A Novel Cognitive Anti-jamming Stochastic Game

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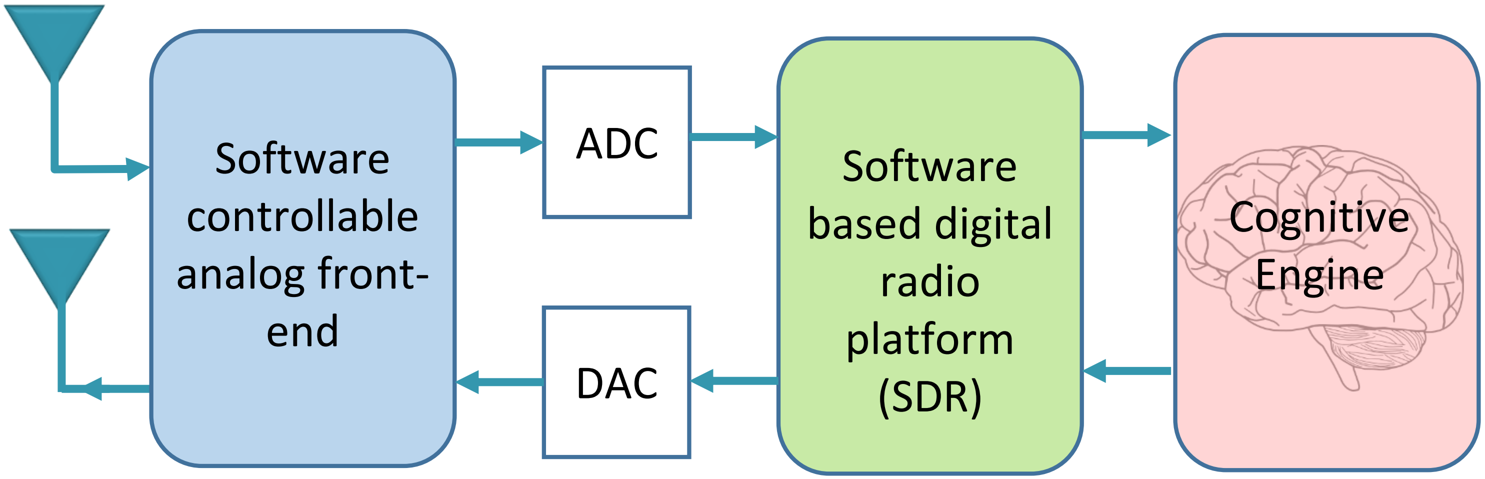
Outline

Introduction

Cognitive radio as an evolution of software-defined radio (SDR)

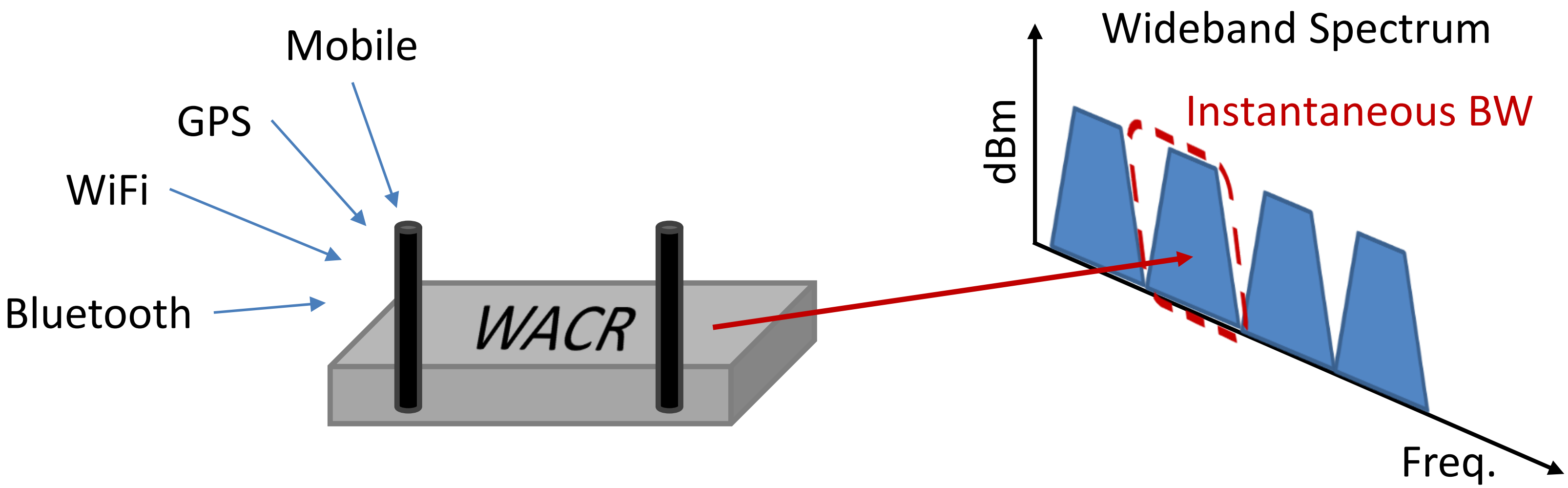


- A cognitive radio is a multiband, multimode, wideband software-defined radio (SDR) with autonomous decision-making and learning abilities that can optimally reconfigure its operation mode in response to its surrounding RF environment and user needs.

Introduction

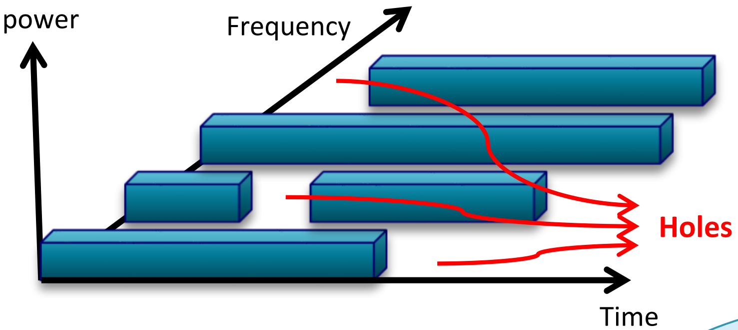
Wideband Autonomous Cognitive Radios (WACR)

- Senses a wide frequency range.
- Comprehend its operating RF environment.
- Autonomous operation.
- Learn communication protocols and policies.

