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Early Forest Fire Detection Using a Protocol for Energy-Efficient Clustering with Weighted-Based Optimization in Wireless Sensor Networks

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Abstract: Wireless sensor networks (WSNs) have proven to be incredibly useful for forest applications that rely on sensing technologies for event detection and monitoring. This radical sensing technology has revolutionized data gathering, analysis, and application. Despite the many advantages of this technology, one key drawback is the rapid drain on sensor batteries caused by their intensive processing activities and communication processes. The effectiveness of sensor nodes is strongly influenced by two factors: the amount of energy they consume and the length of their coverage lifetimes. Using our proposed method, we can find fire zones in a forest, detect and monitor battlefield surveillance, combat monitoring and intruder detection, and then wirelessly send all the information to a central station. So, extending the life of WSNs is essential to ensure that Sensor Nodes (SN) will always be available. Our proposed EEWBP (energy-efficient weighted-based protocol) technique uses a composite weighted metric that includes system elements such as the node degree, residual energy, the number of neighbors' nodes, average flying speed, and trust value, which are evaluated separately and then added together to help in cluster-building and node-scheduling processes. Our proposed protocol makes it easy to set up many clusters of SNs, each with their own cluster head (CH). This way, data can be sent between clusters in a way that uses the least amount of energy and makes coverage last longer. After putting our cluster-based routing strategy in place, we tested how it worked and evaluated it with different network parameters. The simulation results show that EEWBP consumes less energy and maintains a higher level of consistency in the CH than coverage preserving clustering protocol (CPCP), coverage clustering protocol (CACP), coverage aware unequal clustering algorithm (CUCA), and low-energy adaptive clustering hierarchy (LEACH). EEWBP also shows a better packet delivery rate and an improvement in first-node death.

Keywords: clustering; wildfire; IoT; efficient; smart city; LEACH; routing protocol; WSN

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1. Introduction

Devastating human communities and forest ecosystems alike, forest fires have emerged as a global security concern. Such devastation can lead to climatic shifts and the greenhouse effect, among other adverse outcomes. An intriguing fact is that humans cause the majority of forest fires, and because of this, early detection of forest fires is crucial if we are to reduce the amount of damage that these blazes inflict. Wireless Sensor Networks (WSNs) and comparable sensing technologies should be deployed citywide to facilitate the provision of these new services. These sensors, once deployed, self-organize into ad hoc networks to guarantee worldwide connectivity despite their varying and sometimes minimal ranges [1]. Once installed and set up, these sensors can be used to keep tabs on all sorts of data, from motion to temperature to humidity to the detection of a fire, so that immediate safety measures can be taken [2]. They can even set off other actions, directly or indirectly, like turning on a light when they sense motion. Small, lightweight, cheap, and low-powered sensor nodes are the building blocks of WSNs [2,3]. These nodes can collect sensor data, process it, aggregate it, and then send it directly to the base station (BS) through the wireless channel or relay it to the BS via their neighboring nodes.

Each node in a WSN has a nonreplaceable battery [4–8] and uses energy to collect, process, and send data; hence, these networks are typically used in remote sensing applications. This means that in times of crisis, there needs to be effective communication amongst sensor nodes so that aid can be sent more quickly [3]. It may be difficult or expensive to replace worn-out batteries in certain circumstances [4–7], such as in inaccessible places. Since communication and sensing activities reduce a sensor node's battery or power source capacity, designing energy-aware solutions is crucial for extending the lifetime of WSNs. Due to computational and storage limitations in such small and energy-constrained sensors, designing energy-efficient routing strategies for WSNs is challenging [5,6]. To make wireless sensor networks (WSNs) last longer, we offer a new protocol called EEWBP, which is an improved version of weighted clustering. WSNs are wireless networks that can only connect through a base station (BS) and routing is intricate because they have a short battery life, which makes it hard to plan routes. WSN defines a vast network of SNs that keep track of a comprehensive layout of monitoring tasks, such as health monitoring [7,8], environmental supervising, and military intelligence information gathering [1–4]. The BS and a slew of sensor nodes make up a wireless sensor network. SN gather information about their surroundings and impart it to the Base Station or sink via intermediary nodes for analysis [2]. Any protocol for WSNs must consider the network's lifespan as a primary concern since sensor nodes in WSNs are often powered by batteries, limiting the amount of energy available for use and output. Recent developments in WSNs have employed various logical strategies to get over the restrictions placed by traditional WSNs, such as energy gleaning methods, cognitive networking methods, and artificial intelligence-based techniques [4–7]. Due to their elevated position and increased distance from one another, the nodes in an airborne network have excellent visibility and communication. Due to technical constraints, WSNs can only carry a very modest battery. Besides the energy stored in their batteries, other resources, such as processing speed and data transfer capacity, are also restricted [5]. WSN topology is not constrained, changes rapidly, and can be distributed to only a small region, while WSN deployment is either random or structured. WSN interact like remote-controlled alarm systems or wildfire, whereas WSNs may communicate with the environment. Unlike casual WSNs, which rely on broadcasting messages, our proposed algorithm uses point-to-point or clustered communication [8,9]. In WSN, researchers are still working to solve energy limits in homogeneous SNs despite this new phase of WSN research and low energy supply has prompted a systematic approach to creating energy-efficient, lifetime-enhancing algorithms [3–5]. WSN must improve coverage and network lifespan to meet the demands of new emerging scenarios and applications. The sensor nodes in our network have the same energy, hardware, and transmission capabilities since we will work on homogenous sensor networks [4–6]. It is essential to remember that each sensor node has a different battery power drainage rate. A cluster head and several active member nodes work within a single cluster. To send the data to the BS, the cluster head has to aggregate and broadcast it through the cluster member nodes. The nodes in the cluster gather the data and relay it to the cluster's central node (CH) [4]. Cluster members generally use less energy than cluster heads [1,2]. Clustering methods in WSNs can improve the three primary issues: scalability, network lifetime, and energy efficiency. Clustering divides a network into SNs, called Cluster Members, linked together through the CH. The CMs watch over their particular environments and regularly relay the data they gather to the CHs. Clustering methods prevent the CMs from immediately sending information to the BS, which will drain the node's energy very quickly [10–14]. The associated CHs collect data from their corresponding CMs and send it to the BS in a consolidated manner. Energy consumption can be reduced due to decreasing the number of messages sent to BS [6], which is utilized in our proposed technique. Performance criteria such as energy efficiency, network life expectancy, number of CHs per round, and consistency in the number of CH are considered while evaluating clustering algorithms [14–16]. In this paper, an energy-efficient weight-based protocol (EEWBP) is proposed. There are two processes involved in EEWBP: (1) the cluster creation process and (2) the data transmission process, which divides the monitoring field into groups of sensor nodes or clusters [17]. The SN must be operational in each monitoring area for a more extended time to maintain comprehensive coverage. For cluster construction, EEWBP employs the weighted-sum approach. Periodically, the EEWBP makes suitable CMs, and CHs ensure that the network's lifetime is maintained during every operation round. The choice of CMs and CHs are the basic things that provide long-term coverage and efficient efficiency. Residual energy, sensor node degree, trust value, and flying speed are all weighted value parameters in the EEWBP algorithm. The weighted-sum approach assigns weights to the various controlling factors to save energy, extending the monitoring field's lifespan. Governing parameters are selected depending on energy and coverage considerations. Node density, distance from SN to a sink [18–20], and other factors affect network lifespan. So, our current research mostly ends up involving some crucial parameters like residual energy, node density, trust value, and SN degree at the same time and chooses a group of active nodes and CHs that work efficiently as well as in the optimal way.

Our most significant contributions are as follows:

- Reasonable packet data transmission rate and energy-efficient for the WSN nodes using a novel clustering routing algorithm have been developed in this paper;
- We develop a new function that considers energy efficiency through a cluster formation process to make the CH excerption process better;
- Surpassing existing systems in terms of their energy consumption, the number of live nodes, packet delivery rate, and among other metrics too;
- To better comprehend the protocols and related approaches used by WSNs, we provide a thorough analysis and evaluation of the relevant literature based on clustering parameters.

This paper has been distributed in the following ways: In Section 2, a discussion about the background of WSN and how it can be utilized. In Section 3, the literature review is conducted. Section 4 gives a detailed explanation of how our proposed routing protocol would be put into action. Section 5 shows how the proposed routing protocol is doing in terms of performance as well as in energy consumption. Section 6 wraps up with a conclusion and explains the future scope of our research.

