



### Development of an Improved Wildfire Monitoring Scheme Based on an Energy-Efficient Clustering Approach for Flying Adhoc Network

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### ABSTRACT

Wildfires pose significant threats to ecosystems, human lives, and infrastructure. Wireless Sensor Networks (WSNs) are widely used for applications like wildfire monitoring, but one of their limitations is energy consumption. Flying Ad Hoc Networks (FANETs) are a type of WSN that uses Unmanned Aerial Vehicles (UAVs) for communication with each other in a self-organized manner. Several clustering algorithms have been proposed for WSNs such as Low-Energy Adaptive Clustering Hierarchy (LEACH), LEACH with Cluster-head Election Control (LEACH-C), Particle Swarm Optimization-based Hierarchical Adaptive Sink (PSO-HAS), Sensor Emulator for Dynamic Energy-efficient Clustering (SEED), Energy Efficient - Smart Sensor (EE-SS), to conserve energy in WSNs. However, these algorithms consumed energy in the cluster formation leading to network overhead and inefficient bandwidth utilisation. To address these challenges, this paper presents an Energy Efficient Wildfire Monitoring Scheme (EEWMS) to reduce energy consumption inefficient bandwidth utilization in cluster formation. It computes a appropriate cluster count before cluster formation. Simulation was carried out using MATLAD and result obtained showed that the EEWMS reduces energy consumption by 10.25% compared to EE-SS. In addition, EEWMS reduces cluster building time by 10.16%, to EE-SS. These results highlight EEWMS's potential for improving wildfire monitoring in FANETS.

### INTRODUCTION

Wildfires are natural disasters with destructive effects on the environment, human lives, and property (Egorova et al.,2022). Conventional wildfire monitoring methods, such as satellite imaging and ground-based sensors, often suffer from limitations in coverage, response time, and real-time data processing (Chowdary, *et al.*,2018). The introduction of Wireless Sensor Networks (WSNs) and Flying Ad Hoc Networks (FANETs) has present new possibility for efficient and effective wildfire monitoring. FANETs, incorporate Unmanned Aerial Vehicles (UAVs), provide a flexible and dynamic platform for large-scale environmental monitoring (Aadil et al.,2018). WSNs find applications in the following field;

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environmental monitoring, military surveillance, structural monitoring (Abdulwahab *et al.*, 2024), agriculture, healthcare traffic control, and river level variation monitoring (Aikawa et al., 2007). These networks consist of many sensor nodes that detect physical or environmental conditions such as temperature, sound, pressure, and vibration, aggregating data and transmitting it to a base station for processing (Huang et al., 2017).

Given that WSNs typically operate on batteries (Sarkar & Murugan, 2019), energy efficiency is very important, which can be achieved through method like clustering, data aggregation, node deployment, routing protocols and clustering (Jibreel et al., 2022). Clustering, in particular, improves energy consumption by

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grouping nodes and selecting a node to serve as Cluster Heads (CHs) which manage communication with the base station (Nadeem et al., 2022).

Existing clustering algorithms in WSNs like LEACH and PSO-HAS encounter challenges with energy consumption and inefficient bandwidth utilization during cluster formation, impacting network lifetime and reliability crucial for wildfire detection (Hameed & Joshi, 2024; Marshall *et al.*, 2019). Developing improved schemes for efficient CH selection is essential. FANETs extend WSN capabilities, leveraging UAVs for innovative operations like security, traffic surveillance, and wildfire monitoring. However, FANETs face challenges with node mobility and topology changes, necessitating efficient energy utilization and CH selection (Bharany et al., 2021; Khan et al., 2019; Bharany et al., 2022).

This paper presents an Energy-Efficient Wildfire Monitoring Scheme (EEWMS) for FANETs, to enhance clustering efficiency. The proposed algorithm introduces a cluster count in the process of cluster formation. The objective is to reduce clustering overhead and optimize bandwidth usage, thereby improving wildfire monitoring effectiveness within FANETs. The paper is structured as follows: Section II reviews related works, Section III outlines the system model, Section IV describes the proposed EEWMS, Section V presents evaluation results, and Section VI concludes the paper.

### LITERATURE REVIEW

The following present a review of similar works that are relevant to the research area: Bharany et al., (2022) proposed an energyefficient clustering protocol for Flying Ad-Hoc Networks (FANETs), the proposed clustering algorithms consider factors such as the Residual Energy of the Node, Trust Level Value, Total Energy Consumed, Distance between the Base Station and Each Sensor, Node Mobility, and Degree Difference as input criteria for CH selection. The weight of each node is computed, and the node with the minimum weight is elected as the CH. However, these algorithms exhibit higher energy consumption due to the lack of an effective cluster count in the cluster formation.

