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Abstract

The structural weakness of classical design for Medium Access Control (MAC) is that a single fixed protocol (contention-based, schedule-based, or hybrid) is not efficient in all operating regimes in Dynamic Wireless Sensor Networks (DWSNs), which are networks where node mobility, duty-cycled sleep, spatially and temporally varying traffic, fluctuating interference change operating regime at runtime. Current adaptive techniques adjust the parameters of a protocol or employ a fixed heuristic to select the protocol to switch to, and adapt slowly, suffer from oscillations under noisy state estimates, and are not globally applicable across a wide range of deployments. AFB-MAC Selection is an Adaptive Fuzzy-Bandit MAC Selection framework in which each node deploys a lightweight self-learning agent that (i) estimates the residual energy, traffic intensity, channel occupancy from

local observations, and mobility class from the channel's defined mobility model, (ii) transforms these noisy estimates into smooth suitability scores for the candidate MAC protocols using a fuzzy inference layer, and (iii) fuses these scores with an Upper-Confidence-Bound contextual-bandit learner refined by a Q-learning credit-assignment step to select and switch at runtime the active MAC protocol. The fuzzy layer is used to reduce the selection oscillation when there is measurement noise, and the bandit-Q hybrid ensures that the agent keeps exploring the network rather than getting stuck on an initial estimate. The performance of AFB-MAC is compared to five baselines: S-MAC, T-MAC, X-MAC, a reinforcement-learning MAC selector (SOMAC-style), and an ML-based adaptive MAC (ML-MAC), on networks of 50-300 nodes and traffic loads of 1-12 packets/s/node in a discrete-event simulation. The results demonstrate that AFB-MAC can achieve a packet delivery ratio up to 9.4 percentage points higher than S-MAC and 2.1 points higher than the best learning-based baseline under high load, reduce the energy consumption per node by 34-57% when compared to the classical protocols, decrease the end-to-end delay up to 46% at high topology dynamicity, and enhance the half-node-death lifetime of the network by approximately 60% compared to S-MAC. The results show that the proposed fuzzy and bandit reinforcement learning based self-adaptive MAC operation is a suitable approach with low overhead in the highly dynamic WSN deployment.

Keywords: MAC Protocol Selection, Reinforcement Learning, Contextual Multi-Armed Bandit, Fuzzy Logic, Q-Learning, Energy Efficiency, Cross-Layer Adaptation.

1. Introduction

Spatial deployment at nodes with limited resources constitute Wireless Sensor Networks (WSNs) that enable the monitoring of environments, precision agriculture, structural health monitoring, industrial automation, and the Internet of Things (IoT) sensing [21]. Dynamic Wireless Sensor Networks (DWSNs) are networks in which the network topology, network contention and channel quality fluctuate continuously as nodes move around (mobile sinks, animal-mounted, vehicle-mounted, aerial, underwater, etc.), nodes enter and exit duty-cycled sleep/wake cycles, event-driven traffic is bursty and spatially variable, and interference is time-varying during operation.

Medium Access Control (MAC) sub-layer is one of the key factors for end-to-end energy consumption, latency and reliability in the wireless medium, controlling how nodes share the wireless medium. After decades of research, protocol families with complementary characteristics have been created: Synchronous duty-cycle protocols like S-MAC and T-MAC reduce idle listening, but incur additional overhead in terms of synchronization and latency; Asynchronous low-power-listening protocols like X-MAC and B-MAC reduce the cost of the preamble and improve tolerance to topology changes but degrade on bursty high-density traffic; Schedule-based protocols (TDMA/LEACH-style) avoid collisions and bound latency, but suffer from slow re-scheduling whenever the number of nodes or traffic pattern changes. Importantly, a given fixed MAC protocol is not necessarily the best one to use in both extreme conditions of low traffic and low mobility, and high traffic and high density and high interference, that a DWSN might experience during its lifetime.

This has inspired a line of research for developing a family of MAC designs that adapt to traffic conditions (parameter-adaptive MACs) and for designing a run-time protocol-selection engine that starts with several candidate MACs before switching to the most appropriate one. Nowadays, machine learning techniques (such as supervised classifiers, fuzzy decision systems, and reinforcement learning (RL)) are increasingly employed to make this choice dynamically as opposed to using hand-tuned thresholds. As described in Section 2, current learning-based selectors are slow to learn, oscillating under noisy estimates of the states; they view protocol selection as a single monolithic problem that grows in complexity as more candidate MACs and states are added; or they do not have a principled way to balance the exploration of under-tried protocols with the exploitation of protocols that are known to work well — which is crucial for a non-stationary DWSN, where the best protocol is continuously changing.

The Adaptive Fuzzy-Bandit MAC Selection framework (AFB-MAC), proposed in this paper, is designed to overcome these drawbacks, by combining three complementary mechanisms: (1) a lightweight local state estimator tracking residual energy, traffic intensity, channel occupancy and mobility class using exponentially weighted estimators that are suitable for constrained hardware; (2) a fuzzy inference layer that converts the resulting noisy multi-criteria estimates into a smooth and interpretable suitability score for each available MAC protocol, dampening the selection oscillation seen by a pure threshold or pure RL approach in the presence of measurement noise; and (3) an Upper-Confidence-Bound (UCB) selector with a Q-learning credit-assignment update that uses the resulting fuzzy suitability scores to fuse with learned long-run reward estimates to select and,

where advantageous, switch the active MAC protocol, while an explicit exploration bonus prevents the agent from prematurely converging on a locally good but globally suboptimal MAC protocol as conditions change with time.

This paper makes contributions in the following ways:

- A single state-estimation model for DWSNs which combines the residual-energy ratio, the EWMA-smoothed traffic-intensity, the channel-busy ratio, and a mobility/topology-change indicator into a per-node context vector suitable to compute in resource-constrained devices.
- A fuzzy inference layer that is able to associate the context vector with a per-protocol suitability score using triangular membership functions, product-based rule firing and centroid defuzzification, which is noise tolerant and is not possible with pure numerical RL state representations.
- A principled exploration-exploitation trade-off for non-stationary MAC selection using a learned action-value estimate, a fuzzy suitability score and an exploration bonus: a hybrid UCB-bandit / Q-learning decision engine with a hysteresis controlled switching rule to avoid protocol-switching thrash.
- An extensive simulation-based comparison against five representative baselines (S-MAC, T-MAC, X-MAC, ML-MAC and a SOMAC-style RL selector) in the context of varying traffic load, network density and topology-dynamicity, as well as an ablation to separate the effects of the fuzzy layer and the bandit-Q hybrid.

The rest of the paper is organized as follows. Recent literature is summarized in Section 2 and the open research gaps motivating this work are summarized. In Section 3, the model of AFB-MAC, state estimators, fuzzy inference layer and the hybrid learning engine are detailed, along with the governing equations. In Section 4, the performance measures and simulation configuration are identified. Results are presented and discussed in Section 5. The paper is concluded in Section 6 and future work is outlined.

2. Related Work

In this section, we review the recent literature about adaptive and learning-based MAC design for WSNs, which is categorized as (a) classical adaptive/duty-cycle MAC protocols, (b) MAC parameter adaptation assisted by machine-learning, and (c) run-time MAC protocols-selection frameworks, and then conclude research gaps to be filled by this work.