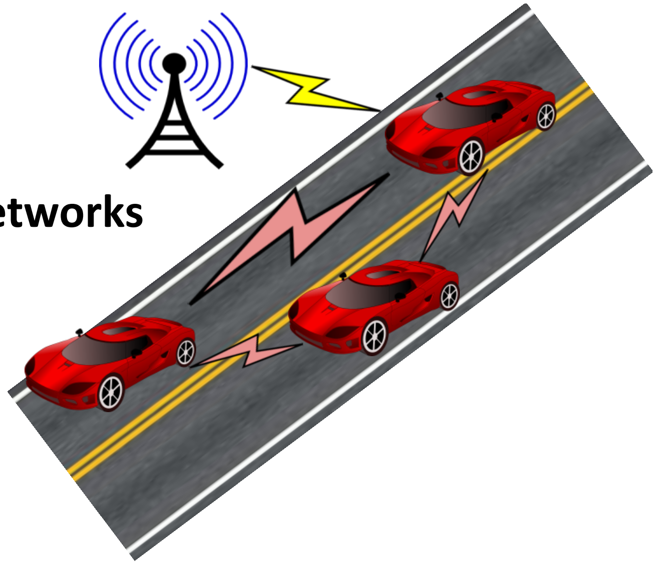


Introduction

Dynamic spectrum sharing (DSS)

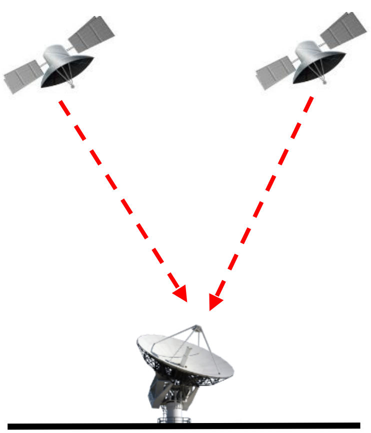


Vehicular networks



Cognitive Radio Applications

Space



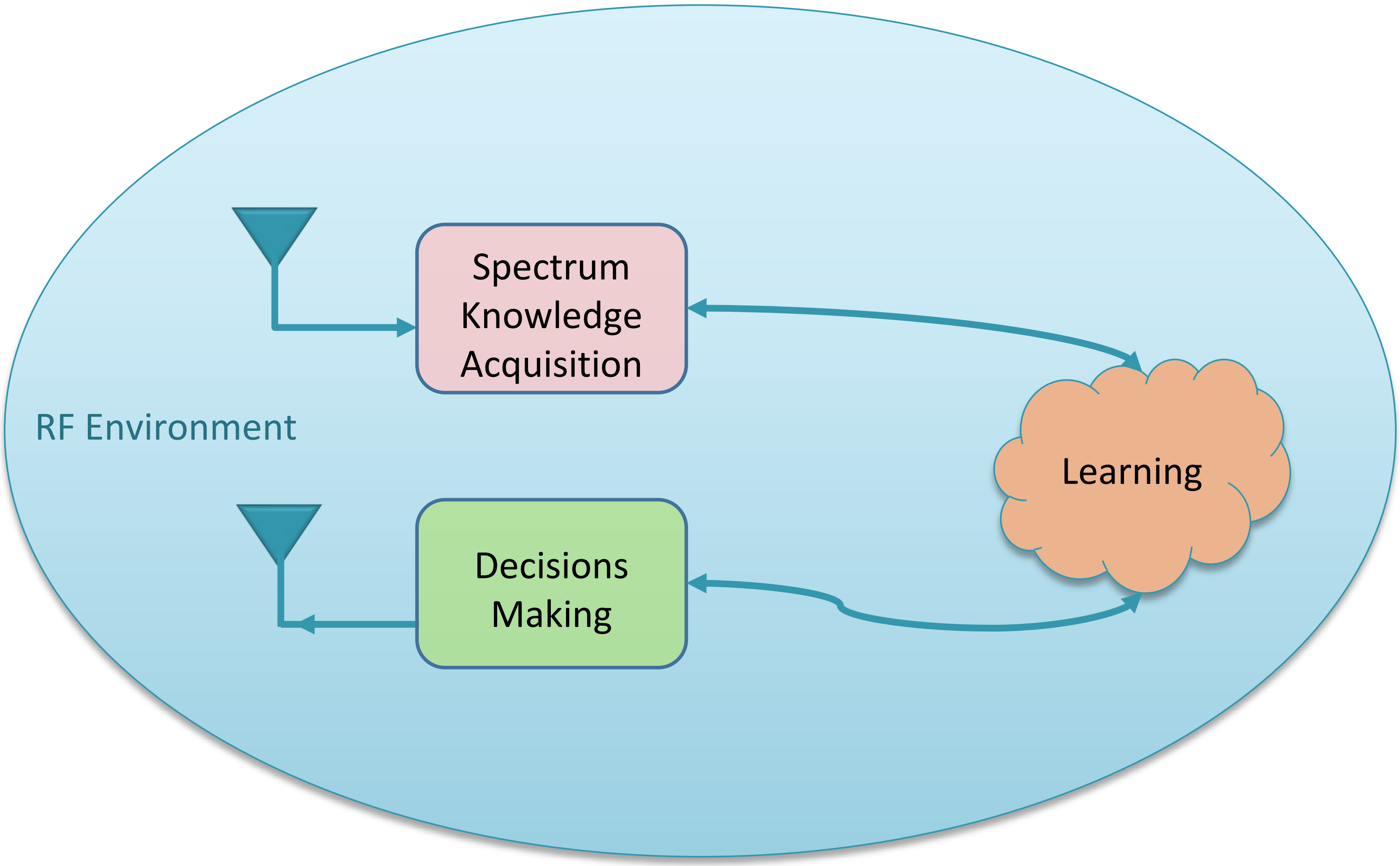
Health care

Smart grid

Military

Source: http://mil-embedded.com/articles/evolving-technology-sdr-cognitive-radio/

Basic Cognitive Radio Functions



Source: S. K. Jayaweera,"Signal Processing for Cognitive Radio," John Wiley & Sons, Hoboken, NJ, USA.