2. Background

Building, health, ecological monitoring, security, housing, transportation (cars, aircraft, ships), and retail are just a few places where innovative technology is applied. However, just like sentient animals, smart surroundings first rely on sensory data from the physical world [20,21]. The emergence of sensors has been made feasible by the rapid development of wireless communication systems, digital electronics, and microelectromechanical system (MEMS) technology in recent years. The tiny devices can measure the surrounding environment's temperature, pressure, humidity, water content, gas presence, and light intensity. Despite the many uses for WSNs, their sensor nodes are constrained in several ways. They have low computational power, limited memory and storage, poor range and bandwidth, and limited energy [21–23]. One sensor cannot cover large regions due to its short communication range. When many sensors are placed near and linked together, they form a Wireless Sensor Network (WSN) that can monitor a larger area. The lifespan of a sensor node, and by extension, the lifetime of the whole network, is determined by its energy consumption, making this the most crucial factor to consider when developing a WSN. For optimal network performance, it is essential to strike a balance between the sensors' energy restrictions and their resource limits [24,25]. However, when there are many nodes in a network, conventional direct routing can be inefficient and severely shorten the system's lifespan. As a carryover from traditional wired networks, hierarchical or cluster-based routing is commonly utilized for massive WSNs due to the benefits it provides in terms of scalability, efficient communication, and fault tolerance. The entire network is broken up into smaller clusters in hierarchical systems. Cluster Head (CH) nodes are in charge of aggregating and fusing information from other nodes in the same cluster [26].

A multi-hop behavior is possible for both inter- and intra-cluster communications when using this routing method [27]. Therefore, to conserve its remaining energy, a sensor node will communicate with its nearest neighbor rather than with a neighbor that is further away. On the other hand, unsupervised learning-based clustering methods try to find a balance between the amount of data collected and the amount of data sent [28]. Probabilistic clustering methods predominate in the classic hierarchical-based algorithms. However, as pointed out by the authors, clustering on WSN remains an NP-hard optimization issue that cannot be efficiently handled using classical methods [29].

Utilizing methods based on some weighted parameters or bio-inspired Machine Learning algorithms allows for a more precise solution to the NP optimization of clustering. The term “optimized clustering algorithms” describes the most recent paradigm shift in clustering methods. Environmental and biological behaviors algorithms and weighted algorithms can be considered to build an efficient clustering algorithm [28]. There is always a need for clustering solutions which should outperform the vast majority of their predecessors in terms of scalability, reliability, fault tolerance, data delivery, energy consumption, better coverage of the experimental field, and extended network lifetime [30,31]. At the same time, the type of application used dramatically impacts how much it costs to set up and run a network.

Using sensors and cameras, real-time photos, audio, and videos are captured by WSNs and the data is instantaneously sent to the BS. Following this, the BS evaluates the data and provides messages, such as alerts, when detecting a disruption or incident. Multi-WSN scenarios considerably influence human life and activities [24,25]. For example, 340,000 accidental injuries and $10 million yearly costs may be reduced using a multi-WSN scenario to identify and monitor wildfires [20]. WSNs are also a kind of WSN that are often used to link hard-to-reach locations in countries prone to natural disasters and military applications [28]. With the aid of WSNs, traditional networks can autonomously shut down in the event of a catastrophic disaster (such as an earthquake, hurricane, storm, tsunami, and dam breakage). Cameras and other sensors prepared to save lives in emergencies can also be installed, giving a constant aerial view. Direct communication between the SNs and the BS on the ground may become impractical in large coverage regions. However, hop-to-hop communication can overcome this problem by using a routing protocol to find the optimum route/path from the source to the destination [21–25].

Routing protocols are responsible for discovering, establishing, and maintaining communication routes between two nodes [15–18]. There are several advantages to using these protocols, including reducing overhead and bandwidth use. Many elements of WSN routing protocols make them more brutal as they are fixed network protocols but also include dynamic topology algorithm, mutual intervention, limited battery capacity, and the restricted resources accessible in SNs. Hence, it is required to use routing information to find other paths [26]. As a result, communication cannot be limited to the radius of the action of each device but rather the aggregate of the radius of the action of all devices. Furthermore, in SN, determining contact paths and their spatial organization is a crucial task. As a result, these routes are frequently restructured such that the SN may operate in unison [28–31]. Therefore, it is critical that routing be dynamically performed with the WSNs autonomy being increased and the time between the source and target nodes being reduced [32–34]. With the help of various sensors, WSN are frequently employed to track areas in images or videos [32–35]. This means that the Quality of Experience (QoE) measures must verify both video streaming consistency and data transfer effectiveness. Search missions, surveillance, agricultural monitoring, disaster monitoring, and environmental monitoring have all used the multi-SN scenario to identify targets (i.e., the location of a target) and to give a birds-eye perspective for surveillance (weather conditions including such wind and temperature as well as light intensity and pollution) [34–36]. Using the multi-sensor nodes scenario, traffic can also be efferent-monitored and managed [22] as a part of smart city monitoring and catastrophe management systems.

2.1. Wireless Sensors Network (WSN)

As the name implies, a Wireless Sensor Network (WSN) comprises a collection of sensors located in different areas of a building or campus that are linked wirelessly. As can be seen in Figure 1, a sensor node, also known as a mote, is an electronic device that incorporates a CPU, memory, a transceiver module, a single sensor or many sensors, an analog-to-digital converter (ADC) [36–38], and a power supply, typically a battery. A positioning unit and a mobilizing unit are available additions. A sensor node's sensor(s) monitors the surrounding environment for changes in the present conditions. To handle these readings, the CPU at the node first converts them from analog to digital form using the ADC unit [39–42]. The data processed by the node can be sent wirelessly to other nodes and a designated sink point, called the Base Station, using the node's transceiver [43].

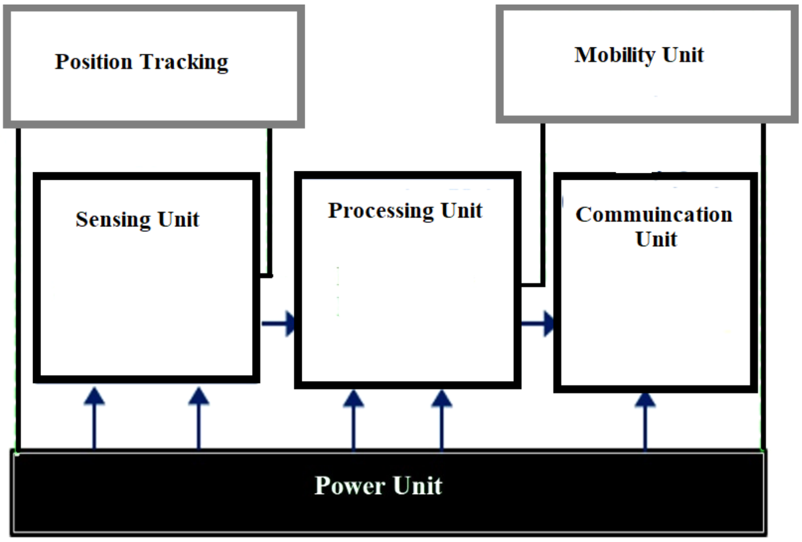

Figure 1. Basic WSN Structure.

The Base Station can exercise supervisory control over the WSN to which it belongs and relay relevant data to either human users or/and other networks by using the data transmitted to itself [44]. By working together, many sensor nodes in a WSN can simultaneously collect data from multiple sites of interest dispersed across large regions. Constant technical progress has made possible the cheap mass production of such sensor nodes, which despite their diminutive stature [45], have incredibly sophisticated sensing, processing, and communication capacities. This is why, even though WSNs were initially employed for military functions, they currently support an ever-expanding variety of uses [32].

2.2. Why WSN Is Important in Forest Fire Detection

The protocol for energy-efficient clustering with weighted-based optimization in wireless sensor networks for early forest fire detection is designed to improve the energy efficiency and detection accuracy of wireless sensor networks used for forest fire monitoring. The protocol uses clustering algorithms to group sensors into clusters and assign a cluster head to each cluster. The cluster head is responsible for collecting data from its member sensors, processing the data, and sending it to the base station. The optimization of the clustering is based on weighted factors such as energy consumption, distance between sensors, and sensing range. This protocol helps to conserve energy in the network and improve the accuracy of forest fire detection. Wildfires pose a significant hazard to both human lives and natural resources. As is well known, forest fires can travel great distances and burn for weeks or months, posing serious threats to the surrounding environment and frequently leading to air pollution in neighboring countries. The forests, however, are typically situated in inaccessible, ungoverned regions. Additionally, the forests typically include dried wood, trees, and leaves, all of which can be used as fire fuel. Both natural and human-caused climate change and human activity present risks for forest fires. As the forest fire is usually discovered after it has already spread across a broad area, putting out such blazes is an arduous task. As a result, forest fires cause substantial economic and ecological losses. Further, forest fires cause lasting harm, such as the loss of biodiversity and the acceleration of climate change. As a result, keeping an eye on forests is crucial for preventing the damage that might be caused by fires. However, due to its continuous, prolonged surveillance of the forest, the network designed to detect fires in the woods uses a great deal of energy. Thanks to its many benefits, the wireless mobile sensor network is increasingly being used for forest fire detection. These include the fact that the network's sensors are able to detect heat from fires, that it can be installed at any time and place, that it can provide access to information about the sensors' locations, that it is self-configuring, that the sensor nodes can function as routers, that it is less expensive than wired sensor networks, that it is scalable and flexible, and that it is highly reliable. However, the lifetime of the network for forest monitoring is limited by the inefficiency of the routing protocols in the field of forest fire networks with regard to data transmission and energy consumption. Energy-Efficient Clustering with Weighted-Based Optimization is a newly developed routing protocol presented in this study. For forest fire monitoring networks, the described EECWO protocol takes into account route length between nodes, energy usage, and the like, to boost network performance. Furthermore, many evaluation metrics are used to assess LARRR therapies' efficacy.

