

Fwsc-Fanet: Fig Tree–Wasp Symbiotic Coevolutionary Optimization For Joint Uav Positioning, Power Control, And Routing In Flying Ad Hoc Networks

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Abstract

Flying Ad Hoc Networks (FANETs) are critical for 6G-enabled applications, but existing frameworks often improve the positioning of UAVs, power control, or routing self-reliantly, which leads to a suboptimal performance. This paper presents FWSC-FANET, a Fig Tree–Wasp Symbiotic Coevolutionary Optimization framework, which equally optimizes adaptive power allocation, positioning of UAVs, and energy-aware routing. The mutualistic coevolution between “wasp” and “fig” agents confirms a balanced exploitation and exploration, enabling robust network operation under dynamic 3D mobility and changing channel conditions. Simulation studies, performed with varying UAV pause times, determine that FWSC-FANET outperforms state-of-the-art approaches, EAR-FANET [16] and DRL-FANET [17], reaching developments in network lifetime (296.4 minutes), packet delivery ratio (95.5%), throughput (17.5 Mbps), energy consumption (132.4 J), semantic accuracy (91.7%), and global fitness (0.862). These results confirm the effectiveness of FWSC-FANET for energy-efficient, resilient, and high-performance UAV networks.

Keywords - Flying Ad Hoc Networks (FANETs), UAV Positioning, Power Control, Routing, Symbiotic Coevolution, Fig Tree–Wasp Optimization, 6G Networks, Energy-Aware Routing, Global Fitness, Semantic Communication, Energy Efficiency, Resilient Networks, Intelligent Infrastructure, Innovation for Sustainability, Green Communication Systems.

1. Introduction

Flying Ad Hoc Networks (FANETs) allow critical UAV applications such as disaster monitoring and 6G IoT services [1]–[3]. Their 3D mobility and dynamic topology pose tests for energy efficiency, robust routing, and maintaining connectivity, particularly under fluctuating SNR and limited bandwidth [4], [5]. Bio-inspired algorithms like PSO, ACO, and firefly-based methods [6], [11], [12] optimize routing, positioning, or power control individually but often ignore UAV interdependence, leading to suboptimal performance. Learning-based frameworks [4] enhance adaptability but incur high computational overhead and slower convergence in large-scale 3D environments. Few studies have discovered mutualistic coevolution among heterogeneous UAV agents, despite their potential to improve efficiency and resilience. To bridge these gaps, this work presents the Fig Tree–Wasp Symbiotic Coevolutionary (FWSC) framework, which models UAVs as cooperative “wasp” and “fig” agents for joint 3D power allocation, positioning, and routing. The approach leverages parameter-driven environmental inputs and adaptive fitness evaluation to attain greater global performance, stable topology, and energy-aware routing. Simulations show enhanced energy efficiency, reliability, and convergence, compared to conventional bio-inspired and learning-based methods under changing channel conditions and node densities. The following section focuses on Related Works, which highlights the existing optimization strategies for UAV networks and positioning FWSC-FANET within the existing research landscape.

2. Related Works

A. UAV Positioning and Power Control Mechanisms

Power control and effective UAV positioning are essential for consistent FANET operations. M. Oubbati et al. [1] and Y. S. Kavitha et al. [2] presented energy-efficient mobility and clustering but depended on static parameters, limiting adaptability. M. Hosseinzadeh et al. [3] presented an energy-aware virtual relay method that minimized retransmissions yet resisted in large topologies. N. Lin et al. [4] applied deep reinforcement learning for joint offloading and routing, offering flexibility but at high computational cost. These studies highlight the need for self-adaptive optimization frameworks that balance the efficiency of power with connectivity stability under dynamic mobility. Additionally, the authors Z. A. Atallah et al. [19] freshly brought in an intelligent access and control system (JomNFC) that makes use of zero-effort learning and adaptive resource allocation principles. This mechanism works parallelly with the requirement for autonomous power control in UAV networks. Similarly, the authors Al-Qaraghuli et al. [35] came up with quantum-enabled, energy-efficient protocols for smart grid communication systems, establishing a foundation for sustainable energy management that is directly translatable to UAV-assisted FANET infrastructures.

B. Routing Optimization in Flying Ad Hoc Networks

Routing in FANETs still remains difficult due to limited energy and frequent topology shifts. Foundational routing models were classified by O. K. Sahingoz [5]. Path stability using ant colony optimization was improved by X. Wei and H. Yang [6], while D. Singh et al. [7] and H. Heidari et al. [8] enhanced the packet delivery and robustness through neural learning and hybrid optimization. A. S. Raja et al. [9] used Q-learning for adaptive routing, yet faced slow convergence. M. Abdel-Salam et al. [10] further improved optimization reliability using a Genghis Khan metaheuristic. Jointly, these works highlight the shift toward hybrid and learning-based routing to improve delay, resilience, and throughput. Recent work by the authors N. A. K. Zghair et al. [24] found an innovative GAN-augmented adversarial training. This method remarkably made better routing robustness under complex jamming environments. This is done by reinforcing the inevitability for protected and adaptive learning strategies in aerial routing. Correspondingly, the authors V. Padmavathi et al. [23] made an adaptive AI-enhanced signal processing framework that are more possibly suitable for optimized underwater communication that provides algorithmic parallels which will perform cross-domain routing resilience in FANETs.

