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A Novel Clustering-Based Scheme for Wildfire Monitoring in Flying Ad Hoc Networks

Samson Bitrus Visa[1], Caleb Gasin Sunday[2], Abubakar Abdulkadir[3]
[1,2]Ahmadu Bello University Zaria, Kaduna State, Nigeria
[3]Federal Polytechnic Bauchi, Bauchi State, Nigeria
samsonbitrusvisa@gmail.com; aabubakar@engineering.abu.edu.ng

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Abstract

This study addresses energy consumption limitations and network overhead in cluster formation within Flying Ad Hoc Networks (FANETs), a type of Wireless Sensor Network (WSN) commonly used for wildfire monitoring. FANETs consist of mobile nodes, represented by Unmanned Aerial Vehicles (UAVs), communicating in a self-organized manner, with clustering playing a crucial role in improving scalability and resource management. This work proposes an Energy Efficient Wildfire Monitoring Scheme (EEWMS) to optimize Cluster Head (CH) selection and reduce the energy costs of cluster formation. The scheme incorporates node remaining energy, trust level, energy consumption, base station proximity, mobility, and CH coverage into a fitness function for intelligent CH selection. EEWMS was validated through simulations in the MATLAB environment, comparing its performance against existing techniques, specifically EE-SS, using metrics including energy consumption, network lifespan, and cluster formation time. The results demonstrate that EEWMS significantly enhances FANET performance, reducing cluster building time by 10.16%, increasing cluster lifetime by 6.96% and improving energy efficiency by 10.25%. These improvements underscore EEWMS's effectiveness in enhancing real-time wildfire monitoring by improving network responsiveness, extending operational periods, and ensuring reliable data transmission. The findings provide a robust solution to energy and scalability challenges, making FANETs more efficient and reliable for emergency response applications.

Keywords: Energy Consumption, Flying Ad Hoc Networks, Wildfire Monitoring, Cluster Head Selection.

INTRODUCTION

Wireless Sensor Networks (WSNs) have become crucial in a variety of applications, including agriculture, healthcare, environmental monitoring, military surveillance, and wildfire detection. These networks are capable of collecting, processing, and transmitting data from remote areas to safer locations, making them invaluable tools for managing natural disasters such as wildfires (Jibreel *et al.,* 2022). However, WSNs encounter significant energy constraints, as sensor nodes rely on non-rechargeable batteries and consume energy during the transmission, processing, and reception of data (Huang *et al.,* 2022). Ensuring energy efficiency is a critical challenge, leading to the development of various techniques such as clustering, data aggregation, and cluster-based routing protocols to mitigate this issue (Shanmugapriya & kousalya, 2023). Among these strategies, clustering has emerged as a particularly effective method for managing energy consumption by reducing the transmission range of sensors (Jibreel *et al.,* 2022).

In recent years, the emergence of Flying Ad hoc Networks (FANETs), a specialized subset of Wireless Sensor Networks (WSNs), has opened up new possibilities for real-time monitoring. FANETs utilize Unmanned Aerial Vehicles (UAVs) for self-organizing communication, offering significant advantages for wildfire detection due to their mobility, scalability, and ability to access remote areas (Bharany *et al.,* 2021). Although FANETs share certain characteristics with Mobile Ad hoc Networks (MANETs) and Vehicular Ad hoc Networks (VANETs), their high node mobility and dynamic topologies necessitate the development of innovative clustering techniques to enhance energy efficiency and overall network performance (Bharany *et al.,* 2022). The applications of FANETs span a variety of fields, including wildfire monitoring, where their rapid deployment capability and extensive aerial coverage are vital for effectively addressing emergencies (Abdulhae et al., 2022).

In Nigeria, wildfires present a significant environmental challenge, predominantly affecting the savanna regions in the northern states. The northern states, including Kaduna, Plateau, and Bauchi, experience frequent fire occurrences due to their distinct ecological characteristics and seasonal patterns (Ajayi et al., 2019). These wildfires are primarily driven by a combination of anthropogenic factors and natural conditions, including traditional agricultural practices, pastoralism, and prolonged dry seasons, rather than being solely attributed to climate change and drought (Oladele & Braimoh, 2021).

