

Throughput Maximization with Coverage Bounds for Lifetime-Constrained Multi-Channel Cooperative Spectrum Sensing Scheduling

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Abstract

Cooperative spectrum sensing scheduling has been studied mainly as a lifetime-maximization problem. Many monitoring deployments, however, face the converse requirement: the operating horizon is fixed in advance, and the question is how much spectrum opportunity the network can deliver across many channels while lasting that long. This paper formulates that converse problem, with the binary assignment of secondary users to channels over time as the decision variable, aggregate throughput as the objective, and the required horizon, per-node energy budgets and per-channel detection and false-alarm levels as constraints. Cooperation bounds are derived for a general k -out-of- N fusion rule by a stochastic-dominance argument; they hold for heterogeneous detection quality and reduce to the known OR-rule results at $k = 1$. These bounds yield a guarantee and a converse on the number of channels that can be monitored for the required horizon, together with an exact flow-based certificate of achievability that meets the converse in the studied regime. Simulations show that a time-shared sensing schedule improves throughput by 29.7% (95% confidence interval - CI [28.6%, 30.8%]) over a lifetime-aware static assignment at the design horizon of 9.72 h, in all 200 paired realizations. Because a repaired lifetime-agnostic assignment performs identically to the static one, the gain appears to stem from time sharing rather than from lifetime awareness. The ratio of time-shared to static energy supply predicts the gain to within 4.7% without fitted parameters, and the schedule attains 98.9% of the proved converse on average.

Keywords: Cognitive Radio Networks, Cooperative Spectrum Sensing, Sensing Scheduling, Network Lifetime, Throughput Maximization, Coverage Bounds, k -out-of- N Fusion.

1. Introduction

Scarcity of usable radio spectrum, set against the sustained growth of wireless traffic, continues to motivate dynamic spectrum access. Cognitive radio networks (CRNs) let unlicensed secondary users (SUs) opportunistically transmit on licensed channels when the corresponding primary user (PU) is idle, provided the SUs can detect PU activity reliably enough to avoid harmful interference [1]–[3]. Because a single SU's local observation is unreliable under fading and shadowing, cooperative spectrum sensing (CSS) combines the decisions of several SUs and has become the standard way to meet a detection target [4]–[6].

The large body of CSS research has, for the most part, treated the problem as one of signal detection: the design objective is the cooperative probability of detection Q_d , and the central trade-off is between sensing time and detection accuracy [7], [8], [9]. This framing has produced a mature understanding of the physical layer. It is, however, a poor match for the questions a network operator actually faces when many channels must be monitored at once by a population of battery-limited devices. The operator does not want to maximize a detection probability; the operator wants to know which SUs should sense which channels, how the limited energy budget should be spent, how many channels can be covered at all, and for how long the arrangement can be

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sustained. These are resource-allocation questions of the kind surveyed for energy-constrained cognitive radio sensor networks in [10], whose allocation objectives include energy efficiency, throughput maximization and network lifetime.

This paper treats cooperative spectrum monitoring as a multi-channel network resource-allocation problem. The decision variable is no longer a fusion rule or a sensing threshold but a binary assignment of SUs to channels, and the objective is aggregate network throughput. Detection quality remains essential for protecting primary users, but it moves from the objective to a per-channel service level: on each served channel the cooperative detection probability must reach a required value and the cooperative false-alarm probability must not exceed a tolerated value.

Energy and the required operating horizon enter as hard constraints derived from finite batteries. Closely related work schedules cooperative sensing over time to maximize network lifetime [11], [12]; the problem studied here is the converse, in which the horizon is fixed in advance and multi-channel throughput is maximized.

1.1. Motivation and challenges

Three features distinguish the resource-allocation view from the detection view. First, coverage is constrained by cooperation: each served channel needs a minimum number of cooperating SUs to meet its detection requirement, so the SU population is a shared, finite resource that limits how many channels can be served at once. Second, the horizon is a hard requirement: an SU that depletes its battery before the horizon ends cannot be relied upon in a static assignment, so the requirement filters the usable population. Third, the two effects interact: a longer horizon shrinks the usable population, which reduces the number of channels that can be served. The technical challenge addressed here is to bound this interaction in closed form and to determine which allocation mechanism, if any, converts lifetime awareness into throughput.

Table 1 contrasts the resulting formulation with the detection-centered and the resource-allocation literatures.

Table 1. Positioning of the proposed formulation against the two neighboring literatures. ✓: treated explicitly; ✗: not addressed.

Feature	Traditional CSS	Resource-allocation CRN	The proposed framework
Primary decision variable	Fusion rule / sensing threshold	Power, time, or sub-band split	Binary channel assignment $x_{i,m}$ ✓
Optimization objective	Detection probability Q_d	Rate, energy efficiency, or cost	Network throughput $R(\mathbf{x})$ ✓
Detection constraint	The objective itself	Frequently ignored	Per-channel service-level agreement (SLA) $Q_d^m \geq P_d^{\text{req}}$ ✓
Energy model	Sensing energy only	Transmit power	Battery budget B_i + Heinzelman radio ✓
Network lifetime	✗	Rarely modeled	Hard constraint via T_{req} ✓
Multi-channel support	Single channel (mostly)	✓	M channels with coverage ✓
Sensing schedule over time	Lifetime-maximizing schedules [11], [12]	✗	Throughput-maximizing time-shared schedule under a horizon constraint ✓
Coverage guarantee	✗	✗	Guarantee and converse for static and time-shared allocation (Theorems 1–4) ✓
Theoretical bounds	Sensing–throughput curve	Convergence / equilibrium	k-out-of-N cooperation bounds for arbitrary heterogeneous detection quality ✓
Feasibility analysis	✗	Limited	Explicit $K_w \leq K^{\text{max}}$ test ✓
Optimization problem	Convex (sensing time)	Convex / game-theoretic	NP-hard binary program (Proposition 1) ✓
Complexity analysis	Seldom reported	Sometimes	Derived from the operations, Eq. (18) ✓
Practical deployment	Physical layer	Link / cell layer	Network-layer assignment ✓

1.2. Contributions

The contributions of this work are as follows:

- **The converse scheduling problem.** Prior work on cooperative spectrum sensing scheduling maximizes network lifetime [11], [12]. We formulate the converse: throughput maximization over multiple channels subject to a required operating horizon, per-node energy budgets, and per-channel detection and false-alarm constraints (Section 4), and we show that the problem is NP-hard (Proposition 1).
- **Cooperation bounds for k -out-of- N fusion.** Existing analyses of scheduled and multi-channel cooperative sensing restrict fusion to the OR rule [11]–[14]. We derive worst- and best-case cooperation levels for a general k -out-of- N rule by stochastic dominance, valid for arbitrary heterogeneous detection quality, and show that the rule itself imposes a cooperation floor of k nodes per channel (Lemmas 1–2).
- **Coverage bounds and an optimality certificate.** We bound the number of channels that can be served for the required horizon from below and from above, for static assignment and for time-shared scheduling (Theorems 1–4), and give an exact flow-based test of achievability (Proposition 3). Unlike the statistical sensor-count analysis of [14], these bounds are deterministic and instance-specific, and in the regime studied the certificate shows the converse to be attained.
- **Attribution of the gain.** Against a lifetime-agnostic baseline that is allowed to repair its own allocation, lifetime awareness alone yields no throughput gain; the gain comes from time-shared scheduling, which improves throughput by 29.7% at the design horizon. A parameter-free predictor, the ratio of time-shared to static energy supply, matches the measured gain to within 4.7% (Section 8).

2. Literature Review

2.1. Cooperative spectrum sensing

Cooperation among SUs to improve detection under fading was established early [4], [5] and remains an active

area, with classical fusion methods surveyed in [6], machine-learning-based cooperative sensing surveyed in [15], [16], and distributed, diffusion-based cooperation among neighboring SUs developed in [17]. Optimal hard-decision fusion is described by the Chair–Varshney rule [18], soft linear combining and its optimization were studied by Quan et al. [8], [19]. The fundamental limits of energy detection under noise uncertainty are captured by the signal-to-noise ratio (SNR-wall) analysis of Tandra and Sahai [20], while the energy-detection statistics we use to populate our constraints follow Urkowitz [21] and Digham et al. [22]. These works treat detection performance as the objective; we reuse their detection model only as a constraint generator. Adversarial threats such as primary-user emulation, against which strategic surveillance has been studied [23], are outside the present scope.

2.2. Sensing–Throughput and Energy Trade-offs

The sensing–throughput trade-off of Liang et al. [7] and the cooperative extension of Peh et al. [9] optimize sensing time against detection at the link level. Energy-aware variants consider sensing energy explicitly, often with energy harvesting [24], [25], and multichannel energy-constrained sensing has been optimized through the time split among harvesting, sequential sensing and transmission [25]. These studies optimize a single SU or a single channel and report throughput as an outcome; none formulates simultaneous multi-channel coverage as the resource being allocated, nor do they provide structural coverage bounds.

2.3. Sensing Scheduling for Network Lifetime

A closely related line of work schedules which sensors are active over time so as to extend network lifetime. In wireless sensor networks, Cardei et al. organized sensors into non-disjoint set covers that are activated successively, showed that the resulting maximum set covers problem is NP-complete, and solved it with linear-programming and greedy heuristics [26]. Deng et al. carried this idea to cooperative spectrum sensing: sensors are divided into non-disjoint feasible subsets, each meeting the cooperative detection and false-alarm thresholds, and the subsets are activated in turn to maximize lifetime [11]. That formulation addresses a

single channel, adopts the OR rule, and identifies multi-channel scheduling as future work. Bagheri et al. treated the multi-channel case as a coalition-formation game in which disjoint coalitions, one per channel, are re-formed in each sensing period to maximize the minimum residual energy [12], and in a companion study derived, for randomly deployed sensors, a statistical expression for the minimum number of sensors needed under OR fusion together with the corresponding false-alarm ceiling [14]. Chauhan et al. formulated multi-channel cooperative spectrum sensing scheduling to maximize a throughput-to-energy utility within each time slot, proved it NP-hard, and proposed a greedy heuristic that orders channels by their expected value [13]. Barazande et al. select a low-complexity, energy-efficient subset of sensors for cooperative sensing [27].

