CableLabs®

From Sensing to Sharing: AI-Optimized Sensing Networks for Dynamic Spectrum Occupancy Prediction

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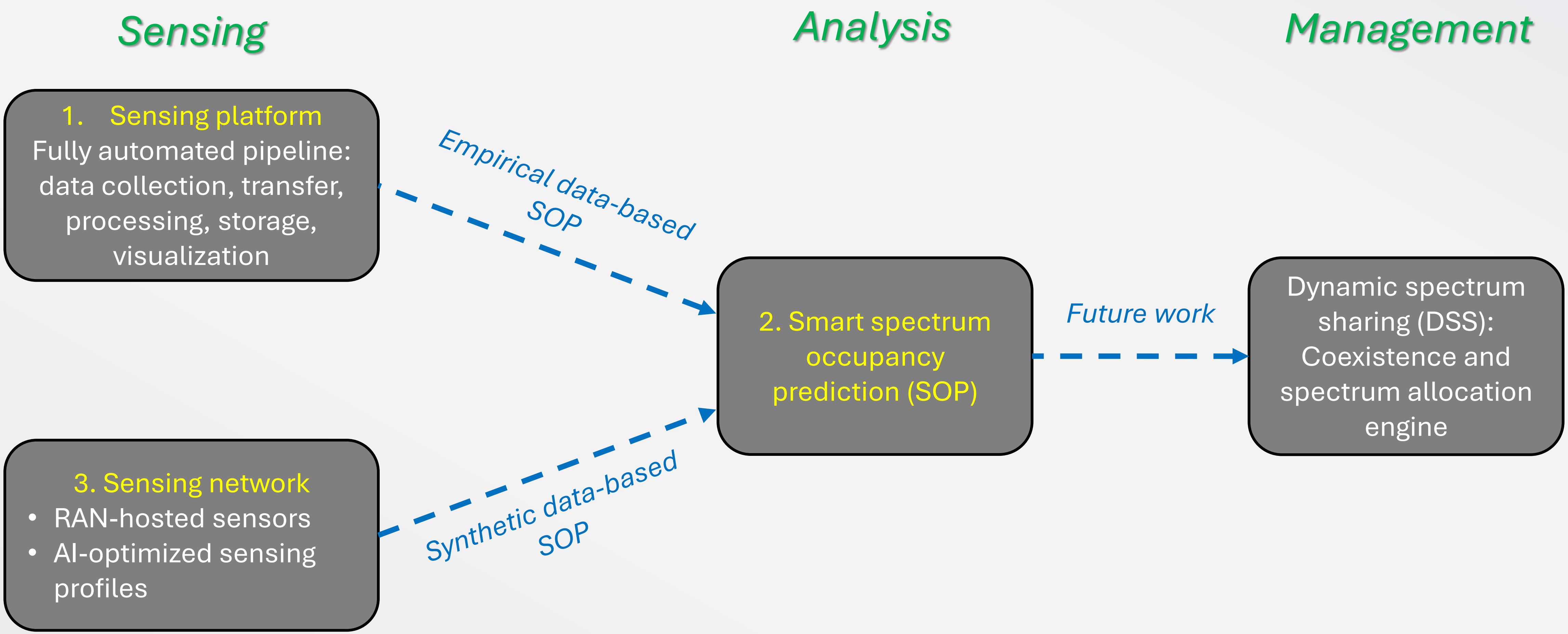
CONTENT FLOW: FROM SENSING TO SHARING

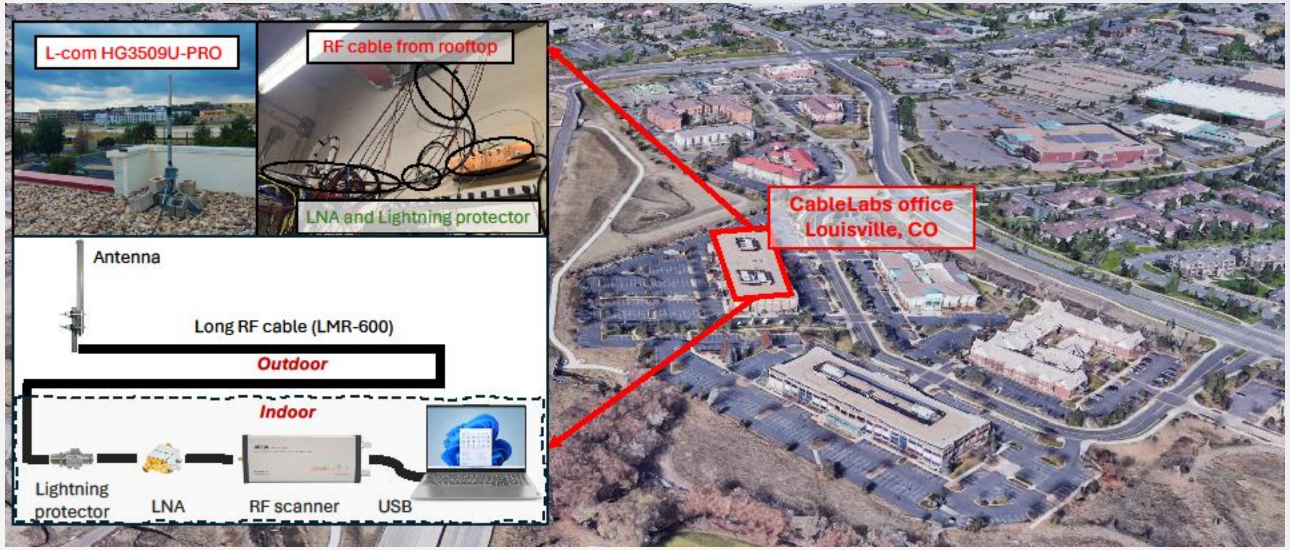


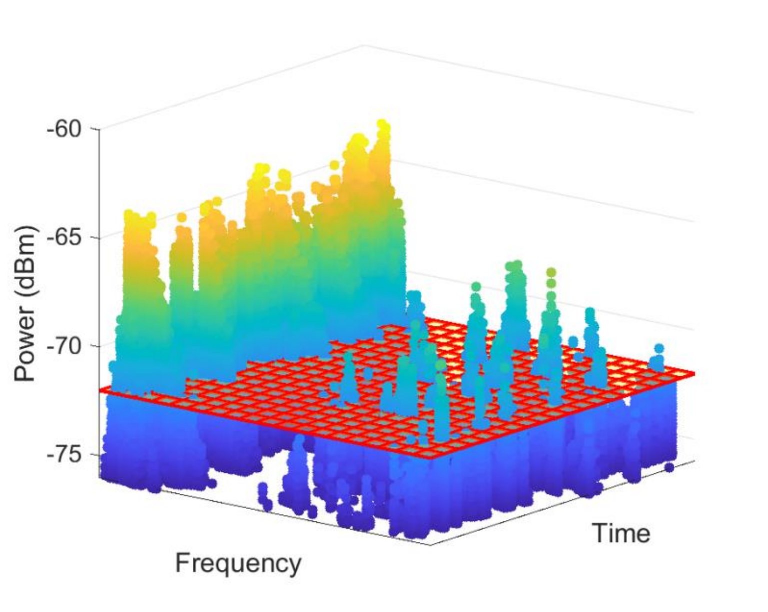
1. Spectrum Sensing Platform

CABLELABS' SPECTRUM SENSING SYSTEM

Key components include:

- RF scanner
- RF chain: outdoor rooftop antenna, long RF cable, low-noise amplifier (LNA), lightning protector
- Laptop: control the RF scanner, uploading data, data collection software





[1] Mark Poletti, Ruoyu Sun, Amir Hossein Fahim Raouf, "Spectrum Utilization: Nationwide Measurements for New Spectrum Opportunities and Government Policy," *SCTE TechExpo 2024*, Atlanta, GA, 14-26 Sept. 2024. Online Available: [Link]

