AN ENERGY OPTIMIZED APPROACH FOR THE DESIGN OF WIRELESS SENSOR NETWORKS

by

MAKWENA IDAH MASOPOGA

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Supervisor: Prof. Mbuyu Sumbwanyambe

Co-Supervisor: Prof. Zenghui Wang

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'I declare that the research dissertation with the title,

"An Energy Optimized Approach for the Design of Wireless Sensor Networks",

It is my own work, and all the sources that I have used or quoted have been indicated and acknowledged by means of a comprehensive list of references.

Signature:

M.I. Masopoga

Date: December, 2025

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Dedication

I dedicate this work to my grandmother, who has gifted me with the value of education. She has taught me resilience, hard work, and dedication in everything I pursue. Moreover, she instilled in me the spirit of ubuntu, along with a deep respect and love for others that I will carry for the rest of my life. She has always been, and will continue to be, my pillar of strength.

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Abstract

In today's data-driven world, we need to ensure reliable wireless access as it is vital. The increasing demand for data connectivity has significantly raised power consumption in wireless networks. Wireless Sensor Networks (WSNs), which rely on battery power, face significant challenges due to this vulnerability. WSNs are widely utilized in various applications, including environmental monitoring, healthcare, industrial machinery, and security. Extending their operational lifetime is crucial for ensuring sustainable network performance. The primary limitation of WSNs lies in their energy-constrained nature. As nodes run out of energy, they begin to fail, resulting in reduced network coverage, connectivity, and throughput. While numerous protocols and algorithms have been proposed to extend network lifetime, overcoming power limitations remains a significant challenge. Existing heuristic approaches provide near-optimal solutions but are often impractical for real-time implementation.

The goal of this research is to develop and assess energy-efficient algorithms that minimize power consumption and prolong the lifespan of WSNs. The specific objectives are to design an algorithm that optimizes energy usage through efficient routing and clustering, to balance energy consumption among nodes, reducing the likelihood of premature node failures, and to improve network throughput. This study adopts a simulation-based approach to evaluate the proposed algorithm. An energy-aware protocol is implemented to evenly distribute network workload and minimize energy wastage. The research contributes by demonstrating that heuristic solutions can be enhanced to achieve near-optimal performance, closing the gap between offline optimization and practical, real-time deployment. Simulation results indicate that the proposed algorithm improves network lifetime and energy efficiency. Specifically, it achieves over 50% improvement in First Node Death (FND), 14% improvement in Last Node Death (LND), and 37% overall energy savings compared to conventional approaches. These results confirm that better energy balancing significantly enhances WSN sustainability and supports their long-term use across diverse applications.

Keywords: *WSN, optimization algorithm, energy efficiency, clustering, routing, energy optimization, LEACH, PSO*

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List of acronyms

ABC	: Artificial Bee Colony
ACA	: Ant Colony Algorithm
BS	: Base station
BTT	: Batteries
CA	: Clustering Algorithm
CH	: Cluster Head
CT	: Citations
DSR	: Design science research
ECN	: Energy Consumption
EE	: Energy Efficiency
EECA	: Energy Efficiency Clustering Algorithm
EOA	: Energy Optimisation Algorithm
FL	: Fuzzy Logic
GA	: Genetic Algorithm
GWO	: Grey Wolf Optimisation
HTR	: Heterogeneity
IEEE	: Institute of Electrical and Electronics Engineers
IOT	: Internet Of Things
LB	: Load Balancing
LEACH	: Low-Energy Adaptive Clustering Hierarchy
MHR	: Multi Hop Routing
MNT	: Monitoring

MN	: Mobile Nodes
MOO	: Multi-objective optimisation
MS	: Mobile Sink
MTH	: Metaheuristics
NLT	: Network Lifetime
OP	: Optimal Path
PSO	: Particle Swarm Optimization
QOS	: Quality Of Service
RA	: Routing Algorithm
SD	: Standard
SSC	: Spread Spectrum Communication
TLS	: Total Link Strength
WOS	: Web Of Science
WSN	: Wireless Sensor Network

List of publications

The following research outputs were published/submitted from this thesis:

Journals:

1) "A Bibliometric Analysis Review on Energy Optimisation while Designing Wireless Sensor Networks," Journal of Engineering Research and Sciences, vol. 3, no. 11, pp. 81–92, 2024. **This journal article is related to Chapter 2 of this dissertation.**
2) "An energy-optimized approach for the design of wireless sensor networks", Submitted to a journal. **This journal article is related to Chapter 4 of this dissertation.**

Chapter 1 : Introduction

1.0 Introduction and Background

Reliable wireless access is essential in today's digital world. The increasing demand for data connectivity has significantly raised power consumption in wireless networks [1]. Wireless Sensor Networks (WSNs), which are typically battery-powered, are particularly affected by this challenge. Since WSNs are pivotal in various applications, such as environmental monitoring, healthcare, industrial automation, and security, extending their operational lifetime is crucial for ensuring sustainable network performance [2].

The significance of Wireless Sensor Networks (WSNs) lies in their diverse applications across various fields. They are used in environmental monitoring, healthcare, industrial automation, military surveillance, smart agriculture, and disaster management [3]. For example, in precision agriculture, WSNs help optimize irrigation and fertilization by providing real-time soil moisture data. In healthcare, they enable remote patient monitoring through wearable sensors. Additionally, WSNs are crucial for developing smart cities, as they enable intelligent traffic control, pollution detection, and effective management of infrastructure.

Wireless Sensor Networks (WSNs) offer several advantages, but they also face significant challenges. These include limited energy resources, scalability issues with the network, data security concerns, and the need for reliable communication [4]. Overcoming these challenges is important for increasing the performance and extending the operating lifetime of sensor networks. Current investigations in wireless sensor networks focus on routing strategies that conserve energy and on dependable approaches for collecting and handling data, as well as secure communication frameworks to expand their applications.

Studying WSNs is vital, as they are indispensable components of both the Internet of Things (IoT) [5] and modern cyber-physical systems. Understanding WSNs is essential for advancing these critical technologies in physical systems. These networks facilitate progress in automation and support data-driven decision-making.

As the need for real-time, wireless sensing grows, WSNs will significantly influence future technological innovations. Thus, this field is essential for research and development. In some specialized applications, specific sensor nodes may also be difficult to access. Additionally, some sensor nodes use non-rechargeable batteries. Therefore, it is crucial to ensure that the nodes remain functional throughout their entire mission duration. One of the primary challenges facing wireless sensor networks is their limited performance, which significantly impacts the overall lifespan of the network [6].

Scalability is also crucial, allowing the network to grow effortlessly to support more sensors without compromising performance [7]. Furthermore, wireless sensor networks can operate over a wide range of densities, making them adaptable to various environments and applications. Programmability allows for the customization of the network's functions and behaviors, while maintainability ensures that the systems can be easily serviced and updated as needed. Together, these attributes contribute to the effectiveness and robustness of wireless sensor networks in diverse settings [8]. Figure 1.1 shows a typical structure of a WSN.

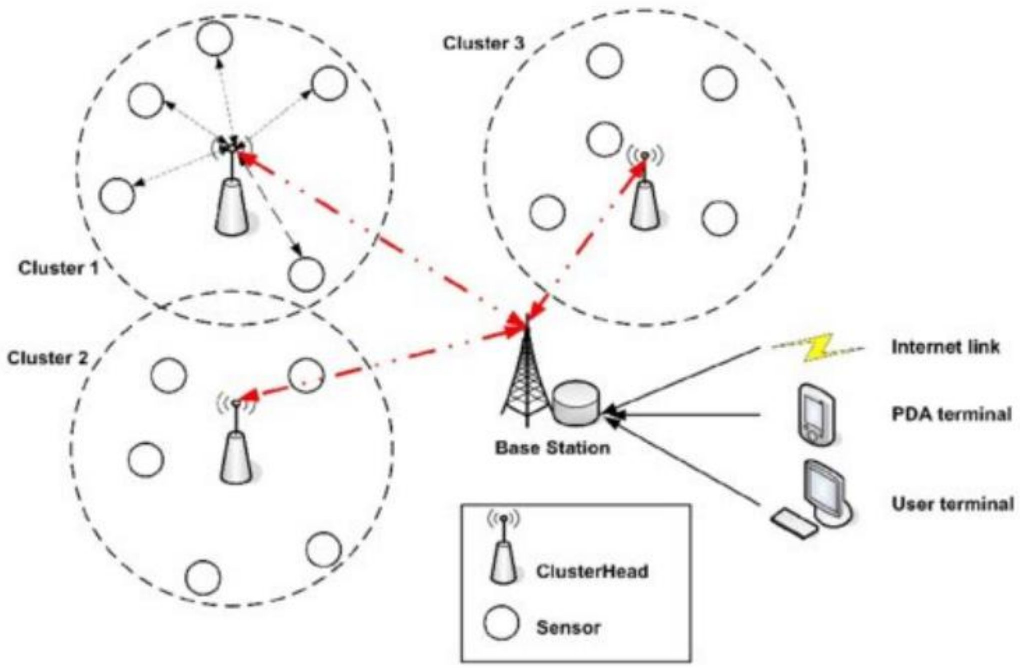

Figure 1.1: Typical Structure of a WSN [9]

1.1 Problem statement

The primary limitation of WSNs lies in their energy-constrained nature. As nodes lose their energy, they begin to fail, resulting in reduced network coverage, connectivity, and throughput. While numerous protocols and algorithms have been proposed to extend network lifetime, overcoming power limitations remains a significant challenge. Existing heuristic approaches provide near-optimal solutions but are often impractical for real-time implementation, leaving a gap between theoretical energy optimization and practical deployment.

SUB-PROBLEMS

1.1.1 Sub-problem 1

Energy is a limited resource in WSNs because nodes are typically tiny compared to the complexity of their task and support high-capacity power supplies [10]. While substantial progress has been achieved in enhancing the efficiency of energy in numerous routing protocols and distributing the consumption of energy throughout the network, there remains an ongoing effort to further refine energy efficiency through advanced modeling of energy consumption patterns within the network.

1.1.2 Sub-problem 2

The size of sensor nodes, particularly in terms of their low-power computing capabilities, remains a limiting factor for renewable energy and self-charging mechanisms. Due to this limitation, a power failure on some nodes in the network poses a severe problem, as it can lead to premature fragmentation of the entire network.

1.2 Research Objectives

The aim of this research is to develop and evaluate energy-aware algorithms that reduce power consumption and extend the lifetime of WSNs [11]. This will increase the performance of WSNs while maximizing throughput and energy efficiency. The limited performance of batteries considerably affects the efficiency and longevity of WSNs, making it a critical concern for their sustained operation.

The specific objectives are:

- To design an algorithm that optimizes energy usage through efficient routing and clustering.

- To ensure balanced energy use across the nodes, reducing the likelihood of premature node failures.
- To enhance network throughput and guarantee dependable data delivery over a long-term operational period.

1.3 Research hypotheses

Considering the identified problems and the sub-problems of this research, the hypotheses can be presented as follows:

- By using a network of several base stations operated with permanent power sources (i.e, without energy challenges) on different sides of the geographical WSN area of operation, instead of a single base station.
- We can achieve a very fair and balanced energy consumption in the system network, thereby ensuring that the route with the lowest energy consumption is used.
- This enables evenly distributed power consumption throughout the network and improves network reliability by providing multiple routing options from a source node to the base station.

1.4 Research methodology

This study employs the Design Science Research (DSR) methodology, also known as constructive research [12]. DSR is chosen over more traditional research approaches because it emphasizes the creation and evaluation of artifacts to address identified problems, a key contribution of this dissertation. This approach aligns well with the objective of creating and simulating an energy-efficient routing solution for WSNs.

The network simulations would be designed and implemented using MATLAB, a widely used simulation environment for WSN research. MATLAB is selected because it is both easily accessible and freely licensed to students for the University of South Africa, making it a practical and cost-effective tool for this research. The software allows for efficient implementation, testing, and comparison of routing algorithms under controlled and repeatable conditions.

The research was carried out in five systematic [13] steps, following the typical flow of a design science study:

Step 1: Literature Review

A comprehensive and critical review of existing energy-efficient routing algorithms in WSNs was conducted [14]. This review provides insight into the current state of research, identified gaps in existing solutions, and established the theoretical foundation for the study.

Step 2: Problem Analysis and Algorithm Selection

The findings from the literature review are analyzed and summarized to clearly define the problem context. This step also involves exploring potential optimization techniques and selecting candidate approaches (LEACH and PSO) that could address the energy efficiency challenges described in the problem statement [15].

Step 3: Algorithm Implementation

The selected algorithms LEACH and PSO are implemented within the MATLAB simulation environment. This implementation provides a baseline for performance comparison and allowed for the evaluation of their effectiveness under similar network conditions.

Step 4: Simulation and Evaluation

The developed algorithms were simulated in MATLAB, and their performance was evaluated using multiple network metrics. This step ensured that the theoretical design is validated in a controlled simulation environment.

Step 5: Results Analysis and Interpretation

The results to be obtained from the simulations are analyzed, interpreted, and compared against the baseline LEACH and PSO approaches. The comparison focuses not only on energy efficiency but also on other key network performance indicators, such as reliability, latency, and scalability. The findings are then used to draw conclusions, highlight the contributions of the study, and formulate recommendations for future research.

1.5 Research strategy

This study intends to investigate and enhance the efficiency of performance in WSNs. by developing a LEACH-based technique through the PSO algorithm. The following approach was employed to achieve this goal:

- By conducting a systematic literature review [16], This delivers a clear and comprehensive overview of available optimization algorithms in WSNs and also identifies the current gaps in the optimization of Wireless Sensor Networks, thereby improving their lifespan.
- Subsequent to a detailed systematic literature review on wireless sensor networks, a software tool, such as MATLAB, is used to develop the model to evaluate the hypothesis.
- To address the hypothesis, a mathematical model to implement power control is developed using a game-theoretic approach as the basis. The model will be developed within the framework of system dynamics.
- To achieve the hypothesis, a system dynamics tool, such as MATLAB, is used to simulate the model. The aim is to achieve a model that can be deployed for future modelling and simulations.

Along with the research questions and hypotheses mentioned earlier, Table 1.1 recaps how the research hypothesis is assessed to address these research questions.

Table 1.1: Summary of research strategy.

S/N	Research question	Research hypothesis	Method
i	Is the shortest path to the BS always the least energy-consuming path?	By further modeling the energy consumption in the network, the quality of routing decisions has improved, minimizing energy usage of sensor nodes and reducing transmission attempts, leading to lower transmission delays.	Subsequent to a detailed systematic literature review on optimisation algorithms in WSNs.
ii	What about a possible hybrid PSO-LEACH [17] algorithm approach?	The development of a more practical approach with balanced energy consumption between sensor nodes in a WSN leads to an extension of the network's life and offers the network user a guarantee that the sensor nodes used will remain operational throughout the network's entire operating life.	To develop a hybrid methodological approach by combining the PSO and LEACH optimisation algorithms.

iii	Can grouping sensor nodes into clusters with a dynamic selection of the cluster head help balance the overall energy consumption throughout the network and ensure a longer network lifetime?	The operation of the battery in the sensor nodes should be maintained over the entire service life.	Modelling the energy consumption in the network using MATLAB to simulate and evaluate the developed model.

1.6 Significance of the research

Intelligent, wireless networked sensors will soon surround us everywhere, collectively processing vast amounts of previously unrecorded data to support factory operations, optimize agriculture, monitor the weather, and many other applications. It is crucial to ensure that wireless sensor networks function reliably throughout their lifespan. This study aims to optimize energy consumption in WSNs [18] by improving the existing above-mentioned algorithms to ensure reliable delivery of services to WSN users.

By successfully completing this research, the following benefits may be achieved:

- By modeling the network's energy consumption, the quality of the routing decisions is improved, the energy consumption of the sensor nodes is reduced, and the transmission attempts can be reduced, which leads to low transmission delays.
- The development of a much more practical approach with balanced energy consumption between the sensor nodes of a WSN leads to an extension of the operational lifespan and offers the network user a guarantee that the sensor nodes used will be operational during the entire operating life of the network.
- The operation of the battery in the sensor nodes should be able to be maintained over the entire service life.

- To publish one conference article and one journal article based on the developed energy optimization technique’s outcomes.

1.6.1 Social Implications

WSNs have become an essential enabling technology for applications that support modern society, including environmental monitoring, precision agriculture, healthcare, industrial automation, disaster management, and smart city infrastructure. Most sensor nodes are battery-powered and are often deployed in remote or hazardous environments where replacing or recharging batteries is difficult, costly, or impractical. Consequently, excessive energy consumption shortens network lifetime, reduces data reliability, and increases maintenance requirements, limiting the effectiveness of these critical applications.

This research addresses these challenges by proposing a PSO-LEACH routing algorithm that improves energy-efficient cluster head selection and balances energy consumption among sensor nodes. By reducing unnecessary energy expenditure and prolonging network lifetime, the proposed approach enables WSNs to operate reliably for extended periods without frequent battery replacement or network maintenance.

The societal benefits of this research arise from the improved reliability and longevity of WSN deployments across several sectors. In environmental monitoring, longer-lasting sensor networks enable continuous observation of air quality, water resources, and wildlife habitats, thereby supporting informed environmental management and conservation efforts. In precision agriculture, energy-efficient WSNs facilitate continuous monitoring of soil moisture, temperature, and crop conditions, allowing farmers to optimise irrigation and resource utilisation while improving food production. Within healthcare, extended sensor network operation enhances remote patient monitoring by ensuring uninterrupted collection and transmission of physiological data, thereby supporting timely clinical intervention. In industrial environments, reliable WSNs enable continuous equipment monitoring and predictive maintenance, reducing operational downtime and improving workplace safety. Similarly, disaster monitoring systems benefit from sustained sensor operation by providing early detection of hazards such as wildfires, floods, or structural failures, enabling faster emergency response and reducing risks to human life and infrastructure.

Furthermore, extending the operational lifetime of battery-powered sensor networks reduces electronic waste and lowers maintenance costs associated with battery replacement and field servicing. These improvements support sustainable resource utilisation, reduce the environmental impact of large-scale sensor deployments, and enhance the economic viability of WSN applications. Therefore, the proposed PSO-LEACH algorithm contributes to more sustainable, reliable, and energy-efficient sensing systems that provide tangible environmental, economic, and societal benefits across multiple application domains.

Firstly, we consider the **environmental benefits**. WSNs are often deployed in remote or harsh environments for monitoring purposes, tracking wildlife, observing climate change indicators, or detecting pollution. By extending the battery life of these sensor nodes, this research directly reduces the need for frequent human intervention to replace or recharge them. This minimizes disruption to sensitive ecosystems and lowers the carbon footprint associated with maintenance operations. A network that can operate autonomously for years, rather than months, is a powerful tool for long-term environmental stewardship.

Secondly, there are profound **economic advantages**. Industries such as agriculture, infrastructure monitoring, and smart cities heavily rely on WSNs. In agriculture, sensors can optimize irrigation and fertilization, leading to reduced resource consumption and increased crop yields. For infrastructure, WSNs can detect early signs of structural fatigue in bridges or buildings, preventing costly failures and ensuring public safety. In smart cities, efficient WSNs underpin everything from intelligent traffic management to waste collection, leading to operational cost savings and improved urban living. Making these networks more reliable and less energy-hungry translates directly into tangible financial savings for businesses and municipalities.

Thirdly, the research contributes to **improved quality of life and safety**. In healthcare, WSNs can remotely monitor patients, providing critical data to medical professionals and enabling proactive care, particularly for the elderly or those in remote areas. In disaster management, robust and long-lasting WSNs can provide early warnings for events like floods, earthquakes, or forest fires, giving communities vital time to prepare and evacuate. The enhanced reliability and extended operational periods resulting from your optimized algorithms mean these life-saving systems are less likely to fail when they are needed most.

Ultimately, this type of research promotes **technological advancement and innovation**. By pushing the boundaries of WSN efficiency, this work opens doors for new applications and more ambitious deployments that were previously impractical due to energy constraints. It provides a foundation for future research in areas like self-sustaining sensor networks, advanced data analytics, and even more sophisticated AI-driven network management, driving the next wave of technological progress.

In essence, by making WSNs more resilient and energy independent, this research isn't just an academic exercise; it's a practical step towards solving real-world problems, conserving resources, saving lives, and building the intelligent infrastructure of tomorrow.

1.7 Delimitations of Study

This research project is intentionally constrained by specific boundaries to maintain focus and feasibility. The scope of this investigation is defined by the following key delimitations:

- **Node Mobility:** Throughout this study, we exclusively consider static sensor nodes. Consequently, the implications and complexities arising from high node mobility are not addressed [19].
- **Sink Node Configuration:** The network architecture assumes that sensor nodes transmit text messages to a single base station (sink node). The scenario involving multiple sink nodes falls outside the purview of this investigation [20].
- **Simulation Environment:** The entire study is conducted within a simulated environment. This means that the proposed approach and its validation are purely theoretical; a physical implementation of the system is not undertaken. The algorithms developed are tested solely on a network simulation platform,

implying that the results reflect a real-world implementation scenario only to a certain extent.

1.8 Dissertation Outline

This section provides a detailed overview of the entire dissertation, summarizing the key themes, methodologies, and findings discussed in the later chapters. This structured approach ensures that readers have a clear understanding of what to expect and the rationale behind the research. Ultimately, this introduction sets the stage for a comprehensive examination of the topic. The dissertation structure is as follows:

Chapter 1: This chapter provides introductory notes, presents the research background, outlines the problems and sub-problems considered in this study, states the project's objectives, articulates the hypotheses, and discusses the limitations associated with the study.

Chapter 2: This chapter presents a detailed literature review and explores existing energy optimization algorithms, focusing on the PSO [21] and LEACH [22] algorithms.

Chapter 3: This chapter outlines the research design and methodology employed to achieve the findings and outcomes of this study. It will also explain the reasons behind selecting the approaches and methods used to model network energy consumption and develop the network optimization algorithm.

Chapter 4: In this chapter, the results of implementing software algorithms in a discrete network simulator are analyzed, interpreted, discussed, and compared with results from previous work.

Chapter 5: This chapter summarizes the study's results, highlighting the contributions of the dissertation.

Chapter 6: This chapter offers concluding remarks and suggestions for future research based on the challenges and limitations encountered.

The following shows a roadmap illustrated in Figure 1.2. This roadmap aims to help the reader easily navigate the outline presented in this dissertation. The chapters are interconnected, as indicated by the lines in the figure. Readers are encouraged to follow solid lines to enhance their understanding. However, each chapter is designed to be read and understood independently.

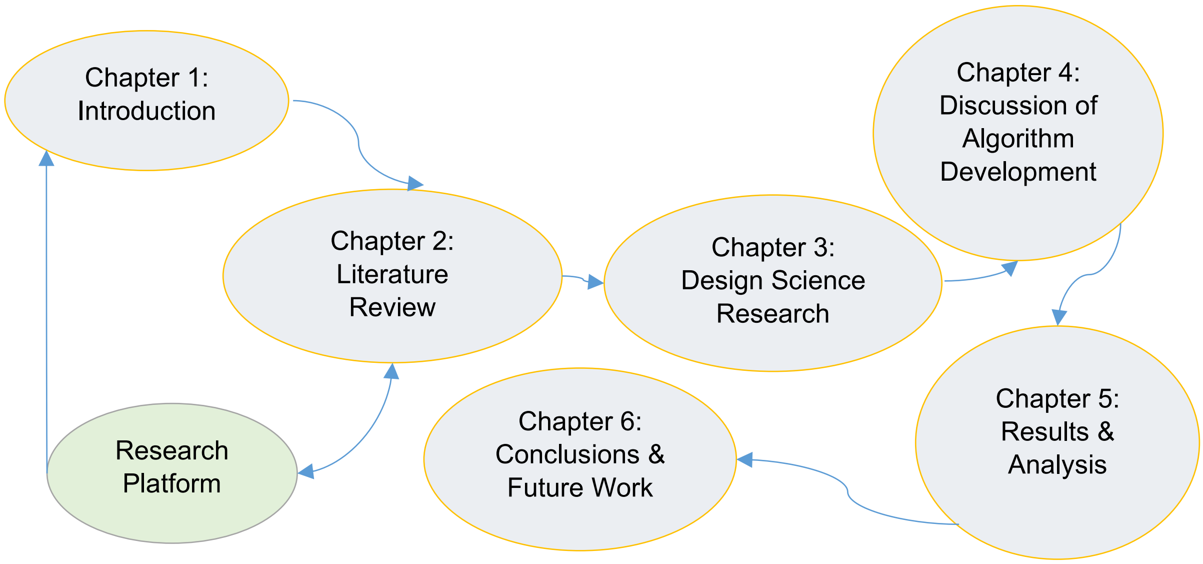

Figure 1.2: Research roadmap

Chapter 2 : Literature review

2.1 Introduction

WSNs have become an important research area due to their wide range of applications in environmental monitoring, healthcare systems, industrial automation, smart cities, and Internet of Things (IoT) environments. However, despite their significant advantages, WSNs continue to face fundamental challenges associated with limited sensor node energy capacity, inefficient communication mechanisms, and reduced network lifetime. Since sensor nodes are generally powered by non-rechargeable batteries and are often deployed in remote or inaccessible environments, efficient energy management remains a critical factor influencing the overall performance and sustainability of WSNs[23].

