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Joint Cross-Layer Optimization Framework for 5G-Enabled Wireless Sensor Networks in Environmental Monitoring Systems

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Abstract: **Especially now that the deployment of 5G is on the increase, requirements for real-time environmental monitoring have put Wireless Sensor Networks (WSNs) in performance demands exceeding that of traditional protocol design. Current WSN architectures merely optimize the protocol layers (MAC, Network, Transport) after an isolated, parallel design on how the three layers behave. The operation prevents networks from reaping optimum advantages from dynamic, low-latency 5G environments. The main thrust of this research is to address the urgent issue of simultaneous and cross-layer optimization in WSNs by building a unified framework that couples up all protocol layers with real-time 5G feedback to maximize throughput and packet delivery ratios (PDR) sets outcomes. We fight the static, layer Isolated tuning shortcomings by introducing five new types of analytical models. Adaptive Layer-wise Graph Neural Network is the initial model, where ALGNN captures inter-layer dependencies through using shared embeddings that abstract cross-layer states. Second, MADRL-SRS (Multi-Agent Deep Reinforcement Learning with Shared Reward Shaping): Encourages cooperative policy learning across protocol layers and synchronized reward signals. Real-Time Cross-Layer Bayesian Optimization with Hierarchical Priors: Third. Fourth, Hybrid Edge-Cloud Feedback Loop using Delay-Aware Kalman Estimators (HECF-KF) corrects time-drift effects across state decisions for network jitter or 5G variability. Finally, Topology-Adaptive Cross-Layer Entropy Minimization- This would minimize entropy over protocols metrics while ensuring stable routes in dynamic network topologies. Together, these models amount to a completely adaptive optimization pipeline that responds in real time to emerging environmental triggers and 5G network conditions. Experimental simulations show improvements of up to 33% on latency reduction, 32% increase in PDR, and 52% reduction in entropy across the network layers. This brings a strong foundation for the next generation of intelligent environmental monitoring systems over 5G-enabled WSNs.**

Keywords: **Cross-Layer Optimization, Wireless Sensor Networks, Environmental Monitoring, 5G Communication, Real-Time Adaptation, Process.**

1. INTRODUCTION

As a result of the world having changed drastically due to growing climate volatility, deterioration of air, water, and land in terms of pollution control, and the early detection of ecological hazards, environmental monitoring systems must now assume increasing significance. Wireless Sensor Networks (WSNs) are the backbone sensing-communicating infrastructure, which can be used in such applications by providing a distributed data acquisition network for a large and often rugged area. With 5G networks emerging, new avenues of promise will be opened up for WSNs [1, 2, 3]. To this end, WSNs will use the ultra-reliable low-latency communication (URLLC), high-bandwidth, and massive device connectivities that are the hallmarks of 5G. It increases stringent demands on performance requirements on communication protocols

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when integrating WSNs with the 5G networks, especially having end-to-end latencies [4, 5, 6], throughput, and packet delivery reliability sets. Most existing WSN protocol architectures presume that the layers are static or loosely coupled, where the MAC, Network, and Transport layers are designed and optimized independently of each other. Layer Isolated optimization would lead to suboptimal performance, especially in dynamic and feedback-driven environmental systems. Most WSNs do not contain real-time cross-layer feedback mechanisms or real-time coordination among the layers prevent its ability to respond appropriately to quickly changing network and environmental conditions. This new dimension introduces a new cross-layer optimization framework designed to cater precisely for 5G-enabled environmental monitoring WSNs. The new structure allows the five integrated methods to act in combination to permit simultaneous tuning to the newly designed integrated architecture's MAC, Network, and Transport layers. Such methods include the Adaptive Layer-wise Graph Neural Network (ALGNN) for learning inter-layer dependencies, Multi-Agent Deep Reinforcement Learning with Shared Reward Shaping (MADRL-SRS) for coordinated decision-making, Real-Time Cross-Layer Bayesian Optimization with Hierarchical Priors (RT-CBO HP) for parameter tuning efficiency, Hybrid Edge-Cloud Feedback Loop using Delay-Aware Kalman Estimators (HECF-KF) for temporal drift correction, and Topology-Adaptive Cross-Layer Entropy Minimization (TACLEM) to ensure stability under mobility sets-all of which are tuned into a republic real-time optimization pipeline that fully utilizes the 5G networking capabilities to improve aggregated system performance. Such flexibility will include in this whole design environmental monitoring systems that also would adapt dynamically to different conditions in sensing and states of a network, thus producing enormous throughput on reduction in latency and on stable packet delivery. Such cross-layer approaches usher in a fundamental shift in thinking from legacy design philosophies in WSN, thus paving way for highly adaptive and intelligent environmental monitoring infrastructures in the making process.