Yang et al., (2022) introduced a Weighted and Location-Based Clustering (IWLC) scheme for FANETs to improve clustering effectiveness, link stability, and network lifetime. It uses a locationbased K-means++ clustering algorithm, a multifactor CH selection algorithm, and an efficient cluster maintenance algorithm. The scheme shows improvements over benchmarks in packet delivery ratio, network lifetime, CH changing ratio, and energy consumption. However, it lacks consideration of security aspects like node authentication and authorization, and does not address the impact of dynamic factors like node mobility and link quality.

Yan et al., (2022) proposed a clustering scheme for UAV clusters using the binary whale optimization (BWOA) algorithm in FANET. The scheme calculates the optimal number of clusters based on network bandwidth and UAV node coverage capacity. CH is selected based on the fitness functions of residual energy, intra-cluster distance, and inter-cluster distance to make the cluster lifetime longer. Some nodes being without clusters reduces network efficiency, indicating a potential area for improvement in the algorithm's design.

From the literature reviewed, most works focused on optimizing various parameters such as energy efficiency, clustering stability, network lifetime, and mobility awareness for clustering in Flying Ad-Hoc Networks (FANETs). However, there is more energy consumption due to the lack of effective cluster count in the cluster formation which increase the energy consumption and inefficient resource utilization, reducing network performance, and decreasing the overall system effectiveness.

### SYSTEM MODEL

The Wildfire Monitoring Scheme (WMS) is modelled as an ad hoc network scenario. Assuming that there are N nodes distributed uniformly in an M X M region. If there are k clusters, there are on average N/k nodes per cluster (one cluster head and (N/k) - 1 non-cluster head nodes). Each cluster head dissipates energy

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(3)

receiving signals from the nodes, aggregating the signals, and transmitting the aggregate signal to the BS. Since the BS is far from the nodes, presumably the energy dissipation follows the multipath model ( $d^4$  power loss). Therefore, the energy dissipated in the cluster head node during a single frame is as shown by (1) ((Heinzelman *et al.*, 2002):

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

Where:  $E_{CH}$  is the energy dissipated in the cluster head node during a single frame,  $E_{elec}$ is the energy required to run the circuitry per bit, N is the total number of nodes in the network.

*K* is number of clusters,  $E_{DA}$  is the energy for data aggregation, *I* is number of bits in each data message,  $\epsilon_{mp}$  is the energy required to transmit a bit of data over a multipath channel,  $d^4$  is distance from the cluster head node to the base station.

Each non-cluster head node only needs to transmit its data to the cluster head once during a frame. Presumably the distance to the cluster head is small, so the energy dissipation follows the Friss free-space model ( $d^2$  power loss). Thus, the energy used in each non-cluster head node is: (Heinzelman, *et al.*, 2002):

$$E_{\text{non-CH}} = lE_{\text{elec}} + l\epsilon_{\text{fs}}d^2$$
 (2)

Where:  $E_{non-CH}$  is the energy dissipated in each non-cluster head node during a single frame.

*I* is the number of bits in each data message,  $E_{elec}$  is the energy required to run the circuitry per bit,  $\epsilon_{fs}$  is energy required to transmit a bit of data over a free space channel.

 $d^2$  is Distance from the node to the cluster head. The network area (M x M) is divided into k clusters, assuming an average number of nodes per cluster. The area occupied by each cluster is approximately M<sup>2</sup>/k, as stated by Heinzelman *et al.* (2002). In general, this is an arbitrary-shaped region with a node distribution $\rho(x, y)$ . The expected squared

distance from the node to the cluster head (assumed to be at the centre of mass of the cluster) is given by: (Heinzelman, *et al.*, 2002)  $d^2 = \iint (x^2 + y^2) p(x, y) dx dy$ 

=∬
$$r^2\rho(r,\theta)rdrd\theta$$
.

