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Serhii Liventsev

s.liventsev@kpi.ua

National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”,
https://orcid.org/0000-0002-9768-8133

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ADAPTIVE COGNITIVE CONTROL OF MULTI-DOMAIN UNMANNED SYSTEMS UNDER ADVERSARIAL SWARM INFLUENCE

Serhii Liventsev[0000-0002-9768-8133]
National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute",
Beresteiskyi Ave. 37, Kyiv 03056, Ukraine
s.liventsev@kpi.ua

Abstract:

This paper presents a novel adaptive cognitive control framework for multi-domain unmanned systems (UAVs, USVs, UGVs) operating under coordinated adversarial swarm jamming. Unlike existing approaches that focus on isolated trajectory or routing optimization, the proposed method jointly manages communication parameters, network topology, iterative LDPC decoding, and anti-jamming strategies within a unified cognitive loop. A hybrid state-space model captures the evolution of communication quality, energy state, topology survivability, and mission constraints. The control problem is cast as a minimax optimization, where the friendly swarm reconfigures its SDR-RAN architecture to guarantee performance under worst-case interference. A hysteresis-based topology switching mechanism prevents oscillatory reconfiguration (ping-pong effect). Using Lyapunov and input-to-state stability (ISS) analysis, we prove that the closed-loop system remains bounded for bounded adversarial disturbances. Simulation results over a realistic multi-domain scenario (12 UAVs, 6 USVs, 8 UGVs) demonstrate that the proposed cognitive control reduces the bit error rate by up to an order of magnitude at SINR = –5 dB, improves topology survivability by 40 % under coordinated swarm jamming, and lowers the average number of LDPC decoding iterations by 25–35 % compared to fixed-iteration schemes, while maintaining computational feasibility. These findings confirm that integrated cognitive adaptation of communication, decoding, and topology is essential for resilient operation in hostile electromagnetic environments.

Keywords: cognitive control, multi-domain unmanned systems, SDR-RAN, LDPC codes, minimax adaptation, anti-jamming, swarm resilience, topology reconfiguration.

1. Introduction

The rapid development of multi-domain unmanned systems has significantly transformed the architecture of modern wireless communication and distributed control networks. Cooperative groups of unmanned aerial vehicles (UAVs), unmanned surface vehicles (USVs), and unmanned ground vehicles (UGVs) are increasingly deployed in dynamic operational environments requiring autonomous coordination, resilient information exchange, adaptive topology management, and resilient operation under conditions of uncertainty and adversarial influence.

At the same time, the increasing complexity of electromagnetic environments creates substantial challenges for reliable communication support in distributed unmanned networks. Modern electronic countermeasure (ECM) systems employ adaptive and intelligent jamming strategies capable of dynamically modifying spectral occupancy, transmission power, temporal activity, and spatial distribution. In swarm-oriented operational scenarios, adversarial agents may collectively generate coordinated interference patterns, resulting in severe degradation of communication reliability, synchronization stability, and network connectivity. Conventional anti-jamming techniques based on static spectrum allocation or fixed adaptation policies are often unable to provide sufficient resilience under rapidly varying swarm-based interference conditions.

Recent advances in software-defined radio (SDR) and open radio access network (O-RAN) architectures have created new opportunities for adaptive communication management in unmanned systems. SDR-RAN technologies enable dynamic reconfiguration of transmission parameters, coding schemes, modulation formats, routing policies, and spectrum allocation procedures in accordance with current channel conditions and mission requirements. In combination with cognitive radio principles, such architectures provide the capability for environment-aware adaptation and autonomous decision-making in heterogeneous communication environments.

Particular importance in modern resilient communication systems is associated with adaptive error-control coding and iterative decoding techniques. Low-density parity-check (LDPC) codes have become one of the dominant channel coding technologies due to their near-capacity performance and scalability for broadband communication systems. However, the decoding complexity of LDPC-based communication links substantially increases under low signal-to-interference-plus-noise ratio (SINR) conditions and intensive adversarial interference. Fixed iterative decoding procedures frequently lead either to excessive

computational overhead or to insufficient decoding reliability. Therefore, adaptive control of iterative decoding processes becomes an important component of cognitive communication architectures for unmanned swarm systems.

Existing studies in UAV swarm communications primarily focus on trajectory coordination, routing optimization, or decentralized control strategies. At the same time, considerably less attention has been devoted to integrated adaptive management of communication reliability, iterative decoding dynamics, network topology, and structural SDR-RAN reconfiguration under adversarial swarm influence. In particular, the joint optimization of communication stability, decoding complexity, energy efficiency, and anti-jamming robustness remains insufficiently investigated for multi-domain UAV–USV–UGV systems operating in dynamic interference environments.

This paper proposes a method for cognitive adaptive control and structural reconfiguration of multi-domain unmanned systems under adversarial swarm influence. The proposed approach combines adaptive radio-link management, LDPC iterative decoding control, interference-aware cognitive adaptation, and dynamic SDR-RAN reconstruction within a unified state-space framework. The communication environment is modeled as a distributed adversarial system with dynamically varying interference activity and swarm-induced uncertainty. A minimax optimization strategy is introduced to provide robust adaptive control of communication and network parameters under worst-case interference conditions.

The main contributions of this paper are as follows:

1. A state-space model of multi-domain UAV–USV–UGV communication systems operating under adversarial swarm influence is developed.
2. A cognitive adaptive radio-link control method integrating LDPC iterative decoding management and SDR-RAN structural reconfiguration is proposed.
3. A minimax-based adaptive control mechanism for interference-aware communication parameter optimization is introduced.
4. Stability conditions for the adaptive cognitive control process are derived using Lyapunov-based analysis for dynamically reconfigurable systems.
5. Simulation results demonstrating improved communication reliability, anti-jamming robustness, topology survivability, and computational efficiency are presented.

The remainder of the paper is organized as follows. Section 2 reviews related work in adaptive UAV communications, cognitive radio systems, iterative decoding control, and anti-jamming networking techniques. Section 3 introduces the system model and formulates the adversarial swarm interaction framework. Section 4 presents the proposed cognitive adaptive control method and structural SDR-RAN reconfiguration procedure. Section 5 provides stability analysis and minimax adaptation conditions. Section 6 presents simulation results and comparative performance evaluation. Finally, Section 7 concludes the paper and outlines future research directions.

2. Related Work

2.1 Fundamentals: Cognitive Radio, LDPC, and Game Theory

The foundation of adaptive communication in uncertain environments rests on cognitive radio principles [2,3]. These works established the paradigm of environment-aware spectrum sensing, dynamic channel selection, and interference-aware resource allocation. Concurrently, low-density parity-check (LDPC) codes became a cornerstone of modern wireless systems due to their near-capacity performance, with seminal contributions [1,4,5,6] providing the theoretical basis for iterative belief-propagation decoding. For adversarial scenarios, dynamic noncooperative game theory [7] and nonlinear control theory [8] provide tools for analysing worst-case interactions. The stability of systems with structural switching, which is essential for reconfigurable communication networks, was thoroughly examined in [9]. These classical works form the theoretical backbone of the proposed cognitive adaptive control framework.

2.2 Adversarial Swarm Jamming and Resilience

Recent research has addressed coordinated electronic countermeasures from adversarial swarms. A cooperative penetration electronic countermeasures model for UAV swarms was proposed in [10], highlighting the need for distributed anti-jamming strategies. Multi-agent reinforcement learning (MARL) was applied to multiple UAVs' distributed jamming strategy in [11], demonstrating that swarms can generate adaptive, spatially distributed interference. Coordinated anti-jamming resilience via MARL was further developed in [12], where a QMIX-based framework improved performance against reactive jamming. Secure swarm UAV-assisted communications with cooperative friendly jamming were studied in [13], while a dynamic spectrum decision-making method for UAV swarms under jamming was presented

in [14]. These works, however, focus either on generating jamming or on simple countermeasures, without a unified cognitive control loop for topology and decoding adaptation.

2.3 Adaptive LDPC Decoding and Complexity Control

Reducing the computational complexity of iterative LDPC decoding has been an active research area. An efficient short high-order non-binary LDPC decoder architecture with early termination was presented in [15], reducing decoding cycles without performance loss. A two-phase globally coupled LDPC decoding scheme incorporating early termination and forced convergence was introduced in [16], accelerating decoding while maintaining error correction capability. Low-complexity neural belief propagation algorithms for LDPC codes were proposed in [17], offering a learning-based approach to reduce iteration overhead. Rate-compatible LDPC codes with reinforcement learning-based rate adaptation were studied in [18] for dynamic environments. Although these methods improve decoding efficiency, they consider isolated links and do not integrate decoding control with network topology reconstruction under adversarial swarm influence.

