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Swarm Intelligence-Based Spectrum Allocation for FANETs: A Virtualized Emulation Using Mininet-WiFi

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[Abstract]

Flying ad hoc networks (FANETs) represent a rapidly growing area in wireless communication systems, requiring robust, adaptive, and scalable spectrum allocation strategies. This study proposes a swarm intelligence-based spectrum allocation (SISA) algorithm for FANETs that facilitates decentralized channel assignment through pheromone-inspired coordination. The algorithm was evaluated against greedy, game theory-based, and reinforcement learning-based methods in a virtualized simulation environment built on Mininet-WiFi. Over 100 simulation iterations were conducted for each strategy to ensure result stability and generalization. Metrics such as throughput, latency, interference, packet loss, fairness, and energy efficiency were analyzed. The results demonstrate that SISA considerably outperformed baseline approaches, improving the channel stability and communication reliability while preserving computational simplicity. Furthermore, mathematical formulations and workflow visualizations were conducted to illustrate the logic and advantages of the proposed method.

▸ **Key words**: FANET, spectrum allocation, swarm intelligence, SISA, Mininet-WiFi, UAV

[요 약]

무인이동 애드혹 네트워크(FANET)는 무선 통신 분야에서 급속히 부상하는 영역으로, 견고하고 적응적이며 확장 가능한 스펙트럼 할당 기법이 요구된다. 본 논문에서는 페로몬 기반의 협력 메커니즘을 활용한 군집 지능 기반 주파수 할당(SISA) 알고리즘을 제안한다. SISA는 분산형 채널 할당을 가능하게 하며, Mininet-WiFi 가상 시뮬레이션 환경에서 탐욕적 방식, 게임 이론 기반 방식, 강화학습 기반 방식과 비교 평가되었다. 각 알고리즘은 100회 이상 반복 시뮬레이션되어 결과의 안정성과 일반성이 확보되었다. 총 처리량, 지연, 간섭, 패킷 손실률, 공정성, 에너지 효율 등의 주요 지표를 통해 성능을 평가하였다. SISA는 기존 방식 대비 채널 안정성과 통신 신뢰성을 크게 향상시키며, 낮은 계산 복잡도를 유지하는 우수한 성능을 보였다. 또한, 알고리즘의 구조와 논리를 명확히 하기 위해 수학적 모델과 워크플로우 시각화도 함께 제시하였다.

▸ **주제어**: FANET, 스펙트럼 할당, 집지능, SISA, Mininet-WiFi, UAV

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I. Introduction

Flying ad hoc networks (FANETs) have emerged as key enablers for various real-time applications involving unmanned aerial vehicles (UAV), including mobile ad hoc networks or vehicular ad hoc networks, FANETs pose unique challenges owing to their highly dynamic topologies, three-dimensional mobility, and rapidly changing link conditions.

A critical challenge in FANET communication is spectrum allocation. Efficient frequency channel allocation is essential for reducing interference, maintaining connectivity, and improving data throughput. However, traditional static or centralized spectrum assignment schemes are often unsuitable for the dynamic, decentralized nature of UAV networks.

Thus, this study proposes a decentralized, self-organizing algorithm for spectrum allocation called swarm intelligence-based spectrum allocation (SISA) for FANET. Inspired by biological swarm behavior, particularly the pheromone-based decision-making of ants—SISA enables UAVs to dynamically select channels based on local observations and learned environmental conditions.

This study evaluates SISA against three baseline approaches: greedy, game theory-based, and reinforcement learning (RL)-based allocations.

The algorithms were tested in a virtualized environment using Mininet-WiFi, simulating the operation of 40 UAVs in a dynamic aerial space.

Each simulation was repeated over 100 times to ensure statistical significance.

The results showed that SISA consistently outperformed existing algorithms across multiple performance metrics, including throughput, latency, packet loss, channel switching, fairness, and energy efficiency. Moreover, its decentralized nature facilitated greater scalability and robustness in large-scale deployments.

