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RESEARCH ARTICLE

Extending the Energy Efficiency of Nodes in an Internet of Things (IoT) System via Robust Clustering Techniques

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Abstract – Wireless sensor networks (WSNs) are useful in many industries due to their capacity to perceive their surroundings and relay that information to base stations. Improving energy efficiency in wireless sensor networks while still meeting Quality of Service (QoS) requirements like low latency and data security is no easy feat. There have been numerous suggestions for making networks more energy efficient without reducing service quality, but only a few have been proven to work. This study recognizes the paucity of prior thorough work in the area and sets out to remedy that. The primary objectives of this research into wireless sensor networks are to optimize energy consumption, reduce latency, and boost service quality. Since these networks are so pervasive in cutting-edge industries like healthcare, defence, and navigation, accurately predicting their energy efficiency and data transfer rates is essential. This study uses a rigorous strategy to isolate and address the underlying causes of energy efficiency and increased delay. Security and the average transmission latency are still taken into account. For this reason, the proposed approach protocol, which enhances the energy efficiency gains by combining the EESAA protocol for effective clustering with the proposed approach Protocol. The proposed algorithm provides high efficiency in terms of energy consumption, which results in increased lifetime of the nodes comprising the wireless sensor network.

Index Terms – Wireless Sensor Network (WSN), Lifetime Maximization, Internet of Things (IoT), Survivability, Quality of Service (QoS), Whale Optimization, LEACH, SEP, H-LEACH, MAMC, PEGASIS.

1. INTRODUCTION

A self-configuring, low-maintenance network design is always an important goal in light of recent developments in the networking industry [1]. The many sensor nodes and central base stations that make up a wireless sensor network are described in [2]. These sensor nodes are placed in a dispersed fashion in predetermined locations, where they may measure and report on factors including air quality, temperature, and humidity [3].

Research into wireless sensor networks' impact on energy use, latency, security, data aggregation, and quality of service has increased in recent years. There are still a lot of obstacles to overcome, though. Sensor nodes pose a multitude of dangers to network safety due to their limited power reserves and poor energy usage. The dispersed nature of WSNs makes data gathering particularly difficult. Humans are unable to do many tasks that would otherwise be accomplished because of the complexity introduced by the lack of clarity surrounding the deployment area for a sensor node in a WSN. Despite the fact that a lot of work has gone into enhancing QOS, it is still impossible to ensure its quality [4].

QOS in WSN is difficult to sustain because of the frequent interruptions caused by the use of energy by sensor nodes. While there is much potential in data aggregation, little has been done to ensure that quality of service and security are not compromised. The fuzzy logic method pioneered by Singh et al. [5] enables the automatic reporting of sensor data that integrates knowledge from multiple fields. However, we still need a more efficient approach to protecting sensitive information and decreasing energy use without lowering service standards. Using LEACH and other protocols, this work aims to present an innovative and superior way for prolonging the lifetime of wireless sensor nodes and reducing their power consumption.

The underlying issue with WSNs is the tension between low latency and high energy efficiency. A promising strategy for the efficient and timely collecting of future data is provided as a potential solution to this problem.

The problem of energy gaps is extremely important in WSNs. It is necessary to create a hybrid approach to reduce the detrimental effects of QOS on sink nodes.

Maintaining continuous communication depends on extending the battery life of wireless nodes. This problem is currently being studied. This area of study needs to be expanded upon so that efficient energy mechanisms can be created, leading to high-quality QOS processes.

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Recent years have seen significant advancements in wireless sensor network technology, particularly in areas like as energy efficiency, network endurance, and service quality. The military and the medical field, among others, both rely heavily on sensor nodes for collecting data. Due to the rise in demand across all sectors, three of the most pressing issues that must be addressed are security, energy efficiency, and node localization.

- The study's goal is to cut down on wait times and lengthen the life of networks.
- A proposed approach will provide for the greatest possible node security during data aggregation. Based on these findings, a better system has been proposed.

The first section presents a brief overview of the research problem, while the second discusses relevant literature and any gaps in the existing knowledge base, and the third describes the technique and experimental design. Results are reported in Section 4, and interpretations are drawn in Section 5.

2. RELATED WORK

The ability to collect and relay sensor data to a central hub is largely responsible for the rise in popularity of wireless sensor networks (WSNs). Thanks to the Internet of Things, WSNs have found a wider range of uses in recent years, which has presented both new obstacles and opportunities. Improved energy economy is essential for IoT-enabled WSNs due to the need of meeting Quality of Service (QoS) standards such as latency and data security. Recent research in this area is evaluated critically in this survey of the relevant literature.

Mokabberi et al. detail how to create QoS-aware and energy-efficient IoT networks[1]. The research is focused on evaluating and improving IoT service composition mechanisms with a specific emphasis on scalability and QoS, strategies to reduce energy use without compromising functionality. This research has helped to shed light on several serious problems plaguing IoT systems.

The research in [2] aims to create a novel networking concept for IoT devices called Light-based IoT (LIoT) that relies on visible light communication (VLC) for data exchange and energy harvesting. The primary goals are to develop a self-sustaining IoT network and improve energy efficiency. The methodology combines theoretical concepts with practical experiments using prototype LIoT nodes equipped with photovoltaic cells and optical transmitters. Notable advantages include reduced reliance on batteries and enhanced network efficiency through energy relay and node prioritization. However, LIoT's effectiveness depends on available indoor illumination, and interference effects can impact performance in well-lit environments. Main results include 18% faster recharge times and validation of the proposed energy relay and node prioritization strategies, highlighting LIoT's potential for sustainable IoT networks, especially in controlled indoor environments.

IoT applications often involve battery-powered devices, making energy efficiency a paramount concern to prolong network lifetimes and reduce environmental impacts. To tackle this challenge, [3] presents an innovative energy-efficient alternating optimization framework. This framework optimizes a range of parameters, including beamforming vectors, power allocation coefficients, and passive-beamforming at backscatter tags, with the primary objective of maximizing energy efficiency in cooperative IoT networks. The proposed methodology employs a two-stage approach, utilizing Zero Forcing (ZF)-based active-beamforming and efficient clustering in the first stage, and transforming the non-convex passive-beamforming optimization problem into a Semi-Definite Programming (SDP) problem in the second stage. The research's advantages lie in its effective optimization of energy efficiency, exploring the potential of Backscatter and NOMA techniques, and offering insights into the complex interplay of various parameters in IoT networks. However, it is essential to acknowledge the complexity of the mathematical techniques involved and the limited applicability outside the context of Backscatter and NOMA-based IoT networks. Nonetheless, this research provides a promising solution to enhance energy efficiency in cooperative IoT networks, contributing to the sustainable and efficient operation of IoT systems.

Fog Computing (FC) enhances the Quality of Service (QoS) for latency-critical IoT applications like autonomous driving, haptics, and Augmented Reality (AR) by bringing cloud processing and storage closer to end devices. Current resource provisioning methods prioritize latency and cost-efficiency, assuming that fog nodes are fully reliable and energy-efficient. However, in practice, fog nodes are neither 100% reliable nor energy-efficient. [4] Introduces a novel resource provisioning framework for fog nodes, considering reliability and energy efficiency alongside latency-sensitivity and cost-effectiveness. It employs an analytical framework to model fog node failures and recoveries, optimizing resource provisioning to minimize cost and energy consumption. Through analysis, it examines the interplay of latency, reliability, cost, and energy in resource provisioning, demonstrating a 35% improvement in cost and a 37% reduction in energy consumption while maintaining latency-sensitivity and reliability compared to non-optimized approaches.

In [6], the author utilizes Node MCU, a microcontroller with Wi-Fi capabilities, to connect various sensors and home appliances, forming an IoT-based home automation system. An Android application facilitates user-friendly control, with sensors collecting data sent to the cloud for analysis and remote operation. This approach harnesses IoT and cloud technology to enhance automation, offering advantages such as energy conservation, remote appliance control, improved security, cost-effectiveness, and customization. Overall, the study successfully implements a promising home automation system with potential for future AI and security enhancements.

The work in [7] addresses the challenge of data consistency in energy-efficient medium access control protocols for IoT applications. It introduces an energy-efficient data consistency protocol with data aggregation to accommodate various data rates. The study categorizes nodes into event and continuous monitoring nodes using machine learning-based logistic classification. Continuous monitoring nodes have their sampling rates optimized through the Optimized sampling rate data aggregation algorithm. The research employs an energy-efficient time division multiple access (EETDMA) protocol for continuous monitoring and proposes an energy-efficient bit map assisted (EEBMA) protocol for event-driven nodes. Simulation results demonstrate the superiority of this approach over existing methods, offering improved energy efficiency and data consistency.

The objective in [8] is to create an efficient fault detection scheme for Solar Insecticidal Lamps in IoT systems (SIL-IoTs) that have limited computational resources. The proposed Binary Sliding Window (BSW) method addresses this challenge by storing consecutive states as binary values, reducing memory consumption, and adjusting fault detection sensitivity using multiple zeros. It outperforms two prior knowledge-based methods and several machine learning algorithms by maintaining a balance between high accuracy, low false alarms, and low missing alarms. Additionally, the BSW method minimizes energy consumption and data transmission, making it suitable for resource-constrained IoT devices. The BSW method offers an effective solution for fault detection in SIL-IoTs, enhancing their energy efficiency and performance.

Ramkumar and Balasubramanian in [9] focus on addressing energy efficiency challenges in IoT networks, aiming to extend network lifespan while reducing energy consumption. Their work employs a novel approach called bacterial colony optimization for Cluster-Head (CH) selection in the LEACH-C clustering algorithm. This approach enhances global search capabilities and optimizes CH placement. Performance analysis using metrics like residual energy, active node count, and throughput reveals significant improvements. Simulation results indicate an extended network lifespan, an increase in active nodes, and reduced energy consumption as the key outcomes of this energy-efficient algorithm.

Ding et al. [10] addresses the challenges of dynamic topology changes in software-defined wireless sensor networks (SDWSNs) for IoT applications, which can lead to performance degradation. It introduces an energy-efficient topology control (TC) mechanism designed to maximize network energy efficiency during dynamic topology maintenance. The proposed approach involves a hierarchical SDWSN architecture comprising cluster-based sensing networks and programmable relay networks. Two TC algorithms, one for cluster subnetworks and another for relay subnetworks, are presented. The cluster subnetwork algorithm mitigates link interference through power control and rate allocation, while the relay subnetwork algorithm utilizes a centralized approach based on a Markov decision process (MDP) model to optimize the relay-network state. Simulation results demonstrate improved energy efficiency in both subnetworks of time-varying SDWSNs.

Nwadiugwu et al. in [11] address the challenge of dealing with redundant data in IoT systems, where devices collect and store information in binary form (0's and 1's), resulting in significant redundancy. Existing solutions involve tier-based network layers that compress and cluster data to reduce energy consumption, but they still lead to packet losses and redundancies. The article proposes a two-tier layered network approach, with packet exchange primarily occurring in the top layer to lower energy consumption and enhance system reliability.

It employs the Voronoi cell-based correlation cluster formation (VC3F) technique to segregate packets into clusters, identifies cluster heads responsible for redundant packet removal, and uses optimized multi-objective flower pollination (MO-FPO) routing to transfer redundant packets to the edge-tier layer. There, novel fast-fully connected neural network (F2CNN) accelerator and Lempel–Ziv–Welch (LZW) data compression techniques are applied to process the redundant data effectively.

To improve routing efficiency and security, in [12] Sivasankari and Kamalakannan propose a Fuzzy Logic based Man-in-the-Middle attack detection and Cuckoo Search Algorithm (FLCSA). Fuzzy logic is used to detect intrusion nodes based on factors like node degree, energy, and delay, while the Cuckoo Search Algorithm optimizes routing by selecting efficient relays considering node energy, link lifetime, and bandwidth. Simulations demonstrate that this approach enhances throughput, increases detection accuracy, and reduces network delay.

IoT-based wireless sensor networks often encounter noise that distorts sensor readings and increases power consumption, reducing the sensor nodes' longevity. To mitigate this issue, [13] introduces the use of Finite-Impulse Response (FIR) filters as a signal pre-processing technique. FIR filter complexity depends on the number of adders and logic depths, with multiplication speed being a critical factor. The Booth method is employed to speed up multiplication by reducing partial product rows.

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The research by Chaurasiya et al [14] focuses on developing an Energy-Efficient Hybrid Clustering Technique (EEHCT) for Multilevel Heterogeneous Wireless Sensor Networks (WSNs), particularly within the context of the Internet of Things (IoT). The primary objective is to enhance energy efficiency and network longevity while addressing challenges like energy consumption, node heterogeneity, multilevel clustering, and IoT integration. The proposed methodology combines various clustering mechanisms to optimize energy efficiency and network scalability. Advantages of EEHCT include improved energy efficiency, support for heterogeneous nodes, scalability, and IoT compatibility, while potential drawbacks include increased network complexity and implementation challenges. Overall, this research offers valuable insights and techniques for achieving energy-efficient clustering in heterogeneous WSNs, making it relevant for IoT applications.

Many IoT devices employ rechargeable batteries, which degrade over time due to various factors. To address this issue, [15] introduces LECA_SOH, an innovative clustering approach that relies on predicting battery State of Health (SoH). LECA_SOH's primary goal is to forecast how cluster head selection impacts battery SoH, enabling the network to opt for nodes that will experience less battery degradation in future rounds, ultimately extending the system's lifespan. Results indicate that this approach enhances the network's long-term durability and augments the number of recharging cycles when compared to conventional energy-efficient methods.

