

# Cognitive Anti-jamming Satellite-to-Ground Communications on NASA's ScaN Testbed



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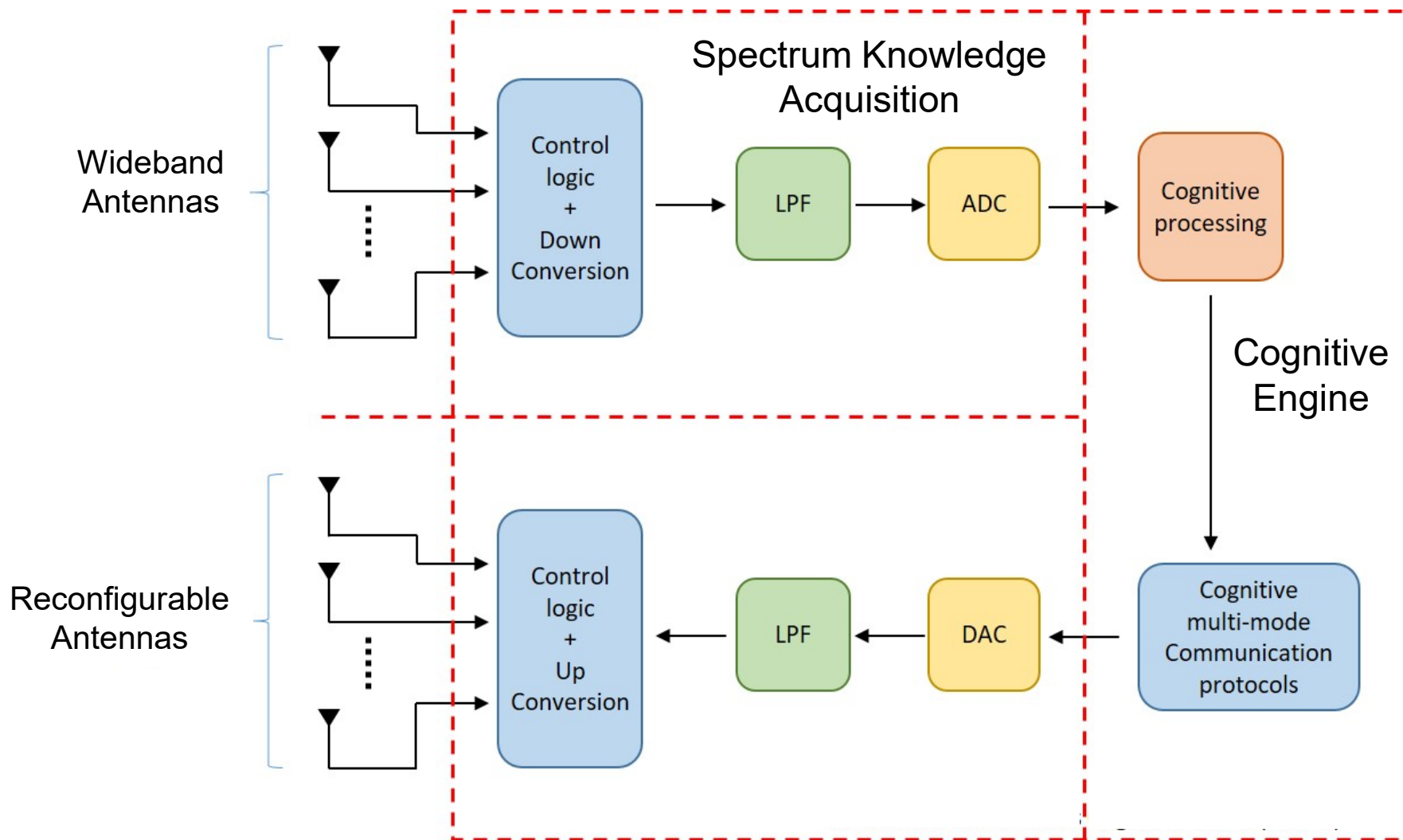
Dale Mortensen, Marie Piasecki, and Mike Evans



