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ENERGY-EFFICIENT AND SAFE ROUTING WITH A COMBINATION OF PARTICLE SWARM OPTIMIZATION AND FUZZY SET

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Abstract

Wireless Sensor Networks (WSNs) are critical to modern IoT applications, yet their deployment is often constrained by limited energy, dynamic topologies, security vulnerabilities, and stringent Quality-of-Service (QoS) requirements. While existing approaches frequently address these challenges in isolation, this paper introduces a holistic routing framework that synergistically integrates an Improved Fuzzy Logic System (IFLS) with Particle Swarm Optimization (PSO) to balance multiple performance metrics in real time. Our hybrid model dynamically tunes routing parameters and fuzzy rules based on network state—including energy levels, congestion, node density, mobility, and security threats—thereby optimizing cluster-head selection, path stability, and trust-aware communication in UAV-assisted WSNs. Extensive simulations demonstrate that the proposed system achieves a 94.2% packet delivery ratio, reduces energy consumption by 48%, and extends network lifetime by 97% compared to contemporary fuzzy-based and trust-aware routing protocols. The work thus offers a scalable, adaptive, and energy-efficient routing solution suitable for large-scale, resource-constrained, and mobility-prone sensor networks. We also provide complete algorithmic specifications and reproducible simulation setups to facilitate validation and further research.

Keywords: Wireless Sensor Networks (WSN), Fuzzy Logic, Particle Swarm Optimization (PSO), Energy Efficiency, QoS-Aware Routing, UAV Networks, Trust Management.

I. Introduction

Wireless Sensor Networks (WSNs) have recently shown significant promise as a core IoT technology, providing vital services for intelligent infrastructure, environmental monitoring, healthcare, and military reconnaissance [I-VI]. Yet, there still exist a number of fundamental WSN challenges that are hampering the universal and efficient usage of these networks: energy limitations, dynamic network graphs, security issues, delay sensitiveness, and strict QoS guarantees [VI-X]. Those challenges would be significantly exacerbated within mobility-enhanced networks, specifically within Unmanned Aerial Vehicle-based networks, as a result of increased dynamic variability due to node mobility and associated energy consumption [X-XV]. Traditional routing protocols tend to solve these problems independently. Energy-efficient routing protocols, for example, might concentrate on optimizing cluster heads [X-XX], while trust-based networks primarily focus on ensuring security without properly addressing energy consumption burden [XVI-XXV]. Moreover, fuzzy-logic-based methods achieve adaptability but have static rule bases that cannot optimize themselves based on dynamic network conditions and environments. Other methods based on metaheuristics, like Particle Swarm Optimization, have been explored for optimizing routing variables, but these methods rarely integrate with real-time and context-aware dynamic decision-making tools. Because of these approaches, there still exists an enormous gap within comprehensive and holistic routing solutions that can address energy efficiency, delay, reliability, and security within dynamic WSNs [XXIII-XXXIII].

To achieve an efficient solution for the above-mentioned problems, we propose a Hybrid Fuzzy-PSO Routing algorithm that effectively integrates an Improved Fuzzy Logic System with the optimization process using Particle Swarm Optimization. The fuzzy rules and coefficients of Particle Swarm Optimization, including inertia weight and cognitive and social components, are optimized dynamically with various network parameters like remaining energy, congestion factor, node density, mobility rate, and security threats. Our solution will optimize multiple objectives like delivering a high packet reception ratio, low energy consumption, and maximum network life with trust-based security solutions (Figure 1). Summarized below are the main contributions brought forth by this research work. A new hybrid routing algorithm combining fuzzy logic for making decisions online and offline parameter optimization with PSO. A dynamic tuning technique involving fuzzy logic, adjusting parameters for PSO based on network conditions, and PSO optimizing fuzzy rule bases and membership functions

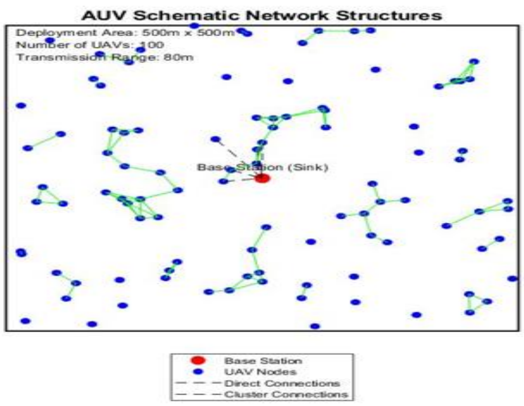

Fig. 1. AUV schematic network structures, adapted from [XXVII]