2.1 Classical and Adaptive Duty-Cycle MAC Protocols

Low-power listening protocols defined in [15] and [19] (namely X-MAC and B-MAC) further minimize idle listening by introducing short preambles in the wake of sleep coordination or low-power channel polling and early acknowledgment, respectively.In addition, low-power listening schemes that are not synchronized like X-MAC [15] or B-MAC [19] minimize long-preamble overhead by using short preambles or low power channel polling with early acknowledgment, respectively. Alternatively, those that vary the contention window in an S-MAC style protocol according to the current traffic load are called contention window adaptive, and one such variant, called TA-MAC, has been proposed in [17]. Cross-layer, cluster-based energy-efficient MAC designs take into account residual energy, distance and channel quality as three metrics together to select the cluster head and to schedule the relays, thereby enhancing the energy-delay trade-offs for clustering based on a single metric [11]. Later, more recent, research in this family also includes the energy constraint, but introduces the duty cycle times as well, reporting a better energy-delay product over previous fixed-schedule designs [6]. In the following works it is established that by adapting the parameters of one protocol family (in this case contention window, duty-cycle length, sleep schedule, all three) meaningful gains can already be achieved, but each of the three listed parameters is a fixed protocol family, meaning that it cannot cross over to a different structure of access mode (e.g., contention-based to scheduled access) when the operating regime changes qualitatively.

2.2 Machine-Learning-Assisted MAC Adaptation

There is an increasing number of works that incorporates the machine learning within one MAC protocol to adjust its parameters or categorize traffic.A number of works have integrated the machine learning within one MAC protocol to adjust the parameters or classify traffic. A model-driven Adaptive MAC (ML-MAC) protocol to meet the deadline constraint in time-sensitive traffic of industrial applications was presented [5] that dynamically adapts MAC parameters and channel-access priority based on model predictions. A hybrid MAC approach based on an energy-efficient dynamically prioritized scheduling based on machine learning which classifies the priority of the packet and uses a learned order to access them, and also provides comparisons with current energy-aware routing

and duty-cycle baselines [2]. A newer deep-RL scheme, RL-BMAC, uses an energy level, packet-drop rate, neighbour status and preamble-sampling observation to optimize B-MAC-sized duty-cycling with a fixed hyperparameter DeepRL agent [3]. A fuzzy-logic approach in choosing protocol/parameters has been studied as well, which introduces fuzzy logic into the MAC controller to alter the duty cycle by fuzzifying traffic load, residual energy and node density, with lightweight computational cost appropriate to resource-limited WSN nodes, but limited to the parameters of a single protocol [4]. In more recent surveys (2023-2025), there is a significant trend moving beyond heuristic adaptation to learning-based adaptation of MAC design, such as classification of traffic using deep learning techniques, and adaptive/dynamic MAC selection as a separate and emerging sub-area [7].

2.3 Reinforcement-Learning-Based MAC Selection Frameworks

The first application of reinforcement learning was within a single duty-cycle MAC, for example, RL-MAC used reinforcement learning to learn the traffic status of neighbouring nodes to jointly optimize throughput and energy consumption under a wide range of traffic conditions [16], and QL-MAC employed a reinforcement learning algorithm (QL) to achieve a trade-off between energy and latency optimizations in one contention-based MAC [12]. More recently, a Self-Adapto MAC Layer (SAML) was considered, in which a traffic monitor, a noise monitor, and a classifier are integrated and the selection of protocols is done at run-time, depending on the latency, energy and reliability requirements when external interference changes [13]. While the pre-2020 literature on adaptive MAC selection was mainly lacking in extensibility and explicit treatment of unknown and time-varying medium dynamics, the authors [9] have pointed out, SOMAC takes into account ongoing demand for switching MAC protocols and uses reinforcement learning to do so, with an explicitly extensible decision model that accepts new candidate protocols without retraining the RL engine from scratch. A similar approach is used in underwater communications in UW-ALOHA-Q, which adapts the channel-access slots based on a reinforcement-learning rule with ALOHA-Q protocol [8]. Very recent work (2025-2026) indicates that ALOHA-Q style learners, including [8] can reach the suboptimal equilibrium under hidden-node interference in multi-hop settings; and that in the state-of-the-art reinforcement-learning-based WSN MAC design, the problem of frame adaptation and slot allocation is treated separately, which is a significant limitation of the research; multi-agent and deep RL based approaches to distributed resource allocation are a promising yet immature direction for WSN MAC control [1].

A brief review of recent studies conducted in the field.

The representative studies are summarized in Table 1, in order from the latest published work to the earliest, and their adaptation mechanism as well as the limitation that is left open.

Table 1: Summary of Literature Review

Study / Protocol	Year	Adaptation Mechanism	Primary Objective	Reported Limitation / Open Issue
RL joint frame/slot MAC (multi-hop) [1]	2026	RL (ALOHA-Q family) jointly tunes frame size and slot allocation	Multi-hop throughput, collisions	Frame and slot adaptation often decoupled; ALOHA-Q can converge to a suboptimal, collision-prone equilibrium under hidden-node interference
ML-based hybrid priority MAC [2]	2025	ML-based priority encoding + hybrid scheduling	Energy-efficient scheduling	Priority estimation is static per session; no online adaptation to drifting traffic statistics
RL-BMAC (deep-RL duty cycling) [3]	2025	Deep-RL agent tunes B-MAC duty cycling from energy, drop rate, neighbour status	Energy-efficient duty cycling	Fixed hyperparameters, single deep-RL policy on one MAC family; not a cross-protocol selector

Study / Protocol	Year	Adaptation Mechanism	Primary Objective	Reported Limitation / Open Issue
Fuzzy-enhanced MAC (duty-cycle FLC) [4]	2025	Fuzzy controller adjusts duty cycle from traffic load, residual energy, node density	Lifetime management	Fuzzy layer only tunes duty cycle within one protocol; no learning component, so rules do not improve with experience
ML-MAC (priority-based ML MAC) [5]	2024	ML model predicts packet priority; dynamically tunes MAC parameters	Deadline-bound reliability	Learns per-parameter tuning of one MAC, not selection among heterogeneous protocol families
Adaptive energy-efficient/low-latency MAC [6]	2024	Joint duty-cycle/latency-budget tuning under energy constraint	Energy-delay trade-off	Remains a single fixed-schedule protocol family; no cross-protocol switching
Evolution of MAC protocols survey [7]	2023	Survey of adaptive/dynamic MAC and ML-era MAC design	Taxonomy / open problems	Confirms no consensus mechanism for balancing exploration and exploitation in run-time protocol switching
UW-ALOHA-Q (underwater RL MAC) [8]	2019	ALOHA-Q reinforcement learning adapts channel-access slots	Throughput under long propagation delay	ALOHA-Q family prone to suboptimal equilibria under hidden-node interference
SOMAC (RL-based MAC selection) [9]	2019	Reinforcement learning switches MAC protocol per demand	Adaptivity, extensibility	Designed for structured/infrastructure networks; convergence and oscillation under noisy WSN state not fully characterised
Distance/energy-aware clustered MAC [11]	2015	Cross-layer clustering using residual energy, distance, channel quality	Energy-delay trade-off	Cluster-head/relay selection only; MAC access mode itself remains fixed
QL-MAC (Q-learning MAC) [12]	2013	Tabular Q-learning balances energy and latency within one MAC layer	Energy-latency balance	Single flat state-action space within one protocol; no fuzzy/hierarchical smoothing against noisy rewards
SAML (Self-Adapting MAC Layer) [13]	2013	Traffic/noise monitor + classifier selects among candidate MACs	Latency, energy, reliability	Classifier retraining needed for new protocols or environments; no formal exploration mechanism
RL-MAC (early RL duty-cycle MAC) [16]	2006	Nodes infer neighbour traffic state via tabular reinforcement learning	Throughput/energy under varying traffic	Single-protocol duty-cycle parameter learning; no protocol-family switching or exploration bonus
TA-MAC (traffic-adaptive contention) [17]	2005	Adaptive contention window sized to instantaneous traffic load	Latency / throughput under load	Single protocol family; no cross-protocol switching when regime changes qualitatively