The objective of the research in [16] is to design and construct a dual-axis solar tracking system aimed at enhancing solar energy collection efficiency by following the sun's movement, overcoming the limitations of fixed solar panels. The system, with its simple and economical design, is applicable for small to medium-sized solar installations, offering significant increase in energy collection compared to fixed panels. This article presents several real-world examples of how IoT energy management solutions have been put into practice.

The principal objective of [17] is to introduce an innovative Opportunistic Backscatter Communication (OBM) protocol tailored explicitly for IoT networks that rely on energy harvesting as their power source. This protocol confronts a multitude of intricate challenges intrinsic to such networks. It addresses the intricate task of harmonizing the coexistence of diverse devices, encompassing both wireless energy harvesting devices and backscatter tags, within the intricate fabric of a heterogeneous IoT milieu. It adeptly manages the mitigation of transmission collisions, thereby substantively elevating the overall network's efficiency. Notably, the protocol excels in the domain of energy efficiency by judiciously maximizing the utilization of harvested energy for data transmission while concurrently minimizing energy wastage. Furthermore, it adeptly establishes a harmonious symbiosis between wireless data communication and energy harvesting through the implementation of pioneering mechanisms. Notably, the OBM protocol yields significant enhancements in throughput for both wireless devices and backscatter tags, all while preserving network performance, even under heightened network density scenarios. Ultimately, the protocol's advantages manifest in its remarkable capacity to augment network throughput and energy efficiency, foster harmonious coexistence, and efficiently manage escalating network density. The primary outcomes of this research underscore the substantial enhancements in network performance when contrasted with conventional systems, with a particular emphasis on superior throughput and energy efficiency. It proficiently harnesses available energy reservoirs for data transmission, thereby facilitating the seamless integration of backscatter communication within wireless-powered networks. In essence, the OBM protocol proffers a comprehensive and sophisticated solution for the optimization of resource utilization in heterogeneous IoT networks.

Energy-harvesting Internet of Things (IoT) networks can benefit from the opportunistic backscatter communication solutions discussed by Iqbal and Lee [17]. Their purpose relies heavily on the utilization of low-power forms of communication.

An enhanced energy-balanced routing method for Mobile Ad-Hoc Networks (MANETs) is provided by Satyanarayana et al. [18]. In the context of MANETs, efficient energy utilization is a pressing concern. To address this challenge, the authors propose an enhancement strategy aimed at reducing energy consumption and prolonging the network's lifespan. Thier approach focuses on achieving better energy equilibrium among sensor nodes within clusters, thereby minimizing energy dissipation during network communications. A pivotal component of this enhanced strategy is the method for selecting cluster heads. The authors also introduced an updated Time Division Multiple Access (TDMA) schedule.

This work in [19] is driven by the imperative challenge of enabling energy harvesting nodes to efficiently integrate into centrally controlled multi-hop wireless networks. Energy harvesting nodes, reliant on ambient energy sources like solar panels, confront a profound predicament due to their constrained and erratic energy availability. Traditional network joining mechanisms often necessitate excessive energy consumption, rendering them infeasible for energy-constrained nodes. To address this pivotal issue, the article introduces the innovative concept of Dual-Range Bootstrapping (DRB). DRB orchestrates the seamless assimilation of energy harvesting nodes into the network through an energy-efficient process. This involves the exchange of long-range packets with a central unit to acquire

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essential network coordination and timing data. Subsequently, nodes enter an energy-efficient dormant state until their involvement in multi-hop network operations is required. DRB exhibits notable advantages, including remarkable energy efficiency by minimizing bootstrapping energy requirements and ensuring low variability, thereby enabling energy harvesting nodes to judiciously manage their limited resources. Furthermore, extensive simulations and testbed experiments underscore DRB's superiority over traditional joining mechanisms in terms of data transmission efficiency, temporal network coverage, and overall network participation. This research makes a substantial contribution to the field by presenting a pragmatic and innovative solution that empowers energy harvesting nodes to seamlessly and effectively integrate into multi-hop wireless networks, thereby enhancing their data transmission capabilities and prolonging their network participation.

The work by Xu et al. [20] endeavors to address the pivotal challenge of energy-efficient relay transmission within the domain of IoT communications. The central quandary it confronts is the imperative to curtail energy consumption while ensuring the effectiveness of data transmission, a critical concern in IoT scenarios where power conservation is paramount. To tackle this issue, the study harnesses an analytical and optimization-driven methodology grounded in mathematical modeling. It meticulously scrutinizes two distinct energy transfer modes, namely time switching and power splitting, employing mathematical expressions and optimization frameworks to derive optimal power allocation and time allocation strategies for each mode. Additionally, the research investigates the intricate interplay between energy consumption and latency constraints. This approach boasts several advantages, including the mathematical rigor that guarantees precision, a thorough examination of the energy-latency tradeoff, and practical applicability to IoT contexts. The principal outcomes of this study encompass the revelation of a pronounced tradeoff between energy consumption and transmission latency, the identification of power splitting as the preferred mode for energy efficiency, and the illumination of conditions under which relay transmission, coupled with wireless power transfer, outperforms direct transmission in energy conservation. Furthermore, the research equips practitioners with insights into the real-time determination of optimal transmission configurations for individual IoT sessions, thereby facilitating the design of IoT systems that prioritize sustainability and energy frugality.

In the context of IoT applications, particularly those involving end nodes (ENs) placed in challenging-to-reach locations where battery replacement is impractical, the demand for high-energy efficiency is paramount. The Long-Range Wide Area Network (LoRaWAN) protocol, designed for IoT, strives for low-energy consumption. However, LoRaWAN's energy efficiency relies heavily on the configuration of transmission power, traditionally determined through path loss and shadow fading modeling and link budget analysis. These conventional methods do not account for variations induced by environmental factors. The study by González-Palacio et al. [21] addresses this gap by analyzing real-life data and demonstrating that path loss and shadow fading are influenced by environmental variables. To optimize energy usage for ENs, the research introduces machine learning models for empirically calculating path loss and shadow fading, incorporating variables such as distance, frequency, temperature, relative humidity, barometric pressure, particulate matter, and signal-to-noise ratio.

The aim of [22] is to introduce an innovative energy-efficient approach for detecting attackers in IoT networks utilizing the RPL protocol. It tackles the challenges associated with securing IoT networks, particularly RPL-related attacks like version number and rank attacks. The proposed methodology relies on Discrete Event Systems (DES) modeling, offering a formal framework to model and analyze network behavior for the identification of anomalous activities and potential attackers. This methodology's advantages include its energy efficiency, formal modeling, scalability, and effectiveness in pinpointing vulnerabilities in the RPL protocol. The study's results demonstrate the methodology's success in identifying attackers, particularly in scenarios involving version number and rank attacks, contributing to enhanced security in RPL-based IoT networks with minimal energy consumption, crucial for IoT devices with limited power resources.

In [23], the authors tackle critical challenges within the realm of multi-UAV networks supporting the Internet of Things (IoT). The primary challenge pertains to energy efficiency, a paramount concern in UAV-based systems due to their limited energy resources. The study also addresses the intricacies of resource allocation, encompassing communication scheduling, power distribution, and UAV trajectories. To approach these challenges, the researchers devise a comprehensive methodology, formulating the problem as a non-convex optimization task. They propose an iterative optimization algorithm that jointly optimizes communication scheduling, power allocation, and UAV trajectories.

The noteworthy advantage of this methodology lies in achieving equitable energy efficiency among UAVs, ensuring that no individual UAV depletes its energy resources disproportionately. This fairness is pivotal for extending the overall network's operational lifespan. Additionally, the holistic joint optimization approach enhances overall network efficiency and sustainability, catering to a range of applications, such as surveillance, data collection, and communication services. The research substantiates its findings through extensive simulations, providing valuable insights into the performance of the proposed method across

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diverse optimization goals and operational scenarios, thus contributing significantly to the advancement of multi-UAV IoT networks.

Boehm and Koenig [24] present a case study on cross-layer optimization in wireless networks, primarily addressing the challenge of energy-efficient Internet of Things (IoT) applications. The study employs Radio-in-the-Loop (RIL) simulation, combining protocol simulation and radio channel emulation, to model and evaluate wireless networks accurately. It focuses on optimizing receiver gain settings based on Link Quality Indicator (LQI) and Energy Detection (ED) measurements to minimize energy consumption while maintaining communication quality. The results demonstrate that adjusting receiver gain settings adaptively reduces energy consumption without compromising reliability. This approach offers a solution to the challenge of achieving energy-efficient wireless communication in dynamic environments. Furthermore, the article discusses its potential applications in combating radio spectrum pollution, improving transmission reliability, and supporting Smart City initiatives, emphasizing the role of RIL in advancing wireless communication research.

In the context of hybrid visible light communication (VLC) and radio frequency (RF) Internet of Things (IoT) systems, where simultaneous lightwave information and power transfer (SLIPT) is essential, relay cooperation is seen as a promising strategy to overcome coverage limitations and energy constraints. The article by Huang et al. [25] addresses two significant challenges in promoting relay cooperation, namely, selfishness and information asymmetry among relay nodes (RNs) operating autonomously. To tackle these issues, a novel incentive scheme based on an agency selling format is proposed. In this scheme, the VLC service provider (VLCSP) charges cooperating RNs for energy harvesting and, upon successful information transmission to the end node (EN), offers a portion of future revenue as an agency payment to the RNs. The pricing and agency payment terms are designed through a mutually agreeable contract, with the goal of maximizing the VLCSP's expected utility. The article formulates and optimizes this contract design problem using a joint adverse selection and moral hazard model, ultimately deriving the optimal contract solution through Lagrangian dual analysis. Numerical results demonstrate the superior performance of the proposed incentive scheme compared to benchmarks in terms of VLCSP and RNs' expected utility, as well as expected social welfare, highlighting its incentive efficiency. Table 1 shows the comparative analysis.

Table 1 Comparative Analysis

Reference	Technique	Stability Time	Total Rounds
[2]	LEACH	25 seconds	8000
[5]	MAMC	25 seconds	8000
[14]	PSO	56 seconds	7500
[17]	KMEANS	35 seconds	4000

3. PROPOSED MODEL

This section summarizes our approach, in which we first provided a theoretical overview of several Data Aggregation models for enhancing QoS and demonstrated the data aggregation mode. We used the Whale optimization technique to further assess the leading model.

Every sensor node in a WSN serves a specific purpose and makes an important contribution to the network as a whole. Wireless sensor networks (WSNs) have many potential uses in a variety of fields, including the environment, the military, healthcare, industrial process management, and even the home. Even relatively modest nodes might be able to process information, forward messages, and gather data. Networked sensor nodes coordinate efforts by exchanging messages via broadcast radio waves. However, there are limits to the data throughput, processing speed, storage space, and energy availability of sensor nodes. A sensor node's main job is to monitor its surrounding environment and report back to the host controller or sink in the form of an answer to a query concerning things like heat, light, and temperature. In WSNs, data transmission consumes more power than data processing [3]. When data is collected and aggregated through methods like sum (), average (), etc., it is not essential to send each individual reading to the sink node.

3.1. Data Aggregation

Gathering and organizing data for subsequent processing is referred to as "data aggregation" when discussing WSNs. To measure inter-node communication quality, the data aggregation method is required. Data aggregation is frequently considered a basic processing operation with the goals of preserving limiting resources and lowering energy use. Figure 1 shows the data aggregation procedure.

The greatest issues with sensor networks are the lag time in data collecting and the battery life. Due to the aforementioned difficulties, it was not possible to optimize both restrictions at the same time. Our goal is to maintain the network working

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smoothly while cutting down on data compilation time. This strategy could be helpful when time is of the essence. By planning a network topology that minimized delay, our method was able to achieve the lowest achievable latency. Power consumption can be reduced by the network by keeping the distances between sensor nodes as short as possible.

Some of the most important results of this research work is as follows:

- Providing a method for building a network architecture that has the least amount of time between each data aggregation.
- Analyzing the similarities and differences between H-LEACH, LEACH and other previous algorithms.

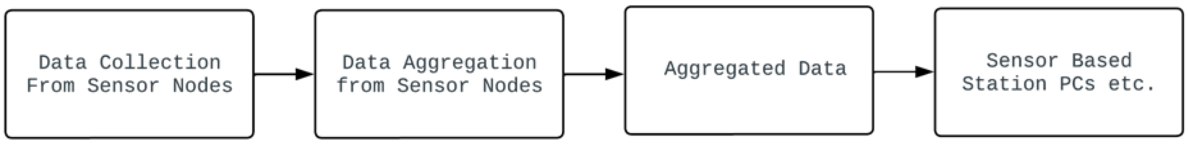

Figure 1 Data Aggregation Process

The Whale Optimization Algorithm allows for a decentralized answer that scales with the network. As the number of nodes in a WSN grows, there are several technical considerations that must be made to keep things running smoothly and manage the data effectively. The primary obstacles to expanding a WSN are discussed below.

Managing a Large Number of Nodes: Managing a growing number of sensor nodes presents challenges for a growing network. The energy needs of individual nodes and the total number of nodes in a network go up quickly. Algorithms that efficiently assign roles, allot addresses, and arrange nodes are crucial. This involves the assignment of responsibility for balancing the communication load between nodes in clustering-based protocols like LEACH.