This chapter presents a comprehensive review of existing research related to energy-efficient routing and clustering optimization techniques in WSNs. The primary focus of this chapter is on two fundamental approaches: the LEACH protocol and PSO[24]. These techniques were selected because they represent two complementary approaches to addressing energy consumption challenges in WSNs. LEACH is one of the most widely adopted hierarchical routing protocols and provides an effective mechanism for reducing communication overhead through clustering and data aggregation. However, its probabilistic cluster-head selection mechanism may result in uneven energy distribution, inefficient cluster formation, and premature node failures. Therefore, although LEACH improves energy efficiency compared with direct communication approaches, it does not always achieve optimal energy balancing across the network.

Conversely, PSO is a population-based metaheuristic optimization algorithm that has demonstrated strong capability for solving complex optimization problems, including cluster-head selection and routing optimization in WSNs. Unlike conventional deterministic approaches, PSO can evaluate multiple candidate solutions simultaneously and optimize cluster formation based on several network parameters. However, standalone PSO-based approaches may introduce additional computational complexity and may not fully exploit the advantages of established clustering protocols such as LEACH. Therefore, integrating PSO with LEACH offers an opportunity to combine LEACH's energy-efficient clustering with PSO's optimization capabilities [25]. Although numerous studies have investigated energy optimization techniques for WSNs, a significant research gap remains regarding the effective balancing of energy consumption among sensor nodes while simultaneously improving throughput and network lifetime. Existing LEACH-based approaches often rely on random cluster-head selection, which may cause some nodes to consume energy faster than others. Similarly, many optimization-based approaches focus primarily on selecting optimal cluster heads based on individual parameters, without considering the combined influence of residual energy, node density, and distance to the base station. This limitation may result in inefficient energy utilization and reduced network stability.

To identify current research trends and establish the relevance of this study, this chapter also presents a bibliometric analysis of WSN energy optimization research. The bibliometric analysis investigates publication trends, influential research areas, collaboration patterns, and frequently studied keywords related to WSN routing, clustering algorithms, LEACH, PSO, and energy efficiency. The findings confirm that energy optimization, clustering algorithms, and metaheuristic techniques remain active research areas, while highlighting the continued need for improved adaptive algorithms that achieve balanced energy consumption and enhanced network performance[26].

Therefore, this chapter establishes the foundation for the proposed research by critically analysing existing LEACH and PSO approaches, identifying their limitations, and justifying the development of a hybrid PSO-LEACH optimization algorithm. The proposed approach aims to address the identified research gap by improving cluster-head selection, balancing energy consumption among sensor nodes, increasing throughput, and extending the operational lifetime of WSNs.

The remainder of this chapter is structured as follows. Section 2.2 presents the fundamentals of Wireless Sensor Networks and their challenges. Section 2.3 discusses existing energy-efficient routing and clustering algorithms, including LEACH and PSO-based approaches. Section 2.4 presents the bibliometric analysis of WSN energy optimization research. Finally, Section 2.5 summarizes the findings from the literature review and identifies the research gap addressed by this study.

2.2 Optimization and Routing Algorithms in WSNs

WSNs have attracted significant research interest due to their applications in environmental monitoring, healthcare, industrial automation, military surveillance, and smart agriculture. Since sensor nodes are typically powered by non-rechargeable batteries, energy efficiency remains a primary challenge for extending network lifetime. Consequently, numerous routing and optimization algorithms have been proposed to minimise energy consumption through efficient cluster formation, routing, and CH selection.

WSN routing protocols are typically categorized into four main types: flat, hierarchical (cluster-based), location-based, and bio-inspired or metaheuristic optimization approaches. Flat routing protocols, such as Directed Diffusion and SPIN, treat all sensor nodes equally and are best suited for small-scale networks. However, as the network size increases, these protocols tend to generate excessive communication overhead and consume more energy, making them less suitable for large-scale WSN deployments.

Hierarchical routing protocols organise sensor nodes into clusters to reduce communication overhead and distribute energy consumption more efficiently. Among these protocols, LEACH remains one of the most widely studied and benchmarked protocols because of its simplicity, distributed operation, and periodic rotation of cluster heads. LEACH reduces long-distance transmissions through local data aggregation, thereby significantly improving network lifetime compared with direct communication approaches. Nevertheless, its random cluster head selection may produce uneven cluster sizes and unbalanced energy depletion, particularly in dense or heterogeneous networks.

To overcome the limitations of deterministic or probabilistic routing protocols, researchers have increasingly adopted metaheuristic optimization algorithms. Techniques such as Genetic Algorithms (GA), Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Firefly Algorithm (FA), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and PSO have been investigated to optimise cluster formation, routing paths, and cluster head selection.

Genetic Algorithms provide effective global search capabilities but generally require higher computational complexity due to crossover and mutation operations. Ant Colony Optimization performs well at identifying optimal routing paths but converges relatively slowly and incurs additional communication overhead due to pheromone updates. Artificial Bee Colony and Firefly algorithms demonstrate competitive optimisation performance but require careful parameter tuning and often involve longer convergence times for large-scale WSNs. More recent algorithms, including Grey Wolf Optimizer and Whale Optimization Algorithm, have shown promising performance; however, they remain comparatively less mature, have fewer benchmark studies within WSN clustering, and are associated with higher implementation complexity in resource-constrained sensor networks.

Among the available optimization techniques, Particle Swarm Optimization has emerged as one of the most suitable algorithms for WSN clustering because of its relatively simple implementation, low computational complexity, rapid convergence, and effective balance between exploration and exploitation. PSO is capable of simultaneously considering multiple optimisation criteria, including residual energy, communication distance, node density, and load balancing, when selecting cluster heads. These characteristics make PSO particularly appropriate for improving the limitations of conventional LEACH clustering.

The selection of LEACH and PSO for this research was therefore based on both theoretical and practical considerations. LEACH provides a well-established, widely accepted benchmark clustering protocol against which improvements can be objectively measured. However, its probabilistic cluster head selection frequently results in uneven energy consumption. PSO complements LEACH by replacing random cluster head selection with an optimisation-driven mechanism that selects more suitable cluster heads based on multiple network parameters. This combination preserves LEACH's low-overhead clustering architecture while improving energy efficiency, cluster stability, and network lifetime without introducing excessive computational complexity.

Therefore, this study adopts a hybrid PSO-LEACH approach to address the limitations of conventional LEACH while avoiding the higher computational demands associated with several alternative metaheuristic algorithms. The proposed approach seeks to achieve more balanced energy consumption, improved cluster head selection, and extended network lifetime for battery-powered Wireless Sensor Networks.

2.2.1 LEACH Algorithm

LEACH is among the earliest and most extensively utilized hierarchical routing protocols for WSNs. It is an energy-efficient routing protocol that guarantees the uniform distribution of cluster heads throughout the network, thereby preventing localized energy depletion regions. It introduced the concept of clustering, whereby nodes are systematically organized into clusters, each with a designated node serving as the cluster head (CH). The CH aggregates data from member nodes and forwards it to the base station, significantly reducing the number of transmissions and saving energy [27]. It balances sensor node energy consumption and extends overall network lifetime. A major drawback is that if a cluster head fails, the cluster becomes ineffective, as collected data may not reach its destination.

LEACH operates in rounds, and in each round, a new set of CHs is elected based on a probabilistic model to ensure energy is fairly distributed among nodes. The expected number of CHs per round can be expressed as

$$E(Nch) = k \tag{2.1}$$

where K is the optimal number of CHs. This ensures a balanced network operation over time.

Threshold for Cluster Head (CH) Selection Equation:

$$T(n) = \{p/([1 - p * (rmod\ 1/p)\} \tag{2.2}$$

where n ∈ G

Energy Dissipation for Transmission Equation:

$$E_{tx(k,d)} = \{k * E_{elec} + k * \varepsilon_{fs} d^2, \quad if\ d\ < d_0 \tag{2.3}$$

$$k * E_{elec} + k * \varepsilon_{mp*d^4}, \quad if\ d\ \geq d_0\}$$

Energy Dissipation for Reception Equation:

$$E_{rx(k)} = k * E_{elec} \tag{2.4}$$

Energy Dissipation Equation for a Cluster Head:

$$E_{ch} = E_{rx*k*(nc-1)} + E_{DA*k*nc} + E_{tx*k*dtoBs^{\alpha}} \tag{2.5}$$

Energy Dissipation at a Structural Node Equation:

$$E_{node} = E_{tx(k,d_{toch})} \tag{2.6}$$

The following table 2.1 shows the symbol description for LEACH equations

Table 2.1: Symbol description for the LEACH protocol

Symbol	Description	Units / Notes
P	Targeted percentage of CHs per round	-
r	Current round number	-
G	Set of nodes that are not CHs in the past 1/P rounds	-
n	Node being evaluated	-
$T(n)$	Threshold for CH selection	-
k	Number of bits in a message	$bits$
d	Distance from transmitter to receiver	$meters$
$d0$	Threshold distance	$meters$
$Eelec$	Energy per bit for electronics	J/bit
$varepsilonfs$	Amplifier energy in free space	$J/bit/m^2$
$varepsilonmp$	Energy in the multipath amplifier	$J/bit/m^4$
$Etx(k,d)$	Transmission energy	J
$Erx(k)$	Reception energy	J
$E\{DA\}$	Energy used for data aggregation	J/bit
nc	Number of nodes in cluster	-
$dtoBS$	Distance from CH to the Base Station	$meters$
$alpha$	Path loss exponent	$2(short), 4(long)$
$dtoCH$	Distance from node to CH	$meters$

Symbol	Description	Units / Notes
ECH	Energy consumed by CH per round	J
$Enode$	Energy consumed by member node	J

a) Strengths of LEACH

The protocol under consideration is designed as a fully distributed system, eliminating the need for centralized control and allowing each node to operate autonomously. One of its key advantages is the use of data aggregation, which reduces network traffic by reducing redundant transmissions and conserving energy. To further enhance network efficiency, CH roles are periodically rotated among nodes, thereby balancing energy consumption and prolonging the network's operational lifetime. Another important feature is that the protocol does not require knowledge of nodes' geographic locations for cluster formation, making it straightforward to deploy in environments where positioning information is unavailable or unreliable. Collectively, these characteristics make the protocol highly effective for clustering energy efficiency in WSNs, while maintaining simplicity and scalability.

b) Weaknesses of LEACH

Despite its advantages, the protocol has certain limitations that may affect its performance in specific scenarios. Since it is fully distributed, coordination among nodes can sometimes be less efficient, potentially leading to suboptimal cluster formation in highly dynamic networks. Additionally, while data aggregation reduces traffic, it may introduce latency or increased processing overhead at the Cluster Heads, particularly when handling large volumes of data. The periodic rotation of CH roles, although beneficial for balancing energy, can also incur additional communication overhead during the reorganization process. Finally, the lack of reliance on location information, while simplifying deployment, may limit the protocol's ability to optimize clusters based on spatial proximity, which can be important in dense or geographically heterogeneous networks.

2.2.2 PSO Algorithm

PSO is a powerful optimization method based on swarm intelligence, inspired by the collective behaviour of natural species such as bird flocks and fish schools. Proposed by Kennedy and Eberhart in 1995, PSO operates on a population of candidate solutions (particles), which move through the solution space to find the optimum value of a given objective function. It optimizes fitness functions by iteratively adjusting particle positions, recording local and global best positions to select optimal cluster heads and minimize overall energy consumption. PSO offers higher efficiency and throughput compared to conventional heuristic methods; however, it can converge prematurely and may be trapped in local minima, especially in complex network [28].

Each particle adjusts its position by learning from two sources:

Its own best-known position (personal experience, pbest) and the best-known position among all particles (global experience, gbest).

The mathematical formulation of PSO is as follows:

$$V_{new} = V_{old} + \Psi_1 * \alpha_1 * (p_i - x_i) + \Psi_2 * \alpha_2 * (p_g - x_i) \quad (2.7)$$

$$X_{new} = X_{old} + V_{new} \quad (2.8)$$

Variables represent:

vi represents the velocity of particle i,

xi is its position,

pi is the particle's personal best, and

pg is the global best.

$\psi 1$ and $\psi 2$ are acceleration coefficients, while $\alpha 1$ and $\alpha 2$ are random numbers that add stochasticity to the process. The process continues iteratively until convergence is achieved.

The following Table 2.2 shows the symbol description for PSO equations

Table 2.2: Tables of symbols and notation for the PSO algorithm

Symbol	**Description**	**Units / Notes**
N	Number of particles in the swarm	-
i	Index of a particle (i = 1, 2, …, N)	-
t	Iteration (time step)	-
$xi(t)$	Position vector of particle i at iteration t	Depends on problem (e.g., cluster head positions)
$vi(t)$	Velocity vector of particle i at iteration t	Same dimension as xi
$pbesti$	Particle i's best position identified so far	-
$gbest$	Highest global position achieved by the entire swarm.	-
w	weight of Inertia	-
$c1$	Cognitive coefficient (weight for personal best influence)	-
$c2$	Social coefficient (weight for global best influence)	-
$r1, r2$	Random numbers uniformly distributed in [0,1]	-
$vi(t+1)$	Updated velocity of particle i at iteration t+1	-

$xi(t+1)$	Updated position of particle i at iteration t+1	-
$f(x)$	Fitness (objective) function value at position x	Depends on optimization goal (e.g., energy consumption)

In WSNs, PSO is widely applied for cluster-head (CH) selection, where the algorithm determines which nodes should serve as CHs to minimize total energy consumption and balance network load.

a) Advantages of PSO

The proposed method is designed with a straightforward structure, making it simple to implement in practice. It is particularly effective in identifying global optima with efficiency, thereby avoiding the common issue of premature convergence to local minima. In addition, the method supports parallel computation, which enhances its scalability when applied to larger or more complex problem spaces. Another key strength lies in its rapid convergence rate, achieved while maintaining relatively low computational complexity, ensuring that the approach remains both efficient and practical for real-world applications [29].

b) Limitations of PSO

Despite its strengths, the method has limitations. One drawback is its sensitivity to parameter initialization, as poorly chosen values may significantly influence overall performance [30]. Additionally, the algorithm may converge prematurely, limiting its ability to explore the search space fully and locate the global solution. This challenge is particularly pronounced in highly complex or dynamic optimization environments, where the method's performance can degrade due to the increased difficulty of maintaining diversity in the search process.

2.3 Bibliometric Analysis

A bibliometric analysis was employed to assess the research landscape on energy optimization algorithms in WSNs [31]. The objectives included identifying publication trends, influential authors and countries, collaboration networks, and research gaps. Peer-reviewed journal articles published between 2019 and 2023 were sourced primarily from the Web of Science (WOS) database, ensuring relevance and quality [32].

The steps below were followed to do this analysis:

Figure 2.1: Steps to complete a bibliometric analysis

2.3.1 Research Design

Bibliometric analysis involved five key steps: defining objectives, selecting databases and search strategies, data cleaning, performing analysis using tools like VOSviewer, and reporting findings through visualizations and narrative interpretations. Techniques employed included co-citation, co-authorship, bibliographic coupling, and keyword co-occurrence to map intellectual structures, collaboration patterns, and emerging trends [33].

Table 2.3 illustrates the research design employed. We propose the following research questions:

Table 2.3: Bibliometric analysis techniques to address the research questions.

RQN	Research Question	Technique	Usefulness
RQ1	What are the current publication trends in WSNs?	Bibliometric coupling	To evaluate the current evolution of topics in WSNs. In this study, we will evaluate it to identify current publications.
RQ2	Who are the most influential authors, countries, and organizations who researched WSNs?	Co-citation analysis	To provide information on the connections between publications and the most influential publications. Counting citations in significant research databases and internet sources keeps track of authors' words, the significance of articles, and the development of research ideas.
RQ3	What is the current state of collaboration involving WSNs?	Co-authorship	To analyze the social interactions and relationships among authors, their affiliations, and the number of publications they have collaborated on.
RQ4	Which areas need additional study or improvement in WSNs?	Co-word/ or co-occurrence analysis	To investigate the existing or future connections between research topics by examining the written content of a publication.

2.3.2 Search Criteria

Keywords used included WSN, LEACH, PSO, energy optimization, routing, and bibliometric analysis. Inclusion criteria were journal articles in English addressing energy optimization in WSNs published after 2019. Exclusion criteria included the removal of duplicates, non-WSN studies, and non-peer-reviewed publications. After screening 442 initial records, 194 relevant articles were retained.

The following search criteria produced the results that were finally used in the entire bibliometric analysis [34].

(1) Identification – in this category, we have identified records by searching through the currently available database, which, in this case, we only concentrated on the WOS.

(2) Screening – during this level, we check if there are any duplicates of papers/journals, so that if there are any, then we remove all the duplicates.

(3) Eligibility – when we check if all the articles match the research topic we are currently working on and remove anything that is not in the same field. Furthermore, we only examined papers published in the past five years and excluded those published before.

The inclusion and exclusion criteria were used and detailed below:

Inclusion – this is where our refinement process was done, and we now know exactly how many articles we will use for the research.

The criteria for inclusion are

- If the content of the article seems to discuss energy optimization of WSN, we obtain its full reference
- Journal articles written in English
- Articles were chosen based on those that address energy optimization in WSNs

The criteria for exclusion are

- Any study that is not about WSNs

- Studies before 2019, we believe someone would have adopted the recent methodology.
- Publications other than journal articles were excluded as they were not peer-reviewed by the top experts in the field
- Any articles addressing anything but WSN were also excluded

The following PRISMA diagram illustrates the search criteria used for the method and the number of documents included in this literature review. The records found during the search were 442 articles. Only articles were selected in this case, as we know they are peer-reviewed by top researchers knowledgeable in the subject area. From this, we went through a screening process that removed all duplicates, resulting in 194 records.

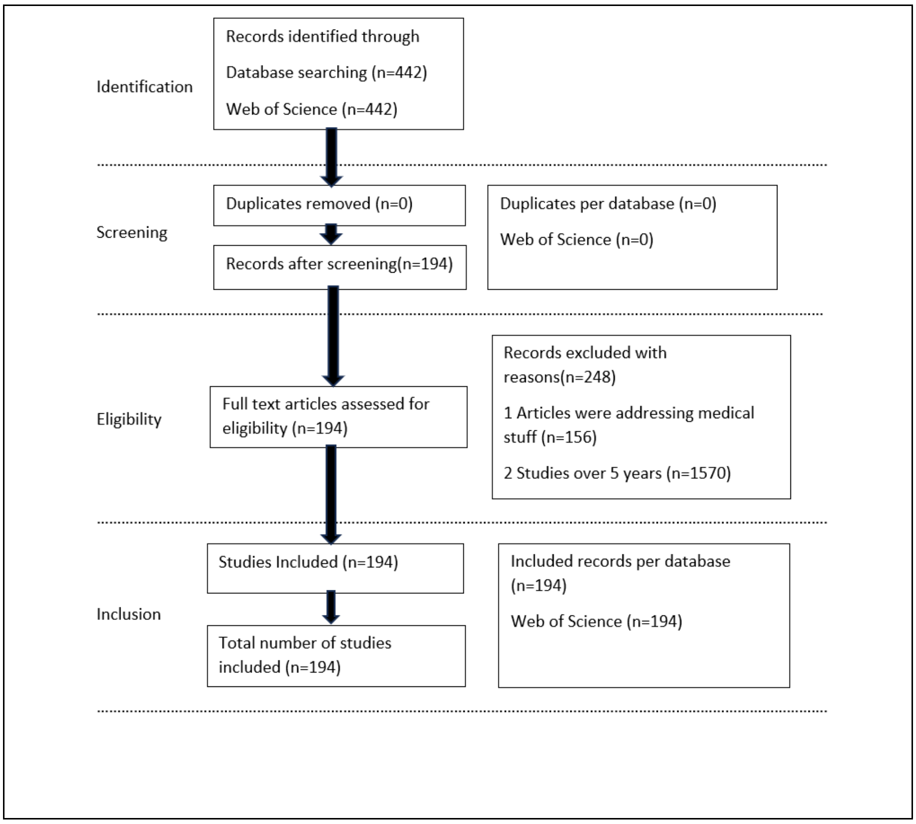

Figure 2.2: Prisma diagram based on our search criteria. Adapted from [35]

2.3.3 Analysis Results - Publications per year:

Steady publication trends indicate ongoing interest in WSN energy optimization. **Bibliometric coupling:** Identified most-cited journals and articles; IEEE Access, Wireless Networks, and Ad Hoc Networks emerged as influential sources.

Country publications: India, China, and South Korea were leading contributors with strong collaboration networks.

Keyword co-occurrence: Dominant keywords included WSN, energy efficiency, clustering algorithm, LEACH, and PSO, highlighting research focus areas.

The bibliometric coupling data are displayed in Table 2.2. It displays the most cited sources and the overall strength of the links. The highest cited sources and the strongest overall link strength are displayed in Figure 2.3.