The present work adopts time-shared scheduling as its mechanism and differs from these studies in three respects. First, it addresses the converse problem: the operating horizon is fixed as a constraint and multi-channel throughput is maximized, rather than lifetime being maximized or energy minimized per slot. Second, its cooperation bounds hold for a general k -out-of- N rule, whereas [11]–[14] restrict fusion to the OR rule. Third, it bounds the number of channels that can be monitored, deterministically and per instance, and certifies when that bound is attained; the analysis of [14] instead bounds the expected number of sensors under a spatial Poisson model.

2.4. Resource allocation, lifetime, and coverage

Resource allocation in CRNs spans game-theoretic and auction-based methods [28], [29], [30], Quality-of-Service-driven (QoS-driven) cost minimization [31], multicell allocation under varying spectrum availability [32], and, more recently, reconfigurable intelligent surface-assisted energy efficiency [33]. Recent studies have also explored learning-based resource allocation, including deep reinforcement learning and graph-based variants [34], [35], [36]. Our approach is deliberately model-based and uses no learning, so it remains interpretable and carries the provable guarantees that learning-based schemes typically lack. Multi-user channel

selection has also been driven by QoS feedback through a multi-armed bandit formulation [37], the performance of cognitive radio-based wireless mesh networks has been analyzed [38], and multi-objective assignment in CRNs has been formulated directly [39]. At the network layer, dynamic channel selection and transmission scheduling [40], channel aggregation strategies [41], routing [42], and short-packet CR-NOMA [43] address how spectrum opportunities are organized across users and links. Unlike these works, which optimize rate, interference, or connectivity for a given set of links, the proposed framework makes the channel-to-user assignment itself the decision variable and couples it to a lifetime guarantee. Viewed abstractly, the problem is a network utility maximization [44] over a constrained binary assignment, which we show to be NP-hard in Section 4.

Network-lifetime maximization is a long-standing concern, surveyed comprehensively for wireless sensor networks [45] and addressed through energy balancing, clustering, and the assignment of energy supplies [46],

[47]. What is missing from both strands, and from the scheduling studies of Section 2.3, is a closed-form link between a required operating horizon and the channel coverage that cooperative detection permits. This paper supplies that link for static and time-shared allocation; Table 2 summarizes the comparison.

3. System Model

3.1. Network and channels

We consider a CRN with a set $\mathcal{N} = \{1, \dots, N\}$ of battery-powered SUs and a fusion center (FC). The network must monitor a set $\mathcal{M} = \{1, \dots, M\}$ of licensed channels. Channel m is idle with probability $\pi_0^m = \Pr\{H_0^m\}$ and, when idle, offers a rate of C_m bit/s. Sensing is periodic with period T_s , of which τ seconds are used for sensing. The SUs are allocatable resources and the channels are service demands; the network decision is which resources serve which demands. Figure 1 illustrates the resulting framework: channel assignments are chosen to maximize network throughput subject to detection, false-alarm, energy and horizon constraints, whereas traditional CSS designs maximize detection performance.

Table 2. Qualitative comparison of the proposed framework with the closest recent studies on multi-channel cooperative sensing and energy- or lifetime-aware resource allocation. MC: multi-channel support; CSS: cooperative spectrum sensing; RA: resource allocation; NLA: network-lifetime awareness; EC: energy constraints; TO: throughput optimization; FC: fair consideration; TA: theoretical analysis; FG: feasibility/coverage guarantee. ✓ full; (✓) partial; ✗ absent.

Reference	MC	CSS	RA	NLA	EC	TO	FC	TA	FG	Optimization type	Main limitation
Deng <i>et al.</i> (2012) [11]	✗	✓	(✓)	✓	✓	✗	✗	✓	(✓)	Scheduling of non-disjoint feasible subsets	Single channel; OR fusion; lifetime is the objective
Bagheri <i>et al.</i> (2020) [12]	✓	✓	✓	✓	✓	✗	(✓)	(✓)	✗	Coalition-formation game (max-min energy)	OR fusion; no throughput objective or coverage bound
Bagheri & Ebrahimzadeh (2021) [14]	✓	✓	✗	✓	✓	✗	✗	✓	(✓)	Statistical lifetime analysis	OR fusion; average-case bound on sensor count
Chauhan <i>et al.</i> (2021) [13]	✓	✓	✓	✗	(✓)	✓	✗	(✓)	✗	Per-slot utility maximization; greedy	OR fusion; no horizon constraint or coverage bound
Gupta & Kumar (2022) [29]	(✓)	✗	✓	✗	(✓)	(✓)	(✓)	(✓)	✗	Auction / Stackelberg game	Market-based selection; no lifetime or coverage analysis
Zhu <i>et al.</i> (2022) [40]	✓	(✓)	(✓)	(✓)	✓	✓	✗	(✓)	✗	Convex time allocation	Time-allocation focus; no decision variable or coverage bound
Wang <i>et al.</i> (2023) [30]	(✓)	✓	(✓)	(✓)	✓	✓	✗	(✓)	✗	Convex time/power allocation	Energy-harvesting specific; no assignment or lifetime bound
Jawad & Derakhshan Fard (2025) [39]	(✓)	✗	✓	✗	(✓)	(✓)	✗	(✓)	✗	Multi-objective assignment	No lifetime constraint or coverage bound
Shang <i>et al.</i> (2026) [33]	(✓)	✗	✓	✗	(✓)	✓	✓	(✓)	✗	Intelligent reflecting surface (IRS) -assisted optimization	Surface-assisted energy efficiency (EE); no lifetime or coverage guarantee
Proposed Framework	✓	✓	✓	✓	✓	✓	(✓)	✓	✓	NP-hard binary program (Proposition 1) + Greedy-R-Rot	Simulation-only evidence; static channel statistics

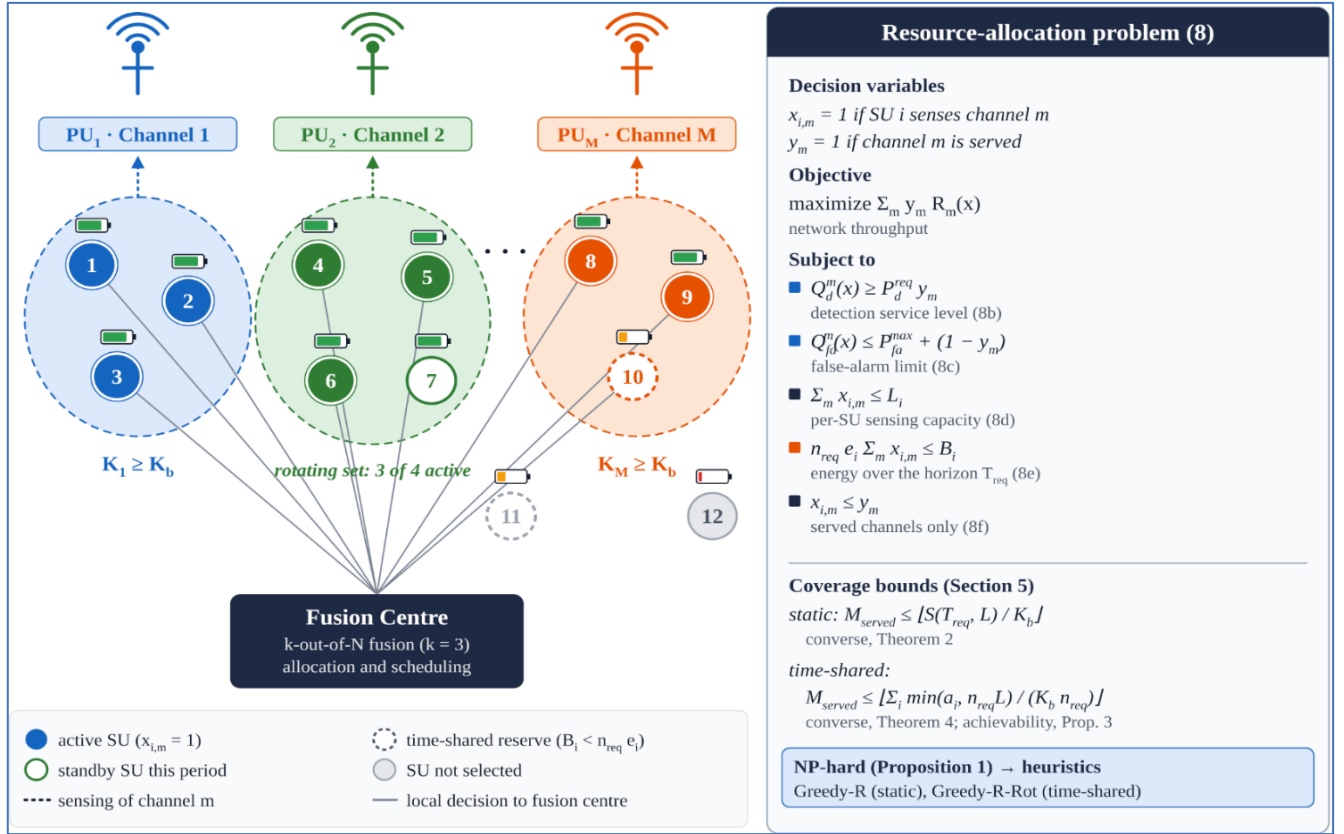


Figure 1. System architecture and optimization framework of the proposed scheme.