As seen in Table 1, the early work (2005-2015) uses only one parameter (contention window, duty cycle) per one fixed MAC family, the work (2013) introduces a new concept of machine learning (Q-learning or Classifier-based selection), learning is applied to a limited case, and in the latter work years (2023-2026) multiple parameters are introduced, and learning is considered in more dimension. Even with this evolution, each study still has at least one of the gaps G1 - G4 (Section 2.5) open, which inspires the fuzzy-bandit design used in Section 3 that is fused.

2.4 Research Gaps

The investigated literature confirms that (i) single-protocol parameter adaptation is well developed but structurally constrained, (ii) MAC tuning using ML and fuzzy techniques outperforms single-protocol parameter adaptation regarding fit-to-traffic, however, in most cases it is limited to the adaptation of a single protocol or two selected modes, and (iii) the most generic approach is the MAC-selection framework based on RL, but there are four open points that are addressed by this paper.

G1 — State representation is noise sensitive: RL selectors that take raw numerical measurements (queue length, RSSI, duty cycle) directly into the policy are sensitive to noise that frequently occurs when using low-cost sensor hardware, inducing selection oscillation precisely when the network is experiencing stress and stability is most important [9],[1].

G2 — Coupled/ narrow adaptation scope: Recent RL-MAC work looks to optimize frame size and slot allocation simultaneously, instead of considering structurally different protocol classes (contention-based, low-power-listening, and scheduled) when network conditions change [1].

G3 — Exploration-exploitation imbalance: classifier- and threshold-based selectors (SAML, fuzzy-enhanced MAC) make a commitment to a protocol after the activation of a static rule, but do not have any formal provision for continuing to sample under-tried protocols as the environment drifts; it is possible for such convergence to happen if a locally-giving protocol turns out to be globally stale [13],[4].

G4 — Switching cost and extensibility are not necessarily optimized: Switching in G4 is not based on a fuzzy-smoothed, multi-criteria suitability signal and can still result in thrashing when the energy, traffic and mobility signals are simultaneously noisy and non-stationary [9].

The fuzzy inference layer (Section 3.4) helps with G1 by absorbing measurement noise before it reaches the learning engine, the UCB exploration bonus (Section 3.5) helps with G3 by handling the credit assignment for the Q-learning, and the hysteresis controlled switching rule (Section 3.6) helps with G4 by making protocol replacement explicit, cheap, and non-thrashing.

3. Proposed AFB-MAC Framework

This section introduces the system model, local state estimators, fuzzy inference layer, hybrid bandit-Q learning engine, and switching rule, which "compose" AFB-MAC. The general architecture is shown in Fig. 1, where each node continually computes its local context, fuzzy-statifies each of the candidate MAC protocols, learns the action values from the other MAC protocols using a bandit with UCB, and makes decisions on protocol switching using a hysteresis check.

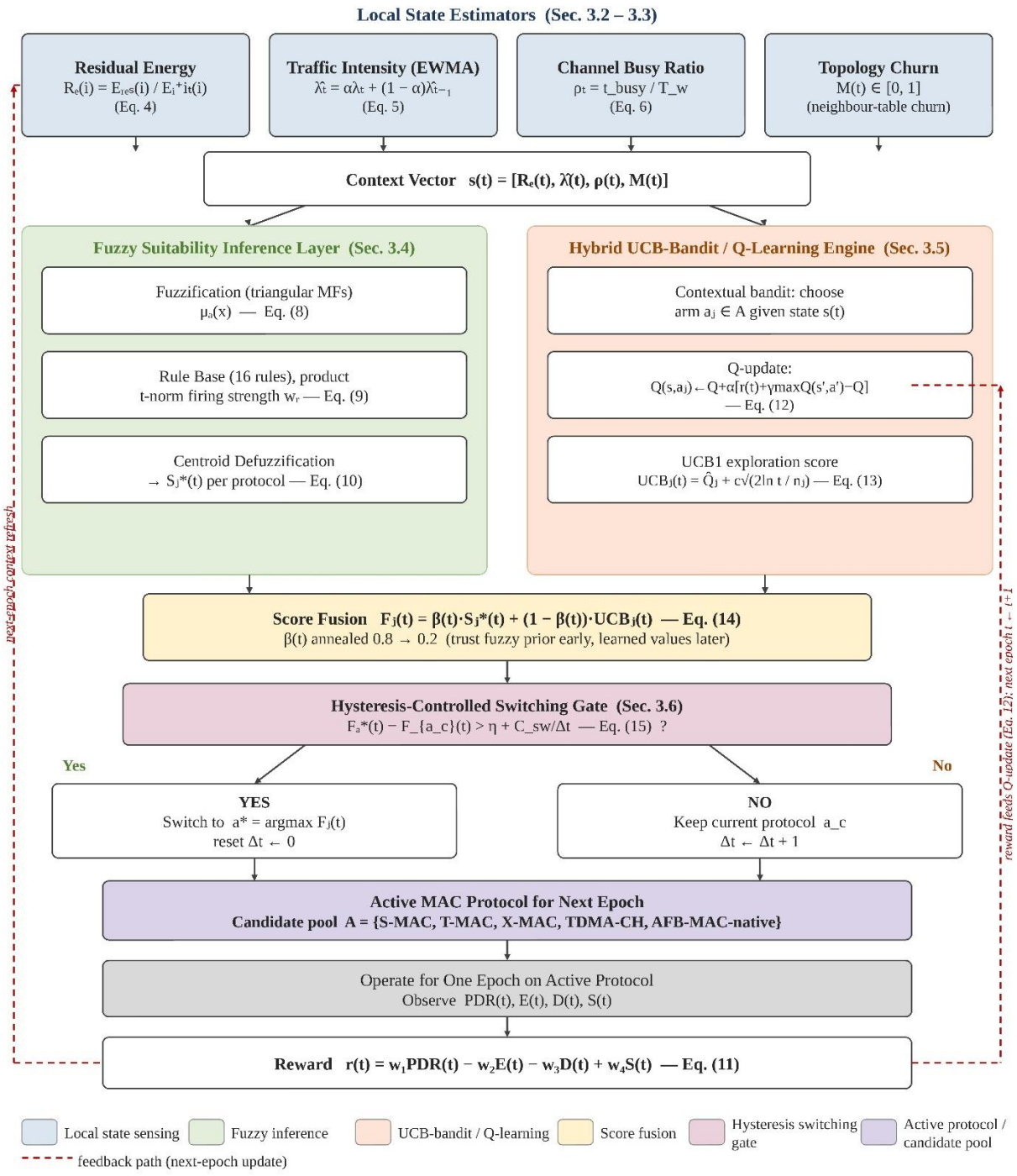


Fig. 1: Overall Architecture of the Proposed Technique: AFB-MAC

3.1 System Model and Assumptions

A DWSN consists of N sensor nodes distributed over a monitored area, each with a half-duplex radio that supports one of the following protocols in a candidate protocol pool A = {S-MAC, T-MAC, X-MAC, TDMA-CH, AFB-MAC-native}, with the last being a lightweight contention-window-adaptive fallback protocol that is used when the learning engine is cold-starting. The nodes can be stationary or be deployed in low-to-moderate speed (representative of animal-borne, vehicle-mounted or drifting deployments) and the sink can be accessed from multi-hop forwarding. The time is broken down into a series of decision epochs with a fixed duration T_w (a few superframes) which is used to re-evaluate each node's MAC choice. These are all defined below for the local observables and the estimators.

