SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I8P105

Volume 13 Issue 8, 65-78, August 2026

Original Article

RF Energy Harvesting-Enabled UAV-Assisted FANET: A Multi-Objective Osprey Optimization Framework for Sustainable Clustering and Energy Management

Keerthana. P[1], A.Vijayalakshmi[2], S. Gobinath[3], C. Venkatesh kumar[4]

[1,2]*Department of ECE, School of Engineering, Vels Institute of Science Technology and Advanced Studies.Chennai, India.*
[3]*Department of Information Technology, V.S.B. Engineering College, Karudayampalayam Post, Karur, Tamilnadu, India.*
[4]*Department of EEE, St. Joseph's College of Engineering, OMR, Chennai, India*

[1]*Corresponding Author: Keerthiperumal@gmail.com*

Received: 11 April 2026 Revised: 02 June 2026 Accepted: 24 July 2026 Published: 31 August 2026

Abstract *- Flying Ad Hoc Networks (FANETs) are Unmanned Aerial Vehicles-assisted and have critical energy depletion problems that extremely reduce network lifetime and persistent IoT operation. Small onboard battery capacity, as well as the lack of smart energy replenishment systems, compromises the reliability of communication over dynamic aerial topologies. An Osprey Optimization Algorithm-based multi-objective model incorporating Radio Frequency Energy Harvesting in UAV-assisted FANET clustering is proposed. The framework is a joint optimization of three-dimensional UAV positioning and selection of cluster heads based on a composite fitness score. Ψ_i Moreover, energy sustainability using a four-objective fitness function that balances harvested power, remaining energy, network life, and packet delivery ratio. The simulation outcomes indicate that the given framework can achieve a network lifetime of 347 rounds, a consumption of 0.0024 J/round, a packet delivery ratio of 94.2%, and a harvested power of 35.8 mW at 50 UAV nodes, with an RF-to-DC conversion efficiency of 80.4%. The framework proposed beats the current clustering algorithms, validating its excellence in providing self-sustainable energy-efficient UAV-IoT network functionality.*

Keywords *- Unmanned Aerial Vehicle, Flying Ad Hoc Network, Radio Frequency Energy Harvesting, Osprey Optimization Algorithm, Cluster head, Cluster member, Improved Osprey Optimization Algorithm.*

1. Introduction

The geometric increase in the number of Internet of Things (IoT) applications in smart cities, precision agriculture, disaster management, and military surveillance has tightened the requirement for flexible, autonomous, and self-sustaining aerial communication infrastructures. FANETs, aerial assisted by Unmanned Aerial Vehicles (UAVs), have become an attractive approach that provides quick deployment, topology reconfiguration, line of sight data communications, and straightforward IoT data integration across sensor fields that are geometrically spread [1]. In comparison to ground-based wireless sensor networks, which are limited by stationary infrastructure, FANET UAV nodes are independent self-organizing clusters working in multi-hop aerial communications to transmit time-sensitive information [2]. The base mobility, altitude adjustability, and coverage capability of UAV-FANET structures predispose them to be fundamental facilitators to the next-generation IoT communication systems, specifically in areas where the service of terrestrial network infrastructures is either not available, destroyed, or economically infeasible to install [3]. Although these are advantageous persuasive features, a fundamental and enduring limitation to UAV-assisted FANETs is the severe limitation of the onboard battery capacity [4]. The nodes of UAVs also use a lot of power when flying through the air, in the wireless transmission of data, receiving signals, and processing data on board. This rapid energy loss significantly reduces the life of the network, causes untimely node failures, and destabilizes cluster formation, which eventually decreases the stability of mission-critical IoT applications. Severe studies on energy-efficient clustering protocols have produced significant work, such as distance-based rotation of cluster heads, residual energy-dependent selection, and topology-sensitive routing schemes [5]. However, these methods only cover the minimization of energy usage, and substantially do not consider the other equally vital aspect of energy replenishment, leaving UAV nodes purely reliant on limited battery capacity with no avenue to self-sustaining operation [6]. The RF energy harvesting has turned out to be a revolutionary paradigm that can overcome this constraint because it allows UAV nodes to harvest and convert the ubiquitous WiFi access points, LTE base stations, and IoT sensor devices into RF radiation into electrical power [7]. The idea of RF-EH integration into the UAV-FANET architectures allows operating the network indefinitely since the energy reserves available to every node are replenished with each communication round. However, the RF-EH can be practically implemented in dynamic UAV settings, leading to complicated technical issues. The spatial resolution and temporal variation of the ambient RF signal are large, and typically, it is challenging to achieve consistency across energy capture at mobile UAV nodes [8]. The current UAV deployment schemes maximize only communication coverage and connectivity indicators, absolutely ignoring RF power density patterns and harvesting capability in the three-dimensional deployment space. Moreover, there is also a fundamental trade-off between locating UAVs in a way that provides them with the greatest RF energy uptake on the one hand and locating UAVs in a way that provides them with the best intra-cluster communication performance on the other hand [9]. The traditional optimization methods, such as Genetic Algorithms and Particle Swarm Optimization, show poor convergence patterns in addressing such a high-dimensional, multi-objective, and nonlinear joint optimization problem where UAV placement, cluster head location, and energy management decisions are to be made simultaneously [10].

The combination of these limitations is the design of a smart, unified optimization system that can jointly tackle the UAV positioning challenges, cluster head placement, RF energy harvesting efficiency, and network performance maintenance of the system under one unified computational system. Recently proposed bio-inspired metaheuristic, the Osprey Optimization Algorithm, which exhibits an excellent balance between global exploration and local exploitation relative to classical swarm algorithms, is an interesting candidate for the control of such multi-objective joint optimization in practical UAV-FANET scenarios [11]. The four main goals of the planned framework are fourfold: Although significant research achievements have been accomplished on UAV-assisted Flying Ad Hoc Networks (FANETs), a number of critical issues have not yet been addressed. The main clustering and routing techniques are mostly based on minimizing the total communication energy consumption, which can be achieved by selecting cluster heads based on residual energy, by using distance-aware routing, or mobility optimization. However, these techniques, in the main, assume a limit on onboard energy and do not include effective energy replenishment mechanisms to enable the network to operate over extended periods. Radio Frequency Energy Harvesting (RF-EH) is a recently proposed method to increase the operational life of wireless networks, but the combination of RF-EH and UAV-assisted FANET environments is still not much explored. Current RF-EH research focuses primarily on terrestrial wireless sensor networks and does not address many of the challenges inherent with a highly dynamic topology in the air, 3D deployment of UAVs, and continuous cluster reconfiguration. A broad summary of the accomplishments of this work is provided here. Design of RF Energy Harvesting Assisted UAV Supported FANET for Sustainable Aerial Communications. Simultaneous UAV placement and cluster-head selection by a multi-objective Osprey optimization algorithm. Development of a 4-objective fitness model that includes harvested power, residual energy, network lifetime and packet delivery ratio. Development of an adaptive cluster formation mechanism for a more stable network in a dynamic topology. Large-scale simulation scenarios, with a variety of UAV deployments, are used to evaluate the proposed framework. Proven performance over the latest optimization and clustering algorithms.

In addition, the optimization frameworks currently available are focusing on separate optimization problems such as UAV placement, cluster head selection, energy harvesting, and communication performance. Such isolated optimization approaches cannot take the interdependency of harvested energy, residual battery capacity, network lifetime, packet delivery ratio, and cluster stability into consideration. However, there are some conventional metaheuristic approaches, such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and the Firefly-based optimization method, which often suffer from premature convergence and poor solution quality for the large-scale multi-objective UAV-FANET optimization problem. Hence, a comprehensive optimization framework is still missing that can optimally extract RF energy from multiple UAVs, extend network lifetime, maximize packet delivery rate and ensure sustainable cluster formation in dynamic UAV-assisted IoT network scenarios. Inspired by these constraints, this work advocates an RF Energy Harvesting-enabled UAV-assisted FANET framework that optimizes the energy sustainability, cluster head selection and 3D UAV deployment jointly using the Multi-Objective Osprey Optimization Algorithm.

