Intelligent and Converged Networks
ISSN xxxx-xxxx
Volume x, Number x, xxxxxxx 20xx
DOI: 10.26599/ICN.20xx.90200xx

Distributed Reinforcement Learning Based Framework for Energy-Efficient UAV Relay against Jamming

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Abstract: Unmanned aerial vehicle (UAV) network is vulnerable to jamming attacks, which may cause severe damage like communication outages. Due to the energy constraint, the source UAV cannot blindly enlarge the transmit power, along with the complex network topology with high mobility, which makes the destination UAV unable to evade the jammer by flying at will. To maintain communications with limited battery in the UAV networks in the presence of a jammer, in this paper, we propose a distributed reinforcement learning (RL) based energy efficient framework for the UAV networks with constrained energy under jamming attacks to improve the communication quality while minimizing the total energy consumption of the network. This framework enables each relay UAV to choose its transmit power independently based on the historical state-related information without being aware of the moving trajectory of other UAVs as well as the jammer. The location and battery level of each UAV is not necessary to be shared with other UAVs. We also propose a deep RL based anti-jamming relay approach for the UAVs with portable computation equipment like Raspberry Pi to achieve higher performance in less time. We study the Nash equilibrium (NE) and the performance bound based on the formulated power control game. Simulation results show that the proposed schemes can reduce the bit error rate (BER) and save the energy consumption of the UAV network compared with the benchmark method.

Key words: Unmanned aerial vehicles; relay; jamming; reinforcement learning.

1 Introduction

With the fast development and increasing functionality, *unmanned aerial vehicles (UAVs)* have become the enablers of more and more advanced applications, such as traffic monitoring and remote sensing[1,2]. Different from mobile ad hoc networks (MANETs) and vehicular ad hoc networks (VANETs), UAV networks are more vulnerable to *jamming attacks* due to the limited battery capacity, time-varying link quality, higher mobility, and dynamic network topology[3]. A jammer may send faked or replayed signals to block the ongoing UAV communications and therefore results in transmission outages[4]. The jamming attack also exhausts the battery energy of the UAVs for retransmissions. Moreover, a UAV may be cheated to land in an unintended spot when its communication links to the operators are blocked by jamming[5].

To overcome possible jamming attacks, *power control* has been applied as an effective technique, which adjusts the transmit power of the device according to some well-designed strategies so that the received signal-to-interference-plus-noise ratio (SINR) can be greater or

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Manuscript received: year-month-day; accepted: year-month-day

equal to a minimum acceptable threshold. However, most of the existing solutions[8, 16, 18] are not applicable for the UAV networks due to the high mobility of the UAVs. Besides, the rapid variant channel conditions and the unknown jamming model lead to great challenges to the pre-modeling of the channel for power control against jamming.

In the UAV-aided communication network, the UAV acts as a relay to help forward messages to the target device, which is suffering from jamming attacks. Under the unknown network models and jamming models, the UAV has to select its relay power by adopting smart strategies. *Reinforcement learning (RL)*, which has been widely used in UAV-aided VANETs[9] and mobile communications[10], enables a UAV to optimize the relay power via trial-and-error without knowing the network topology and jamming model. The RL-based UAV relay system can not only reduce the bit error rate (BER) but also save the energy consumption of message relays. Note that a single UAV may be seriously jammed or has a limited battery, UAVs deployed as swarms provide great potentials to mitigate the damage of jamming by cooperative message relays. It fully exploits the line-of-sight (LoS) links between the UAVs and the target device to improve the communication performance[1].

However, most of the works adopt the centralized learning framework in the UAV networks, where a learning center is operated to send control signals to the other UAVs. The learning center has to deal with huge state spaces when the UAV network grows large. To the best of our knowledge, the distributed learning framework learned individually by each relay UAV is rarely discussed. Compared with the centralized framework, the distributed framework is more robust against a large scale UAV network. Besides, the UAV under the distributed framework does not need to share the state-related information to the learning center, i.e., received jamming power and the current battery level, which may cause the leak of privacy and require additional communication overheads.

In this paper, we propose a distributed framework for multi-relay UAV networks against jamming attacks, where each relay UAV independently determines the optimal transmit power for message relays from the source UAV to the destination UAV. The system objective is to maximize the communication performance and meanwhile minimize the overall energy consumption. To cope with the external jamming attacks, two RL-based approaches, i.e., the **R**L-based **E**nergy efficient **A**nti-jamming UAV **R**elay (REAR) approach and the enhanced deep REAR (DREAR) approach, are provided to maximize the expected long-term utility of each relay UAV in terms of Q-value, which depends on the communication performance as well as the energy consumption. The REAR approach exploits the historical state-related information to construct a distributed RL model for each relay UAV without being aware of the moving trajectory of other UAVs as well as the jammer. In each time slot, each relay UAV selects its optimal transmit power according to the relay policy derived by the proposed RL model and then updates the model parameters after receiving the acknowledge (ACK) frame from the destination UAV. Specifically, to share the UAV relay experiences to other similar UAV-aided communication networks, a transfer learning technique, i.e., hotbooting, is applied to initialize the Q-values in order to accelerate the initial relay exploration. To further enhance the efficiency of the anti-jamming UAV relay, the DREAR approach utilizes two deep neural networks (DNNs), i.e., an E-network and a T-network, to compress the state space and estimate the Q-value for each UAV relay policy. The E-network outputs the estimated Q-values and the T-network outputs the target Q-values so as to mitigate the over-estimation.

Our main contributions are summarized as follows.

1. We propose a distributed framework for multi-relay UAV networks against jamming attacks. Different from the centralized learning framework, the state space of the proposed distributed approach does not grow with the number of relay UAVs in the network, and the UAV does not need to share its location and battery level to a learning center or the other UAVs.
2. The RL-based REAR is provided to enable each relay UAV to independently choose its transmit power in the dynamically variant environment without knowing the network topology and jamming strategy. We also propose a DREAR approach to further improve the performance of the UAV network,

which applies the DNN technique to compress the state space and estimate the Q-values for each relay policy. The DREAR is suitable for portable computation equipment like Raspberry Pi.

3. The interactions between the relay UAVs and the jammer is formulated as an anti-jamming power control game. We study the Nash equilibrium (NE) and also provide the performance bound in terms of the BER, the energy consumption, and the utility of the overall network. Simulation results show that the proposed schemes can improve energy efficiency and reduce the BER compared with the benchmark scheme[8].

