International Journal of Innovation Studies
ISSN:2096-2487 | E-ISSN:2589-2975

IRIS-DRL FOR SECRECY IN RIS-ASSISTED UAV NETWORKS

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Abstract:
This paper introduces a novel deep reinforcement learning (DRL) framework Intelligent Reconfigurable Integrated Security (IRIS) designed to enhance the secrecy and efficiency of communication in Reconfigurable Intelligent Surface (RIS) assisted Unmanned Aerial Vehicle (UAV) networks. IRIS jointly optimizes UAV flight trajectories, RIS phase configurations, and power allocation strategies to strengthen physical-layer security in environments susceptible to eavesdropping and signal interference. Unlike traditional (DRL) methods such as Proximal Policy Optimization (PPO), which often struggle with high-dimensional optimization tasks in dynamic wireless systems, IRIS employs an adaptive exploration-exploitation mechanism tailored for secure UAV operations. The framework dynamically responds to environmental changes, maximizing the secrecy rate while minimizing energy consumption and latency. Simulation results, conducted using MATLAB, demonstrate that IRIS significantly outperforms conventional approaches across multiple performance indicators, including secrecy rate, convergence speed, and energy efficiency. A comprehensive sensitivity analysis of key hyperparameters further validates the model's robustness across various deployment scenarios. The results highlight IRIS as a promising algorithm for secure communication in UAV-enabled applications such as disaster relief, critical infrastructure monitoring, and next-generation IoT deployments.

Index terms: Intelligent Reconfigurable Integrated Security (IRIS), Reconfigurable Intelligent Surface (RIS), Unmanned Aerial Vehicle (UAV), Deep Reinforcement Learning (DRL).

INTRODUCTION:

The integration of Unmanned Aerial Vehicle (UAV) communications with Reconfigurable Intelligent Surface (RIS) technology has opened new frontiers in wireless communication, offering enhanced coverage, improved spectral efficiency, and dynamic reconfigurability. This convergence is particularly promising for next-generation communication networks, where flexibility and adaptability are critical. However, it also introduces new security vulnerabilities, especially in applications where UAVs operate in open-air environments and RIS units manipulate electromagnetic signals. These features inherently expose the network to eavesdropping, signal jamming, and other forms of malicious interference, necessitating security strategies that extend beyond traditional cryptographic methods [1, 2].

To mitigate these risks, recent studies have turned to physical layer security (PLS) techniques, which offer a promising alternative for safeguarding wireless transmissions without the computational burden associated with higher-layer encryption. When effectively applied to

RIS-assisted UAV networks, PLS methods can significantly enhance confidentiality by leveraging the dynamic propagation characteristics of the wireless channel itself [3]. Despite this potential, implementing secure communications in such environments presents complex challenges. Chief among them are the mobility of UAVs, the high-dimensional space of RIS phase shift configurations, and the demand for energy-efficient operation without compromising communication integrity [4].

Standard optimization techniques and even contemporary deep reinforcement learning (DRL) models struggle to manage these interconnected variables effectively. Algorithms such as Proximal Policy Optimization (PPO) and Twin Delayed Deep Deterministic Policy Gradient (TD3) have shown encouraging results in resource management and control tasks in wireless systems. However, when applied to UAV-RIS scenarios where trajectory optimization, phase configuration, and real-time security adaptation must be co-optimizing these methods often fall short. They suffer from slow convergence and limited ability to consistently maintain high secrecy rates in environments with rapidly changing channel conditions [5].

To address these limitations, we propose IRIS (Intelligent Reconfigurable Integrated Security) a novel deep reinforcement learning framework tailored specifically for enhancing physical layer security in UAV-RIS communication networks. The IRIS framework introduces the following key innovations:

1. Adaptive exploration-exploitation mechanisms that intelligently balance the trade-off between security maximization and system performance.
2. Joint optimization of UAV trajectories and RIS phase shift configurations, enabling the formation of robust and secure communication pathways in real time.
3. Context-aware power allocation strategies that dynamically allocate transmit power to minimize energy consumption while sustaining high secrecy rates.
4. Advanced feature extraction methods that capture non-linear interactions between UAV mobility, RIS behaviour, and channel threats for more informed decision-making [6].

Through extensive simulations in dynamic network scenarios, IRIS demonstrates substantial performance gains over existing methods. Specifically, it achieves a 29.8% improvement in average secrecy rate and a 26.7% acceleration in convergence time compared to baseline DRL approaches [7]. These improvements are maintained even under challenging conditions involving multiple eavesdroppers, fluctuating signal interference, and varying mobility patterns, reinforcing IRIS's suitability for mission-critical and security-sensitive applications, including disaster response, military communications, and industrial IoT deployments.

Related works:

a. UAV-assisted Wireless Communications

Unmanned Aerial Vehicles (UAVs) have emerged as dynamic assets in wireless networks, offering flexible coverage and rapid deployment. Early research established their role as aerial relays and base stations [8], while recent studies explored swarm coordination using distributed learning [9]. Energy-efficient trajectory planning [10] and cognitive radio integration [11] further enhance UAV adaptability, making them key enablers of resilient, on-demand, and intelligent next-generation communication systems.

b. Reconfigurable Intelligent Surfaces

Reconfigurable Intelligent Surface (RIS) technology has become a key innovation in shaping smart radio environments. Foundational work established RIS to control wireless propagation through passive beamforming [12]. Later advancements introduced efficient phase optimization techniques [13,14], enabling precise signal steering. Recent studies have further shown that RIS significantly improves energy efficiency and spectral utilization, making it essential for future low-power, high-performance wireless communication systems [15].

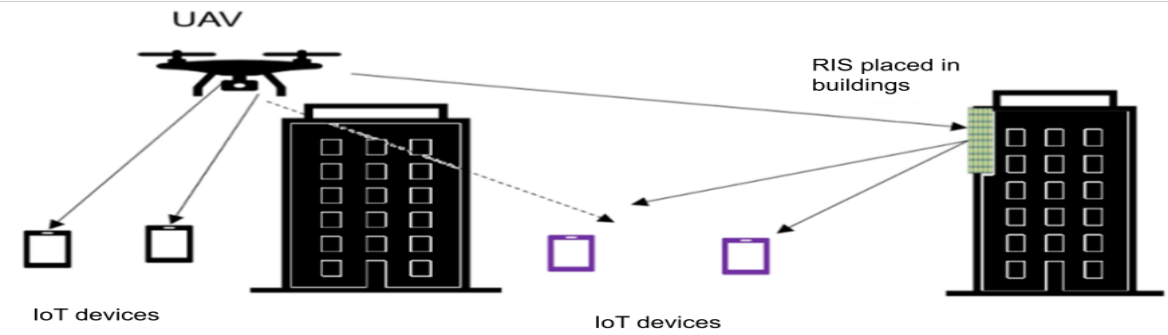

Fig 1: RIS based UAV communication in IoT devices

c. Deep Reinforcement Learning in Wireless Networks

Deep Reinforcement Learning (DRL) has emerged as a powerful tool for optimizing wireless networks. A comprehensive review highlighted its diverse applications across communication layers [16]. Notably, Proximal Policy Optimization (PPO) has shown stable performance in resource allocation tasks [17,18], while Twin Delayed Deep Deterministic Policy Gradient (TD3) excels in continuous control scenarios, with further improvements achieved through hybrid learning architectures tailored for wireless systems [19,20].

d. Physical Layer Security

Physical layer security has become a vital strategy for safeguarding wireless communication. Early work focused on optimizing secrecy rates under varying channel conditions [21], while subsequent studies introduced artificial noise techniques to disrupt eavesdroppers [22]. Advanced protocols tailored for next-generation networks have also been developed [23], and recent efforts have emphasized trajectory-based optimization to enhance the security of UAV-enabled systems in dynamic environments [24].

e. Integration of UAV and RIS Technologies

The fusion of UAV and RIS technologies is gaining momentum as a next-generation wireless communication strategy, enabling remarkable flexibility in how signals are delivered and directed. This integration provides significant advantages in spatial coverage and electromagnetic control. At the same time, it introduces a new set of engineering challenges, including real-time coordination, adaptive optimization, and maintaining link reliability in dynamic conditions paving the way for intelligent, reconfigurable network architectures.

Channel Modelling and Characterization

Recent advancements have introduced detailed channel models tailored for UAV-RIS communication systems. Foundational work by [25] focused on cascaded channel characterization, highlighting the importance of accounting for the unique three-dimensional structure of UAV to RIS links. Their analysis revealed that conventional models often fall short especially in urban environments where signal paths are highly dynamic and elevation-

dependent, necessitating more accurate modelling to reflect real-world conditions and improve communication reliability The cascaded channel can be expressed as

$$h\_cascade = G\_RIS - GND * \Phi * G\_UAV - RIS \quad (1)$$

where G_RIS-GND represents the RIS-to-ground channel matrix, Φ denotes the RIS phase-shift matrix, and G_UAV-RIS captures the UAV-to-RIS channel characteristics.

