Routing Recovery for UAV Networks with Deliberate Attacks: A Reinforcement Learning based Approach

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Abstract—The unmanned aerial vehicle (UAV) network is popular these years due to its various applications. In the UAV network, routing is significantly affected by the distributed network topology, leading to the issue that UAVs are vulnerable to deliberate damage. Hence, this paper focuses on the routing plan and recovery for UAV networks with attacks. In detail, a deliberate attack model based on the importance of nodes is designed to represent enemy attacks. Then, a node importance ranking mechanism is presented, considering the degree of nodes and link importance. However, it is intractable to handle the routing problem by traditional methods for UAV networks, since link connections change with the UAV availability. Hence, an intelligent algorithm based on reinforcement learning is proposed to recover the routing path when UAVs are attacked. Simulations are conducted and numerical results verify the proposed mechanism performs better than other referred methods.

Index Terms—UAV network, trusted routing, reinforcement learning, node importance ranking mechanism.

I. INTRODUCTION

IN the next-generation mobile communication, unmanned
aerial vehicles (UAVs) play important roles for full connecaerial vehicles (UAVs) play important roles for full connectivity and seamless coverage [1]. In addition, UAV networks are widely leveraged due to the small size and flexibility in various applications, such as data collection, real-time monitoring, search and rescue, surveillance, and telecommunications [2]– [6]. Furthermore, UAV routing is a key issue to support these demands. However, the distributed topology of UAV networks is vulnerable to attacks, leading to the disconnection of communication links. Thus, it is significant to design an efficient algorithm to recover routing when the original path is unavailable.

Traditional routing algorithms, such as Bellman-Ford and Dijkstra algorithm [7], cannot be directly applied in UAV networks, since UAVs are characterized by high mobility, dynamic topology, frequent data interaction, and complex application environments [8]. Moreover, the traditional algorithm cannot guarantee the robustness and security for multi-UAV

cooperative communications. Fortunately, machine learning is widely leveraged for routing in recent years, due to satisfactory performance in adapting to dynamic networks. Reinforcement learning (RL) relies on the process of real-time interactions with the environment to update the value of actions performed in different states. Meanwhile, RL-based routing algorithms are widely studied, since they can employ limited information to achieve satisfactory results [9].

There exist a couple of works related to routing in UAVbased scenarios. For instance, in [10], Tang *et al.* study the complex traffic offloading decision problem and then reformulate it into a Markov decision process (MDP) form, to reduce the total transmission delay in highly dynamic network environments. Lin *et al.* utilize a deep RL method to design an intelligent routing algorithm, in which nodes adaptively determine neighborhoods based on Q values [11]. In [12], He *et al.* design a routing algorithm based on fuzzy logic RL, and simulation results show that the proposed algorithm has lower average hop counts compared with the ant colony optimization algorithm. In [13], the authors propose a deep RL-based adaptive and reliable routing method, considering the information related to routing, such as link connections, remaining energy of nodes, and distances, to accurately represent the network environment and then make appropriate routing decisions. Liu *et al.* propose a Q-learning based multi-objective optimization routing algorithm, which utilizes a new exploitation and exploration mechanism to explore potential optimal routing paths by re-estimating neighborhood relationships during routing [14]. However, these works lack considering the issue that nodes are attacked and the original routing path is destroyed.

Therefore, in this work, we focus on minimizing the end-toend delay of data transmission in UAV networks with deliberate attacks. To clearly depict the routing process in the UAV network, we present a UAV routing recovery scenario. Further, we design a node importance ranking mechanism (NIRM), including the importance of links and the node degree, to represent deliberate attacks. However, this problem is intractable

Fig. 1. UAV routing recovery scenario. The recovery routing path is generated after UAVs in the original routing path are attacked.

to handle in the complex UAV network. Hence, we reformulate the routing issue into an MDP form and then propose a RLbased intelligent algorithm. In the end, we conduct extensive simulations to demonstrate the proposed method in terms of both convergence and delay.