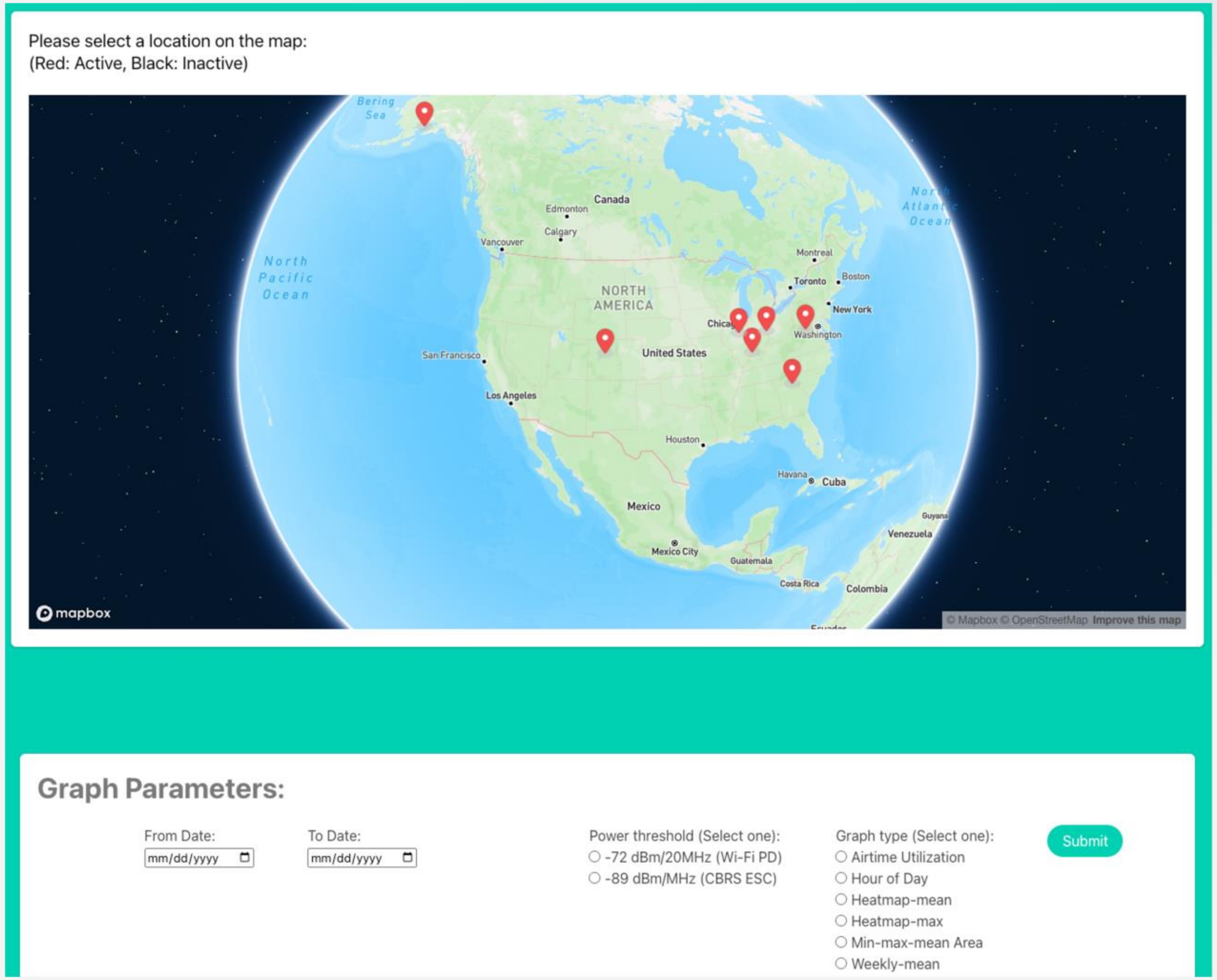
COLLABORATION PLATFORM

Established a platform collaborating with academia and industry

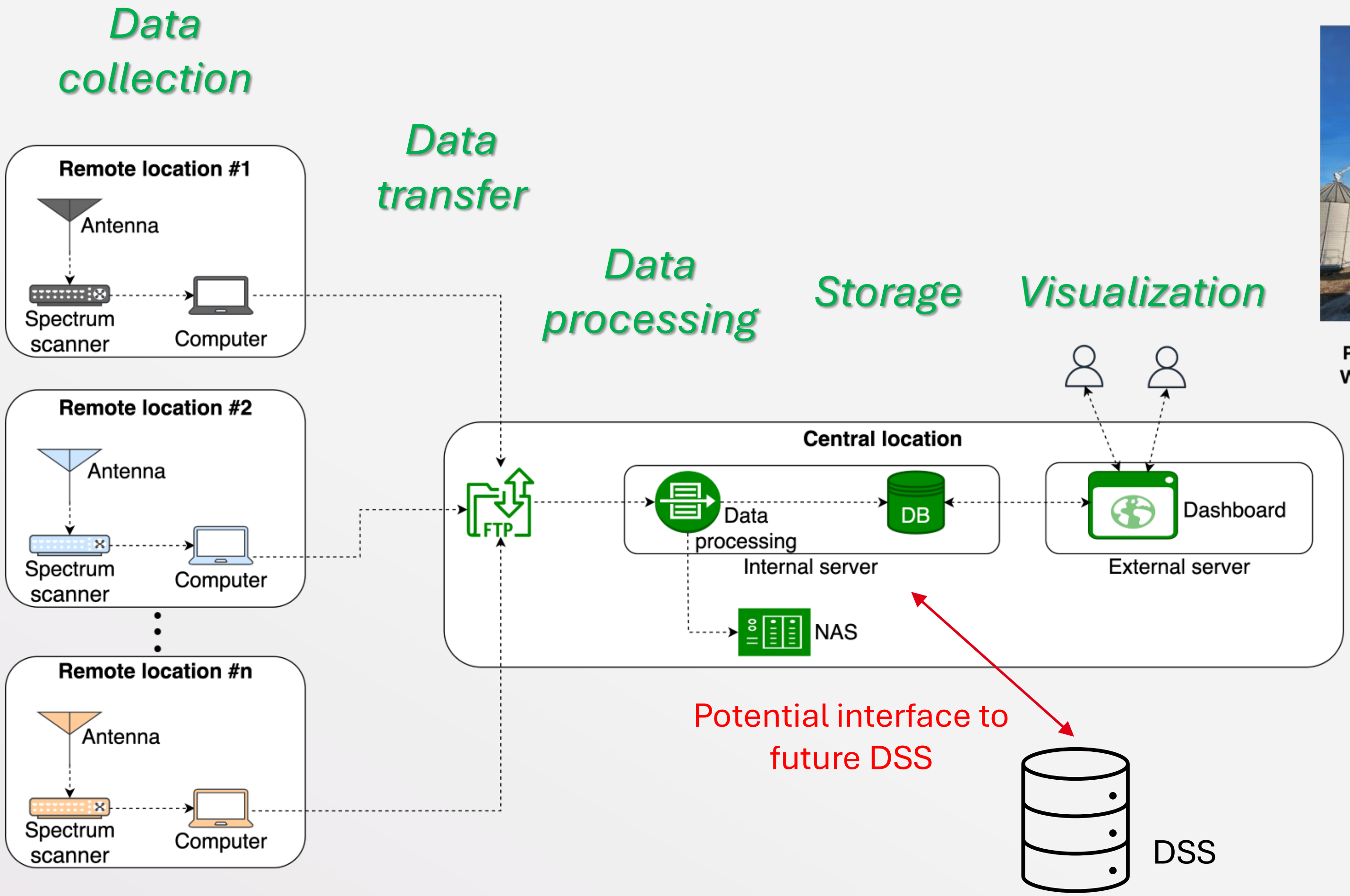
- Sharing data, ideas, and resources

Seven operating sites:

- CableLabs headquarters office, CO (Jan. 2024)
- University of Louisville, KY (Jul. 2024)
- GCI: Anchorage, AK (Jan. 2025)
- NCTA: Washington D.C. (Mar. 2025)
- The Ohio State University: Columbus, OH (May 2025)
- Purdue: West Lafayette, IN (June 2025)
- University of South Carolina: Columbia, SC (Aug. 2025)



AUTOMATED SPECTRUM SENSING PIPELINE



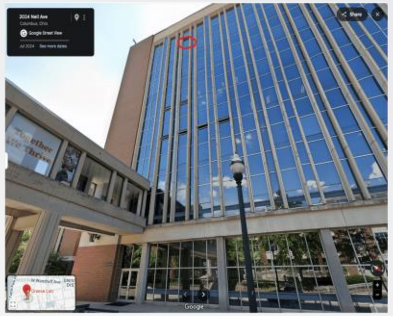
NCTA
Washington D.C.