Assume this area is a circle with radius R is  $(M/\sqrt{\pi k})$  and  $\rho(r, \theta)$  is a constant for r and  $\theta$ , (3) simplifies to: (Heinzelman, *et al.*, 2002)

$$d^{2} = \rho \int_{\theta=0}^{2\pi} \int_{r=0}^{\frac{M}{\sqrt{\pi k}}} r^{3} dr d\theta.$$

$$= \frac{\rho}{2\pi} \frac{M^{4}}{k^{2}}$$
(4)

If the density of nodes is uniform throughout the cluster area, then  $\rho$  equal to  $(1/M^2/k)$  and (Heinzelman, *et al.*, 2002).

$$d^2 = \frac{1}{2}\pi \frac{M^2}{k}$$
 (5)

Therefore, in this case, the energy dissipated in each non-Cluster Head (CH) node during a single frame (Heinzelman, *et al.,* 2002) is:

$$E_{\text{non-CH}} = lE_{elec} + l\epsilon_{fs} \frac{1}{2}\pi \frac{M^2}{k}.$$
 (6)

The energy dissipated in a cluster during the frame (Heinzelman, et al., 2002) is:

$$E_{cluster} = E_{CH} + \left(\frac{N}{k} - 1\right) E_{\text{non-}}$$

$$\approx E_{CH} + \frac{N}{k} E_{\text{non-CH}}$$
(7)

And the total energy for the frame (Heinzelman, et al., 2002) is

$$E_{total} = kE_{cluster}$$
  
=  $l\left(E_{elec}N + E_{DA}N + k\epsilon_{MP}d^{4}toBS + E_{elec}N + \epsilon_{fs}\frac{1}{2}\pi\frac{M^{2}}{k}N\right)$  (8)

Find the number of clusters by setting the derivative of  $E_{total}$  with respect to k to zero: (Heinzelman, *et al.*, 2002)

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(9)



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

Where:  $k_{eff}$  is effective number of clusters, N is the total number of sensor nodes in the network

 $\epsilon fs$  is the energy required to transmit a bit of data over a free space channel,  $\epsilon mp$  is the energy required to transmit a bit of data over a multi-path channel, *M* is the amount of data that each node generates per unit time,  $d^2$  is distance between a sensor node and the base station.

The effective number of clusters ( $k_{eff}$ ) in the Improved Energy Efficient Wildfire Monitoring Scheme (WMS) is calculated using Equation (9). This equation aims to maximize energy consumption by determining an effective number of clusters for energy efficient wildfire monitoring operations over FANETs.

### METHODOLOGY

The following methodology was adopted to developed improved wildfire monitoring scheme:

### **Input Parameters**

The set of sensor nodes were defined with attributes such as Residual Energy (RES), trust value (Ti), degree difference (Di), mobility speed (Mi), total energy (Eri), distance to Base Station (Disti). (Bharany et al., 2022).

### Residual Energy of the Node Equation

In FANETs, the residual energy is one of the critical factors affecting the network life. The energy of the UAV nodes is related to the number of neighbours, flight speed, and moving distance. If a node serves as the CH for a long time, its energy depletes dramatically, which reduces the lifetime of the whole network (Yang *et al.*, 2022). Thus, the residual energy needs to be involved in the CH selection criteria. The residual energy of a node is defined as (Bharany et al., 2022):

Where RES stands for Remaining Energy, IE stands for Initial Energy, CE stands for Consumed Energy.

### Trust Level Value

The value of trust in the beginning is same as all nodes. Anomaly detection algorithms lower this level if a node is functioning incorrectly (Drishya and Vijayakumar, 2019). It is possible for an abnormal node to be a distrusted node or a malicious node. The nodes' trust level is set as (Bharany et al., 2022):

Normal Sensor node:  $0.7 \le Ti \le 1$ Distrusted Sensor node:  $0.3 \le Ti < 0.7$  (11) Malicious Sensor node: 1 < Ti < 0.3

Where, Ti represents the Trust Level of a sensor node. The trust level is a metric used to assess the reliability or trustworthiness of a sensor node within a wireless sensor network. In order for a cluster head to be elected, only normal nodes are allowed to participate. There is a possibility that the node could become malicious at any point in time, and thus Distrusted Sensor node and Malicious Sensor node cannot participate in the election of a cluster head. If a normal node's residual energy is less than the average residual energy of all nodes, then it is also considered as a malicious node (Bharany et al., 2022).

### **Degree Difference**

The node's stability as a cluster head increases with its node degree (Bharany et al., 2022). The degree of a node is the number of connections that it has to other nodes in the network. Degree difference  $D_D$  is defined as shown (Bharany et al., 2022):

$$D_{\rm D} = |\text{Di-Max}_{\rm D}|. \tag{12}$$

Where Di is node i's practical degree,  $Max_D$  is its maximum degree

Node i will perform better as a cluster head if the value of  $D_{\rm D}$  is smaller.