Ensuring Efficient Communication: More nodes might lead to a rise in communication overhead. It is important for routing protocols to dynamically adjust to changes in network size and structure. Effectiveness in routing, balancing loads, and dealing with congestion are all of paramount importance. Hierarchical routing, multipath routing, and energy-aware routing are just a few examples of the more complex routing strategies that may be required.

Energy Management: Energy becomes more of a premium in more extensive networks. Low-power modes, duty cycling, and dynamic power control are all examples of effective energy management measures that can help extend the life of the network. In addition, in-network processing and data aggregation that use little energy become crucial.

Scalable Data Aggregation: One of the difficulties of having more nodes is that they produce more data. In order to eliminate communication overhead and unnecessary data transfer, scalable data aggregation techniques must be used. Both energy and data transfer capacity are reduced as a result.

Safety and Confidentiality: The larger a network gets, the more vulnerable it is to security flaws. It is becoming more difficult to protect data privacy and security. Security measures such as strong authentication, encryption, and intrusion detection are essential.

Topology Management: It can be difficult for large-scale WSNs to keep their network topology optimized. In order to deal with node failures and environmental changes, it is necessary to employ self-organization, adaptive topology control, and dynamic reconfiguration techniques.

Data Quality and Integrity: The likelihood of running into malfunctioning nodes or noisy data rises as the network size grows higher. The quality and integrity of data can only be maintained by the use of rigorous data filtering, error detection, and fault tolerance methods.

3.2. System Model

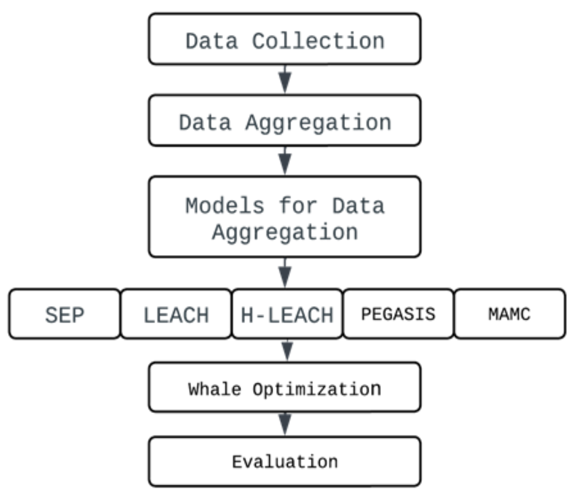

Figure 2 System Model

The system model is shown in Figure 2.

After determining the most precise reduction and delay calculations possible using five different aggregation models, we employed the Whale Optimization Algorithm (WOA) to further optimize the network. The network consists of multiple wireless sensors, up to N in total. The locations of the sensor nodes and BS are not changed after deployment.

3.2.1. Theoretical Presentation of Data Aggregation

Direct connections between sensors and the BS and other nodes are possible if their transmission ranges can be increased.

The sensor nodes' data is aggregated and transmitted to the sink via the aggregation channels. Full data fusion will be possible once a standard data packet size is agreed upon by all parties involved. A slot is the medium through which a child node can send messages to its parent. It is impossible for numerous nodes to receive information at once since each sensor only has one transmitter. Sensors based on code division multiple access (CDMA) can reduce the disruption brought on by concurrent transmissions.

Cheng et al. [7] offer a network architecture designed to speed up data collection. Tree-like in appearance, with each node standing in for a degree that is a power of two (2p). The CH is the progenitor of all the other cluster nodes. This data connection allows for bidirectional communication and data sharing between the CH and BS. The number of data links a node has establishes its relative location within the network. Figure 3 depicts the network design and scheduling for a seven-node network.

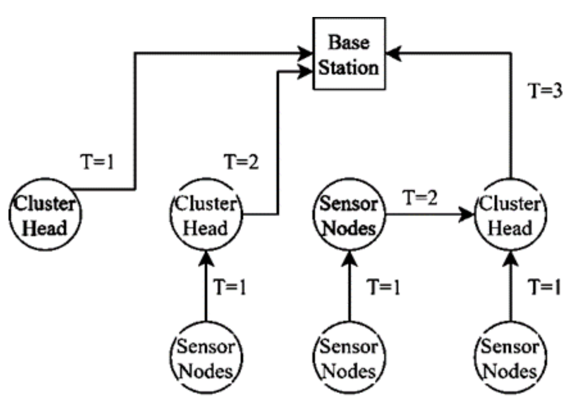

Figure 3 The Network Structure and Scheduling with 7 Nodes

Our aggregation method is based on carefully planned networks and schedules. As the network takes shape, one or more data aggregation trees are created. Each tree is constructed using the least-delayed strategy, as was previously explained.

Data transmissions between sensor nodes are scheduled when the network's infrastructure has been set up. In a network, each node has a set length of time to report back to the central server. This is the single window of opportunity for contact.

By fusing together two identical clusters, the quickest delay structure is created. When direct connections between clusters of the same size, or to the BS, are exhausted, the process starts over. The final network architecture can include clusters of varying sizes using this method.

The scheduling algorithm is straightforward. A node's lifespan is proportional to its relative importance in the network. A node's offspring are ordered by their average transmission rates. This indicates that a parent node can never have more than one child node. CH structures might look different depending on the cluster size. Because of this, the CHs can only reliably update the BS at irregular periods.

3.3. LEACH

The Energy Adaptive Clustering Hierarchy (LEACH) [26] is a pioneering protocol in the realm of wireless sensor networks (WSNs) renowned for its emphasis on energy efficiency. In WSNs, where sensor nodes are often battery-powered and deployed in challenging or remote environments, energy conservation is paramount. LEACH addresses this challenge by adopting a novel approach to selecting cluster heads, which are nodes responsible for aggregating and forwarding data from other sensor nodes within their respective clusters. Through the random selection of cluster heads, LEACH ensures a fair distribution of the energy load among all the sensor nodes in the network. This probabilistic selection mechanism allows nodes with varying energy levels to have the opportunity to participate as cluster leaders, effectively preventing rapid energy depletion in specific nodes.

One of LEACH's notable features is its dynamic and autonomous cluster formation process. In contrast to fixed or predefined cluster structures, LEACH generates clusters in a dynamic and adaptive manner. This approach introduces flexibility, allowing the network to adapt to changing network topologies, node failures, and other real-world variations. It's particularly valuable in scenarios where sensor nodes may be subject to mobility, such as environmental monitoring or precision agriculture, as it enables the network to reconfigure itself as needed.

LEACH excels in its ability to coordinate and monitor data transmission at the neighborhood level, which is a pivotal advantage. Cluster heads serve as local coordinators and data aggregators, reducing the need for extensive long-range communication, which typically consumes a significant amount of energy. Localized coordination implies that data is processed and aggregated within the cluster before being transmitted to a base station or sink. This localized approach minimizes the distance over which data is transmitted, reducing energy consumption and ensuring a more efficient utilization of the limited resources available to sensor nodes.

The randomized selection of cluster heads and dynamic cluster formation contribute to proactive energy management within the network. By avoiding the concentration of energy-intensive tasks in a single or a few nodes, LEACH extends the network's lifetime. Additionally, the protocol's adaptability and randomness allow for the distribution of the energy load more evenly among nodes, thus preventing the premature depletion of the power supply in specific nodes. As a result, the network can continue its operations for an extended duration, even in resource-constrained environments.

The versatility of LEACH and its applicability across a wide range of domains is a noteworthy aspect. Whether deployed in environmental monitoring, surveillance, smart agriculture, or disaster response, LEACH can be adapted to effectively manage energy resources and ensure the reliable collection and transmission of data. Its capacity to address dynamic and unpredictable scenarios while optimizing energy use positions it as a valuable protocol for the increasingly interconnected world of the Internet of Things (IoT) and wireless sensor networks (WSNs).

3.4. Hetero-LEACH

Figure 4 exemplifies the Hetero-Leach. Hetero-LEACH is an extension and enhancement of the well-known LEACH (Low-Energy Adaptive Clustering Hierarchy) protocol [27]. It introduces a heterogeneous approach to clustering in wireless sensor networks (WSNs), aiming to further improve energy efficiency and network performance. Hetero-LEACH recognizes that in many WSN deployments, sensor nodes may have varying capabilities and energy resources. By taking these differences into account, it optimizes cluster formation, data aggregation, and energy management, making it a valuable protocol for WSNs with heterogeneous nodes.

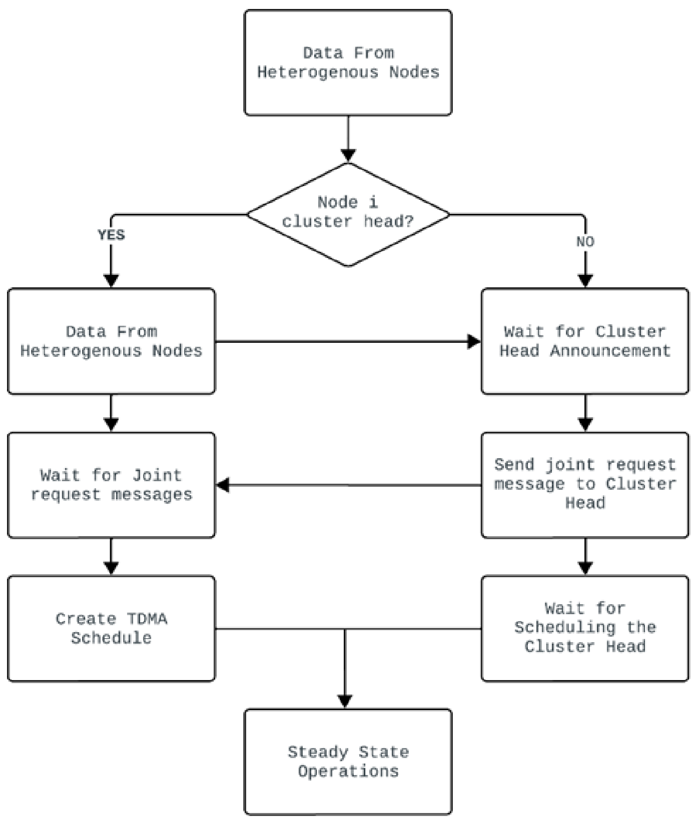

Figure 4 Hetero-Leach

One of the key features of Hetero-LEACH is its dynamic cluster formation process, which is adaptive and responsive to the heterogeneity within the network. Unlike traditional clustering protocols, Hetero-LEACH considers nodes with differing energy levels and computational capacities. It classifies nodes into different roles, such as cluster heads, relay nodes, and regular nodes, based on their characteristics. Cluster heads are selected not only for their energy but also for their computational capabilities, ensuring that they can handle the additional data processing requirements. Hetero-

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LEACH is designed to balance the energy load across the network more effectively. By assigning specific roles to nodes based on their abilities, it ensures that energy-intensive tasks, such as data aggregation and processing, are distributed optimally. This approach reduces the risk of premature energy depletion in critical nodes, enhancing the network's longevity. Moreover, Hetero-LEACH incorporates adaptive data aggregation techniques that allow nodes to tailor their data processing based on their roles, further improving energy efficiency and data quality.

Hetero-LEACH's suitability for WSNs with heterogeneous nodes is particularly valuable in real-world applications. For instance, in an agricultural setting, where sensor nodes may have different energy sources and computational abilities, Hetero-LEACH can ensure efficient data collection, processing, and transmission. Similarly, in urban environments with various sensor types, it can help optimize energy consumption and data quality. The protocol's adaptability and flexibility make it a promising solution for emerging IoT applications where diverse sensor node characteristics are the norm. By addressing heterogeneity and optimizing energy use, Hetero-LEACH contributes to more robust and reliable WSNs in various domains.

3.5. MAMC

In MACM [28], nodes initially exchange HELLO messages to learn each other's coordinates, and the communication band is divided into frames for safety message transmission. Clusters are formed based on node mobility patterns, with faster clusters receiving more frames to ensure successful transmission. These frames are further divided into slots, with each node assigned to a slot for message transmission. Safety messages are initiated at a node and relayed to clusters up to 4 hops away, with the hop count increasing by 1 at each hop. The relay continues as long as the hop count is less than or equal to 4, after which the message is discarded. MAMC process flow is depicted in Figure 5. The major steps of MAMC can be highlighted as follows:

As an initial step, nodes in the network exchange HELLO messages to learn each other's coordinates. Then, divide the DSRC (Dedicated Short-Range Communication) band into frames to make the complete bandwidth available for safety message transmission. Followed by clusters creation of nodes based on their mobility patterns, particularly in response to the HELLO messages. Then, frame assignment to the clusters based on their mobility patterns, giving more frames to clusters with higher speeds to ensure successful transmission and efficient channel utilization. Each frame is then split into multiple slots, with each node being assigned to a specific slot for message transmission. A crucial step is the safety message initiation: where a start a safety message at a node (let's call it node i) and transfer it to clusters at a hop distance of (i+hc), where hc represents the message hop count. Initially, set hc to 1. When clusters one hop away receive the message, check if the hc value is less than M (e.g., M = 4). If it is, transmit the message and increase hc by 1.

Finally, nodes continue relaying and broadcasting the message up to M nodes away from the source cluster, assuming hc remains less than or equal to 4. When hc becomes greater than M, stop relaying the message.