CableLabs Headquarters
Louisville, CO

University of Louisville
Louisville, KY

Purdue University
West Lafayette, IN

University of South Carolina
Columbia, SC



Ohio State University
Columbus, OH

[2] R. Gandotra, R. Sun, M. Poletti, J. Mao, and H. Guo, "Automated spectrum sensing and analysis framework," arXiv:2601.11748, Jan. 2026. [Online]. Available: https://arxiv.org/abs/2601.11748

EXAMPLE DATA

Raw data

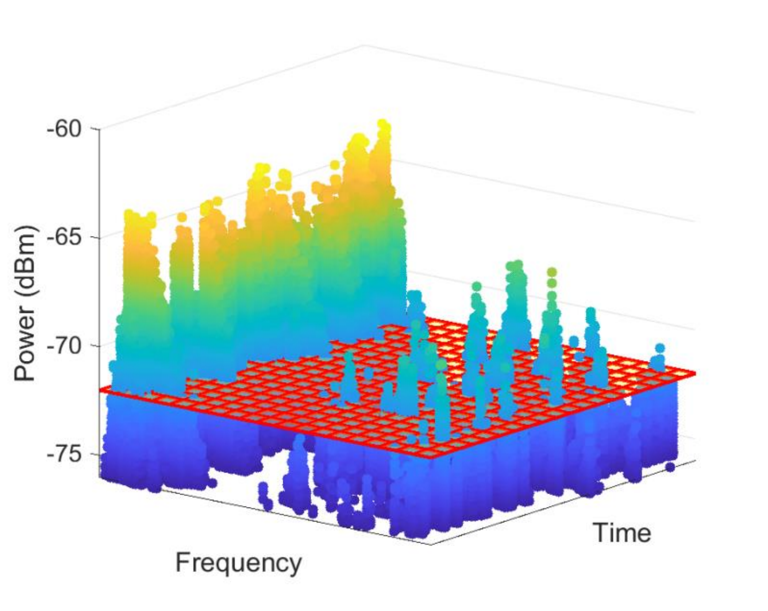
- Power (dBm) vs. frequency (per 10 kHz resolution BW) vs. time (sweeping)
- Power threshold: power spectral density (PSD) equivalent to
  - -72 dBm/20MHz (Wi-Fi energy detection threshold), or
  - -89 dBm/MHz (CBRS Environmental Sensing Capability (ESC) threshold)

Channel Occupancy (per 5-MHz channel per minute)

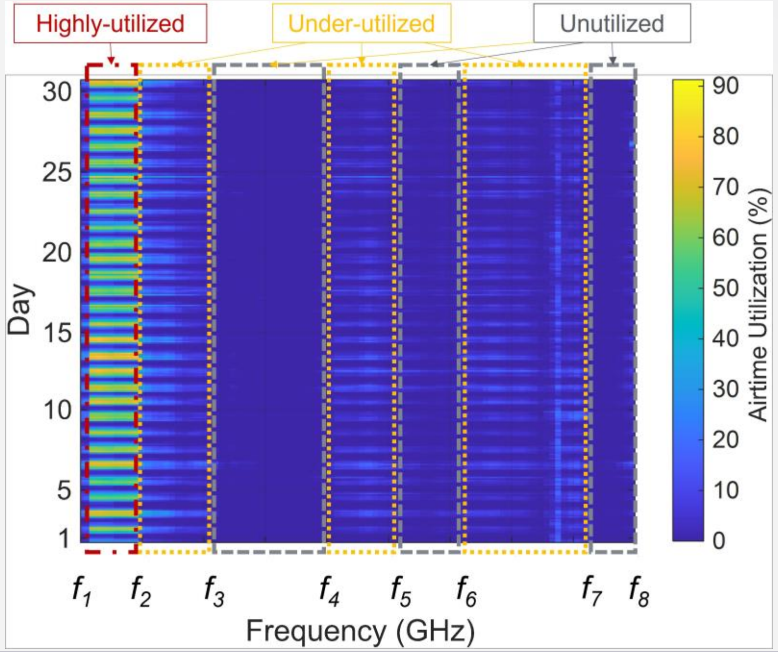
- $\text{Channel Occupancy} = \begin{cases} 0, & \textit{if the channel is not used, zero sample above threshold} \\ 1, & \textit{if the channel is used, at least one sample above threshold} \end{cases}$

Airtime Utilization

- Airtime utilization measures the percentage of time a channel is actively transmitting data relative to the total available time
- $\text{Airtime utilization (\%)} = \dfrac{\text{Number of occupied minutes}}{60} \times 100\%$



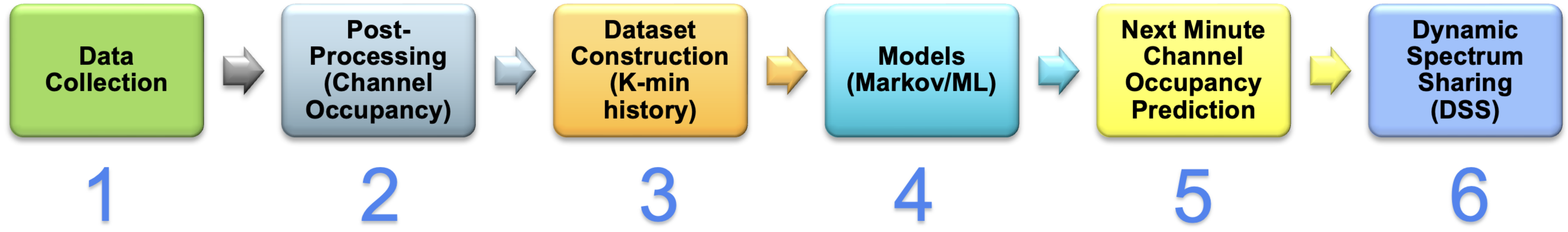
Example data collected in CO



[3] A. H. F. Raouf, R. Sun, M. Poletti, "Spectrum Usage Monitoring and Airtime Utilization: Insights from a Practical Case Study," in *IEEE Network*, vol. 40, no. 2, pp. 287-294, March 2026.

2. Empirical Data-Based Smart Spectrum Occupancy Prediction

SOP PIPELINE



[4] J. Mao, R. Sun, A. Yener, R. Gandotra, S. Dai, M. Poletti, H. Guo, “Multi-Timescale Transformer-Based Spectrum Occupancy Prediction for Real-Time Dynamic Spectrum Sharing,” *2026 Wireless Innovation Forum Workshop on AI/ML and Agentic AI in Advanced Wireless Communications and Spectrum Management*, Washington DC, USA, 14 May 2026. **(Won the best paper award)**

[5] J. Mao, R. Sun, M. Poletti, R. Gandotra, H. Guo, and A. Yener, "AI-driven spectrum occupancy prediction using real-world spectrum measurements," Jan. 2026, *arXiv:2601.11742*. [Online]. Available: https://arxiv.org/abs/2601.11742

PROBLEM FORMULATION

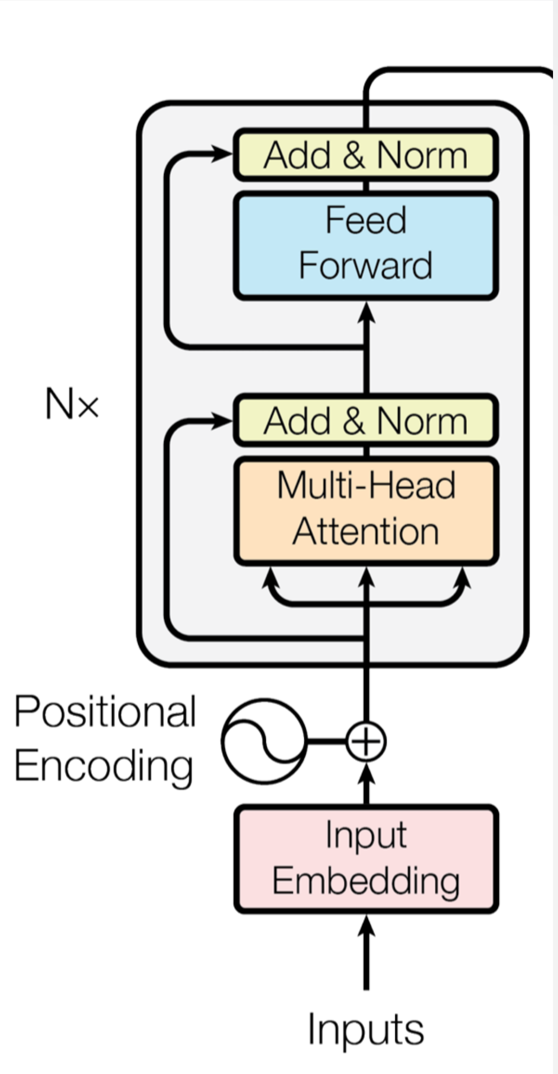
- **Problem Statement:** Next-minute channel occupancy prediction
  - Predict channel occupancy (0/1) of 90 frequency bins at time t given the last K minutes (t-1, t-2,…,t-K).