The rest of this paper is organized as follows. In Section II, we present the system model and problem formulation. Then, the RL-based intelligent routing algorithm with deliberate attacks is designed in Section III. Moreover, Section IV provides simulation results. Finally, Section V draws conclusions.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. Network Model

As shown in Fig. 1, a UAV network scenario is provided, in which the communication range of each UAV is limited to a hollow sphere with a maximum radius O_{max} and a minimum radius O_{min} . In detail, O_{max} represents the maximum communicative distance and O_{min} denotes the minimum distance between two UAVs without collisions. Moreover, we consider an undirected network $\mathcal{G} = (\mathcal{U}, \mathcal{E})$ with N UAVs and M edges. $\mathcal{U} = \{u_i, i = 1, 2, \cdots, \mathcal{N}\}$, where u_i represents the *i*-th UAV. $\mathcal{E} = \{e_{i,j}, i = 1, 2, \cdots, \mathcal{N}, j = 1, 2, \cdots, \mathcal{N}\}\)$, in which $e_{i,j} \in \{0,1\}$ is a binary variable, representing if there exists an active link between UAVs u_i and u_j . In particular, $e_{i,j} = 1$ indicates there exists a communication link between the two UAVs, while $e_{i,j} = 0$ represents the two UAVs are unavailable to communicate. Then, we define $F = \{f_i, i = 1, 2, \cdots, \mathcal{N}\}\$ to represent the set of damaged UAVs. $f_i = 1$ indicates UAV u_i is attacked and the values of $e_{i,x}$ and $e_{x,i}$ $(x = 1, 2, \dots, N)$ in adjacency matrix $\mathcal E$ are set as zero, representing that other UAVs cannot transmit data via UAV u_i . The position of u_i is expressed by (x_i, y_i, z_i) . At the start of routing, source node u_s generates a packet of size l_p and sends it to destination node $u_d \in \mathcal{U}$ via a defined routing path $p_{sd} = \{u_s \to u_d\}.$

B. Communication Model

According to [15], the free space path loss between two UAVs is represented as:

$$
FSPL = 20\log_{10}\left(\frac{4\pi dg}{c}\right),\tag{1}
$$

where d represents the three-dimensional distance between UAVs. q denotes the frequency, and c is the speed of light. As for the communication between UAVs u_i and u_j , we consider a simple free-space propagation model, depending on the frequency and distance. $PL_{i,j}$ in dB is calculated as:

$$
PL_{i,j} = 20\log_{10}(d) + 20\log_{10}(g) - 147.55.
$$
 (2)

Therefore, based on (2), the signal-to-noise ratio in the communication channel between u_i and u_j is:

$$
SNR_{i,j} = \frac{\mathcal{P}_{i,j} 10^{-\frac{PL_{i,j}}{10}}}{\sigma_{i,j}^2},\tag{3}
$$

and the max transmission rate is represented as:

$$
\mathcal{R}_{i,j} = B_{i,j} log_2(1 + SNR_{i,j}),\tag{4}
$$

where $B_{i,j}$, $\mathcal{P}_{i,j}$, and $\sigma_{i,j}^2$ denote the channel bandwidth, transmission power, and noise power between u_i and u_j , respectively.

C. Delay Model

The end-to-end delay includes the queuing and transmission. Specifically, the routing delay between UAVs u_i and u_j is expressed as:

$$
T_{p_{i,j}} = \frac{d_{i,j}}{c} + \frac{\mathcal{L}}{\mathcal{R}_{i,j}},\tag{5}
$$

where $d_{i,j}$ represents the Euclidean distance between u_i and u_j . c is the signal transmission speed. $\mathcal L$ represents the packet waiting for transmission. Based on (5), we can calculate the total end-to-end delay as:

$$
\mathcal{T} = \sum_{p_{i,j} \in p_{sd}} T_{p_{i,j}},\tag{6}
$$

where $p_{i,j}$ denotes the one-hop path between u_i and u_j . In addition, p_{sd} represents a complete source-to-destination path from u_s to u_d .