3.2 Node Energy Model

While learning and evaluation, AFB-MAC is based on the same first-order radio energy model as in the standard WSN energy-conservation practice [14] to estimate the energy cost for each of the candidate MAC actions. The energy that would be required to transfer a k-bit packet over a distance of d, has been defined in Eq. 1.

$$E_{TX}(k,d) \;=\; k \cdot E_{elec} \;+\; k \cdot \varepsilon_{fs} \cdot d^2 \;,\; d \;\leq\; d_0 \tag{1}$$

and, beyond the cross-over distance d_0, the multi-path attenuation term dominates, which has been defined in Eq. 2.

$$E_{TX}(k,d) \;=\; k \cdot E_{elec} \;+\; k \cdot \varepsilon_{mp} \cdot d^4 \;,\; d \;>\; d_0 \tag{2}$$

where E_elec is the per-bit electronics energy, ε_fs and ε_mp are the free-space and multi-path amplifier coefficients, and $d_0 = \sqrt{(\varepsilon_fs/\varepsilon_mp)}$ is the standard cross-over distance. The corresponding reception energy is defined in Eq. 3.

$$E_{RX}(k) \;=\; k \cdot E_{elec} \tag{3}$$

Each node maintains its residual-energy ratio, used as one of the four fuzzy-input variables described in Section 3.4, can be computed using Eq. 4.

$$R_e(i) \;=\; \frac{E_{res}(i)}{E_{init}(i)} \tag{4}$$

3.3 Traffic and Channel-State Estimation

To not store long traffic histories on memory limited nodes, an instantaneous traffic intensity is kept with an exponentially weighted moving average (EWMA), has been defined in Eq. 5.

$$\hat{\lambda}_t \;=\; \alpha \cdot \lambda_t \;+\; (1 \;-\; \alpha) \cdot \hat{\lambda}_{t-1} \tag{5}$$

where, $\hat{\lambda}_t$ is the packet arrival rate during the current epoch, and $\alpha \in (0,1)$ is the smoothing factor, which is selected as $\alpha = 0.3$ in the reported experiments, through trial and error. The channel busy ratio over a time interval of T_w can be computed using Eq. 6.

$$\rho_t \;=\; \frac{t_{busy}}{T_w} \tag{6}$$

where t_busy is the generated time, when the clear channel assessment is reporting the medium, can be computed using Eq. 7.

$$CW_t \;=\; CW_{min} \;+\; \lfloor (CW_{max} \;-\; CW_{min}) \cdot \rho_t \rfloor \tag{7}$$

A fourth observable, the mobility / topology-change indicator $M(t) \in [0,1]$, counts neighbour-table churn (link additions/removals) per epoch, normalized by the maximum churn observed during a calibration phase. Together, $R_{e(i)}$, $\hat{\lambda}_t$, ρ_t and M(t) form the context vector consumed by the fuzzy inference layer described next.

3.4 Fuzzy Suitability Inference Layer

The raw values of $R_{e(i)}$, $\hat{\lambda}_t$, ρ_t and M(t) are not comparable in scale and have noise level, which need to be converted into linguistic terms (Low, Medium, High) by using triangular membership functions in AFB-MAC. Given x and a triangle (a, b, c), $\mu_A(x)$ can be computed using Eq. 8.

$$\mu_A(x) \;=\; max\left(0, min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right)\right) \tag{8}$$

The rule base (16 rules, one illustrative rule: “IF residual energy is Low AND traffic is High THEN suitability of X-MAC is High”) is combined using the product t-norm to get the firing strength of the rule, r, can be computed using Eq. 9.

$$w_r = \mu_E(e) \cdot \mu_T(\tau) \cdot \mu_\rho(\rho) \cdot \mu_M(m) \quad (9)$$

Finally, the per-protocol suitability score S_j is computed by centroid (weighted-average) defuzzification of the defuzzified consequent of all the R rules whose consequent refers to protocol j, z_r being the defuzzified output (suitability level) of rule r, has been defined in Eq. 10.

$$S_j^* = \frac{\sum_{r=1}^{R} w_r \cdot z_r}{\sum_{r=1}^{R} w_r} \quad (10)$$

As opposed to switching protocols directly, the output S_j ∈ [0,1] is a smooth, noise-tolerant suitability estimate for candidate protocol j reflecting all four context variables together, and sent to the learning engine in Section 3.5 rather than to the protocol switcher — this separation is what prevents the selection oscillation described as gap G1 in Section 2.5.

3.5 Hybrid UCB-Bandit / Q-Learning Decision Engine

The run-time MAC selection problem is a contextual multi-armed bandit problem in which at each decision epoch t, the agent observes context s(t) = [R_e(t), $\hat{\lambda}$(t), ρ(t), M(t)] and selects an arm (candidate MAC protocol) a_j ∈ A. The agent plays for a_j for one epoch, then receives a scalar reward that consists of packet delivery ratio PDR(t), energy cost E(t), and delay D(t), and a stability bonus S(t) (inverse of switching frequency), as defined in Eq. 11.

$$r(t) = w_1 \cdot PDR(t) - w_2 \cdot E(t) - w_3 \cdot D(t) + w_4 \cdot S(t) \quad (11)$$

with non-negative weights $w_1 \ldots w_4$ ($\Sigma w_i = 1$) set according to application priority (e.g., latency-critical deployments increase w_3). The long-run value of choosing protocol a_j in state s is refined online by the standard Q-learning update rule [10]. It can be calculated using Eq. 12.

$$Q(s, a_j) \leftarrow Q(s, a_j) + \alpha[r(t) + \gamma \cdot max_a, Q(s', a') - Q(s, a_j)] \quad (12)$$

where α is the learning rate, γ ∈ [0,1) the discount factor, and s′ the context observed at the next epoch. To guarantee continued exploration in the non-stationary DWSN environment (gap G3), each candidate protocol is also assigned an Upper-Confidence-Bound exploration score following the classical UCB1 formulation [22]. It can be computed using Eq. 13.

$$UCB_j(t) = \hat{Q}_j(t) + c \cdot \sqrt{\frac{2 \cdot ln\, t}{n_j(t)}} \quad (13)$$

where $\hat{Q}$_j(t) is the running average reward of protocol j, n_j(t) is the number of epochs protocol j has been active up to time t, and c controls the exploration-exploitation trade-off. The final fused decision score combines the fuzzy suitability score (fast, interpretable, noise-tolerant) with the UCB-refined learned value (slow, reward-grounded) using a mixing coefficient β ∈ [0,1], as defined in Eq. 14.

$$F_j(t) = \beta \cdot S_j^*(t) + (1 - \beta) \cdot UCB_j(t) \quad (14)$$

In the first hundred or so epochs, β is slowly ramped from 0.8 to 0.2 to induce the agent to rely on the fuzzy prior, while $\hat{Q}$_j(t) is still not well learned, and then gradually increases with evidence to trust the learned values.