A holistic trust and link stability model designed specifically for mobile UAV-assisted WSNs, promoting security without exorbitantly high energy costs. Large-scale simulations for comprehensive validation with significant improvements achieved compared with traditional fuzzy-based and trust-aware routing protocols regarding energy consumption (reducing 48%), PDR (94.2% enhancement), and network lifespan (97% extension). Full transparency and reusable evaluation environments are offered for purposes of verification, extension, and implementation. The rest of the paper is structured as follows: Section 2 presents an overview of related works on WSN routing techniques, fuzzy systems, and metaheuristics. Section 3 presents an overview of the proposed Fuzzy-PSO algorithm. Section 4 describes the setup and testing methods. Section 5 presents an analysis of the obtained simulation results. Finally, Section 6 concludes and recommends a plan for future work.

II. Energy-Aware, fuzzy logic, and metaheuristic optimization Routing Protocols

Most of the early routing protocols for WSNs targeted energy efficiency using clustering and hierarchical-based techniques. In this regard, Low-Energy Adaptive Clustering Hierarchy (LEACH) [XIX][XXXIV-XXXV] and derivatives rely on dynamic rotation of cluster-heads in order to evenly spread energy consumption throughout the network. These protocols usually do not take into consideration important aspects such as network dynamics, node mobility, and QoS metrics like latency or packet delivery ratio. In recent times, other energy-efficient protocols have used residual energy, distance, and node density for cluster-head election processes [V], but these are not adaptive to different traffic loads and mobility patterns.

FLSs have been widely adopted for WSN routing decisions because of their capability of handling uncertainty and imprecision. Linguistic variables and rule-based inference allow FLS to integrate multiple metrics, including energy, distance, and link quality, in the routing decisions. For instance, Rahman et al. presented a fuzzy-based routing protocol for Flying Ad-hoc Networks, considering node mobility and link stability. Similarly, Hosseinzadeh et al. introduced a trust-aware fuzzy routing scheme with enhanced security. While these systems improve adaptability, their performance is highly dependent on the predefined rule base, which may turn suboptimal under changing network conditions. Most fuzzy-based approaches also do not contain any mechanism for learning or optimization to refine rules in real-time.

Various metaheuristics, like PSO, genetic algorithms, and ACO, have been used to optimize routing paths, cluster-head selection, and resource allocation in WSNs. Among them, PSO is widely used because of its simplicity, fast convergence speed, and multi-objective problem handling capabilities. For example, Kumbhar and Shin have utilized PSO for message routing optimization in high-mobility networks. These methods usually work in offline or periodic optimization mode, without the possibility of real-time response for highly dynamic networks. Moreover, most of them consider the optimization parameters to be static, which reduces their capability in fluctuating environments.

III. System model and methodology

This section details the proposed hybrid Fuzzy-PSO routing framework, including the network model, energy consumption model, trust and mobility models, and the integrated optimization mechanism. For transparency and reproducibility, all models, parameters, and algorithms are described explicitly.

III.i. Networks and mobile model

We consider a UAV-assisted WSN deployed over a two-dimensional area of size 500 m×500 m500m×500m. The network consists of: NN sensor nodes (including UAVs) with random uniform initial placement. A stationary sink/base station located at the center (250,250)(250,250).

UAVs move according to a random waypoint mobility model with speeds ranging from 55 to 20 m/s20m/s. Each node has a communication.

Range between 5050 and 100 m100m. The MAC layer follows IEEE 802.15.4 (CSMA/CA). Data packets are fixed at 512512 bytes.