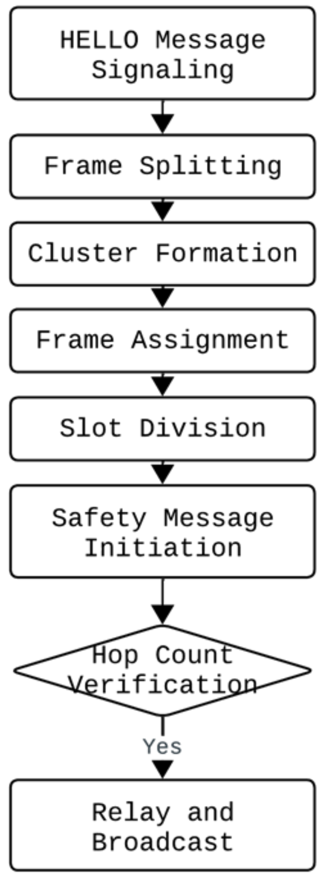

Figure 5 MAMC

3.6. PEGASUS

The PEGASIS (Power-Efficient GAthering in Sensor Information Systems) algorithm [29], is a data gathering protocol used in wireless sensor networks (WSNs) to improve energy efficiency and extend the network's lifetime. It organizes sensor nodes into a linear chain and facilitates energy-efficient data aggregation and transmission. This algorithm is designed to reduce energy consumption in WSNs, making it suitable for various applications where energy efficiency is crucial. Figure 6 provides an overview of the algorithm, which can be summarized as follow:

Chain Formation: PEGASIS organizes sensor nodes into a linear chain. This chain structure is established during the network initialization phase. Each node is connected to its

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neighboring nodes in this chain, creating a unidirectional flow for data transmission.

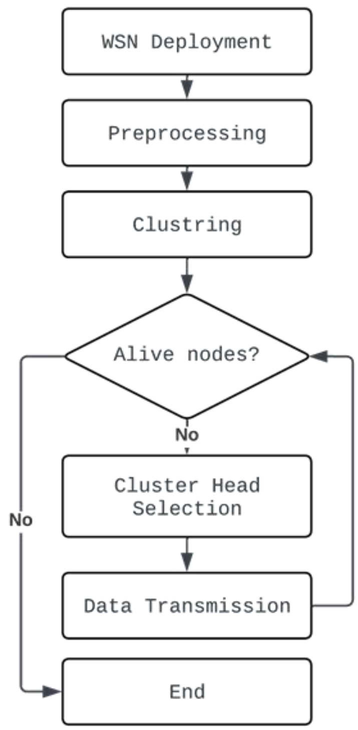

Figure 6 PEGASIS

Data Aggregation: PEGASIS minimizes energy consumption by aggregating data sequentially along the chain. Each node collects data from its immediate neighbors, processes it, and then forwards the aggregated data to the next node in the chain. This process continues along the entire chain, reducing the need for long-distance radio transmissions.

End-to-Destination Transmission: The last node in the chain, often referred to as the sink or base station, is responsible for transmitting the aggregated data to the central destination or external infrastructure. This design minimizes energy consumption during data transmission, as the majority of the data aggregation occurs within the chain.

Energy Efficiency: PEGASIS is designed with energy efficiency in mind. By reducing long-distance radio transmissions and allowing for easy adaptation to changes in network conditions, such as node failures or energy depletion, it helps to extend the network's lifetime and conserve energy resources.

Adaptive Clustering: The algorithm can adapt to network changes, ensuring data continues to flow even in the presence of node failures. If a node in the chain becomes depleted of energy or fails, the chain can be reconfigured to bypass the problematic node. This adaptive clustering approach helps maintain data flow and network connectivity.

Applications: PEGASIS is commonly used in wireless sensor networks for applications where energy efficiency is a critical concern, such as environmental monitoring, wildlife tracking, precision agriculture, and other scenarios where sensor nodes are distributed over a large area and battery life is a crucial factor.

In particular, PEGASIS optimizes data gathering and transmission in wireless sensor networks by minimizing energy consumption and adapting to changing network conditions, ultimately extending the network's operational lifetime.

3.7. Stable Election Protocol

The Stable Election Protocol (SEP) is a clustering algorithm designed for wireless sensor networks (WSNs). Its primary goal is to extend the network's lifetime and reduce energy consumption by electing stable cluster heads, which are responsible for aggregating and forwarding data in a WSN. SEP operates in rounds, and during each round, nodes assess their energy levels and the quality of their connections. Those nodes that are deemed stable and energy-efficient are eligible to become cluster heads for the next round. Cluster heads play a crucial role in data aggregation and help reduce energy consumption by directing data traffic.

The Stable Election Protocol (SEP) is designed for wireless sensor networks to ensure the stability and efficiency of cluster-based data gathering. Here are the main steps of the SEP protocol:

- Initialization: All sensor nodes are initially in the "normal" state.
- Cluster Head Election: Nodes periodically assess their remaining energy and elect themselves as cluster heads based on a probability model that balances energy levels. Nodes with more energy are more likely to become cluster heads.
- Cluster Formation: Nodes join the cluster of the nearest cluster head, creating a hierarchical structure. Cluster heads are responsible for aggregating data from member nodes.
- Data Aggregation: Cluster heads collect data from their member nodes and aggregate it to minimize the amount of data transmitted to the base station, conserving energy.
- Data Transmission: Aggregated data is transmitted from cluster heads to the base station.
- Re-clustering: After a set number of rounds, new cluster heads are elected to distribute the energy load more evenly and prolong the network's lifetime.
- Stability Monitoring: Nodes continuously monitor their energy levels and neighboring nodes to assess their stability. Unstable nodes may enter a sleep state to save energy.

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The SEP protocol aims to create stable clusters by electing cluster heads based on energy, which leads to efficient data gathering and longer network lifetime. SEP's approach to cluster head selection helps prolong the network's lifetime by evenly distributing the energy load among the nodes and mitigating the risk of rapidly draining the batteries of a few nodes. By electing stable and energy-efficient cluster heads in a distributed manner, SEP contributes to improved network performance, reliability, and energy efficiency, making it suitable for various applications in WSNs, such as environmental monitoring, surveillance, and industrial automation. Figure 7 depicts the Stable Election Protocol.

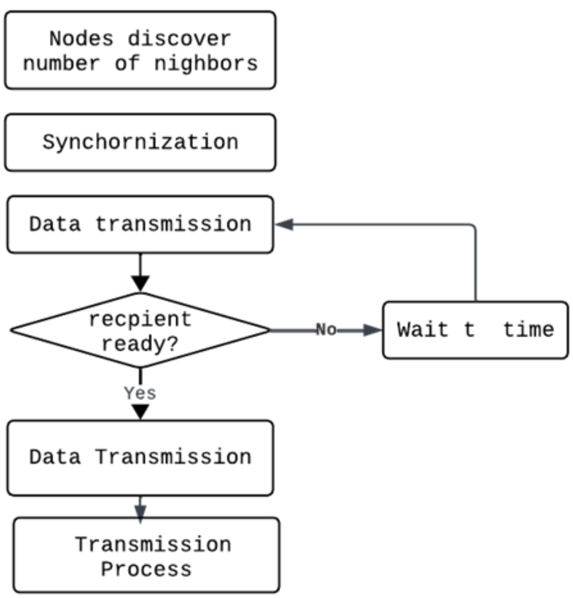

Figure 7 Stable Election Protocol

3.8. Data Aggregation Using Multi Objective Optimization Techniques

Optimization methods play a crucial role in finding the most practical and efficient solutions or estimations across various problem domains. These methods are particularly useful when dealing with optimization problems, where the objective may involve maximizing or minimizing one or more criteria. In scenarios where multiple objectives are involved, these challenges are commonly referred to as "multiple objectives problems" or MOO.

The significance of multi-objective problems is far-reaching and extends to a wide array of fields and everyday life. In engineering, for instance, one might need to optimize a design for both cost and performance. In economics, the aim could be to maximize profit while minimizing environmental impact. In social sciences, trade-offs between various societal objectives need to be considered, and similar instances can be found in agriculture, transportation (including the design of vehicles and aircraft), and numerous other areas.

One of the inherent challenges in addressing multi-objective problems is the potential conflict between these objectives. The pursuit of an optimal solution for one objective may inadvertently lead to negative consequences for another. To navigate this complexity, it's essential to explore a range of possible solutions and strike a balance among competing priorities.

In response to the multifaceted nature of these challenges, researchers and practitioners have developed specialized algorithms. Among these, Genetic Algorithms (GA) and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) have proven to be highly effective in handling multi-objective scenarios. These algorithms have been customized to accommodate the unique demands of multi-objective optimization problems.

In essence, these strategies permit the exploration of a diverse set of solutions and the application of tailored fitness functions, effectively extending the capabilities of classical GA and NSGA-II into the realm of multi-objective problems. This adaptation empowers decision-makers to make more informed choices while considering multiple, often conflicting, objectives.

The most useful and optimal solution or estimation can be discovered with the help of an optimization method. Problems with optimization include pursuing the lowest or highest value, as well as one or more objectives. These issues have repercussions in many areas of study and daily life, including engineering, mathematics, economics, sociology, agriculture, transportation (cars and planes), and more. There are several commonplace situations in which the aims are at odds with one another. In addition, there may be unintended consequences of optimizing a specific strategy for one aim. When trying to find a solution to a problem with multiple objectives, it's important to think about all the ways it could be solved without being overwhelmed by others. Based on these findings, we develop two different GA and NSGA-II algorithms tailored to handle situations with multiple targets. The following section will list the types of problems for which GA and NSGA-II are the best meta-heuristics. Strategies that permit a variety of solutions and the use of individualized fitness functions are used to extend classical GA and NSGA-II to the realm of multi-objective problems.

3.8.1. Complexity of Data Aggregation

Dealing with Noisy Data in the realm of wireless sensor networks presents unique challenges, primarily due to the inherent unpredictability and dynamic nature of the environments in which these networks operate. Sensor nodes, responsible for data collection, are susceptible to various sources of noise, including interference, external factors, and

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inherent sensor limitations. In this context, ensuring the extraction of accurate and reliable information becomes crucial. Several methodologies have been developed to mitigate the effects of noisy data.

Firstly, Data Filtering Techniques are employed, harnessing algorithms such as moving average filters and Kalman filters to smoothen sensor data and eliminate transient noise. Outlier Detection is another strategy, involving the development of methods to identify and subsequently discard data outliers that deviate significantly from the expected sensor readings. Statistically rigorous approaches, such as the Tukey method or z-score analysis, are commonly used for this purpose. Redundancy is introduced by setting up multiple sensor nodes to record the same information, enabling the detection and dismissal of anomalies and incorrect readings.

To ensure data integrity throughout the process, a set of protective measures is put in place. Encryption methods like the Advanced Encryption Standard (AES) or Elliptic Curve Cryptography (ECC) are employed to secure data in transit, safeguarding it against interception and tampering. Authentication procedures are established to confirm the legitimacy of sensor nodes and data sources, ensuring that data collection is limited to authenticated nodes. Data Signing is used for the verification of data authenticity and origin, with digital signatures added to data packets for subsequent verification. Secure Routing Protocols are crucial for safeguarding data during its transit through the network, employing features like secure key exchange and secure data forwarding.

Access Control policies are enforced to restrict access to sensitive data to authorized users or nodes, enhancing data integrity. Data Validation measures, including checksums and hash functions, are used to ensure data accuracy and consistency. In case of discrepancies, data can be resent or corrected. Physical security is also of paramount importance, protecting sensor nodes from theft or tampering and ensuring that unauthorized individuals cannot access the physical setup.

By addressing the challenges posed by noisy data and ensuring data integrity, wireless sensor networks become more reliable and dependable. This reliability allows the confident deployment of these networks in various fields, including environmental monitoring, healthcare, and industrial automation, with an assurance in the reliability and safety of the data they collect and communicate.

Furthermore, the field of wireless sensor networks faces the critical challenge of Temporal and Spatial Averaging. This process involves the aggregation of data over time and space, strategically designed to reduce the impact of transient noise spikes. Temporal averaging combines data from different time intervals, effectively smoothening variations and enhancing data reliability. Spatial averaging, on the other hand, merges data from nearby sensor nodes. By spatially averaging data from proximate sources, the network can mitigate isolated noise sources and enhance the overall quality and trustworthiness of the aggregated data.

In the pursuit of data integrity and reliable data aggregation, it is essential to recognize the diverse range of applications that depend on wireless sensor networks. These applications span environmental monitoring, healthcare, industrial automation, and more. Ensuring the quality and reliability of data collected in these contexts is not only a matter of technical significance but also one of real-world consequence. In environmental monitoring, accurate and reliable data is crucial for assessing ecological trends and environmental changes, guiding conservation efforts, and understanding the impact of climate change. In healthcare, the precision of data gathered from sensor networks is a matter of life and death, where reliable monitoring of vital signs and medical conditions is essential for patient well-being. In industrial automation, data quality determines the efficiency and safety of operations, influencing productivity and minimizing risks. By addressing the issues of noisy data and safeguarding data integrity, wireless sensor networks become a cornerstone of data-driven decision-making across these and many other domains, ensuring reliable, accurate, and trustworthy information that can be acted upon with confidence. Data aggregation implementation algorithm using Whale Optimization is shown in Algorithm 1.

3.8.2. Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA), a novel approach that has proven effective in addressing various optimization challenges. While natural algorithms like the Artificial Bee Colony (ABC) and Particle Swarm Optimization (PSO) have been extensively researched, the WOA community has not yet conducted a comprehensive studies.

Input:

- Data Aggregation Model (e.g., H-LEACH)

Output:

- Optimized Cost Function

- Optimized Fitness Value

1. Initialize the Whale Population.

2. Set the location of Whale W to Wnew.

3. If the whale moves from a location to a new location at a new distance:

- $W = W_{new} + D$

4. Create an Echo Coefficient C from Whale W at distance D to Search for a Prey or Agent.

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5. If C > 0.5:

- Search for Prey.

