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Wildfire Monitoring Based on Energy Efficient Clustering Approach for FANETS

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Abstract: Forest fires are a significant threat to the ecological system's stability. Several attempts have been made to detect forest fires using a variety of approaches, including optical fire sensors, and satellite-based technologies, all of which have been unsuccessful. In today's world, research on flying ad hoc networks (FANETs) is a thriving field and can be used successfully. This paper describes a unique clustering approach that identifies the presence of a fire zone in a forest and transfers all sensed data to a base station as soon as feasible via wireless communication. The fire department takes the required steps to prevent the spread of the fire. It is proposed in this study that an efficient clustering approach be used to deal with routing and energy challenges to extend the lifetime of an unmanned aerial vehicle (UAV) in case of forest fires. Due to the restricted energy and high mobility, this directly impacts the flying duration and routing of FANET nodes. As a result, it is vital to enhance the lifetime of wireless sensor networks (WSNs) to maintain high system availability. Our proposed algorithm EE-SS regulates the energy usage of nodes while taking into account the features of a disaster region and other factors. For firefighting, sensor nodes are placed throughout the forest zone to collect essential data points for identifying forest fires and dividing them into distinct clusters. All of the sensor nodes in the cluster communicate their packets to the base station continually through the cluster head. When FANET nodes communicate with one another, their transmission range is constantly adjusted to meet their operating requirements. This paper examines the existing clustering techniques for forest fire detection approaches restricted to wireless sensor networks and their limitations. Our newly designed algorithm chooses the most optimum cluster heads (CHs) based on their fitness, reducing the routing overhead and increasing the system's efficiency. Our proposed method results from simulations are compared with the existing approaches such as LEACH, LEACH-C, PSO-HAS, and SEED. The evaluation is carried out concerning overall energy usage, residual energy, the count of live nodes, the network lifetime, and the time it takes to build a cluster compared to other approaches. As a result, our proposed EE-SS algorithm outperforms all the considered state-of-art algorithms.

Keywords: clustering; energy efficiency; WSN; FANETS; LEACH; IoT

1. Introduction

Nowadays, the deployment of WSNs is becoming increasingly popular worldwide. Due to its tremendous potential for significant advancement in flood catastrophe monitoring [1]. It has its advantages in terms of disaster monitoring by WSN, some of which are related to low cost, high tractability, and scalability [2]. In addition, the unpredictable nature of natural disasters restricts the distribution of the appropriate information to the corresponding sensor nodes with the smallest amount of delay. There is always a need for clustering techniques to manage information and make it reach the final destination. When using an energy-efficient clustering protocol, it is possible to randomly minimize energy consumption in a network while simultaneously increasing the network lifespan. WSN has several applications in the Internet of Things, the medical area, transportation field, industrial field, and smart cities [1,2]. When used with a WSN, the cluster routing protocol provides energy-efficient data transfer between the sensor node and the base station. Cluster members (sensor nodes) are denoted by the SN and CH used in the clustering routing protocol to designate the cluster head. UAVs are equipped with a compact lithium battery with around 30–35 min of flying time and can be recharged quickly. A technique for replacing UAVs has been developed to complete a lengthy operation. When an UAV is nearing the end of its battery life, it returns to the base station re-energized and re-inducted into the network, allowing the mission to be completed successfully [3], as seen in Figure 1. The limited lifespan and frequent replacement of UAVs are barriers to the widespread use of FANET in various applications.

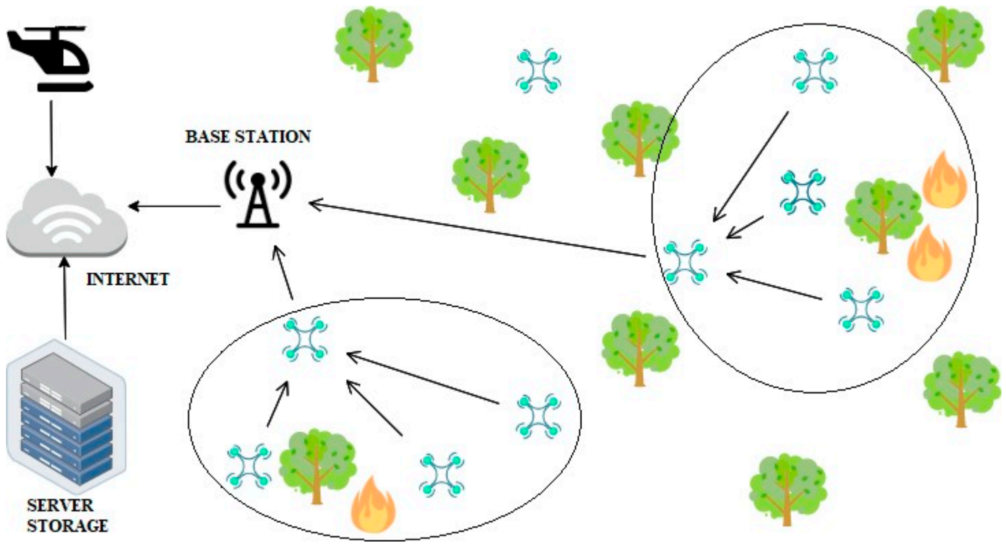

Figure 1. Disaster management using FANETS.

FANETs are a new vehicular ad hoc network (VANET) and mobile ad hoc network (MANET) that may be installed anywhere and can communicate. Many of its characteristics are derived from the VANET and the MANET [4]. It uses the same peer-to-peer communication technology as the previous versions of the ad hoc network. Nodes in a network are dependent on one another to communicate with one another properly. Due to the high mobility of nodes, the network's topology changes frequently. FANET also possesses unique characteristics separate from the other ad hoc networks described below. These characteristics are as follows [5]: The FANET network comprises mobile nodes that are provided as unmanned aerial vehicles that can travel at speeds of about 30–60 km/h in open air space and perform a wide range of missions, including surveillance and reconnaissance. In order to facilitate direct communication, they have relatively lengthy inter-node distances and a clear line of sight between nodes. Node mobility patterns differ in FANET, which is another point of differentiation. FANET can be used for many things, from surveillance and monitoring to disaster management, environmental sensing, ecological damage detection, communication, and many more [1–3]. The goal of clustering is to reduce the time spent on route discovery and maintenance. It categorizes the whole network into several logical subgroups.