Table 2.4: The topmost sources with high citations per publication, Citations: TC, Total link strength: TLS

ID	**Source**	**Documents**	**CT**	**TLS**
1	ad hoc networks	8	196	926
2	annals of telecommunications	1	0	191
3	applied system innovation	1	0	152
4	computer communications	5	67	204
5	computer networks	5	55	464
6	eurasip journal on wireless communications and networking	6	128	475
7	ict express	1	0	21
8	ieee access	26	474	2164

9	ieee communications letters	2	78	180
10	ieee internet of things journal	6	100	457
11	ieee open journal of the communications society	1	0	0
12	ieee systems journal	2	45	359
13	ieee transactions on green communications and networking	2	62	129
14	ieee transactions on vehicular technology	1	47	137
15	iet wireless sensor systems	1	12	17
16	international journal of ad hoc and ubiquitous computing	1	0	20
17	international journal of communication systems	21	129	1587
18	international journal of distributed sensor networks	5	77	604
19	international journal of mobile computing and multimedia communications	1	2	84
20	international journal of network management	1	0	82

21	international journal of wireless information networks	3	13	272
22	internet of things	1	5	90
23	journal of ambient intelligence and humanized computing	9	231	518
24	journal of communications software and systems	1	0	98
25	journal of internet technology	1	0	93
26	ksii transactions on internet and information systems	3	22	244
27	mobile information systems	2	17	226
28	mobile networks & applications	2	50	141
29	peer-to-peer networking and applications	9	31	624
30	personal and ubiquitous computing	1	29	127
31	security and communication networks	1	14	5
32	telecommunication systems	3	88	420
33	transactions on emerging	3	12	78

	telecommunications technologies			
34	wireless communications & mobile computing	2	224	111
35	wireless networks	15	320	1460
36	wireless personal communications	41	485	2962

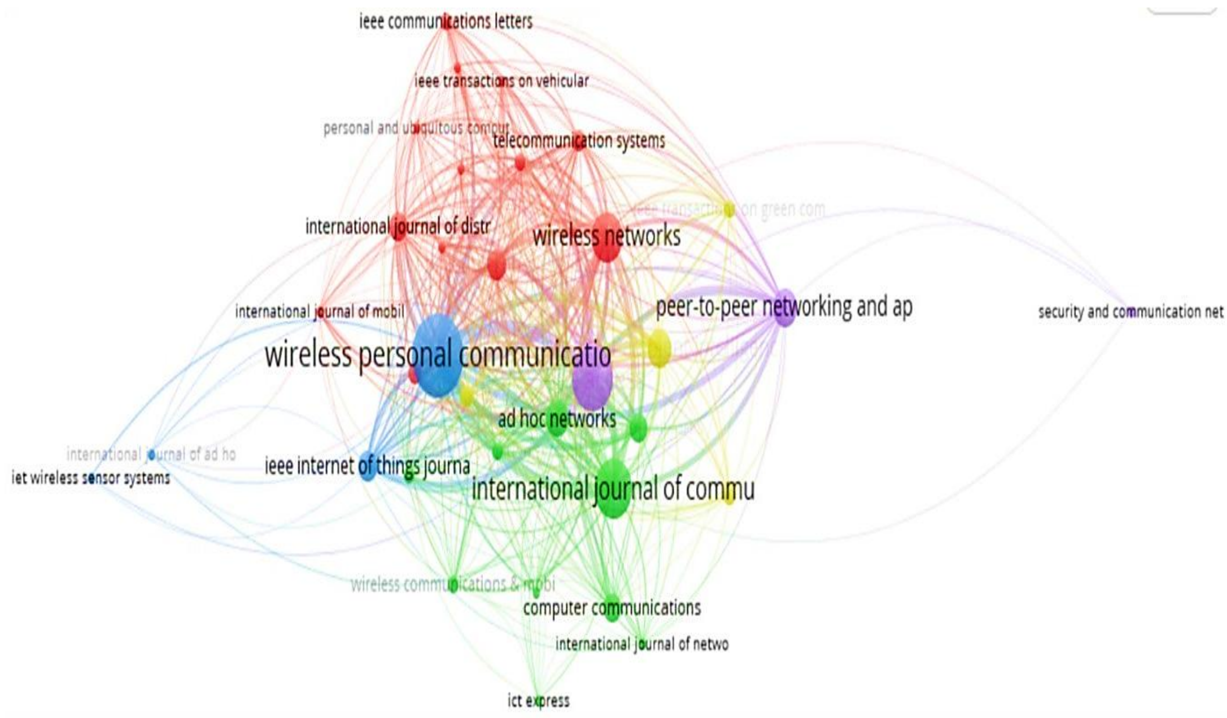

Figure 2.3: Sources showing from high to low citations and strong TLS.

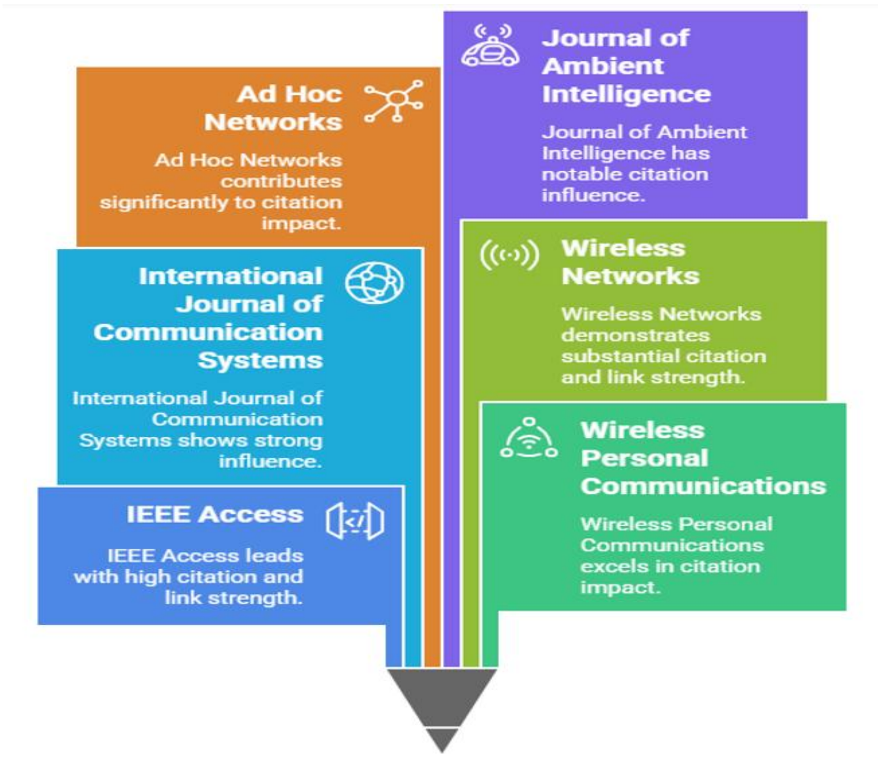

Figure 2.4: Top sources of citation influence

Publication impact of countries and journal articles

The maximum number of authors per document selected was 25, with the minimum number of authors per document being 1 and the minimum number of citations of an author being 1. By looking at the results shown in Table 2.3, we can see that the topmost 3 countries are India leading with a total citation of 1722 and a link strength of 37 and followed by the Peoples's Republic of China with a total citation of 792 and a link strength of 28, the 3rd one being South Korea with a total citation of 348 and total link strength of 4.

Table 2.5: The topmost countries with high citations per publication, Citations: TC, Total link strength: TLS

ID	Country	Documents	CT	TLS
1	australia	4	125	4
2	canada	2	43	6
3	egypt	4	76	9

4	england	6	157	8
5	finland	1	4	4
6	india	121	1722	37
7	iran	6	151	8
8	iraq	3	55	5
9	italy	2	23	4
10	japan	1	14	4
11	jordan	3	74	4
12	malaysia	5	72	12
13	pakistan	5	94	9
14	peoples r china	41	795	28
15	russia	1	14	4
16	saudi arabia	11	225	21
17	south korea	7	348	4
18	taiwan	4	51	8
19	tanzania	1	4	4
20	usa	10	76	13
21	yemen	1	4	4

The following figure shows the topmost countries with high citations and the strongest total link strength. India is the first top country out of this category.

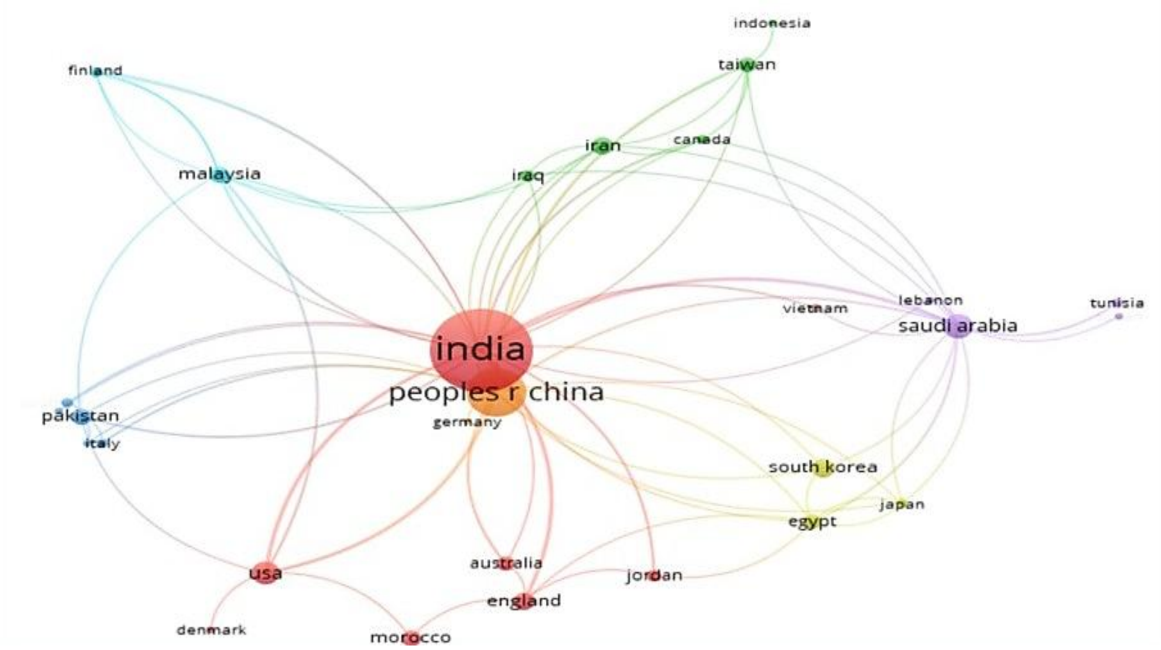

Figure 2.5: Network visualization of country collaboration in this research

2.4 Co-occurrences of keywords

Table 2.8 demonstrates unequivocally that WSNs remain the most explored keyword, appearing over 150 times more frequently than the others and having the strongest overall link strength of over 1500. Also, in both Figures 2.6 and 2.7, it is evident that “WSNs [36]” is the leading keyword being researched by authors.

2.4.1 Co-occurrences word count

Table 2.6: Co-occurrences of keywords in a publication, Total link strength: TLS.

ID	Keyword	Occurrences	TLS
1	wsn	26	291
2	WSNs	104	1071
3	wireless sensor network	34	324
4	scheme	26	307

5	routing protocols	25	320
6	routing protocol	36	419
7	routing algorithm	14	165
8	routing	49	500
9	protocols	10	135
10	protocol	47	460
11	particle swarm optimisation	9	102
12	optimisation	40	466
13	network lifetime	30	321
14	mobile sink	9	104
15	lifetime	31	362
16	leach	11	111
17	iot	11	150
18	internet of things	17	219
19	internet	23	288
20	fuzzy logic	12	114
21	energy-efficient	28	253
22	energy efficiency	81	814
23	energy consumption	30	353
24	energy	12	105
25	efficient	12	115
26	data aggregation	12	152
27	clustering-algorithm	11	113
28	clustering algorithms	20	273
29	clustering	69	590
30	cluster head selection	12	115
31	cluster head	10	103
32	aware	10	119
33	algorithm	64	663

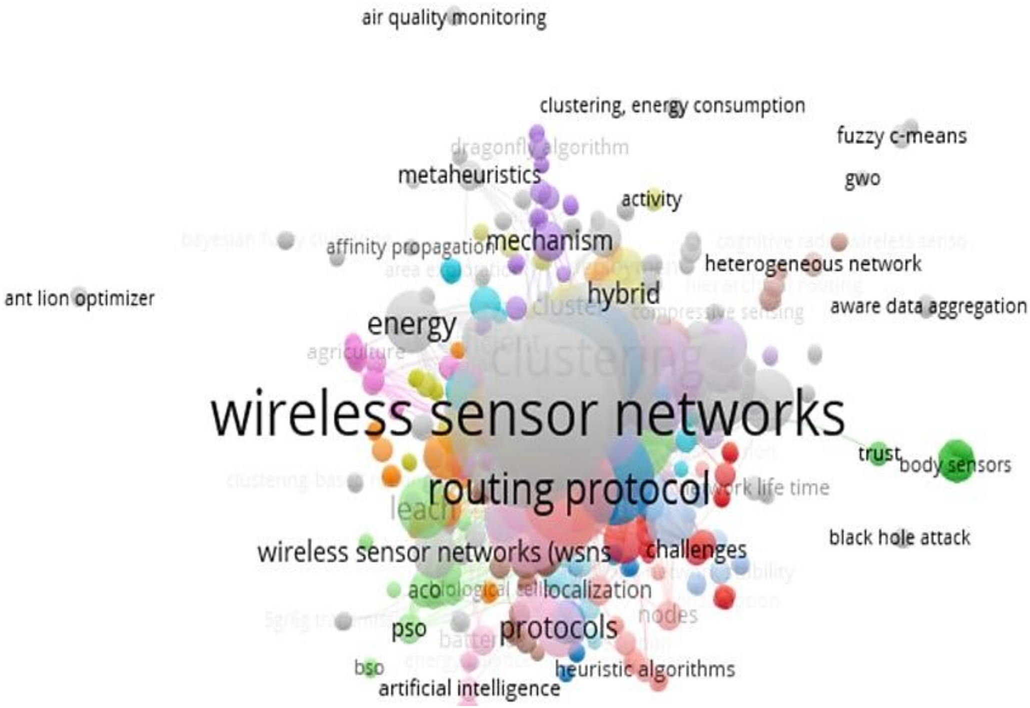

Figure 2.6: Network visualisation map of co-authorship based on all keywords.

2.4.2 Keywords co-occurrence statistical analysis

The following statistical analysis was done on the keyword occurrences, and the results for each keyword were combined to get the total occurrences. The top 30 words were selected to complete this exercise. The results for the most keywords with 50 occurrences and above are shown in Table 2.5.

The highest count being WSN; we found 6 occurrences of this word, the first word having 80, the second one having 32, the third one having 22, the fourth one having 8, followed by the fifth also having 8, and the last one having 6, which makes a total of 156. The lowest count is the Genetic Algorithm (GA) [37] with 4 occurrences, the first word having 5, followed by the second word with 4, while the third word has 3 and the fourth word having 2, which makes a total of 14.

Table 2.7: Author's keywords with high occurrences.

ID	Author's keywords	Acronyms	Occurrences
1	WSNs	WSN	156
2	clustering algorithm	CA	102
3	energy efficiency	EE	92
4	routing algorithm	RA	85
5	network lifetime	NL	40
6	cluster head	CH	34
7	energy consumption	EC	33
8	internet of things	IOT	25
9	particle swarm optimisation	PSO	25
10	leach	LEACH	19
11	fuzzy logic	FLG	18
12	genetic algorithm	GA	14
13	quality of service	QOS	9
14	delay	DLY	8
15	mobile sink	MS	7
16	multi-hop routing	MHR	6
17	heterogeneity	HTR	6
18	sensor node	SN	6
19	ant colony algorithm	ACA	6
20	grey wolf optimisation	GWO	6
21	monitoring	MNT	5
22	base stations	BS	5
23	metaheuristics	MTH	5
24	multi-objective optimisation	MOO	5
25	load balancing	LB	4
26	mobile nodes	MN	4

27	batteries	BTT	3
28	spread spectrum communication	SSC	3
29	artificial bee colony	ABC	3
30	optimal path	OP	2

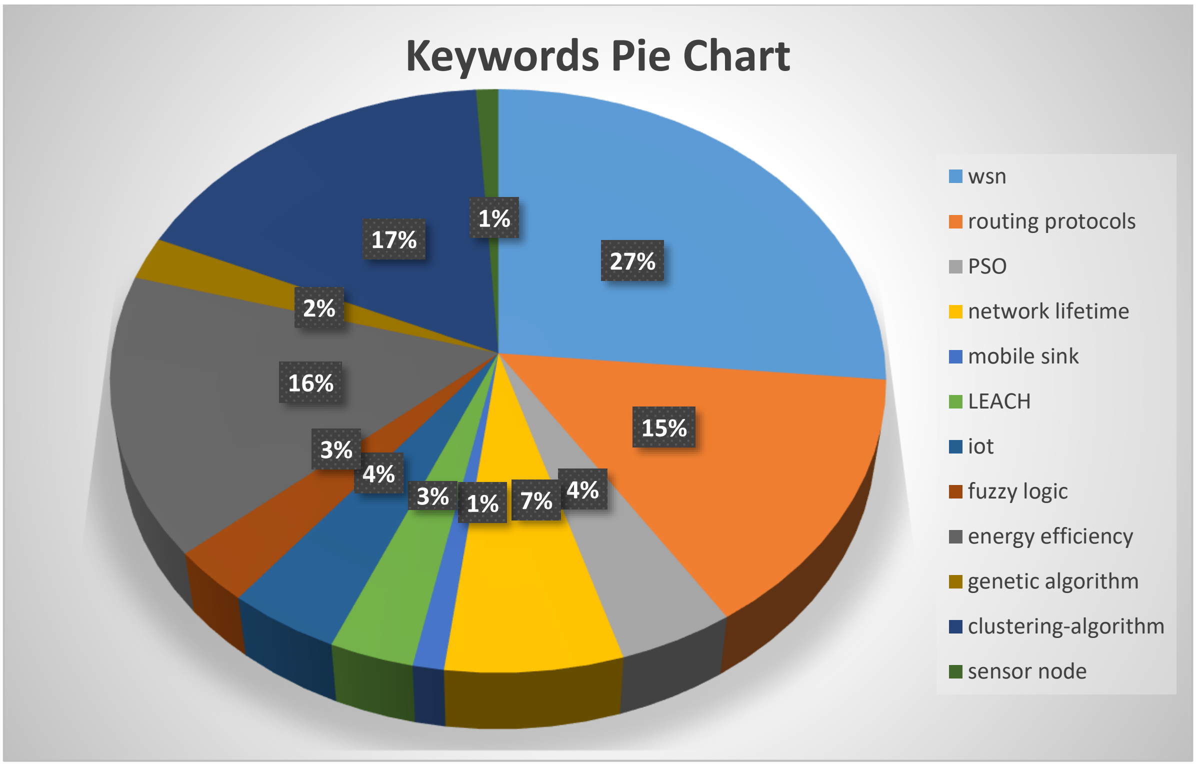

Figure 2.7: Pie graph of keywords with high occurrences.

2.4 Discussion

The analysis confirms that energy optimization in WSNs remains a critical and actively researched domain. LEACH and PSO algorithms continue to serve as benchmarks for performance evaluation. Bibliometric results reveal key contributors, collaboration trends, and emerging research themes, providing a foundation for future studies.

2.5 Summary of Literature Review

This review is worth carrying out as it seeks to make the following contributions:

1. Identifying current publication trends in WSN energy optimization.
2. Highlighting influential authors, countries, and institutions.
3. Mapping collaboration networks.
4. Demonstrating the relevance and utility of bibliometric analysis in evaluating research on LEACH and PSO algorithms.

2.6 Conclusions

This comprehensive literature review underscores the enduring relevance and critical importance of ongoing research into WSNs. The analysis, particularly evident from the robust total link strength and consistent publication trends, reveals WSNs as a persistently active and vital field of inquiry within academic discourse. A central theme emerging from the surveyed literature is the pervasive challenge of energy optimization, which remains a fundamental determinant of network longevity and operational efficacy. Despite significant scholarly attention, the pursuit of substantial advancements in this domain is not merely beneficial but essential for enhancing the sustainable deployment and practical utility of WSNs.

WSNs continue to face energy constraints that necessitate effective optimization algorithms. LEACH provides foundational clustering strategies, while PSO-based approaches offer enhanced performance, particularly in medium to large-scale networks. Bibliometric analysis reveals ongoing research interest, identifies key contributors, and highlights areas for future exploration. These insights form a crucial background for subsequent chapters focused on developing and evaluating energy optimization strategies in WSNs.

Chapter 3 : Research Design and Methodological Approach

3.1 Introduction

WSNs are integral to numerous domains, encompassing environmental observation, medical monitoring, and defence operations. In these contexts, energy efficiency is not just important but rather it's critical for ensuring prolonged operation in remote and inaccessible locations. This research employs the Design Science Research (DSR) methodology, also known as constructive research, which involves a series of systematic steps. The simulation network will be designed and developed using MATLAB software, where various routing algorithms will be tested and compared based on their performance. While existing research has explored energy optimization in WSNs, a significant gap remains in the development of hybrid algorithms that dynamically adapt to network conditions and remaining energy levels. The following outlines the steps undertaken to conduct this study:

- Step 1: Conduct a comprehensive literature survey on available energy algorithms to clearly understand the current state of research in wireless sensor networks.
- Step 2: Summarize and analyze the gathered literature, identifying novel optimization algorithm approaches in WSNs that can address the problems articulated in the problem statement section.
- Step 3: Implement the LEACH and PSO optimization techniques within the Matlab simulator to facilitate performance comparison.
- Step 4: Assess the developed theoretical optimization algorithm protocols using simulation software for validation.
- Step 5: The results of the various simulations conducted have are analyzed and compared to the existing LEACH and PSO approaches. This comparison emphasizes energy efficiency alongside key network performance metrics, such as reliability and scalability. Based on the

findings, a conclusion regarding the contributions of this study will be drawn, and directions for future work will be proposed.

This research aims to develop an energy consumption model and present the results of the energy optimization technique.

3.2 Overview of research methodology

To achieve the research objectives of this dissertation, the research design utilizes modelling and simulation, specifically employing the Design Science Research (DSR) methodology. DSR is particularly appropriate for this study because its primary goal is not merely to describe, explain, or predict a problem, but to develop artifacts that assist individuals in meeting their needs and resolving practical issues. Since this research aims to create a new artifact, the PSO-LEACH algorithm's DSR provides a structured framework for its rigorous design, implementation, and evaluation. These artifacts are designed to address real-world challenges while also contributing to the advancement of the scientific community.

When conducting DSR methodology, the framework has been designed with a flow of five different steps, as shown in Figure 3.1:

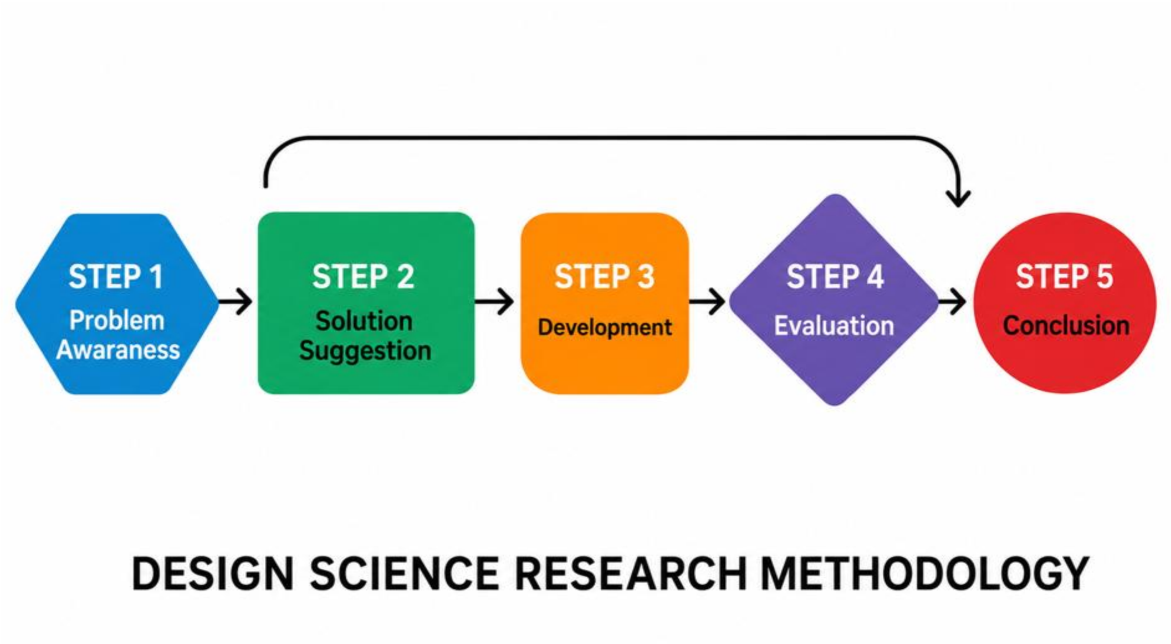

Figure 3.1: DSRM Process Flow.

The description of each of the activities in figure 3.1 are as follows:

The **first step** of the method is to become aware of the problem. In this step, we need to identify and understand the issue at hand, as well as define the required performance for the system being analyzed and the application of potential solutions.

The **second step** involves suggesting possible solutions. Here, we propose concepts to help address the problem, setting objectives that may be quantitative, qualitative, or a combination of both.

The **third step** is Development. In this phase, we focus on developing one of the proposed artifacts to tackle the problem. After this development, we evaluate the artifact in the fourth step to assess its effectiveness in solving the issue. If we find that the artifact does not meet the research requirements during development or evaluation, we can revisit the awareness step for a clearer understanding of the problem and continue our research from there.

The **fourth step** is Evaluation. In this step, we assess how effectively the artifact addresses the problem. The constructed networks are analyzed using simulation software to evaluate their performance.

The **final step** is the Conclusion. Here, we present our results. Based on our findings, we may conclude that our initial awareness of the problem was insufficient, which could lead to an unsuccessful development of the artifact.

Figure 3.2 provides a summary of the activities related to the design research approach that will be addressed in this dissertation.