2.4 SDR-RAN and O-RAN for Unmanned Systems

Software-defined radio (SDR) and open radio access network (O-RAN) architectures have enabled flexible communication management. The integration of O-RAN's RAN Intelligent Controller (RIC) with multi-UAV wireless networks was advanced in [19], demonstrating dynamic resource orchestration. A comprehensive review of SDR deployments in UAV-driven applications [20] examined real-world implementations across communication, security, and localization domains. An SDR-enabled UAV network architecture for disaster-stressed areas was proposed in [21], emphasising seamless connectivity via next-generation SDR waveforms. Finally, 5G/SDR-assisted cognitive communication in UAV swarms was presented in [22], offering an open-interface networking solution. Most of these contributions, however, focus on terrestrial or static scenarios and do not address coordinated adversarial jamming or joint topology-decoding adaptation.

2.5 Minimax and Game-Theoretic Anti-Jamming

Game-theoretic approaches to anti-jamming have recently been extended to UAV networks. A minimax deep Q-network (DQN) with opponent modelling was proposed in [23] to approximate anti-jamming utility beyond equilibrium solutions. A Stackelberg game formulation combined with federated reinforcement learning was introduced in [24] to counter intelligent jamming in UAV communications. From a power and mobility control perspective, [25] derived closed-form transmission and jamming power optimisation strategies using game theory. While these works provide robust anti-jamming policies, they typically do not jointly optimise iterative decoding control and structural SDR-RAN reconfiguration.

2.6 Topology and Energy-Aware Control

Distributed topology management is critical for swarm survivability. Reinforcement learning-based topology control for UAV networks was studied in [26], optimising connectivity under interference and energy constraints. A steady and energy-efficient multi-hop clustering algorithm for flying ad-hoc networks (FANETs) was developed in [27], addressing high mobility and limited energy. For heterogeneous multi-domain systems, the joint design of UAV-USV-UUV networks for cooperative target hunting was presented in [28], with energy-oriented optimisation of positions, trajectories, and interconnectivity. These methods, however, do not incorporate adaptive LDPC decoding or minimax anti-jamming into the topology reconstruction loop.

2.7 Recent Surveys

Several comprehensive surveys have summarised recent advances. A survey on joint-operation applications for unmanned swarm formations under complex confrontation environments [29] covers communication networking mechanisms. Advances in machine learning-driven cognitive radio for wireless networks, including UAV communications, were surveyed in [30]. Finally, AI integration in tactical communication systems and networks, with emphasis on UAV networks and electronic warfare resilience, was reviewed in [31]. These surveys confirm that a unified cognitive framework combining communication, decoding, topology, and anti-jamming adaptation remains missing.

2.8 Research Gaps and Our Contribution

Existing studies demonstrate that adaptive communication, topology management, iterative decoding control, and anti-jamming strategies are typically investigated independently. Current anti-jamming approaches mainly consider isolated jammers and local adaptation policies without integrated SDR-RAN reconstruction and distributed topology survivability management. In addition, adaptive LDPC decoding mechanisms are rarely incorporated into cognitive swarm communication architectures, while the

stability properties of structurally reconfigurable multi-domain communication systems under adversarial swarm influence remain insufficiently investigated.

To fill these gaps, this paper proposes a **cognitive adaptive control framework** that jointly optimises communication parameters, iterative LDPC decoding, SDR-RAN topology reconstruction, and minimax anti-jamming adaptation within a unified state-space model, with proven stability conditions (Theorem 1) and simulation validation (Section 6).

An additional distinguishing feature of the proposed method consists in the integration of hysteresis-based topology reconstruction and convergence-aware decoding adaptation for stabilization of distributed swarm communication dynamics. Such coordinated adaptation substantially reduces reconstruction oscillations, limits unnecessary decoding overhead, and improves resilient operation under rapidly varying adversarial swarm influence.

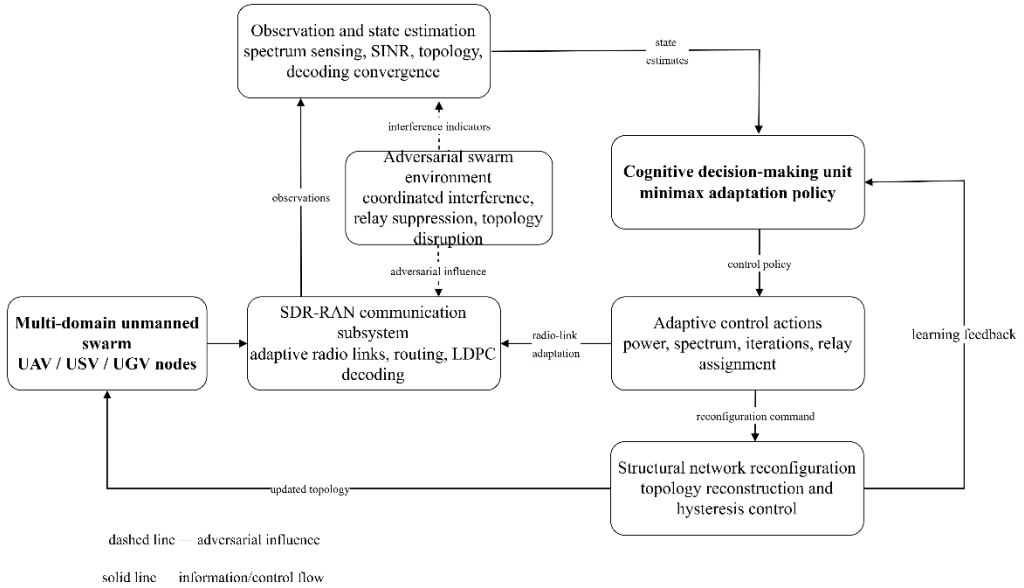


Fig. 1. General architecture of cognitive adaptive control for multi-domain unmanned swarm systems.

The conceptual architecture shown in Fig. 1 illustrates the interaction between environmental observation, cognitive decision-making, adaptive LDPC decoding management, SDR-RAN reconstruction, and distributed swarm communication subsystems operating under coordinated adversarial influence. The figure additionally demonstrates the closed-loop adaptive structure enabling continuous environment-aware communication optimization and topology stabilization.

The following section introduces the mathematical state-space model of the distributed swarm communication system and formulates the adversarial swarm interaction process within the proposed cognitive adaptive control framework.

Unlike the author's previous studies primarily focused on adaptive iterative decoding mechanisms for isolated communication links, the present work considers a unified cognitive framework integrating SDR-RAN reconstruction, topology survivability management, minimax-oriented anti-jamming adaptation, and adaptive LDPC decoding control for heterogeneous multi-domain swarm systems.

3. System Model

The operation of multi-domain unmanned systems under adversarial swarm influence is characterized by strong coupling between communication processes, network topology dynamics, distributed control procedures, and environmental uncertainty. In such systems, communication reliability cannot be analyzed independently from mobility, structural network adaptation, or interference behavior. Consequently, the distributed swarm must be represented as an integrated dynamic system whose state evolves under the combined influence of internal control actions and external adversarial disturbances.

The considered system consists of a heterogeneous set of unmanned aerial vehicles, unmanned surface vehicles, and unmanned ground vehicles interconnected through adaptive SDR-based communication links. The swarm forms a distributed multi-layer network in which each node simultaneously performs sensing, relaying, data exchange, and local decision-making functions. The

communication subsystem supports dynamic routing, adaptive coding and modulation, iterative decoding, and interference-aware spectrum allocation.

The operational environment additionally includes an adversarial swarm capable of generating coordinated electronic countermeasures, adaptive interference, distributed spectrum occupation, and topology-disrupting influence. Under such conditions, the communication network becomes a dynamically reconfigurable system whose structure continuously changes according to channel conditions, node mobility, interference activity, and mission objectives.