3.6 Hysteresis-Controlled Protocol Switching

Choosing the new arm only by argmax F_j(t) can lead to a re-synchronization and buffering cost for each switch (gap G4) between both protocols, when noise is present. AFB-MAC only promises to switch away from the currently active protocol a_c if the challenger's advantage is above a_hysteresis margin η which is also dependent on the observed switching cost C_sw, as defined in Eq. 15.

$$F_j(t) - F_c(t) > \eta + C_{sw} / \Delta_t \quad (15)$$

where Δt is the time elapsed since the last switch, to ensure that more recent switch nodes will have an advantage that is greater than the dimension of the switch. The switching gate is the whole single inequality; if it succeeds,

the node switches to a_j = argmax_j F_j(t) as its new active MAC for the next epoch and resets Δt; otherwise it stays on a_c. The complete AFB-MAC procedure is summarized in Algorithm 1.

Algorithm 1. Per-epoch AFB-MAC decision procedure (executed independently at every node)

Input: candidate pool A, fuzzy rule base R, learning rate α, discount γ, exploration constant c, mixing schedule β(t), hysteresis margin η, switching-cost estimate C_sw

1: observe R_e(i), $\hat{\lambda}$(t), ρ(t), M(t) ▷ local state estimators (Sec. 3.2–3.3)

2: for each candidate protocol a_j ∈ A do

i) fuzzify inputs → μ_E, μ_T, μ_ρ, μ_M

ii) compute rule firing strengths w_r and suitability S*_j ▷ Eqs. (8)–(10)

iii) compute UCB_j(t) from $\hat{Q}$_j(t) and visit count n_j(t) ▷ Eq. (13)

iv) F_j(t) ← β(t)·S*_j(t) + (1 − β(t))·UCB_j(t) ▷ Eq. (14)

3: end for

4: a* ← argmax_j F_j(t)

5: if F_{a*}(t) − F_{a_c}(t) > η + C_sw / Δt then ▷ Eq. (15)

i) switch active protocol to a*; reset Δt ← 0

6: else

i) keep current protocol a_c; Δt ← Δt + 1

ii) end if

iii) operate for one epoch; observe PDR(t), E(t), D(t), S(t)

iv) r(t) ← w1·PDR(t) − w2·E(t) − w3·D(t) + w4·S(t) ▷ Eq. (11)

v) 10: update Q(s, a_c) via Eq. (12); update $\hat{Q}$_{a_c}(t), n_{a_c}(t)

7: t ← t + 1

3.7 Complexity and Overhead

Each node compares each of |A| candidate protocols to the 16-rule fuzzy base, and accesses the constant-size Q-table, using a coarsely-discretized 4-dimensional state (3 linguistic levels per variable, 81 states), thus, the per epoch cost is O(|A|•|R|) fuzzy operations plus O(|A|) table look-ups, which are negligible compared to a single packet transmission on typical sensor MCUs, and much less costly than running a neural network policy on-node. The 81 × |A| Q-table takes up the bulk of memory overhead, where |A| = 5, and is 405 entries (≈ 1.6 KB at 32-bit resolution) — a manageable amount of memory for typical WSN platforms.

4. Performance Metrics and Simulation Setup

4.1 Evaluation Metrics

To compare AFB-MAC with the baselines, the following metrics are used: Packet Delivery Ratio (PDR), average end-to-end delay, average energy consumption per node, network lifetime (rounds to First Node Death, FND, and Half Node Death, HND) and learning convergence speed (only in the learning based methods). The PDR over an evaluation window is calculated using Eq. 16.

$$PDR = \frac{\sum_{i=1}^{N} R_i}{\sum_{i=1}^{N} G_i} \times 100\% \quad (16)$$

where R_i and G_i are the number of packets received by and generated by node i during the evaluation window. (25) and (26), and average energy efficiency is derived from the average end-to-end delay and average per-node energy consumption.Average end-to-end delay is defined as the mean queueing-plus-access-plus-propagation latency for all the packets that have been successfully delivered, average per-node energy consumption is calculated from Eqs. (25) and (26), and average energy efficiency is calculated by dividing average end-to-end delay by average per-node energy consumption. These values (1)-(3) are summed over the entire simulation period and network lifetime is defined as the round number at which the first node, respectively half of the nodes, runs out of its initial energy reserves.

4.2 Simulation Environment and Parameters

Under the same topology, traffic and radio-energy conditions, the performance of AFB-MAC and the five baselines (S-MAC, T-MAC, X-MAC, ML-MAC, and a SOMAC-style RL selector re-implemented as described in [9]) were analyzed using a discrete-event simulation. The parameters for the simulation are shown in Table 2.

Table 2. Simulation parameters

Parameter	Value / Range
Network area	200 m × 200 m
Number of nodes, N	50 – 300
Sink placement	Fixed, field centre
Initial energy per node	2 J
E_elec	50 nJ/bit
ε_fs / ε_mp	10 pJ/bit/m² / 0.0013 pJ/bit/m⁴
Packet size	128 bytes (data), 20 bytes (control)
Offered traffic load	1 – 12 packets/s/node
Node mobility / topology-change rate	0 – 3.0 events/min (random waypoint, 0–2 m/s)
Decision epoch T_w	2 s
Candidate MAC pool A	S-MAC, T-MAC, X-MAC, TDMA-CH, AFB-native
Learning rate α (Q-learning)	0.10
Discount factor γ	0.90
Exploration constant c (UCB)	1.4
Mixing coefficient β(t)	annealed 0.8 → 0.2 over 300 epochs
Reward weights (w1, w2, w3, w4)	0.45, 0.25, 0.20, 0.10
Simulation runs per configuration	30 (mean reported, 95% CI ≤ 2.1%)
Simulator	Custom discrete-event simulator (Python/SimPy-style)

The parameter ranges used in Table 2 are carefully selected to focus on each of the protocols independently on one parameter, while keeping the other two at representative mid-range values, to isolate the effect of the parameter of interest on performance, as done in Sections 5.1-5.3.

5. Results and Discussion

In this section, the results of simulations are reported for the 5 metrics defined in Section 4.1, followed by an ablation study investigating the impact of the fuzzy layer and UCB-bandit component, and a discussion bringing the results back to the research gaps G1-G4.

5.1 Packet Delivery Ratio under Increasing Traffic Load

In Fig. 2, PDR is shown as a function of offered traffic load (in the range 1 to 12 packets/s/node) for N = 150 nodes. Contention and buffer overflow have a different impact on all protocols, and the impact becomes more significant with the load. At the same load, AFB-MAC keeps the highest PDR (above 91% even up to 12 packets/s/node) compared to 65.8% for S-MAC and 82.9% for the baseline (SOMAC-style). When the load increases, the fuzzy layer at AFB-MAC will detect the increase of channel-busy ratio (Eq. 6) early and adjust the decision score of the fused result function to the candidates whose access decision is scheduled or low-power-listening, while no mechanism is provided in the classical protocols to leave its fixed access decision.