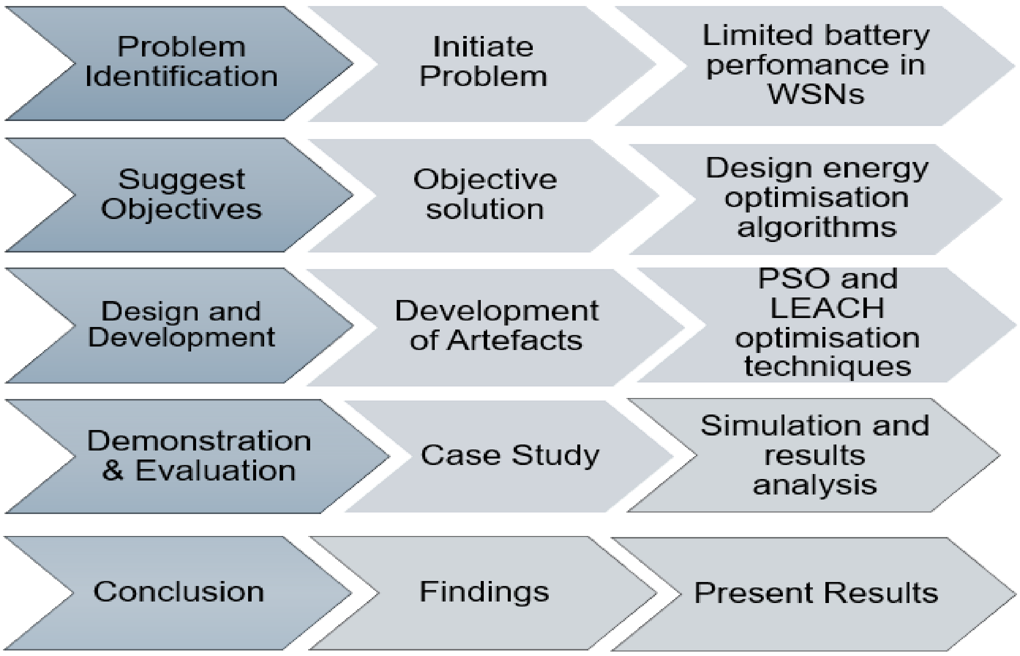

Figure 3.2: Design Process Flow of Optimization Algorithms.

3.2.1 Research approach

Many current WSN technologies rely on inexpensive processors, which inherently lead to limited energy budgets and reduced storage capacity. Consequently, a prolonged lifespan for sensor nodes is critical in numerous applications, particularly because these networks are frequently deployed in remote, hazardous, and inaccessible environments where recharging or replacing power supplies is challenging [38]. This research specifically addresses the critical challenge of limited battery life for sensor nodes in WSNs, focusing on enhancing the optimization efficiency of the LEACH and PSO [39] algorithms.

The performance of sensor nodes is directly influenced by battery life, which in turn impacts the overall efficiency and longevity of the sensor networks. Indeed, the failure of even a few nodes can lead to the premature fragmentation of the entire network, underscoring the significance of this concern. Furthermore, many existing energy consumption models primarily focus on homogeneous WSNs and smaller to medium-sized networks. However, this perspective does not accurately reflect the reality of modern applications, such as smart cities, where billions of heterogeneous sensor nodes are deployed. It is essential to consider the heterogeneity and high density of wireless sensor networks when modeling energy consumption for both uplink and downlink communications.

While existing LEACH [40] and PSO approaches, when applied to WSNs, aim to optimize energy consumption, they often do not explicitly consider the remaining energy at each node during the routing decision process for packet transmission to the base station. Consequently, there is a clear need for a hybrid approach that implements a PSO-optimized LEACH algorithm on each link, considering the remaining energy at each node and its neighbours as part of the energy optimization variable [41]. The following problems are investigated and addressed to fulfil the research objectives:

- To enhance existing energy optimization algorithms, the PSO algorithm will be simulated in conjunction with the LEACH protocol. This aims to minimize the energy consumption of nodes within the WSN [42].
- To propose an intelligent clustering approach that ensures the total energy consumption is balanced across the network. This involves adaptively selecting cluster heads based on a well-defined energy gradient.

- To extend the battery life of the network by ensuring that no node fails before the network completes its deployment mission.

3.2.2 Suggestions for possible solutions

One viable option for reducing energy usage in WSNs involves employing metaheuristic optimization algorithms, such as PSO. Specifically, the hybrid PSO algorithm [43] effectively optimizes the election of optimal Cluster Heads (CHs), a critical step in the clustering process. Concurrently, LEACH is a protocol designed to lower power consumption in WSNs by improving the efficiency of the cluster formation process. By combining the PSO algorithm with LEACH, an optimized LEACH approach can be implemented to cluster the network, leading to a significant reduction in energy consumption and a substantial increase in network stability during data collection in WSNs [44]. The novelty of this research is in the creation of a dynamic fitness function for the PSO algorithm. This function considers not only the residual energy of the nodes but also their density and their distance from the base station. As a result, this approach leads to a more effective and reliable process for selecting Cluster Heads (CHs).

LEACH alone often results in unequal cluster sizes, which contributes to uneven energy consumption [45]. In contrast, PSO optimizes CH selection to achieve a more balanced energy distribution. The integration of PSO and LEACH efficiently targets specific areas while also searching across multiple regions, which helps reduce energy consumption and prolong the network's lifetime.

Figure 3.3 illustrates the typical Matlab sensor field structure of these two algorithms integrated together. This structure outlines the integration of PSO with the LEACH protocol to enhance the performance of WSNs. The goal is to leverage PSO's global optimization capabilities to address LEACH's limitations [46], thereby improving energy efficiency and extending network lifetime.

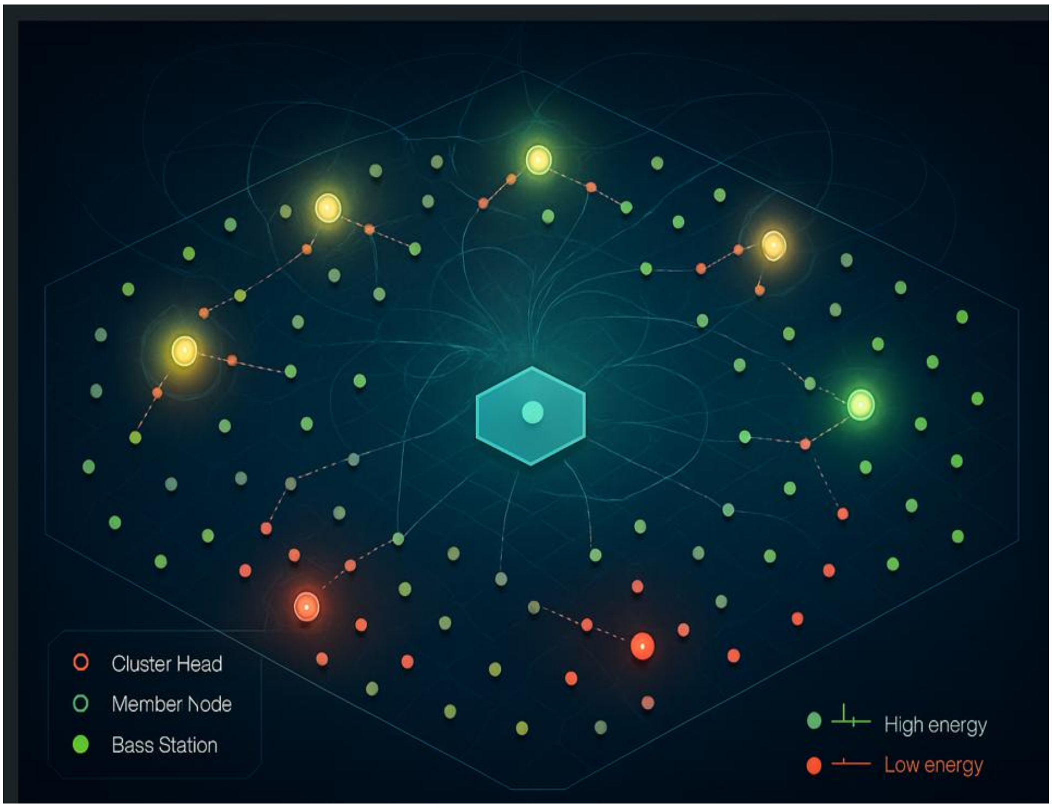

Figure 3.3: The sensor field showing integration of PSO and LEACH

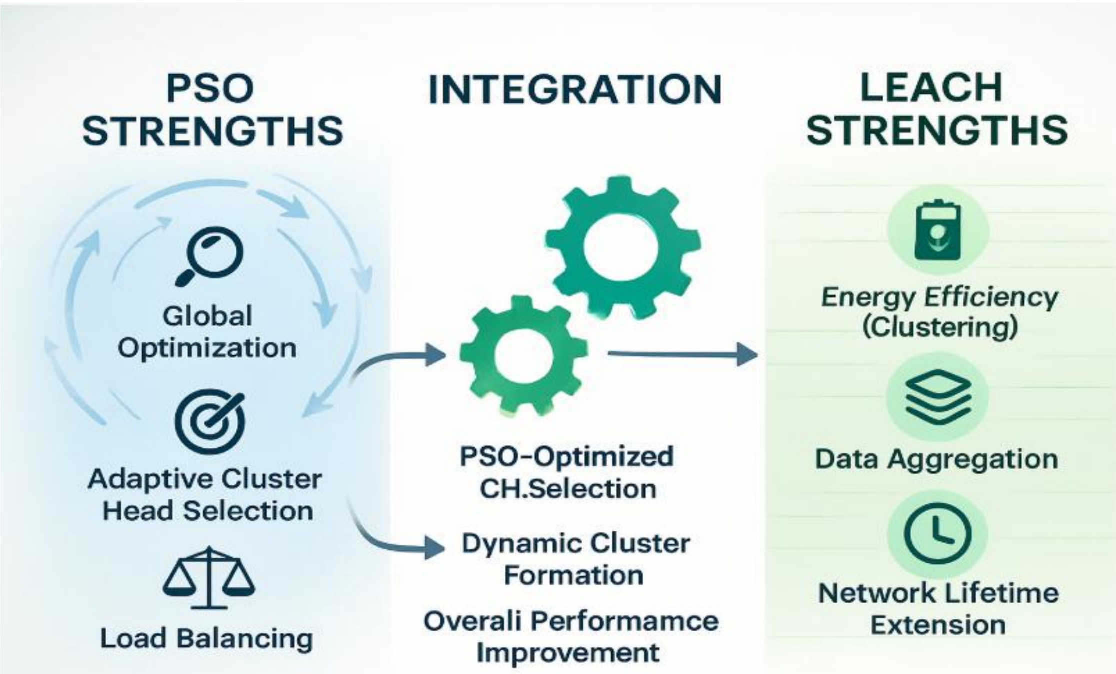

Figure 3.4: Diagram showing PSO-LEACH integration mechanism

The integration of PSO with the LEACH protocol, as effectively illustrated in Figure 3.4, demonstrates how PSO enhances the conventional LEACH method through selection of CHs. In the initial phase, both LEACH and PSO-LEACH begin with sensor nodes broadcasting their energy levels, positions, and the density of neighbouring nodes. LEACH employs a randomized, probabilistic method for selecting cluster heads, which can lead to irregular energy distribution and premature node failures. In contrast, PSO-LEACH utilizes a fitness-based optimization process to enhance this selection. This strategic enhancement ensures a more efficient and balanced energy distribution throughout the network, ultimately prolonging its operational lifespan and enhancing overall performance. Furthermore, the use of a dynamic fitness function in PSO-LEACH, which considers residual energy, node density, and proximity to the base station, represents a significant advancement over static CH selection mechanisms.

3.2.3 Evaluation in the Context of PSO-LEACH Integration

The evaluation phase constitutes a critical component of the DSRM, as it determines whether the developed artifact satisfies the objectives established during the problem identification and solution design stages. In this study, the artifact under evaluation is the PSO-LEACH algorithm, which is proposed to improve the energy efficiency and operational lifetime of WSNs. The evaluation process aims to determine whether integrating PSO with the LEACH routing protocol results in measurable improvements in network performance.

The effectiveness of the proposed algorithm is assessed through simulation experiments conducted in MATLAB. Simulation provides a controlled environment in which network parameters can be systematically varied while observing their influence on the routing protocol's overall behavior. Unlike real-world deployments, simulation enables repeated experimentation under identical conditions, thereby ensuring consistency and reproducibility of the results.

To provide a comprehensive assessment of the proposed PSO-LEACH algorithm, several performance metrics are considered. These metrics collectively evaluate the algorithm's ability to minimize energy consumption, maintain balanced cluster formation, and improve data transmission efficiency throughout the network's operational lifetime.

In the specific context of evaluating the PSO-LEACH [47] algorithm integration for WSNs, the evaluation step would typically involve:

3.2.3.1 Performance Metrics

Energy Consumption

Energy consumption is regarded as one of the most important performance indicators in Wireless Sensor Networks because sensor nodes operate using limited battery resources that are generally difficult or impossible to replace after deployment. The proposed PSO-LEACH algorithm is designed to reduce unnecessary energy expenditure by optimising cluster-head selection and balancing communication loads among sensor nodes.

The total residual energy of the network is monitored throughout the simulation to determine the rate at which energy is depleted during successive communication rounds. Lower energy consumption indicates that the routing protocol effectively minimises transmission costs while distributing energy usage evenly among the participating nodes.

Network Lifetime

Network lifetime represents the duration for which the sensor network remains operational before energy depletion prevents effective communication. In this research, network lifetime is evaluated using commonly accepted performance indicators, including:

- **First Node Dies (FND):** The communication round during which the first sensor node exhausts its energy.
- **Half of the Nodes Die (HND):** The point at which approximately 50% of the deployed sensor nodes become inactive.
- **Last Node Dies (LND):** The communication round during which the final sensor node depletes its available energy.

These indicators provide a comprehensive understanding of how efficiently the proposed algorithm utilises the available energy resources throughout the network's operation.

Throughput

Throughput measures the total amount of useful information successfully transmitted from sensor nodes to the base station during the simulation period. It is commonly expressed as the number of packets received by the base station.

A higher throughput indicates that the routing protocol maintains reliable communication while minimising packet losses caused by node failures or inefficient routing decisions. Since PSO-LEACH aims to improve cluster-head selection, an increase in throughput is expected as communication paths become more stable and energy-efficient.

Latency

Latency refers to the time required for sensed information to travel from the source sensor node to the base station. Although LEACH-based protocols primarily focus on energy conservation, transmission delay remains an important Quality of Service (QoS) parameter, particularly in applications requiring timely event reporting such as environmental monitoring, military surveillance, and disaster detection.

The proposed algorithm is therefore evaluated to determine whether improvements in energy efficiency are achieved without introducing excessive communication delays.

Packet Delivery Ratio

The Packet Delivery Ratio (PDR) represents the percentage of data packets successfully received by the base station relative to the total number of packets transmitted by the sensor nodes. It is calculated as

A higher Packet Delivery Ratio indicates improved communication reliability and demonstrates that the routing algorithm effectively maintains network connectivity despite energy depletion and changing network conditions.

Cluster Formation Efficiency

The effectiveness of cluster formation significantly influences the overall performance of hierarchical routing protocols. In the proposed PSO-LEACH algorithm, PSO is employed to determine an optimal set of cluster heads based on multiple fitness criteria, including residual energy, node distribution, communication distance, and cluster balance.

Cluster formation efficiency is evaluated by examining:

- the spatial distribution of cluster heads;

- the number of member nodes assigned to each cluster;
- communication distances between sensor nodes and their respective cluster heads;
- the balance of energy consumption across clusters; and
- the frequency of cluster-head rotation throughout the simulation.

Efficient cluster formation reduces communication overhead, prevents premature energy depletion of individual nodes, and extends the operational lifetime of the entire network.

3.2.3.2 Evaluation Techniques

To determine the effectiveness of the proposed PSO-LEACH algorithm, several complementary evaluation techniques are employed.

Simulation-Based Evaluation

Simulation experiments are conducted using MATLAB because it provides a flexible environment for modelling WSNs and analysing network behaviour under controlled conditions. The simulation environment includes randomly deployed sensor nodes within a predefined sensing area, a fixed base station location, and configurable communication parameters such as transmission range, packet size, and initial node energy.

Each simulation is executed for multiple communication rounds until all sensor nodes have exhausted their available energy. During each round, network statistics are collected and stored for subsequent analysis.

3.2.3.2 Comparative Performance Analysis

The performance of the proposed PSO-LEACH algorithm is evaluated through comparison with the original LEACH routing protocol. Both algorithms are implemented under identical simulation conditions to ensure that observed performance differences result solely from the optimisation strategy introduced by PSO.

The comparison focuses on the following aspects:

- overall network lifetime
- average residual energy
- number of alive and dead nodes per communication round

- throughput
- packet delivery ratio
- communication delay and
- cluster stability.

Comparative analysis enables the effectiveness of the proposed optimisation technique to be objectively quantified.

Sensitivity Analysis

Sensitivity analysis is performed to investigate the robustness of the PSO-LEACH algorithm under different network configurations. This analysis determines how changes in simulation parameters influence the algorithm's performance and whether the proposed solution remains effective across a variety of deployment scenarios.

The parameters considered include:

- **Network density:** varying the number of deployed sensor nodes to investigate scalability.
- **Network size:** modifying the dimensions of the sensing field to evaluate communication performance over different geographical areas.
- **Initial energy levels:** assigning different battery capacities to determine the influence of available energy on network lifetime.
- **Transmission range:** varying communication distances to assess their effect on energy consumption and connectivity.
- **Base station location:** positioning the sink node at different locations inside and outside the sensing field to evaluate routing efficiency.
- **Environmental conditions:** introducing different communication scenarios, including increased transmission distances, random node failures, and varying traffic loads, to simulate realistic operating environments.

Sensitivity analysis provides valuable insight into the adaptability and robustness of the proposed PSO-LEACH algorithm and demonstrates whether the optimisation strategy consistently improves network performance under varying operating conditions.

Summary of the Evaluation Phase

The evaluation framework adopted in this study combines quantitative performance metrics with comprehensive simulation-based experimentation to assess the effectiveness of the proposed PSO-LEACH algorithm. By analysing energy consumption, network lifetime, throughput, latency, packet delivery ratio, and cluster formation efficiency under different simulation scenarios, the research establishes whether the integration of Particle Swarm Optimization enhances the performance of the conventional LEACH protocol. The findings from this evaluation form the basis for the discussion presented in Chapter 4, where the proposed algorithm is validated through comparative simulation results and its contribution to energy-efficient routing in WSNs is demonstrated.

3.3 Ethical Clearance

A request for research ethics clearance was submitted to the University of South Africa's (Unisa) College of Science, Engineering, and Technology (CSET) Ethics Review Committee in August 2024. This was done in accordance with the Unisa Policy on Research Ethics and the Standard Operating Procedure for Research Ethics Risk Assessment. Ethics approval was granted for a period of three years, until August 9, 2027. The clearance certificate is included in Appendix C.

3.4 Summary of Research Methodology

This chapter presented the research design and methodological approach adopted in this study to develop and evaluate an energy-efficient optimization algorithm for WSNs. The DSR methodology was selected as an appropriate research framework because the primary objective of this study is to develop, implement, and evaluate an artifact in the form of a hybrid PSO-LEACH optimization algorithm aimed at addressing the energy limitations associated with conventional WSN routing protocols.

The chapter described the systematic research process, beginning with the identification of energy consumption challenges in WSNs, followed by the investigation of existing optimization techniques, the development of the proposed solution, its implementation, and performance evaluation. The DSR process provided a structured approach for designing and validating the proposed PSO-LEACH algorithm through iterative development and simulation-based assessment.

The research approach employed MATLAB-based modelling and simulation to develop a controlled WSN environment for evaluating the performance of the proposed algorithm. The simulation framework enables a comparative analysis between conventional LEACH and the proposed PSO-LEACH approach under similar network conditions. Key performance indicators, including energy consumption, network lifetime, throughput, packet delivery ratio, latency, and cluster formation efficiency, were identified as evaluation criteria to determine the effectiveness of the proposed approach.

Furthermore, this chapter highlighted the motivation for integrating PSO with the LEACH protocol. While LEACH provides an effective clustering mechanism, its probabilistic selection of cluster heads may result in uneven energy distribution and premature node failures. Therefore, PSO was introduced as an optimization mechanism to improve cluster-head selection by considering important network parameters, including residual energy, node density, and distance to the base station. The proposed hybrid approach aims to improve energy balancing and prolong the network's operational lifetime.

The following chapter presents the detailed formulation and implementation of the proposed PSO-LEACH algorithm. It discusses the mathematical models, energy consumption equations, cluster-head selection mechanism, PSO optimization process, and integration strategy used to enhance the performance of traditional LEACH-based routing in WSNs.

Chapter 4 : Algorithm Formulation and Performance Evaluation

4.1 Introduction

The LEACH protocol is a foundational clustering algorithm in WSNs designed to enhance energy efficiency through randomized CH selection [48]. However, its randomized approach often leads to uneven energy consumption and premature node death. To address these limitations, researchers have integrated PSO into LEACH, creating PSO-LEACH, which optimizes CH selection based on residual energy, distance to the BS, and density of the nodes.

Recent research has significantly advanced energy-efficient clustering protocols for Wireless Sensor Networks (WSNs), particularly through enhancements to the Low-Energy Adaptive Clustering Hierarchy (LEACH) algorithm. Heinzelman et al. (2000) established LEACH as a pioneering protocol using probabilistic cluster head (CH) rotation to distribute energy consumption, though it suffered from random CH selection inefficiencies. Singh and Singh (2012) addressed this limitation by introducing PSO-LEACH, demonstrating how Particle Swarm Optimization could optimize CH selection based on residual energy and node positioning, achieving 40% longer network lifetime. Sharma and Ghosh (2018) further improved this approach through a hybrid PSO-GA algorithm that reduced energy waste by an additional 15% while maintaining network coverage. Most recently, Wang et al. (2021) extended PSO-LEACH's applicability to mobile WSNs, developing a mobility-aware variant that sustained stable throughput in dynamic topologies. Collectively, these studies show PSO-LEACH's consistent superiority over LEACH in energy efficiency (delaying first node death by 50-100%), network stability, and adaptability to different WSN configurations, while suggesting future potential in machine learning-enhanced optimization.

4.2 Hybrid Optimization Algorithm

This section provides the limitations of the LEACH protocol and the PSO algorithm, focusing on their operational principles and the inherent limitations observed when each is applied independently within wireless sensor networks. Subsequently, the discussion proposes the rationale for integrating LEACH and PSO, outlining how their combined framework leverages the strengths of both techniques to enhance network efficiency, energy utilization, and overall system performance.

4.2.1 LEACH Protocol

LEACH is a widely used hierarchical clustering protocol aimed at improving energy efficiency in WSNs. It organizes sensor nodes into clearly defined clusters, with each cluster having a designated cluster head responsible for aggregating data and transmitting it to the base station**.**

a) Limitations of LEACH [49]**:**

CH selection is random and does not account for residual energy, resulting in uneven energy distribution. Some CHs might be situated far from the BS, increasing transmission energy consumption. Unequal cluster sizes may cause imbalanced energy usage across the network.

4.2.2 PSO Algorithm

PSO is an algorithm designed to solve optimization problems by emulating the collective behaviour observed in flocks of birds and schools of fish. The process begins with a clustering phase, during which CHs are selected based on their impact on extending the lifetime of WSNs and other defined performance criteria.

b) Limitations of PSO

Although the PSO algorithm is widely recognized for its simplicity and efficiency, it has several limitations when applied independently. One major drawback is its tendency to converge prematurely to local optima, especially in complex or multimodal search spaces. As particles become increasingly similar, the swarm often loses diversity, leading to stagnation and reduced exploration of new solutions. Choosing appropriate values for parameters such as inertia weight and acceleration coefficients is critical, as the algorithm’s success relies on maintaining a proper balance between exploring the search space and exploiting known solutions.