Wideband Spectrum Knowledge Acquisition

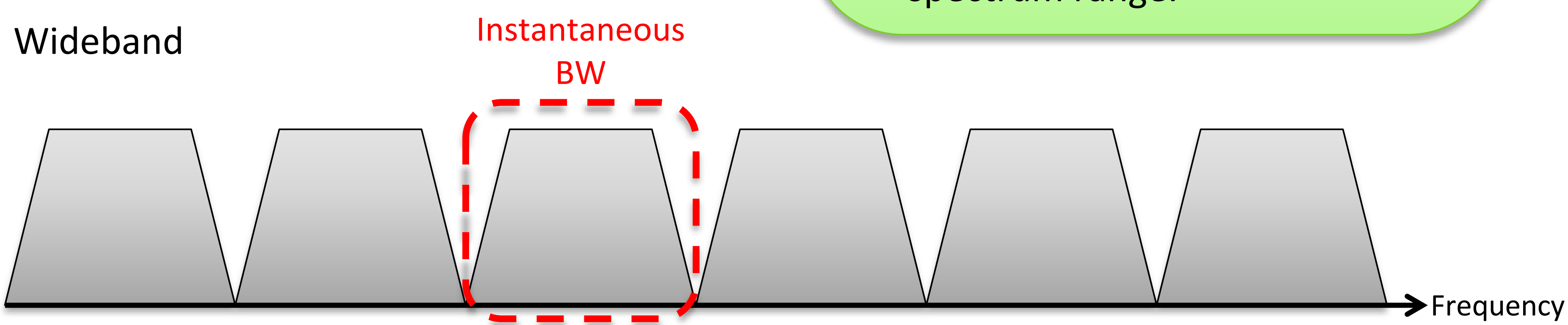
Spectrum Knowledge Acquisition

Wideband spectrum scanning

Spectral activity detection

Signal classification

- Hardware constraints limit the instantaneous sensing bandwidth of most state-of-the-art software-defined radio (SDR) platforms to about 100MHz.
- There is a need to design an efficient scheme to achieve real-time sensing over a wide spectrum range.



Wideband Spectrum Knowledge Acquisition

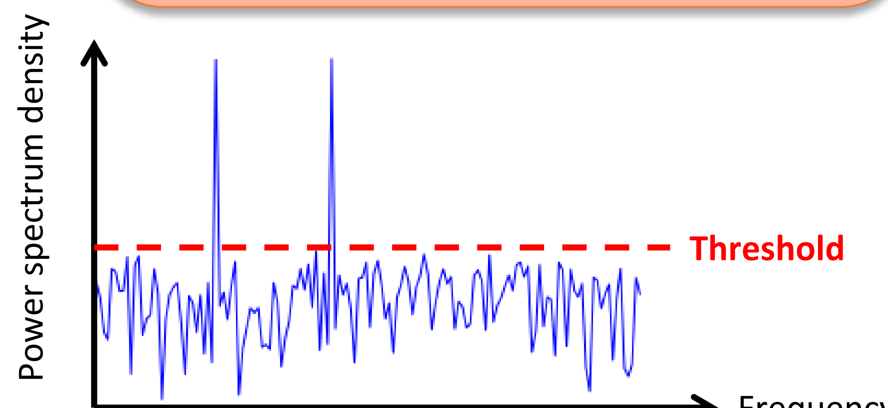
Spectrum Knowledge Acquisition

Wideband spectrum scanning

Spectral activity detection

Signal classification

- Detection can be done by defining a threshold (simple).
- Any power spectral activity above this threshold is considered as an active signal.



Wideband Spectrum Knowledge Acquisition

Spectrum Knowledge Acquisition

Wideband spectrum scanning

↓

Spectral activity detection

↓

Signal classification →

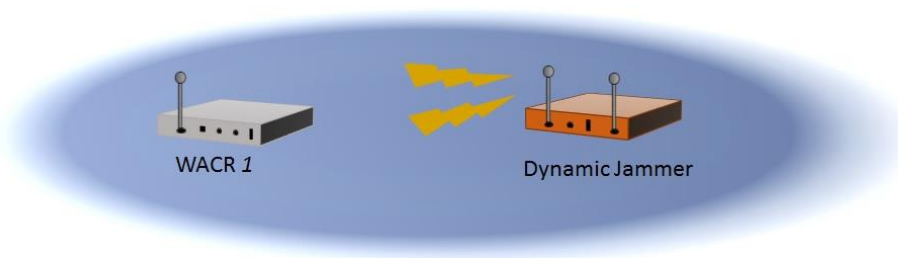
- Detected signals may belong to different radio systems.