Historical data indicates that major fire incidents have occurred across different ecological zones, with the Guinea and Sudan savanna regions being particularly vulnerable. For instance, the Yankari Game Reserve in Bauchi State has documented significant fire events that have impacted wildlife habitats and biodiversity (Mohammed et al., 2018). The Nigerian government's response to wildfire management has evolved to include both traditional and modern approaches, incorporating indigenous knowledge systems alongside contemporary fire management strategies (Usman & Abdulhamid, 2020).

Despite these efforts, significant challenges persist in wildfire management across Nigeria. These include not only the previously mentioned early detection systems but also fundamental issues such as insufficient funding for forest management programs, limited technical capacity for fire prevention and control, and poor coordination among various stakeholders involved in forest protection (Bakare & Adewumi, 2022). Moreover, the effectiveness of current fire management strategies is often compromised by factors such as inadequate research data, limited community engagement, and the absence of comprehensive fire management policies at both state and federal levels (Ibrahim & Lamidi, 2021).

This research aims to create a novel, energy-efficient algorithm for wildfire monitoring utilizing Flying Ad-Hoc Networks (FANETs). The primary objective is to enhance the number of active nodes and improve packet forwarding to the base station (BS), thereby optimizing bandwidth usage. Such advancements are essential for bolstering wildfire monitoring and detection systems, with the potential to save lives and protect property during forest fire emergencies. FANETs, consisting of Unmanned Aerial Vehicles (UAVs), encounter challenges related to energy-efficient clustering. Current methodologies, such as those described by Bharany *et al.* (2022), suffer from excessive energy consumption due to inadequate cluster sizes and inefficient selection of cluster heads (CHs). This research seeks to refine the CH selection process by taking into account factors such as residual energy, trust levels, and CH coverage, to enhance clustering efficiency.

The proposed Energy Efficient Wildfire Monitoring Scheme (EEWMS) will be evaluated against the EE-SS approach based on key metrics, including cluster building time, cluster lifetime, energy efficiency, and reliability. The overarching goal of this research is to develop an Improved Wildfire Monitoring Scheme (WMS) grounded in an Energy Efficient Clustering (EEC) approach for FANETs. Specific objectives include devising a more effective CH selection method, implementing the WMS using MATLAB R2020a, and assessing its performance relative to existing techniques through metrics such as cluster building time, cluster lifetime, energy consumption, and delivery success probability.

METHODS

1. Wildfire Monitoring System (WMS) Model

The model assumes N sensor nodes are uniformly distributed across an M×M area, divided into k clusters. Each cluster contains approximately N/k nodes, including one cluster head (CH). The CH dissipates energy by receiving signals, aggregating data, and transmitting it to the base station (BS). Since the BS is far from the CH, energy dissipation follows a multipath model (d^4 power loss). The energy dissipated by a CH as expressed in equation (1) (Heinzelman *et al.,* 2002):

$$\mathrm{E_{CH}} = \mathrm{E_{elec}}\left(\frac{\mathrm{N}}{\mathrm{k}} - 1\right) + \mathrm{kE_{DA}}\frac{\mathrm{N}}{\mathrm{k}} + l\mathrm{E_{elec}} + l\epsilon_{\mathrm{mp}}d^4 \tag{1}$$

In the given equation (1), $\mathrm{E_{CH}}$ is the energy dissipated by the cluster head per frame, where $\mathrm{E_{elec}}$ is the energy per bit for circuitry, N is the total nodes, k is the number of clusters, $\mathrm{E_{DA}}$ is the energy for data aggregation, l is the message size in bits, ϵ_{mp} is the energy per bit for multipath transmission, and d^4 is the distance from the cluster head to the base station. Each non-cluster head (non-CH) node only transmits data to the CH, with energy dissipation modelled as: (Heinzelman, *et al.,* 2002).

$$\mathrm{E_{non-CH}} = l\mathrm{E_{elec}} + l\epsilon_{\mathrm{fs}}d^2 \tag{2}$$

where: $\mathrm{E_{non\text{-}CH}}$ is the energy dissipated in each non-cluster head node, l is the number of bits in each data message, $\mathrm{E_{elec}}$ is the energy per bit circuitry, ϵ_{fs} is the energy for transmission over a free space channel, d^2 is the distance to the cluster head. The energy consumed by a cluster (Heinzelman, *et al.,* 2002) is:

$$E_{cluster} = E_{CH} + \frac{N}{k} \mathrm{E}_{\mathrm{non-CH}} \tag{3}$$

The total energy dissipation for the network is:

$$E_{total} = kE_{cluster} \tag{4}$$

Minimizing E_{total} with respect to k yields the effective number of clusters:

$$k_{eff} = \frac{\sqrt{N}}{\sqrt{2\pi}} \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}} \frac{M}{d^2}} \tag{5}$$

Where, k_{eff} is the effective number of clusters, where N is the total number of nodes, ϵfs is the energy for free-space transmission, $\epsilon_{mp}$is the energy for multi-path transmission, M is the data generated by each node per unit time, and d^2 is the distance to the base station.