C. Coevolutionary and Bio-Inspired Optimization Strategies

Bio-inspired algorithms handle multi-objective optimization in UAV networks efficiently. W. Alnumay et al. [11] and S. Ahmed et al. [12] used whale and particle swarm optimisers to enhance clustering and power allocation but suffered local optima issues. H. Li et al. [13] and L. Abualigah et al. [14] presented quantum and coevolutionary models improving convergence speed. F. Kiani et al. [15] validated multi-swarm coevolution for UAV formations. M. Abdel-Salam et al. [10] and R. Abu Zitar et al. [16] displayed adaptive coevolution's productivity in large search spaces. These results expose coevolutionary mechanisms' potential to balance exploitation and exploration, which are the basis for the proposed Fig Tree-Wasp Symbiotic Coevolutionary (FWSC) model. Apart from conventional methods, the authors A. I. Lawah et al. [21] implemented Grey Wolf Optimization jointly with chaotic mapping for cryptographic substitution box design, displaying hybridization potential for high-dimensional optimization tasks. Additionally, the authors O. D. Okey et al. [20] developed a quantum-driven key-distribution selector by making use of machine learning to equilibrium optimization accuracy and security—principles that complement the cooperative intelligence in FWSC. The authors S. A. Ahmed et al. [22] even more focused UAV semantic segmentation advancements, representing that biologically inspired frameworks are possibly good enough to perception-driven network control.

In recent research works conducted, Quantum-enabled optimization are applied to intelligent communication networks. This combination of quantum intelligence and coevolutionary dynamics makes higher convergence and secure task coordination. The authors O. D. Okey et al. [20] performed validation by amalgamating quantum key-distribution learning in next-generation networks, whereas S. Al-Qaraghuli et al. [25] made use of energy-aware quantum protocols that serves the fuel for green and secure communication. It is evident that, all the above mentioned advancements align with the proposed FWSC-FANET framework's vision of symbiotic adaptation under dynamic and low-SNR conditions.

D. Research Gap and Motivation

Present FANET approaches often address positioning, routing, and power control separately [4]–[9], yielding limited global optimization. Bio-inspired methods [6], [11], [12] reach fast convergence but lack real-time flexibility, while learning-based techniques [4] incur substantial computational cost. Most frameworks overlook mutualistic coevolution among UAV agents, focusing instead on independent or competitive learning, which restricts stability in dynamic 3D networks. FWSC-FANET proposed framework addresses these gaps by modeling symbiotic adaptation between “wasp” and “fig” agents for joint

optimization of topology, energy, and routing, confirming resilient performance under varying mobility and SNR conditions.

The following part of the paper is proposed work, which introduces a Fig Tree–Wasp Symbiotic Coevolutionary Optimization mechanism that unifies UAV transmit-power adaptation, positioning, and route selection into a coadaptive process to bridge these gaps. By leveraging mutualistic evolution between two populations (wasps and figs), FWSC-FANET ensures improved network lifetime, faster convergence, and robust performance in low-SNR and high-mobility environments, establishing a new benchmark for integrated UAV communication optimization.

3. Proposed Work

A. System Model and FANET Representation

The proposed Fig Tree–Wasp Symbiotic Coevolutionary Optimization (FWSC) framework is developed to enhance aerial network reliability and spectral efficiency through adaptive UAV positioning, dynamic power control, and resilient routing. The FANET is treated as a multi-layer self-organizing airborne mesh, where aerial nodes interact through both air-to-air (A2A) and air-to-ground (A2G) links under limited power and mobility constraints. Each UAV periodically adjusts its altitude, heading, and transmission power to preserve end-to-end connectivity while minimizing interference and energy consumption.

Let the FANET be modeled as a directed time-varying graph

$$G(t) = \{U(t), L(t)\} \quad \dots(1)$$

where $U(t) = \{u_1, u_2, \dots, u_N\}$ represents NUAVs and $L(t)$ denotes the set of communication links that dynamically change with mobility and channel quality. Each UAV's kinematic behavior is governed by the three-dimensional mobility equation

$$PV_a(t + \Delta t) = PV_a(t) + V_a(t)\Delta t + \frac{1}{2}Acl_a(t)(\Delta t)^2 \quad \dots(2)$$

where $PV_a(t) = [p_a(t), q_a(t), r_a(t)]$ is the position vector, $V_a(t)$ the velocity, $Acl_a(t)$ the acceleration, and Δt the control interval.