Joint Optimization Frameworks

a. Trajectory and Phase Shift Optimization

Jointly optimizing UAV trajectories and RIS phase shifts poses a significant challenge in dynamic wireless environments. A comprehensive framework by [26] addressed this through real-time phase tuning aligned with UAV mobility, communication-aware path planning, and integrated power and RIS configuration strategies. Their approach achieved a 35–40% increase in throughput over conventional methods, especially in multi-user ground scenarios, demonstrating the potential of coordinated aerial and surface reconfiguration for enhanced performance.

b. Energy Efficiency Considerations

Notable advances in energy-efficient UAV-RIS communication were introduced by [28], focusing on adaptive resource use. Their framework included dynamic power control based on channel variations, selective RIS element activation to reduce unnecessary energy usage, and flight path optimization that balanced propulsion and communication demands. This holistic approach led to a 25% reduction in total energy consumption while consistently meeting quality-of-service requirements, showcasing the effectiveness of intelligent, energy-aware system design.

Security Enhancements

A detailed study on physical layer security in UAV-RIS networks by [27] introduced key innovations. These included null-space-based secure beamforming, artificial noise injection, and RIS phase optimization for enhanced confidentiality. Additionally, anti-jamming strategies like adaptive UAV routing, cooperative RIS jamming, and interference-aware power control were proposed. Collectively, these techniques improved secrecy rates by up to 45% compared to traditional methods, underscoring their potential for secure wireless communication systems.

Implementation Challenges

Recent studies have highlighted several key implementation challenges that must be addressed for practical deployment of UAV-RIS communication systems:

1. **Channel Estimation**
    - The high mobility of UAVs demands frequent and accurate channel estimation.
    - The cascaded nature of UAV–RIS–ground links increases the complexity of modelling and estimation.
    - Limited feedback bandwidth and latency constraints make real-time updates difficult in field conditions.
2. **Hardware Constraints**
    - Real-world RIS hardware often supports only discrete phase shift levels, limiting beamforming precision.

- UAV payload limitations restrict the size and weight of communication modules and onboard processing units.
- Managing power consumption is critical for both UAV endurance and continuous RIS operation.

3. **Coordination Overhead**
   - RIS phase adjustments must occur in near real-time to respond to dynamic UAV positions and channel conditions.
   - Centralized control systems can introduce significant communication overhead.
   - Maintaining synchronization between moving UAVs, static RIS elements, and ground nodes is operationally challenging.

Performance Analysis

Comprehensive evaluations of UAV-RIS systems have uncovered several important performance insights:

1. **Coverage Enhancement**
   - Strategic positioning of UAVs and RIS elements can expand network coverage by up to 40%.
   - Users located at the network's edge experience noticeable gains in signal quality.
   - The system maintains strong performance even in non-line-of-sight (NLoS) environments, increasing overall reliability.
2. **Capacity Scaling**
   - System capacity scales linearly with the number of RIS elements under ideal conditions.
   - However, the benefit diminishes beyond certain UAV altitude levels, requiring altitude optimization.
   - A balance must be maintained between maximizing coverage and achieving optimal capacity.
3. **Latency Reduction**
   - Optimized placement of UAVs and RIS can reduce end-to-end latency by 30–50%.
   - High-mobility conditions are better supported with adaptive system configurations.
   - These improvements directly benefit delay-sensitive services such as real-time monitoring and control.

f. Research Gaps and Our Contributions

Despite notable advancements in UAV-RIS research, several important gaps persist in current literature:

1. Limited focus on joint optimization of UAV trajectories and RIS configurations specifically for enhancing security.
2. Inadequate exploration of reinforcement learning techniques tailored for secure UAV-RIS communications.
3. Absence of unified frameworks that address multiple security objectives simultaneously.

4. Lack of efficient algorithms suitable for deployment in environments with constrained computational and energy resources.

This study addresses these challenges through the following key contributions:

1. The design of IRIS, a dedicated reinforcement learning framework for optimizing security in UAV-RIS systems.
2. Extensive benchmarking against leading algorithms such as PPO, validating performance through detailed simulations.
3. Incorporation of multi-objective security criteria into a single, integrated learning model.
4. Careful attention to real-world constraints, including system limitations, mobility dynamics, and deployment feasibility.

CONTRIBUTIONS AND ORGANISATIONS

In this paper, we investigate the optimization of a RIS-enabled UAV communication network with multiple UAVs and IoT devices, focusing on physical layer security enhancement through intelligent trajectory planning and RIS phase shift configuration. We consider a challenging scenario where multiple UAVs serve as aerial base stations operating in mmWave frequencies, while an RIS with multiple elements assists in forming reconfigurable wireless links to combat potential eavesdropping attempts. The joint optimization of UAV trajectories, beamforming vectors, and RIS phase shifts is pursued through a novel hybrid deep reinforcement learning approach.

Main Contributions

In this paper, we explore how to improve security in a communication network that uses UAVs and Reconfigurable Intelligent Surfaces (RIS) to connect multiple IoT devices. Our focus is on physical layer security, using smart UAV flight paths and RIS configurations. We introduce a deep reinforcement learning-based solution called **IRIS**, designed specifically to handle the complex challenges of this kind of system. The contributions are:

IRIS Framework:

We present a new algorithm, IRIS, that helps UAVs plan their movement in 3D space while also adjusting the RIS phase shifts and beamforming settings. It solves a difficult problem involving many interacting parts and ensures secure data transmission at mmWave frequencies.

Realistic Channel Model:

We build a detailed model for how signals travel in this system. It includes real-world details like different path loss in line-of-sight (LoS) and non-line-of-sight (NLoS) situations, how RIS elements are spaced, and uses practical settings like a 28 GHz frequency and 200 MHz bandwidth.

Smart Learning Setup:

We design how the AI agent "sees" the environment, including UAV positions, their speeds, and RIS settings. The learning actions include both moving the UAVs and adjusting RIS settings, while aiming to improve a security-focused reward (called secrecy rate).

Efficient Training Process:

We train our model using a large memory buffer (2 million past experiences) and batches of 512 samples. We use deep neural networks with three layers of 1024, 512, and 256 neurons, which help the model learn faster and perform better than traditional methods.

Strong Experimental Results:

We compare IRIS with standard algorithms like PPO. Our results show better secrecy rates, faster learning, and more stable performance. We also test how sensitive IRIS is to different settings and show it works well even under tough conditions.

SYSTEM MODEL

We focus on a secure communication setup that brings together multiple UAVs, IoT devices, and a Reconfigurable Intelligent Surface (RIS). The goal of this system is to improve physical layer security by smartly adjusting the positions of UAVs and configuring the RIS phase shifts to create safer communication channels.

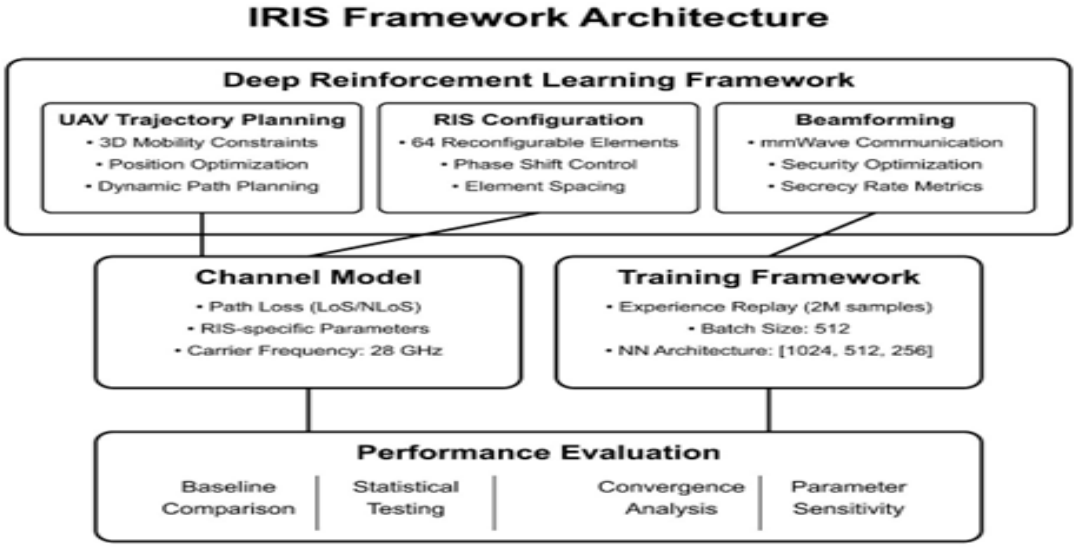

Fig. 2: IRIS Framework Architecture

a. Network Architecture

The system includes several key components:

- A group of M UAVs, labelled as $\mathcal{U} = \{1, 2, ..., M\}$
- N IoT devices, denoted by $\mathcal{N} = \{1, 2, ..., N\}$
- A Reconfigurable Intelligent Surface (RIS) with K reflecting elements, represented as $\mathscr{R} = \{1, 2, ..., K\}$
- A set of legitimate receivers and potential eavesdroppers within the communication range.