2. Fitness Function for Cluster Formation

To optimize clustering, a weighted fitness function combines various node attributes, including residual energy (Res_i), trust value (T_i), degree difference (D_i), total energy (Eng_i), distance to the BS ($Dist_i$), and CH coverage ($CH_{coverage}$). The fitness function is given by:

$$W_i = \frac{w_1\, T_i + w_2 Res_i + w_3 D_i + w_4\, Eng_i + w_5 Dist_i + w_6 CH_{coverage}}{Mobiliy_i} \tag{6}$$

The $CH_{coverage}$ parameter ensures all nodes participate in clustering (Gupta and Jha 2018):

$$\mathrm{CH_{coverage}} = \frac{(\mathrm{N}-\mathrm{m}) - \sum_{\mathrm{j}=1}^{\mathrm{m}} |\mathrm{CM_j}|}{\sum_{\mathrm{j}=1}^{\mathrm{m}} |\mathrm{CM_j}|} \tag{7}$$

Where N is the total number of sensor nodes, m is the number of CHs, $|CM_j|$ represents the number of cluster members in the j^{th} cluster.

The methodology adopted in actualizing this research work is as follows: Cluster Head (CH) Selection are systematic approach is used to optimize CH selection based on coverage area. The system assumes N nodes distributed across an M×M area, divided into k clusters, with one CH and (N/k−1) nodes per cluster. CH energy dissipation for receiving, aggregating, and transmitting signals is calculated using a multipath radio energy dissipation model from equation (1), while non-cluster nodes' energy usage is computed via the Friss free-space model from equation (2). Assuming circular cluster areas with uniform node density, equations (3) to (4) are simplified to derive total energy dissipation and using equation (5) to compute the optimal number of clusters for maximizing network lifetime and CH coverage using equation (6).

Improved Wildfire Monitoring Scheme Implemented in MATLAB R2020a, the scheme characterizes sensor nodes using residual energy, degree difference, mobility speed, total energy, trust value, and CH coverage. A weighted fitness function with specific coefficients determines the optimal CH. Clusters are formed using the K-Means algorithm, assigning nodes within transmission range as members. CHs with less than 25% energy are replaced to ensure sustained operation. Data is compressed using SPIHT before transmission, and a Semi-Random Circular Movement model enhances delivery probability. The base station applies XOR operations to remove redundant data.

3. Simulation Parameters

Table 1 presents the simulation parameters used to evaluate the performance of the Novel Clustering-Based Scheme for Wildfire Monitoring in Flying Ad Hoc Networks

Table 1. Simulation Parameter

Parameters	**Values**
Monitoring field	100m × 100m
Count of nodes	100
Minimal distance between nodes	$2m$
Simulation runs	10
Simulation time	120s
Base station position	(50,50)
Initial energy	0.5 J
Transmission range	40 m
Probability of turning a node as CH	0.1
Energy for transmitting each bit	50×10^{-9} J
Tx/Rx electronics constant	50nj/bit
Amplifier constant	10pJ/bit/m^2
CH energy threshold	10^{-4}J
Size of packet	30 bytes
Packet rate	1 packet/s
Sensing range	10 m
Cluster radius	25m

4. Flowchart of the Proposed Protocol

An enhanced wildfire monitoring protocol leveraging an energy-efficient clustering strategy for Flying Ad Hoc Networks (FANETs), is illustrated in Figure 1. The flowchart outlines the key steps and processes involved in implementing the protocol, focusing on efficient energy utilization while monitoring wildfires.