Nodes geographically close to one another are grouped to form a cluster. Cluster heads (CH) are maintained in each cluster, and these CHs are responsible for the overall maintenance and management of the cluster's communication. It is in charge of communication between clusters and within clusters. When communicating with all of their cluster members (CMs), CH always functions as the first hop node, and it is its responsibility to deliver the message to its final destination. CHs communicate with their cluster managers (CMs) to keep up-to-date information on the cluster. In proactive and reactive routing, the process of clustering and election of the CH takes the place of the route request. Cluster creation and cluster maintenance phases primarily influence cluster overhead [6,7]. A large number of messages are sent between network nodes as a part of the cluster building process. For example, to determine node fitness, they exchange their location and other characteristics [5,6]. They run calculations to choose CHs based on these factors. Communication and calculations to establish clusters and elect CHs to consume network resources like bandwidth, processing power, and battery capacity are considered energy waste.

IoT is a massive network of disseminated nodes that can detect and communicate with each other across great distances [5]. As they enable a wireless link between constrained devices, WSNs are regarded as the essential players in the IoT networks [4–6]. IoT-based WSNs use a wireless channel to send collected data (environmental data) to a central terminus known as a sink node [7]. Sensor node devices are becoming smaller and more economical due to recent developments in hardware design, allowing them to be used in adverse settings such as nuclear power plants and forests [7,8]. On the other hand, sensor nodes have limited battery capacity, necessitating the creation of energy-efficient algorithms. As sensors with low batteries might create network disconnections and, as a result, packet losses, energy resource limits directly impact the application's performance [6–8]. Reduced energy use in multi-hop sensor networks necessitates the development of methodologies and procedures that select the most energy-efficient way for data transfer [8]. There are several types of Internet of Things applications, each with specifications and needs. Safety-critical IoT applications must fulfil high criteria for dependability and punctuality. Apps for disaster management are defined as behaviors and actions that help people prevent, control, and recover from disasters (fires and earthquakes). A disaster management approach is characterized as one that focuses on developing algorithmic and protocol solutions to improve service quality in safety-critical applications [9]. Forest fire detection is an example of a safety-critical application, since an unplanned fire can cause considerable environmental and ecological devastation and jeopardize human lives [10]. Calamities such as quakes and forest fires, regardless of their cause, put people in a situation of urgency and have lasting implications for human society [8–11]. Academics have recently focused on developing disaster warning and remote-control systems due to the rising frequency and severity of disasters [11,12]. It is possible to design more energy-efficient, portable, and scalable solutions to a wide range of catastrophic situations by utilizing IoT protocols and algorithms. This technology opens the door to disaster-resilient intelligent environments, such as intelligent community solutions, where calamities may be minimized. This study leverages the Internet of Things networks to propose a potential technique for remotely monitoring forest fires. As soon as a disaster occurs, an early warning system is anticipated to send a signal to a central control unit, taking the appropriate precautions. Forest fires may exhibit sudden behavioral changes in reaction to changes in climatic circumstances, making monitoring more challenging as the fire's position and spread fluctuate over time. Furthermore, SNs are unlikely to consume energy consistently because of the non-uniform distribution of events and the unpredictable behavior of fire. Forest fire management approaches that employ clustering and routing techniques have been the subject of several papers in the literature. These efforts have concentrated on quick-fire detection, with network energy efficiency being one of the most critical factors [5], as seen in Figure 2.

Figure 2. FANET in wildfire.

As a result, to successfully manage catastrophes using IoT-based WSNs, a suitable routing channel from the cluster heads (CHs) to the sink in the disaster zone must be established. Clustering is one of the most often used hierarchical routing algorithms, and it is detailed in-depth below. Clustering aims to feasibly find and identify the most optimal CH nodes [13]. Due to the difficulties of finding appropriate nodes to act as CHs and the accompanying complexity, clustering in WSNs takes a long time. In computer science, clustering is an NP-hard problem [14–20]. On the other hand, previous research has shown that evolutionary algorithms are necessary to improve network efficiency when using traditional methods to choose cluster heads [21–24].

This article proposes an energy-efficient clustering algorithm that can be used for data transmission purposes in sensor nodes during emergency disaster supervision in WSN [25–32]. The routing purpose in the clustering manner is done with the help of optimal CH, which is selected by involving different concerned parameters. An image compression method named SPIHT is employed to decrease the transmission load. Moreover, an SRCM model is employed to find the best route towards the destination, compensating for the node energy level and communication link quality [33–40]. All these steps are followed by aggregation techniques using an XOR gate operation, eliminating identical information from different nodes [41–46].

The following are some of the critical contributions made by this paper:

- In this paper, we develop a strategy to cluster WSNs in a way that is both energy-efficient and sensitive to the characteristics of emergencies.
- We try to Improve the CH excerption method by devising a new function that takes energy efficiency, cluster construction time, trust value and other parameters.
- Surpassing existing systems in terms of their energy consumption, the number of live nodes, network development time, and the number of sink sites in catastrophic scenarios, among other metrics.

The remainder of the paper is arranged in the following manner. Section 2 provides an overview of relevant research, followed by Section 3, which presents our suggested technique. Section 4 discusses the simulation findings and evaluations that were conducted. In Section 5, there is a brief discussion about the result. Finally, at last, the conclusion and potential future work has been discussed in Sections 6 and 7.

2. Literature Review

The authors of [6] presented a low-energy adaptive clustering hierarchy (LEACH), a famous disseminated heuristic approach that uses adaptive clustering. Clustering occurs in this approach in a dynamic, unpredictable, probabilistic, and periodic manner, among other ways. LEACH is responsible for determining a threshold for CH selection. It generates a random number among [0, 1] to choose a CH throughout that period. One of the drawbacks of the LEACH protocol is the random selection of CHs, which is necessary since any node might be qualified to serve as a CH under certain conditions [40–42]. LEACH-C [7] is an improved variation of the LEACH algorithm. All of the sensor nodes broadcast information to the base station, such as position and residual energy, to maximize the network's efficiency. It has the added benefit of minimizing the energy consumption of each node in the network when LEACH-C is used as a centralized method, which is particularly advantageous. However, LEACH-C has several faults that need to be addressed. For example, when it comes to becoming a CH in the LEACH-C network, each node has an equal probability of becoming one. As the network's energy supply depletes, the nodes with the least amount of energy should be selected to serve as CHs, which will reduce the network's efficiency and place an unfair amount of energy demand on the network. TEEN (threshold-sensitive energy-efficient sensor network protocol) [8] is another hierarchical heuristic technique that uses the two-layer clustering structure to reduce energy consumption. This approach uses both a hard (HT) and a soft (ST) threshold. The threshold values determined by each CH are communicated to the CH's members. Both thresholds have been implemented to limit the number of transmissions during routing intervals and the overall amount of energy used. Since the CH selection is based on chance, the CH distribution [8] will be non-uniform. Regarding clustering, TEEN surpasses LEACH in terms of stability and energy efficiency. There is a fundamental drawback: If the requirements are not satisfied immediately, nodes will not be able to establish communication.