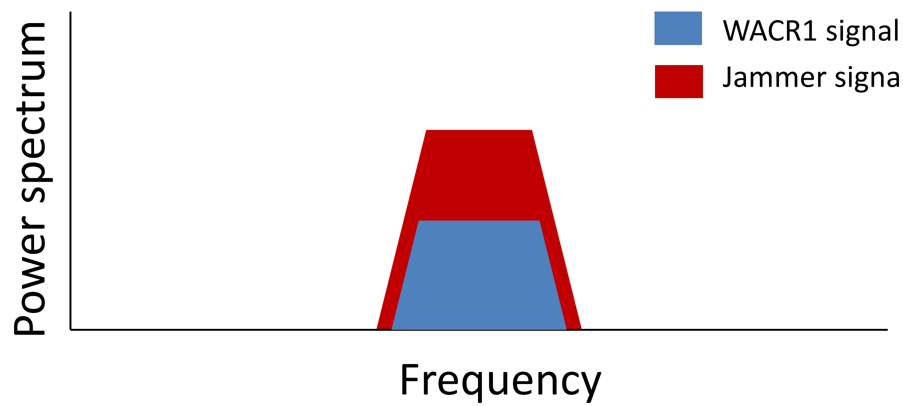
Classification

Wi-Fi | Bluetooth | Mobile | … | Others

Problem formulation

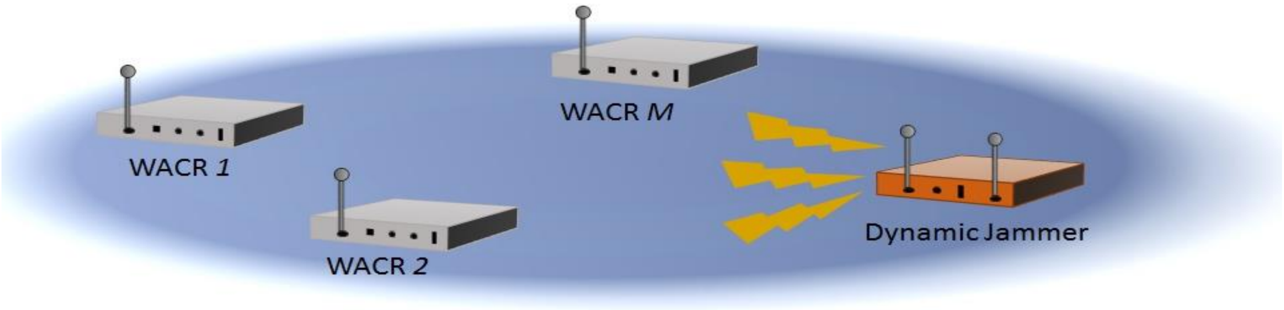
- Deliberate radio jammers and unintentional interference can disrupt communication systems.
  - In both commercial and military systems

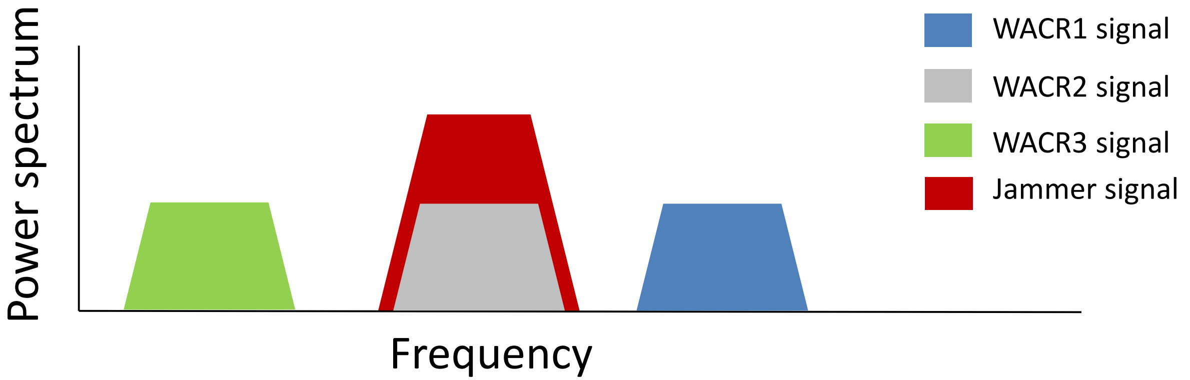




Problem formulation

- In practice, this will result in a complicated multi-agent environment.

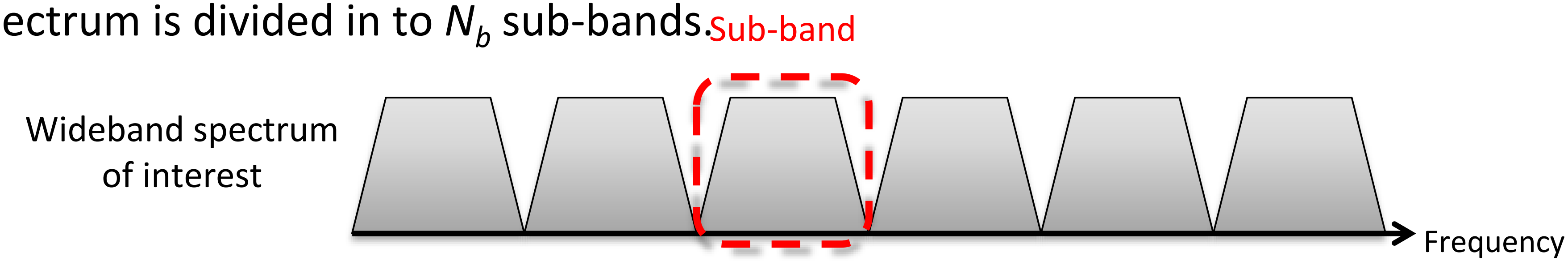




- Goal: find optimal anti-jamming and interference avoidance policies for the WACRs that switches transmission before getting jammed.

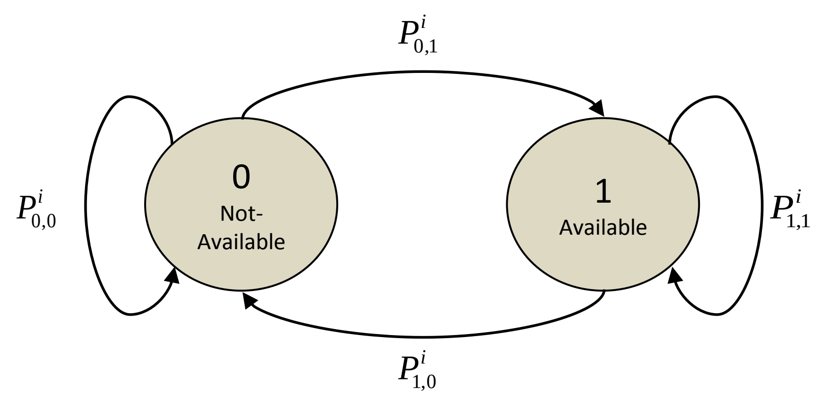
System model

- Spectrum is divided in to N_b sub-bands.

