate CSI via pilot sequence

Sensing-probing-transmitting



- Harvest: energy package arrives each time slot (uncontrollable)
- Sense: measure channel output to detect and track PU activity
- Probe: estimate CSI via pilot sequence
- Transmit: based on CSI, adapt transmission power and send data

Sensing-probing-transmitting

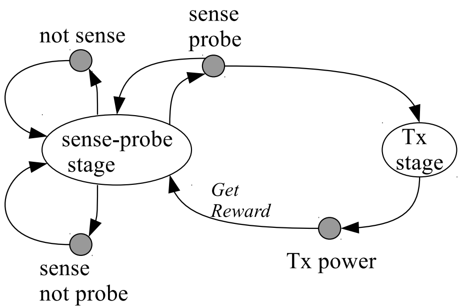


- Harvest: energy package arrives each time slot (uncontrollable)
- Sense: measure channel output to detect and track PU activity
- Probe: estimate CSI via pilot sequence
- Transmit: based on CSI, adapt transmission power and send data

Problem

Based on energy status, PU activity and CSI, the node needs to decide whether or not to sense and probe, and how much power for transmission, in order to maximize long-term throughput.

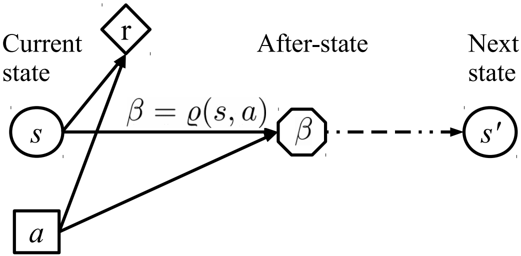
Two-stage MDP for long-term optimization



Goal: solving a policy π^* that maximizes expected throughput

$$\pi^* = \arg\max_{\pi} \left\{ \mathbb{E} \left[\sum_{t=0}^{\infty} \gamma^t r(s_t, \pi(s_t)) \right] \right\}$$

After-state simplification



$$\pi^*(s) = \underset{a \in \mathbb{A}(s)}{\arg\max} \left\{ r(s, a) + \gamma \mathbb{E}[V^*(s') | s, a] \right\}$$

$$= \arg\max \left\{ \text{immed. reward} + \text{expected furture value} \right\}$$

$$= \underset{a \in \mathbb{A}(s)}{\arg\max} \{ r(s, a) + J^*(\underbrace{\varrho(s, a)}_{\text{after-state } \beta}) \}$$

Solve J^* with RL

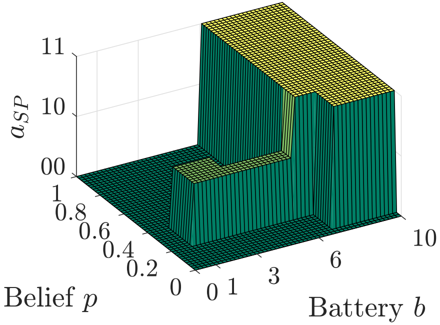
Exactly solving J^* requires the pdfs of EH and fading processes, which can be hard to obtain.

Solve J^* with RL

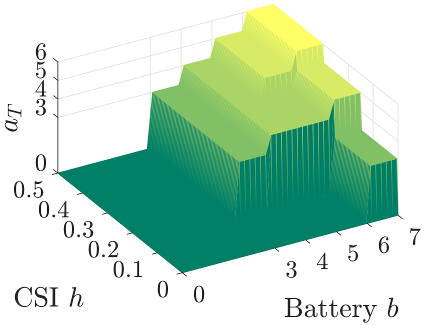
Exactly solving J^* requires the pdfs of EH and fading processes, which can be hard to obtain.

We consider to (approximately) learn J^* with RL algorithm without distribution information.

