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COGNITIVE SDR-RAN ADAPTATION UNDER ACTIVE ADVERSARIAL INFLUENCE

Modern SDR-RAN systems require adaptive mechanisms to maintain communication reliability under intelligent adversarial interference. Conventional anti-jamming approaches focus on isolated parameter adaptation, ignoring the interaction between decoding dynamics, topology reconstruction, and distributed control. In practice, adversarial influence becomes an active process that reacts to network behavior, causing signal degradation, higher decoding complexity, and unstable topology reconstruction.

This paper presents a cognitive SDR-RAN adaptation framework for active adversarial environments. It integrates adaptive LDPC decoding control, interference-aware parameter adaptation, topology reconstruction, and minimax optimization within a unified closed-loop architecture. A nonlinear state-space model jointly describes communication parameters, decoding convergence, and interference dynamics, enabling prediction of worst-case scenarios.

The adaptive control algorithm dynamically adjusts transmission parameters and iterative decoding depth based on observed SINR and convergence conditions. A hysteresis-based topology reconstruction mechanism prevents unnecessary reconfigurations and stabilizes routing. Minimax optimization ensures robust adaptation without explicit knowledge of the interference strategy.

Simulation results show that the proposed framework significantly improves reliability and reduces decoding overhead compared to conventional methods. Specifically, it reduces the average number of decoding iterations by 25–30%, improves BER under low SINR, and stabilizes SDR-RAN topology reconstruction under coordinated adversarial influence. These results confirm the effectiveness of joint cognitive control over decoding, parameter adaptation, and network reconfiguration.

Keywords: SDR-RAN, cognitive adaptation, adversarial interference, LDPC decoding, anti-jamming communication, topology reconstruction, minimax optimization, cognitive radio.

1. Introduction

The rapid development of software-defined radio (SDR) and O-RAN technologies has signifycantly transformed modern wireless communication systems. Contemporary SDR-RAN platforms support programmable signal processing, adaptive spectrum allocation, and distributed network reconstruction, enabling flexible operation in heterogeneous communication environments. Such systems are increasingly applied in tactical communications, Industrial Internet-of-Things infrastructures, and next-generation 5G/6G wireless networks.

At the same time, the openness and programmability of SDR-based infrastructures increase their vulnerability to intelligent adversarial influence. In practical electromagnetic environments, interference can no longer be considered a stationary stochastic process. Modern adversarial systems continuously monitor communication activity, estimate transmission parameters, and dynamically adapt interference strategies according to network behavior. Consequently, communication quality depends on both physical-layer conditions and interaction with adaptive interference sources.

Under such conditions, conventional anti-jamming approaches based on isolated parameter optimization demonstrate limited effectiveness. Existing adaptive communication methods typically focus on separate communication components, including transmission power adaptation, spectrum allocation, routing optimization, or iterative decoding control. However, practical SDR-RAN systems

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require coordinated adaptation of communication parameters, topology reconstruction, and decoding dynamics within a unified cognitive control architecture.

An additional challenge arises from the interaction between communication reliability and computational complexity. Under severe interference conditions, degradation of the signal-to-interference-plus-noise ratio (SINR) increases the number of decoding iterations required for reliable LDPC convergence, leading to higher latency, energy consumption, and instability of distributed communication processes.

Therefore, the development of cognitive SDR-RAN adaptation mechanisms capable of jointly controlling communication parameters, decoding procedures, and topology reconstruction under active adversarial influence constitutes an important scientific and practical problem.

The objective of this work is the development of a cognitive SDR-RAN adaptation architecture operating under active adversarial influence. The proposed approach integrates adaptive LDPC decoding control, interference-aware communication management, minimax-oriented adaptation, and hysteresis-based topology reconstruction within a unified closed-loop cognitive architecture.

2. Problem Statement and Related Work

2.1. Statement of the problem

Ensuring resilient SDR-RAN communication under intelligent adversarial influence is a critical unsolved problem. Unlike stochastic interference, modern adversarial sources actively monitor the network and adapt jamming in real time. Consequently, the communication environment becomes an active adversary coupled with the system's own behavior.