2.3. Author Contribution

In addition to providing the reader with assistance in selecting a clustering method tailored to their particular application's requirements, this paper's primary objective is to provide a concise review of several clustering methodologies [22]. In order to accomplish this goal, we conducted a comprehensive analysis of the most up-to-date optimized clustering solutions [40]. As a result, multiple performance parameters are utilized to compare and assess them. LEACH is a fascinating routing system for WSNs, yet it is plagued with several flaws that adversely impair its performance. These deficiencies result from many variables connected to its operation, some of which are highlighted below.

- In subsequent rounds, we will choose the CH without considering the excess energy of the sensor nodes;
- Therefore, a sensor node with low residual energy will pass away rapidly if it is picked to be the CH;
- Due to this, the network's resilience is diminished and its lifetime is shortened;
- Since they are placed near the edge of the clusters, the CHs would lose more energy, which would hurt the overall performance of the network;
- When it comes to data transmission, CHs that are further away from the BS use up more energy than CHs that are positioned closer to the BS. Due to this, the lifespan of the network may be reduced.

We may sum up our primary contributions as follows.

- Create a clustering protocol using weighted parameters. Review the state-of-the-art WSN clustering;
- Extensive comparison and assessment of the offered algorithms based on the parameters;
- Compared to state-of-the-art algorithms, the proposed one has significantly lower energy requirements while maintaining or improving performance.

3. Literature Review

A huge variety of clustering methods are available for maximizing energy efficiency and increasing the lifetime of a node. Algorithms for this will offer both advantages and disadvantages. This section reviews some existing research on these algorithms [4,5]. A longer network lifetime can be achieved by balancing the energy consumption of SN and distributing the load among them. Uniform/non-uniform/equal/unequal clustering is possible in these techniques [9]. These clustering techniques employ characteristics like distance, residual energy, node density, etc., in a probabilistic manner known as the weighted-sum approach to optimize network lifetime [7]. However, there is still room for improvement in these energy-efficient clustering algorithms to maximize each node's lifespan. Algorithms for energy-efficient power consumption are commonly based on battery conservation, node scheduling, load balancing, coverage area size, clustering, and routing techniques [13]. These algorithms reduce energy usage as much as possible to maximize network longevity and coverage. We will discuss several newly proposed guidelines that deal with energy and coverage in the following.

Low-energy adaptive clustering hierarchy (LEACH) [1] is a first-of-its-kind WSN clustering routing technique that chooses CHs based on rotation and a random value. LEACH operations are done in rounds; each round has two parts: setting up and staying steady. During setup, a CH is chosen, a cluster is made, and a Time Division Multiple Access (TDMA) schedule is given to each member node. In the CH selection process, each node comes up with a random precedence value between 0 and 1. If the random number that SN comes up with is less than T(n), it becomes CH. Choosing the CH based on residual power is vital to how well a network works and how long it lasts.

The network can live longer if the chosen CH is a sensor node with the most energy left out of all the cluster members. Based on residual energy, node location, and neighbors' numbers, the Improved-Low-energy adaptive clustering hierarchy (I-LEACH) [5] clustering routing system selects the CHs. There are considerations for additional characteristics that affect the network's lifespan, as they are not in the original LEACH algorithm's CH selection. The residual energy, the number of neighbors' nodes, and the distance to the BS are all accounted for in the threshold function of the I-LEACH approach. Coverage Preserving Clustering Protocol (CPCP) [6] was presented to preserve coverage through CH selection approaches. The CPCP considers numerous cost parameters that will affect the lifespan and range. In addition, it prioritizes SN with a high deployment density as CHs, active nodes, and routing nodes. It is a good solution for network coverage. However, CPCP has a colossal processing burden on sensors, making it inefficient. Choosing a CH and active node in a randomly dispersed network can be more accessible with the Coverage-Aware Clustering Protocol (CACP). CACP, on the other hand, requires each CH to submit the aggregated data straight to the sink. As a result, the CHs die more quickly and consume more energy.

Centralized Low-energy adaptive clustering hierarchy (LEACH-C) [7] is a centralized clustering algorithm that uses the excess energy of nodes to select CHs and thus creates clusters within the network. The typical LEACH protocol's efficiency problem is addressed by LEACH-C, which uses a centralized method to pick the most skilled CH from a pool of nominated CHs. During the first phase, sensor nodes communicate with the sink to learn how much energy they have left and where they are. To identify which nodes are to be chosen as CHs, the sink uses these data to calculate the average power of all grounded nodes in the system. As a result, CHs will be selected from nodes with more energy remaining than the average in this round. Each stage of this retransmission wastes a small amount of energy, which is not ideal. The authors of article [20] suggest a jamming-resilient multipath routing protocol to ensure that purposeful interruption and jamming and isolated and localized failures do not interfere with the overall performance of networks. The JarmRout relies on a mix of three critical schemes to accomplish this objective. These are connection quality, traffic load, and geographic distance schemes. For fast and secure data transfer, the authors of article [17] suggest a stochastic packet forwarding (SPF) technique. The

SPF's fundamental tenet is utilizing a number of real-time network indicators to create a random selection of forwarding drones. The SPF calculates the forwarding availability of each candidate drone by objectively allocating the weight to several real-time network parameters based on the entropy weight theory. To facilitate effective, trustworthy communication and data transfer in network, the authors of paper [31] suggest a link-quality and traffic-load-aware optimal link state routing protocol (also known as LTA-OLSR). The suggested link quality system uses the statistical information of received signal strength indication (RSSI) of packets to discriminate between the connection qualities of a node and its neighbor nodes. To effectively and safely transmit data packets to ground targets in WSNs, authors propose a hybrid packet forwarding method, HYBD fwd, in an article [42]. End-to-end routing and delay-tolerant forwarding make up the HYBD fwd. In order to get data packets from the drone to their final destination on the ground, end-to-end routing uses a route discovery technique.

The Distributed Energy and Coverage Aware Routing algorithm (DECAR) [12] has been developed to extend the lifespan of WSN. DECAR solves the problem of data transmission hot spots. Tables 1–3 provide a comprehensive summary of the above material and reveal the common shortcomings of the algorithms. These difficulties are solved to some extent by CPCP but the computational cost on sensor nodes is prohibitive. As a result, a new algorithm, EEWBP, has been developed to address these concerns. To save energy, EEWBP employs some simple techniques in an algorithm. This reduces the computational strain on SN, resulting in a more extended period for complete area coverage, flexibility, and enhanced scalability. There are substantial tactical differences between the cluster creation processes used in CPCP and CUCA. Our weighted-sum approach chooses the most efficient CMs and CHs. The remaining energy, node density, and degree of the SN are all energy and trust value criteria considered when determining weight values. During cluster creation, the CPCP only feels each sensor node's energy. However, the EEWBP considers all factors that have the highest impact on the network's lifespan.

Table 1. Comparison of various algorithms.

Protocol	Published Year	Type of Mode	Approach	Sensing Model	Drawbacks
LEACH [1]	2000	Homogenous	Centralized	Disc	CH nodes are distributed in a non-uniform manner. CH is chosen at random and in each cluster, the nodes are not spread uniformly.
I-LEACH [5]	2015	Homogenous	Centralized	Disc	Unlike nodes that receive distinct data, CH combines collected data to cut data transmission costs.
CPCP [6]	2009	Homogenous	Distributed	Disc	Sensor node computation load is high.
CACP [19]	2012	Homogenous	Distributed	Hexagonal	Death of CHs owing to direct transmission of aggregate data. Useful for small networks only.
LEACH-C [7]	2020	Homogenous	Distributed	Disc	The position of nodes is required every time. Transmission with a single hop adds an additional overhead to the sink when centralization is used.
FBR [8]	2013	Homogenous	Centralized	Disc	No change in sensor load when communication overhead rises.

Table 1. *Cont.*

Protocol	Published Year	Type of Mode	Approach	Sensing Model	Drawbacks
DEECIC [9]	2012	Homogenous	Distributed	Disc	Clustering algorithms that are more energy-efficient than those that are more coverage efficient.
ECDC [11]	2014	Heterogeneous	Distributed	Disc	Routing requires retransmission of control packets, consuming additional energy.
CUCA [15]	2017	Homogenous	Distributed	Disc	Useful for small networks only.
DECAR [12]	2014	Homogenous	Distributed	Disc	Send aggregate data to sink is not possible in a huge network.

Table 2. Comparability based on certain metrics.