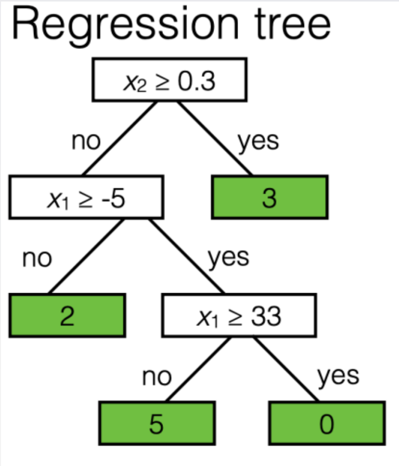
- **Dataset Construction:**
  - Raw series: 2 months data (May & June 2025), 61 days×24 hr×60 min → 87840 time steps
  - Step 1: Concatenate & sort all per-hour CSVs → single table
  - Step 2: Sliding window
  - Input X_t: flatten bins at t–K…t–1 → shape (K×90 frequency bins)
  - Label y_t: bins at t → shape (90)
  - Step 3: Save X (n_samples×K·90) and Y (n_samples×90) once for any K (K is a parameter)
  - Step 4: For dual-input transformer, add long-term data, dataset is (X_{short}, X_{long}, Y)

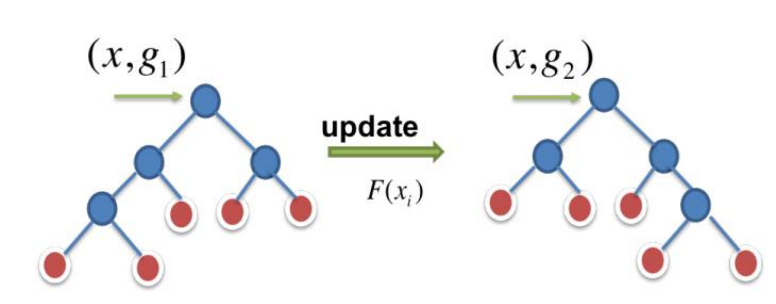
MACHINE LEARNING METHODS

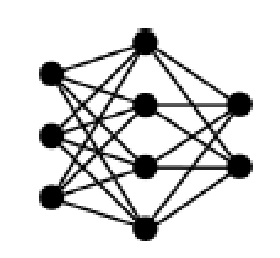
- Random Forest
- XGBoost (Extreme Gradient Boosting)
- Long Short-Term Memory (LSTM, Neural Network)
- Transformer
  - Single-input transformer
  - Dual-input transformer