SDR-RAN architectures are especially vulnerable. Programmable processing, open interfaces, and distributed control create multiple attack points. Under strong jamming, instability simultaneously affects link quality, LDPC decoding complexity, topology reconstruction, and routing. Isolated parameter adaptation therefore fails to guarantee stable operation.

2.2. Analysis of recent studies and publications

Cognitive radio adaptation foundations were laid in [1]–[4]. Iterative LDPC decoding enables near-capacity error correction [5]–[9]. Anti-jamming, reinforcement learning, and distributed routing under adversarial conditions were studied in [10]–[15].

However, critical gaps remain. Most existing methods perform adaptation only within single layers. Joint control of transmission parameters, decoding dynamics, and SDR-RAN topology reconstruction is absent. Moreover, the active nature of jamming and stabilization of topology reconstruction under rapidly varying interference are largely ignored.

To close these gaps, this paper introduces a cognitive SDR-RAN adaptation architecture for active adversarial environments. The proposed approach integrates adaptive LDPC decoding control, interference-aware parameter adaptation, minimax anti-jamming, hysteresis-based topology reconstruction, and closed-loop cognitive control.

3. System Model of Active Adversarial Environment

Modern SDR-RAN communication systems operating under intelligent adversarial influence represent dynamic environments in which communication quality depends on the interaction between transmission parameters, decoding dynamics, topology reconstruction, and adaptive interference behavior. Unlike conventional stochastic interference models, the adversarial environment continuously adapts to observed communication activity and network state.

The considered communication architecture consists of distributed SDR-enabled nodes interconnected through adaptive wireless links supporting dynamic spectrum allocation, programmable signal processing, iterative LDPC decoding, and topology reconstruction procedures. The global SDR-RAN communication state is represented as:

$$x(k)=xcT(k),xdT(k),xtT(k)T, \tag{1}$$

where $x_c(k)$ — communication parameter vector, $x_d(k)$— iterative decoding state vector, $x_t(k)$ — topology state vector.

The communication process evolves according to:

$$x(k+1) = f\big(x(k), u(k), w(k)\big), \tag{2}$$

where $u(k)$— adaptive control vector, $w(k)$— adversarial influence vector.

The aggregate adversarial interference level is described by:

$$I_a(k) = \sum_{i=1}^{N_a} \alpha_i\,(k) J_i(k), \tag{3}$$

where $J_i(k)$— interference activity of the i-th adversarial source, $\alpha_i(k)$— dynamic influence coefficient.

Communication quality is evaluated using:

$$\mathrm{SINR}(k) = \frac{P_s(k)}{P_n + I_a(k)}, \tag{4}$$

where $P_s(k)$— useful signal power, P_n— noise power.

To support adaptive LDPC decoding control, convergence dynamics are represented by:

$$\Delta L(k) = \| L(k) - L(k-1) \|, \tag{5}$$

where $L(k)$— average log-likelihood-ratio vector, $\Delta L(k)$— convergence variation metric.

The network topology additionally evolves according to:

$$x_t(k+1) = \Phi(x_t(k), u(k), w(k)),$$

where $\Phi(cdot)$— topology reconstruction operator.

Under rapidly varying adversarial conditions, uncontrolled topology adaptation may produce oscillatory reconstruction behavior and increased signaling overhead. Therefore, topology reconstruction must be coordinated with communication adaptation and decoding control within a unified cognitive control process.