6. If Echo reflects back in a certain direction:

- W = W_{new} + (2 * cosine(nrl)) + W

- Move the whale to this direction. This path determines the prey.

7. Make the fitness value (x, y) Optimize (x, y).

8. End.

Algorithm 1 Data Aggregation Implementation Algorithm with Whale Optimization

The adaptability and potential hybridization of the WOA hold particular significance. Our research explores the synergy between WOA and BAT approaches. While the BAT algorithm is primarily conceptual for scanning tasks, it's the WOA method that is practically applied. When tested against 16 benchmarking functions, the statistical results from the WOA-BAT merger surpass those from the WOA alone.

Our work also delves into the optimization of administration, engineering, and web-based navigation—a multifaceted challenge. These domains continually strive for improvements in speed, accuracy, and profitability. Efficient resource allocation, accounting for all relevant constraints, is central to solving the resource scarcity problem. Our approach employs mathematical formulas and computer simulations to employ effective search strategies, aiming for optimal solutions in various contexts.

The distinction between local search and metaheuristic algorithms is vital. While local search builds on recently discovered optimal solutions, metaheuristic algorithms encompass a range of search strategies, striving for the best solutions and maximum flexibility. Furthermore, these techniques navigate the balance between precision and approximation, with the potential to unveil unconventional discoveries during exploration [14].

Swarm-based metaheuristic algorithms, inspired by collective animal behavior, are integral in addressing optimization problems. Lewis and Mirjalili have introduced strategies for optimizing whale behavior, employing both efficient and random search engines and a bubble net hunting approach. This innovative approach is particularly significant in the context of Wireless Sensor Networks (WSNs), consisting of sink nodes, sensors, gateway nodes, and base stations.

Our research introduces a novel technique that leverages Quality-of-Service (QoS) requirements for optimizing whales (WOA) in data storage applications. This approach combines the global search capabilities of WOA with subsequent local search for routing paths meeting QoS requirements, resulting in superior local search efficiency compared to other heuristic algorithms. Additionally, we explore the clone operator, which intervenes when creating an ideal environment. This enhanced WOA iteration offers a faster convergence rate and a more efficient performance, making it a valuable tool for creating robust, cost-effective, and environmentally friendly WSN networks.

WOA is a promising approach with versatile applications, including its merger with the BAT algorithm, which demonstrates superior performance in benchmarking functions. This research extends the WOA's utility to optimize data storage in UWSNs, providing an efficient and adaptive approach to address complex optimization challenges. Figure 8 shows the flow of the Whale Optimization Algorithm.

Encoding represents the initial stage in applying the Whale Optimization Algorithm (WOA) to address energy consumption routing challenges within Wireless Sensor Networks (WSNs). Achieving optimal routing under Quality of Service (QoS) constraints is more intricate when employing conventional decimal encoding. Binary encoding, in contrast, offers a simpler approach for both encoding and decoding. In binary notation, the presence of '1' denotes a successfully functioning node, while '0' signifies a failed node. Notably, the binary string commences and concludes with '1' to account for the necessity of traversing nodes initiating and concluding the routing journey. Moreover, the third and fourth bits within the binary representation of the first, third, fourth, and fifth nodes are all set to '1" as shown in Equation 1 and 2. This process involves encoding the characteristics and status of nodes in a WSN into binary form, where each bit holds significance in determining the routing path's efficiency and the fulfillment of QoS requirements. Binary encoding simplifies the identification of operational nodes and aids in the decision-making process for route selection, aiming to minimize energy consumption while ensuring data transmission under QoS limitations. Additionally, the consistent use of '1' bits in specific positions of the binary representation enhances the accuracy and reliability of the routing path, particularly for nodes that play critical roles in the network's data transmission process. This strategy contributes to more efficient routing decisions and better overall network performance, which is crucial in energy-constrained WSNs.

$$W = X.C - Xi \dots (1)$$

$$X\ new = A.X - W \dots (2)$$

The Whale Optimization Algorithm (WOA) involves the utilization of key components, such as the coordinates of the whales denoted as X, and coefficient random vectors represented as C and A. A significant aspect of the WOA process is the evaluation of fitness and the prediction of the top-performing whale. In WOA, fitness evaluation serves as a crucial step in determining the energy consumption of a

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specific route. The fitness value signifies the amount of energy expended on the most energy-efficient path. To identify the current leading whale within the algorithm, it is imperative to compute the fitness of all participants before proceeding with any further WOA operations.

This fitness evaluation process aids in distinguishing the best-performing whale, which is vital for directing the optimization efforts effectively. By quantifying the energy consumption associated with each route, the algorithm can make informed decisions about the route with the least energy expenses, subsequently guiding the entire optimization process in a more productive and energy-efficient direction.

3.8.3. Invasion of the Netted Bubbles

The approach inspired by whales' bubble-net attack offers valuable insights into the efficient management of extensive data without incurring exorbitant costs. This strategy can be replicated through two distinct mechanisms: the "retrenched enclosure" and the "spiral update."

In the case of the "spiral improvement posture," whales execute a spiral motion on the water's surface, generating bubbles of various sizes. These bubbles, strategically dispersed, facilitate the movement of smaller aquatic creatures like shrimp and fish, allowing them to navigate more effectively within their environment.

This approach demonstrates how nature's mechanisms can inspire innovative solutions for data management challenges. Much like the bubbles assist smaller marine life, this concept encourages the development of strategies that enhance the accessibility and utilization of data resources, making them more readily available and navigable. By studying these natural behaviours, we can derive principles for optimizing data handling in a cost-effective and resource-efficient manner.

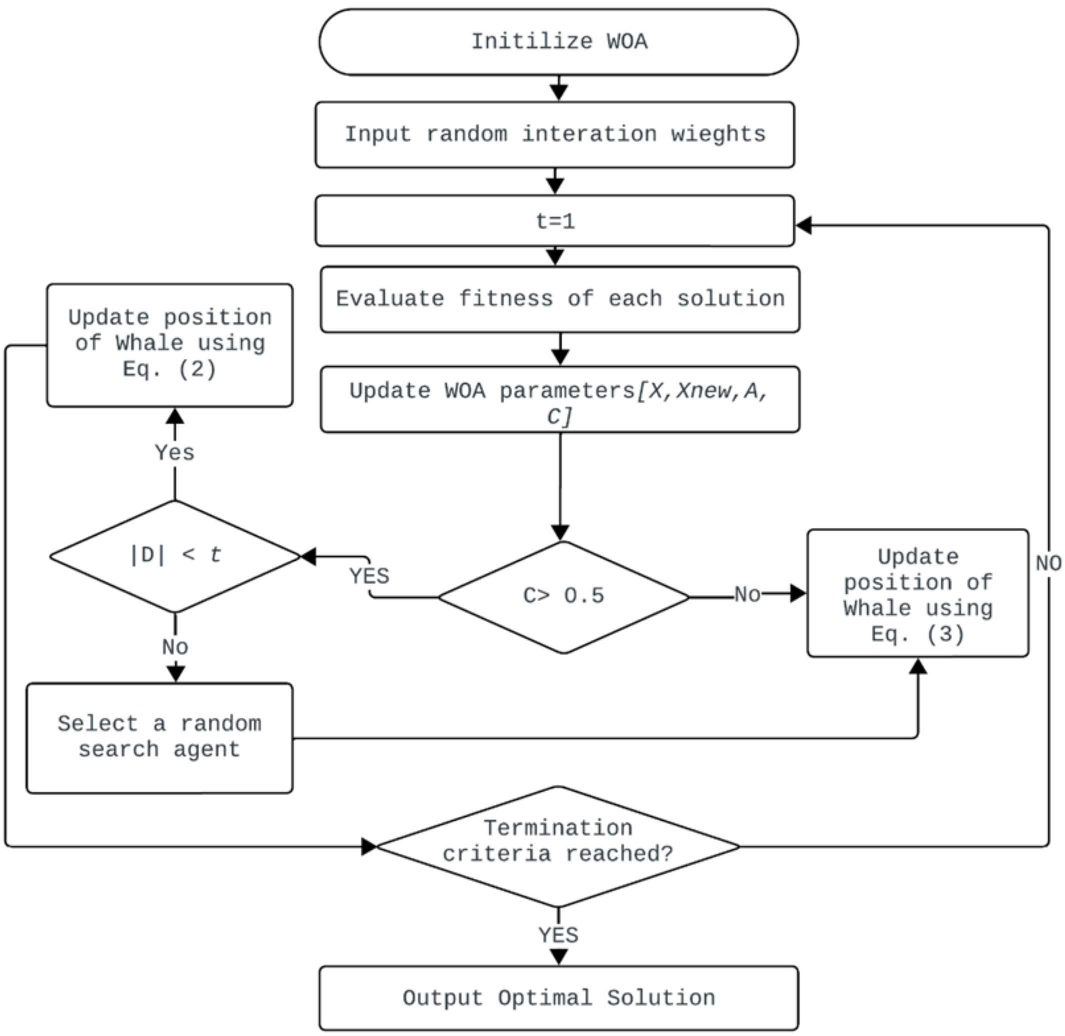

Figure 8 Whale Optimization Algorithm

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3.8.4. Totally Unsystematic Methods of Locating Prey

In the pursuit of solving the optimization routing problem within predefined cost constraints, it becomes necessary to adapt the whale's location update strategy. Instead of constantly synchronizing the whale's position with that of the dominant leader, a less frequent update mechanism coordinated with fellow whales proves more effective.

This adjustment, known as the "Spiral Updating" stage, takes inspiration from the anatomical and behavioral characteristics of whales. In particular, it draws from their unique way of swimming in spirals on the water's surface. By implementing this update strategy alongside the exploitation stage, the optimization process can benefit from the whales' natural behavior.

The rationale behind this adaptation lies in optimizing the routing problem while minimizing computational overhead. Synchronizing the whale's location less frequently reduces the computational burden and aligns with the efficient use of computational resources. The incorporation of the spiral update stage introduces a more dynamic and nature-inspired approach, enhancing the overall efficiency of the optimization process within cost constraints. This methodology underscores the importance of drawing insights from the natural world to devise innovative solutions for complex optimization challenges.

Change X to Xi to obtain as shown in Eq. (3)

$$X\,new = |X_{new} - X_i| \,.\, cos(2\pi l) + X \quad (3)$$

In the context of the preceding discussion, it's essential to understand that most whale migrations appear to follow a seemingly random direction (referred to as "l"), which primarily signifies the areas where whales are likely to locate their food sources. During this stage, the Whale Optimization Algorithm (WOA) incorporates a random search procedure, taking into consideration various coefficients, to precisely identify the subsequent whale location.

The outlined steps in this process can be systematically documented for clarity. To initiate the generation of random whale locations, the initial steps involve determining a target population size and randomly distributing sensor nodes across the monitored area. Subsequently, as the iteration proceeds, parameters are continually adjusted to enhance the optimization process.

The subsequent phase involves employing a mathematical equation to ascertain the healthiest whale within the population and evaluating the corresponding results. This assessment plays a pivotal role in selecting the most suitable candidates for further optimization efforts.

Furthermore, as the whales dynamically refresh their positions, the primary algorithm loop commences. During this phase, the whales explore various regions and adapt their positions to potentially find the most efficient routes.

Step 5, as part of the first method, introduces a distinctive element involving high-probability mutations in the cloned population. These mutations are performed after fitness assessment of the initial whaling population. This approach aims to diversify the population, potentially leading to the discovery of more effective routing solutions in the optimization process.

In essence, this approach mimics the seemingly random yet purposeful nature of whale migrations, offering a structured and systematic framework for optimizing routing problems while ensuring diversity, adaptability, and effective exploration of potential solutions.

3.8.5. Performance Metrics for Evaluating WOA

The evaluation of the Whale Optimization Algorithm (WOA) necessitates the use of a comprehensive set of performance metrics to assess its effectiveness in solving optimization problems. These metrics cover various aspects of WOA's performance. They include convergence rate, which measures how quickly WOA reaches a solution in terms of iterations and the progression of the fitness function value. Solution quality is evaluated by comparing the quality of WOA-generated solutions to industry standards, primarily focusing on minimizing the objective function value. WOA's ability to balance exploration and exploitation is assessed by examining the diversity of approaches and the speed of solution utilization. Robustness is analyzed to understand how WOA responds to changes in problem parameters, including constraints, dimension rescaling, and noise in the fitness function.

The scalability of WOA is examined to determine how it performs as problem complexity increases, a vital consideration for real-world applications. The algorithm's consistency in reaching the global optimum for problems with known solutions is assessed, taking into account the percentage of successfully solved problems and solution proximity to the optimal solution. WOA's effectiveness is compared with other optimization algorithms, considering solution quality, convergence speed, and computational efficiency. The computational resources required by WOA, especially for large-scale optimization challenges, are evaluated. Sensitivity studies help understand the impact of variations in WOA's hyperparameters on its performance, using solution quality as a metric.

The use of visual aids, such as fitness landscape plots, convergence trajectories, and heatmaps, enhances the understanding of WOA's behavior during the optimization process. Additionally, researchers explore how different initializations of WOA influence its behavior and measure variations in solution quality and convergence rates. In cases

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where WOA is applied to real-world problems, domain-specific metrics pertinent to the objectives and constraints of those problems are considered. By employing this comprehensive set of performance criteria, researchers can conduct a thorough and systematic assessment of WOA's suitability for addressing a wide range of optimization challenges.