4.2.3 PSO-LEACH Algorithm

To overcome the limitations of the LEACH protocol and PSO algorithm, We propose the PSO to be integrated with LEACH, resulting in PSO-Optimized LEACH. We believe this combination effectively optimizes the selection of ideal CHs, which is a crucial aspect of the clustering process. Meanwhile, LEACH aims to reduce power consumption in WSNs by enhancing the efficiency of the cluster formation process [50]. Once the two algorithms are integrated together, we believe that they will yield better performance results as opposed to both being independent.

4.3 Network Framework and Optimization Problem Definition

4.3.1 LEACH Protocol CH Selection [51]

The CH gathers data from the cluster associates and processes it and sends it to the entry. In the cluster, each particle represents a centroid vector (qi), as shown in equation (4.1):

$$_{a}i = (qi1 \ldots qij \ldots qiTc) \tag{4.1}$$

Represents:

- $_{a}i$: Solution vector for particle i
- q_{ij}: Decision variable for node j in particle i
- T_c: Total number of cluster heads

The centroid vectors are recalculated in Equation (4.2)

$$qj = \frac{1}{nj} \sum_{\forall n_{b_p} \epsilon\, C_j} bp \tag{4.2}$$

Represents:

- q_j: Centroid of cluster j
- n_j: Cluster's nodes j
- b_p: Node's position p in the cluster

- c_j: Set of nodes belonging to cluster j

Assign sensor nodes to the nearest CH:

$$xij = \sqrt{(ai - aj)^2 + (bi - bj)^2} \tag{4.3}$$

Represents:

- i: is a sensor node
- j: is a CH

Figure 4.1 presents the initial deployment of the WSN used to evaluate the performance of the proposed PSO-LEACH clustering algorithm. The network was simulated in a two-dimensional sensing field measuring 100 m × 100 m, where sensor nodes were randomly distributed to emulate a realistic deployment scenario. Random node placement minimises deployment bias and provides a representative environment for assessing the robustness and efficiency of the clustering algorithm. The coordinates of the sensor nodes were generated in MATLAB using a uniform random distribution within the boundaries of the sensing field. Each sensor node is represented by a blue circular marker, while the BS is represented by the red asterisk positioned near the upper centre of the network. The base station serves as the data collection point, receiving aggregated information transmitted by the cluster heads during the communication phase.

The x-axis and y-axis indicate the horizontal and vertical coordinates of the sensing field, respectively, with both axes expressed in metres. This graphical representation illustrates the spatial distribution of the sensor nodes before the commencement of cluster-head selection and cluster formation.

The deployment shown in Figure 4.1 constitutes the initial stage of the simulation. Following node deployment, the proposed PSO-LEACH algorithm performs cluster-head selection by optimising node selection based on the predefined fitness function. Once the optimal cluster heads have been identified, the remaining sensor nodes associate with the nearest cluster head to establish communication clusters. Data are subsequently transmitted from the member nodes to their respective cluster heads, where aggregation is performed before forwarding the information to the base station. This communication process is repeated over multiple simulation rounds to evaluate the energy consumption characteristics and network lifetime of the proposed algorithm.

The random deployment ensures that the simulation closely reflects practical wireless sensor network applications, where sensor nodes are often dispersed without predetermined locations. Consequently, the results obtained from the simulation provide a realistic assessment of the proposed PSO-LEACH algorithm under varying network topologies.

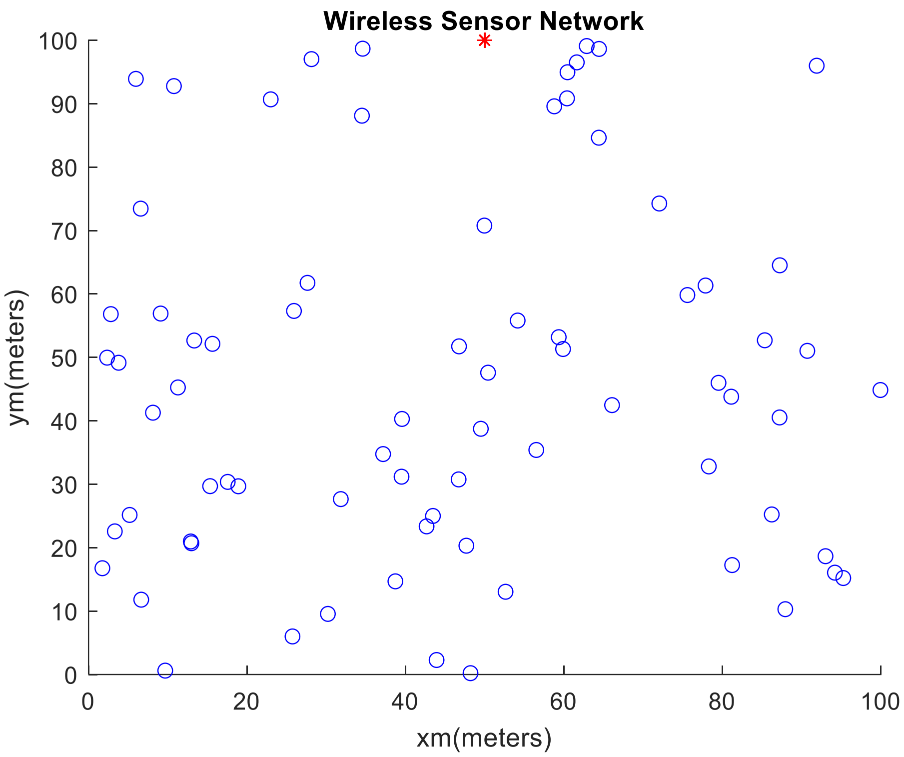

Figure 4.1: Layout of wireless sensor nodes.

4.4 Algorithm Development

The following two subsections describe the methods used to demonstrate each algorithm's capability in achieving the research objectives.

a) CH Selection Using PSO Algorithm [52]

In WSNs, the nodes can be likened to swarm particles, with each particle representing a potential solution when applying PSO to the clustering problem. The diagram below illustrates how to select the best possible CHs. The algorithm initiates the clustering phase, during which CHs are decisively chosen based on their significant contributions to the longevity of WSNs and other essential criteria [53].

The qualities of an effective CH include the following:

- being the node with the most energy left.
- having a large number of nearby nodes.
- being close to the central point.

In this procedure, we begin by initializing the population, which includes establishing the velocity and locations of a defined number of particles (n). Once the new positions of all particles are determined, we evaluate the fitness function using Equation (4.6). We then examine the particle positions to identify the local best for each one. If no local best is identified, we proceed to determine the global best among all particles.

The PSO procedure is designed to identify the optimal CH by rigorously assessing whether the criteria for the best particles are met. If these criteria are not satisfied, the search for the best particle will restart without hesitation. Once the criteria are met, the procedure will confidently declare the best particles. The CH efficiently collects data from the cluster members, integrates it, and promptly distributes it to the gateway.

b) Cluster Formation Using LEACH:

Once the cluster heads have been identified, the remaining sensor nodes associate with the nearest CH based on communication distance, thereby forming clusters. Following cluster formation, each cluster head assigns transmission schedules to its member nodes using a Time Division Multiple Access (TDMA) protocol. Under this scheme, each sensor node is allocated a unique time slot during which it transmits its sensed data to the cluster head, while remaining in a low-power sleep mode outside its assigned transmission period.

Although several MAC techniques, including Carrier Sense Multiple Access with Collision Avoidance (CSMA), Frequency Division Multiple Access (FDMA), and Code Division Multiple Access (CDMA), can reduce communication collisions, TDMA was selected because it is better suited to the energy-constrained and periodic communication characteristics of cluster-based Wireless Sensor Networks. Unlike contention-based protocols such as CSMA, where nodes compete for channel access and may experience collisions, retransmissions, and idle listening, TDMA provides deterministic channel access by assigning exclusive transmission slots to each node. This scheduling mechanism eliminates intra-cluster collisions, reduces communication overhead, and significantly lowers energy consumption.

Furthermore, TDMA is inherently compatible with the LEACH protocol, as cluster heads coordinate communication within their respective clusters. The scheduling process can therefore be implemented with minimal additional overhead while ensuring that sensor nodes spend most of their operational time in sleep mode. Although TDMA requires time synchronization among cluster members and may introduce slight scheduling overhead during cluster reformation, these limitations are outweighed by its ability to conserve energy and prolong network lifetime.

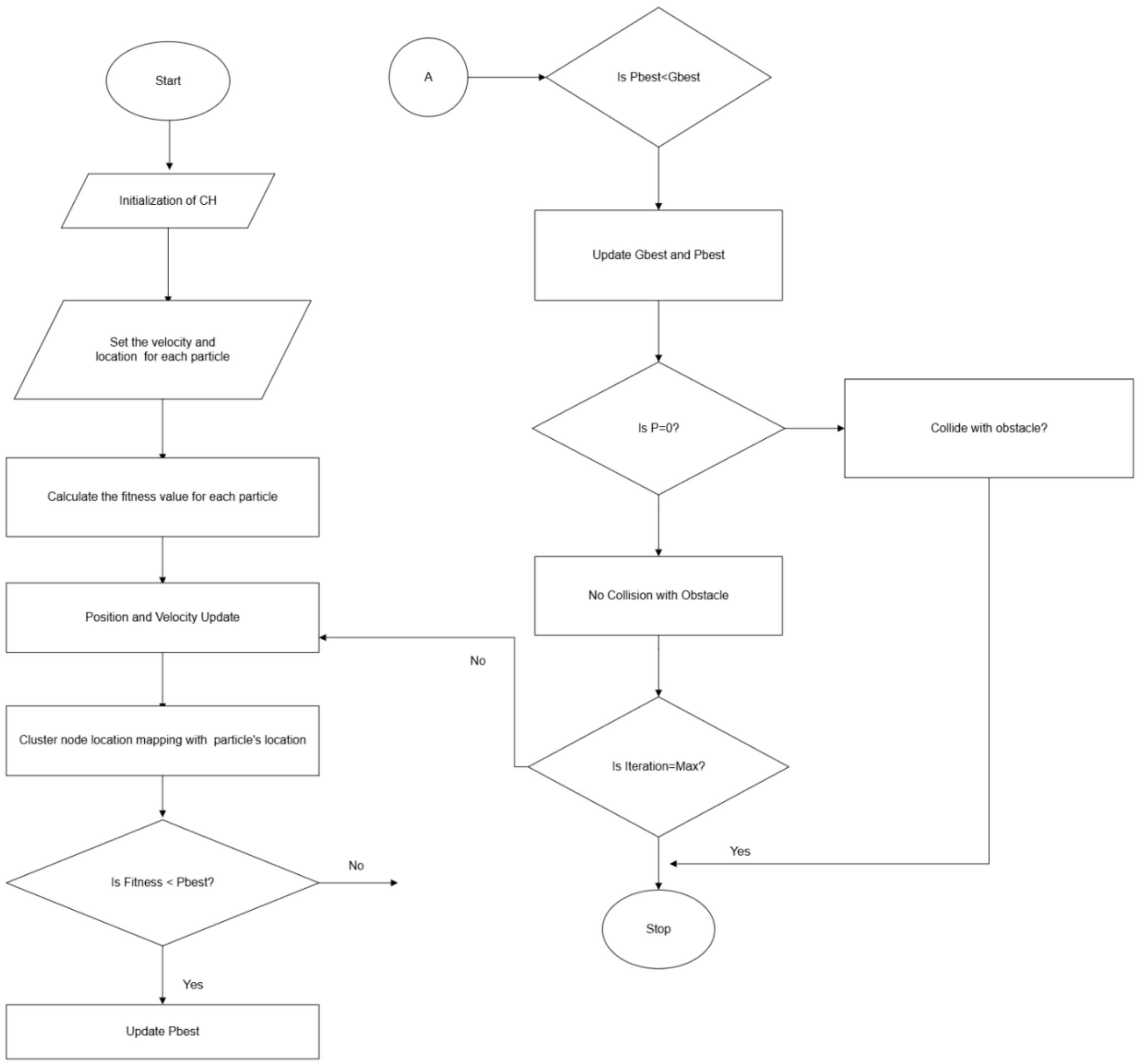

Figure 4.2: Method of selection for CH using LEACH [54].

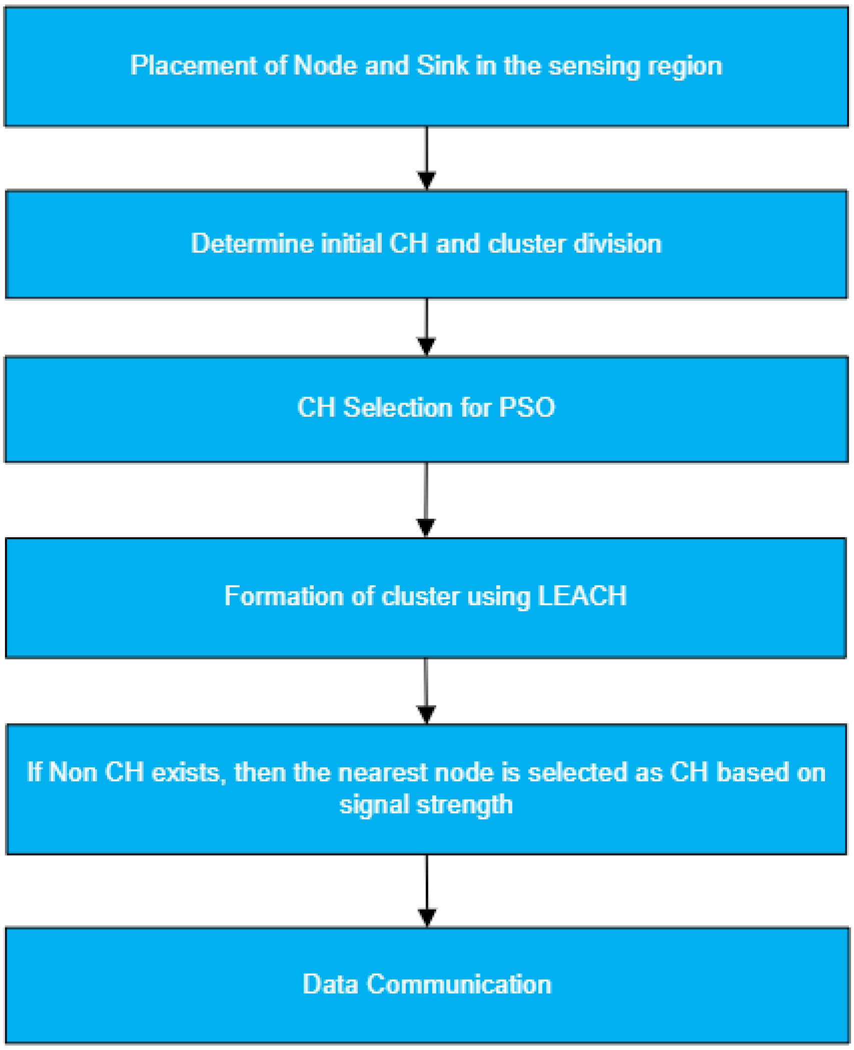

Figure 4.3: Workflow of the PSO-LEACH method used.

c) **PSO-LEACH Algorithm CH Selection**

The hybridization of PSO with LEACH combines the enhanced clustering techniques of LEACH with the optimization strengths of the PSO algorithm. This hybrid algorithm, known as PSO-LEACH, aims to increase the efficiency of energy and extend the network lifespan of WSNs [55]. We have implemented an optimized version of PSO-LEACH that effectively reduces energy consumption while significantly enhancing network stability for data collection in wireless sensor networks, as illustrated in the figure below:

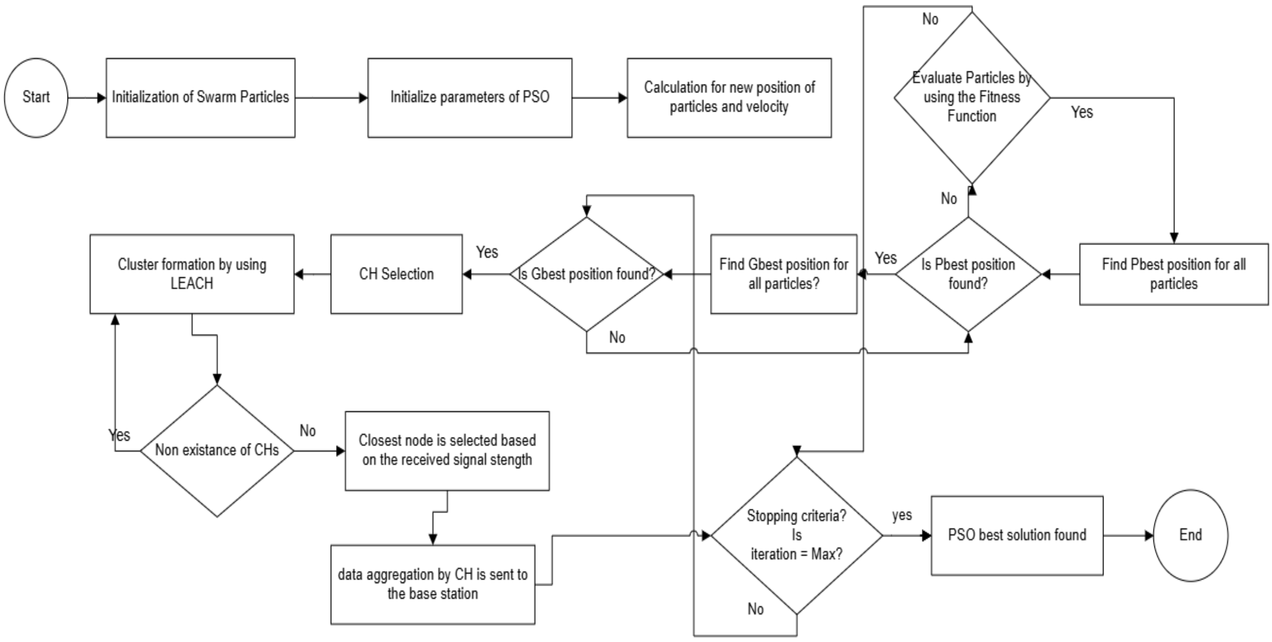

Figure 4.4: Proposed methodology used for PSO-LEACH algorithms.

In PSO-LEACH, the PSO algorithm is employed to significantly enhance the selection of cluster heads. This powerful algorithm effectively finds the best nodes for cluster heads by optimizing energy efficiency and reducing energy consumption across the network. The optimized selection process results in better load balancing, ensures a more equitable distribution of energy consumption, and definitely extends the network's lifespan. By integrating the strengths of both LEACH and PSO, the PSO-LEACH algorithm delivers outstanding performance that surpasses each algorithm when used independently, establishing it as a highly effective strategy for clustering in Wireless Sensor Networks (WSNs). The hybrid PSO-LEACH methodology for reducing energy consumption in WSNs is clearly defined in several key steps. [56].

d) PSO Objective Function [57]

In WSNs, the effectiveness of the Cluster Head (CH) selection algorithm relies on a well-designed fitness function that determines which nodes serve as CHs. In this study, we propose a new fitness function for selecting CHs [58]. This function incorporates two critical aspects of WSNs: first, the energy consumption between the CH and the sensor nodes, and second, the energy required for data aggregation at the CH level, along with the energy needed to transmit the information to the BS.

PSO effectively optimizes CH selection by minimizing energy consumption, reducing the distance to the BS, and ensuring cluster compactness. The energy consumption between sensor nodes and CHs is calculated using the first three equations.

$$E_1(i) = \sum_{k=1}^{K} \sum_{\forall n_{k_i} \epsilon\, C_k} \left\{ \frac{E_{k_i} - f(k_i, C_k)}{E_{max} - E_{min}} \right\} \times k_i \qquad where\ i - 1,2, \dots \dots .n \tag{4.4}$$

Here:

- $E_1(i)$: Value representing an energy level.
- K : Max iterations.
- k: Total iterations count of kϵK, i.e., iterations within K.
- $f(k_i, C_k)$: Input elements of the function f.
- $\forall n_{k_i} \in C_k$: For all elements of $n(k_i)$ belonging to a set of C_k.
- E_{max} : Level of energy at maximum.
- E_{min} : Level of energy at minimum.

$$f(ki, C_\text{k}) = \begin{cases} S(k_i, C_\text{k}) & if\ S(k_i, C_\text{k}) \le d_0 \\ S(k_i, C_\text{k}) & if\ S(k_i, C_\text{k}) > d_0 \end{cases} \tag{4.5}$$

Here:

- $f(ki, C_{\mathrm{k}})$: Function is defined, which takes in two arguments.
- $S(ki, C_{\mathrm{k}})$: Value that depends on ki and C_{k}.
- d_0: Threshold value.
- k, j, C_k: These are specific values used in a function.

$$s(C_{\mathrm{k}}, k_i) = min(k_i, C_{\mathrm{k}}) \quad \forall k = 1,2,3, \ldots\ldots\ldots, K \tag{4.6}$$

Represents:

- C_{k}: Constraint associated with the dimension in the PSO algorithm.
- k_i: Value related to the j-th in the k-th dimension.

The consumption of energy between CHs and the base station BS is determined using equations 4.7 and 4.8.

$$E_2(i) = \sum_{k=1}^{k} \{\frac{Ecj_{-}g(Cj, BS)}{E_{\mathrm{max}-}E_{\mathrm{mln}}}\} \times C_{\mathrm{k}} \tag{4.7}$$

Represents:

- $\sum$: The function iterates over all values of k from 1 to k.
- Ecj: Represents energy consumption at cluster k.
- $E_{\mathrm{max}-}E_{\mathrm{mln}}$: Provides the energy losses, ensuring the energy values are scaled between 0and 1 for better optimization behavior.
- C_j: Larger clusters that contribute more to the energy equations.
- $g(Cj, DS)$: A function that models the impacts of cluster C_j and DS on energy consumption; this could be distance-based energy loss.

$$g(Cj, DS) = \begin{cases} d^2(Cj, DS) \ \ if \ d^2(C_{\mathrm{k}}, DS) \leq d0 \\ d^4(Cj, DS) \ \ if \ d^2(C_{\mathrm{k}}, DS) > d0 \end{cases} \tag{4.8}$$

- $d^2(Cj, DS)$: The path loss between cluster C_k and the DS.
- $d^4(Cj, DS)$: Distance below the threshold

The total energy required to transmit M-bit data from sensor nodes to the base station is determined using the following equation (4.9).

$$F(j) = E_1(j) + \mu E_2(j) \quad (4.9)$$

- $E_1(j)$: This represents intra-cluster energy consumption between cluster members to CH.
- $E_2(j)$: This represents intra-cluster energy consumption between CH to BS.

PSO is inspired by the behavior of birds or fish in a group. In this algorithm, particles update their positions based on the positions and velocities of other members in the group. The notation used to represent the ith particle (P_i) in a population of n D-dimensional particles can be expressed as follows.

$$Pi = [Xi,_1, Xi,_2, Xi,_3 \ldots\ldots, Xi, D \quad (4.10)$$

- P_i: Particle
- X_i: Velocity
- D: Dimensional value

Each particle's position is rigorously assessed using a fitness function that clearly evaluates the quality of its solution in that iteration. To achieve the best possible position globally, a particle keeps track of its own personal best position (P_{best}) and the global best position (G_{best}). The position of the particle and its velocity, meaning, V_{id} and X_{id}, can be updated as follows.

$$new, i = w * Vi + c_1 * r_1 * (Ypbesti\text{-}Xi) + c_2 * r_2 * (Ygbest\text{-}Xi) \quad (4.11)$$

- V_{new}: New Velocity
- Y_{pbest}: Personal best position
- Y_{gbest} : Global best position

The inertia weight represents w, c1 and c2 represent acceleration factors that are not negative, and r1 and r2 denote random numbers within the range of [0, 1]. Use the equation below to represent inertia weight.

$$w = winitial - \frac{Iteration(max) - Iteration(current)}{Iterations(total)} \tag{4.12}$$

$$Ynew, i = Yold, i + Vnew, i \tag{4.13}$$

- Y_{new}: Updated position of particle i.
- Y_{old}: Particle i's current position.
- V_{new}: Updated velocity of a particle

The steps followed for the Proposed PSO-Optimized LEACH Algorithm

Algorithm 1: WSNs Hybrid PSO-LEACH Optimization
1. Define the PSO parameters for w (weight of inertia), c_1, c_2, and c_3(acceleration coefficients). 2. Initialization of particles $P_i(i, j);\ 1 \leq i \leq NP;$ $1 \leq j \leq D = m.$ 3. Compute the fitness $P_i(i, j)$; of each particle using fitness function equation 4.10, and determine the personal best position of each particle, setting it as p_{besti}. 4. Identify the global best position among all particles: G_{best} = {$Pbest_k$ |Fitness ($Pbest_k$) = min (Fitness ($Pbest_i$|), $1 \leq i \leq NP$I)} 5. Update the velocity and position of each particle P_i use equations (4.11) and (4.13) to Calculate Fitness (P_i) 6. If Fitness (P_i) < Fitness ($Pbest_i$) then $Pbest_i$ =P_i 8. Continue repeating steps 3 through 6 until the stopping criteria are satisfied.