3.2. Physical layer as a constraint tool

Each SU performs energy detection over $N_s = \tau f_s$ samples, where f_s is the effective sensing bandwidth. For a common local false-alarm target $\bar{\alpha}$, the individual detection probability of SU i on channel m with received SNR $\gamma_{i,m}$ is the standard expression [7]:

$$P_{d,i}^m = Q\left(\frac{Q^{-1}(\bar{\alpha}) - \sqrt{N_s} \gamma_{i,m}}{\sqrt{2\gamma_{i,m} + 1}}\right), P_{fa,i}^m = \bar{\alpha} \quad (1)$$

where $Q(\cdot)$ is the Gaussian tail function. Expression (1) relies on the central-limit approximation of the

energy statistic, which is accurate for the sample counts used here ($N_s = 15\,000$ in Section 7).

The detection model is heterogeneous in (i, m) through $\gamma_{i,m}$, which absorbs distance, shadowing and fading; no homogeneity is assumed. Its only role in this paper is to supply the detection probabilities used in the service-level constraints introduced below.

3.3. Assignment variable and cooperative fusion

The network decision is the binary assignment

$$x_{i,m} = \begin{cases} 1, & \text{if } SU_i \text{ is assigned to } m, \\ 0, & \text{otherwise,} \end{cases} \quad (2)$$

$$\mathbf{x} \in \{0,1\}^{N \times M}$$

Let $\mathcal{K}_m(\mathbf{x}) = \{i: x_{i,m} = 1\}$ be the cooperating set on channel m and $K_m = |\mathcal{K}_m|$. Each node reports a hard decision, and the fusion center declares the channel busy when at least k of the K_m reports are positive (the k -out-of- N rule; $k = 1$ is the OR rule). Local decisions are assumed conditionally independent given the channel state. The cooperative detection and false-alarm probabilities are then

$$Q_d^m(\mathbf{x}) = \Pr\left[\sum_{i \in \mathcal{K}_m} D_i \geq k\right] \quad (3)$$

$$Q_{fa}^m(\mathbf{x}) = \sum_{j=k}^{K_m} \binom{K_m}{j} \bar{\alpha}^j (1 - \bar{\alpha})^{K_m-j} \quad (4)$$

where $D_i \sim \text{Bern}(P_{d,i}^m)$ independent,

Eq. (3) is the upper tail of a Poisson-binomial distribution and is evaluated exactly by convolving the K_m Bernoulli distributions; (4) is a binomial tail. The same rule, with $k = 3$, is used in the analysis of Section 5 and in every simulation of Section 8, so all bounds apply directly to the reported experiments.

3.4. Energy, battery, and lifetime

Following the Heinzelman radio model [46], one sensing-and-reporting operation costs SU i

$$e_i = P_s \tau + E_{\text{elec}} b + \varepsilon_{\text{amp}} b d_{i,FC}^\kappa, \quad (5)$$

where P_s is the sensing power, τ the sensing time, b the size of a report in bits, $d_{i,FC}$ the distance from node i to the fusion center, and κ the path-loss exponent. A report carries the hard decision inside a medium access control (MAC) frame with framing and addressing overhead, so we take $b = 500$ bit rather than the single decision bit; with a one-bit report the two reporting terms would be below 0.1% of the sensing term and the deployment geometry would have no effect on any reported quantity. Sensing is periodic with period T_s rather than continuous, so a required horizon T_{req} corresponds to $n_{\text{req}} = \lceil T_{\text{req}}/T_s \rceil$ sensing operations on each assigned channel. Node i holds a total energy budget B_i for the sensing task; the energy spent on secondary data transmission is outside the model. Under a static assignment node i performs one operation per period on each of its $\ell_i = \sum_m x_{i,m}$ channels, so the network lifetime is

$$T_{\text{life}}(\mathbf{x}) = T_s \min_{i: \ell_i > 0} \left\lfloor \frac{B_i}{\ell_i e_i} \right\rfloor, \quad (6)$$

and $T_{\text{life}}(\mathbf{x}) \geq T_{\text{req}}$ holds if and only if $n_{\text{req}} \ell_i e_i \leq B_i$ for every active node.

3.5. Network utility

A served channel yields the sensing-throughput reward of [7] per unit time,

$$R_m(\mathbf{x}) = \left(1 - \frac{\tau}{T_s}\right) \pi_0^m (1 - Q_{fa}^m(\mathbf{x})) C_m, \quad (7)$$

$$R(\mathbf{x}, \mathbf{y}) = \sum_{m=1}^M y_m R_m(\mathbf{x})$$

where π_0^m is the probability that channel m is idle, C_m its rate in bit/s when the primary user is idle, and $y_m \in \{0,1\}$ indicates that channel m is served (Section 4). R is therefore an expected transmission opportunity: the rate available when a channel is idle and correctly declared idle, net of the sensing overhead τ/T_s . It does not deduct collision losses after a missed detection or link-level transmission failures. Fairness of the sensing load ℓ_i is measured by Jain's index $\mathcal{F} = (\sum_i \ell_i)^2 / (N \sum_i \ell_i^2)$, which is reported as an outcome in Section 8 rather than imposed as a constraint, for the reason given in Section 4.

4. Problem Formulation

The proposed framework problem maximizes network throughput subject to per-channel service-level constraints and per-node capacity, energy and horizon constraints. A binary indicator y_m marks the channels that are served; a channel whose constraints cannot be met is left unserved and contributes no throughput:

$$\max_{\mathbf{x} \in \{0,1\}^{N \times M}, \mathbf{y} \in \{0,1\}^M} \sum_{m=1}^M y_m R_m(\mathbf{x}) \quad (8a)$$

$$s. t. Q_d^m(\mathbf{x}) \geq P_d^{\text{req}} y_m, \forall m, \quad (8b)$$

$$Q_{fa}^m(\mathbf{x}) \leq P_{fa}^{\text{max}} + (1 - y_m), \forall m \quad (8c)$$

$$\sum_m x_{i,m} \leq L_i, \forall i, \quad (8d)$$

$$n_{\text{req}} e_i \sum_m x_{i,m} \leq B_i, \forall i, \quad (8e)$$

$$x_{i,m} \leq y_m, \forall i, m. \quad (8f)$$

Constraints (8b)–(8c) are the detection and false-alarm service levels of served channels, (8d) is the per-node sensing capacity, and (8e) is the energy budget over the horizon, which is the operational form of $T_{life}(\mathbf{x}) \geq T_{req}$ by (6). Constraint (8f) prevents nodes from being assigned to unserved channels. The detection probability appears only in the constraints, never in the objective. We take $L_i = L$ for all nodes in Sections 5–8.

Two requirements are deliberately absent. We do not require every channel to be covered: when energy or detection quality is insufficient, (8) serves the subset of channels that maximizes throughput. Nor do we impose a fairness floor. Nodes that cannot sustain the horizon carry zero load, so by the Cauchy–Schwarz inequality Jain’s index over all N nodes is at most $|\mathcal{A}(T_{req})|/N$ however evenly the eligible nodes are used; a fixed floor therefore makes (8) infeasible as soon as it exceeds this ratio, which happens at long horizons. Fairness is therefore reported as an outcome. Formulation (8) describes a static assignment. Its time-shared counterpart, in which the assignment may change from one sensing period to the next subject to (8b)–(8d) in every period and to the energy budget over the whole horizon, is analyzed in Section 5.3 and solved in Section 6.

Proposition 1 (Complexity). Problem (8) is NP-hard, even when the energy and lifetime constraints are not binding and every node may serve at most one channel.

Proof: We reduce from Exact Cover by 3-Sets (X3C), which is NP-complete [48]: given a set X with $|X| = 3q$ and a collection C of three-element subsets of X , decide whether C contains q pairwise disjoint subsets whose union is X . Given an instance, create one node for each element of X and one channel for each subset in C , all with the same reward R . Let $k = 3$, $L_i = 1$ for every node, and choose the batteries so that (8e) is never binding. Set $P_{d,i}^m = 0.99$ if element i belongs to subset m and $P_{d,i}^m = 0.5$ otherwise, and let $P_d^{req} = 0.9$, $\bar{\alpha} = 0.1$ and $P_{fa}^{max} = 0.002$. Since $\Pr[\text{Bin}(3,0.1) \geq 3] = 0.001 \leq 0.002 < \Pr[\text{Bin}(4,0.1) \geq 3] = 0.0037$, the false-alarm constraint (8c) admits at most three nodes on a served channel, and the 3-out-of- N rule requires at least three, so every served channel has exactly three nodes. The three nodes of its own subset give $Q_d^m = 0.99^3 = 0.970 \geq 0.9$, whereas any coalition containing a node outside the subset gives $Q_d^m \leq 0.99^2 \times 0.5 = 0.49 < 0.9$. A channel is therefore served if

and only if it receives exactly the three nodes of its subset, and because $L_i = 1$ the served subsets are pairwise disjoint. Hence a throughput of qR is attainable if and only if C contains an exact cover. The construction is polynomial in $|X| + |C|$, so (8) is NP-hard unless $P = NP$. With $n_{req} = 1$ a time-shared schedule reduces to a static assignment, so the hardness extends to the sensing-scheduling problem of Section 6.

Proposition 1 justifies a polynomial-time heuristic rather than exact optimization, which we develop in Section 6 after establishing the structural bounds.

5. Theoretical Analysis

This section derives what the network can guarantee before any allocation algorithm is chosen. Section 5.1 bounds the size of the coalition that a channel needs under the k -out-of- N rule. Section 5.2 converts these cooperation bounds into a guarantee and a converse on the number of channels that a static assignment can serve for the required horizon, and Section 5.3 does the same for a time-shared sensing schedule and gives an exact test of achievability. Sensing is periodic with period T_s , so a required horizon T_{req} corresponds to $n_{req} = \lceil T_{req}/T_s \rceil$ sensing operations on every assigned channel, each costing e_i joules at node i by (5). Every node has the same per-period sensing capacity L . Under a static assignment node i must sustain all of its channels for the whole horizon, so it can serve at most c_i channels, where:

$$c_i = \left\lfloor \frac{B_i}{n_{req} e_i} \right\rfloor, \quad \mathcal{A}(T_{req}) = \{i: c_i \geq 1\}, \quad (9)$$

and the number of usable slots is

$$S(T_{req}, L) = \sum_{i \in \mathcal{A}(T_{req})} \min\{L, c_i\}. \quad (10)$$

Under time-shared scheduling node i may instead spend its battery on any sensing periods. Its total supply is $a_i = \lfloor B_i/e_i \rfloor$ sensing operations, of which at most L fall in any one period. Throughout, $p_{\min} = \min_i \min_m P_{d,i}^m$ is taken over all N nodes, and $\Phi_k(K, p) = \Pr[\text{Bin}(K, p) \geq k]$.