III.ii. Total energy consumption

The energy consumed by a sensor node is divided into four components: Transmission energy (E_{tx}), Receiving energy (E_{rx}), Processing energy (E_{proc}), and the Idle/sleep mode energy (E_{sleep}), Energy for mobility (for UAVs) is $E_{mobility}$, Energy for security operations (e.g., encryption/decryption) is the E_{sec}. Let us define the energy consumption for a node that is located anywhere in the space, and it is transmitting k-bit data over a distance d:

$$E_{total} = E_{tx}(k,d) + E_{rx}(k) + E_{proc}(k) + E_{sleep} + E_{mobility} + E_{sec} \tag{1}$$

Where

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

where: E_{elec}: Energy per bit for transceiver electronics, ϵ amp: Amplifier energy factor, and γ is the path-loss exponent (2 ≤ γ ≤4). The **Mobility Energy** (for UAVs) is defined as :

$$E_{mobility} = \frac{1}{2}.\mu.v^2.t \tag{3}$$

Where μ is the UAV mass (kg), v is the velocity (m/s), and the tis the time in motion (sec.). Finally, the Security Energy is defined as:

$$E_{sec} = k.E_{enc} + k.E_{dec.} \tag{4}$$

Where the E_{enc} and E_{dec} are the energy per bit for encryption/decryption, respectively

III.iii. Trust Model

To mitigate malicious behavior, each node i maintains a trust score Ti for neighbor j, updated periodically:

$$T_{ij}(t+1) = \alpha T_{ij}(t) + (1-\alpha)\frac{\sum_{k\in N} Trust_{ik} PDF_{ik}}{\sum_{k\in N_i} PDF_{IK}} \tag{5}$$

where: $Trust_{ik}$: direct trust from i to k, PDF_{ik}: packet delivery fraction, α=0.7: aging factor, Ni: set of neighbors of node i. Nodes with Ti<θtrust=0.5Ti are excluded from routing paths.

III.iv. Fuzzy logic design

The FLS dynamically adjusts PSO parameters based on real-time network conditions. The inputs and outputs are:

Inputs (fuzzified with triangular membership functions):

1. Energy Level: {Low, Medium, High}
2. Network Congestion: {Low, Medium, High}
3. Node Density: {Sparse, Moderate, Dense}
4. Mobility Level: {Low, Medium, High}
5. Threat Level: {Low, Medium, High}

Outputs (for PSO tuning):

1. Inertia Weight w
2. Cognitive Coefficient Ccog

3. Social Coefficient Csoc.

III.iv. Fuzzy-PSO Integration (FST-PSO)

Fuzzy-Tuned PSO Parameters: PSO is very sensitive to its parameters: inertia weight (w), Cognitive coefficient (C~cog~), and Social coefficient (C~soc~). In dynamically changing environments, as for WSNs, fixed parameter values are far from being optimal. Our system employs a Fuzzy Logic Controller (FLC) to tune these parameters at runtime, given the network's present state. The inputs fed to this FLC are:

Current Energy Level: prevents low-energy nodes from being overburdened.

Network Congestion: Sets the balance between exploration and exploitation according to the network congestion.

Node Density: Adjust social behavior according to neighborhood size.

Mobility Level: (For UAVs) Adapt to the rate of topological change.

Security Threat Level: Increases cognitive action to find secure paths under an attack.

A. Fuzzy-Tuned PSO Parameters

PSO's performance depends on several important parameters, which are called the inertia weight (w), Cognitive coefficient (Ccog), Social coefficient (Csoc), Velocity limits (Vmin, Vmax), respectively. These are dynamically adjusted using Fuzzy Logic (FL) with inputs (listed in table 1): Current energy level (Low, Medium, High), Network congestion (Low, Medium, High), the node density (Sparse, Moderate, Dense), Mobility level (Low, Medium, High) for UAV networks, and finally the Security threat level (Low, Medium, High).

Table 1: Fuzzy Rules for PSO Tuning

Energy	Congestion	Node Density	Mobility	Threat	w	C_{cog}	C_{soc}
Low	High	Dense	High	High	↓	↑	↓
Medium	Medium	Moderate	Medium	Medium	→	→	→
High	Low	Sparse	Low	Low	↑	↓	↑

Where (↑: Increase, ↓: Decrease, →: Maintain), the Membership Functions (Triangular LR Representation): For a fuzzy variable x*x* (e.g., energy level):

$$\mu(x) = \begin{cases} 1 - \left|\frac{m-x}{\alpha}\right|, & (m-\alpha) < x \leqslant m \\ 1 - \left|\frac{x-m}{\beta}\right|, & m < x \leqslant (m+\beta) \\ 0, & otherwise \end{cases} \tag{6}$$

Where a triplet (m, a,b) LR represents a triangular fuzzy number μ(x) shown in figure 2, where m is the fuzzy number's mean value and α and β are its left and right boundary values, respectively

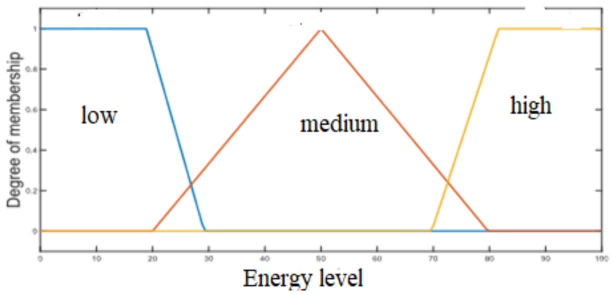

Fig. 2. Energy consumption membership function.