2. REVIEW OF EXISTING MODELS USED FOR NETWORK ANALYSIS

The emergence of 5G has changed the design paradigms for wireless sensor networks (WSNs), especially for environmental monitoring, where integrity of data, low latency, and adaptable response time are all essential. While much progress has been made in the area of design of antennas, intelligent communication, and resource aware computation, yet literature today shows fragmentation in the area of cross-layer integration techniques, especially under real-time constraints in dynamic sensing environments. Tandel and Trapasiya [1] noted the changes in configurable antenna designs for wireless systems, stressing that though improvements in the physical layer have increased reliability of the links, those improvements would remain underutilized without the simultaneous optimization of protocols. Hence, the importance of merging reconfiguration at antenna levels with the adaptability of the MAC and the network layers. Similarly, Xu et al. [2] formulated the concept of resolution-aware beam scanning for joint sensing and communication in ISAC systems, stating that the core of dynamic beamforming must exist. Nevertheless, their model constrains the applicability of physical layer configurations without extending the coordination to transport or network protocols. Gugulothu and Ramarakula [3] projected the green wireless communication frameworks, optimizing for energy efficiency using lightweight algorithms; however, their approach lacks context-aware learning and does not accommodate high-frequency environmental feedback loops needed in WSN applications. By contrast, Vishwakarma et al. [4] conducted a thorough survey on IRS-assisted beamforming methods for energy harvesting, establishing the importance of intelligent surface control. However, their work remains mostly detached from protocol stack adaptation, completely disregarding throughput and latency in real-time WSN scenarios. Zhou et al. [5] introduced heterogeneous multi-agent reinforcement learning (MARL) for joint UAV trajectory and communication design. While their reinforcement learning approach is also in the direction of this paper, it is limited to physical node mobility and lacks consideration of the inter-layer protocol dependencies. The current model builds on this idea, through placing MARL agents within the MAC, Network, and Transport layers for a cooperative decision-making framework across multiple protocol levels. Rouhifar et al. [5] proposed the DITRA algorithm for event-driven bandwidth allocation in IoT environments using multi-objective optimization. While effective in constrained bandwidth scenarios, DITRA assumes isolated optimization targets and lacks a unified cross-layer perspective in process.

Chai et al. [7] provided a perspective overview on future wireless mesh networks, advocating for decentralized intelligence and self-organizing architectures. This supports the architectural philosophy of the proposed model, particularly its graph neural network-based abstraction and entropy-aware routing stability mechanism sets. Cost and resource efficiency in edge computing were systematically reviewed by Cao et al. [8], who underscored the importance of balancing processing offload between cloud and edge devices. This resonates with the proposed hybrid edge-cloud feedback loop integrated in the model, where Kalman estimators at the edge correct for temporal drift introduced by network jitter. Nooh [9] further extended the vision of beyond-5G systems using hybrid deep learning for AP association. Their application-specific optimization highlights the necessity of adaptable learning-based techniques, which this work generalizes into a real-time, cross-layer optimization framework for environmental WSNs. Majumdar et al. [11] discussed the use of 5G in precision agriculture, outlining integration strategies for UAVs, low-power devices, and AI. However, the study stops short of providing a protocol stack-level co-optimization, particularly under bursty data flow conditions. Fatima and Kondamuri [13] provided a broad review of machine learning in wireless communication, noting the growing trend towards multi-agent systems and GNN-based architectures, yet they also emphasized the open challenge of real-time deployment in edge scenarios, which this paper addresses directly sets. Unlike VANET [14] and cyber-twin systems for 6G [15], which primarily focus on vehicular data and digital twin modeling respectively, the present work emphasizes real-time adaptability and cross-layer protocol reconfiguration specifically for environmental sensor networks. In summary, while existing literature has made important contributions to individual layers of the communication stack, or isolated applications of learning and optimization in WSNs, there exists a clear gap in unified, real-time, cross-layer adaptive models. The proposed model fills this void by integrating multiple learning mechanisms and optimization strategies across the protocol stack, supported by empirical validation under realistic environmental conditions.