Meta-heuristic methods for optimal CH selection have been developed to overcome the limitations of heuristic algorithms, such as the wasteful exploration of the search space [18], and obtain more outstanding performance than traditional heuristic algorithms. A key component in improving algorithm efficiency is having access to every segment of the whole search space during each period. Using an evolutionary PSO for energy-aware CH selection, the authors proposed an algorithm in [10]. This method combines the Euclidean distance between nodes and CHs, and the remaining energy from particle energy to node energy. According to the results, the addition of energy criteria in the fitness function significantly impacted the total energy efficiency of the exercise programming efforts. It should be noted that the CHs in [10] were chosen based on probabilities, and the distribution of CHs was constant throughout the group. In this method, the exploration step was likewise given precedence over the exploitation stage in terms of importance. Moreover, the authors in [9] created a hybrid approach for energy-efficient CH selection based on PSO and HS algorithms. The suggested meta-heuristic algorithm covers a global optimal in the search space (exploration) while also extending beyond the local optimal by integrating the advantages of both techniques (exploitation). PSO–HSA [9] is a search space optimization approach in which particles based on the PSO algorithm are allowed to migrate from one zone to another in the search space. As PSO faces optimization constraints at high-dimensional scales due to optimization limits, finding any viable solution in the whole search space is challenging. As a result of its great-seeking capacity, HSA aids PSO. The authors [11] offered an evolutionary HSA for CH selection influenced by musical compositions. Musicians attempt to choose better notes so that their music may be heard more clearly, and this is the primary premise behind the presentation of the harmony fitness function. In other words, the most suited group of nodes is picked as CHs. The authors suggested a TPSO-CR protocol [12], a two-layered PSO protocol for clustering and routing in wireless sensor networks. While calculating the fitness function of the clustering, three factors were considered: network coverage, residual energy of the nodes, and link communication quality (all of which were utilized simultaneously) [37]. The two criteria applied in the fitness function for clustering are energy efficiency and connection communication quality. The novel method was applied for clustering, an updated HSA was used for multi-hop routing in WSNs in [13], and the cuckoo approach was used for clustering and routing of nodes. One of the most critical issues in this area is uniform energy consumption in the clustering and routing of large-scale wireless sensor networks since nodes near the sink spend considerable energy owing to high traffic loads. This study also contains criteria for the fitness function, including energy, node degree, cluster intra-distance, and coverage ratio. Author [14] developed an enhanced version of LEACH, dubbed LEACH-B (LEACH-Balanced), in which the number of CHs is kept as close to ideal levels as possible. It is a decentralized technique for cluster creation [14] that involves increasing election CHs to maximize the number of clusters formed while maintaining the lowest possible energy consumption by nodes during the set-up stage. The LEACH-B protocol comprises three primary stages: selecting the CH, the construction of clusters, and the transmission of data. LEACH-ME (Mobile Enhanced-LEACH) is a protocol suggested by the authors of [15] as an enhancement to the LEACH-M protocol. LEACH-ME is intended to alleviate the shortcomings of LEACH-M. As CHs, it selects nodes with the least mobility than their neighbors. Each node contains all the CH transitions performed throughout the steady-state while transferring information. [15] Nodes use TDMA slots to send several transitions to their CH [16]. The primary goal of LEACH-ME is to ensure that the mobility of CHs is kept to a bare minimum in comparison to other nodes in the network, with the result that when clusters move and change locations, the disruption caused by the movement of CHs will be kept to a bare minimum to the greatest extent possible.

The authors have proposed a strategy for transmitting messages to a WSN-aided opportunistic network (WAON) under catastrophe situations [23]. In this scenario, the forwarding method is referred to as net spray. Disaster messaging services are provided and support static-to-mobile, mobile-to-mobile, mobile-to-static, and static-to-static operations and mobile-to-static operations. The message forwarding to a WSN-assisted opportunistic network ensures that messages are delivered with the least possible delay in catastrophe circumstances and that storage is better managed [38].

A G.9959-based IPv6 packet delivery mechanism for industrial IoT via WSN has been proposed in [24] by the authors. G.9959 is an industrial Internet of Things (IIoT) protocol. IPv6 retains very high Internet users, allowing for a high degree of scalability. Packet delivery speed and energy efficiency are strong points of the IPv6 energy-efficient system. According to the authors' paper [25], loss of transmission reduction by inspired ant colony optimization (ACO) with a Monte Carlo Markov chain in an underwater WSN environment was achieved using a Monte Carlo Markov chain [39]. In this paper, they describe ACO routing, which includes the Markov chain Monte Carlo (MCMC) technique for capturing transmission loss on the MCMC strategy, as well as the channel status information (CSI) forecast prediction (FP) algorithm, which is proposed in the literature. To reduce transmission loss, the implementation of inspired ACO combined with Markov chain Monte Carlo (MCMC) in a subsea WSN environment yields a positive loss of transmission, probability distribution function, average latency, and throughput. An additional CH selection approach was developed in [26], which uses a fuzzy logic-based energy adequate clustering (FLEAC) method based on five descriptors to pick the best CH. We can see the comparison of algorithms by certain metrics and network characteristics in Tables 1 and 2.

Table 1. Compassion of various algorithms by certain parameters.

Protocol	Clustering Type	Energy Efficiency	Clustering Stability	No of CH's	Cluster STABILITY	Network Type	No. of Nodes in Cluster
LEACH	Random	Low	Low	Indecisive	Low	Homogenous	Changeable
LEACH-C	Centralized	Medium	Low	Decisive	Medium	Homogenous	Changeable
TEEN	Probability Centralized	Medium	Low	Indecisive	Low	Homogenous	Changeable
PSO-HSA	PSO And HSA Centralized	High	Low	Indecisive	High	Homogenous	Changeable
PSO-SD	Pso Centralized	Moderate	High	Indecisive	High	Homogenous	Changeable
HSA-N	HSA-Based Centralized	Medium	High	Indecisive	Low	Homogenous	Changeable
TPSO-CR	PSO-Based Centralized	Moderate	Low	Decisive	High	Homogenous	Changeable
iCSHS	Cuckoo-Based Distributed	Moderate	High	Indecisive	Low	Homogenous	Changeable
LEACH-B	Distributed	High	Low	Decisive	Medium	Homogenous	Changeable
LEACH-ME	Distributed	High	High	Indeterminate	Medium	Homogenous	Changeable

Table 2. Comparison on the basis of network characteristics.