This model permits cooperative aerial mobility influenced by neighboring UAVs and mission constraints. A communication link exists only if the Euclidean distance satisfies

$$d_{ab}(t) = \|PV_a(t) - PV_b(t)\| \leq C_r \quad \dots(3)$$

where C_r is the maximum sustainable communication radius determined by propagation and antenna parameters. For a valid A2A link, the received signal strength at node b from node a is

$$TP_{r,ab}(t) = P_{t,a}(t)G_tG_r \left(\frac{\lambda}{4\pi d_{ab}(t)} \right)^2 \quad \dots(4)$$

where $TP_{t,a}(t)$ is the instantaneous transmit power of UAV a, G_t, G_r are antenna gains, and λ is the carrier wavelength. The resulting link quality in terms of Signal-to-Noise Ratio (SNR) is expressed as

$$SNR_{ab}(t) = \frac{TP_{r,ab}(t)}{NS_0BW} \quad \dots(5)$$

where NS_0 is the noise spectral density and BW is the assigned bandwidth. This dynamic formulation establishes how mobility and transmit power jointly influence connectivity and link robustness—providing the fundamental substrate upon which the proposed FWSC algorithm operates.

B. Coevolutionary Encoding of UAV Positioning and Power Control

In the natural fig–wasp relationship, each wasp colony fertilizes a specific fig species, ensuring both reproduction and resource sharing. Translating this biological synergy into computational logic, FWSC-FANET constructs two co-dependent populations:

1. Fig Population ($\mathcal{F}$) $\rightarrow$ Candidate UAV position sets.
2. Wasp Population ($\mathcal{W}$) $\rightarrow$ Associated transmit-power configurations.

Each pair (f_c, w_c) symbolizes a potential network state balancing spatial distribution and link energy optimization.

Position–Power Encoding Vector

$$X_c = [i_{1c}, j_{1c}, k_{1c}, \dots, i_{Nc}, j_{Nc}, k_{Nc}, TP_{1c}, TP_{2c}, \dots, TP_{Nc}] \quad \dots(6)$$

where i_{ac}, j_{ac}, k_{ac} denote the 3-D coordinates of UAV a in candidate c, and TP_{ac} its transmit power. This unified chromosome allows simultaneous evolution of geometry and energy distribution.

Fitness Evaluation for Figs (UAV Placement)

$$F_{fig}^{(c)} = \alpha_1 \left(\frac{1}{\bar{ad}_c} \right) + \alpha_2 \left(\frac{CD_c}{CD_{max}} \right) + \alpha_3 \left(\frac{AR_c}{R_{max}} \right) \quad \dots(7)$$

where $\bar{ad}_c$ is the average inter-UAV distance (measures spatial spread), CD_c is the connectivity degree of topology c, AR_c is the aggregate achievable rate, and $\alpha_1, \alpha_2, \alpha_3$ are weighting factors satisfying $\sum \alpha_a = 1$. Higher fitness implies a more stable, well-distributed formation with efficient communication reach.

Fitness Evaluation for Wasps (Power Control)

$$F_{wasp}^{(c)} = \beta_1 \left(\frac{1}{E_c} \right) + \beta_2 \left(\frac{SNR_c}{SNR_{ref}} \right) + \beta_3 \left(\frac{Link_{survive,c}}{TL_c} \right) \quad \dots(8)$$

where $E_c = \sum_a TP_{ac}$ is total power consumption, SNR_c is mean network SNR, SNR_{ref} is required threshold, $Link_{survive,c}$ is number of stable links above SNR threshold, and TL_c total links. Coefficients $\beta_1, \beta_2, \beta_3$ maintain energy-quality equilibrium.

Symbiotic Coevolution Rule

$$X_c^{(t+1)} = X_c^{(t)} + \eta_1 (Fig_{best}^{(t)} - X_c^{(t)}) + \eta_2 (Wasp_{best}^{(t)} - X_c^{(t)}) + \xi \quad \dots(9)$$

where η_1, η_2 are adaptive cooperation coefficients simulating pollination intensity, $Fig_{best}^{(t)}$ and $Wasp_{best}^{(t)}$ are elite fig and wasp solutions, and ξ is a stochastic exploration vector reflecting environmental turbulence. This mechanism ensures that improved UAV placements (figs) guide power allocations (wasps) and vice versa, producing mutual refinement over iterations. Through this coevolutionary adaptation, FWSC-FANET achieves a balanced aerial topology minimizing both coverage voids and redundant power expenditure. The synergistic encoding directly maps to real-time FANET dynamics where UAVs continuously reposition and regulate their power based on cooperative feedback.

C. Routing Optimization via Fig-Wasp Interactions

After coevolution convergence of UAV placement and power control, each UAV maintains a neighbor-aware link matrix indicating the probability of successful packet delivery toward the destination. The FWSC algorithm employs mutual reinforcement between fig (structural) and wasp (link) agents to determine optimal multi-hop routes.

Link Reliability Estimation

$$\phi_{ab}(t) = \exp\left(-\frac{d_{ab}(t)}{C_r}\right) \times \frac{SNR_{ab}(t)}{SNR_{thr}} \quad \dots(10)$$

where $\phi_{ab}(t)$ is the normalized link reliability between UAV a and b ; C_r is maximum communication range; and SNR_{thr} is minimum acceptable SNR. This term decays with distance and amplifies with stronger link quality.