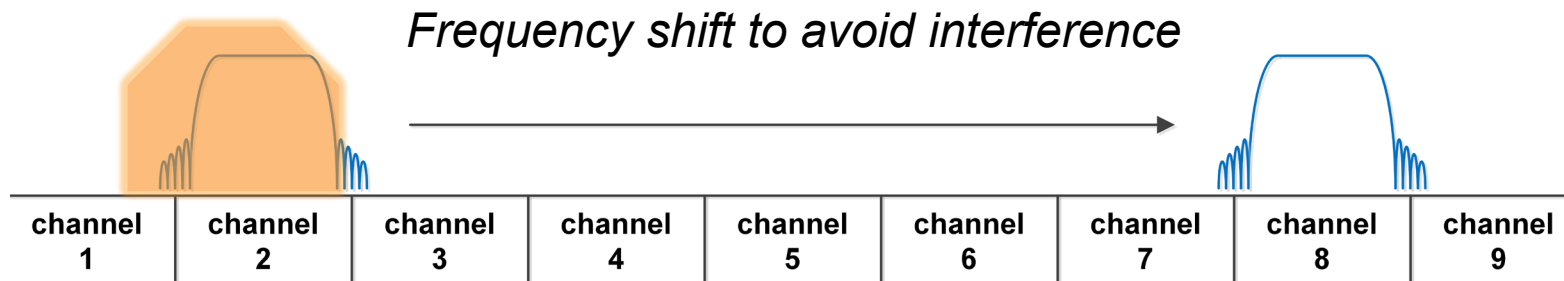
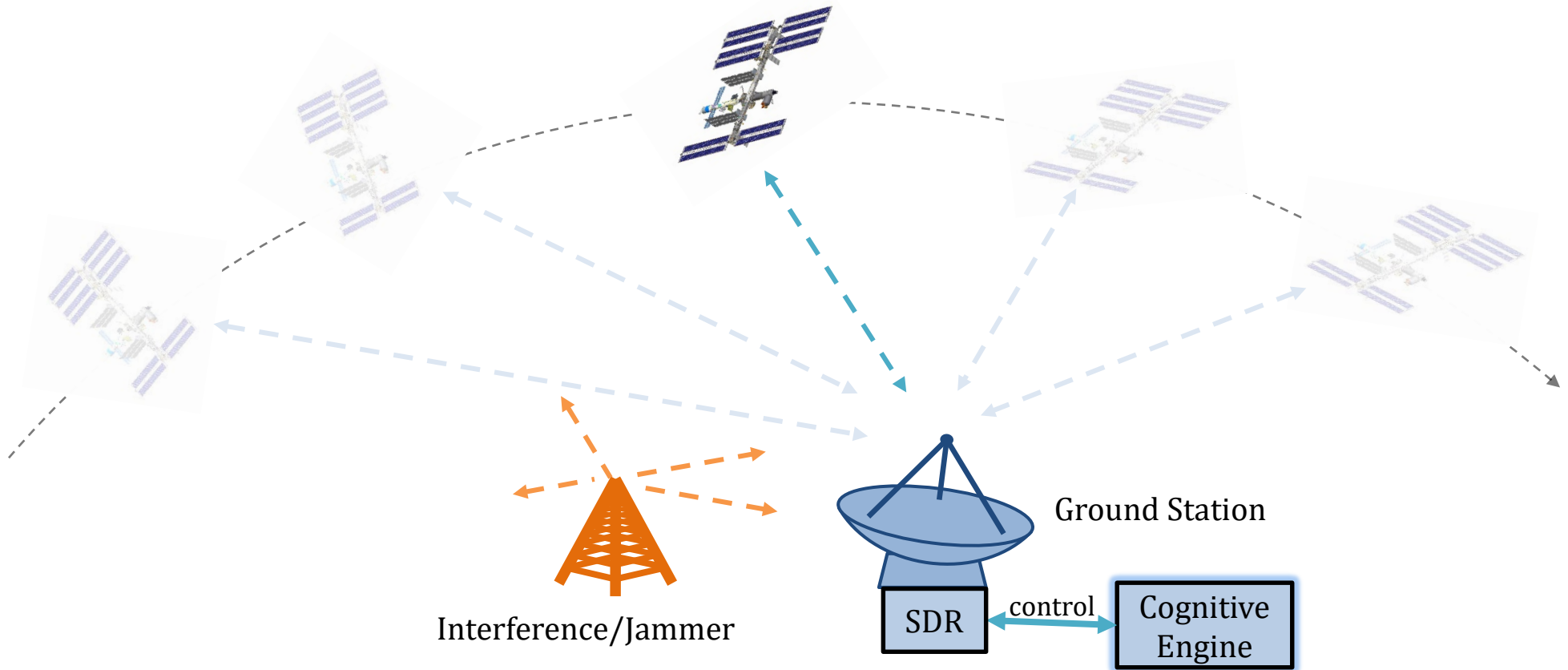
**NASA Glenn Research Center, Cleveland, OH.**

