ENERGY EFFICIENT MULTI-QoS CENTRIC ROUTING ALGORITHMS IN IoT-BASED SOFTWARE DEFINED WIRELESS SENSOR NETWORKS

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by

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CANDIDATE'S DECLARATION

I, **Nitesh Kumar,** hereby certify that the work which is being presented in the thesis entitled ***"Energy Efficient Multi-QoS Centric Routing Algorithms in IoT-Based Software-Defined Wireless Sensor Networks"*** in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy, submitted in the **Department of Computer Science and Engineering**, Delhi Technological University is an authentic record of my own work carried out during the period from 2020 to 2025 under the supervision of **Dr. Rohit Beniwal**.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other institute.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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CERTIFICATE BY THE SUPERVISOR(s)

Certified that **Nitesh Kumar** (enrollment no. 2K20/PHDCO/12) has carried out their search work presented in this thesis entitled ***"Energy Efficient Multi-QoS Centric Routing Algorithms in IoT-Based Software-Defined Wireless Sensor Networks"*** for the award of **Doctor of Philosophy** from Department of **Computer Science and Engineering**, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University / Institution.

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Abstract

The rapid expansion of the internet of things has led to the widespread deployment of sensor nodes, creating a need for energy-efficient and scalable communication frameworks. Software-defined wireless sensor networks have emerged as a promising solution by offering centralized control, dynamic reconfiguration, and enhanced flexibility. However, these networks face critical challenges, including limited battery life, routing inefficiencies, and the need to meet multiple quality of service constraints.

This thesis addresses these challenges by proposing a set of novel, energy-efficient, multi-QoS-centric routing algorithms for IoT-enabled SDWSNs. A detailed systematic literature review is conducted to classify existing clustering and routing methods into classical, metaheuristic-based, and machine learning-based categories, highlighting research gaps. To overcome existing limitations, three metaheuristic-based protocols are developed: the Energy-Optimized Artificial Hummingbird Algorithm (EOAHA), a Nature-Inspired Multi-Objective Green Routing Protocol (EO-C), and a Multi-Constrained Hybrid Protocol (EQ-AHA). These algorithms are designed to optimize cluster head selection and routing paths by using multi-objective fitness functions based on energy, distance, load, and network stability. Extensive simulations and performance evaluations confirm that the proposed models significantly outperform existing state-of-the-art techniques in terms of network lifetime, energy consumption, data delivery, and robustness. The research offers valuable contributions to the development of intelligent, adaptive, and sustainable routing protocols for future IoT-enabled smart environments.

List of Publication

Journals

1. R. Beniwal and N. Kumar, "Energy optimized artificial hummingbird algorithm for routing in IoT-based software-defined WSN," *International Journal of Communication Systems*, vol. 37, no. 8, Wiley **(SCIE)**, Mar. 2024. **[Published]**

2. N. Kumar and R. Beniwal, "A Multi-Constrained Green Routing Protocol for IoT-Based Software-Defined WSN," *Concurrency and Computation: Practice and Experience*, vol. 36, no. 28, Wiley **(SCIE)**, Oct. 2024. **[Published]**

3. R. Beniwal and N. Kumar, "A Nature-Inspired Multi-Objective Green Routing Protocol for IoT-Enabled SDWSNs," *Transaction on Emerging Telecommunication Technology*, Wiley **(SCIE)** May. 2025. **[Published]**

Conference Papers

4 N. Kumar and R. Beniwal, "Energy-Efficient Techniques in IoT-based Software-Defined Wireless Sensor Networks: A Systematic Review," *7th International Conference on Energy, Power and Environment (ICEPE)*, IEEE, NIT Meghalaya, India, May 2025. **[Presented]**

5 N. Kumar and R. Beniwal, "Green Routing Protocols for IoT-Based Software-Defined Wireless Sensor Networks: A Comparative Analysis," *7th International Conference on Energy, Power and Environment (ICEPE)*, IEEE, NIT Meghalaya, India, May 2025. **[Presented]**

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LIST OF ABBREVIATIONS

Acronym	Description
ABC	Artificial Bee Colony
ALO	Ant Lion Optimization
BES	Bald Eagle Search
BOA	Butterfly Optimization Algorithm
BS	Base Station
CD	Inter-cluster Distance
CH	Cluster Head
CR	Convergence Rate
CRO	Chemical Reaction Optimization
CSO	Chicken Swarm Optimization
DP	Data Packets
DNR	Dead Node per Round
ED	Energy Dissipated
ER	Energy Ratio
FFO	Farmland Fertility Optimization
FND	First Node Died
FV	Fitness Values
GA	Genetic Algorithm
GWO	Grey Wolf Optimizer
HHO	Harris Hawk Optimization
HND	Half Node Died
HSA	Harmony Search Algorithm
ICD	Intra-cluster Distance
LB	Load Balancing
LND	Last Node Died

Continued on next page

Acronym	**Description**
MRFO	Manta Ray Foraging Optimization
MSSO	Multi-strategy Fusion Snake Optimizer
ND	Node Degree
NL	Network Lifetime
NND	Neighbour Node Distance
NN	Normal Node
PCSO	Powell Cat Swarm Optimization
PDR	Packet Delivery Ratio
PSO	Particle Swarm Optimization
RE	Residual Energy
SA	Simulated Annealing
SD	Sink Distance
SFO	Sailfish Optimization
SHO	Spotted Hyena Optimization
SDWSN	Software Defined Wireless Sensor Network
TAN	Total Alive Node per Round
TD	Transmission Distance
TS	Tabu Search
TV	Trust Value
WOA	Whale Optimization Algorithm
WSN	Wireless Sensor Network

CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

The Internet of Things (IoT) is a network of devices that communicate with each other over existing World Wide Web infrastructure. The major advantage of these devices is their ability to make intelligent decisions based on evolving situations. As a result, IoT devices find applications in nearly every domain. Health [1], manufacturing [2], smart homes [3], smart vehicles [4], smart appliances, farming [5], and smart cities are just a few examples. Managing a smart city involves deploying a large number of smart sensors with features like remote reconfiguration and internet connectivity. Over the past few decades, the demand for IoT has grown significantly, prompting advances in both software and hardware for sensor nodes capable of monitoring and collecting diverse types of data [6]. IoT devices take intelligent decisions based on data gathered through sensors or sensor networks. The growing IoT ecosystem demands increasingly complex Wireless Sensor Network (WSN) architectures [7]. Traditional WSNs consist of sensor nodes that can sense and route data but have limited connectivity, storage, and processing capabilities [8]. Managing large-scale networks, especially in remote or inaccessible locations, is very difficult and increases operational costs [9, 10]. The solution to this problem is the Software-Defined Wireless Sensor Networks (SDWSNs).

IoT applications, like the smart cities, uses the concept of SDWSNs to manage services such as smart transportation, traffic control, and power optimization in urban areas [11–13]. The major advantage offered by IoT-enabled SDWSNs is dynamic reconfiguration of network nodes centrally [14]. This feature allows the network operator to easily add or remove nodes and ensures adaptability to changing environmental conditions. Hence the operation cost decreases drastically and improves network performance. As there are billions of connected IoT devices and the trend continues to grow exponentially [15], so does the demand for energy, which poses substantial environmental concerns. One critical issue in IoT-enabled SDWSNs is the limited battery life of sensor nodes [16]. There are two commonly adopted strategies for mitigating energy constraints: energy-efficient routing protocols and energy harvesting. Since transmission energy is directly proportional to the distance between the sender and receiver, routing protocols aim to minimize transmission distances by optimizing the routing path to the central controller [17]. Energy harvesting, on the other hand, leverages external sources such as solar or kinetic energy to automatically recharge node batteries [16, 18]. These approaches are essential for improving the long-term sustainability of SDWSNs.

Among the techniques explored for reducing energy consumption, clustering has emerged as particularly effective. In this approach, the network is divided into logical groups, each managed by a Cluster Head (CH) [19]. CHs aggregate data from member nodes and transmit it to the base station—an energy-intensive task that significantly affects network lifetime [20]. However, selecting optimal CHs is an NP-hard problem [21], necessitating the use of advanced optimization strategies. Efficient CH selection, therefore, is central to the development of sustainable and scalable routing protocols for IoT-enabled SDWSNs [8, 22].

1.2 Key Concepts

1.2.1 Internet of Things

The Internet of Things (IoT) has attracted great attention and interest from many researchers, industrial organizations, and users, being considered the next-generation Internet [23]. As shown in figure 1.1, there were 8.6 billion IoT devices in 2019, and the number is expected to rise to 3.5 times by 2030 [24]. IoT devices are physical objects connected via the internet that exchange data with other machines or humans. These devices enable automation across various domains by integrating sensing, processing, and communication capabilities. IoT devices are often heterogeneous, built by different manufacturers and using diverse communication protocols. This heterogeneity introduces complexity in enabling seamless interoperability and data exchange. IoT networks can be broadly classified based on their connectivity technologies, communication range, and energy requirements. Traditionally, they are grouped into six major categories, but additional and emerging types also exist to address specific use cases [25].

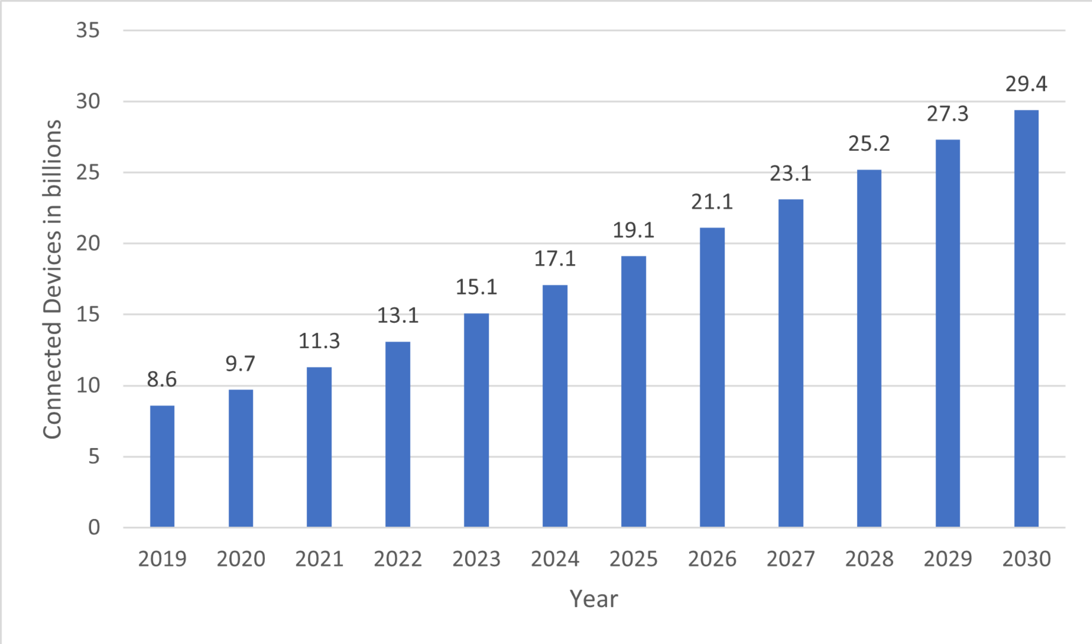

Figure 1.1: Projected Growth of IoT-Devices

1. **Cellular Networks:** Cellular networks offer long-range connectivity and are commonly used for IoT devices that require wide-area coverage, such as vehicle tracking or smart city applications. With declining costs and advances in low-power cellular protocols (e.g., NB-IoT, LTE-M), cellular IoT is gaining traction [26, 27]. Devices can be deployed anywhere within network coverage without custom infrastructure. However, power consumption remains a concern for battery-operated devices [28].

2. **Local and Personal Area Networks (LAN/PAN)**: These short-range networks are suitable for indoor and proximity-based IoT deployments. Technologies such as Wi-Fi, Bluetooth, Zigbee, and Z-Wave fall under this category. While they are easy to deploy and cost-effective, their limited communication range and interference in dense environments may affect reliability [29].

3. **Low-Power Wide Area Networks (LPWAN)**: LPWAN technologies such as LoRaWAN, Sigfox, and NB-IoT are designed for long-range, low-power, low-bandwidth communication. These are ideal for devices that transmit small packets of data infrequently, such as in environmental monitoring or smart metering. LPWANs can operate over tens of kilometers while consuming minimal energy [30].

4. **Satellite IoT Networks:** Satellite-based IoT enables connectivity in remote, maritime, and disaster-prone areas where terrestrial networks are unavailable. These systems are increasingly used in applications such as asset tracking, wildlife monitoring, and offshore operations. Examples include Iridium, Swarm, and Inmarsat [31].

5. **Wired IoT Networks:** Although wireless technologies dominate the IoT landscape, wired networks still play a crucial role, especially in scenarios where high bandwidth and low latency are essential, such as in industrial automation and smart buildings. They are required where real-time data transmission and security are critical, ensuring reliable communication and robust performance in smart environments [32].

6. **Hybrid Architectures:** Some IoT systems integrate multiple networking types to address complex environments. These hybrid architectures leverage the strengths of various technologies, ensuring robust connectivity and adaptability in diverse applications. For example, a smart agriculture system may use LPWAN for field sensors and 5G or Wi-Fi for backhaul communication. Hybrid architectures balance latency, power, cost, and reliability [33].

1.2.2 Wireless Sensor Networks

Wireless Sensor Networks (WSNs) are an important part of the Internet of Things (IoT). They consist of many small, low-cost, low-power sensor devices that can collect and share information. WSNs are used in many areas like environmental monitoring, agriculture, smart homes, and even underwater systems [34–37].

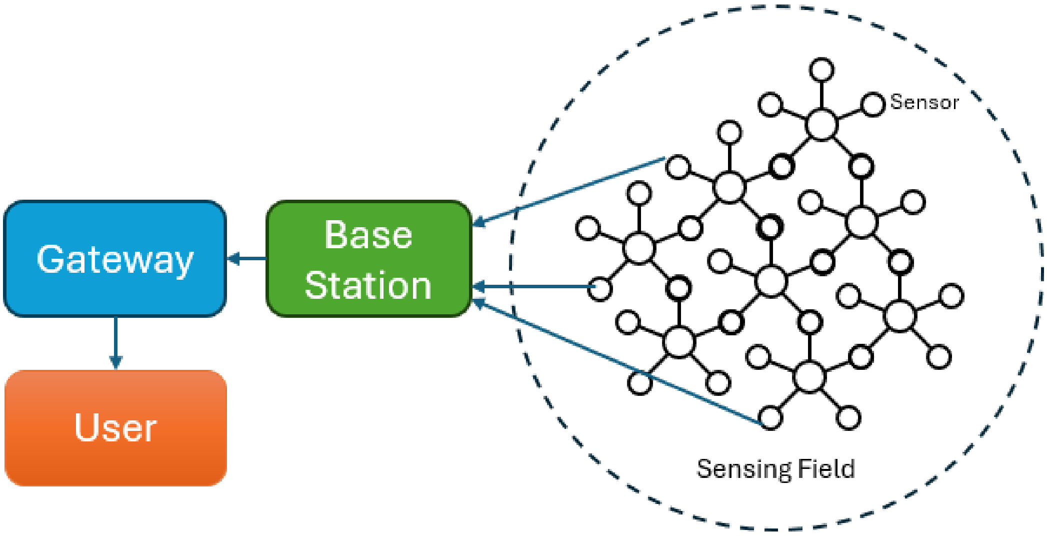

Figure 1.2: WSN Architecture

Figure 1.2 shows a basic architecture of a WSN system. The sensor nodes are deployed across a sensing field to monitor environmental parameters. These nodes are connected in a mesh-like structure and communicate with a centralized base station, either directly or through other sensor nodes. The base station collects the sensed data and forwards it to a gateway, which acts as a bridge between the WSN and external networks. Finally, the data is sent to the user for analysis or further processing. This setup enables remote monitoring and decision-making in real time.

One of the biggest challenges in WSNs is energy conservation, as the sensor nodes run on limited battery that cannot be replaced or recharged [38]. The node stops working once the battery is drained and the node becomes obsolete due to its remote location. Therefore, it is very important to save energy to make the network last longer [39]. The major part of the node's energy gets exhausted in the transmission of data. To extend the life of the network, sensor nodes must be smart about how they send their data. If a sensor is close to the base station (called a Sink), it can send data directly [40]. But in many cases, sensors are placed far from base stations; therefore, direct communication would use too much energy. A better way is multihop communication, where data is passed through other nodes until it reaches the sink. This method uses less energy and extends the overall network lifetime [41]. Besides energy, other important aspects are security, timely data delivery, fault tolerance, and scalability. Some applications of WSN also need mobility for proper data aggregation and coverage of the monitored area. Furthermore, the network should be reliable, adaptable to different topologies, and capable of integrating heterogeneous sensors. All these features together can help WSNs to function efficiently in various real-world IoT applications.

1.2.3 Software-Defined Networking

Software-defined networking (SDN) is the most important concept in modern communication networks. SDN architecture (shown in Figure 1.3) has separated the data plane and the control plane in devices [42]. Due to this separation, the network operators can manage the network more efficiently by controlling it centrally and enabling programmability [43]. This separated control plane feature allows easy addition of new devices that are configured through centralized software, making the system more flexible and scalable. As the SDN is managed centrally, all the devices have a global view of the network. This feature helps network operators to create and enforce automated rules to optimize network resource usage and improve service delivery [44, 45].

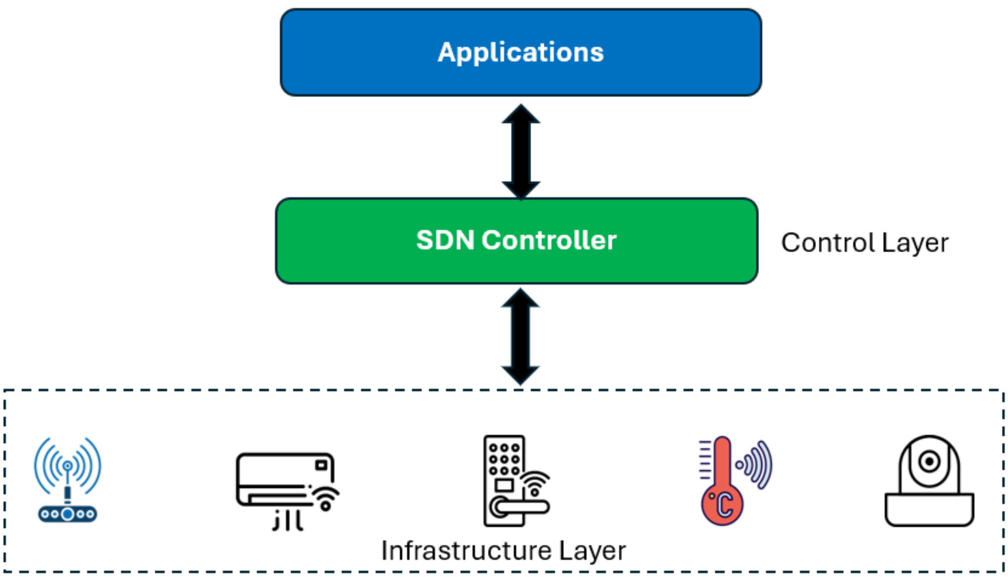

Figure 1.3: SDN Architecture

As shown in Figure 1.3, an SDN architecture consists mainly of three layers: the application layer, a control layer, and an infrastructure layer that forms the data plane. The role of the centralized controller is to handle all network control logic, while the devices in the data plane simply follow the instructions provided by the controller. This arrangement allows network operators to implement policies for traffic control, load balancing, security, and quality of service [46–49] .

1.2.4 IoT-enabled Software Defined Wireless Sensor Networks

Building upon the principles of SDN, Software-Defined Wireless Sensor Networks (SDWSNs) have emerged as a more specialized network [50, 51]. SDWSNs inherited the concepts of SDN in wireless sensor networks, which are beneficial for IoT applications. These networks are constituted using many sensor nodes, which collect data from the environment and communicate wirelessly. The major limitations of traditional WSNs were lack of flexibility and difficulty in management at scale. However, by applying SDN principles, SDWSNs easily adapt to changing conditions in wireless environments [19].

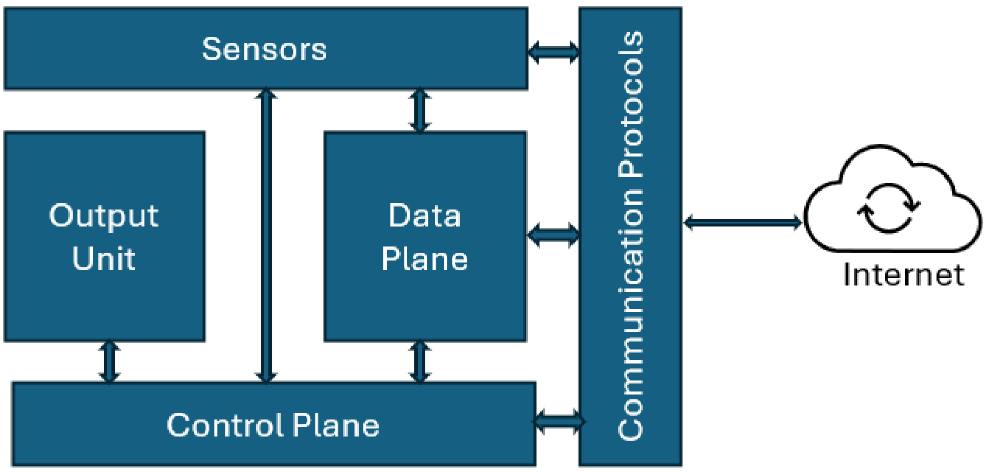

Figure 1.4: Block Diagram of IoT-enabled SDWSN Node

Figure 1.4 depicts the model of an IoT-based SDWSN node. The sensors are responsible for detecting environmental changes. After sensing, the sensors then send the data to the data collection module. In the next step, the collected data is forwarded to the data processing module, where it undergoes filtering, transformation, or local analysis to reduce redundancy and prepare it for transmission. A key component of each node is the control plane, which interacts with the other modules and enables dynamic control based on network requirements. Finally, the processed data is transmitted over the internet using standardized IoT communication protocols [52].

This evolution of SDWSNs over traditional wireless sensor networks is significant. With the help of a centralized controller, SDWSNs can implement advanced control strategies that improve system performance, energy efficiency, robustness, and reliability in modern IoT-based applications.

1.2.5 Clustering and Metaheuristic Approaches

In IoT-enabled SDWSNs, energy consumption during data communication is a major issue due to the limited battery capacity of sensor nodes. Clustering is one of the powerful techniques to resolve this problem [53]. Therefore, to increase the network lifespan, the nodes are organized into clusters, and a CH is selected from each group or cluster. The data is transferred to the CH from every associate SDSN of the cluster, which in turn forwards it to the BS. However, a potential issue arises when the same set of nodes is repeatedly chosen as the CH, which can result in the exhaustion of the node's energy, hence limiting network life. Moreover, finding which nodes should take this role is a complex task that depends upon many factors like residual energy, node position, and network conditions [54].

Metaheuristic algorithms are widely used to solve this efficiently. These are smart optimization techniques that are inspired by natural or logical processes that help find the best solutions from a large set of possibilities [55]. Algorithms like particle swarm optimization [56], grey wolf optimization [57], and hybrid models have shown promising results in dynamically selecting CH and determining the energy-efficient communication paths. Metaheuristic algorithms allow the system to readjust to changing conditions and optimize for multiple goals at once, such as energy efficiency, balancing the load across the network, and ensuring timely delivery of data. These algorithms make the clustering process adaptive and intelligent, significantly improving the network's lifetime and reliability [58, 59]. In this thesis, metaheuristic algorithms are used to design an energy-aware and QoS-focused clustering and routing strategy.

The goal is to reduce communication energy, avoid hotspots, and extend the lifetime of the network in real-world conditions.

1.3 Thesis Contributions

This thesis contributes to the research on energy-efficient and QoS-aware communication in IoT-enabled Software-Defined Wireless Sensor Networks (IoT-enabled SDWSNs) by addressing critical limitations in existing routing protocols. The key contributions of this work are as follows:

1. **Comprehensive Systematic Review:** A detailed and structured systematic literature review of clustering and routing algorithms in IoT-based SDWSNs is presented. The review classifies existing methods into classical, metaheuristic-based, and machine learning-based categories, highlighting their strengths, limitations, and key research gaps.

2. **Energy-Optimized Metaheuristic Framework:** In this thesis, three novel energy-efficient routing frameworks are proposed using nature-inspired metaheuristic algorithms. The algorithms intelligently select cluster heads and optimize routing paths by considering multi-objective fitness functions based on energy, distance, traffic load, and network stability.

3. **Context-Aware Fitness Function Design:** Fitness functions are the core of metaheuristic-based optimization techniques. Therefore, robust and flexible fitness functions are developed that incorporate dynamic parameters such as residual energy, inter-node distance, intra-cluster distance, energy consumption, energy ratio, alive nodes, etc. This enhances the adaptiveness and scalability of the proposed routing solutions.

4. **Comparative Performance Evaluation:** Extensive simulations are conducted using MATLAB to evaluate the proposed protocols under varying network sizes, energy distributions, and traffic scenarios. The results demonstrate significant improvements in metrics such as network lifetime, energy consumption, packet delivery ratio, and scalability when compared with existing benchmark protocols.

1.4 Organization of the Thesis

This thesis is organized into seven chapters as follows:

Chapter 1: Introduction
This chapter introduces the background, key concepts, challenges, objectives, and contributions of the research. It sets the context for the need for energy-efficient and QoS-aware routing protocols in IoT-enabled SDWSNs.

Chapter 2: Systematic Literature Review
In this chapter, a detailed and structured systematic literature review of clustering and routing algorithms in IoT-based SDWSNs is presented. The review classifies existing methods into classical, metaheuristic-based, and machine learning-based categories, highlighting their strengths, limitations, and key research gaps.

Chapter 3: Energy-optimized artificial hummingbird algorithm for routing in IoT-based software-defined WSN
In this chapter, an energy-optimized artificial hummingbird algorithm for routing in IoT-based SDWSNs is proposed to enhance energy efficiency. The proposed algorithm aims to outperform existing methods by optimizing the selection of cluster heads, thereby reducing energy consumption and improving overall network performance.

Chapter 4: A Nature-Inspired Multi-Objective Green Routing Protocol for IoT-enabled SDWSN
This chapter introduces a multi-objective optimization framework for energy-efficient routing using a nature-inspired algorithm based on the law of equilibrium. The protocol dynamically adjusts the number of clusters and cluster heads to balance energy consumption.

Chapter 5: A Multi-Constrained Green Routing Protocol for IoT-based Software-Defined WSN
In this chapter, a hybrid model is proposed that integrates clustering and routing using Artificial Hummingbird and equilibrium optimizer algorithms named EQ-AHA. The EQ-AHA algorithm aims to outperform existing methods by optimizing the process of cluster heads selection and implementing a multi-hop strategy to find the optimum route between base station and cluster heads.

Chapter 6: Conclusion and Future Scope

The final chapter summarizes the key findings of the research and outlines future directions, including the integration of machine learning for intelligent adaptation and the implementation of the proposed models in real-world IoT scenarios.

CHAPTER 2

LITERATURE REVIEW

To explore existing solutions and research trends, this chapter presents a systematic literature review of state-of-the-art energy-efficient clustering techniques developed for SDWSNs and IoT based networks.

2.1 Introduction

The rapid growth of IoT technologies [24] has increased the development of intelligent, energy-aware, and scalable solutions. As the sensors play crucial role in decision making in IoT based networks, SDWSNs have emerged as an evolution of traditional WSNs. SDWSN address the inherent limitations of WSN through the integration of Software-Defined Networking (SDN) concepts. SDWSNs are easy to reconfigure as it can be managed through centralized control which makes it efficient in real-time resource management for IoT environments. However, combining the SDN with WSNs introduces additional challenges like energy efficiency and QoS provisioning. Sensor nodes typically have limited energy as they operate on battery. Furthermore, In IoT based applications there is demand of QoS parameters, such as low latency, high reliability, and sufficient throughput. So, there is a huge demand for development of lightweight, robust, and adaptive protocols. In order to identify the research gaps a Systematic Literature Review (SLR) is conducted on existing routing protocols in the WSNs, SDWSNs and IoT-based SDWSNs. This chapter provides critical evaluation of existing state-of-the-art techniques. SLR begins with a formulation of key research questions. This is followed by a detailed explanation of the review methodology which includes literature search strategies, selection criteria, quality assessment, and data synthesis techniques. The chapter then surveys the existing work and categorizes approaches into classical, metaheuristic-based, and machine learning-based methods. Key clustering parameters and evaluation metrics relevant to SDWSNs are also examined.

The goal of this chapter is to establish a comprehensive understanding of the current research landscape, highlight critical limitations, and motivate the novel models proposed in subsequent chapters.

2.2 Systematic Review Process

This review was planned according to the Systematic Literature Review (SLR) guidelines established by Kitchenham and Charters [60]. The review process was divided into three main stages, as illustrated in Figure 2.1. The initial stage is termed as the *"Planning of the Review"* and comprised two phases named "research question formulation" and "search strategy". The second stage is the *"Selection of Primary Studies"* which includes selection and rejection criteria for studies. The subsequent stage is known as the *"Research Review Phase"* which included quality assessment, data extraction, and reporting review results.

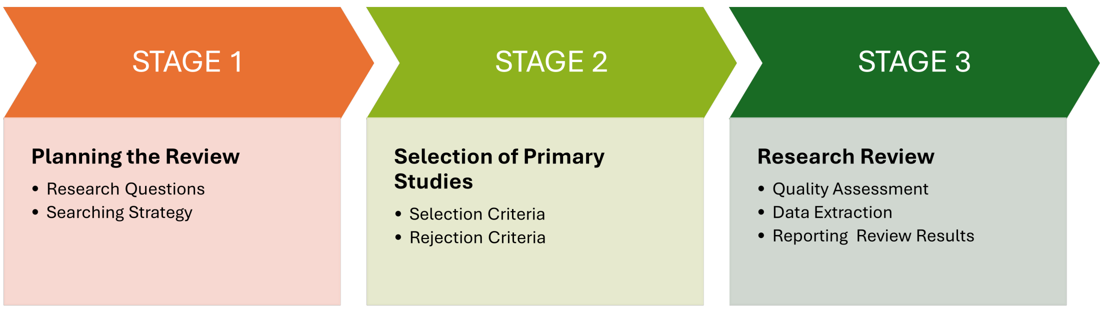

Figure 2.1: SLR Process Stages

The research questions, related to routing protocols in WSN, SDWSNs and IoT-based SDWSNs, were articulated during the first stage. Following this, a search strategy was developed and implemented to determine the methodology for conducting the search. This step was essential for locating relevant research studies to address the formulated research questions. To refine the scope of the review during the study selection phase specific selection criteria are applied which is termed inclusion-exclusion criteria. The quality of the papers was subsequently evaluated using weighted parameters in the Quality Assessment phase. Both the study selection and quality assessment phases aimed to ensure the included studies met certain quality standards and were comparable and thereby establishing the boundaries of the review. After completing the screening and eligibility determinations, data extraction was performed to critical analyze the research domain. This process aimed to address the research questions and conduct a critical analysis of the research domain. The outcome was a summarized critique that evaluates, extends, or identifies implications for practice, highlights any gaps or inconsistencies, and suggests directions for future research.

The subsequent sections represents report writing of this SLR which includes the findings of this review, organized to directly answer these research questions. The analysis details the classification of existing clustering techniques, the role of dynamic clustering, the design of fitness functions, and the evaluation of QoS parameters. This discussion highlights the dynamic and evolving research landscape aimed at resolving the intricate relationships between QoS demands, energy constraints, and the integration of SDN principles into wireless sensor networks

2.2.1 Research Questions

In this phase a set of well-defined research questions (RQs) was formulated in order to conduct this SLR . These RQs serve as foundations of research and help in identifying gaps in the research . The detailed RQs are listed in Table 2.1 which provides a clear framework for addressing key challenges, trends, and advancements in the field.

Table 2.1: Research Questions

RQ No.	Research Question
RQ1	Which are the most prestigious and relevant journals with published studies?
RQ2	What are the different types of clustering-based energy-efficient techniques in SDWSNs?
RQ3	What role do dynamic clustering techniques play in optimizing energy consumption and network performance in SDWSNs?
RQ4	What are the critical considerations in designing fitness functions for meta-heuristic algorithms to achieve optimal clustering and routing performance?
RQ5	What are the key Quality of Service (QoS) parameters to consider for the evaluation of energy-efficient clustering algorithms in SDWSNs?

2.2.2 Search Strategy

In this section search strategy for SLR is discussed. In order to find relevant research articles over the vast online database firstly the search keywords were identified, for example **"IoT-enabled SDWSN," "energy-efficient routing," "multi-QoS," "QoS-aware protocols," "software-defined networks," and "wireless sensor networks"**. As the searching based on keywords alone is not sufficient to find relevant research articles. We have also applied various boolean operators with these keywords to further refine the search results. For example the query: *"IoT-enabled SDWSN" OR "Software-Defined Wireless Sensor Networks") AND ("energy-efficient routing" OR "QoS-aware routing") AND ("multi-QoS" OR "latency" OR "reliability" OR "throughput")* was formulated to find relevant studies. In the next step, searches were conducted on well-known academic databases like IEEE Xplore, SpringerNature, ACM, Google Scholar, and ScienceDirect. The article published in journals or conferences indexed by SCI, SCIE, and SCOPUS were included only in order to focus on high quality articles.

In additional to this, filters such as publication date range, English language, and document type (journal articles and conference papers), were applied to make the search results more relevant. This process led to the selection of studies that were related to clustering, CH selection, meta-heuristic, multi-QoS, energy efficiency, and IoT-enabled SDWSN.

Table 2.2: Inclusion and Exclusion Criteria for Research Articles

Criteria Type	Description
Inclusion Criteria	• Studies published in SCI/SCOPUS-listed journals. • Studies published in the last 10 years (with exception for old benchmark algorithms). • Studies available in English language. • Studies focusing on energy-efficient routing in IoT-based networks, SDWSNs, or WSNs. • Studies focusing on efficient cluster head selection. • Studies using metaheuristic algorithms in IoT-based networks, SDWSNs, or WSNs. • Studies focusing on hierarchical routing in IoT-based networks, SDWSNs, or WSNs. • Studies that present clear evaluation metrics and results related to energy-efficient routing in SDWSNs.
Exclusion Criteria	• Studies published in conferences (extended versions published in journals were included). • Studies without proper benchmark comparisons or empirical analysis. • Studies not related to IoT-enabled SDWSN, SDWSN, WSN, or that do not address energy-efficient routing and QoS. • Studies that are only surveys or reviews on energy-efficient routing without implementation.

2.2.3 Study Selection

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [61] was used throughout the screening and selection process to ensure a rigorous and systematic review of the literature. PRISMA approach helped us in promoting transparency, reproducibility, and thoroughness in identifying relevant research articles. The process was executed in two key stages: initial screening and full-text screening.

(i) **Initial Screening:** In the initial screening phase, the titles and abstracts of studies were retrieved from various selected databases for review. The primary goal was to eliminate studies that were irrelevant or did not align with the predefined inclusion criteria (given in Table 2.2). Specifically, articles that did not concern IoT-enabled SDWSN, energy-efficient routing strategies, or multi-QoS parameters were excluded. Additionally, we omitted opinion pieces, editorials, and studies published in non-peer-reviewed sources. This critical step helped to narrow the literature pool to those studies that are closely aligned with our research objectives.

(ii) **Full text screening:** The second stage involved a comprehensive review of the full texts of articles that had passed the initial screening. These articles were evaluated against stringent inclusion and exclusion criteria (provided in Table 2.2) to affirm their relevance. The inclusion criteria specified that studies must explicitly focus on multi-QoS requirements—such as latency, reliability, throughput, and energy efficiency related to IoT-enabled SDWSN. At this stage, articles not published in English or lacking significant technical depth were also excluded.

By employing this systematic methodology, the initial pool of studies was refined into a concentrated collection of high-quality research papers pertinent to the review's objectives. The final selection laid a solid groundwork for data extraction and subsequent synthesis, facilitating a comprehensive understanding of energy-efficient routing protocols within the context of IoT-enabled SDWSN.

2.2.4 Quality Assessment

To maintain the quality standards of the selected research articles, a comprehensive evaluation process was implemented. This involved a thorough examination of the novelty of the proposed techniques as well as the technical depth of the studies. Quality assurance was further reinforced by exclusively selecting studies from high-quality, high-impact journals published in reputable digital libraries such as SCI or SCOPUS.

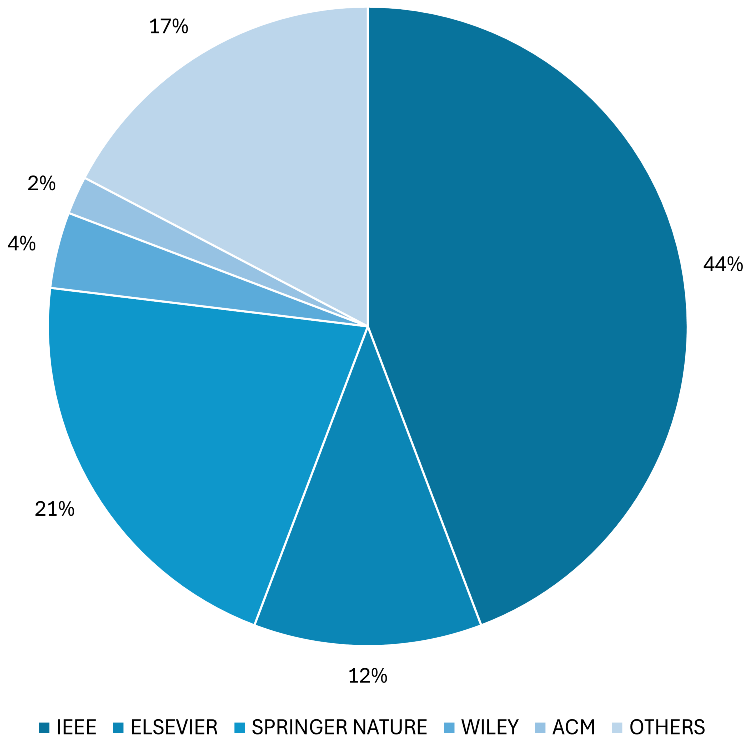

Figure 2.2: Publisher-wise distribution of papers

2.2.5 Data Extraction

In this step, the important data was extracted from the selected research articles and mapped with the research questions. The extracted data included information on the authors, the publication year, the techniques implemented, the simulation tool, the results, and the limitations. This comprehensive information was subsequently organized into a table for further data synthesis.

2.2.6 Data Synthesis

The data synthesis phase involved critical analysis and discussions of research articles. In this phase, we systematically summarized and interpreted the extracted data to provide direct answers to the defined research questions (RQs). Figure 2.3 shows the overall filtration process to find the most relevant studies. The research process commenced with the application of identified keyword terms across five major

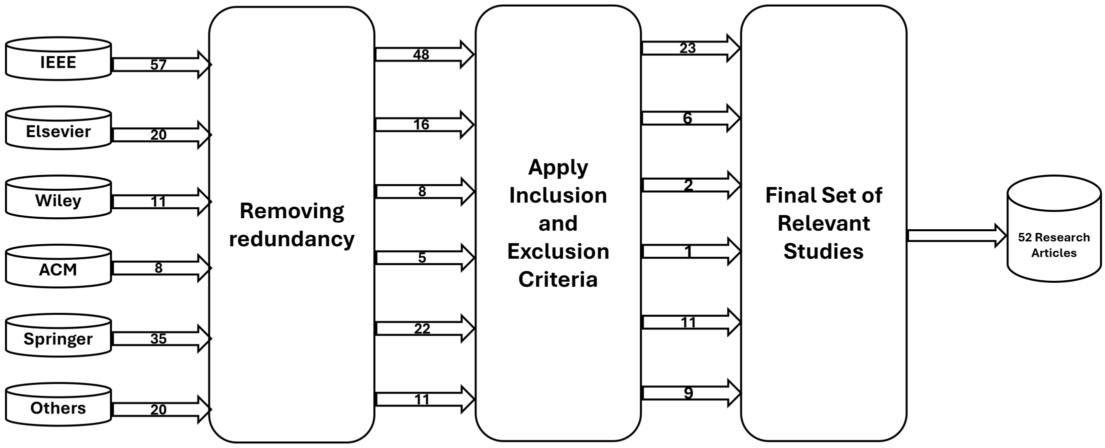

Figure 2.3: SLR Filtration Process

selected digital libraries, yielding a total of 155 papers. After eliminating duplicate studies, we refined our focus to 115 studies. Subsequently, applying our inclusion and exclusion criteria allowed us to identify 70 potentially relevant studies for further analysis.