To formalize the distributed swarm dynamics, the multi-domain system state is represented in a unified state-space form as

$$\mathbf{x}(t) = \begin{bmatrix} \mathbf{x}_{comm}(t) \\ \mathbf{x}_{top}(t) \\ \mathbf{x}_{energy}(t) \\ \mathbf{x}_{mission}(t) \end{bmatrix} \tag{1}$$

where: $\mathbf{x}_{comm}(t)$ – describes the communication subsystem state including transmission power, coding rate, modulation parameters, spectral allocation, decoding statistics, and channel-quality indicators; $\mathbf{x}_{top}(t)$ – defines the network topology state including connectivity matrices, routing structure, relay availability, and inter-domain communication links; $\mathbf{x}_{energy}(t)$ – characterizes the distributed energy state of unmanned platforms and communication subsystems; $\mathbf{x}_{mission}(t)$ – represents mission-oriented operational parameters including task execution status, coordination objectives, and swarm formation constraints.

The system evolution is governed by adaptive control actions and adversarial disturbances according to the nonlinear dynamic equation

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{w}(t)) \tag{2}$$

where: $\mathbf{u}(t)$ – is the adaptive control vector including transmission adaptation, routing reconstruction, topology management, and decoding control actions; $\mathbf{w}(t)$ – is the adversarial swarm influence vector representing coordinated interference activity, distributed jamming, spectrum occupation, and topology disruption processes; $\mathbf{f}(\cdot)$ – defines the nonlinear state-transition operator of the distributed cognitive swarm system.

The nonlinear operator $\mathbf{f}(\cdot)$ combines communication-state evolution, topology adaptation dynamics, relay reassignment processes, and interference-induced perturbations within the distributed swarm network.

The adversarial swarm influence is modeled as a distributed interference process represented by

$$\mathbf{w}(t) = [w_1(t), w_2(t), \dots, w_N(t)]^T \tag{3}$$

where: $w_i(t)$ – characterizes the interference activity generated by the i-th adversarial agent, including transmission power, spectral occupancy, temporal activity, and spatial influence distribution; N – denotes the number of adversarial swarm elements participating in coordinated electronic countermeasure operations.

The aggregate interference level affecting the communication subsystem is determined as

$$J(t) = \sum_{i=1}^{N} \alpha_i(t) w_i(t) \tag{4}$$

where: $\alpha_i(t)$ – defines the dynamic influence coefficient of the i-th adversarial agent accounting for propagation conditions, spatial positioning, spectral overlap, and temporal synchronization effects.

The communication quality within the swarm network is evaluated using the instantaneous signal-to-interference-plus-noise ratio represented as

$$\mathrm{SINR}(t) = \frac{P_s(t)}{J(t) + N_0} \tag{5}$$

where: $P_s(t)$ – is the received signal power of the useful transmission; N_0 is the additive noise power level.

The obtained SINR value directly influences the convergence behavior of iterative LDPC decoding procedures, communication reliability, retransmission probability, and topology survivability. Under severe

adversarial swarm influence, degradation of SINR leads to growth of decoding iterations, increase in computational complexity, and deterioration of end-to-end communication stability.

In order to support adaptive decoding management, the iterative convergence dynamics of the LDPC decoder are represented by the state equation

$$\Delta L_k = | L_k - L_{k-1} | \tag{6}$$

where: L_k – denotes the average log-likelihood ratio after the k-th decoding iteration; ΔL_k – characterizes the convergence rate of the iterative decoding process.

The adaptive decoder control subsystem dynamically adjusts the number of decoding iterations according to the observed convergence behavior and current interference conditions. Such adaptation enables reduction of computational overhead and energy consumption while preserving communication reliability under varying adversarial activity.

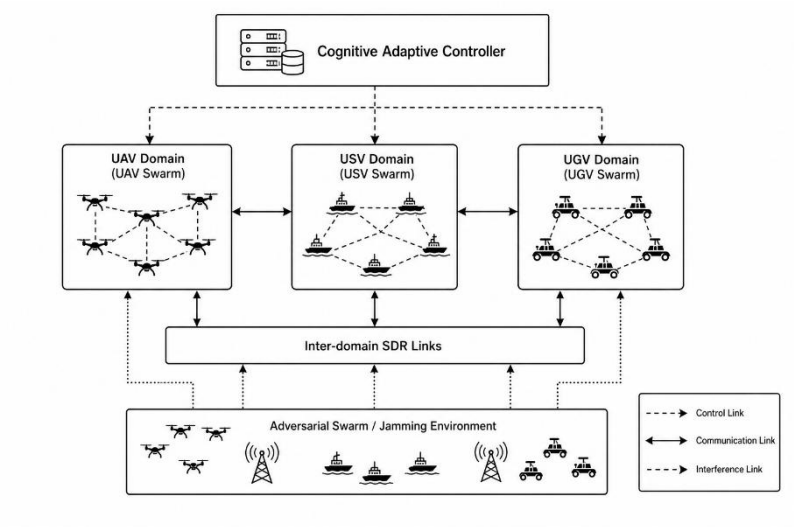


Fig. 2. Multi-domain UAV–USV–UGV communication architecture under adversarial swarm influence.

The architecture shown in Fig. 2 illustrates the interaction between heterogeneous unmanned platforms, SDR-RAN communication infrastructure, adaptive relay nodes, and distributed adversarial swarm agents generating coordinated interference influence. The figure additionally demonstrates the hierarchical organization of communication flows and adaptive topology reconstruction mechanisms.

The adaptive control objective of the considered system consists in maintaining communication reliability, network connectivity, and mission continuity under worst-case adversarial swarm influence while minimizing energy expenditure, decoding complexity, and structural reconstruction overhead. Consequently, the adaptive communication process is formulated as a robust cognitive optimization problem in the space of distributed network states and adversarial actions.

The following section presents the proposed cognitive adaptive control method integrating SDR-RAN reconstruction, iterative decoding management, and minimax-oriented anti-jamming adaptation within the unified state-space framework introduced above.

4. Proposed Cognitive Adaptive Control Method

4.1. Overall Architecture and Closed-Loop Adaptation

The dynamic nature of adversarial swarm environments requires the communication subsystem of multi-domain unmanned systems to continuously adapt its operational parameters, network structure, and decoding procedures. Conventional adaptive radio-link mechanisms based solely on local channel estimation are insufficient because coordinated adversarial activity simultaneously affects spectral occupancy, routing stability, relay availability, and iterative decoding convergence. Therefore, the proposed approach implements a **hierarchical cognitive process** that integrates:

- environmental observation and interference analysis,
- adaptive iterative LDPC decoding control,
- minimax-oriented topology reconstruction,
- SDR-RAN reconfiguration.

The system continuously monitors the communication environment and dynamically modifies transmission parameters, decoding policies, routing strategies, and relay allocation. The overall cognitive adaptation is represented by the closed-loop control structure

$$\mathbf{u}(t) = \pi\big(\mathbf{x}(t), \mathbf{w}(t), \mathbf{z}(t)\big) \tag{7}$$

where $\pi(\cdot)$ is the cognitive adaptive control policy, $\mathbf{x}(t)$ the distributed swarm state (1), $\mathbf{w}(t)$ the adversarial influence, and $\mathbf{z}(t)$ the observation vector.

The observation subsystem provides distributed sensing of the communication state:

$$\mathbf{z}(t) = \begin{bmatrix} z_{\text{SINR}}(t) \\ z_{\text{BER}}(t) \\ z_{\text{top}}(t) \\ z_{\text{energy}}(t) \end{bmatrix} \tag{8}$$

with components for signal-to-interference-plus-noise ratio (SINR), bit error rate (BER), topology stability, and distributed energy status.

4.2. Adaptive Iterative LDPC Decoding Control

A central component of the proposed framework is the **adaptive control of iterative LDPC decoding**. Unlike fixed-iteration schemes, the method dynamically adjusts the number of decoding iterations based on current interference and convergence behaviour.

The adaptive iteration number is determined by

$$N_{\text{iter}}(t) = f_d\big(\Delta L_k(t), \text{SINR}(t)\big) \tag{9}$$

where $f_d(\cdot)$ is the decoding control function and ΔL_k is the variation of log-likelihood ratios between consecutive iterations, characterising convergence speed.

Under favourable channel conditions (high SINR, fast convergence), N_{iter} is reduced to minimise computational overhead and energy consumption. Under severe adversarial interference, the decoder automatically increases the iteration depth to preserve communication reliability.