Protocol	Converge	Routing	Clustering Category	Mobility	Scalability	Complexity
LEACH	No	Single Hop	Residual Energy	Static	Limited	Low
LEACH-C	No	Single Hop	Centralization	Static	Good	High
TEEN	No	Single Hop	Centralization	Static	Very Good	High
PSO-HSA	Moderate Balanced	Single Hop	Centralization	Static	Very Good	High
PSO-SD	Moderate	Single Hop	Centralization	Static	Good	Medium
HSA-N	Medium	Single Hop	Centralization	Static	Good	High
TPSO-CR	Moderate Balanced	Single Hop	Centralization	Mobile	Good	High
iCSHS	Moderate Balanced	Multi-Hop	Centralization	Static	Average	High
LEACH-B	No	Single Hop	Residual Energy	Static	Limited	High
LEACH-ME	Medium	Single Hop	Mobility	Mobile	Good	High

3. Proposed Methodology

In this section, first, the metrics used by our proposed algorithm are described, and then the proposed algorithm steps are discussed, after which the network model is explained.

3.1. Metrics Used by Our Proposed Algorithm

In our proposed algorithm, we are including certain metrics on which basis we will select an optimal and efficient node as CH. Mostly every metric has its own importance and concern to select the nest nodes as CH.

3.1.1. Residual Energy of the Node

Equation (1).

$$\text{RES energy} = \text{Initial energy} - \text{consumed energy} \tag{1}$$

3.1.2. 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. It is possible for an abnormal node to be a distrusted node or a malicious node. The nodes' trust level is set as [1,8]:

$$\text{Normal\_Sensor\_node: } 0.7 \leq \text{Ti} \leq 1$$

$$\text{Distrusted\_Sensor\_node: } 0.3 \leq \text{Ti} \leq 0.7$$

$$\text{Malicious\_Sensor\_node: } 1 \leq \text{Ti} < 0.3$$

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 [29].

3.1.3. Degree Difference

The node's stability as a cluster head increases with its node degree. The degree of a node is the number of connections that it has to other nodes in the network. Where Di is node i's practical degree and Max_D is its maximum degree, we define degree difference D_D as $|\text{Di-Max}_D|$. Node I will performs better as a cluster head if the value of D_D is smaller.

3.1.4. Total Energy Consumed

The residual energy of a node ni as denoted by Eri after transmitting k bits to a node nj within a distance d is given by [1] and can be calculated by Equation (2).

$$\text{Eri} = \text{E} - (\text{ETx(k,d)} + \text{ERx\_elec(k)} \tag{2}$$

where E is the current energy of the node E_{Tx} is energy for transmit a message, which is calculated by Equation (3).

$$\text{ETx(k,d)} = \text{kEelec} + \text{K Eampd2} \tag{3}$$

In this equation, Eelec is energy of electrons and Eamp is required amplified energy. ERx_elec is energy consumed to receive a message, which is calculated by Equation (4).

$$\text{ERx\_elec(K)} = \text{kEelec} \tag{4}$$

3.1.5. Distance between the Base Station and Each Sensor

Calculate the distance between the base station to each sensor nodes, where, (XBS, YBS, ZBS) and (x1, y1, z1) are the coordinate positions of the base station and each sensor node, respectively, [2] as computed by Equation (5).

$$Dist = \sqrt{((\text{XBS} - \text{x1})\hat{}2 + (\text{YBS} - \text{y1})\hat{}2 + (\text{ZBS} - \text{z1})\hat{}2)} \tag{5}$$

3.1.6. Mobility of a Node

Mobility is an important factor to consider when selecting a cluster head. Consider electing a cluster head who is more stationary; that would be more reliable [2]. 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 [1]. In this scenario, only a small amount of information can be sent between the node and the cluster head, so in our proposed methodology, we use the mobility of a node as a dividing factor which is being calculated by Equation (6).

$$\mathrm{Mi} = \frac{\frac{1}{\mathrm{T}}\sum_{t=1}^{T}\sqrt{(\mathrm{Xt}-\mathrm{Xt}-1)^2+(\mathrm{Yt}-\mathrm{Yt}-1)+(\mathrm{Zt}-\mathrm{Zt}-1)}}{} \tag{6}$$

Calculate the weight of the node W_i using Equation (7) as follows for each node participating in the cluster head election:

$$W_i = (w1 \times T_i + w2 \times Res_i + w3 \times D_i + w4 \times \text{Total Eng}_{\,i} + w5 \times Dist_i)/\text{Mobility of a node }(M_i) \tag{7}$$

where w1, w2, w3, w4 and w5 are coefficients to system criteria with certain values.

3.2. Our Proposed Algorithm

A node's degree, transmission power, mobility, starting out energy of each sensor node, trust value node and distance from the base station to each sensor node are all taken into account when determining how fit a node is to be a cluster head. Our clustering technique takes into account the following factors:

- Elections for cluster heads take place in a parodic nature.
- Ideally, only M nodes may be supported by each cluster head. The maximum node degree is M.
- It is more stable as a cluster head if the node's degree is greater. Degree difference DD as ∣di-M∣, where di is the practical degree of node i and M is the maximum degree. The better node I is as a cluster head, the smaller the i.
- Trust level value: value assigned to an anode to anticipate its behavior.
- Mobility: In choosing who will be the cluster head, mobility is a key consideration.

  Choosing a cluster leader who is less mobile is a good idea.
- If two nodes are within a particular transmission range of one other, it requires less power to communicate with each other, i.e., the initial energy can be efficiently used within a certain transmission range. Due to the additional obligations that cluster heads have to perform for their members, they consume more battery power than an ordinary node would do.
- It is also vital to note that the distance between the base station and each sensor node is a key factor in the cluster head section process.

3.3. Network Model

Consider a sensor field, which is made up of a collection of sensors that are randomly distributed throughout a specific area. The sensing activities and data reporting in this network are done on a regular basis [30,31]. The method is predicated on the following characteristics of the model of a sensor network:

- Sensor nodes are densely distributed and homogeneous in their distribution.
- Sensor nodes are mostly similar in terms of their sensing, processing, and communication capabilities.
- Each sensor node has a unique ID.

Using the hello ER paradigm, sensor nodes broadcast data to the cluster head that is immediately adjacent to them.