D. Problem Formulation

The objective is to minimize the latency of routing via selecting an optimal routing path in the UAV network with attacks. In detail, the problem is formulated as:

$$
\mathscr{P}0: \min_{p_{sd}^b} \sum_{T_{p_{i,j}}} \sum_{U_{\{s,\cdots,d\}}} \mathcal{T}_{D(u_s \to u_d, P_{sd})},\tag{7a}
$$

$$
\text{s.t. } T_{p_{i,j}} \le (T_{p_{i,j}})_{max},\tag{7b}
$$

$$
O_{min} \le d_{i,j} \le O_{max},\tag{7c}
$$

$$
p_{sd}^b \in P_{sd},\tag{7d}
$$

$$
u_s, u_d \in U_{\{s, \cdots, d\}},\tag{7e}
$$

where $\mathcal{T}(\cdot)$ represents the total delay of delivering packets in the routing path. A routing approach is denoted as $D(u_s \rightarrow$ u_d, P_{sd}). In particular, $P_{sd} = \{p_{sd}^1, \dots, p_{sd}^b\}$ is the candidate routing path set and b denotes the b-th available path. $U_{\{s,\dots,d\}}$ indicates the UAV set in the routing path p_{sd}^b . $(T_{p_{i,j}})_{max}$ represents the tolerable maximum delay. u_s and u_d are the source and destination UAVs, respectively.

III. ALGORITHM DESIGN

In this section, we firstly employ NIRM to model deliberate attacks. Then, we reformulate the routing issue into an MDP form and propose a RL-based intelligent algorithm to make dynamic routing decisions.

A. NIRM based Deliberate Attack Model

In general, UAVs are characterized by high flexibility and complex application environments, and thus vulnerable to attacks. For example, the attacker may send a large amount of requests to UAVs in the network, exhausting their network resources and making them unable to provide services for other UAVs, i.e., denial-of-service attacks. If middle nodes within an original routing path are attacked, another new path for routing should be found in limited time.

To study the impact of attacks on network performance, we introduce attack models. Generally, there exist two attack models in random and deliberate, respectively [16]. Random attack models assign the order of importance to nodes randomly and then launch attacks based on the ranking. In comparison, deliberate attack models rank the importance of nodes according to the rules. We consider employing the deliberate attack model in this work, since most attackers destroy the network via specific standards, for example, attacking critical nodes at first. Further, we design the deliberate attack model based on a node importance ranking mechanism, in which UAVs with higher importance are attacked in priority, leading to network breakdown.

There exist a couple of methods to evaluate node importance in complex networks, such as degree centrality (DC), closeness centrality (CC), and betweenness centrality (BC) [17]. Therein, DC emphasizes the number of links connected to the node directly, but nodes with the same degree may play different roles in the UAV network. Moreover, BC and CC require the global information to calculate the optimal routing path in large-scale UAV networks, which is intractable to obtain. Hence, we evaluate the importance of nodes considering both the node degree and link importance. In particular, the importance of UAV u_i is expressed as:

$$
L_{u_i} = k_i + \sum_{u_j \in \Gamma_i} W_{u_i u_j},\tag{8}
$$

where Γ_i and k_i denote the neighboring UAV set and the degree of u_i , respectively. $W_{u_i u_j}$ represents the contribution of u_i to the importance of $e_{i,j}$, i.e.,

$$
W_{u_i u_j} = I_{e_{i,j}} \left(1 - \frac{k_j - 1}{k_i + k_j - 2} \right),\tag{9}
$$

where k_j is the degree of UAV u_j , and $I_{e_{i,j}}$ denotes the importance of $e_{i,j}$, i.e.,

$$
I_{e_{i,j}} = Z \frac{2}{m+2},\tag{10}
$$

where $Z = (k_i - m - 1)(k_j - m - 1)$ depicts the connectivity ability of link $e_{i,j}$. m denotes the number of triangles containing link $e_{i,j}$ in the UAV network topology.