**Presenter: Dale Mortensen**

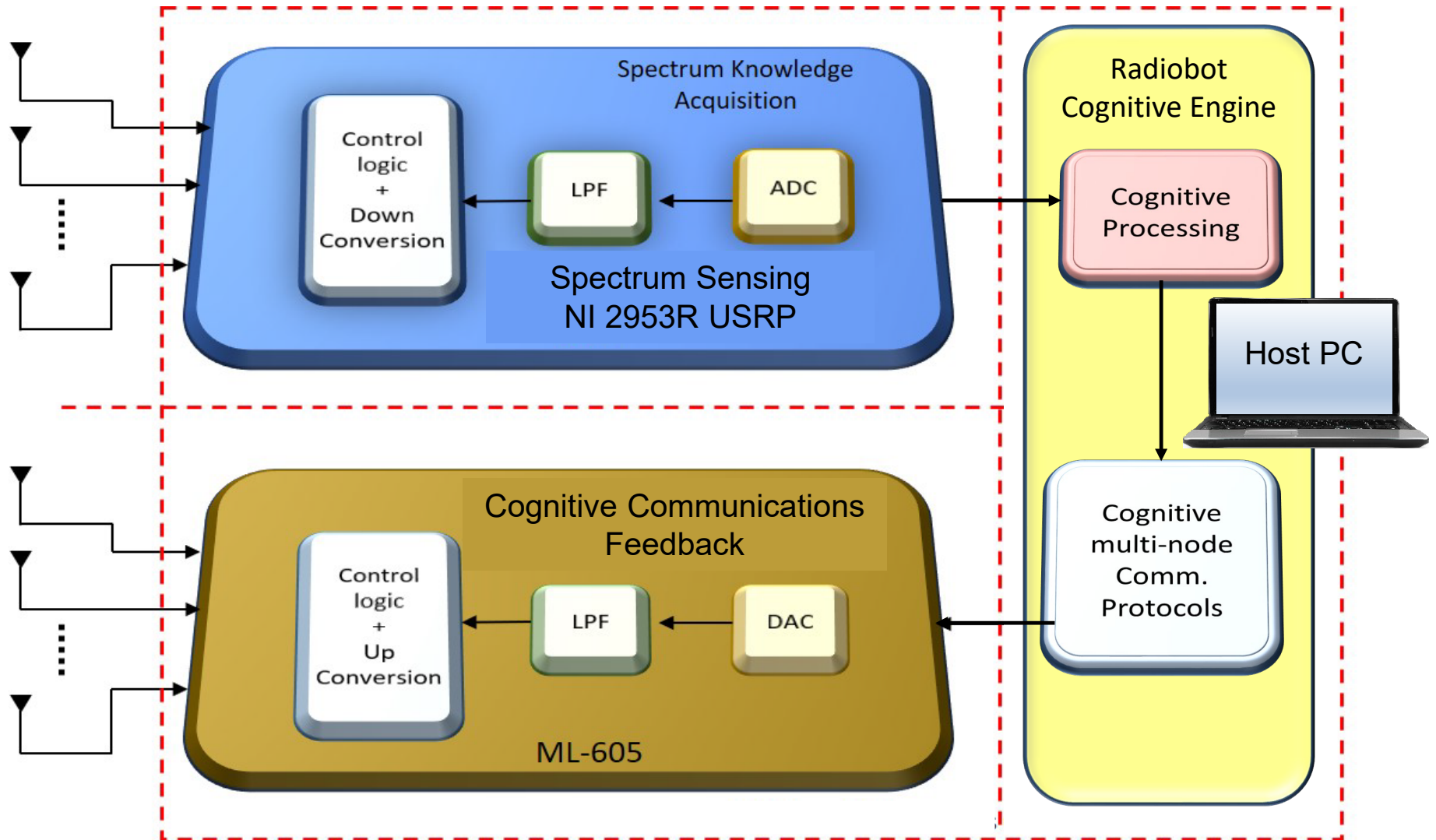
# Wideband Autonomous Cognitive Radio (WARC) Architecture