Protocol	Energy-efficient	Position of Base Station	Number of Cluster Nodes	Number of CH	Cluster Method	Mobility
LEACH [1]	Yes	Outside	Unpredictable	Uncertain	Distributed	Static
I-LEACH [5]	Yes	Outside	Unpredictable	Certain	Distributed	Static
CPCP [6]	Yes	Centre	Unpredictable	Uncertain	Distributed	Static
CACP [19]	Yes	Outside	Unpredictable	Uncertain	Distributed	Static
LEACH-C [7]	Yes	Outside	Unpredictable	Certain	Centralized	Static
FBR [8]	Yes	Outside	Unpredictable	Uncertain	Distributed	Static
DEECIC [9]	Yes	Outside	Unpredictable	Uncertain	Distributed	Static
ECDC [11]	Yes	Outside	Unpredictable	Uncertain	Distributed	Static
CUCA [15]	Yes	Outside	Unpredictable	Uncertain	Distributed	Static
DECAR [12]	Yes	Inside	Unpredictable	Uncertain	Distributed	Static

Table 3. Comparability based on physical metrics.

Protocol	Network Size in m^2	Number of Nodes	Location Aware	Deployment Model	Coverage Type	Residuary Energy Involved
LEACH [1]	100×100	100	Yes	Random	No	No
I-LEACH [5]	100×100	100	Yes	Random	No	Yes
CPCP [6]	200×200	400	Yes	Random and non-uniform	Area	No
CACP [19]	120×120	1000	Yes	Random and uniform	Area	Yes
LEACH-C [7]	100×100	100	Yes	Random	Yes	Yes
FBR [8]	150×150	1000	Yes	Random		No
DEECIC [9]	100×100	100	No	Random	Bounded Area	Yes
ECDC [11]	200×200	100–200	Yes	Random and non-uniform	Area and point	Yes
CUCA [15]	40×40	60–100	Yes	Not discussed	Area	No
DECAR [12]	40×40	100	Yes	Random and Grid	Area	Yes

4. Proposed Algorithm EEWBP

4.1. Energy Model

This study was carried out to decrease energy consumption during the execution of the main tasks by WSNS nodes within a network. Therefore, there is a great need for an effective energy model for the WNSs to increase lifespan and coverage. The energy categories included in this model correspond to the following operational stages: activation, channel auditing, receiving packets, packets transmitting, switching, processing, and shutting off microcontrollers. The proposed EEWBP measures energy dissipation using a simple radio model. The radio model has a transmitter, amplifier, and receiver. The transmitter uses energy to execute circuitry operations like a radio signal to broadcast, amplify, and receive signals.

During data transmission to a receiver, the power amplifier gives off heat and the receiver uses energy to maintain the circuitry on the receiver end. There are two models of how information spreads: free space and multipath. Open space or multi-channel propagation models can be used depending on how far the sender and receiver are from each other [19]. If the distance is less than a certain threshold, the free space model (fs) is used. The multipath model (Mp) is used if the distance exceeds the threshold. Equation (2) shows how much energy it takes to send a message with l-bits at a distance of d.

$$\mathrm{E_{Tx}}\ (\mathrm{l,d}) = \mathrm{E_{Tx-elc\ (l)}}\ +\ \mathrm{E_{Tx-amp}}\ (\mathrm{l,d}) \tag{1}$$

$$\mathrm{lE_{elc}} + \mathrm{l}\ \in_{\mathrm{fs}}\ \mathrm{d}^2 \quad \mathrm{d} < \mathrm{d_0}$$

$$\mathrm{lE_{elc}} + \mathrm{l}\ \in_{\mathrm{fmp}}\ \mathrm{d}^4 \quad \mathrm{d} < \mathrm{d_0}$$

$$\mathrm{d_0} = \frac{\sqrt{\in_{\mathrm{fs}}}}{\in_{\mathrm{fmp}}} \tag{2}$$

Moreover, the energy expected for obtaining a one-bit message is provided as follows.

$$\mathrm{E_{Rx}(l)} = \mathrm{lE_{elc}} \tag{3}$$

The electronics energy denoted by $\mathrm{E_{elc}}$ depends upon digital coding, intonation, filtering, and disseminating of the signal. The amplifier energies ($\in_{\mathrm{fs}}\ \mathrm{d}^2$ and $\in_{\mathrm{fmp}}\ \mathrm{d}^4$) depend upon the distance to the receiver. The novelty of this model is that it has a basic design that consumes less energy than the potential network in wireless sensor models with anomalies in which the consumption of energy is relatively high. In the proposed model, energy is considered a vital indicator of a typical high lifetime of WSNS [18] nodes in a network. Moreover, this enables energy usage to be optimized for individual node operations and overall network performance. The analysis done in this paper is described by monitoring the performance measures that might influence such a model favorably or unfavorably. These are some key points where this study makes a significant contribution. As in our suggested model, it is demonstrated that there is a change in network performance, easy implementation, and no higher processing demands that have led to less consumption of energy.

4.2. Network Model

1. In our setup, low energy SNs and high energy SNs are the two types of accessible SNs. Both types of nodes are static (plain nodes);
2. The sink or BS is stationary and intended to be known by other SNs in the center of the field under surveillance;
3. The networks have the same type of sensor nodes and communication capabilities, where in all SNs are similar;
4. A unique identification number is issued to each SN;

5. There is always a limited sensing range for each SN. It is assumed that the SN is in the middle [3] of the disc and that the SNs can interact with other's nodes through changing power levels, depending on their distance from their neighbors;
6. A sensor node's transmission range is described in 2-D space as the disc-sensing model and all SNs in the area of its transmission range can acquire the data supplied from each SN [3];
7. The range of transmission is at least twice that of the sensor range [4], e.g., Trange = 2 × R sensor, where the range of transmission and sensor range are indicated as Transmission Range (Trange) and Range of Sensor (RS);
8. The connection between wireless sensor nodes is symmetrical and bidirectional and the coordinates of them are known to other SNs.

The proposed EEWBP considers an area for WSN with the N number of WSN nodes referred to as {SN1, SN2, . . . , SNN}. In our proposed protocol, we are using a 100 m × 100 m space as a monitoring field, the sensor nodes are planted randomly in a circular region known as a cluster around the sink, and in the core of the network, there is the BS. We assume the following assumptions on the sensor nodes during the design and implementation phase of EEWBP algorithms.

4.3. Network Operation

Algorithms for EEWBP are made up of two steps.

4.3.1. Cluster Formation Phase

In the first phase, active nodes and CHs were picked to represent a cluster. The EEWBP sum up assigned weight values according to the criteria as different performance parameters for every operation. EEWBP identifies active nodes and CHs, and then executes data transmission operations using the weighted-sum methodology. The data transmission procedure is executed in the second process. For example, data is sent from CMs to their respective cluster hosts (intra-cluster communication) and from various designated cluster hosts to sink hosts (inter-cluster communication) in each cycle of communications. As part of the EEWBP algorithm, SNs collect information about residual energy and other parameters. In addition to their coordinates, the SNs know the distance between them and the distance to the sink. Based on the Euclidian formula, these distance estimates are made.

After each communication cycle, all SNs are used to update their information, considering the amount of battery power that they have left. As a result, each SN broadcasts a new packet of information in its cluster radius, corresponding to the sensor's detecting range. As soon as each node receives the message, it calculates its Sum weight (Sw). Based on the excess energy of the SN, the distance between node and sink, the degree of a SN, and the trust value, Sum weight (Sw) is determined. The procedures required in selecting active nodes and CHs during the first communication round of EEWBP can be seen in Algorithm 1 and Figure 2, and the detailed procedure is mentioned below:

1. Dismantle SNs to cover the entire required region;
2. Computation of residual energy R_e of each node is done in the starting and if it is less than the threshold value, then it is skipped from the current round and can participate only in the next round of communication;

$$\text{Residual energy} = \text{initial energy} - \text{current energy} \tag{4}$$

3. Calculation of all the minimum distances between each node to the sink as denoted by Dist(i,j). To calculate distance among every node to CH and between CH to BS, we use a Basic Equation (5) known as three-dimensional Cartesian space, in which two locations have three coordinates each. In order to determine the distance spanning between two points, A(x1, y1, z1) and B(x2, y2, z2), use the formula:

$$D^2 = (\Delta x)^2 + (\Delta y)^2 + (\Delta z)^2 \tag{5}$$

where $\Delta x = x1 - x2$, $\Delta y = y1 - y2$, $\Delta z = z1 - z2$;

4. Calculation of each sensor node's net weight using a weighted-sum equation (Sw)

$$\text{Sum weight (Sw)} = \text{Re} \times x1 + \text{Avg\_FS} \times x2 + \text{SND} \times x3 + \text{Nbq} \times x4 + \text{TTV} \quad (6)$$

The values of x1, x2, x3, and x4 are 0.6, 0.3, 0.2, and 0.1 for particular application;

5. Identification of the SN with the highest value of 'Sw' as the active node for a certain region;
6. Each active node inside its sensing network radius broadcasts an updated packet to the rest of the network;
7. Calculation of 'CH wpp' (CH weighted-sum) using the determined 'Sw' of the sensor node and the distance between it and the sink;
8. Nodes with the lowest 'CH wpp' values are picked as candidates for CH for the specified active nodes;
9. Each selected CH broadcasts an updated packet inside the cluster radius;
10. If residual energy of CH is less than 25% then again CH re-selection process is repeated.