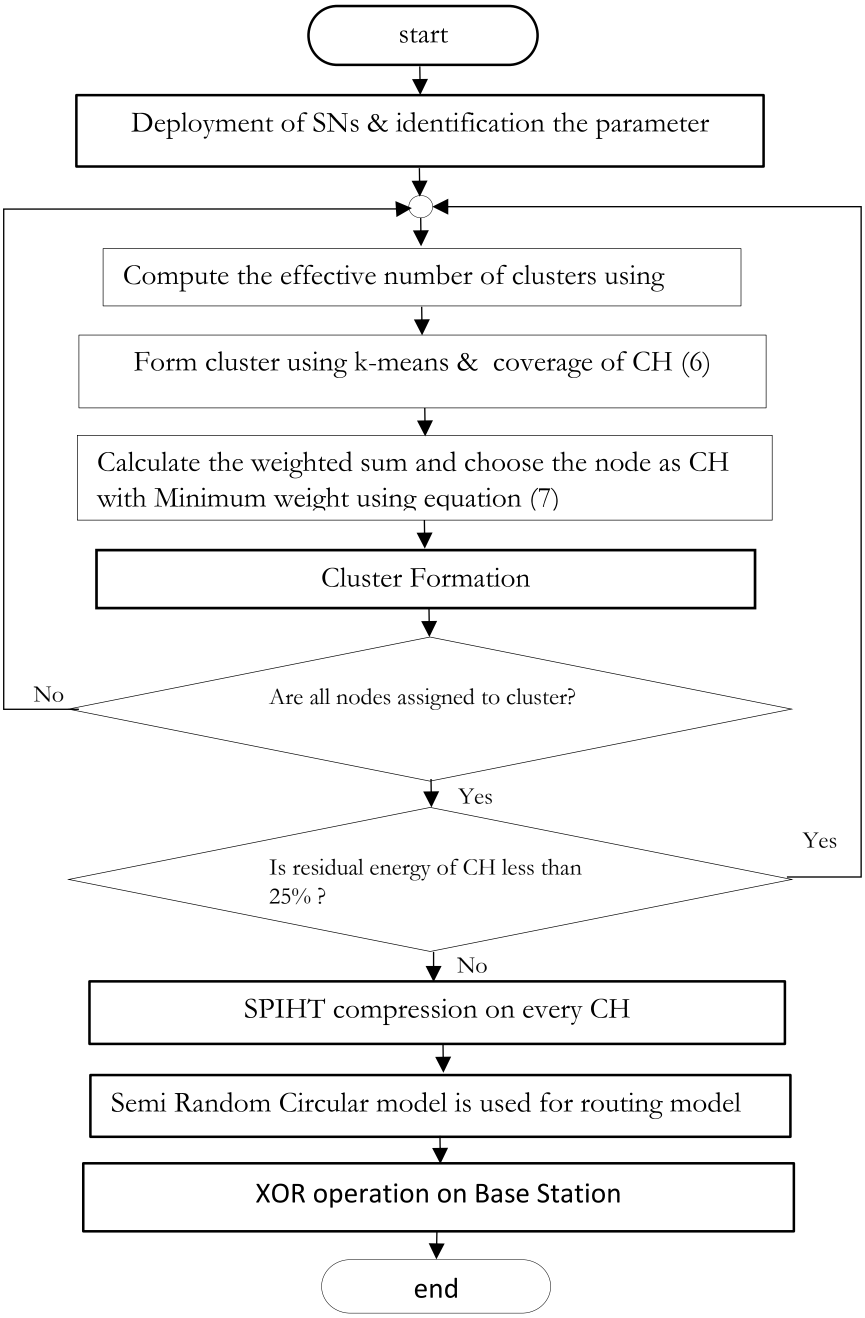

Figure 1: Wildfire Monitoring Based on an EE Clustering Approach for FANETS Flowchart.

RESULTS

The performance metrics evaluated include cluster formation time, cluster lifetime, and energy consumption. A detailed discussion of each metric is provided in Sub-Sections A, B, and C.

1. Cluster Formation Time

Cluster formation time is a vital metric in UAV networks, as it measures the duration required to form clusters, including the selection of cluster heads (CH) and the assignment of members. Prolonged cluster formation can lead to increased energy consumption and diminished performance, making optimization essential for achieving efficient UAV operations and extending their lifespan.

As shown in Figure 2, an increase in the number of UAVs results in longer cluster-building times. The Enhanced Energy with More Slots (EEWMS) method achieves a 10.16% reduction in cluster formation time compared to the Enhanced Energy - Slot Selection (EE-SS) method, as highlighted in Table 1. The average cluster formation time per iteration is 3.810 seconds for EEWMS, compared to 4.057 seconds for EE-SS. This improved efficiency facilitates real-time clustering, reduces energy consumption, and enhances the performance of Flying Ad hoc Networks (FANET) in wildfire monitoring.

