

WIDEBAND COOPERATIVE SPECTRUM SENSING IN 5G VIA MRC-AIDED ENERGY DETECTION AND K-OUT-OF-N DECISION FUSION: A SCALABLE NOISE RESILIENT FRAMEWORK FOR DYNAMIC SPECTRUM ACCESS

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ABSTRACT

The rapid expansion of 5G use cases and dense IoT deployments has intensified pressure on scarce spectrum, making reliable wideband sensing indispensable for dynamic spectrum access (DSA). This work targets energy detector-based cooperative wideband spectrum sensing (CWSS) over multiple sub-bands in complex AWGN channels, where noise uncertainty and very low SNR commonly affect performance. We propose a CWSS architecture that applies maximal-ratio combining (MRC) at the pre-detection stage and employs a k-out-of-N fusion rule at the decision center. MRC boosts the effective per-sub-band SNR before thresholding, while the fusion mechanism aggregates local binary decisions to improve global reliability with modest reporting overhead. Comparative evaluations indicate that the MRC-aided ED with k-out-of-N consistently achieves higher detection probability for a given false-alarm rate across challenging low-SNR conditions, outperforming non-cooperative sensing and conventional CSS baseline. The results demonstrate that combining MRC with k-out-of-N fusion mitigates noise-uncertainty effects, strengthens wideband hole detection, and provides a practical sensing frontend for policy-compliant DSA in 5G environments.

KEYWORDS

Dynamic Spectrum Access, 5G Networks, Internet of Things, Wideband Cooperative Spectrum Sensing, Energy Detection, Maximal-Ratio Combining, k-out-of-N Fusion Rule, Noise Uncertainty, Low-SNR

1. INTRODUCTION

The surge in wireless services and the massive rollout of Internet of Things (IoT) endpoints have intensified pressure on the radio spectrum, a fundamentally limited resource with most bands already assigned. Even so, measurements show that numerous licensed allocations are seldom fully utilized, leaving temporal and spatial gaps that could be utilized by the unlicensed users without harming incumbents [1]. Therefore, cognitive radio (CR) has emerged as a practical mechanism for next-generation networks to alleviate scarcity and improve utilization efficiency [2].

Reliable spectrum sensing is essential for safe coexistence. Therefore, secondary users must detect incumbent activity with high confidence to avoid harmful interference [3]. In practice, noise uncertainty can severely degrade sensing reliability of energy detection (ED), especially

under adverse operating conditions [4]. Cooperative spectrum sensing (CSS), where multiple CRs collaborate, was introduced to counter these limitations [5]. However, in low SNR regimes wideband settings, CSS can still yield unreliable outcomes at the fusion center, mainly when decisions are made from weak pre-detection statistics [6,8]. Hard-decision fusion using the k-out-of-N rule may raise decision fidelity, yet its effectiveness lessens when the per-CR SNR is poor before thresholding [7,8]. This motivates raising each node's effective SNR before fusion. Maximal-ratio combining (MRC) is a well-established diversity technique that improves post-combining SNR [9,10]. It has been successfully applied in several communication contexts, including multi-channel repetitions to mitigate potential channel congestion in safety-critical V2V communications [11], and large-range underwater acoustic communication [12]. Selection combining and MRC have been implemented as effective diversity reception strategies for suppressing interference and improving reliability in resource allocation in massive MIMO industrial automation [13].

This work analyzes ED strategies for cooperative wideband spectrum sensing across multiple sub-bands under i.i.d. complex AWGN. We developed an architecture that applies MRC at the pre-detection stage and then aggregates local hard decisions with a k-out-of-N rule at the fusion center. The study uses $K=8$ cognitive radios and selects $k=3$ as the operating vote threshold, yielding more reliable global decisions. Simulations show notable gains in detection accuracy and faster decision formation compared with non-cooperative baselines and fusion-only designs. Overall, integrating MRC with k-out-of-N fusion provides a practical path to robust 5G spectrum sensing and supports future enhancements in dynamic spectrum access.

The remainder of the paper is organized as follows: Section II reviews key concepts for wideband spectrum sensing. Section III presents the proposed design, including the design architecture and the integration of MRC with k-out-of-N fusion rule. Section IV presents the performance evaluation and discusses results demonstrating the reliability and gains of the MRC-aided cooperative scheme. Section V concludes the paper and outlines directions for future work.