The rest of this paper is organized as follows. We review the related works in Section 2 and present the system model in Section 3. We propose the two RL-based anti-jamming relay approaches for energy-efficient UAV networks in Section 4. We formulate the anti-jamming relay game in Section 5 and provide the simulation results in section 6. Finally, the conclusion are drawn in Section 7.

2 Related Works

UAV-aided relay networks have been widely applied in many areas recently[12–15]. A two-hop UAV relay network applies a genetic algorithm to determine the data volume and design the trajectory of the mobile relays to improve the data downloading rate and reduce the latency[12]. Another cooperative UAV relay scheme for the wireless sensor networks[13] optimizes the packet load scheduling strategy via solving a min-max problem to reduce the energy consumption with the BER guarantee. A UAV-aided communication system[14] applies numerical research to derive the optimal location for UAVs under both static and mobile air-to-ground communication scenario to maximize the communication efficiency in terms of energy consumption and outage probability. A multiple UAV relay network[15] optimizes the UAVs placement to increase the transmission quality and compares the performance of a single multi-hop link and multiple dual-hop links in terms of the outage probability and BER.

The jamming attack in UAV networks degrades the communication performance and has drawn great research attention on the countermeasures of jamming attacks[8,16–18]. A cooperative anti-jamming scheme[16] applies a pricing mechanism based best-response algorithm to optimize the channel utilization of different users to improve the network throughput. A joint power control and user scheduling scheme against jamming[8] uses dynamic programming to obtain the optimal power allocation and user scheduling strategy sequentially at each slot to improve data rate for the wireless network. A robust anti-jamming beamforming scheme[17] uses linearly constrained optimization to improve the jamming resistance and the signal-to-interference-plus-noise ratio (SINR) of navigation signal with a minimum computation load. A cooperative relay scheme against the radio frequency jamming attacks for vehicular networks[18] applies a heuristic selection algorithm to select the vehicles that are out of the jammed area as relays and exploits the spatial diversity of selected relays to improve the SINR of the messages the jammed vehicles received by combining signals from all relays.

Without the stringent requirement of the knowledge of the channel or jamming model, RL based methods have been widely applied in anti-jamming communications[4,9,19–21]. A power control anti-jamming scheme for massive multiple input multiple output (MIMO) systems[19] uses a policy hill-climbing (PHC) algorithm to choose the transmit power of the base station based on previous SINR and received jamming power to improve the average SINR and the sum data rate of all user equipments in the system. A deep Q-network based anti-jamming scheme[20] formulates a Stackelberg dynamic game between an intelligent jammer UAV and the mobile users on the ground and then optimizes the user mobility to reduce the received jamming power of the users. A Q-learning based power control scheme[4] formulates the UAV to ground channel model and optimizes the UAV transmit power to the base station under the presence of a jammer to improve the SINR. A deep Q-learning based anti-jamming scheme[21] enables the UAVs to allocate the transmit power over multiple frequency channels based on the received jamming power to improve the secrecy capacity of the UAV system against a smart jammer. A UAV-aided

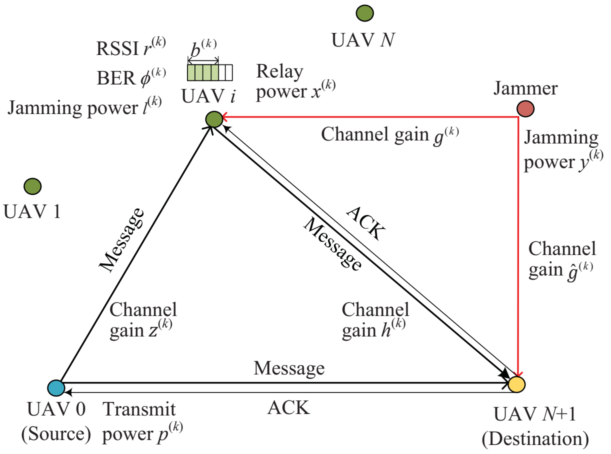


Fig. 1 RL-based UAV-aided wireless relay networks against jamming attacks.

anti-jamming relay scheme in VANETs[9] applies the PHC algorithm to help the UAV relay determine whether to relay the message according to its radio channel condition and previous transmission quality to reduces the BER of the forwarded messages.

3 System Model

As shown in Fig. 1, we consider a UAV network, in which a *source UAV* broadcasts messages intermittently to its intended *destination UAV* with multiple UAVs as relays. Specifically, a malicious *jammer* located near the destination tries to send jamming signals at the same spectrum to interfere with the communications. To cope with the external jamming attacks, a total N *relay UAVs* located between the source and destination can act as the relay nodes to help maintain the communication quality of the source-destination link without extra flying.

In the proposed time-slotted system, for simplicity, the source UAV is assumed to only broadcast one message in each time slot. At time slot k, the source UAV broadcasts a message with the transmit power $p^{(k)}$. It should be noted that both the destination UAV and the relay UAVs may receive this message. For an arbitrary relay UAV, it decodes the message received from the source UAV, and therefore the received signal strength indicator (RSSI) $r^{(k)}$ as well as the BER $\phi^{(k)}$ can be measured. Note that the battery power equipped at the UAV is usually limited and crucial, the relay UAV needs to decide its transmit power $x^{(k)}$ for message relay, which has an

Table 1 List of Key Notations

Symbol	Description
N	Number of the relay UAVs
$x^{(k)} \in [0, X]$	Relay power of UAV i at time slot k
$y^{(k)} \in [0, Y]$	Jamming power
$p^{(k)} \in [0, P]$	Transmit power of the source
$r^{(k)}$	RSSI of the message received by UAV i
$z^{(k)}$	Channel gain from the source to UAV i
$h^{(k)}$	Channel gain from UAV i to the destination
$\hat{g}^{(k)}$, $g^{(k)}$	Channel gain from jammer to the {destination UAV, UAV i}
$b^{(k)}$, $\tilde{b}^{(k)}$	{Measured, estimated} battery level of a relay UAV
ϑ	Battery threshold
ς	Minimum SINR for successful transmission
ε	Maximum BER for successful transmission
$\phi^{(k)}$	BER of the message received by UAV i from the source
$\rho_i^{(k)}$	BER of the message received by the destination from UAV i
$l^{(k)}$	Jamming power received by UAV i
$E^{(k)}$	Energy consumption of the UAV i

upper limit denoted by X. To lower the BER of the target messages, each relay UAV determines its relay power independently with the power constraint. Specifically, the relay UAV has to make sure whether the energy left is sufficient to relay the message or not by observing its current battery level $b^{(k)}$.