3. PROPOSED MODEL DESIGN ANALYSIS

The system is structured in an end-to-end integrated cross-layer optimization architecture for environmental monitoring systems that have been implemented into 5G-distributed wireless sensor networks. The model integrates adaptive learning, probabilistic optimization, distributed control, and real-time estimation in a single dynamic feedback loop for joint optimization across MAC, Network, and Transport Layers. It uses the oscillations that arise from high-frequency 5G data and environment Induced changes to dynamically and continuously reconfigure protocol parameters, ensuring maximum throughput and packet delivery in variable time situations across dynamically changing topologies in the processing network. The analysis process starts with the abstraction of cross-layer states through a graph-based neural encoding approach. First of all, as per figure 1, The whole protocol stack is wrapped as a layered graph G(V,E), where nodes correspond to protocol parameters and edges define their functional interdependencies in the process. Let, hi(l) be the hidden representation of the i-th node at layer l, updated using a graph convolutional function via equation 1,

$$hi(l+1) = \sigma\left(\sum\{j \in N(i)\}\left(\frac{1}{\sqrt{di\ dj}}\right)Wl * hj(l)\right)\ldots(1)$$

Where, W' (l) represents the learnable weight matrix for layer l, di and dj are node degrees, and σ is a non-linear activation function in process. This representation captures latent cross-layer dependencies used for joint decision-making in the process. Thus, in parallel, the distributed reinforcement agents are working across each of a set of protocol layers using policy gradients. The global reward Rt shared amongst all agents drives the loss function for each agent and optimizes the expected rewards via equation 2,

$$\nabla\theta\ J(\pi\theta) = E\{\pi\theta\}[\nabla\theta\ log\ \pi\theta(at|st)Q\{\pi\theta\}(st, at)]\ldots(2)$$

Where πθ reflects the policy parameterized by θ, Q{πθ} is the action Value function, and st, at are the state and action at timestamp ‘t’ in process. In this way independent agents are made to converge to globally optimal strategies while responding to localized metrics. Parameter tuning is even more accelerated via Bayesian optimization using a surrogate Gaussian Process model f(x) ~ GP(μ(x), k(x,x′)), with the acquisition function α(x) guiding exploration via equation 3,

$$\alpha(x) = \int max(f(x) - f'+, 0) \cdot N\big(f(x);\ \mu(x), \sigma^2(x)\big)df(x)\ldots(3)$$

Where, f'+ is the current best observation in process. Thus, it makes real-time high-performance configuration choices without exhaustive searches sets. Temporal estimation of state variables, especially under the jitter-affected scenario of 5G, is tackled by Kalman Filter-based feedback correction model sets. The predicted estimate x̂{t|t−1} and the update step are defined via equations 4 & 5,

$$\hat{x}\{t|t-1\} = A\ \hat{x}\{t-1|t-1\} + B\ u\{t-1\}\ldots(4)$$

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$$\hat{x}\{t|t\} = \hat{x}\{t|t-1\} + Kt\,(zt - H\,\hat{x}\{t|t-1\}) \ldots (5)$$

Where, Kt is the Kalman gain, zt is the observation, and H the measurement matrix in the process. This ensures temporal consistency across cross-layer decisions. The total entropy inherent in network performance is kept under observation and minimized via equation 6,

$$H = -\sum pi\ log\ pi \ldots (6)$$

Where, 'pi' is the normalized occurrence of a routing state or packet drop pattern in process. This guides routing decisions of packets within highly mobile or volatile environments by minimizing uncertainty of performance sets. Temp input signals are injected to the "nature" environmental triggers of temperature or gas concentration e(t) which will ultimately reach decision via equation 7,

$$\Phi(t) = \int e(\tau) \cdot \lambda(\tau)\, d\tau \ldots (7)$$

Where λ(τ) is a weight function mirroring priority or risk sensitivity in process. The signal controls the speed of policy update and urgency of selecting parameter settings. Finally, throughput is modeled analytically by a differential performance change with time: equation 8 describes it in process,

$$\frac{dT}{dt} = \beta \cdot \frac{d\theta}{dt} + \gamma \cdot \frac{dR}{dt} \ldots (8)$$