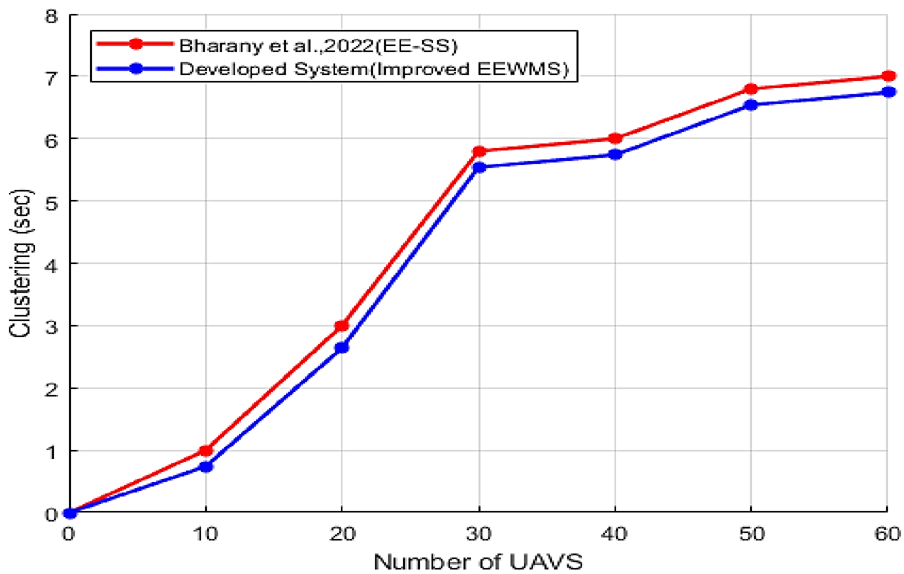

Figure 1: Cluster Building Time Comparison of EEWMS and EE-SS

Table 2: Percentage Reduction Computation of Cluster Formation Time

No. of UAV	EE-SS (Seconds)	EEWMS (Seconds)	EE-SS vs EEWMS (%)
00	0.000	0.000	0.00
10	1.000	0.735	26.50
20	3.000	2.635	12.17
30	5.800	5.535	4.01
40	6.000	5.735	4.42
50	6.800	6.535	4.86
60	7.000	6.735	3.57
Average	**4.057**	**3.810**	**10.16**

2. Cluster Lifetime

Cluster lifetime refers to the duration for which a cluster remains active and is affected by factors such as node mobility, energy consumption, and the overall number of clusters. Shorter lifetimes necessitate more frequent re-clustering, which consequently increases both communication and computational overhead. As illustrated in Figure 3, an increase in the number of UAVs leads to a reduction in cluster lifetime. However, the Energy-Efficient Weighted Multi-Selection (EEWMS) method enhances network lifetime by 6.96% compared to the Energy-Efficient Selecting Strategy (EE-SS), as shown in Table 3. This improvement stems from the inclusion of cluster head (CH) coverage in the CH selection process, which minimizes the need for frequent re-clustering. Overall, EEWMS effectively extends cluster lifetime, optimizes resource utilization, and enhances network performance, making it an excellent choice for robust and long-lasting operations in Flying Ad-Hoc Network (FANET) applications, such as wildfire monitoring.