2.3 Literature Survey

The continuous evolution of Wireless Sensor Networks (WSNs), particularly in the context of IoT and Software-Defined Networking (SDN), has driven extensive research into energy-efficient clustering and routing strategies. To provide a structured overview, this literature survey categorizes existing techniques into three main groups: classical approaches, metaheuristic-based approaches, and machine learning-based approaches. Classical techniques primarily rely on rule-based heuristics, while metaheuristic methods draw inspiration from nature to solve optimization problems. In contrast, machine learning-based approaches leverage data-driven models to adapt dynamically to network conditions. This categorization enables a comprehensive understanding of the progression, strengths, and limitations of various protocols developed to address energy efficiency and network performance in WSNs.

2.3.1 Classical Approaches

Since early 2000s various energy efficient clustering protocols have been proposed to improve the life of sensor nodes in WSN. These routing protocols were simple rule based heuristic techniques. These techniques reduce the communication overhead, balance the energy consumption hence increases the network life. In this section, classical routing protocols in the field of WSNs are discussed. These protocols have laid the foundation for energy-aware routing in WSNS. Table 2.3 presents a comparative analysis of classical clustering techniques in WSNs and SDWSNs, such as LEACH, TEEN, and PEGASIS, highlighting their simulation tools, evaluation metrics (e.g., network lifetime, energy dissipation), and key findings regarding their operational efficiency. Heinzelman et al. [62] introduced Low-Energy Adaptive Clustering Hierarchy (LEACH). LEACH is one of the widely used clustering techniques and server as foundation for modern clustering algorithms. LEACH improved the network life by randomly rotating the role of CH among the sensor nodes in WSNs. The simulation results proved that LEACH optimized the energy consumption by sensor nodes and was eight times more efficient than older methods. Later, Manjeshwar et al. [63] proposed Threshold sensitive Energy Efficient sensor network (TEEN) protocol. TEEN was designed for real-time applications where quick response matters, like monitoring disasters. To achieve the energy optimization goal sensors nodes transmit the sensed data only after the threshold is crossed. The results proved that TEEN helped the sensor nodes in reducing energy consumption and performed better than LEACH.

Table 2.3: Comparison of Classical Clustering Techniques in WSNs

Technique	**Comparison Metrics**	**Simulation Tool**	**Findings**
LEACH [62]	FND, LND, Energy, NL	MATLAB	Enhances system lifetime by distributing energy load; delays first node death by 8×.
TEEN [63]	ED, TAN	NS-2 Simulator	Introduces TEEN protocol for reactive WSNs, improving energy efficiency.

Continued on next page

Technique	Comparison Metrics	Simulation Tool	Findings
Modified-LEACH [64]	FND, HNA, LND, ED	YANASim	Outperforms LEACH by approximately 30%, improving energy metrics.
LEACH-C [65]	NL, Latency, ED	NS-2 Simulator	Delivers 10× more effective data transfer than MTE routing.
PEGASIS [66]	NL, Latency, ED	NS-2 Simulator	Greedy approach: creates chains by connecting neighbor nodes.
HEED [67]	RE, CH Selection	Not Mentioned	Ensures scalable, fault-tolerant multi-hop clustering.
BCDCP [68]	NL, Energy Efficiency	MATLAB	Outperforms LEACH and PEGASIS in energy savings.
UCR [69]	ED, CH Count per Round	Not Mentioned	Balances load among CHs, solving the hot-spot problem.
ILP-Two Phase [9]	Coverage Ratio, Sensing Range	Not Mentioned	Proposes a two-phase reprogramming technique for WSNs.
WECRR [70]	Data Latency, PDR, NL, Delay, Route Load	NS-2 Simulator	Incorporates RE, packet error ratio, and traffic density in routing decisions.
Novel Routing in SDWSN [71]	ED, TAN, Data Packets	MATLAB	Introduces distance queue-based energy-efficient routing for SDWSNs.
CLP [72]	TAN, FND	MATLAB	Combines LEACH for cluster formation and PEGASIS for routing.

Continued on next page

Technique	Comparison Metrics	Simulation Tool	Findings
Clustered SDWSN [73]	Energy, Load Balancing, NL	OMNeT++	Implements a fixed grid-based cluster along with a mobile data mule.
SDN Clustering [74]	NA	OpenDaylight Helium SR4	Distributed SDN Cluster Architecture Proposed
SDN Clustering [75]	RE, TAN, NL	MATLAB	The protocol creates clusters of unequal size, based on the node's distance to the BS

Heinzelman et al. [64] proposed another version of the LEACH protocol called LEACH-C. LEACH-C was a centralized clustering protocol based on LEACH, where the base station was responsible for controlling the routing in WSN centrally. Another variation of the LEACH protocol, modified-LEACH, was proposed by Handy et al. [65]. They modified the LEACH protocol by using the deterministic cluster head selection method based on energy levels, location, and data needs. The simulation results show that the modified LEACH protocol outperformed the original LEACH by 30%. The paper also introduced three new metrics to define the lifetime of microsensor networks: FND, LND, and HND. Another improvement over LEACH was proposed by Lindsey and Raghavendra [66] using Power-Efficient GAthering in Sensor Information Systems (PEGASIS). PEGASIS makes use of a greedy algorithm to construct chains of sensor nodes; using these chains or paths, each node communicates with close neighbors, thereby minimizing energy expenditure. The simulation results of PEGASIS outperformed the LEACH protocols.

Younis et al. [67] presented a Hybrid Energy-Efficient Distributed (HEED) clustering protocol to optimize energy consumption in WSNs. HEED selects cluster heads based on a hybrid of node RE and secondary parameters like proximity to neighbors, ensuring uniform distribution of cluster heads. Simulation results indicate that HEED effectively minimizes communication costs and achieves a uniform distribution of cluster heads, enhancing data aggregation capabilities. Muruganathan et al. [68] presented the Base-Station Controlled Dynamic Clustering Protocol (BCDCP), a centralized routing protocol designed for WSNs. Simulation results demonstrated that BCDCP outperforms existing protocols by increasing network life by at least by 30%

when compared with LEACH, LEACH-C, and PEGASIS. The limitation of BCDCP was the decrease in performance with a decrease in area size, and also its performance depends on the location of BS.

Chen et al. [69] proposed an Unequal Cluster-based Routing (UCR) protocol to address the hot spot problem. The hot spot problem occurs when cluster heads near the base station experience heavier traffic and deplete their energy faster. UCR organizes nodes into clusters of unequal sizes, allowing cluster heads closer to the base station to manage smaller clusters, thus conserving energy for data forwarding. Zeng et al. [9] proposed an energy-efficient reprogramming algorithm for SDWSN while considering quality of sensing (coverage ratio). They achieved energy efficiency by jointly considering two critical factors: firstly, selecting which sensor nodes to reprogram and optimizing the routing of the program distribution to these sensors. Haseeb et al. [70] presented a deterministic approach for cluster head selection based on weighted factors named Weighted Energy-Efficient Clustering with Robust Routing (WECRR) for WSNs. WECRR is a three phase protocol designed to improve energy efficiency and routing robustness. In WECRR CH was selected based on CH score which was calculated using RE, NC and distance to BS. Due to high transmission cost of direct transmission WECRR uses multi-hop paths to deliver data collected by CHs. Junli et al. [71] presented a novel energy-efficient routing algorithm based on SDWSN architectures. The algorithm operates through a centralized controller. The controller constructs a distance based queue of all the sensor nodes. After each round the controller updates the nodes energy and re-created the routing paths. In this way the algorithm balanced the energy consumption, reduced overhead, and extended the network life.

Oudani et al. [72] proposed an improved hierarchical routing protocol named CLP for sensor networks by combining LEACH and PEGASIS. The CLP protocol selects the CH using probabilistic approach of LEACH. To reduce the energy consumption of CH it uses multi-hop chaining technique of PEGASIS and the last node in the chain (near to BS) delivers the data to BS. Hot-spot is a major issue in WSNs and to address this issue Singh et al. [**?**] presented unequal fixed grid-based clustering. To balance the energy consumption they formed small clusters near the BS and larger cluster far from BS. To select the CH they considered parameter like RE, proximity to BS and node density. The protocol reduced the traffic load of nodes near to BS by using multi-hop transmission between CHs. One of the major challenges with traditional WSN is the deployment of sensor nodes at remote locations which make it very difficult to manually update every device. Flauzac et al. [74] proposed a solution by integrating Software-Defined Networking (SDN) with Wireless Sensor Networks (WSNs) in IoT environments. They introduced the Software-Defined Networking Clustered Head (SDNCH) concept and also evaluated the effectiveness of SDN deployment in IoT clusters.

2.3.2 Metaheuristic-based Approaches

Clustering is recognized as a more energy-efficient approach than direct transmission in WSNs. But selecting CH is an NP-hard problem. This problem can be solved with the help of a meta-heuristic-based algorithm. In this section, the application of various nature-inspired approaches in the domain of WSN or IoT-SDWSNs is discussed. Table 2.4 provides a detailed comparison of metaheuristic-based approaches for clustering and routing, the simulation tools used, and the fitness function parameters utilized to optimize network performance. Hoang et al. [76] presented an HSA-based clustering protocol. The HSA clustering protocol optimizes energy consumption by minimizing ICD. The simulation results proved the superiority of HSA over LEACH, K-Means, Fuzzy C-Means, GA, and PSO. HSA, like many clustering algorithms, may face challenges in adapting to dynamic changes in the network, such as node mobility or heterogeneous nodes.

Table 2.4: Comparison of Metaheuristic-based Approaches

Technique	**Meta-heuristic Algorithm**	**Comparison Metrics**	**Simulation Tool**	**Fitness Function Parameters**	**Cou-nt**
HSA-Clustering [76]	HSA	FND, NL, ED, TAN	MATLAB	ER, Distance Ratio	2
PSO-ECHS [77]	PSO	EC, Data Sent, BS Position	MATLAB	Avg. ICD, Sink Distance, CH Energy	3

Continued on next page

Technique	Meta-heuristic Algorithm	Comparison Metrics	Simulation Tool	Fitness Function Parameters	Cou-nt
K-meansPSO [78]	K-means with PSO	TAN, RE	MATLAB	RE(CH), Distance, Distance threshold	3
NWPSO [79]	Non-linear PSO	FV, FND, NL, ED, TAN, CH Count	MATLAB	RE, Transmission Distance	2
nCRO-UCRA [80]	CRO	RE, NL, CR	MATLAB	RE, Distance, Avg. NND, ER	4
FJAPSO [81]	Fork-and-Join Adaptive PSO	NL, Delay, Jitter	MATLAB	Avg. RE, Distance, RE Ratio	3
ALO-Clustering [82]	ALO	DN, TAN, RE, Throughput, NL, NN Count, CH Count, Tour Length	MATLAB	Energy, NN Count, ICD, CD	4
CRHS [83]	HSA	TAN, RE, Data Packet Received	MATLAB	RE(CH), ICD, CD, ND	4
GWO-C [84]	GWO	RE, Dead Nodes, BS Position, Data Packets	MATLAB	Avg. CD, SD, RE, CH Balancing Factor	4
HFAPSO [85]	FF with PSO	FND, LND, RE, Throughput	NS-2	RE and Distance	2

Continued on next page

Technique	Meta-heuristic Algorithm	Comparison Metrics	Simulation Tool	Fitness Function Parameters	Cou-nt
EBGWO [86]	GWO	NL, RE, Throughput, CR	MATLAB	BS-CN Distance, ICD, Node RE	3
Hybrid Routing [87]	BOA (CH), ACO (Route)	TAN, Energy, Delay, Packets, Throughput, FND, HND, LND	MATLAB	CH: RE, Neighbor Distance, BS Distance, ND, Centrality; Route: Distance, RE, ND	7
Two-way PSO [88]	PSO	MTTF, Delay, Jitter, RE	MATLAB	RE, Distance and Cluster count	3
PSOGA [89]	PSO and GA	FND, HND, LND, RE, Throughput, TAN, PDR	Not Mentioned	Energy-Distance Ratio, TV	2
MWCSGA [90]	CSO with GA	Energy, Delay, NL, PDR	NS-2	RE, Distance, ND	3
HHO-UCRA [91]	HHO	ED, NL, CR, Data Received	Java and MATLAB	ND, Successor-BS Distance, ER, BS Distance, NND	5
GA-UCRA [92]	GA	FND, HND, LND, Hotspot, EC, NL, CR, Packets Received	MATLAB	RE, BS Distance, Inter-cluster Separation	3

Continued on next page

Technique	Meta-heuristic Algorithm	Comparison Metrics	Simulation Tool	Fitness Function Parameters	Cou-nt
TAMOMO-SCRP [93]	MO-BES	NL, Stability, HND, LND, RE, Data Sent	Not Mentioned	Clustering: TV, Comm. Cost, RE, ND; Routing: Queue Length, Link Quality	6
ICITS [94]	GA and BAT	NL, Packets Sent, DN, RE	MATLAB	RE, Sink Distance, ICD, Avg. Energy, CH Count, TV	6
WOA-SA [95]	WOA with SA	TAN, Workload, ED	MATLAB	Energy, Load, Latency, Comm. Length, Heat	5
MSO-Tabu [96]	TS	CH Count, ED, E2E Delay, Packet Loss, NL	MATLAB	RE, Transmission Range, Node Mobility	3
MRFO-C [97]	MRFO	ED, NL, Data Packets, LND	MATLAB	ICD, SD, RE, CH Balancing	4
EAFFO–CS [98]	FFO	NL, Hotspot, Overhead, RE, Throughput	MATLAB	Neighbor Distance, BS Distance, Energy	3
LCPSO-CRP [99]	Modified PSO	NL, RE, TAN	MATLAB	ICD, CD, RE(NN), RE(CH)	4
ICOOT [100]	COOT Bird Optimizer	RE, NL, PDR, Throughput	MATLAB	RE, Distance, ND	3

Continued on next page

Technique	Meta-heuristic Algorithm	Comparison Metrics	Simulation Tool	Fitness Function Parameters	Cou-nt
Ref. [101]	MSSO with Fuzzy C-Means	NL, FND, HND, LND, RE, ED, Throughput	MATLAB	ICD, CD, CH-BS Distance, RE, ER, Distance Ratio	5
Ref. [102]	ABC and ACO	Coverage, Sensing, Energy Dissipation	MATLAB	ND, RE, CH-BS Distance, Energy-Distance Ratio	4
Ref. [103]	SFO and SHO	NL, PDR, RE, Throughput, DN, TAN, Latency	MATLAB	SFO:RE, Coverage area, Latency; SHO: RE, Distance, Latency	4
Ref. [104]	WOA with Block Chain	NL, Alive nodes, RE, Security Robustness	MATLAB	NE, Distance between CH and BS	4
EOAMRCL [105]	GWO	RE, FND, HND, LND, Overhead, Live Nodes, Packet Received	MATLAB	CH-BS Distance, RE, CH-NN Distance	4

Rao et al. [77] developed the PSO-ECHS algorithm for CH selection in WSNs. The optimization parameters included IDC, SD, and RE of sensor nodes. This particle swarm optimization-based approach minimized energy consumption and prolonged NL, outperforming traditional clustering methods. Xiang et al. [79] introduced an energy-efficient protocol for SDWSNs named the Non-Linear Weight PSO (NWPSO) algorithm. NWPSO calculated the optimum number of cluster heads required in SDWSNs considering RE and communication distance. The results proved the NWPSO outperformed other SoA algorithms in terms of network life. Solaiman and Sheta [78] presented energy optimization in WSNs using hybrid K-means PSO clustering. In their work, firstly, they used k-means clustering to create the network clusters, and then cluster heads were selected using PSO and got impressive results as compared with the LEACH algorithm. Rao and Banka [80] suggested a novel approach to address the hot spot problem in WSNs using CRO-based algorithms. The algorithms were tested with varying numbers of sensor nodes and CHs. They demonstrated superior performance compared to existing algorithms, showing improvements in metrics such as RE, NL, and CR.

Kumar and Vidyarthi [81] introduced Fork and Join Adaptive PSO (FJAPSO), a hybrid metaheuristic-based green routing protocol designed for IoT-enabled SDWSNs to find the optimum number of CH counts and hence efficiently create clusters. FJAPSO optimizes the network energy consumption, data delay, and jitter using the distance, RE, and energy ratio as fitness parameters. In another study, Yogarajan and Revathi [82] proposed an ALO-based clustering protocol utilizing energy, number of neighboring nodes, ICD, and CD. The ALO-based algorithm improves the NL of the network by at least 13% compared to other clustering algorithms. In a paper presented by Lalwani et al. [83], they introduced a hybrid meta-heuristic algorithm for the optimization of the CH selection process in IoT-enabled SDWSNs. Their approach combined the competitive swarm optimization and harmony search algorithm. The proposed routing protocol [83] demonstrated faster convergence rates by leveraging global search solutions. It also improved search efficiency and dynamic ability, ultimately extending the lifespan of nodes. Aggarwal et al. [84] introduced the GWO-based Clustering (GWO-C) technique for WSNs. The GWO-C protocol effectively selects cluster heads based on average ICD, SD, RE, and CH balancing factors. The simulation results of GWO-C outperformed other protocols like FIGWO and PSO-ECHS. Pitchaimanickam et al. [85] proposed a clustering algorithm using the global search behavior of fireflies to achieve optimal CH. The aim of their work was to improve network lifetime and reduce the energy utilization of nodes. Simulation results exhibit better residual energy and throughput than other SoA. In the process of clustering, the CH selection plays an important role in the health of the network. As discussed, the role of CH is to forward the data collected by the sensor nodes to BS. The CH generally uses direct transmission to communicate with BS. Hence, this process consumes a large amount of CH's energy. Mishra et al. [86] proposed an Energy-Balanced GWO (EBGWO) routing protocol for IoT-enabled SDWSNs. By considering the distance from the BS to cluster nodes, CD, and the RE of nodes, the EBGWO algorithm improved NL, throughput, and CR compared to other SoAs. Maheshwari et al. [87] presented a hybrid metaheuristic approach by using the BOA to select the best CHs and ACO to find the optimum route between the CH and the BS. The hybrid approach used heads RE of the CH, distance to neighbors, distance to the base station, ND, and node centrality to select optimum CHs. The routing process is optimized by ACO, considering parameters such as distance, RE, and ND. In another paper, Kumar et al. [88] presented a routing based on 2-way PSO for distributing traffic data in the social internet of vehicles. This paper was an application of SD-WSN routing in SIoV. They calculated two forward and backward solutions and compared them to select the best CH. Mishra et al. [89] introduced a hybrid routing protocol combining PSO and GA for IoT applications. The PSOGA algorithm optimizes parameters such as RE, hop count, and path reliability for CH selection. This approach achieves higher throughput, energy efficiency, and a high packet delivery rate. Comparative analysis showed PSOGA outperformed traditional LEACH protocols across multiple scenarios. An energy optimization solution named a Multi Weight CSO and GA (MWCSGA) was modeled by Ajmi et al. [90] to improve NL and PDR. Parameters such as RE, distance, and ND were incorporated into a comprehensive fitness function. The CH selection process was further refined using genetic operations like crossover and mutation to maximize the population's diversity. MWCSGA achieved lower end-to-end delay, reduced packet drop, and improved PDR, indicating its effectiveness in maintaining communication quality within the network.

To solve the hotspot issue, Jain et al. [91] proposed HHO-based algorithms. The process was divided into two algorithms. The first algorithm optimizes the process of cluster head selection by considering CH's RE, ND, distance between CH and nodes, and distance between CH and BS. The second algorithm proposed HHO-based, optimized energy-efficient multi-hop routing using CH's RE, ND, and distance between CH and nodes. Gunjan et al. [92] proposed a GA-based UCR (GA-UCR) protocol designed for WSNs to enhance energy conservation and NL. GA-UCR employed a GA for CH selection and inter-cluster routing. The fitness functions for GA-UCR considered RE, distance to the base station, and CD for optimizing energy usage and handling hotspot issues.

To address the security and energy efficiency issue of Industrial IoT (IIoT), a Trust-Aware Multi-Objective Metaheuristic Optimization-based Secure Route Planning Technique (TAMOMO-SCRP) developed by Nagappan et al. [93]. TAMOMO-SCRP used BES for secure clustering and routing. The objective function of TAMOMO-SCRP for CH selection was designed using four parameters: RE, trust value, ND, and communication cost. The decision for route selection for data transmission was made using queue length and link quality. To address the security and energy concerns of WSN-based Intelligent Transportation Systems (ITS), Verma et al. [94] presented an Intelligent Clustering for ITS (ICITS). ICITS used GA and BAT algorithms (GABAT) to optimize the clustering and routing processes. The ICITS approach integrated multiple parameters for CH selection, such as RE, distance from the sink, ICD, the network's average energy, CH count control, and TV for security.

Khan et al. [95] developed a CH selection protocol named WOA with SA (WOA-SA) to improve network life in IoT-based WSNs. The study aimed to improve NL and enhance performance metrics such as load distribution, temperature control, and energy utilization. WOA-SA selects CH using a fitness function incorporating five network parameters, i.e., energy, load, latency, communication length, and heat. Moreover, the WOA-SA was compared with other SoAs in terms of alive nodes per round and RE. In 2022, Suganthi et al. [96] introduced the Multi-Swarm Optimization with TS (MSO-Tabu) algorithm, targeting energy-efficient clustering in WSNs. This hybrid approach combined the exploratory capabilities of MSO with the local search strengths of TS. The MSO-Tabu algorithm aimed to enhance CH selection, improve routing efficiency, and extend NL. The approach accounted for parameters such as RE, transmission range, and node mobility to optimize CH selection. Experimental simulations were conducted by comparing with other SoAs with a focus on metrics such as the number of clusters formed, energy dissipation, end-to-end delay, packet loss, and NL. A novel energy-efficient algorithm, named MRFO-C, for CH selection in WSNs using the MRFO technique was developed by Khodeir et al. [97] in 2022. The primary objective of MRFO-C was to extend NL, reduce energy consumption, and increase the PDR. MRFO-C considered matrices like ICD, sink distance, RE, and CH balancing for optimized CH selection. Overall, the MRFO-C algorithm demonstrates significant improvements in WSN performance under various conditions.

Balasubramanian and Govindasamy [98] proposed EAFFO-CS, a clustering scheme for WSNs using FFO. The EAFFO-CS technique considers a fitness function that incorporates three critical input variables: distance to neighbors, distance to the BS, and energy, which enhances the selection of optimal CHs. Simulations demonstrate that the EAFFO-CS technique outperforms existing methods by achieving a maximum RE of 11% with 1000 sensor nodes. Zhang et al. [99] proposed LCPSO-CRP, a clustering and routing scheme for industrial wireless sensor networks using an improved Levy Chaotic Particle Swarm Optimization algorithm. The LCPSO-CRP method employs a multi-objective fitness function that integrates intra-cluster distance, CH-to-BS distance, residual energy of cluster members, and energy of cluster heads. It further enhances global search capability using Levy flights and chaotic perturbations to escape local optima. Simulations in MATLAB demonstrate that LCPSO-CRP significantly extends network lifetime and reduces energy consumption, outperforming LEACH, SEP, and DEEC protocols under various network scales. Alkhayyat et al. [100] introduced an optimized COOT Bird Optimization (ICOOT) method for clustering and routing in IoT-assisted WSNs. This approach dynamically adapts to changing network conditions, allowing for efficient data transmission while conserving energy. The study compared ICOOT with existing methods such as CBR-ICWSN, TSGWO, iASEF, and EENFC-MRP, displayed significant advantages in terms of NL, RE management, and PDR. Yang et al. [101] introduced a hybrid clustering and routing approach that combines the MSSO with a minimum spanning tree algorithm. This method enhances cluster head selection by incorporating dynamic parameter updates, adaptive alpha mutation, and bidirectional search optimization. Unlike traditional clustering methods, this approach balances energy consumption more effectively by considering factors such as node location, energy levels, and distance from the BS. Results from experimental simulations demonstrated that this protocol reduces energy consumption by at least 26.64% and extends network lifetime by over 25%, while also improving stability and throughput performance.

Khediri et al. [102] proposed a hybrid metaheuristic approach to enhance energy efficiency in WSNs and extend their NL. This approach integrates the ABC algorithm for optimal CH selection and ACO for efficient routing. The CH election considers parameters such as RE, distance to neighbors, distance to the BS, ND, and centrality. ACO is utilized to determine the most energy-efficient path for data transmission. The proposed method was evaluated against traditional protocols like LEACH, BeeCluster, iABC, and BeeSensor, demonstrating a significant improvement in network lifetime by at least 15.49%, respectively. Roberts et al. [103] introduced a dual-phased hybrid optimization framework combining SFO and SHO. This approach leverages SFO's rapid exploration for efficient CH selection and SHO's refined exploitation for routing optimization, achieving significant improvements in packet delivery ratio, energy efficiency, and network lifetime. Xiao et al. [104] presented BS-SCRM, a secure clustering routing method that integrates blockchain with a WOA. BS-SCRM significantly enhances network security and efficiency, achieving a 24–73% improvement in network lifetime under various attack scenarios. Kaddi et al. [105] proposed an algorithm called EOAMRCL to improve energy efficiency in WSNs using

GWO and enhanced CSMA/CA protocol. EOAMRCL integrates GWO to help in the selection of best CHs. A key feature of this method was its ability to adjust duty cycles dynamically, allowing nodes to switch between active and sleep modes more effectively. Additionally, an improved CSMA/CA mechanism reduced the collisions and enhanced the reliability. The simulations showed that EOAMRCL outperforms other well-known clustering protocols such as EEUC, DWEHC, and CGA-GWO.

2.3.3 Machine Learning-Based Approaches

Machine learning algorithms have emerged as powerful tools for addressing the dynamic and complex nature of IoT-enabled SDWSNs. By leveraging data-driven decision-making, these approaches enhance network adaptability, optimize energy consumption, and improve QoS beyond the capabilities of traditional heuristic methods. Table 2.5 provides a comprehensive summary of these machine learning-based approaches, categorizing them by the specific ML technique employed. Misra et al. [106] proposed a situation-aware protocol-switching framework for SDWSNs. Using supervised learning, the framework dynamically adjusted routing protocols based on application-specific requirements, achieving significant improvements in network performance. The optimization parameters included were energy consumption, throughput, packet delivery ratio, and delay. Mukherjee et al. [107] developed a clustering protocol for IoT-based networks called a Hybrid Neural Network (HNN) model by integrating a Gaussian copula for inter-cluster and intra-cluster correlation analysis. The HNN model utilizes Back Propagation Neural Network (BPNN) and Convolutional Neural Network (CNN) to optimize clustering phases, ensuring balanced resource allocation and enhanced NL.

Table 2.5: Comparison of Machine Learning-Based Approaches

Technique	**ML Technique**	**Comparison Metrics**	**Simulation Tool**	**Findings**
Ref [106]	Supervised learning	Energy consumption, throughput, packet delivery ratio, and delay	NS3	Delay in deployment at sensor level and low PDR.

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Technique	ML Technique	Comparison Metrics	Simulation Tool	Findings
HNN [107]	CNN, BPNN	Calculation time and energy consumption	Not Mentioned	The hybrid NN model reduces computational complexity and energy consumption compared to existing methods, making it suitable for advanced IoT applications.
FCMDE [108]	Fuzzy C-Means	Average energy usage, NL, stability, and throughput	Python	It improved RE by at least 26% and NL by at least 38.5%.
EECA [109]	ANN	FND, LND	Python	It selects CHs based on parameters such as residual energy, number of events detected, distance to the base station, and number of neighbors.
EFUCSS [110]	Fuzzy C-Means	FND, HND, LND, NL, RE, TAN	Python and MATLAB	It selects CHs using distance, remaining energy, and centrality of CH.
PCSOA-CHS [111]	PCSO with K-means	RE, NL, DP, TAN	MATLAB	It uses RE and relative position to find the best CH.

Abdulzahra et al. [108] presented a Fuzzy C-Means-based protocol called Fuzzy C-Means with Distance-and-Energy (FCMDE) clustering technique for IoT-based WSNs. FCMDE considers parameters such as node location and residual power to choose the most suitable CH. Instead of frequently changing CHs for dynamic clustering, FCMDE uses an energy threshold to determine the dynamism of CHs based on existing energy levels. Kumar et al. [109] proposed an Energy-Efficient

Clustering Algorithm (EECA) using an Artificial Neural Network (ANN) for selecting cluster heads. EECA used the backpropagation method to train ANN based on a data set consisting of many combinations of four parameters, i.e., distance to the base station, number of neighbors, number of events detected, and RE. In another paper, Abdulzahra et al. [110] developed an energy-efficient protocol for IoT-based WSNs named an Energy-Efficient Fuzzy-based Unequal Clustering with Sleep Scheduling (EFUCSS) protocol. EFUCSS used fuzzy C-means to create unequal clusters and CH selection using distance, remaining energy, and centrality of CH. Lakshmaiah et al. [111] developed a metaheuristic-based clustering method called MEECR to improve the energy efficiency of WSNs. This approach combines K-Means clustering with the PCSO Algorithm to optimize Cluster Head (PCSOA-CHS) selection. The selection process considers RE levels and node positioning, ensuring a balanced energy distribution across the network. Comparative evaluations showed that MEECR performs better than EECA, EECRP, and EDDUCA by reducing traffic congestion, minimizing energy loss, and significantly extending NL.

2.4 Role of Dynamic Clustering

Based on the studies reviewed in this SLR, dynamic clustering techniques play a significant role in optimizing energy consumption and improving network performance in IoT-enabled SDWSNs. Unlike static clustering techniques, dynamic clustering allows cluster formation based on real-time network conditions, hence balance the load and improve NL. Techniques such as meta-heuristic-based clustering (e.g., PSO, GWO, and HHO) adjust CH selection by considering parameters like RE, ICD, CH Count, CD, and ND, ensuring more efficient energy usage and robust network operation. Dynamic clustering also addresses hot-spot problem by CHs near the BS hence preventing uneven energy depletion. Moreover, hybrid approaches (e.g., BOA-ACO and PSOGA) combine multiple optimization algorithms for both clustering and routing, reducing communication overhead and improving throughput.These methods can dynamically adjust, making them vital for accommodating the changing workloads and energy limitations present in IoT settings.

2.5 Fitness Parameters for Effective Clustering

Energy-efficient clustering (CH selection) is a complex optimization problem where traditional methods often fail to perform effectively. Metaheuristic algorithms are a class of powerful problem-solving techniques used to find optimal or near-optimal solutions to complex optimization problems.

Table 2.6: Fitness Parameters for Effective Clustering in IoT-Enabled SDWSNs

Fitness Parameter	**Objective**	**References**
RE, ER	Maximize network lifetime	[76, 79–82, 84, 86, 87, 89–98, 100–102, 105]
ICD	Minimize energy consumption and improve communication	[82, 86, 93, 94, 97, 101]
CD	Minimize inter-cluster transmission delays	[82, 92, 101]
Distance to BS	Reduce energy consumption in data forwarding	[79, 87, 89, 90, 92, 98, 100, 102, 105]
NND	Improve local data aggregation and clustering efficiency	[80, 87, 91, 93]
TD	Reduce energy expenditure and packet loss	[79, 96]
DR	Optimize energy usage and minimize delays	[101, 102]
ND	Optimize network connectivity and data aggregation performance	[87, 90, 93, 94, 102]
Load Balancing	Extend network lifetime and reduce congestion	[95]
PDR	Maximize data reliability and reduce retransmissions	[89, 97, 100]
CH Balancing Factor	Enhance network stability and efficiency	[84, 97]
Communication Overhead	Reduce overhead and improve throughput	[98]

Continued on next page

Fitness Parameter	Objective	References
Trust Value (TV)	Enhance network security and prevent malicious activities	[89, 93, 94]
FND	Indicate network energy imbalance or inefficiency	[76, 89, 92, 101, 105]
HND	Mark a critical threshold in network performance	[89, 92, 93, 101, 105]
LND	Represent maximum achievable network lifetime	[89, 92, 93, 101, 105]
EC	Reflect energy efficiency of the network	[96, 101]
Average EC	Ensure fairness in energy distribution among nodes	[87, 94, 105]
Throughput	Assess network performance and efficiency	[82, 86, 92, 95, 98, 100, 101]
Latency	Reduce delay, particularly for time-critical applications	[81, 87, 95]
Jitter	Minimize packet reordering delays	[81]
DP Transmitted	Measure data transmission capability and network congestion	[91–94, 105]
TAN	Indicate network stability and node survivability	[76, 79, 82, 87, 89]
CR	Ensure sufficient sensing coverage for the network's purpose	[80, 86, 92, 95, 102]

Metaheuristic algorithms uses fitness function to assess candidate solution quality. These functions aim to optimize multiple parameters simultaneously to address energy efficiency, network stability, and communication reliability. Fitness function provides a score to every solution and helps our algorithm move to a better solution. These algorithms maximize the efficiency of this process by striking a balance between exploration and exploitation, exploring the search space to avoid local optima and exploiting promising solutions for optimal performance. Mutation, crossover, swarm intelligence, and evolutionary algorithms, for example, heuristically refine solutions according to their fitness values over several iterations. By iteratively assessing and refining solutions, meta-heuristic algorithms effectively approach towards near-optimal or optimal solutions, thus making them suitable for addressing complex optimization challenges in the real world.

The Table 2.6 provides a comprehensive summary of key fitness parameters used in clustering algorithms. The energy-related parameter (eg, RE, ER, or EC) is often the most used parameter for the fitness function. The ultimate goal of these metrics is mainly towards enhancing the lifespan of the network and increasing the energy efficiency. Besides energy-based parameters, distance-related parameters (for example, Distance to BS and NND) are commonly used to decrease communication cost and enhance the performance of data aggregation. Parameters like Latency, Throughput, and TV are also significant, focusing on enhancing network performance, reliability, and security. Balancing these parameters ensures the development of robust and efficient clustering algorithms for IoT-enabled SDWSNs.

2.6 QoS Parameters for Evaluation

1. **Network Lifetime**: Network life is defined as the duration for which a network can operate effectively before maintenance or resource depletion becomes necessary. This metric plays a critical role in evaluating the overall efficiency of IoT-enabled SDWSNs, particularly in the context of energy management. The NL can be measured in the following ways:
   (a) **First Node Died**: It is the point in time when a network experiences failure of its first node. An early FND indicates imbalance or inefficiencies in resource allocation in the network.
   (b) **Half Node Died**: HND occurs when 50% of the sensor nodes exhaust their energy or no longer operational. This indicator acts as a critical threshold where communication efficiency declines significantly.
   (c) **Last Node Died**: LND happens when the last active node experiences failure. This parameter is used to indicate maximum achievable energy efficiency.

2. **Network Energy**: As the sensor operates on limited battery energy, it is important to keep track of energy consumption by nodes in the SDWSN. Network energy can be measured in the following ways:
   (a) **Initial energy**: It is the sum of energy available in the network at the beginning of its operation. It acts as a baseline for energy consumption analysis.

(b) **Residual energy**: It is the total energy available after a certain number of transmission rounds. RE indicates how efficiently the network conserves energy over time and helps in predicting NL.
(c) **Energy consumed**: It measures total energy depleted after certain rounds of transmission. EC reflects the energy efficiency.
(d) **Average energy consumption**: It reflects energy consumed per sensor node over a specified period. This parameter determines energy distribution fairness among nodes.
(e) **Energy consumption per packet**: This parameter measures energy required to transmit a single data packet.
(f) **Energy Efficiency**: It is defined as the amount of data successfully transmitted per unit of energy consumed.

3. **Load Balancing**: This parameter measures the even distribution of network traffic across sensor nodes. LB prevents energy depletion and congestion in the network.

4. **Data Packets Transmitted**: Total data packet sent by sensor node to BS is measure of data transmission capabilities of the SDWSN. It also helps in finding PDR and network congestion.

5. **Packet Delivery Ratio**: PDR is a ratio of packets successfully received at the destination to the total packets transmitted from the source. PDR acts as a key metric for network reliability.

6. **Latency**: The time taken for a data packet to travel from the sensor node to the destination BS is called latency. It is a very important parameter for time-critical applications where delay may lead to serious consequences (e.g., healthcare monitoring, industrial automation).

7. **Jitter**:The variation in the sequence of data packets arrived at the destination is defined as jitter. It is undesirable as package reordering is required before processing, which leads to a delay in decision-making.

8. **Throughput**: Throughput is the rate at which data is successfully transmitted over the SDWSN. It determines the performance and efficiency of IoT-enabled SDWSNs.

9. **Communication Overhead**: Communication overhead is defined as the percentage of extra data packet sent for successful transmission. A high value of CO

may lead to a reduction in network efficiency and increased energy consumption.

10. **Total Alive Nodes**: TAN represents the number of sensor nodes having sufficient energy to perform their assigned task at the end of each transmission round. It indicates the stability of the network.

2.7 Chapter Summary

This systematic review has provided a comprehensive analysis of energy-efficient clustering techniques in IoT-enabled SDWSNs, highlighting their significance in enhancing network performance and optimizing energy consumption. The study categorized existing approaches into classical and meta-heuristic-based. Classical techniques such as LEACH and PEGASIS have laid the groundwork for energy-efficient clustering, but their limitations in scalability and adaptability are evident in dynamic IoT environments. Meta-heuristic-based approaches, including PSO, GWO, and ACO, have demonstrated significant improvements in network lifetime, energy efficiency, and load balancing through optimized cluster head selection and routing. Dynamic clustering techniques play a critical role in optimizing network performance by adapting to real-time changes, preventing energy depletion, and distributing network traffic evenly. The use of well-designed fitness functions in meta-heuristic algorithms incorporating parameters such as residual energy, communication distance, and node centrality has been instrumental in improving cluster formation and routing efficiency. Furthermore, the study emphasized the importance of key QoS parameters—such as network lifetime, packet delivery ratio, throughput, latency, and energy consumption—in evaluating and benchmarking the performance of clustering protocols.

In conclusion, this chapter lays a solid foundation for developing next-generation, adaptive, and QoS-centric routing protocols tailored to the challenges of IoT-enabled SDWSNs. The outlined research objectives provide clear direction and set the stage for the novel models—EOAHA, EO-C, and EQ-AHA—introduced in the subsequent chapters to address the identified limitations of existing state-of-the-art techniques.

CHAPTER 3

ENERGY-OPTIMIZED ARTIFICIAL HUMMINGBIRD ALGORITHM FOR ROUTING IN IOT-BASED SOFTWARE-DEFINED WSN

With the proliferation of IoT-enabled wireless sensor networks and the integration of software-defined networking (SDN) principles, the need for adaptive, energy-efficient routing algorithms has become increasingly vital [112, 113]. Conventional routing protocols often fail to adequately address the dynamic and resource-constrained nature of IoT-enabled SDWSNs. In this scenario, metaheuristic approaches inspired by natural processes have emerged as promising alternatives that are characterized by their feasibility, scalability, and efficiency in addressing multi-objective optimization operations [114–116]. In this chapter, a novel energy-efficient routing method based on the behavioral intelligence of hummingbirds is proposed to optimize the CH selection and routing schemes in the IoT-SDWSN architecture.

3.1 Introduction

The previous chapter presented a systematic literature review of energy-efficient and QoS-aware routing mechanisms in IoT-enabled software-defined wireless sensor networks. Through a structured methodology encompassing defined research questions, search strategies, and quality assessment criteria, the review synthesized and categorized existing approaches into classical, metaheuristic, and machine learning-based techniques. The chapter also highlighted critical challenges such as energy constraints, dynamic network topologies, scalability, and the need for multi-QoS provisioning. These identified gaps serve as the foundational motivation for the work proposed in this chapter.

In view of these challenges, this chapter introduces the Energy-Optimized Artificial Hummingbird Algorithm (EOAHA), a novel nature-inspired routing protocol tailored for IoT-enabled SDWSNs. The algorithm builds upon the Artificial Hummingbird Algorithm (AHA), which mimics the foraging strategies of hummingbirds—guided, territorial, and migration foraging. AHA's adaptive behavior makes it well-suited for complex optimization tasks such as routing in resource-constrained and dynamically changing network environments.