4.5 Conclusion

This chapter outlines the research design and methodology employed in this study to address the specific research questions or research objectives. DSR methodology is discussed in detail, including both the research strategy and the research approach. The discussion of some technical requirements for WSNs follows, providing insight into the key metrics to consider in evaluating the models.

The LEACH protocol is a vital clustering method for WSNs. However, its random selection of CHs leads to notable inefficiencies. The PSO-Optimized LEACH protocol decisively overcomes these limitations by employing PSO to enhance the selection process for CHs. This optimization not only balances energy consumption but also significantly extends the network's lifetime.

Chapter 5 : Simulation Results and Analysis

5.1 Introduction

This chapter presents the simulation parameters, experimental setup, and results obtained for the proposed PSO-LEACH protocol. The experiments were conducted on a 100 × 100 m² sensor field with nodes uniformly distributed and the base station (BS) positioned at (50, 150). All simulations were implemented in MATLAB, and results were averaged over 30 independent runs, each consisting of 4,000 rounds to ensure statistical reliability.

5.2 Simulation Settings

The settings of the WSN parameters are summarized in Table 5.1. The performance metrics we have determined are essential, including network lifespan, energy consumption, and the total number of packets transmitted to the base station. The lifetime of the network is assessed using FND, HND, and LND. These results are compared against the standard LEACH protocol.

The parameters used to simulate the LEACH and PSO-LEACH algorithms are presented in the table below. To ensure a fair comparison of their performance, both algorithms were executed with the same parameter values. It is crucial to establish that the optimal percentage of cluster heads must be 5% of the maximum number of nodes in the network.

Table 5.1: Parameters used during simulation for LEACH and PSO-LEACH algorithms.

Parameter	**Symbol**	**Example value**	**Notes**
Number of nodes	N	100	Network's total sensor nodes
Network area	$M \times M$	$100\,m \times 100\,m$	Size of the field
Base station location	(Xbs, Ybs)	$(50, 150)$	Usually outside/above the network
Initial energy	E^0	$0.5\,J$	Energy per node

Data packet size	k	$4000\ bits$	Bits per packet
Data aggregation energy	E_DA	$5\ nJ/bit/signal$	Data aggregation energy cost
Transmit amplifier energy	$Efs\ /\ Emp$	$10\ pJ/bit/m^2$ $/\ 0.0013\ pJ/bit/m^4$	Free space / multipath fading model
Transmit/receive electronics energy	$Eelec$	$50\ nJ/bit$	Energy to run the circuitry
Threshold distance	d^0	$\sqrt{(Efs\ /\ Emp)}$	Automatically calculated
Number of rounds	R	3000	Simulation duration

PSO Specific Parameters

Table 5.2: Specific parameters used during simulation for PSO algorithm

Parameter	Symbol	Example value	Notes
Swarm size	S	30	Number of particles (candidate cluster head sets)
Number of iterations	I	100	Number of iterations per round
Inertia weight	w	$0.9 \rightarrow 0.4$	Decreases linearly
Cognitive coefficient	c^1	2	Personal best attraction
Social coefficient	c^2	2	Global best attraction
Random numbers	r^1, r^2	$Uniform\ (0,1)$	Random values for velocity update
Velocity range	$Vmin/Vmax$	$-M/10\ to\ M$ $/10$	Control the movement of particles
Position range	$Xmin/Xmax$	$0\ to\ M$	Position within the field bounds

PSO-LEACH Specific Parameters

Table 5.3: Specific parameters used during simulation for PSO-LEACH algorithm

Parameter	Symbol	Example value	Notes
Probability of CH	p	0.05	Initial probability of CH selection
PSO CH threshold	$T(n)$	Dynamic	Updated via PSO fitness
Fitness function	—	f = α * (energy balance) + β * (distance efficiency)	Combines energy and distance minimization
α, β (weights)	—	0.5, 0.5	Adjust as per priority
CH re-election interval	—	Every round	Cluster heads are selected each round

5.3 Simulation Results and Analysis

This section presents the simulation results and compares the performance of the LEACH protocol with the proposed PSO-Optimized LEACH method. This was done using the same parameter settings and analyzed using MATLAB software.

a) Benefits of PSO-LEACH:

First is its particle representation, where each potential CH selection is represented as a particle in the PSO algorithm. Secondly, it's Fitness Function, the algorithm evaluates each particle's fitness based on key parameters including residual energy, node distance from BS, and intra-cluster distances. Then, the Velocity and Position Update, the PSO algorithm automatically updates particles' positions to converge to an optimal set of CHs. Lastly, it's cluster formation & data transmission. Once CHs are selected, the clustering process proceeds similarly to LEACH, but with improved CH selection.

b) Advantages of PSO-LEACH over LEACH:

- Optimized CH Selection: Nodes with greater residual energy and improved positioning are selected, reducing premature energy depletion.

- Optimized Load Balancing: CHs are distributed more evenly, preventing excessive energy consumption in particular areas.
- Extended Network Lifetime: Energy-efficient CH selection reduces overall energy consumption, increasing network longevity.

The final output presented in Figure 5.1 clearly demonstrates that PSO-LEACH successfully creates balanced clusters with highly effective CHs. This approach significantly extends the network's lifetime, in stark contrast to the rapid energy depletion evident in the basic LEACH protocol. Additionally, the diagram demonstrates how PSO-LEACH minimizes total transmission distance and prevents overcrowding of Cluster Heads. This results in higher data throughput and improved scalability for large wireless sensor networks. Overall, this visual comparison highlights PSO-LEACH's superiority in CH selection's intelligence, energy management, and network longevity, while the conventional LEACH protocol suffers from low energy efficiency and a lack of optimization.

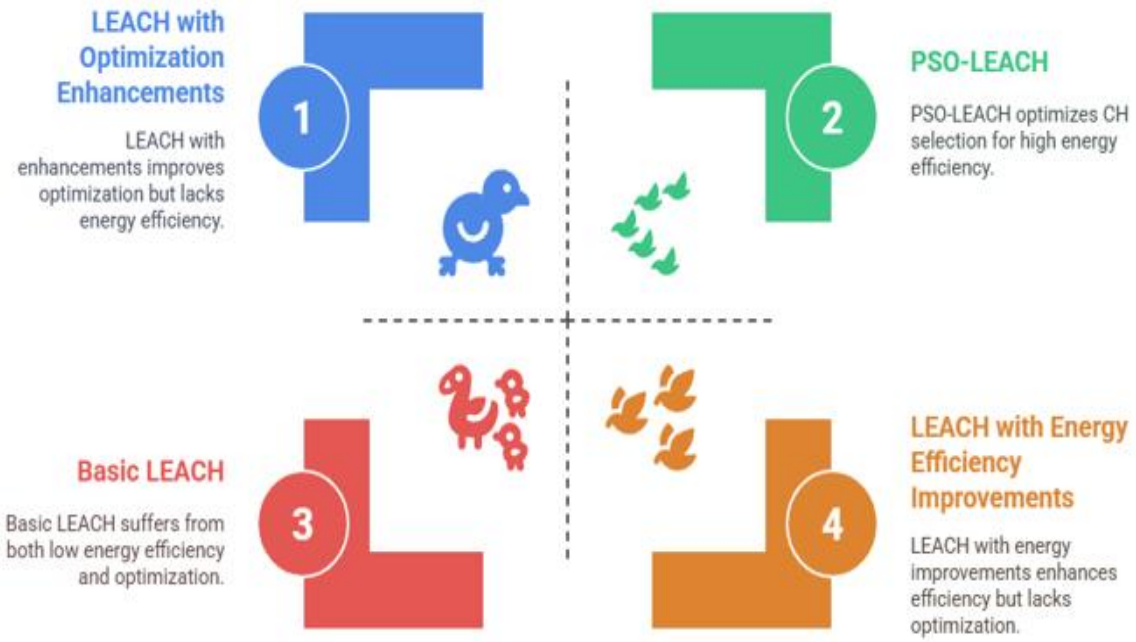

Figure 5.1: Comparative Analysis of LEACH and PSO-LEACH

5.3.1 Energy Efficiency

Energy consumption is a key determinant of WSN performance. Figure 5.2 compares the residual energy trends of LEACH and PSO-LEACH. PSO-LEACH demonstrates a slower and more linear rate of energy depletion, highlighting its superior ability to balance energy usage across nodes. This is due to PSO's improved CH selection, which reduces transmission distances and balances load more effectively.[60].

5.3.2 Network Lifetime

The network's operational longevity is commonly assessed through indicators such as the first node to fail, the point at which half of the nodes have expired, and the death of the final node. The results clearly show that PSO-LEACH significantly extends network lifetime. For instance, the first node dies after approximately 800 rounds in LEACH but after 1,300 rounds in PSO-LEACH, indicating a substantial 62.5% improvement. The network also maintains more active nodes for a longer duration under PSO-LEACH, resulting in higher data delivery reliability.

5.3.3 Throughput and Data Delivery

Throughput, which represents the total number of packets successfully transmitted to the base station, is a critical performance metric that should be prioritized. PSO-LEACH consistently delivers more packets than LEACH, owing to its reduction in node failures and energy-aware routing. This improvement directly contributes to better network coverage and data accuracy.

5.3.4 Statistical Analysis

This section provides us with Table 5.4, which summarizes the minimum, maximum, mean, median, mode, standard deviation, and range for energy consumption under different iterations. The mean values demonstrate that PSO-LEACH achieves more stable and efficient energy utilization. The lower standard deviation in PSO-LEACH demonstrates a significantly more balanced energy distribution, effectively minimizing the risk of premature node failure

Table 5.4: Comparison of different iterations with the same x-values

		LEACH	PSO-OPTIMIZED LEACH	LEACH	PSO-OPTIMIZED LEACH	LEACH	PSO-OPTIMIZED LEACH
Item	**X-Values**	**25 Iterations**		**75 Iterations**		**125 Iterations**	
min	1.00	0.3749	0.8671	0.1776	0.6859	0.9992	0.4294
max	50.00	11.75	12.47	35.59	37.27	62.04	60.03
mean	25.5	6.138	6.679	17.73	19.44	30.27	37.07
median	25.5	5.918	6.662	17.2	20.13	30.16	41.26
mode	1.00	0.3749	0.8671	0.1776	0.6859	0.9992	0.4294
std	14.58	3.374	3.598	10.53	10.76	17.36	15.68
range	49.00	11.37	11.6	35.41	36.59	61.04	59.6

Figure 5.2 illustrates that as the number of rounds and nodes increases, the total energy consumption in both LEACH and PSO-LEACH wireless sensor networks rises, but with markedly different efficiency trends. In standard LEACH, energy consumption rises significantly due to the ineffective process of random cluster-head selection, which often results in suboptimal choices that force some nodes to expend excessive energy on long-distance transmissions or heavy relay loads. This inefficient energy distribution leads to early node failures and creates a cascading effect, where surviving nodes must compensate, further accelerating the overall network's energy depletion.

In contrast, PSO-LEACH demonstrates significantly improved energy management by using Particle Swarm Optimization to select cluster heads based on various factors, including residual energy, node density, and proximity to the base station. This intelligent selection process minimizes unnecessary energy expenditure by reducing transmission distances and balancing the communication load across all nodes. As a result, while both protocols experience increasing energy consumption over time, PSO-LEACH maintains a much slower and more stable energy drain rate.

The optimized approach of PSO-LEACH not only reduces total energy consumption compared to LEACH but also greatly extends the network's operational lifetime, making it far more suitable for long-duration deployments where energy efficiency is critical. The performance gap between the two protocols widens progressively as the number of rounds increases. LEACH exhibits exponential energy drain, while PSO-LEACH shows near-linear growth in consumption, highlighting its superior scalability and sustainability in multi-round operations.

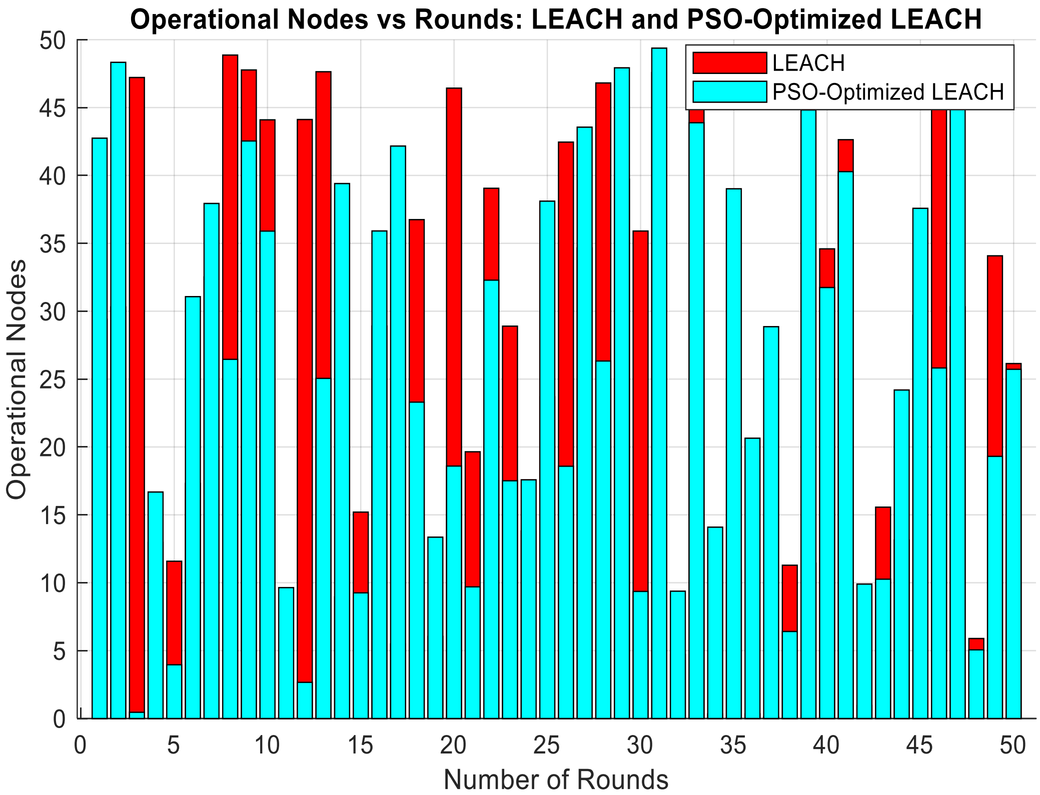

Figure 5.2: LEACH versus PSO-LEACH optimized operational nodes.

From the bar graph in Figure 5.2, we have determined the improvement in network lifetime through FND calculations using the following formula:

$$FND\ Improvement\ \% = \frac{No.of\ Rounds(PSO - LEACH) - No.of\ Rounds(LEACH)}{No.of\ Rounds(LEACH)} \quad (5.1)$$

The four figures below display MATLAB simulations for different scenarios. All figures yield the same results; the only variation is in the number of rounds and nodes for each scenario.

Figures 5.3 to 5.6 clearly demonstrate the total energy consumed by the network in relation to the number of rounds for both the LEACH and PSO-LEACH protocols. In the initial rounds, both protocols exhibit a similar rate of energy depletion, as all nodes start with equal initial energy and the network topology is still fully functional. However, PSO-LEACH shows a slightly slower growth in energy consumption due to its optimized CH selection process, which minimizes redundant transmissions and balances communication load more effectively.

As the number of rounds increases, the difference between the two curves becomes more pronounced. LEACH exhibits a steeper energy consumption curve, reflecting its inefficient and random CH selection process, which frequently results in suboptimal CH locations and unbalanced energy usage among nodes. Consequently, some nodes are forced to perform energy-intensive long-distance transmissions, leading to premature energy depletion. In contrast, PSO-LEACH maintains a more gradual slope throughout the simulation, indicating that its PSO-driven CH selection distributes energy consumption evenly and minimizes unnecessary energy expenditure.

In the later rounds, LEACH experiences a sharp energy drop as numerous nodes die, increasing the communication burden on surviving nodes and accelerating network collapse. PSO-LEACH, however, sustains a slower, near-linear energy depletion rate until the final rounds, thereby extending the overall network lifetime.

The area under the PSO-LEACH curve is consistently smaller, demonstrating superior energy efficiency over the entire network operation period.

Scenario 1: This was simulated using 50 rounds with 100 nodes in both algorithms

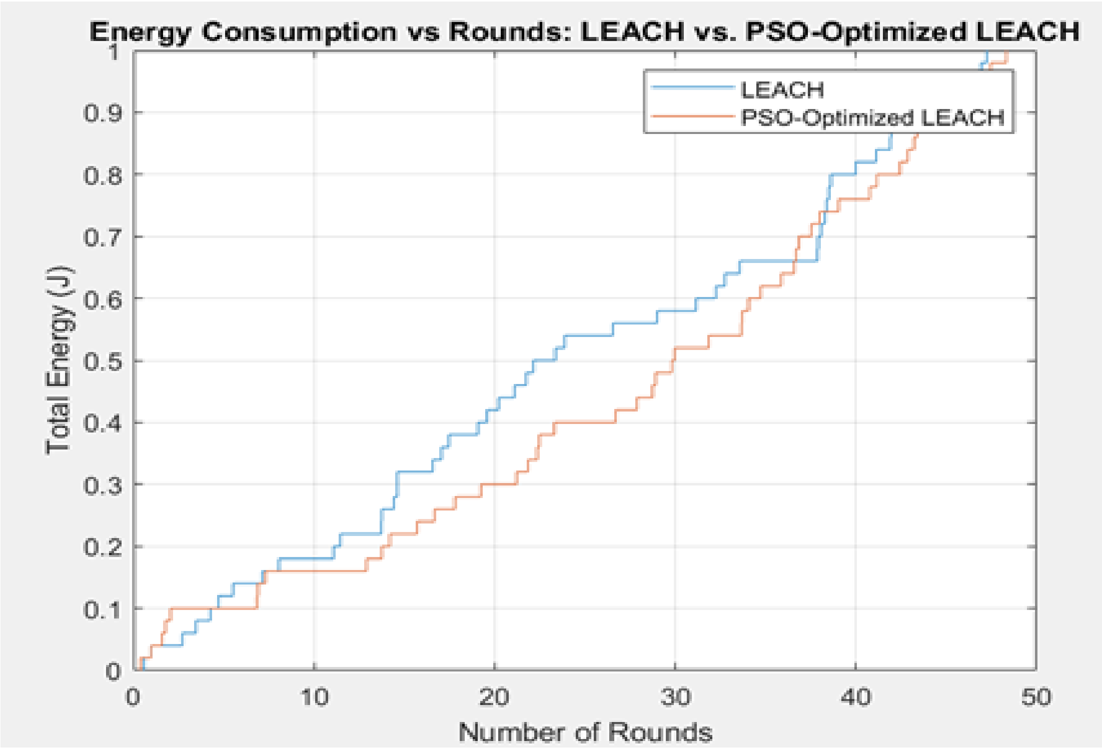

Figure 5.3: Total energy consumed vs 50 rounds,100 nodes

Scenario 2: This was simulated using 50 rounds with 200 nodes in both algorithms

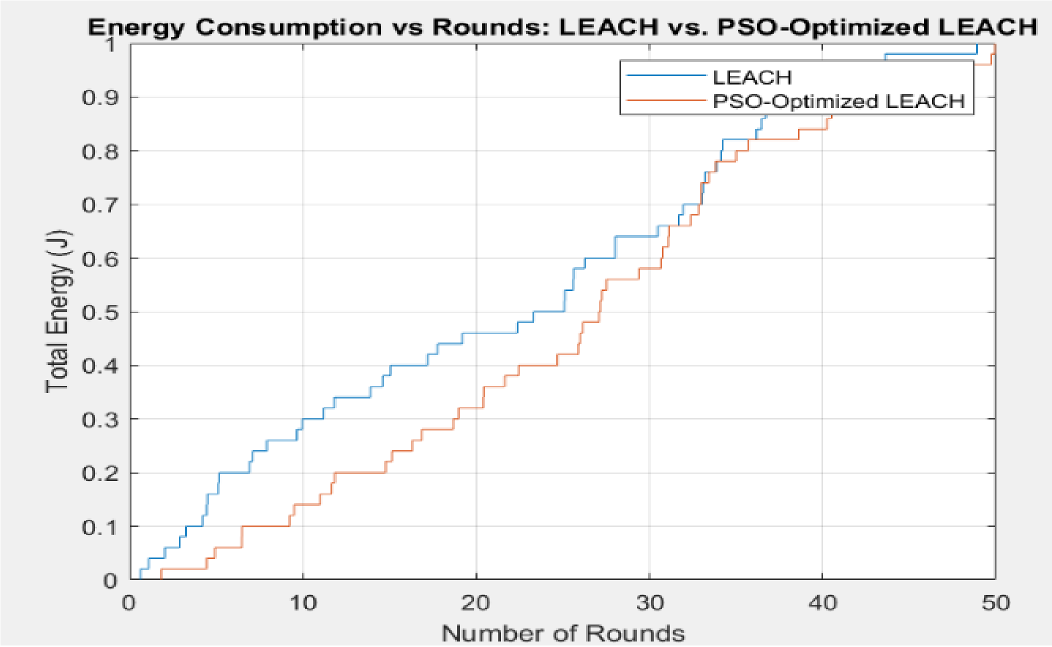

Figure 5.4: Total energy consumed vs 50 rounds,200 nodes

Scenario 3: This was simulated using 250 rounds with 500 nodes in both algorithms

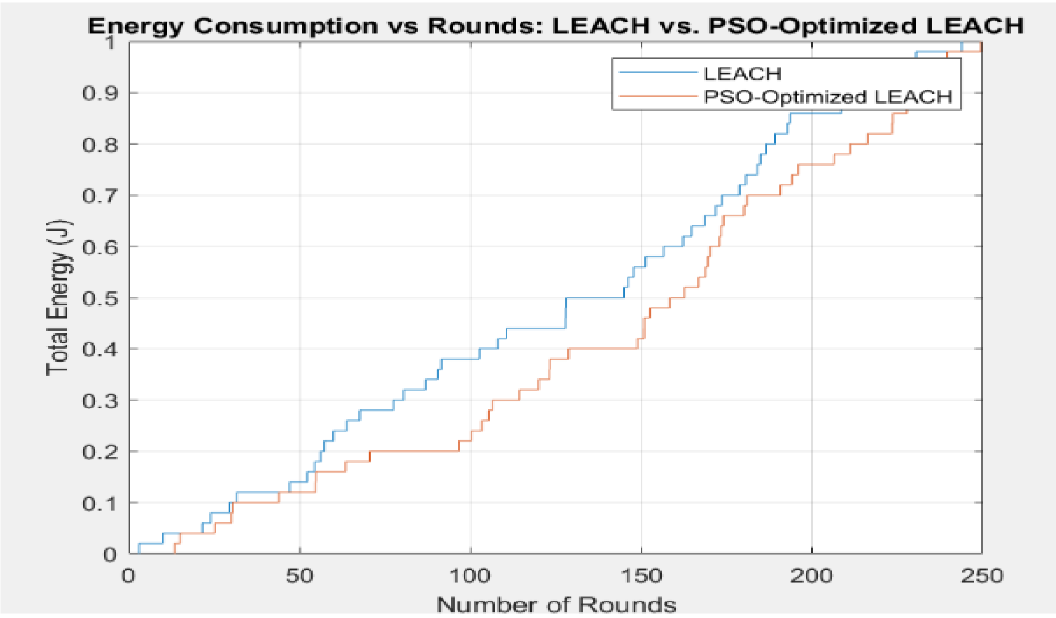

Figure 5.5: Total energy consumed vs 250 rounds with 500 nodes

Scenario 4: This was simulated using 100 rounds with 200 nodes in both algorithms