Algorithm 1 CH selection and Cluster Establishment

Start
1: **For** every SN in network deployed on space;
2: **Calculate** residual energy R_e **of every node**
3: **If** (R_e < threshold)
4: **Skip** the node for current round
5: **Calculate** of all the minimum distances between each node to the sink Dist(i,j).
6: **Calculate** each sensor node's net weight using a weighted-sum equation including **Min Avg flying** speed, 'SND(**degree of a sensor node)**, nbq(**number of neighbors**), and **Trust value**
7: Highest value of weighted-sum of a SN is denoted as active node
8: Each active node inside its sensing network radius, **Transmit** an updated packet to the rest of the network.
9: **Calculate** the 'CH wpp' (CH weighted-sum) using weighted-sum of the sensor node and the distance between it and the sink.
10: Nodes with the lowest 'CH wpp', **Declare (Itself as CH)**;
11: Each selected CH **Transmit** an updated packet inside the cluster radius
12: **End If**
End

Residual energy, flying speed, SN density, and other regulating characteristics all play a role in determining whether a SN is appropriate for use as an active node or CH. In our proposed algorithm, some key terms are used, which are described as follows:

1. Residual energy, abbreviated as "Re", is the first performance measure for weight value. Each simulation cycle ends with some leftover energy from the SN, which is known as residual energy. The larger the residual energy of the SN, the more likely it is to become an active node;
2. The next performance measure for the weight value is Average flying speed. Every node distance covered is divided by the time taken, which is considered flying speed. Then, the average of all nodes is considered as Avg flying speed. If a node's flying speed is less than Avg flying speed, it is disqualified;
3. The 'SND' denotes the degree of a sensor node, which is the third performance criteria for weight value. SND refers to the number of sites in SNi's sensing range that are reached. Initiation probability is higher for SNs to become active as it covers many locations;
4. The next functioning parameter for weight value is a number of neighbors i.e., 'Nbq'. Number of neighbors is delineated as several other SNs within its cluster range;

5. The other considered criteria in the implementation are the Trust Value [13,14] denoted as (TVL).

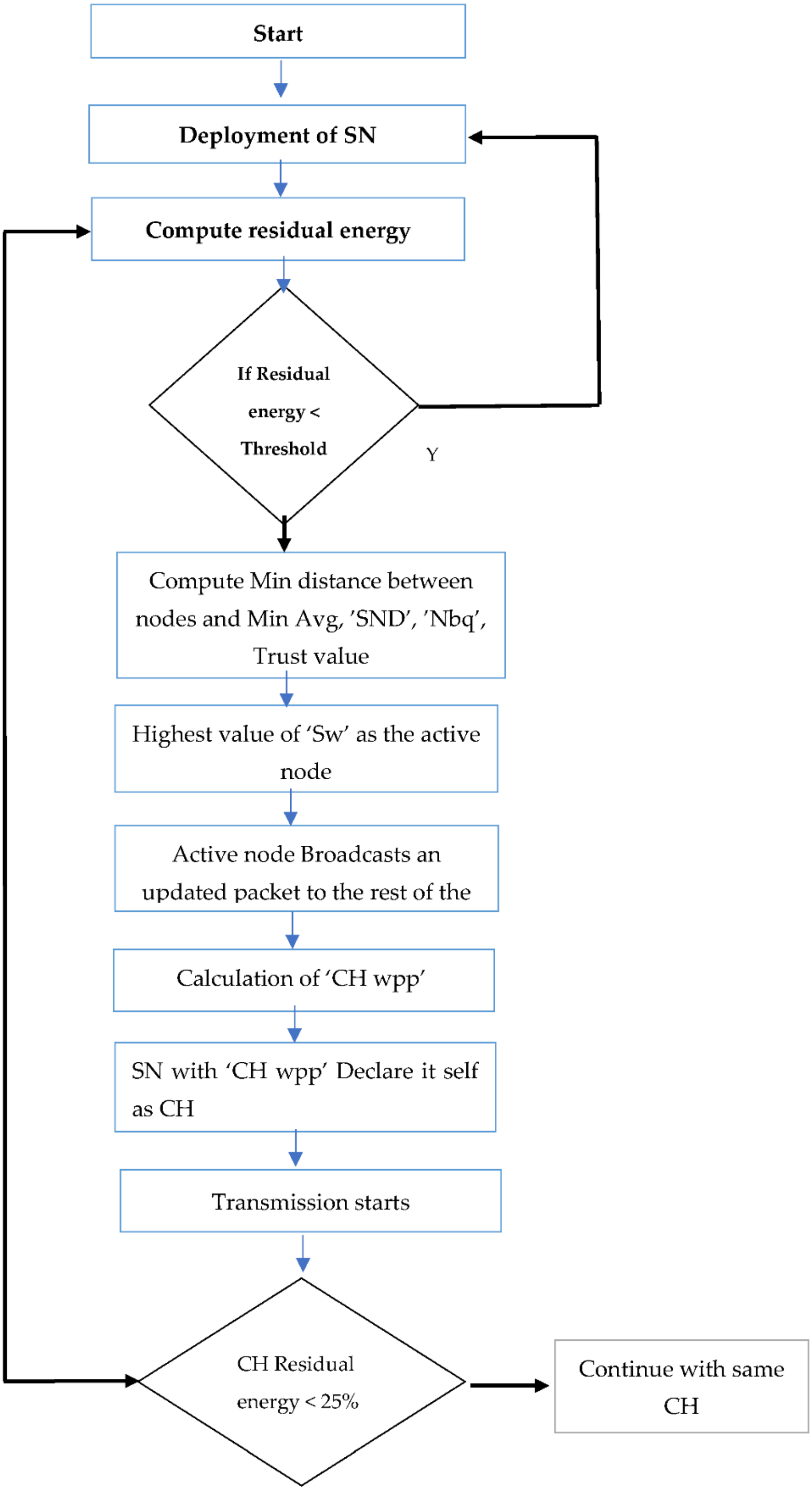

Figure 2. Proposed protocol flow.

The proposed WSN clustering eventually includes the trust value as a new parameter. The performance of the SNs is reflected in the level of trust. The trust value will be larger than the non-cooperative SNs that delay the packet's propagation to the destination; if the SN is cooperative, it will forward the packets with minor delays. Direct Trust Value and Indirect Trust Value [12–15] are two sub values of the trust value. Packet delay will be utilized to determine which packets are accepted and which ones the Direct Trust rejects. This decision is put into effect as follows:

$$\begin{array}{l} \mathrm{If} \mid \Delta \mathrm{dl}(\mathrm{n},\mathrm{m}) <= \Delta \mathrm{dl\ average}\ (\mathrm{n},\mathrm{m}) \times\ \alpha \text{ the packet is forwarded} \\ \mathrm{Else} \mid \text{the packet is dropped} \end{array} \tag{7}$$

where:

- $\Delta \mathrm{dl}(\mathrm{n},\mathrm{m})$ Sending and receiving packets from one SN n to another SN m might take some delay;
- $\Delta \mathrm{dl}(\mathrm{n},\mathrm{m})$ average, is the average delay of packets sent SN n to another SN m;
- α is the threshold constant which can range from 0 to 2. Therefore, Direct Trust can be calculated as shown in (8):

  Hence, Direct Trust [13] can be computed as demonstrated in Equation (8):

$$\mathrm{Direct\ Trust}\ (\mathrm{n.m}) =\ \mathrm{Tpf}\ /\ \mathrm{Tpr} \tag{8}$$

where:

- $\mathrm{T_{pf}}$ is the Total packets requested by SN n to be sent to SN n in the situation when $\mathrm{n} \neq \mathrm{m}$ and m is a neighbor of n;
- $\mathrm{T_{pr}}$ is the number of packets sent by SN n to SN m.

Indirect Trust: Indirect Trust between SN n and other SNs m is the sum of the Direct Trust values for SNs m that are sent to SN n from all neighboring nodes [14,15]. So, Equation (9) is used to figure out how much Indirect Trust there is:

$$\mathrm{Indirect\ Trust}\ (\mathrm{n},\mathrm{m}) = \textstyle\sum_{\mathrm{i}\alpha\mathrm{Q}} \mathrm{Direct\ Trust\ dl}(\mathrm{n},\mathrm{m}) \tag{9}$$

Here, the trustor node (SN computing the trust) is n, The Trustee (Neighbor nodes for n) is called m, and Q is one of the SNs.

Equations (8) and (9) are weighted summation to get the total Trust shown in Equation (10):

$$\mathrm{Trust}\ (\mathrm{TVL})(\mathrm{n},\mathrm{m}) =\ \alpha \times\ \mathrm{direct\ trust}\ (\mathrm{n},\mathrm{m}) + (1 -\ \alpha) \times\ \mathrm{indirect}\ (\mathrm{n},\mathrm{m}) \tag{10}$$

While there is a constant threshold $\boldsymbol{\alpha}$, it ranges from 0 to 1.