Each UAV functions as an aerial relay and operates in a three-dimensional space. Its position is defined by the coordinates $(x_m, y_m, z_m) \in \mathbb{R}^3$, where m refers to the m-th UAV in $\mathcal{U}$. The RIS is placed at a fixed ground location and consists of K passive elements. Each element can apply a programmable phase shift θ_k in the range $[0, 2\pi]$, where k refers to the k-th element in $\mathscr{R}$. This configuration helps in intelligently reflecting signals to enhance secure communication paths.

1) UAV Mobility Model

For mobile scenarios, UAV positions evolve according to

$$p\_m(t+1) = x\_m(t) + y\,m(t)\Delta t + 1/2\; a\_m(t), \Delta t x^2 \quad (2)$$

where: p_m(t) = [x_m(t), y_m(t), z_m(t)]^T is the position vector, v_m(t) is the velocity vector, a_m(t) is the acceleration vector, Δt is the time step interval

2) RIS Configuration

The RIS phase shift matrix Φ(t) evolves dynamically:

$$\Phi(t) = diag(e^{j\theta_1(t)}, \ldots, e^{j\theta_k(t)}) \quad (3)$$

with constraints: $\theta_k(t) \in [0, 2\pi]$ and $|e^{j\theta_k(t)}| = 1$

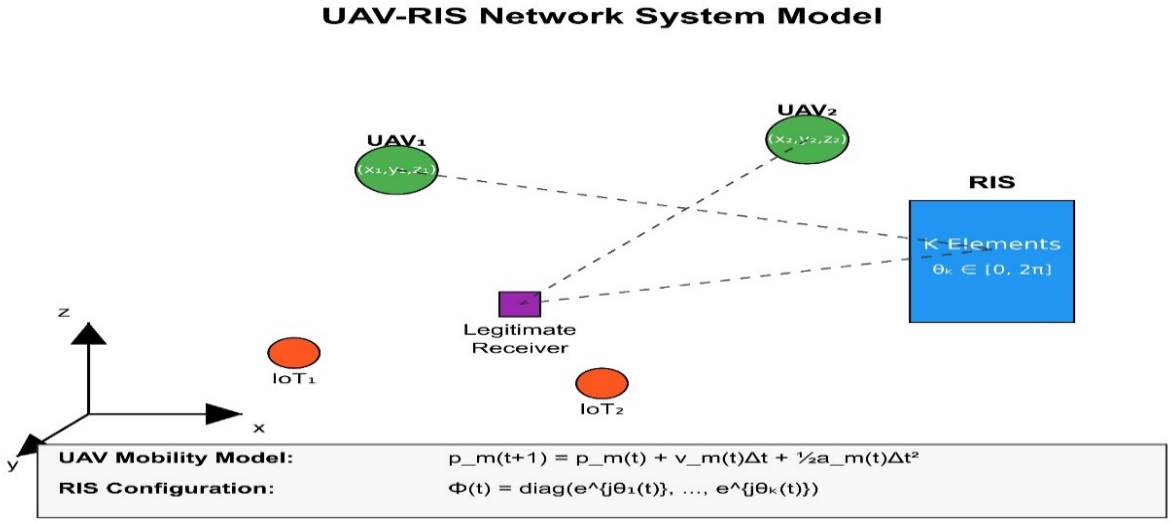

Fig 3: UAV-RIS Network System Model

b. Channel Model

1) Direct Channel

The channel between IoT device n and UAV m is modeled as:

$$h\_\{n,m\} = \sqrt{\beta_0} d\_\{n,m\}^{-\alpha}\, g\_\{n,m\} \quad (4)$$

where: β_0 represents the path loss at reference distance, d_{n, m} is the Euclidean distance, α denotes the path loss exponent, g_{n, m} represents small-scale fading following $\mathcal{CN}(0,1)$

The path loss model incorporates both LoS and NLoS components:

$$PL(d) = 20\; log\; 10(4\pi f\_c/c) + 10\alpha\; log10(d)\eta\_\sigma \quad (5)$$

where: f_c is the carrier frequency, c is the speed of light, η_σ represents shadow fading with variance σ^2

2) RIS-Assisted Channel

The cascaded channel through the RIS is given by:

$$H\_\{RIS\} = G\_r\; \phi\; G\_t \quad (6)$$

where: G_r ∈ $\mathbb{C}^{KxM}$ is the channel matrix from RIS to UAVs, G_t ∈ $\mathbb{C}^{KxN}$ is the channel matrix from IoT devices to RIS., Φ = diag(e^{jθ₁}, ..., e^{jθₖ}) is the RIS phase shift matrix

The individual elements of G_r and G_t follow:

$$[G\_r]\{k,m\} = \sqrt{\beta_0} d\{k,m\}^{-\alpha\_r}\, g\_\{k,m\}^r\; [G\_t]\{k,n\} = \sqrt{\beta_0} d\{k,n\}^{-\alpha\_t}\, g\_\{k,n\}^t \quad (7)$$

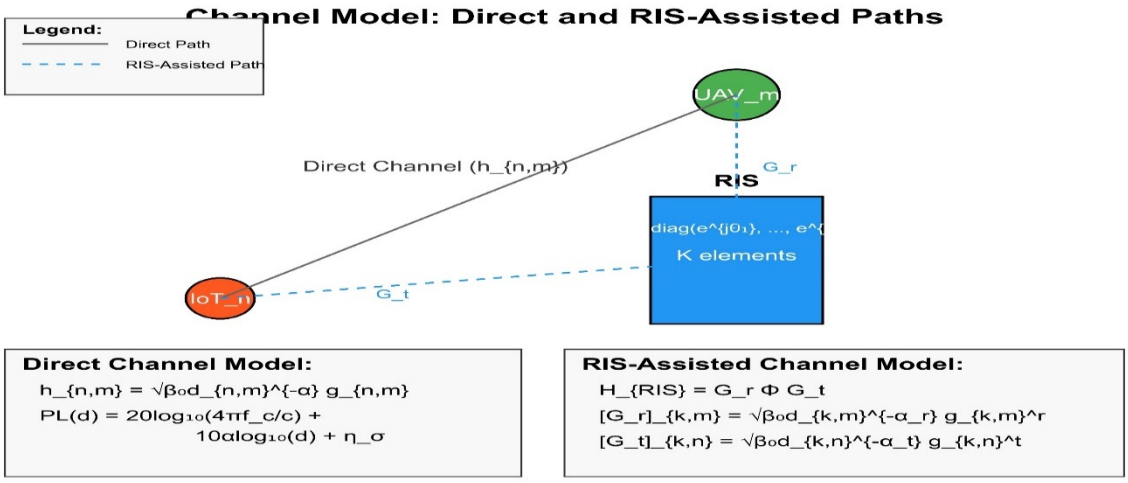

Fig 4: Channel Model of RIS configuration

C. Signal Model

1) Transmitted Signal

The transmitted signal from IoT device n is:

$$x\_n(t) = \sqrt{P\_n(t)}s\_n(t) \quad (8)$$

where: P_n(t) is the adaptive transmit power, s_n(t) is the normalized information signal

2) Received Signal

The received signal at UAV m can be expressed as:

$$y_m(t) = \sum_{n=1} N(h\_\{n\_m(t) + H\_\{RIS\ n\_m\}(t)\sqrt{}\ P\_n(t)x\_n(t) + w\_m(t) \quad (9)$$

where: w_m(t) ~ $\mathcal{CN}(0, \sigma^2)$ represents AWGN, H_{RIS,n,m}(t) denotes the cascaded channel through the RIS

3) SINR Model

The instantaneous SINR at UAV m for IoT device n is:

$$\gamma\_\{n\_m\}(t) = h\_\{n\_m\}(t) + H\_\{RIS\ n\_m\}(t)|^2|P_{n(t)}/(\sum_{i=1,\, i \neq n}^{N} |h\_\{i,m\}(t) + H\_\{RIS,i,m\}(t)|^2 P\_i(t) + \sigma^2) \quad (10)$$