2. CONCEPTS IN WIDEBAND SPECTRUM SENSING

This section reviews the foundations for our 5G sensing pipeline: single-node energy detection under complex AWGN, cooperative hard-decision fusion (k-out-of-K), and pre-detection diversity combining via MRC. We also outline practical wideband considerations-subband channelization (PFB/FFT), per-subband CFAR thresholding, and noise-uncertainty effects that motivates the proposed design.

2.1. General Single Node Wideband Sensing Format

In a single nose wideband sensing, each CR inspects the spectrum independently and decides on occupancy using only its own local measurements. This independence keeps overhead low and the workflow straightforward. However, it also exposes two well-known weaknesses: (i) noise uncertainty, which distorts the test statistic and undermines threshold reliability, and (ii) the hidden-node effect, where blockage or distance prevents a CR from observing an active primary user (PU), leading to missed detections and potential interference [14].

The received PU signal, corrupted by additive white Gaussian noise (AWGN), is captured at the secondary user (SU) antenna and processed by an energy detector. With discrete-time sampling, the n -th sample $y(n)$ follows the binary hypothesis model:

$$y(n) = \begin{cases} w(n), & H_0 \\ s(n) + w(n), & H_1 \end{cases} \quad (1)$$

Where $y(n)$ is the SU observation for $n = 1, 2, \dots$, $w(\cdot)$ denotes AWGN, and $s(\cdot)$ is the PU signal as seen by the SU. The hypotheses H_0 and H_1 corresponds to PU absence and presence, respectively.

The energy-detector test statistic is:

$$E = \sum_{n=1}^N |y(n)|^2 \quad (2)$$

Which is compared against a fixed threshold λ to infer channel occupancy. Under complex AWGN, the threshold is defined as:

$$\lambda = Q^{-1}(Pf) \cdot \sqrt{2(P_s + \sigma^2 N)} \quad (3)$$

Where $Q^{-1}(\cdot)$ is the inverse Q-function specifying λ for a target false-alarm probability (PFA), N is the number of samples, and P_s is the signal power employed for detection. Appropriately setting λ via (3) yields the desired false-alarm operating points for subsequent comparisons [7].

2.2. Cooperative Framework for Wideband Sensing

In cooperative wideband sensing, multiple CRs jointly infer the presence of primary activity across the band. By pooling observations, cooperation reduces the risk of incumbent interference and improves the utilization of spectral gaps. The trade-off is increased reporting and fusion complexity as the number of nodes grows. Moreover, operation at low SNR, common in wideband settings, amplifies missed detections and false alarms in AWGN and fading channels, stressing conventional designs [15]. This work considers hard-decision cooperation with local energy detectors and a fusion center.

Assume K CRs sense the primary user channel in a 5G environment under additive white

Gaussian noise (AWGN). The discrete-time sample at CR k is modelled as:

$$y_k(i) = \begin{cases} w_i(n), & H_0 \\ s_i(n) + w_i(n), & H_1 \end{cases} \quad (4)$$

Where $w_k(\cdot)$ is AWGN and $s_k(\cdot)$ is the received PU signal at CR k . Each CR applies energy detection to form the local test statistic E_k , compares E_k to a threshold to produce a one-bit local decision, and forwards this hard decision to the fusion center [7,8].

$$E_k = \sum_{i=1}^N |y_k(i)|^2 \quad (5)$$

2.3. MRC-Aided Pre-Detection Combining

In cooperative spectrum sensing, maximal-ratio combining (MRC) aggregates the measured signal contributions from multiple diversity branches (e.g., antenna/paths per CR), weighting each contribution by its reliability (instantaneous SNR) so that higher-quality observations influence the decision more strongly [10].

In the proposed cooperative design, MRC is applied before energy detection (ED) at each CR. Each CR (or each diversity branch within a CR) observes complex, i.i.d. AWGN:

$$y_l(n) = \begin{cases} w_l(n), & H_0 \\ h_l(n) + w_l(n), & H_1 \end{cases} \quad l = 1, \dots, L, n = 1, \dots, N \quad (6)$$

Where h_l is the complex gain branch l , $s(n)$ is the PU waveform, and $w_l(n) \sim \mathcal{CN}(0, \sigma_n^2)$ are independent across l and n .