Probabilistic Route Selection

$$PS_{ab}^{(r)} = \frac{\phi_{ab}(t)^\gamma}{\sum_{m \in \Omega_a} \phi_{am}(t)^\gamma} \quad \dots(11)$$

where $PS_{ab}^{(r)}$ is the probability of selecting neighbor b from the neighbor set Ω_a of UAV a ; γ controls exploitation versus exploration.

Routes evolve dynamically as UAVs move, guided by this probabilistic bias.

Cumulative Route Cost Function

$$CF_{route} = \sum_{(a,b) \in \mathcal{R}} [\omega_1 EC_{ab} + \omega_2 ED_{ab} + \omega_3 (1 - \phi_{ab})] \quad \dots(12)$$

where $\mathcal{R}$ is the chosen route set, EC_{ab} is per-link energy consumption, ED_{ab} the expected delay, ϕ_{ab} the reliability from (10), and $\omega_1, \omega_2, \omega_3$ are balancing weights satisfying $\sum \omega_a = 1$. This objective integrates energy efficiency, latency, and reliability in a single cost metric.

Algorithm 1: FWSC-FANET: Fig Tree-Wasp Symbiotic Coevolutionary Optimization

Input: Initial UAV positions $VP_a(0)$, transmit powers $TP_{t,a}(0)$, populations P_f, P_w , cooperation coefficients C_f, C_w , and parameters $C_r, BW, N_0, \lambda, T_{max}, \epsilon$.

Output: Optimized UAV positions, transmit powers, and routing paths.

1. Initialize

- Deploy $NUAVs$ randomly in 3D space.
- Assign random velocity $V_a(0)$, acceleration $Acl_a(0)$, and transmit power $TP_{t,a}(0)$.
- Initialize fig population P_f and wasp population P_w .

2. Evaluate Initial Fitness

- For each UAV u_a , compute:
 - SNR using Eq. (5).
 - Link reliability, energy consumption, and throughput.
 - Fitness:

$$F_a = \alpha \cdot \text{Reliability} + \beta \cdot \text{Throughput} - \gamma \cdot \text{Energy}$$

Mutualistic Coevolution Phase

- For each iteration $t = 1$ to T_{max} :
 - For each fig agent:
 - Adjust UAV positions based on wasp interaction:

$$P_i^{new} = P_i + C_f \times \text{rand}() \times (P_w - P_i)$$

- For each wasp agent:
 - Adjust transmit power:

$$P_{t,i}^{new} = P_{t,i} + C_w \times \text{rand}() \times (P_f - P_{t,i})$$
 - Update both populations using exploration variance ϕ .

3. Fitness Evaluation
 - Recalculate link SNR, energy, and routing reliability.
 - Update fitness F_i for all UAVs.
4. Selection and Reinforcement
 - Select top agents based on global fitness.
 - Update pheromone trails and reinforcement factor:

$$\kappa_{ij} = (1 - \rho)\kappa_{ij} + \eta F_i$$
5. Convergence Check
 - If $|F_{best}^t - F_{best}^{t-1}| < \epsilon$, terminate.
 - Else, continue iteration.
6. Output
 - Return optimized UAV positions, power allocation, and routing tables.

Coevolutionary Update for Routing Priority

$$\Psi_{ab}^{(t+1)} = \Psi_{ab}^{(t)} + \rho (F_{fig}^{(t)} + F_{wasp}^{(t)}) PS_{ab}^{(r)} - \delta C_{route} \quad \dots(13)$$

where Ψ_{ab} is the routing pheromone intensity between nodes a and b ; ρ represents reinforcement rate; δ denotes cost penalty factor. Routing preference strengthens for links that enhance both spatial and power fitness, simulating symbiotic reinforcement.

Optimal Route Selection Criterion

$$\mathcal{R}^* = \arg \min_{\mathcal{R}} (CF_{route} - \kappa \bar{\Psi}_{\mathcal{R}}) \quad \dots(14)$$

where $\mathcal{R}^*$ is the best route set; $\bar{\Psi}_{\mathcal{R}}$ is mean pheromone intensity along route $\mathcal{R}$; and κ controls the trade-off between path efficiency and learned preference. This ensures the algorithm prioritizes routes offering minimal cost yet high reinforcement value.

Through these equations, FWSC-FANET dynamically constructs multi-hop routes that adapt to UAV mobility, varying SNR, and environmental uncertainty. The routing phase tightly integrates with earlier coevolutionary stages, yielding an end-to-end autonomous communication structure capable of sustaining aerial links even under sparse or rapidly changing topologies.

D. Convergence, Fitness Evaluation, and Communication Stability

The interaction between the fig and wasp populations continues until both reach a stable equilibrium in which changes to UAV positions or power configurations yield negligible improvement in routing efficiency. In the context of a FANET, this convergence implies that aerial nodes have established a geometry ensuring sustained connectivity, minimal energy overhead, and balanced load distribution across airborne links.