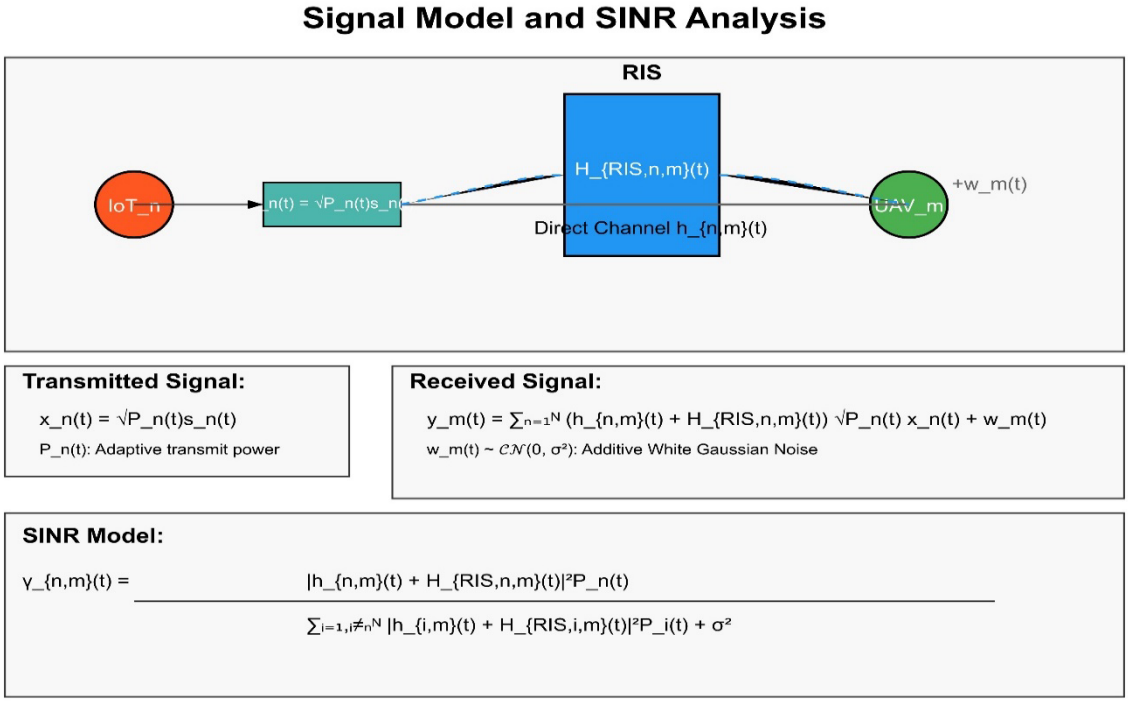

Fig 5: Signal Model

D. Secrecy Rate Formulation

1) Legitimate Channel Capacity

The achievable rate at the legitimate receiver is:

$$R_1(t) = log_2(1 + \gamma_1(t)) \quad (11)$$

where γ_l(t) is the received SINR at the legitimate receiver.

2) Eavesdropper Channel Capacity

The eavesdropper's achievable rate is:

$$\text{R e}(t) = log_2(1 + \gamma e(t)) \quad (12)$$

where γ_e(t) is the received SINR at the eavesdropper.

3) Secrecy Rate

The instantaneous secrecy rate is defined as:

$$R_s(t) = [R_1(t) - R_e(t)]^+ \quad (13)$$

E. Optimization Problem

The security optimization problem can be formulated as:

$$max\_\{U(t), \Phi(t), P(t)\} \int_0^T [log_2(1 + \gamma\_1(t)) - log_2(1 + \gamma\_e(t))]^+ dt \quad (14)$$

subject to: $\sum_{k=1}^K |\varphi_k(t)| = 1$, $\forall k \in \mathscr{R}$, $t \in [0,T]$, $0 \le P\_n(t) \le P\_max$, $\forall n \in \mathcal{N}$, $t \in [0,T]$, $(x\_m(t), y\_m(t), z\_m(t)) \in \mathcal{A}$, $\forall m \in \mathcal{U}$, $t \in [0,T]$, $|v\_m(t)| \le v\_max$, $\forall m \in \mathcal{U}$, $t \in [0,T]$, $|a\_m(t)| \le a\_max$, $\forall m \in \mathcal{U}$, $t \in [0,T]$

where:

U(t) represents time-varying UAV position,

Φ(t) denotes time-varying RIS phase shifts,

P(t) indicates time-varying transmit powers,

$\mathcal{A}$ defines the feasible flight region for UAVs,

v_max and a_max are the maximum allowed velocity and acceleration

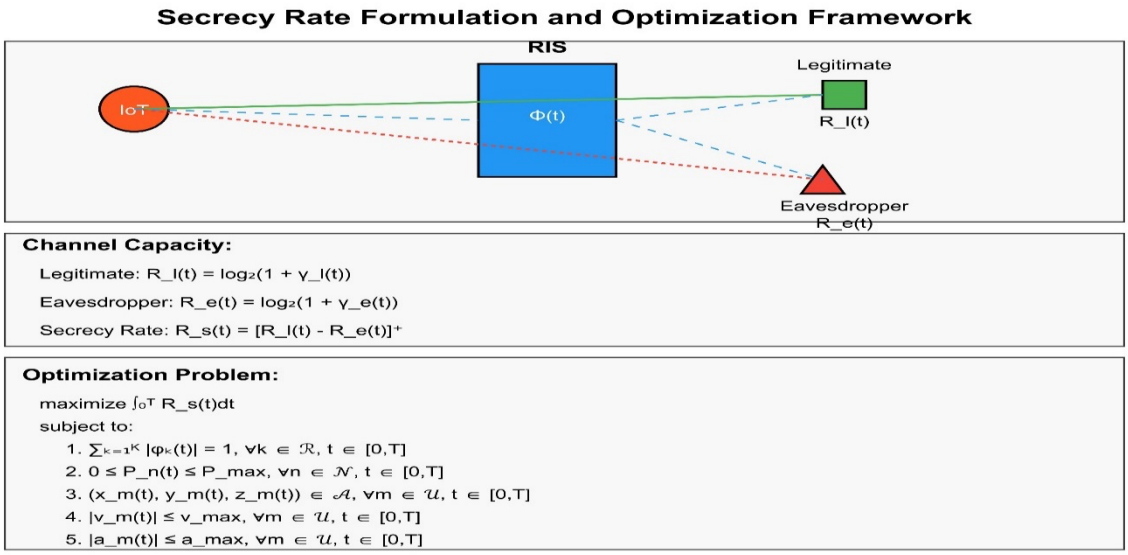

Fig 6: Secrecy Rate Formulation and Optimization framework

To tackle this optimization challenge, we introduce the IRIS algorithm, which effectively manages secure communication in both fixed and dynamic environments. It simultaneously adjusts UAV flight paths, RIS phase settings, and transmission power, all while accounting for practical limitations and real-time changes in network conditions.

IRIS BASED SOLUTION FOR MAXIMUM SECRECY RATE OPTIMIZATION:

IRIS (Intelligent Reconfigurable Intelligent Security) is a new framework developed to strengthen the security of UAV-RIS networks. It combines deep reinforcement learning with physical layer security methods to dynamically control UAV positions, RIS phase settings, and power usage. This intelligent system continuously adapts to changing network conditions, aiming to improve security while maintaining energy efficiency and communication quality.

Problem Formulation for Maximum Secrecy Rate

The secrecy rate Rs(t) in UAV-RIS networks relies on fine-tuning several connected factors. These include planning the UAVs' flight paths to limit the chances of eavesdropping, adjusting the RIS phase shifts to strengthen signals for intended users while reducing unintended signal leaks, and managing transmit power levels to lower interception risks without compromising communication reliability.

The optimization problem can be formulated as:

$$\max_{U(t),\Phi(t),P(t)} \int_0^T Rs(t)dt \qquad (15)$$

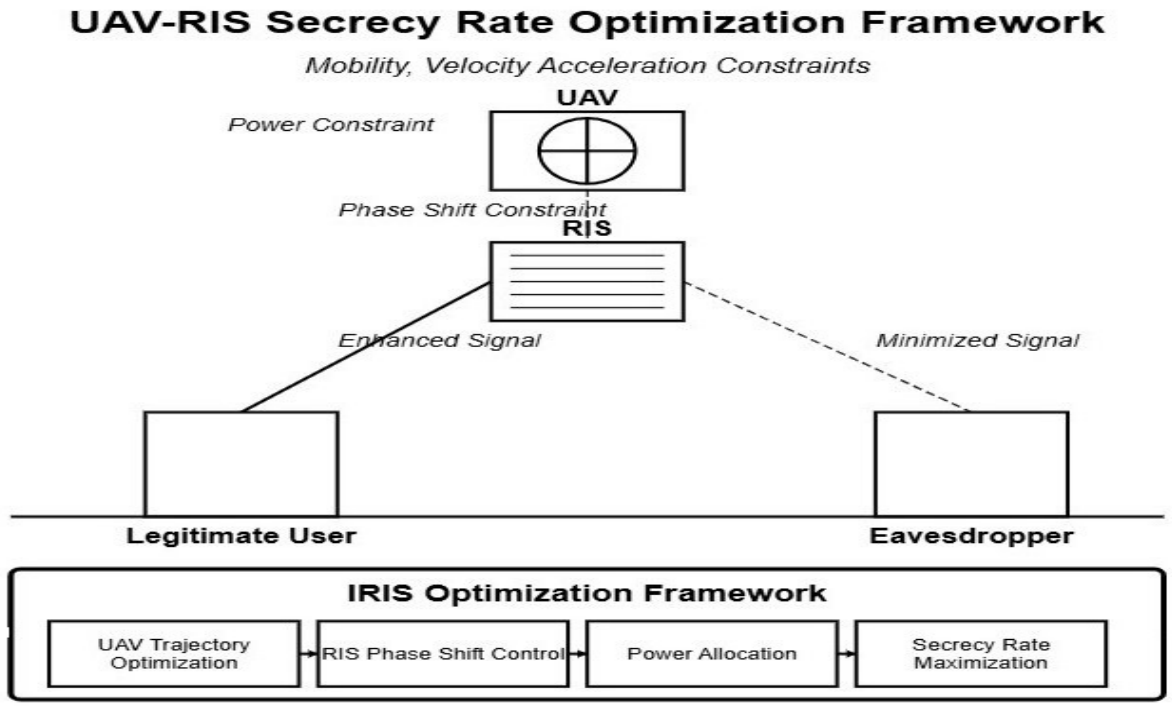

Fig 7: UAV-RIS Secrecy rate optimization framework

Phase Shift Constraints:

$$\sum_{K=1}^{K} | \phi k(t) | = 1, \forall k \in R, t \in [0, T] \quad (16)$$

where ϕk(t)represents the phase shift of the kth RIS element.