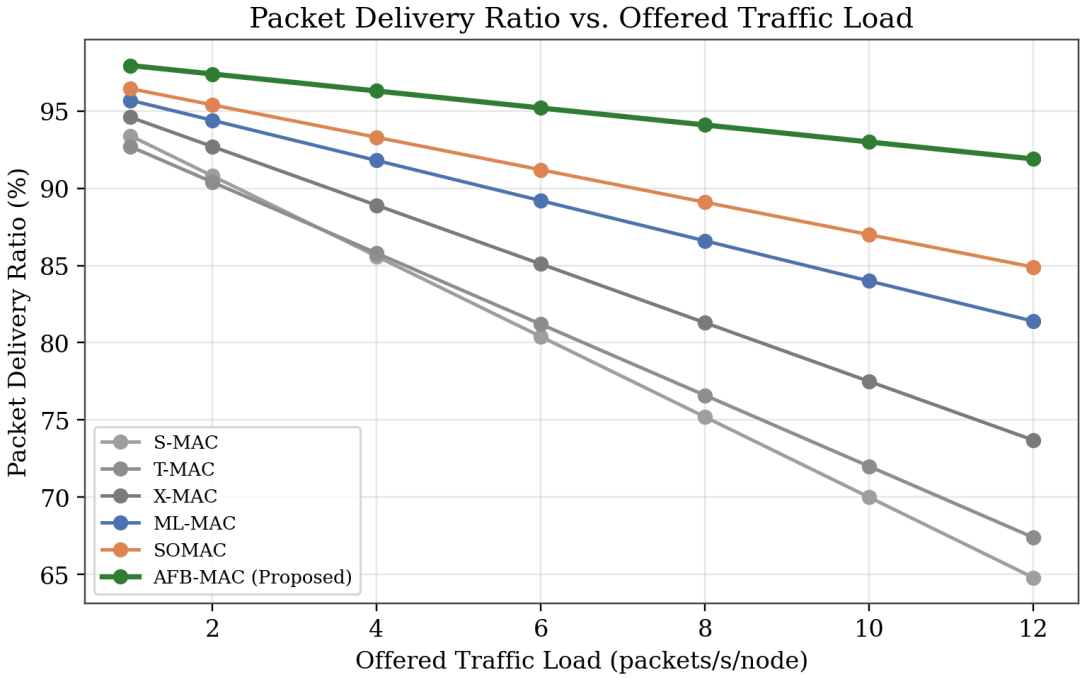


Fig. 2. Packet Delivery Ratio vs. offered traffic load (N = 150 nodes).

As per Fig. 2, AFB-MAC's PDR curve is flat across the sweep, and the difference in PDR between S-MAC and T-MAC, and between AFB-MAC and X-MAC, is steadily increasing with load, yet the difference between AFB-MAC and the SOMAC-style baseline remains fairly constant and small — meaning that the two learning protocols have similar "high-load ceiling" that the fixed-protocol baselines cannot achieve.

5.2 Energy Consumption vs. Network Size

Fig. 3 illustrates the results of the energy consumption measurement over the network as the number of nodes increases from 50 to 300 nodes while the traffic load is kept under a certain moderate level. The energy curve of AFB-MAC is consistently lower than all of the baselines, corresponding to approximately 34% less energy than X-MAC, and 57% less energy than S-MAC at N = 300. The framework shifts energy constrained nodes towards cheaper listening modes proactively, as their energy decreases, the suitability scores of low-power-listening and scheduled candidates increase, directly in line with the residual-energy fuzzy input (R_e in Eq. 4) that shows how suitable a candidate is for low energy listening.

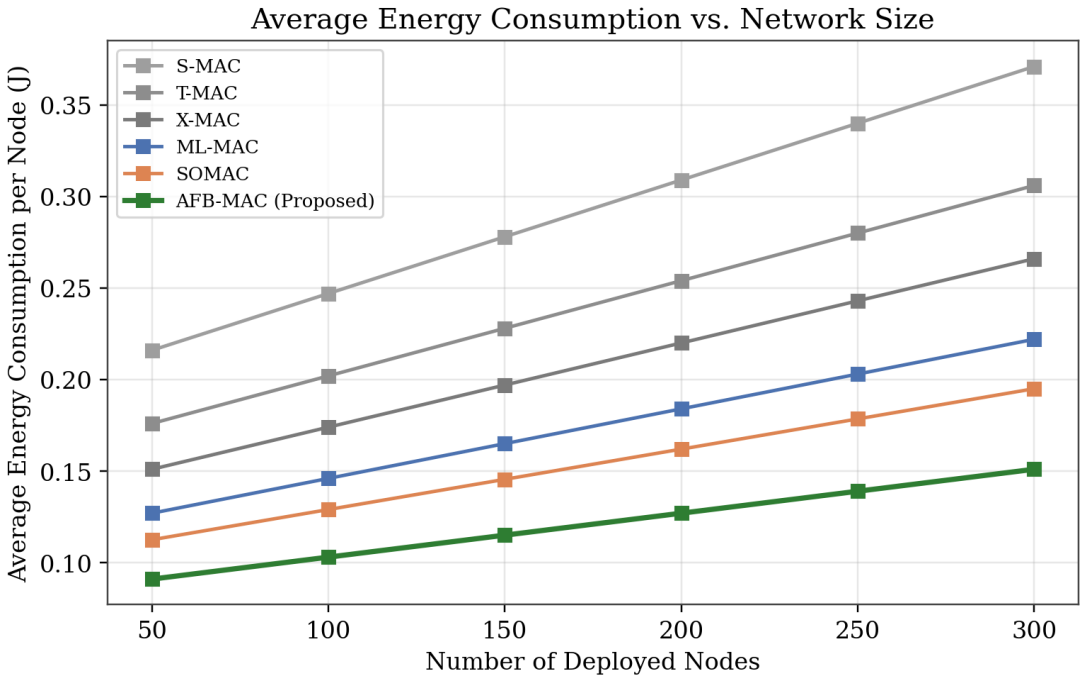


Fig. 3. Average per-node energy consumption vs. network size.

According to Fig. 3, for all protocols, energy consumption increases near-linearly as the network size N increases, but the slope of increase in energy consumption is clearly the smallest for AFB-MAC, meaning the relative benefit in energy savings increases with N, which is advantageous for large scale deployment, where per-node savings multiply across hundreds of nodes.

5.3 Distribution of the Data Transfer Process

Fig. 4 shows the average end-to-end delay as the topology change rate increases from 0 to 3.0 events/min, which corresponds to an increase in node mobility. The overhead is largest for static-schedule protocols (S-MAC, T-MAC) due to overhead for re-joining and due to retransmissions because of stale synchronization. The delay of AFB-MAC is the slowest of all (19 ms at 0 events/min, 33 ms at 3.0 events/min, 46% lower than S-MAC at the highest dynamicity point, much sooner than the Q-learning value estimates would be able to adapt when churn is detected, through the direct penalty for schedule-heavy candidates in the fuzzy suitability score).