Due to the broadcast nature, the destination UAV may receive multiple copies of the target message at time slot k, each of which is either directly sent from the source UAV or relayed by some relay UAVs. For each received message, the address of the sender and the corresponding BER $\rho^{(k)}$ can be estimated and further assembled together into one ACK frame. The destination UAV broadcasts this ACK frame as feedback. Successful message delivery to the destination UAV requires that at least one message with BER less than the maximum BER ε for successful transmission. In some cases, the target message may not be successfully received by the destination UAV even with the assistance of those relay UAVs. We introduce a flag denoted by $\omega^{(k)}$ to indicate the message state: if the target message is successfully received, $\omega^{(k)} = 0$; otherwise, $\omega^{(k)} = 1$. The fail of the message delivery is regarded as a punishment in the utility of the relay UAV for learning and decision.

The jammer of the proposed scheme is more smart and detrimental compared with the static jammer with fixed or random jamming power. The greedy jammer chooses its moving strategy and the transmit power $y^{(k)}$ within the range of $[0, Y]$, to degrade the UAV communication with less jamming cost. Sending jamming signals for a random period may reduce the energy consumption of the jammer, making the attacks last longer. In the proposed system, *each relay UAV aims to optimize the transmit power to achieve energy efficiency when providing message relay against the greedy jammer*. The key notations of this paper are listed in Table 1.

4 RL-Based Energy Efficient UAV Relay Against Jamming

In this section, we propose a **R**L-based **E**nergy efficient **A**nti-jamming UAV **R**elay (REAR) approach, which is applied by each relay UAV independently, to determine the optimal relay power to mitigate the jamming attacks. The proposed REAR approach decreases the BER of the target message and reduces the overall network energy consumption thereby improving communication reliability. The hotbooting method is used in REAR to exploits the UAV relay power control experiences in the similar network model and anti-jamming scenarios to initialize the Q-values for each relay policy to accelerate the initial exploration. It should be noted that the proposed REAR approach is efficient for those UAVs with limited computing resources. With the development of single-board computers, such as portable Raspberry Pi, some UAV can learn and optimize its relay policy under much more complex environments with higher dimensional states. To enhance the efficiency of the anti-jamming UAV relay, we further propose a Deep REAR (DREAR) approach by utilizing the DNN technique.

4.1 REAR Approach for UAV Relay

In the proposed REAR approach, we define a state vector $\boldsymbol{s}^{(k)}$ at time slot k for each UAV relay as follows:

$$\boldsymbol{s}^{(k)} =[\phi^{(k)}, r^{(k)}, h^{(k)}, b^{(k)}, l^{(k)}, \min_{0\le i\le N} \rho_i^{(k-1)}, \rho^{(k-1)}, \omega^{(k-1)}]. \quad (1)$$

The BER of the message $\phi^{(k)}$ and the RSSI of its signal $r^{(k)}$ are the key metrics measured by the relay UAV to reflect the transmission quality of the UAV network, The channel gain of the relay-destination link $h^{(k)}$ can be estimated based on the preambles of the messages [22]. The current received jamming power is calculated by $l^{(k)} = y^{(k)} g^{(k)}$. From the ACK frame delivered by the destination UAV, the BER $\rho^{(k-1)}$ and the message state $\omega^{(k-1)}$ of the relay message at the previous time

Algorithm 1 REAR approach for UAV relay

Initialize parameters: $\min_{0\le i\le N} \rho_i^{(0)}$ and $\omega^{(0)}$
Obtain $\tilde{\mathbf{Q}}$ from similar scenarios based on hotbooting
Initialize Q-function as $\mathbf{Q}=\tilde{\mathbf{Q}}$
for $k = 1, 2, \cdots$ **do**
  Relay UAV receives a message from the source UAV
  Measure $\phi^{(k)}$, $r^{(k)}$, $l^{(k)}$, $h^{(k)}$ and observe $b^{(k)}$
  Formulate $\boldsymbol{s}^{(k)}$ by (1)
  Select $x^{(k)} \in \{mX/M : m \in \{0, \cdots, M\}\}$ via ϵ-greedy method
  if $b^{(k)} - x^{(k)} \ge \vartheta$ **then**
    Relay the message with power $x^{(k)}$
  else
    Set $x^{(k)} = 0$ (insufficient power, mute relaying)
  end if
  if Receive the ACK frame **then**
    if $\rho^{(k)}$ is contained **then**
      Calculate the minimum BER $\min_{0\le i\le N} \rho_i^{(k)}$
    else
      Calculate $\max_{0\le i\le N} \rho_i^{(k)}$ and $\min_{0\le i\le N} \rho_i^{(k)}$
      Set $\rho^{(k)} = \max_{0\le i\le N} \rho_i^{(k)}$
    end if
    if $\min_{0\le i\le N} \rho_i^{(k)} \le \varepsilon$ **then**
      Set $\omega^{(k)} = 0$ (successful transmission)
    else
      Set $\omega^{(k)} = 1$ (failed transmission)
    end if
  else
    Set $\omega^{(k)} = 1$ (failed transmission)
  end if
  Calculate $u^{(k)}$ by (2)
  Update $Q\left(\boldsymbol{s}^{(k)}, x^{(k)}\right)$ by the Bellman iterative equation
end for