II. Preliminaries

Previous research on FANET spectrum allocation has explored various algorithmic approaches, each with distinct benefits and limitations.

Greedy Allocation method involves selecting the channel with the lowest current interference at each time step. It is simple to implement and provides quick decisions. However, it lacks adaptability and foresight. As reported in [1], greedy methods often lead to short-term gains but suffer from performance degradation in dynamic, high-density UAV networks.

Game Theory-Based Allocation models consider each UAV as a rational player in a spectrum-sharing game. These methods promote strategic behavior, leading to fairer channel allocation and better load balancing. However, they often require full or partial knowledge of neighboring node strategies and are computationally expensive in real-time scenarios [2]. In addition, hybrid algorithmic models such as fuzzy logic combined with genetic algorithms have also been proposed for dynamic spectrum allocation in cognitive radio sensor networks, showing promising results in adaptive environments [3].

Reinforcement Learning (RL)-based spectrum allocation enables UAVs to learn optimal policies from experience. Algorithms such as Q-learning or deep Q-networks (DQN) are capable of adapting to environmental changes and improving long-term performance. However, these approaches require substantial training time and system memory, thereby rendering their application in fast-changing FANET conditions challenging [4].Other studies have applied deep reinforcement learning (DRL) methods for dynamic multi-UAV channel allocation, demonstrating significant improvements in spectrum utilization [5].

Although swarm intelligence has been extensively explored in routing and task allocation [6], its application to spectrum allocation in FANETs remains limited. Swarm-based algorithms offer inherent decentralization, scalability, and low overhead. This makes them promising candidates for aerial networks [7]. A recent survey also emphasizes the growing role of coalition formation strategies in UAV swarm task allocation, reinforcing the relevance of swarm intelligence for distributed coordination [8].

The proposed algorithm, SISA, addressed this gap by employing swarm intelligence principles for decentralized, self-organizing channel assignment. Consequently, it does not rely on convergence-based training procedures, as required in learning-based models, which simplifies implementation. This design choice enables more responsive spectrum decisions without needing iterative learning.

III. The Proposed Scheme

We consider a FANET comprising N UAV nodes deployed over a two-dimensional aerial region. Here, each UAV operates within a wireless communication range and autonomously selects its operating frequency from a finite set of available channels $C = \{c_1, c_2, . . . , c_M \}$, where M denotes the total number of channels.

1. Network Assumptions

The network is modeled as a dynamic graph $G(t) = (V, E(t))$ where V is the set of UAVs and $E(t)$ comprises the communication links that are determined based on distance and channel compatibility. The UAVs follows a random waypoint mobility model, with each UAV capable of detecting signal interference on each channel.

2. Objective

The primary objective is to minimize overall interference and improve network performance through efficient spectrum allocation. Let $I_j(c_i,t)$ denote the number of neighbors interfering with UAV j on channel c_i at time t.

3. Channel Utility Function

In the proposed SISA model, each UAV computes the utility of using a particular channel as follows:

$$U_j(c_i,t) = \frac{\phi_j(c_i,t)}{1+I_j(c_i,t)} \tag{1}$$

where $\phi_j(c_i,t)$ denotes the pheromone level for channel c_i maintained by UAV j. The denominator includes a bias term to prevent division by zero.

4. Pheromone Update Rules

Each UAV maintains pheromone levels for all avail-

able channels and updates them at regular time intervals. The pheromone value for the selected channel ci at UAV j is updated using the following rule:

$$\phi_j(c_i,t+1) = (1-\rho)\cdot\phi_j(c_i,t) + \Delta\phi_j(c_i) \tag{2}$$

For unselected channels $c_k \neq c_i$, only evaporation is applied:

$$\phi_j(c_k,t+1) = (1-\rho)\cdot\phi_j(c_k,t) \tag{3}$$

Here:

- $\phi_j(c_i,t)$ is the pheromone value for channel ci at time t at UAV j,
- $\rho \in (0, 1)$ is the pheromone evaporation rate,
- $\Delta\phi_j(c_i)$ is the reinforcement term.