To model ambient RF energy harvesting across heterogeneous IoT RF sources with the Friis transmission model, to solve three-dimensional UAV placement based on RF power density mapping, and to carry out three-fold energy-concerned cluster head selection using a composite fitness score that combines residual energy, harvested power, network lifetime, and packet delivery ratio. Its main contributions are an all-encompassing RF-Eh integrated UAV-FANET system framework, a novel. Ψ_i based cluster head eligibility measure, a four-objective OOA fitness measure F, and an integrated closed-loop optimization structure that interrelates UAV placement and real-time energy harvesting and cluster reformation [12]. The simulation findings demonstrate that the proposed framework achieves a network lifetime of 347 rounds, an energy consumption of 0.0024 J/round, a packet delivery ratio of 94.2%, and a harvested power of 35.8 mW under the adopted simulation settings, indicating the effectiveness of integrating RF energy harvesting with multi-objective Osprey optimization for sustainable UAV-assisted FANET operation. The rest of the paper has the following structure: Section II is a review of related literature, Section III introduces the proposed system model and OOA framework and explains the setup of the simulation and the characteristics of the data, Section IV discusses the results, and finally, the conclusion can be found in Section V, where future directions are offered.

2. Literature Review

The concept of radio frequency energy harvesting has received significant momentum as an option of power replenishment option in energy-limited wireless communication nodes that operate in the dense IoT deployment infrastructure [13]. Its most basic working concept is the ability to sense and capture ambient electromagnetic radiations emitted by the heterogeneous RF sources, such as WiFi access points, cellular base stations, and low-power IoT transmitters, and transform captured signals into useful direct current in rectenna circuits and impedance-matched harvesting front-ends [14]. Conversion efficiency η becomes the most important parameter of performance, and practical harvesting circuits have conversion efficiencies ranging between 60% to 85% depending on the power of inputs, frequency bands of carriers, and rectifier topology arrangements [15]. Multi-band harvesting designs that can run concurrently at 2.4 GHz WiFi, 1800 MHz LTE, and 915 MHz ISM bands are shown to display significantly greater performance. $P_{total,i}$ of harvested power than single-band implementations, and multi-source ambient RF harvesting is the architecture of choice in densely populated IoT settings to power wireless nodes.

The Flying Ad Hoc Networks that have been investigated in intensive research have been focused on UAV-assisted due to their ability to provide flexible, quickly deployable aerial communication infrastructure in areas in which ground-based access to the network is non-existent or operationally infeasible [9]. The deployment optimization in three dimensions is one of the main research issues because the altitude of UAV directly affects the quality of communication links and the spatial distributions of the interceptable RF signal power of terrestrial sources [16].

The current placement techniques are mainly based on maximizing the two-dimensional coverage footprint and connectivity values, and ignore the positioning of the vertical axis with respect to the distributions of ambient RF power density, producing a systematic difference between communication-optimal and energy-harvesting-optimal positions of the UAVs [17]. Trajectory planning algorithms that include mobility models have been shown to have better network lifetime than strategies of deploying a network that are based on a static deployment strategy, although dynamic repositioning presents a new source of propulsion energy consumption that should be closely offset by the benefit of harvesting. Introduction of three-dimensional RF power density mapping $\Phi(\mathrm{p}_i)$ into the UAV placement equations is a technically required next step of coverage-based deployment models into truly energy-conscious aerial network arrangements.

The protocols in clustering energy-constrained multi-hop wireless networks make use of varied cluster head selection criteria in an attempt to allocate energy load evenly among the involved nodes and also reduce all the intra-cluster communication costs [18]. Early protocols, such as LEACH, proposed probabilistic CH rotation solely on the thresholds of residual energy, and this formed the base on which further protocols have been built to improve the protocol [19].

The use of distance-weighted methods to select the networks based on average intra-cluster separation $\bar{d}_i$ and the residual energy $E_{res,i}$ shows significantly better network lifetime than those of single-criterion methods by avoiding energetically undesirable long-range intra-cluster transmissions [20]. The composite fitness scoring schemes, which jointly implement a set of node-level parameters, energy state, communication overhead, and topological centrality into a single eligibility score Ψ_i are found to be more effective than the threshold-based rotation schemes at any network density [21]. The methodical omission of harvested RF energy $P_{total,i}$ as an overt CH eligibility variable in currently used models; however, it is a severe flaw, as nodes with high harvesting potential are swept out of CH candidacy by ad hoc energy-only thresholding criteria.

The bio-inspired metaheuristic algorithms have also been widely used to solve the wireless network optimization problems due to their ability to explore the high-dimensional, non-convex, multimodal solution space with no gradient information and problem-related mathematical structure [22]. The background capabilities that have been developed in the Particle Swarm Optimization and Genetic Algorithms have paved the way to the single-objective optimization of UAV placement and routing, although both are prone to premature convergence in problems of higher than moderate dimensionality [23].

The Osprey Optimization Algorithm proposes a biologically-inspired two-step search protocol for world exploration by locating prey and exploiting it with local precision in the form of a special-purpose dive behavior that has been shown to outperform both PSO and GA on benchmark optimization functions of rate of convergence, quality of solution, and local optima escape [24]. Multi-objective bio-inspired algorithms with Pareto front construction and hypervolume measures can also be applied in order to optimize conflicting objectives such as energy consumption reduction, harvested power maximization, network life time extension, and QoS preservation capabilities, which are essentially unavailable within single objective models [25]. The lack of research in the area of OOA exploration in the framework of UAV-FANET multi-objective optimization is a testable knowledge gap that should be addressed in systematic research.

The final performance goal of network lifetime maximization under continuous QoS constraints is a unifying energy management, clustering, and routing decisions in UAV-assisted IoT communication systems [26]. Network lifetime $T_{lifetime}$ is given as an analytical model of network lifetime as the time when node energy is depleted, which gives a manageable optimization objective, but more complex definitions that include graceful degradation limits and partial connectivity survival are more realistic operational goals [27].

The adaptive performance benefits of deep reinforcement learning methods to joint UAV trajectory and resource allocation problems are only supported in a dynamic environment, but may pose significant computational demands, which are beyond the onboard UAV processing limits in real-time [28]. The multi-objective optimization models that balance between the packet delivery ratio δ_{QoS}, the total energy consumption E_{total}, the harvested power $P_{harvest}$, and the network lifetime $T_{lifetime}$ With unified fitness functions F with objective weights that are calibrated, always provide better trade-off solutions than sequential single-objective optimization pipelines do.

The recent literature results obtained in simulation agree that the network lifetime benefits of RF-EH integration in the form of a combination of RF energy harvesting, intelligent clustering, and intelligent placement are indeed greater by 15% to 40% over non-harvesting baselines, indicating that RF-EH integration is a very high-impact enabler of sustainable UAV-IoT network operation.

3. Proposed Work

The proposed framework will overcome the two-fold problem of energy loss and ineffective cluster development within UAV-aided FANETs and combine RF energy harvesting with a multi-objective optimization engine, which is based on the Osprey Optimization Algorithm (OOA). The framework, in combination, optimizes UAV three-dimensional positioning, Cluster Head (CH) selection, and energy sustainability based on a single fitness function. These sub-problems are coupled together in the proposed system, and are not solved in isolation, as is the case in conventional approaches.

3.1. RF Energy Harvesting Model for UAV Nodes in Ambient IoT Environments

The UAV nodes in the FANET will be deployed in an IoT-rich environment where there are constant ambient RF radiations of WiFi access points, cellular base stations, and IoT sensor nodes. The Friis transmission equation modified to apply to the aerial nodes can be used to model the harvested RF power at UAV node *i* at RF source j is defined in Equation (1).

$$P_{h,i} = \eta \cdot P_{t,j} \cdot G_t \cdot G_r \cdot \left(\frac{\lambda}{4\pi d_{ij}}\right)^2 \tag{1}$$

Where $\eta \in (0,1)$ is the RF-to-DC conversion efficiency of the energy harvesting circuit, $P_{t,j}$ is the transmitted power of the RF source j, G_t and G_r are the gain of the antenna of transmitters and receivers, respectively, λ is the wavelength of the carrier, and d_{ij} is the Euclidean distance between the UAV *i* and the RF source *j*.