Learned policies



(a) Sensing-probing sub-policy

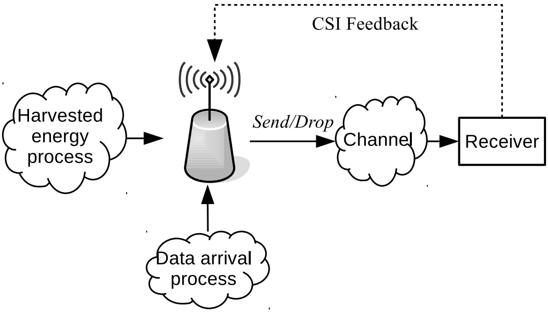


(b) Transmitting sub-policy

a_{SP}: '00', no sense; '10', sense but no probe; '11', sense and probe
Energy for: sense, 1; probe, 2; transmit, $\{\text{no tx}, 3, 4, 5, 6\}$.

Outline

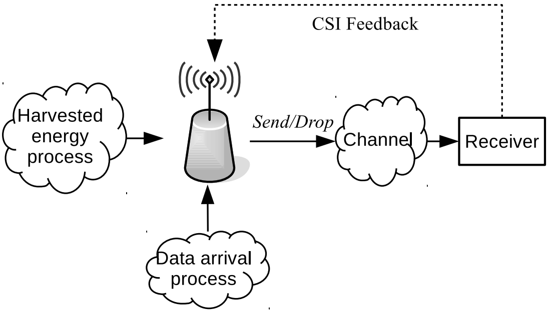
Selective transmission for EH sensor



Incorporating data-centric consideration

- packets associated different priorities
- drop low priority packet to save energy

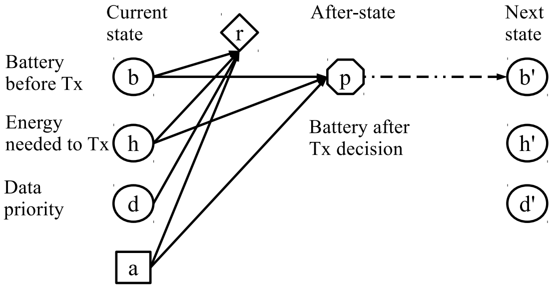
Selective transmission for EH sensor



Problem

Based on EH, energy status, CSI and packet priority, the node needs to decide whether or not to send each packet, in order to maximize the total priority values of sent packets.

MDP formulation with after-state



Structural results of J^* and π^*

Theorem

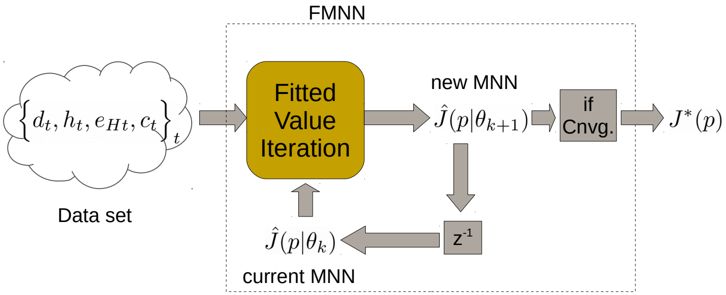
After-state value function $J^*(p)$ is differentiable and non-decreasing.