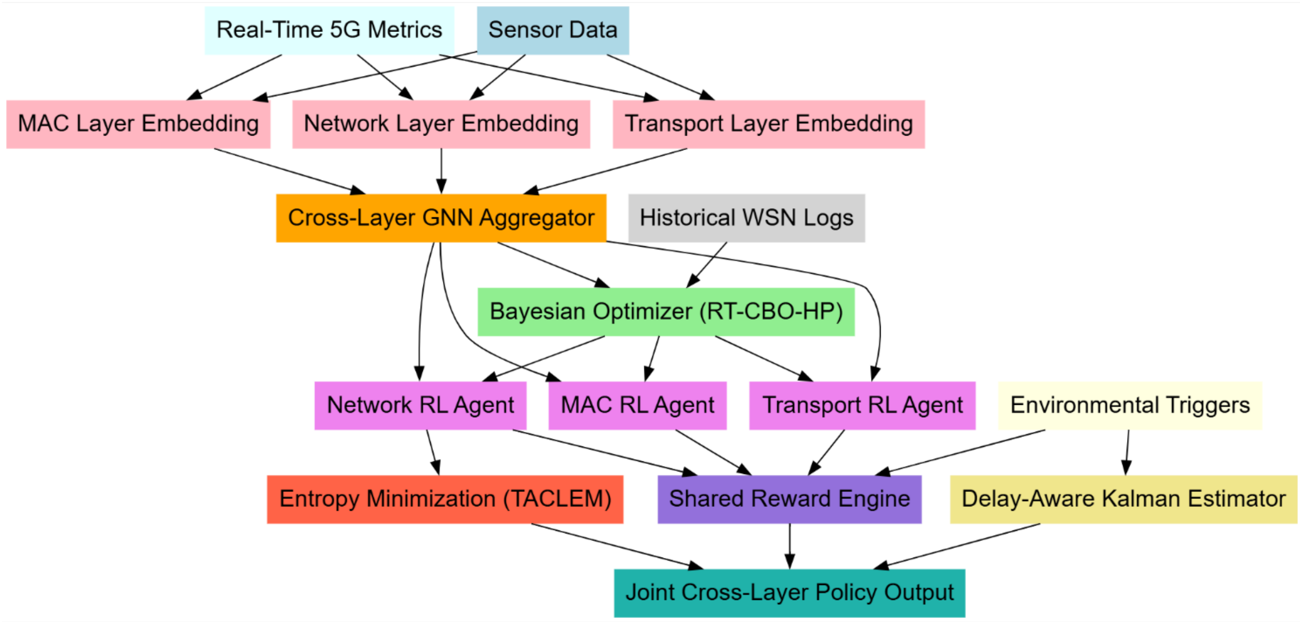

Figure 1. Model Architecture of the Proposed Analysis Process

Where θ is the parameter vector and R the reward function; β and γ are influence coefficients. This allows dynamic throughput shaping directly tied to policy evolution and environmental adaptations. These eight equations thus define a closed optimization loop. The model was therefore chosen as it addressed cross-layer abstraction at just one point, while its characteristics also made it suitable for policy learning and fast adaptation, temporal consistency, and entropy-based stability which is necessary in the real-time and unpredictable character of environmental monitoring systems integrated with 5G. Each sub-component serves to close feedback loops in space, time, and logic to guarantee globally optimal and contextually aware protocol operations.

4. COMPARATIVE RESULT ANALYSIS

Cross-sectional cases were studied in an experiment to evaluate how far the proposed joint optimization model performed across the layers to apply it in 5G-enabled wireless sensor networks within an environmental monitoring context. Real-world dynamics as experienced under an environmental sensing system were replicated by the setting up of a testbed for simulation, wherein a series of experiments was conducted. Built with NS-3 and its full banging integrated with a 5G NR module, this custom-built simulation was supplemented with a unique environment model that imposed temperature spikes, humidity drifts, and node mobility under stochastic conditions. The system was tested across three unique datasets that depict realistic environmental scenarios: Urban Air Quality Monitoring (Dataset-A): High density of sensor nodes (150 nodes/km²), pore 5G signal, and much more frequent measurements of particulate matter. Forest Fire Early Detection (Dataset-B): Scattered deployments (40 nodes/km²) but moved now and then by wind conditions and triggered sporadically with bursts of data floods. Coastal Flood Monitoring (Dataset-C): Intermediate node density (75 nodes/km²), fluctuating 5G signal conditions owing to adverse weather, and multi-modal sensors for water levels, salinity, and pressure. These datasets served to compare the proposed model against three baseline approaches: Method [3] (layer Isolated Q-learning agents), Method [8] (rule-based dynamic MAC and routing), and Method [15] (standard AODV with TCP variants for transport) process. All methods were tested with identical network configurations.