Global Fitness Function

$$\mathcal{F}_{global} = \lambda_1 \left(\frac{R_{avg}}{R_{max}} \right) + \lambda_2 \left(\frac{\Phi_{avg}}{\Phi_{max}} \right) + \lambda_3 \left(\frac{1}{EC_{tot}} \right) - \lambda_4 \left(\frac{D_{avg}}{D_{max}} \right) \quad \dots(15)$$

where R_{avg} is the average throughput of all routes, Φ_{avg} is the mean reliability index, EC_{tot} is the aggregate energy consumption, D_{avg} is the mean end-to-end delay, and $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are weighting coefficients. A higher $\mathcal{F}_{global}$ corresponds to a more energy-efficient and stable FANET configuration.

Coevolutionary Convergence Criterion

$$\varepsilon^{(t)} = \frac{|\mathcal{F}_{global}^{(t+1)} - \mathcal{F}_{global}^{(t)}|}{\mathcal{F}_{global}^{(t)}} < \epsilon_{thr} \quad \dots(16)$$

where $\varepsilon^{(t)}$ measures relative improvement between consecutive iterations and ϵ_{thr} is the pre-defined convergence threshold. When satisfied, the algorithm halts as both populations have reached ecological equilibrium analogous to the natural fig-wasp cycle.

Stability Index of FANET Topology

$$T_s(t) = \frac{1}{N} \sum_{a=1}^N \left(\frac{\sum_{b \in \Omega_a} \phi_{ab}(t)}{|\Omega_a|} \right) \quad \dots(17)$$

where $T_s(t)$ quantifies overall topological stability; Ω_a is the neighbor set of UAV a , and $\phi_{ab}(t)$ is link reliability from Eq. (10).

A value of $T_s(t) \approx 1$ denotes a highly resilient topology capable of tolerating UAV mobility without connectivity loss.

Converged Update Rule for UAV State Vector

$$X_a^* = X_a^{(t)} + \zeta_1 (X_{gbest} - X_a^{(t)}) + \zeta_2 \nabla_{X_a} \mathcal{F}_{global} \quad \dots(18)$$

where X_a^* is the final stabilized state (position + power) of UAV a ; X_{gbest} denotes the globally optimal vector; ζ_1, ζ_2 are adaptive learning coefficients, and $\nabla_{X_a} \mathcal{F}_{global}$ is the gradient of global fitness. This formulation enables fine-tuning of UAV configuration in real-time to maintain optimal network performance.

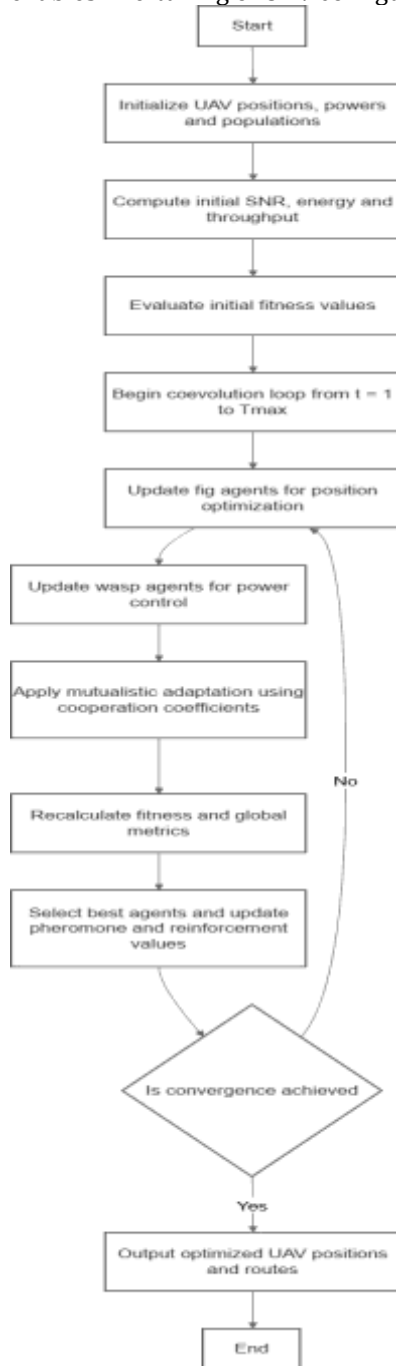


Figure – 1. Workflow of FWSC-FANET

At convergence, each UAV in the FANET achieves a symbiotically optimized state—its position maximizes coverage and link strength, its power level minimizes interference, and routing paths adapt seamlessly to topology fluctuations. The FWSC-FANET framework thus ensures:

- Sustainable energy utilization through cooperative power balance,
- Persistent link reliability under mobility, and
- Autonomous topology reconfiguration without centralized control.

The entire proposed work is presented as pseudocode in Algorithm – 1. The workflow of the proposed FWSC-FANET is portrayed in Figure – 1.