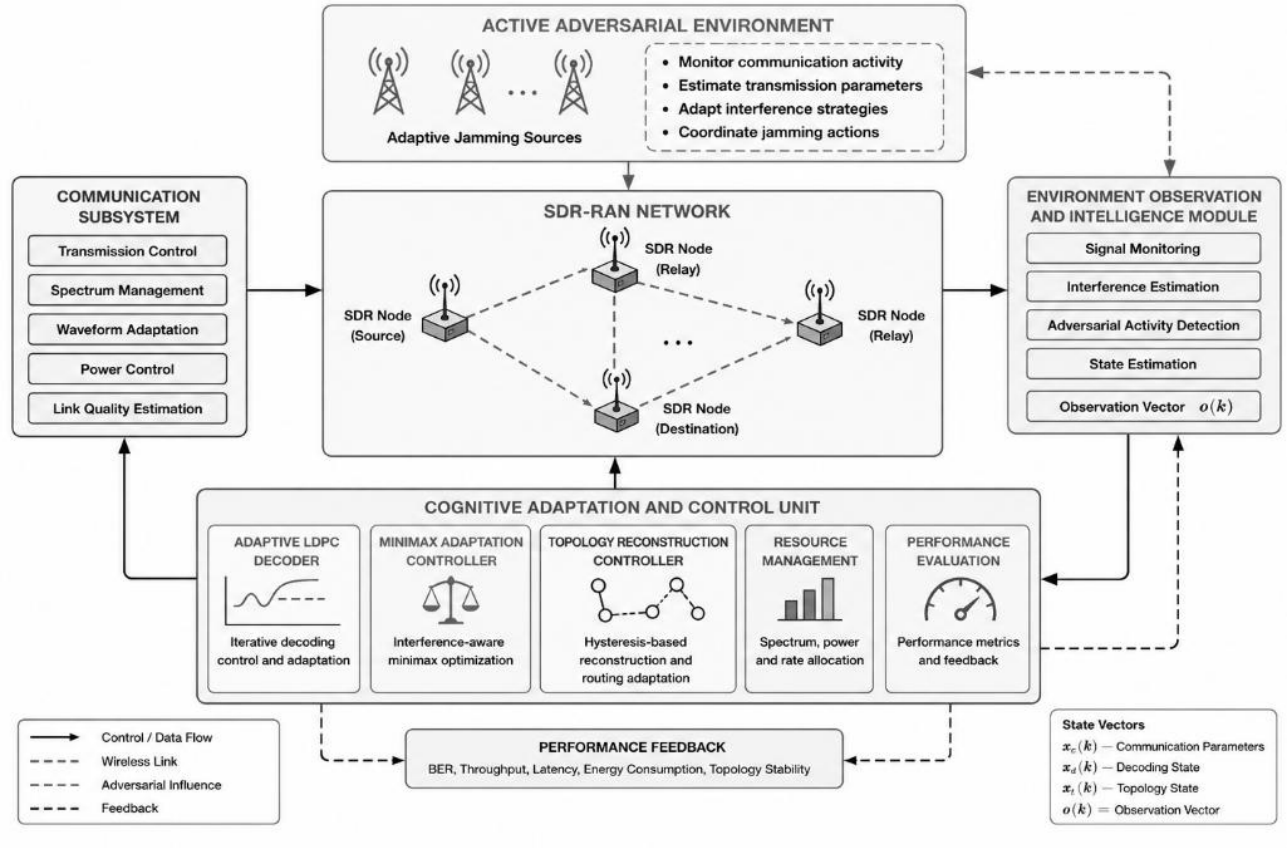


Fig. 1. Architecture of cognitive SDR-RAN communication system under active adversarial influence

Fig. 1 illustrates the interaction between the communication subsystem, adaptive LDPC decoder, topology reconstruction controller, and adversarial environment observation module within the proposed cognitive SDR-RAN adaptation architecture.

4. Cognitive Adaptive SDR-RAN Control Method

4.1. General Cognitive Adaptation Principle

The proposed cognitive SDR-RAN adaptation architecture is based on closed-loop communication control under active adversarial influence. Unlike conventional adaptive communication methods relying on isolated parameter optimization, the proposed approach jointly coordinates transmission adaptation, iterative LDPC decoding control, topology reconstruction, and interference-aware communication management.

The communication subsystem continuously observes the electromagnetic environment, estimates adversarial activity, evaluates decoding convergence conditions, and dynamically reconstructs SDR-RAN parameters according to the current operational state.

The cognitive adaptation process is represented as:

$$u(k) = \pi(x(k), o(k)) , \tag{6}$$

where $u(k)$— adaptive control action, $x(k)$— global communication state vector, $o(k)$— observation vector.