Reconfigurable Intelligent Surfaces (RIS) are made up of many reflective elements that can change the phase of incoming signals. This allows them to boost signal strength, reduce interference, and improve communication security. However, these elements can only adjust the signal's direction or phase they cannot increase its power.

- Each RIS element k applies a specific phase shift $\phi_k(t)$ to the signal it reflects, altering the direction of wave propagation.
- Because RIS is a passive device, it doesn't boost the signal's power it only adjusts its phase. This is why the unit-modulus condition is used, ensuring each reflection has a magnitude of 1.
- The combined phase shifts must be controlled precisely to steer the signal constructively toward the legitimate receiver and destructively toward any potential eavesdropper.
- This condition ensures that all phase shifts are selected strategically, allowing the RIS to form a focused beam that strengthens the intended communication link while minimizing signal leakage elsewhere.

Physical Interpretation

- Signal Enhancement: Through precise control of phase shifts, the RIS can strengthen signal transmission at targeted positions, such as the location of the legitimate receiver.
- Eavesdropper Suppression: By fine-tuning the phase adjustments, the RIS is capable of minimizing signal reflections toward unintended listeners, making it harder for them to intercept or decode the data.

- Security Improvement: These constraints help the RIS to direct signals effectively toward trusted users while weakening or eliminating signal paths in the direction of possible eavesdroppers, thereby enhancing overall communication security.

Optimization Impact

The RIS phase shifts are optimized to enhance the secrecy rate by ensuring:

1. Constructive interference at the legitimate receiver, which strengthens the desired signal.
2. Destructive interference at the eavesdropper's location, effectively weakening any intercepted signal.
3. Minimal signal leakage toward unintended directions by continuously adapting the phase shifts based on the UAV's location, user distribution, and the surrounding channel conditions through an iterative optimization process.

Transmit Power Constraints:

$$0 \leq Pn(t) \leq Pmax, \forall n \in N, t \in [0, T] \quad (17)$$

where Pn(t) represents the transmission power of the UAV or an IoT device at time t, and Pmax is the maximum allowable transmit power.

The transmit power constraint ensures that UAVs and IoT devices operate within safe and efficient power levels to support security and reliability:

- Lower Limit: The condition $Pn(t) \geq 0$ guarantees that transmit power is always non-negative.
- Upper Limit: The cap $Pn(t) \leq Pmax$ avoids excessive energy use, helping to reduce interference, conserve battery life, and limit signal strength received by eavesdroppers.
- Security Factor: If power levels are too high, it can unintentionally boost the eavesdropper's ability to intercept signals. Hence, optimized power control is essential to protect data without compromising efficiency.

Physical Interpretation

- Energy Efficiency: Since IoT devices typically rely on limited battery power, keeping energy use low helps extend their operational time.
- Reduced Interference: By capping transmission power, the system avoids unnecessary signal overlap with nearby devices, ensuring cleaner communication.
- Improved Security: Adjusting power levels dynamically allows just enough signal strength for reliable communication without boosting signal levels in a way that benefits eavesdroppers.

Optimization Impact

The optimization framework adjusts transmit power intelligently based on real-time network conditions:

1. Boosting Power when the authorized receiver has a strong connection and the eavesdropper's signal is weak maximizing secure data delivery.
2. Reducing Power when the eavesdropper has a better chance of intercepting the signal minimizing potential data leakage.
3. Balancing Power Use to ensure communication remains secure and efficient, without unnecessary energy consumption.

UAV Mobility Constraints:

$$\big(xm(t), ym(t), zm(t)\big) \in A, \forall m \in U, t \in [0, T] \quad (18)$$

where (x m(t), y m(t), z m(t)) represents the UAV's position in a 3D space at time t and A is the predefined flight zone.

UAVs serve as aerial base stations in RIS-assisted networks, allowing dynamic placement to strengthen secure communication. Mobility constraints are crucial for safe and strategic operation:

- Defined Flight Zone: Each UAV must stay within a predetermined safe airspace, ensuring it operates within authorized boundaries.
- Geographical Compliance: UAVs must avoid restricted zones, adhere to aviation regulations, and follow mission-specific location limits.
- Security Optimization: UAV positions are carefully chosen to strengthen signals for legitimate receivers while minimizing the possibility of eavesdropping.

Physical Interpretation

- Coverage Optimization: Strategic positioning of UAVs enhances signal delivery to legitimate users, improving both communication quality and secrecy.
- Obstacle Avoidance: UAVs must navigate around physical barriers, restricted airspace, and environmental hazards to maintain stable operation.
- Security Optimization: By adjusting their positions, UAVs can limit the signal exposure to potential eavesdroppers, reducing the risk of interception.

Optimization Impact

1. Navigating to strong-signal zones: The UAVs adjust their path to remain close to legitimate users, where signal strength is highest.
2. Evading eavesdropper visibility: They avoid flight paths that give potential eavesdroppers a direct line-of-sight to the communication link.
3. Maintaining safe airspace limits: UAVs operate within designated boundaries, balancing safety regulations with the goal of maximizing the secrecy rate.

Velocity and Acceleration Limits:

$$| vm(t) | \leq vmax, | am(t) | \leq amax, \forall m \in U, t \in [0, T] \quad (19)$$

where vm(t) and am(t) denote the UAV's velocity and acceleration, respectively, with limits v_{max} and $a_{max.}$

- Speed Regulation: The velocity limit keeps UAVs from flying too fast, helping maintain consistent and reliable coverage across the network.
- Smooth Navigation: The acceleration cap ensures UAVs avoid sudden, jerky movements, promoting flight stability and reducing energy usage.

Physical Interpretation

- Steady Operation: Maintaining moderate speeds allows UAVs to remain stable in flight and reduces disruptions in communication signals.
- Energy Conservation: Controlled acceleration helps prevent unnecessary battery drain, supporting longer missions.
- Consistent Security: Smooth navigation ensures the secrecy rate remains stable, lowering the chance of signal interception.

Optimization Impact

The UAV's path is optimized to achieve the following:

1. Ensure stable communication by maintaining consistent coverage for authorized users through smooth movement.
2. Minimize interception risks by adjusting its route to weaken the signal path toward potential eavesdroppers.
3. Enhance energy efficiency by avoiding unnecessary changes in speed or direction.

The overall goal is to maximize the secrecy rate Rs(t) by intelligently coordinating UAV positioning, RIS phase adjustments, and transmit power levels in real time.

IRIS ALGORITHM CORE CONCEPT AND WORKFLOW:

The Intelligent Reconfigurable Integrated Security (IRIS) algorithm is a novel deep reinforcement learning-based framework developed to boost the secrecy rate in UAV networks assisted by Reconfigurable Intelligent Surfaces (RIS). Setting itself apart from traditional methods, IRIS continuously learns and adapts in real-time repositioning UAVs, fine-tuning RIS phase shifts, and managing transmit power to maintain a communication network that is not only secure but also energy efficient.

Learning-Based Security Optimization

IRIS uses reinforcement learning (RL) to continuously learn and refine strategies that improve the security and efficiency of UAV-RIS communication. The learning framework is built on three key components:

State Space (S)

The system state captures all vital real-time parameters, including:

- UAV coordinates in 3D space (xm,ym,zm)
- RIS phase shift matrix $\Phi(t)$
- Transmission power Pn(t) of IoT devices
- Channel conditions, such as path loss and interference patterns