### Distance between the Base Station and Each Sensor

Calculate the distance between the base station to each sensor nodes, where, (XBS, YBS, and ZBS) and (x1, y1, z1) are the coordinate positions of the base station and each sensor

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node, respectively, as computed by Equation (13) (Bharany et al., 2022):

$$Dist =$$

$$\sqrt{(XBS - x1)^2 + (YBS - y1)^2 + (ZBS - z1)^2}$$
(13)

### Mobility of a Node

Mobility is an important factor to consider when selecting a cluster head. Consider *Mi* 

$$= \frac{1}{T} \sum_{t=1}^{T} \sqrt{(X_t - X_{t-1})^2 + (Y_t - Y_{t-1})^2 + (Z_t Z_{t-1})^2}$$
(14) numbe

### Weighted Function Calculation:

The combined weight for each node is computed using Equation (15), incorporating coefficients for trust value, residual energy, degree difference, total energy consumption, distance between nodes and Base Station, and mobility of the node.

# $\frac{W_{i}}{W_{i} \cdot T_{i} + w_{2} \cdot Res_{i} + w_{3} \cdot D_{i} + w_{4} \cdot Total \cdot Eng_{i} + w_{5} \cdot Dist_{i}}{Mobility \ of \ a \ node}$ (15)

### Effective Cluster Number Determination:

The effective number of clusters is calculated using Equation (16).

$$k_{eff} = \frac{\sqrt{N}}{\sqrt{2\pi}} \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \frac{M}{d^2}.$$
 (16)

where:

*k*<sub>eff</sub> is effective number of clusters, *N* is the total number of sensor nodes in the network, *efs* is the energy required to transmit a bit of data over a free space channel, *emp* is the energy required to transmit a bit of data over a multi-path channel, *M* is the amount of data that each node generates per unit time,  $d^2$  is distance between a sensor node and the base station.

### **Cluster Head Selection:**

The node with the lowest combined weight is chosen as the cluster head, and then clusters are forming base on nodes within transmission range and base on the effective electing a cluster head who is more stationary; that would be more reliable. Re-affiliation may occur if the cluster head moves rapidly, causing nodes to become detached from one another. This occurs when a node leaves an existing cluster and joins a newer one. In this scenario, only a small amount of information can be sent between the node and the cluster head, the mobility of a node serves as a dividing factor (Bharany et al. 2022):

number of clusters, clustering process iterated until all nodes are assigned to a cluster.

### Cluster Head Energy Check:

If the remaining energy of the Cluster Head falls below 25% of its total energy, recall the Data

### Compression and Transmission:

Apply the SPIHT compression technique for data compression before sending it to the Base Station

### Data Transmission Strategy:

Implement Semi-Random Circular Movement model for sending data to the destination, enhancing the probability of success.

### Data Fusion at Base Station:

Use XOR operation at the Base Station to remove redundant data received from different Cluster Heads.

With these steps, the Improved Energy-Efficient Wildfire Monitoring Scheme was successfully implemented using MATLAB R2020a for a solution for monitoring wildfires scheme.

## IMPROVED CHANNEL SELECTION ALGORITHM

The flowchart in Figure 1 presents the step-by-step process of the Improved Wildfire Monitoring Based on Energy Efficient Clustering Approach for FANETs. The red portion is where improvement was carried out. It begins by initializing the sensor nodes with parameters such as residual energy, trust value, degree difference, total energy, distance to the base station. The

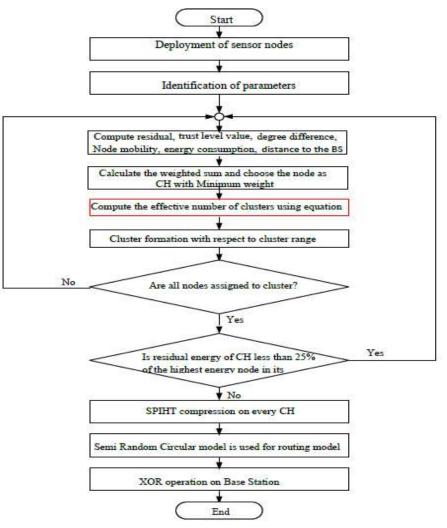
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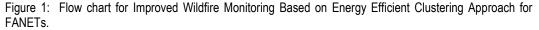
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residual energy, trust value, degree difference, total energy, node mobility, are computed for each node. Subsequently, the combined weight of each node is calculated using a weighted function that incorporates the aforementioned parameters. The effective number of clusters is then computed, and the node with the lowest combined weight is chosen as the cluster head. Clusters are formed by considering nodes within the transmission range of the cluster head as member nodes. The cluster head and its neighbouring nodes are then removed from the set of sensor nodes. This process is repeated until all nodes are assigned to a cluster. If the remaining energy of a cluster head falls below 25% of its total energy, the cluster head selection process is recalled. Next, the SPIHT compression technique is applied to compress the data before transmission to the base station. The Semi-Random Circular Movement model is implemented for data transmission, enhancing the probability of successful delivery. Finally, an XOR operation is performed at the base station to remove redundant data received from different cluster heads.