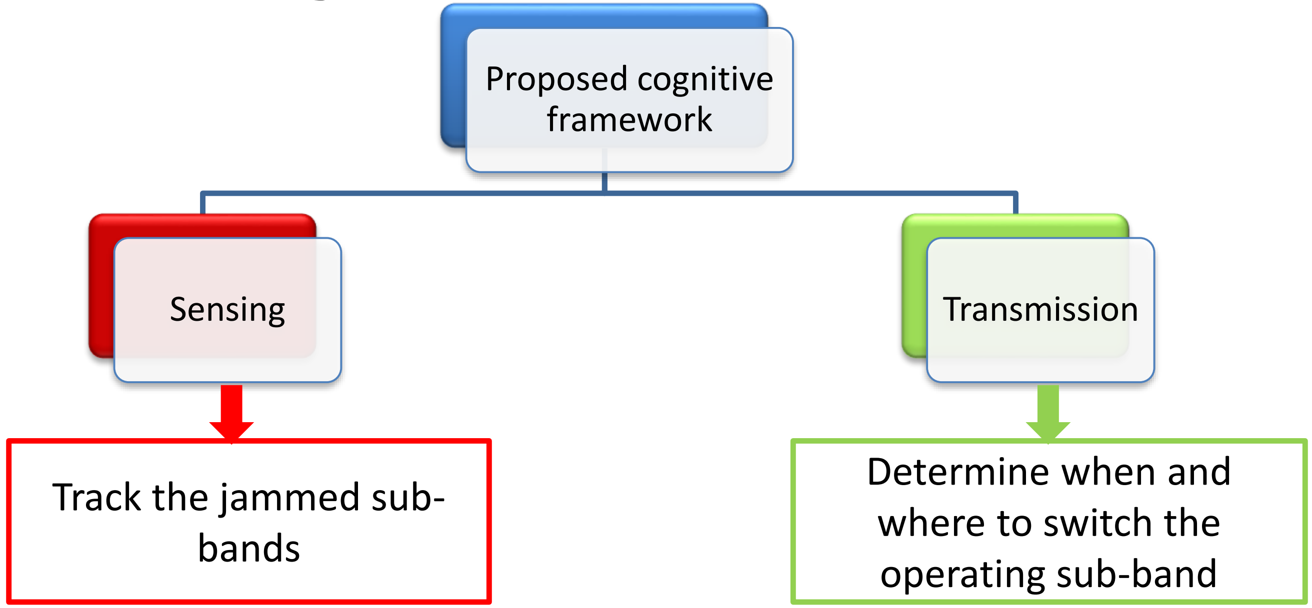


Sub-band dynamics:

- Single sub-band has 2 Markov states: available/not-available.
  - If the sub-band is jammed or faces interference, it is considered to be in state “0” (not-available).
  - Otherwise, it is considered to be in state “1” (available).
- The set of sub-band states can be denoted by $\mathcal{V} = \{0, 1\}$.



System model



- Each operation will have its own learning algorithm with different targets, but they both will experience the same RF environment.

- Essentially, if the sensing operation were to learn an optimal policy, the WACR would be able to accurately predict the jammed/interfered sub-bands.

- This will help the transmission operation as follows:
  - if the current operating sub-band is predicted to be jammed during the next time instant by the sensing policy, the WACR will switch to another sub-band thereby avoiding the possibility of getting jammed.

System model

- For the game state, we choose a simple definition for both sensing and transmission operations, where $s_s[n] \in \mathcal{S}$ and $s_t[n] \in \mathcal{S}$ represent the index of selected sub-bands for sensing and transmission, respectively, at time *n*. Thus, the state space is given by $\mathcal{S} = \{1, \cdots, N_b\}$.

- At any time instant, the state of operating sub-bands for both sensing and transmission (the value of $v \in \mathcal{V}$ for sub-band index $s \in \mathcal{S}$) has to be identified.
  - During sensing operation: the WARC will perform *spectral activity detection* (spectrum sensing) to detect any active signals in the sensed sub-band and hence identify whether the sub-band is available or not.
  - During transmission operation: the communications link quality will determine if transmission over the current operating sub-band is acceptable.

- After determining the states of both operating sub-bands, the WACR will select and execute actions for both operations.
  - We define actions $a_s[n]$ and $a_t[n]$ as the indices of the selected new operating sub-bands for sensing and transmission, respectively, at time *n*.

- The action space can thus be defined as $\mathcal{A} = \{1, \cdots, N_b\}$.

Q-learning-aided Cognitive Anti-jamming

Algorithm 1 Q-learning-aided cognitive anti-jamming communications algorithm

1: **Initialize:**
$\alpha, \gamma, \epsilon \in [0,1]$
$Q(s,a) \leftarrow 0 \; \forall s \in \mathcal{S}, \forall a \in \mathcal{A}$
2: **for** each stage n **do**
3: Identify the state $(v \in \mathcal{V})$ of operating sub-band s
4: **if** sub-band state $v = 0$ **then**
5: Compute reward r for current state s and action a
6: Update Q-value $Q(s,a)$ as follow:
7: $Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha[r + \gamma \max_{a} Q(s',a)]$
8: Select new action $a' \in \mathcal{A}$ for the new state s' according to the following:
9: $$a' = \begin{cases} \arg\max_{a \in \mathcal{A}} Q(s',a) & \text{with probability } 1-\epsilon, \\ \sim U(\mathcal{A}) & \text{with probability } \epsilon, \end{cases}$$

- Learning parameters and Q-table initialization.

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- Identify the state of the current operating sub-band.
- If the sub-band state is “1” (available), no further action is required.

Q-learning-aided Cognitive Anti-jamming Algorithm

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- If the sub-band state is “0” (not-available), the WACR updates the Q-table based on a certain observed reward (r).