4. Simulation Settings and Performance Metrics

The proposed FWSC-FANET framework is estimated under a parameter-driven simulation environment. The UAV network comprises 10UAVs to 50UAVs deployed over a vertical range of 120 meters, horizontal area of 1000 meters by 1000 meters and with a maximum altitude of 120 meters. Each UAV has a channel bandwidth of 5 megahertz, a communication range of 200 meters, and a carrier wavelength of 0.125 meters. Noise spectral density is set as 1e-9 watts per hertz, with a reference signal-to-noise ratio threshold of 10 decibels. Antenna increases for both receiving and transmitting antennas are 3 decibels isotropic. UAV mobility parameters include random initial positions, velocities ranging between 5 and 15 meters per second, and acceleration profiles of plus or minus 2 meters per second squared. UAV motion is updated at a time step of 0.5 seconds.

Table - 1: Simulation Settings and Performance Metrics

Parameter / Metric	Value / Range	Unit
Number of UAVs	10 – 50	Nodes
Deployment area	1000 x 1000 x 120	Meters
Maximum altitude	120	Meters
Communication range	200	Meters
Channel bandwidth	5	Megahertz
Carrier wavelength	0.125	Meters
Noise spectral density	1e-9	Watts per Hertz
Reference SNR threshold	10	Decibels
Antenna gains (Tx/Rx)	3	Decibels isotropic
Velocity range	5 – 15	Meters per second
Acceleration range	±2	Meters per second squared
Time step	0.5	Seconds
Fig agent population	30	Agents
Wasp agent population	30	Agents
Cooperation coefficients	0.7, 0.6	-
Exploration variance	0.2	-
Convergence threshold	0.00001	-
Iteration limit	200	Iterations
Link reliability decay constant	0.05	-
Reinforcement factor	0.1	-
Pheromone evaporation rate	0.05	-
Cost-balancing coefficients	0.4, 0.3, 0.3	-

The FWSC algorithm uses populations of 30 wasp agents and 30 fig agents, with cooperation coefficients of 0.6 and 0.7, and an exploration variance of 0.2. Fitness composition is equally weighted among reliability, throughput, energy efficiency, and stability. Convergence is attained at a threshold of 0.00001 or a maximum of 200 iterations. Routing parameters include dynamically updated neighbor sets, a reinforcement factor of 0.1, a link reliability decay constant of 0.05, and a pheromone evaporation rate of 0.05. Cost-balancing coefficients are set as 0.4, 0.3, and 0.3. The performance of this framework is compared with DRL-FANET [17] and EAR-FANET [16]. The evaluation focuses on the following six primary metrics. They are semantic accuracy, packet delivery ratio, energy consumption, throughput, network lifetime, and global fitness. These metrics calculate the framework's ability to maintain efficient power allocation, stable UAV topology, and energy-aware routing under varying network conditions.

5. Simulation Results

The performance of the proposed FWSC-FANET framework is estimated against two benchmark approaches: EAR-FANET [16] and DRL-FANET [17] under varying pause times. The simulation settings detailed in Table – 1 were used to assess six key performance metrics. Table – 2 and Table – 3 present the consolidated simulation results.

A. Semantic Accuracy

Semantic Accuracy (SA) replicates the effectiveness of information delivery in UAV networks. As represented in Figure – 2 and Table – 2, the proposed FWSC-FANET reliably attains the highest SA across all pause times. For instance, at a pause time of 10 s, FWSC-FANET reaches 91.7%, outperforming DRL-FANET (85.1%) and EAR-FANET (82.3%). The gradual failure in SA with increasing pause time indicates that higher UAV mobility slightly affects semantic information preservation. The FWSC-FANET's coevolutionary optimization guarantees robust semantic communication.

B. Packet Delivery Ratio

Network reliability is measured by the Packet Delivery Ratio (PDR). From Figure – 3 and Table – 2, FWSC-FANET validates superior PDR, reaching 95.5% at 10 s pause time compared to DRL-FANET (90.2%) and EAR-FANET (88.4%). The mutualistic cooperation between “wasp” and “fig” agents helps to sustain high link reliability, even under dynamic mobility patterns, which improves multi-hop data delivery.

C. Energy Consumption

Energy Consumption (EC) shows the efficiency of power management in UAVs. As presented in Table – 2 and Figure – 4, FWSC-FANET attains the lowest energy consumption at all pause times. At 10s pause time, the energy consumption is 132.4 J, while EAR-FANET consume 156.7 J and DRL-FANET consume 148.5 J. The energy-aware routing and adaptive transmit-power allocation contribute to decreased energy expenditure while ensuring the reliability of network.