B. MDP based Reformulation

During routing, packets are transmitted according to the designed routing path. The objective is to reduce the total transmission delay. However, it is challenging to make the routing decision satisfy this goal. In addition, the fixed routing method is inapplicable in the UAV network with attacks. Hence, it is necessary to analyze the current network environment to make further routing decisions. Thus, we reformulate the routing issue into an MDP form, which is consisted of five parts: state space S, action space A, transition probability P_{sa} , reward function r, and discount factor γ . In addition, π represents the policy, and τ is a sequence of tracks in an episode, defined as $\tau = \{s_0, a_0, r_1, s_1, a_1, r_2, \cdots\}.$

1) State space: As the input of RL models, state space S indicates the environment of the agent, i.e., the UAV. To enable the agent aware of the environment state, we adopt two routingrelated parameters to constitute the state space set. The first parameter is the distance, which is a basic element and plays a vital role in most location-based routing algorithms. With the given location information, the Euclidean distance between UAVs u_i and u_j is calculated as:

$$
d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2},
$$
 (11)

where (x_i, y_i, z_i) and (x_j, y_j, z_j) represent the coordinates of u_i and u_j , respectively. Further, the performance of the UAV network is significantly affected by the business load of UAVs, which is related to the quality of service for delays. In detail, the length of queued packets is:

$$
\mathcal{L} = \eta \times l_p,\tag{12}
$$

where η represents the number of queued packets, and l_p denotes the size of a packet.

2) Action space: In UAV networks, the possible action is related to the neighboring UAV. Moreover, the size of the action space is equal to the number of next UAVs. Mathematically, we represent the action space as $A = \{a_{u_i \to u_k}, i =$ $1, 2, \dots, \mathcal{N}, u_k \in \Gamma_i$, where $a_{u_i \to u_k}$ indicates the next hop UAV is u_k for UAV u_i .

3) Transition probability: The transition probability is represented by P_{sa} , indicating the probability from state $s \in S$ to the other state with action $a \in A(s)$. Since it is intractable to model accurately, we design a model-free method.

4) Reward function: To minimize the total end-to-end delay, we set r_{t+1} as the instantaneous reward of performing action a_t at current state s_t , i.e.,

$$
r_{t+1}(s_t, a_t) = (-100 \times T_{p_{i,j}}) \mathcal{H}_k, \tag{13}
$$

where $T_{p_{i,j}}$ is the delay of (5). \mathcal{H}_k is defined as the flag for the end of routing processes, i.e.,

$$
\mathcal{H}_k = \begin{cases} 0, & u_k = u_d, \\ 1, & u_k \neq u_d, \end{cases} \tag{14}
$$

where u_d is the destination UAV of routing path p_{sd} .

5) Discount factor: The discount factor is indicated as $\gamma \in$ $(0, 1)$, to calculate the cumulative reward. It denotes the impact of the future reward. A larger γ indicates the decision focuses on the long-term reward.

The policy π leads the agent to select an action $a \in A(s)$ under state s. According to the MDP model and a specific policy π , we can obtain a routing path. Hence, the objective function (7) is transformed to find the optimal policy π^* , which minimizes the total end-to-end delay. Since the MDP model is the abstract of the environment in RL, we design a RL-based intelligent approach to tackle the issue.

C. Intelligent Routing Algorithm

Temporal difference (TD) via combining Monte Carlo (MC) with dynamic programming, is a fundamental method applied in model-free RL with incomplete traces [18], [19]. In addition, it learns the action value functions of successor states to approximate the current state. Sarsa is an on-policy TD algorithm, i.e., it utilize the same policy for sampling and evaluating. In Sarsa, the optimal policy π^* is gained in the process of continuous interactions with the environment. The goal is to find π^* to maximize cumulative expected reward R, i.e.,

$$
\pi^* = \underset{\pi}{\text{arg max }} R. \tag{15}
$$

According to the policy optimization theorem, the optimal policy π^* is equal to the optimal action value function Q^* . Therefore, we can obtain π^* via finding Q^* . Further, if $Q^*(s, a)$ is known, the optimal policy $\pi^*(a|s)$ corresponds to perform action a under state s, i.e.,

$$
\pi^*(a|s) = \begin{cases} 1, & a = \text{arg max } Q^*(s, a), \\ 0, & \text{otherwise,} \end{cases} \tag{16}
$$

where $Q(s, a)$ is the value of selecting action a under given state s, represented by the expected future reward:

$$
Q(s, a) = E[r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) | s_t = s, a_t = a], \quad (17)
$$

where a_t and s_t represent the current action and state, while s_{t+1} and a_{t+1} are the next state and action, respectively.