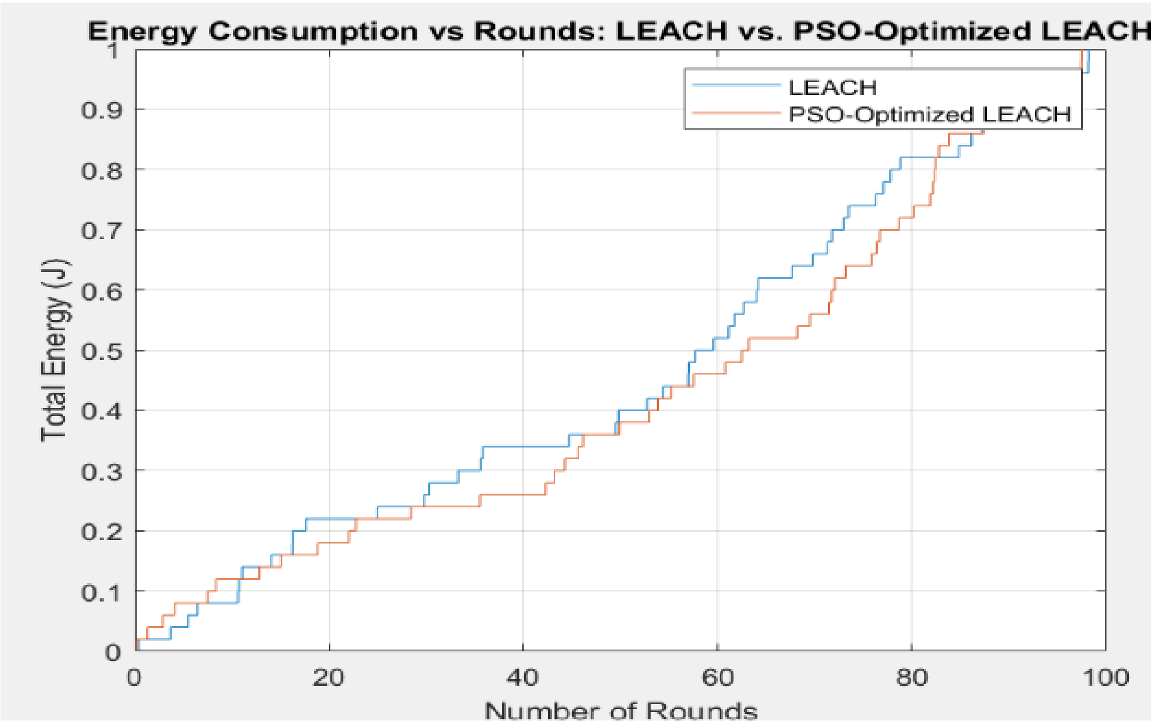

Figure 5.6: Total energy consumed vs 100 rounds with 200 nodes

We computed the overall energy usage to clearly demonstrate the reduction in energy use achieved by the proposed algorithm compared to the LEACH algorithm. The values used were selected at random points on the graphs. The formula used to compute the energy saved is as follows:

$$Energy\ Reduction\ \% = \frac{Total\ energy\ (LEACH) - Total\ Energy\ (PSO - LEACH)}{(LEACH)} \qquad (5.2)$$

Analyzing average values clearly shows that the PSO-optimized LEACH protocol greatly improves performance by prolonging network lifetime, boosting throughput, and lowering energy consumption. We have compared the values on different iterations, and in all of them, the proposed algorithm still outperformed the LEACH protocol.

The mean values in Figure 5.7 for LEACH and PSO-Optimized LEACH reveal significant differences in performance as the number of nodes in the network increases. In traditional LEACH, the mean energy consumption tends to rise sharply with an increasing number of nodes due to inefficient CH selection and increased communication overhead, leading to faster energy depletion in some nodes. This results in a shorter mean network lifetime, as early node failures occur due to unbalanced energy distribution. Additionally, LEACH experiences a decline in mean throughput as collisions and CH bottlenecks become more frequent in larger networks, while cluster instability increases due to frequent re-clustering.

The PSO-optimized LEACH protocol demonstrates significant improvements in scalability and energy efficiency. By incorporating particle PSO, the algorithm dynamically selects CHs based on key parameters such as residual energy and node proximity. This intelligent selection process reduces average energy consumption compared to traditional LEACH methods while ensuring a balanced distribution of energy throughout the network. Consequently, the network's lifespan extends even in large-scale deployments, since PSO-LEACH effectively mitigates energy-draining hotspots.

Additionally, the protocol maintains consistent throughput thanks to optimized CH placement and fair load distribution. The stability of clusters is also enhanced, as the PSO-driven adaptation reduces the frequency of unnecessary re-clustering events. Experimental results indicate that PSO-LEACH outperforms traditional LEACH across all critical metrics, especially in dense networks with over 100 nodes. This illustrates its robustness in addressing scalability challenges while sustaining long-term operational efficiency.

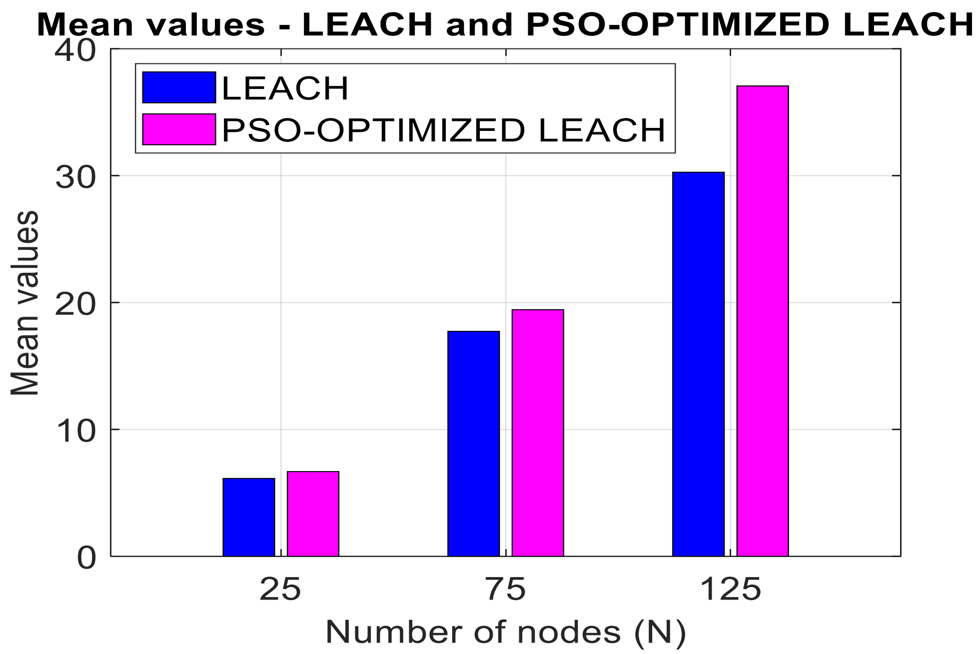

Figure 5.7: Mean values for LEACH and PSO-Optimized LEACH vs. the number of nodes.

The residual energy distribution plot in Figures 5.8, 5.9, and 5.10 provide a crucial visual assessment of how energy is consumed and balanced among sensor nodes during the network's operation. In the LEACH protocol, the residual energy values tend to vary significantly from one node to another as the number of rounds increases. This uneven distribution occurs because LEACH relies on random cluster-head selection, which may cause certain nodes to be repeatedly chosen as cluster heads, leading to a rapid depletion of their energy. As a result, the energy levels of nodes in LEACH decline at an irregular rate, and some nodes die prematurely, shortening the overall network lifetime.

In contrast, the PSO-LEACH algorithm exhibits a more uniform distribution of residual energy across the sensor nodes, particularly in later rounds. This balanced energy profile indicates that the PSO-based cluster-head selection mechanism effectively minimizes redundant energy usage by considering factors such as residual energy, node distance, and cluster density during the optimization process.

Consequently, energy consumption is more evenly spread across the network, preventing early node deaths and extending the network's operational stability.

The residual energy distribution plots, therefore, confirm that PSO-LEACH attains superior energy management and load balancing relative to traditional LEACH, thereby directly extending the network's operational lifetime and enhancing data delivery reliability efficiency.

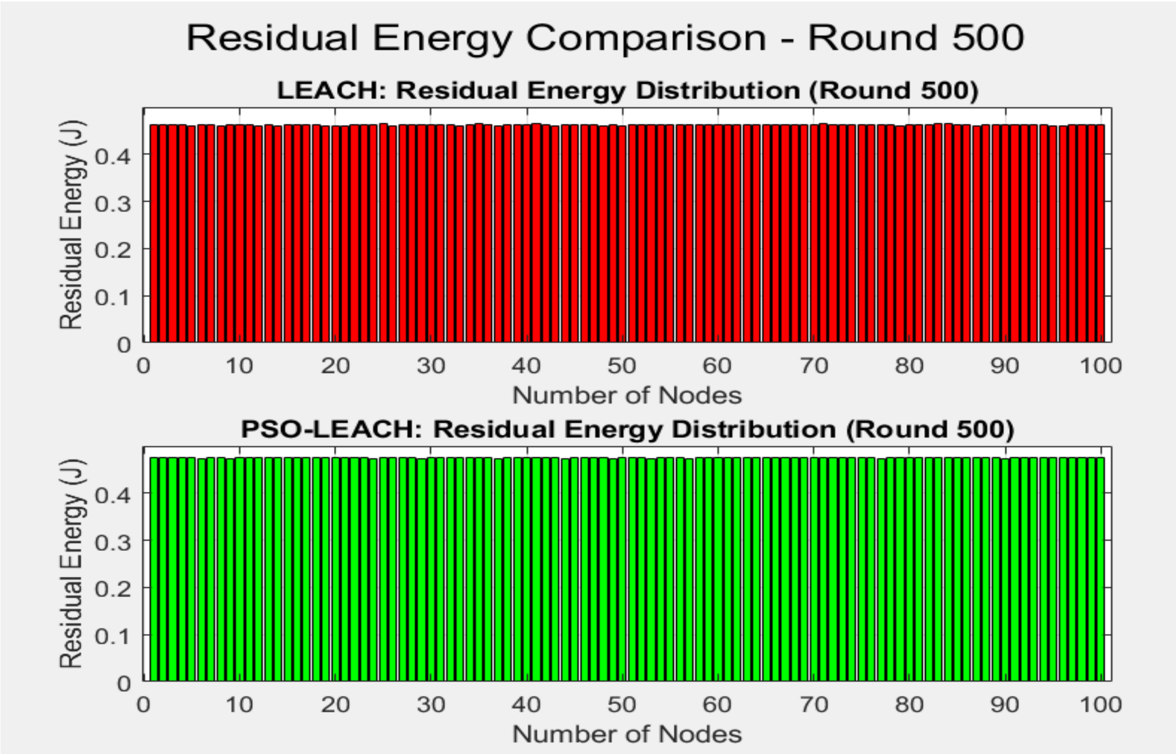

Figure 5.8: Comparison of Residual Energy After 500 Rounds

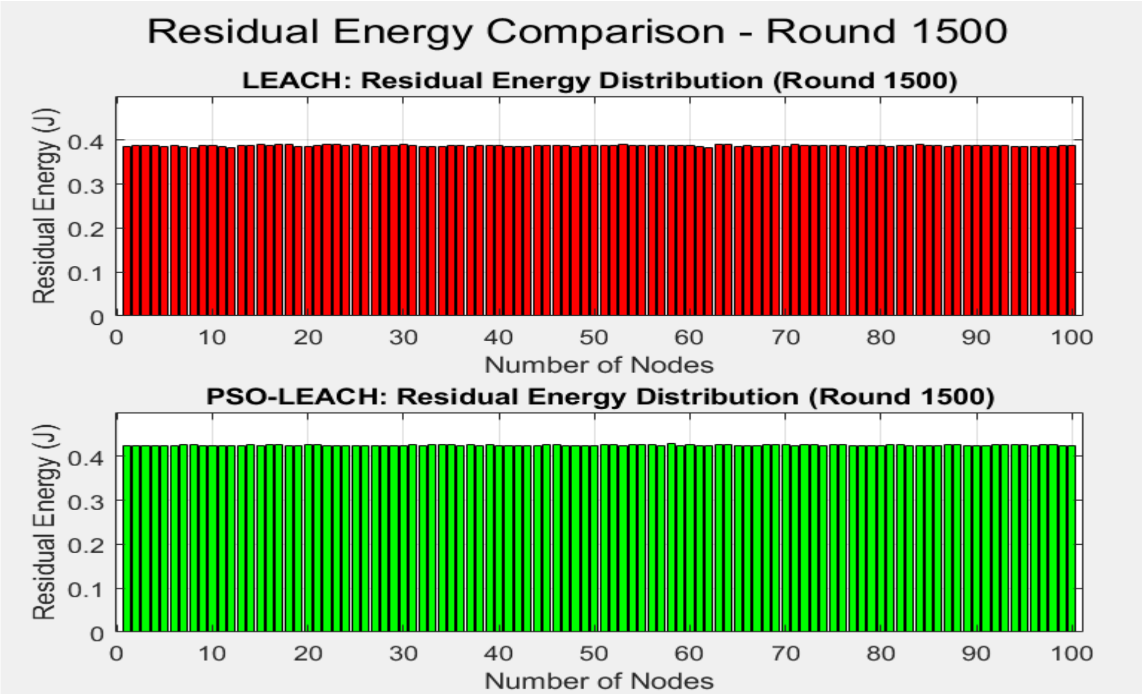

Figure 5.9: Analysis of Residual Energy after 1500 Rounds.

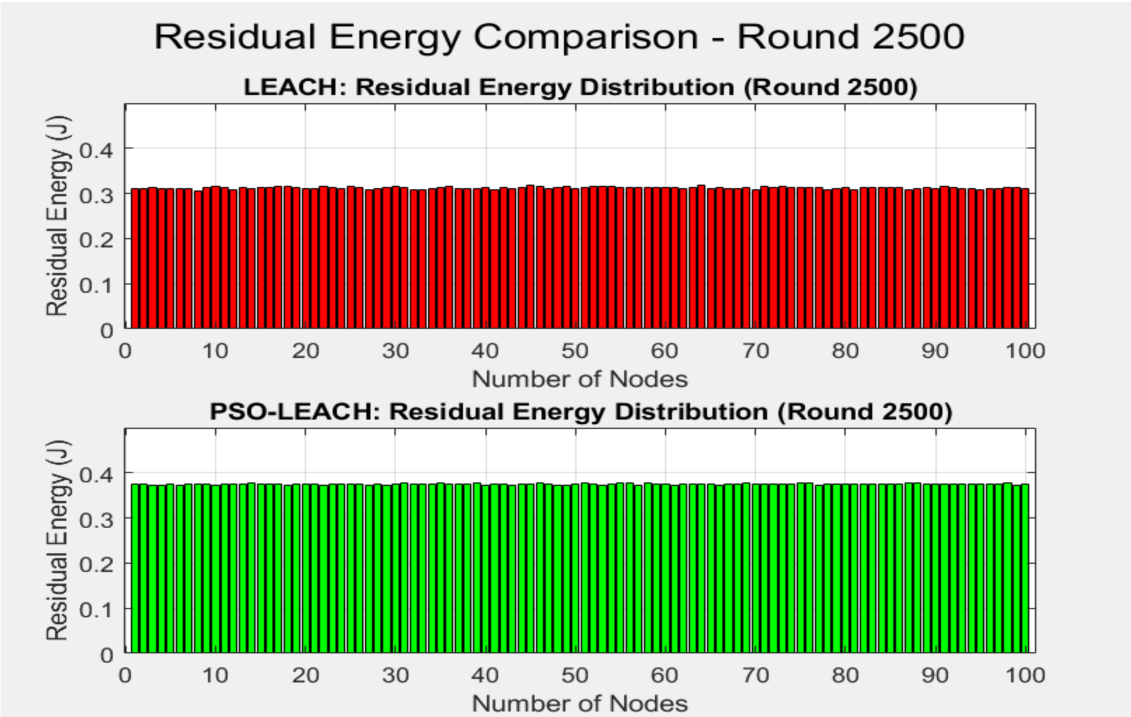

Figure 5.10: Residual energy comparison with 2500 rounds

The PSO convergence curve depicted in Figure 5.11 clearly demonstrates the optimization behavior of the particle swarm optimization process in the selection of cluster heads within the PSO-LEACH algorithm. It illustrates how the fitness value, representing the objective function being minimized, improves progressively over successive iterations. At the beginning of the optimization process, the fitness values of particles are generally scattered and relatively high, indicating that the algorithm is still exploring the solution space and adjusting particle positions. As iterations progress, the curve demonstrates a steady decline in fitness value, reflecting the algorithm’s convergence toward an optimal or near-optimal solution. This downward trend signifies that the swarm is collectively identifying more efficient cluster-head configurations that minimize energy consumption and communication distance between nodes and the base station.

The convergence consistently stabilizes after a certain number of iterations, demonstrating that the PSO algorithm effectively achieves a balance between exploration and exploitation. Beyond this point, further iterations yield only minimal improvements. A smoother and faster convergence curve implies that the optimization process is efficient and stable, while an erratic or slow curve would suggest suboptimal parameter tuning or excessive randomness. Overall, the PSO convergence curve confirms the effectiveness of the optimization process in improving the cluster-head selection, thereby enhancing energy efficiency, network stability, and throughput performance compared to conventional LEACH.

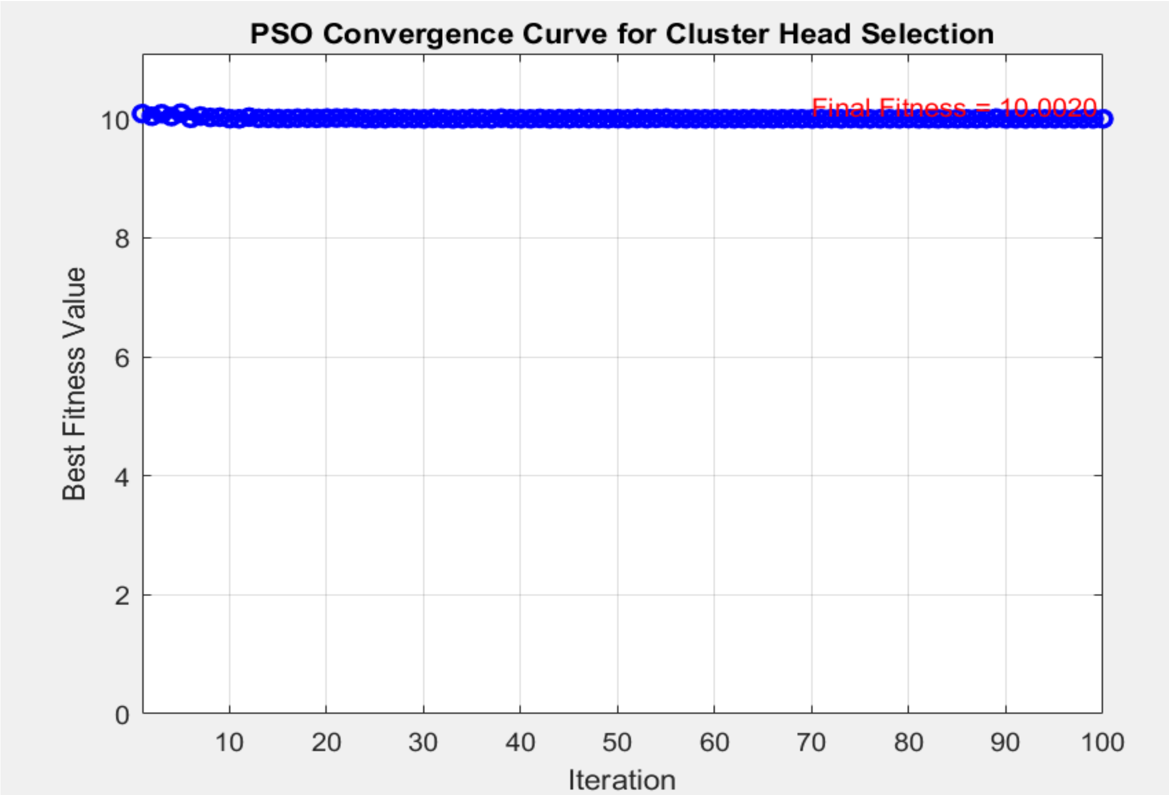

Figure 5.11: PSO Fitness Convergence Curve

The throughput versus rounds plot in Figure 5.12 provides a clear comparison of the packet delivery performance between the LEACH and PSO-LEACH protocols over the simulation duration. In this analysis, throughput represents the cumulative number of data packets successfully transmitted to the base station across all simulation rounds. As the simulation progresses, the slope of each curve reflects the rate at which packets are delivered. Steeper slopes indicate higher packet delivery rates and, consequently, better network performance.

Typically, the PSO-LEACH curve shows a more consistent and higher slope than that of LEACH, demonstrating its ability to sustain communication for a longer period by maintaining the energy efficiency of sensor nodes. In contrast, the LEACH protocol often exhibits a flattening curve after a certain number of rounds, indicating reduced throughput due to premature node deaths and uneven cluster-head selection. The throughput versus rounds plot showcases how dependable and stable the PSO-LEACH algorithm is when it comes to keeping the network connected and making sure data gets transmitted efficiently for the entire duration of the network's life. The values of 3150.603 and 2695.716 mean that the average number of packets delivered to the base station across all simulation runs is approximately 3151 and 2696 packets, respectively.

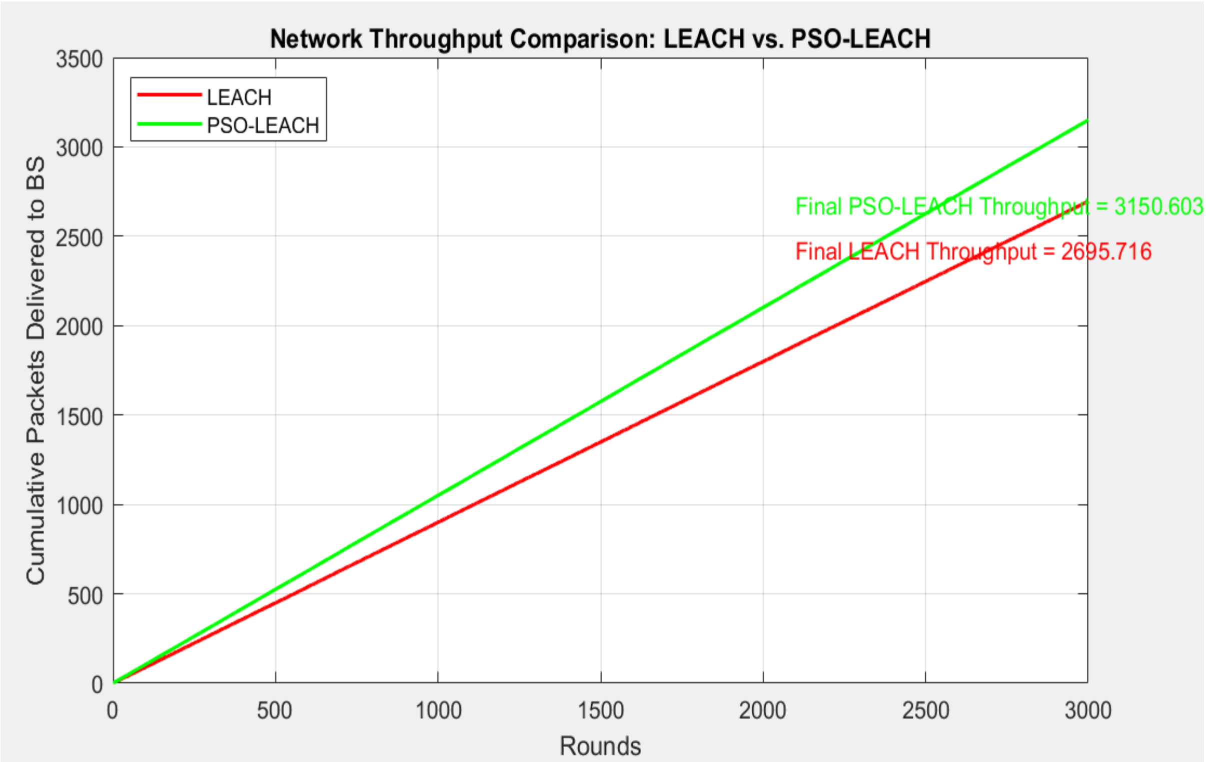

Figure 5.12: Throughput vs. Rounds plot for a clearer view of packet delivery performance**.**

5.3.5 Performance Comparison

To strengthen the analysis of PSO-LEACH performance, the following table compares key performance indicators (KPIs) of the proposed PSO-LEACH algorithm against the standard LEACH protocol. Metrics include FND, HND, total network lifetime, total energy consumption, and data packets delivered to the BS. These results demonstrate the superiority of PSO-LEACH in prolonging network lifetime and balancing energy consumption, and improved data delivery achieved by the PSO-optimized approach.