Baseline: Markov chain



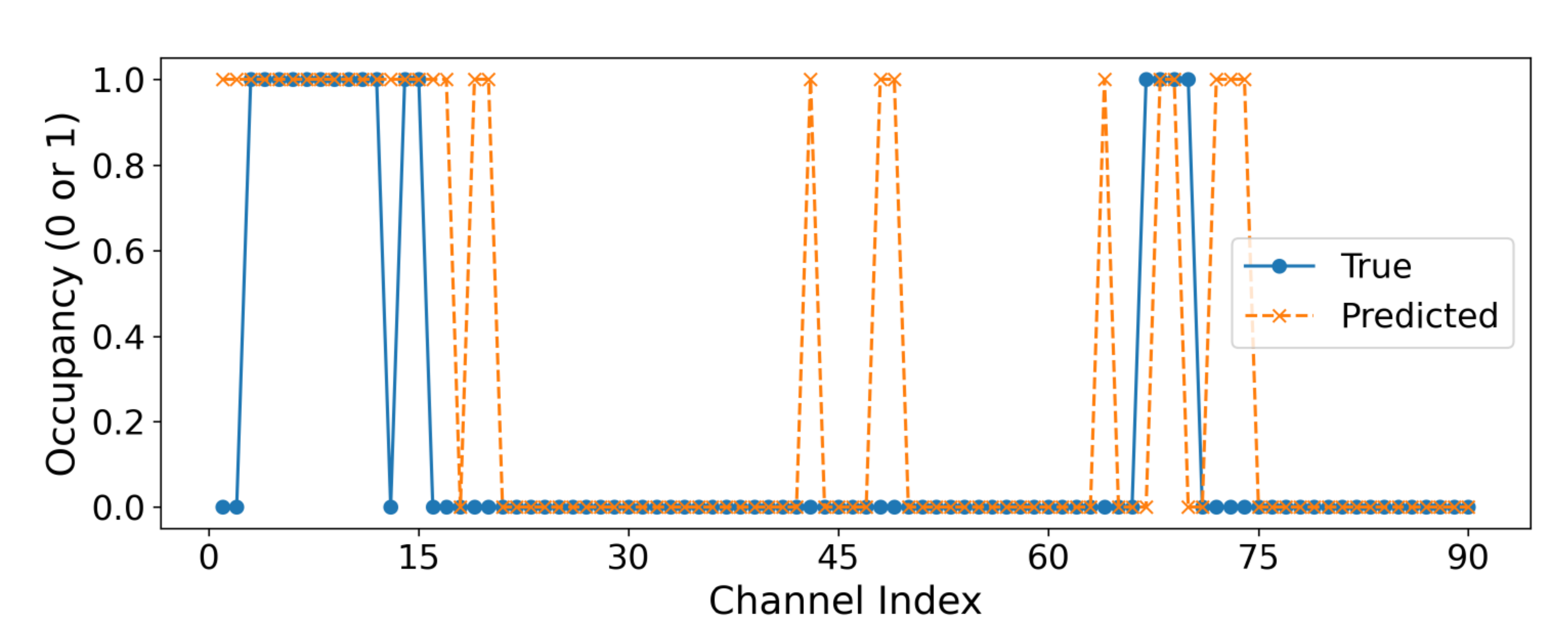




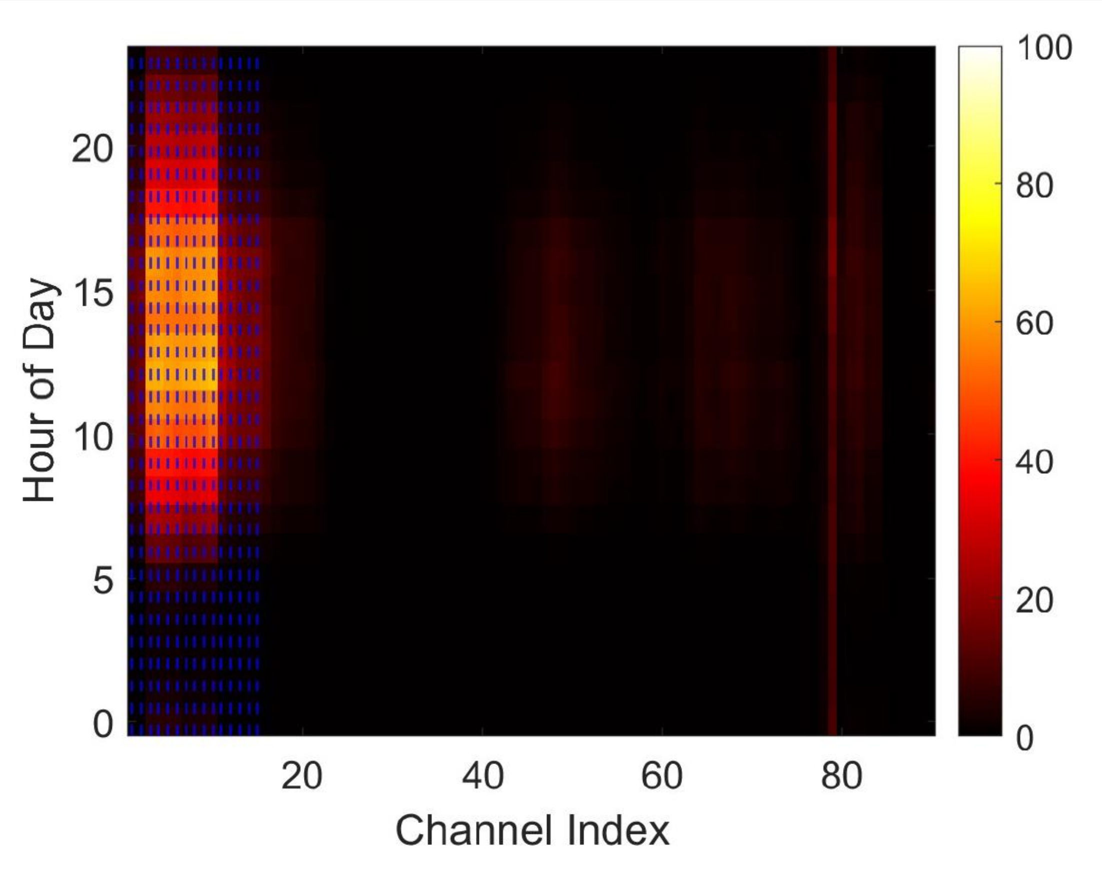


EXAMPLE PREDICTION RESULTS

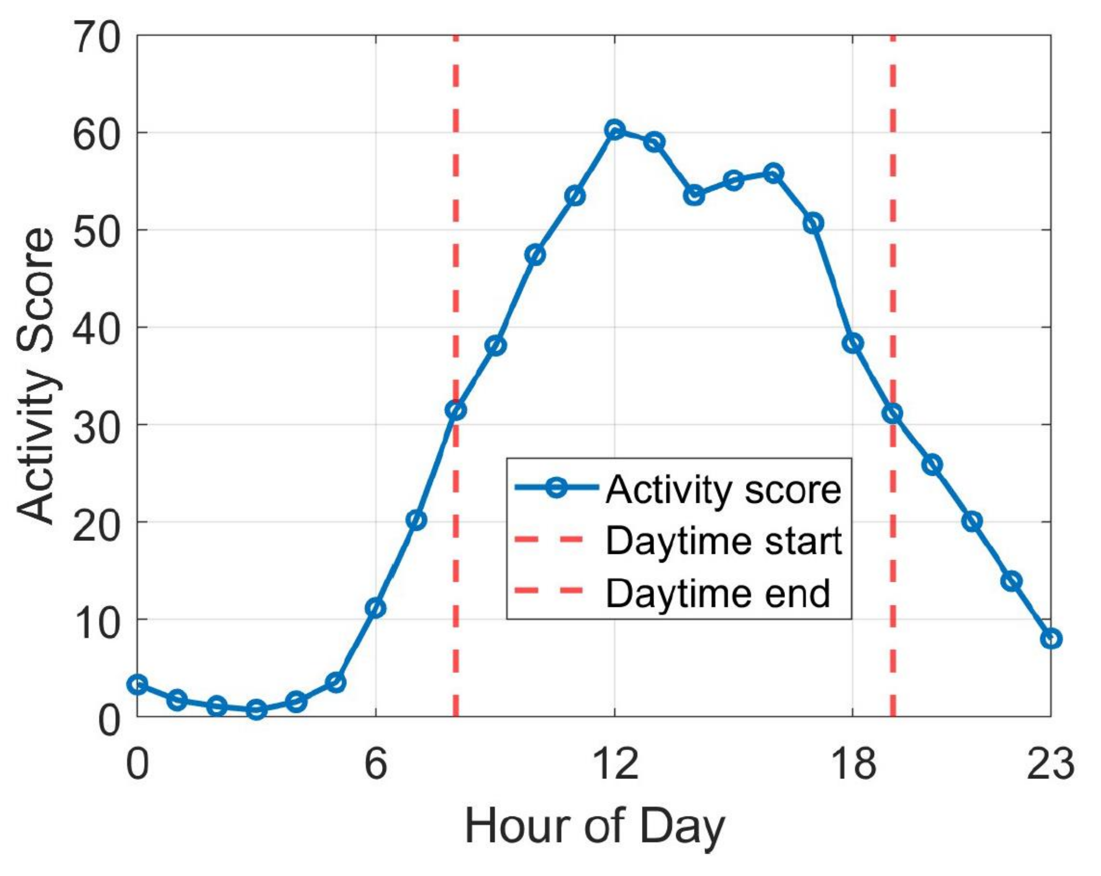
Example of Random Forest predictions at a single minute.



MULTI-TIMESCALE: LONG TERM DATA CONSTRUCTION



Spectrum airtime utilization heatmap



Hourly channel activity score

Result: daytime interval is 08:00–19:00. $X_{long} = 1$ if daytime, 0 if night.

PERFORMANCE COMPARISON

Table 1: Main comparison with fixed *K* (*K*=10)

Method	Average accuracy	Balanced accuracy	Pd@1%Pfa	Pd@5%Pfa
Markov (1st order)	76.9%	61.2%	25.0%	50.4%
Random Forest	86.3%	68.9%	40.2%	59.2%
XGBoost	86.4%	69.6%	40.5%	59.7%
LSTM	86.4%	69.6%	40.5%	60.0%
Single-input transformer	86.5%	69.9%	40.8%	60.1%
Dual-input transformer	86.6%	70.0%	40.8%	60.2%

Observations

- ML outperforms Markov
- Transformer is slightly more accurate than other ML methods
- More complicated ML methods have limited performance improvement

Issue:

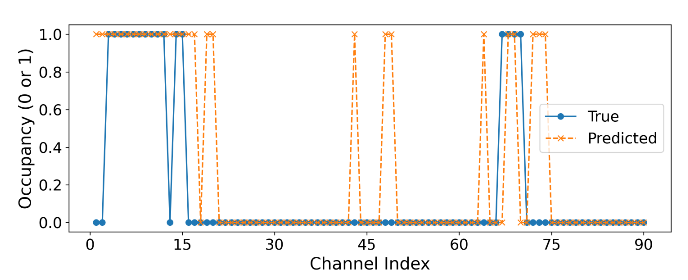
- Accuracy bounded around 87%, likely due to the sensing data instead of ML methods

- **Balanced Accuracy** — Average of true positive and true negative
- **Pd@5%Pfa** — “Probability of detection at 5% probability of false alarm”

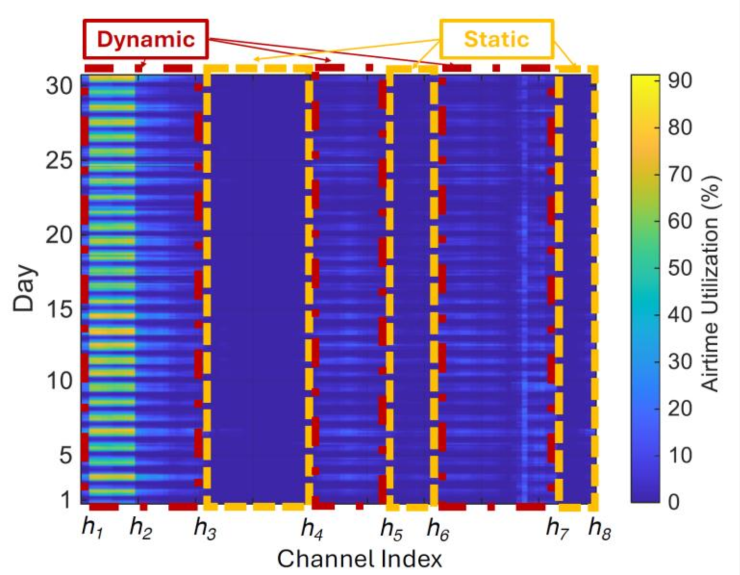
SOP ACCURACY VS. CHANNEL DYNAMICS

Observations

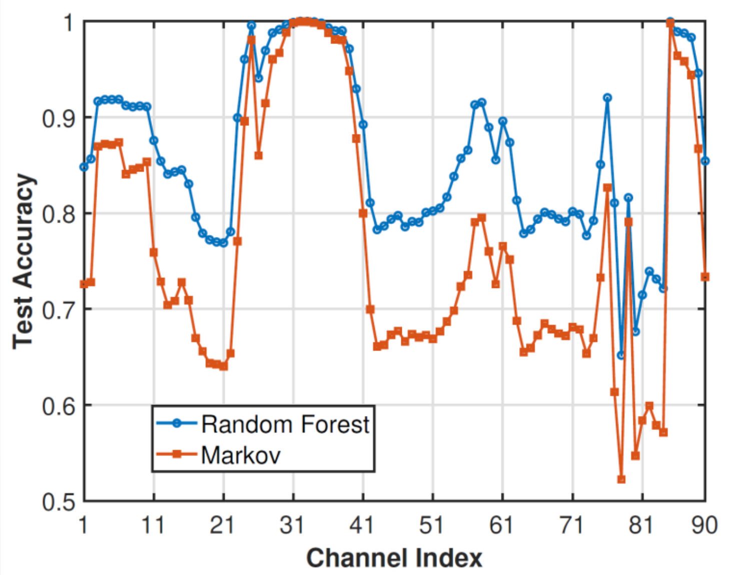
- Prediction accuracy is highly dependent on transition rate
- It is harder to predict a fast-changing channel



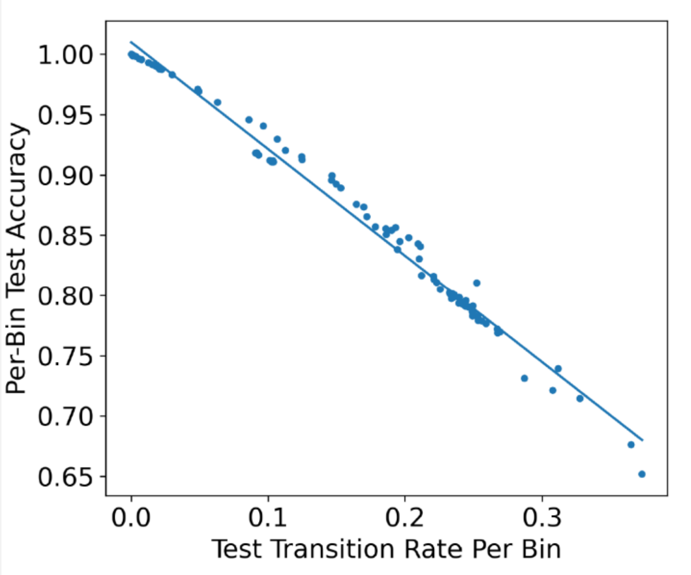
Channel transition rate: How often channel occupancy state flips from *t* to *t*+1 across the dataset