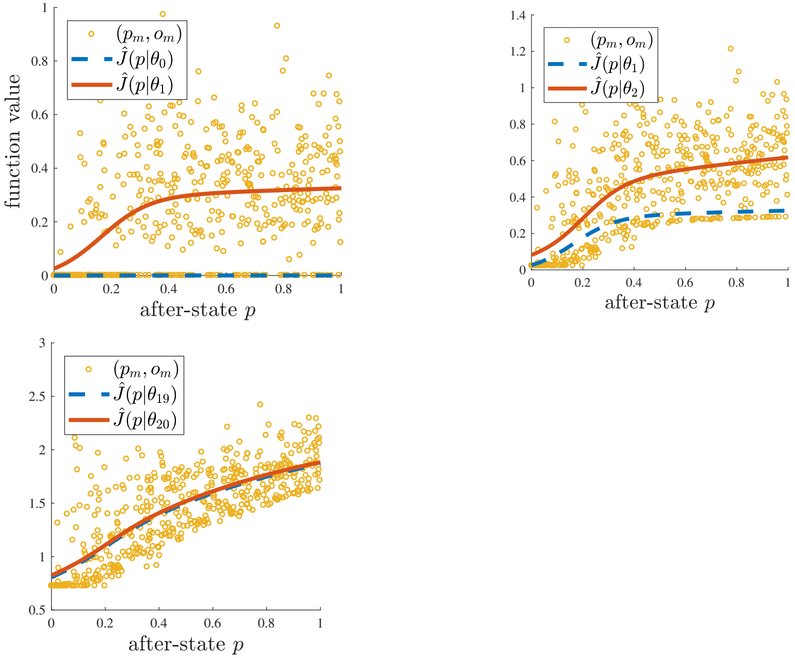
Theorem

The optimal policy π^* has the following structure

$$\pi^*([b,h,d]) = \begin{cases} 1 & \text{if } b \geq h \text{ and } d \geq J^*(b) - J^*(b-h), \\ 0 & \text{otherwise.} \end{cases}$$

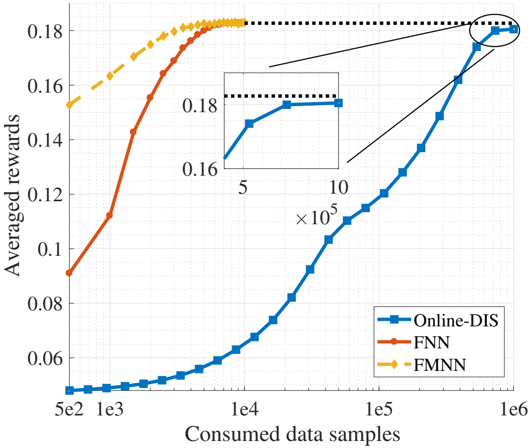
Learn J^* with monotone neural network





(p_m, o_m)
$\hat{J}(p|\theta_0)$
$\hat{J}(p|\theta_1)$
function value
after-state p
(p_m, o_m)
$\hat{J}(p|\theta_1)$
$\hat{J}(p|\theta_2)$
after-state p
(p_m, o_m)
$\hat{J}(p|\theta_{19})$
$\hat{J}(p|\theta_{20})$
after-state p

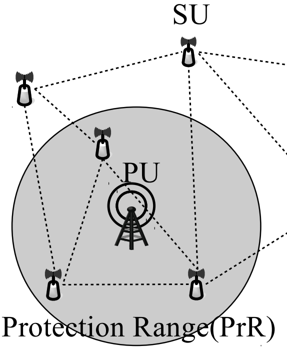
Learning efficiency



Learning curve

Outline

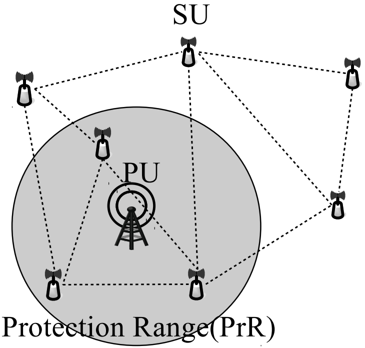
CSS under spectrum heterogeneity



Spectrum heterogeneity

SUs at different spatial locations may experience different spectrum statuses.

CSS under spectrum heterogeneity



Spectrum heterogeneity

SUs at different spatial locations may experience different spectrum statuses.

Problem

Under spectrum heterogeneity, how to exploit neighbor information to fuse SU observations for improving sensing performance.

Fuse data via MAP-MRF

MAP-MRF CSS framework

Compute maximum a posterior estimation

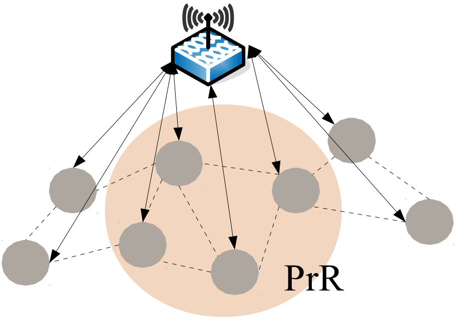
$$\boldsymbol{x}^{\mathrm{MAP}} = \arg\max_{\boldsymbol{x}} \left\{ \Phi_{\boldsymbol{X}}(\boldsymbol{x}) \prod_{i=1}^{N} \gamma^{x_i} f_{Y|X}(y_i \mid x_i) \right\},$$

weight $\gamma > 0$ introduces tradeoff

Existing works in references [99–102] fuse data via solving marginal distributions.