Table – 2. Simulation Results for Semantic Accuracy, Packet Delivery Ratio and Energy Consumption Performance Metrics

	Semantic Accuracy (%)			Packet Delivery Ratio (%)			Energy Consumption (J)		
Pause Time (s)	EAR-FANET [16]	DRL-FANET [17]	FWSC-FANET	EAR-FANET [16]	DRL-FANET [17]	FWSC-FANET	EAR-FANET [16]	DRL-FANET [17]	FWSC-FANET
10	82.3	85.1	91.7	88.4	90.2	95.5	156.7	148.5	132.4
20	80.9	84.2	90.8	87	89.1	94.8	158.2	150.1	134
30	78.5	82.6	89.9	85.6	87.9	94	160.5	152.8	136.3
40	76.2	81.3	89	84.2	86.5	93.2	162.9	155.4	138.6
50	74.8	79.7	88.3	82.8	85	92.5	165.1	157.8	140.7

D. Throughput

Throughput (TP) represents the effective data rate achieved by the UAV network. As shown in Table – 3 and Figure – 5, FWSC-FANET constantly achieves the highest throughput, reaching 17.5 Mbps at 10 s pause time, compared to 14.1 Mbps for DRL-FANET and 12.8 Mbps for EAR-FANET. This development is attributed to optimal UAV positioning and joint routing-power control that decreases retransmissions and packet collisions.

Table – 3. Simulation Results for Throughput, Network Lifetime and Global Fitness Performance Metrics

	Throughput (Mbps)			Network Lifetime (minutes)			Global Fitness (nearing 1 denotes better)		
Pause Time (s)	EAR-FANET [16]	DRL-FANET [17]	FWSC-FANET	EAR-FANET [16]	DRL-FANET [17]	FWSC-FANET	EAR-FANET [16]	DRL-FANET [17]	FWSC-FANET
10	12.8	14.1	17.5	245.3	258.7	296.4	0.712	0.745	0.862
20	12.4	13.7	17.1	242.1	255	292.5	0.699	0.731	0.851
30	12	13.3	16.7	238.7	251.4	288.7	0.684	0.717	0.839
40	11.6	12.9	16.4	235.5	247.8	284.9	0.67	0.703	0.828
50	11.2	12.5	16.3	232.3	244.2	281.2	0.658	0.69	0.817

E. Network Lifetime

Network Lifetime (NL) reflects the operational sustainability of the UAV swarm. As per Table – 3 and Figure – 6, FWSC-FANET prolongs network lifetime, achieving 296.4 minutes at 10 s pause time, which is higher

than DRL-FANET (258.7 minutes) and EAR-FANET (245.3 minutes). Load-balanced routing and efficient energy management contribute to this extended lifetime.

F. Global Fitness

Global Fitness (GF) calculates the overall integrating throughput, optimization performance, reliability, and energy efficiency. As presented in Table – 3 and Figure – 7, FWSC-FANET attains the highest global fitness, 0.862 at 10 s pause time, surpassing EAR-FANET (0.712) and DRL-FANET (0.745). This demonstrates that the coevolutionary framework effectively balances exploration and exploitation, achieving an optimal UAV network configuration.

Overall, the proposed FWSC-FANET validates substantial performance improvements across all six metrics compared to the benchmark approaches. The combination of Fig Tree–Wasp Symbiotic Coevolutionary optimization enables joint UAV positioning, energy-aware routing, and adaptive power control, resulting in higher semantic accuracy, lower energy consumption, improved reliability, improved throughput, superior global fitness, and prolonged network lifetime. These results validate the effectiveness of the proposed framework for efficient and resilient 6G-oriented UAV networks.