5.1. Per-channel cooperation bounds

Lemma 1 (Worst-case cooperation level). Under the k -out-of- N rule, any coalition of K distinct nodes satisfy $Q_d^m \geq P_d^{req}$ on every channel m provided

$$K \geq K_w \triangleq \min\{K \geq k: \Phi_k(K, p_{\min}) \geq P_d^{req}\} \quad (11)$$

Proof: Represent each local decision as $D_i = \mathbf{1}\{U_i \leq P_{d,i}^m\}$ with independent $U_i \sim \mathcal{U}(0,1)$. Since $P_{d,i}^m \geq p_{\min}$, $D_i \geq \mathbf{1}\{U_i \leq p_{\min}\}$ in every realization, so the count $\sum_i D_i$ dominates a $\text{Bin}(K, p_{\min})$ variable path by path. The event $\{\sum_i D_i \geq k\}$ is monotone, hence $Q_d^m \geq \Phi_k(K, p_{\min})$, and $\Phi_k(K, p)$ is non-decreasing in K . The argument places no restriction on how the detection probabilities differ across nodes and channels. With $k = 1$, $\Phi_1(K, p) = 1 - (1 - p)^K$ and (11) reduces to the OR-rule bound $\lceil \ln(1 - P_d^{req}) / \ln(1 - p_{\min}) \rceil$.

Lemma 2 (Best-case cooperation level). Let $p_{(1)}^m \geq p_{(2)}^m \geq \dots$ be the detection probabilities of the N nodes on channel m , sorted for that channel. No coalition with fewer than

$$K_b^m \triangleq \min \left\{ K \geq k: \Pr \left[\sum_{j=1}^K \text{Bern}(p_{(j)}^m) \geq k \right] \geq P_d^{req} \right\} \quad (12)$$

nodes can meet the detection constraint on channel m . In particular $K_b^m \geq k$ for every channel, whatever the SNR distribution. We write $K_b = \min_m K_b^m$.

Proof: Q_d^m is non-decreasing in each $P_{d,i}^m$, so among coalitions of a given size it is largest for the K strongest detectors on that channel; if these fail, every coalition of that size fails. A k -out-of- N decision needs k positive reports and therefore at least k nodes.

Proposition 2 (False-alarm ceiling). The false-alarm constraint (8c) holds on a channel served by K nodes if and only if

$$K \leq K^{\max} \triangleq \max\{K: \Phi_k(K, \bar{\alpha}) \leq P_{fa}^{\max}\} \quad (13)$$

A channel can therefore be served only if $K_b^m \leq K^{\max}$. Under the OR rule this ceiling also appears in [14]; (13) extends it to the k -out-of- N rule.

Proof: Under H_0 the local decisions are independent Bernoulli variables with parameter $\bar{\alpha}$, so $Q_{fa}^m = \Phi_k(K, \bar{\alpha})$, which is increasing in K .

The fusion rule matters for coverage through (13). Under the OR rule $\Phi_1(K, \bar{\alpha}) = 1 - (1 - \bar{\alpha})^K$ grows almost linearly in K and caps the coalition size severely, whereas for $k > 1$ the false-alarm tail is of order $\bar{\alpha}^k$, so a larger k admits larger coalitions.

5.2. Coverage under static assignment

Theorem 1 (Coverage guarantee, static assignment). Assume $K_w \leq K^{\max}$. A static assignment can serve, with every constraint of (8) met for the horizon T_{req} , can serve at least the following number of channels:

$$M_{served}(T_{req}, L) \geq \max \left\{ M' \leq M: M'K_w \leq \sum_{i \in \mathcal{A}(T_{req})} \min\{L, c_i, M'\} \right\} \quad (14)$$

Proof: Fix M' satisfying the condition and let $b_i = \min\{L, c_i, M'\}$. Consider the network with a source, one vertex per node, one vertex per channel and a sink, with capacity b_i from the source to node i , capacity 1 from every node to every one of the M' channels, and capacity K_w from every channel to the sink. The fractional flow that sends $b_i/M' \leq 1$ from node i to each channel delivers $\sum_i b_i/M' \geq K_w$ to every channel, so the maximum flow equals $M'K_w$. By the integrality theorem for network flows, an integral flow of the same value exists: an assignment in which every channel receives exactly K_w distinct nodes and node i serves at most b_i channels. Constraints (8d) and (8e) hold because $b_i \leq L$ and $b_i \leq c_i$, detection holds on every channel by Lemma 1, and false alarm holds by Proposition 2 since $K_w \leq K^{\max}$.

The term M' inside the minimum is essential. A node contributes at most one slot to each channel, because $x_{i,m} \in \{0,1\}$ and the fusion rule assumes distinct reports. Dividing the pooled slot count $S(T_{req}, L)$ by K_w ignores this and can overstate the guarantee, as Example 1 shows; the two forms agree whenever the guarantee is at least L .

Theorem 2 (Converse, static assignment). Any feasible static assignment satisfies

$$M_{served}(T_{req}, L) \leq \left\lfloor \frac{S(T_{req}, L)}{K_b} \right\rfloor \quad (15)$$

Proof: By Lemma 2 every served channel needs at least K_b assigned nodes. Node i can hold at most $\min\{L, c_i\}$ assignments without violating (8d)–(8e), and nodes outside $\mathcal{A}(T_{req})$ hold none. Summing over served channels gives $K_b M_{served} \leq S(T_{req}, L)$.

Because $K_w \geq K_b$ and $\sum_i \min\{L, c_i, M'\} \leq S(T_{req}, L)$, the guarantee (14) never exceeds the converse (15).

Example 1. Let $k = 2$, $p_{\min} = 0.8$ and $P_d^{req} = 0.9$. Then $\Phi_2(3, 0.8) = 0.896$ and $\Phi_2(4, 0.8) = 0.973$, so $K_w = 4$. With $\bar{\alpha} = 0.1$ and $P_{fa}^{\max} = 0.1$, $\Phi_2(5, 0.1) = 0.081$ and $\Phi_2(6, 0.1) = 0.114$, so $K^{\max} = 5$ and the premise of Theorem 1 holds. Let four nodes have $L = 3$ and $c = (3, 3, 3, 1)$, so $S = 10$. Dividing the slot count gives $\lceil 10/4 \rceil = 2$ channels, but a second channel would need four distinct nodes and node 4 is exhausted by the first. Bound (14) gives the correct value: $M' = 1$ satisfies $4 \leq 4$, whereas $M' = 2$ fails because $2 + 2 + 2 + 1 = 7 < 8$. If the best detection probability on every channel is 0.95, then $K_b = 2$ since $0.95^2 = 0.9025$, and (15) gives at most $\lceil 10/2 \rceil = 5$ channels. Hence $1 \leq M_{served} \leq 5$.

Corollary 1 (Monotonicity). The bounds (14) – (17) are non-increasing in T_{req} .

Proof: n_{req} is non-decreasing in T_{req} , so every c_i and every a_i/n_{req} is non-increasing and $\mathcal{A}(T_{req})$ can only shrink, while K_w , K_b and $K^{\max}$ do not depend on T_{req} .

5.3. Coverage under time-shared sensing scheduling

A static assignment requires every assigned node to sustain its channels for the whole horizon unaided, so a node with $B_i < n_{req} e_i$ contributes nothing however much energy it holds. Under time-shared sensing scheduling, a channel is served in each sensing period by a coalition

drawn from a larger scheduled set, and node i may spend its a_i operations on any periods, at most L per period and at most one per channel per period. The detection and false-alarm constraints must hold in every period.

Theorem 3 (Coverage guarantee, time-shared scheduling). Assume $K_w \leq K^{\max}$. A time-shared schedule that meets the detection, false-alarm, capacity and energy constraints in every one of the n_{req} sensing periods can serve at least the following number of channels:

$$M_{served} \geq \max\{M' \leq M: M' K_w \leq \sum_{i=1}^N \min\left\{\frac{a_i}{n_{req}}, L, M'\right\}\} \quad (16)$$

Proof: Fix M' satisfying the condition. Consider the time-expanded network with a source, one vertex per node i , one vertex per node-period pair (i, t) , one vertex per channel-period pair (m, t) , and a sink. Arcs carry capacity $\min\{a_i, n_{req} L\}$ from the source to node i , capacity L from i to each (i, t) , capacity 1 from (i, t) to each (m, t) , and capacity K_w from each (m, t) to the sink. Let $b_i = n_{req} \min\{a_i/n_{req}, L, M'\}$ and send $b_i/(n_{req} M') \leq 1$ on every arc $(i, t) \rightarrow (m, t)$. Node i then carries $b_i/n_{req} \leq L$ in each period and $b_i \leq \min\{a_i, n_{req} L\}$ in total, and each (m, t) receives $\sum_i b_i/(n_{req} M') \geq K_w$. The maximum flow therefore equals $K_w n_{req} M'$, and by integrality an integral flow of this value exists. It assigns exactly K_w distinct nodes to every channel in every period and respects the per-period capacity and the battery of every node; by Lemma 1 and Proposition 2 it meets both detection and false-alarm constraints in every period.