The proposed EOAHA enhances the original AHA by incorporating energy-aware decision-making and SDWSN-specific constraints. It dynamically selects optimal cluster heads and constructs efficient routing paths based on a multi-parameter fitness function that exclusively takes into account the remaining energy of nodes, the distance between CHs and BS, and the distance within clusters. This approach aims to balance energy consumption across the network, minimize overhead, and extend overall network longevity while ensuring reliable data transmission. The key contributions of this chapter are:

- The Energy-Optimized Artificial Hummingbird Algorithm (EOAHA) has been suggested to enhance network longevity by aiding in the identification of optimal CHs.
- A fitness function is designed to be effective by taking into account two components. The first component calculates the ratio of the sum of the energy left in CH to the energy left in common nodes. The second component considers the distance between CHs and BS, as well as the distance between SDSNs and CH, in order to minimize transmission energy.
- To validate its effectiveness, the performance of the EOAHA algorithm is tested under various conditions.
- The experimental study provided evidence that EOAHA outperforms other state-of-the-art methods

3.2 The System Model

The network architecture of the IoT-based SD-WSN, shown in Figure 3.1, showcases the important incorporation of SDN principles. In this network paradigm, cluster heads use wireless communications to facilitate connections between all nodes and the base station. The integration of SDN in this design introduces a revolutionary element, specifically in the real-time modification of nodes inside the network. Using the SDN concept, the network acquires the ability to swiftly reconfigure and update nodes in real-time, enabling adaptive and responsive improvements to evolving network conditions. The dynamic management of nodes improves the flexibility, scalability, and responsiveness of the IoT-based SD-WSN, guaranteeing an optimal and robust network infrastructure. The system model is divided into two subsections, namely the network model and the energy model, which are as follows:

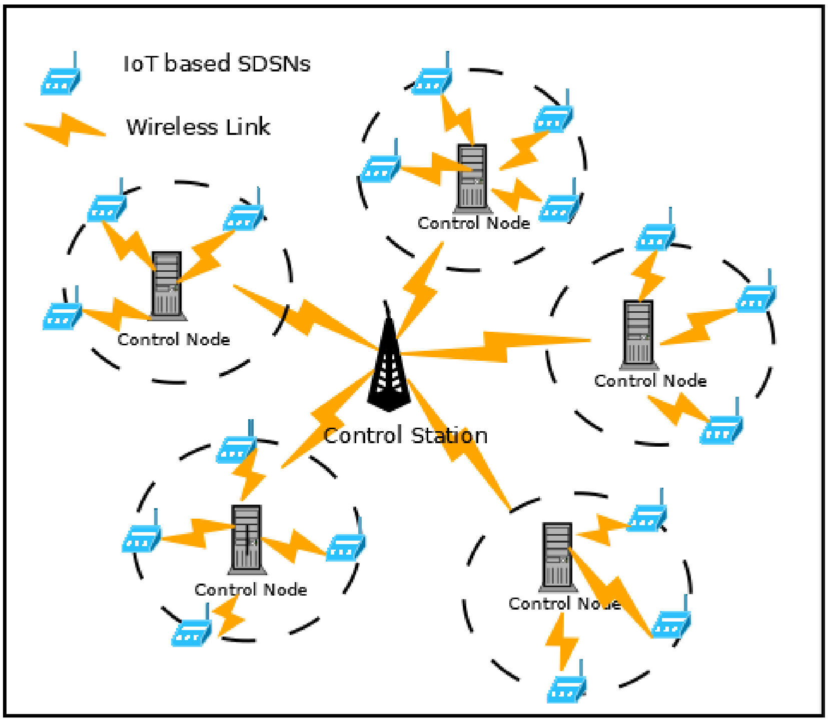


Figure 3.1: An illustration of an IoT-SDWSN network scenario with a Base station and CH.

3.2.1 The Network Model

The IoT-based SD-WSN network architecture is shown in the Figure 3.1. In this figure, all nodes are connected to the base station via a cluster head or CH through a wireless link. This architecture is a directed graph G(V, E). In this graph G, the V represents the vertex set of randomly deployed BS, CH, and SDSN in an area. In this graph G and E represents the set of direct wireless communication links between BS, CHs, and SSDNs to transfer data. The network model for EOAHA is based on the following assumptions:

- All SDSNs are deployed randomly in the SD-WSN region and battery power.
- $|IoT - SDWSN| = |BS| \cup |CH| \cup |SDSN|$ and each device has identification number $I = 1, 2, 3 \ldots, i, \ldots., N$
- All the nodes, BS, CHs, and SDSN are stationary.
- The BS is on external power.
- The SD-WSN is homogeneous, and the initial energy of all the SDSNs is equal.
- Each node in the SD-WSN can act in either sensing mode or communication mode.
- The task of SDSNs is to sense the assigned parameter and then communicate that data to the CHs or the BS using wireless communication links. If the SDSN acts as a CH, it gathers the information from all the SDSNs in the cluster and then transmits it to the BS.
- Each SDSN is unaware of the location and is without GPS-enabled equipment.

3.2.2 The Energy Model

The path attenuation model [62] is used as an energy consumption model for data communication. In this model, energy consumed by the transmitter k-bits message for distance (d) is calculated considering both multi-path fading, (E_{mp}), and free space fading(E_{fs}). The distance, d, is the Euclidean distance between the receiver and transmitter SSDN, which is calculated using the following equation (3.1).

$$d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \tag{3.1}$$

Here,(x_i, y_i) and (x_j, y_j) is the locations of the transmitter and receiver, respectively. In addition, path loss may be compensated by using the power control mechanism. In this model, the free space model is applied if d is less than a threshold distance (d_{th}); otherwise, the multi-path energy model gets employed [1]. The energy consumption $E^{ij}_{SSDN_{TX}}$ for a general SSDN node to transmit k-bits data over distance, d is calculated using the following equation (3.2).

$$E^{ij}_{SSDN_{TX}} = \begin{cases} k * E_{elec} + k * E_{mp} * d^4, & \text{for } d \geq d_{th}. \\ k * E_{elec} + k * E_{fs} * d^2, & \text{otherwise.} \end{cases} \tag{3.2}$$

The energy consumption by the CH, $E^{ij}_{CH_{TX}}$, for transmitting k-bits over distance, d, is calculated using equation (3.3).

$$E^{ij}_{CH_{TX}} = \begin{cases} k * (E_{elec} + E_{DA}) + k * E_{mp} * d^4, & \text{for } d \geq d_{th}. \\ k * (E_{elec} + E_{DA}) + k * E_{fs} * d^2, & \text{otherwise.} \end{cases} \tag{3.3}$$

Where E_{DA} is the energy consumed in data aggregation by CH. The threshold distance d_{th} is calculated using equation(3.4).

$$d_{th} = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{3.4}$$

Where E_{fs} and E_{mp} represent free space amplification energy and amplification energy for multi-path models respectively.

3.3 Overview of Artificial Hummingbird Algorithm

Hummingbirds are considered to be the tiniest birds on the planet, and they are the most intelligent species on Earth in terms of the brain-to-body ratio [117]. Zhao et al. [118] proposed AHA as a method of global search optimization. It models the foraging behavior of hummingbirds. The structure of the AHA [118] is shown in the following algorithm: 3.1.

Algorithm 3.1 Artificial Hummingbird Algorithm

Initialization
while *stop criterion is not satisfied* **do**
    if *condition met* **then**
        Guided Foraging (Algorithm 3.2)
    else
        Territorial Foraging (Algorithm 3.3)
    if *lack of food* **then**
        Migration Foraging (Algorithm 3.4)

Hummingbirds exhibit three behaviors related to foraging, namely guided, territorial, and migrating foraging. In AHA, n population of birds on n food sources are initialized and a visiting table with visit levels [118] of food sources is initialized using the following equation (3.5). The health of the food source is represented by the visit level here.

$$visitTable_{i,j} = \begin{cases} 0, & i \neq j. \\ null, & i = j. \end{cases} \quad for\ i, j = 1, 2..., n \tag{3.5}$$

Hummingbird's flight is modeled using a direction switch vector in the AHA algorithm, which includes omnidirectional, diagonal, and axial flight [118]. The axial A^i, diagonal D^i, and omnidirectional OD^i flight are determined using the following equations (3.6), (3.7) and (3.8), respectively [118].

$$A^i = \begin{cases} 1, & if i = rand([1, d]). \\ 0, & otherwise. \end{cases} \quad for\ i, j = 1, ..., d \tag{3.6}$$

$$D^i = \begin{cases} 1, & if\ i = P(i);\ j\varepsilon[i,k];\ P = randperm(k); \\ & i,j = 1,2...,d;\ k\varepsilon = [2, \lceil r_1 * (d-2) + 1 \rceil]. \\ 0, & otherwise. \end{cases} \tag{3.7}$$

$$OD^i = 1,\ for\ i,j = 1,...,d \tag{3.8}$$

1. Guided foraging: Hummingbirds have a natural tendency to prefer food sources with the highest nectar volume and cling onto them. If visit levels are equal, a food source with the highest nectar refilling rate is selected during guided foraging; otherwise, the food source with the topmost visit level is picked. To simulate the guided foraging behavior, the following equation (3.9) is used.

$$v_i(t+1) = x_{i,tar}(t) + a * D * (x_i(t) - x_{i,tar}(t)) \tag{3.9}$$

Whereas $x_{i,tar}(t)$ is the location of the target food to be visited by i^{th} hummingbird; guide factor $a \sim N(0,1)$, $N(0,1)$ is normal distribution, represents the location of i^{th} food source at time t; and D is axial, diagonal or omnidirectional flight. The hummingbird uses the following equation (3.10) to select a food source with a higher rate of nectar filling.

$$x_i(t+1) = \begin{cases} x_i(t), & if\ fitness(x_i(t)) \leq fitness(v_i(t+1) \\ v_i(t+1), & otherwise \end{cases} \tag{3.10}$$

Where $fitness(x(t))$ is the value of the fitness function for the food source.

Algorithm 3.2 Guided Foraging

Find $v_i^j(t)$ using equation (3.9)
$[S_t(t)] = SPV[v_i^j(t)]$
$newFitness = fitness(S_t(t), nCH)$
for k-th food from 1 to n ($k \neq \text{tar}, i$) **do**
    $visitTable(i, k) = visitTable(i, k) + 1$
$visitTable(i, \text{tar}) = 0$
if $newFitness > f_i$ **then**
    $x_i^j(t) = v_i^j(t)$
    $f_i = newFitness$
    for k-th food from 1 to n ($t \neq k$) **do**
        $visitTable(k, i) = \max(visitTable(k, t)) + 1$

2. Territorial foraging: Hummingbirds probably look for a new food source within their region once their current food source is exhausted. The following equation (3.11) simulates the territorial foraging behavior of hummingbirds.

$$v_i(t+1) = x_i(t) + b * D * x_i(t) \tag{3.11}$$

Where territorial factor $b \sim N(0,1)$, $N(0,1)$ is a normal distribution with mean=0 and standard deviation=1; D is axial, diagonal, or omnidirectional flight. Hummingbirds can use the above equation (3.11) to discover a new food source in their territory. If the new food source refills at a faster rate as compared to a current source, the newer one gets selected by using equation (3.10). In each iteration, the visitor table is updated when the hummingbird performs either guided or territorial foraging behavior. The visit level in the visitor table is set to zero for the target food, while for all other sources, it is incremented by 1. If the hummingbird moves to a new source of food, then for the old food source, the visit level for other birds in the population is set to the bird's highest visit level increased by one [118].

Algorithm 3.3 Territorial Foraging

Find $v_i^j(t)$ using equation (3.11)
$[S_t(t)] = SPV[v_i^j(t)]$
$newFitness = fitness(S_t(t), nCH)$
for k-th food from 1 to n $(k \neq i)$ **do**
  $visitTable(i, k) = visitTable(i, k) + 1$
$visitTable(i, tar) = 0$
if $newFitness > f_i$ **then**
  $x_i^j(t) = v_i^j(t)$
  $f_i = newFitness$
  for k-th food from 1 to n $(k \neq i)$ **do**
    $visitTable(k, i) = visitTable(k, t) + 1$

3. Migration foraging: When the hummingbird faces scarcity of food within its territory, it usually migrates to a different region. The following equation (3.12) generates a new food source at random in the domain. The hummingbird will migrate to it to feed on a new food source and update its visitor table.

$$x_{worst}(t + 1) = Low + r * (Up - Low) \tag{3.12}$$

Where x_{worst} represents food sources with the slowest nectar refill rate, In AHA, if the iteration exceeds the migration coefficient, the migration foraging behavior of hummingbirds gets simulated.

Algorithm 3.4 Migration Foraging

Find $v_i^j(t)$ using equation (3.12)
for k-th food from 1 to n $(k \neq i)$ **do**
  $visitTable(i, k) = visitTable(i, k) + 1$
for k-th food from 1 to n $(k \neq i)$ **do**
  $visitTable(k, i) = visitTable(k, t) + 1$

3.4 The Proposed Model

Here, we divided this section into two subsections. In the first subsection, we discuss the proposed Energy Optimized Artificial Hummingbird Algorithm (EOAHA) model. Further, in the second subsection, the fitness function used in the

EOAHA model is defined.

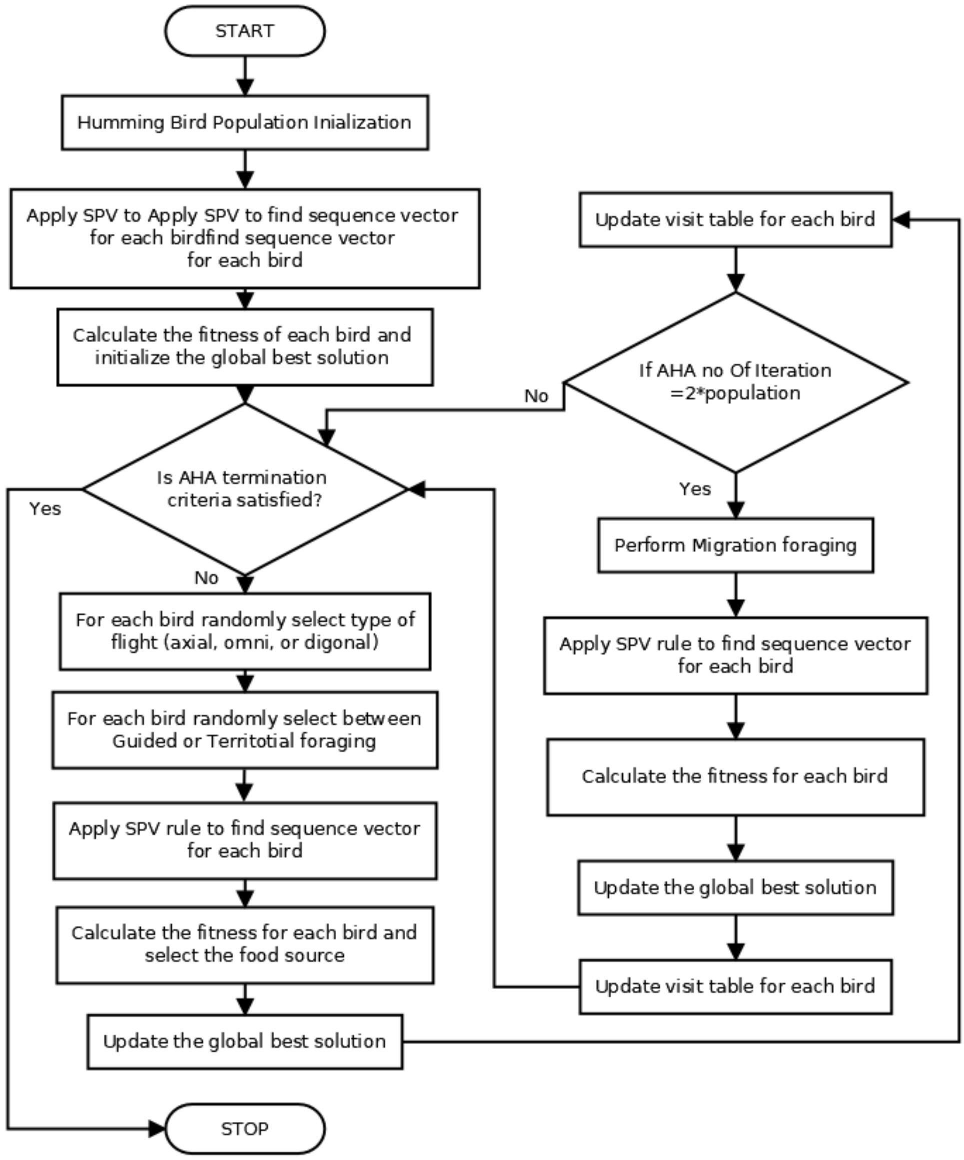


Figure 3.2: EOAHA flowchart.

3.4.1 The EOAHA Model

The proposed EOAHA is a nature-inspired metaheuristic-based algorithm. The Algorithm 3.5 explains the EOAHA pseudo-code used to address the energy optimization problem in an IoT-based SD-WSN. The algorithm comprises two distinct phases, namely the initialization phase and the updation phase.

1. **Initialization Phase:** It begins with the initialization of the population. The position of the predefined number N of randomly generated hummingbirds on N number of food sources is determined using the following equation (3.13).

$$x_i^j(r) = LB + rand * (UB - LB) \tag{3.13}$$

whereas, $rand$ is a random vector in $[0, 1]$; the random food positions are represented as a vector $x_i(r)$ with continuous random values. Here, LB and UB denote the lower and upper bounds, respectively, for a multi-dimensional problem with j dimensions. The location of the i^{th} food source is represented by $x_i^j(r)$. To determine the position of each bird in the sequence, the Smallest Position Vector (SPV) rule (for description, see [119]) is applied on $x_i(r)$, resulting in a sequence position vector $S_i(r)$. In this proposed algorithm, a total of 10% of the active nodes in the network are selected as CHs for each bird, using SPV [119]. The fitness of each hummingbird is determined by evaluating its position using the fitness function $fitness(S_i(r), nCH)$. The resulting fitness value is then stored in F_i. After initializing the fitness value for each bird, using equation (3.5), the VisitTable is initialized. At the end of this phase, the global best solution $(globalBestFit)$ is initialized with the bird having the best fitness value.

2. **Updation Phase:** The updation phase includes five steps. In the first step, the type of flight for each bird is selected randomly from the omnidirectional, axial, and diagonal flight. Next, during the second step, for each bird, the type of foraging behavior is chosen randomly, i.e., guided or territorial foraging. If the guided foraging is selected, the new food vector $v_i(n)$ is calculated using equation (3.9); in the case of territorial foraging, equation (3.11) is used to calculate the new food vector $v_i(n)$. The third step of the algorithm involves the utilization of the SPV rule [84] to determine the sequence vector, represented by $S_i(r)$, for each bird. Subsequently, during the fourth step, for each bird, the fitness value is calculated, and if the new values are smaller than the older one, the fitness value f_i and the visit table for that bird are updated (as described in the previous section). In the final step, the algorithm checks if the number of iterations exceeds the migration coefficient. If so, the migration foraging behavior of hummingbirds is simulated. In migration foraging, new food sources are created in the entire search space using equation (3.12). If the fitness value computed in this step is

greater than the old global best value, the global best solution is updated.

Algorithm 3.5 EOAHA

Input: $NetworkModel, Nodes$

Output: $Optimal\ selection\ of\ CHs$

$r = 0$
while $aliveNodes \neq 0$ **do**
  $nCH = 10\%$ of $aliveNodes$
  for each i^{th} hummingbird from 1 to n **do**
    Randomly initialize the position of both hummingbird and food, i.e., $x^i_j(r)$ of i^{th} particle in j^{th} dimension for k^{th} iteration
    $[S_i(r)] = SPV[x^i_j(r)]$
    $f_i = fitness(S_i(r), nCH)$
    for each j^{th} food from 1 to n **do**
      if $i \neq j$ **then**
        $visitTable(i, j) = 1$
      else
        $visitTable(i, j) =$ null
  $globalBestFit = \min[f_i]$
  while $t <$ maxIteration **do**
    for each i^{th} hummingbird from 1 to n **do**
      if $rand2 < \frac{1}{3}$ **then**
        perform equation 3.6
      else if $rand2 > \frac{2}{3}$ **then**
        perform equation 3.7
      else
        perform equation 3.8
      if $rand1 \leq 0.5$ **then**
        Do Guided foraging
      else
        Do Territorial foraging
    if $\mathrm{mod}(t, 2n) = 0$ **then**
      Do Migration foraging
    $globalBestFit = \min[f_i]$
  $r = r + 1$

3.4.2 Smallest Position Value

Tasgetiren et al. [120] proposed heuristic rule called smallest position value. To adapt the continuous nature of standard PSO for this discrete sequencing problem, the authors propose a novel Smallest Position Value (SPV) rule. This technique enables the algorithm to translate continuous position vectors into discrete job permutations by sorting the vector values to determine processing order.

The fundamental function of the SPV rule is to transform a continuous position vector $\mathbf{v}_k^i = \{v_{k,1}^i, v_{k,2}^i, \ldots, v_{k,n}^i\}$ into a discrete permutation sequence $\mathbf{S}_k^i = \{s_{k,1}^i, s_{k,2}^i, \ldots, s_{k,n}^i\}$. This is achieved by sorting the continuous position values in ascending order and retrieving their corresponding indices to determine the processing order. Formally, for a dimension n (representing the number of jobs or nodes), the discrete sequence is derived such that:

$$\mathbf{S}_k^i = \mathrm{argsort}(\mathbf{v}_k^i) \tag{3.14}$$

whereby the indices are reordered based on the magnitude of the values in $\mathbf{X}_k^i$. Furthermore, to enhance the robustness of this approach, the original model embeds a local search mechanism to improve the quality of solutions discovered by the swarm.

3.4.3 Fitness Function

The following parameters are utilized in the fitness function's development:

1) **Total Residual Energy:** The longevity of the network heavily relies on the residual energy of its nodes. The following equation (3.15) provides the general formula for calculating total residual energy.

$$E_{total} = \sum_{i=1}^{n} E_r \tag{3.15}$$

Where E_r is the energy left in i^{th} node, equation (3.16) is utilized to determine the total remaining energy of the CH, whereas the calculation of the total residual energy of a normal node within the cluster is performed using Equation (3.17).

$$E_{totalCH} = \sum_{i=1}^{nCH} E_{CH}^{iBS}(l, d) \tag{3.16}$$

The variables used in the calculation include nCH, which denotes the number of CH; l represents the number of bits; d, which indicates the distance between CH and BS; and $E_{CH_{TX}}^{iBS}$, which represents the residual energy in the i^{th} node.

$$E_{totalCommon} = \sum_{j=1}^{nCH} \sum_{i=1}^{nNode} E_{SDSN}^{ij}(l, d_{i,j}) \tag{3.17}$$

Whereas the $d_{i,j}$ is the distance from the j^{th} CH and i^{th} node; nNode rest of nodes in the network excluding CH. The equation (3.18) represents the first objective function f_1 for the calculation of fitness while f_1 is the ratio of total energy left in CH and the rest of the nodes after transmission.

$$f_1 = \frac{E_{totalCH}}{E_{totalCommon}} \tag{3.18}$$

2) **Distance:** The distance is directly proportional to the energy required to send data in space, i.e., the larger the distance between the receiver and sender, the greater the energy required to transmit the data. Therefore, if we need to reduce the energy consumption for transmission, it will be required to minimize the distance between the sender and receiver. Here we considered the distance between BS & CH and the distance between CH & its cluster nodes to optimize the results. The total distance between the BS and all the cluster heads is calculated using the following equation (3.19).

$$D_{totalCHtoBS} = \sum_{i=1}^{nCH} \sqrt{(x_{CH_i} - x_{BS})^2 + (y_{CH_i} - y_{BS})^2} \tag{3.19}$$

Whereas, the location of the i^{th} CH is (x_{CH_i}, y_{CH_i}) and the location of the base station as (x_{BS}, y_{BS}).

$$D_{totalNodetoCH} = \sum_{j=1}^{nCH} \sum_{i=1}^{nNode} \sqrt{(x_{CH_j} - x_{NODE_i})^2 + (y_{CH_j} - y_{NODE_i})^2} \tag{3.20}$$

The total distance between the CH and all the nodes in the cluster is calculated using the above equation (3.20). Whereas, the $(x_{CH_j}, y_{CH_j})$is the location of the j^{th} base node and (x_{NODE_i}, y_{NODE_i}) is the location of the i^{th} node in a cluster. Equation (3.21) represents the second objective function f_2, which is based on the average total distance covered between CH & BS and nodes & CH in the cluster

$$f_2 = \frac{1}{(D_{totalCHtoBS} + D_{totalNodetoCH})/2} \tag{3.21}$$

$$fitness = \gamma * f_1 + \delta * f_2 \tag{3.22}$$

The above equation (3.22) represents the fitness function, which balances the residual energy and the distance covered during transmissions. Here, γ and δ are constants.

3.5 The Performance Analysis

Table 3.1 outlines the various parameters of IoT-based SD-WSN and EOAHA, which are used to evaluate performance through computer simulation in this section. All the experiments are performed in the MATLAB (version 2019a) tool on an Intel i5 processor with 8GB RAM.

Table 3.1: Parameters for Testing

Category	**Parameter**	**Value**
Network	Area (m^2)	100x100
	BS (Position)	50,50
	Node Energy	0.5J
	No. of SDSNs	100
Application	Data Packet length	100 bits
	Broadcast packet size	25 bits
EOAHA	Initial POP	30
	Iteration	50
	γ, δ	0.5, 0.5

3.5.1 Parameter Settings

The behavior of SD-WSN nodes is simulated in a geographical area of 100 m x 100 m with a base station at the center using the testing settings listed in Table 3.1. A network of 100 nodes is deployed at random, as shown in Figure 3.3. An energy allocation of 0.5 J is assigned to each node in the network. The location of the base station is the center of the area of deployment.

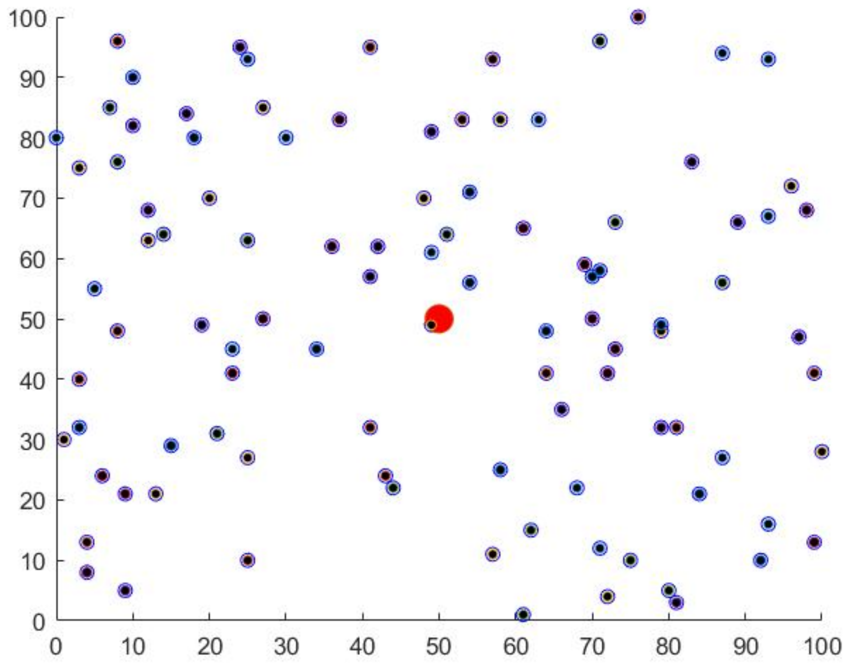


Figure 3.3: Random deployment of sensor nodes in 100m x 100m field

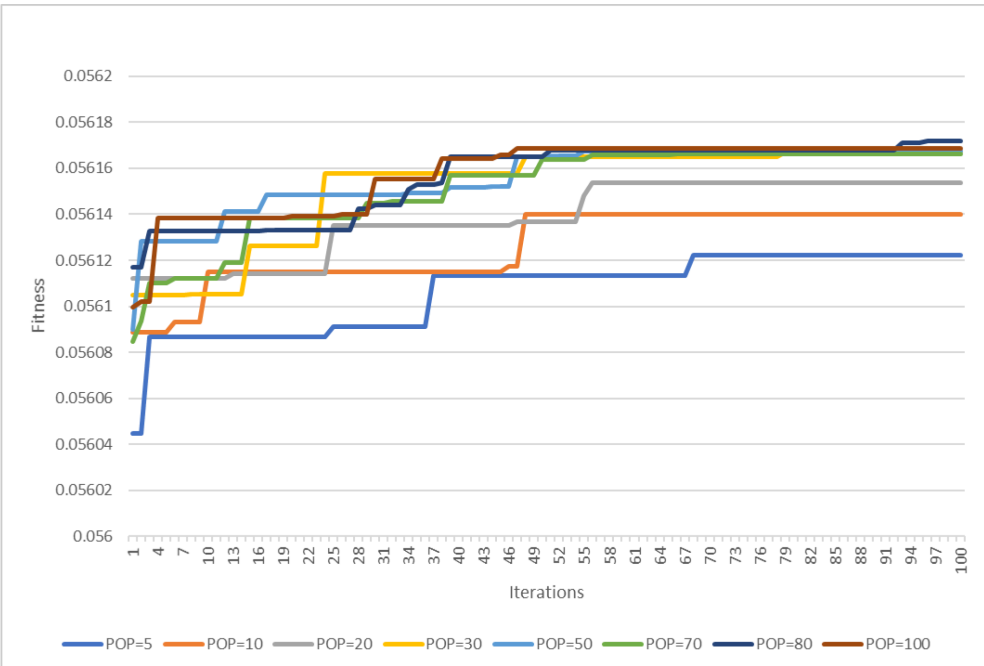


Figure 3.4: The fitness response of EOAHA on population and iterations.

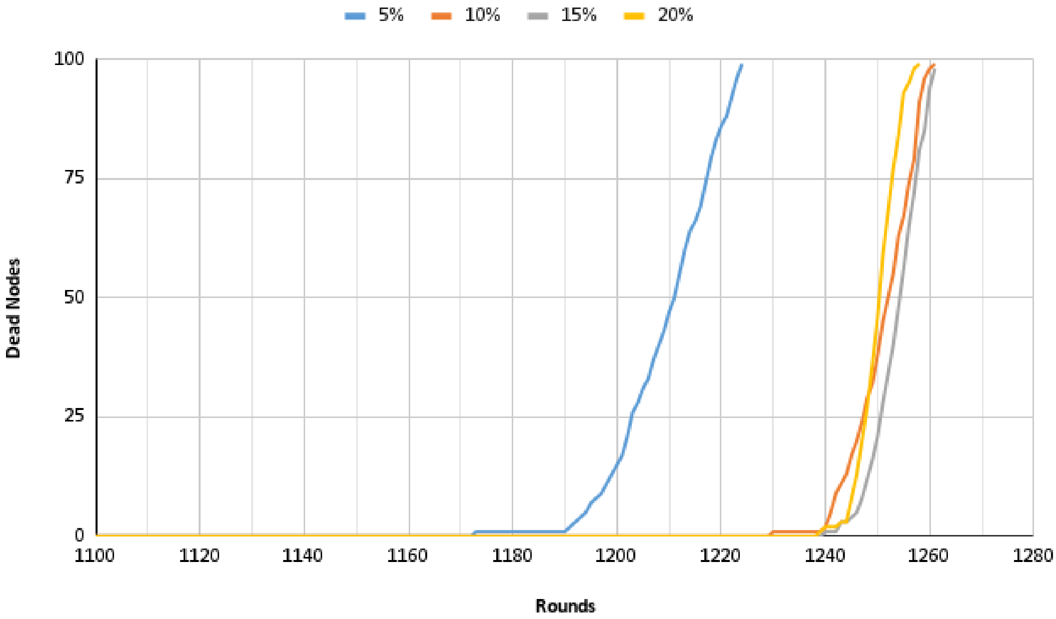


Figure 3.5: Comparison of performance with different % of CHs.

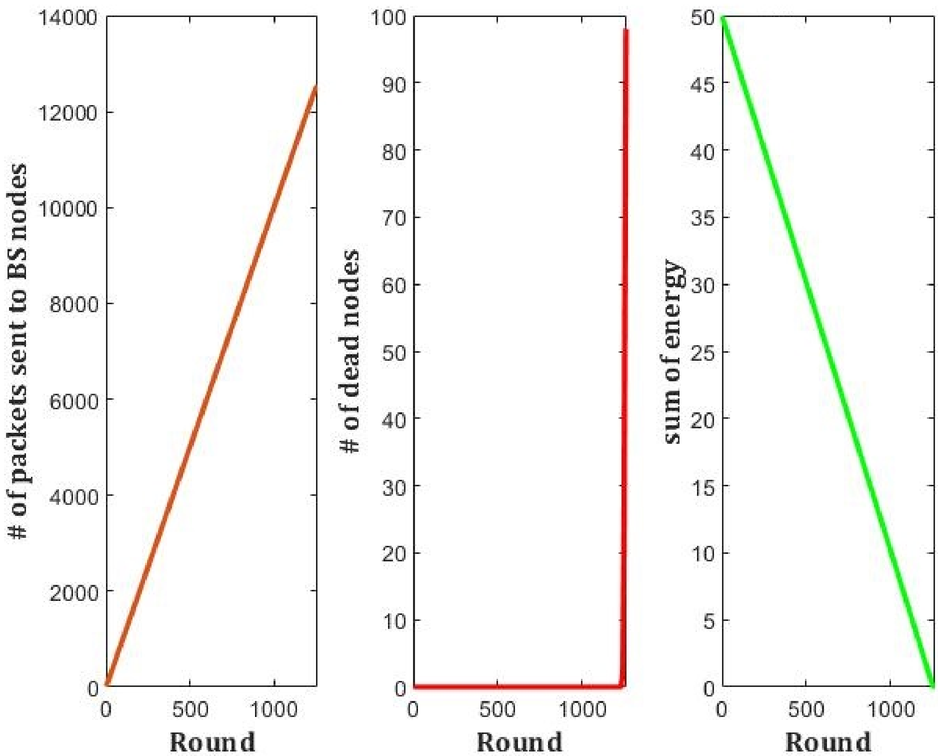


Figure 3.6: EOAHA outcome for the packet transmitted to BS, total residual energy, and no. of dead/failed nodes.

In order to evaluate the optimum number of hummingbird populations and the maximum iteration, the fitness function is tested with a different set of populations ranging from 5 to 100, as shown in the above Figure 3.4. As we can observe from the given Figure 3.4, the optimum fitness value can be achieved with the initial population size of 30 and a maximum of 50 iterations. Thus, a population of 30 hummingbirds is initialized with a food position vector that lies in the [-4 to 4] range using equation (3.13) in multi-dimension search space. In EOAHA, the number of CH is set to 10% of the alive nodes after comparing the performance of the EOAHA, as shown in Figure 3.5, with different numbers of CHs, i.e., 5%, 10%, 15%, and 20% of the total alive nodes.

3.5.2 Performance Evaluation

From Figure 3.6, we can observe that for the EOAHA algorithm, the first node died at 1224 rounds with steady decay of total network energy. The last node of the network died at the 1261 round with no energy left in the network. As the network lasted for 1261 rounds, the number of packets transmitted to the base station was 12519.

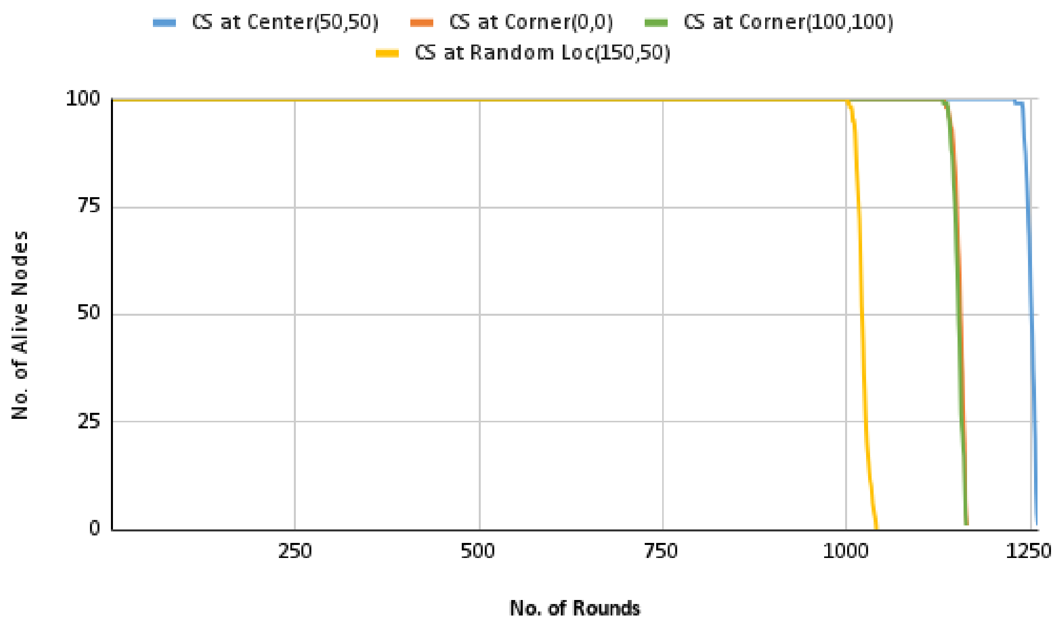


Figure 3.7: No. of alive node comparison based on the position of BS.

To test the impact of the position of BS on the performance of the proposed algorithm, the algorithm is simulated with different positions of BS, i.e., at the center (50,50), origin (0,0), corner (100,100), and random location (150,50) outside the area of deployment. The results shown in Figure 3.7 depict that the performance of EOAHA is almost the same when BS is placed at the corners of the area of deployment. However, the performance of the algorithm when the BS is outside the area of deployment decreases significantly, and the proposed algorithm performs best when the BS is in the center of the deployment area.

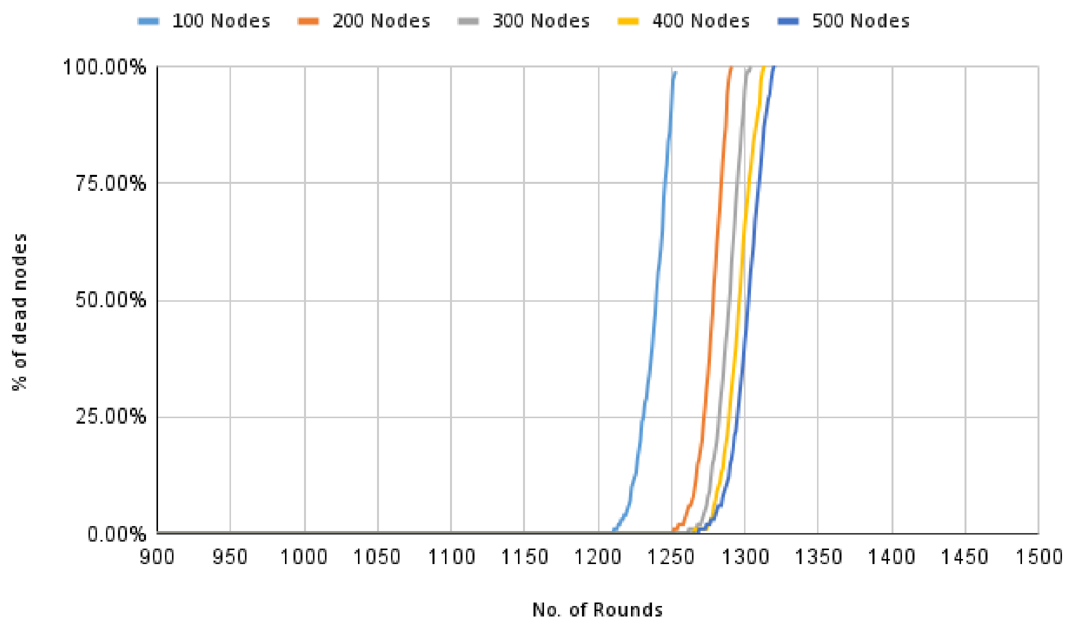


Figure 3.8: Dead node comparison based on different node densities of deployment.

This algorithm is further tested with the different densities of nodes deployed in networks, i.e., 100, 200, 300, 400, and 500 nodes. As the number of nodes distributed within the same region increases, the results shown in Figure 3.8 indicate that the proposed method exhibits greater efficiency. This result may also be verified with the data shown in Figure 3.9; it is observed that as the area of the network is increased with the same number of nodes (i.e., decrease in density), the network lifetime decreases significantly.

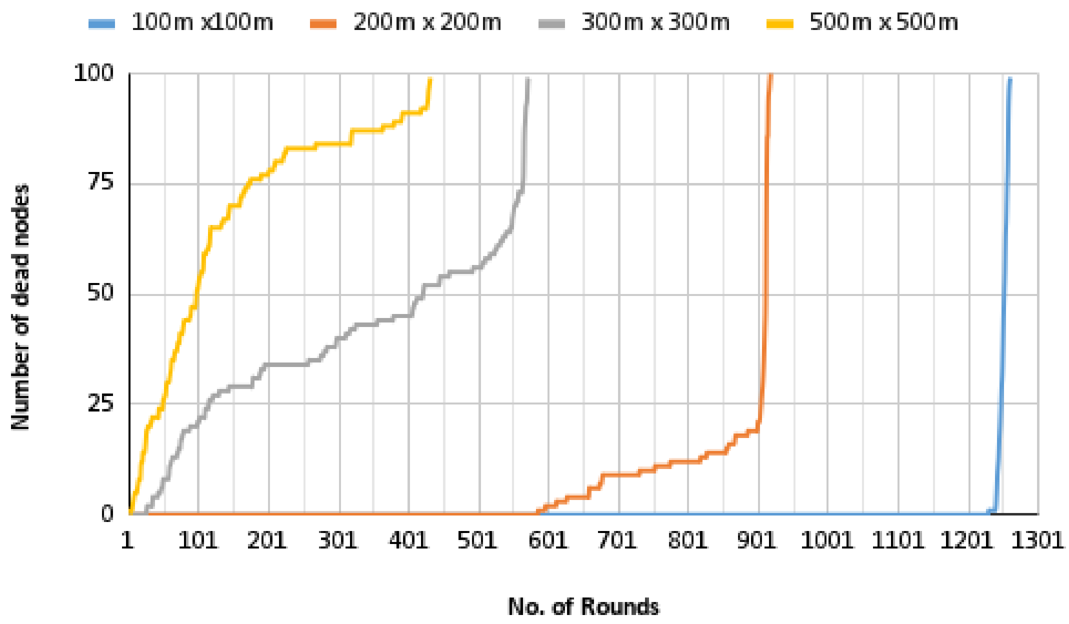


Figure 3.9: Dead node comparison based on different areas of deployment.