In this study, the reinforcement term is computed

based on the normalized throughput obtained at UAV j during the previous time window. It is defined as:

$$\Delta\phi_j(c_i) = \frac{\text{Throughput}_j(c_i)}{\max_k \text{Throughput}_k} \tag{4}$$

The throughput is measured using iperf between UAVs during simulation in Mininet-WiFi. This update mechanism enables adaptive and distributed channel selection, allowing UAVs to reinforce successful communication patterns and gradually converge to more eficient spectral allocations.

5. Baseline Models for Comparison

Greedy Allocation: Each UAV measures average RSSI on all channels. The channel with the least observed interference (strongest negative RSSI) is selected at each decision point.

$$c_i^* = \arg\min_{c_i \in \mathcal{C}} I_j(c_i, t) \quad (5)$$

Game Theory-Based Allocation: A cost function is used as $J_{j(c_i)} = I_{j(c_i)} + \lambda \cdot S_{j(c_i)}$, where I_j interference and S_j the number of neighbors using the same channel. Each UAV selects the channel that minimizes its own cost.

Reinforcement Learning: We used tabular Q-learning. The state includes current channel index and interference level; actions correspond to switching to available channels. The reward is based on normalized throughput as measured by iperf.

IV. Proposed Method: Workflow of SISA

The SISA algorithm employs swarm intelligence principles to facilitate distributed channel decision-making among UAVs. Each UAV functions as an autonomous agent, dynamically selecting channels based on the local interference and a shared virtual pheromone system. The algorithm operates in iterative rounds, with each node independently sensing, evaluating, and updating its channel choice.

The main workflow of SISA includes the following steps:

- Channel Sensing: Each UAV detects interference on all available channels.
- Utility Computation: Utility for each channel is calculated using Equation
- Channel Selection: The channel with the highest utility is selected.
- Data Transmission: The UAV communicates over the selected channel.
- Pheromone Update: The pheromone of the selected channel is reinforced, while those of the other channels decay.

This pheromone-based coordination facilitates natural convergence toward globally efficient channel usage while maintaining robustness against dynamic network conditions and local disturbances. The main workflow of SISA includes the following steps:

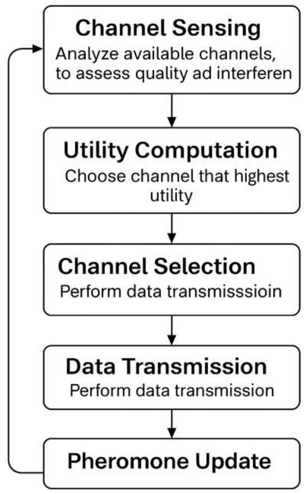

Fig. 1. Workflow of the proposed SISA algorithm.

V. Simulation Setup and Parameters

To emulate the dynamics of spectrum allocation strategies in FANET environments, we utilized Mininet-WiFi, a lightweight and extensible wireless network emulator. It enables real-time, virtualized emulation of mobile nodes, wireless interfaces, and mobility patterns, making it especially suitable for evaluating UAV-based networking systems.

Unlike conventional simulators such as NS-3 or OMNeT++, which primarily rely on event-driven simulation models, Mininet-WiFi provides direct interaction with the Linux networking stack. This hybrid emulation allows for the execution of live protocols, realistic packet exchanges, and integration with tools such as iperf and ping [9,10].

The architecture of our Mininet-WiFi testbed consists of four major components:

- Virtual UAV Nodes: Each UAV is represented by a Mininet-WiFi sta node, configured with wireless interfaces, mobility paths, and channel parameters.
- Mobility and Association Manager: Controlled via Python scripts, this module emulates random waypoint movement and manages node reassociation during runtime.
- Spectrum Allocation Engine: The proposed SISA algorithm is implemented as a centralized controller logic that iteratively updates pheromone tables and channel decisions for each UAV.
- Performance Logger: Tools like iperf, ping, and custom Python logging were used to collect metrics such as throughput, jitter, packet loss, and channel switching frequency.