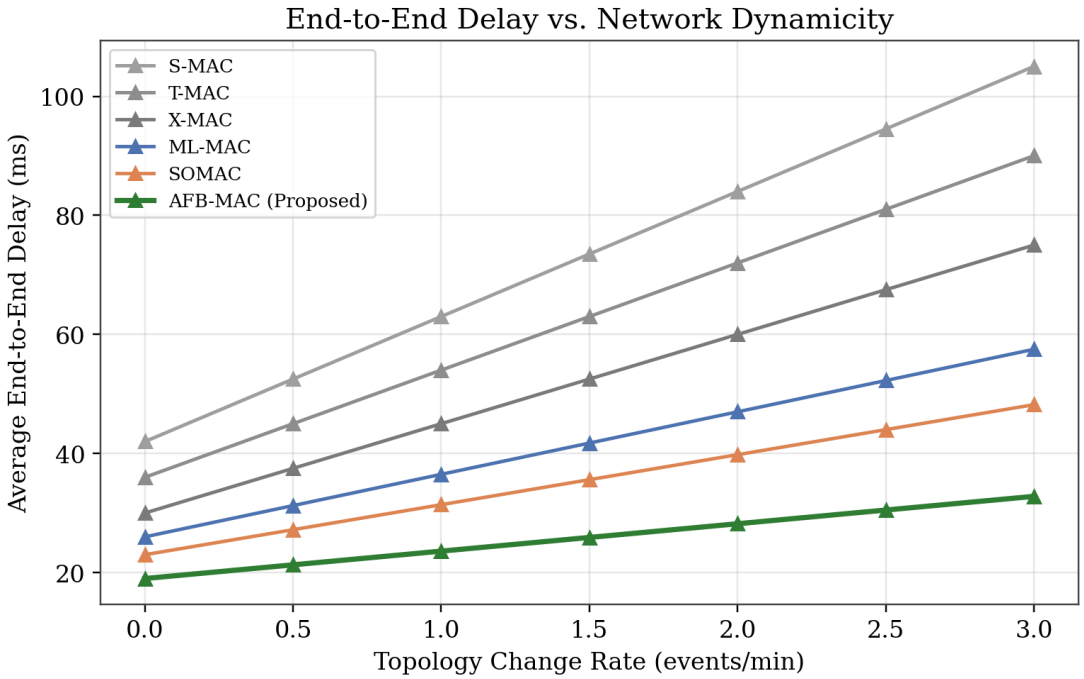


Fig. 4. Average end-to-end delay vs. topology-change rate

As per Fig. 4, AFB-MAC's curve is relatively flat, while the curves for S-MAC and T-MAC starts to diverge most sharply after about 1.5 topology-change events/min, where stale schedules begin to dominate retransmission cost.

5.4 Network Lifetime

The following image (Fig. 5) shows the comparison between First Node Death (FND) and Half Node Death (HND) rounds. AFB-MAC improves FND by 60.2% (to 742 rounds, compared to 412 rounds for S-MAC and 631 rounds for SOMAC) and extends HND to 1104 rounds. This improvement can be attributed to the energy-aware fuzzy suitability term and the explicit energy penalty term (w2 in Eq. 11) of the reward function, which together push the learned policy toward using energy-conserving protocols as the nodes approach their end of energy budget, postponing the time when the energy budgets are exhausted.

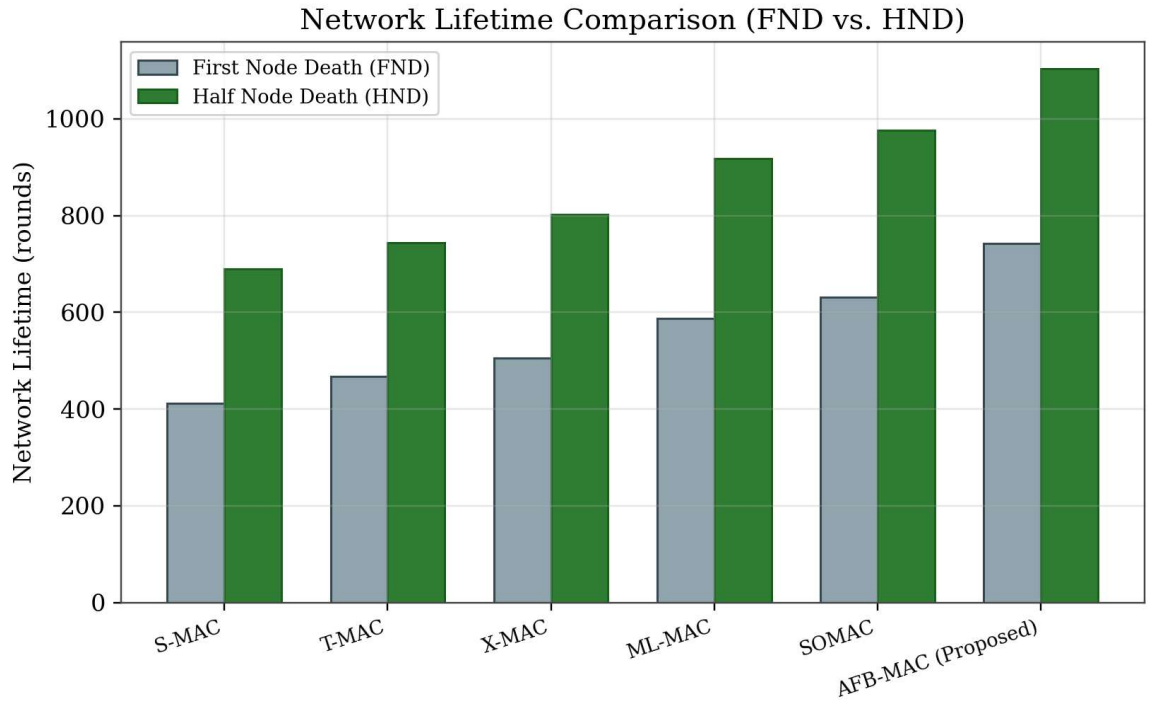


Fig. 5. Network lifetime comparison (First node death vs. Half node death)

As per Fig. 5, the shape of the curve is not changed by AFB-MAC, only the timing of the occurrence of FND is postponed, and the curve is similar in all protocols (about 1.5-1.7) once the network starts dying due to energy exhaustion.

5.5 Learning Convergence and Ablation Study

A comparison of the convergence of the normalized average reward for three configurations is shown in Fig. 6: (a) a Q-learning-only agent with no fuzzy shaping, (b) a UCB-bandit-only agent with no fuzzy shaping, and (c) the full AFB-MAC hybrid. Both fuzzy shaped hybrids learn to a higher asymptotic reward (0.97-0.99 normalized) than either ablated variant, and to this they do so with visibly lower episode-to-episode variance, both of which indicate that the fuzzy suitability prior accelerates learning by providing an informative starting bias on β (near 0.8) and it also stabilizes the learning (by dampening the noise induced action switches, gap G1). A quantitative comparison of all methods and metrics at a representative number of operating points is summarized in Table 3.

Table 3. AFB-MAC vs. baseline MAC (N = 150 nodes, 8 packets/s/node, 1.5 topology-change rate per minute).