The total power collected by all N_s sources of RFs in the surrounding environment are written as: Since there are several coexisting ambient RF sources, the cumulative power of the N_s Sources of RFs are summarized in Equation (2),

$$P_{total,i} = \sum_{j=1}^{N_s} \eta \cdot P_{t,j} \cdot G_t \cdot G_r \cdot \left(\frac{\lambda}{4\pi d_{ij}}\right)^2 \tag{2}$$

The remaining energy of the UAV node *i* at the end of the communication round *t* is replaced in Equation (3),

$$E_{res,i}(t) = E_{res,i}(t-1) - E_{comm,i}(t) + P_{total,i} \cdot \Delta t \tag{3}$$

Where $E_{comm,i}(t)$ is the amount of energy used in transmission and reception on round *t*, and *Δt* is the time spent in harvesting on a round. The energy balance model will make sure that the framework clearly describes the process of consumption and replenishment, which is the foundation of the self-sustainable UAV operation paradigm.

Figure 1 represents the entire OOA-based multi-objective optimization pipeline comprising bio-inspired and swarm algorithms, OOA, GA, PSO, ACO, and objective functions minimizing E_{total}, maximizing $P_{harvest}$, and $T_{lifetime}$ subject to constraints d_{min}, $z_{min} \le z \le z_{max}$, and $E_{res} \ge 0$ generating Pareto-optimal UAV-FANET deployment arrangements.

3.2. Three-Dimensional UAV Placement Optimization based on RF Power Density Mapping

Traditional strategies of UAV placement optimize coverage or connection. The proposed model presents an RF power density map on the deployment area to determine spatial zones of the maximum harvestable energy. Candidate's UAV position $\mathrm{p}_i = (x_i, y_i, z_i)$ in the three-dimensional space is judged by an RF power density score in Equation (4),

$$\Phi(\mathrm{p}_i) = \sum_{j=1}^{N_s} \frac{P_{t,j}}{4\pi d_{ij}^2 \cdot L_{path}} \tag{4}$$

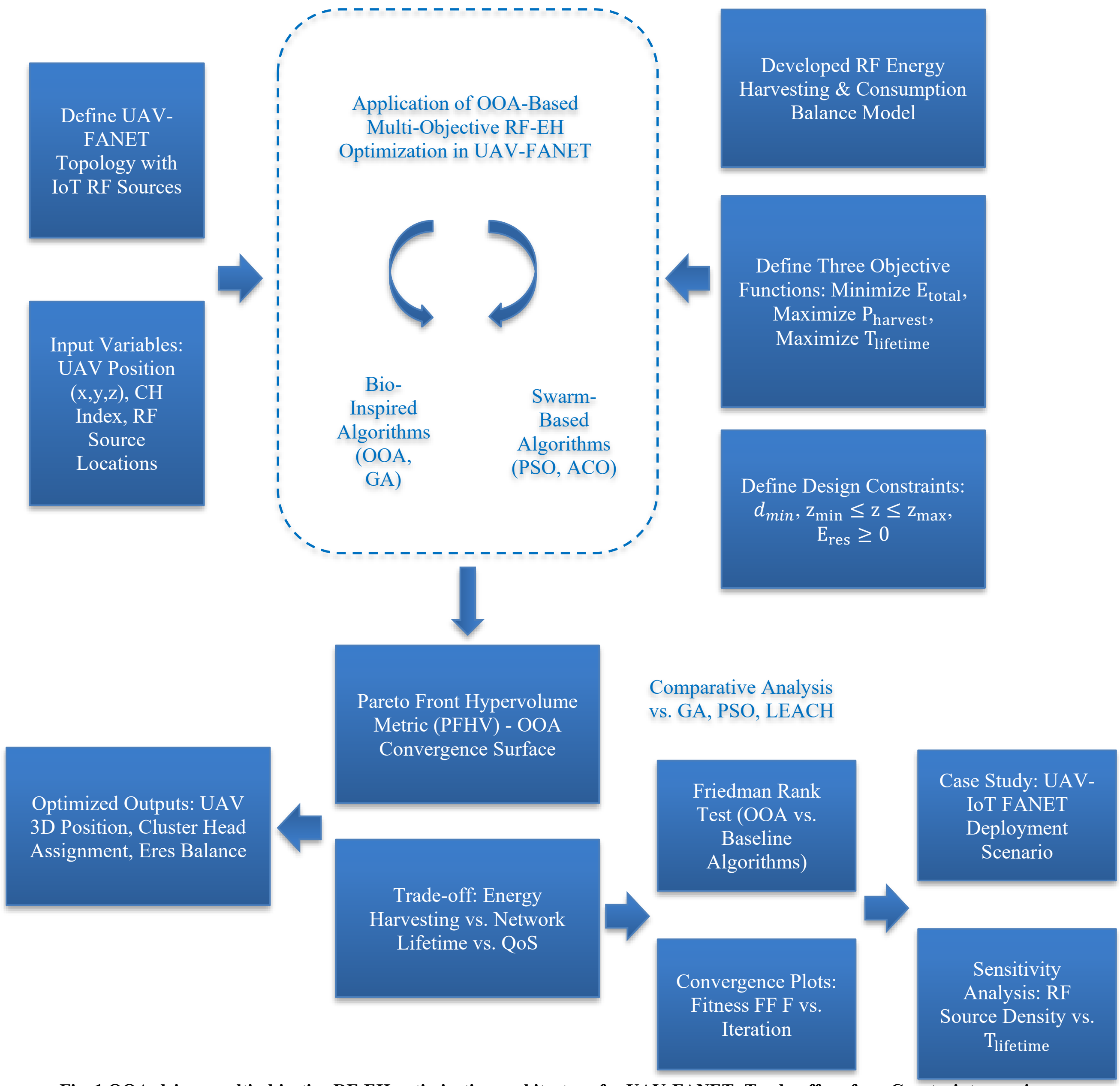

Fig. 1 OOA-driven multi-objective RF-EH optimization architecture for UAV-FANET: Trade-off surface, Constraint mapping, and Comparative validation pipeline

Where L_{path} is the path loss factor, which includes the free-space loss and environmental loss caused by UAV altitude and terrain.

The optimal UAV position is determined by maximizing $\Phi(\mathrm{p}_i)$ with a minimum-inter-UAV-distance constraint d_{min} would ensure that there is no signal interference in Equation (5),

$$\mathrm{p}_i^* = \arg\max_{\mathrm{p}_i} \ \Phi(\mathrm{p}_i) \text{subject to} \parallel \mathrm{p}_i - \mathrm{p}_k \parallel \geq d_{min}, \forall k \neq i \quad (5)$$

The altitude element z_i is in $[z_{min}, z_{max}]$ to ensure that there is operational safety and quality of line of sight to the ground IoT devices. This optimization makes sure that UAV nodes are placed at such positions that optimize both the RF energy gain and maintain the integrity of communication. Figure 2: The residual energy screening against $\bar{E}_{avg}(t)$ of each of the UAV nodes preceding CH candidacy is carried out. Nodes with a threshold value go into the RF-EH recovery mode, and qualified nodes are prioritized by Ψ_i summing up the residual energy, harvested power $P_{total,i}$ and distance within cluster $\bar{d}_i$ within radius d_{max}.