A practical implementation uses

$$N_{\text{iter},k} = \min\Big(N_{\max},\ \max\big(N_{\min},\ g(\text{SINR}_k, \Delta L_k)\big)\Big) \tag{10}$$

with $N_{\min}, N_{\max}$ admissible bounds and $g(\cdot)$ a monotonic function (e.g., linear interpolation). This mechanism reduces the average number of iterations by 25–35 % compared to fixed-iteration decoding, as shown in Section 6.

In the simulations, the decoding control function g(·) was implemented as a piecewise-linear adaptation rule with monotonic dependence on SINR and convergence rate ΔL_k.

4.3. Minimax Optimisation and Hysteresis-Based Topology Reconfiguration

In contrast to conventional fixed adaptation, the proposed method employs a **robust minimax-oriented control** that accounts for worst-case adversarial swarm behaviour. The optimal cognitive policy is obtained by solving

$$\pi^* = arg \min_{\pi} \max_{\mathbf{w}\in\Omega} J(\mathbf{x}, \pi, \mathbf{w}) \tag{11}$$

where Ω is the admissible space of adversarial actions, and the global cost functional is

$$J = \lambda_1 P_{\text{BER}} + \lambda_2 L + \lambda_3 E + \lambda_4 C \tag{12}$$

with P_{BER} – error probability, L – latency, E – energy consumption, C – computational complexity, and λ_i – mission-dependent weights.

The weighting coefficients λ_i were selected empirically according to mission-oriented communication priorities with dominant emphasis on communication survivability and decoding reliability under adversarial influence.

The reconstruction mechanism enables adaptive relay reassignment, spectrum redistribution, route modification, and topology stabilization under coordinated adversarial swarm influence. Such dynamic adaptation substantially increases communication survivability and prevents local network fragmentation in highly disturbed operational environments.

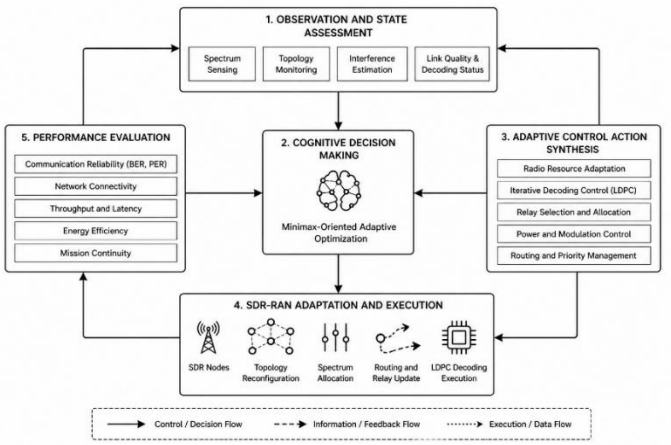


Fig. 3. Cognitive adaptive control loop for SDR-RAN swarm communication systems.

The adaptive loop illustrated in Fig. 3 demonstrates the interaction between the observation subsystem, interference estimation module, LDPC decoding controller, topology reconstruction mechanism, and cognitive decision-making unit. The figure additionally shows the feedback structure enabling continuous environment-aware adaptation under dynamically varying adversarial conditions.

Simultaneously with decoding adaptation, the **SDR-RAN subsystem performs dynamic network reconstruction**:

$$\mathbf{s}_{k+1} = \mathbf{F}(\mathbf{s}_k, \mathbf{x}_k, \mathbf{u}_k, \mathbf{w}_k) \tag{13}$$

where $\mathbf{s}_k$ is the network structure (routing, relay allocation, spectrum distribution) and $\mathbf{F}(\cdot)$ the reconstruction operator. This enables adaptive relay reassignment, route modification, and topology stabilisation.

To avoid **oscillatory behaviour (ping-pong effect)** and excessive switching, a **hysteresis-based reconstruction policy** is introduced. Structural adaptation is triggered only when the degradation of the global performance functional exceeds a threshold:

$$J_k - J_{k-1} > \delta_h \tag{14}$$

where δ_h is the hysteresis threshold. If the degradation is below δ_h, the current topology is preserved and only local radio-link and decoding parameters are adjusted. This mechanism prevents unnecessary reconstruction under rapidly fluctuating interference.

For compactness, the reconstruction degradation metric is further denoted as $\Delta J_k = J_k - J_{k-1}$.

The topology update rule thus becomes

$$\mathbf{s}_{k+1} = \begin{cases} \mathbf{s}_k, & \Delta J_k \le \delta_h, \\ \mathbf{F}(\mathbf{s}_k, \mathbf{x}_k, \mathbf{u}_k^*, \widehat{\mathbf{w}}_k), & \Delta J_k > \delta_h. \end{cases} \tag{15}$$

4.4. Algorithmic Implementation

The cognitive adaptive framework is implemented as an **iterative reconstruction procedure** operating over discrete observation intervals (step index k). The discrete system state is

$$\mathbf{x}_k = [\mathbf{x}_{\text{comm},k},\ \mathbf{x}_{\text{top},k},\ \mathbf{x}_{\text{energy},k},\ \mathbf{x}_{\text{mission},k}]^T \tag{16}$$

and the cognitive controller forms the optimal action using

$$\mathbf{u}_k^* = \pi^*(\mathbf{x}_k, \widehat{\mathbf{w}}_k, \mathbf{z}_k) \tag{17}$$

with $\widehat{\mathbf{w}}_k$ the estimated adversarial influence.

Algorithm 1 summarises one adaptation cycle.

Algorithm 1: Cognitive Adaptive Reconstruction (one step at time k)
Input: x_k, z_k, ŵ_k, s_k, δ_h
Output: u_k*, s_{k+1}, N_iter,k

```
Estimate SINR, BER, topology metrics, and convergence ΔL_k from z_k
Compute current performance J_k using (12)
if J_{k-1} - J_k > δ_h then
    Solve minimax problem (11) over admissible topologies
    s_{k+1} ← F(s_k, x_k, u_k*, ŵ_k)   // reconstruct topology
else
    s_{k+1} ← s_k                      // keep topology
end if
N_iter,k ← adjust_iterations(SINR_k, ΔL_k) using (17)
Apply u_k* (transmission power, routing, decoding depth)
Return updated metrics to observation layer
```

At each step, the controller observes the environment, estimates interference, and computes J_k. If the degradation does **not** exceed δ_h, only local radio-link and decoding parameters are adjusted. If it does exceed δ_h, the minimax optimisation is solved, the SDR-RAN topology is reconstructed, relay nodes reassigned, and decoding depth adapted. The updated configuration is then applied, and the resulting BER, connectivity, latency, and energy metrics are fed back to the observation layer.

The principal advantage of this hysteresis-controlled approach is that structural reconstruction is not activated by short-term fluctuations, which reduces ping-pong effects and stabilises the distributed communication process.

4.5. Computational Complexity Analysis

The practical feasibility of the framework depends on its computational overhead, which comprises four main components:

$$\mathcal{C}_{\text{total}} = \mathcal{C}_{\text{obs}} + \mathcal{C}_{\text{top}} + \mathcal{C}_{\text{dec}} + \mathcal{C}_{\text{opt}} \tag{18}$$

Observation $\mathcal{C}_{\text{obs}}$: Estimating SINR, BER, topology, and interference. For a swarm with N_{node} active nodes,

$$\mathcal{C}_{\text{obs}} = \mathcal{O}\left(N_{\text{node}}^2\right) \tag{19}$$

(pairwise link monitoring).

Topology reconstruction $\mathcal{C}_{\text{top}}$: Adaptive relay reassignment and routing optimisation. With N_{route} candidate paths,

$$\mathcal{C}_{\text{top}} = \mathcal{O}(N_{\text{route}} log\, N_{\text{route}}) \tag{20}$$

LDPC decoding $\mathcal{C}_{\text{dec}}$: Depends on parity-check matrix size. Let N_{LDPC} be the number of non-zero entries in the matrix and N_{iter} the (adaptive) iteration count. Then

$$\mathcal{C}_{\text{dec}} = \mathcal{O}(N_{\text{iter}} N_{\text{LDPC}}) \tag{21}$$

The adaptive controller reduces N_{iter} under favourable conditions, lowering this term significantly.