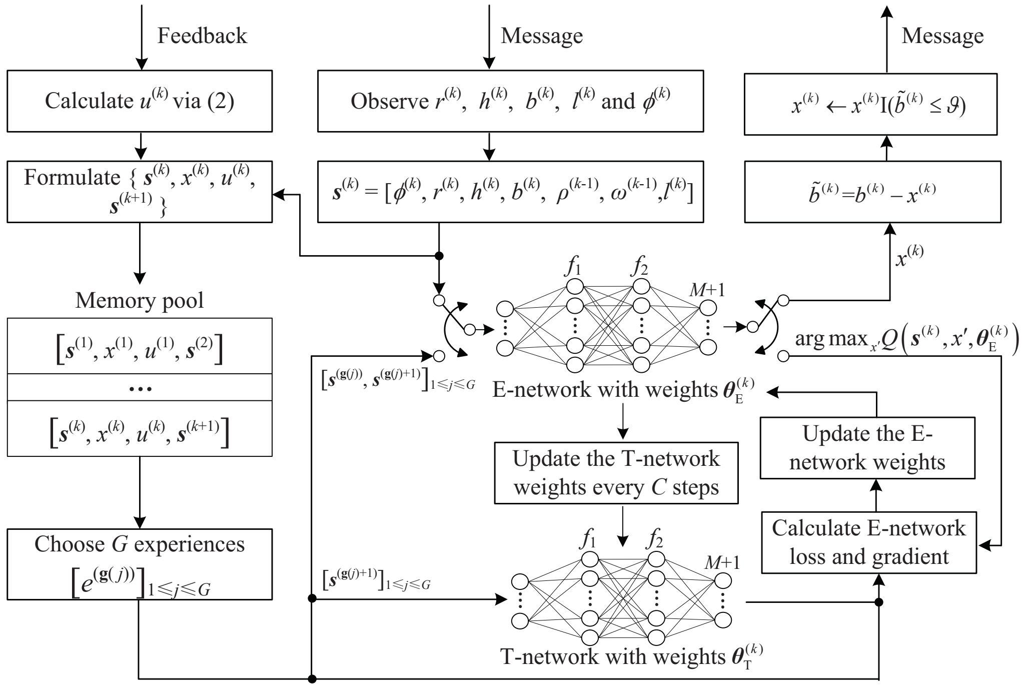


Fig. 2 Illustration of DREAR for UAV networks.

slot $k-1$ are known. Specifically, the minimum BER $\min_{0\leq i\leq N} \rho_i^{(k-1)}$ is recorded. The measurements in the state metric are quantized into limited discrete levels, in which the BER $\phi^{(k)}$ and $\min_{0\leq i\leq N} \rho_i^{(k-1)}$ are quantized by exponential region, the others are quantized uniformly in the range of possible values. The granularity of quantization will influence the size of the state space, thus when it becomes finer, the algorithm needs more exploration steps before convergence, but the algorithm is more likely to obtain the theoretical optimal value. Basing on the current state vector $\boldsymbol{s}^{(k)}$, the relay UAV chooses its transmit power $x^{(k)}$ according to the Q-function table, which is quantized in the range $[0, X]$ with total $M+1$ discrete levels, i.e., $x^{(k)} \in \{mX/M : m \in \{0, \cdots, M\}\}$.

If a relay UAV determines to help forward the message, then $x^{(k)} > 0$ should be guaranteed; otherwise, $x^{(k)} = 0$. The relay UAV uses ϵ-greedy method to choose the action, i.e., relay power, with the probability ϵ for randomly choosing to avoid stopping at a local optimal policy during the learning process. To ensure the feasibility of a selected relay power $x^{(k)}$, it should be satisfied that the remaining battery level after this message relay should be greater or equal to a minimum battery threshold ϑ, i.e., $b^{(k)} - x^{(k)} \geq \vartheta$. If the remaining battery level is not sufficient, then the relay power should be set to zero, that is, the relay UAV denies this message relay.

When an ACK frame of the current message is received, the minimum BER $\min_{0\leq i\leq N} \rho_i^{(k)}$ will be calculated and record, if $\min_{0\leq i\leq N} \rho_i^{(k)} \leq \varepsilon$, the flag of the message state is set as $\omega^{(k)} = 0$ to indicate a successful transmission, else, set the flag $\omega^{(k)} = 1$. In this case, if the corresponding BER is not contained in the ACK frame, e.g., the relay UAV i has denied forwarding the message or the relay message fails to reach the destination UAV due to the jamming, the minimum BER $\min_{0\leq i\leq N} \rho_i^{(k)}$ and the maximum BER $\max_{0\leq i\leq N} \rho_i^{(k)}$ should be recorded, where the maximum BER is regarded as a conservative estimation of the actual BER for this message. If no an ACK frame is received, the flag is set as $\omega^{(k)} = 1$. It should be noted that the flag $\omega^{(k)}$ is utilized as a punishment in the utility of the relay UAV to represent the transmission outages.

Furthermore, the utility of the relay UAV denoted by $u^{(k)}$ is evaluated upon receiving the ACK frame from the destination UAV:

$$u^{(k)} = -E^{(k)} - c_1 \min_{0\le i\le N} \rho_i^{(k)} - c_2\omega^{(k)}, \quad (2)$$

where c_1 and c_2 are the weights of the minimum BER received by the destination and the transmission outage punishment, respectively, and c_2 is determined to be an empirically large number. The energy consumption $E^{(k)}$ is measured to evaluate the energy efficiency by observing the battery level $b^{(k+1)}$ at the end of relay, i.e., $E^{(k)} = b^{(k)} - b^{(k+1)}$. The Q-function is exploited to obtain the optimal transmit power for the relay UAV and is updated via the Bellman iterative equation based on the current relay experience and the utility with the learning rate α and the discount factor γ.

The pseudocode of the proposed REAR approach is presented in Algorithm 1. We can observe that a transfer learning based hotbooting method is applied to improve the the efficiency of the exploration at the beginning of the learning process. This method initializes the Q-values for each relay policy with the anti-jamming UAV relay experiences randomly selected from several similar UAV relay scenarios.

4.2 Enhanced DREAR Approach for UAV Relay

In the enhanced DREAR approach, two isomorphic fully connected DNNs are used to compress the state space of the UAV relays, i.e., a E-network and a T-network. As shown in Fig. 2, each network consists of an input layer, two hidden layers with f_1 and f_2 units, and an output layer with $M+1$ units. All of them use the leaky rectified linear unit as the activation function. The two networks decouple the action selection and the computation of target Q value[23]. Specifically, the E-network outputs the maximum estimated Q-value of each state with weights $\boldsymbol{\theta}_{\mathrm{E}}^{(k)}$ while the T-network outputs the target Q-value with weights $\boldsymbol{\theta}_{\mathrm{T}}^{(k)}$.