# Satellite-to-Ground Cognitive Anti-Jamming (CAJ) Communications: Concept of Operations



# Implemented WACR System



*WARC operation with two separate SDR modules instead of a single SDR module.*

# Radiobot Cognitive Engine: CAJ Policy Options

1. Load a pre-learned policy from a file and keep updating the policy during the communications phase.
2. Learn a policy during a training period and keep updating the policy during the communications phase.
3. Learn a policy during a training period and keep it fixed during the communications phase.

# CAJ Policy with Reinforcement Learning: Watkin's Q-Learning Algorithm

$$Q(s, a) = (1 - \alpha)Q(s, a) + \alpha \left( r + \gamma \max_{a'} Q(a, a') \right)$$

NOTE: Learning rate ( $\alpha$ ) and Forgetting factor ( $\gamma$ ) both held constant for this experiment.

# Exploration vs Exploitation

$$\pi_t(s) = \mathop{\text{arg max}}_a Q_t(s, a)$$

$$a_t(s) = \begin{cases} \pi_t(s) & \text{with probability } 1 - \varepsilon \\ U(A \setminus \{s\}) & \text{with probability } \varepsilon \end{cases}$$

- Learned policies can be used with an exploration rate ( $\varepsilon$ ) during the communications phase.
  - Allows discovery of possible new optimal (state, action) pairs.
  - Must be balanced with exploitation of the already learned policy.
- Complete exploitation of previously learned policy is obtained setting  $\varepsilon$  to zero.

## CAJ with a Random Policy

- Set the exploration rate to unity during communications phase to achieve a random channel selection policy.
- Random channel selection policy does not mean it is a traditional radio.
  - Even when the policy is to select channels randomly, the radio is still a WACR.
- Random policy is used to evaluate the effectiveness of the learning process, not the effectiveness of cognitive communications.
  - To perform anti-jamming communications, even with a random policy, the radio still needs the spectrum knowledge of the cognitive radio.
  - Hence, it is still autonomously mitigating the jammer.