3.5.3 Comparative Analysis

The system is configured using all the parameters in Table 3.1. The simulation results of EOAHA are compared with state-of-the-art algorithms, i.e., EBGWO [86], LEACH [62], KmeansPSO [78], GWO-C [84], and EAFFO [98], in terms of the number of dead nodes and total residual energy per round. The performance of network models is measured using network lifespan [81], and it is defined as the period from the deployment of the network until the last node dies [65]. The network lifespan for periodic data collection is calculated as the time between the first node becoming operational and when the First Node Dies (FND) [65] in the SD-WSN.

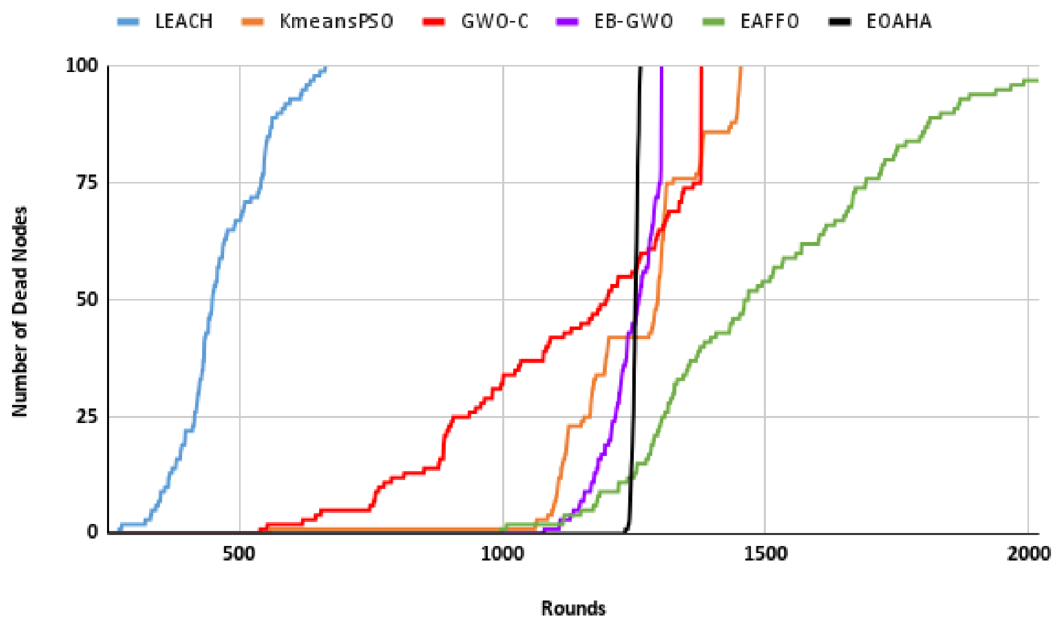


Figure 3.10: Dead node comparison based on the number of rounds.

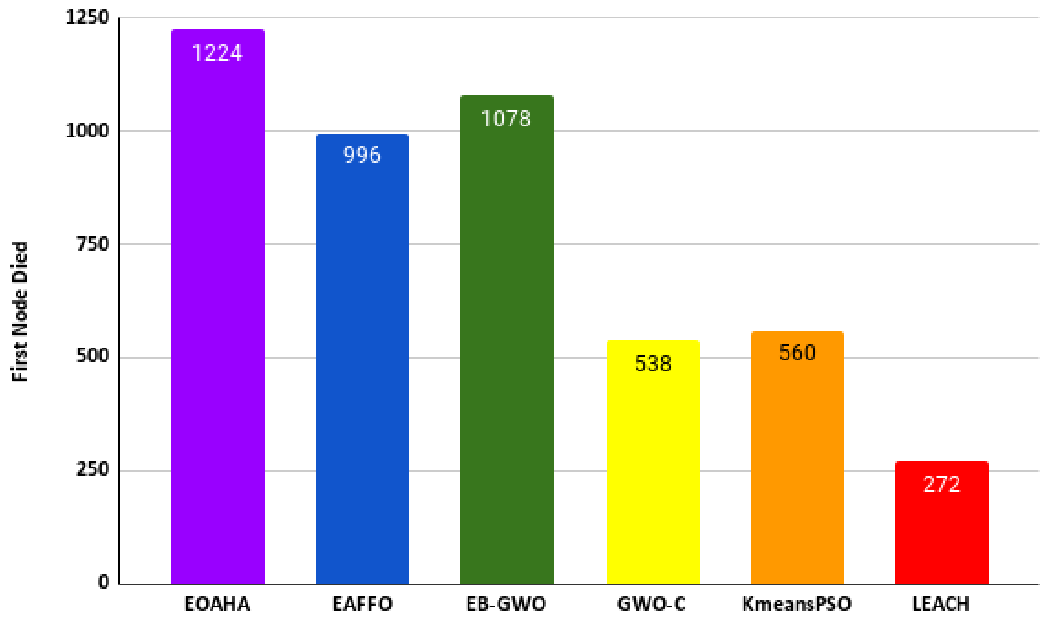


Figure 3.11: FND and number of rounds comparison.

In Figures 3.10 and 3.11, the result shows that for LEACH, the first node died at 270 rounds; for Kmeans-PSO FND at 560 rounds; for GWO-C FND at 543 rounds; for EB-GWO FND at 1078 rounds; for EAFFO FND at 996; and for EOAHA FND at 1224 rounds. According to the findings, EOAHA has enhanced the network lifespan for periodic data collection by over 13.5 percent when compared to EBGWO, and if we compare it with LEACH, Kmeans-PSO, EAFFO, and GWO-C, the network lifespan is enhanced by more than 350%, 118%, 123% and 125% respectively. If we compare the proposed solution with LEACH, the overall network lifespan with respect to the last node died; the result shows SD-WSN lasted for 562 more rounds than LEACH (in which LND at 662). Figure 3.11 clearly shows that EOAHA prolongs the network lifespan for periodic data gathering.

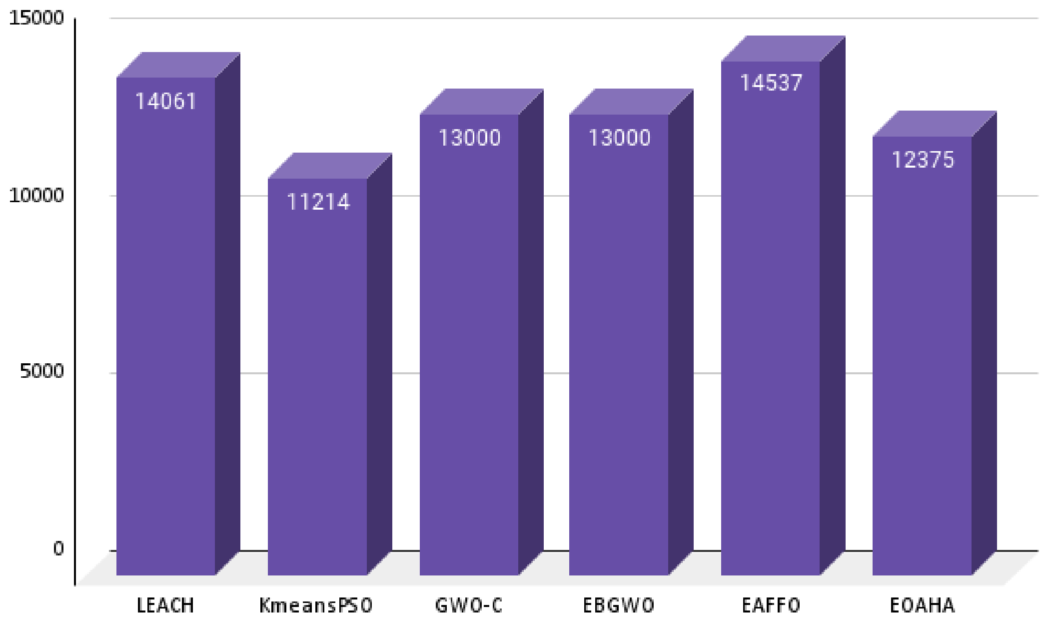


Figure 3.12: The number of data packets by different algorithms to Base Station.

Figure 3.12 shows that the EOAHA transmits fewer packets to BS than LEACH, GWO-C, EAFFO, and EBGWO. Here, Figure 3.13 shows the comparison between the number of rounds and total residual energy. Due to the energy and distance-balanced fitness function, energy-draining for EOAHA is steady. To test the stability of all the state-of-the-art algorithms and EOAHA with the increase in density of nodes in a defined area, all the algorithms are simulated with node densities of 100, 200, 300, 400, and 500, and the results are exhibited in Figure 3.14. The data displayed in Figure 3.14 proves that the performance of EOAHA is consistent or even improves with the increase in the density of nodes, whereas the performance of others is inconsistent, i.e., performance decreases in some cases and increases in other cases.

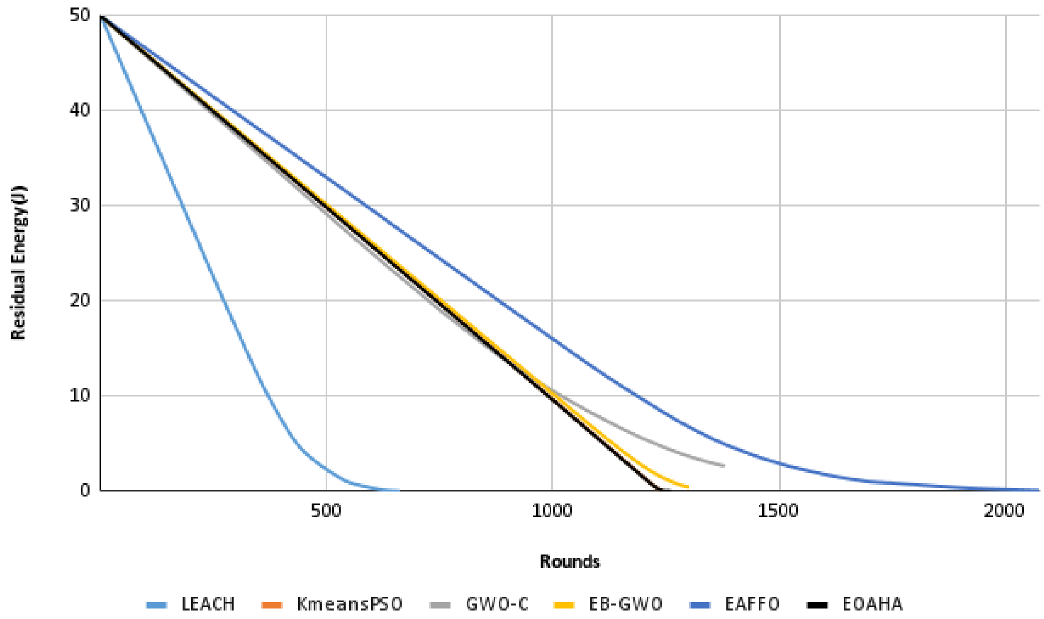


Figure 3.13: Comparison of energy drain of EOAHA.

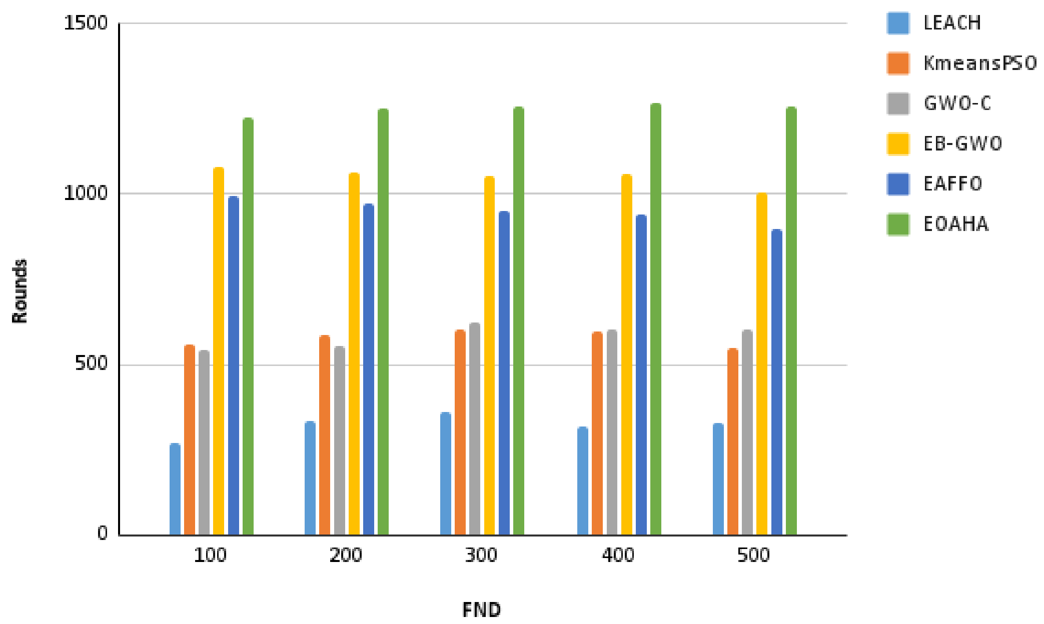


Figure 3.14: FND and the number of rounds comparison with state-of-the-art algorithms.

The experiment results depict that EOAHA is significantly superior than the state-of-the-art algorithm in extending the network lifespan for periodic data gathering, as the energy consumption in the network is steady.

3.6 Chapter Summary

This chapter addresses the critical challenge of energy conservation and prolonged network longevity in IoT-SDWSNs by introducing EOAHA. Leveraging the behavioral intelligence of hummingbirds, the EOAHA methodology optimizes the complex process of CH selection through a specialized fitness function designed to balance transmission costs with node vitality. This function prioritizes the selection of optimal CHs by maximizing the ratio of residual energy between CHs and member nodes while simultaneously minimizing the communication distance to both the CH and cluster members. Extensive simulations validated the protocol's superior robustness, demonstrating that EOAHA achieved a FND metric of 1224 rounds and delivered significant network lifespan improvements ranging from 13.5% against EBGWO to over 350% against LEACH. Furthermore, the results confirmed the algorithm's ability to maintain consistent energy stability and performance superiority even as node density increased, establishing EOAHA as a resilient solution for scalable IoT deployments.

CHAPTER 4

A NATURE INSPIRED MULTI-OBJECTIVE GREEN ROUTING PROTOCOL FOR IOT-ENABLED SDWSN

In the previous chapter, the EOAHA was introduced as a novel metaheuristic routing protocol designed to enhance energy efficiency and prolong network lifetime in IoT-enabled SDWSNs. Inspired by the foraging behavior of hummingbirds, EOAHA effectively optimized energy consumption and improved packet transmission by intelligently selecting CHs. However, a key limitation of the approach was that the number of CHs remained fixed during the entire network operation. Since the role of CH is energy-critical and incurs higher energy costs, fixing the number of CHs can lead to suboptimal performance under dynamic network conditions. Therefore, it is essential to adaptively determine both the selection and the number of CHs based on real-time parameters such as node density, residual energy, and traffic load. Building upon the foundational insights and limitations identified in Chapter 3, this chapter introduces an enhanced energy-efficient routing framework, Equilibrium Optimization-based Clustering (EO-C).

4.1 Introduction

EO-C is a multi-objective green routing protocol, inspired by the natural phenomenon of equilibrium, tailored for IoT-enabled SDWSNs. While the previously proposed EOAHA effectively selected CHs based on behavioral intelligence and residual energy, EOAHA operated under the constraint of a fixed number of CHs, limiting adaptability under dynamic network conditions. To overcome this limitation, EO-C introduces a dynamic and adaptive mechanism that adjusts both the selection and quantity of CHs based on real-time network conditions such as node density, residual energy, communication distance, node availability, and current communication load. The protocol simultaneously optimizes key Quality of Service (QoS) metrics such as energy consumption, network longevity, load distribution, and data packet delivery, making it more suitable for scalable and IoT-based SDWSN environments.

EO-C defines a comprehensive fitness function that integrates multiple parameters: energy ratio, residual energy, and node alive. These metrics collectively guide the adaptive clustering and routing process, enabling the formation of balanced and energy-aware topologies. EO-C is based on the equilibrium optimizer algorithm [121]. EO-C intelligently selects CHs based on factors like total residual energy, energy balance ratio, and alive nodes. The key contributions of this chapter are as follows:

- This chapter introduces an energy-efficient EO-C algorithm. The goal of this algorithm is to improve the network's life and mitigate the hot-spot problem.
- A novel fitness function is proposed, which is based on constraints such as total residual energy, energy balance ratio, and alive node count.
- EO-C dynamically selects the optimum cluster count based on network conditions.
- The performance of the EO-C algorithm is evaluated under various conditions to validate its effectiveness.
- The experimental study provided evidence that EO-C outperformed other state-of-the-art (SoA) methods

By leveraging evolutionary principles and intelligent decision-making, EO-C advances beyond single-objective models and positions itself as a robust candidate for real-world deployments in energy-constrained, data-intensive IoT-SDWSNs.

4.2 Preliminaries

This section presents the network model, energy model, and terminology used in the proposed EO-C algorithm.

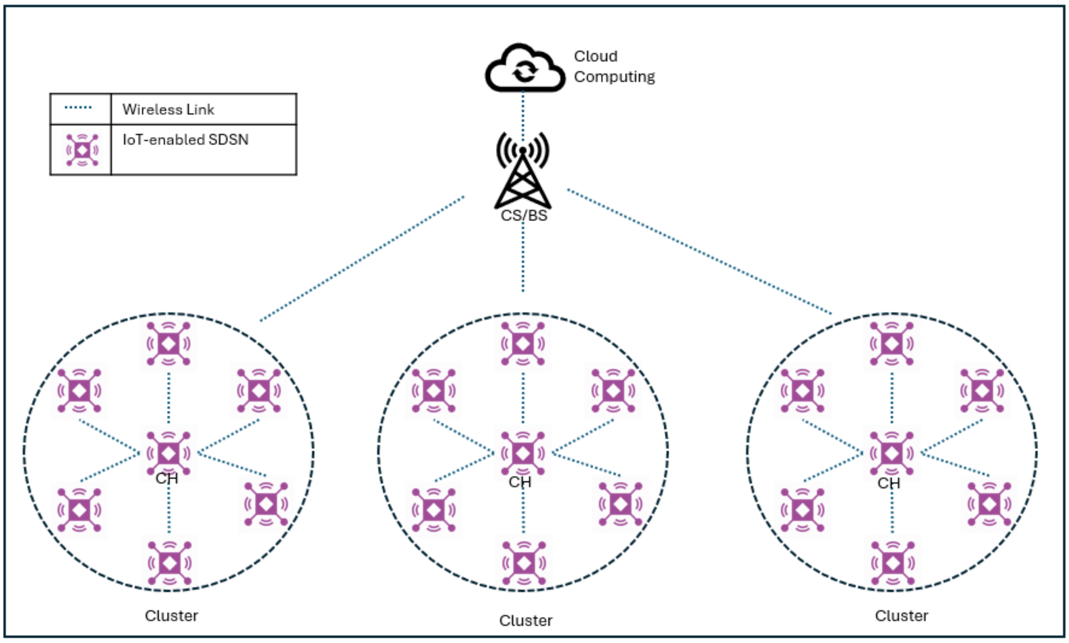


Figure 4.1: An illustration of an IoT-SDWSNs scenario with a CH and BS.

4.2.1 The Network Model

The network architecture of the IoT-enabled SDWSN is depicted in Figure 4.1. The integration of SDN principles in IoT introduced a groundbreaking element, particularly in the real-time modification of nodes within the network. Leveraging SDN, the network gains the capability to swiftly reconfigure and update nodes in real time, facilitating adaptive and responsive adjustments to evolving network conditions. This dynamic node management enhances the flexibility, scalability, and responsiveness of the IoT-enabled SDWSNs, ensuring an optimal and robust network infrastructure. In Figure 4.1, the IoT-enabled SDWSN architecture portrays the wireless connections of nodes with BS via CH. The network model is based on clustering to minimize energy consumption, where Normal Nodes (NN) monitor the environment and transmit sensory data to the cluster heads, aiding in data aggregation before transmission to the base station. The CH aggregates the data received from CN and forwards it to the BS. The task of BS is to collect data, select CH, and create clusters. Here are the assumptions regarding the network:

- All deployed nodes in the network architecture are homogeneous, possessing equivalent energy, computational capability, and data transmission range.
- $|IoT - SDWSNs| = |BS| \cup |CH| \cup |NN|$ and each device has identification number $I = 1, 2, 3 \ldots, i, \ldots., N$
- All the nodes CHs and SDSN are stationary.
- The BS is on external power.
- All nodes are deployed randomly in the area.
- Every node inside the SDWSNs has the capability to function in either sensing mode or communication mode.
- The task of SDSNs is to sense the assigned parameter and then communicate that data to CHs or base stations using wireless communication links. If the SDSN acts as a CH, It gathers the information from all the SDSNs in the cluster and then transmits it to the BS.
- Each SDSN is without GPS.

4.2.2 The Energy Model

The EO-C algorithm employs the path attenuation model [81] as the basis for its energy consumption model during data communication. This model helps to estimate the energy required for transmitting data by considering how the signal weakens or loses strength as it travels over a distance. By incorporating the path attenuation model, the energy consumption for communication can be more accurately calculated, ensuring efficient use of resources in the network.

$$s(i, j) = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \tag{4.1}$$

Here,(x_i, y_i) and (x_j, y_j) are the locations of the transmitter and receiver, respectively. In addition, path loss may be compensated by using the power control mechanism. In this model, the free space model is applied if d is less than a threshold distance (s_{th}); else, the multi-path energy model gets employed. The energy consumption $E^{ij}_{SSDN_{TX}}$ for a general SSDN node to transmit k-bit data over distance (s) is calculated using the following equation (4.2).

$$E_{SSDN_{TX}} = \begin{cases} k * E_{elec} + k * E_{mp} * s^4, & \text{for } s \geq s_{th}. \\ k * E_{elec} + k * E_{fs} * s^2, & \text{otherwise.} \end{cases} \tag{4.2}$$

The energy consumption by the cluster head, $E_{CH_{TX}}$, for transmitting k-bits over distance, s, is calculated using equation (4.3).

$$E_{CH_{TX}} = \begin{cases} k * (E_{elec} + E_{DA}) + k * E_{mp} * s^4, & \text{for } s \geq s_{th}. \\ k * (E_{elec} + E_{DA}) + k * E_{fs} * s^2, & \text{otherwise.} \end{cases} \tag{4.3}$$

Where E_{DA} is the energy consumed in data aggregation by cluster heads. The threshold distance s_{th} was calculated using equation (4.4).

$$s_{th} = \sqrt{\frac{E_f}{E_m}} \tag{4.4}$$

Where E_f and E_m represent free space amplification energy and amplification energy for multi-path models respectively.

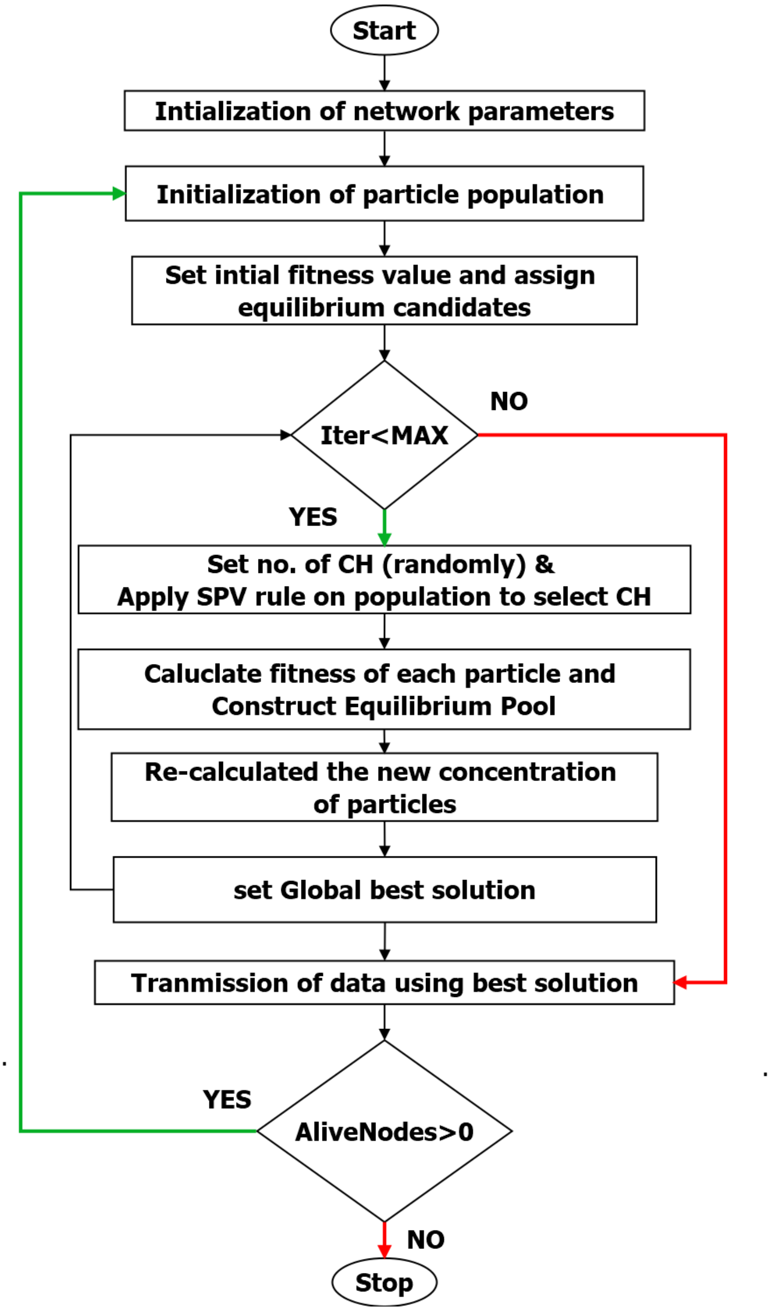


Figure 4.2: EO-C Flow Chart

4.3 The Proposed Model

The EO-C algorithm is discussed in this section. EO-C is based on the equilibrium optimizer algorithm by Faramarzi et al. [121]. The equilibrium optimizer algorithm is a meta-heuristic optimization method based on physics' fundamental principle of equilibrium. It is designed to identify the most favorable solution for a specific optimization problem by emulating the behavior of particles with different concentrations as they approach the state of equilibrium. By incorporating these principles, EO-C optimizes the clustering process in IoT-enabled SDWSNs using the principle of exploration and exploitation within the framework of meta-heuristic optimization.

Algorithm 4.1 explains the pseudocode of the EO-C algorithm, which is structured into two main phases: initialization and optimization. Figure 4.2 illustrates the detailed flowchart of the EO-C algorithm, outlining its sequential workflow. The process begins with the initialization phase, where the network parameters, particle population, and the number of CHs are initialized randomly (explained in subsection 4.3.1). Following this, the algorithm assigns initial fitness values and equilibrium candidates to the particles. In the optimization phase (explained in subsection 4.3.2), the process begins by identifying the best CH candidate nodes using the Smallest Position Value (SPV) rule [120]. In the following step, the fitness of each particle is recalculated using the fitness function, which is explained in subsection 4.3.3. The algorithm subsequently updates the concentration of particles and constructs an equilibrium pool, selecting the global best solution to achieve optimization. Once the global best solution is identified, the data transmission phase is executed using the best CH configuration. If nodes are alive, the process loops back to re-optimize and continue the transmission cycle; otherwise, the process terminates.

4.3.1 The Initialization Phase

This phase starts with the initialization of n particles. The number of particles and the size of the search space define the initial particle concentrations. In the next step, the initial concentration of all n particles is randomly initialized with a uniform distribution across the search space using equation 4.5.

$$C_i^{initial} = C_{min} + rand * (C_{max} - C_{min}) \\ , for\ i = Natural\ Number\ upto\ n \tag{4.5}$$

$C_i^{initial}$ denotes i_{th} particle's initial concentration, where $rand$ is a random

Algorithm 4.1 Equilibrium Optimizer Clustering

Input: $Network\ Model,\ Nodes$

Output: $Optimal\ selection\ of\ CHs\&\ cluster\ count$

Initialize the particles and randomly initialize their concentrations using equation 4.5
Set $a_1 = 2$, $a_2 = 1$, and $GP = 0.5$
while $Itera < Max_{\text{iter}}$ **do**
    $n_{CH} = rand[min(5, ceil(alive * 0.1)), max(ceil(alive * 0.25), 1)]$
    for $i = 1$ to number of particles **do**
        $chList = SPV[n_{CH}, C_i]$
        Calculate the fitness of the i_{th} particle.
$fit(C_i) = fitness(C_i, NetworkModel, n_{CH}, chList)$
        if $\text{fit}(C_i) < \text{fit}(C_{\text{eq1}})$ **then**
            $C_{\text{eq1}} = C_i$
            $\text{fit}(C_{\text{eq1}}) = \text{fit}(C_i)$
        else if $\text{fit}(C_i) > \text{fit}(C_{\text{eq1}})\ \&\ \text{fit}(C_i) < \text{fit}(C_{\text{eq2}})$ **then**
            $C_{\text{eq2}} = C_i$
            $\text{fit}(C_{\text{eq2}}) = \text{fit}(C_i)$
        else if $\text{fit}(C_i) > \text{fit}(C_{\text{eq1}})\ \&\ \text{fit}(C_i) > \text{fit}(C_{\text{eq2}})\ \&\ \text{fit}(C_i) < \text{fit}(C_{\text{eq3}})$ **then**
            $C_{\text{eq3}} = C_i$
            $\text{fit}(C_{\text{eq3}}) = \text{fit}(C_i)$
        else if
$\text{fit}(C_i) > \text{fit}(C_{\text{eq1}})\ \&\ \text{fit}(C_i) > \text{fit}(C_{\text{eq2}})\ \&\ \text{fit}(C_i) > \text{fit}(C_{\text{eq3}})\ \&\ \text{fit}(C_i) < \text{fit}(C_{\text{eq4}})$
then
            $C_{\text{eq4}} = C_i$
            $\text{fit}(C_{\text{eq4}}) = \text{fit}(C_i)$
    $C_{\text{avg}} = (C_{\text{eq1}} + C_{\text{eq2}} + C_{\text{eq3}} + C_{\text{eq4}})/4$
    Find $C_{\text{pool,eq}}$ using equation (4.7)
    if $Itera > 1$ **then**
        Find t using equation (4.10)
        for $i = 1$ to number of particles **do**
            Choose one candidate from $C_{\text{pool,eq}}$ (randomly)
            Generate random vectors λ and r
            Generate vectors E using equation (4.9)
            Generate vectors GCP using eq. (4.13)
            Generate vectors G_0 using eq. (4.12)
            Generate vectors G using eq. (4.11)
            Update C using eq. (4.8)
    $Itera = Itera + 1$
    $bestFitness = \text{fit}(C_{\text{eq1}})$

vector that lies within the $[0, 1]$ range; C_{min} and C_{max} represents the minimal and maximum values of the dimensions. The number of particles in the population is represented by n.

4.3.2 Optimization Phase

The equilibrium state refers to the ultimate convergence state of the algorithm [121], known as the global optimum. This phase is crucial for improving the algorithm's performance and convergence. The optimization process starts by entering into the main loop bounded by a maximum number of iterations, i.e. (Max_{iter}). After entering the loop, it first randomly selects the number of clusters (n_{CH}) within a certain range based on the number of alive nodes using equation (4.6).

$$n_{\text{CH}} = \text{rand}\left[\min\left(5, \lceil \text{alive} \times 0.1 \rceil\right), \max\left(\lceil \text{alive} \times 0.25 \rceil, 1\right)\right] \tag{4.6}$$

where $alive$ is the total number of nodes with energy greater than 0.

During the second step, it calculates the fitness of each particle by executing the novel fitness function discussed in subsection 4.3.3. The particles are evaluated using the fitness function (fit) based on energy ratio, energy, and alive nodes. The third step starts with the creation of an equilibrium pool vector, $C_{pool,eq}$. During the initial stages of the optimization process, there is a lack of information regarding the equilibrium state. $C_{pool,eq}$ created using equation (4.7) by selecting the four best-so-far particles based on their fitness values ($C_{eq1}, C_{eq2}, C_{eq3}, C_{eq4}$) and arithmetic average (C_{avg}) of these four. The inclusion of these four candidates enhances the exploration capability, whereas the average candidate contributes to the exploitation aspect.

$$C_{\text{pool,eq}} = \left(C_{\text{eq1}}, C_{\text{eq2}}, C_{\text{eq3}}, C_{\text{eq4}}\right) \tag{4.7}$$

In the fourth step, the concentration for each particle is updated using equation (4.8).

$$C = C_{eq} + (C - C_{eq}) * E + \frac{G}{\lambda V} * (1 - E) \tag{4.8}$$

Where $\lambda \sim [0, 1]$ is a random vector, and V is a unit vector. Here is a concise explanation of every element:

- **Equilibrium Component**:C_{eq}: The first term in equation (4.8), C_{eq}, corresponds to the equilibrium concentration, serving as a reference point for the particle's concentration. It is calculated using equation (4.7).

- **Exploration Component:** $(C - C_{eq}) * E$: The second term plays a crucial role in exploring the solution space globally, aiming to locate an optimum point. It emphasizes exploration by capitalizing on large concentration variations, such as the direct disparity between an equilibrium state and a sampled particle. The exponential term, denoted as $\vec{E}$, is responsible for updating concentration and is calculated using the equation 4.9.

$$\vec{E} = a_1 sign(\vec{r} - 0.5)\left[e^{-\vec{\lambda}t} - 1\right] \tag{4.9}$$

In equation (4.9), the constant value a_1, specifically set to 2, represents the exploration capability. The second component, $sign(\vec{r} - 0.5)$, holds significant importance in determining both exploration and exploitation capabilities. Here, a random vector spanning a range of 0 to 1 is indicated by $sign(\vec{r})$. Using the equation (4.10), the variable t is computed as a function of the iteration.

$$t = \left(1 - \frac{iter}{iterMax}\right)^{\left(a_2 \frac{iter}{iterMax}\right)} \tag{4.10}$$

In the given equation, $iter$ denotes the current iteration count, while $iterMax$ signifies the maximum iteration count in the optimization process. Furthermore, a_2 serves as a constant (typically set to 1), utilized to regulate the extent of exploitation capability.

- **Exploitation Component:** $\frac{G}{\lambda V} * (1 - E)$: Once a solution is identified, the third term fine-tunes the solution further. This term focuses on exploitation, leveraging minor concentration variations to enhance solution accuracy. It relies on generation rates, which are calculated using equation (4.11) to navigate these subtle concentration changes effectively.

$$\vec{G} = \vec{G_0}.\vec{E} \tag{4.11}$$

Where $\vec{G_0}$ is the initial generation rate [121] and is calculated using the equation (4.12).

$$G_0 = GCP * (C_{eq} - \lambda * C) \tag{4.12}$$

The generation rate control parameter, or GCP, is defined in equation 4.13 as the generation term's potential contribution to the updating process.

$$GCP = \begin{cases} 0.5, & r_2 \geq GP. \\ 0, & else. \end{cases} \tag{4.13}$$

Where $r1$ and $r2$ represent random numbers ranging from 0 to 1. The term Generation Probability (GP) represents the proportion of particles that used the generation term to update their states [121]. To achieve a balance between exploration and exploitation ($GP = 0.5$) is used [121]. This balance enables particles to explore the search space for better potential solutions while exploiting promising regions to effectively converge toward optimal solutions.

Finally, after updating the concentration of each particle, if the fitness of the updated particle is better than the old fitness value, the global best value is updated.

4.3.3 Fitness Function

The fitness function is a foundational component of the EO-C algorithm, developed to optimize the selection of CHs in IoT-enabled SDWSNs. It addresses multiple objectives, including prolonging the network lifetime, mitigating the hot-spot problem, and maintaining energy efficiency across the network. The fitness function is mathematically formulated as:

$$\text{fitness} = \gamma \cdot f_1 + \delta \cdot f_2 + \eta \cdot f_3 \tag{4.14}$$

where f_1, f_2, and f_3 represent *total residual energy*, *energy balance ratio*, and *alive node count*, respectively. The weighting factors γ, δ, and η are used to balance the contribution of each criterion.

1) **Total Residual Energy (f_1):** The sustainability of the network significantly hinges upon the residual energy of its nodes. The equation (4.15) gives the general formula for determining total residual energy, $E_{residual}$ which represents the first objective function f_1.

$$f_1 = E_{totalCH} + E_{totalCommon} \tag{4.15}$$

where E_{totalCH} and E_{totalNN} denote the residual energy of CH and normal nodes, respectively. By prioritizing configurations with higher residual energy, the fitness function ensures sustained operation of critical network components and extends the overall network lifespan. The total remaining energy of the CH is calculated using equation (4.16), whereas the calculation of the total residual energy of a normal node within the cluster is performed using equation (4.17).

$$E_{totalCH} = \sum_{i=1}^{nCH} E_{CH_{TX}}^{iCS}(l, d) \tag{4.16}$$

Where nCH is the number of cluster heads; l represents the number of bits; d, which indicates the distance between CH and BS; and $E_{CH_{TX}}^{iCS}$, which represents the residual energy in the i^{th} node.

$$E_{totalCommon} = \sum_{j=1}^{nCH} \sum_{i=1}^{nNode} E_{SDSN_{TX}}^{ij}(l, d_{i,j}) \tag{4.17}$$

Whereas the $d_{i,j}$ is the distance from the j^{th} CH and i^{th} node; nNode represents the rest of the nodes in the network excluding CH.

2) **Energy Balance Ratio:** Cluster heads typically perform more energy-intensive tasks such as data aggregation, coordination, and communication. If cluster heads have higher energy levels, they are more likely to remain stable and operational for a longer duration, enhancing the reliability and longevity of the network. To ensure the longevity of CH, we have considered the ratio of the average energy of selected CH to the average energy in normal nodes in the network, defined in equation (4.18).

$$f_2 = \frac{E_{avg}(CH)}{E_{avg}(NN)} \tag{4.18}$$

This ratio provides a measure of the relative energy distribution between cluster heads and normal nodes within the cluster. A value greater than 1 indicates that, on average, cluster heads have more energy than normal nodes, which potentially addresses the hot spot problem, where certain nodes become overburdened due to excessive energy consumption.

The average energy of CHs, $E_{avg}(CH)$, and the average energy of normal nodes, $E_{avg}(NN)$, is calculated using equations (4.19) and (4.20) respectively.

$$E_{avg}(CH) = \frac{E_{totalCH}}{N_{CH}} \tag{4.19}$$

$$E_{avg}(NN) = \frac{E_{totalCommon}}{N_{NN}} \tag{4.20}$$

Where N_{CH} is the total number of CH in the network and $E_{avg}(NN)$ represents normal nodes in the network.

3) **Total Alive Nodes:** The count of alive nodes provides a crucial metric for assessing the overall health and status of the network at any given time. Maintaining a higher number of alive nodes is essential for ensuring robust connectivity and uninterrupted data flow. The objective function f_3 encourages configurations that keep more nodes alive. Equation 4.21 is used to calculate the number of alive nodes in the network.

$$N_{\text{alive}} = \sum_{i=1}^{N} \text{countIF}(E_i(node) > 0) \tag{4.21}$$

Where $E_i(node)$ is the energy left in i^{th} node.

By leveraging this fitness function, EO-C achieves optimal energy efficiency, longevity, and resilience, addressing both the hot-spot problem and overall network performance challenges.

4.4 Result and Analysis

Table 4.1 provides an overview of the many factors associated with EO-C and IoT-enabled SDWSN, which form the basis for the performance analysis presented in this section using computer simulations. All experimental procedures were conducted using the MATLAB (version 2023a) software on an Intel i5 processor equipped with 8GB of RAM technology.

Table 4.1: Parameters for Testing

Category	**Parameter**	**Value**
Network	Deployment Area (m^2)	100×100
	BS (Position)	50, 50
	Energy	0.5J per Node
	No. of SDSNs	100
Application	Data Packet Length	100 bits
	Broadcast Packet Size	25 bits
EO-C	Initial POP	20
	Iteration	100
	γ, δ, η	0.6, 0.2, 0.2

4.4.1 Simulation Parameters

The behavior of IoT-enabled SDWSNs nodes is simulated in a geographical area of 100m x100 m with a base station at the center using the testing settings listed in Table 4.1. A network of 100 nodes is deployed at random, as shown in Figure 4.3. An energy allocation of 0.5J is assigned to each node in the network.