Signal-level MRC (pre-ED): The branch signals are coherently combined to form a single stream $z(n) = \sum_{l=1}^L \alpha_l y_l(n)$, $\alpha_l = \frac{(h_l^*)}{\sigma_n^2}$ (α_l : combining weight for each branch l) (7)

which maximizes the instantaneous post-combining SNR.

The per-branch SNR and the post combining SNR are given as:

$$\Upsilon_l = \frac{(|h_l|^2 P_s)}{\sigma_n^2}, \quad \Upsilon_{MRC} = \sum_{l=1}^L \Upsilon_l \quad (8)$$

Energy detection operates on $z(n)$ with the static, E and a CFAR threshold λ .

$$E = \sum_{n=1}^N |z(n)|^2 \quad (9)$$

Under the Gaussian approximation for complex AWGN, the operating probabilities are:

$$PFA_{MRC} = Q\left(\frac{\lambda - N \sigma_n^2}{\sigma_n^2 \sqrt{2N}}\right) \quad (10)$$

$$PD_{MRC} = Q\left(\frac{\lambda - N(\sigma_n^2 + \Upsilon_{MRC})}{(\sigma_n^2 + \Upsilon_{MRC}) \sqrt{2N}}\right) \quad (11)$$

Where $Q(\cdot)$ is the complementary CDF of a standard normal distribution, N is the samples per decision, L is the number of diversity branches per CR, σ_n^2 is the noise variance, P_s is the signal power, and λ is the ED threshold.

2.4. k-out-of-N Decision Fusion

Each cognitive radio (CR) forms a local hard decision aggregated at a fusion center. Under the k-out-of-N rule, the channel is declared occupied if at least k of the K CRs report detection [16]. This strategy improves robustness while keeping reporting and computation simple.

Local hard decision (per CR)

$$u_k = \begin{cases} 1, & E_k \geq \lambda \\ 0, & otherwise \end{cases} \quad (12)$$

Global fusion rule:

$$D = \begin{cases} 1, & \sum_{k=1}^K u_k \geq K \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

Assuming i.i.d local decisions with false-alarm P_{FA} and detection P_D , the global operating points are binomial tails [8,10].

$$P_{FA}^k = \sum_{j=k}^K \binom{K}{j} (P_{FA})^j (1 - P_{FA})^{K-j} \quad (14)$$

$$P_D^k = \sum_{j=k}^K \binom{K}{j} P_D^j (1 - P_D)^{K-j} \quad (15)$$

For the local ED under the Gaussian (CLT) approximation,

$$P_{FA} = Q\left(\frac{\lambda - N\sigma^2}{\sigma^2 \sqrt{2N}}\right), P_D = Q\left(\frac{\lambda - N(\sigma^2 + \Gamma)}{(\sigma^2 + \Gamma)\sqrt{2N}}\right) \quad (16)$$

Where Γ is the effective SNR at the detector input ($\Gamma = \gamma_{MRC}$) for MRC-aided cooperation, or the per-CR SNR in the non-cooperative case), N is the sample count, σ_n^2 is the noise variance, and λ is the detection threshold.

3. PROPOSED METHODOLOGY

3.1. Design Architecture

A wideband primary transmission (3.3–3.5 GHz) is received by K cooperative cognitive radios (CRs). Each CR band-limits and samples the signal, channelizes it into M subbands via a polyphase filter bank / fast Fourier transform (PFB/FFT), and for each subband m , applies maximal-ratio combining (MRC) before detection to raise the effective SNR [7,8,10]. Energy detection followed by constant- false- alarm- rate (CFAR) thresholding at λ_m yields a one-bit decision; these bits form the local vector $d_k = [d_k, 1 \dots d_k, M]$.

The fusion center collects the K local vectors and, on each subband, applies a hard k -out-of- N rule (default $K = 8$, $k=3$) to produce the global decision vector, $D = D_1 \dots D_M$. An optional feedback link can refine λ_m (CFAR adaptation) or acknowledge results. This design strengthens per-CR evidence in low-SNR conditions through MRC, while the k -out-of- N rule balances sensitivity and false alarms at the network level. The reporting overhead is modest M -bits per CR per sensing interval (e.g., $K=8$, $M=5 \rightarrow 40$ bits total), and latency is low because only hard decisions are transmitted. The identical subband processing chain also makes the approach easy to scale to wider bands or additional CRs. The block diagram of the design is shown in figure 1 below:

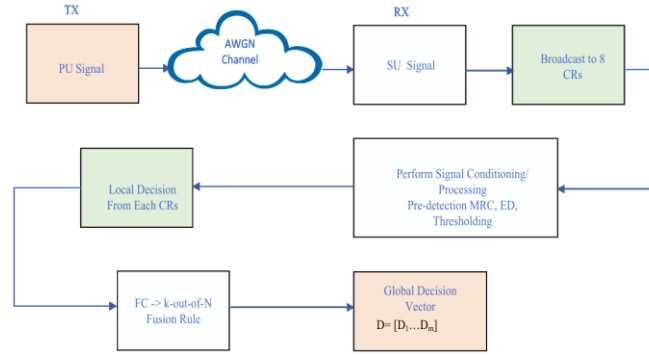


Figure 1: Design Architecture

3.2. System Flow Chart

The flow chart condenses the evaluation into a single loop over SNR. After loading the inputs (number of radios K , SNR range, target/maximum false-alarm level, MRC weights, and noise power) and initializing the state, the procedure iterates across SNR points. At each SNR, a per sub-band CFAR threshold λ baseline is set; the non-cooperative energy-detector P_D is computed; then MRC is applied at each CR/subband to obtain local operating points $(P_{FA}^{MRC}, P_{FA}^{MRC})$.

The fusion center sweeps the k -out-of- K vote threshold, forming global pairs $(P_D, k, P_{FA,k})$, and selects the k that satisfies the false-alarm constraint while maximizing P_D, k . The selected k^* is recorded for that SNR, and the loop advances. Outputs are: (i) the non-cooperative P_D curve versus SNR, (ii) the array of optimal k^* values across SNR (minimum votes required to declare detection), and (iii) the cooperative performance at the chosen operating point, highlighting the gain of MRC + k -of- K over the baseline. The system flow chart is shown in figure 2:

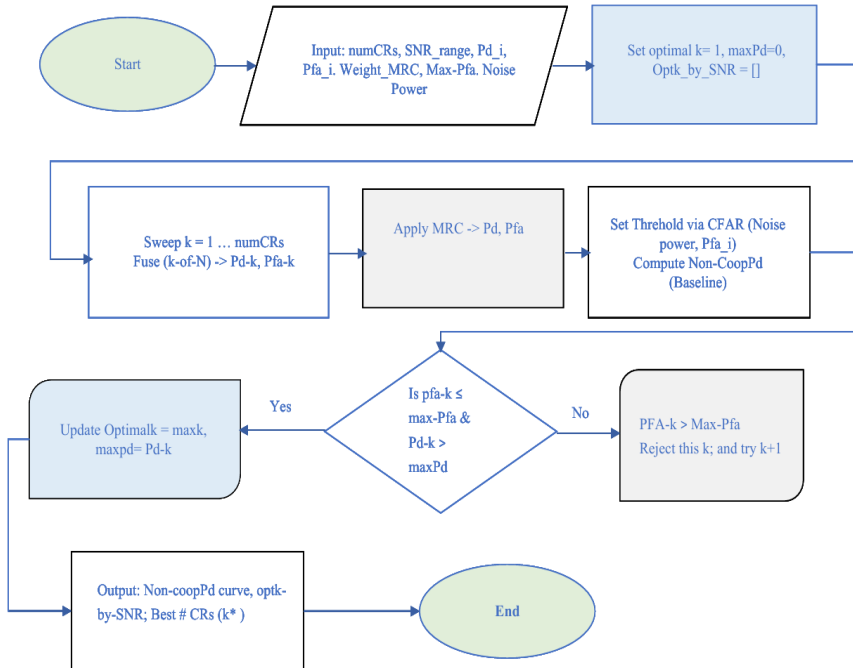


Figure 2: Design Flow Chart

3.3. MRC with k-out-of-N Integrated Fusion Design

This subsection explains how maximal-ratio combining (MRC) is paired with k-out-of-K fusion. At each cognitive radio (CR), the per-branch energies are combined via MRC to form a single local statistic; a binary report is then obtained by thresholding this statistic. The fusion center aggregates the CR reports using the k-out-of-K rule to produce the global decision and operating characteristics.