Theorem 4 (Converse, time-shared scheduling). Any time-shared schedule that meets the detection constraint in every period satisfies

$$M_{served} \leq \left\lfloor \frac{\sum_{i=1}^N \min\{a_i, n_{req} L\}}{K_b n_{req}} \right\rfloor. \quad (17)$$

Proof: By Lemma 2 each served channel uses at least K_b node-operations in each of the n_{req} periods, and node i can supply at most $\min\{a_i, n_{req} L\}$ operations over the horizon.

Proposition 3 (Achievability certificate). Fix a coalition size K with $k \leq K \leq K^{\max}$, let $\theta(K) = \min\{p: \Phi_k(K, p) \geq P_d^{\text{req}}\}$, and call node i admissible on channel m if $P_{d,i}^m \geq \theta(K)$. A time-shared schedule in which each of a given set of M' channels is served in every period by K distinct admissible nodes exists if and only if the maximum flow in the following network equals $Kn_{\text{req}}M'$: source to node i with capacity $\min\{a_i, n_{\text{req}}L\}$, node i to each channel on which it is admissible with capacity n_{req} , and channel to sink with capacity Kn_{req} .

Proof: Necessity follows by summing a feasible schedule over the periods. For sufficiency, take an integral maximum flow $f_{i,m}$ and divide it evenly over the periods, placing $f_{i,m}/n_{\text{req}} \leq 1$ on each arc $(i, t) \rightarrow (m, t)$ of the time-expanded network of Theorem 3, restricted to admissible pairs and with sink capacity K . This fractional flow respects every capacity and has value $Kn_{\text{req}}M'$, so an integral flow of the same value exists. It gives every channel exactly K distinct admissible nodes in every period, and Lemma 1 with $p_{\min}$ replaced by $\theta(K)$ yields $Q_d^m \geq P_d^{\text{req}}$.

When the certificate holds with M' equal to the converse (17), the optimal coverage under time-shared scheduling is determined exactly rather than bracketed. Section 8 reports that this is the case in every instance tested at the design horizon.

6. Proposed Greedy-R Algorithm

Since (8) is NP-hard (Proposition 1), we use polynomial-time heuristics. Algorithm 1, Greedy-R, is the static allocator and serves as the reference policy. Algorithm 2, Greedy-R-Rot, is the time-shared sensing-scheduling heuristic evaluated in Section 8. Both process channels in decreasing order of expected reward $\pi_0^m C_m$, as in the channel ordering of [13], and both leave a channel unserved ($y_m = 0$) when its constraints cannot be met.

Algorithm 1 is lifetime-aware through the eligibility test of line 4: a node is admitted to a channel only if it can sustain its resulting load for the whole horizon, so every assignment it returns satisfies (8b)–(8f). Channels are scanned in decreasing reward, so that when energy runs short the channels left unserved are those that contribute least.

Algorithm 1: Greedy-R (static assignment, reference policy)

Input: $\{P_{d,i}^m\}, \{e_i, B_i\}, L, T_{\text{req}}, T_s, P_d^{\text{req}}, P_{fa}^{\max}, \bar{\alpha}, k$

Output: assignment $\mathbf{x}$, served set $\mathcal{S}$, throughput R

1. $n_{\text{req}} \leftarrow \lceil T_{\text{req}}/T_s \rceil$; $K^{\max}$ by (13); $\mathbf{x} \leftarrow \mathbf{0}$; $\ell_i \leftarrow 0 \forall i$; $\mathcal{S} \leftarrow \emptyset$
 2. sort channels by $\pi_0^m C_m$ in decreasing order (ties: smaller m first)
 3. **for** each channel m in this order **do**
 4. $\mathcal{C} \leftarrow \{i: \ell_i < L, n_{\text{req}}(\ell_i + 1)e_i \leq B_i\}$ (eligible nodes)
 5. sort $\mathcal{C}$ by $P_{d,i}^m$ in decreasing order (ties: larger B_i/e_i , then smaller i)
 6. $\mathcal{K} \leftarrow \emptyset$
 7. **for** each $i \in \mathcal{C}$ in this order **do**
 8. $\mathcal{K} \leftarrow \mathcal{K} \cup \{i\}$; update the distribution of the number of detections by one convolution
 9. **if** $|\mathcal{K}| > K^{\max}$ **then** stop scanning $\mathcal{C}$
 10. **if** $|\mathcal{K}| \geq k$ **and** $Q_d^m(\mathcal{K}) \geq P_d^{\text{req}}$ **then**
 11. $x_{i,m} \leftarrow 1, \ell_i \leftarrow \ell_i + 1$ for all $i \in \mathcal{K}$; $\mathcal{S} \leftarrow \mathcal{S} \cup \{m\}$; stop scanning $\mathcal{C}$
 12. **if** $m \notin \mathcal{S}$ **then** leave m unserved ($y_m = 0$)
 13. $R \leftarrow \sum_{m \in \mathcal{S}} R_m$ by (7); **return** $\mathbf{x}, \mathcal{S}, R$
-

In Algorithm 2 every member of a scheduled set passes the admission test of line 10. By Lemma 1 with $p_{\min}$ replaced by $\theta(K_m)$, any K_m of its members meet the detection constraint, and $K_m \leq K^{\max}$ ensures the false-alarm constraint by Proposition 2, so both constraints hold in all sensing period whichever members are active. A period-by-period schedule realizing the counts $u_{i,m}$ exists: on each channel $u_{i,m} \leq n_{\text{req}}$ and $\sum_i u_{i,m} = K_m n_{\text{req}}$, each node's total load is at most $n_{\text{req}}L$ by line 11, and the integrality argument in the proof of Proposition 3, with K replaced by K_m on channel m , yields an integral schedule with exactly K_m distinct nodes on channel m in every period and at most L channels per node per period.

Complexity. Sorting the channels costs $O(M \log M)$ and sorting the nodes for every channel $O(MN \log N)$. The distribution of the number of detections is updated by one convolution per added node rather than recomputed, so building a coalition cost $O((K^{\max})^2)$ per channel, and the thresholds $\theta(K)$ are computed once by bisection to tolerance ε .

Algorithm 2: Greedy-R-Rot (time-shared sensing scheduling)

Input: as Algorithm 1

Output: scheduled sets $\mathcal{A}_m$ with operation counts $u_{i,m}$, coalition sizes K_m , served set $\mathcal{S}$, throughput R

1. $n_{req} \leftarrow \lceil T_{req}/T_s \rceil$; $K^{\max}$ by (13); $a_i \leftarrow \lfloor B_i/e_i \rfloor$, $\phi_i \leftarrow 0 \forall i$; $\mathcal{S} \leftarrow \emptyset$
 2. compute $\theta(K)$ for $K = k, \dots, K^{\max}$ by bisection on p
 3. sort channels by $\pi_0^m C_m$ in decreasing order (ties as in Algorithm 1)
 4. **for** each channel m in this order **do**
 5. sort all nodes by $P_{d,i}^m$ in decreasing order, giving the order π
 6. $K_m \leftarrow$ smallest $K \in [k, K^{\max}]$ with $\Pr[\sum_{j \leq K} \text{Bern}(P_{d,\pi(j)}^m) \geq k] \geq P_d^{req}$
 7. **if** no such K exists
 8. **then** leave m unserved; **continue**
 9. $D \leftarrow K_m n_{req}$; $G \leftarrow 0$; $\mathcal{A}_m \leftarrow \emptyset$
 10. **for** each node i in the order π **do**
 11. **if** $P_{d,i}^m < \theta(K_m)$ **then** stop scanning (admission test)
 12. $u \leftarrow \min\{a_i, \lfloor n_{req}(L - \phi_i) \rfloor, n_{req}, D - G\}$
 13. **if** $u > 0$ **then** $\mathcal{A}_m \leftarrow \mathcal{A}_m \cup \{i\}$, $u_{i,m} \leftarrow u$, $G \leftarrow G + u$
 14. **if** $G = D$ **then** stop scanning
 15. **if** $G < D$ **then** leave m unserved; **continue**
 16. **for** each $i \in \mathcal{A}_m$: $a_i \leftarrow a_i - u_{i,m}$, $\phi_i \leftarrow \phi_i + u_{i,m}/n_{req}$
 17. $\mathcal{S} \leftarrow \mathcal{S} \cup \{m\}$; R_m by (7) with K_m nodes per period
 18. $R \leftarrow \sum_{m \in \mathcal{S}} R_m$; **return** $\{\mathcal{A}_m, u_{i,m}, K_m\}, \mathcal{S}, R$
-

The total running time of either algorithm is

$$T(N, M) = O(M \log M + MN \log N + M(K^{\max})^2 + K^{\max} \log(1/\epsilon)), \quad (18)$$

which reduces to $O(MN \log N)$ whenever $(K^{\max})^2 = O(N \log N)$, as in the regime of Section 7 where $K^{\max} = 11$. Memory is $O(NM)$ for the detection table and the assignment. Time sharing therefore adds no asymptotic cost. Neither algorithm carries a proved approximation ratio; Section 8 instead measures Greedy-R-Rot against

the converse (17), which bounds the coverage of every policy.

7. Simulation Setup

The network is simulated in MATLAB R2024a without specialized toolboxes, except that the Wilcoxon test uses the Statistics and Machine Learning Toolbox; Figure 2 shows one realization of the topology.

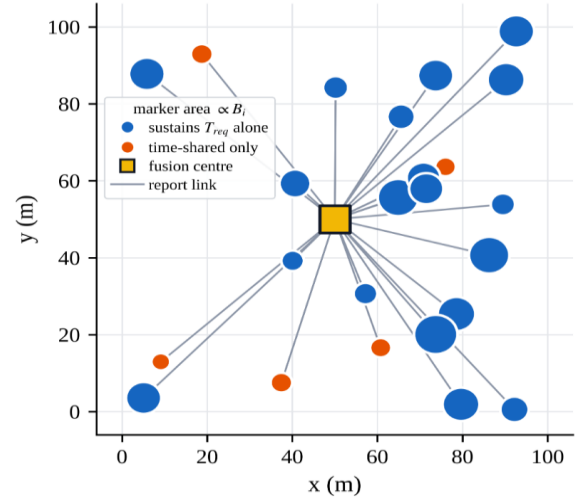


Figure 2. Simulation topology of one realization: $N = 24$ secondary users placed uniformly in a 100×100 m area, with the fusion center at (50,50) m.