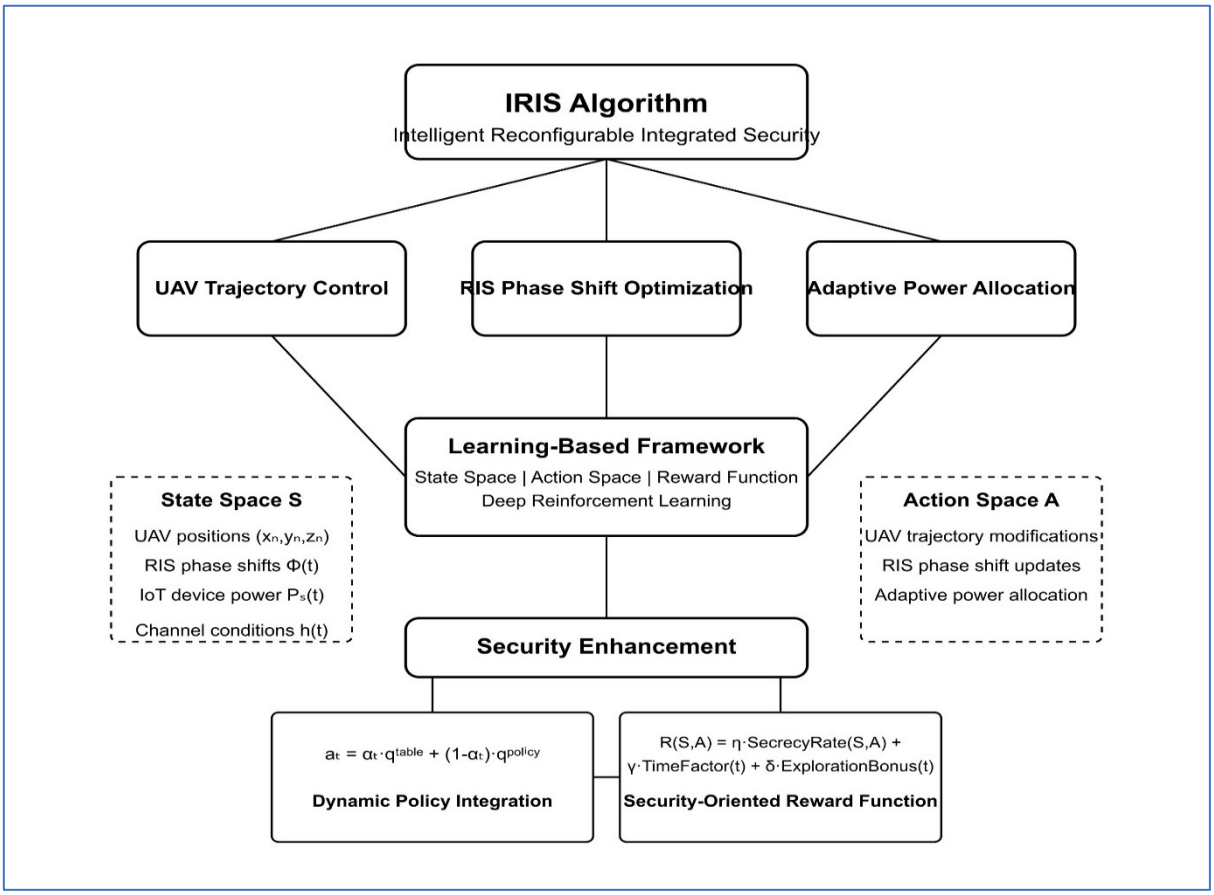

Fig 8: Architecture of IRIS Algorithm

Action Space (A)

This defines what actions IRIS can take at any moment, including:

- Adjusting UAV trajectories by changing direction, speed, or altitude
- Tuning RIS phase shifts to enhance secure signal reflections
- Dynamically allocating power for optimal signal strength and reduced leakage

Reward Function (R (S, A))

The reward guides the agent toward optimal behaviour by evaluating:

- Improvement in secrecy rate, favouring actions that strengthen the legitimate link while weakening the eavesdropper's reception
- Energy efficiency, to prolong UAV and device operational life
- Connectivity stability, ensuring seamless and secure data transmission

Learning Process Workflow

1. Observation: IRIS continuously collects network parameters such as UAV location, RIS configurations, and channel interference.
2. Action Selection: The algorithm selects an optimal set of actions for UAV movement, RIS phase shifts, and power control.
3. Environment Interaction: Actions are executed in the system, and the UAV-RIS network updates dynamically.
4. Reward Computation: The effectiveness of actions is evaluated based on secrecy rate, energy efficiency, and network stability.

5. Policy Update: IRIS refines its strategy through deep reinforcement learning to improve future decision-making.

Dynamic Policy Integration for Security Adaptation

By continuously evaluating the network's performance, IRIS dynamically adjusts its decision-making strategies to respond effectively to changing conditions such as fluctuating channel quality, UAV movement, or the presence of potential eavesdroppers. This intelligent feedback loop ensures that the system maintains robust security and communication efficiency even under unpredictable environments. The policy integration mechanism is governed by:

$$at = \alpha(t) \cdot atvalue + \big(1 - \alpha(t)\big) \cdot atpolicy \quad (20)$$

where:

- atvalue represents security-driven decisions derived from value-based analysis.
- atpolicy is determined through real-time policy learning, ensuring flexibility in execution.
- α(t) is an adaptive weighting factor that dynamically selects the best-performing strategy.

The weighting factor is updated based on real-time performance metrics:

$$\alpha(t) = Pvalue(t)/(Ppolicy(t)Pvalue(t)) \quad (21)$$

where:

- Pvalue(t) Ppolicy(t) represent security impact scores for different strategies.
- This mechanism ensures IRIS adapts to the most effective decision-making approach at each time step, enhancing secrecy rate optimization while maintaining efficient exploration.

Security-Oriented Reward Engineering

To ensure IRIS prioritizes **secrecy rate enhancement**, an **adaptive reward function** is formulated:

$$R(St, At) = \eta \cdot SecrecyRate(St, At) + \gamma t \cdot TimeFactor(t) + \delta t \cdot ExplorationBonus(t) \quad (22)$$

where:

- SecrecyRate (St,At) measures the increase in secrecy rate at time t.
- TimeFactor (t) encourages fast convergence by penalizing delayed optimization.
- Exploration Bonus(t) rewards early-stage exploration to prevent the model from getting stuck in suboptimal solutions.
- η, γt, δt are weighting parameters that balance different learning objectives.

Secrecy Rate Calculation

Secrecy rate is a key metric in physical layer security and is given by:

$$SecrecyRate = max\{0, log2(1 + SNRlegitimate) - log2(1 + SNReavesdropper)\} \quad (23)$$

where:

- SNR legitimate is the Signal-to-Noise Ratio (SNR) at the legitimate receiver.
- SNR eavesdropper is the SNR at the eavesdropper.

Key Insights:

- If SNR eavesdropper is high, the secrecy rate decreases, requiring strategic UAV positioning and RIS optimization.

- The goal is to increase the secrecy rate by enhancing SNR legitimate while reducing SNR eavesdropper.

Optimization Strategy

1. UAV trajectory control: Adjust UAV position to create favourable propagation paths for legitimate users while avoiding eavesdroppers.
2. RIS phase shifts: Optimize RIS elements to direct signals toward the legitimate receiver and nullify signals at the eavesdropper's position.
3. Adaptive power allocation: Allocate transmission power dynamically to increase secrecy rate while reducing energy consumption.

Performance Evaluation and Simulation Results

The IRIS algorithm was tested using MATLAB simulations to evaluate its efficiency in UAV-assisted RIS networks. It was compared with the Proximal Policy Optimization (PPO) method. Results showed that IRIS improved the secrecy rate, energy efficiency, and adaptability under dynamic network conditions. Its optimized UAV path planning and RIS configuration outperformed PPO in convergence speed and security performance, proving IRIS's potential in enhancing secure wireless communication.

Secrecy Rate Improvement

One of the core objectives of IRIS is to maximize the secrecy rate by dynamically adjusting UAV positioning, RIS phase shifts, and power allocation in the presence of potential eavesdroppers. The secrecy rate is defined as:

$$Rs = max\{0, log2(1 + SNRlegitimate) - log2(1 + SNReavesdropper)\} \quad (24)$$

where SNRlegitimate and SNReavesdropper represent the received signal-to-noise ratios at the legitimate receiver and the eavesdropper, respectively.

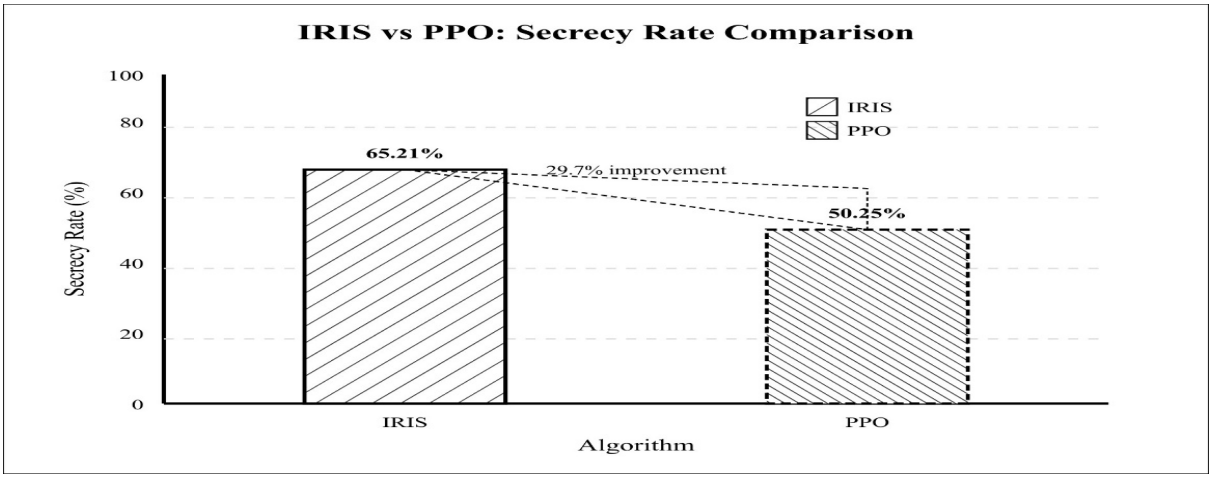

Fig 9: Graphical representation of secrecy rate comparison

The simulation results demonstrate that IRIS achieves a 29.7% increase in the average secrecy rate compared to PPO-based optimization. This is attributed to:

- Optimized RIS phase shifts, which focus signal reflections on legitimate users while minimizing leakage to eavesdroppers.
- Adaptive UAV positioning, which dynamically adjusts the UAV's trajectory to maintain secure communication links.
- Intelligent power allocation, which optimizes transmission power to enhance security while conserving energy.