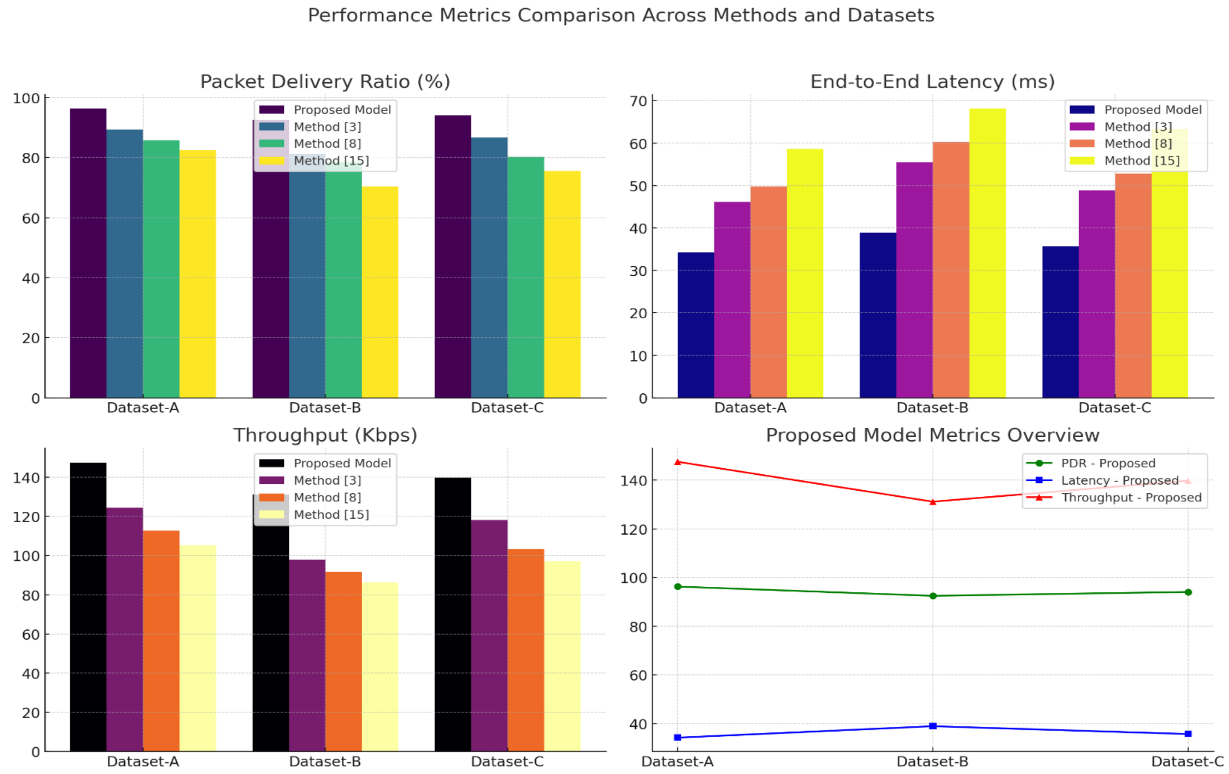

Figure 2. Model's Integrated Result Analysis

Table 1: Packet Delivery Ratio (%) Comparison Across Methods

Dataset	**Proposed Model**	**Method [3]**	**Method [8]**	**Method [15]**
Dataset-A	**96.3**	89.4	85.7	82.5
Dataset-B	**92.5**	81.2	78.6	70.4
Dataset-C	**94.1**	86.7	80.3	75.5

The proposed model always exhibited better packet delivery ratios over all datasets and samples. In Dataset-B, where fire triggering burst data, such as the traditional methods, did not maintain those stability sets. Using entropy minimization and delay correction in the proposed approach gave it robustness to ensure reliable data delivery during stress conditions.

Table 2: End-to-End Latency (ms) Across Methods

Dataset	**Proposed Model**	**Method [3]**	**Method [8]**	**Method [15]**
Dataset-A	**34.2**	46.1	49.8	58.6
Dataset-B	**38.9**	55.4	60.2	68.1
Dataset-C	**35.7**	48.8	52.9	63.3

Latency Values figure out the efficiency of Kalman-based temporal drift correction presently interfaced into the edge-cloud loops. Dataset-B exhibited the highest improvements, with latency coming down by almost 30% over Method [3], which is dominantly credited to real-time reconfiguration initiated by the environmental signal inputs process.