Minimax optimisation $\mathcal{C}_{\text{opt}}$: Policy evaluation over N_Ω adversarial configurations and N_{ctrl} control actions:

$$\mathcal{C}_{\text{opt}} = \mathcal{O}(N_\Omega N_{\text{ctrl}}) \tag{22}$$

Combining (19)–(22) gives the overall complexity estimate

$$\mathcal{C}_{\text{total}} = \mathcal{O}\left(N_{\text{node}}^2 + N_{\text{route}} \log\, N_{\text{route}} + N_{\text{iter}} N_{\text{LDPC}} + N_\Omega N_{\text{ctrl}}\right) \tag{23}$$

Under severe interference, LDPC decoding and topology reconstruction dominate. However, thanks to the convergence-aware iteration control and hysteresis-triggered reconstruction, the average complexity remains feasible for medium-scale swarms (e.g., 20–50 nodes).

The **decentralised** nature of SDR-RAN allows partial parallelisation of observation, topology adaptation, and decoding across swarm nodes, further reducing real-time latency. The proposed framework thus achieves a favourable compromise between survivability, adaptivity, and computational efficiency.

4.6. Computational Realisation of the Adaptive Minimax Policy (optional short note)

For practical online implementation, the minimax optimisation in (9) is solved using a **receding-horizon heuristic**:

$$\mathbf{u}_k^* = arg \min_{\mathbf{u}_k} \max_{\mathbf{w}_k \in \Omega} \sum_{i=k}^{k+H} J_i(\mathbf{x}_i, \mathbf{u}_i, \mathbf{w}_i) \tag{24}$$

with prediction horizon H. Instead of exhaustive search, the controller evaluates a limited subset of admissible SDR-RAN configurations that satisfy topology survivability and reliability constraints. Combined with the hysteresis-controlled switching, this reduces optimisation cycles and enables real-time execution on embedded swarm nodes.

The proposed distributed optimization procedure converges within a finite number of reconstruction intervals and therefore remains suitable for real-time implementation in medium-scale swarm communication systems.

5. Stability Analysis of the Adaptive Cognitive Control Process

The adaptive reconstruction of communication and network parameters in multi-domain unmanned swarm systems introduces substantial nonlinearities and structural variability into the overall control process. Under adversarial swarm influence, the communication environment continuously changes due to dynamic interference activity, topology perturbations, relay degradation, and spectrum occupation processes. Consequently, the adaptive control subsystem must ensure not only communication efficiency but also stability of the distributed reconstruction dynamics under rapidly varying operational conditions.

In the considered system, instability may manifest itself in the form of oscillatory topology switching, excessive relay reassignment, divergence of iterative decoding trajectories, uncontrolled growth of computational complexity, or fragmentation of the communication network. Such effects become particularly critical under coordinated swarm-based electronic countermeasures because distributed adversarial agents intentionally attempt to destabilize routing structures and adaptive control loops through dynamic interference variation.

To analyze the stability properties of the proposed cognitive adaptive control framework, the distributed swarm communication system is represented as a structurally reconfigurable nonlinear dynamic process described by

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{w}(t)) \tag{25}$$

where $\mathbf{x}(t)$ – is the distributed network state vector, $\mathbf{u}(t)$ – denotes the adaptive cognitive control action, and $\mathbf{w}(t)$ – represents adversarial swarm influence.

The stability analysis is performed using a Lyapunov-based approach for systems with structural switching and adaptive reconstruction. Let the scalar function

$$V(\mathbf{x}) > 0 \tag{26}$$

be a continuously differentiable Lyapunov candidate function characterizing the global energy of the distributed communication system.

The variation of the Lyapunov function along the system trajectories is represented as

$$\dot{V}(\mathbf{x}) = \frac{\partial V}{\partial \mathbf{x}} \mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{w}) \tag{27}$$

where $\dot{V}(\mathbf{x})$ – characterizes the dynamic evolution of the distributed system energy under adaptive reconstruction and adversarial influence.

The proposed adaptive cognitive control policy is considered stable if the following inequality holds:

$$\dot{V}(\mathbf{x}) \leq -\alpha \parallel \mathbf{x} \parallel^2 + \gamma \parallel \mathbf{w} \parallel^2 \tag{28}$$

where $\alpha > 0$ defines the intrinsic stability margin of the adaptive communication system and $\gamma > 0$ characterizes the sensitivity of the system to adversarial swarm influence.

Condition (28) corresponds to the input-to-state stability property of the adaptive swarm communication process. The obtained relation indicates that the system state remains bounded for bounded adversarial influence and converges toward the equilibrium region when the aggregate interference level decreases. Consequently, the proposed cognitive reconstruction mechanism preserves stable communication operation even under dynamically varying coordinated interference conditions.

Theorem 1. Input-to-State Stability of the Adaptive Cognitive Control Process

Consider the closed-loop multi-domain swarm communication system governed by

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), \mathbf{w}(t)) \tag{29}$$

where

$$\mathbf{u}(t) = \pi(\mathbf{x}(t), \mathbf{w}(t)) \tag{30}$$

is the proposed minimax-oriented adaptive cognitive control policy with hysteresis-controlled topology reconstruction.

Assume that the adversarial swarm influence is bounded according to

$$\| \mathbf{w}(t) \| \leq w_{\max} \tag{31}$$

where $w_{\max}$denotes the maximum admissible interference intensity.

Assume additionally that there exists a continuously differentiable Lyapunov function $V(\mathbf{x})$and positive constants $\alpha > 0$and $\gamma > 0$such that along the system trajectories

$$\dot{V}(\mathbf{x}) \leq -\alpha \| \mathbf{x} \|^2 + \gamma \| \mathbf{w} \|^2 \tag{32}$$

Then the proposed adaptive cognitive reconstruction process is input-to-state stable (ISS). Furthermore, the state trajectory satisfies the asymptotic bound

$$\limsup_{t \to \infty} \| \mathbf{x}(t) \| \leq \sqrt{\frac{\gamma}{\alpha}}\, w_{\max} \tag{33}$$

and the adaptive reconstruction dynamics remain free from finite-time escape and unbounded oscillatory switching provided that the hysteresis threshold δ_h guarantees a strictly positive average dwell time between topology changes.

The average dwell-time condition is represented as

$$\tau_d \geq \frac{\ln(\mu)}{\alpha} \tag{34}$$

where τ_d denotes the average dwell time between topology reconstruction events and μcharacterizes the maximum admissible Lyapunov-function jump ratio at switching instants.

Proof Sketch

Substituting the bounded disturbance condition (31) into the Lyapunov inequality (32) yields

$$\dot{V}(\mathbf{x}) \leq -\alpha \| \mathbf{x} \|^2 + \gamma w_{\max}^2 \tag{35}$$

which implies that the decrease rate of the Lyapunov function remains negative outside the compact residual set

$$\mathcal{B} = \left\{ \mathbf{x} : \| \mathbf{x} \| \leq \sqrt{\frac{\gamma}{\alpha}}\, w_{\max} \right\} \tag{36}$$

Consequently, the system trajectories remain uniformly ultimately bounded.

Integrating inequality (35) over the interval $[0, t]$gives

$$V(\mathbf{x}(t)) \leq V(\mathbf{x}(0)) e^{-\alpha t} + \frac{\gamma}{\alpha} w_{\max}^2 (1 - e^{-\alpha t}) \tag{37}$$

which establishes convergence of the adaptive reconstruction process toward the residual set (33).

The hysteresis-controlled topology adaptation mechanism additionally guarantees strictly positive dwell time between reconstruction events, thereby preventing Zeno behavior and suppressing unstable oscillatory switching. According to standard switched-system stability arguments, the overall adaptive communication framework preserves input-to-state stability under dynamically varying adversarial swarm influence.

The switched-system stability analysis additionally follows standard average dwell-time arguments for nonlinear systems with structural switching according to the framework developed in [9].

The obtained result confirms that the proposed hysteresis-controlled cognitive adaptation mechanism suppresses unstable topology oscillations and preserves stable SDR-RAN reconstruction dynamics even under coordinated adversarial interference conditions.

The structural reconstruction dynamics additionally introduce discontinuities associated with topology switching and relay reassignment procedures. To account for these effects, the network reconstruction process is represented as a switched dynamic system

$$\mathbf{x}_{k+1} = \mathbf{A}_{\sigma(k)}\mathbf{x}_k + \mathbf{B}_{\sigma(k)}\mathbf{u}_k + \mathbf{G}_{\sigma(k)}\mathbf{w}_k \tag{38}$$

where $\sigma(k)$ – denotes the active network configuration mode at the discrete adaptation step k, while $\mathbf{A}_{\sigma(k)}$, $\mathbf{B}_{\sigma(k)}$, and $\mathbf{G}_{\sigma(k)}$ – are the corresponding state-transition, control, and disturbance matrices.