- The base station (BS) is stationary and situated a long distance away from the sensors.
- Each node can communicate with the BS on a one-to-one basis

Initially, all nodes have the same amount of energy, and the network is homogenous in its energy distribution.

The sink is in charge of clustering and routing operations. As a result, the technique that has been presented is centralized.

- All nodes are energy restricted and execute tasks that are comparable to one another.

The details of the EE-SS algorithm for homogenous sensor networks are stated below in Algorithm 1 and the flow of the approach can be seen in Figure 3.

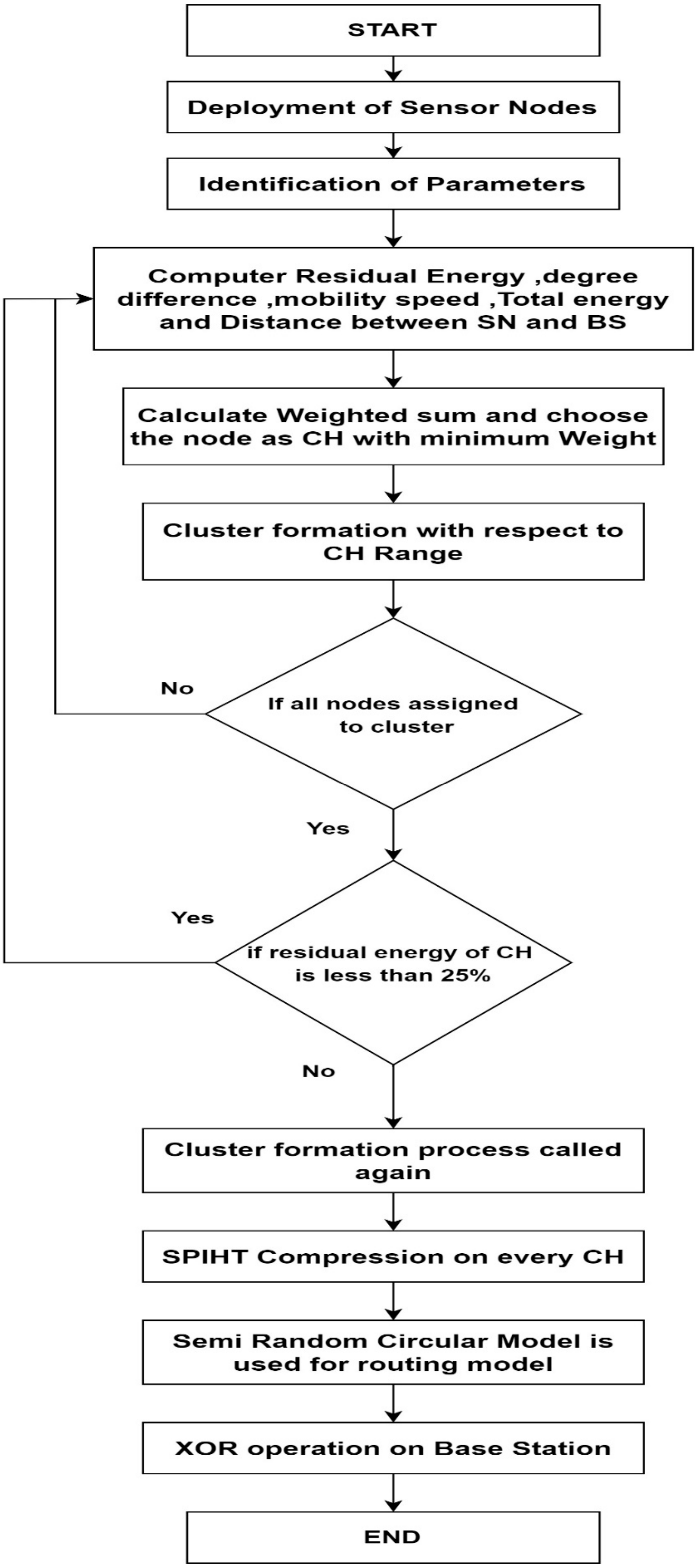

Figure 3. EE-SS proposed algorithm flowchart.

Algorithm 1. Our proposed clustering approach EE-SS

Input:*A set of sensor nodes, each with the Residual energy RES, degree difference Di, mobility speed Mi, its individual residual energy, total energy as Eri, Distance between Base station to each sensor node Dist, and Ti as the trust value for a node are the five coefficients for the weighted function (fitness function).*
Step 1: Find and compute Residual energy, Trust value, degree difference, total energy consumption and the distance between the nodes
Step 2: Computer the mobility speed of every node
Step 3: Calculate the combined weight with the help of Equation(7) by adding weight from W1 to W5
W1 for trust value = 0.5, w2 for residual energy = 0.3, w3 for degree difference = 0.1, w4 total energy consumption = 0.2, w5 coefficient for distance between SNs and BS = 0.4
Step 4: The node with the lowest Wi should be chosen to serve as the cluster head node
Step 5: Consider the nodes that are within the transmission range to be member nodes of the cluster for investigation.
Step 6: First cluster formation takes place as seen in Figure 4.
Step 7: Remove the cluster head and its neighbor from the original set of sensor nodes after cluster formulation.
Step 8 Repeat the process Step 1 to Step 7 util all nodes are assigned to a cluster
Sep 9: if the left-over energy of CH is less the 25 % of its total energy, the CH selection process is again called.
Step 11: Before sending data to base state an compression techniques is being used by CH known as SPIHT.
Step 10: for sending data to the destination Semi Random Circular Movement model is being implemented for better getting probability of success.
Step 11: On the Base Station a basic XOR operation is operated to remove the redundant data received by different CHs

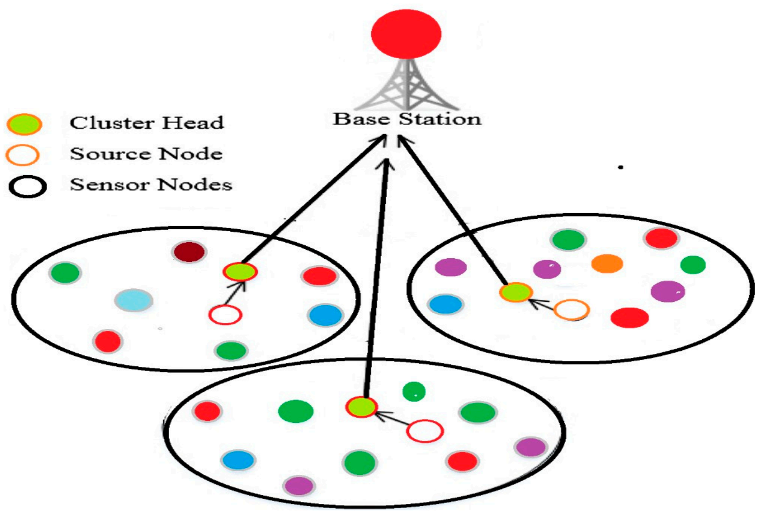

Figure 4. Clustering of SNs.