Local statistic and decision (per CR):

$$E_{mrc} = \sum_{l=1}^L (w_l E_l) \quad (17)$$

$$u_{MRC} = \begin{cases} 1, & \text{if } E_{MRC} > \lambda(\text{detection}) \\ 0, & \text{otherwise} \end{cases} \quad (18)$$

Where L is the number of diversity branches and λ is the CFAR threshold. Let P_{FA}^{MRC} and P_D^{MRC} denote the local false-alarm and detection probabilities after MRC and thresholding.

Fusion at the center using the MRC-based local operating points yield the global probabilities:

$$P_{FA}^{(K-out-of-K, MRC)} = \sum_{j=K}^K \binom{K}{j} (P_{FA}^{MRC})^j (1 - P_{FA}^{MRC})^{K-j} \quad (19)$$

$$P_D^{(K-out-of-K, MRC)} = \sum_{j=K}^K \binom{K}{j} (P_D^{MRC})^j (1 - P_D^{MRC})^{K-j} \quad (20)$$

Replacing raw energy with the MRC-combined statistic strengthens each CR's evidence (effective SNR gain). The k-out-of-K fusion selects how many positive votes are required, enabling a tunable trade-off between sensitivity and false alarms under a specified constraint. Together, these steps improve robustness in low-SNR regimes while preserving a straightforward detection workflow.

4. PERFORMANCE EVALUATION

4.1. Simulation Setup

All experiments were performed in MATLAB to assess ED performance for wideband sensing under complex AWGN. We compared (i) a non-cooperative baseline, (ii) cooperative ED with hard k-out-of-N fusion, and (iii) the proposed MRC-aided ED with k-out-of-N. The network uses K=8 cognitive radios, and the fusion rule is set to k=3 at the fusion center (local nodes only perform ED and thresholding). Detection probability P_D is evaluated as a function of SNR and summarized against the false-alarm probability P_{FA} ; thresholds are chosen via CFAR per subband following [7,8].

4.2. Detection Performance of the Diversity Aided Cooperative Wideband Spectrum Sensing Scheme

Figure 3 shows the probability of detection (P_D) versus the probability of false alarm (P_{FA}) for a representative subband, comparing a non-cooperative energy detector (solid lines) with the proposed cooperative scheme that applies MRC (per-CR diversity LMRC=6) and k-out-of-N

fusion with $K=8$ CRs and $k=3$ (dashed lines). With N = number of samples and SNRs of -25, -20, and -15 dB (red, yellow, green), the cooperative ROCs lie markedly above the non-cooperative curves across the full P_{FA} range. The advantage is most pronounced at low-moderate P_{FA} , where the cooperative detector reaches $P_D \approx 1$ quickly even at -25 dB. At the same time, the non-cooperative baseline requires much higher P_{FA} to approach similar reliability.

Relative to the results in [7.8], where the k -out-of- N rule was used without pre-combining, the integration of MRC provides an effective SNR boost at each CR, mitigates noise uncertainty, and yields consistently higher P_D at all tested SNRs. These plots confirm that MRC-aided cooperative wideband sensing with k -out-of- N fusion delivers a clear and distinct detection improvement over the non-cooperative approach.

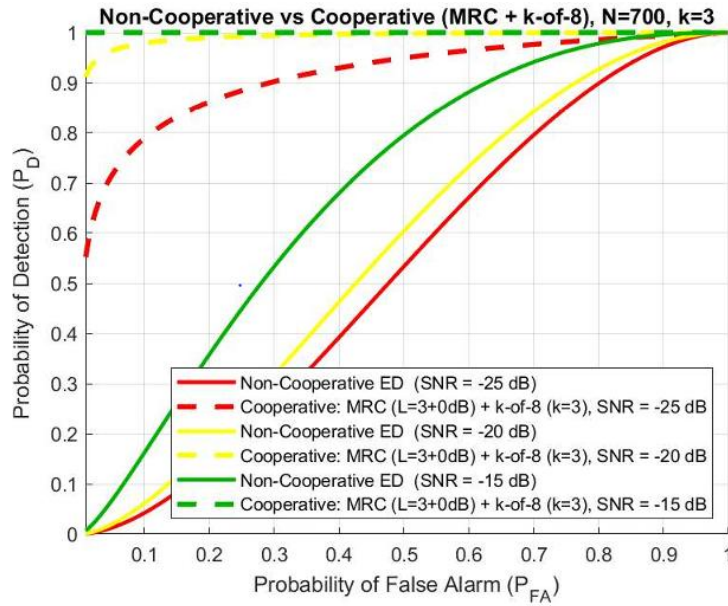


Figure 3: Plot of P_D versus P_{FA} with MRC and k -out-of- N Rule across varying SNR