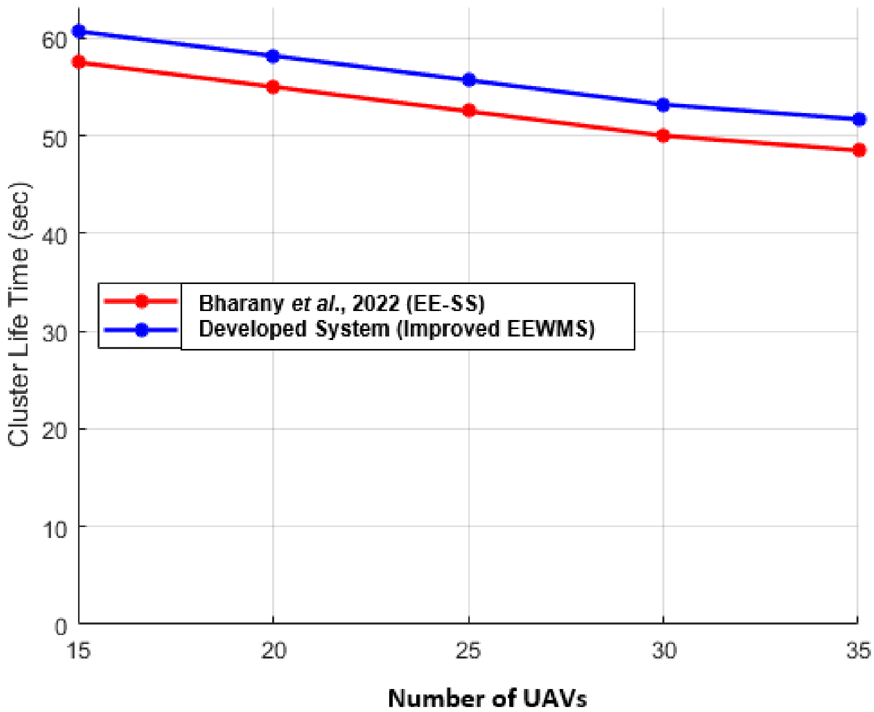

Figure 2: Cluster Lifetime Comparison of EEWMS and EE-SS

Table 3: Percentage Improvement Computation for Network Lifetime

No. of AV	EE-SS (Seconds)	EEWMS (Seconds)	EE-SS vs EEWMS (%)
15	57.5	61.52	6.96
20	55.0	59.02	7.32
25	52.5	56.52	7.81
30	50.0	54.02	8.04
35	48.5	52.52	8.47
Average	**52.7**	**56.32**	**7.52**

3. Aggregate Remaining Energy

Efficient energy consumption is essential for UAVs due to their limited battery capacity. Energy is expended through various activities, including operation, sensing, and communication. By optimizing energy usage, we can significantly extend the lifespan of UAVs and ensure successful mission outcomes. As depicted in Figure 4, energy consumption rises with an increasing number of UAVs and larger grid sizes.

The Energy Efficient Wireless Management System (EEWMS) achieves an average energy consumption of 2.600 Joules, reflecting a 10.25% reduction compared to the 3.09 Joules consumed by the Energy Efficient Sensor Selection (EE-SS) method, as outlined in Table

3. This improvement is attributed to EEWMS's effective selection of cluster heads and its optimized cluster management. The enhanced energy efficiency of EEWMS not only boosts UAV operational performance but also extends mission duration, positioning it as a superior choice for energy management in Flying Ad Hoc Networks (FANETs).