When it comes to power-constrained WSNs, implementing SPIHT [16] is an excellent choice since it delivers a better compression ratio while requiring less computing complexity, less power consumption, and a more straightforward implementation than other well-known compression algorithms [32–34]. Therefore, in our proposed algorithm, we implement SPIHT before sending data to a base station by al CHs. By avoiding the need for an entropy encoder, SPIHT generates a highly compact output bitstream, allowing for greater efficiency in terms of computing complexity and a reduction in the quantity of data that must be transmitted [20,47,48].

4. Results and Experimentation

This section explains the experimental setup and evaluates the recommended model's performance involving parameters shown in Table 3. LEACH, LEACH-C, PSO-NSA, and SEED are compared with our proposed algorithm EE-SS. Cluster lifetime, building time, and energy consumption are all taken into account when evaluating the performance of this clustering order to arrive at an average value, and we ran a total of ten simulations for each possible scenario. Initial nodes are planted in a three-dimensional free space, and their positions and directions are randomly determined. Nodes are assigned a transmission power based on their proximity to other nodes. When the new CHs are chosen, the CM works with the new CHs to plan their moment and communicate with them. Since they must rely on the messages of their constituents, CHs use more energy than CMs. In order to describe the clustering (re-clustering) criteria, we use the term pending (un-clustered) nodes. Clustering is required for pending nodes only. In Figure 5, we can see the virtual node's distribution in the concerned area.

Table 3. Simulation parameter.

Parameter	Default Value
Monitoring field	100 × 100
Count of nodes	100
Minimal distance among nodes	2 m
Simulation runs	10
Simulation time	120 s
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 of each bit energy consumed for receiving	50 × 0.000000001
Tx/Rx electronics constant [2]	50 nJ/bit
Amplifier constant [1,2]	10 pJ/bit/m^2
CH energy threshold [2]	10–4 J
Size of packet [2]	30 bytes
Packet rate [2]	1 packet/s
Sensing range [2]	10 m
Cluster radius [2]	25 m

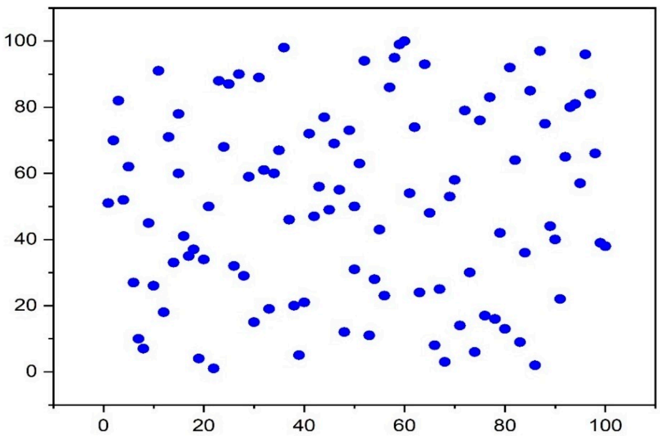

Figure 5. Deployment of nodes.

All nodes are pending nodes in the first iteration of the round; however, in following iterations, two conditions must be met to declare a node as pending: (i) the node must be pending, and (ii) the node must be pending. Furthermore, when CH's energy falls below 25% of the energy of the cluster member with the highest energy in the cluster, all nodes in that cluster will be labeled as pending nodes. When two clusters come close enough to merge into a single cluster while moving through the operational area, nodes from both clusters will be labeled as pending nodes. If the total number of pending nodes in the network surpasses 25% of the nodes, clustering will be re-enabled. The CHs will maintain the cluster structure if the number of pending nodes in the network is less than 20% of the total nodes, and nodes will communicate with the elected CHs.

4.1. Clusters Building Time

Cluster construction time refers to the time necessary to construct the clustering. The suggested method takes into account the various input values. Following these input values, the CH is picked, their cluster members are also produced, and the CH is selected. In this case, the time required between receiving the input and creating the output is called cluster formation or building time. This is also referred to as the algorithm's computational complexity or algorithmic complexity. As unmanned aerial vehicles (UAVs) have limited memory and power, long cluster formation times negatively influence their performance. It will also shorten the lifespan of UAVs since they would consume more energy. The suggested technique is evaluated compared to the current methods, including LEACH, LEACH-C, PSO-NSA, and SEED. The PSO-based approach requires less time throughout the construction phase than leach. This is because LEACH and LEACH-C are based on randomization and repeatedly converge, so they are used. As seen in Figure 6, an increase in the number of nodes will increase the time required for clusters to form. On the other hand, the suggested model employs clustering, which creates just one solution and updates it sequentially to progress towards a globally optimal solution. It is well-known for its lack of temporal complexity. The time required for route discovery is reduced due to the low complexity of the services and provisioning. It also helps to keep nodes' energy usage low.

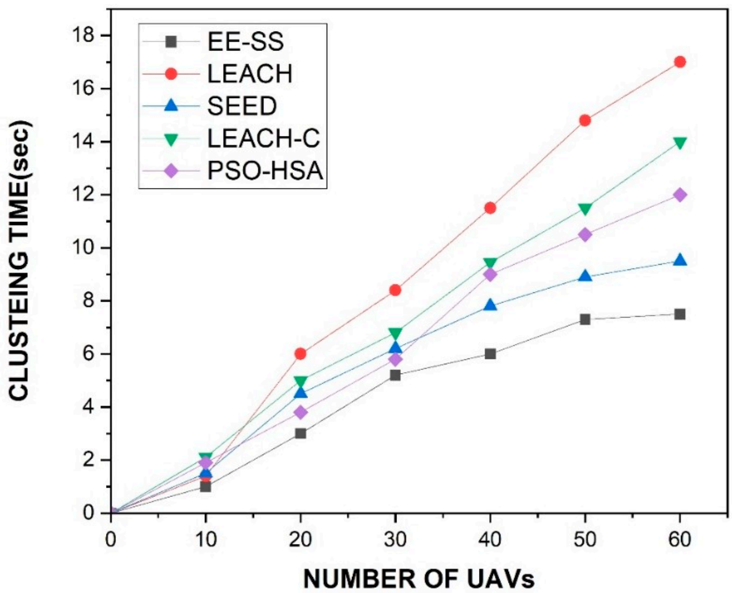

Figure 6. Clustering building time.