When a relay UAV receives the message from the source at time slot k, it measures the BER of the message $\phi^{(k)}$ and the RSSI of its signal $r^{(k)}$. Besides, the current battery level $b^{(k)}$ and the received jamming power $l^{(k)}$. These parameters formulate the current state $\boldsymbol{s}^{(k)}$ as (1), which is treat as the input of the E-network. The transmit power is the output of the E-network to maximize the

Algorithm 2 DREAR approach for UAV relay

```
Initialize min_{0≤i≤N} ρ_i^(0), ω^(0), θ_E^(k) = θ_E^* and θ_T^(1) = θ_E^(1)
for k = 1, 2, ··· do
    Relay UAV receives a message from the source UAV
    Measure and observe φ^(k), r^(k), l^(k), h^(k) and b^(k)
    Formulate s^(k) by (1)
    Input s^(k) to the E-network
    E-network outputs x_max^(k)(s^(k), θ_E^(k))
    Select x^(k) ∈ {mX/M : m ∈ {0, ··· , M}} by ε-greedy
    method
    if b^(k) − x^(k) ≥ ϑ then
        Relay the message with power x^(k)
    else
        Set x^(k) = 0 (insufficient power, mute relaying)
    end if
    if Receive the feedback for message then
        Calculate the minimum BER min_{0≤i≤N} ρ_i^(k)
        if min_{0≤i≤N} ρ_i^(k) ≤ ε then
            Set ω^(k) = 0 (successful transmission)
        else
            Set ω^(k) = 1 (failed transmission)
        end if
        if ρ^(k) is contained in the feedback then
            Calculate max_{0≤i≤N} ρ_i^(k) and min_{0≤i≤N} ρ_i^(k)
            Set ρ^(k) = max_{0≤i≤N} ρ_i^(k)
        end if
    else
        Set ω^(k) = 1 (failed transmission)
    end if
    Calculate u^(k) by (2)
    Formulate s^(k+1) by (1)
    D ← D ∪ {s^(k), x^(k), u^(k), s^(k+1)}
    for j = 1, 2, ··· G do
        e^(g(j)) = D (g(j))
    end for
    Update θ_E^(k+1) via (4)
    Update θ_T^(k+1) with θ_E^(k+1) every C time slots
end for
```

Q-value, i.e., the estimated long term utility as follows:

$$x_{\max}^{(k)}\left(\boldsymbol{s}^{(k)}, \boldsymbol{\theta}_{\mathrm{E}}^{(k)}\right) = \arg\max_{x'} Q\left(\boldsymbol{s}^{(k)}, x'; \boldsymbol{\theta}_{\mathrm{E}}^{(k)}\right), \quad (3)$$

based on which the relay UAV selects its transmit power $x^{(k)} \in \{mX/M : m \in \{0, \cdots, M\}\}$ by ϵ-greedy method at the current time slot k, on the other hand, the output transmit power is further used as the input of the T-network for Q-value calculation. Similar to

$$\boldsymbol{\theta}_{\mathrm{E}}^{(k+1)} \leftarrow \arg\min_{\boldsymbol{\theta}_{\mathrm{E}}^{*}} \mathbb{E}_{e(\mathbf{g}(j))\in\mathcal{B}}\left[\left(u^{(\mathbf{g}(j))}+\gamma Q\left(\boldsymbol{s}^{(\mathbf{g}(j)+1)}, \arg\max_{x'} Q\left(\boldsymbol{s}^{(\mathbf{g}(j)+1)}, x'; \boldsymbol{\theta}_{\mathrm{E}}^{*}\right); \boldsymbol{\theta}_{\mathrm{T}}^{(k)}\right)-Q\left(\boldsymbol{s}^{(\mathbf{g}(j))}, x^{(\mathbf{g}(j))}; \boldsymbol{\theta}_{\mathrm{E}}^{*}\right)\right)^{2}\right]. \tag{4}$$

Algorithm 1, the relay UAV estimates the battery power after relaying the message and then calculates the utility $u^{(k)}$ by (2) basing on the received ACK frame.

Specifically, there is a memory pool $\mathcal{D}$ to store the experiences of the relay UAV at time slot k denoted by $e^{(k)} = \{\boldsymbol{s}^{(k)}, x^{(k)}, u^{(k)}, \boldsymbol{s}^{(k+1)}\}$. In this way, the UAV can randomly and uniformly sample total G experiences from $\mathcal{D}$ to formulate a minibatch $\mathcal{B}$, in which we use $\mathbf{g}(j)_{j\in[1,G]}$ to represent the serial number of the selected experiences, i.e., $\mathbf{g}(\cdot) \sim U(1,k)$. Furthermore, the weights of E-network $\boldsymbol{\theta}_{\mathrm{E}}^{(k+1)}$ is updated by (4) in order to minimize the mean square error (MSE) between the target Q-value and the estimated Q-value. The weights of the E-network $\boldsymbol{\theta}_{\mathrm{E}}^{(k+1)}$ is also utilized to update the weights of the T-network $\boldsymbol{\theta}_{\mathrm{T}}^{(k+1)}$ every $\mathcal{C}$ time slots. The overall description of the proposed DREAR approach is summarized in Algorithm 2.

5 Equilibrium Analysis for Anti-Jamming Power Control Game

So far, we have introduced the proposed REAR and DREAR approaches for optimal relay power control against jamming attacks. Note that the jammer expects to degrade the UAV communication by choosing its jamming power while the relay UAVs have to optimize the transmit power for successful message relay and energy efficiency. In this section, we model the interactions between the relay UAVs and the jammer as an anti-jamming power control game and study its NE.

5.1 Power Control Game

There are two sides to the proposed power control game: one side is the N relay UAVs, the other side is the smart jammer. To against the jamming attack, each relay UAV optimizes its relay power among range $[0, X]$ and therefore the power control strategy of total N relay UAVs is represented by a vector $\boldsymbol{x}^{(k)} = \{[x_i^{(k)}]_{1\le i\le N} | 0 \le x_i^{(k)} \le X\}$. On the contrary, the smart jammer adjusts its transmit power $y^{(k)} \in [0, Y]$ with the intention of minimizing the utility of the relay UAVs and meanwhile saving its energy, where Y is the maximum transmit power of the jammer.

In the multi-relay enabled UAV network, there are total N possible paths from the source UAV to the destination UAV. The SINR of the i-th path is constrained by the lower one between the source-to-relay-i link and the relay-i-to-destination link [9]. As we have discussed, the destination UAV only picks the message with minimum BER, namely the message with maximum SINR. When the direct channel from the source to the destination is during an outage, the SINR of the UAV network is determined by the maximum SINR of those possible paths:

$$\xi_{\mathrm{S,D}} = \max_{1\le i\le N}\left\{\min\left\{\frac{pz_i}{\sigma^2 + y^{(k)}g_i}, \frac{x_i^{(k)}h_i}{\sigma^2 + y^{(k)}\hat{g}}\right\}\right\}. \tag{5}$$

Consider the quadrature phase-shift keying (QPSK) modulation, the corresponding minimum BER of the UAV network can be represented by

$$\min_{1\le i\le N} \rho_i = \frac{1}{2}\mathrm{erfc}\left(\sqrt{\frac{\xi_{\mathrm{S,D}}}{2}}\right). \tag{6}$$