Q-learning-aided Cognitive Anti-jamming Algorithm

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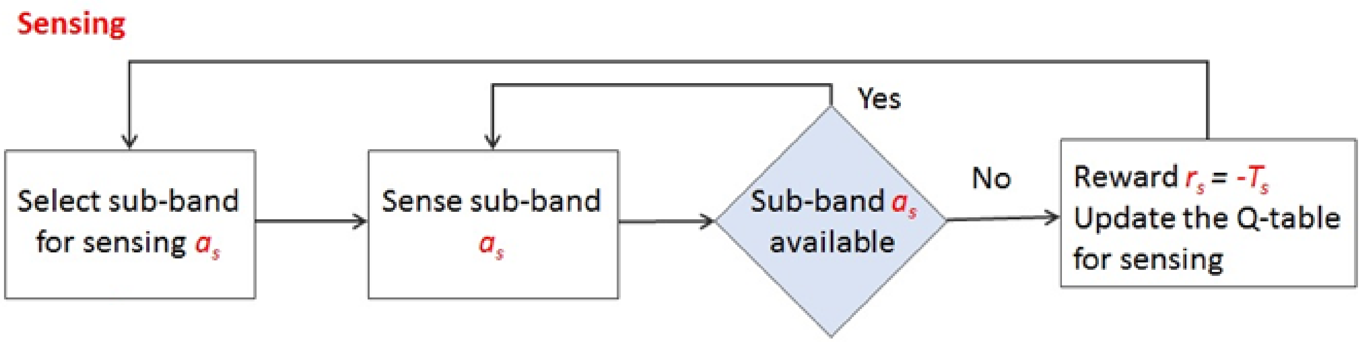
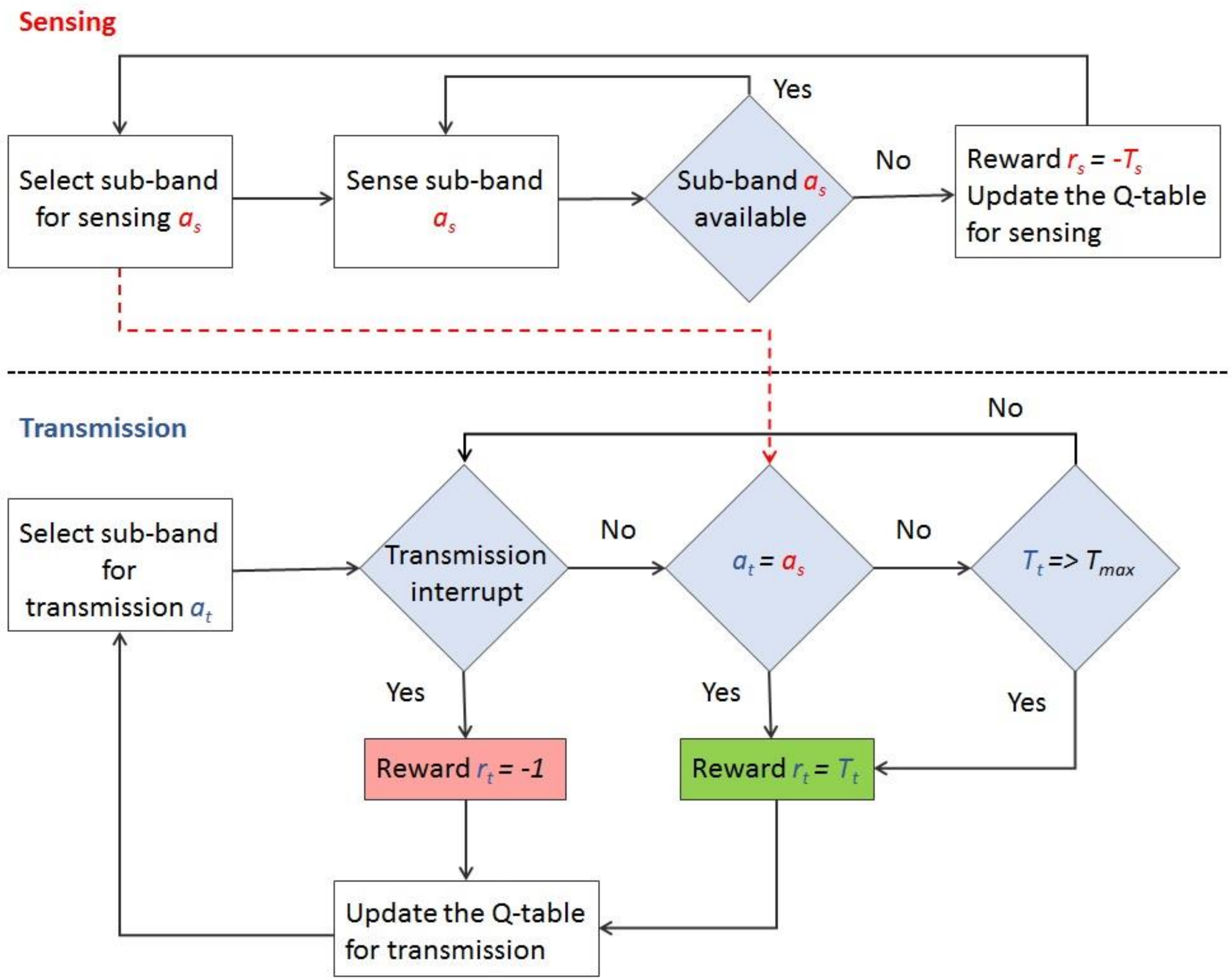
- Once the Q-table is updated, the WACR selects a new action a' representing the new operating sub-band.

Proposed Anti-jamming Stochastic Game



Proposed Anti-jamming Stochastic Game



Simulation results

Performance metric:

Normalized accumulated reward $$R_N = \frac{1}{N} \sum_{n=1}^{N} r_t(s_t[n], a_t[n])$$

$r_t(s_t[n], a_t[n])$:immediate non-negative reward for transmission operation at time *n*

N: number of iterations

Jammer model:

Sweeps the spectrum of interest from the lower to the higher frequency.