4.2. Cluster Lifetime

Cluster lifespan is defined as the time that has transpired between the establishment of a cluster and the point at which the cluster formation has ended. Several factors influence this, including the relative mobility of nodes, the pace at which nodes use energy, and the overall number of clusters in the network. When the level of mobility is high, nodes may be able to alter their cluster assignments more quickly than usual. Similarly, when high energy consumption rates, a chosen CH may quickly become invalid, necessitating a re-clustering effort. Due to the shorter lifetime of the cluster, it is necessary to recall the clustering factor regularly. Therefore, there is a rise in the need for computational power. Figure 7 depicts the cluster lifetimes between the proposed model and the LEACH, LEACH-C, PSO-NSA, and SEED models. The suggested model outperforms all other models by a wide margin in this metric. When considering the size of the cluster, it is too large to incorporate all of the clusters inside the transmission coverage of the CHs. The results demonstrate that increasing the number of nodes in cluster results in a decrease in the cluster's lifetime. Due to the mobility nature of UAVs, which causes topology to alter regularly, this might be the case.

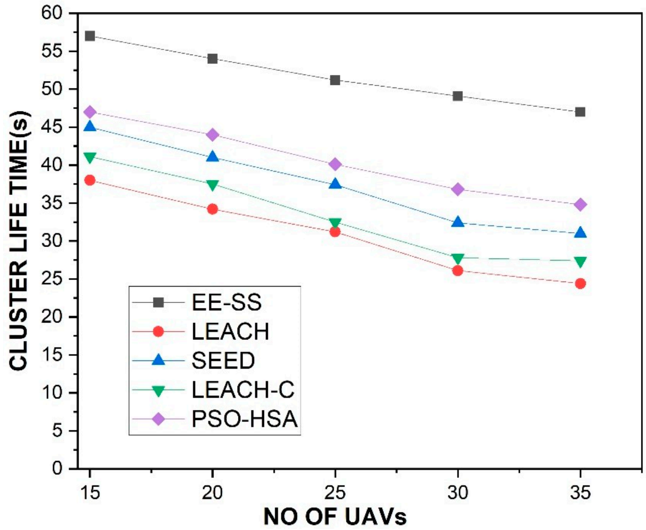

Figure 7. Clustering life time.

4.3. Alive Node Analysis

The number of active nodes in the network may be gleaned by examining the active nodes per transmission round. Nodes that are still alive can be used to estimate the network's lifespan. Alive node analysis is shown in Figure 8 and Table 4, where the first 6000 cycles of the network are analyzed. An initial node density of 60 is used for this. This shows that PSO-HSA is more efficient than LEACH and LEACH-C node life expectancy. Comparison findings are presented in tabular form in Table 4.

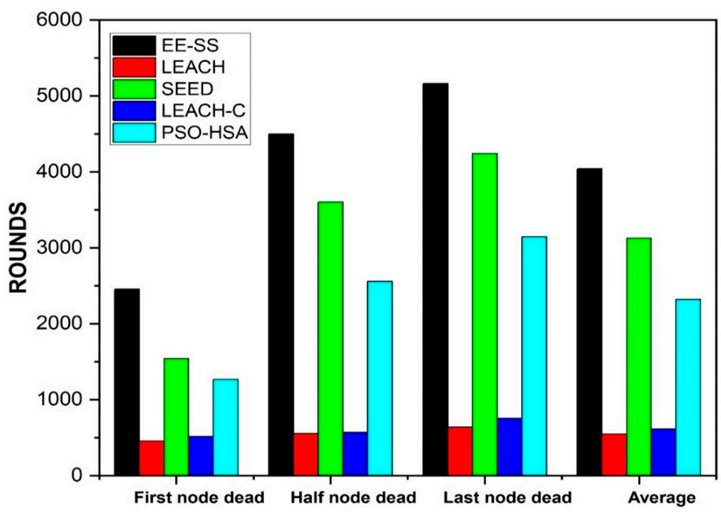

Figure 8. Lifetime of nodes.

Table 4. ANA for all algorithms.

Number of Rounds	LEACH	LEACH-C	PSO-HSA	SEED	EE-SS
First node dead	457	515	1267	1542	2456
Half node dead	549	567	2555	3601	4498
Last node dead	634	754	3145	4242	5164
Average	548	612	2322	3128	4039.3

4.4. Overall Residual Energy

Due to the limited battery capacity of the UAVs, it is vital that regulated energy drain is implemented as soon as possible. The energy consumption is measured for a predetermined number of transmissions (transmissions). UAVs rely on energy as their primary source of propulsion. The limited availability of energy resources places significant restrictions on the extensive range of uses for unmanned aerial vehicles (UAVs). Energy is dissipated by three main mechanisms in unmanned aerial vehicles (UAVs): the energy required to operate the UAV, the energy consumed by the various sensors mounted on the UAV, and the energy consumed by the UAV for communication with other unmanned aerial vehicles (which is the primary source of energy consumption). With the help of LEACH, LEACH-C, PSO-HAS, and SEED, we could compute the total energy consumed by the FANET during the 120 s. Figure 9 illustrates how the energy consumption of UAVs in a FANET grows as the number of UAVs in the FANET increases. The lower energy usage of our proposed system is due to the application of energy—conscious CH selection and cluster management techniques. It is undeniable that EE-SS outperforms the other method, which translates into lower energy consumption and a more extended network lifetime. With increasing node distance, energy consumption increases linearly, with the suggested technique growing slower than the previous competing models, indicating more excellent performance.

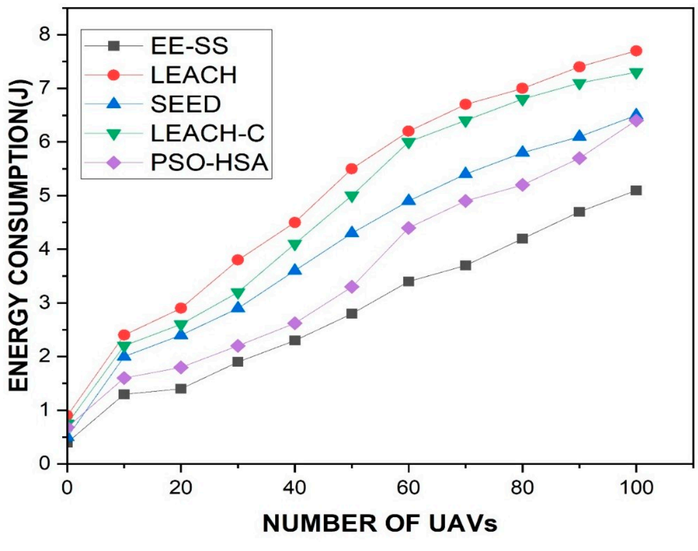

Figure 9. Clustering building time.