The objective of the UAV network is to improve the network utility, which depends on the minimum BER of the target message and the total energy consumption. Similar to the utility function (2), we use the maximum SINR from the source UAV to the destination UAV $\xi_{\mathrm{S,D}}^{(k)}$ instead of the minimum BER $\min\limits_{1\le i\le N} \rho_i^{(k)}$ for simplicity, and the maximum BER for successful transmission ε is also converted to the minimum SINR ς. Besides, to omit the transmission outage punishment $\omega^{(k)}$ in the theoretical analysis, we have to consider the successful transmission constrain, i.e., $\xi_{\mathrm{S,D}}^{(k)} > \varsigma$. In this way, the utility of the UAV network is calculated by

$$u_{\mathrm{R}}^{(k)} = c_3\xi_{\mathrm{S,D}}^{(k)} - \sum_{1\le i\le N} E_i^{(k)}, \tag{7}$$

$$\text{s.t.} \quad \xi_{\mathrm{S,D}}^{(k)} \ge \varsigma, \tag{8}$$

where c_3 represents the weight of the maximum SINR $\xi_{\mathrm{S,D}}^{(k)}$. Accordingly, the utility of the smart jammer, which aims to interrupt the message transmission of the UAV network, is expressed as the negative of the UAV network utility u_{R} minus the jamming power consumption, that is,

$$u_{\mathrm{J}} = -u_{\mathrm{R}}^{(k)} - c_4 y^{(k)}, \tag{9}$$

where c_4 is an invariable cost coefficient.

5.2 Equilibrium Analysis

To study the NE, we assume that all channel gains are fixed in the rest of this section, i.e., g_i, $\hat{g}$, h_i, z_i. We also assume that the transmit power of the source UAV p and the transmission delay T are constant.

Theorem 1 Given a fixed jamming power y, the optimal solution to the relay power control is

$$\boldsymbol{x}^* = \Big[\underbrace{0,...,0}_{i'-1}, x_{i'}^*, \underbrace{0,...,0}_{N-i'}\Big], \tag{10}$$

where $x_{i'}^*$ is the optimal relay power determined by the relay UAV i' and

$$i' = \arg\max_{1\le i\le N} \left\{ \min\left\{ \frac{pz_i}{\sigma^2 + yg_i}, \frac{x_i h_i}{\sigma^2 + y\hat{g}} \right\} \right\}. \tag{11}$$

The utility achieved by the UAV network could be reduced to

$$\hat{u}_{\mathrm{R}} = c_3 \min\left\{ \frac{pz_{i'}}{\sigma^2 + yg_{i'}}, \frac{x_{i'} h_{i'}}{\sigma^2 + y\hat{g}} \right\} - Tx_{i'}. \tag{12}$$

Proof. We denote the index of the relay UAV with maximum SINR by i' according to (11). It should be noted that the destination UAV only picks the message with minimum BER, namely the message forwarded by the relay UAV i'. The best strategy of the other relay UAVs except i' is to keep silent in order to save the unnecessary energy consumption. In this way, the optimal solution to the relay power control can be represented by $\boldsymbol{x}^* = \Big[\underbrace{0,...,0}_{i'-1}, x_{i'}^*, \underbrace{0,...,0}_{N-i'}\Big]$, where $x_{i'}^*$ is the optimal relay power determined by the relay UAV i'. According to the definition in (7), we have

$$\begin{aligned} u_{\mathrm{R}} &= c_3 \min\left\{ \frac{pz_{i'}}{\sigma^2 + yg_{i'}}, \frac{x_{i'} h_{i'}}{\sigma^2 + y\hat{g}} \right\} - \sum_{1\le i\le N} Tx_i \\ &\le c_3 \min\left\{ \frac{pz_{i'}}{\sigma^2 + yg_{i'}}, \frac{x_{i'} h_{i'}}{\sigma^2 + y\hat{g}} \right\} - Tx_{i'} = \hat{u}_{\mathrm{R}}. \end{aligned} \tag{13}$$

Therefore, u_{R} could be reduced to $\hat{u}_{\mathrm{R}}$ when the UAV network tries to maximize its utility. ■

Accordingly, given the optimal power control as (10), the utility function of the jammer could be reduced to

$$\hat{u}_{\mathrm{J}} = Tx_{i'} - c_3 \min\left\{ \frac{pz_{i'}}{\sigma^2 + yg_{i'}}, \frac{x_{i'} h_{i'}}{\sigma^2 + y\hat{g}} \right\} - c_4 y. \tag{14}$$

We observe that different network environments may lead to different NEs basing on (12) and (14). In the followings, we divide the power control game into two cases:

Case 1. The SINR of the source-relay-i' link is greater than the relay-i'-destination link, that is,

$$\frac{pz_{i'}}{\sigma^2 + yg_{i'}} > \frac{x_{i'} h_{i'}}{\sigma^2 + y\hat{g}}. \tag{15}$$

In this way, the transmit power of the relay UAV i' should satisfy the following condition:

$$x_{i'} < \frac{pz_{i'}(\sigma^2 + y\hat{g})}{h_{i'}(\sigma^2 + yg_{i'})}. \tag{16}$$

Basing on (15), we have

$$\hat{u}_{\mathrm{R}} = x_{i'}\Big(\frac{c_3 h_{i'}}{\sigma^2 + y\hat{g}} - T\Big), \tag{17}$$

$$\hat{u}_{\mathrm{J}} = -x_{i'}\left(\frac{c_3 h_{i'}}{\sigma^2 + y\hat{g}} - T\right) - c_4 y. \tag{18}$$

The first and second order derivative of $\hat{u}_{\mathrm{J}}$ with respect to y will be

$$\frac{\partial \hat{u}_{\mathrm{J}}}{\partial y} = \frac{c_3 x_{i'} h_{i'} \hat{g}}{(\sigma^2 + y\hat{g})^2} - c_4, \tag{19}$$

$$\frac{\partial^2 \hat{u}_{\mathrm{J}}}{\partial^2 y} = -\frac{2c_3 x_{i'} h_{i'} \hat{g}^2}{(\sigma^2 + y\hat{g})^3}. \tag{20}$$

Obviously, $\hat{u}_{\mathrm{J}}$ is a concave function of y because its second derivative is always negative when $x_{i'} \neq 0$. Since y should be ranged within $[0, Y]$, the optimal jamming power will be

$$y^* = \begin{cases} \hat{y}, & 0 < \hat{y} < Y \\ 0, & \hat{y} \le 0 \\ Y, & \text{o.w.} \end{cases}, \tag{21}$$