Node positions are uniform in the deployment area, SNRs are drawn independently for every node–channel pair, and idle probabilities and energy budgets are drawn per channel and per node from the ranges in Table 3. All policies are evaluated on identical network realizations (common random numbers). The design-point comparison (Table 4 and Figure 3) uses 200 realizations with seeds $1000 + r$. The horizon sweep, which comprises Figures 4–7 and Tables 5 and 6, uses the same 80 realizations at each of seven horizons, $n_{req} \in \{500, 1500, \dots, 5500, 7000\}$, with seeds $2000 + r$, so the bounds of Table 5 are checked 560 times. The achievability certificate is evaluated on 12 realizations with seeds $5000 + r$, and the sensitivity study (Figure 8) uses 20 realizations for each of the twelve (N, M) pairs, also with seeds $5000 + r$. Throughput is computed by (7) and averaged over realizations; uncertainty is reported as 95% confidence intervals, and comparisons between policies use paired differences. A channel that a policy cannot serve contributes zero throughput, and no realization is discarded.

Table 3. Simulation parameters. Energy-model constants follow the standard Heinzelman radio model.

Parameter	Symbol	Value
Number of secondary users	N	24
Number of licensed channels	M	25
Deployment area	—	100×100 m
Fusion-center location	—	(50, 50) m
Sensing period	T_s	10 s
Sensing time	τ	15 ms
Sensing overhead	τ/T_s	0.15%
Sensing bandwidth	f_s	1 MHz
Samples per sensing operation	$N_s = \tau f_s$	15 000
Fusion rule (k-out-of-N)	k	3
Local false-alarm rate	$\bar{\alpha}$	0.10
Detection requirement	P_d^{req}	0.90
False-alarm limit	P_{fa}^{max}	0.10
Received SNR (uniform in dB)	$\gamma_{i,m}$	$[-19, -9]$ dB
Channel idle probability (uniform)	π_0^m	$[0.4, 0.8]$
Channel rate when idle	C_m	1 Mbit/s
Energy budget (uniform)	B_i	$[2.10, 7.81]$ J
Sensing power	P_s	50 mW
Electronics energy	E_{elec}	50 nJ/bit
Amplifier energy	ε_{amp}	100 pJ/bit/m ²
Path-loss exponent	κ	2
Report size	b	500 bits
Per-node sensing capacity	L	2
Required horizon (sweep)	T_{req}	1.39–19.44 h ($n_{req} = 500$ –7000, 7 values)
Design horizon	T_{req}	9.72 h ($n_{req} = 3500$)
Monte Carlo realizations	—	200 at the design point

The parameters are chosen so that the premise of the coverage theorems holds and cooperation actually occurs. With $N_s = 15\,000$ samples and SNRs in $[-19, -9]$ dB, $p_{\min} = 0.6014$, so the worst-case cooperation level (11) is $K_w = 7$, while the false-alarm ceiling (13) is $K^{\max} = 11$; the premise $K_w \leq K^{\max}$ holds with a margin of four nodes. A local false-alarm rate of 0.10 is admissible because the 3-out-of- N rule suppresses it: $\Phi_3(3, 0.1) = 1.0 \times 10^{-3}$, and the cooperative false-alarm probability

stays below 0.10 for every coalition of up to eleven nodes. The energy budgets are calibrated so that the horizon constraint binds inside the sweep. With $b = 500$ bit, reporting accounts for 3–27% of the per-operation energy and e_i varies by a factor of 1.32 across the deployment.

Three allocation policies are compared: Greedy-R-Rot (Algorithm 2); the static Greedy-R (Algorithm 1); and a lifetime-agnostic allocation that runs Algorithm 1 without the horizon test and then repairs its allocation by re-forming the coalition of each selected channel from nodes that can sustain the horizon, dropping channels that cannot be re-formed. The repaired baseline uses the same information and the same feasibility rules as the other two policies, so any difference between them reflects the allocation method rather than constraint awareness. Five experiments are reported: (A) the design-point comparison at $T_{req} = 9.72$ h; (B) the gain across the horizon sweep; (C) the coverage bounds and the certificate; (D) the mechanism of the gain; and (E) the sensitivity to $N \in \{12, 24, 36, 48\}$ and $M \in \{10, 20, 30\}$.

8. Results and Discussion

8.1. Experiment A: design-point comparison

Table 4 and Figure 3 compare the three policies at the design horizon $T_{req} = 9.72$ h ($n_{req} = 3500$) on 200 paired realizations. Greedy-R-Rot delivers 8.258 Mbit/s (95% CI ± 0.073), against 6.367 Mbit/s (± 0.107) for both the static Greedy-R and the repaired lifetime-agnostic allocation. The paired gain is +29.7% (95% CI $[28.6\%, 30.8\%]$), an absolute difference of 1.891 Mbit/s. Greedy-R-Rot is better in all 200 realizations, and a one-sided Wilcoxon signed-rank test gives $p = 7.2 \times 10^{-35}$. It also serves more channels: 11.85 on average, against 8.84 for the two other policies.

The static and repaired allocations give identical throughput and coverage. Once repaired, the lifetime-agnostic allocation can draw only on nodes that sustain the whole horizon unaided, which is the same restriction the static allocation obeys, and in this regime the two allocations coincide. Lifetime awareness alone therefore yields no gain in this regime (+0.0%). The gain in Table 4 comes from time sharing, which lets nodes that cannot sustain the horizon alone contribute for part of it.

Table 4. Design-point comparison at $T_{req} = 9.72$ h ($n_{req} = 3500$), $N = 24$, $M = 25$, $L = 2$, over 200 paired realizations (seeds 1000 + r). CI: 95% confidence-interval half-width; SD: standard deviation. Gain is the ratio of mean throughputs with its 95% CI. Greedy-R-Rot is better in 200 of 200 realizations; one-sided Wilcoxon signed-rank $p = 7.2 \times 10^{-35}$.

Policy	Throughput (Mbit/s)	95% CI	SD	Channels served	Gain vs. repaired
Greedy-R-Rot (time-shared)	8.258	± 0.073	0.527	11.85	+29.7% [28.6%, 30.8%]
Greedy-R (static)	6.367	± 0.107	0.775	8.84	+0.0%
Lifetime-agnostic + repair	6.367	± 0.107	0.775	8.84	reference

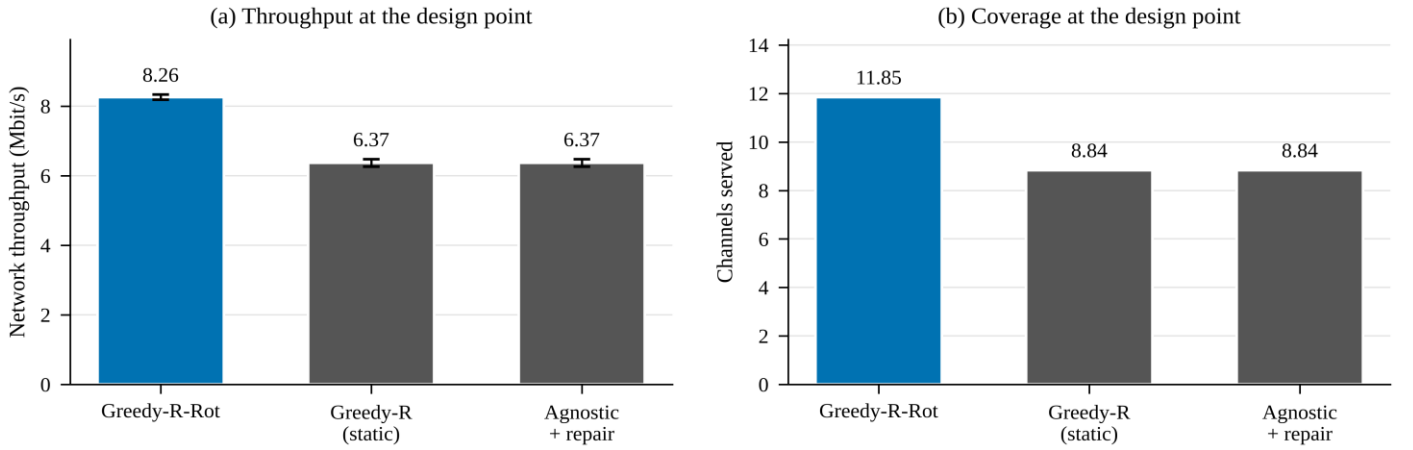


Figure 3. Design point ($T_{req} = 9.72$ h, $N = 24$, $M = 25$, $L = 2$; 200 realizations). (a) Network throughput with 95% confidence intervals. (b) Mean number of channels served. The static and repaired allocations coincide.

Table 5. Channels monitored by Greedy-R-Rot against the guarantee of Theorem 3 and the converse of Theorem 4 (means over 80 realizations per horizon, seeds 2000 + r; 560 checks in all). The served/converse column is the ratio of the means; the per-realization ratio averages 98.9% with a minimum of 83.3%.