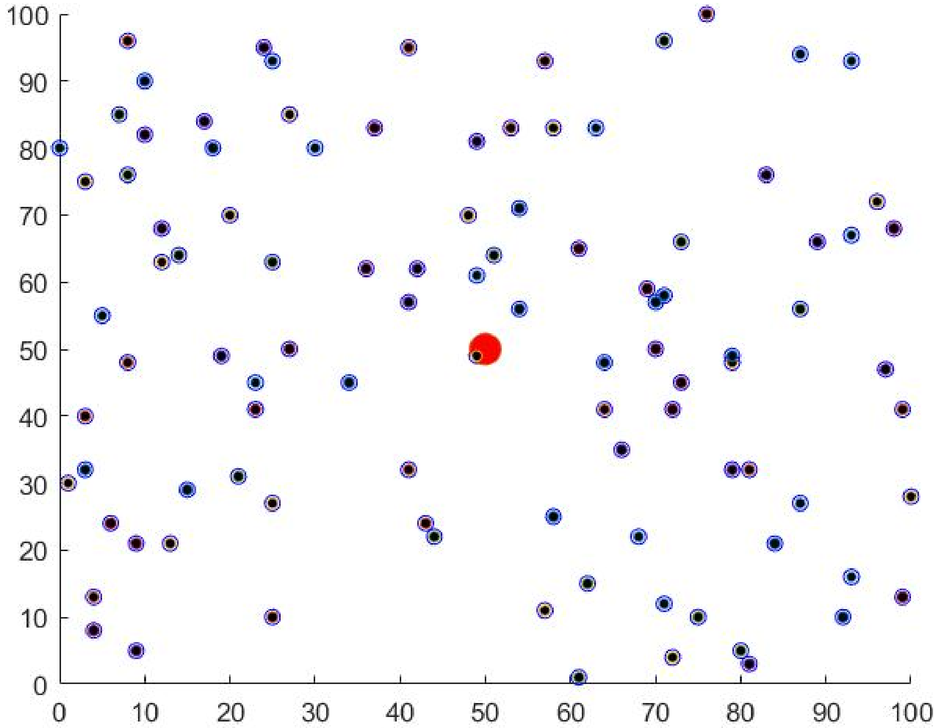


Figure 4.3: Network scenario: Random deployment of 100 nodes in a 100m x 100m area.

The particle population was initialized using equation 4.5 to generate their initial concentration. The search domain was configured as a multidimensional space, with particle concentration vectors confined to the range [-4, 4]. The Population size and number of cluster plays important role in the optimization process. Both parameters are discussed below:

- **Optimal Population Size and Iterations count:** In order to determine the optimal number of particle populations and the minimum number of iterations, the fitness function was evaluated using various population sizes ranging from 5 to 50. The findings, illustrated in Figure 4.4, demonstrated that the optimal fitness value was achieved by setting the initial population size to 20 and imposing a maximum restriction of 100 iterations. The parameter configurations employed in this algorithm effectively balanced the exploration and exploitation aspects within the search space, hence promoting efficient convergence toward optimal solutions.

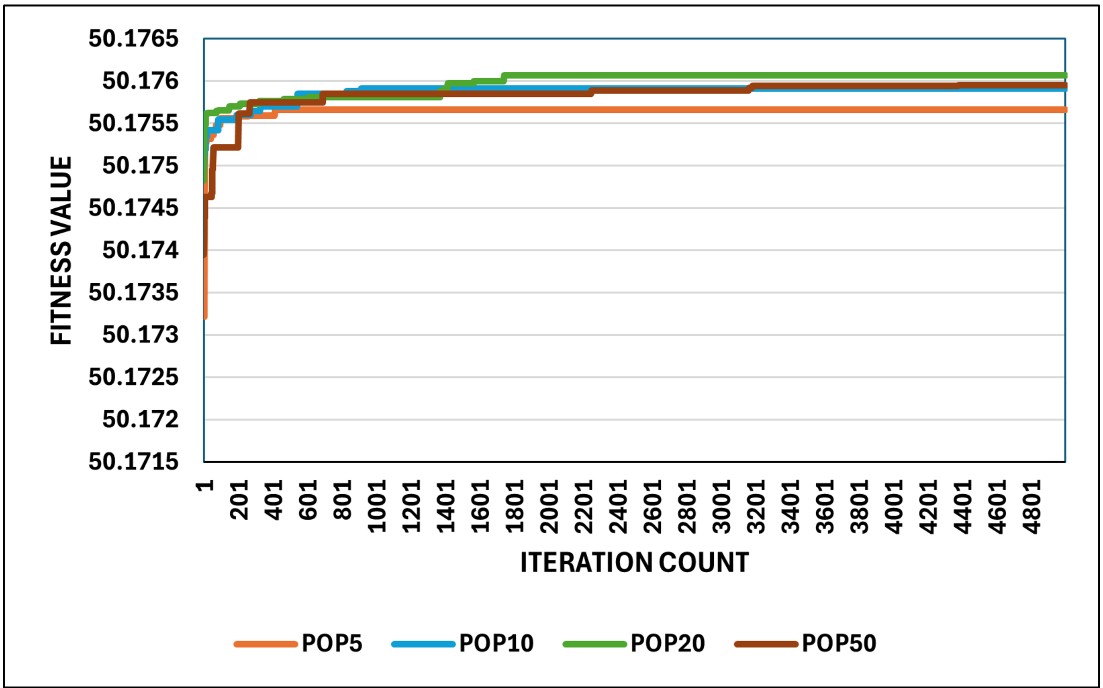


Figure 4.4: Fitness of EO-C evaluated with various population sizes.

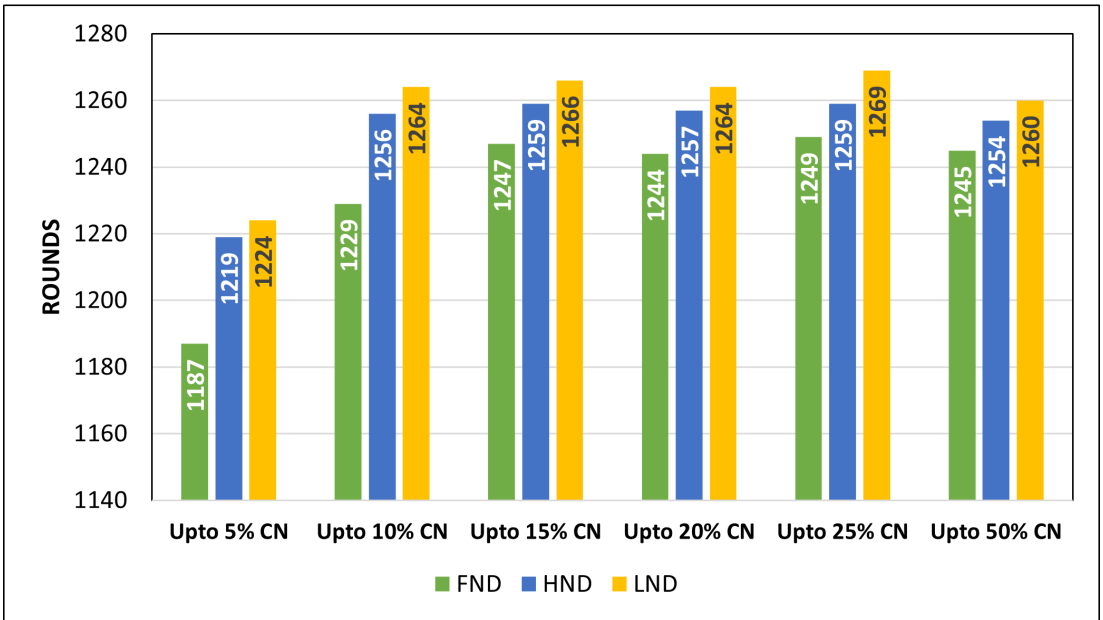


Figure 4.5: Performance of EO-C with different ranges of CH count.

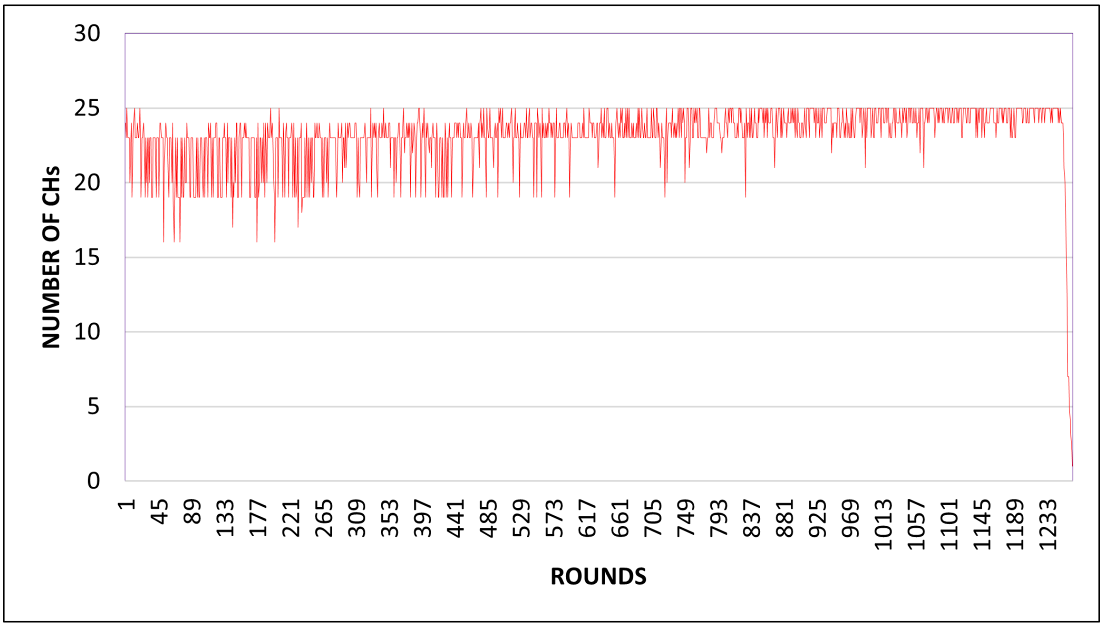


Figure 4.6: Random Number of CHs per Round.

- **The Optimal range of CH count:** In the proposed algorithm, the number of CH is not fixed; instead, the algorithm selects the best CH count based on network conditions. To determine the optimal range for CH count, we evaluated the EO-C with CH ranges of 5%, 10%, 15%, 20%, 25%, and 50%, as seen in Figure 4.5. The Figure 4.5 shows that the First Node Died (FND), Half Node Died (HND), and Last Node Died (LND) [65] metrics continually grow and reach a peak when the CH range is up to 25% of alive nodes; when the CH range is up to 50%, the performance of EO-C somewhat falls. Based on the previous observations, we may conclude that the optimal range for CH count is up to 25%.

In subsequent experiments, a population size of 20 was selected, with an iteration limit of $iterMax = 100$. Additionally, The cluster head count was randomly chosen to be between 5% and 25% of the alive nodes.

4.4.2 EO-C Performance Evaluation

In this sub-section, the performance of the EO-C algorithm under various conditions is examined.

- **Network Performance:** To test the network performance 100 nodes are deployed in 100 m x 100 m area with initial energy $100 \times 0.5J = 50J$ where each node is assigned $0.5J$ initial energy. As discussed in the preceding section, the CH count is capped at 25% of the total alive nodes. In EO-C, the cluster count varies dynamically with each round. Figure 4.6 shows that EO-C selects cluster numbers randomly based on fitness value. From the initial round until the 1260th round, the cluster count fluctuated between 16% and 25% of alive nodes and subsequently started decreasing from the 1261st round onward.

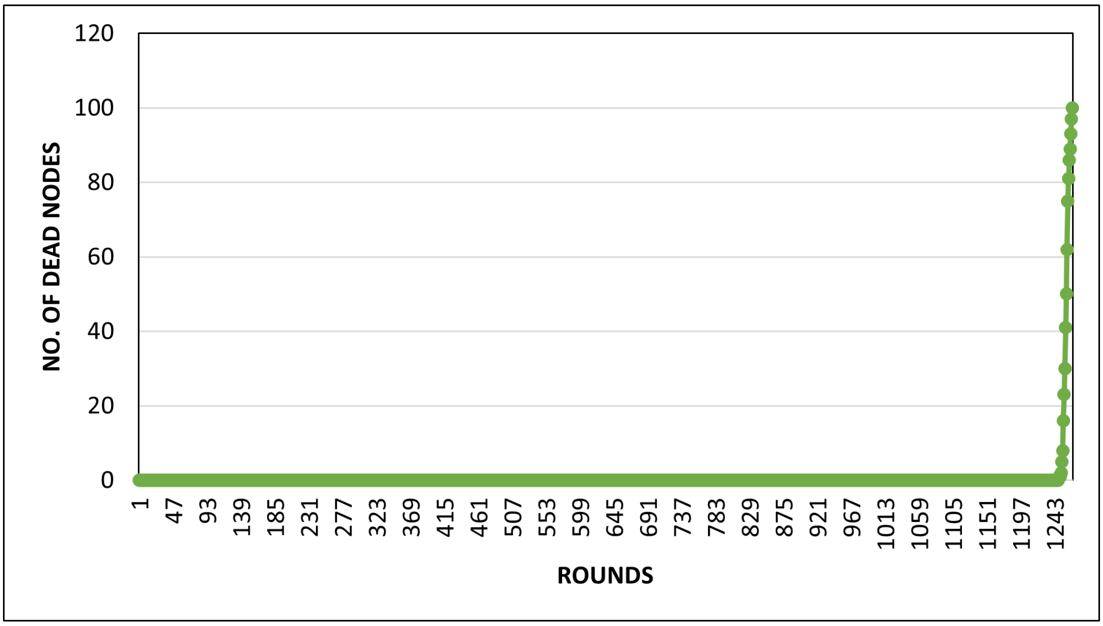


Figure 4.7: Dead Nodes per Round.

The performance of EO-C is illustrated in Figure 4.7. The results demonstrate that the proposed algorithm sustained the transmission till 1248th round. This delayed node failure demonstrates the proposed algorithm's robustness, as it lasted several rounds before experiencing the initial node failure at the 1249th round. Figure 4.8 depicts the total energy remaining in the network after each round, indicating a consistent and gradual energy decay.

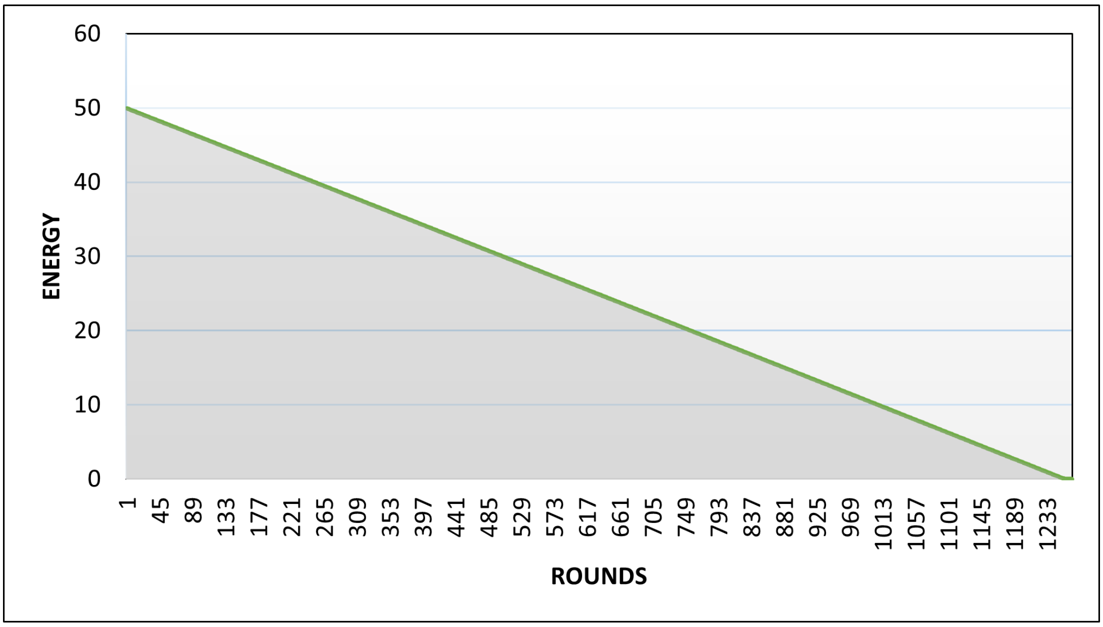


Figure 4.8: Total Network Energy Left per Round.

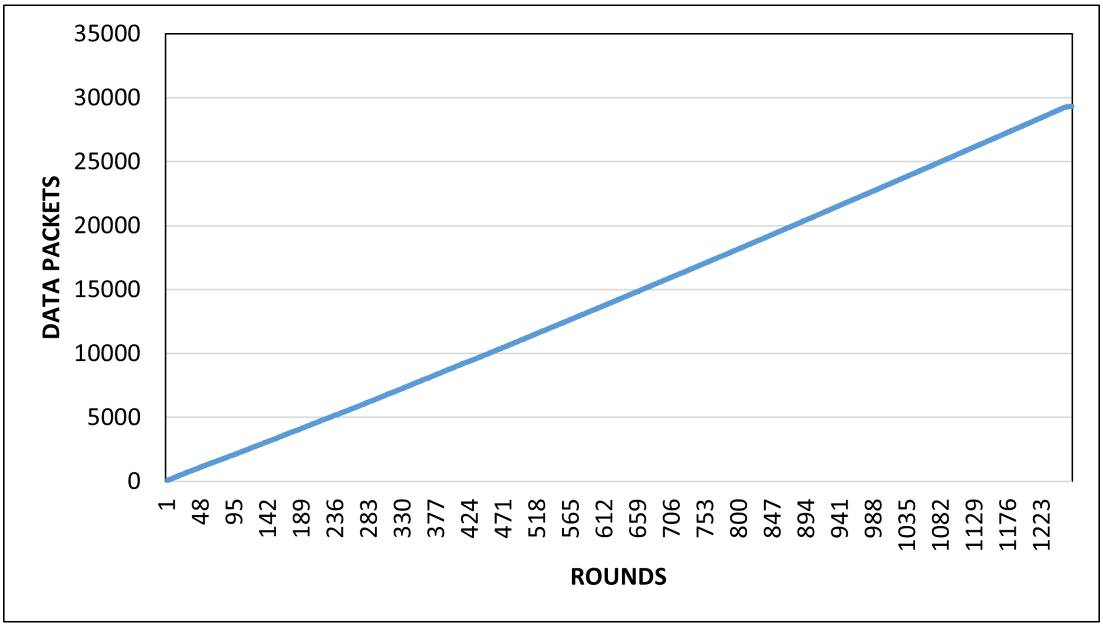


Figure 4.9: Total Data Packet Sent to BS per Round.

The proposed algorithm transmitted a total 29320 number of packets before exhausting their energy, which is shown below in Figure 4.9. The energy consumption analysis in Figure 4.10 reveals the distribution of energy usage among different activities within the network. The CH consumed the highest proportion of energy, accounting for 96.64% of the total 50 joules. Neighboring node communication (energyNN) utilized

3.51%, while energy aggregation (energyAgg) required only 0.0003%. These findings highlight the significant energy demands of the CH role, underscoring the importance of optimizing CH selection to enhance network energy efficiency. By addressing this imbalance, the proposed EO-C algorithm effectively mitigates energy hotspots and improves network lifespan, as demonstrated in the simulation results.

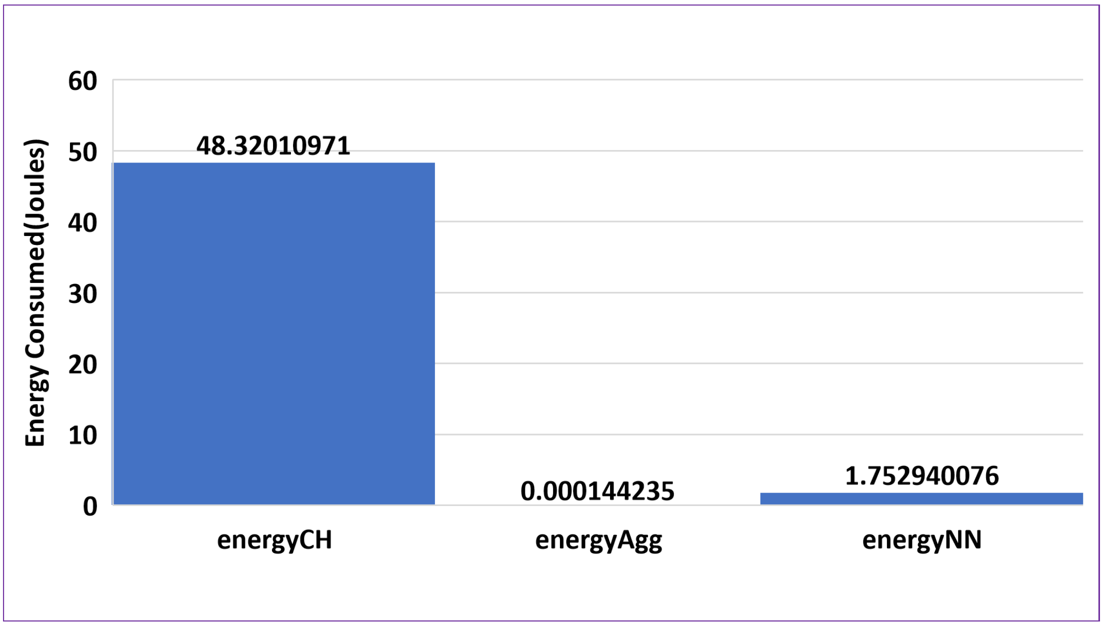


Figure 4.10: Energy Consumption by different phases.

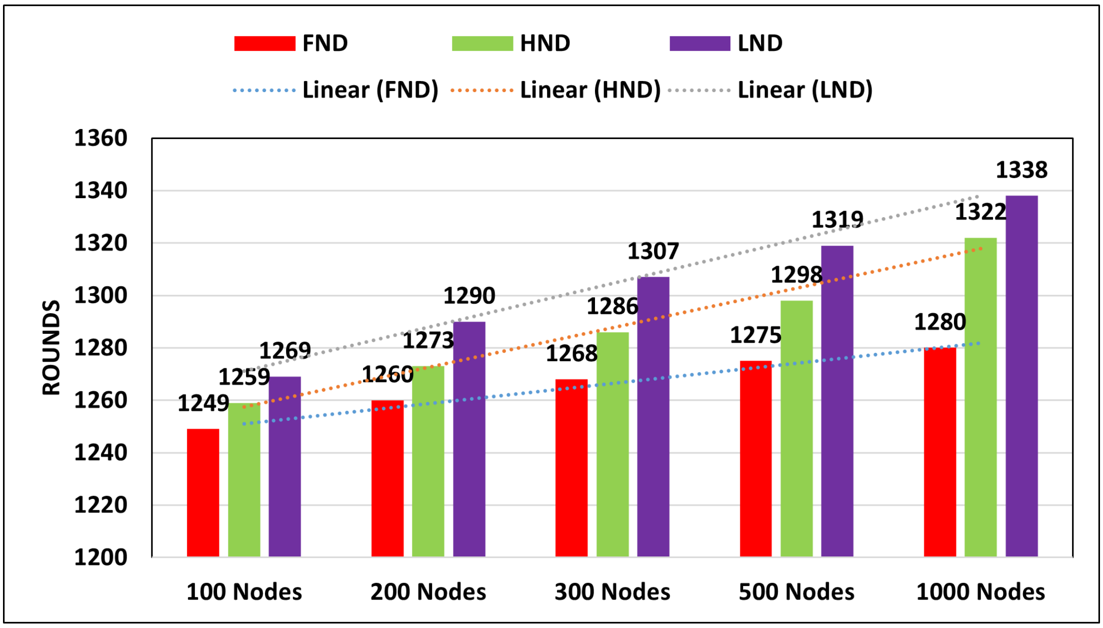


Figure 4.11: Performance of EO-C with respect to various node densities.

- **Impact of Node Density:** To study the scalability and robustness of the proposed algorithm, we tested the EO-C algorithm with node density of 100, 200, 300, 500, and 1000 nodes in an area of 100 m x 100 m. The igure 4.11 shows the performance of the network in terms of the FND, HND, and LND. These metrics provide insights into the network's resilience and efficiency as node density changes. The results depict that, as the number of nodes increases, the performance of the network (in terms of FND, HND, and LND) shows an upward trend, peaking at 1000 nodes. This observation highlights the proposed algorithm's scalability, as it can effectively handle larger node populations while remaining robust and resilient. Furthermore, it emphasizes the algorithm's ability to adapt and optimize performance across varying node densities, an important aspect in real-world network deployments where node populations may fluctuate.

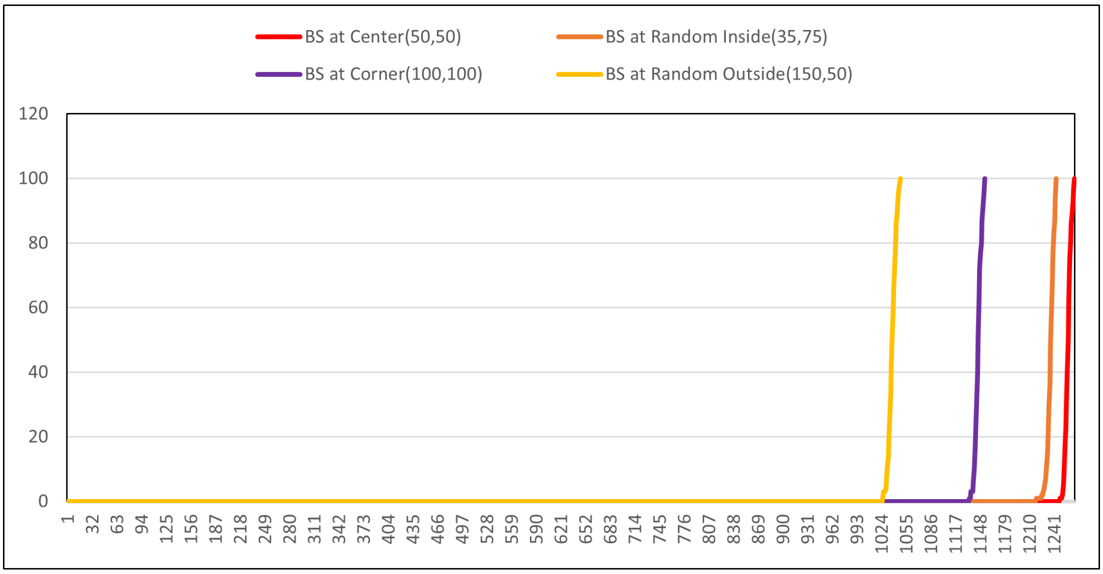


Figure 4.12: Performance of EO-C with respect to various BS positions.

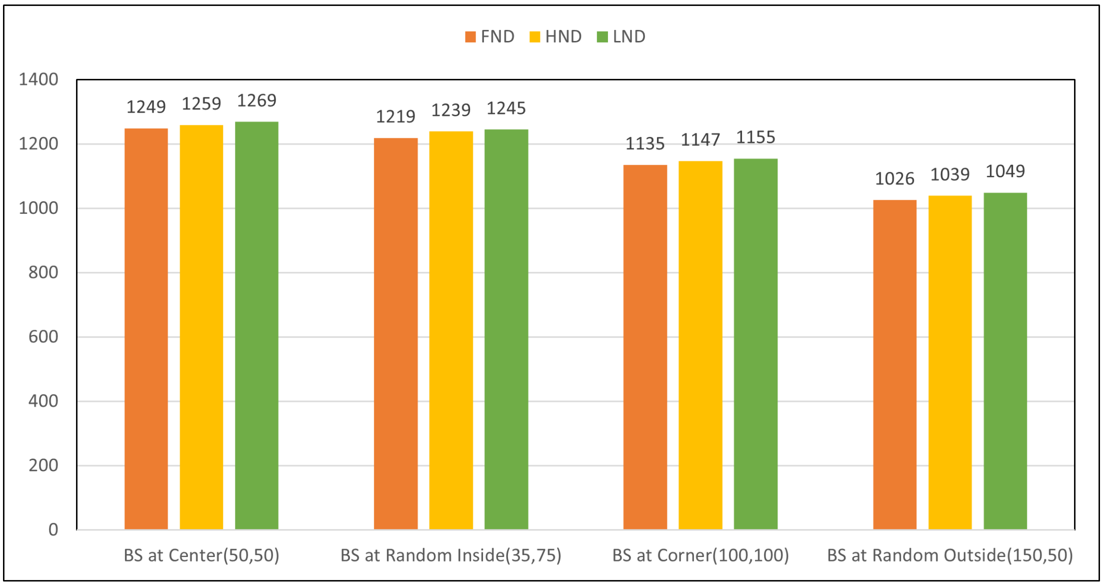


Figure 4.13: FND, HND, and LND of EO-C network at various BS positions.

- **Impact of BS Location:** The base stations serve as central points for network management, data collection, and coordination. The location of BS has a great impact on network life. To test the performance of the proposed algorithm, we deployed 100 nodes in a 100 m x 100 m area with the BS at the center location (50,50), random location (35,75) inside the deployment area, random location (50,150) outside the deployment area, and at the corner (100,100). From Figure 4.12, we can observe that the network performs best when the location of BS is at the center (50,50) and worst when BS is outside the deployment area, i.e., location (50,150). This suggests that BS placement directly influences network performance, with central locations facilitating better network management and coordination. In Figure 4.13, metrics such as FND, HND, and LND exhibit minimal variation across all cases, with deviations ranging between 20 to 30 rounds. However, a clear trend emerges, network performance peaks when BS is located at the center, gradually declining as BS moves away from this optimal position, with the best performance observed at (50,50), followed by (35,75), (100,100), and worst at (50,150). By strategically locating BS, network designers can maximize efficiency and ensure robust operation, particularly in scenarios where network resources are limited.

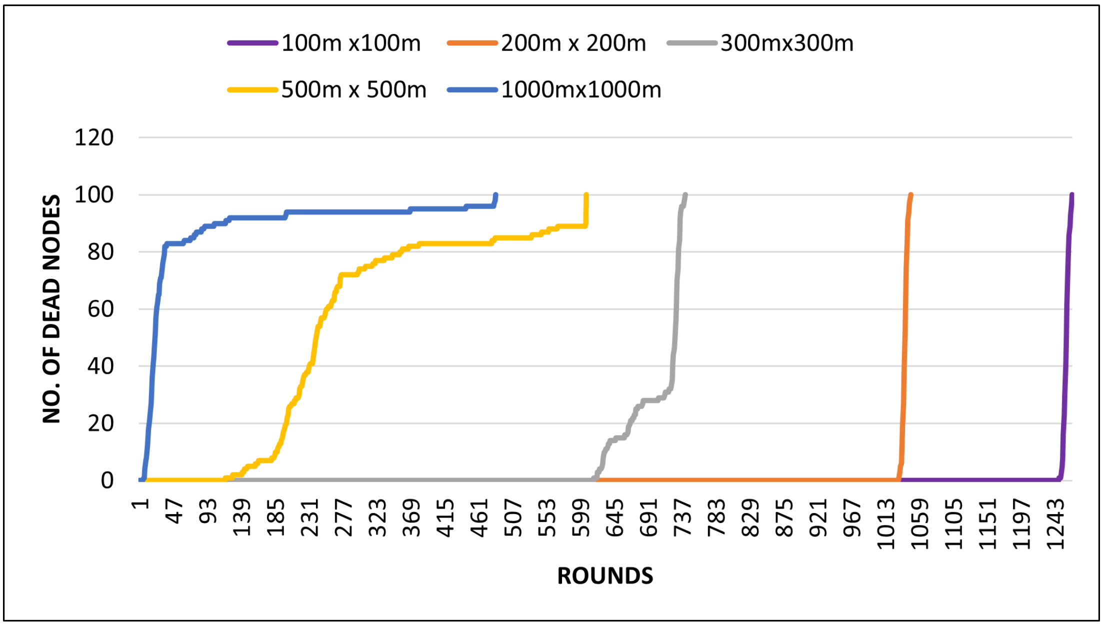


Figure 4.14: Performance of EO-C in different deployment area sizes.

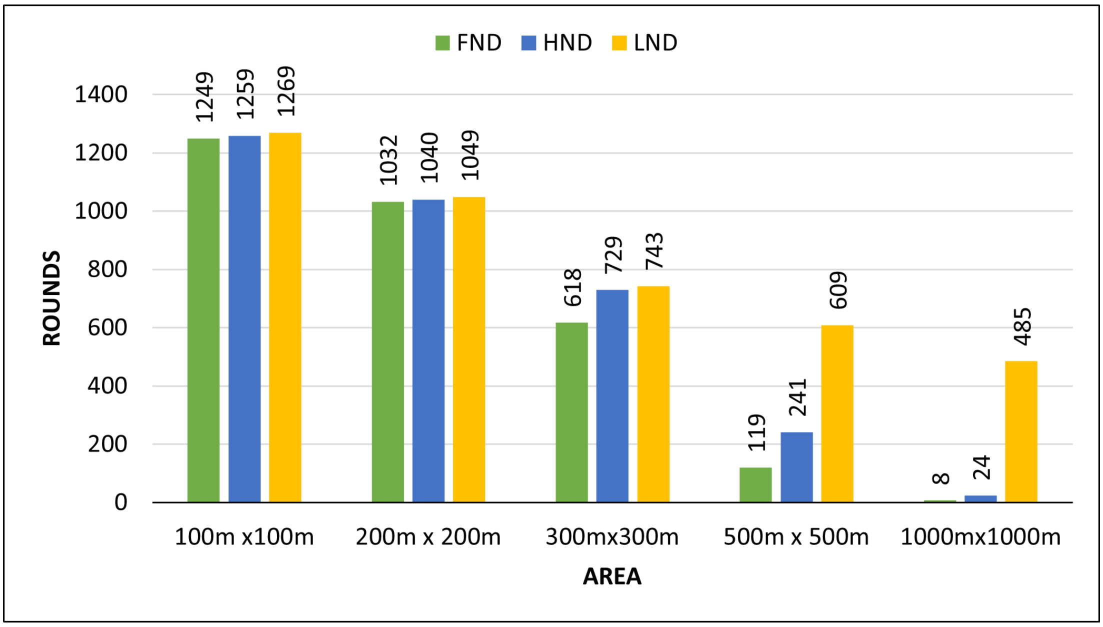


Figure 4.15: Impact of deployment area size on FND, HND, and LND of the EO-C algorithm.

- **Impact of area of deployment:** Understanding the effect of area on a network is critical for design, optimization, and management. By considering the size of the deployment area, network planners can make informed decisions to address coverage, connectivity, resource allocation, scalability, and energy efficiency. To test the performance of EO-C in different coverage areas, we deployed 100 nodes in areas of sizes 100 m x 100 m, 200 m x 200 m, 300 m x 300 m, 500 m x 500 m, and 1000 m x 1000 m. From igure 4.14 and 4.15, we can observe that the performance of the network decreases as the area of deployment increases. Specifically, the EO-C algorithm performed best when the area is 100 m x 100 m and worst when the area is 1000 m x 1000 m. Also, from igure 4.15, we can observe a trend in FND and HND metrics. Both parameters experience a sharp decline as the deployment area increases. However, with LND, the value decreases gradually. FND for deployment areas 100 m x 100 m, 200 m x 200 m, 300 m x 300 m, 500 m x 500 m, and 1000 m x 1000 m are 1249, 1032, 618, 119, and 6 rounds, respectively. This trend highlights the impact of deployment area size on network performance, with larger areas leading to quicker exhaustion of network resources and, consequently, earlier node failures.

4.4.3 Comparative Analysis

In this section, we evaluate the simulation results of EO-C in comparison to several SoA algorithms, including LEACH [62], GWO-C [84], EBGWO [86], and EAFFO [98]. EO-C is configured using all parameters listed in Table 4.1. To evaluate the effectiveness of each algorithm, we consider performance metrics such as FND, HND, LND, residual energy, and the number of data packets sent to the BS.

Table 4.2: Comparison of Performance Metrics

Algorithm	**FND**	**HND**	**LND**
LEACH	270	447	662
GWO-C	538	1195	1377
EB-GWO	1078	1258	1303
EAFFO	998	1466	2062
EO-C	1249	1259	1269

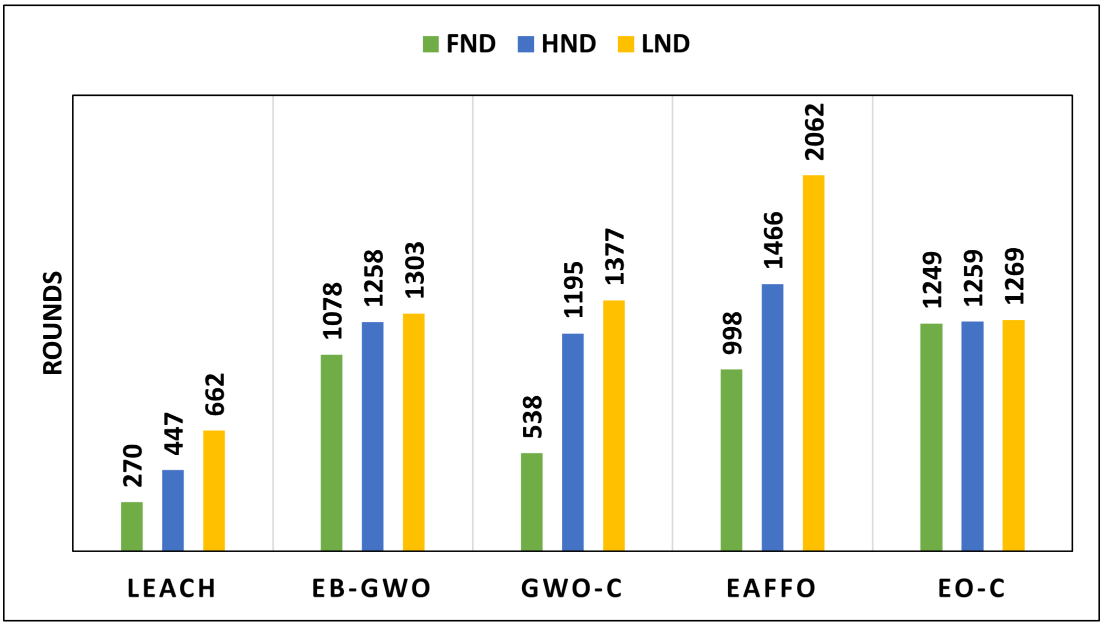


Figure 4.16: Comparison of FND, HND, and LND of EO-C with SoA algorithm.

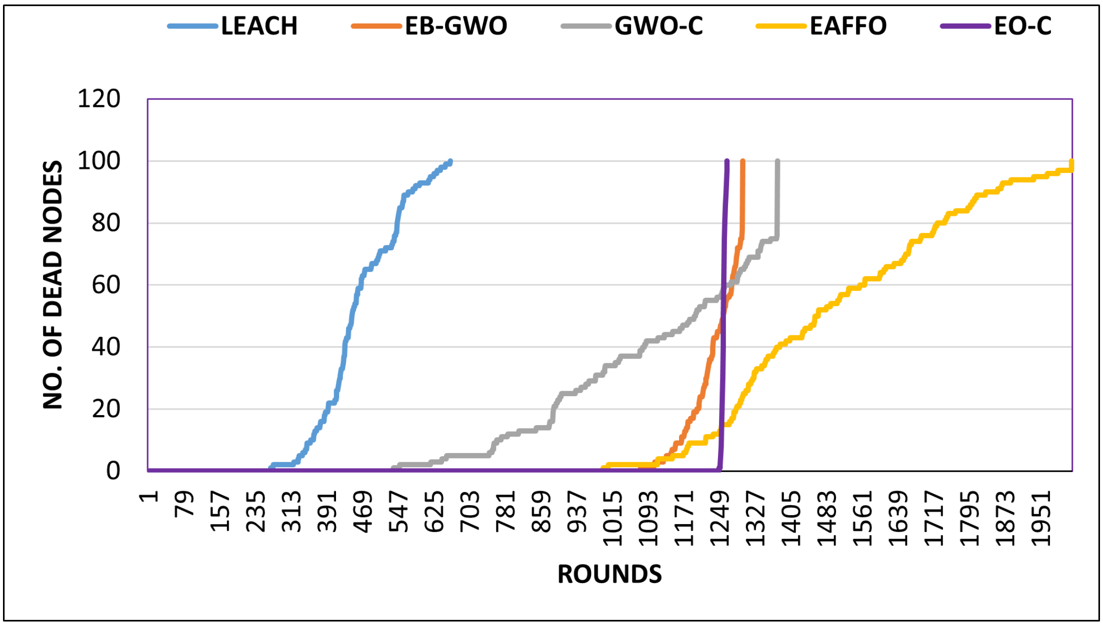


Figure 4.17: Dead node comparison of EO-C with SoA algorithms.