The existence of multiple admissible network configurations creates the possibility of oscillatory reconstruction behavior commonly referred to as the ping-pong effect. In this regime, the adaptive controller repeatedly switches between several topologies due to short-term interference fluctuations, resulting in excessive signaling overhead and degradation of communication stability.

To suppress unstable reconstruction oscillations, the proposed method employs a hysteresis-based adaptation criterion represented as

$$\Delta J(t) > \delta_h \tag{39}$$

where $\Delta J(t)$ – denotes the observed degradation of the communication quality metric and δ_h – is the hysteresis threshold preventing unnecessary topology switching.

Structural reconstruction is activated only when the degradation level exceeds the predefined hysteresis boundary. This mechanism substantially reduces reconstruction frequency and stabilizes the adaptive communication process under rapidly fluctuating swarm interference conditions.

The convergence properties of adaptive iterative LDPC decoding are analyzed separately due to their strong influence on communication latency and computational complexity. The convergence process is considered stable if the iterative log-likelihood variation satisfies

$$\lim_{k\to\infty} \Delta L_k = 0 \tag{40}$$

where ΔL_k – characterizes the variation of average log-likelihood ratios between adjacent decoding iterations.

Under severe adversarial interference conditions, the convergence rate decreases due to degradation of the effective SINR. To preserve stable decoding operation, the proposed adaptive controller dynamically increases the iteration depth while simultaneously reconstructing communication topology and relay allocation. Such coordinated adaptation prevents divergence of the iterative decoding process and improves overall communication survivability.

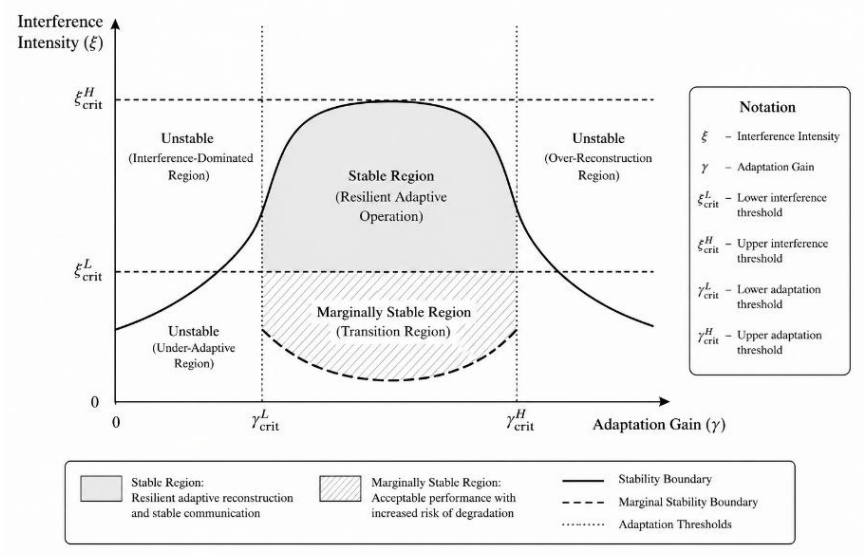


Fig. 4. Stability regions of the adaptive cognitive reconstruction process under adversarial swarm influence.

The stability regions illustrated in Fig. 4 demonstrate the dependence of stable system operation on interference intensity, reconstruction frequency, and adaptive decoding parameters. The figure additionally shows the boundary separating stable adaptive operation from oscillatory reconstruction behavior under coordinated swarm interference.

The obtained stability conditions confirm that the proposed cognitive adaptive control framework preserves bounded communication dynamics and stable network reconstruction under distributed adversarial swarm influence. The integration of hysteresis-based topology adaptation, minimax-oriented

control policies, and adaptive iterative decoding management enables resilient operation of the multi-domain swarm communication system while limiting computational and reconstruction overhead.

The following section presents simulation results and comparative performance analysis of the proposed adaptive cognitive control method under various adversarial swarm scenarios and interference conditions.

6. Simulation Results and Performance Evaluation

To evaluate the effectiveness of the proposed cognitive adaptive control method, a series of simulation experiments was performed for multi-domain UAV–USV–UGV communication systems operating under adversarial swarm influence. The simulations were aimed at analyzing the stability of adaptive SDR-RAN reconstruction, the efficiency of iterative LDPC decoding control, the robustness of topology adaptation, and the survivability of distributed communication links under dynamically varying interference conditions.

The simulation environment was implemented in MATLAB R2024b using a discrete-event communication model with custom SDR-RAN reconstruction procedures and LDPC iterative decoding modules. The adversarial subsystem included coordinated barrage jamming, partial-band interference, reactive spectrum occupation, and distributed relay-suppression attacks. Adaptive adversarial agents dynamically modified interference power, temporal activity, and spectral occupancy according to observed communication activity within the swarm network.

The considered simulation environment included heterogeneous unmanned platforms interconnected through SDR-based wireless communication channels with adaptive routing and relay support. The friendly swarm consisted of aerial, surface, and ground nodes forming a distributed multi-hop communication architecture. The adversarial swarm generated coordinated interference with dynamically varying spatial distribution, temporal activity, and spectral occupancy. Both stationary and adaptive jamming strategies were considered in order to evaluate the robustness of the proposed minimax-oriented adaptation framework.

The communication subsystem employed LDPC-coded transmission with iterative belief-propagation decoding. The adaptive cognitive controller continuously adjusted transmission power, decoding iteration depth, relay allocation, routing structure, and topology configuration according to observed channel conditions and interference activity. The proposed method was compared with two baseline approaches corresponding to static communication control and conventional adaptive radio-link management without structural cognitive reconstruction.

The principal simulation parameters used for performance evaluation of the proposed cognitive adaptive control framework are summarized in Table 1. The selected parameter set reflects a realistic multi-domain swarm communication environment with heterogeneous unmanned platforms, adaptive SDR-RAN infrastructure, LDPC-coded transmission, and coordinated adversarial interference conditions.

Table 1. Simulation parameters

Parameter	Value
Number of UAV nodes	12
Number of USV nodes	6
Number of UGV nodes	8
Carrier frequency	3.5 GHz
Channel bandwidth	20 MHz
LDPC code rate	1/2
LDPC block length	1944 bits
Maximum decoding iterations	15
Mobility model	Gauss-Markov
Communication range	2 km
Interference model	Coordinated adaptive barrage jamming
Channel model	AWGN + Rayleigh fading
Simulation duration	500 s
Monte-Carlo runs	10^4 packets

The considered simulation environment combines heterogeneous UAV, USV, and UGV communication nodes interconnected through adaptive SDR-based wireless links with distributed relay support. The adversarial subsystem generates coordinated swarm-oriented interference with dynamically varying spectral occupancy and transmission activity. Communication performance was evaluated under

both static and adaptive jamming conditions using Monte-Carlo simulations with statistically averaged BER, connectivity, latency, and decoding convergence metrics. All reported simulation results were statistically averaged over 10^4 Monte-Carlo packet transmissions for each operating point. The observed confidence interval width did not exceed 5% for the considered BER and topology survivability estimates.

The communication quality was evaluated using the bit-error-rate metric represented as

$$P_{BER} = \frac{N_{err}}{N_{bits}} \tag{41}$$

where N_{err} – denotes the number of erroneously decoded bits and N_{bits} – is the total number of transmitted information bits.

The topology survivability of the distributed swarm network was characterized using the connectivity coefficient

$$K_{conn} = \frac{N_{active}}{N_{total}} \tag{42}$$

where N_{active} – is the number of communication links remaining operational under adversarial influence and N_{total} – denotes the total number of network connections.

The computational efficiency of adaptive iterative decoding was evaluated through the average iteration number

$$\bar{N}_{iter} = \frac{1}{M}\sum_{i=1}^{M} N_{iter}^{(i)} \tag{43}$$

where $N_{iter}^{(i)}$ – denotes the decoding iteration number for the i-th transmitted packet and M – is the total number of decoding procedures during the observation interval.