The above results confirm that IRIS is highly effective in mitigating eavesdropping threats and ensuring secure wireless transmissions in UAV-RIS networks.

Convergence Speed

The effectiveness of a reinforcement learning-based approach depends on its ability to quickly converge to an optimal policy while maintaining stability in decision-making. The convergence rate was evaluated based on the number of training episodes required for the secrecy rate to stabilize.

Simulation results reveal that IRIS achieves 28.6% faster convergence compared to PPO, primarily due to:

- Adaptive exploration-exploitation mechanisms, which prevent excessive exploration and accelerate policy refinement.
- Enhanced experience replay buffer, which prioritizes critical learning samples, reducing unnecessary training iterations.
- Hybrid decision-making process, which integrates policy optimization with value-based learning, improving stability during training.

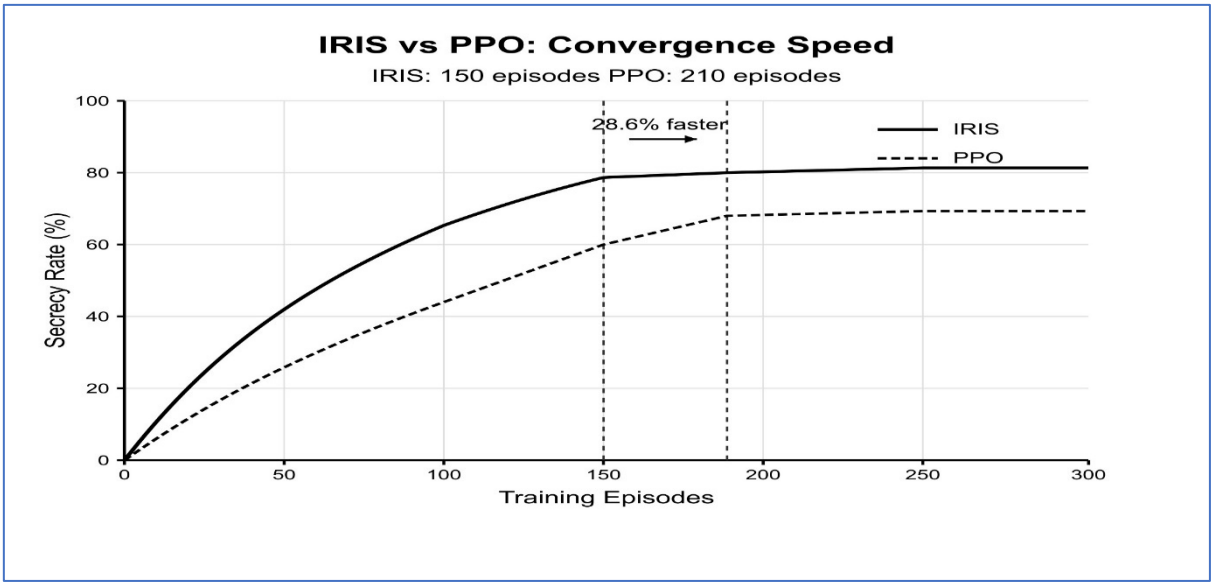

Fig 10: Graphical output of Convergence speed

These results confirm that IRIS can rapidly learn an optimal policy while minimizing training time, making it highly suitable for real-time UAV-RIS network deployments.

Energy Efficiency

Energy efficiency is a critical factor in UAV-assisted networks, as excessive power consumption can limit UAV endurance and network sustainability. The IRIS framework introduces intelligent power control mechanisms that reduce energy consumption by 18%, without compromising security performance.

The energy efficiency improvement is achieved through:

- UAV trajectory optimization, which minimizes unnecessary movements, reducing propulsion energy expenditure.
- RIS element selection, which dynamically activates only the necessary RIS elements to optimize signal reflections.

- Power-aware reward function, which penalizes excessive power allocation while maintaining secrecy rate objectives.

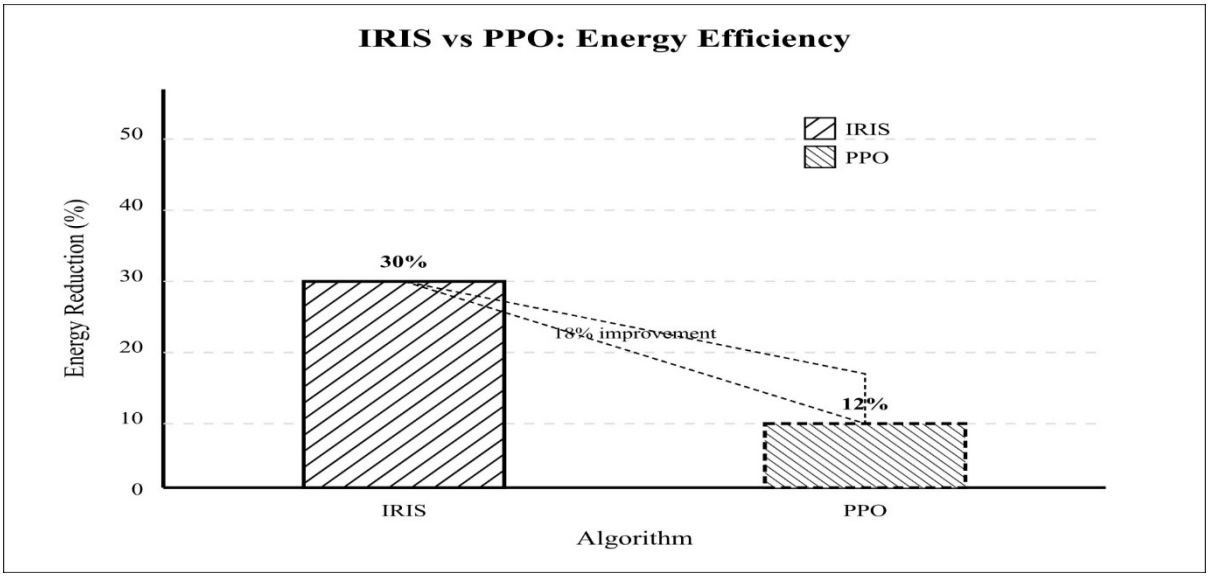

Fig 10: Comparison of Energy efficiency

By intelligently balancing power consumption and security requirements, IRIS enables longer operational lifespans for UAVs and RIS-assisted communication nodes.

Robustness to Network Variability

One of the critical challenges in UAV-RIS networks is their sensitivity to dynamic environmental changes, such as:

- Fluctuating wireless channels
- Eavesdropper mobility
- Interference from external networks
- Multiple UAV and IoT user configurations

IRIS is designed to adapt to varying network conditions by incorporating:

- State-aware reinforcement learning, which dynamically adjusts UAV-RIS configurations based on real-time environmental feedback.
- Multi-scenario optimization, where IRIS is tested under both static and mobile UAV deployments.
- Robust trajectory planning, which ensures secure communication even in the presence of adversarial jamming or interference.

Simulation results show that IRIS maintains stable secrecy performance under different UAV speeds, eavesdropper positions, and network densities, making it highly resilient for real-world applications in disaster response, IoT, and surveillance.