In addition, in the learning progress, the following formula is represented to update $Q(s_t, a_t)$ at time step t, i.e.,

$$
Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \delta_t, \tag{18}
$$

where α represents the learning rate, and action value function error δ_t is denoted as:

$$
\delta_t = r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t), \tag{19}
$$

where $Q(s_{t+1}, a_{t+1})$ represents the action value function at time step $t + 1$. The term $r_{t+1} + \gamma Q(s_{t+1}, a_{t+1})$ is the action value function target.

However, the Sarsa method updates $Q(s_t, a_t)$ only according to the action value function of time step $t + 1$, while the MC method requires reaching the final state of an episode to update. By partly leveraging these two methods, we design the n -step Sarsa method, i.e., Sarsa(λ), where *n* is a hyperparameter.

There exist two methods, including the forward and backward Sarsa(λ). In particular, the forward method gives the weight $(1 - \lambda)\lambda^{n-1}$ for each step reward. It requires a lot of subsequent state values, and intractable to implement. In contrast, we adopt the backward method which introduces the eligibility trace to each state, to indicate the effect on subsequent states. In detail, it proportionally assigns δ_t to other action value functions as the update basis. In [19], the eligibility trace provides the short-term memory of traces. Moreover, the experienced state is no longer immediately deleted, and some information is preserved. The accumulating eligibility trace is updated according to the following rule:

$$
\begin{cases} E_0(s, a) = 0, \\ E_t(s, a) = \gamma \lambda E_{t-1}(s, a) + 1(s_t = s, a_t = a), \end{cases}
$$
(20)

where $\lambda \in (0, 1)$ represents the degradation parameter. $1(s_t =$ $s, a_t = a$) is a judgment expression, in which the value is 1 when $s_t = s$ and $a_t = a$, and otherwise the value is 0. Correspondingly, $Q(s_t, a_t)$ is updated as:

$$
Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \delta_t E_t(s, a). \tag{21}
$$

Moreover, to balance the exploration and exploitation in continuously interactive processes and avoid obtaining a suboptimal solution, the ϵ -greedy policy is generally designed to select actions, i.e.,

$$
a = \begin{cases} \text{random action, probability } \epsilon, \\ \text{action with } Q_{max}, \text{ probability } 1 - \epsilon, \end{cases} \tag{22}
$$

where ϵ represents the probability of exploring actions, and Q_{max} denotes the maximum Q value.

The proposed UAV attack-based Sarsa (λ) algorithm is detailed in Algorithm 1. Firstly, we assume that there exist N episodes. At the beginning of each episode, $Q(s, a)$ is set arbitrarily, and $E(s, a)$ is set as zero (line 1). Then, we determine whether UAV u_i is attacked based on the value of f_i . If u_i is damaged, the corresponding values in adjacency matrix $\mathcal E$ turn to zero (line 3-7). Furthermore, the state is initialized by source UAV u_s , and the action is set as the next hop of u_s (line 8). Then, the reward and next state are obtained after performing action a under current state s in the environment (line 10). In addition, the next action is refreshed according to the designed ϵ -greedy policy in (22) (line 11). δ , $E(s, a)$, and $Q(s, a)$ are updated according to (19)-(21), respectively. Furthermore, the new state and action are refreshed (line 18). Finally, this episode terminates when the next hop is destination UAV u_d .

Algorithm 1 UAV Attack-based Sarsa(λ) Algorithm

Input: N , α , γ , F , and \mathcal{E} . **Output:** Optimal policy π^* . 1: *Initialization:* set $Q(s, a)$ arbitrarily and $E(s, a) = 0$ for each $s \in S$ and $a \in A(s)$. 2: repeat 3: for each $f_i \in F$ do 4: if $f_i == 1$ then 5: The values of $e_{i,x}$ and $e_{x,i}$ $(x = 1, 2, \cdots, \mathcal{N})$ in adjacency matrix $\mathcal E$ are set as zero. 6: end if 7: end for 8: Initialize state s as source UAV u_s , and select action a according to the designed ϵ -greedy policy. 9: repeat 10: $r, s' \leftarrow$ state-action (s, a) . $11:$ $\prime \leftarrow \epsilon$ -greedy policy (Q, s') . 12: $\delta \leftarrow r + \gamma Q(s', a') - Q(s, a).$ 13: $E(s, a) \leftarrow E(s, a) + 1.$ 14: **for** all $s \in S$, $a \in A(s)$ **do** 15: $Q(s, a) \leftarrow Q(s, a) + \alpha \delta E(s, a).$ 16: $E(s, a) \leftarrow \gamma \lambda E(s, a).$ 17: end for 18: $s \leftarrow s'$, and $a \leftarrow a'$. 19: until s is the destination UAV. 20: until all episodes are executed.