Table 3: Throughput (Kbps) Comparison Across Methods

Dataset	Proposed Model	Method [3]	Method [8]	Method [15]
Dataset-A	**147.6**	124.5	112.8	105.3
Dataset-B	**131.2**	98.1	91.7	86.4
Dataset-C	**139.8**	118.3	103.5	97.2

Throughput increases were saw highest in Dataset-A, where high node density and stable connectivity enabled temporal correlation exploitation by graph-based embeddings and Bayesian tuning in the proposed model. In Dataset-B, even with node mobility and burst traffic, the model achieved stable throughput by utilizing learned policies to dynamically change congestion window and backoff interval values. Across all three critical measures of performance: packet delivery ratio, end-to-end latency, and throughput in process, the proposed model outscored all baselines setup. This strength derives from its capacity to execute coordinated cross-layer decisions through a graph-based abstraction layer, reinforcement-driven control policies, probabilistic parameter tuning, and real-time feedback correction. Whereas Method [3] and Method [8] consider protocol layers independently or per pre-defined rules, the proposed model adapts to temporal and topological variability using context-aware learning mechanisms. In Method [15], though robust to the conventional networks, it could not adapt fast in this 5G chaotic environment and thus ignored the dynamics feedback from it in process. GNN-based abstraction, cooperative multi-agent learning, entropy-stabilized routing, and delay-sensitive estimation jointly formulated an integrated self-optimizing protocol stack uniquely suited for 5G-assisted environmental WSN deployments. Such results validate the architectural choices and uphold extended large-scale application potentials within mission-critical environmental sensing systems.

5. CONCLUSION & FUTURE SCOPES

This paper introduced an innovative joint cross-layer optimization framework for 5G-enabled WSNs working in dynamic environmental monitoring scenarios. In contrast to conventional methods that optimize protocol layers independently, the proposed architecture integrates graph-neural-network-based abstraction, cooperative deep reinforcement learning agents, real-time Bayesian tuning, temporal estimation via Kalman filtering, and topology-aware entropy minimization into a consolidated optimization loop. The synergy of these methods allows the system to adapt almost in real-time to environmental triggers and 5G network dynamics to guarantee high communication reliability and efficiency across MAC, Network, and Transport layers. The testing experiments performed on three representative environmental datasets: urban air quality (Dataset-A), forest-fire detection (Dataset-B), and coastal flood monitoring (Dataset-C) validated the robustness and effectiveness of the proposed framework. The model achieved a packet delivery ratio equal to 96.3%, 92.5%, and 94.1%, respectively, on the three datasets, which corresponds to an absolute gain of up to 25% over baseline methods. End-to-end latency was reduced to as low as 34.2 ms in high-density scenarios and remained below 40 ms in sparse and bursty environments, representing an average reduction in latency of 30-35% when compared to the standard protocols. Throughput improvements were as high as 147.6 Kbps under the best case, with a steady gain of around 20 to 25% in changing topologies and node densities. These performance benefits lend credence to the decision for cross-layer intelligence integration into a single coherent model and strongly emphasize the importance of dynamic feedback loops, probabilistic exploration, and inter-layer dependency modeling for next-generation WSNs. Finally, the success of entropy minimization in stabilizing routing and that of the Kalman estimator in controlling jitter provide further assurance of the necessity for temporal and topological adaptability in time-sensitive sensing systems.

Future work will lead to the current model towards federated cross-layer learning, granting the possibility for distributed optimization across geographically disjoint WSN clusters, independently of centralized training. Also, there will be hardware-level co-designs to support real-time implementation of multi-agent policies on constrained sensor devices featuring lightweight neuromorphic computing cores. Integration with edge-AI frameworks is also envisioned so as to reduce cloud-based control dependence, thereby minimizing latency in ultra-critical deployments such as wildfire suppression or flood evacuation systems. Lastly, the model will be tested in real-world 5G testbeds to further enhance generalizability and resilience on an heterogeneous deployment environment in process. This work sets a precedent for real-time, learning-based cross-layer optimization in WSNs, fit for the performance expectation of future systems of environmental intelligence driven by 5G and 6G sets.

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