The simulation results demonstrated that the proposed cognitive adaptive control framework substantially improves communication reliability under coordinated adversarial swarm influence. In comparison with the static baseline architecture, the proposed method achieved significantly lower BER values across the entire investigated SINR range due to adaptive topology reconstruction, interference-aware relay reassignment, and dynamic LDPC decoding control.

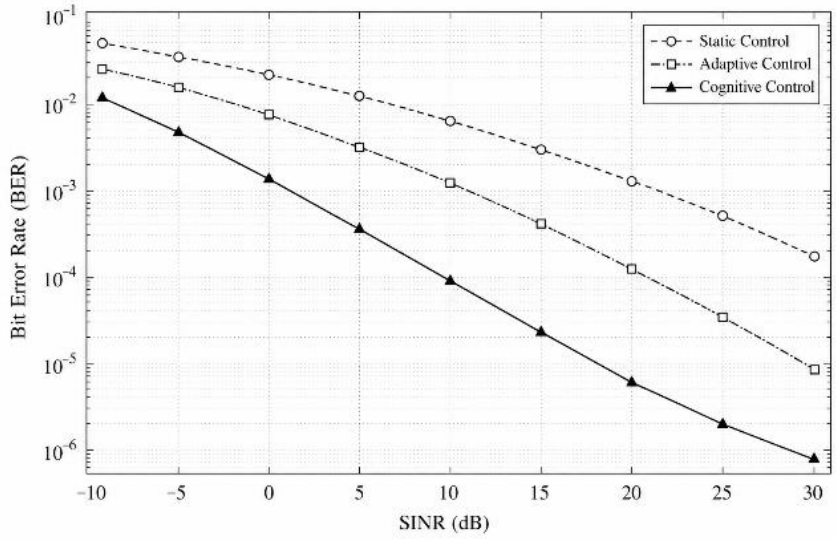


Fig. 5. BER versus SINR for static, adaptive, and cognitive communication control modes.

The results shown in Fig. 5 indicate that the proposed cognitive adaptation method preserves stable communication operation even under severe interference conditions corresponding to low SINR values. In contrast to conventional adaptive control approaches, the proposed framework demonstrates increased robustness due to coordinated joint optimization of transmission parameters, decoding convergence, and network topology reconstruction.

The confidence interval width for the presented BER estimates did not exceed 5% over the considered Monte-Carlo simulation ensemble. For clarity of graphical presentation, confidence intervals

are not explicitly shown in Fig. 5–7 because the corresponding error bars remain smaller than the marker dimensions in most operating regions.

An important result of the simulations concerns the behavior of iterative LDPC decoding under dynamically varying adversarial activity. The proposed adaptive decoding controller automatically reduced the average number of decoding iterations under favorable channel conditions while increasing iteration depth during severe interference periods. Such behavior enabled substantial reduction of computational overhead without degradation of communication reliability.

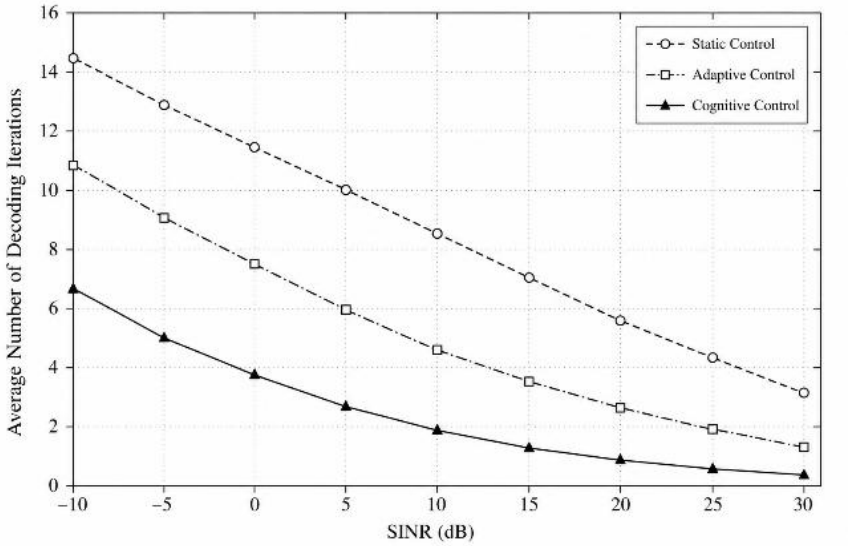


Fig. 6. Average number of decoding iterations versus SINR under adversarial swarm influence.

The dependence illustrated in Fig. 6 demonstrates that the cognitive adaptation mechanism dynamically stabilizes decoding complexity according to current interference conditions. Under moderate interference levels, the proposed method reduced the average iteration number by approximately 25–35% compared with fixed-iteration decoding strategies, resulting in lower energy consumption and reduced processing latency.

The topology survivability analysis additionally confirmed the effectiveness of adaptive SDR-RAN reconstruction. Under coordinated swarm interference, conventional static communication structures experienced rapid degradation of network connectivity due to relay suppression and localized channel disruption. Conversely, the proposed cognitive reconstruction framework dynamically redistributed relay nodes and routing paths, thereby preserving stable end-to-end communication.

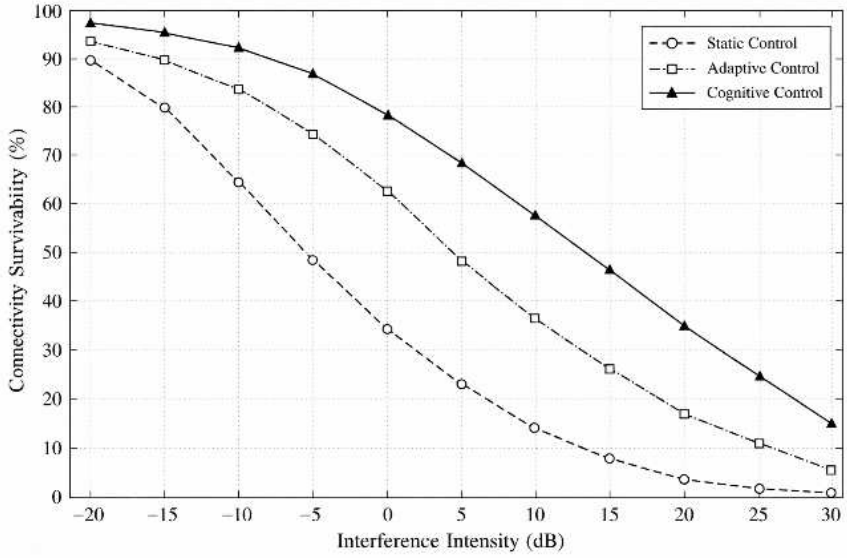


Fig. 7. Connectivity survivability of the distributed swarm network under coordinated adversarial interference.

The results presented in Fig. 7 show that the proposed adaptive reconstruction mechanism maintains significantly higher connectivity coefficients under increasing adversarial swarm activity. The introduction of hysteresis-based reconstruction control additionally prevented unstable oscillatory topology switching and reduced unnecessary relay reassignment procedures.

The energy efficiency of the communication subsystem was also improved due to adaptive decoding control and topology-aware transmission management. In the proposed framework, computational resources were dynamically allocated according to current communication conditions, thereby reducing excessive decoding activity and minimizing redundant transmission procedures.

To further evaluate the contribution of individual components of the proposed framework, an additional comparative analysis was performed for several reduced adaptive configurations with partially disabled cognitive reconstruction mechanisms.

Table 2. Influence of adaptive framework components on communication performance

Configuration	BER	Connectivity survivability	Average decoding iterations	Energy efficiency
Full cognitive framework	Low	High	Low	High
Without hysteresis control	Medium	Medium	Medium	Medium
Without adaptive LDPC control	High	High	High	Low
Without SDR-RAN reconstruction	High	Low	Medium	Medium
Conventional adaptive control	Medium	Medium	Medium	Medium

The comparative results presented in Table 2 demonstrate that the principal performance improvements are achieved through coordinated interaction between adaptive LDPC decoding control, hysteresis-based topology stabilization, and SDR-RAN structural reconstruction. In particular, disabling adaptive decoding substantially increases computational overhead and energy expenditure, whereas removal of SDR-RAN reconstruction mechanisms leads to degradation of topology survivability under coordinated adversarial swarm influence. The obtained results confirm that resilient operation of distributed unmanned communication systems requires joint cognitive adaptation of communication, topology, and decoding processes rather than isolated parameter optimization.