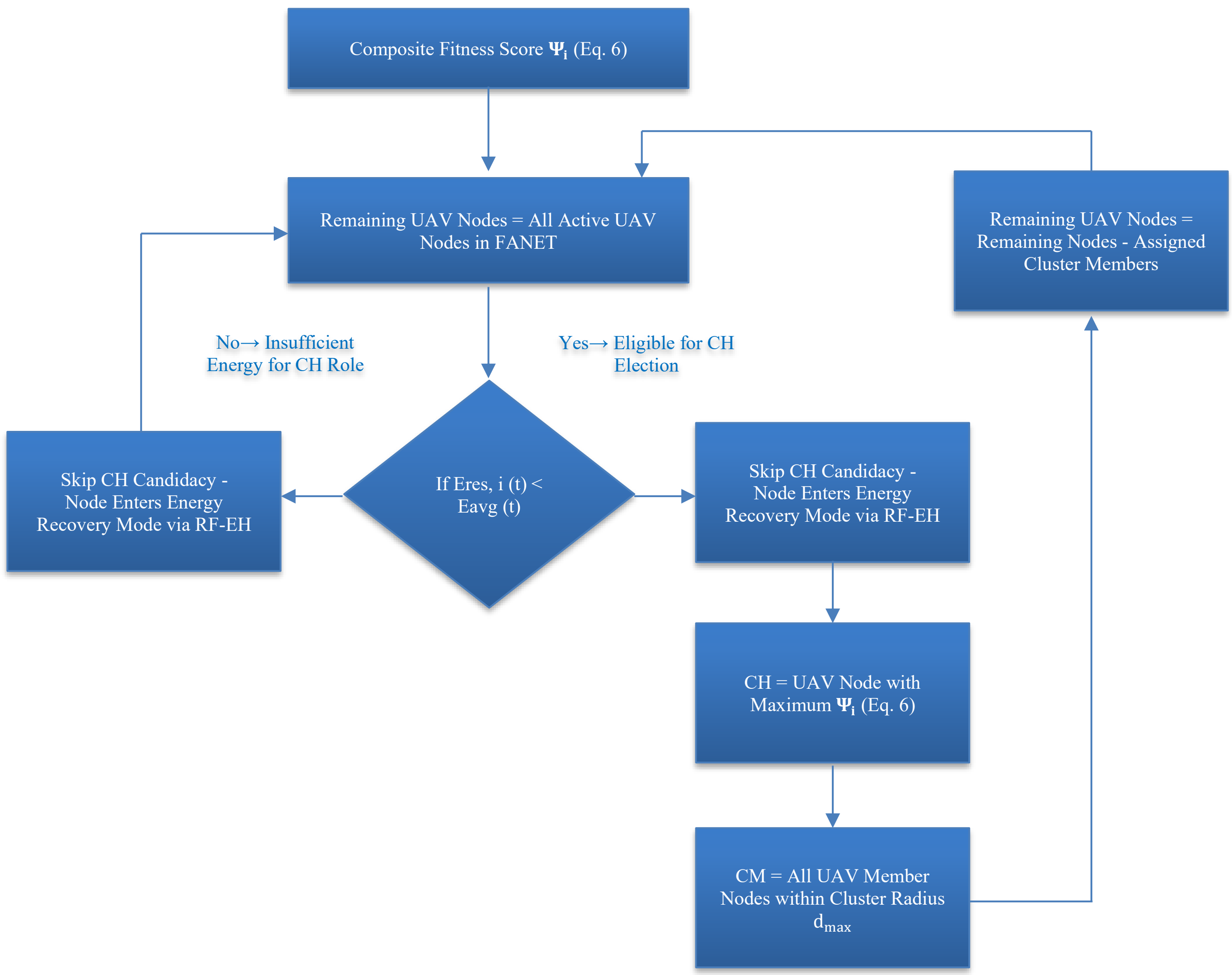

Fig. 2 Energy-Threshold-Triggered cluster head election mechanism using composite $\Psi_i$fitness scoring in OOA-RF-EH FANET

3.3. Energy-Aware Cluster Head Selection using Harvested RF Metrics and Residual Energy Weighting

The traditional criteria used in the selection of cluster head only depend on the distance or density of the nodes, but not on the energy state of the candidate nodes.

The CH selection model proposed here is a composite eligibility score. Ψ_i of each UAV node *i* that is a weighted sum of residual energy, potentials of the harvested power, and intra-cluster distance in Equation (6),

$$\Psi_i = \alpha \cdot \frac{E_{res,i}}{E_{max}} + \beta \cdot \frac{P_{total,i}}{P_{max}} - \gamma \cdot \frac{\bar{d}_i}{d_{max}} \tag{6}$$

Where $E_{max}$and P_{max} are the maximum possible residual energy and power harvested in the network, respectively, and $\bar{d}_i$ is the average distance between node *i* and the member nodes in its cluster, and α, β, γ are weighting coefficients such that $\alpha + \beta + \gamma = 1$. The power used to transmit a k-bit data packet between a cluster member node *i* and its cluster head at a distance *d* is given by Equation (7),

$$E_{tx}(k, d) = k \cdot E_{elec} + k \cdot \epsilon_{amp} \cdot d^2 \tag{7}$$

Where E_{elec} is the energy lost per bit of the transceiver electronics, and ϵ_{amp} is the amplifier energy coefficient. The nodes that have a bigger Ψ_i Scores are chosen as cluster heads, which means that CH roles are always allocated to the UAVs that have plenty of energy sources and good harvesting capabilities, so that energy will not run out of the vital relay nodes.

Figure 3: UAV node inputs of (x_i, y_i, z_i), $E_{res,i}$, $P_{total,i}$ and RF source maps are fed sequentially through RF power density scoring of $\Phi(p_i)$, energy-conscious Ψ_i cluster formation, and OOA joint optimization of maximizing fitness *F* per Equation (8), resulting in optimized UAV positions, CH assignments, and outputs of residual energy balance.

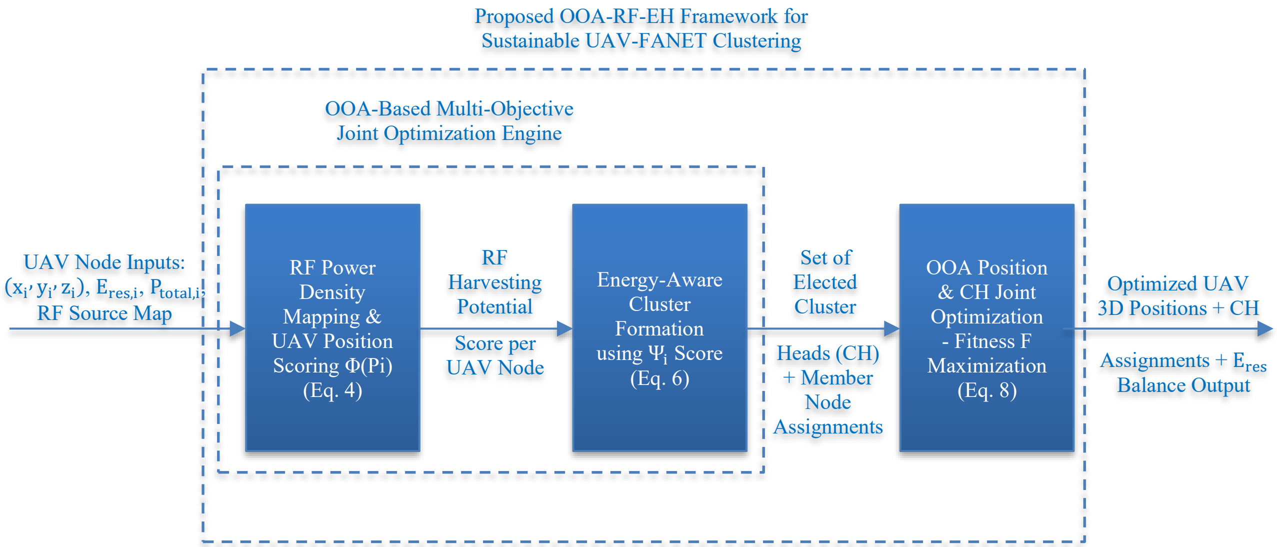

Fig. 3 End-to-End signal flow of proposed OOA-RF-EH framework: From UAV node input telemetry to optimized 3D cluster assignment output

3.4. Multi-Objective Fitness Function Design for Joint Optimization of Energy and Network Performance

The combined optimization problem is in itself multi-objective with four conflicting performance dimensions, including energy consumption minimization, harvested energy maximization, increased network lifetime, and maintained communication Quality of Service (QoS).

These goals are brought together in a single composite fitness function F to achieve the OOA optimization engine in Equation (8),

$$F = w_1 \cdot \frac{1}{E_{total}} + w_2 \cdot P_{harvest} + w_3 \cdot T_{lifetime} - w_4 \cdot \delta_{QoS} \quad (8)$$

Where E_{total} is the total energy expended by all UAV nodes on a single communication round, $P_{harvest}$ is the sum of the harvested power of all the nodes in the network, $T_{lifetime}$ The lifetime is the estimated lifetime of the network, expressed in rounds, where a round is one complete round of communication. δ_{QoS} is the factor by which the network end-to-end packet delivery ratio is degraded and w_1, w_2, w_3, w_4 are objective weights such that $\sum_{n=1}^{4} w_n = 1$ in Equation (9),

$$T_{lifetime} = \min_{i \in \mathcal{N}} \left\lfloor \frac{E_{res,i}(0)}{E_{round,i} - P_{total,i} \cdot \Delta t} \right\rfloor \quad (9)$$

Where $E_{round,i}$ averages the energy used in node i per round, and N is a complete set of UAVs.

The maximization of F has the effect of driving the OOA to find the optimal trade-off between the UAV position and CH assignment and the operational parameters, which will maximize the value of all four objectives.