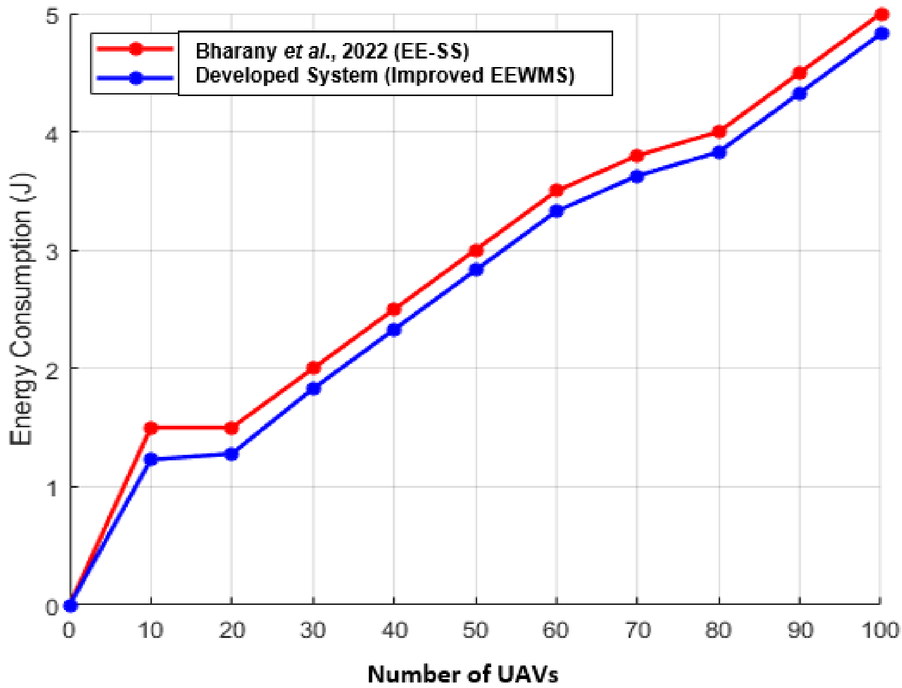

Figure 3: Energy Consumption Comparison of EEWMS and EE-SS

Table 4: Percentage Reduction Computation of Energy Consumption

No. of UAV	EE-SS (Joules)	EEWMS (Joules)	EE-SS vs EEWMS (%)
0	0.50	0.4129	17.42
10	1.50	1.3130	12.46
20	1.50	1.363	9.80
30	2.50	1.913	23.48
40	2.50	2.413	3.48
50	3.00	2.913	2.90
60	3.50	3.413	2.57
70	3.80	3.713	2.95
80	4.00	3.913	2.17
90	4.50	4.413	1.97
100	5.00	4.913	1.73
Average	**3.09**	**2.600**	**10.25**

DISCUSSION

The comparison of performance between EEWMS and EE-SS, as depicted in Figure 4 and summarized in Table 5, showcases the notable advantages of EEWMS across essential UAV network metrics. Notably, EEWMS reduces cluster building time by 10.16%, thereby enhancing the efficiency of network organization. Furthermore, it achieves a 7.52% improvement in network lifetime, which is vital for prolonged missions. EEWMS also lowers energy consumption by 10.25%, optimizing the limited energy resources available to UAVs, and enhances packet processing efficiency by 4.09%, leading to a more agile communication network. These results demonstrate EEWMS's superiority over EE-SS in aspects of efficiency, sustainability, and reliability. Ultimately, these findings advance the field of energy-efficient wildfire monitoring in FANETs and emphasize the practical significance of the proposed EEWMS model for ensuring reliable and sustainable UAV applications.

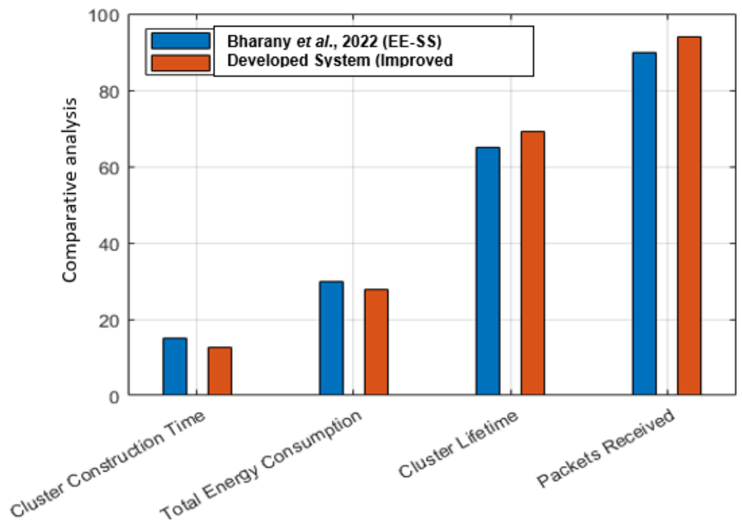

Figure 5: Overall Performance Comparison of EEWMS and EE-SS

Table 5: Percentage Reduction/Improvement Computation

Performance Metric	Average Reduction/Improvement (%)
Clustering Building Time	10.16
Network lifetime	7.52
Energy Consumption	10.25

CONCLUSION

In conclusion, this study introduces an Improved Wildfire Monitoring Scheme utilizing an Energy-Efficient Clustering Strategy for Flying Ad Hoc Networks (FANETs), known as EEWMS. By incorporating Cluster Head Coverage (CCH) into the fitness function and optimizing the number of clusters, EEWMS significantly improves energy efficiency. Simulations performed in MATLAB R2020a confirm that EEWMS surpasses the performance of EE-SS across various metrics. Notably, EEWMS reduces clustering build time by 10.16%, achieves a 6.96% enhancement in cluster lifetime, and lowers energy consumption by 10.25%. These findings underscore its effectiveness in optimizing UAV operations.

Nonetheless, further research is necessary to evaluate the scalability of this methodology in large-scale UAV networks and its overall applicability. Future studies should also investigate the influence of heterogeneous UAV capabilities on the EEWMS approach to ensure its adaptability across diverse UAV networks with differing performance characteristics.

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