The observation vector includes communication-quality indicators, decoding metrics, topology information, and adversarial activity estimates:

$$o(k) = [\mathrm{SINR}(k), \mathrm{BER}(k), \Delta L(k), C_t(k)]^T , \tag{7}$$

where $\Delta L(k)$— decoding convergence variation, $C_t(k)$— topology connectivity indicator.

The cognitive controller dynamically modifies SDR-RAN parameters according to current adversarial conditions.

4.2. Adaptive LDPC Decoding Control

One of the central components of the proposed architecture is adaptive control of iterative LDPC decoding complexity. Unlike fixed-iteration decoding schemes, the proposed approach dynamically modifies the number of decoding iterations according to observed communication quality and convergence behavior.

The adaptive iteration number is determined as:

$$N_{it}(k) = g(\mathrm{SINR}(k), \Delta L(k)) , \tag{8}$$

where $N_{it}(k)$— adaptive decoding iteration number, $g(cdot)$— decoding adaptation function.

Under favorable communication conditions, the decoder reduces iteration depth, decreasing latency and energy consumption. Under severe adversarial influence, the number of iterations increases to preserve communication reliability.

The adaptive decoding rule satisfies:

$$N_{min} \le N_{it}(k) \le N_{max} , \tag{9}$$

where N_{min}— minimum admissible iteration number, N_{max}— maximum admissible iteration number.

4.3. Minimax-Oriented Communication Adaptation

Because the adversarial environment continuously adapts to communication activity, the proposed architecture employs minimax-oriented cognitive adaptation. The communication subsystem selects the control strategy minimizing the worst-case influence of adversarial interference.

The optimal adaptive policy is represented as:

$$u^*(k) = \arg\ \min_{u(k)} \max_{w(k)} J(x(k), u(k), w(k)) , \tag{10}$$

where $u^*(k)$— optimal adaptive control action, $w(k)$— adversarial influence vector, $J(cdot)$— global communication cost functional.

The cost functional jointly evaluates BER, decoding complexity, communication delay, energy consumption, and reconstruction overhead:

$$J = \lambda_1 \mathrm{BER} + \lambda_2 E + \lambda_3 D + \lambda_4 C \tag{11}$$

The minimax-oriented adaptation mechanism enables robust communication control under dynamically varying adversarial influence.

4.4. Hysteresis-Based SDR-RAN Reconstruction

Rapidly varying interference conditions may produce unstable topology reconstruction characterized by excessive switching between network configurations. Such oscillatory adaptation increases signaling overhead and destabilizes routing processes.

To suppress unstable reconstruction dynamics, topology reconstruction is activated only if communication degradation exceeds a predefined threshold:

$$\Delta J(k) > \gamma_h \,, \tag{12}$$

where $\Delta J(k)$— degradation of the global communication functional, γ_h— hysteresis threshold.

If the degradation remains below the hysteresis boundary, the current SDR-RAN topology is preserved and only local communication parameters are modified.

The topology reconstruction process is represented as:

$$x_t(k+1) = R(x_t(k), u(k)) \,, \tag{13}$$

where $R(cdot)$— SDR-RAN reconstruction operator.

The reconstruction subsystem performs relay reassignment, routing adaptation, spectrum redistribution, and communication link stabilization.

4.5. Cognitive Closed-Loop Adaptation Process

The proposed cognitive adaptation architecture operates iteratively over discrete observation intervals. At each adaptation step, the communication subsystem estimates adversarial interference, evaluates communication quality, analyzes LDPC convergence behavior, determines the optimal adaptive action, and reconstructs SDR-RAN topology if necessary.