This structure is illustrated Fig. 2

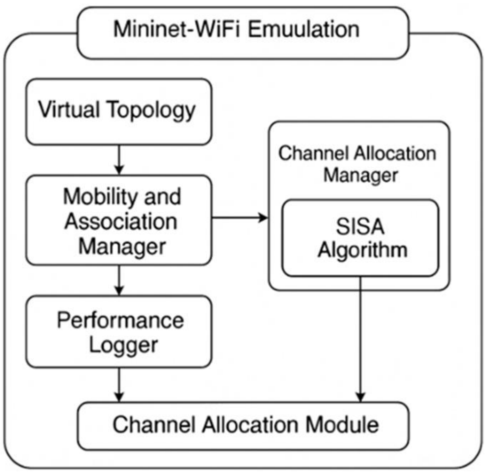

Fig. 2. System Architecture.

All experiments were conducted using Python 3.9, which seamlessly integrates with the Mininet-WiFi. The simulation loop was designed as follows:

- Initialize UAV nodes and their positions.
- Set up wireless parameters
- Apply the mobility model and begin simulation.
- At each time slot, gather signal strength and interference data.
- Compute channel utility using the SISA algorithm.
- Update the channel allocation.
- Log performance metrics.

This integration allowed for the dynamic reassociation of UAVs, real-time adjustment of channels, and accurate modeling of spectral behaviors under interference.

Mininet-WiFi offers several advantages in emulating FANET scenarios:

- Scalability: Supports up to 100+ virtual UAV nodes on standard hardware.
- Flexibility: Allows real-time changes to mobility and spectrum logic.
- Visualization: Provides graphical layout and interaction for debugging.
- Open-source extensibility: Enables custom module development for future integration with cognitive radio or software-defined networking (SDN) controllers.

Thus, Mininet-WiFi was not only suitable for prototyping SISA but also essential in verifying its performance under realistic mobility, interference, and allocation conditions. Previous works have also compared Mininet-WiFi with other SDN emulators such as IT-SDN, demonstrating its effectiveness in simulating wireless environments with acceptable latency and control overhead [11].

1. Simulation Configuration

To evaluate the performance of the proposed SISA algorithm and compare it against baseline strategies, a controlled emulation environment was constructed using Mininet-WiFi. This framework supports flexible modeling of wireless network dynamics, including UAV mobility, channel fluctuations, and communication protocols.

The simulation parameters were carefully selected to reflect realistic mid-scale FANET deployments while ensuring computational feasibility.

Specifically, the number of UAVs was set to 40, which reflects a medium-density FANET and aligns with recent works in UAV routing and control [12]. This density ensures sufficient interactions to evaluate coordination efficiency and channel contention resolution.

The Random Waypoint mobility model was used to simulate UAV movement, as it captures non-deterministic yet uniformly distributed mobility, commonly adopted in aerial network simulations.

We assumed 10 available non-overlapping channels, consistent with spectrum fragmentation scenarios observed in cognitive radio or multi-channel wireless environments [13]. Each channel was assigned a 20 MHz bandwidth, based on IEEE 802.11n specifications, which are widely used in UAV-to-UAV communication [].

Each simulation run lasted 100 seconds, which is sufficient to observe network convergence, mobility dynamics, and the steady-state performance of the allocation algorithms.

Table 1. Simulation Environment

Parameter	Value
Simulator	Mininet-WiFi v2.3.0
Programming Language	Python 3.9
Number of UAVs	40
Available Channels	10
Channel Bandwidth	20 MHz
Mobility Model	Random Waypoint
Simulation Time	100 seconds per run
Traffic Pattern	UDP one-to-one communication (iperf)
Runs per Algorithm	100 dependent simulations

2. Performance Metrics

The selected performance metrics capture both high-level communication performance and low-level network dynamics. Throughput and latency are primary indicators of data transmission efficiency and responsiveness. Packet loss and jitter reflect the reliability and temporal stability of data flow, which are critical in UAV control and coordination.