We have a grid of central points in our deployment-monitoring field. This ensures that each sensor covers an equal distance from the other. A sum of all SNs weight (Sw) is computed for each SN in the entire monitoring region. One of the sensors with more considerable residual energy and faster flying speed is chosen to participate in a communication round when two or more sensor nodes cover the same area. The SN activates a communication round by announcing an activation message. The chosen active nodes can effectively monitor every part of the monitoring region [46,47]. These active nodes are selected based on how much energy they use, how big their sense area is, and how many nodes are in the area they are monitoring. On the other hand, sleeping nodes are all nodes that stay inactive [48,49]. All cluster members should be equidistant from the cluster head in most protocols. Therefore, distance is one of the primary weighted factors in our suggested formula. It is probably chosen as the CH if it has the lowest space to the most neighbors and highest Sum weight (Sw) value.

4.3.2. Data Transmission Phase

Inter and intra-cluster communication in the second stage is known as data transmission. The active nodes use a one-hop mechanism for intra-cluster communication to transmit their detected data straight to their respective CH. In contrast, in inter-cluster communication, CHs use a multi-hop approach to convey selective information from one cluster to another [48]. In this case, the communication path is chosen using the shortest path technique as shown in Figure 3. As a result, EEWBP selects the most optimal CHs and active nodes to ensure long-term coverage. A data compression method merges all the acquired data from all the CH's. A critical XOR operation is now performed on the data detected by neighbor nodes to ensure that the CH does not send a copy of this information to the BS [38–40]. Bit scrambling is accomplished using the XOR algorithm. A "True" result is deemed to have two copies of the data, whereas a "False" result is considered to have just one copy. The duplicate-gathered data would not be transmitted if the data sent out were identical bit for a bit [16]. As a result, duplicate data can be avoided and the amount of data sent to BS has decreased automatically. Due to this, the entire system is going to utilize less energy [46].

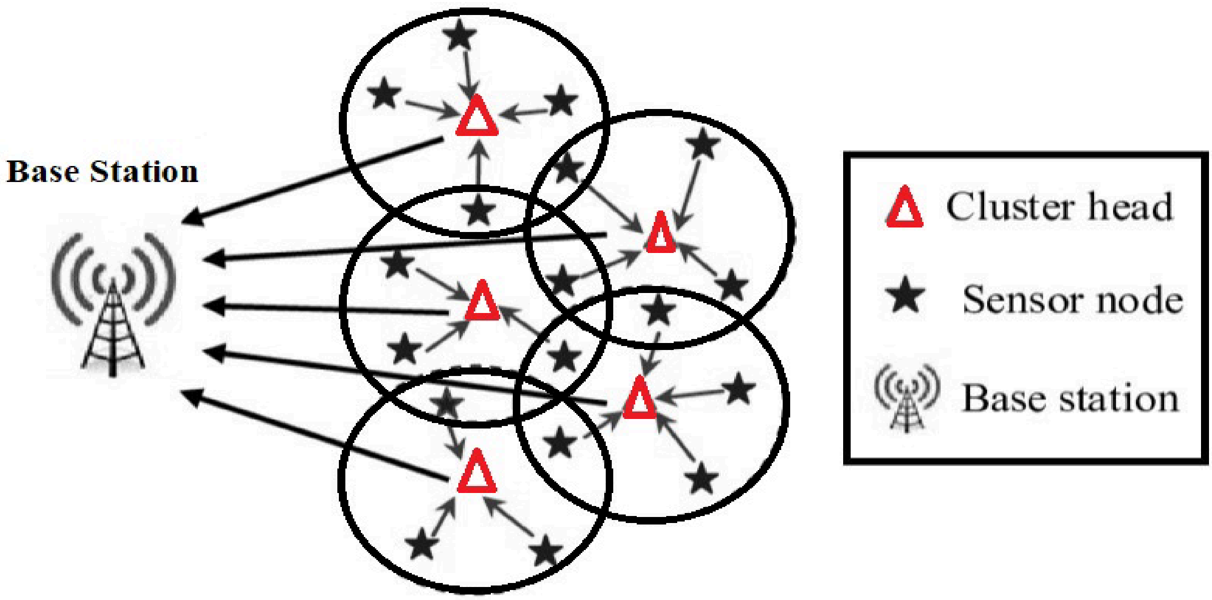

Figure 3. Proposed protocol structure.

5. Performance Analysis

5.1. Deployment of Nodes

Consider a 100 m × 100 m square area with N sensor nodes distributed at random as shown in Figure 4, using the following settings: a total of 50 nJ/bit is the initial energy, with a maximum transmission distance of 200 m and a data aggregation energy of 5 nJ/bit/message. By our proposed EEWBP method, nodes' weights are calculated using a variety of parameters, as shown in the following Table 4. Our optimized weighted clustering method uses less energy than LEACH, CACP, CPCP, and CUCA when it comes to average node energy consumption or overall power consumption. We have the ability to lower the number of transmissions by a large margin since our technique selects CH by using multi-weight parameters like residual energy, the distance between and the degree of each node, an average flight speed, and a trust value [41].

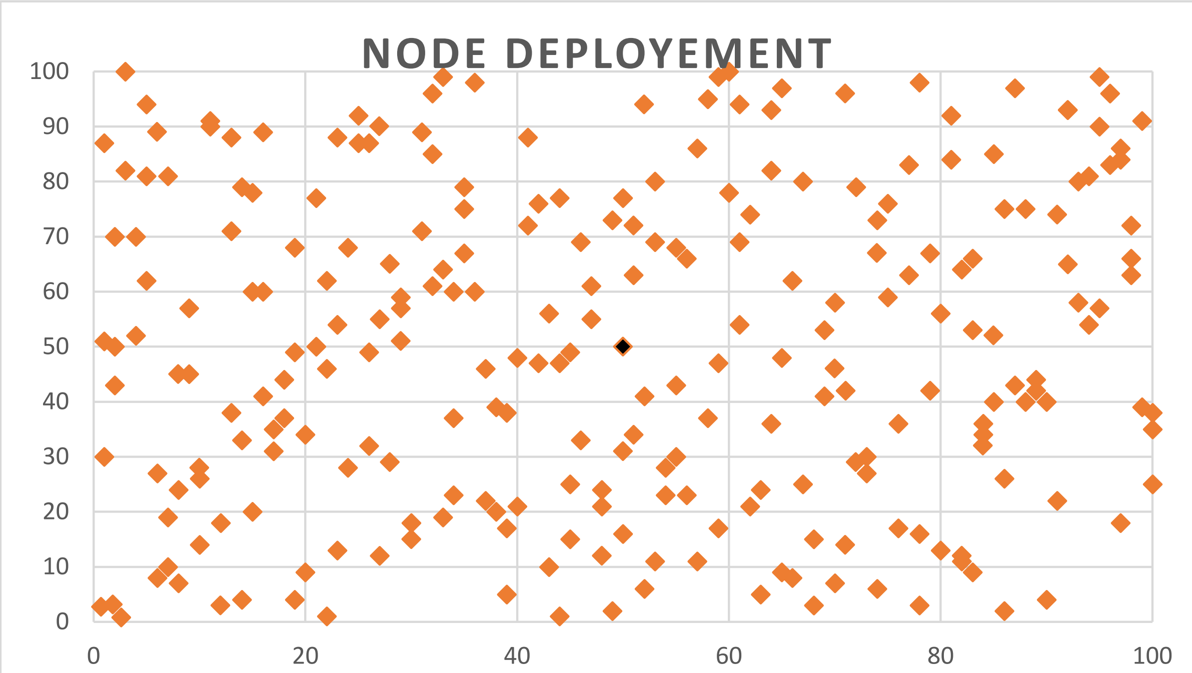

Figure 4. The distribution of network nodes, in which ♦ is conceived as SNs and ♦ as BS.

Table 4. Feigning Parameter.

Parameter	Default Value	Parameter	Default Value
Monitoring area	100 m × 100 m	Amplifier constant [1,2]	10 pJ/bit/m^2
Network node count	200	CH energy threshold [2]	10–4 J
Shortest possible path between nodes	2 m	Size of packet [2]	30 bytes
Number of simulations performed	100	Rate of packets [2]	1 packet/s
Simulation clock time	120 s	Detection distance [2]	10 m
Position of BS	(50, 50)	Size of a cluster [2]	25 m
Initial energy	0.5 J	Energy used to send each bit	50 × 0.000000001
Transmission scope	40 m	Energy used to receive	50 × 0.000000001
Chance of a node becoming a CH	0.1	Tx/Rx electronics constant [2]	50 nJ/bit

Cluster headcount, cluster construction, and consistency are the most critical factors that we employ in our evaluation process. Time, energy expenditure, network lifetime [42–44], and the probability of success are all considered. In our proposed protocol, MATLAB is used as a simulation platform in this experiment.

5.2. Number of Clusters

It has been seen that an increase in number of clusters will automatically reduce energy use because the number of nodes will be far from the CH causing a more rapid energy drainage [45]. A decrease in the number of clusters reduces the number of nodes close to CHs, increasing the rate at which network energy is used. The number of CHs required to transmit data to the BS over long distances will also increase if the clusters exceed the optimal number. In Figure 5, EEWBP has 24% fewer CHs than LEACH, CACP, CPCP, and CUCA at any given point in network operation.