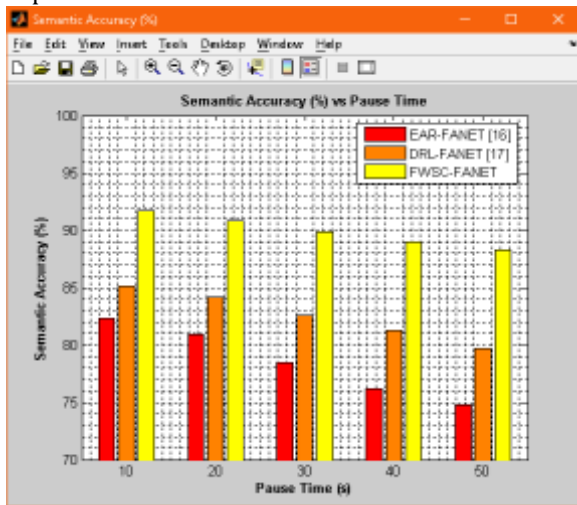


Figure - 2. Pausetime Vs Semantic Accuracy

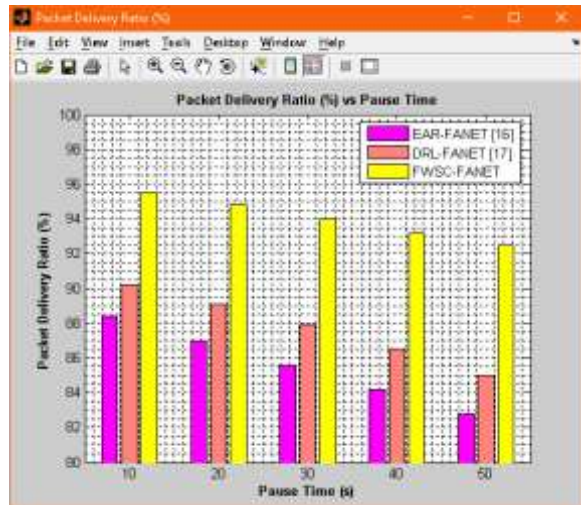


Figure - 3. Pausetime Vs Packet Delivery Ratio

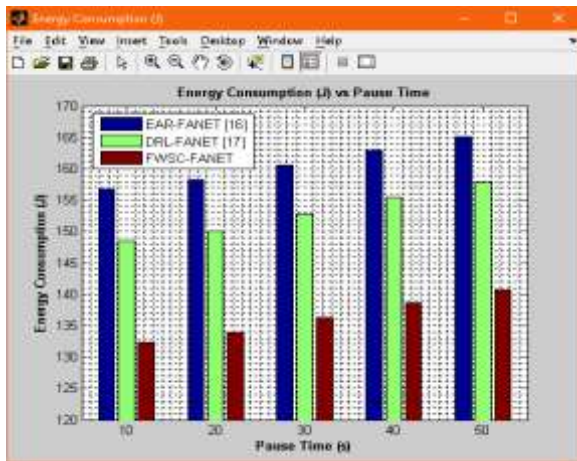


Figure - 4. Pausetime Vs Energy Consumption

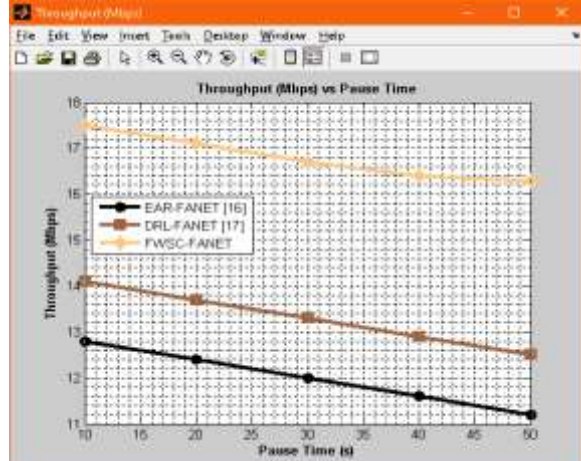


Figure - 5. Pausetime Vs Throughput

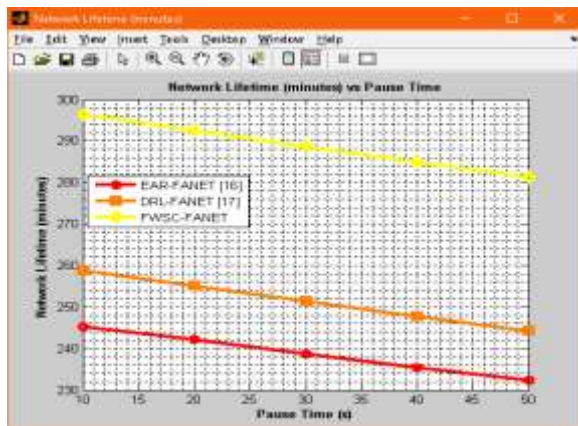


Figure - 6. Pausetime Vs Network Lifetime

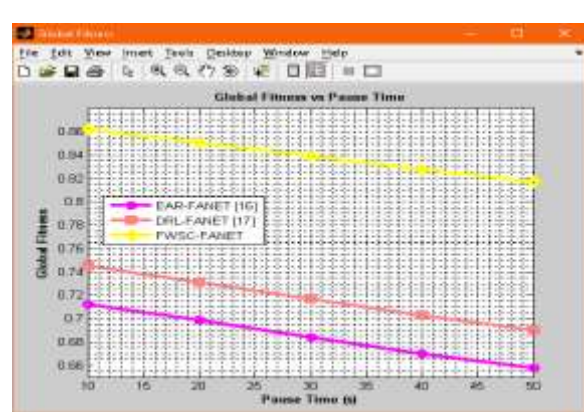


Figure - 7. Pausetime Vs Global Fitness

6. Conclusion

In conclusion, this work presented FWSC-FANET, a novel coevolutionary framework for power control, joint UAV positioning, and routing in dynamic FANETs. By making use of the symbiotic interaction between “wasp” and “fig” agents, the proposed method efficiently balances exploitation and exploration, confirming optimized 3D topology, energy-efficient routing, and adaptive power allocation. Whilst doing simulation and the obtained results against EAR-FANET [16] and DRL-FANET [17] the proposed work favor considerable performance gains across semantic accuracy, packet delivery ratio, energy consumption, throughput, network lifetime, and global fitness. The FWSC-FANET demonstrates that integrating mutualistic coevolutionary optimisation into UAV networks can achieve prolonged network lifetime, enhanced reliability, and superior global network performance. The upcoming work will extend this framework to consider real-time channel variability, heterogeneous UAV swarms, and security-aware optimization to improve the adaptability and robustness of 6G FANETs.

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