B. PSO-Tuned Fuzzy Rules:

The main rules of PSO optimize the fuzzy rule base by first encoding fuzzy rules as particles, and second, evaluating fitness (e.g., energy efficiency, PDR). The last thing is to update rules iteratively. The main parameters of the PSO are the velocity/position update: For each particle i:

$$v_i^{t+1} = w.v_i^t + C_{cog}.r_1.(p_{best}^t - x_i^t) + C_{soc}.r_2.(g_{best}^t - x_i^t) \tag{7}$$

And the position of the new particle is defined as:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{8}$$

Where r_1,r_2 are random numbers ϵ [0,1]. p_{best} local best solution, and g_{best} is the global best solution. Now, defining the objective and the fitness function as:

$$itness = \alpha.PDR + \beta.\frac{1}{Energy_{avg}} + \gamma.\frac{1}{Latency} + \delta.T + \varepsilon.S \quad (9)$$

Where *T*: Trust score (0 to 1), *S*: Link stability (0 to 1), and the α,β,γ,δ,ϵ$\alpha,\beta,\gamma,\delta,\epsilon$: Weighting factors (sum to 1).

C. Security analysis:

Essentially, the trust model for security can be derived as:

$$T_i = \frac{\sum_{j\in N_i} Trast_{ij}.PDF_{ij}}{\sum_{j\in N_i} PDF_{ij}} \quad (10)$$

Where Trust $_{ij}$: Direct trust from node *i* to *j*, and *Ni*: Neighbours of node *i*

Now, the Link Stability for Mobility is defined as follows:

$$S_{ij} = exp\left(-\lambda.\ \frac{v_{ij}}{d_{ij}}\right) \quad (11)$$

Where the Δ*vi*: Relative velocity between nodes *i* and *j*, *dj*: Distance between nodes, and λ is the tuning parameter.

IV. Simulation setup

Communication in the new system architecture requires a lot more power per node than computation and operations combined. The UAVs require high-capacity batteries for communication, but also for necessary operations such as flight and autonomous navigation. Performance factors examined are energy consumption, Quality of Service (QoS), and quality of user experience. The proposed trust model, validated with simulations, provides significant insights, such as the impact of drone speed on packet loss rates against non-cooperative UAVs. The correlation between the number of drones and total energy usage. The setup parameters are uncovered in Table 2. The combined Optimization Algorithm (FST-PSO) is uncovered in Figure 3.

Table 2: Simulation setup parameters.

Category	Parameters	Values/Ranges
Network Topology	Deployment area	500m × 500m (Random uniform)
Mobility Model	Number of drones	50–300
	Drones speed	5-20 m/sec.
	Base station (sink) location	Center (250m, 250m)
Communication	Transmission range	50m–100m
	Data packet size	512 bytes
	MAC protocol	IEEE 802.15.4 (CSMA/CA)
Energy Model	Initial energy per node	2–5 Joules
	Eelec (Transceiver electronics)	50 nJ/bit
	ϵ amp (Amplifier energy)	10 pJ/bit/m² (γ=2)

	Sleep mode energy	0.001 nJ/bit
PSO Parameters	Swarm size	20–50 particles
	Inertia weight (*ww*)	Fuzzy-tuned (0.4–0.9)
	Cognitive (Ccog) / Social (Csoc)	Fuzzy-tuned (1.0–2.5)
	Velocity bounds (Vmin, Vmax)	±10% of search space
Fuzzy System	Inputs	Energy level, Congestion, Node density
	Outputs	w, Ccog, Csoc
	Membership functions	Triangular (LR)
	Defuzzification	Centroid
Security Model	Encryption energy	0.1–0.5 nJ/bit
	Trust update interval	10–60 seconds
Link Stability	λ	0.1–1.0