T_{req} (h)	Guarantee (Thm. 3)	Greedy-R-Rot	Converse (Thm. 4)	Served / converse (%)	Violations
1.39	6.00	15.74	16.00	98.4	0
4.17	6.00	15.04	15.07	99.8	0
6.94	5.78	13.72	13.86	99.0	0
9.72	4.85	11.72	11.86	98.8	0
12.50	3.94	9.53	9.71	98.1	0
15.28	3.04	7.78	7.90	98.4	0
19.44	2.17	6.06	6.09	99.6	0

The coalitions formed by Greedy-R-Rot have $K = 3.00$ members on average, the minimum that the 3-out-of- K rule allows. Because $p_{\max} = 1$ in this regime (Table 3), the best nodes detect almost surely, so the cooperation floor of Lemma 2 is attained, $K_b = k = 3$. Each channel is served by a rotating set of 4.04 nodes on average, so about one node in four is held in reserve and swapped in as others deplete. Time sharing also spreads the sensing load more evenly. Jain's index on the per-node load is 0.911 for Greedy-R-Rot and 0.744 for the static

allocation, a factor of 1.23. Fairness is reported here as an outcome; it is not a constraint of (8).

8.2. Experiment B: gain across the required horizon

Figure 4 shows the gain over the repaired baseline across the horizon sweep, on 80 realizations per horizon. The gain is the ratio of mean throughputs, $(\bar{R}_{ts} - \bar{R}_{rep}) / \bar{R}_{rep}$, the same definition as in Table 4. It is negligible at

short horizons (0.1% at 1.39 h and 1.7% at 4.17 h), where almost every node can sustain the horizon alone. It rises to 9.8% at 6.94 h and 31.1% at 9.72 h, consistent with the design-point estimate of Table 4, which uses a different set of 200 realizations. Beyond the design point it grows to 65.6% at 12.50 h and 88.9% at 15.28 h. At 19.44 h it reaches 186.9%, but there the baseline delivers only 1.56 Mbit/s, so this value is shown for completeness and is not the basis of any claim. The benefit of time sharing is therefore conditional on the operating regime: it appears only when the required horizon is long enough to exclude a substantial share of nodes from static allocation.

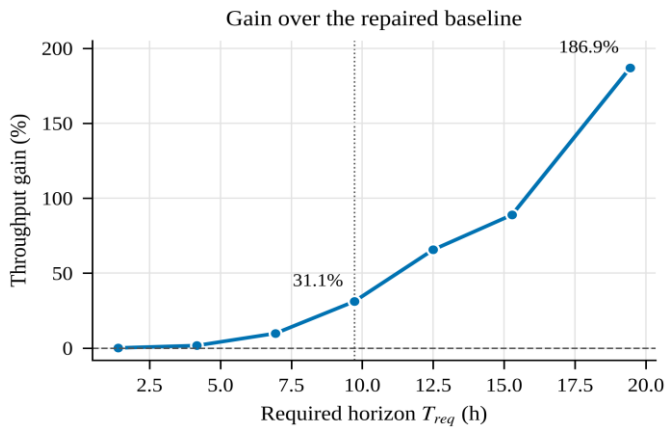


Figure 4. Throughput gain of Greedy-R-Rot over the repaired lifetime-agnostic baseline versus the required horizon (80 realizations per horizon). The gain is the ratio of mean throughputs. The value at the longest horizon rests on a small baseline throughput and is not used for any claim.

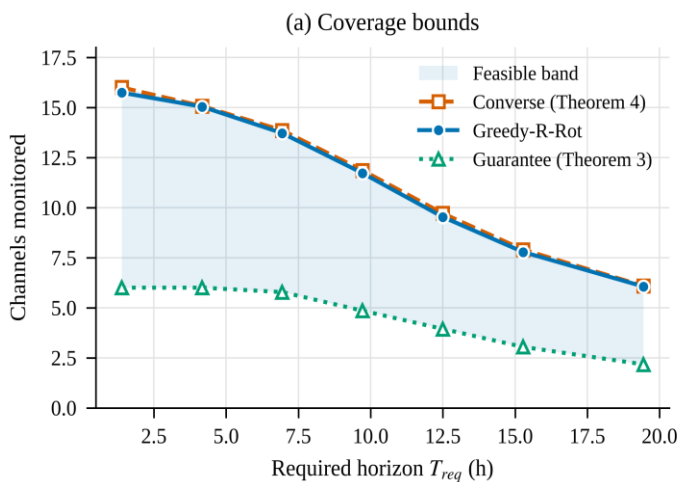
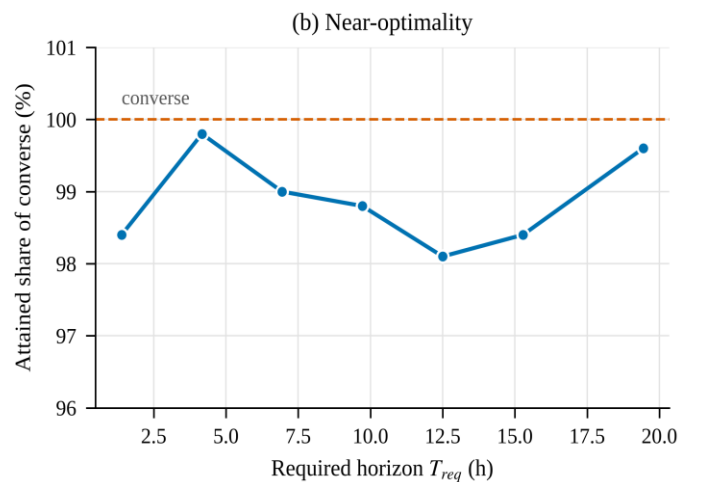


Figure 5. (a) Channels monitored by Greedy-R-Rot, between the guarantee of Theorem 3 and the converse of Theorem 4, versus the required horizon. (b) Share of the converse attained. 560 checks, no violation.

8.3. Experiment C: Coverage bounds and achievability

Table 5 and Figure 5 compare the number of channels monitored by Greedy-R-Rot with the guarantee of Theorem 3 and the converse of Theorem 4. The bounds are established by proof in Section 5; these checks confirm that the implementation is consistent with them. Over 7 horizons and 80 realizations each, 560 checks in all, no realization falls outside the band. Greedy-R-Rot attains on average 98.9% of the converse, computed per realization, and never less than 83.3%. The guarantee is conservative because it assumes the worst-case cooperation level $K_w = 7$, whereas the coalitions actually formed have $K_b = 3$ members. The two bounds differ by a factor of 2.4 to 2.8 across the sweep, of the same order as $K_w/K_b = 2.33$.

The converse is also achievable. At the design horizon the flow certificate of Proposition 3, evaluated with M' equal to the converse, succeeds in all 12 instances tested. In these instances, the optimal coverage under time-shared scheduling is therefore known exactly, and Greedy-R-Rot is measured against that optimum rather than against a relaxation. The certificate concerns coverage, the number of channels served; throughput additionally weights each channel by its idle probability and rate.



8.4. Experiment D: Mechanism of the gain

The gain can be predicted before any allocation is run. The converse (15) of Theorem 2 depends on the static supply of node–channel assignments, $S_{\text{stat}} = S(T_{\text{req}}, L) = \sum_i \min\{L, c_i\}$, and the converse (17) of Theorem 4 on the time-shared supply, $S_{\text{rot}} = \sum_i \min\{a_i, n_{\text{req}} L\} / n_{\text{req}}$. Both policies form coalitions of the same size $K_b = 3$, so if each serves close to its converse, the ratio of their coverages, and to first order of their throughputs, is $S_{\text{rot}}/S_{\text{stat}}$. This ratio contains no fitted parameter. It is computed from the energy budgets alone.

Figure 6 shows how the two supplies diverge. As the horizon lengthens, the share of nodes that can sustain at least one channel for the whole horizon, $|\mathcal{A}(T_{\text{req}})|/N$, falls from 100% to 29.7%. Static allocation can use only these nodes, so its coverage falls from 15.69 to 2.04 channels. Time sharing still draws on the energy of the other nodes, and its coverage falls only to 6.06. The throughput curves follow the coverage curves.

Table 6 and Figure 7 compare the predicted ratio with the observed throughput ratio of the time-shared and static schedules. The prediction is within 4.7% of the observation at every horizon, and within 3.0% on average, over a range in which the ratio itself grows from 1.00 to 2.87.

The prediction is not an independent fit: it holds because each policy operates close to its own converse. Per realization, the static allocation attains on average 98.9% of the converse (15) (minimum 66.7%, over the 557 realizations in which that converse is non-zero), and Greedy-R-Rot attains 98.9% of the converse (17) (minimum 83.3%). The ratio of coverages therefore follows the ratio of supplies. Table 6 shows this directly:

the observed coverage ratio equals $S_{\text{rot}}/S_{\text{stat}}$ to within about 1% at five of the seven horizons. The largest departures are at 4.17 h (1.01 against 1.04) and at 19.44 h (2.98 against 2.76). At 19.44 h the static converse is only about two channels, so the integer rounding in (15) dominates the ratio. The remaining difference between the coverage and throughput ratios arises because throughput weights each channel by its idle probability and rate, whereas the supply ratio counts channels only. The size of the gain is thus explained by how much energy time sharing recovers, which the network's budgets determine in advance.

8.5. Experiment E: Sensitivity to network size and channel count

Figure 8 repeats the comparison for $N \in \{12, 24, 36, 48\}$ and $M \in \{10, 20, 30\}$ at the design horizon, with 20 realizations for each of the twelve (N, M) pairs. The bounds of Theorems 3 and 4 hold in all 240 checks. The gain ranges from 0% to 35.6%. It increases with M for every N , and broadly decreases with N : it is largest when channels are many and nodes few, and vanishes for $N \geq 36$ at $M = 10$, which is consistent with enough nodes being able to sustain the horizon alone to serve all ten channels without time sharing. This is the dependence predicted by the supply ratio, since a higher channel load per node leaves more energy that static allocation cannot use. The design point ($N = 24$, $M = 25$, 29.7%) lies between the neighbouring cells (22.5% at $M = 20$ and 30.4% at $M = 30$). One cell departs slightly from monotonicity in N (23.5% at $N = 36$ against 22.5% at $N = 24$, both at $M = 20$), a small difference that we do not interpret, given 20 realizations per cell.