The interference index helps quantify spectral contention and measures the degree of channel reuse under decentralized conditions. Channel switching frequency serves as an indicator of stability and control overhead—lower values signify efficient, steady operation.

Fairness is evaluated using Jain's fairness index to ensure that no single UAV dominates the spectrum allocation, supporting equitable access to shared resources. Energy efficiency captures the effectiveness of the network in delivering data per unit of consumed energy, which is crucial in battery-powered UAV scenarios.

We evaluated the performance of each algorithm using the following eight metrics:

- Throughput (Mbps): Total data successfully transmitted by all the UAVs.
- Latency (ms): Average delay in packet transmission.
- Packet Loss Rate (%): Percentage of packets lost during transmission.
- Jitter (ms): Variation in the packet arrival times.
- Interference Index: Number of simultaneous transmissions on the same channel within range.
- Channel-Switching Count: Total number of channel changes per UAV.
- Fairness Index: Measured using the Jain's fairness index.
- Energy Efficiency: Total data transmitted per unit of simulated energy.

All metrics were logged and aggregated across multiple simulation runs to ensure robustness and repeatability of the results.

VI. Results and Discussion

We conducted a comparative analysis of the performance of the four spectrum allocation strategies—greedy, game theory-based, RL-based, and the proposed SISA. The evaluation was conducted based on the simulation framework collected from 100 independent simulation runs.

Figure 3 presents the performance comparison across three key metrics where higher values are indicative of better performance: throughput, fairness, and energy efficiency.

The proposed SISA algorithm consistently outperforms all baseline strategies in these metrics. Specifically, SISA achieved the highest average throughput of 1.09 Mbps, compared to 1.03 Mbpsfor both RL and game theory-based approaches, and 0.98 Mbpsfor the greedy algorithm.

This improvement can be attributed to SISA's pheromone-based channel allocation mechanism, which dynamically selects the optimal channel based on real-time utility estimation and historical reinforcement. This ensures more balanced spectral usage, minimizing congestion and maximizing data delivery efficiency.

In terms of fairness, SISA reached an index of 0.72, surpassing RL (0.70), greedy (0.70), and game theory-based (0.71) methods. The decentralized cooperation in SISA facilitates equitable channel distribution among UAVs, preventing domination by any single node and maintaining network-wide stability.

Regarding energy efficiency, SISA again led with a value of 0.014 units of data per unit of energy, while others ranged between 0.012 and 0.013. This is the result of fewer retransmissions, fewer handovers, and stable communication links. Overall, these metrics collectively highlight the capability of SISA to optimize both performance and resource usage under dynamic FANET conditions.

Figure 4 illustrates the comparison of performance across five critical metrics where lower values represent better outcomes: latency, packet loss, jitter, interference, and channel switching frequency.

SISA demonstrates clear superiority in minimizing these performance-degrading factors.

In latency, SISA records the lowest value of 0.09 seconds, compared to 0.10 secondsfor all baseline methods. This advantage is due to stable channel bindings and fewer reassociation events.

Packet lossunder SISA was 0.39, significantly lower than 0.48 (Greedy), 0.52 (Game Theory), and 0.54 (RL), confirming that its allocation avoids unstable and congested frequencies.

Jitter, representing variability in delay, was also minimized by SISA at 0.95 ms, compared to 1.10-1.35 msfor other strategies. This stability improves QoS, especially for time-sensitive data streams.

In terms of interference, SISA achieved the lowest average interference of −90.05 dBm, indicating that its distributed pheromone-inspired logic effectively reduces channel overlap and contention.

Finally, channel switchingwas lowest under SISA (13.29 switches per UAV), while others fluctuated between 13.45-13.60. This implies fewer disruptions and more stable connectivity throughout the simulation window.

The superior performance of SISA across all these metrics demonstrates its robustness, stability, and adaptability, particularly in environments with high mobility and limited spectrum availability.