3.5. Osprey Optimization Algorithm Applied to UAV Clustering and Placement in FANET

The Osprey Optimization Algorithm (OOA) is a bio-inspired metaheuristic algorithm that recapitulates the two-stage hunting strategies of ospreys: identification of the prey (global search) and then capture of the target prey (local search).

Any candidate solution would encode a three-dimensional position $S = [p_1, p_2, \ldots, p_N, CH_1, CH_2, \ldots, CH_M]$ of all the N UAV nodes and the index of cluster head assignment of MM clusters. P=30 ospreys: The population size will be $P= 30$, maximum iterations $T_{max} = 200$, and the dimensionality of the solution $D=3N+M$.

3.5.1. Phase 1 - Prey Identification (Global Exploration)

Every osprey updates its solution to the global best solution S_{best} in Equation (10),

$$S_i^{new} = S_i + r \cdot (S_{best} - I \cdot S_i) \quad (10)$$

Where $r \sim \mathcal{U}(0,1)$ is a uniform random number, and $I \in \{1,2\}$ is used to regulate the intensity of the influence of the best solutions.

3.5.2. Phase 2 - Precision Dive (Local Exploitation)

Every osprey streamlines its location in a refining neighborhood δ about S_{best} is defined in Equation (11),

$$S_i^{refined} = S_{best} + \delta \cdot (2r - 1) \cdot \left(1 - \frac{t}{T_{max}}\right) \quad (11)$$

Where t is the iteration of the current iteration, and δ is the local search radius. The workable solutions are only accepted when the composite fitness F strictly increases, hence a monotonic convergence is guaranteed.

3.5.3. Pseudocode: OOA for UAV-FANET Clustering

```
INPUT: Population size P=30, T_max=200, D=3N+M,
       UAV bounds: x,y∈[0,1000]m, z∈[20,200]m
OUTPUT: S_best → Optimal UAV positions + CH assignments
Initialize population S_i (i=1,...,P) randomly within bounds
Evaluate F(S_i) using Equation (8) for all i
S_best ← argmax F(S_i)
FOR t = 1 TO T_max DO
  FOR each osprey i DO
    // Phase 1: Global Exploration
    r ← U(0,1);  I ← randint{1,2}
    S_i_new ← S_i + r·(S_best - I·S_i)    [Equation 10]
    Clip S_i_new within UAV position bounds
     IF F(S_i_new) > F(S_i) THEN S_i ← S_i_new
     // Phase 2: Local Exploitation
     δ ← local search radius
   S_i_ref ← S_best + δ·(2r-1)·(1 - t/T_max) [Equation 11]
  IF F(S_i_ref) > F(S_i) THEN S_i ← S_i_ref
  END FOR
  Update S_best ← argmax F(S_i)
  Record T_lifetime, E_total, P_harvest, δ_QoS
END FOR
RETURN S_best → {p_1,...,p_N, CH_1,...,CH_M}
```

3.6. Model Architecture

The OOA optimization engine is connected with three sub-modules: (i) the RF Power Density Mapper calculates $\Phi(\mathrm{p}_i$According to Equation (4), (ii) the CH Eligibility Scorer calculates Ψ_i According to Equation (6) and (iii), the Multi-Objective Fitness Evaluator calculates F according to Equation (8). At every iteration, the new positions of UAVs are introduced to the RF mapper, and the calculation of power $P_{total,i}$ is renewed using the equation of two, the update of residual energy $E_{res,i}(t)$ is made using the equation of three, and the calculation of Ψ_i Scores to define CH re-elections are performed. This architecture is a closed loop, which provides real-time interactions between UAV placement, energy harvesting, and cluster formation during OOA convergence.

3.7. Dataset Source and Characteristics

The framework is tested on a simulation dataset of UAV-IoT on an NS-3 (v3.38) platform with MATLAB R2023a, simulating 50 UAV nodes in a 1000m x 1000m x 200m operational field. RF sources comprise 15 WiFi access points, 2.4 GHz, 100 mW, 5 LTE base stations, 1800 MHz, 2 W, and 100 IoT sensor nodes, 915 MHz, 10 mW. $E_{res} = 2\mathrm{J}$ is the initializing value of each UAV. A total of 30 independent topologies were created and analyzed to test the robustness of the proposed framework, OOA-RF-EH. Different seeds were used for the simulations of each topology to simulate different UAV distributions and communication conditions. The metrics listed are the averaged results for all topology scenarios that ensure reliable and statistically representative metrics are assessed. The partitioning method allowed for the evaluation of the robustness of the framework under a variety of UAV deployment scenarios while simultaneously allowing for an evaluation of network lifetime, harvested energy, packet delivery ratio, and cluster formation stability. The proposed OOA-RF-EH framework has been tested using a large number of simulation experiments in a three-dimensional UAV-assisted FANET environment. The simulation space was set up as a 1000 m × 1000 m × 200 m area for deploying various UAV nodes and IoT devices randomly throughout the network. Random Waypoint Mobility Model was used to model UAV mobility to capture realistic UAV movement patterns and dynamic topology changes. During network communication, each UAV was equipped with a limited amount of energy and performed a cluster formation, cluster-head selection, data forwarding, and RF energy harvesting task. The communication system used IEEE 802.11 wireless links for communicating between UAVs and between UAVs and IoT.

Various communication rounds were used for packet transmission, routing, and maintenance of the cluster to assess the sustainability of the network. Ambient RF energy sources such as WiFi access points, LTE base stations, and IoT communication devices were taken into account for the proposed RF energy harvesting model. The harvested RF power was transformed to usable electrical power via an RF-to-DC conversion process and then used to recharge the energy stored in the nodes. The harvested energy contribution was added to the multi-objective fitness function for the purpose of helping the operation of the cluster-heads to be sustainable and in order to prolong the network lifetime. Optimum placement of UAVs and selection of a cluster head were achieved by using an optimization technique called the Osprey Optimization Algorithm. In the exploration stage, the candidate UAV positions were spread through the search space to better cover the population and the global search capability.

In the exploitation stage, it concentrated on the attractive solutions and enhanced the overall fitness value. Harvested energy, residual energy, Packet Delivery Ratio, and network lifetime were taken into consideration during optimization to provide a balanced network performance. Network lifetime, packet delivery ratio, energy consumption, harvested power, residual energy, cluster-head re-election frequency, and optimization convergence characteristics were used to conduct the performance evaluation. Many runs of the simulations have been carried out for different topologies, and the results presented here are the average of the various independent simulation runs. For all the experimental evaluations presented in this work, the same simulation framework, communication parameters, and optimization configuration were used for all the topology scenarios. This helped to ensure uniform evaluation conditions and allowed for the evaluation of the proposed framework under different network deployments to be carried out with consistency.

4. Results

The performance measures of harvesting of the five UAV node densities show that there is a consistent and technically significant trend of the increase in the network population growth between 10 and 50 nodes. In Table 1, When the UAV node density is 10 UAV nodes, the average power harvested $\boldsymbol{P_{total,i}}$ is 18.4 mW and RFtoDC conversion efficiency η of 72.1%, and a resultant residual energy $\boldsymbol{E_{res,i}(t)}$ of 1.74 J at 100 communication rounds. The 0.61 energy replenishment ratio at this density proves that not yet the entire harvested energy is used to compensate communication expenditure, whereas the full self-sufficiency is not yet achieved at the sparse topologies, where the distance between inter- nodes is maximally large, and the ambient RF exposure per node is diluted. The power collected on the node steadily increases to 27.9 mW, and the conversion efficiency is 76.8% that drives the replenishment ratio to 0.84 as node density is continuously increased to 30 UAVs. This change of state is the beginning of nearly balanced operation of energy, which means that the power of RF collected will start approaching the size of the per-round communication energy drain $\boldsymbol{E_{comm,i}}$. The contribution of the WiFi decreases to 41% at the same time when LTE source contribution increases to 38%, and the distance between the denser UAVs and the fixed LTE infrastructure is even more geometrical. At full load of 50 nodes, the framework has the optimal harvested power of 35.8 mW, conversion efficiency of 80.4%, and energy replenishment ratio of 0.97 that effectively attains near unity self-sustained operation. The remaining energy is at 1.47 J, which is in accordance with the fact that although collective communication load increases with increased densities, the energy amplified RF gained by harvesting WiFi, LTE, and IoT sources equally offsets increased energy spending. The source contribution of the IoT evenly reaches 22%, which proves the multi-source ambient harvesting to be a viable and scalable energy input system in the framework of the proposed OOA-RF-EH.