Channel dynamics



Accuracy vs. channel

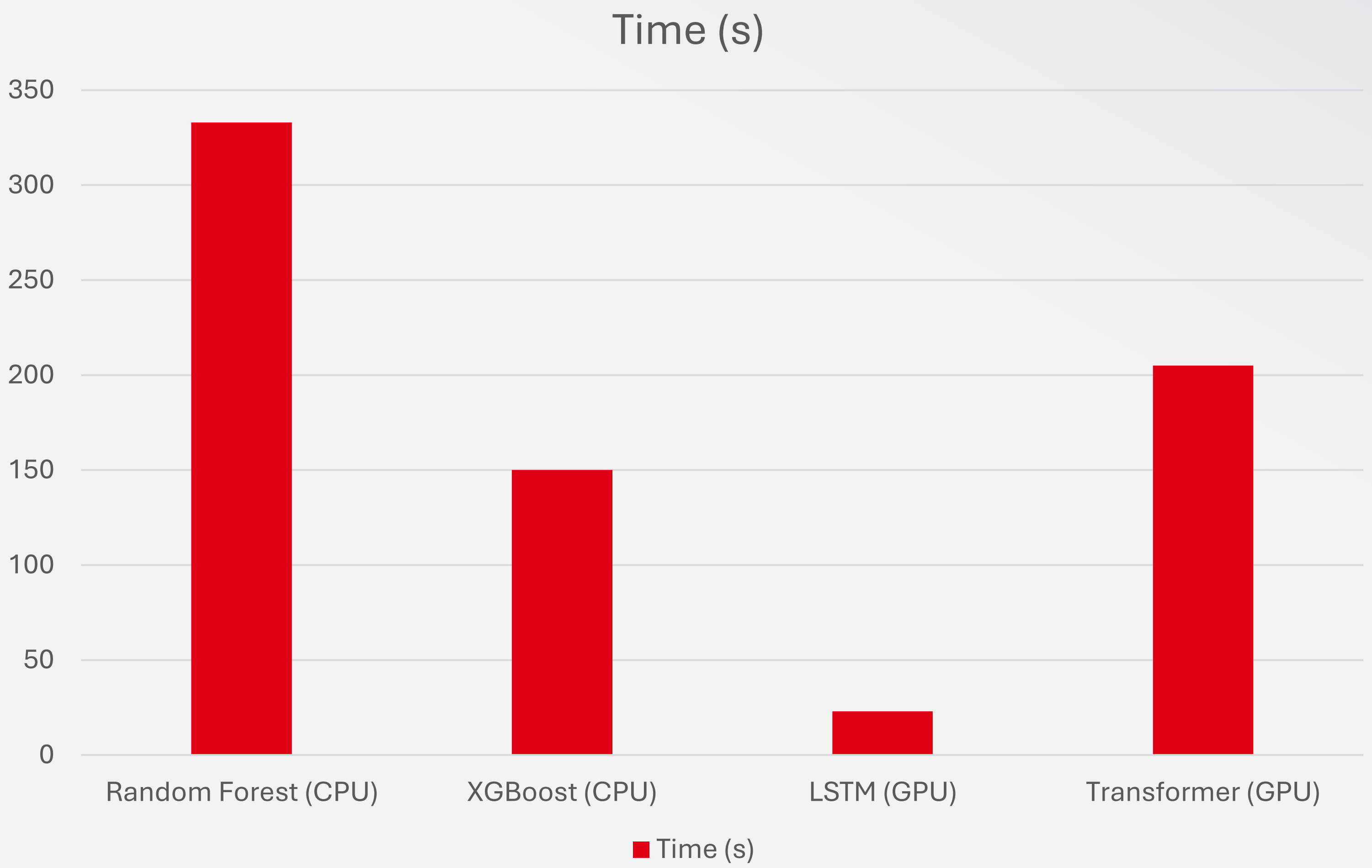


Accuracy vs. channel dynamics

COMPLEXITY COMPARISON

Hardware Information

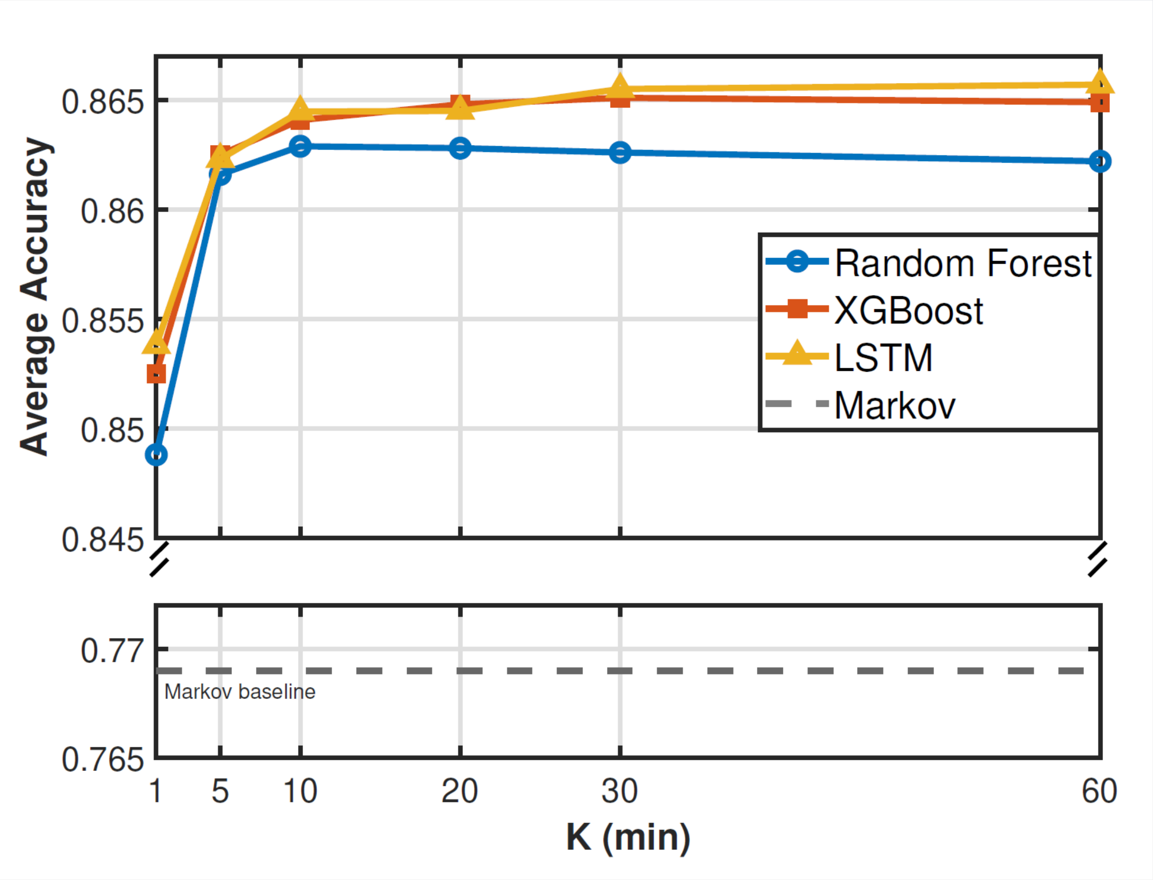
- CPU: AMD Ryzen 9 5900X 12-Core Processor
- Python version: 3.10.20
- GPU: NVIDIA GeForce RTX 3080 Ti



Training Time Comparison

K SENSITIVITY ANALYSIS

- *K*-minutes of channel occupancy data is used to predict next-minute occupancy
- *K*=10 is selected
  - Best performance for Random Forest
  - *K*>10 only slightly improve for XGBoost and LSTM
  - *K* does not apply to Markov chain



LESSON LEARNED FROM SOP

- Real-world spectrum measurements for short-horizon occupancy prediction
- Five ML methods are implemented in [4]: Random Forest, XGBoost, LSTM, and two transformer designs
  - Single-input transformer and dual-input transformer
  - Dual-input model incorporates long-term usage patterns, e.g., day/night regimes
  - Transformer performance is comparable to standard ML baselines
- In June/July 2026, we further tried 12 additional ML models with different feature-engineering approaches, but the accuracy improvement is limited.
- Given the marginal performance difference, Random Forest/XGBoost is preferred for practical DSS deployment due to its simplicity
  - Support Federated learning/prediction on remote locations, and even on smartphone
- Achieved around 86% accuracy across ML models, likely limited by the sensing data instead of ML methods
- Future work: determined by SOP accuracy targets (90%, 99%), reverse engineering to study the corresponding sensing data requirements

[4] J. Mao, R. Sun, A. Yener, R. Gandotra, S. Dai, M. Poletti, H. Guo, "Multi-Timescale Transformer-Based Spectrum Occupancy Prediction for Real-Time Dynamic Spectrum Sharing," *2026 Wireless Innovation Forum Workshop on AI/ML and Agentic AI in Advanced Wireless Communications and Spectrum Management*, Washington DC, USA, 14 May 2026. **(Won the best paper award)**