3.8.6. Optimizing Link Weighting for Efficient Cluster Head Clustering

In the context of link weighting and its role in cluster head clustering, it's crucial to ensure that the weight assigned to connections accurately represents the physical distance between end nodes. As previously mentioned, the total weight of the components of two Cluster Communication Heads (CCHs) plays a pivotal role in determining the strength of their connection. The objective here is to optimize sensor transmission times by aligning the connection weight with the real distance between the involved end nodes.

Following the merger of two clusters into a unified composite cluster, the consolidation process primarily involves the nodes designated as CCHs within the newly formed cluster. The remaining nodes merely require the specification of their respective parents to finalize their algorithms. Consequently, the CCHs tend to distribute themselves more evenly, increasing the space between individual nodes. To address this issue and facilitate more efficient data transfer, it is imperative that the link weight is directly proportional to the physical distance separating the two end nodes and the Base Station (BS).

In the context of Convergent Hub Clusters (CCHs), these clusters naturally gravitate towards the BS and tend to form in proximity to neighboring nodes. Reducing the intervals between CCHs in subsequent iterations significantly expedites data transmission. This convergence of terminal Cluster Heads within the clusters effectively cuts the travel time to the BS in half, contributing to enhance network efficiency.

4. RESULTS AND DISCUSSIONS

In the process of evaluating the efficacy of the proposed model, it is imperative to formulate and employ established performance benchmarks that align with the objectives of the research endeavor. These metrics serve as quantifiable indicators of the model's accomplishments. Detailed metrics for success are provided below:

- Accuracy

Accuracy is the percentage of cases that were correctly labeled. It is a standard measure for classifying data, and its formula is (4):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \; ... \; (4)$$

TP (True Positives) is the number of correctly predicted positive instances.

TN (True Negatives) is the number of correctly predicted negative instances.

FP (False Positives) is the number of actual negatives incorrectly classified as positives.

FN (False Negatives) is the number of actual positives incorrectly classified as negatives.

- Precision and Recall

Precision measures the model's ability to correctly identify positive instances among the predicted positives as shown in Equation (5):

$$Precision = \frac{TP}{TP + FP} \; ... \; (5)$$

4.1. The Proposed Protocol

The proposed protocol is digitally tested alongside four other protocols to gauge its performance. It is compared to others based on their parameters, including HLEACH, PEGASIS, MAMC, LEACH, and SEP. During the stability phase. The fraction of a network's nodes that will die within the first 1, 10, and 50 minutes.

Network instability time is the elapsed time between the launch of the first node and the shutdown of the last node.

Load balancing's primary goal is to maximize output by making more efficient use of available resources. Power consumption at sensor nodes can be minimized according to current optimization options. Using the clustering method can significantly reduce network energy expenses.

By minimizing unused resources and maintaining constant data packet transmission rates, clustering helps networks last longer. Results from the proposed protocol in MATLAB are displayed in Figure 10.

When all nodes have the same starting energy level (Eo), the active nodes will select themselves as CH in the first round using a distributed procedure that takes into account the probabilities of each candidate.

The selection process for the EESAA Protocol is outlined in Table 2. Each node performs load balancing by randomly selecting an integer between 0 and 1, and then determining if that number is greater than or equal to a specified threshold value, as shown in Eq. (6).

$$\begin{cases} \dfrac{Pd}{1 - Pd} \; first\ round\ [1]\ if\ n \in A \\ \quad 0 \;\; otherwise \end{cases} \; ... \; (6)$$

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Table 2 Parameters for EESAA

Parameter	Value
Dimensions	$X_m = 100$, $Y_m = 100$
Sink (x,y)	Sink (0.5,0.5)
Nodes	100
Energy Model	$E = 0.5$, $E_{fs} = 0.0001$, $E_{amp} = 0.005$
Heterogeneity Percentage	M = 0.1, A = 1
Maximum Rounds	7000

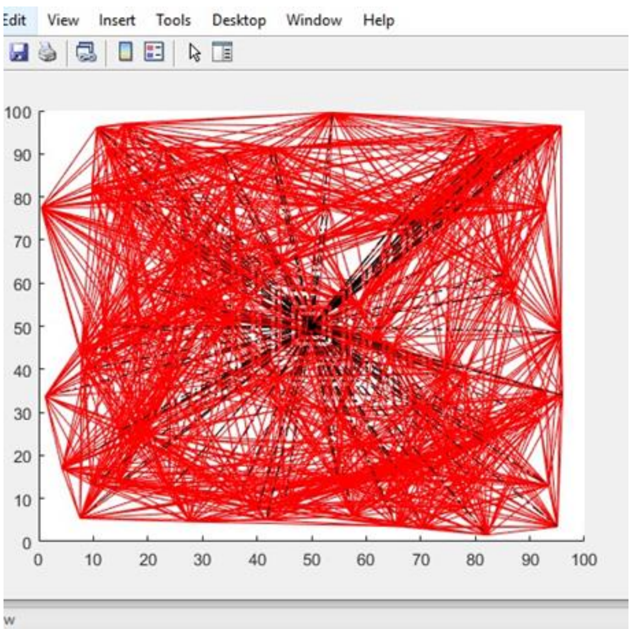

Figure 9 Results of the New Protocol

4.2. Hetero-LEACH

Each cluster's internal communications employ a direct spread spectrum sequence (DSSS), which significantly reduces the likelihood of interference from outside the cluster. Each device in a network employs a unique spreading code sequence to talk to the others. When sensors are organized into a cluster, they may more effectively share the power they consume. Let's pretend M vertices exist in this region. There will be a total of k clusters, each containing one CH node and (N/k)-1 non-CH nodes. Compared to LEACH, H-LEACH has fewer rounds and fewer dead nodes for each cluster head, as seen in Figure 10. Initially, the work was relied on the Hetero-Leach Algorithm. Descriptions of H-features LEACH and values for some of its most important parameters can be found in Table 3.

This table presents the key parameters and values employed in the Heterogeneous LEACH (H-LEACH) protocol, a clustering approach for wireless sensor networks. These parameters are critical in defining the network's configuration and performance.

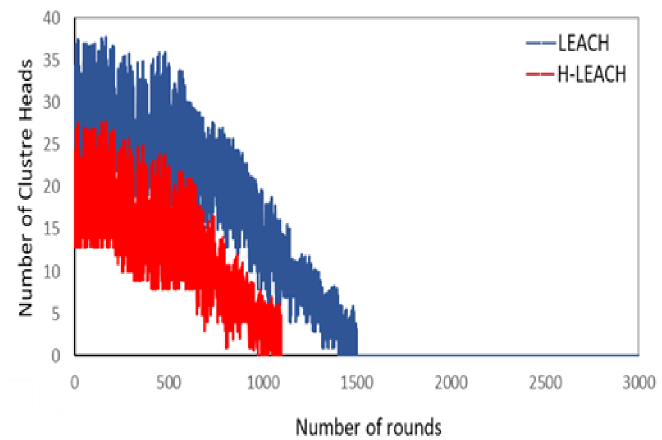

Figure 10 The Difference of Rounds and Dead Nodes in Between H-LEACH and LEACH with Respect to Each Cluster Head

Sink (x, y): Specifies the coordinates of the sink node within the network, with x and y values denoting its position, often at the center of the network.

Nodes: Indicates the total number of sensor nodes deployed in the network, which in this case is 7000.

Optimal Energy (E): Set at 0.5, this value represents the ideal energy level that nodes aim to maintain for efficient network operation.

Heterogeneity (M): Reflecting the level of heterogeneity in the network, this parameter is defined as 0.1, indicating a moderate degree of variation in node characteristics.

Maximum Probability of Model (P): With a value of 0.2, this parameter represents the maximum probability associated with the network model.

Percentage Rounds Node to Become (Initial Cluster Head Energy): Denoted as X_m and Y_m, these parameters are set at 100, indicating that nodes require this percentage of energy to become initial cluster heads.

E_{fs}: Represents the energy threshold for free space transmission, set at 0.0001, and is a crucial factor in energy-efficient data transmission.

A: With a value of 1, A is a constant parameter in the network's energy model, influencing power consumption calculations.

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E_{amp}: This parameter is set at 0.005 and stands for the energy required for amplifier operation, contributing to the overall energy consumption model within the network.

These parameters play a vital role in configuring H-LEACH for optimal performance, energy efficiency, and network reliability.

Table 3 Selection of Parameters for H-LEACH

Dimension	Value
Sink (x, y)	(100, 100)
Nodes	7000
Optimal Energy	E = 0.5
Heterogeneity	M = 0.1
Maximum Probability of Model	P = 0.2
Percentage Rounds Node to Become (Initial Cluster Head Energy)	Xm = 100
Ym	100
Efs	0.0001
A	1
Eamp	0.005

Figure 11 shows the two types of energetic nodes. Figure 12 displays the cluster formation with cluster heads indicated by '*', while 'o' represent normal nodes, '+' represent advanced nodes, and 'x' represent the base station.

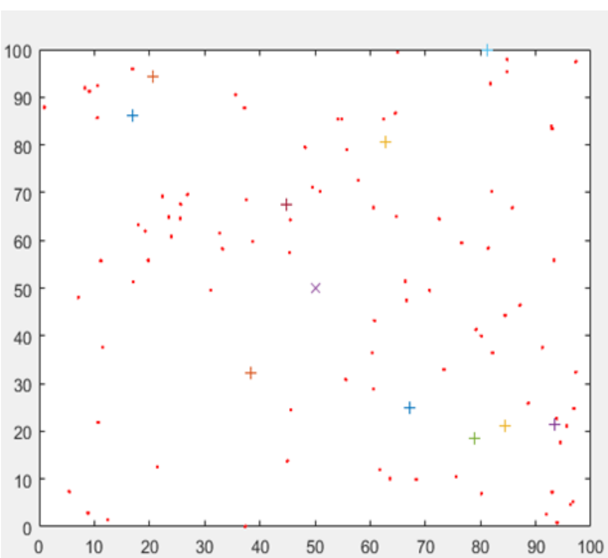

Figure 11 Heterogeneous LEACH Protocol Test Network

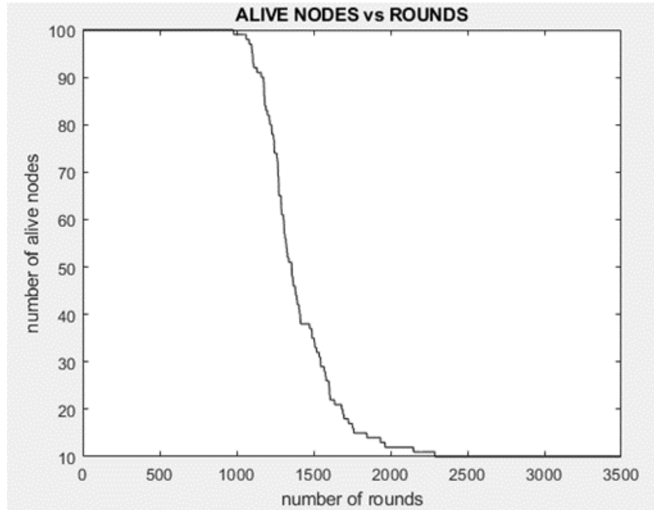

Figure 12 Performance of H-LEACH Algorithm

The ratio of active to inactive nodes is displayed in Figure 12. The peak time for the prevalence of dead nodes is around 2300. However, after roughly the 1200th round, the wireless network's reliability began to deteriorate.

Dead node counts peak around the 2500th round, demonstrating that H-LEACH is effective (Figure 13). Despite the fact that by the 1200th round, the wireless systems can be considered reliable.

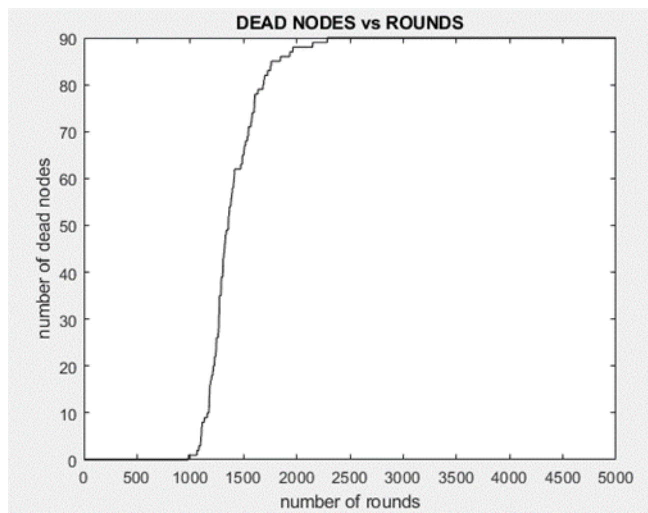

Figure 13 Performance of H-LEACH Algorithm for Number of Dead Nodes

4.3. LEACH

Using a random selection of cluster heads, the Low Energy Adaptive Clustering Hierarchy (LEACH) is a self-organizing clustering mechanism for distributing the energy burden throughout a network of sensor nodes. In Table 4 we summarize the most important attributes of LEACH. Clusters

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generated via randomization, self-organization, and adaptation, local data transmission coordination and monitoring.