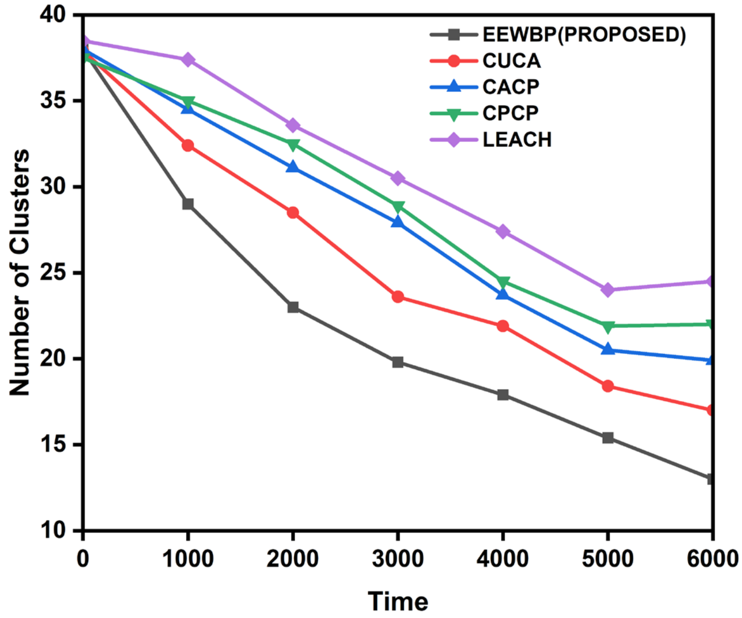

Figure 5. Number of clusters and time.

5.3. Consistency in Number of CH

Cluster headcount has a significant impact on protocol efficiency, as there will be additions in node energy consumption and over-consumption of energy. If the number of CHs is low, the number of SNs per CH will be high and the SN data transmission duration will be belonged. The total energy consumption of each round of networks grows as the number of CH increases; it decreases the network's data fusion efficiency and longevity. In Figure 6, it can be seen that our recommended EEWBP protocols' headcounts fluctuation number is better than LEACH, CACP, CPCP, and CUCA. It is easy to observe that the cluster headcount in the LEACH protocol swings between $3 \leq k \leq 19$, $4 \leq k \leq 15$ in CUCA, $5 \leq k \leq 16$ in CACP, $4 \leq k \leq 18$ in CPCA and our proposed protocol swings between $3 \leq k \leq 13$ which is the most ideal.

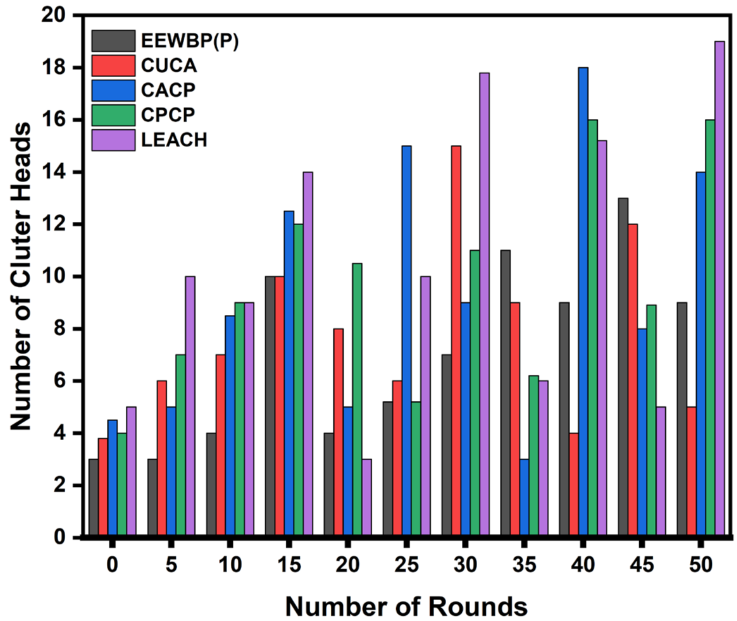

Figure 6. Cluster count vs. number of rounds.

Optimal cluster headcount should be calculated using the weighted value, which contains several energy characteristics, to reduce the unpredictability of cluster headcounts in the suggested protocol. This means that the cluster's total capacity will be reduced to balance energy usage if many dead nodes are present.

5.4. Cluster Lifetime

The clustering algorithm's performance is assessed using some very important performance measures, such as network longevity as measured by the First Node Dead (FND) time, Half Node Dead (HND) time, Last Node Dead (LND) time, and residual energy. In the context of a cluster, a life cycle is a period that elapses between the cluster's creation and its eventual demise which is known as FND. The node with the best acceptable value is selected as CH during the algorithm run and assumes responsibility for managing a given cluster. There are two portions to the measurement parameter that we may use to track the life cycle of sensor nodes: the stable period and the unstable period. However, in our situation, we primarily utilize what is known as the unstable period between the first and last node deaths. This is generally used for environmental monitoring. If a large number of SNs dies, the information gathered will not make it to its intended destination because of the vast spread of SNs. There is uncertainty about the period based on the time from the FND to the Last Death Node (LND). In the case of many nodes dying, some of the gathered data cannot be used to adequately analyze the surrounding circumstances. While evaluating our suggested technique, this research analyzes network life using FND and reveals evident benefits over the other protocols. Compared with CUCA, CPCP, CACP, and LEACH, our proposed algorithm has better HND 11.72%, 4.37%, 13.83 as compared with the above algorithms. Furthermore, the experimentation shows that our proposed EEWBP algorithm increases LND by 81.48% compared with LEACH; CUCA increased by 56.84% and 64.56% over the CPCP algorithm. Figure 7 illustrates a comparison of residual network energy at FND, HND, and LND with EEWBP at the three different network timings [21,50–54].

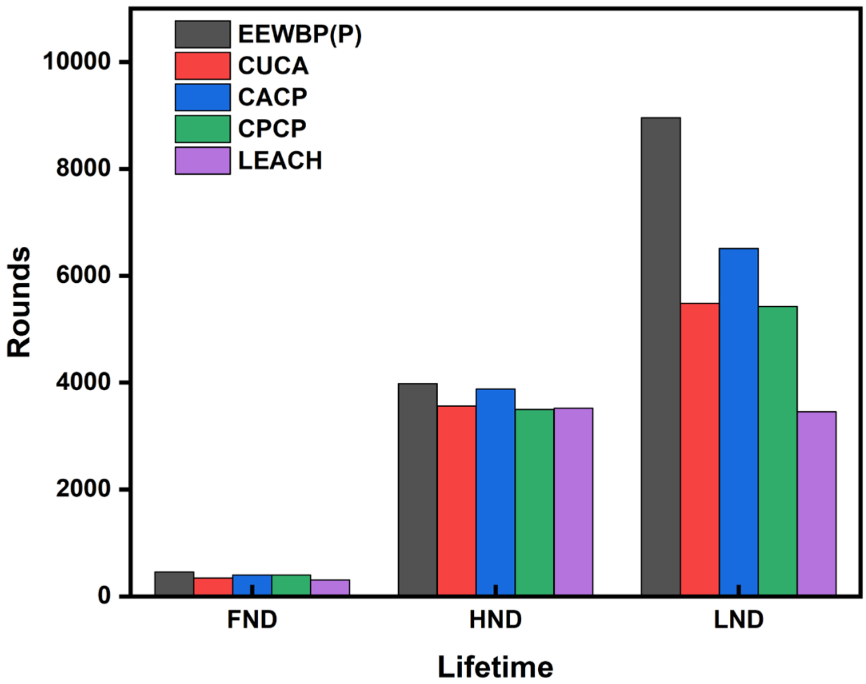

Figure 7. Rounds vs. lifetime.

5.5. Residual Energy

Data transmission, data reception, and communication with other nodes are the three main types of node energy consumption. The more time a node is online, the more evenly its energy use will be spread out. As seen in Figure 8, the suggested protocol's energy consumption is more consistent than the LEACH, CACP, CPCP, and CUCA protocols. Reduced energy usage across clusters and within each one can be achieved with this approach.

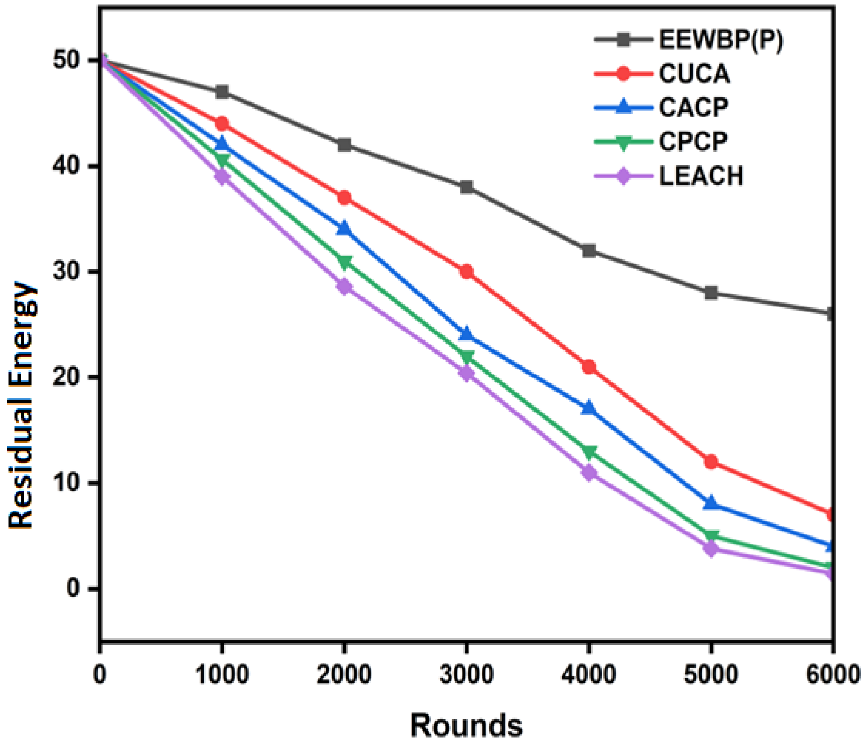

Figure 8. Average residual energy vs. rounds.