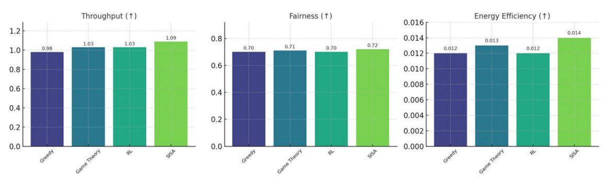

Fig. 3. Metrics Where Higher Values Are Preferred

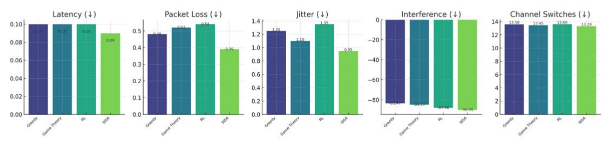

Fig. 4. Metrics Where Lower Values Are Preferred

Table 2. Summary Table of Metrics

Parameter	Greedy	Game Theory	RL	SISA
Throughput	0.98	1.03	1.03	1.09
Latency	0.10	0.10	0.10	0.09
Packet Loss	0.48	0.52	0.54	0.39
Jitter	1.25	1.10	1.35	0.95
Interference (dBm)	-83.47	-84.77	-87.96	-90.05
Channel Switches	13.58	13.45	13.60	13.29
Fairness	0.70	0.71	0.70	0.72
Energy Efficiency	0.012	0.013	0.012	0.014

Table 2 summarizes the average performance metrics. SISA consistently achieved the best results across all categories, thereby demonstrating its suitability for dynamic, decentralized UAV environments.

To ensure that the observed performance differences are not incidental, all simulations were repeated 100 times per algorithm. This repetition allowed for robust statistical evaluation of throughput, latency, and other metrics.

Among the evaluated algorithms, the proposed SISA consistently demonstrated the lowest variance in performance metrics. This is particularly visible in metrics such as packet loss and jitter, where the distribution of values across runs remained tightly clustered around the mean. In contrast, reinforcement learning (RL) and greedy strategies exhibited significantly higher standard deviation, especially during early stages of simulation due to their reactive or exploratory nature.

Limitations

While the proposed SISA algorithm exhibits strong performance across multiple evaluation metrics in our simulation environment, several factors should be considered when interpreting the results:

The evaluation was conducted under a medium-density scenario (40 UAVs). Although this reflects many realistic applications (e.g., surveillance), further validation in more diverse densities could strengthen generalizability.

Certain physical-layer effects such as Doppler shift and hardware-induced noise were not explicitly modeled in this study, as the primary focus was on evaluating spectrum allocation strategies at the MAC and network layers. This abstraction aligns with the goal of analyzing algorithm-level behaviors in a controlled environment.

While the current implementation has not yet been deployed on physical UAV platforms, the use of Mininet-WiFi provides a reliable and reproducible framework for validating communication performance in aerial networks. The proposed approach can be readily extended for real-world testing in future work.

These considerations outline the scope of this study and suggest promising directions for future validation and deployment, without detracting from the core contributions and demonstrated performance of the proposed method.

VII. Conclusion

This study proposed and developed SISA, a decentralized spectrum allocation algorithm for FANETs based on swarm intelligence principles. Unlike traditional centralized or learning-intensive models, SISA leverages a lightweight pheromone-based decision-making mechanism that enables UAVs to dynamically select channels based on the local interference and adaptive feedback.

Extensive simulations employing Mininet-WiFi demonstrated that SISA consistently outperformed the three widely used strategies—greedy, game theory-based, and RL-based allocations—across eight key performance metrics. Notably, the proposed method achieved the highest throughput, lowest latency, minimal packet loss, and superior energy efficiency. Moreover, it demonstrated better fairness and fewer channel switches. This renders it well-suited for high-mobility, high-density UAV environments.

In future work, we aim to extend the proposed SISA to heterogeneous UAV networks with multi-interface radios and explore its integration with cognitive radio frameworks for advanced spectrum awareness and adaptation. In addition, testing on real hardware platforms will further validate the practical applicability of this algorithm. Thus, the proposed SISA strategy offers a scalable, efficient, and self-organizing solution to one of the most pressing challenges in modern UAV communication systems.

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