4.5. Probability of Delivery Success

The possibility of a packet being successfully delivered to the BS while going through intermediate nodes is defined as the probability of success. The success of sending data is primarily dependent on the average number of hops taken by each packet throughout the delivery process. According to Figure 10, an increase in the number of UAVs also improves the density of the network and the likelihood of success. The probability of delivery success improves as the number of unmanned aerial vehicles (UAVs) grows, but the packet loss ratio decreases.

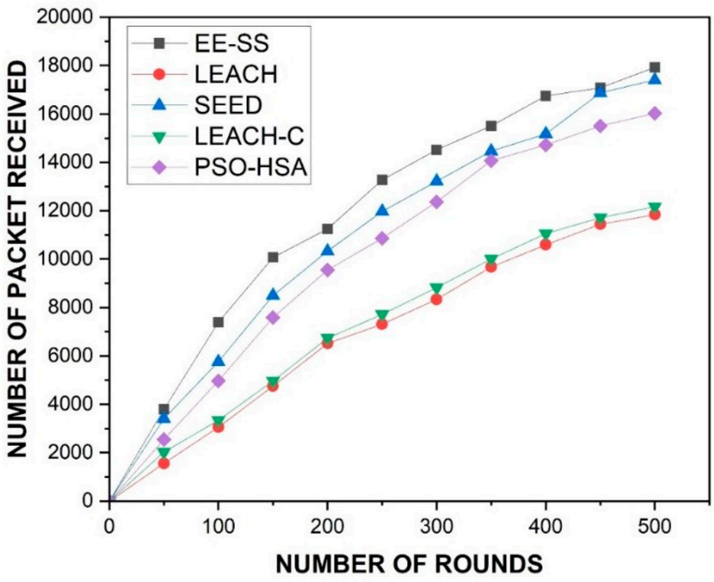

Figure 10. Packet received comparison.

5. Discussion

As a result of the research presented in this paper, a new approach for early detection and warning of wildfires has been developed. This research shows that wireless sensor networks (WSNs) are a viable environmentally friendly technology for spotting forest fires. Secondly, based on experimentation tests on simulators, we summarize the findings of Section 4. The computational study covered energy usage, cluster construction time, and alive node determination. While observing the findings, the superiority of the offered strategy was proven concerning the examined parameters. Energy consumption wise, EE-SS was the most efficient, followed by the PSO-HSA, SEED, and LEACH-C, whereas LEACH absorbed the most energy. Usually, PSO-HSA performance was better than others, but below our proposed algorithm with all evaluated parameters, but in alive node analysis, SEED works better than PSO-HSA. From the above figures and explanations for comparing different algorithms with our proposed algorithm, as seen in Figure 11, none of the related WSNs are considered unsuitable for disaster application. Moreover, these techniques can be beneficial as many people are killed each year in forest fires, and their property is destroyed. At the same time, the discharge of dangerous greenhouse gases and smoke particles contributes to air pollution and global warming through the removal of green cover.

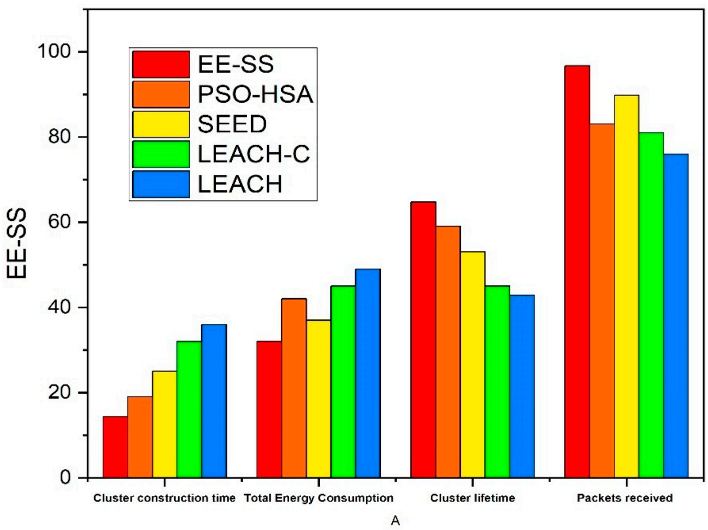

Figure 11. Overall performance comparison.

6. Conclusions

In our proposed algorithms, it has been seen that it is an energy-efficient clustering approach that supports an optimized way to elect CH for safety-critical WSN applications, with a particular emphasis on a forest fire. Energy efficiency has been identified as a critical concern for IoT networks. It was proposed to address this difficulty by using an enhanced CH exercise approach with a unique fitness function that included factors for energy efficiency, cluster building, and other parameters. We tested the effectiveness of the suggested strategy in a forest fire scenario, comparing it to previous studies and taking into account varied sink node locations. The results were promising. Various performance parameters, such as overall residuary energy, the count of live nodes, and network building, were considered in simulation evaluations. These are the following conclusions that we reached: (1) our proposed EE-SS performs significantly better in a disaster area than the current best practices; (2) the sink node's location (the distance between the nodes) affects the execution of the algorithm. (3) In a catastrophic scenario, probabilistic algorithms such as LEACH and LEACH-C do not function as expected. Compared with the conventional algorithms, the simulation results proved the effectiveness of the proposed EE-SS clustering algorithm.

7. Future Scope

In the future, we want to use this approach to design efficient medium-range communication (MAC) protocols, especially for heterogeneous networks, to prevent lengthy delays and broaden simulation scenarios. In the future, we will focus on establishing a routing protocol to make the network more cost-effective while also minimizing the end-to-end delay, which we plan to deploy shortly. Furthermore, integrating encryption, decryption, and blockchain models to give high-security levels to WSN encourages the development of security algorithms. The energy efficiency of the EE-SS methodology can be improved even more in the future by including more optimized data aggregation methods in its development. Additionally, techniques for allocating resources based on metaheuristic algorithms could be made to make sure that the resources are used as well as possible.

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