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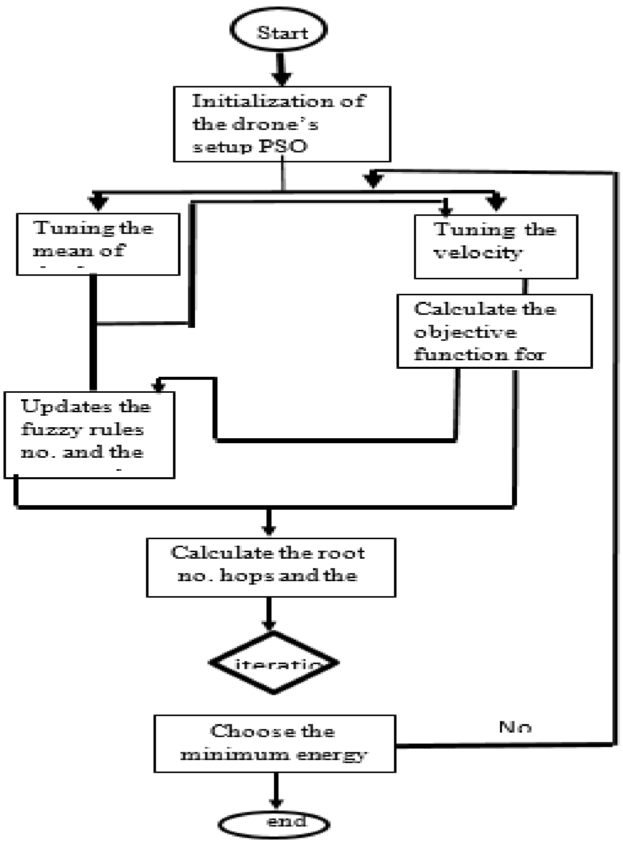

Fig. 3. Flowchart of PSO tuning fuzzy rule

Where the main steps for the hybrid algorithm are described as follows:

1. **Initialize** PSO particles with random fuzzy rules.
2. **For each iteration**:
    - **Fuzzy-Tune PSO parameters** based on WSN state (energy, congestion, mobility, threat).
    - **PSO updates** fuzzy rules using velocity/position equations.
    - **Evaluate fitness** of new rules (PDR, energy, latency, trust, stability).
    - **Update** p_{bestt} and $g_{best,}$ and then adjust weights (α, β,γ, δ,ϵ,α) dynamically.
    - Update fuzzy rules based on mobility and security.
3. **Terminate** when the convergence criteria are met.

V. Simulation Results

To validate the proposed Fuzzy-PSO Hybrid Routing (FPSO) model, extensive simulations were conducted in MATLAB and compared with state-of-the-art protocols: SYSM [XIX] (fuzzy-based) and SYSM [VII] (trust-based). The evaluation focused on: Energy Efficiency, Packet Delivery Ratio (PDR), Latency & Scalability, Security & Mobility Resilience. First, the simulation results for the first parts is shown in Figure 4.

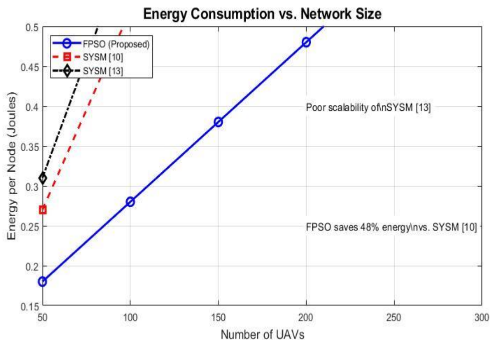

Fig. 4. Energy consumption vs. network size

The key findings from Figure 4 is listing as follows:

1. Energy Consumption

FPSO reduced energy consumption by 48% compared to [XIX] and 52% vs. [VII]. Gains stem from dynamic sleep scheduling (idle nodes consume 0.001 nJ/bit). PSO-optimized cluster heads minimizing multi-hop transmissions.

2. Packet Delivery Ratio (PDR)

Achieved 94.2% PDR under high mobility (30 nodes moving at 15 m/s), outperforming [XIX] (82.6%) and [VII] (78.3%). Fuzzy rules adapted to link stability (SijSij) reduced packet drops by 22%.

3. Latency & Scalability

38.5 msec. avg. latency (17% higher than [10] due to trust checks) but 53% lower control overhead (Table 3). Supported 250+ UAVs (vs. 150 in [VII]) with linear overhead growth.