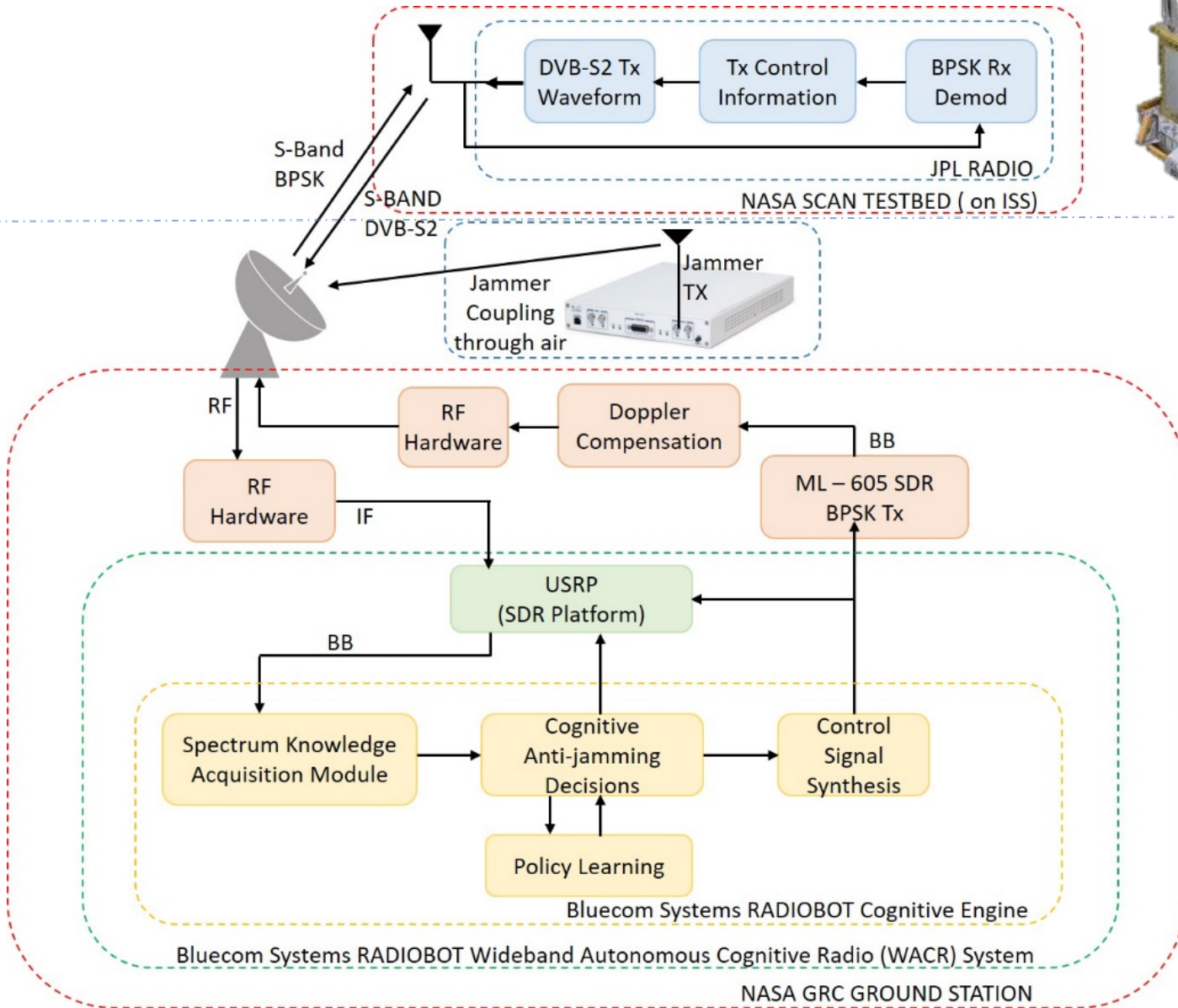


# Flight Testing System Configuration

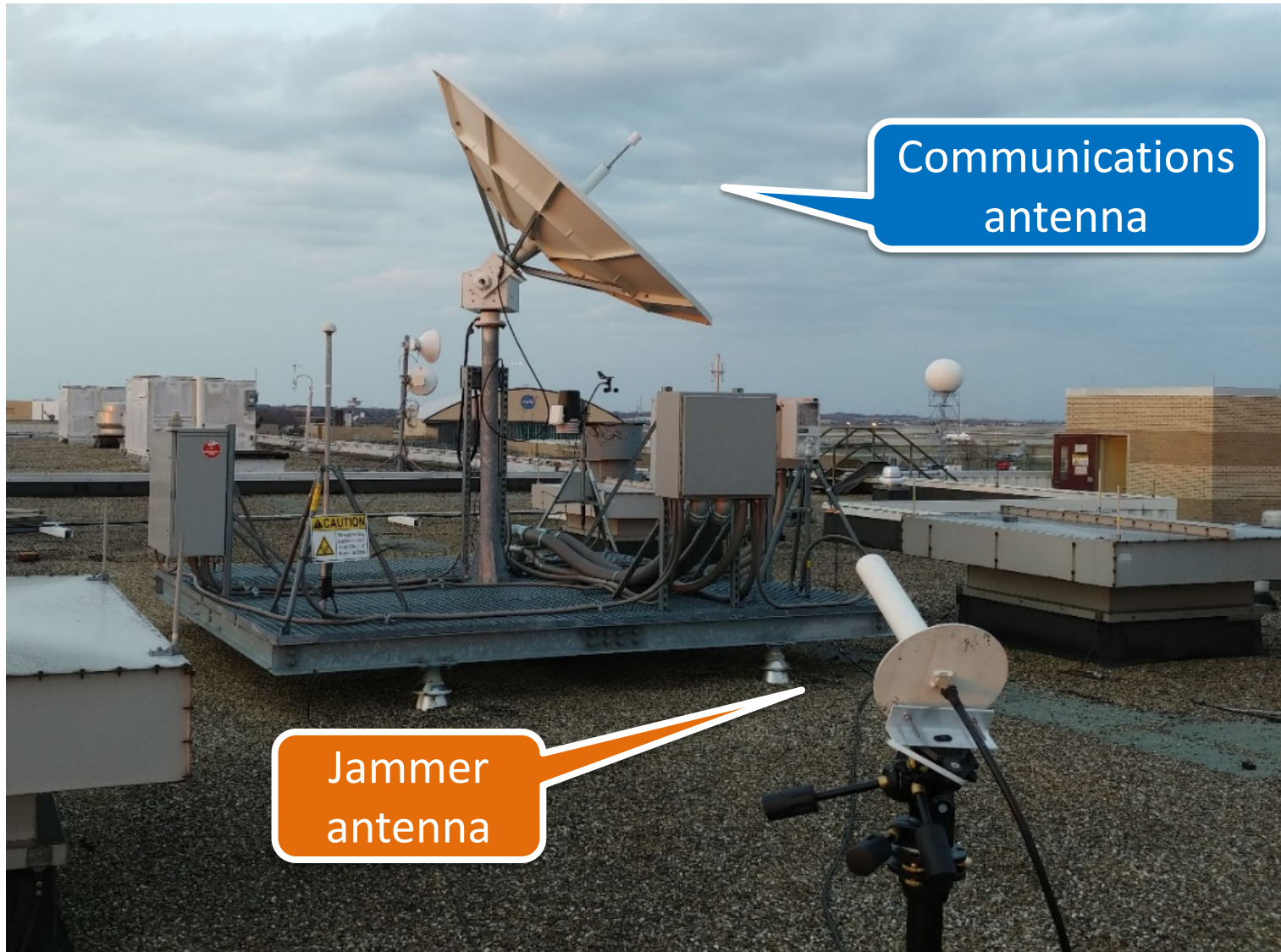


FLIGHT SYSTEMS

GROUND SYSTEMS

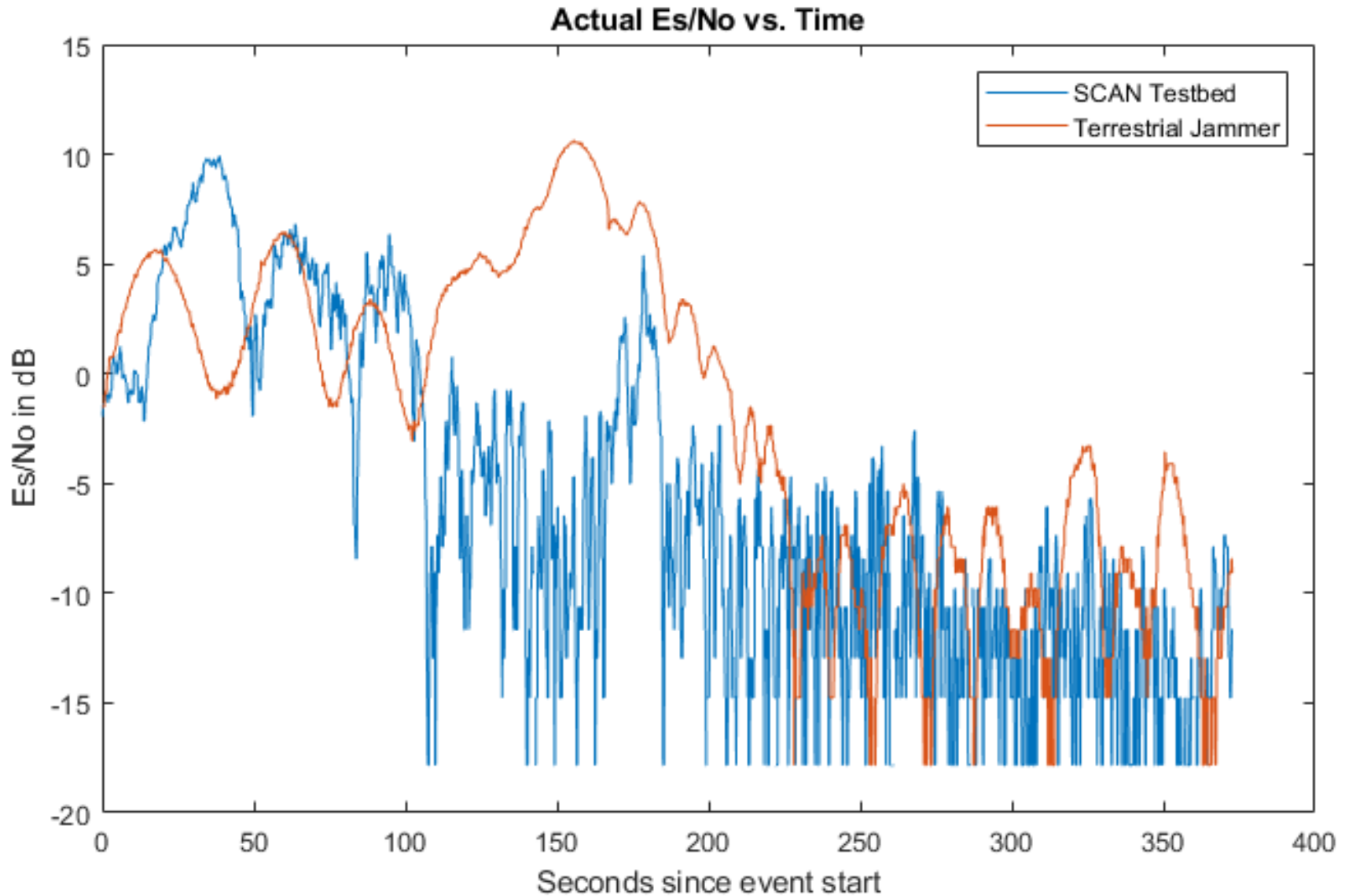


# Flight Testing Ground Station Antenna Setup



*Over-the-air jammer antenna setup on same rooftop as main ground station.*

# Flight Testing: Relative Powers of Satellite and Jammer Signals



# Flight Testing Event Data

Test #	Jammer Type	Policy Type	Exploration Rate ( $\epsilon$ )	Total Number of Sensing Periods During the Complete Event-pass	Total Number of Sensing Periods with Sufficient Signal Quality Between Channel Transitions	Number of Channel Transitions
1	sweep	random	1.0	214710	29380	21
2	sweep	random	1.0	218545	96337	77
3	sweep	pre-learned	0.3	235192	132380	81
4	sweep	pre-learned	0.3	120370	298	4
5	Markov	random	1.0	192751	51412	67
6	Markov	pre-learned	0.0	229520	72908	79
7	Markov	pre-learned	0.3	266661	112660	115

Learning rate ( $\alpha$ ) set to 0.3, and Forgetting factor ( $\gamma$ ) set to 0.8 for all tests.