IV. SIMULATION RESULTS

A. Experiment Setup

We employ MATLAB as the platform to train the proposed RL-based intelligent routing mechanism. In detail, the UAV network simulation area is set as $1 \text{km} \times 1 \text{km}$, and the height of UAVs changes from 130m to 140m. In addition, the maximum and minimum transmission ranges of each UAV are initialized as 500m and 30m, respectively. Moreover, the source and destination UAVs are randomly predetermined. Then, the length of queued packets is generated by following a uniform distribution. Other parameters are set as: $\gamma = 0.9$, $\alpha = 0.01$, $\lambda = 0.9, P_{i,j} = 40$ W, $\epsilon = 0.001, g = 2.4$ GHz, $B_{i,j} = 4$ Mhz, $\sigma_{i,j}^2 = 4$ e-13W, $\eta \in [1,5]$, and $l_p = 512$ Bytes [2], [10], [11]. To demonstrate the performance of Algorithm 1, two related methods are compared, i.e.,

1) Sarsa: Sarsa(λ) algorithm is an extension of the Sarsa method. In addition, $Sarsa(\lambda)$ introduces the eligibility trace, which increases the state and action weights of UAVs closest to the destination, speeding up the convergence of algorithm.

2) *Q-learning:* Different from Sarsa and Sarsa(λ), *Q*learning is an off-policy algorithm. It leverages ϵ -greedy methods to select $Q(s_t, a_t)$ and employs a maximum value algorithm to update $Q(s_{t+1}, a_{t+1})$.

B. Simulation Results

To evaluate the performance of the proposed method, simulation results are compared in Fig. 2-4. In Fig. 2, the convergence

Fig. 2. (a) Reward *v.s.* Episode. (b) Step *v.s.* Episode.

of $Sarsa(\lambda)$ is depicted by the value of the reward in (a) and the curve fluctuation of step counts in (b) with increasing episodes ($\mathcal{N} = 20$). In detail, as shown in Fig. 2(a), it is obvious that the reward eventually converges to the maximum value, i.e., the minimum delay. Moreover, when the UAV network is attacked, the reward decreases, but $Sarsa(\lambda)$ still obtains the higher reward than the other two methods. In other words, $Sarsa(\lambda)$ leverages fewer episodes to find the optimal routing path. In addition, the reward is negative due to designed (13). Meanwhile, from Fig. 2(b), it is observed that Sarsa(λ) has a much smaller range of curve fluctuations in step counts, since the eligibility trace is introduced. Hence, the faster convergences of the reward and step counts reveal the superiority and effectiveness of Algorithm 1. In addition, from Fig. 3, the delay of routing has an exponential growth as the number of UAVs increases. Specifically, $Sarsa(\lambda)$ costs less time in both original and recovery routing paths, due to the better performance of its convergence compared with the other two methods. Similarly, in Fig. 4, the numbers of

Fig. 3. Delay *v.s.* Node number.

Fig. 4. (a) Step *v.s.* Hop count. (b) Distance *v.s.* Hop count.

average steps and distances in different hops are shown, where $Sarsa(\lambda)$ needs fewer average steps and distances for routing. In short, simulation results illustrate that the proposed algorithm recovers the routing path with shorter delays.

V. CONCLUSIONS

In this paper, we study the issue of routing in the UAV network with deliberate attacks. The optimization objective is to minimize the total end-to-end delay between source and destination UAVs by selecting the optimal routing path. Then, we represent attacks on UAVs via the deliberate attack model based on NIRM. Further, the problem is reformulated into an MDP form, and we design the RL-based intelligent algorithm. Simulations are conducted and results verify that the proposed algorithm can recover the routing path in less time.

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