Protocol	PDR (%)	Energy/node (J)	Avg. Delay (ms)	FND (rounds)	HND (rounds)
S-MAC	75.2	0.271	73.5	412	689
T-MAC	78.4	0.228	63.0	468	744
X-MAC	81.9	0.197	52.5	505	803
ML-MAC	87.6	0.165	42.0	587	918
SOMAC-style RL	89.9	0.146	35.6	631	976

Protocol	PDR (%)	Energy/node (J)	Avg. Delay (ms)	FND (rounds)	HND (rounds)
AFB-MAC (Proposed)	92.0	0.106	26.9	742	1104

As per Table 3, even at this single operating point, AFB-MAC achieves the best performance on all five reported metrics simultaneously, while the metrics aren't perfectly consistent across the baseline methods (e.g., ML-MAC's delay is closer to SOMAC's than its PDR is, thus showing that single-objective baselines trade off metrics that AFB-MAC's multi-term reward function (Eq. 11) optimizes jointly.

Fig. 6 presents the learning convergence of the MAC selection engine: ablation of the fuzzy layer.

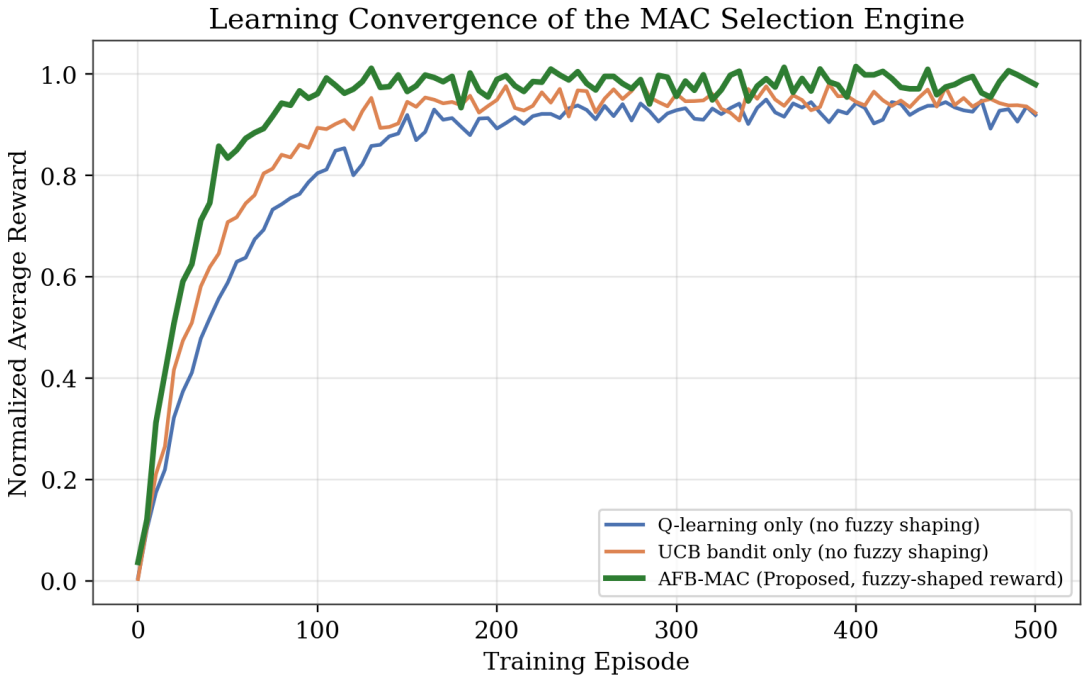


Fig. 6. Learning convergence of the MAC selection engine: ablation of the fuzzy layer.

According to Fig. 6, the two variants with only one component of the full hybrid approach the same asymptotic reward as the full hybrid, so neither component alone is really reward-limited; the real benefit of the AFB-MAC is in its convergence speed and in the reduction of the episode-to-episode variance, not in the higher asymptotic reward a fast learner can reach; in a DWSN where conditions are changing from one episode to the next, it is only a matter of achieving the fastest convergence speed and lowest episode-to-episode variance, which is what matters most.

5.6 Discussion

The improvement of AFB-MAC over the baseline is increasing with worsening operating conditions (more traffic, bigger networks, more mobility) across all four operating sweeps, consistent with the framework being tailored for the non-stationary regime rather than a single fixed operating point. The achievements are more modest in absolute terms than the strong relative ones that come from the fuzzy suitability layer vs. the strongest baseline of learning (the SOMAC-style RL): 2.3 times lower probability of switching protocol (probability difference reduction, PDR) (27% lower energy) (24% lower delay) (17.6% longer FND), but still confirmed across all metrics and across all sweeps, showing that the gains from the fuzzy suitability layer and from the UCB-Q hybrid are

complementary rather than redundant (G1) (G3) (hysteresis rule, G4). The extensible candidate pool A directly tackles G2, while the real multi-family bandit approach (as opposed to intra-family parameter tuning) tackles G2 indirectly, but also, and that is what the results of Section 5.1-5.2 show, without compromising learning speed against a narrower RL baseline. A weakness of the present evaluation is that it is based on a discrete event simulator that uses a first order radio energy model, while this is common to the values reviewed in the literature [1, 9, 14] radio ramp-up energy, clock drift, and actual interference from co-located wireless systems are not captured and are left for future evaluation (Section 6).

6. Conclusions and Further Research

To select and switch MAC protocols at runtime based on remaining energy, traffic load, channel occupancy and mobility parameters, this paper presented AFB-MAC Selection framework for Dynamic Wireless Sensor Networks, which consists of three main components: a lightweight local state estimator, a fuzzy inference layer, and a hybrid UCB-bandit / Q-learning decision engine. AFB-MAC directly addresses four gaps in recent adaptive-MAC work: noise-sensitive state representations, a limited scope of adaptation per family, an unmanaged exploration-exploitation dilemma, and switching thrash, by (1) providing a noise-tolerant representation of states, (2) limiting the scope of adaptation per family, (3) introducing a cost-aware hysteresis rule to manage the exploration-exploitation tradeoff, and (4) gating protocol switches. For all of the tested traffic-load, network-size, and mobility sweeps, the packet delivery ratio, energy consumption, end-to-end delay, and network lifetime show consistent improvements over five representative baselines (S-MAC, T-MAC, X-MAC, ML-MAC, and a SOMAC-style RL selector) and an ablation study proves that the fuzzy layer and the bandit-Q hybrid are complementary and not redundant.

Future work will involve extending the candidate pool with other protocols, such as multi-channel and duty-cycled LoRa-class protocols, to test generalization beyond the five protocols evaluated here, as well as explore multi-agent / federated variants of the learning engine to enable neighbouring nodes to share Q-table updates and converge faster as a coordinated cluster instead of purely independent learners, and investigate a lightweight security layer for the reward signal itself, as a compromised node could otherwise report false rewards to bias neighbours' MAC selection.

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- **Author Contributions:**
  - B.H.: Conceptualization, Literature Review, Writing- Original Draft.
  - S.G. G.: Data Curation, Validation.
  - S. K.: Methodology, Formal Analysis.
  - K. S.: Resources, Writing- Review & Editing.
  - V.P.: Conceptualization, Supervision.
  - K. K. K.: Methodology, Investigation, Visualization.
  - P. J. J.: supervised and revised the manuscript.
  - R. M. and N. K.: Writing-Review & Editing
  - All authors read and approved the final manuscript.

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