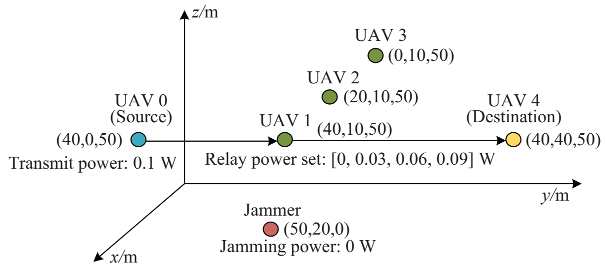
where $\hat{y}$ is derived from $\partial \hat{u}_{\mathrm{J}} / \partial y = 0$ and given as follows:

$$\hat{y} = \sqrt{\frac{c_3 x_{i'} h_{i'}}{c_4 \hat{g}}} - \frac{\sigma^2}{\hat{g}}. \tag{22}$$

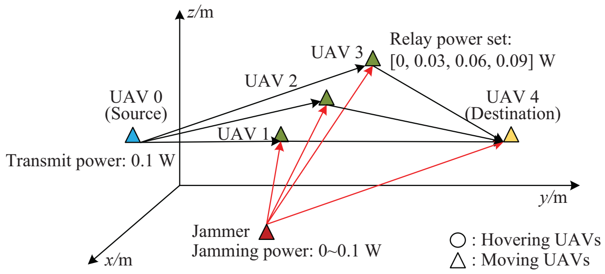
Besides, the first derivative of $\hat{u}_{\mathrm{R}}$ of $x_{i'}$ is

$$\frac{\partial \hat{u}_{\mathrm{R}}}{\partial x_{i'}} = \frac{c_3 h_{i'}}{\sigma^2 + y\hat{g}} - T. \tag{23}$$

When the condition $c_3 h_{i'} \ge T(\sigma^2 + y^*\hat{g})$ is satisfied, $\hat{u}_{\mathrm{R}}$ will be an increasing function of $x_{i'}$. Note that $x_{i'}$



(a) Static scenario for NE analysis



(b) Initial topology for dynamic UAV realy network

Fig. 3 Simulation settings for performance evaluations.

should be ranged within $[0, X]$, the optimal relay power $x_{i'}^*$ is X. Combining with (16) and (8), we have

$$\max\left\{\frac{T(\sigma^2+y\hat{g})}{c_3}, \frac{\varsigma\left(\sigma^2+y\hat{g}\right)}{X}\right\} \leq h_{i'} \leq \frac{pz_{i'}(\sigma^2+y\hat{g})}{X(\sigma^2+yg_{i'})}. \tag{24}$$

Otherwise, $\hat{u}_{\mathrm{R}}$ become an decreasing function of $x_{i'}$ with the constrain (8) and $x_{i'}^* = \left(\varsigma\left(\sigma^2+y\hat{g}\right)\right)/h_{i'}$ is the optimal relay power if the following condition is guaranteed:

$$0 < h_{i'} < \frac{T(\sigma^2+y\hat{g})}{c_3}. \tag{25}$$

Case 2. The SINR of the source-relay-i' link is lower or equal to the relay-i'-destination link, that is,

$$\frac{pz_{i'}}{\sigma^2+yg_{i'}} \leq \frac{x_{i'}h_{i'}}{\sigma^2+y\hat{g}}. \tag{26}$$

Similar to Case 1, the optimal jamming power will be

$$y^* = \begin{cases} \hat{y}, & 0<\hat{y}<Y \\ 0, & \hat{y}\leq 0 \\ Y, & \text{o.w.} \end{cases}, \quad \text{where} \tag{27}$$

$$\hat{y} = \sqrt{\frac{c_3pz_{i'}}{c_4g_{i'}}} - \frac{\sigma^2}{g_{i'}}. \tag{28}$$

Specifically, the first derivative of $\hat{u}_{\mathrm{R}}$ of $x_{i'}$ is

$$\frac{\partial\hat{u}_{\mathrm{R}}}{\partial x_{i'}} = -T < 0, \tag{29}$$

which means that $\hat{u}_{\mathrm{R}}$ is monotonically decreasing with $x_{i'} \in [0, X]$. Basing on (26), the optimal relay power should be

$$x_{i'}^* = \frac{pz_{i'}(\sigma^2+y\hat{g})}{h_{i'}(\sigma^2+yg_{i'})}. \tag{30}$$

We utilize the derived conditions above and have the following theorem:

Theorem 2 The power control solution $(\boldsymbol{x}^*, y^*) = ([0, ..., 0, x_{i'}^* = X, 0, ..., 0], 0)$ is a NE of the anti-jamming power control game when

$$\max\left\{\frac{T\sigma^2}{c_3}, \frac{\sigma^2\varsigma}{X}\right\} \leq h_{i'} \leq \min\left\{\frac{pz_{i'}}{X}, \frac{\sigma^4c_4}{c_3X\hat{g}}\right\}. \tag{31}$$

The performance bound under this NE is given by

$$\xi_{\mathrm{S,D}} = \frac{Xh_{i'}}{\sigma^2} \tag{32}$$

$$\sum_{1\leq i\leq N} E_i = XT \tag{33}$$

$$\min_{1\leq i\leq N} \rho_i = \frac{1}{2}\mathrm{erfc}\left(\sqrt{\frac{Xh_{i'}}{2\sigma^2}}\right) \tag{34}$$