Table 1. RF energy harvesting performance metrics of proposed OOA-RF-EH framework under varying UAV node densities

UAV Node Count (N)	Avg. Harvested Power $P_{total,i}$ (mW)	RF-to-DC Conversion Efficiency η (%)	Residual Energy $E_{res,i}(t)$ after 100 Rounds (J)	Energy Replenishment Ratio $\frac{P_{total,i} \cdot \Delta t}{E_{comm,i}}$	Harvesting Source Contribution: WiFi / LTE / IoT (%)
10	18.4	72.1	1.74	0.61	45 / 35 / 20
20	22.7	74.3	1.68	0.73	43 / 37 / 20
30	27.9	76.8	1.61	0.84	41 / 38 / 21
40	31.5	78.2	1.55	0.91	40 / 39 / 21
50	35.8	80.4	1.47	0.97	38 / 40 / 22

The dynamics of the convergence of the OOA fitness function F and cluster head selection dynamics across 700 rounds of communication reveal several technically important operation properties of the proposed framework. In Table 2, The composite CH fitness score Ψ_i is 0.847 at round 100 with total energy used 0.312 J, network lifetime is 412 rounds, and packet delivery ratio is very strong, 96.4%. The re-elections of 3 CH are only within this initial phase, implying that there is topological stability in which elected cluster heads have enough residual energy. $E_{res,i}(t)$, That is way above the average energy threshold $\bar{E}_{avg}(t)$, hence causing the leadership to change little in the FANET. A gradual and steady tightening of the performance measures can be observed between rounds 200 and 400. The total energy consumption exceeds 1.134 J at an approximate value of 400, and Ψ_i advances to 0.889, which is a stronger indication of selective CH election with weaker nodes starting to reach the re-election threshold as it is presented in Equation (6). CH re-elections increase between 5 and 8 in this window, which proves that node energy heterogeneity increases gradually in all the network nodes as the cumulative communication load becomes unevenly distributed between cluster formations. From around 500 onward, the OOA fitness $F\ demonstrates$ particularly notable behavior rising from 0.8267 at round 500 to 0.8504 at round 700 despite simultaneous network lifetime contraction from 347 to 308 rounds. This counterintuitive enhancement is due to fitness function weights, $w_1 = 0.30$, and $w_3 = 0.30$. It is a combination of exactly rewarding the management of energy lifetime trade-off more tightly, and partially compensating for the increasing consumption by harvested power contributions. PDR stabilizes at 93.3% at round 700 with 12 CH re-elections, which validates the fact that despite operational stress over extended periods of time, the OOA remains intact in cluster integrity and communications reliability long beyond acceptable levels of QoS during the entire simulation. Figure 4, the network lifetime is decreasing gradually with the communication round 100 to 308, and OOA fitness F is increasing continuously from 0.7821 to 0.8504. This negative correlation proves the fact that the proposed framework supports the stable cluster formation and QoS maintenance during the long-term energy consumption stress during the long-term FANET operation. Figure 5 illustrates the gradual variation in packet delivery ratio as communication rounds increase. The proposed OOA-RF-EH framework consistently maintains reliable packet transmission, demonstrating robust communication stability and sustained network performance throughout prolonged operation. Figure 6 demonstrates the relationship between composite cluster-head fitness and total energy consumption throughout successive communication rounds. The proposed framework maintains adaptive cluster-head optimization while efficiently managing cumulative network energy utilization.

Table 2. OOA-based multi-objective fitness convergence and cluster head selection performance across communication rounds

Communication Round	Network Lifetime $T_{lifetime}$(rounds)	Composite CH Fitness Score Ψ_i(max)	Total Energy Consumed E_{total}(J)	Packet Delivery Ratio δ_{QoS}(%)	No. of CH Re-elections	OOA Fitness F
100	412	0.847	0.312	96.4	3	0.7821
200	398	0.861	0.598	95.7	5	0.7934
300	381	0.874	0.871	95.1	6	0.8012
400	364	0.889	1.134	94.6	8	0.8145
500	347	0.902	1.389	94.2	9	0.8267
600	329	0.918	1.621	93.8	11	0.8391
700	308	0.931	1.847	93.3	12	0.8504