Table 4 Selection of Parameters for LEACH

Dimension	Value
Sink (x, y)	(50, 50)
Number of Nodes	7000
Optimal Energy	E = 0.23
Heterogeneity	M = 0.3
Maximum Probability of Model	P = 0.25
Initial Cluster Head Energy	$X_m = 50$
Y_m	50
Energy Free Space Path Loss (E_{fs})	0.0005
Path Loss Exponent (A)	2
Amplifier Energy (E_{amp})	0.0023

The plus sign in Figure 14 represents the sensor cluster head, the o symbol represents the sensor nodes, and the x symbol represents the base station to which the data has been transmitted.

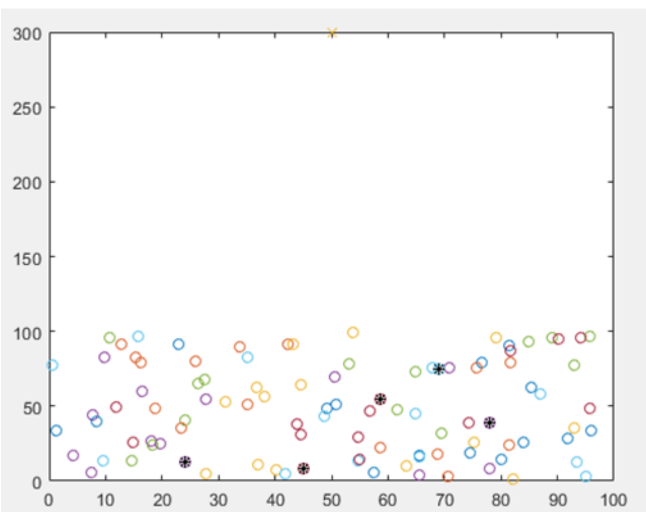

Figure 14 Data Aggregation using LEACH

Figure 15 shows LEACH's effectiveness in terms of the number of connected nodes. By around round 4,000, all of the nodes had died, and no data had been transmitted to the base station as a result of QoS issues brought on by the WSN's instability.

Activated nodes and the selected cluster head are displayed for the LEACH algorithm in Figure 16. After about 1200 rounds, a cluster head's power is depleted to the point where it can no longer send as many data packets to the base station.

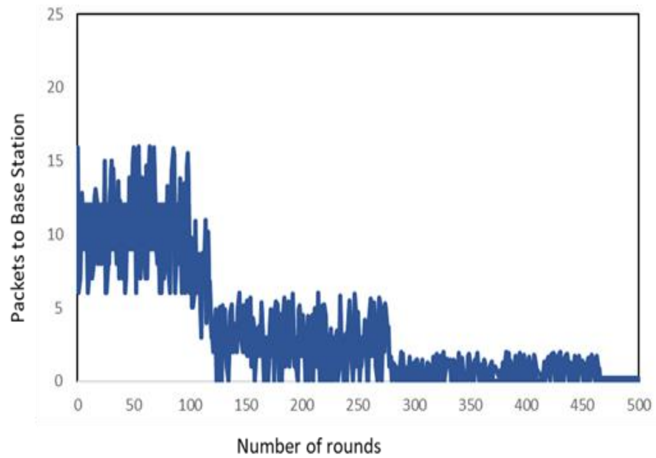

Figure 15 Performance of LEACH Algorithm for Number of Alive Nodes

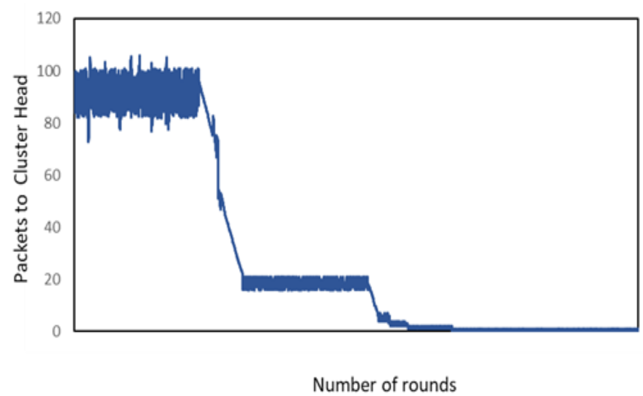

Figure 16 Performance of LEACH Algorithm for Number of Cluster Heads

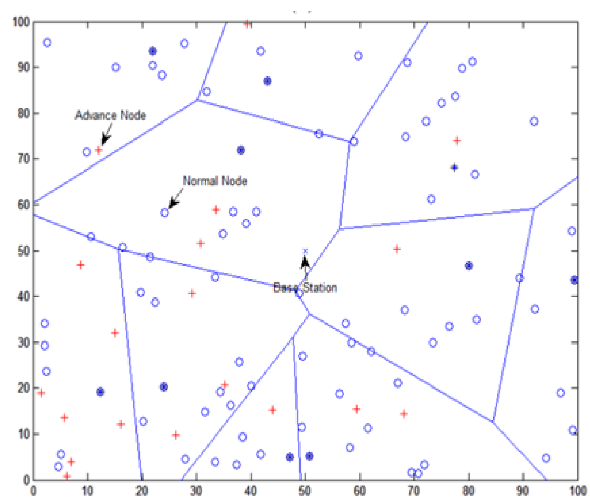

Figure 17 Calculating Link-Weight Functions

The LEACH base station link weight functions are depicted in Figure 17. All of the chosen cluster nodes devised a function of link weights to divide up the future power among themselves, ensuring that the base station and the cluster nodes could keep transmitting data and being connected at all times. Since we aim for lower sensor transmission times, the link should strengthen as the distance between the two end nodes decreases. The only nodes in a cluster that will be affected by a merger are the CCH ones that are part of both clusters. All remaining network nodes' algorithms must be completed, and their parents must be defined. Therefore, as rounds progress and the distance between nodes increases, the number of CCHs decreases. This problem can be resolved if the link weight is proportional to the distance between the two end nodes and the BS. Clusters with CCH prefer nearby nodes, while those without it transition to BS. Both the inter-CCH and inter-transmission distances will shrink in later rounds. The distance between the clusters' terminal CHs decreases as they grow closer to one another and the BS.

4.4. MAMC

To cope with these shifts and promote dynamic interoperability, a new approach is needed. Context, as described by our approach, is an explicit representation of WSN changes in metadata components that informs decisions about how to keep dynamic compatibility. The MAMC algorithm's parameters are broken down in Table 5.

Table 5 Selection of Parameters for MAMC

Dimension	Value
Sink (x, y)	(50, 50)
Number of Nodes	7000
Optimal Energy	E = 0.23
Heterogeneity	M = 0.3
Maximum Probability of Model	P = 0.25
Initial Percentage of Rounds for Node to Become Cluster Head (Cluster Head Energy)	X_m = 50
Y_m	50
Energy Free Space Path Loss (Efs)	0.0005
Path Loss Exponent (A)	4

Figure 18 shows how the MAMC algorithm aggregates data by indicating the link weight functions between cluster heads and base stations as lines.

4.5. PEGASIS

PEGASIS is a communication protocol designed for wireless sensor networks. It leverages a chain-based routing strategy to facilitate efficient data transfer among sensor nodes. This strategy involves organizing the sensor nodes in a chain, where data is passed from one node to the next in a sequential manner, ultimately reaching a designated sink node.

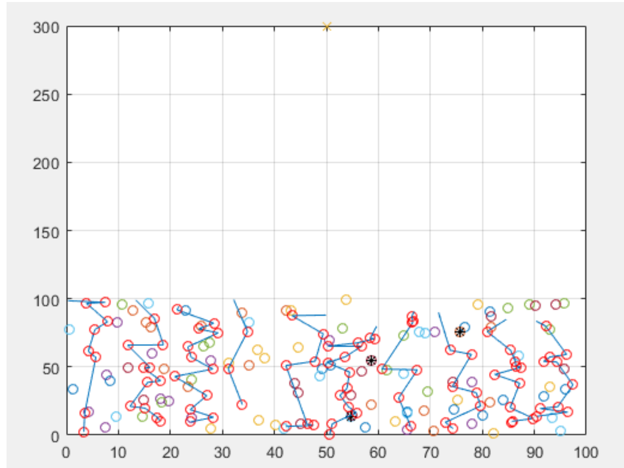

Figure 18 Data Aggregation and Link Weights Using MAMC Algorithm

In the context of data transfer in a PEGASIS chain, the protocol employs a relay node selection mechanism. This mechanism is responsible for determining the optimal relay node in terms of potential connection distance. By choosing the most suitable relay node, PEGASIS optimizes data transmission and energy efficiency within the network.

One notable feature of PEGASIS is the implementation of a failsafe mechanism. This failsafe is based on the median residual energy of neighboring nodes. It serves to prevent localized nodes from depleting their energy resources too quickly. By carefully monitoring the energy levels of nearby nodes and selecting relay nodes accordingly, PEGASIS helps distribute the energy load more evenly across the network. This ensures that no single region of the network becomes power-starved, enhancing the network's overall resilience and prolonging its operational lifespan.

Furthermore, PEGASIS introduces the concept of using a mobile sink, often a mobile node or device that traverses the network. The mobile sink's role is to gather information about the energy consumption patterns of different regions within the network. This information can be valuable for network optimization and management, allowing for strategic adjustments in routing and resource allocation.

Table 6 contains specific parameters and settings for configuring the PEGASIS algorithm. These parameters govern aspects such as relay node selection criteria, energy threshold values, and routing strategies. By adjusting these parameters, network administrators can fine-tune PEGASIS to suit the specific requirements and characteristics of their

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wireless sensor network, ultimately enhancing its performance and efficiency.

The parameters below highlight its key characteristics:

- Sink (x, y) at coordinates (4, 4): The sink node's position within the network, typically situated at the network center.
- Number of Nodes: A total of 84 sensor nodes deployed in the network.
- Heterogeneity (M = 0.3): Reflecting the degree of diversity in node characteristics, indicating a moderate level of variation.
- Initial Percentage of Rounds for Node to Become Cluster Head (X_m = 50): Nodes need to accumulate 50% energy to qualify as initial cluster heads.
- Sink Coordinates at (0.5, 0.5): The sink node's mobile position, crucial for data gathering and network management.
- Maximum Rounds set to 50: The maximum number of rounds or iterations within the PEGASIS protocol.
- Optimal Energy (E = 0.23): The target energy level for nodes to maintain efficient network operation.
- Energy Free Space Path Loss (E_{fs}) at 0.0005: The energy threshold for free space transmission, impacting energy-efficient data transfer.
- Amplifier Energy (E_{amp}) set at 0.0023: Reflects the energy consumption associated with amplifier operation, contributing to the overall energy model.
- Path Loss Exponent (A) specified as 7: A constant parameter in the energy model, influencing power consumption calculations.
- Additional Nodes (if applicable): This parameter accounts for any extra nodes introduced into the network, which may be relevant for larger-scale deployments.

These parameters collectively define the network's configuration and operational characteristics, enabling PEGASIS to optimize data transmission, manage energy efficiently, and ensure the network's reliable and effective performance.

Table 6 Parameters of PEGASIS

Dimension	Value
Sink (x, y)	(4, 4)
Number of Nodes	84
Heterogeneity	M = 0.3
Initial Percentage of Rounds for Node to Become Cluster Head (X_m)	X_m = 50
Sink Coordinates	(0.5, 0.5)
Maximum Rounds	50
Optimal Energy	E = 0.23
Energy Free Space Path Loss (E_{fs})	0.0005
Amplifier Energy (E_{amp})	0.0023
Path Loss Exponent (A)	7
Additional Nodes (if applicable)	7000

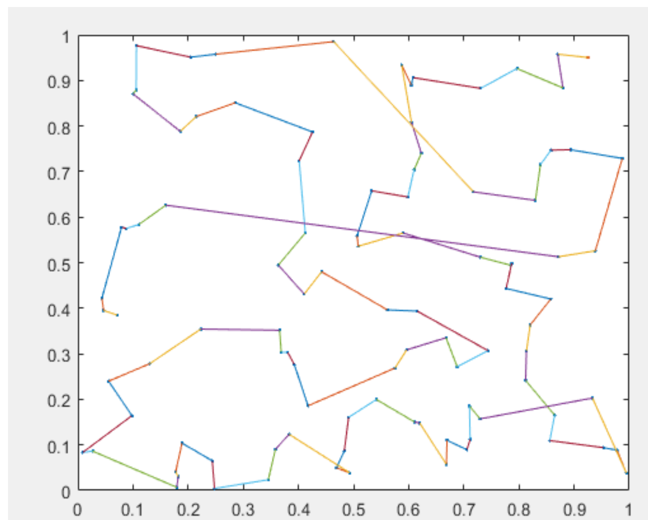

Figure 19 Data Aggregation and Link Weights Using PEGASIS Algorithm

Figure 20 shows the data aggregation and link weights using PEGASIS algorithm.

4.6. Stable Election Protocol

The test network for the Stable Election Protocol is seen in Figure 20. There are two distinct energies of nodes in use. The letter 'o' stands for standard nodes, the plus sign ('+') indicates high-level nodes, and the letter 'x' represents the home base. Figure 20 represents the cluster formation in the cluster heads as a '*'. Table 7 shows the Selection of Parameters for SEP protocol.

Figure 19 depicts the link weight function graphically. If the algorithm comes up with a link weight function, it means the cluster leader doesn't have enough bandwidth to send out data

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packets. Due to the long stability time of the H LEACH algorithm, Link Weights are superfluous in Hetero LEACH.