The aggregate energy expenditure per successfully delivered information packet was evaluated as

$$E_{pkt} = \frac{E_{tx} + E_{dec} + E_{rec}}{N_{succ}} \tag{44}$$

where E_{tx} – denotes transmission energy, E_{dec} – represents decoding energy expenditure, E_{rec} – characterizes topology reconstruction overhead, and N_{succ} – is the number of successfully delivered packets.

The obtained results indicate that the proposed cognitive adaptive control framework reduces total energy expenditure while simultaneously increasing communication survivability and decoding reliability. Such behavior becomes particularly important for distributed unmanned systems operating under severe energy constraints and prolonged mission durations.

Table 3. Comparative performance of communication control methods under adversarial swarm influence

Performance Metric	Static Communication Control	Conventional Adaptive Control	Proposed Cognitive Adaptive Control
BER under low SINR	High	Medium	Low
Communication survivability	Low	Medium	High
Network connectivity stability	Low	Medium	High
Resistance to coordinated jamming	Low	Medium	High
Average decoding iterations	Fixed and excessive	Partially adaptive	Dynamically optimized
Decoding convergence stability	Low under severe interference	Medium	High
SDR-RAN topology reconstruction	Not supported	Limited	Full adaptive reconstruction
Relay reassignment capability	Absent	Partial	Dynamic and distributed

Energy efficiency	Low	Medium	High
Reconstruction overhead	Absent	Medium	Controlled by hysteresis mechanism
Adaptation to swarm interference	Weak	Moderate	Robust minimax-oriented adaptation
Computational efficiency	Low under adverse conditions	Medium	High
Packet delivery reliability	Low	Medium	High
Scalability for large swarm systems	Limited	Moderate	High
Stability under topology switching	Unstable	Partially stable	Stable
Mission continuity under adversarial influence	Low	Medium	High

The comparative results presented in Table 3 demonstrate that the proposed cognitive adaptive control framework provides superior communication robustness and topology survivability under coordinated adversarial swarm influence. In contrast to static and conventional adaptive approaches, the proposed method simultaneously optimizes iterative decoding dynamics, SDR-RAN reconstruction, relay allocation, and interference-aware communication adaptation. As a result, the system preserves stable network connectivity and communication reliability while reducing computational and energy overhead under dynamically varying electromagnetic conditions.

To further position the proposed framework relative to existing adaptive anti-jamming communication approaches, a comparative analysis with representative literature methods was additionally performed.

Table 4. Comparison with representative adaptive anti-jamming communication methods

Method	**Joint topology adaptation**	**Adaptive LDPC control**	**SDR-RAN reconstruction**	**Minimax robustness**	**Stability analysis**	**Multi-domain swarm support**
MARL anti-jamming [12]	Partial	No	No	No	No	Partial
Stackelberg RL [24]	No	No	No	Partial	No	UAV only
SDR-UAV adaptive networking [21]	Partial	No	Partial	No	No	UAV only
Proposed framework	Yes	Yes	Yes	Yes	Yes	UAV–USV–UGV

The comparative analysis presented in Table 4 demonstrates that existing anti-jamming communication methods typically focus on isolated adaptation mechanisms such as routing optimization, reinforcement learning-based spectrum management, or topology control. In contrast, the proposed framework integrates adaptive LDPC decoding, SDR-RAN structural reconstruction, minimax-oriented anti-jamming adaptation, and stability-aware topology management within a unified cognitive control architecture for heterogeneous multi-domain swarm systems.

In particular, existing approaches typically optimize either routing adaptation or anti-jamming resource allocation independently, whereas the proposed framework simultaneously coordinates topology survivability, iterative LDPC decoding adaptation, SDR-RAN reconstruction, and minimax-oriented interference suppression within a unified cognitive control loop.

The following section summarizes the obtained results and outlines future research directions associated with distributed learning mechanisms, predictive cognitive adaptation, and autonomous swarm coordination under intelligent adversarial influence.

7. Conclusion

This paper has presented a cognitive adaptive control method for multi-domain UAV–USV–UGV communication systems operating under adversarial swarm influence. The proposed approach addresses the problem of resilient communication support in distributed unmanned networks subjected to coordinated electronic countermeasures, dynamically varying interference conditions, and structural uncertainty. In contrast to conventional adaptive radio-link methods, the developed framework jointly considers communication reliability, iterative LDPC decoding control, SDR-RAN reconstruction, topology survivability, and minimax-oriented anti-jamming adaptation within a unified cognitive control architecture.

A distributed state-space model of the multi-domain swarm communication system has been developed. The proposed representation integrates communication parameters, topology dynamics, energy state variables, and mission-oriented operational indicators into a single adaptive control framework. The adversarial environment has been modeled as a coordinated swarm-based interference process capable of dynamically modifying spectral occupancy, relay availability, and communication stability. Such formalization enables the analysis of communication survivability and adaptive reconstruction dynamics under distributed adversarial influence.

A cognitive adaptive control loop combining environmental observation, interference estimation, iterative decoding management, and structural SDR-RAN reconstruction has been proposed. The adaptive control process has been formulated as a minimax optimization problem in which the communication subsystem dynamically modifies transmission parameters, decoding strategies, and network topology in response to worst-case adversarial swarm actions. The proposed framework additionally incorporates hysteresis-based reconstruction control mechanisms preventing unstable oscillatory topology switching and reducing excessive structural adaptation overhead.

Particular attention has been devoted to adaptive iterative LDPC decoding control. The proposed method dynamically adjusts decoding iteration depth according to observed convergence behavior and interference conditions. This approach enables simultaneous reduction of computational complexity and preservation of communication reliability under dynamically varying SINR levels. The integration of adaptive decoding management with topology-aware SDR-RAN reconstruction forms a coordinated communication control architecture suitable for energy-constrained distributed unmanned systems.

The stability properties of the proposed adaptive communication framework have been analyzed using Lyapunov-based methods and input-to-state stability principles for structurally reconfigurable systems. The obtained conditions confirm boundedness of the adaptive reconstruction dynamics under coordinated adversarial swarm influence and demonstrate the robustness of the proposed cognitive control mechanism in the presence of dynamically varying interference activity.

Simulation results have demonstrated substantial improvements in communication reliability, topology survivability, decoding efficiency, and energy consumption compared with conventional static and adaptive baseline approaches. The proposed framework preserves stable network connectivity under coordinated swarm interference conditions while simultaneously reducing decoding overhead and limiting unnecessary reconstruction procedures. The obtained results confirm that coordinated cognitive adaptation of communication, topology reconstruction, and iterative decoding is essential for resilient operation of distributed multi-domain unmanned systems under dynamically varying adversarial swarm influence.

The presented research may be further extended toward distributed machine-learning-based adaptation, predictive interference estimation, autonomous swarm coordination, and cooperative multi-agent cognitive decision-making mechanisms. Additional promising direction is the integration of reinforcement learning and game-theoretic adaptation procedures for fully autonomous resilient communication management in large-scale heterogeneous unmanned swarm systems operating under intelligent adversarial influence.

Despite the obtained improvements in communication survivability and adaptive reconstruction efficiency, the proposed framework currently assumes partially synchronized distributed control and sufficiently reliable state observation within the swarm communication environment. In large-scale unmanned systems with highly dynamic topology variation, delayed state information, intermittent relay availability, and constrained embedded computational resources may reduce adaptation accuracy and increase reconstruction latency. In addition, the present study primarily considers simulation-based

validation under modeled adversarial interference conditions. Therefore, further investigation is required toward hardware-in-the-loop experimentation, distributed real-time implementation, and integration of predictive learning mechanisms for large-scale autonomous swarm systems operating under intelligent adversarial influence.

Statements and Declarations

Ethics approval and consent to participate. Not applicable. This study did not involve human participants, human data, or animal experiments.

Consent for publication. The manuscript does not contain any individual person's data in any form

Availability of data and materials. All data generated or analysed during this study are included in this published article.

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Authors' information. Serhii Liventsev. National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute", Kyiv, Ukraine

Associate Professor, Department of Electronic Communications and Internet of Things

Ph.D. in Technical Sciences (Candidate of Technical Sciences), Associate Professor

ORCID: 0000-0002-9768-8133

Phone: +380672445165

E-mail: s.liventsev@kpi.ua

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