The Table 4.2 and Figure 4.16 provide a comparison of performance metrics (FND, HND, & LND) for various algorithms, including EO-C, EAFFO, EB-GWO, GWO-C, and LEACH. The performance of EO-C surpasses that of other SoA algorithms across all metrics. EO-C records 1249 for FND, 1259 for HND, and 1269 for LND. In Figure 4.17, the number of dead nodes is plotted against the number of rounds.

The results show that FND for EO-C, EAFFO, EB-GWO, GWO-C, and LEACH at 1249, 998, 1078, 538, and 270, respectively. EO-C exhibits a notable enhancement in network lifespan for periodic data collection when compared to several other algorithms. Although the network life span is high in EAFFO, i.e. 2062, but EO-C outperforms EAFFO in terms of FND by more than 25.15%. Moreover, EO-C outperforms LEACH, GWO-C, and EB-GWO, increasing network lifespan by over 362.6%, 132.15%, and 15.86%, respectively. Since EO-C exhibits the longest time to FND happened, these findings highlight EO-C's effectiveness in mitigating the hot spot problem, as well as its potential as an effective strategy for improving network longevity in the context of periodic data collection.

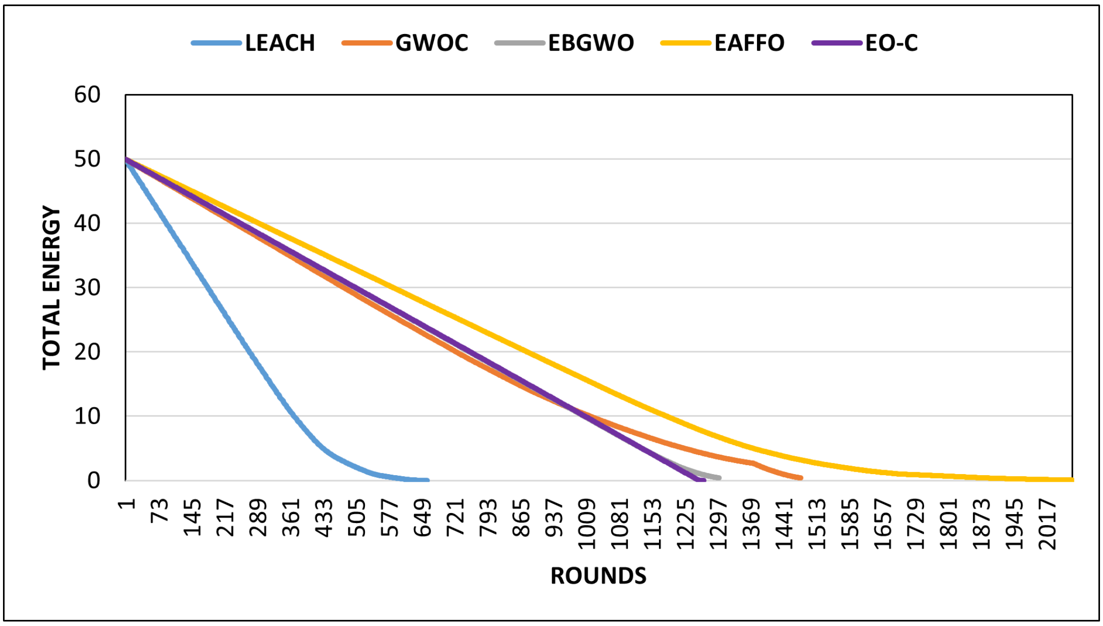


Figure 4.18: Comparison of energy decay in EO-C with SoA algorithm.

Figure 4.18 shows the network's residual energy per round. The graph shows a steady energy decline, which is important because it allows the algorithm to maintain network stability, with nodes failing only in the final 5% of rounds. This characteristic is especially important in scenarios where the failure of a single node might endanger the entire network.

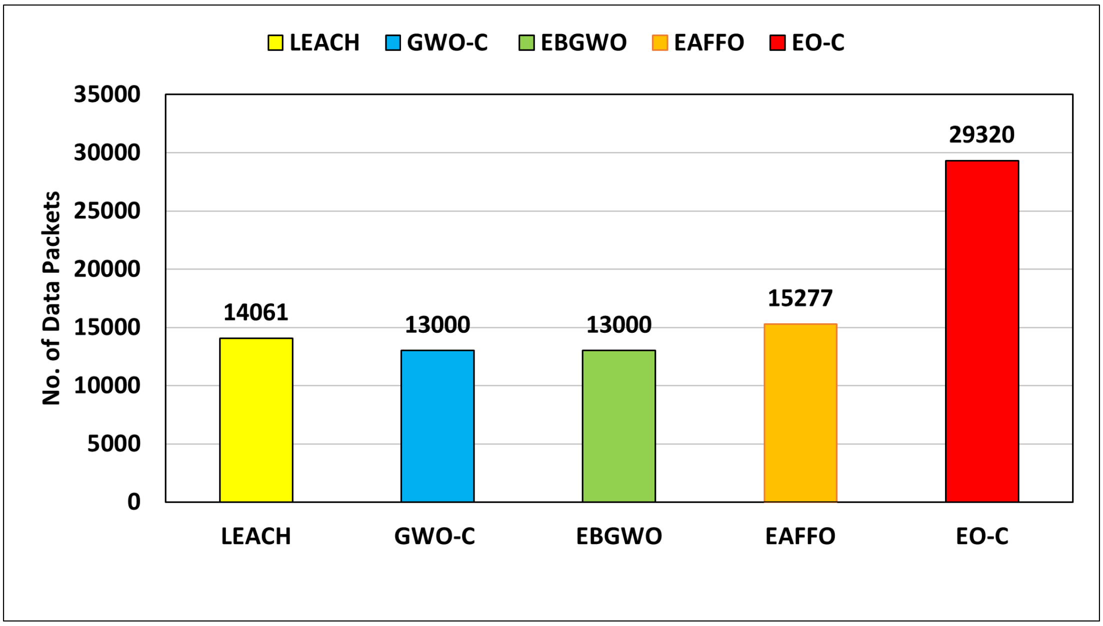


Figure 4.19: Comparison of data packets sent to BS in EO-C with SoA algorithm.

Figure 4.19 illustrates the comparison of various SoA with the EO-C algorithm. The graph demonstrates that EO-C outperforms the EAFFO, EB-GWO, GWO-C, and LEACH algorithms in terms of data transmission volume, with 29320 data packets, which is 108.5% higher than LEACH.

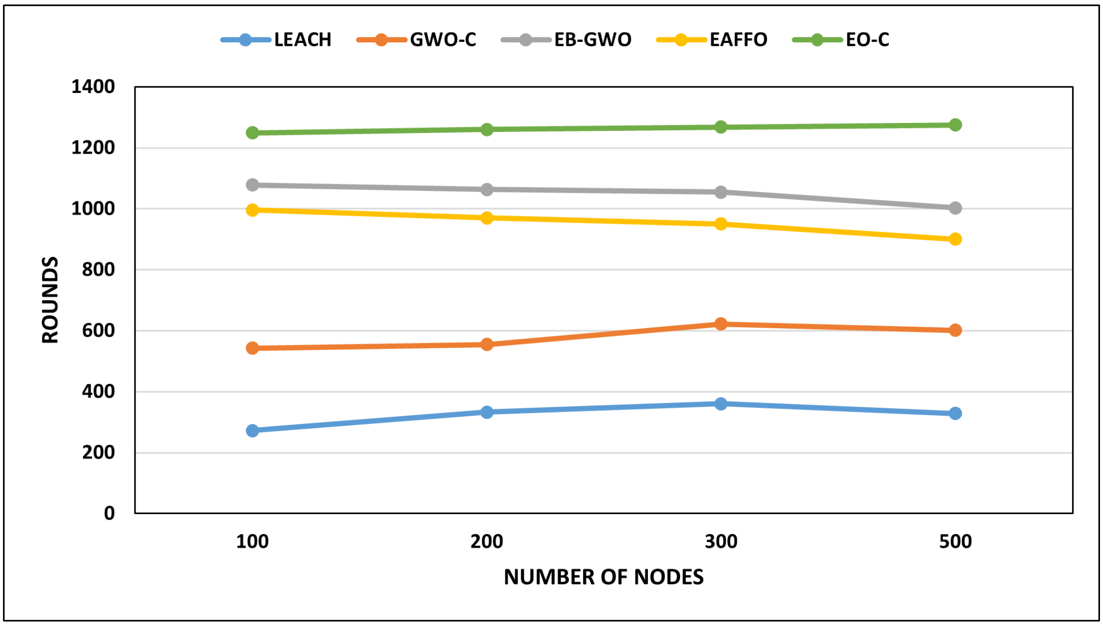


Figure 4.20: Comparison of performance of EO-C with SoA algorithm with respect to node density.

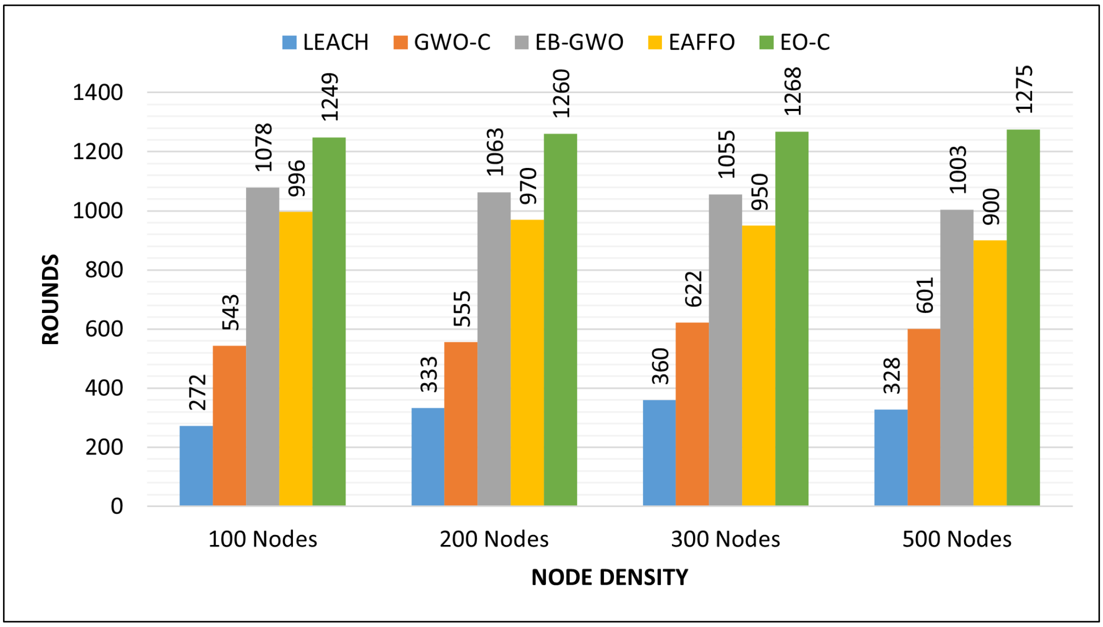


Figure 4.21: Comparison of EO-C with SoA algorithm with respect to FND vs node density.

To compare the robustness & the scalability of the proposed algorithm with SoA like EAFFO, EB-GWO, GWO-C, and LEACH. We tested our algorithm with 100, 200, 300 and 500 nodes in 100 m x 100 m area of deployment, as shown in Figures 4.20 and 4.21. From the analysis of the results depicted in the graph, it is evident that EO-C outperforms all the state-of-the-art algorithms across all tested network sizes. EO-C's ability to maintain superior performance as network size increases demonstrates its effectiveness in handling larger-scale deployments and resilience to scalability challenges. Thus, based on these findings, EO-C appears to be a promising solution for robust and salable IoT-enabled SDWSNs applications.

4.4.4 Mitigating Hot-Spot Problems

The simulation results highlight EO-C's superior performance in mitigating the hot-spot problem compared to SoA algorithms. EO-C achieved a FND metric of 1249 rounds, significantly outperforming LEACH (270 rounds), GWO-C (538 rounds), EAFFO (998 rounds), and EB-GWO (1078 rounds). This demonstrates that EO-C effectively prevents premature energy depletion in nodes near the base station by dynamically balancing energy consumption across the network. Furthermore, the energy decay analysis (Figure 4.18) demonstrates that EO-C promotes a gradual reduction in energy levels, ensuring that nodes in critical regions retain sufficient energy to prolong the network's lifespan. This balanced energy consumption effectively minimizes the formation of energy hotspots, enhancing the network's reliability, stability, and overall performance.

These results confirm EO-C's capability to alleviate hotspot issues, making it a robust and energy-efficient solution for IoT-enabled SDWSN applications, where network longevity and resilience are critical.

4.4.5 Statistical Validation

To evaluate the performance of EO-C in comparison to other methods (LEACH, GWO-C, EB-GWO, and EAFFO), a pairwise t-test was conducted. The results (shown in Table 4.3) revealed statistically significant differences in performance between EO-C and SoA algorithms.

Table 4.3: Pairwise t-test Results Between EO-C and Other SoA Methods

Comparison	**t-statistic**	**p-value**	**Cohen's d**	**95% CI**	**Significance**
LEACH vs EO-C	48.698	5.03×10^{-9}	6.12	[942.57, 1017.93]	Yes
GWO-C vs EO-C	34.975	3.64×10^{-8}	5.23	[680.94, 819.06]	Yes
EB-GWO vs EO-C	12.380	1.70×10^{-5}	2.78	[183.27, 274.73]	Yes
EAFFO vs EO-C	14.667	6.31×10^{-6}	3.12	[224.86, 275.14]	Yes

1. **LEACH vs EO-C:** EO-C significantly outperformed LEACH with a large t-statistic ($t = 48.698$) and an extremely low p-value ($p = 5.03 \times 10^{-9}$). The effect size (Cohen's $d = 6.12$) indicates a substantial difference, while the 95% confidence interval ([942.57, 1017.93]) confirms consistent performance gains.

2. **GWO-C vs EO-C:** A strong performance advantage was observed for EO-C, with a t-statistic of $t = 34.975$ and a p-value ($p = 3.64 \times 10^{-8}$). The effect size (Cohen's $d = 5.23$) reflects a substantial difference, supported by the confidence interval ([680.94, 819.06]).

3. **EB-GWO vs EO-C:** EO-C showed significant improvement over EB-GWO, evidenced by a t-statistic of $t = 12.380$ and a p-value ($p = 1.70\times10^{-5}$). The effect size (Cohen's $d = 2.78$) highlights a meaningful difference, with a confidence interval of [183.27, 274.73].

4. **EAFFO vs EO-C:** EO-C also outperformed EAFFO, with a t-statistic of $t = 14.667$ and a p-value ($p = 6.31 \times 10^{-6}$). The effect size (Cohen's $d = 3.12$) indicates a large difference, and the confidence interval ([224.86, 275.14]) reinforces the result.

The results strongly support the effectiveness of EO-C in achieving energy-efficient operation, delaying node failures, and sustaining network operations for longer durations. These findings highlight EO-C's potential for critical applications such as environmental monitoring, disaster management, and IoT-based systems.

4.5 Chapter Summary

In this chapter, we proposed and evaluated an equilibrium optimizer clustering algorithm. EO-C is based on an equilibrium optimizer algorithm and is designed to address the energy conservation, optimum CH selection, optimum CH count selection, and hot spot problem in IoT-enabled SDWSNs. EO-C addresses these challenges with the help of dynamic CH count and a novel fitness function based on total residual energy, energy balance ratio, and total number of alive nodes in the network. Further, the performance of EO-C under various conditions is compared with several SoA algorithms, including EAFFO, EB-GWO, GWO-C, and LEACH. The results indicate that the EO-C outperforms other SoA algorithms in terms of network longevity, resilience, scalability, and coverage. The simulation results demonstrate that the proposed algorithm shows improvement ranging from 15.9% to 372.6% when compared with EAFFO, EB-GWO, GWO-C, and LEACH. However, despite these enhancements, EO-C was observed to suffer from uneven energy depletion and routing instability, particularly in scenarios involving high node density, large deployment areas, or when the base station is positioned outside the network field. To effectively address these specific stability issues, the subsequent chapter introduces a hybrid multi-constrained approach named EQ-AHA.

Overall, EO-C has the potential to significantly improve the reliability and efficiency of IoT applications in various domains, including smart cities, environmental monitoring, and industrial automation.

CHAPTER 5

A MULTI-CONSTRAINED GREEN ROUTING PROTOCOL FOR IOT-BASED SOFTWARE-DEFINED WSN

The evolution of energy-efficient routing protocols in IoT-enabled SDWSNs, as presented in Chapters 3 and 4, marks significant strides toward addressing energy constraints and QoS challenges in resource-constrained environments. Chapter 3 introduced the *Energy-Optimized Artificial Hummingbird Algorithm*, a single-objective, nature-inspired approach that demonstrated considerable improvements in energy-aware clustering and routing. By focusing on residual energy and transmission cost, EOAHA effectively extended network lifetime and reduced communication overhead. To overcome these limitations, Chapter 4 proposed the *Equilibrium Optimizer Clustering* protocol—a multi-objective routing framework that balanced total residual energy, energy ratio, and node alive. This holistic design enabled EO-C to outperform EOAHA by delivering enhanced reliability and scalability across varying network densities and topologies. In high-density networks or highly dynamic scenarios, EO-C was observed to suffer from uneven energy depletion among nodes and routing instability.

Building upon the insights and performance gaps identified in the preceding chapters, this chapter introduces an advanced solution: the *EQ-AHA* (Equilibrium Optimizer and Artificial Hummingbird Algorithm).

5.1 Introduction

The limitation of the EOAHA and EO-C routing algorithms was the use of direct transmission techniques between CH and BS, which exhausts the CH energy. To solve this problem, we have extended our work by proposing a hybrid algorithm named EQ-AHA, i.e., Equilibrium Optimizer (EO) [121] with Artificial Hummingbird Algorithm (AHA) [118]. The proposed solution acts in two steps: Firstly, EQ-AHA utilizes the AHA to find the best CHs among the live nodes in the IoT network, and in the next step, it finds an optimized route between CHs and BS using EO. In this way, we optimize the allocation of energy resources and achieve an even distribution of load among sensor nodes. This newly designed protocol extends the capabilities of EOAHA and EO-C by integrating a multi-constrained optimization strategy that jointly considers communication distance, energy consumption, load balancing, packet delivery ratio, latency, and residual energy in the routing process. The main contributions of this chapter are as follows:

- This chapter introduces EQ-AHA, a novel approach to improve networks' longevity by utilizing two meta-heuristic algorithms, AHA and EO. Specifically, the AHA is used to determine the CH and form clusters, while the EO algorithm finds the optimal route among the clusters for delivering aggregated data to the BS.
- The fitness functions for both meta-heuristic algorithms are designed separately while considering various constraints. These constraints include the distance between CH & BS and the residual energy. The shortest route to the BS, and the distance between the CH & the cluster nodes.
- To evaluate the effectiveness of the EQ-AHA algorithm, its performance is evaluated under diverse conditions.
- The experimental study on EQ-AHA yielded compelling evidence indicating that it outperforms other SoA methods.

5.2 The System Model

The system model is divided into two parts: the network model and the energy model. The explanation of the network model is as follows:

5.2.1 The Network Model

The following Figure 5.1 shows the IoT-SDWSN network model, which can also be represented by a graph G = (V, C). In this model, C represents the communication links connecting the vertices, while V represents the set comprising SDSNs, CHs, and BS.

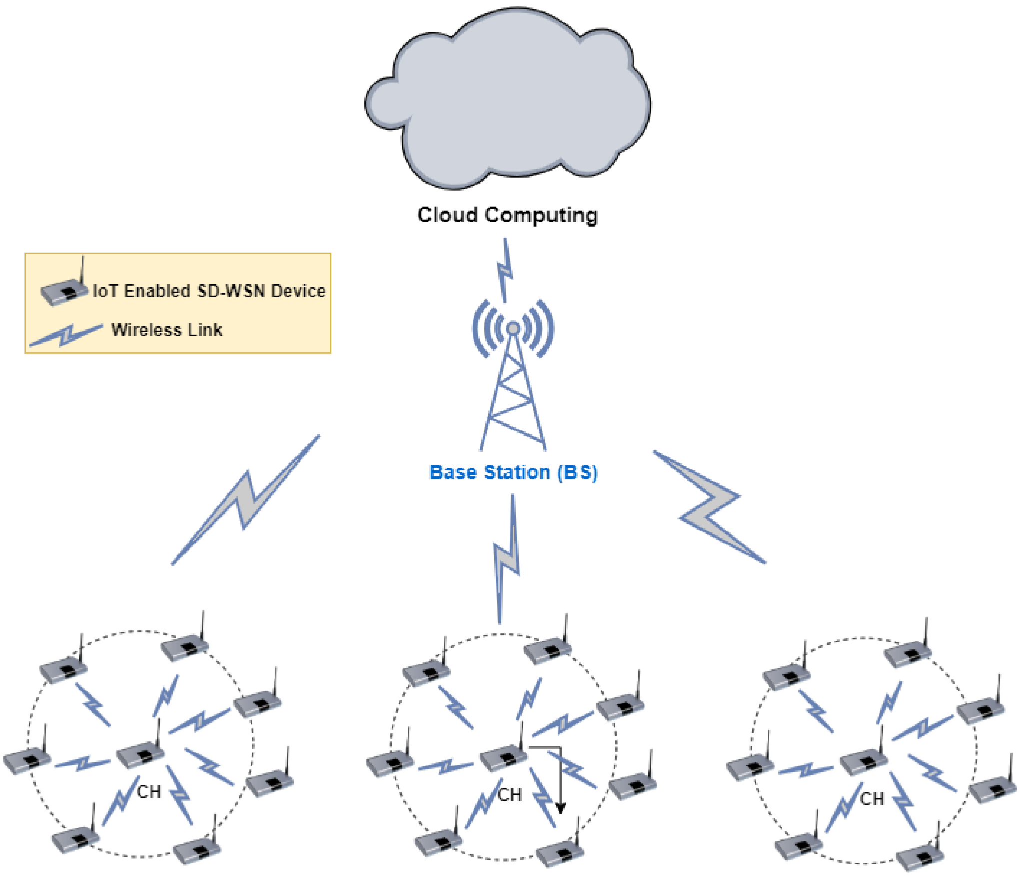


Figure 5.1: A scenario of an IoT-enabled SD-WSN with a BS and CH.

The various characteristics of this model are defined, which are as follows:

- All devices remain immobile and |SDSN| = |NN| ∪ |CH|. Where, Device IDs are represented by $ID = 1, 2, \ldots\ldots, N$, and NN is a normal node.
- Every node performs some task denoted as $\lambda_j = \lambda_{pressure}, \lambda_{vibrations}, \ldots, \lambda_{sensing}$. BS controls these tasks through programming.

- The location of the SDSN is represented as $SDSN(x, y)_i \in [x_{\min}, x_{\max}], [y_{\min}, y_{\max}]$.
- The complete path followed by sensing node i, denoted as $Path_i$, consists of two segments: l_{i-CH} and l_{CH-BS}. (i.e., from sensor node to CH and then CH to BS)
- In this system, the communication links exhibit symmetry, indicating that the link l_{j-i} connecting node j and node i is indistinguishable from the link l_{i-j} connecting node i and node j. This symmetry implies that the communication link is a full-duplex link.
- Each SDSN has the capability to operate in two different modes: sensing mode, denoted as $M = 0$, or CH mode, denoted as $M = 1$. In the sensing mode, the SDSN primarily functions as a sensor node, collecting and transmitting data from its assigned tasks. On the other hand, in the CH mode, the SDSN takes on the role of CH, responsible for processing and forwarding data received from other sensor nodes within the network. The SDSN can switch between these modes based on the system's requirements.
- Each SDSN lacks knowledge of its location and does not possess GPS-enabled equipment (i.e. $SDSN_i(GPS) = 0$).
- The IoT-enabled SD-WSN is homogeneous, which means that all the SDSNs within the network have the same characteristics and functionality.
- The BS is powered by an external power source.

5.2.2 The Energy Model

The EQ-AHA employs the path attenuation model [62] as the basis for its energy consumption model during data communication. Moreover, in this energy model, energy consumed by the transmitter m-bits message for distance (d) is calculated considering both multi-path fading (E_{mp}) and free space fading (E_{fs}). The distance d is the Euclidean distance between the receiver and transmitter SSDN, calculated using equation (5.1).

$$d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \tag{5.1}$$

Here,(x_i, y_i) and (x_j, y_j) are the locations of the transmitter and receiver, respectively. The power control mechanism can be used to compensate for this path loss. The free space model is applied if d is less than a threshold distance (d_{th}); otherwise, the multi-path energy model acts. The energy consumption $E^{ij}_{SSDN_{TX}}$ for a general SSDN node to transmit k-bits data over distance (d) is calculated using equation (5.2).

$$E^{ij}_{SSDN_{TX}} = \begin{cases} k * E_{elec} + k * E_{mp} * d^4, & \text{for } d \geq d_{th}. \\ k * E_{elec} + k * E_{fs} * d^2, & \text{otherwise.} \end{cases} \tag{5.2}$$

The energy consumed by the cluster head $E^{ij}_{CH_{TX}}$ for transmitting k-bits over distance (d) is calculated using equation (5.3).

$$E^{ij}_{CH_{TX}} = \begin{cases} k * (E_{elec} + E_{DA}) + k * E_{mp} * d^4, & \text{for } d \geq d_{th}. \\ k * (E_{elec} + E_{DA}) + k * E_{fs} * d^2, & \text{otherwise.} \end{cases} \tag{5.3}$$

Where E_{DA} is the energy consumed in data aggregation by cluster heads. E_{elec} is the energy consumed per bit at the receiver/transmitter. d_{th} is the threshold distance and is calculated using equation (5.4).

$$d_{th} = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{5.4}$$

Whereas E_{fs} and E_{mp} represent free space amplification energy and multi-path models.

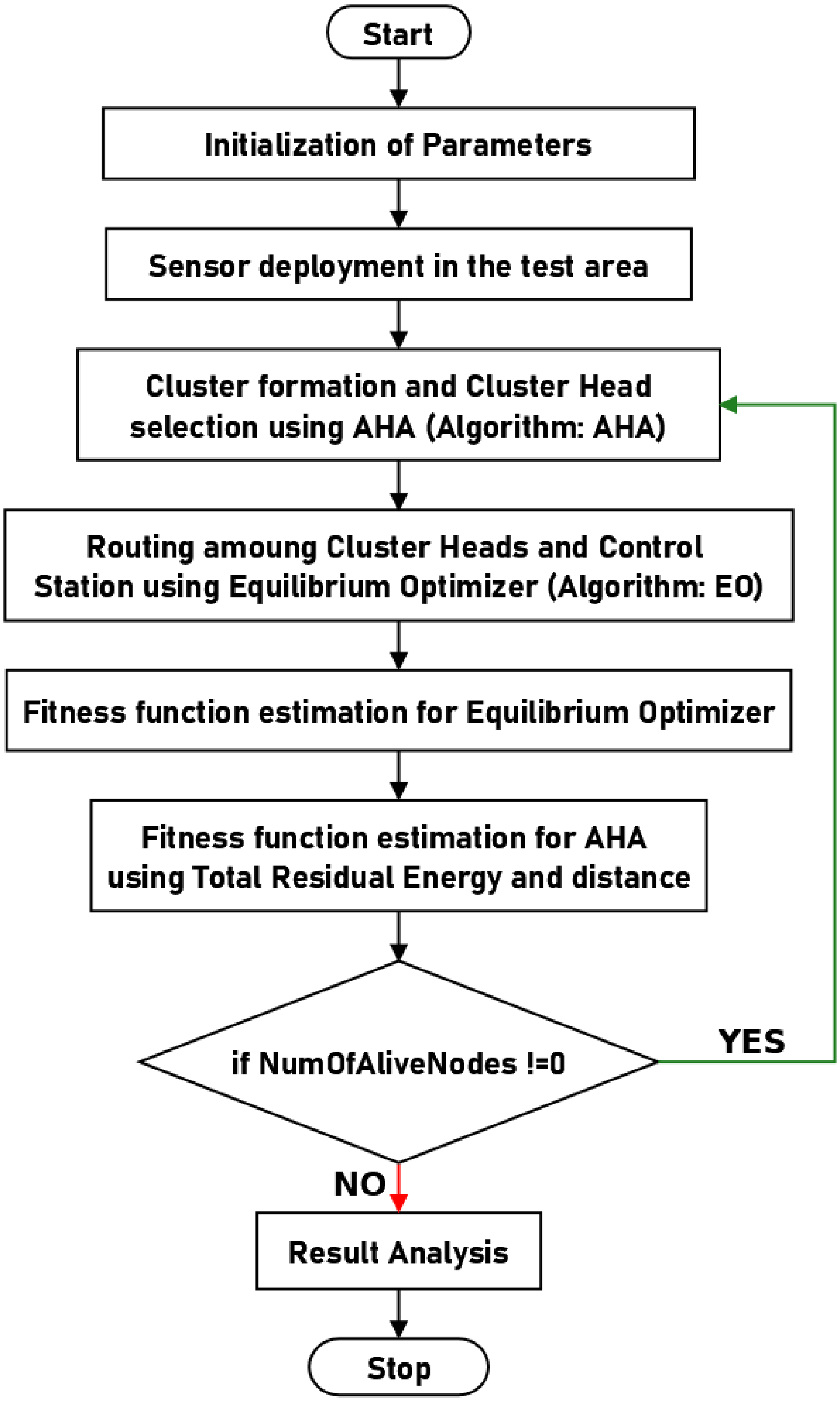


Figure 5.2: Flowchart of EQ-AHA.

5.3 The Proposed Model

The proposed approach introduces a new algorithm named EQ-AHA, which incorporates two meta-heuristic algorithms. The artificial hummingbird algorithm selects optimal CH, which is as defined in the subsection 5.3.1, while the equilibrium optimizer algorithm determines the best route among CHs to BS and is described in subsection 5.3.2. The data collected by CHs is then transmitted to BS via the path generated by EO. Further details of the proposed technique are described in the subsequent section, and the complete process is illustrated in the flowchart presented in Figure 5.2. This flowchart provides a comprehensive visual representation of the various steps and stages involved in the proposed method, offering a holistic view of the entire process.

5.3.1 CH selection and cluster formation using AHA

Zhao et al. [118] developed the AHA, a meta-heuristic algorithm inspired by nature, to simulate the foraging behavior of hummingbirds. Hummingbirds are considered the most intelligent species on Earth regarding the brain-to-body ratio [122]. Hummingbirds exhibit three behaviors related to foraging: guided, territorial, and migrating foraging. The structure of the modified AHA (i.e., EQ-AHA) is as given in Algorithm 5.1. This algorithm is structured into two distinct phases: the initialization phase and the update phase. At last, this subsection explains the fitness function used by AHA to make decisions.

A. Initialization Phase

This algorithm starts with the establishment of the population, where N randomly generated hummingbirds are placed on N food sources. Each bird's location is determined by applying the equation (5.5).

$$x_i^j(r) = LB + rand * (UB - LB) \tag{5.5}$$

where r is a random vector with values ranging from 0 to 1 in j a multi-dimensional problem; $x_i^j(r)$ denotes the position of the i_{th} food source; LB and UB represents the lower and upper bounds, respectively.

In the following step, the Smallest Position Vector (SPV) rule [119] is applied to $x_i(r)$ to obtain the sequence position vector for each bird. Then, the fitness value and list of CHs are calculated and stored in F_i and $S_i(r)$, respectively. Once the fitness values are initialized for each bird, the visit table matrix is initialized using equation (5.6). The initialization phase concludes by setting the global best solution for the bird with the best fitness value.

$$visitTable_{x,y} = \begin{cases} 0, & x \neq y. \\ null, & x = y. \end{cases} for\ x, y = 1, 2..., n \tag{5.6}$$

B. Update Phase

This update phase includes five steps. In the first step, the type of flight for each bird is selected randomly from the omnidirectional, axial, and diagonal flights using equations (5.7), (5.8), and (5.9) respectively.

$$AF^x = \begin{cases} 1, & if\ x = rand([1, d]). \\ 0, & otherwise. \end{cases} for\ x = 1, ..., d \tag{5.7}$$

$$DF^x = \begin{cases} 1, & if\ x = P(y);\ y\varepsilon[i, k];\ P = randperm(k); \\ & k\varepsilon[2, \lceil r_1 * (d-2) + 1 \rceil];\ x = 1, ..., d; \\ 0, & otherwise. \end{cases} \tag{5.8}$$

$$ODF^x = 1,\ for\ x = 1, ..., d \tag{5.9}$$

Algorithm 5.1 EQ-AHA

Input: *NetworkModel, Nodes*
Output: *Optimal selection of CNs*

$r = 0$
while aliveNodes $\neq 0$ **do**
    nCN = 10% of aliveNodes
    for each k^{th} **hummingbird from** 1 **to** n **do**
        Randomly initialize the position of both hummingbird and food i.e. $x_j^k(r)$ of k^{th} particle in j^{th} dimension for n^{th} iteration
        $[S_k(r)] = \text{SPV}[x_j^k(r)]$
        Find the route to BS using EO (Algorithm: 5.5)
        $f_k = \text{fitness}(S_k(r), nCN)$
        for each j^{th} **food source from** 1 **to** n **do**
            if $k \neq j$ **then**
                visitTable$(k, j) = 1$
            else
                visitTable$(k, j) =$ null
    globalBestFit = $\min[f_k]$
    while $z <$ maxIteration **do**
        for each k^{th} **hummingbird from** 1 **to** n **do**
            if rand2 $< \frac{1}{3}$ **then**
                perform equation 5.8
            else if rand2 $> \frac{2}{3}$ **then**
                perform equation 5.9
            else
                perform equation 5.10
            if rand1 ≤ 0.5 **then**
                Do Guided foraging (Algorithm: 5.2)
            else
                Do Territorial foraging (Algorithm: 5.3)
        if $\text{mod}(z, 2n) = 0$ **then**
            Do Migration foraging (Algorithm: 5.4)
        globalBestFit = $\min[f_k]$
    $r = r + 1$

Next, during the second step, for each bird, the type of foraging behavior is chosen randomly, i.e., guided (Algorithm 5.2) or territorial foraging (Algorithm 5.3). If the guided foraging is selected, the new food vector $v_i(t + 1)$ is calculated using equation (5.10). Else, in the case of territorial foraging, equation (5.11) is used.

$$v_i(t+1) = x_{i,tar}(t) + a * D * (x_i(t) - x_{i,tar}(t)) \tag{5.10}$$

Algorithm 5.2 Guided Foraging

Find $v_i^j(t)$ using equation (5.11)
$[S_t(t)] = \text{SPV}[v_i^j(t)]$
Find the route to BS using EO (Algorithm: 5.5)
$newFitness = \text{fitness}(S_t(t), nCN)$
for r^{th} food from 1 to n $(r \neq \text{tar}, i)$ **do**
    $\text{visitTable}(i, r) = \text{visitTable}(i, r) + 1$
$\text{visitTable}(i, \text{tar}) = 0$
if $newFitness > f_i$ **then**
    $x_i^j(t) = v_i^j(t)$
    f_i = newFitness
    for r^{th} food from 1 to n $(t \neq r)$ **do**
        $\text{visitTable}(r, i) = \max(\text{visitTable}(r, t)) + 1$

$$v_i(t+1) = x_i(t) + b * D * x_i(t) \tag{5.11}$$

whereas $x_{i,tar}(t)$ is the location of the target food to be visited by i^{th} hummingbird; $v_i(t)$represents the location of i^{th} food source at time t; and D is axial, diagonal or omnidirectional flight, guide factor $a \sim N(0,1)$ and territorial factor $b \sim N(0,1)$, $N(0,1)$ is a normal distribution with mean=0 and standard deviation=1.

$$x_i(t+1) = \begin{cases} x_i(t), & if\ fit(oldS_i(r)) \leq fit(newS_i(r)) \\ v_i(t+1), & otherwise \end{cases} \tag{5.12}$$

Algorithm 5.3 Territorial Foraging

Find $v_i^j(t)$ using equation (5.13)
$[S_t(t)] = \text{SPV}[v_i^j(t)]$
Find the route to BS using EO (Algorithm: 5.5)
$newFitness = \text{fitness}(S_t(t), nCN)$
for r^{th} food from 1 to n $(r \neq i)$ **do**
    $\text{visitTable}(i, r) = \text{visitTable}(i, r) + 1$
$\text{visitTable}(i, \text{tar}) = 0$
if $newFitness > f_i$ **then**
    $x_i^j(t) = v_i^j(t)$
    f_i = newFitness
    for r^{th} food source from 1 to n $(r \neq i)$ **do**
        $\text{visitTable}(r, i) = \text{visitTable}(r, t) + 1$

Algorithm 5.4 Migration Foraging

Find $v_i^j(t)$ using equation (5.14)
$[S_t(t)] = \text{SPV}[v_i^j(t)]$
Find the route to BS using EO (Algorithm: 5.5)
$newFitness = \text{fitness}(S_t(t), nCN)$
for r^{th} food source from 1 to n $(r \neq i)$ **do**
    $\text{visitTable}(i, r) = \text{visitTable}(i, r) + 1$
for r^{th} food source from 1 to n $(r \neq i)$ **do**
    $\text{visitTable}(r, i) = \text{visitTable}(r, t) + 1$

In the third step, the SPV rule [120] is employed on $v_i(t+1)$ to determine the new sequence vector, $newS_i(r)$. The fourth step involves computing the new fitness value,$fit(newS_i(r))$, of each bird. In the fifth step, in-case the updated fitness is less than the previous step, the food source for i_{th} bird is updated with the new food source $v_i(t+1)$, and the visit table for that bird is updated using equations (5.12) and (5.6). Finally, in the sixth step, the migration foraging (Algorithm 5.4) behavior of hummingbirds is simulated if the number of iterations exceeds the migration coefficient, i.e., 2 times $MaxIteration$. In migration foraging, new food sources are created in the entire search space using equation (5.13).

$$x_{worst}(t+1) = Low + r * (Up - Low) \tag{5.13}$$

Whereas the food sources with the slowest rate of nectar replenishment are represented by x_{worst} in AHA. At the end of the update phase, the global best solution is replaced with the latest one if the fitness value obtained is greater as compared to the prior global best.

C. Fitness Function for CH Selection

Fitness function is a measure used in evolutionary algorithms to assess the fitness of potential solutions. In this proposed algorithm, we have considered two constraints, i.e., the ratio of residual energies of CH & NN and the distance between NN and BS, to assess the performance. The equation (5.14) represents the fitness function used to identify the most suitable CH for the network.

$$fitness = \gamma * f_1 + \delta * f_2 \tag{5.14}$$

Whereas γ and δ are constants. In this case, the fitness function is developed using two variables: residual energy and distance covered during transmissions.

(a) **Total Residual Energy:** The remaining energy of nodes in a network plays a critical part in determining the longevity of the network. Equation (5.15) provides a generic formula for determining the sum of the residual energy in each node, denoted by E_r, known as the total residual energy $E_t otal$.

$$E_{total} = \sum_{i=1}^{n} E_r \tag{5.15}$$

Equation (5.16) is used to calculate the total residual energy left in CH, while equation (5.17) is used to calculate the total residual energy left in a CH within the cluster.

$$E_{totalCH} = \sum_{i=1}^{nCH} E_{CH}^{iBS}(k, d) \tag{5.16}$$

In the above equation (5.16), k denotes the number of bits, nCH represents the total number of CH in the system, d refers to the distance between the CH and the BS, and E_{CH}^{iBS} represents the remaining energy in the i^{th} CH.

$$E_{totalCommon} = \sum_{j=1}^{nCH} \sum_{i=1}^{nNode} E_{SDSN}^{ij}(k, d_{i,j}) \tag{5.17}$$

Whereas the variable $d_{i,j}$ denotes the distance between the j^{th} CH and the i^{th} node; $nNode$ rest of nodes in the network excluding CH. The ratio of total energy left in the CHs and the remaining nodes after the transmission is represented by the first objective function, f_1, which is calculated using equation (5.18).

$$f_1 = \frac{E_{totalCH}}{E_{totalCommon}} \tag{5.18}$$

(b) **Distance:** The energy needed to transmit data in space is directly related to the distance between the receiver and sender; a greater distance requires more energy for transmission. Consequently, reducing the transmission energy necessitates minimizing the distance between the source and the recipient. The total distance between the BS and all the cluster heads is calculated using the following equation (5.19).

$$D_{totalCHtoBS} = \sum_{i=1}^{nCH} \sqrt{(x_{CH_i} - x_{BS})^2 + (y_{CH_i} - y_{BS})^2} \tag{5.19}$$

Whereas, the (x_{CH_i}, y_{CH_i}) is the location of the i^{th} cluster head and (x_{BS}, y_{BS}) is the location of the base station.

$$D_{totalNodetoCH} = \sum_{j=1}^{nCH} \sum_{i=1}^{nNode} \sqrt{(x_{CH_j} - x_{NODE_i})^2 + (y_{CH_j} - y_{NODE_i})^2} \tag{5.20}$$

The equation (5.20) calculates the total distance between the head and all the nodes present in the cluster. The variable (x_{CH_j}, y_{CH_j}) represents the location of the j^{th} CH, while (x_{NODE_i}, y_{NODE_i}) represents the location of the i^{th} node in the cluster. On the other hand, equation (5.21) represents the second objective function f_2, which is based on the average of the total distance covered between the CH and the base station and between the nodes and the CH in the cluster.

$$f_2 = \frac{1}{(D_{totalCHtoCH} + D_{totalNodetoCH})/2} \tag{5.21}$$

5.3.2 Route Selection using EO

The EO [121] is a physics-based search algorithm that uses particles with concentrations as search agents to find optimal solutions. It is inspired by the control volume mass balance model [121], and the particles update their concentrations randomly based on best-so-far solutions to reach the equilibrium state, i.e., the global best solution. The EO algorithm starts with the initialization of the population and setting candidate equilibrium solutions. To find the best solution globally, it conducts exploration and exploitation in the next phase. The EO algorithm is divided into two phases: initialization and update phases. Lastly, this subsection provides an explanation of the fitness function employed by EO to facilitate decision-making.