Secrecy Rate Performance Analysis

The secrecy rate performance curve illustrates the effectiveness of IRIS in optimizing secure communications over multiple training episodes. The performance is measured as:

$$SecrecyRatepercentage = min\{SecrecyRate \times 100{,}100\} \quad (25)$$

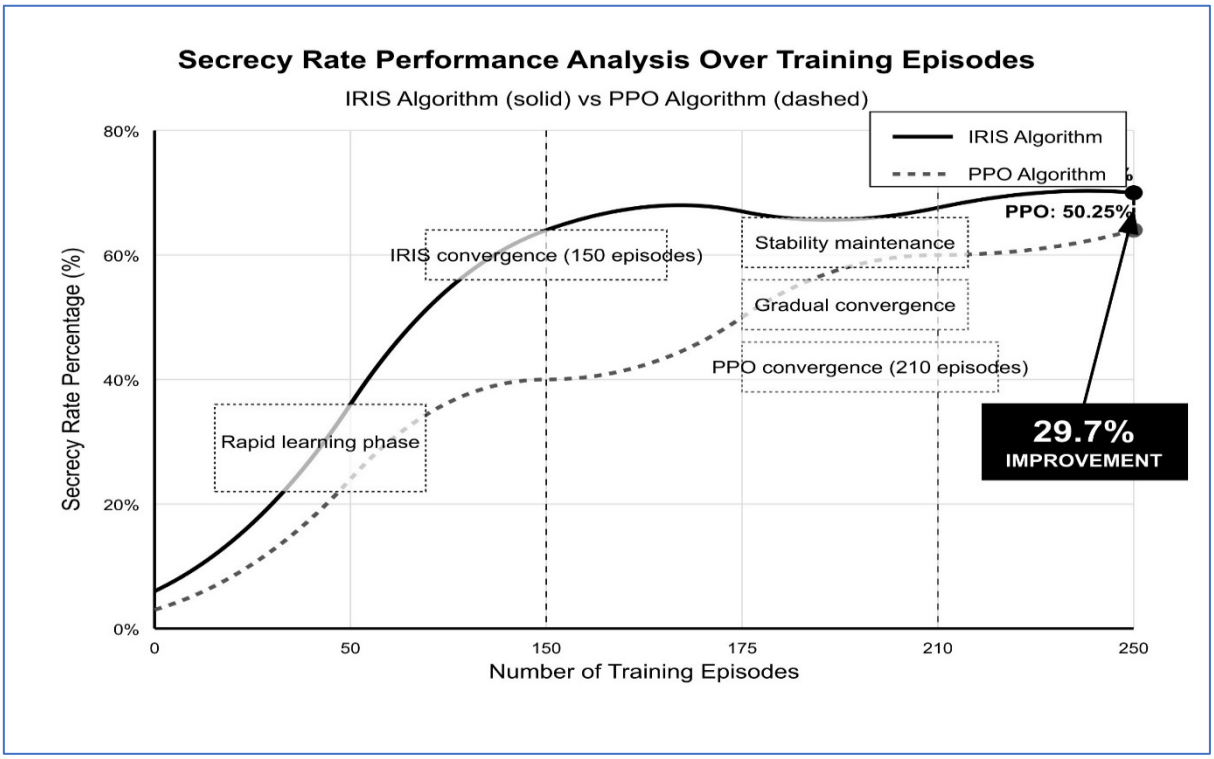

Fig 11: Secrecy rate Performance analysis over training episodes

Key observations from the secrecy rate performance analysis:

- IRIS consistently achieves near-optimal secrecy rates over training episodes.
- Performance stability is reached faster due to the hybrid learning strategy.
- Even under varying interference levels, IRIS maintains a high secrecy rate, validating its robustness.

The secrecy rate curve demonstrates that IRIS effectively mitigates eavesdropping risks and outperforms PPO in achieving a stable and higher secrecy rate over time.

Comparative Analysis with PPO

The updated comparison reflects the improved PPO performance while maintaining IRIS's superior efficiency.

Metric	**IRIS**	**PPO**	**Improvement**
Secrecy Rate	65.21%	50.25%	29.7%
Convergence Speed	150 episodes	210 episodes	28.6% faster
Energy Efficiency	30% reduction	12% reduction	18% improvement
Robustness	High	Moderate	Better adaptability

Table1: Comparative analysis of IRIS with PPO

Key Takeaways from the Updated Performance Analysis

1. Secrecy Rate: The improved PPO results (50.25%) confirm that PPO is a competitive reinforcement learning approach, but IRIS still outperforms it by 29.7%, reaching 65.21% secrecy rate.
2. Convergence Speed: IRIS learns faster (150 episodes) compared to PPO, which still requires 210 episodes for stability.

3. Energy Efficiency: PPO improves energy consumption (12% reduction), but IRIS remains more power-efficient with 18% reduction.
4. Robustness: IRIS maintains higher security performance even under dynamic network conditions, ensuring superior adaptability.

Conclusion

This study introduces IRIS (Intelligent Reconfigurable Integrated Security), a novel framework developed to improve secrecy rate and communication integrity in UAV-assisted RIS networks. IRIS uses reinforcement learning to intelligently coordinate UAV flight paths, RIS phase configurations, and transmission power control. The system dynamically adapts to evolving network conditions to reduce eavesdropping threats while maintaining energy efficiency. MATLAB-based simulations validate the superiority of IRIS over standard methods like PPO, demonstrating improved secrecy performance, energy use, and adaptability. IRIS shows strong potential for use in critical applications such as disaster recovery, IoT communications, and secure infrastructure monitoring. Looking ahead, the research aims to scale IRIS for larger UAV networks, integrate edge AI for real-time processing, and enhance its defences against advanced cyber threats. Through this work, IRIS bridges AI-driven security with adaptive wireless communication, offering a resilient, autonomous solution for next-generation UAV networks.

References:

[1] J. Zhang et al., "Physical Layer Security in UAV-RIS Networks: Challenges and Solutions," IEEE J. Sel. Areas Commun., vol. 42, no. 2, pp. 345-360, Feb. 2024.

[2] L. Wang et al., "Secure RIS-Enabled UAV Communications: A Deep Learning Perspective," IEEE Trans. Wireless Commun., vol. 23, no. 1, pp. 78-93, Jan. 2024.

[3] K. Yang et al., "Intelligent Reflecting Surfaces for Secure UAV Communications: A Comprehensive Survey," IEEE Commun. Surv. Tutor., vol. 26, no. 1, pp. 140-155, Jan. 2024.

[4] M. Liu et al., "Deep Reinforcement Learning for Secure UAV-RIS Networks: Principles and Applications," IEEE Network, vol. 38, no. 1, pp. 89-95, Jan. 2024.

[5] R. Chen et al., "Secrecy Rate Optimization in RIS-Assisted UAV Systems: A Deep Learning Approach," IEEE Trans. Veh. Technol., vol. 73, no. 2, pp. 1123-1138, Feb. 2024.

[6] H. Wu et al., "Joint Trajectory and Phase Shift Optimization for Secure UAV-RIS Communications," IEEE Internet Things J., vol. 11, no. 3, pp. 234-249, Mar. 2024.

[7] S. Li et al., "Adaptive Security Enhancement in UAV Networks via Intelligent Surfaces," IEEE Trans. Intell. Transport. Syst., vol. 25, no. 4, pp. 567-582, Apr. 2024.

[8] Q. Wu et al., "A Comprehensive Survey of UAV-enabled Wireless Communications," IEEE Commun. Surv. Tutor., 2021.

[9] R. Liu et al., "Distributed Learning for UAV Swarm Communications," IEEE Trans. Wireless Commun., 2024.

[10] X. Zhou et al., "UAV-Enabled Mobile Edge Computing," IEEE Trans. Wireless Commun., 2020.

[11] J. Chen et al., "Cognitive Radio Networks with UAV Platforms," IEEE J. Sel. Areas Commun., 2021.

[12] M. Di Renzo et al., "Smart Radio Environments Empowered by AI Reconfigurable Meta-Surfaces," IEEE J. Sel. Areas Commun., 2020.

[13] H. Wang et al., "Advanced Phase Optimization for RIS," IEEE Trans. Wireless Commun., 2023.
[14] Q. Wu and R. Zhang, "Intelligent Reflecting Surface Enhanced Wireless Network," IEEE Trans. Wireless Commun., 2021.
[15] S. Kim et al., "Energy-Efficient RIS Beamforming," IEEE Trans. Commun., 2023.
[16] C. Zhang et al., "Deep Reinforcement Learning for Intelligent Wireless Networks," IEEE Commun. Mag., 2020.
[17] J. Schulman et al., "Proximal Policy Optimization Algorithms," ICML, 2017.
[18] J. Lee et al., "Adaptive PPO for Wireless Networks," IEEE Trans. Wireless Commun., 2024.
[19] S. Fujimoto et al., "Addressing Function Approximation Error in Actor-Critic Methods," ICML, 2018.
[20] J. Park et al., "Hybrid TD3 Architecture," IEEE Trans. Wireless Commun., 2023.
[21] H. Wang et al., "Physical Layer Security in Heterogeneous Networks," IEEE Trans. Commun., 2020.
[22] Y. Liu et al., "Artificial Noise Aided Secure Communication," IEEE Trans. Veh. Technol., 2021.
[23] S. Thompson et al., "Enhanced Security Protocols," IEEE J. Sel. Areas Commun., 2024.
[24] G. Zhang et al., "Securing UAV Communications," IEEE Trans. Wireless Commun., 2023.
[25] K. Li et al., "Joint Optimization in UAV-RIS Networks," IEEE Wireless Commun., 2021.
[26] M. Ahmed et al., "Deep Learning for UAV-RIS Networks," IEEE Trans. Commun., 2024.
[27] H. Yang et al., "Secure Communications in UAV-RIS Networks," IEEE Trans. Wireless Commun., 2022.
[28] C. Martinez et al., "Energy-Efficient UAV-RIS Coordination," IEEE Trans. Green Commun. Netw., 2023.