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### SIMULATIONS AND RESULTS

For validation and comparison, the performance of the EEWMS model was evaluated

against the EE-SS approach from prior work. The percentage improvement and reduction in key metrics were computed using:

Table 2. Simulation Parameter (Bharany et al., 2022)

SN	Parameters	Default Values
1	Monitoring field	100m × 100m
2	Count of nodes	100
3	Minimal distance between nodes	2 <i>m</i>
4	Simulation runs	10
5	Simulation time	120s
6	Base station position	(50,50)
7	Initial energy	0.5 J
8	Transmission range	40 m
9	Probability of turning a node as CH	0.1
10	Energy for transmitting each bit	50 x 10 <sup>-9</sup>
11	Tx/Rx electronics constant	50nj/bit
12	Amplifier constant	10pJ/bit/m <sup>2</sup>
13	CH energy threshold	10 <sup>-4</sup> J
14	Size of packet	30 bytes
15	Packet rate	1 packet/s
16	Sensing range	10 m
17	Cluster radius	25m

### SIMULATION RESULT

The results for the considered performance metrics; cluster building time, energy consumption. Each of these results is separately discussed in detail in Sub-Section 7.1, 7.2.

### **Cluster Building Time**

Cluster building time, crucial in UAV networks, is the duration from receiving input values to cluster creation, involving CH selection and member assignment. This metric, reflecting the algorithmic complexity, is vital for UAVs with limited resources. Extended cluster formation times degrade performance and escalate energy consumption. Optimizing this time is crucial for efficient UAV network operation and prolonged UAV lifespan. Figure 2 shows that increasing the number of UAVs in the network increases the cluster building time. The cluster building time comparison of EEWMS and EE-SS. EEWMS demonstrates a reduction of 10.16% in clustering building time compared to EE-SS. This is due to the appropriate number of clusters computed in EEWMS algorithm which reduced clustering overhead. The average time for clustering building per iteration with EEWMS is 3.810 seconds, showcasing its efficiency in comparison to EE-SS, which requires an average of 4.057 seconds. The relatively lower complexity of EEWMS supports effective real-time clustering building, making it a valuable choice for FANETs.

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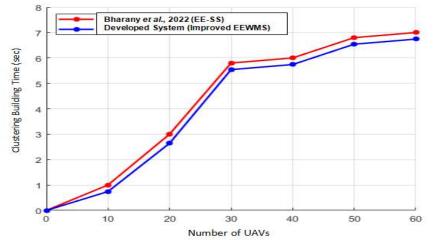


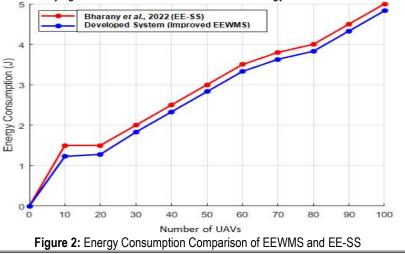
Figure 3: Cluster Building Time Comparison of EEWMS and EE-SS

### **Residual Energy**

The energy consumption in unmanned aerial vehicles (UAVs) is a critical concern due to limited battery capacity. Energy dissipation occurs through three main mechanisms: UAV operation, sensor usage, and inter-UAV communication. Maximizing energy efficiency is essential for UAV lifespan and mission success. As the number of UAVs and the grid size increase, the network's energy usage also rises as shown in the Figure 2. The comparison between EE-SS and the improved methodology EEWMS, as shown in the Table 3 in Appendix D, reveals a consistent advantage of EEWMS in terms of energy consumption across varying numbers of UAVs. The average energy consumption across all scenarios for EE-SS is 3.09 Joules, while EEWMS achieves a lower average of 2.600 Joules, indicating an overall energy efficiency improvement of 10.25% with the proposed enhancement.

The reduced energy consumption in EEWMS is attributed to the selection of appropriate right CHs and efficient cluster head selection. This consistent reduction in energy consumption underscores the effectiveness of

EEWMS in optimizing the energy efficiency of UAVs compared to the baseline EE-SS methodology.



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### CONCLUSION

In conclusion, this work has presented an Improved Wildfire Monitoring Scheme based on an Energy-Efficient Clustering Approach for Flying Ad Hoc Networks (FANETs). The approach involves determining the appropriate number of clusters in the network. The research, conducted using MATLAB R2020a, aimed to enhance the Energy Efficiency (EE) of FANETs. The obtained results validated the strengths of EEWMS over EE-SS.

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