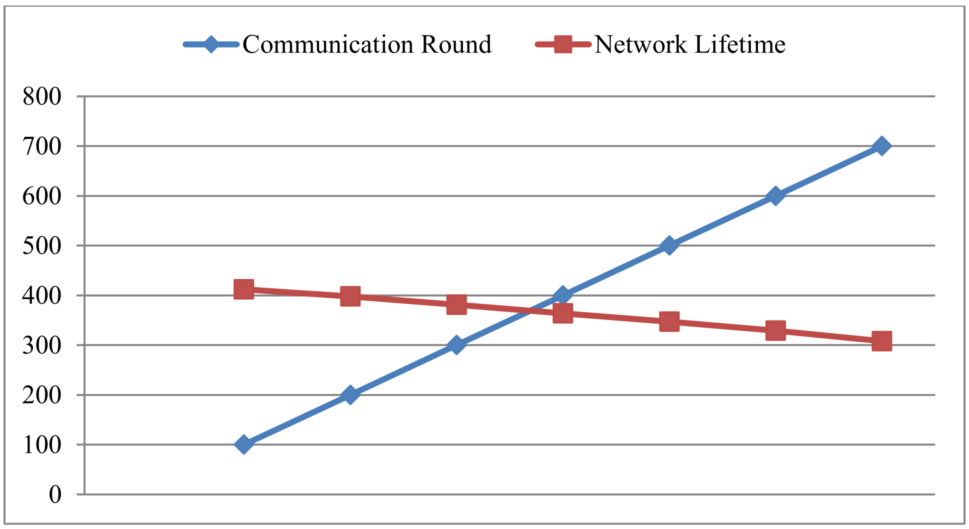

Fig. 4 OOA fitness convergence vs. Network lifetime across communication rounds

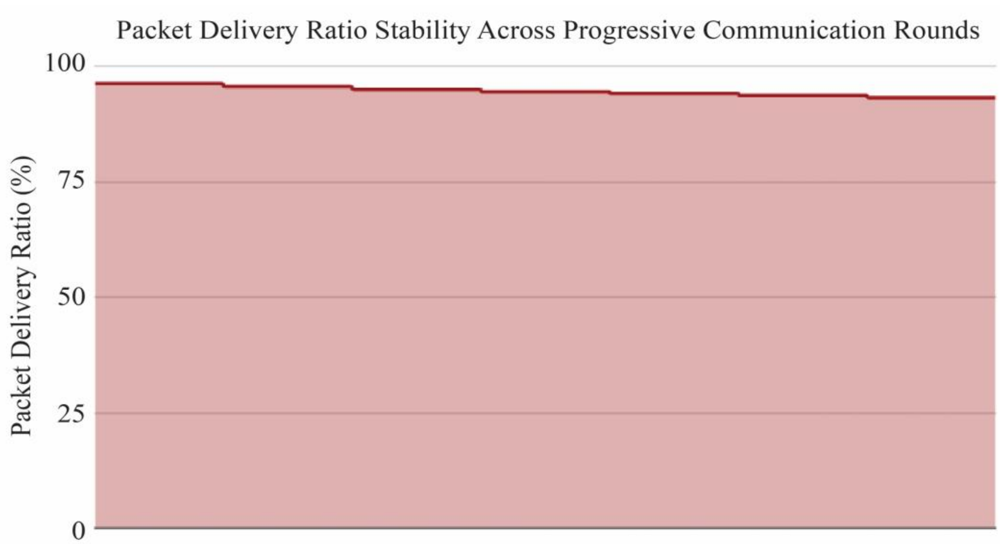

Fig. 5 Packet delivery ratio stability across progressive communication rounds

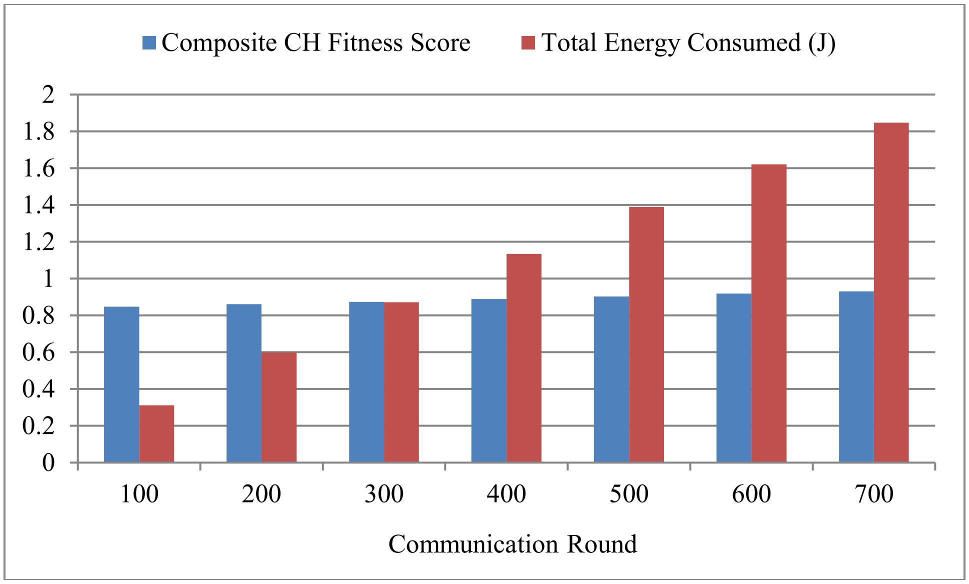

Fig. 6 Relationship between composite cluster-head fitness and total energy consumption across communication rounds

The performance metrics available in literature and the ones achieved by the developed OOA-RF-EH framework are compared in Table 3 in a balanced way in order to have a representative comparison of different energy-efficient clustering approaches. The reported numerical results are reported in the format in which it is given in the various published studies because the numerical results are relevant to the specific wireless network architectures, optimization objectives, simulation platforms, and baseline algorithms used in each study. Both Somula et al. [17] and Sennan et al. [18] used relative improvements with respect to their own baseline algorithms, while the proposed OOA-RF-EH framework reported absolute performance numbers within the adopted and adopted NS-3.38 simulation environment. There are also several recent works which focus on other specific aspects of the problem, such as energy harvesting capability, routing efficiency or UAV deployment strategies, but do not explicitly report on values of network lifetime or packet delivery comparable to those reported here. This means that their published results are presented exactly as stated in the original articles in the table. The numerical values are not intended to be interpreted as a direct comparison, as they depend on the differences in simulation environments and node deployment models, communication protocols, optimization objectives, and evaluation methodologies. Rather, Table 3 offers a summary of the performance of the performance indicators reported in typical studies as well as the performance of the proposed framework when evaluated in its own framework. The proposed OOA-RF-EH framework resulted in the lifetime of the network 347–412 communication rounds with average energy consumption of 0.0024 J/round using the adopted NS-3 simulation scenario and gained a PDR of 94.2–96.4%. These results are presented in order to show the performance of the proposed framework, in its own experimental setup, and not to assert numerical superiority over experimental setups that were different - Figure 7. The comparison is represented using a feature-based visualization, where supported capabilities are indicated using binary representation (1 = supported, 0 = not reported). This provides a meaningful comparison of the methodological contributions of different approaches without incorrectly combining incompatible performance metrics. The reported results from existing studies are obtained using different network configurations, optimization objectives, baseline algorithms, and simulation environments. Therefore, the numerical values presented in Table 3 should not be interpreted as a direct head-to-head performance comparison. The table is intended to summarize the reported evaluation metrics and methodological characteristics of existing approaches, while the performance of the proposed OOA-RF-EH framework is evaluated independently under the adopted NS-3.38 simulation environment.

Table 3. Comparative summary of reported performance metrics in representative energy-efficient clustering frameworks

Metrics	Network Type	Optimization Method	Simulation Platform	Performance Reporting Method	RF Energy Harvesting	UAV Mobility
Somula et al. [17]	WSN-IoT	Osprey Optimization Algorithm	MATLAB R2019a	Relative improvement over LEACH (+10% Network Lifetime, +10% PDR)	No	No

Sennan et al. [18]	WSN-IoT	Fuzzy Harris Hawks Optimization	MATLAB R2019a	Relative improvement over comparison methods (+18–44% Network Lifetime, +5–20% Throughput)	No	No
Vikhyath and Achyutha Prasad [24]	WSN	Tuna-Osprey Optimization with Deep Learning	MATLAB	Absolute performance reported under independent simulation settings	No	No
Kumar et al. [21]	UAV Wireless Network	PPO-Based RIS Energy Harvesting Optimization	MATLAB	Absolute energy harvesting performance under independent simulation settings	Yes	Yes
Zhang et al. [22]	IRS-Assisted UAV Network	Energy-Efficient Resource Allocation	MATLAB	Absolute energy efficiency reported under independent simulation settings	No	Yes
Proposed OOA-RF-EH	UAV-FANET-IoT	Multi-Objective Osprey Optimization + RF Energy Harvesting	NS-3.38 + MATLAB R2023a	Absolute performance under NS-3 simulation (347–412 rounds, 94.2–96.4% PDR, 0.0024 J/round)	Yes	Yes

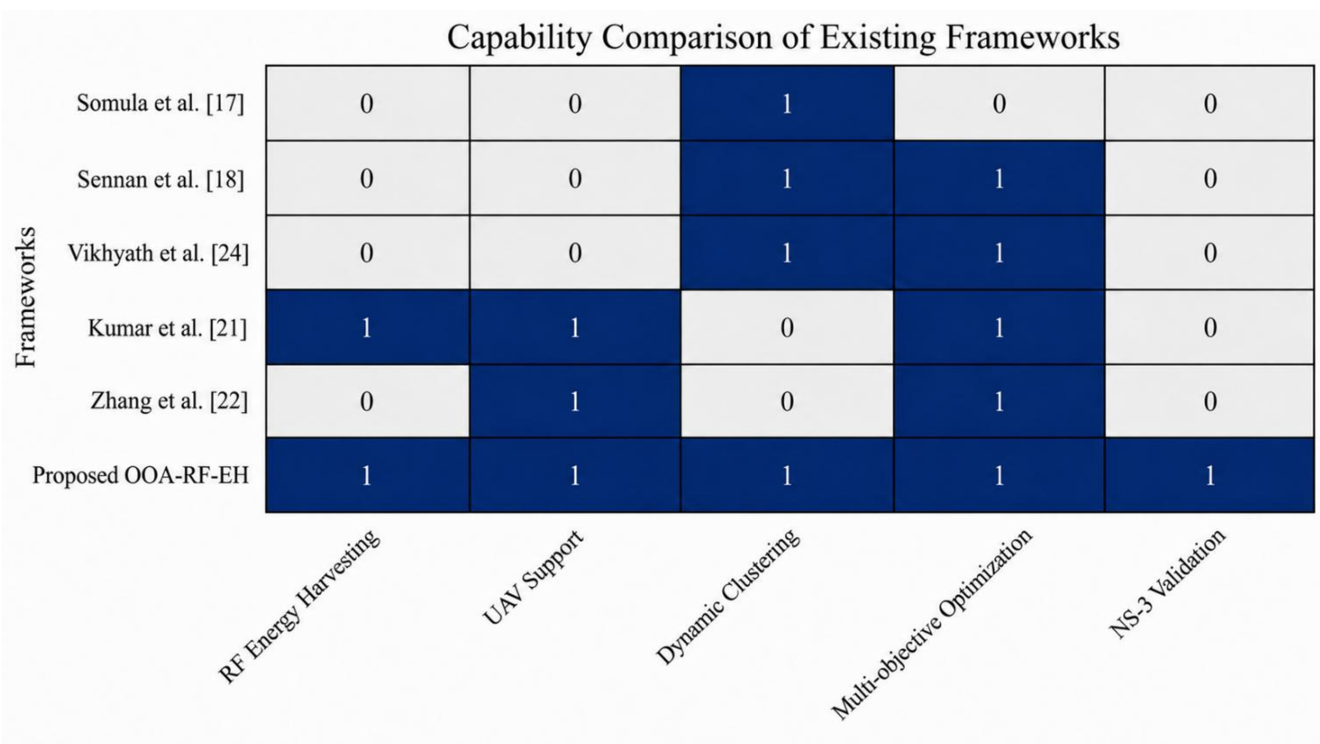

Fig. 7 Capability-based comparison of existing energy-efficient UAV/WSN frameworks