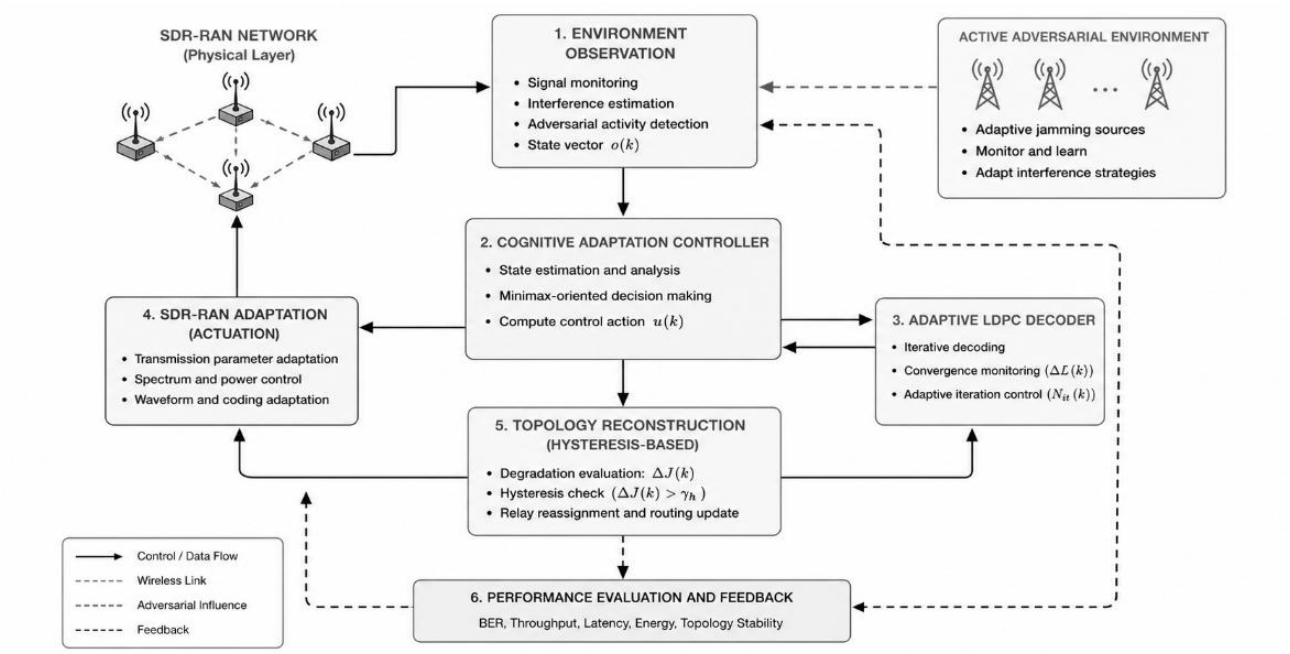


Fig. 2. Closed-loop cognitive SDR-RAN adaptation process

Fig. 2 illustrates the interaction between the environment observation subsystem, adaptive LDPC decoder, minimax-oriented controller, and SDR-RAN reconstruction module. The proposed architecture enables coordinated adaptation of communication parameters, topology dynamics, and decoding procedures while preserving stable SDR-RAN operation under dynamically varying adversarial influence.

5. Simulation Results and Discussion

The effectiveness of the proposed cognitive SDR-RAN adaptation framework was evaluated using a simulation model of a distributed wireless communication system operating under active

adversarial influence. The simulation environment included adaptive SDR-based communication links, iterative LDPC decoding procedures, dynamic topology reconstruction, and coordinated interference generation.

The communication subsystem employed LDPC-coded transmission with adaptive decoding control and programmable SDR-RAN parameter management. The adversarial environment generated dynamically varying interference with adaptive spectral occupancy and transmission activity. Both static and adaptive jamming scenarios were considered during performance evaluation. The principal simulation parameters are summarized in table 1.

Table 1

Simulation parameters

Parameter	**Value**
Carrier frequency	3.5 GHz
Channel bandwidth	20 MHz
LDPC code rate	1/2
LDPC block length	1944 bits
Maximum decoding iterations	15
Channel model	AWGN + Rayleigh fading
Interference model	Adaptive adversarial interference
SDR adaptation mode	Dynamic
Reconstruction control	Hysteresis-based
Simulation duration	500 s

Communication reliability was evaluated using the bit-error-rate metric:

$$\mathrm{BER} = \frac{N_e}{N_b}, \tag{14}$$

where, N_e— number of erroneously decoded bits, N_b— total number of transmitted bits.