Learning parameters:

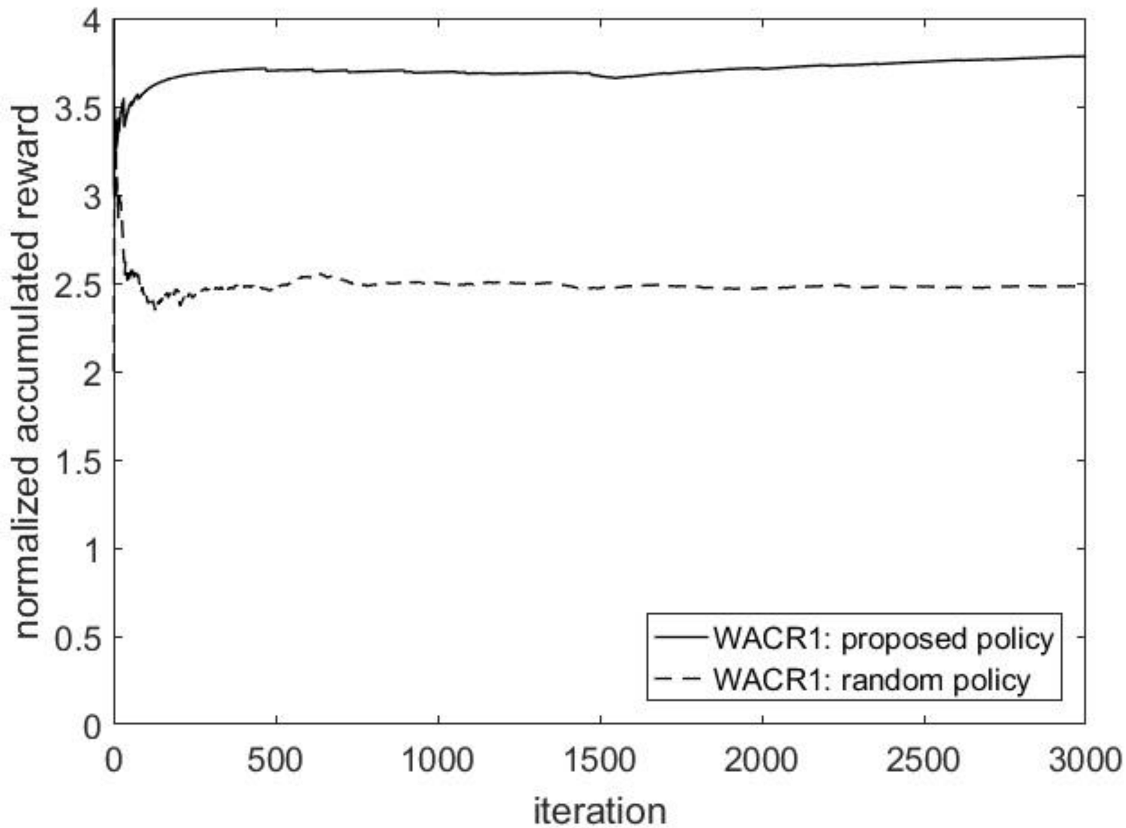
ϒ=0.8

ϵ=0.9, α =0.4 → Before Q-table convergence

ϵ=0.01, α =0.1 → After Q-table convergence

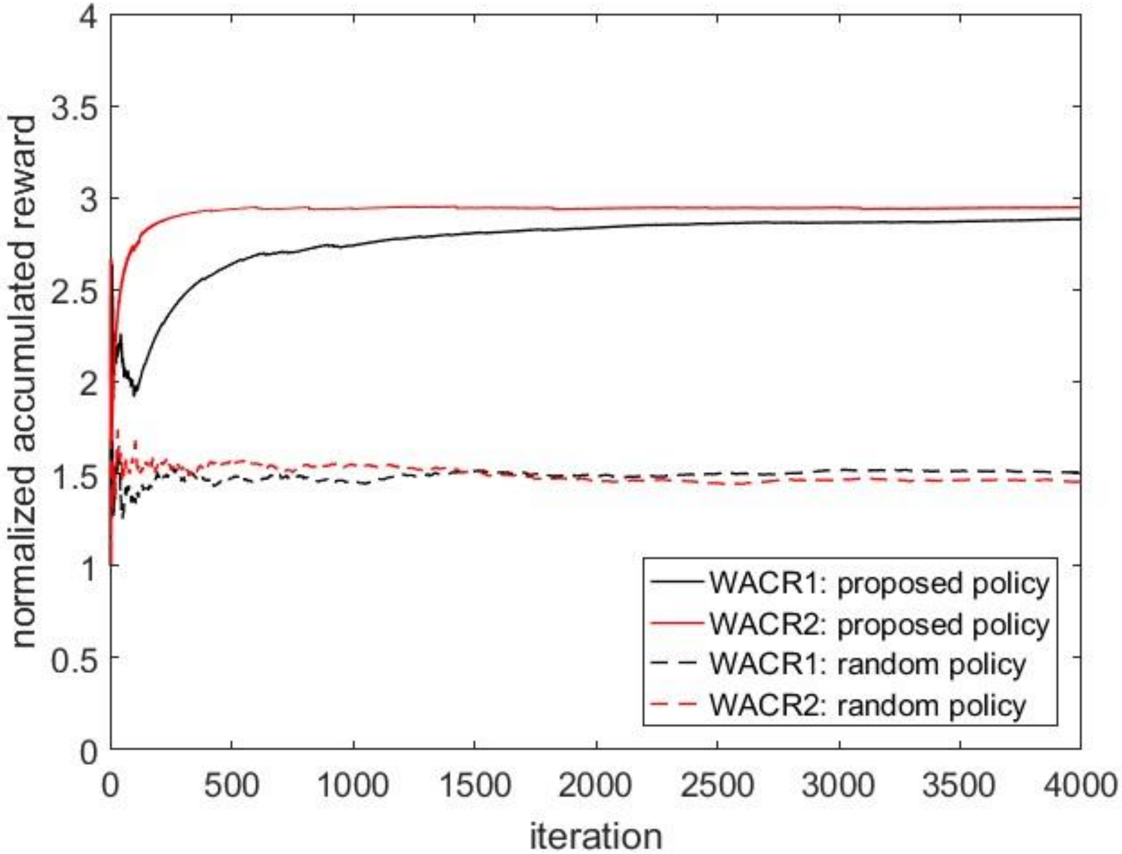
Simulation results

Experiment 1: 1 WACR and 5 Sub-bands



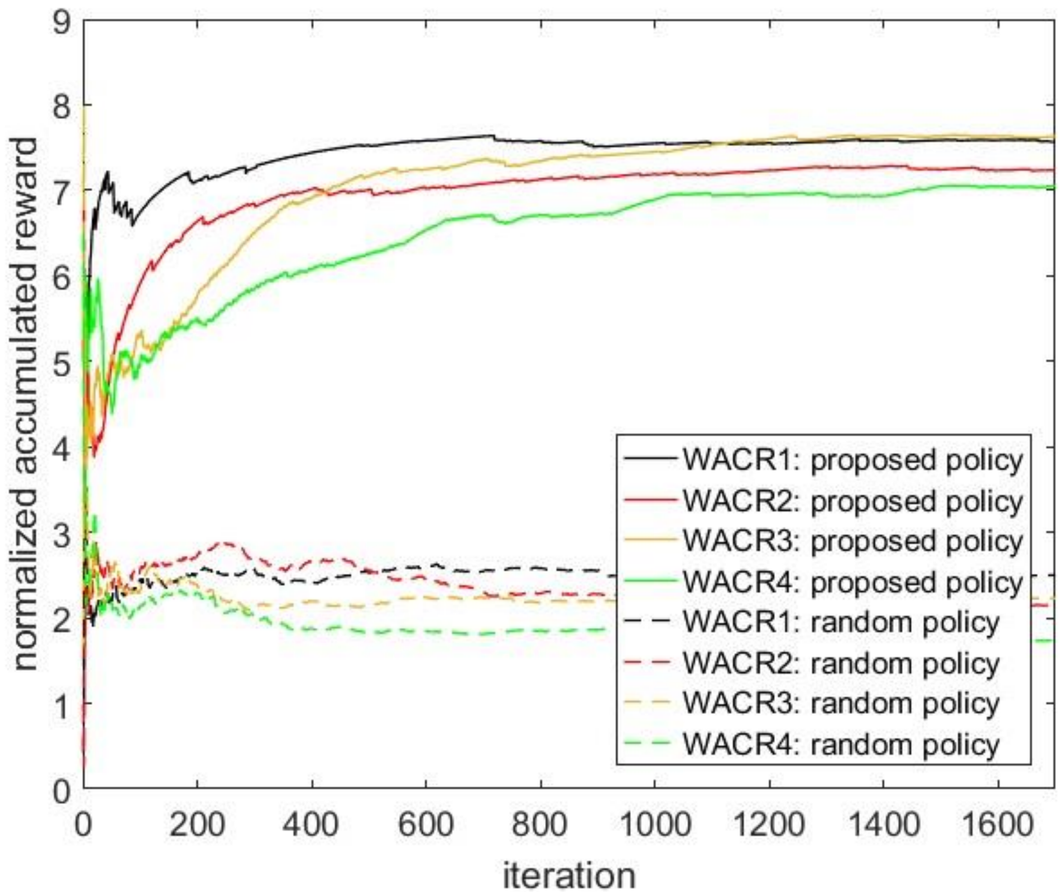
Simulation results

Experiment 2: **2 WACRs and 6 Sub-bands**



Simulation results

Experiment 3: **4 WACRs and 16 Sub-bands**



Simulation results

Table I
NORMALIZED ACCUMULATED REWARD VALUES FOR DIFFERENT SIMULATION SCENARIOS

Test case	**Scenario**	**Reward upper bound**	**WACR 1**	**WACR 2**	**WACR 3**	**WACR 4**	**Average**
1	1 WACR and 5 sub-bands	4	Proposed:3.8 Random: 2.5				Proposed:3.8 Random: 2.5
2	2 WACRs and 6 sub-bands	4	Proposed:2.8 Random: 1.5	Proposed:3 Random: 1.4			Proposed:2.9 Random: 1.45
3	4 WACR and 16 sub-bands	12	Proposed:7.5 Random: 2.5	Proposed:7.2 Random: 2.2	Proposed:7.5 Random: 2.2	Proposed:7 Random: 1.8	Proposed:7.3 Random: 2.17

Simulation results

Table II
PROBABILITIES OF GETTING JAMMED FOR DIFFERENT SIMULATION SCENARIOS

Test case	Scenario	WACR 1	WACR 2	WACR 3	WACR 4	Average
1	1 WACR and 5 sub-bands	Proposed: 0.86% Random: 1.8%				Proposed: 0.86% Random: 1.8%
2	2 WACRs and 6 sub-bands	Proposed: 2.6% Random: 47.2%	Proposed: 2.1% Random: 48%			Proposed: 2.35% Random: 47.6%
3	4 WACR and 16 sub-bands	Proposed: 6.4% Random: 64.8%	Proposed: 7.6% Random: 66.3%	Proposed: 12.4% Random: 66.3%	Proposed: 12.3% Random: 72.6%	Proposed: 9.6% Random: 67.5%

Conclusions

- Proposed a novel cognitive anti-jamming stochastic game based on *Q*-learning for WACRs to avoid a dynamic jammer signal as well as unintentional interference from other WACRs .

- Developed new definitions for state, actions and rewards that enable the WACR to switch its operating sub-band before getting jammed, compared to previously proposed anti-jamming techniques in literature that switch the operating sub-band only after getting jammed.

- The cognitive framework is divided into two operations:
  - sensing and transmission.
  - Each is helped by its own learning algorithm based on *Q*-learning.

- The objective of the sensing operation is to track the jammed sub-bands. On the other hand, the transmission operation determines when and where to switch the operating sub-band.
  - The key difference from the previous work is that the radio will switch the sub-band before getting jammed.
  - This can be especially useful against a smart jammer since it will prevent the jammer from learning the radio's behavior.

- Simulation results showed that the proposed cognitive protocol has a very low probability of getting jammed and acceptable value for accumulated reward.

Questions

References

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