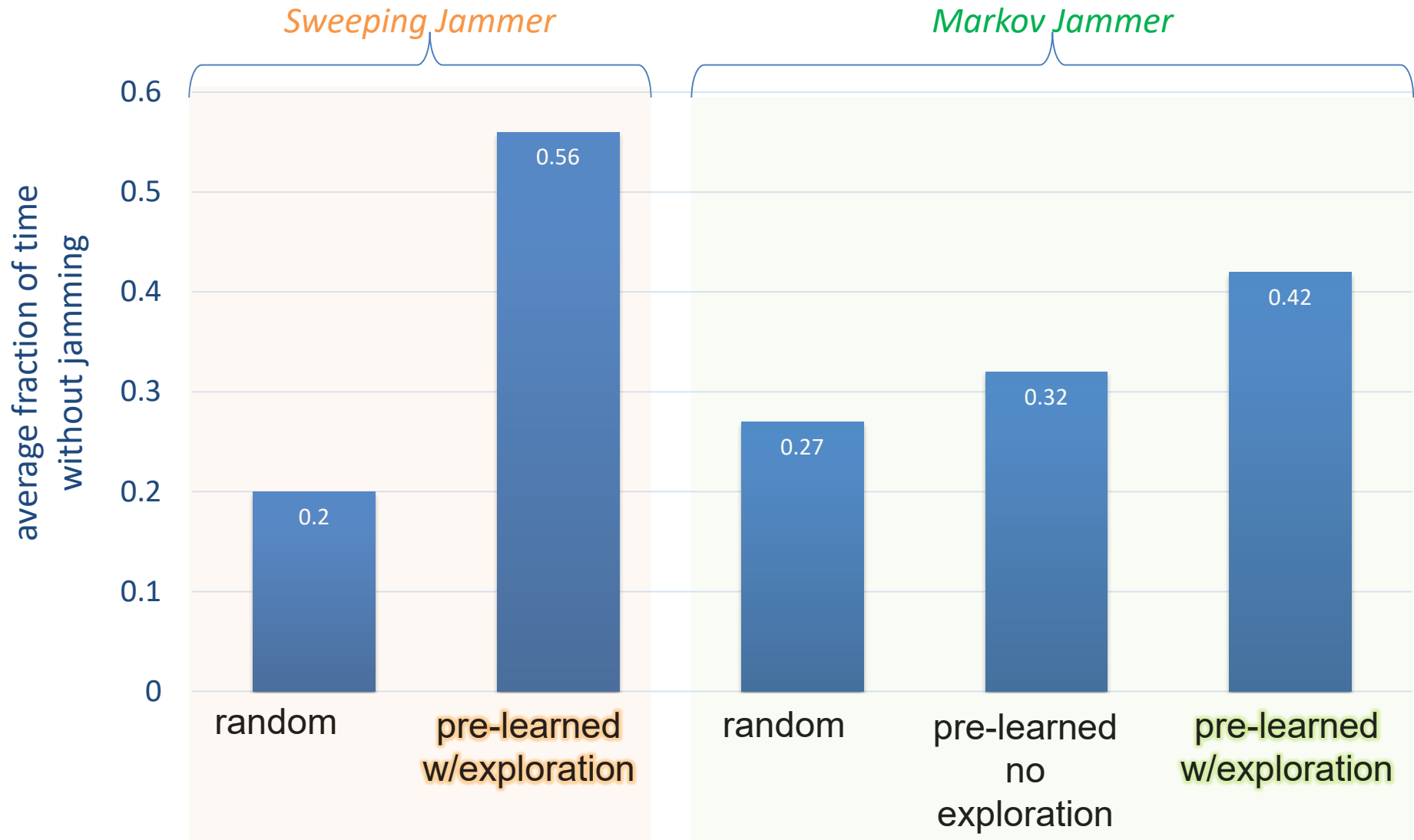
# Flight Testing: Performance

## Evaluation of CAJ Communications

Test #	Jammer type	Policy Type	Exploration Rate ( $\epsilon$ )	Average time in a Channel Without Being Jammed	Average Fraction of time in a Channel Without Being Jammed
1	Sweep	Random	1.0	1399	0.14
2	Sweep	Random	1.0	1251	0.44
1 & 2	Sweep	Random	1.0	1325	0.20
3	Sweep	Pre-learned, continuously updated through exploration	0.3	1634	0.56
5	Markov	Random	1.0	767	0.27
6	Markov	Pre-learned and fixed.	0.0	922	0.32
7	Markov	Pre-learned, continuously updated through exploration	0.3	980	0.42



# Flight Testing: Policy vs Random Performance



## Conclusions

- Results show that the developed WACR approach is an effective anti-jamming tool, regardless of learning type and channel selection algorithms are used.
- Reinforcement learning aided cognitive anti-jamming communications policy significantly outperforms the random channel selection policy, both in terms of the average unjammed time in a channel as well as the fraction of time in a channel without being jammed.
- Performance is consistent regardless of the type of the jammer: Sweep or Markov.
- Allowing learning-based policy update and policy exploration during actual RF environment will lead to better performance with cognitive anti-jamming communications.
- Best possible performance improvements with the CAJ communications policy can be expected to be higher than what is observed in these tests since these tests only allowed a very short learning period length, and parameters of the algorithms (i.e. learning rate, and forgetting factor, etc.) were unoptimized arbitrary values.

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