A. Initialization Phase

The EO algorithm is defined in Algorithm 5.5. Like many other meta-heuristic algorithms, it starts the optimization process with an initial population. The initial particle concentrations are determined by the number of particles and the dimensions of the search space. These initial concentrations are randomly initialized with a uniform distribution across the search space using equation **??**.

Algorithm 5.5 Equilibrium Optimizer CH Routing Algorithm

Initialize the number of particles = number of CH
Randomly initialize the concentrations of particles using equation (5.22)
Set $a_1 = 2$, $a_2 = 1$, and $GP = 0.5$
while $Itera < Max_{iter}$ **do**
  for $i = 1$ to number of particles **do**
    Calculate the fitness of the i_{th} particle
    if $FF(\vec{CO_i}) < FF(\vec{CO}_{eq1})$ **then**
      $\vec{CO}_{eq1} = \vec{CO_i}$
      $FF(\vec{CO}_{eq1}) = FF(\vec{CO_i})$
    else if $FF(\vec{CO_i}) > FF(\vec{CO}_{eq1})$ & $FF(\vec{CO_i}) < FF(\vec{CO}_{eq2})$ **then**
      $\vec{CO}_{eq2} = \vec{CO_i}$
      $FF(\vec{CO}_{eq2}) = FF(\vec{CO_i})$
    else if $FF(\vec{CO_i}) > FF(\vec{CO}_{eq1})$ & $FF(\vec{CO_i}) > FF(\vec{CO}_{eq2})$ & $FF(\vec{CO_i}) < FF(\vec{CO}_{eq3})$ **then**
      $\vec{CO}_{eq3} = \vec{CO_i}$
      $FF(\vec{CO}_{eq3}) = FF(\vec{CO_i})$
    else if $FF(\vec{CO_i}) > FF(\vec{CO}_{eq1})$ & $FF(\vec{CO_i}) > FF(\vec{CO}_{eq2})$ & $FF(\vec{CO_i}) > FF(\vec{CO}_{eq3})$ & $FF(\vec{CO_i}) < FF(\vec{CO}_{eq4})$ **then**
      $\vec{CO}_{eq4} = \vec{CO_i}$
      $FF(\vec{CO}_{eq4}) = FF(\vec{CO_i})$
  $\vec{CO}_{avg} = (\vec{CO}_{eq1} + \vec{CO}_{eq2} + \vec{CO}_{eq3} + \vec{CO}_{eq4})/4$
  Find $\vec{CO}_{pool,eq}$ using equation (5.23)
  if $Itera > 1$ **then**
    Find t using equation (5.26)
    for $i = 1$ to number of particles **do**
      Choose one candidate from $\vec{CO}_{pool,eq}$ (randomly)
      Generate random vectors $\vec{\lambda}$ and $\vec{r}$
      Generate vectors $\vec{E}$ using equation (5.25)
      Generate vectors $\overrightarrow{GCP}$ using equation (5.29)
      Generate vectors $\vec{G_0}$ using equation (5.28)
      Generate vectors $\vec{G}$ using equation (5.27)
      Update concentrations $\vec{C}$ using equation (5.24)
  $Itera = Itera + 1$
  $bestFitness = FF(\vec{CO}_{eq1})$

$$CO_i^{initial} = CO_{min} + rand * (CO_{max} - CO_{min}) \\ , for\ i = Natural\ Number\ upto\ n \tag{5.22}$$

The starting concentration of the i_{th} particle is indicated by $CO_i^{initial}$, where Rand i is a vector created at random that falls inside the $[0, 1]$ range; CO_{min} and CO_{max} determine the dimensions' minimum and maximum values. A population's size is represented by the variable n. The particles are assessed using the fitness function and subsequently arranged in order to identify the four most optimal equilibrium candidate values, i.e., $CO_{eq1}, CO_{eq2}, CO_{eq3}, CO_{eq4}$.

B. Update Phase

This phase is crucial for improving the algorithm's performance and convergence. It consists of two major steps. Firstly, an equilibrium pool vector, $CO_{pool,eq}$, is created using equation (5.23) by selecting the four best-so-far particles based on their fitness values ($CO_{eq1}, CO_{eq2}, CO_{eq3}, CO_{eq4}$) and arithmetic average (CO_{avg}) of these four. In the second step, the concentration for each particle is updated using equation (5.24), and if this updated concentration is better, then the global best value is updated.

$$CO_{p\vec{o}ol,eq} = (C\vec{O}_{eq1}, C\vec{O}_{eq2}, C\vec{O}_{eq3}, C\vec{O}_{eq4}) \tag{5.23}$$

The first component of equation (5.24) indicates the concentration at equilibrium, while the second and third components account for changes in concentration. The function's 2nd term carry out a global search of the space to locate the best solution, and incorporating the 3rd term enhances the precision of the solution.

$$C\vec{O} = C\vec{O}_{eq} + (\vec{C} - C\vec{O}_{eq}) * \vec{E} + \frac{\vec{G}}{\vec{\lambda} V} * (1 - \vec{E}) \tag{5.24}$$

Whereas $\vec{E}$ is the exponential term responsible for concentration updation and is calculated using equation (5.25). Furthermore, generation rate ($\vec{G}$) is calculated using equation (5.27).Here, $\lambda \sim [0, 1]$ is a random vector, and V is a unit vector.

$$\vec{E} = a_1 sign(\vec{r} - 0.5)\left[e^{-\vec{\lambda} t} - 1\right] \tag{5.25}$$

In equation (5.25), a_1 is a constant value, i.e. 2, that accounts for the exploration ability. The second component, $sign(\vec{r} - 0.5)$, plays a critical role in both exploration and exploitation capabilities. Here, $sign(\vec{r})$ denotes a random vector ranging from 0 to 1. The variable t is a function of the iteration and is calculated using the equation (5.26).

$$t = \left(1 - \frac{iter}{iterMax}\right)^{\left(a_2 \frac{iter}{iterMax}\right)} \tag{5.26}$$

In the aforementioned equation, $iter$ represents the current iteration, while $iterMax$ corresponds to the maximum number of iterations. These variables play a crucial role in calculating the value of time and ensuring the progression of the algorithm within the defined iteration limits. Additionally, a_2 is a constant value (set to 1) employed to control the level of exploitation ability.

$$\vec{G} = \vec{G_0}.\vec{E} \tag{5.27}$$

In equation (5.27), $\vec{G_0}$ is the initial generation rate [121] and is calculated using the equation (5.28).

$$\vec{G_0} = G\vec{C}P * (C\vec{O}_{eq} - \vec{\lambda}\vec{C}) \tag{5.28}$$

Where the Generation rate Control Parameter ($\overrightarrow{GCP}$) [121] is defined to incorporate the contribution of the generation term into the updating process and is calculated using equation (5.29). The Generation Probability (GP) is a term that determines the likelihood of this contribution and specifies the number of particles that will utilize the generation term to update their states. Setting the Generation Probability (GP) to 0.5 results in a suitable equilibrium between exploration and exploitation.

$$\overrightarrow{GCP} = \begin{cases} 0.5, & r_2 \geq GP. \\ 0, & else. \end{cases} \tag{5.29}$$

Where $r1$ and $r2$ represent random numbers ranging from 0 to 1.

C. Fitness Function for Route Selection

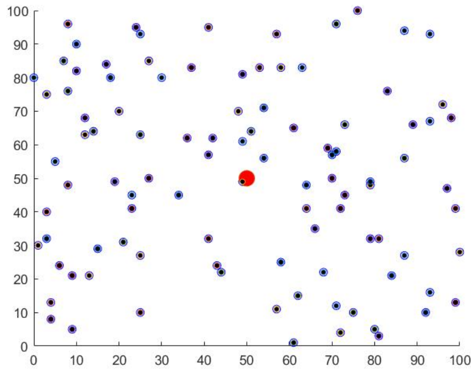
In this scenario, the total energy used throughout the transmission path serves as the basis for the fitness function for EO. Each particle in this problem represents a candidate route from the CH (i.e., source node) to the BS (i.e., destination node). The evaluation of these particles is based on their energy consumption during transmission from CHs to the BS. The particle having the lowest energy consumption is chosen as the global best solution. The fitness function for EO route selection can be expressed mathematically as equation (5.30). It calculates the total energy consumed while transmitting data between CHs on the selected route (muti-hop transmission) and the energy consumed by the last CH on the route to send the accumulated data from all CHs to the BS.

$$fitness_{EO}(E_{route}) = \sum_{i=1}^{n-1} E_{CH(i),CH(i+1)}(k,d) + E_{CH(n),BS}(k,d) \tag{5.30}$$

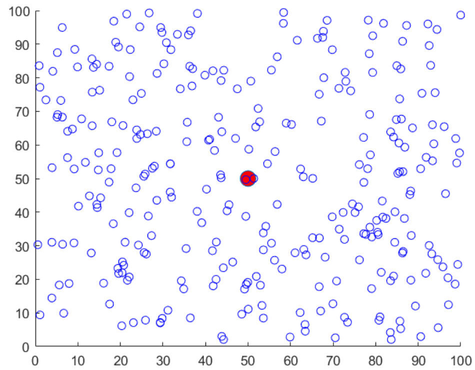
In the above equation, n is the total number of CHs; d is the distance, $E_{CH(i),CH(i+1)}(k,d)$ represents energy required to send $k - bits$ data from CH_i to CH_{i+1}; $E_{CH(n),BS)}(k,d)$ is the power needed to send the data from end CH node ($n^{th}\ CH$) to BS.

5.4 Results

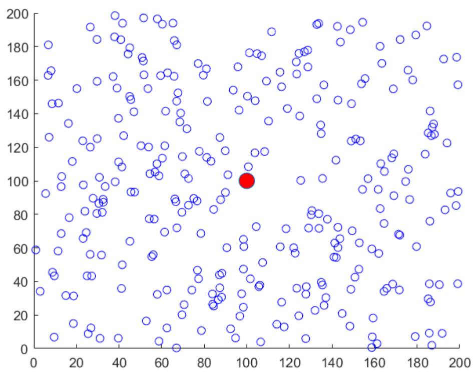
The performance of the IoT-based SD-WSN and EQ-AHA is evaluated under different scenarios to determine the best combination of parameters for EQ-AHA. The parameters in Table 5.1 are used to generate a variety of scenarios for simulation. All experiments are performed in MATLAB (version R2023a) on an Intel i5 processor with 8GB of RAM.



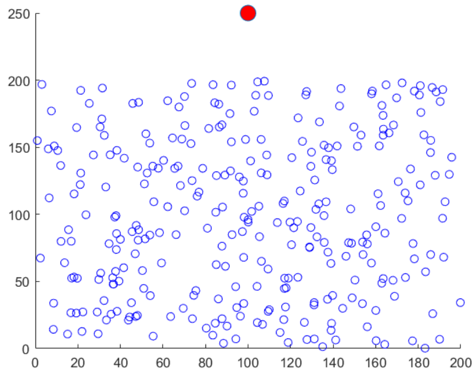
(a) Scenario 1



(b) Scenario 2



(c) Scenario 3



(d) Scenario 4

Figure 5.3: Network Map

Table 5.1: Parameters for Testing

Category	**Parameter**	**Value**
Network	Area (m^2)	100×100
	Position of BS	(50, 50)
	Initial Energy	0.5 J
	No. of Nodes	100
Application	Data Packet Length	100 bits
	Broadcast Packet Length	25 bits
EQ-AHA	Initial POP	30
	Iteration	50
	γ, δ	0.5, 0.5

5.4.1 Parameter Settings

The testing parameters specified in Table 5.1 are employed to emulate the behavior of SD-WSN nodes through four different scenarios, as illustrated in Figure 5.3. Each node in the network is allocated an energy of 0.5 J. Each scenario examines specific aspects of the network's behavior and is defined below:

- **Scenario 1:** In this scenario, there are 100 nodes deployed within a 100 x 100 m^2 area. The BS is at the center (50, 50) of the area. This scenario is focused on analyzing short-range communications within the given area.
- **Scenario 2:** To evaluate the scalability of the proposed algorithm, the number of nodes is increased by 200%. The area size remains 100 x 100 m^2, and the location of BS is (50,50), similar to Scenario 1. However, the number of nodes deployed is 300. This scenario assesses how the algorithm handles the increased node density while maintaining optimal communication performance.
- **Scenario 3:** In this scenario, to assess the performance of the proposed algorithm in a large coverage area, the area size is increased to 200 x 200 m^2. There are still 300 nodes deployed within this larger area. The BS is placed at center (100, 100) of the area. This scenario explores short-range communications in a larger coverage area.
- **Scenario 4:** The goal of this arrangement is to analyze the effect of change in the position of BS on the results of the proposed algorithm. In this setup, a total of 300 nodes are deployed in 200 x 200 m^2 area. However, the BS is kept outside the area at random location (100, 250), which differs from the previous scenarios.

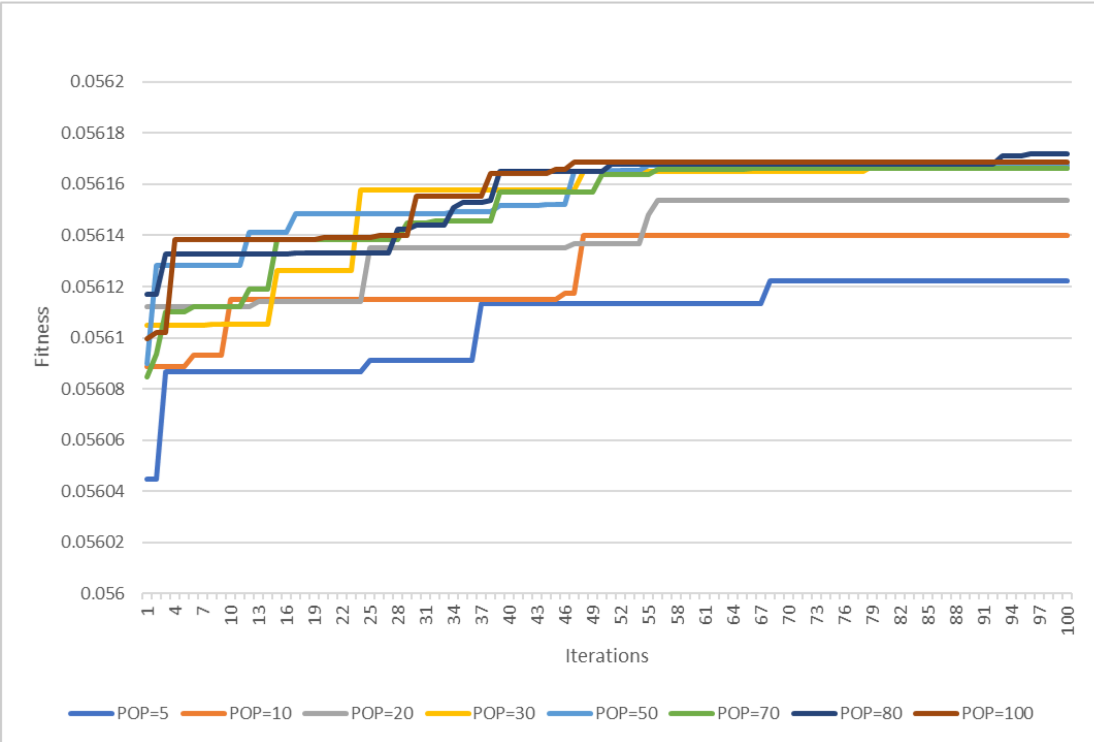


Figure 5.4: EQ-AHA is evaluated using various population sizes.

To initialize the hummingbird population, Equation (5.5) was utilized to generate their food position vectors. The search space was defined as a multi-dimensional domain, and the food position vectors were constrained within the range of [-4, 4]. The fitness function was assessed using different population sizes ranging from 5 to 100 in order to establish the ideal number of hummingbird populations and the minimum number of iterations. The findings, illustrated in Figure 5.4, indicated that the maximum number of iterations was set at 50, and the optimal fitness value was achieved when the initial population size was set at 30. These parameter settings balanced exploration and exploitation in the search space, facilitating effective convergence toward optimal solutions. Consequently, a population size of 30 was selected for subsequent experiments.

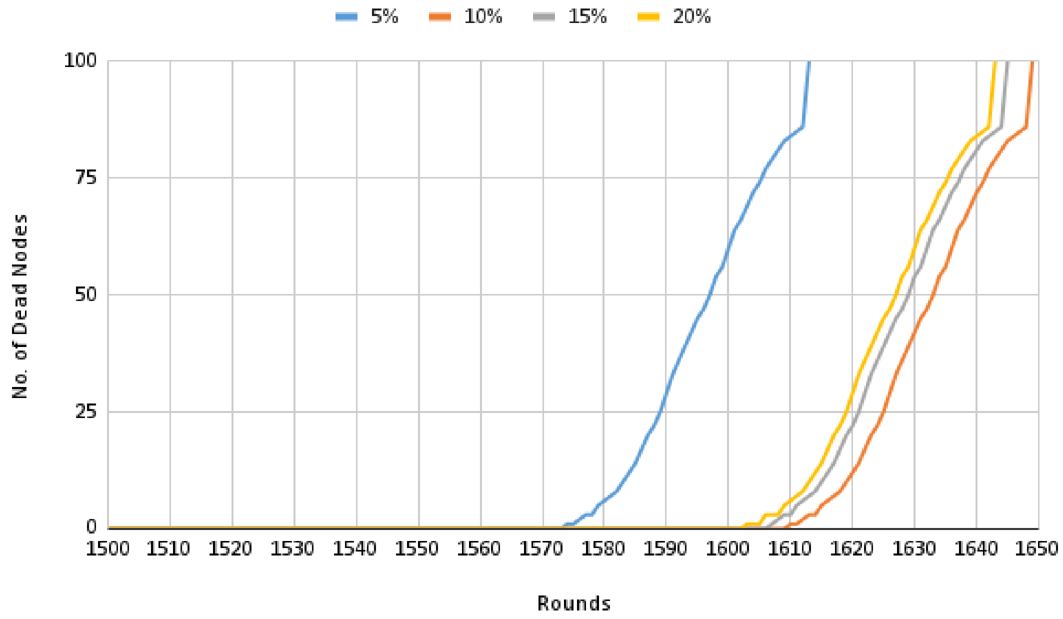


Figure 5.5: Comparison of performance with different % of CHs.

In Figure 5.5, a comprehensive analysis of EQ-AHA's performance is presented, showcasing the performance variations achieved at different CH percentages, specifically 5%, 10%, 15%, and 20% of the total surviving nodes. Through careful examination of this performance comparison, it was concluded that establishing the number of CHs as 10 % of the surviving nodes would yield the most favorable outcomes. A careful balance between network coverage and operational efficiency can be achieved by setting the CH percentage at 10%.

According to Handy et al. [65], the network lifespan is commonly understood as the duration spanning from the moment of network deployment to the eventual demise of the last node. Specifically, when dealing with periodic data collection in the context of an SD-WSN, the network lifespan can be computed by determining the time interval commencing with the activation of the initial node and terminating at the occurrence of the FND event [65]. The performance of the EQ-AHA for scenario 1 is illustrated in the following Figure 5.6. The experimental results demonstrated that the proposed algorithm experienced the first node failure at the 1612th round, and the network sustained transmission until the 1649^{th} round. The energy level of the network exhibited a gradual decline, as depicted in Figure 5.6. Throughout the operation, a total of 16335 data packets were transmitted.

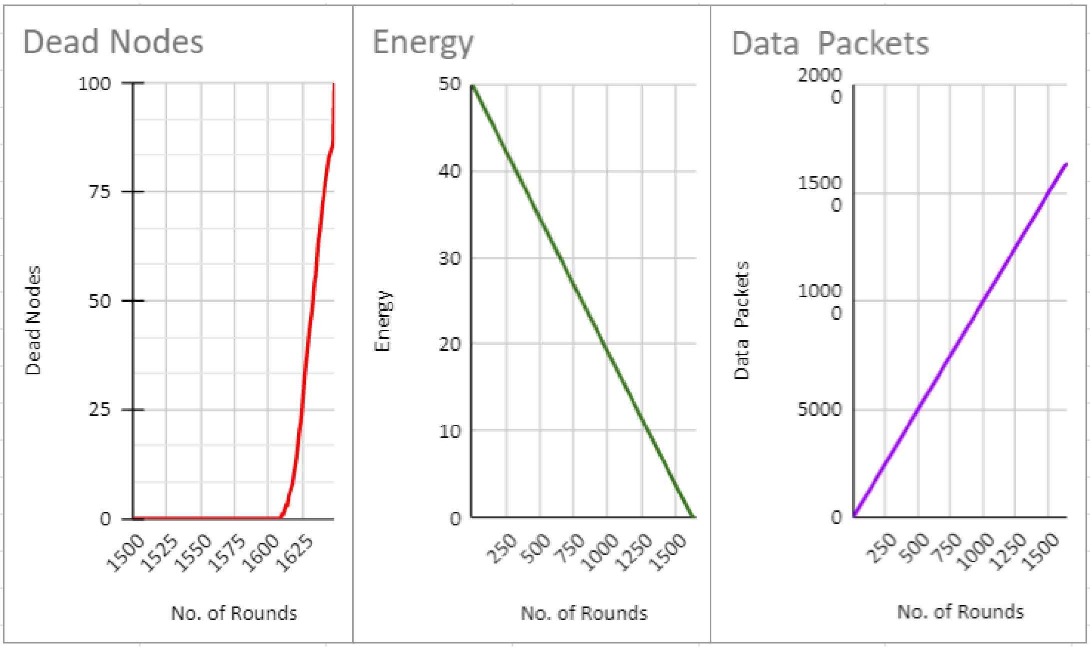


Figure 5.6: Performance of EQ-AHA (Scenario:1): Dead Node, Residual Energy, and Data Packets Sent per round.

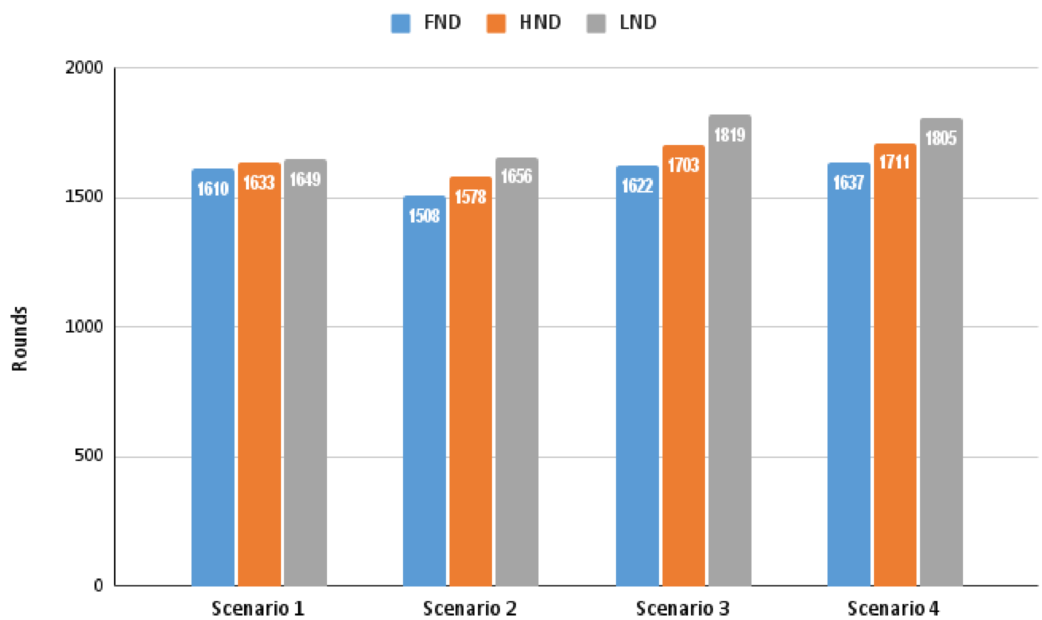


Figure 5.7: Dead node comparison based on different scenarios of deployment.

The EQ-AHA algorithm was evaluated in four different scenarios, and the results are presented in Figure 5.7. The Figure illustrates each scenario's FND, HND, and LND metrics. These observations provide insights into the performance of the EQ-AHA algorithm in different scenarios, showcasing the variation in the time at which the first, half, and last nodes experienced failure during the transmission rounds. In Scenario 1, the FND occurred at the 1610th round, followed by the HND at the 1633rd round, and finally, the LND at the 1649th round of transmission. Scenario 2 showed the earliest node deaths (FND: 1508, HND: 1578, LND: 1656), while Scenario 4 exhibited slightly delayed deaths (FND: 1637, HND: 1711, LND: 1805). For Scenario 3, FND, HND, and LND are observed at the 1622, 1703, and 1805 rounds. Overall, the average performance across all scenarios indicated an FND of 1594 rounds, an HND of 1656 rounds, and an LND of 1732 rounds. These results prove that the proposed algorithm performed well in all the scenarios with slight variation.

From the observations presented in Figure 5.7 and the characteristics of each scenario, several conclusions can be drawn, which are as follows:

- **Scalability:** To check the performance, the EQ-AHA is evaluated under various scenarios. Scenarios 1 and 2 suggest that as the number of nodes increases by 200, the FND earlier in scenario 2. However, despite this earlier node failure, the network in Scenario 2 still lasts for 1656 rounds (LND). This suggests that overall network stability and lifespan remain relatively unaffected even with a significant increase in node count. Therefore, we can conclude that increasing the number of nodes has a negligible effect on the network's longevity, indicating that the EQ-AHA protocol scales well with higher node densities.
- **Change in size of area:** When comparing Scenario 2 and Scenario 3, which differed in the size of the deployment area, it was found that increasing the size of the deployment area or decreasing the node density significantly improved the performance of the EQ-AHA algorithm. The significant increase of 114 rounds in the FND between Scenario 2 and Scenario 3 suggests that the algorithm was more effective in handling the communication challenges in the scenario with a larger deployment area and lower node density.
- **Change in BS position:** As shown in Figure 5.7, the network performance was independent of the BS position for the same number of nodes and the same size of deployment area (Scenarios 3 and 4). The network performance metrics did not exhibit significant differences between the two scenarios, even though the BS position was changed. This indicates that the EQ-AHA algorithm successfully

preserves network energy and ensures reliable communication, irrespective of the base station's position.

5.4.2 Comparative Study

To evaluate the performance of EQ-AHA, we compare its simulation results with five SoA algorithms. The algorithms selected for comparison are LEACH [62], KmeansPSO [78], GWO-C [84], EB-GWO [86], and EOAHA [7]. The comparison is based on FND, HND, LND, average node life, the number of dead nodes per round, total data packets transmitted, and the total residual energy remaining in the network per round.

Table 5.2: Comparison of Performance Metrics

Algorithms	FND	HND	LND
LEACH	272	447	662
KmeansPSO	560	1294	1452
GWO-C	538	1195	1377
EB-GWO	1078	1258	1301
EOAHA	1224	1254	1263
EQ-AHA	1612	1633	1649

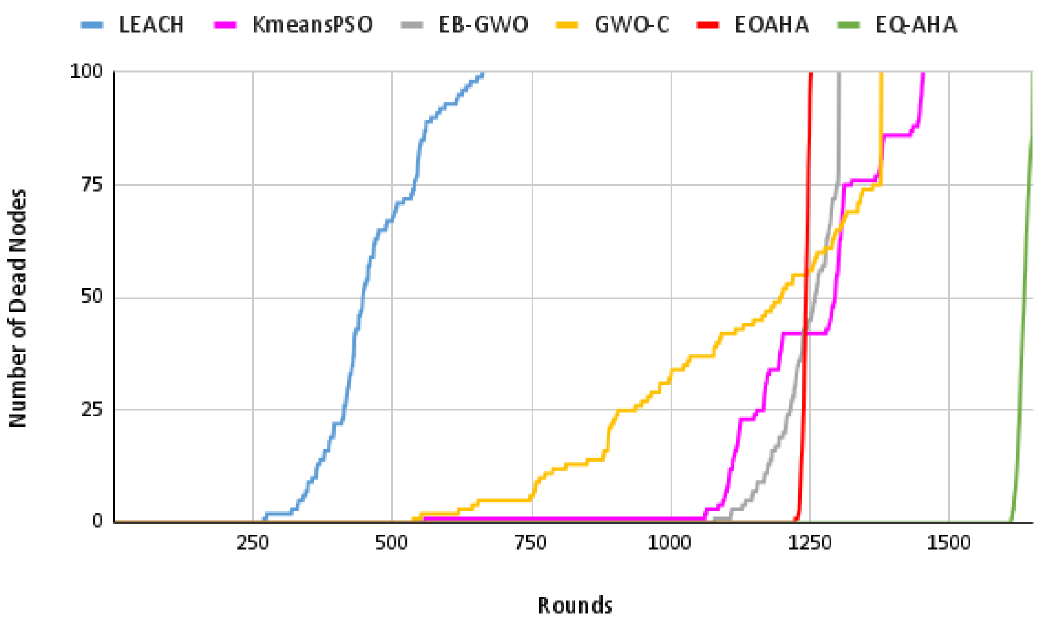


Figure 5.8: Performance of different state-of-the-art algorithms w.r.t. EQ-AHA.

Table 5.2 and Figure 5.8 show the FND, HND, and LND of LEACH, KmeansPSO, GWO-C, EBGWO, EOAHA, and EQ-AHA. These metrics measure network longevity with higher values and better performance. The first node died for LEACH, Kmeans-PSO, GWO-C, EB-GWO, and EOAHA at 270 rounds, 560 rounds, 543 rounds, 1078 rounds and 1224. Meanwhile, for EQ-AHA FND, it happened at 1612 rounds. These findings highlight the significant impact of EQ-AHA on extending the network lifespan for periodic data collection, surpassing EBGWO by over 49.5% and EOAHA by 31.7%.

Moreover, when comparing EQ-AHA to LEACH, Kmeans-PSO, GWO-C, EB-GWO, and EOAHA, it is evident that EQ-AHA outperforms them by extending the network lifespan by more than 492.65%, 187.86%, 199.63%, 49.54% and 31.70% respectively. Additionally, in terms of the overall network lifespan until the last node dies, comparing EQ-AHA with LEACH, the SD-WSN lasts an additional 987 rounds beyond LEACH (where the LND occurs at 662 rounds). The LEACH has the lowest values across all metrics, showing the shortest node life. EQ-AHA performs the best, with the highest FND (1612), HND (1633), and LND (1649) values, indicating the longest node lifespan. EQ-AHA contributes to a more balanced and consistent network performance, hence making it more robust. EQ-AHA achieved this performance by distributing network traffic evenly across all the nodes. As a result, nodes are less likely to fail, and the network is more likely to remain operational. This stability is a highly desirable characteristic, as it promotes consistent and reliable performance throughout the network's lifespan.

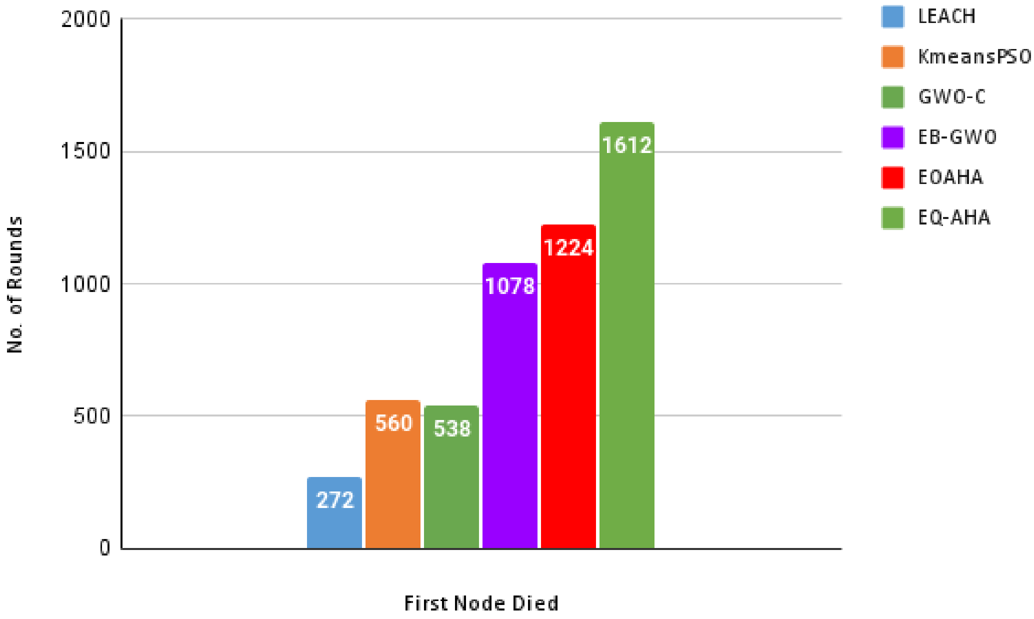


Figure 5.9: FND comparison of state-of-the-art algorithms.

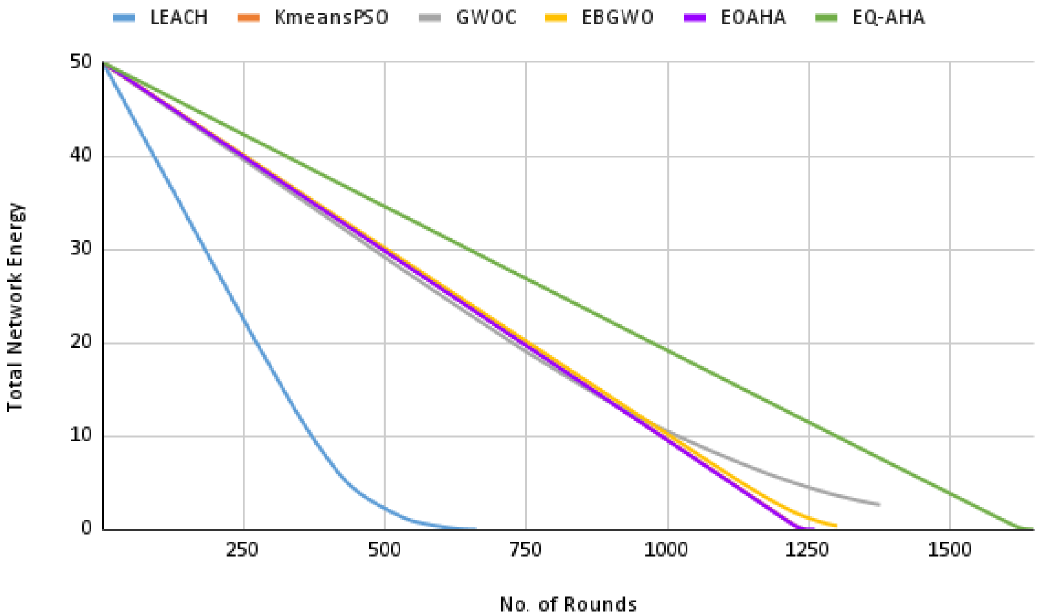


Figure 5.10: Total network energy left per round.

These results are visually represented in Figure 5.9, demonstrating how EQ-AHA significantly prolongs the network lifespan for periodic data gathering. Figure

5.10 shows that the energy decay in EQ-AHA is more stable compared to other SoA algorithms. This finding highlights the superior energy management capabilities of EQ-AHA

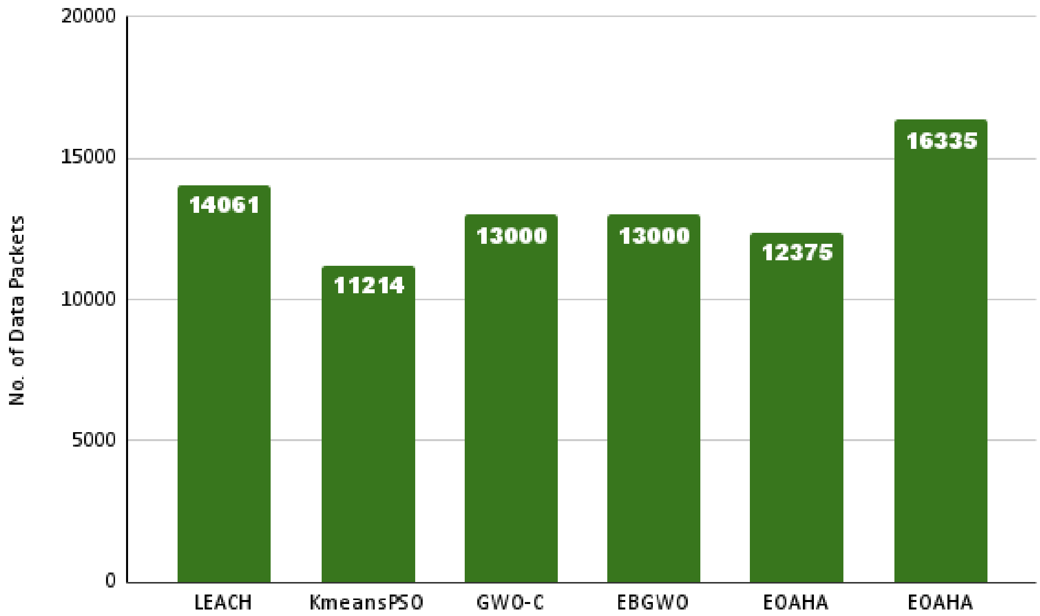


Figure 5.11: The number of data packets sent to BS.

Figure 5.11 illustrates that LEACH transmitted 14,061 data packets, Kmeans-PSO transmitted 11,214 data packets, GWO-C transmitted 13,000 data packets, EBGWO transmitted 13,000 data packets, EOAHA 12375 packets and EQ-AHA transmitted 16,335 data packets. EQ-AHA stands out with the highest number of data packets transmitted, suggesting its improved data collection or transmission performance compared to the other algorithms.

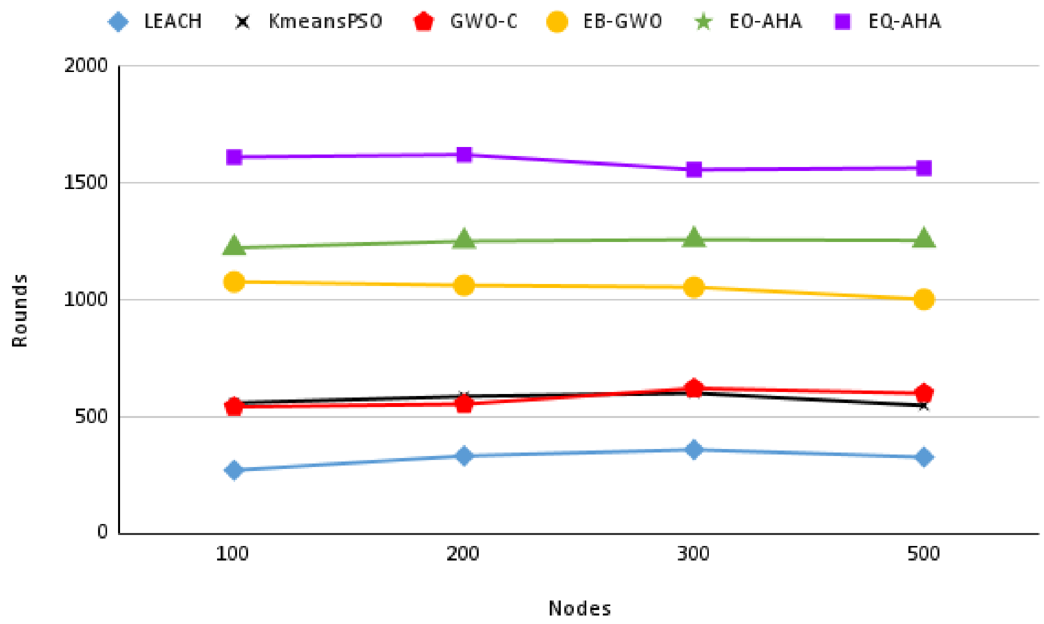


Figure 5.12: FND and the number of rounds comparison

To test the stability of all the SoA algorithms and EQ-AHA with increasing node density in a defined area, simulations are conducted with 100, 200, and 300 node densities. The results, as shown in Figure 5.12, demonstrate that the performance of EQ-AHA remains consistent. In contrast, the performance of other algorithms is inconsistent, with fluctuations in some cases. These experimental results indicate that EQ-AHA is better than the other SoA algorithms by prolonging the network's life for periodic data collection and ensuring steady energy consumption throughout the operation. These results highlight the effectiveness and efficiency of EQ-AHA in addressing the challenges associated with network longevity and energy management.