Figure 4 plots P_D versus SNR (-25 to -5 dB) for $K=8$ CRs comparing the proposed MRC-aided cooperative scheme with $k=3$ (dashed) against a non-cooperative ED baseline (solid) at two operating points, P_{FA} . The cooperative curves dominate across the entire SNR range in both cases; with the separation most pronounced at low SNR. At $P_{FA} = 0.1$, the cooperative detector reaches $P_D = 0.9$ at about -19 dB, whereas the non-cooperative curve achieves this near -9 dB. With $P_{FA} = 0.01$, cooperation attains $P_D = 0.9$ around -17dB, while the baseline requires roughly -7 dB. This reflects an SNR saving of ≈ 10 -15 dB at $P_D = 0.9$. The gains arise from MRC (per-CR diversity boosting effective SNR before detection) combined with k -out-of-8 hard fusion, which mitigates noise uncertainty and yields markedly more reliable wideband sensing for 5G cognitive radio scenarios.

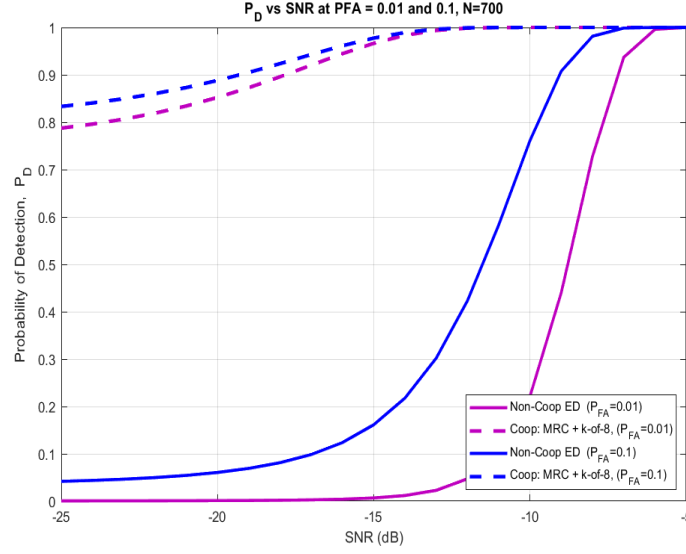


Figure 4: Plot of P_D versus SNR with MRC and k-out-of-N Rule across varying P_{FA}

5. CONCLUSIONS

We presented and validated a cooperative wideband sensing scheme for 5G in which maximal-ratio combining (MRC) is applied at each cognitive radio (CR) before hard k-out-of-N fusion at the fusion center. Under complex AWGN and per-subband CFAR thresholding, the proposed pipeline, evaluated with $K=8$ CRs, $k=3$, and SNRs from -25 to -5 dB, consistently delivers higher detection probability than both the non-cooperative baseline and a cooperative design that relies on fusion alone. ROC and P_D -SNR results show significant gains at stringent false-alarm constraints ($P_{FA}=0.01$) and in noise-limited regimes; at the same P_{FA} , the MRC-aided system reaches near-unit P_D at substantially lower SNR. These improvements stem from MRC's pre-detection SNR boost at each CR combined with a well-chosen k that balances sensitivity and false alarms at the network level, while keeping reporting overhead low (one hard bit per subband).

Compared with prior work where k-out-of-N was applied without pre-combining [7,8], integrating MRC materially reduces the impact of noise uncertainty and strengthens performance across all tested subbands. The architecture is lightweight, hard decisions only, and scales naturally with additional CRs and wider bands.

This present study assumes independent branches for MRC, ideal reporting links, and i.i.d. AWGN channels, which bounds the absolute gains.

In the future, we will (i) extend the channel model to include path loss, log-normal shadowing, and small-scale fading (Rayleigh/Rician/Nakagami-m); (ii) investigate adaptive k-selection, including ML-driven policies; and (iii) prototype the pipeline on a low-cost SDR/FPGA platform to evaluate latency, energy cost, and real-world reliability.

ACKNOWLEDGEMENTS

This research work was supported by the funding from the National Science Foundation (NSF), account number 424300- 00001.

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