Table 7 Selection of Parameters for SEP

Dimensions	$X_m = 50$, $Y_m = 50$
Sink (x, y)	Sink (0.5, 0.5)
Nodes	50
Energy Model (Initial Energy)	E= 0.23, $E_{fs} = 0.005$, $E_{amp} = 0.0023$
Heterogeneity %	M = 0.3, A = 7
Maximum Rounds	7000

Table 8 displays how well each algorithm performs in terms of delay and energy reduction. It provides a comparison of various techniques in terms of their performance metrics in the wireless sensor network simulation. The metrics include the number of rounds for different events and the energy remaining at specific nodes for each technique.

The "Round for First Dead" metric measures the number of rounds it takes for the first sensor node in the network to deplete its energy. Our new solution has a higher value compared to LEACH and PEGASIS but is similar to SEP. H-LEACH performs better than the proposed protocol in this aspect.

Round for First 10 Dead signifies the number of rounds required for the first ten sensor nodes to exhaust their energy. The proposed approach performs similarly to SEP in this aspect and outperforms MAMC, PEGASIS, and LEACH. H-LEACH outperforms the proposed approach in this regard. The "Stability Period" indicates how long the network remains stable before significant energy depletion occurs. The stability period of our solution is similar to that of MAMC but shorter than H-LEACH, PEGASIS, and SEP. It significantly outperforms LEACH in terms of network stability.

This metric measures the amount of energy remaining in the first ten sensor nodes. Our proposed solution retains the highest energy among the first ten nodes, outperforming H-LEACH, LEACH, MAMC, PEGASIS, and SEP in this category.

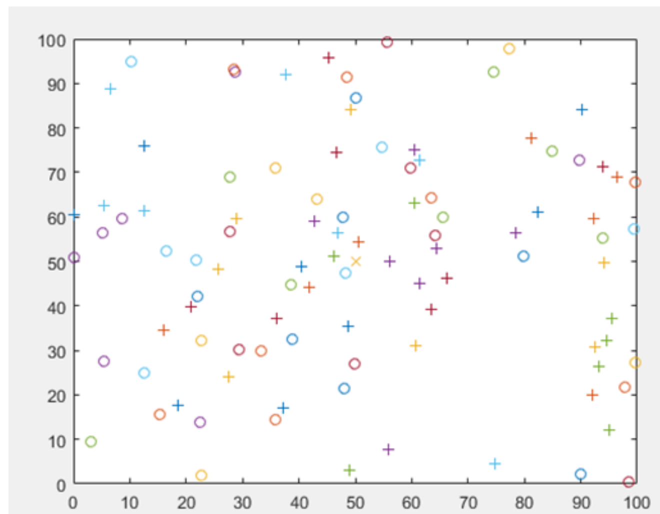

Figure 21 Performance of SEP Protocol

In summary, the proposed protocol performs well in terms of maintaining energy in the initial nodes and demonstrating a reasonable stability period. It lags H-LEACH in terms of the "Round for First Dead" and "Round for First 10 Dead" metrics. Overall, the choice of routing technique depends on the specific network requirements and priorities, as different techniques excel in various aspects of performance.

Table 8 Comparative Performance of Techniques

Technique	Round for first Dead	Round for first 10 Dead	Round for first half alive Nodes	Round for all dead nodes	Stability Period	Energy Remaining at first 10 nodes
Proposed [this article]	3000	4500	6500	7200	2300	4800J
H-LEACH[27]	2300	3230	4500	5400	1152	2300J
LEACH[26]	456	1200	3243	1500	322	1000J
MAMC[28]	1329	2500	3554	4000	900	600J
PEGASIS[29]	1200	1500	2100	2400	849	530J
SEP[30]	2190	3100	4000	5000	1003	1300J
[6]	1000	2500	3554	4000	900	600J
[7]	1100	1500	2100	2400	849	530J
[10]	1500	3100	4000	5000	1003	1300J

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5. CONCLUSIONS

The choice of a routing technique should align with the specific requirements and goals of the application. Based on our analysis of different routing techniques in a wireless sensor network, several key insights can be drawn to inform network administrators and researchers: It's essential to compare routing techniques against relevant benchmarks to determine their suitability for a particular application. The provided metrics offer a comparative benchmark, enabling network administrators to make informed decisions. If network longevity is a priority, the proposed approach offers a solid choice. If rapid data transmission and early-stage energy conservation are crucial, H-LEACH might be preferred.

The proposed approach retains a significant amount of energy in the first ten nodes, indicating its ability to prolong network operation. However, H-LEACH outperforms our solution in terms of the "Round for First Dead" and "Round for First 10 Dead" metrics, suggesting that it may be more energy-efficient during the early stages of network operation.

Moreover, the proposed solution offers a reasonable stability period, which is the duration for which the network remains stable before energy depletion becomes a significant concern. It outperforms LEACH in terms of network stability.

Different routing techniques have their strengths and weaknesses. While the proposed approach excels in energy preservation, it may trade this for slightly longer times before the first node failure. On the other hand, H-LEACH is efficient in early-stage energy consumption but may have a shorter stability period.

In conclusion, no single routing technique is universally superior. The choice should be tailored to the specific needs of the wireless sensor network. The proposed solution emerges as a strong contender, excelling in energy preservation. Ultimately, understanding the trade-offs and priorities of a given application is crucial for selecting the most appropriate routing technique.

REFERENCES

[1] Mokabberi, A. Iranmehr, and M. Golsorkhtabaramiri, "A Review of Energy-efficient QoS-aware Composition in the Internet of Things," in 2023 8th International Conference on Technology and Energy Management (ICTEM), 2023: IEEE, pp. 1-6.

[2] A. Perera and M. Katz, "Novel Data and Energy Networking for Energy Autonomous Light-based IoT Nodes in WPAN Networks," in 2023 IEEE Wireless Communications and Networking Conference (WCNC), 2023: IEEE, pp. 1-6.

[3] M. Asif, A. Ihsan, W. U. Khan, A. Ranjha, S. Zhang, and S. X. Wu, "Energy-efficient beamforming and resource optimization for AmBSC-assisted cooperative NOMA IoT networks," IEEE Internet of Things Journal, 2023.

[4] K. E. S. Desikan, V. J. Kotagi, and C. S. R. Murthy, "Decoding the Interplay Between Latency, Reliability, Cost, and Energy While Provisioning Resources in Fog-Computing-Enabled IoT Networks," IEEE Internet of Things Journal, vol. 10, no. 3, pp. 2404-2416, 2022.

[5] H. Shang, D. Lu, and Q. Zhou, "Early warning of enterprise finance risk of big data mining in internet of things based on fuzzy association rules," Neural Comput. Appl., vol. 33, no. 9, pp. 3901–3909, 2021, doi: 10.1007/s00521-020-05510-5.

[6] N. Rathour, V. Kumar, S. S. Kundu, Y. Gehlot, and A. Gurung, "Sigma Home: An IoT-Based Home Automation Using Node MCU," in 2023 2nd International Conference on Edge Computing and Applications (ICECAA), 2023: IEEE, pp. 1317-1322.

[7] Y. Alzahrani, J. Shen, and J. Yan, "Energy-Efficient Data Consistency based Sampling Rate Optimization and Aggregation Method for IoT," in 2023 26th International Conference on Computer Supported Cooperative Work in Design (CSCWD), 2023: IEEE, pp. 1348-1353.

[8] X. Yang, L. Shu, K. Li, Z. Huo, S. Shu, and E. Nurellari, "Silos: An intelligent fault detection scheme for solar insecticidal lamp iot with improved energy efficiency," IEEE Internet of Things Journal, vol. 10, no. 1, pp. 920-939, 2022.

[9] R. Ramkumar and C. Balasubramanian, "A novel cluster head selection scheme based on BCO for Internet of Things," in 2023 Third International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), 2023: IEEE, pp. 1-6.

[10] Z. Ding, L. Shen, H. Chen, F. Yan, and N. Ansari, "Energy-Efficient Topology Control Mechanism for IoT-Oriented Software-Defined WSNs," IEEE Internet of Things Journal, 2023.

[11] W.-P. Nwadiugwu, W. Ejaz, M. Kaneko, and A. Anpalagan, "Neural-Network Assisted Packet Accelerators for Internet of Things Network Systems," IEEE Internet of Things Journal, 2023.

[12] N. Sivasankari and S. Kamalakannan, "Fuzzy Logic-based Man-in-the-Middle Attack Detection and Improving Routing Efficiency in the IoT Network," in 2023 International Conference on Applied Intelligence and Sustainable Computing (ICAISC), 2023: IEEE, pp. 1-6.

[13] M. Majid, "Optimizing Energy Efficiencies of IoT-based Wireless Sensor Network Components for Metaverse Sustainable Development using Carry Resist Adder based Booth Recoder (CRABRA)," in 2023 20th Learning and Technology Conference (L&T), 2023: IEEE, pp. 91-96.

[14] S. K. Chaurasiya, S. Mondal, A. Biswas, A. Nayyar, M. A. Shah, and R. Banerjee, "An Energy-Efficient Hybrid Clustering Technique (EEHCT) for IoT-Based Multilevel Heterogeneous Wireless Sensor Networks," IEEE Access, vol. 11, pp. 25941-25958, 2023.

[15] M. S. Batta, H. Mabed, Z. Aliouat, and S. Harous, "Battery State-of-Health Prediction-Based Clustering for Lifetime Optimization in IoT Networks," IEEE Internet of Things Journal, vol. 10, no. 1, pp. 81-91, 2022.

[16] C. Kathirvel and P. Deepa, "Design and Implementation of IoT based Dual Axis Solar Tracking System," in 2023 3rd International Conference on Smart Data Intelligence (ICSMDI), 2023: IEEE, pp. 542-545.

[17] A. Iqbal and T.-J. Lee, "Opportunistic Backscatter Communication Protocol Underlying Energy Harvesting IoT Networks," IEEE Access, 2023.

[18] P. Satyanarayana, K. Bhoomika, D. Mukesh, P. Srujana, R. M. Bai, and Y. S. Sriramam, "Implementation of Improved Energy Balanced Routing Protocol to Enlarge Energy Efficiency in MANET for IoT Applications," in 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), 2023, vol. 1: IEEE, pp. 380-385.

[19] N. Stricker, J. Hora, A. Gomez, and L. Thiele, "Energy-Efficient Bootstrapping in Multi-hop Harvesting-Based Networks," in 2023 18th Wireless On-Demand Network Systems and Services Conference (WONS), 2023: IEEE, pp. 1-8.

[20] F. Xu, H.-C. Yang, and M.-S. Alouini, "Ultra-Green Relay Transmission with Wireless Power Transfer for Advanced IoT: Session-Specific Analysis and Optimization," IEEE Internet of Things Journal, 2023.

[21] M. González-Palacio, D. Tobón-Vallejo, L. M. Sepúlveda-Cano, S. Rúa, and L. B. Le, "Machine-learning-based combined path loss and

RESEARCH ARTICLE

shadowing model in LoRaWAN for energy efficiency enhancement," IEEE Internet of Things Journal, 2023.

[22] D. Ray, P. Bhale, S. Biswas, P. Mitra, and S. Nandi, "A Novel Energy-efficient Scheme For RPL Attacker Identification In IoT Networks Using Discrete Event Modeling," IEEE Access, 2023.

[23] X. Liu, Z. Liu, B. Lai, B. Peng, and T. S. Durrani, "Fair energy-efficient resource optimization for multi-UAV enabled Internet of Things," IEEE Transactions on Vehicular Technology, vol. 72, no. 3, pp. 3962-3972, 2022.

[24] S. Boehm and H. Koenig, "Radio-in-the-Loop Simulation Modeling for Energy-Efficient and Cognitive IoT in Smart Cities: A Cross-Layer Optimization Case Study," in 2023 18th Wireless On-Demand Network Systems and Services Conference (WONS), 2023: IEEE, pp. 126-133.

[25] S. Huang, G. Chuai, W. Gao, and K. Zhang, "Agency Selling Format-Based Incentive Scheme in Cooperative Hybrid VLC/RF IoT System With SLIPT," IEEE Internet of Things Journal, vol. 10, no. 8, pp. 7366-7379, 2022.

[26] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," in Proceedings of the 33rd annual Hawaii international conference on system sciences, 2000: IEEE, p. 10 pp. vol. 2.

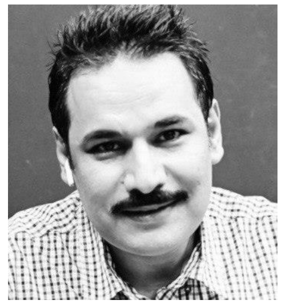
[27] A. Razaque, S. Mudigulam, K. Gavini, F. Amsaad, M. Abdulgader, and G. S. Krishna, "H-LEACH: Hybrid-low energy adaptive clustering hierarchy for wireless sensor networks," in 2016 IEEE Long Island Systems, Applications and Technology Conference (LISAT), 2016: IEEE, pp. 1-4.

[28] P. Harichandan, A. Jaiswal, and S. Kumar, "Multiple Aggregator Multiple Chain routing protocol for heterogeneous wireless sensor networks," in 2013 International Conference on Signal Processing and Communication (ICSC), 2013: IEEE, pp. 127-131.

[29] S. Lindsey and C. S. Raghavendra, "PEGASIS: Power-efficient gathering in sensor information systems," in Proceedings, IEEE aerospace conference, 2002, vol. 3: IEEE, pp. 3-3.

[30] M. Islam, M. Matin, and T. Mondol, "Extended Stable Election Protocol (SEP) for three-level hierarchical clustered heterogeneous WSN", IET Conference on Wireless Sensor Systems (WSS 2012).

Author



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