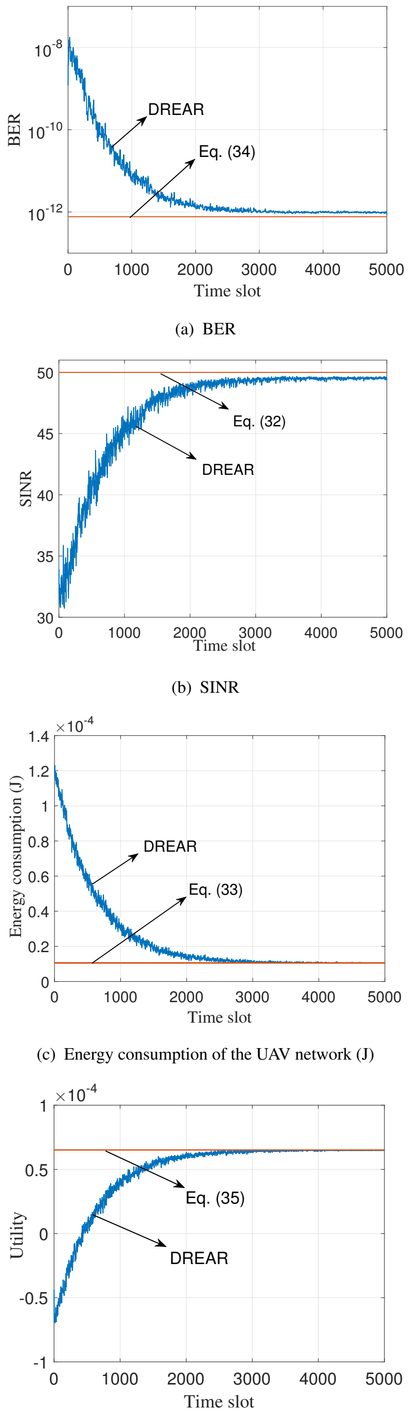
$$u_{\mathrm{R}} = \frac{c_3Xh_{i'}}{\sigma^2} - XT \tag{35}$$

That is, only the relay UAV i' with the best channel condition chooses to relay the message with the maximum transmit power X and the others keep silent. The jammer chooses to stop jamming to save energy.

6 Simulation Results

In the performance evaluations, we consider one source UAV, one destination UAV, three relay UAVs, and a jammer on the ground, as shown in Fig. 3. The first simulation is conducted under the static theoretical analysis scenario in Section 5 with $N = 3$ relays and a mute jammer which satisfies the condition given by (31), as shown in Fig. 3(a). The simulation results in Fig. 4 show that the proposed DREAR approach can converge to the optimal relay strategy after around 2500 time steps. For example, the BER, the SINR, the total network energy consumption, and the overall utility almost converge to the performance bound given by (32)-(35).

Another simulation is conducted under a dynamic network model with a moving jammer, as shown in Fig. 3(b). The transmit power of the source is 0.1 W. The relay UAVs choose the relay power among a set discretized uniformly into 4 levels among $[0, 0.9]$ W.



(a) BER

(b) SINR

(c) Energy consumption of the UAV network (J)

(d) Utility of the UAV network

Fig. 4 Performance of the deep RL based energy efficient UAV relay scheme averaged over 50 episodes for the UAV network with 3 relays in the theoretical analysis scenario compared with the performance bound.

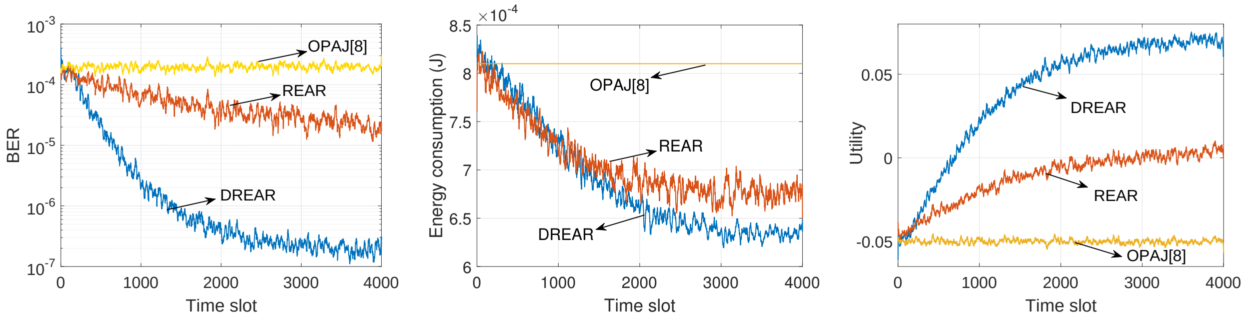
The jamming power received by the destination changes among 9.0 dBm, 9.5 dBm, and 10.0 dBm. Relays are also influenced by the jammer, the jamming power received by each relay is different and changes from 3.0 dBm, 6.0 dBm, and 7.0 dBm.

The system performance is evaluated by the minimum BER of the received relay messages by the destination, the total energy consumption of 3 relays, and the utility of the network is calculated based on the minimum BER and the total energy consumption. We use the optimal power control against jamming (OPAJ) algorithm[8] with fixed optimal relay power as the benchmark algorithm. To control that the relay power is the only variable in the comparison between the proposed algorithm with the benchmark, the BER used to represent the performance of the overall system is chosen from the relay message of the same relay in the two algorithms at every time slot.

Fig. 5 presents the performance of the dynamic energy-efficient UAV relay against jamming based on RL with the learning rate $\alpha = 0.5$ and the discount factor $\gamma = 0.7$. Due to the fixed relay power of the benchmark algorithm, the energy consumption of it remains unchanged, but the BER of it decreases a little because that it is chosen from the relay message of the same relay as in the proposed algorithm. The results show that both the REAR and the DREAR approaches improve UAV communication performance and save the relay energy consumption compared with the benchmark scheme. For instance, the REAR approach reduces the BER by an order of magnitude and saves energy consumption by 17.3% compared with OPAJ after 3500 time slots. The DREAR approach further decreases the BER by two orders of magnitude to 1.5×10^{-7} and save the energy consumption by 6.7% to 0.625 mJ.

7 Conclusion

In this paper, we have proposed a distributed framework for energy-efficient UAV relay networks that aims at maintaining the transmission quality in the presence of a jammer. The relay UAV can help relay messages cooperatively without sharing its real-time location and battery level with each other. The proposed reinforcement learning based approaches enable each



(a) BER (b) Energy consumption (c) Utility

Fig. 5 Performance of the RL based energy efficient UAV relay schemes averaged over 50 episodes for the UAV network with 3 relays against a greedy jammer.

relay UAV to choose the optimal relay strategies derived based on the game theory without awareness of the moving trajectory of other UAVs as well as the jammer. We have also provided the performance bound including the BER, the total network energy consumption, and utility, and verified them via simulation in a static scenario. Simulation results show that the proposed approaches can improve the transmission quality of the UAV relay network in terms of BER while reducing the total energy consumption. For instance, the DREAR approach saves energy consumption by 22.8% and decreases the BER by three orders of magnitude compared with the benchmark scheme.

Acknowledgment

This work was supported in part by the Natural Science Foundation of China under Grants 61971366 and 61731012.

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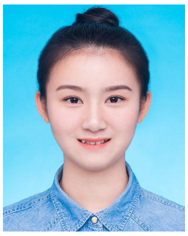

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