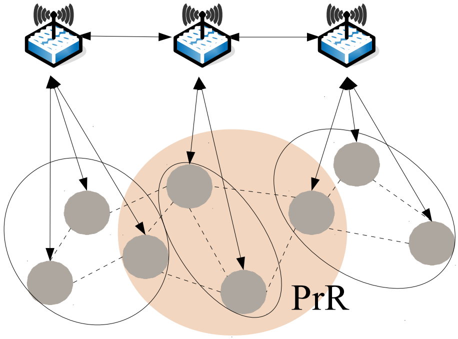
Compared with [99–102], the proposed MAP-MRF can be solved more flexibly and efficiently.

Three CSS algorithms based on MAP-MRF



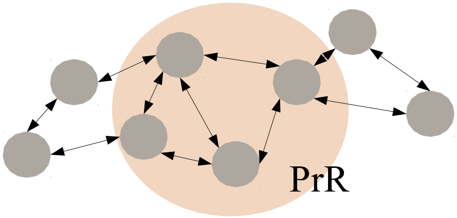
Via graph cut theory, GC-CSS algorithm solves $\boldsymbol{x}^{\mathrm{MAP}}$ exactly; complexity order: $\mathcal{O}(N \cdot |\mathcal{E}|^2)$.

Three CSS algorithms based on MAP-MRF



Via dual decomposition theory, DD-CSS estimates $\boldsymbol{x}^{MAP}$ distributedly (at cluster-level); complexity: $\mathcal{O}(T \cdot N_l \cdot |\mathcal{E}_l|^2)$.

Three CSS algorithms based on MAP-MRF

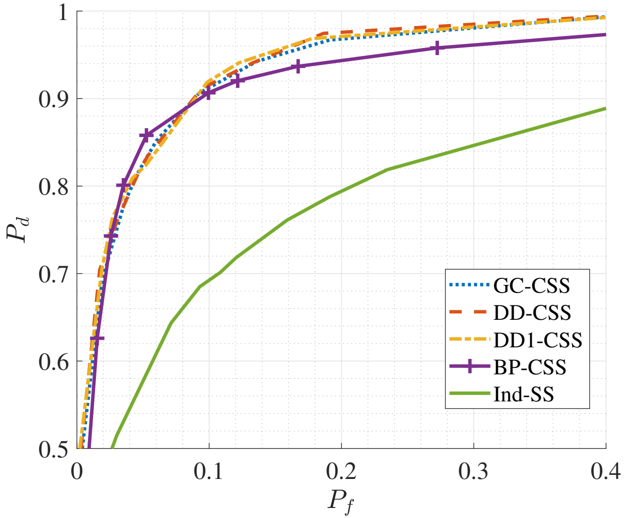


Distributed network: clusters with size 1, DD1-CSS becomes fully distributedly message passing algorithm; guaranteed for solving $\boldsymbol{x}^{MAP}$; complexity order $\mathcal{O}(T \cdot |\mathcal{N}(i)|^3)$.

Three CSS algorithms based on MAP-MRF

Existing algorithms (based on belief propagation) only work in distributed setting; complexity: $\mathcal{O}(T \cdot |\mathcal{N}(i)| \cdot 2^{|\mathcal{N}(i)|})$.

Performance comparison



ROC for various algorithms.

Outline

Conclusion

- In EH CR, the joint optimization of sensing, probing and transmitting is modeled as a two-stage MDP, whose structure is exploited for after-state simplification.
- In EH WSNs, the optimal selective transmission policy is investigated, which is proved to be threshold-based and derived by training a monotone neural network.
- CSS under spectrum heterogeneity is formulated via MAP-MRF, which can be effectively solved by graph cut theory and dual decomposition theory with polynomial complexity.

Future research

- Optimal sensing-probing policy without primary user model
- Multi-link selective transmission for energy-harvesting sensors
- Learn MRF model from data

Thank you!