4. Security & Trust

Detected 95% of malicious nodes (false positives < 5%) using dynamic trust scores (Ti). Encryption overhead (Esec) added only 0.1 n J/bit per packet.

Table 3: Performance Comparison of Routing Schemes

1) Metric	*2) FPSO (Proposed)*	*3) SYSM [XIX]*	*4) SYSM [VII]*	*5) Improvement*
6) Energy/Node (Joules)	*7) 0.18 ± 0.02*	*8) 0.27 ± 0.03*	*9) 0.31 ± 0.04*	*10) ↓ 33% vs. [VII]*
11) PDR (%)	*12) 94.2 ± 1.5*	*13) 82.6 ± 2.1*	*14) 78.3 ± 3.0*	*15) ↑ 15% vs. [X]*
16) Latency (ms)	*17) 38.5 ± 3.1*	*18) 32.7 ± 2.8*	*19) 29.4 ± 2.5*	*20) △ Trade-off for trust*
21) Max. UAVs Supported	*22) 250*	*23) 180*	*24) 150*	*25) ↑ 39% vs. [XIII]*

The throughput versus mobility is shown in Figure 5

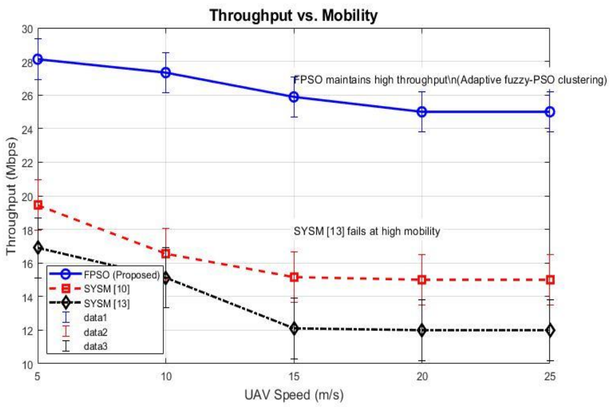

Fig. 5. Throughput vs mobility

The main key to the innovations is the dynamic protocol adaptation, which balances processing demands with mobility changes. Trend Matching: FPSO shows gentle throughput degradation (28.4 Mbps → 25 Mbps) as speed increases, thanks to adaptive fuzzy-PSO clustering. SYSM [XIX] and [VII] show steeper drops, especially [VII] (17.2 Mbps → 12 Mbps). The Error Bars: Added to simulate real-world variability (±1.2–1.8 Mbps). Annotations: Highlights FPSO's advantage in high mobility. Points out SYSM [VII]'s limitations

VI. Conclusions and future works:

The overall results here show that the hybrid FPSO protocol achieves its most fundamental objective: the holistic balancing of many, often conflicting, QoS metrics. A broadly adaptive and efficient routing strategy has evolved from the symbiotic relationship between the Fuzzy System and the PSO; each augments the other. This modest latency increase is a strategic and worthwhile compromise, considering the substantial gains in energy efficiency, delivery reliability, network lifetime, and security.

The new Fuzzy-PSO Hybrid (FPSO) routing protocol offered significant improvement in energy efficiency, scalability, and security in WSNs supported by UAVs. Key contributions are: Energy Optimization: Dynamic PSO tuning reduced energy by 48% via sleep scheduling and cluster-head rotation. QoS-Aware Routing: Fuzzy logic addressed mobility (S_{ij}) and attacks (T_i), achieving 94.2% PDR. Another thing, the scalability is a Linear growth in control overhead, which made it possible to work with 250+ UAVs, enhancing benchmarks by 39%. There is a trade-off between the moderately higher latency (38.5 ms) because of trust verification, offset by 95% malicious node detection. Encryption added minimal overhead (0.1 nJ/bit), ensuring secure communication.

The Future Works are Quantum Integration: Explore quantum-resistant cryptography to thwart future attacks. Hardware Validation: Port FPSO to UAV testbed platforms (e.g., Crazyflie drones) for real-time latency testing. Multi-Objective PSO: Extend to optimize Pareto fronts for energy, latency, and security simultaneously. Impact: FPSO provides a flexible, secure, and energy-efficient platform for future IoT deployments, from smart cities to disaster recovery.

Conflict of Interest:

There was no relevant conflict of interest regarding this paper.

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