5.4.3 Statistical Validation

The Table 5.3 (statistical analysis) provides a comprehensive evaluation of the algorithms by examining their mean, variance, Standard Error (SE), t-statistic, and p-value. The mean represents the average node life across the metrics, with EQ-AHA achieving the highest mean (average node life) of 1639.5 (rounds), indicating its consistent node life in the case of EQ-AHA. Variance measures the variability of performance metrics, and the low value of variance for EOAHA (20.28) and EQ-AHA

Table 5.3: Statistical Analysis of Algorithms Compared to EQ-AHA

Algorithms	Mean	Variance	SD	SE	t-Statistic	p-Value
LEACH	560.2	5600.84	74.83	23.79	-45.36	5.16×10^{-20}
KmeansPSO	1333.0	8723.78	93.39	29.64	-10.34	5.31×10^{-9}
GWO-C	1175.1	25851.66	160.80	50.90	-9.12	3.60×10^{-8}
EB-GWO	1255.5	1445.17	37.99	12.27	-31.30	3.79×10^{-17}
EOAHA	1245.5	20.28	4.50	2.83	-139.01	9.71×10^{-29}
EQ-AHA	1639.5	60.06	7.75	2.45	–	–

(60.06) suggests that its performance is stable and exhibits minimal node failure. SE reflects the precision of the mean estimate and is also the lowest for EQ-AHA at 2.45, further underscoring the reliability and consistency of its performance. The t-statistic compares each algorithm's performance with that of EQ-AHA, with negative t-statistics for all other algorithms indicating that they perform worse than EQ-AHA. For instance, LEACH has a t-statistic of -45.36, highlighting a significant performance gap between it and EQ-AHA. The p-value, which measures the statistical significance of these performance differences, is extremely low for all algorithms (e.g., 5.16×10^{-20} for LEACH).

Table 5.4: ANOVA Test for Algorithm Performance Comparison

Source	Sum of Squares (SS)	df	Mean Square (MS)	F-Statistic	p-Value
Between Groups	2.185×10^6	5	437034.86	5.53	0.0072
Within Groups	9.485×10^5	12	79043.72	–	–
Total	3.134×10^6	17	–	–	–

Further, to validate the results of EQ-AHA, an ANOVA test was conducted as we were comparing more than two SoA algorithms. Table 5.4 displays the result of the ANOVA test. The ANOVA table for algorithm performance comparison shows a statistically significant difference among the groups at a 95% confidence level (p-value = 0.0072). The p-value is less than 0.05, leading to the rejection of the null hypothesis and confirming a significant difference between the groups. This suggests that the observed differences in performance are highly significant, confirming that EQ-AHA consistently outperforms the other algorithms.

5.5 Chapter Summary

This chapter addresses energy conservation challenges and network lifetime optimization in IoT-based SDWSNs. EQ-AHA was proposed to enhance the performance of IoT-based SDWSNs. EQ-AHA is a hybrid technique that utilizes AHA and EO metaheuristic algorithms to optimize communication in IoT-based networks. First, the AHA meta-heuristic algorithm is used to optimize the CH selection process while considering the energy ratio and an average of the total distance of CH and normal nodes. Secondly, the EQ meta-heuristic approach is used to determine the optimal path for delivering the data aggregated by CH to BS while considering the shortest route between BS and CH. In this way, the EQ-AHA helps the sensor nodes find paths at a minimum cost, hence extending the life of the network. The EQ-AHA was tested under various conditions and was compared with other SoA algorithms, such as EOAHA, EBGWO, GWO-C, Kmeans-PSO, and LEACH, to assess its effectiveness. The simulation results demonstrated that EQ-AHA outperformed these algorithms by enhancing the network lifetime for periodic data gathering by achieving an improvement of at least 31.6%.

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

This chapter presents the concluding remarks of the thesis by summarizing the key research contributions, outlining the limitations of the work, highlighting its potential social impact, and discussing future directions for further research and development.

6.1 Research Summary

This research focuses on developing energy-efficient and QoS-aware routing protocols for IoT-enabled SDWSNs. These networks serve as the core of emerging smart systems such as smart cities, intelligent agriculture, and real-time environmental monitoring. However, their effectiveness is often limited by the restricted energy capacity of sensor nodes and the complexity of meeting diverse QoS requirements like latency, reliability, and throughput. To address these challenges, four key research objectives (ROs) were formulated. Each objective has been successfully accomplished through the publication of research articles, as summarized in Table 6.1.

To achieve RO1, a detailed and structured systematic literature review of clustering and routing algorithms in IoT-based SDWSNs is presented. The review classifies existing methods into classical, metaheuristic-based, and machine learning-based categories, highlighting their strengths, limitations, QoS parameters, and key research gaps. This comprehensive review serves as a foundation for developing novel algorithms that address the identified gaps and enhance the performance of IoT-enabled SDWSNs.

Table 6.1: Research objectives and their corresponding publications

Research Objective	**Publication(s)**
RO1: To perform a systematic literature review of the routing algorithms in SD-WSNs.	1. N. Kumar and R. Beniwal, "Energy-Efficient Techniques in IoT-based Software-Defined Wireless Sensor Networks: A Systematic Review," *7th International Conference on Energy, Power and Environment (ICEPE)*, IEEE, NIT Meghalaya, India, May 2025. **[Presented]**
RO2: To propose novel energy-efficient routing algorithms to optimize network lifetime in SD-WSN.	1. R. Beniwal and N. Kumar, "Energy optimized artificial hummingbird algorithm for routing in IoT-based software-defined WSN," *International Journal of Communication Systems*, vol. 37, no. 8, Wiley **(SCIE)**, Mar. 2024. **[Published]**
RO3: To propose multi-objective routing algorithms considering QoS constraints for SD-WSN.	1. N. Kumar and R. Beniwal, "A Multi-Constrained Green Routing Protocol for IoT-Based Software-Defined WSN," *Concurrency and Computation: Practice and Experience*, vol. 36, no. 28, Wiley **(SCIE)**, Oct. 2024. **[Published]** 2. R. Beniwal and N. Kumar, "A Nature-Inspired Multi-Objective Green Routing Protocol for IoT-enabled SDWSNs," *Transaction on Emerging Telecommunication Technology*, Wiley **(SCIE)** May. 2025. **[Published]**
RO4: Comparative analysis of the proposed algorithms with existing state-of-the-art algorithms.	1. R. Beniwal and N. Kumar, "Energy optimized artificial hummingbird algorithm for routing in IoT-based software-defined WSN," *International Journal of Communication Systems*, vol. 37, no. 8, Wiley **(SCIE)**, Mar. 2024. **[Published]** 2. N. Kumar and R. Beniwal, "A Multi-Constrained Green Routing Protocol for IoT-Based Software-Defined WSN," *Concurrency and Computation: Practice and Experience*, vol. 36, no. 28, Wiley **(SCIE)**, Oct. 2024. **[Published]** 3. R. Beniwal and N. Kumar, "A Nature Inspired Multi-Objective Green Routing Protocol for IoT-enabled SDWSNs," *Transaction on Emerging Telecommunication Technology*, Wiley **(SCIE)** May. 2025. **[Published]** 4. N. Kumar and R. Beniwal, "Green Routing Protocols for IoT-Based Software-Defined Wireless Sensor Networks: A Comparative Analysis", *7th International Conference on Energy, Power and Environment (ICEPE)*, IEEE, NIT Meghalaya, India, May 2025. **[Presented]**

In order to attain RO2, a new green computing algorithm, EOAHA, is proposed to address this challenge based on a relatively new metaheuristic algorithm, i.e., AHA. The EOAHA solves the optimal CH selection problem in SD-WSN through a novel fitness function. The model aims to optimize network energy consumption by ensuring a balance between the distance between receiver and transmitter nodes and the amount of energy utilized.

RO3 was accomplished by proposing two different routing protocols, i.e., EO-C and EQ-AHA. EO-C is based on an equilibrium optimizer algorithm and is designed to address the energy conservation, optimum CH selection, optimum CH count selection, and hot spot problem in IoT-enabled SDWSNs. EO-C addresses these challenges with the help of dynamic CH count and a novel fitness function based on total residual energy, energy balance ratio, and total number of alive nodes in the network. Further, the performance of EO-C under various conditions is compared with several SoA algorithms, including EAFFO, EB-GWO, GWO-C, and LEACH. The results indicate that the EO-C outperforms other SoA algorithms in terms of network longevity, resilience, scalability, and coverage. EQ-AHA is a hybrid routing algorithm that employs two meta-heuristic algorithms. First, the AHA meta-heuristic algorithm is used to optimize the CH selection process while considering the energy ratio and an average of the total distance of CH and normal nodes. Secondly, the EQ meta-heuristic approach is used to determine the optimal path for delivering the data aggregated by CH to BS while considering the shortest route between BS and CH. In this way, the EQ-AHA helps the sensor nodes find paths at a minimum cost, hence extending the life of the network. The EQ-AHA was tested under various conditions and was compared with other SoA algorithms.

In order to achieve RO4, all three proposed models were rigorously evaluated against existing state-of-the-art algorithms through MATLAB-based simulations and compared. The results demonstrate significant improvements in network longevity, energy consumption, data packet delivery, and resilience compared to state-of-the-art techniques. The results consistently demonstrate that the proposed models significantly outperform traditional approaches, confirming their effectiveness for IoT-enabled SD-WSN applications.

6.2 Limitations of the Work

While the proposed routing protocols demonstrate significant improvements in energy efficiency and QoS provisioning for SDWSNs, certain limitations remain:

- **Simulation-Based Validation:** The performance evaluation has been conducted using MATLAB-based simulations. Real-world deployment and testing on physical hardware platforms have not been included, which may affect practical applicability.
- **Assumption of Static Topology:** The proposed algorithms assume a static network topology. Scenarios involving mobile sensor nodes or dynamic node failures are not thoroughly explored, which could limit applicability in more dynamic or mobile environments.
- **Computational Overhead:** Metaheuristic algorithms, while effective, can introduce significant computational complexity and convergence delays, particularly in large-scale networks or applications requiring real-time decision-making.
- **Security Aspects Not Considered:** The research does not address security concerns such as data confidentiality, node authentication, or secure routing, which are critical in many IoT applications.
- **Limited QoS Metrics:** Although the work focuses on key QoS parameters such as energy efficiency, data packets, distance, and load balancing, other aspects like jitter, fairness, and support for heterogeneous traffic are not extensively investigated.

6.3 Social Impact

The proposed energy-efficient and QoS-centric routing protocols for IoT-enabled Software-Defined Wireless Sensor Networks (SDWSNs) have the potential to deliver significant social and environmental benefits. By intelligently optimizing the selection of cluster heads and routing paths, the proposed models significantly reduce the energy consumption of sensor nodes—devices that are often deployed in large numbers across smart cities, environmental monitoring systems, healthcare infrastructures, and agricultural fields. Lower energy consumption directly translates to reduced battery usage and less frequent maintenance, thereby making these networks more sustainable and cost-effective, especially in remote or underdeveloped regions. More importantly, this energy efficiency contributes to a broader environmental goal. In most parts of the world, electricity is still predominantly generated using fossil fuels, which release considerable amounts of carbon dioxide and other greenhouse gases into the atmosphere. These emissions are major contributors to global warming, environmental degradation, and adverse climate change effects. By extending network lifetimes and reducing the power demand of IoT infrastructures, the proposed protocols help minimize the indirect carbon footprint associated with digital technology.

Consequently, the research promotes not only technological advancement but also aligns with global sustainability goals by reducing dependence on frequent energy replenishment and ultimately aiding in the mitigation of the greenhouse effect and global temperature rise. This work supports the development of green IoT systems that are both environmentally responsible and socially impactful.

6.4 Future Scope

The research presented in this thesis opens several promising directions for future work. While the proposed routing protocols have demonstrated strong performance in simulation environments, future studies can focus on real-world implementation using hardware platforms. Such deployment would provide deeper insights into the practical challenges of latency, memory constraints, and communication overhead. Moreover, the current work assumes a static network topology. Extending the protocols to support mobility and dynamically changing environments can significantly broaden their applicability, especially in domains like vehicular IoT, mobile healthcare systems, and disaster recovery operations. Integration with machine learning models also presents an exciting avenue for making the network more adaptive. Techniques like reinforcement learning and neural networks can assist in intelligent cluster head selection, anomaly detection, and predictive routing based on historical patterns.

Security and privacy concerns were beyond the scope of this work but are critical in sensitive applications. Future extensions can incorporate lightweight encryption and secure routing protocols to enhance trustworthiness. Another potential direction is the inclusion of energy harvesting mechanisms, such as solar or RF-based recharging, to create self-sustaining sensor nodes and extend network lifetime even further.

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Appendix A

List of Publication

Journals

1. R. Beniwal and N. Kumar, "Energy optimized artificial hummingbird algorithm for routing in IoT-based software-defined WSN," *International Journal of Communication Systems*, vol. 37, no. 8, Wiley **(SCIE)**, Mar. 2024. **[Published]**

2. N. Kumar and R. Beniwal, "A Multi-Constrained Green Routing Protocol for IoT-Based Software-Defined WSN," *Concurrency and Computation: Practice and Experience*, vol. 36, no. 28, Wiley **(SCIE)**, Oct. 2024. **[Published]**

3. R. Beniwal and N. Kumar, "A Nature-Inspired Multi-Objective Green Routing Protocol for IoT-Enabled SDWSNs," *Transaction on Emerging Telecommunication Technology*, Wiley **(SCIE)** May. 2025. **[Published]**

Conference Papers

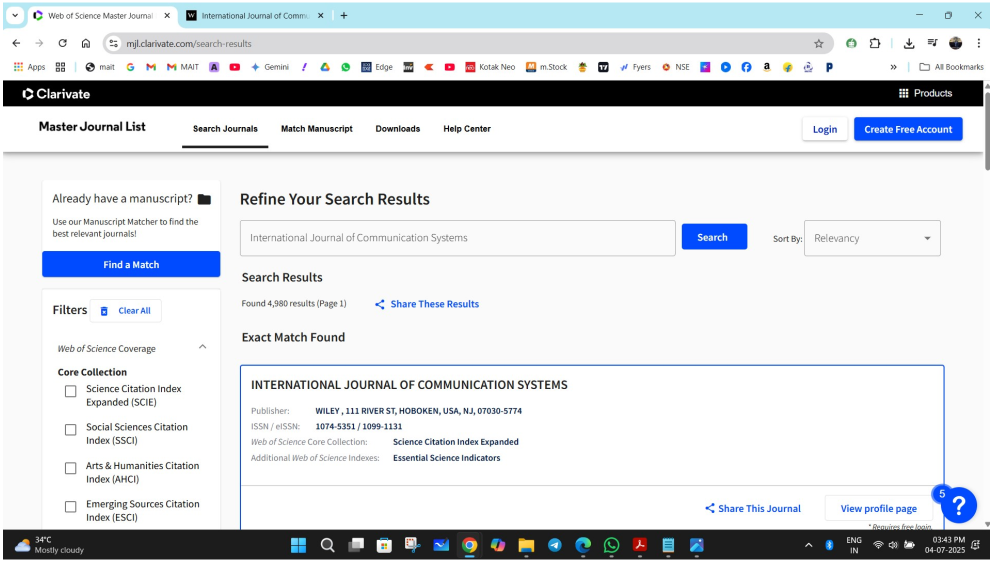
4 N. Kumar and R. Beniwal, "Energy-Efficient Techniques in IoT-based Software-Defined Wireless Sensor Networks: A Systematic Review," *7th International Conference on Energy, Power and Environment (ICEPE)*, IEEE, NIT Meghalaya, India, May 2025. **[Presented]**

5 N. Kumar and R. Beniwal, "Green Routing Protocols for IoT-Based Software-Defined Wireless Sensor Networks: A Comparative Analysis," *7th International Conference on Energy, Power and Environment (ICEPE)*, IEEE, NIT Meghalaya, India, May 2025. **[Presented]**

Appendix B

Proof of Publication

1. R. Beniwal and N. Kumar, “Energy optimized artificial hummingbird algorithm for routing in IoT-based software-defined WSN,” *International Journal of Communication Systems*, vol. 37, no. 8, Wiley **(SCIE)**, Mar. 2024. **[Published]**



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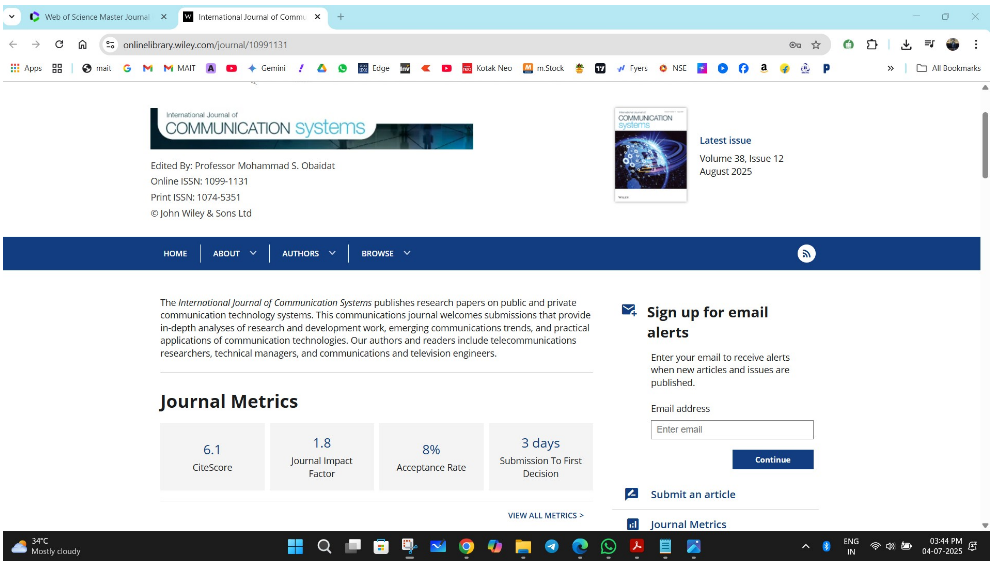

IJCS Journal Metrics

Received: 16 June 2023 | Revised: 2 December 2023 | Accepted: 25 January 2024

DOI: 10.1002/dac.5748

RESEARCH ARTICLE

WILEY

Energy optimized artificial hummingbird algorithm for routing in IoT-based software-defined WSN

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Summary

The Internet of Things (IoT) has become widely used in applications such as smart homes, industrial automation, and transportation due to its affordable hardware and fast internet connectivity. However, the increase in IoT-enabled gadgets, particularly those running on batteries or connected to other sources, is putting strain on the world's energy requirements. Therefore, this study focuses on a green routing solution for battery-powered IoT-enabled Software-defined Wireless Sensor Networks (IoT-SDWSN). Finding green solutions for IoT-based networks to address this energy challenge has become crucial. This study focuses on developing a green routing solution for battery-powered IoT-SDWSN. Energy efficiency in IoT-SDWSN is attained by the process of clustering nodes. The network is partitioned into small clusters, and a Control Node (CN) is set up by a Control Server (CS) to transmit the data packets sent by sensor nodes. Choosing a CN in these networks is a critical concern due to the substantial energy consumption involved in delivering data to the CS. This research focuses on the problem of energy-efficient cluster routing in IoT-based SD-WSN. It introduces the Energy-optimized Artificial Hummingbird Algorithm (EOAHA) as a green routing technique. EOAHA aims to extend the lifespan of IoT-based SD-WSNs by intelligently selecting (based on a new fitness function) CNs to distribute the network load and increase its overall longevity. To evaluate the performance of EOAHA, a comparative analysis is conducted against other state-of-the-art algorithms. The results demonstrate that EOAHA outperforms these algorithms by a minimum of 13.5% in terms of network longevity.

KEYWORDS

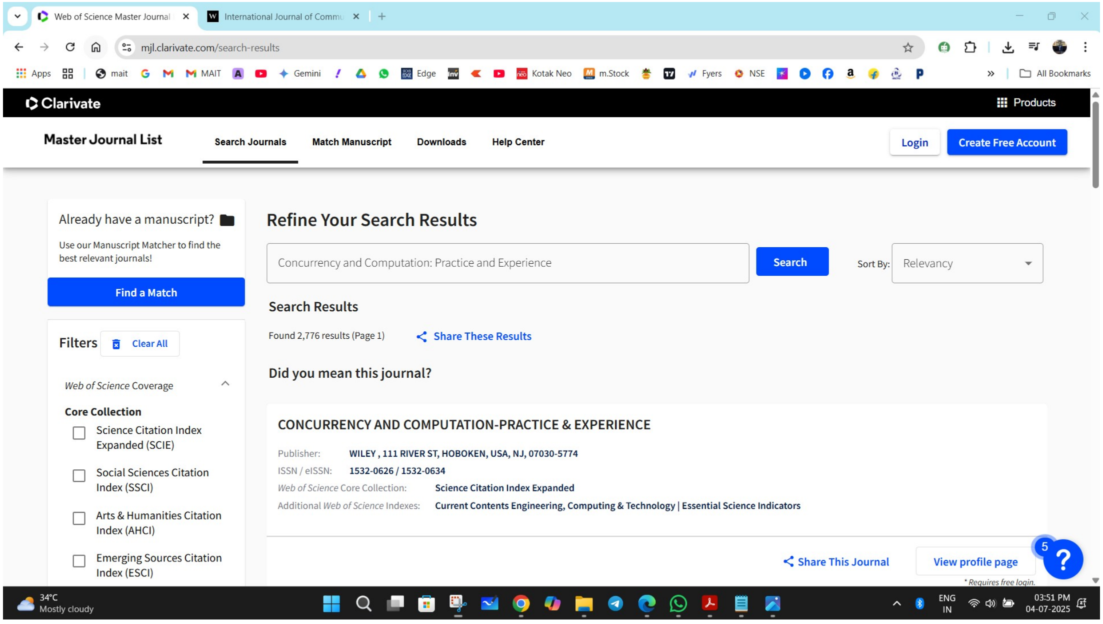
AHA, EOAHA, IoT, residual energy, SD-WSN, WSN

1 | INTRODUCTION

In today's world, demand for IoT devices and their applications, such as intelligent transport systems or internet of vehicles,[1] industrial Internet of Things (IIoT),[2] automation,[3] medical,[4] social networks of IoT devices,[5] smart homes/offices,[6,7] and so forth, is increasing exponentially. According to the article,[8] there are currently 19.8 billion IoT devices

Abbreviation: WSN, wireless sensor network.

2. N. Kumar and R. Beniwal, “A Multi-Constrained Green Routing Protocol for IoT-Based Software-Defined WSN,” *Concurrency and Computation: Practice and Experience*, vol. 36, no. 28, Wiley **(SCIE)**, Oct. 2024. **[Published]**



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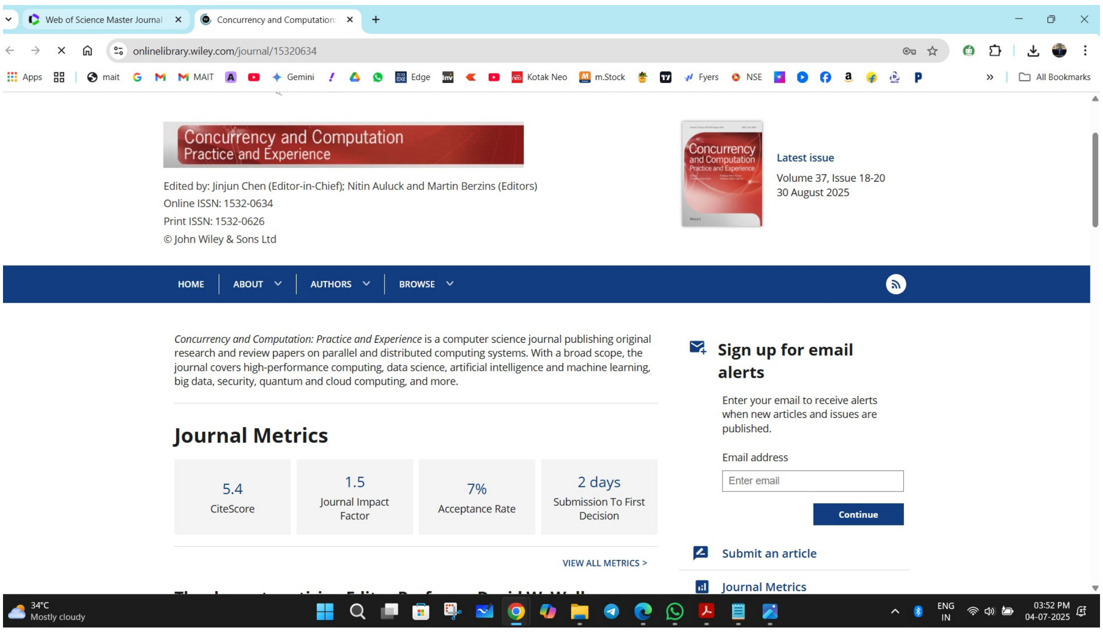

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RESEARCH ARTICLE

A Multi-Constrained Green Routing Protocol for IoT-Based Software-Defined WSN

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Received: 21 June 2024 | **Revised:** 15 September 2024 | **Accepted:** 25 September 2024

Keywords: energy aware | IoT | residual energy | SD-WSN | WSNAHA

ABSTRACT

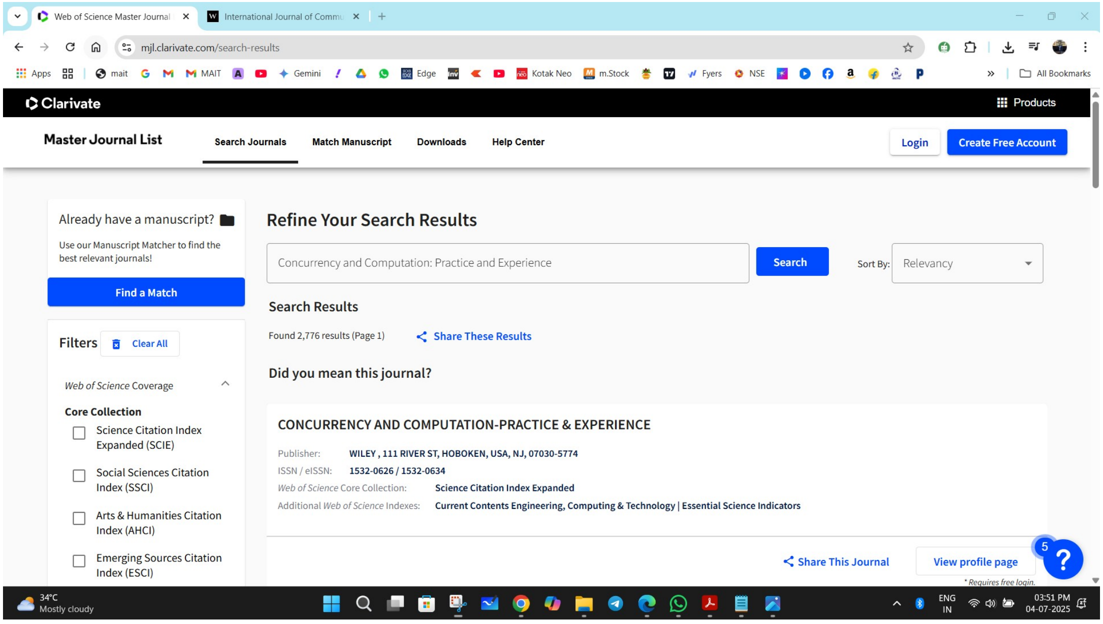
In recent times, there has been a notable surge in the utilization of Internet of Things (IoT) network devices due to their vast applications. However, this rapid growth has undoubtedly led to raised energy consumption, which, in turn, has raised significant concerns about the environment. Consequently, there is a growing demand for green computing techniques that can mitigate IoT device's energy usage and carbon footprint. Clustering IoT networks is a useful strategy for extending their lifespan. However, clustering presents a complex optimization problem that falls under the category of NP-hard; hence making it a challenging issue. Nevertheless, using meta-heuristics algorithms has greatly improved our ability to tackle such challenges. Therefore, this study introduces a clustering scheme called EQ-AHA, which combines Equilibrium optimization and artificial hummingbird optimization techniques to enhance the efficiency of IoT-based Software-Defined Wireless Sensor Networks (IoT-SDWSN). The primary goal of EQ-AHA is to select the Cluster Heads (CHs) and determine the optimal path between CHs and the Base Station (BS). EQ-AHA employs a fitness function that considers three important factors: the distance between CHs, the distance between nodes and the CHs, and the energy levels of the nodes. Overall, this strategy improves the network's performance by 31.6% compared to other State-of-the-Art (SoA) algorithms.

1 | Introduction

The Internet of Things (IoT) is a network of devices that communicate with each other over existing World Wide Web infrastructure. The major advantage of these devices is that they can make intelligent decisions depending on the evolving situations. Due to this advantage, IoT devices find vast applications in almost every domain. Starting with health, manufacturing industries, smart homes, smart vehicles, smart appliances, and smart cities are a few examples of applications of IoT. Managing a smart city involves the deployment of a large number of smart sensors (IoT-enabled SD-WSN) with features like remote reconfiguration and internet connectivity. The smart city concept involves extensive usage of software-defined wireless sensor nodes (IoT-SDSN) in IoT networks to manage various services such as smart transportation, traffic control, and smart power consumption in urban areas [1–3]. Over the past few decades, the demand for IoT has grown significantly, leading to software and hardware development of sensor nodes that can monitor and collect different types of information [4]. A wireless sensor network (WSN) that uses SDN concepts to enable dynamic network reconfiguration, management, and resource optimization is known as an IoT-SDWSN [5]. IoT-SDWSNs, in contrast to conventional WSN [6, 7], depend on software to manage network setup, updating behavior of nodes, and routing and communication protocols.

Dynamic configuration is one of the major advantages offered by IoT-SDWSN. Due to this attribute, the network seamlessly

3. R. Beniwal and N. Kumar, “A Nature-Inspired Multi-Objective Green Routing Protocol for IoT-Enabled SDWSNs,” *Transaction on Emerging Telecommunication Technology*, Wiley **(SCIE)** May. 2025. **[Published] [Published]**



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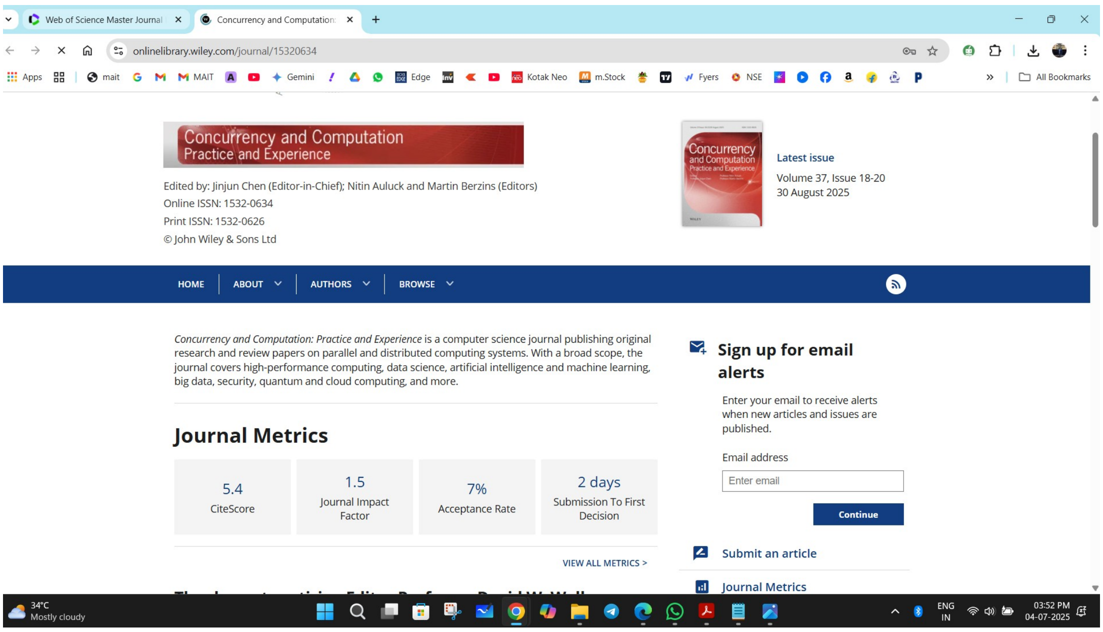

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RESEARCH ARTICLE

A Nature-Inspired Multi-Objective Green Routing Protocol for Iot-Enabled SDWSNs

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Correspondence: Nitesh Kumar (nit.wadhera@gmail.com)

Received: 31 May 2024 | **Revised:** 13 December 2024 | **Accepted:** 24 May 2025

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Keywords: clustering | green computing | internet of things | SDN | SDWSNs | wireless sensor networks

ABSTRACT

A smart city leverages technology and data to enhance the quality of life for its residents, improve urban services, and optimize resource management. The rapid rise in Internet of Things (IoT) devices has led to a significant surge in energy requirements, making energy optimization critical to mitigate this growing global demand. Clustering is a widely adopted technique to achieve energy optimization in IoT-enabled Software-Defined Wireless Sensor Networks (SDWSNs). In clustering, the network is divided into small groups, and a Cluster Head (CH) is chosen by a Control Station (CS) to forward data packets from sensing nodes. The role of CH is power-consuming as it aggregates data from its cluster and forwards it to CS; this may lead to hot-spot problems. Therefore, it is very important to select CH wisely. Hence, this article proposes an EO-C algorithm to address multiple objectives like hot-spot problems, network life, energy optimization, and reliability. EO-C aims to enhance energy efficiency in IoT-enabled SDWSNs by dynamically optimizing the selection process of CH using a novel fitness function based on residual energy, energy balance ratio, and alive node count. The simulation findings demonstrated that EO-C surpasses other SOA algorithms with an improvement in network lifespan ranging from 15.86% to 372.6%, showcasing its effectiveness across various scenarios. Additionally, EO-C exhibits robust scalability, effectively handling diverse node densities and deployment areas, making it a promising solution for sustainable IoT networks.

1 | Introduction

Today, the demand for IoT devices and their applications is rapidly increasing. Some of the applications of IoT-based networks include intelligent transit systems [1], industrial automation [2], healthcare [3], smart homes [4], intelligent farming [5, 6], environmental monitoring [7], etc. Due to their wide range of applications, IoT-based networks have become important in our everyday lives. At the heart of IoT devices lies their ability to make informed decisions based on data gathered through sensors or sensor networks. The growing IoT ecosystem demands the complex structure of Wireless Sensor Networks (WSN) [8]. WSN consists of sensor nodes that sense and route data but have limited connectivity, storage, and processing capabilities. Managing extensive IoT device networks, particularly in scenarios like WSNs operating in remote or inaccessible locations, poses significant challenges, including energy constraints, network scalability, network security [9], and data transmission reliability [10]. As WSN complexity grows, manual management and maintenance of dense networks become unfeasible in real-time. The SDWSNs address the constraints of standard WSNs by separating the data plane and control plane. The data plane

Abbreviations: IoT, internet of things; SDWSNs, software defined wireless sensor networks; WSN, wireless sensor networks.

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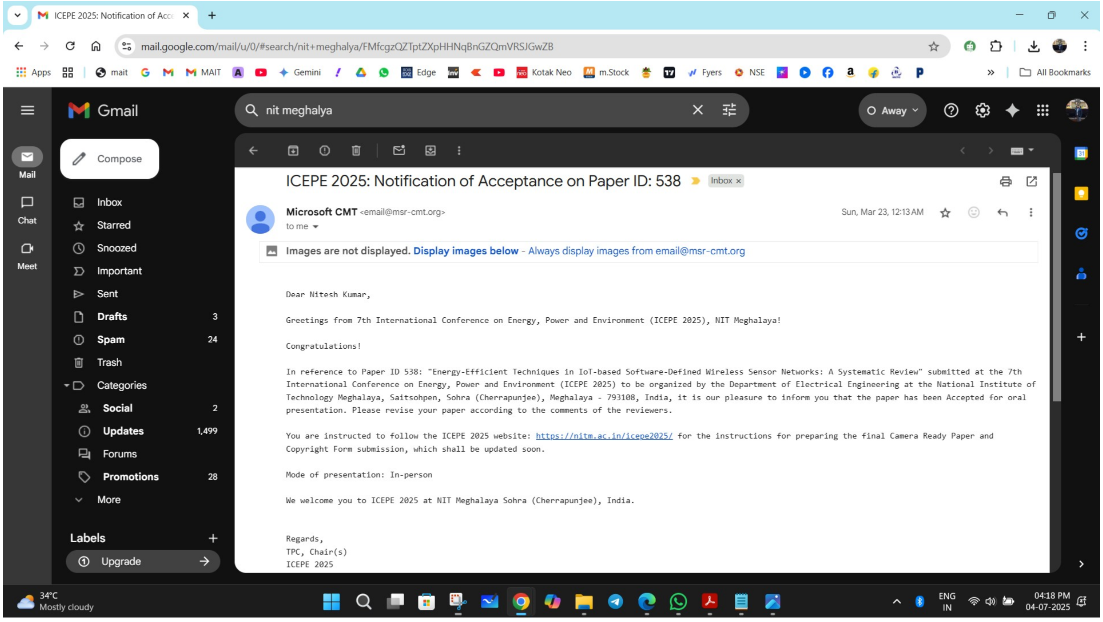

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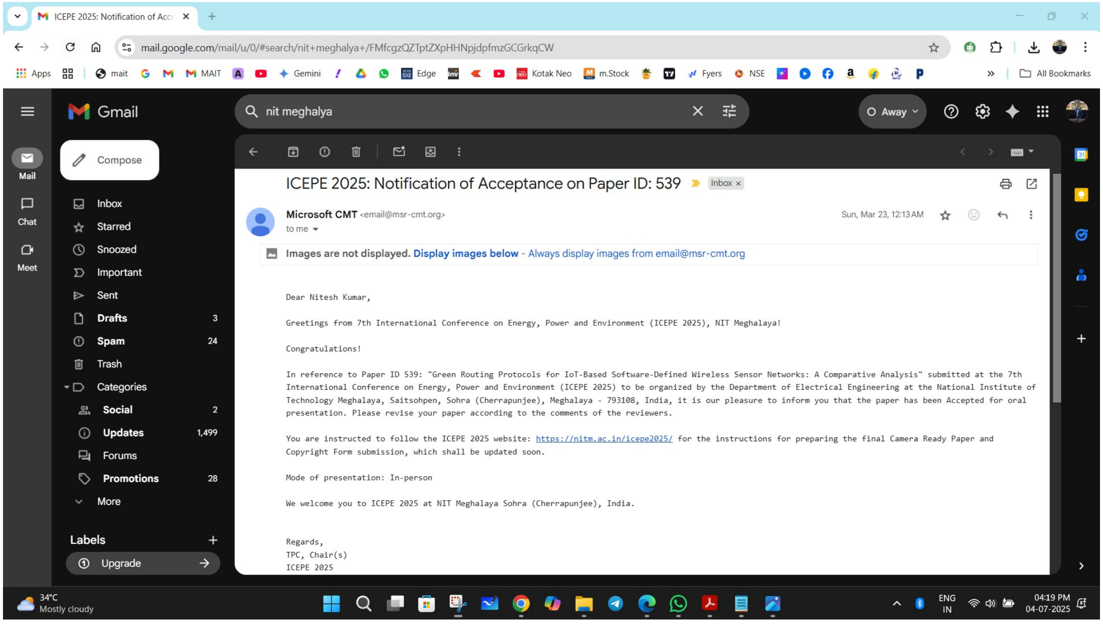

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Appendix C

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Appendix D

Biography

Nitesh Kumar is currently pursuing a Ph.D. in Computer Science and Engineering at Delhi Technological University, India. He received his M.Tech. degree in Information Technology from Guru Gobind Singh Indraprastha University, Delhi, where he was the Gold Medalist of the 2010 batch. He also holds a B.Tech. degree in Electronics and Communication from the same university. He has qualified for prestigious national examinations, including the UGC JRF, UGC NET, and GATE. Currently, he serves as an Assistant Professor in the Department of Information Technology at Maharaja Agrasen Institute of Technology (affiliated with GGSIPU), Delhi. His primary research interests include Wireless Sensor Networks (WSNs), the Internet of Things (IoT), and Machine Learning.