The decoding complexity was evaluated using the average number of iterative decoding operations:

$$\bar{N}_{it} = \frac{1}{N_p}\sum_{i=1}^{N_p} N_{it}^{(i)}, \tag{15}$$

where $N_{it}^{(i)}$— decoding iteration number for the i-th packet, N_p— total number of transmitted packets.

The simulation results demonstrated that the proposed cognitive SDR-RAN adaptation architecture improves communication reliability under dynamically varying adversarial conditions. Compared with conventional adaptive communication approaches, the proposed algorithm achieved lower BER values across the investigated SINR range due to coordinated SDR adaptation, decoding control, and topology reconstruction.

Under severe adversarial influence, the minimax-oriented adaptation mechanism preserved stable communication operation by dynamically increasing decoding depth and reconstructing SDR-RAN topology according to current interference conditions. Simultaneously, the adaptive LDPC control mechanism reduced unnecessary decoding iterations under favorable channel conditions, decreesing average decoding complexity by approximately 25–30% compared with fixed-iteration decoding strategies.

An additional advantage of the proposed architecture consists in stabilization of topology reconstruction dynamics. The hysteresis-based reconstruction criterion reduced oscillatory SDR-RAN switching behavior under rapidly varying interference conditions, improving routing stability and reducing signaling overhead.

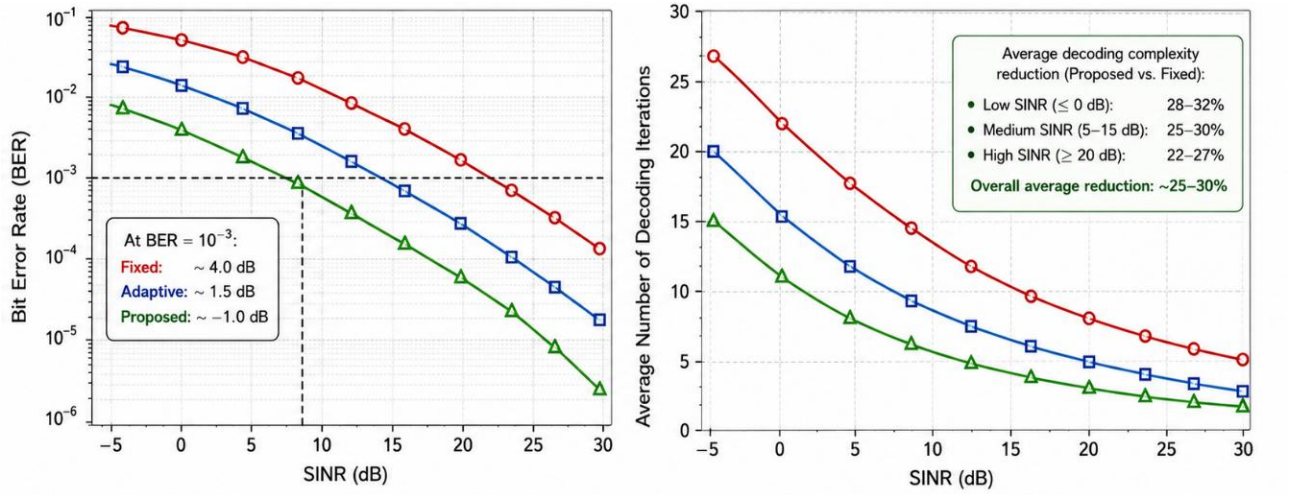


Fig. 3. BER and decoding-complexity comparison for conventional and cognitive SDR-RAN adaptation methods

a) BER performance versus SINR for conventional and cognitive SDR-RAN adaptation methods

b) Average decoding complexity versus SINR for conventional and cognitive SDR-RAN adaptation methods

The results shown in fig. 3 demonstrate that the proposed cognitive approach simultaneously improves communication reliability and reduces computational complexity within a unified closed-loop SDR-RAN adaptation process.