5. Conclusion

It proposed an Osprey Optimization Algorithm-based multi-objective Radio Frequency Energy Harvesting framework of sustainable clustering and UAV placement in Flying Ad Hoc Networks. It was a three-dimensional positioning of UAVs, selection of the cluster head based on a composite fitness score. $\boldsymbol{\Psi_i}$, and energy sustainability based on a four-objective fitness function F balancing harvested power, residual power, network lifetime, and the ratio of packets delivered, which were proposed to optimize. It was found that the OOA efficiently converged between 200 iterations with P=30 population size and generated the optimal UAV-cluster design using dual-phase exploration and exploitation dynamics. For all the experimental evaluations presented in this work, the same simulation framework, communication parameters, and optimization configuration were used for all the topology scenarios. This helped to ensure uniform evaluation conditions and allowed for the evaluation of the proposed framework under different network deployments to be carried out with consistency. The energy replenishment ratio of 0.97 obtained for the evaluated UAV deployment demonstrates the effectiveness of the proposed RF energy harvesting mechanism in supporting sustainable network operation. Further developments will further expand the framework to include heterogeneous RF source settings, such as millimeter-wave (mmWave) and 5G signal harvesting, the dynamic re-election of CHs through reinforcement learning, and hardware-in-loop validation of the work under uncertain conditions posed by mobility in physical UAV testbeds.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

References

[1] Zaheer Aslam et al., "An Intelligent Bio-Inspired Multi-Objective and Scalable UAV-Assisted Clustering Algorithm in Flying Ad Hoc Networks," *Scientific Reports*, vol. 16, pp. 1-26, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[2] Nguyen Thanh Nam, Truong Van Truong, and Ha Huy Hung, "Energy and Security Analysis of a Radio Frequency Energy Harvesting UAV-NOMA MEC Network with a Passive Eavesdropper," *ETRI Journal*, vol. 48, no. 3, pp. 391-570, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[3] Awadhesh Dixit, and Sunil Kumar Singh, "Bio-Inspired Optimal Path Planning for UAVs with Obstacle Avoidance and Energy Efficiency," *Cluster Computing*, vol. 29, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[4] Haipeng Yao, and Tianle Mai, *Intelligent UAV Swarm Network Resource Scheduling*, UAV Swarm Cooperation: A Networking Perspective, pp. 89-124, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[5] Babacar Toure et al., "Optimizing Energy and Data Collection in UAV-Aided IoT Networks Using Attention-Based Multi-Objective Reinforcement Learning," *IEEE Internet of Things Journal*, vol. 13, no. 15, pp. 32565-32577, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[6] Jian Tang et al., "Joint Design of UAV Energy Harvesting and Heterogeneous User Communications Based on Dynamic STAR-RIS Partitioning," *Scientific Reports*, vol. 16, pp. 1-12, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[7] Parisa Khoshvaght et al., "Computational Intelligence-Based Routing Schemes in Flying Ad Hoc Networks (FANETs)," *Vehicular Communications*, vol. 53, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[8] Gaurav Kumar Pandey et al., "UAV-Assisted Communications With RF Energy Harvesting: A Comprehensive Survey," *IEEE Communications Surveys & Tutorials*, vol. 27, no. 2, pp. 782-838, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[9] Iman Dakhil Idan Saeedi, and Ali Kadhum M. Al-Qurabat, "Integrated Clustering and Optimization for IoT Sensor Networks in Space–Air-Ground Frameworks: A Focus on Energy Savings," *International Journal of Communication Systems*, vol. 38, no. 10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[10] Juhi Agrawal, and Muhammad Yeasir Arafat, "Bio-Inspired Algorithms for Efficient Clustering and Routing in Flying Ad Hoc Networks," *Sensors*, vol. 25, no. 1, pp. 1-25, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[11] Xu Zhu, Junyu He, and Ming Zhao, "Adaptive Multi-Objective Optimization for UAV-Assisted Wireless Powered IoT Networks," *Information*, vol. 16, no. 10, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[12] Yu Gu, Hongbing Qiu, and Baoqing Chen, "AoI-Minimal Task Assignment and Trajectory Optimization in Multi-UAV-Assisted Wireless Powered IoT Networks," *Drones*, vol. 9, no. 2, pp. 1-28, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[13] P. Rajakumar et al., "Osprey Optimization Algorithm for Distributed Generation Integration in a Radial Distribution System for Power Loss Reduction," *Scientific Reports*, vol. 15, pp. 1-19, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[14] Stella N. Arinze et al., "RF Energy-Harvesting Techniques: Applications, Recent Developments, Challenges, and Future Opportunities," *Telecom*, vol. 6, no. 3, pp. 1-40, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Zheng Zhang, Xiangkun Wang, and Yinggao Yue, "Heuristic Optimization Algorithm of Black-Winged Kite Fused with Osprey and Its Engineering Application," *Biomimetics*, vol. 9, no. 10, pp. 1-23, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Koteeswaran Seerangan et al., "A Novel Energy-Efficiency Framework for UAV-Assisted Networks Using Adaptive Deep Reinforcement Learning," *Scientific Reports*, vol. 14, pp. 1-23, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Ramasubbareddy Somula, Yongyun Cho, and Bhabendu Kumar Mohanta, “SWARAM: Osprey Optimization Algorithm-Based Energy-Efficient Cluster Head Selection for Wireless Sensor Network-Based Internet of Things,” *Sensors*, vol. 24, no. 2, pp. 1-19, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Sankar Sennan et al., “Energy-Efficient Cluster Head Selection in Wireless Sensor Networks-Based Internet of Things (IoT) Using Fuzzy-Based Harris Hawks Optimization,” *Telecommunication Systems*, vol. 87, pp. 119-135, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Xiaodong Wen et al., “IOOA: A Multi-Strategy Fusion Improved Osprey Optimization Algorithm for Global Optimization,” *Electronic Research Archive*, vol. 32, no. 3, pp. 2033-2074, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] T. Gopala, and V. Raviram, “Tuna-Osprey Optimization for Energy Efficient Cluster-Based Routing: Modified Deep Learning for Node's Energy Prediction,” *International Journal of Intelligent Systems and Applications in Engineering*, vol. 12, no. 21s, pp. 1102-1110, 2024. [Publisher Link]

[21] Praveen Kumar et al., “Maximizing Energy Harvesting With the Aid of Reconfigurable Intelligent Surface for UAV Using Proximal Policy Optimization Algorithm,” *Wireless Personal Communications*, vol. 139, pp. 2253-2283, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Shuang Zhang et al., “Energy Efficient Resource Allocation of IRS-Assisted UAV Network,” *Electronic Research Archive*, vol. 32, no. 7, pp. 4753-4771, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Majd Shakhatreh, Hazim Shakhatreh, and Ahmad Ababneh, “Efficient 3D Positioning of UAVs and User Association Based on Hybrid PSO-K-Means Clustering Algorithm in Future Wireless Networks,” *Mobile Information Systems*, vol. 2023, no. 1, pp. 1-11, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Kotagi Basavarajappa Vikhyath, and Narasimhaiah Achyutha Prasad, “Combined Osprey-Chimp Optimization for Cluster-Based Routing in Wireless Sensor Networks: Improved DeepMaxout for Node Energy Prediction,” *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12314-12319, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[25] T. Rehannara Beegum et al., “Optimized Routing of UAVs Using Bio-Inspired Algorithm in FANET: A Systematic Review,” *IEEE Access*, vol. 11, pp. 15588-15622, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[26] Siji Chen et al., “Firefly Swarm Intelligence Based Cooperative Localization and Automatic Clustering for Indoor FANETs,” *Plos One*, vol. 18, no. 3, pp. 1-29, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[27] Attai Ibrahim Abubakar et al., “A Survey on Energy Optimization Techniques in UAV-Based Cellular Networks: From Conventional to Machine Learning Approaches,” *Drones*, vol. 7, no. 3, pp. 1-69, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[28] Mohammad Dehghani, and Pavel Trojovský, “Osprey Optimization Algorithm: A New Bio-Inspired Metaheuristic Algorithm for Solving Engineering Optimization Problems,” *Frontiers in Mechanical Engineering*, vol. 8, pp. 1-43, 2023. [CrossRef] [Google Scholar] [Publisher Link]