5.6. Probability of Successful Information Delivery

WSN nodes are known for their high-energy efficiency. A node's battery life is limited because of the tiny size of its dry cell. These nodes have a limited quantity of energy and thus optimizing energy in these nodes is particularly useful to the long-term viability of a WSN. The three energy-consuming processes for the WSN nodes are sensors, communications, and motor control. The probability of successfully transmitting the packet to the BS is an essential aspect for optimizing the energy in WSNs. Grounded on the average number of packets obtained by the BS, this metric points to how well the packet is transmitted to the intermediate nodes. According to Figure 9, our suggested protocol can transmit 85% of packets to BS and has a success rate of 89% as compared with others as their success rate is LEACH at 34%, CPCP at 71%, and CACP at 63%. A packet's delivery to BS is more likely to be successful if the CH is effectively selected, increasing the network's density. Packet drops are reduced by using the right count of clusters and the right number of CHs in a network [53–61].

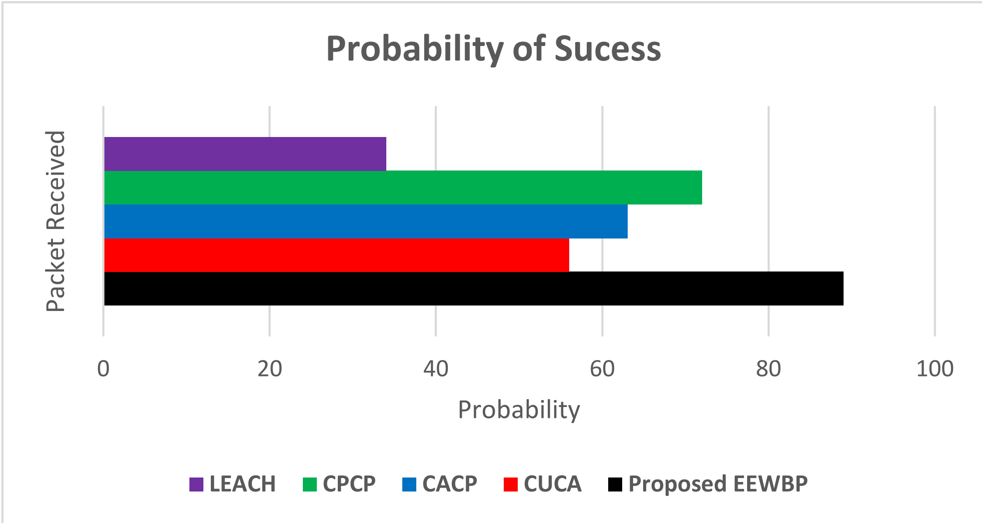

Figure 9. Packet success ratio.

6. Discussion and Analysis of Results

This study presents the EEWBP model as a solution to the WSN routing issue. Utilizing our suggested strategy, one may locate search space solutions that are both energy-efficient and optimal. The EEWBP approach speeds up the wireless sensors network cluster-building process, lowers energy use, and increases the likelihood of successful packet delivery by maintaining a healthy distribution of cluster heads. Additionally, the EEWBP approach aided in reducing the cost of routing, helped to conserve WSN energy by limiting transmission range, and reduced the amount of unnecessary broadcasting. In Figure 10, a side-by-side comparison of our suggested procedure with the four previously mentioned techniques can be seen.

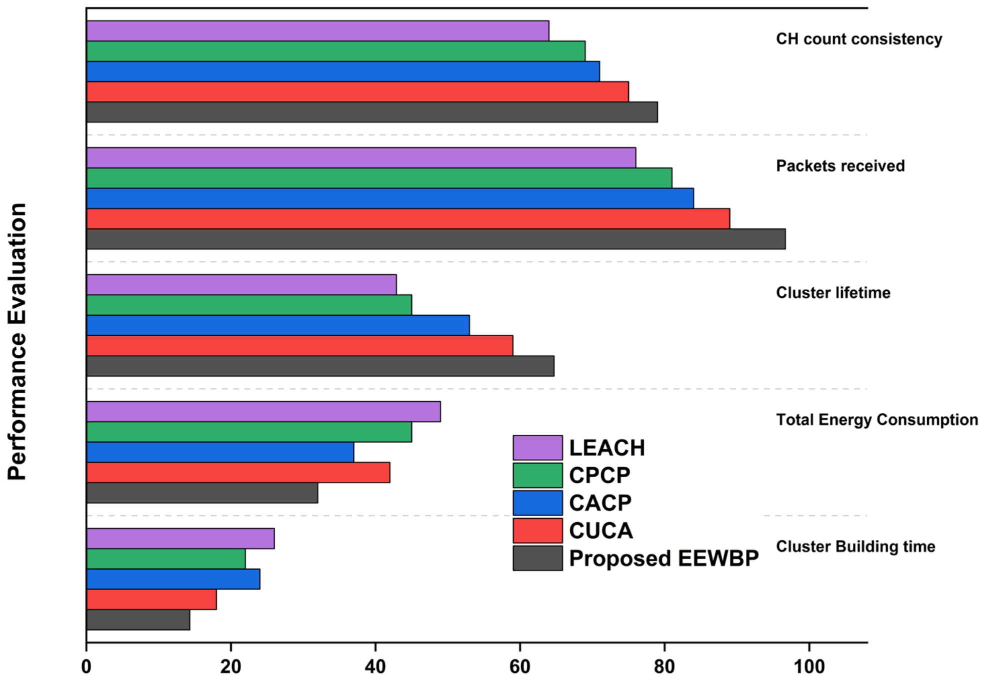

Figure 10. Comparison using various metrics.

Every metric used in the evaluation confirms that EEWBP is the best method for selecting a CH and a cluster's best neighbor nodes. In contrast, there is no way to agree on a single algorithm that is as great as CPCP that can perform better if we discuss the second best algorithm. While SN has a better chance of success over the long term, CACP does better in the short term. CUCA is the apparent runner-up to our cluster number and clustering time proposal. Hence, we are unable to even approach the second most efficient technique. A significant shortcoming of the proposed approach is that it does not offer any aggregation mechanism to discard the identical packet for processing, even though doing so would save a great deal of computational work and WSN energy. A packet scheduling system is necessary to solve these problems and address the congestion management issue. To further the development of WSNs and the Internet of Things, we want to build a dynamic model in a heterogeneous environment, along with basic security measures to protect data and devices [62–65].

7. Conclusions and Future Scope

Wireless sensor networks have significant barriers to deployment due to the need to conserve battery energy in forest field monitoring. Protocols for network routing have been devised to maximize the efficiency with which sensors use energy while transmitting data. This article suggests enhancing the energy-efficient weighted clustering based routing protocol by using a clustering algorithm in conjunction with a strategy that considers node degree, residual energy, the number of neighbors' nodes, average flying speed, and trust value to choose sensors as cluster heads which are being deployed in the environment to detect forest fire in an optimized way. In order to minimize the amount of data sent back and forth between nodes inside a cluster and the base station, the cluster head is chosen using the optimal weighting factor in the area.

The weighted clustering algorithm developed in this study provides an improved method for selecting CH in WSNs by picking and combining specified characteristics with additional restrictions. As a result, our proposed algorithm's essential contribution is ensuring that a genuine CH is selected with the best performance parameters, primarily in signal strength and residual energy. Our proposed scheme addresses both the concerns of extended network longevity and energy efficiency. The simulation results demonstrate, evaluate, and compare our proposed method to various routing algorithms on a static network. In addition, WSN difficulties can be easily tackled using our suggested method and may be used more effectively in monitoring and surveillance services. In the future, we can evaluate our proposed approach with several new metrics, such as the number of SNs increasing, each SN having variation in initial energy, and how many nodes per square meter are in a particular region.

Our selection procedures limit the transmission of redundant data in areas, preserve sparse areas for as long as feasible, and lessen the load on the network. Simulations demonstrate that the new protocol is superior to the old one in terms of network longevity, including mean sensor lifetime, mean energy dissipation per round, and several dead sensors after each round. Future research will examine the protocol's potential for use in different settings and also try to implement our protocol to flying ad hoc networks so that wildfire monitoring does not stick to the limitation of fixed nodes.

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