Table 2. Comparative performance evaluation of adaptive communication approaches.

Table 2

Comparative performance evaluation

Performance metric	**Conventional adaptive control**	**Proposed cognitive SDR-RAN adaptation**
BER under low SINR	Medium	Low
Decoding complexity	High	Reduced
Topology stability	Medium	High
Reconstruction overhead	High	Reduced
Anti-jamming robustness	Medium	High
Communication survivability	Medium	High

The obtained results confirm that isolated communication adaptation is insufficient for stable operation under active adversarial influence. Effective communication management in SDR-RAN systems requires coordinated cognitive adaptation integrating decoding control, topology reconstruction, and interference-aware communication optimization.

The proposed framework demonstrates that joint adaptive control of communication parameters and reconstruction dynamics substantially improves communication survivability while limiting computational and signaling overhead under dynamically varying adversarial conditions.

6. Conclusions and prospects for further research

The paper proposed a cognitive SDR-RAN adaptation framework operating under active adversarial influence. The developed approach integrates adaptive LDPC decoding control, minimax-oriented communication adaptation, and hysteresis-based topology reconstruction within a unified cognitive architecture.

The proposed method improves communication reliability, reduces decoding complexity, and stabilizes SDR-RAN reconstruction under dynamically varying interference conditions. Simulation

results confirmed improved BER performance and increased communication survivability compared with conventional adaptive communication methods.

Future research will focus on predictive cognitive adaptation and AI-driven SDR-RAN communication control under intelligent adversarial influence.

Declaration on artificial intelligence

Artificial intelligence technologies were used for language refinement, structural optimization of scientific text, and improvement of manuscript presentation quality. All scientific results and conclusions were verified and approved by the author.

Conflict of interest

The author declares that there is no conflict of interest. The work was performed in accordance with the principles of academic integrity and ethical standards for scientific research.

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С. Лівенцев

КОГНІТИВНА АДАПТАЦІЯ SDR-RAN В УМОВАХ АКТИВНОГО ВОРОЖОГО ВПЛИВУ

Сучасні системи SDR-RAN потребують адаптивних механізмів для забезпечення надійності зв'язку в умовах інтелектуального ворожого впливу. Традиційні методи протидії завадам зосереджуються на ізольованій адаптації параметрів, ігноруючи взаємозв'язок між динамікою декодування, реконфігурацією топології та розподіленим керуванням. На практиці ворожий вплив стає активним процесом, який реагує на поведінку мережі, спричиняючи погіршення сигналу, збільшення складності декодування та нестабільність топології.

У роботі представлено когнітивну архітектуру адаптації SDR-RAN для активного ворожого середовища. Вона інтегрує адаптивне керування LDPC-декодуванням, SDR-адаптацію з урахуванням завад, реконфігурацію топології та мінімаксну оптимізацію в єдиній замкненій системі. Нелінійна модель простору станів спільно описує параметри зв'язку, збіжність декодування та динаміку завад, що дає змогу прогнозувати найгірші сценарії.

Алгоритм адаптивного керування динамічно змінює параметри передавання та глибину ітераційного декодування на основі поточного SINR і умов збіжності. Гістерезисний механізм реконфігурації топології запобігає непотрібним перебудовам мережі та стабілізує маршрутизацію. Мінімаксна оптимізація забезпечує стійку адаптацію без явного знання стратегії завад.

Результати моделювання показали, що запропонована архітектура суттєво підвищує надійність зв'язку та знижує обчислювальне навантаження порівняно з традиційними методами. Зокрема, вона зменшує середню кількість ітерацій декодування на 25–30%, покращує BER за низького SINR та стабілізує реконфігурацію топології SDR-RAN в умовах координованого ворожого впливу. Це підтверджує ефективність спільного когнітивного керування декодуванням, адаптацією параметрів та реконфігурацією мережі.

Ключові слова: SDR-RAN, когнітивна адаптація, ворожий вплив, LDPC-декодування, протидія завадам, реконфігурація топології, мінімаксна оптимізація, когнітивне радіо.

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