3. AI-Optimized Large-Scale Spectrum Sensing Network

LARGE-SCALE SPECTRUM SENSING NETWORK (LARS-NET) SIMULATOR

Definition

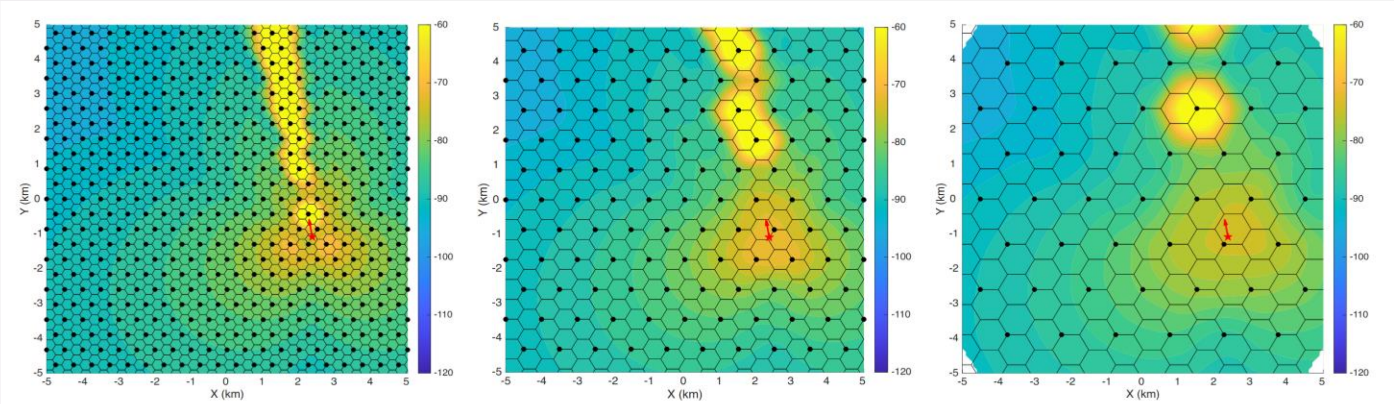
- A large-scale sensing network can be hosted by RAN base stations (BSs), Wi-Fi networks, UEs/CPEs, vehicles/drones, IoT devices, and other platforms, as long as they meet common sensing requirements

Why is LarS-Net needed?

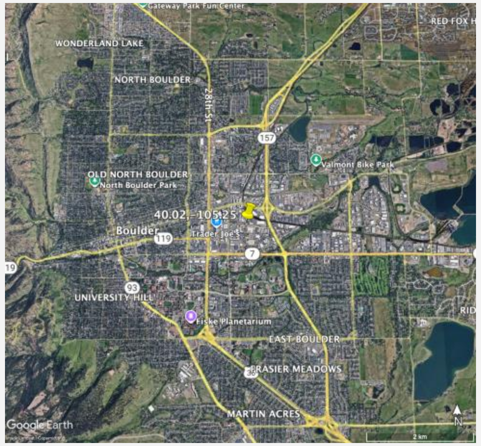
- Compared to individual sensors, a large-scale sensing network provides enhanced capability to detect and **protect incumbent systems**
- Reduce sensing network deployment cost by leveraging existing BS sites, backhaul, and power supply infrastructure
- Seeking a technology commercially implementable to next-gen cellular or Wi-Fi. LarS-Net aligns closely with 6G ISAC and Wi-Fi sensing

Current CableLabs' LarS-Net studies

- CableLabs has built preliminary LarS-Net simulator to evaluate the min number of sensors required in a homogeneous RAN network
- Dynamically optimize sensing profiles for each sensor to enhance sensing performance and minimize sensing data and overhead
- Spectrum occupancy prediction based on LarS-Net synthetic data



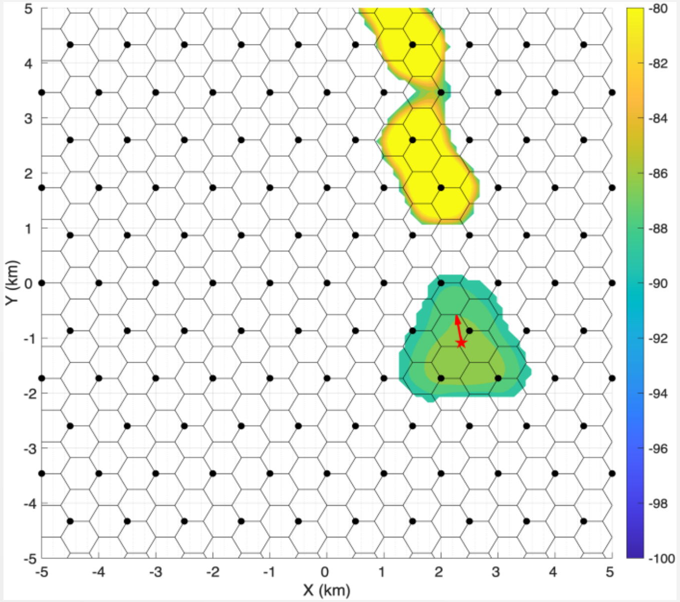
(a) ISD = 500 m (b) ISD = 1000 m (c) ISD = 1500 m



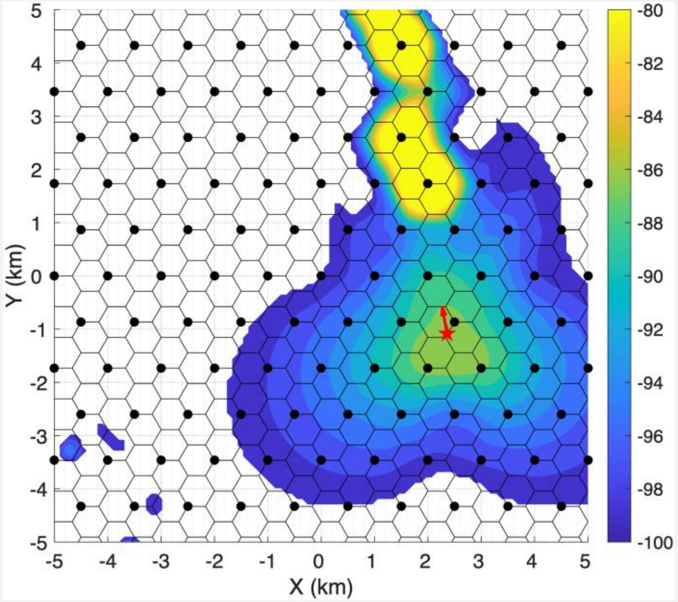
[6] H. Guo, R. Sun, A. H. F. Raouf, R. Gandotra, J. Mao, M. Poletti, "LarS-Net: A Large-Scale Framework for Network-Level Spectrum Sensing," *2026 IEEE 103rd Vehicular Technology Conference (VTC-2026* Spring), Nice, France, 9-12 June 2026.

SENSING PROFILE OPTIMIZATION

- Sensing profile for each sensor in LarSNet consists of
  - Sensing power threshold, resolution BW, sleep/awake time, etc.
  - A high-performance sensing profile generate a large amount of data: “payload” of the sensing network
- Each sensor in the network could use different profiles
- Sensing profiles could be updated dynamically



Sensing threshold = -89 dBm/MHz
Energy detection threshold (EDT)