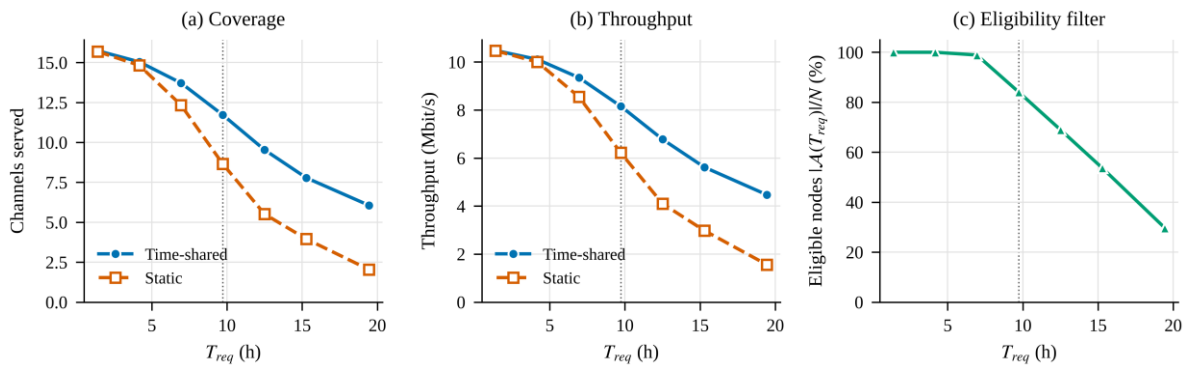


Figure 6. Lifetime–coverage trade-off versus the required horizon. (a) Channels served and (b) network throughput of the time-shared and static schedules. (c) Share of nodes that can sustain at least one channel for the whole horizon, $|\mathcal{A}(T_{\text{req}})|/N$.

Table 6. Predicted ratio S_{rot}/S_{stat} against the observed throughput and coverage ratios of the time-shared and static schedules, and the share of its own converse that each schedule attains (Theorem 2 for the static schedule, Theorem 4 for the time-shared one). Means over 80 realizations per horizon, seeds 2000 + r; converse shares are ratios of the means. No parameter is fitted.

T_{req} (h)	S_{stat}	S_{rot}	Predicted ratio	Throughput ratio (obs.)	Error (%)	Coverage ratio (obs.)	Static / own converse (%)	Time-shared / own converse (%)
1.39	48.00	48.00	1.00	1.00	0.1	1.00	98.0	98.4
4.17	45.86	47.60	1.04	1.01	2.7	1.01	99.3	99.8
6.94	38.50	43.25	1.12	1.09	2.7	1.11	98.6	99.0
9.72	27.32	37.19	1.36	1.31	3.8	1.36	98.4	98.8
12.50	17.64	30.57	1.73	1.66	4.7	1.73	98.9	98.1
15.28	12.89	25.09	1.95	1.89	3.1	1.97	99.4	98.4
19.44	7.14	19.72	2.76	2.87	3.7	2.98	99.4	99.6

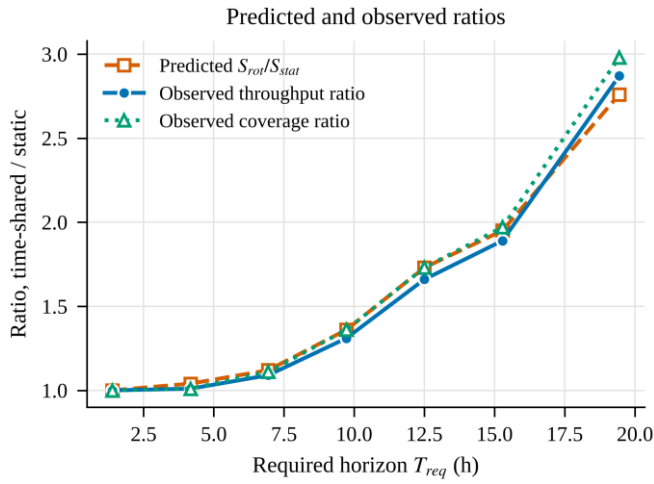


Figure 7. Predicted ratio S_{rot}/S_{stat} and the observed throughput and coverage ratios of the time-shared to the static schedule versus the required horizon. No parameter is fitted; the throughput ratio deviates from the prediction by at most 4.7% (Table 6).

9. Limitations

Limitations of the model. The detection model uses the Gaussian approximation to the energy-detection statistic, which is accurate for the sample counts considered here, and it abstracts channel quality into a per-pair SNR instead of placing primary transmitters geographically. Local decisions are assumed conditionally independent, and correlated or falsified reports are not modelled. The fusion rule is k -out-of- N with k fixed by design; optimizing k jointly with the allocation is not attempted. The energy model charges a fixed cost per sensing-and-reporting operation, assumes that reports are delivered, and excludes the energy of secondary data transmission. The schedule is computed once for a known horizon and known channel statistics,

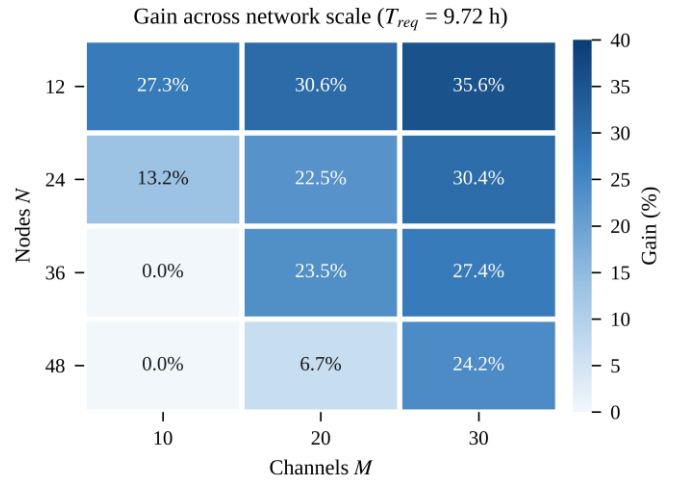


Figure 8. Throughput gain of Greedy-R-Rot over the repaired baseline across network size N and channel count M at $T_{req} = 9.72$ h (20 realizations per cell, seeds 5000 + r). The bounds of Theorems 3 and 4 hold in all 240 checks.

so time-varying SNR or primary activity would require it to be recomputed. Primary-user activity enters only through an idle probability per channel, so throughput is an expected transmission opportunity rather than a realized data rate that includes collision losses.

Limitations of the evidence. All results come from Monte Carlo simulation of the model above; no measurement or over-the-air validation is reported. The gains are specific to the parameter regime of Table 3. The sensitivity study spans $N \in \{12, 24, 36, 48\}$ and $M \in \{10, 20, 30\}$, but the conclusions should not be extrapolated to regimes in which the premise $K_w \leq K^{\max}$ fails. Relative gains at the longest horizons rest on a baseline whose absolute throughput is small; they are shown in Figure 4 for completeness but are not the basis

of any claim, which rests instead on the design-point comparison and its confidence interval. Greedy-R-Rot has no proved approximation ratio: its near-optimality is measured against a proved converse on the configurations tested, not guaranteed in the worst case.

10. Future Work

Four extensions follow. First, the schedule is computed once for a known horizon; an online controller that recomputes it as channel statistics drift would extend the framework to non-stationary deployments. Second, the fusion parameter k is a design constant here, and optimizing it jointly with the allocation is open. Third, a proved approximation ratio for Greedy-R-Rot, or a Lagrangian relaxation with a duality-gap bound, would turn the measured near-optimality of Section 8 into a worst-case guarantee. Fourth, allowing correlated or falsified reports would make the admissible node set depend on trust as well as on energy and detection quality, which would require the cooperation bounds of Section 5 to be re-derived.

11. Conclusion

This paper studied the converse of lifetime-maximizing cooperative spectrum sensing scheduling: maximizing multi-channel throughput when the operating horizon is fixed in advance and the detection and false-alarm probabilities are per-channel service levels. We showed that the problem is NP-hard and derived cooperation bounds for a general k -out-of- N rule that hold for arbitrary heterogeneous detection quality and reduce to the OR-rule results at $k = 1$. From them we obtained a guarantee and a converse on the number of channels that can be served, under both static assignment and time-shared scheduling, together with an exact flow-based certificate of achievability.

The simulations isolate where the throughput gain comes from. A static lifetime-aware assignment gives no gain over a lifetime-agnostic assignment that is allowed to repair itself, because both must rely on nodes that can sustain the whole horizon unaided; at the longest horizon studied this excludes 70% of the nodes. Time-shared scheduling recovers that capacity and improves throughput by 29.7% (95% CI [28.6%, 30.8%]) at the

design horizon of 9.72 h, in all 200 paired realizations. The magnitude of the gain is predicted to within 4.7% by the ratio of time-shared to static energy supply, with no fitted parameters, and the schedule attains 98.9% of the proved converse on average at unchanged asymptotic complexity. The principal limitations, static channel statistics and simulation-only evidence, are the directions for future work identified in Section 10.

Competing Interests Statement

The author declares no competing financial or non-financial interests in relation to this work. The research received no external funding, and no commercial entity had any role in the study design, the simulations, the analysis or interpretation of results, the writing of the manuscript, or the decision to submit it for publication.

Data Availability Statement

The complete MATLAB implementation, the configuration used for every reported experiment, and the raw result files underlying every figure and table in this article are openly available at <https://doi.org/10.5281/zenodo.23387916>, released under the MIT License (code) and CC BY 4.0 (result files). The code requires no specialized toolboxes, except the Statistics and Machine Learning Toolbox for the Wilcoxon test. Every reported number was produced in MATLAB R2024a; the bound checks also run in GNU Octave 8.4, where different random-number streams give slightly different values and no bound violation. No external datasets were used; all results derive from the Monte Carlo simulation described in Section 7, which is fully specified by the deposited configuration and the random-seed policy given there.

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