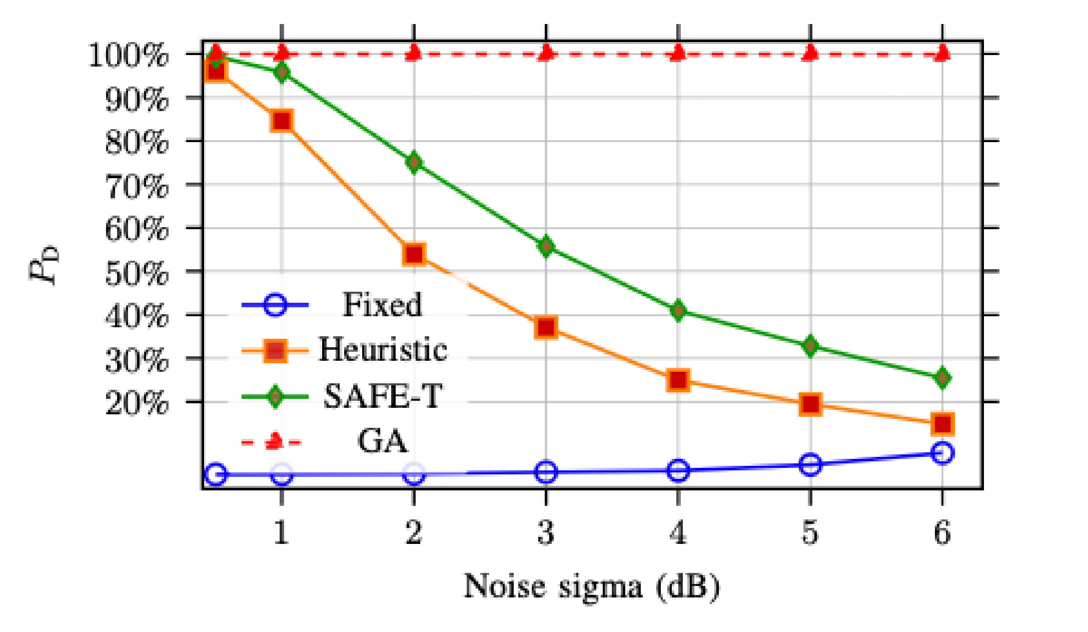


Sensing threshold = -99 dBm/MHz

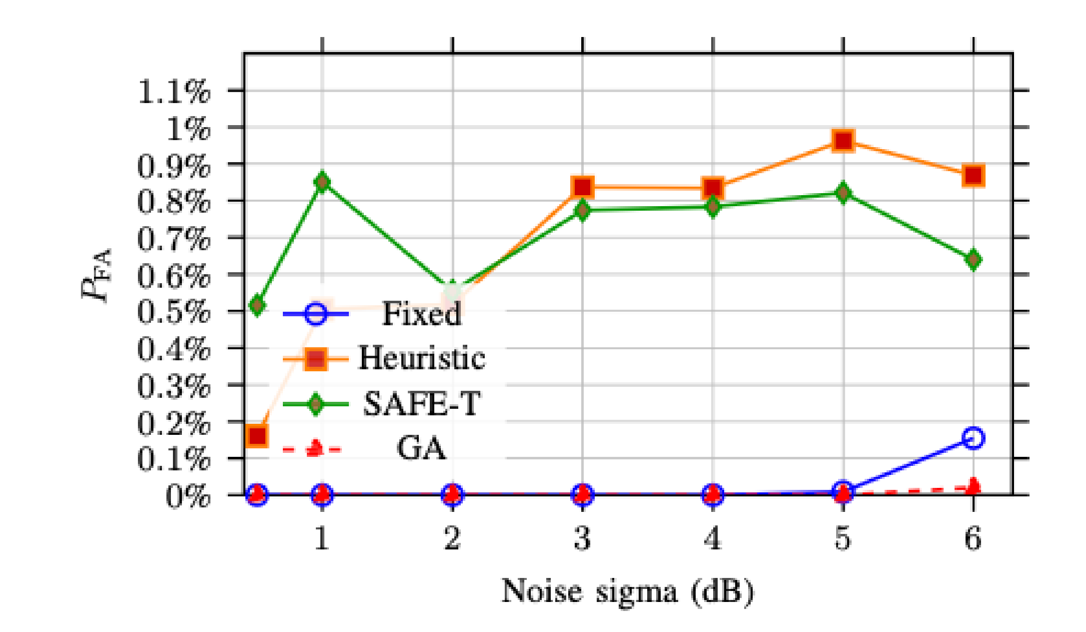
- Colored areas are the places where the received power exceeds the EDT.
- Clearly, with lower EDT, more areas ”detect” the incumbent.
- Is it good or bad? (Detection probability vs. False-alarm)

AI-ASSISTED SENSING PROFILE OPTIMIZATION: DYNAMIC EDT

1. Fixed EDT
2. Heuristic EDT: sub-optimal EDT based on average noise
3. SAFE-T: AI-assisted Structure-Aware False-alarm-constrained Energy Threshold
4. GA: Genie-aided (GA) upper bound



Detection Probability



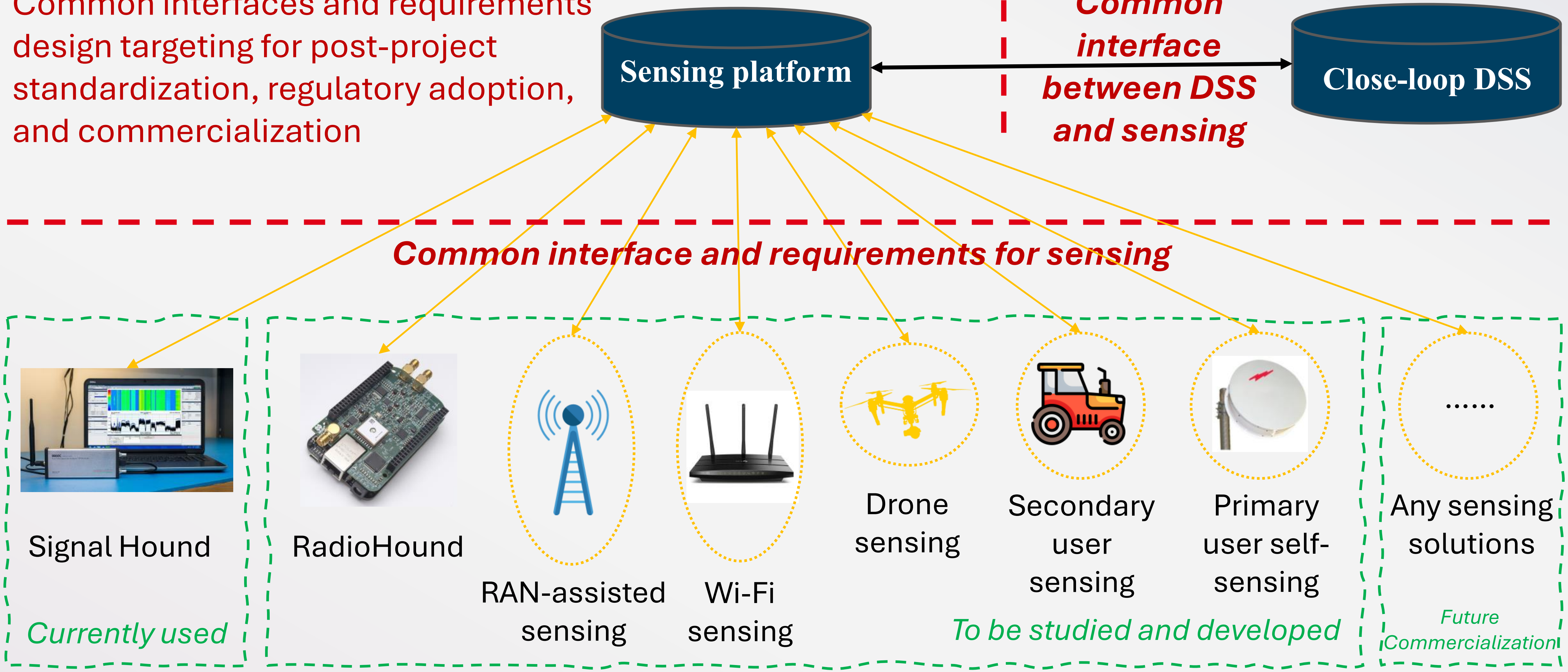
False-alarm Probability

- Fixed EDT in [7] and literature is NOT optimal for dynamic spectrum sharing (DSS).
- Slot-adaptive AI-assisted EDT selection outperforms fixed EDT and heuristic method, approaching to the GA upper bound, with the cost of knowing the per-slot observation.
- Limitations/Future work: Using different EDT for each sensor.

[7] H. Guo, R. Sun, R. Gandotra, J. Mao, M. Poletti, "SAFE-T: AI-Driven Adaptive Thresholding for Cooperative Spectrum Sensing," *2026 Wireless Innovation Forum Workshop on AI/ML and Agentic AI in Advanced Wireless Communications and Spectrum Management*, Washington DC, USA, 14 May 2026.

SENSING STANDARDIZATION AND ECO-SYSTEM

Common interfaces and requirements design targeting for post-project standardization, regulatory adoption, and commercialization



ROADMAP OF THE CABLELABS' SPECTRUM SENSING PROJECT

Completed tasks
Collaboration platform and automated SS framework

09/2024 – 08/2025

- Compare available sensing solutions, design our own solution
- Define channel occupation and airtime utilization matrices based on our data
- Calibration method and tests for the RF system
- Establish the platform collaborating with academia and industry to share data, resources, and ideas
- Deploy sensors to seven US cites
- Develop fully automated spectrum sensing framework
- Initial study on spectrum occupancy prediction (SOP)

On going tasks
SOP, LarS-Net, and DSS design

02/2025 – 12/2028

- Large-scale spectrum sensing network (LarS-Net) simulation development
- LarS-Net generated synthetic data for SOP
- AI-optimized sensing profile in LarS-Net
- Sensing requirements assessment
- Waveform classification
- Secondary user assisted sensing
- Primary user self sensing
- Design of sensing-aided DSS

Future tasks
Standardization, regulation, and commercialization of LarS-Net assisted DSS

TBD

- Propose new study item and work item to 3GPP Rel-21 or Rel-22 about spectrum sensing/scanning
- Collaborating with industrial partners (vendors, operators, and governments) developing standards and solutions
- Potential regulatory Ex Parte
- May establish a working group on LarS-Net and DSS if necessary
- LarS-Net planning for operators
- Lab, interop, and field tests
- Support more bands, incumbents, users in more countries

Bullets highlighted in green: discussed in this presentation

CONCLUSION: CALL BACK "FROM SENSING TO SHARING"

Sensing

Analysis

Management

1. Sensing platform
Fully automated pipeline: data collection, transfer, processing, visualization

Empirical data-based SOP

Reverse engineering: Requirements for sensing data (sensitivity, resolution BW, swapping time, etc.)

2. Smart spectrum occupancy prediction (SOP)

Future work

DSS: Coexistence and spectrum allocation Engine

3. Sensing network
- RAN-hosted sensors
- AI-optimized sensing profiles

Synthetic data-based SOP

- Five ML SOP methods implemented
- Accuracy bounded by 87%, likely limited by the empirical sensing data

CableLabs Spectrum Sensing Team

- Roy Sun
- Mark Poletti
- Rahil Gandotra
- Hao Guo
- Jiayu Mao
- Songwei Dong
- Mark Walker
- Jessica Almond

Thank you!