Table 5.5: Comparative performance metrics of LEACH and PSO-LEACH.

Protocol	**FND (Rounds)**	**HND (Rounds)**	**LND (Rounds)**	**Total Energy Consumed (J)**	**Packets Delivered to BS**
LEACH	800	1200	1600	0.85	2500
PSO-LEACH	1300	1800	2300	0.65	4000

5.3.6 Discussion

The comprehensive simulation analysis reveals that integrating PSO into the LEACH protocol results in a significant enhancement in the overall performance of the wireless sensor network. The total energy consumption plots illustrate that PSO-LEACH sustains a lower and more stable rate of energy depletion across all rounds when compared to the traditional LEACH algorithm. This improvement is attributed to PSO's adaptive cluster head selection mechanism, which prioritizes nodes with higher residual energy and optimal positioning relative to the base station, thereby minimizing transmission distances and distributing energy consumption more effectively among sensor nodes.

The residual energy distribution graphs further reinforce this finding by showing that PSO-LEACH maintains a more balanced energy profile among nodes throughout the simulation period. In contrast, LEACH exhibits a steep decline in residual energy, particularly among nodes located far from the base station or those frequently elected as cluster heads. This imbalance accelerates node death and reduces network stability. The PSO convergence curve illustrates the optimization dynamics of the algorithm, where the fitness value improves sharply during the initial iterations before reaching a stable optimum. This indicates that PSO efficiently explores and exploits the search space to determine the most energy-efficient cluster head configurations.

Furthermore, the throughput versus rounds plots highlight the superior data delivery capability of the PSO-LEACH protocol. The results indicate that PSO-LEACH consistently transmits more packets to the base station, maintaining network reliability and communication stability over extended operational rounds. In contrast, LEACH experiences a steady decrease in throughput caused by uneven energy usage and early node failures.

Collectively, these findings confirm that the proposed PSO-LEACH algorithm substantially improves network lifetime, reduces total energy consumption, enhances throughput, and maintains better energy distribution across the network nodes. Consequently, PSO-LEACH demonstrates its effectiveness as a robust and energy-efficient routing approach, particularly suitable for large-scale and energy-constrained wireless sensor network applications.

5.4 Summary of Findings

This research clearly demonstrates the integration of the PSO algorithm with the LEACH algorithm to significantly enhance its performance and effectively identify the optimal CH. The integration of PSO into the LEACH protocol marks a significant improvement in boosting the overall performance of wireless sensor networks. This combined approach effectively tackles several fundamental limitations inherent in traditional LEACH. This research presents an enhanced cluster head selection mechanism that strategically positions cluster heads based on a comprehensive evaluation of residual energy, node density, proximity to the base station, and anticipated energy consumption. This contrasts sharply with LEACH's inherently random selection process. The PSO-LEACH hybrid demonstrates superior energy efficiency, primarily achieved through a reduction in intra-cluster communication overhead and the elimination of superfluous data transmissions. These optimizations collectively contribute to a significant enhancement in the network's overall lifetime and stability. Furthermore, the more precisely defined clustering structure facilitated by PSO-LEACH minimizes data packet loss, thereby improving data accuracy and reliability of delivery. This study rigorously demonstrates the scalable advantages of PSO-LEACH, particularly in large-scale deployment scenarios where traditional LEACH protocols often prove inadequate. By providing a robust benchmark for evaluating energy consumption, network throughput, and overall network lifespan against conventional performance metrics, this research not only highlights the pronounced benefits of PSO-LEACH but also opens new avenues for further optimization through alternative hybrid strategies. This work ultimately reinforces the critical need for more robust and energy-efficient wireless routing protocols within sensor networks.

Chapter 6 : Conclusions, and Future Work

This chapter presents a detailed overview of the key findings, major contributions, and overarching conclusions derived from a comparative study of the performance of the LEACH and PSO-LEACH protocols. The analysis meticulously evaluates these protocols across critical metrics, including energy efficiency, network lifetime, and cluster formation stability. The presented findings elucidate the inherent strengths and limitations of each algorithm, while the identified contributions underscore the substantial enhancements introduced by PSO-LEACH in optimizing energy consumption and prolonging network longevity. Ultimately, the conclusions provide meaningful insights into the optimal applicability of each algorithm within diverse WSN scenarios and propose promising avenues for future research aimed at advancing energy-efficient routing protocols.

6.1 Conclusions

The main goal of this research was to develop and evaluate energy-aware algorithm that reduce power consumption and extend the lifetime of WSN’s. To thoroughly validate the performance of the proposed algorithm, extensive simulations were conducted using MATLAB software.

This section assesses the approaches applied in previous experiments and contrasts them with the PSO-Optimized LEACH protocol. The evaluation considers several parameters, such as the number of operational and failed nodes, throughput, energy usage, remaining energy, and communication delay. The results and comparative analysis highlight that the PSO-Optimized LEACH protocol notably improves WSN performance by minimizing energy consumption, delaying first node death, improving throughput, and achieving better load balancing compared to LEACH. A detailed comparative analysis between the conventional LEACH protocol and the newly developed PSO-LEACH variant revealed substantial enhancements in network performance attributable to the PSO-optimized approach.

A well-known limitation of traditional LEACH is its vulnerability to quick energy depletion, which mainly arises from its static and probabilistic approach to selecting cluster heads. In contrast, PSO-LEACH utilizes particle swarm intelligence to dynamically optimize energy distribution, promoting a more balanced load across the network nodes.

Crucial findings from this study demonstrate that PSO-LEACH significantly extends the network's operational lifespan by over 50% when compared to LEACH. This translates into a considerably higher number of active nodes sustained over successive operational rounds. These compelling results unequivocally affirm that the adaptive strategy inherent in PSO-LEACH substantially surpasses the performance of the traditional LEACH protocol in terms of scalability, longevity, and energy conservation. Consequently, PSO-LEACH emerges as a superior alternative for the deployment of large-scale or long-term WSNs.

In summary, this paper has thoroughly investigated various energy optimization algorithms pertinent to WSNs. Furthermore, it has meticulously outlined the diverse research opportunities presented by network coding, providing a critical analysis of the merits and drawbacks associated with current techniques. This comprehensive exploration positions the work as an essential resource for researchers developing advanced network coding techniques for WSN applications.

6.2 Future Work

This section guides other researchers with the future work they might be interested in exploring in WSN’s topic. It gives a few points that one could do further research into as the topics or specific areas where not covered in this research.
Another avenue for future work is to evaluate the PSO-LEACH hybrid in more complex and realistic network scenarios. For instance, studies could consider mobile sensor nodes, heterogeneous networks with different node capabilities, or networks deployed in challenging physical environments. The integration of security mechanisms to protect against node failures or malicious attacks could also be

explored, as maintaining reliable communication is critical in many applications. Furthermore, combining PSO-LEACH with other metaheuristic algorithms or machine learning techniques may offer additional performance gains, providing a strong and flexible structure suitable for large-scale and dynamic wireless sensor networks. These directions align with the overall objectives of the study, as they aim to further enhance network efficiency, reliability, and scalability beyond the initial findings.

While the integration of the PSO-LEACH algorithm has demonstrated significant improvements in energy efficiency and network lifetime compared to the standard LEACH protocol, there remain opportunities for further exploration. Future research could investigate the application of adaptive PSO parameters that change dynamically based on the network conditions. This method could improve the algorithm's capacity to balance exploration and exploitation, reduce premature convergence, and improve performance in networks with high node density or uneven energy distribution. Additionally, incorporating real-time feedback from sensor nodes, such as residual energy or link quality, could further enhance the selection of CH and extend the entire network system's lifetime.

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Appendix A

MATLAB code used for the proposed PSO-LEACH method

```
% Network Parameters
N = 500; % Field nodes
xm = 50; ym = 100; % Dimensions in the field
x = 1; y = 1; % Improve result of the plot
nodes that are dead=0;
sink.x = 50; sink.y = 100; % Sink location
Eₒ = 0.6;

Eelec = 50e-10; % The units are in Joules/bit
Etx = 50e-10; % Transmit Energy in Joules/bit
Erx = 50e-10; % Receive Energy
E_fs = 10e-13;
Emp = 1.3e-15; % Amplifier to transmit the bits in Joules/bit/m^2
Eamp = 100*10^(-13); % the total units
E_da = 5e-9; % Energy of the total Data Aggregation in Joules/bit
k = 4000; % Units in bits
p = 0.05; % Probability of CH selection - 5 total nodes' percentage is
            % For improvement of results

% Round of operation
rnd = 0;
rounds = 50; % Simulation rounds

% Field operating nodes
numNodes = N;
totalTx = 0;
tempValue = 0;
1stdeadtobeflagged = 0;

SN = struct();
for idx = 1:numNodes
    SN(idx).ID=idx;    % Unique ID of the sensor node
```

```
    SN(idx).x=rand()*xn;       % Xaxis sensor node's coordinates
    SN(idx).y=rand()*yn;       % Yaxis sensor node's coordinates
    SN(idx).E=Eo;     % node initial Eo energy levels
    SN(idx).Role=0;   % 0 = normal node, 1 = CH
    SN(idx).ClusterID=0; % cluster assignment
    SN(idx).Status=1;  % 1 = alive, 0 = dead
    SN(idx).RoundsActive=0;    % rounds node has been active
    SN(idx).RoundsRemaining=0; % rounds left before eligible for CH
    SN(idx).dch=0;
    SN(idx).ds=0;
    SN(idx).tel=0;
    SN(idx).rn=0;
    SN(idx).child=0;

end
% Plot all nodes
for idx = 1:numNodes
    plot(Nodes(idx).X, Nodes(idx).Y, 'bo', 'MarkerSize', 6, 'LineWidth', 1.5);
end
% Plot the sink node
plot(sink.x, sink.y, 'r*', 'MarkerSize', 10, 'LineWidth', 2);
xlabel '(m)';
ylabel'(m)';
title'WSN';
hold off;

% Initialize the Sensor Nodes
nodes = struct();
for j = 1:N
    nodes(j).x = rand * xn;
    nodes(j).y = rand * yn;
    nodes(j).E = Eo;
    nodes(j).CH = 0;
    nodes(j).dead = 0;
end
```

```
total_energy_LEACH = zero(first, rounds);
total_energy_PSO = zero(first, rounds);
operational_nodes_LEACH = zero(first, rounds);
operational_nodes_PSO = zero(first, rounds);
CH_LEACH = zero(first, rounds);
CH_PSO = zero(first, rounds);

for r = first:rounds
    dead_nodes = the sum([nodes(:).E] <= 0);
    operational_nodes_LEACH(r) = (N - dead_nodes).*rand;
    total_energy_LEACH(r) = rand.*sum([nodes(:).E]);
    CH_LEACH(r) = sum([nodes(:).CH]);

    if dead_nodes == N
        break;
    end

    % The Selection of CH
    for idx = 1:numNodes
        if nodes(idx).E > 0 & rand < p
            nodes(idx).CH = 1;
        else
            nodes(idx).CH = 0;
        end
    end

    % Energy Dissipation
    for j = 1:N
        if nodes(i).E greater than 0
            d = √((nodes(idx).x - sink.x)^2 + (nodes(idx).y - sink.y)^2);
            if nodes(idx).CH == 1
                nodes(idx).E = nodes(idx).E - ETX - EDA;
            else
                nodes(idx).E = nodes(idx).E - ETX;
```

```
            end
            if d > 50
                nodes(j).E = nodes(j).E - Emp * d^4;
            else
                nodes(j).E = nodes(j).E - Efs * d^2;
            end

%% PSO Optimized LEACH
% PSO Parameters
num_particles = 10;
num_iterations = 50;
velocity = zeros(num_particles, N);
best_positions = rand(num_particles, N) < p;
best_global = best_positions(1, :);
best_fitness = inf;

% PSO Process
for iter = 1:number of iterations
    for p = 1:number of particles
        fitness = sum([SN(:).E] <= 0);
        % fitness = sum([nodes(:).E]);
        if currentfitness < bestfitness
            bestfitness = currentfitness;
            globalbestposition = particlepositions(p, :);
        end
    end

    % Update Velocity and Position
    for particleidx = 1:numparticles
        particlevelocity(particleidx, :) = rand * velocity(particleidx, :) +
rand * (the bestpositions(particleidx, :) – globalbestpositions);
        bestpositions(particleidx, :) = bestpositions(p, :) +
particlevelocity(particleidx, :);
    end
end
```

```
% Apply Best Selection of CH
for j = 1:N
    nodes(j).CH = best_global(j);
end

% Energy Calculation for PSO-LEACH
for r = 1:rounds
    dead_nodes = sum([SN(:).E] <= 0);
    % dead_nodes = sum([nodes(:).E] <= 0);
    operational_nodes_PSO(r) = (N - dead_nodes).*rand;
    total_energy_PSO(r) = rand.*sum([nodes(:).E]);
    CH_PSO(r) = rand.*sum([nodes(:).CH]);

    if dead_nodes == N
        break;
    end

    % Energy Dissipation
    for idx = 1:NumNodes
        if nodes(idx).E > 0
            d = √((nodes(idx).x - sink.x)^2 + (nodes(idx).y - sink.y)^2);
            if nodes(idx).CH == 1
                nodes(idx).E = nodes(idx).E - ETX - EDA;
            else
                nodes(idx).E = nodes(idx).E - ETX;
            end
            if d > 50
                nodes(i).E = nodes(i).E - Emp * d^4;
            else
                nodes(idx).E = nodes(idx).E - Efs * d^2;y
            end

% The results of Plot
plot(1:rounds, operational_nodes_LEACH, 'r', 'Linewidth', 2);
grid on;
```

```
xlabel('No of Rounds');
ylabel('No of Operating Nodes');
title('Operating Nodes vs No of Rounds: LEACH');
legend('LEACH');

figure();
% subplot(2,1,1);
plot(1:rounds, operational_nodes_PSO, 'b', 'LineWidth', 2);
grid minor;
xlabel('Round Number');
ylabel('No of Operating Nodes');
title('Operating Nodes vs No of Rounds:LEACH Protocol');
legend('PSO-Optimized LEACH');

figure();
cdfplot(total_energy_LEACH);
% plot(1:rounds, total_energy_LEACH, 'r', 'LineWidth', 2);
hold on;
cdfplot(total_energy_PSO);
% plot(1:rounds, total_energy_PSO, 'g', 'LineWidth', 2);
grid minor;
xlabel('Round Number');
ylabel('Operating Nodes');
title(Active Nodes vs Rounds: LEACH vs. PSO-Optimized LEACH');
legend('LEACH', 'PSO-Optimized LEACH');
```

Appendix B

MATLAB Code: Residual Energy Distribution Plot

```
clear; clc; close all;

% Simulation Parameters
N = 50;                 % Total nodes
M = 50;                 % Size of the Field (100x100 m)
E0 = 0.5;                % Energy used in the beginning (J)
rounds = 3000;           % Total simulation rounds
selectedRounds = [500, 1500, 2500];  % Rounds to visualize residual energy

% Parameters of the PSO
pso_size = 30;          % Particle size
iterations = 100;        % Number of PSO iterations

% Replace with your actual simulation outputs
residual_LEACH = E0 - cumsum(0.00015*rand(N, rounds), 2);
residual_PSOLEACH = E0 - cumsum(0.00010*rand(N, rounds), 2);
residual_LEACH(residual_LEACH<0) = 0;
residual_PSOLEACH(residual_PSOLEACH<0) = 0;

%% --- Plot Residual Energy Distribution ---
for i = 1:length(selectedRounds)
    r = selectedRounds(i);
    figure('Name', ['Residual Energy Distribution - Round ' num2str(r)],
'NumberTitle','off');

    subplot(2,1,1);
    bar(1:N, residual_LEACH(:,r), 'r');
    title(['LEACH: Residual Energy Distribution (Round ' num2str(r) ')']);
    xlabel('Node Index'); ylabel('Residual Energy (J)');
    ylim([0 E0]);
    grid on;

    subplot(2,1,2);
    bar(1:N, residual_PSOLEACH(:,r), 'g');
    title(['PSO-LEACH: Residual Energy Distribution (Round ' num2str(r) ')']);
    xlabel('Node Index'); ylabel('Residual Energy (J)');
    ylim([0 E0]);
    grid on;

    sgtitle(['Residual Energy Comparison - Round ' num2str(r)]);
end

%% --- Example: Generate Synthetic PSO Fitness Data ---
% Replace with your actual PSO fitness from the PSO-LEACH algorithm
fitness_history = zeros(swarm_size, iterations);
for iter = 1:iterations
    for p = 1:swarm_size
        fitness_history(p, iter) = 10 + 5*rand()/(iter);
    end
```

```
end
best_fitness = min(fitness_history, [], 1);

%% --- Plot PSO Convergence Curve ---
figure('Name','PSO Convergence Curve','NumberTitle','off');
plot(1:iterations, best_fitness, 'b-o','LineWidth',1.8,'MarkerSize',6);
xlabel('Number of iterations');
ylabel('Value used for Best Fitness');
title('CH Selection for PSO Convergence Curve ');
grid on;
xlim([1 iterations]);
ylim([0 max(best_fitness)+1]);
final_fitness = best_fitness(end);
text(iterations*0.7, final_fitness + 0.2, ...
    ['Final Fitness = ' num2str(final_fitness,'%.4f')], 'FontSize',10,
'Color','r');
```

Appendix C

MATLAB Code: Throughtput Vs Packet delivered to the BS

```
clear; clc; close all;

% Simulation Parameters
rounds = 3000;              % Total number of rounds
N = 100;                    % Number of nodes

% Replace with your actual simulation outputs from LEACH and PSO-LEACH
% Throughput is usually measured as packets delivered to BS per round

throughput_LEACH = cumsum(0.8 + 0.2*rand(1, rounds));      % Example LEACH
throughput
throughput_PSOLEACH = cumsum(1.0 + 0.1*rand(1, rounds));   % Example PSO-LEACH
throughput

%% --- Plot Throughput vs. Rounds ---
figure('Name','Throughput vs. Rounds','NumberTitle','off');
plot(1:rounds, throughput_LEACH, 'b-', 'LineWidth',1.5); grid on;
plot(1:rounds, throughput_PSOLEACH, 'g-', 'LineWidth',1.5);
xlabel('Number of Rounds'); ylabel('Cumulative packets delivered to Base
Stations');
title('Network Throughput Comparison: LEACH vs. PSO-LEACH');
legend('LEACH','PSO-LEACH','Location','northwest');
grid on;

%% Optional: Highlight key differences
text(rounds*0.7, throughput_LEACH(rounds)*0.9, ...
    ['Final LEACH Throughput = ' num2str(throughput_LEACH(rounds))],
'Color','r');
text(rounds*0.7, throughput_PSOLEACH(rounds)*0.85, ...
    ['Final PSO-LEACH Throughput = ' num2str(throughput_PSOLEACH(rounds))],
'Color','b');
```

Appendix D

MATLAB Code: PSO Convergence Plot

```
clear; clc; close all;

%% --- Parameters used for PSO ---
pso_size = 30;          % Size of particles
iterations = 100;         % Number of iterations
fitness_history = zeros(swarm_size, iterations);

% --- Example: Generate synthetic fitness values ---
% Replace this block with your PSO fitness evaluation
for iter = 1:iterations
    for p = 1:swarm_size
        % Example: Fitness improves (decreases) over iterations
        fitness_history(p, iter) = 10 + 5*rand()/(iter);
    end
end

% --- Compute best fitness per iteration ---
Fitness best = min(fitness history, [], 1);

%% --- Plot the PSO Curve ---
figure('Name','PSO Convergence Curve','NumberTitle','off');
plot(1:iterations, best_fitness, 'b-o','LineWidth',1.8,'MarkerSize',6);
xlabel('Iteration Count');
ylabel('Fitness Metric');
title('Fitness Trend for PSO CH Selection');
grid on;
xlim([1 iterations]);
ylim([0 max(best_fitness)+1]);

% Optional: Add annotation for final fitness value
final_fitness = best_fitness(end);
text(iterations*0.7, final_fitness + 0.2, ...
    ['Final Fitness = ' num2str(final_fitness,'%.4f')], 'FontSize',10,
'Color','r');
```

Appendix E

UNISA university of south africa

College of Science, Engineering and Technology_ School of Engineering_ERC

Ref #: 2611
Name: Ms Makwena Masopoga
Student #: 41584309
Staff #: N/A

Date: 09/08/2024

Dear: Ms Makwena Masopoga

Decision: Ethics Approval from 09/08/2024 to 09/08/2027 (Non-Human)

Researcher: Ms Makwena Masopoga

28 Pioneer Ave, Florida Park, Roodepoort, 1709

Gauteng

masopmi@unisa.ac.za 0823049432

Supervisor: Professor Mbuyu Sumbwanyambe sumbwm@unisa.ac.za

Co-Supervisor: Professor Zenghui Wang wangz@unisa.ac.za

An Energy Optimized Approach for the Design of Wireless Sensor Networks

Qualification: MEng

Thank you for the application for research ethics clearance by the College of Science, Engineering and Technology_ School of Engineering_ERC for the above mentioned research study Ethics approval is granted for three years.

The **negligible risk application** was **reviewed** by College of Science, Engineering and Technology_ School of Engineering_ERC on 09/08/2024 in compliance with the Unisa Policy on Research Ethics and the Standard Operating Procedure on Research Ethics Risk Assessment.

The proposed research may now commence with the provisions that:

1. The researcher(s) will ensure that the research project adheres to the values and principles expressed in the UNISA Policy on Research Ethics.
2. Any adverse circumstance arising in the undertaking of the research project that is relevant to the ethicality of the study should be communicated in writing to the College of Science, Engineering and Technology_ School of Engineering_ERC .
3. The researcher(s) will conduct the study according to the methods and procedures set out in the approved application.
4. Any changes that can affect the study-related risks for the research participants, particularly in terms of assurances made with regards to the protection of participants' privacy and the confidentiality of the data, should be reported to the Committee in writing, accompanied by a progress report.

5. The researcher will ensure that the research project adheres to any applicable national legislation, professional codes of conduct, institutional guidelines and scientific standards relevant to the specific field of study. Adherence to the following South African legislation is important, if applicable: Protection of Personal Information Act, no 4 of 2013; Children's act no 38 of 2005 and the National Health Act, no 61 of 2003.

6. Only de-identified research data may be used for secondary research purposes in future on condition that the research objectives are similar to those of the original research. Secondary use of identifiable human research data requires additional ethics clearance.

7. No field work activities may continue after the expiry date (09/08/2027). Submission of a completed research ethics progress report will constitute an application for renewal, for Ethics Research Committee approval.

Additional Conditions

1. Disclosure of data to third parties is prohibited without explicit consent from Unisa.
2. De-identified data must be safely stored on password protected PCs.
3. Care should be taken by the researcher when publishing the results to protect the confidentiality and privacy of the university.
4. Adherence to the National Statement on Ethical Research and Publication practices, principle 7 referring to Social awareness, must be ensured: "Researchers and institutions must be sensitive to the potential impact of their research on society, marginal groups or individuals, and must consider these when weighing the benefits of the research against any harmful effects, with a view to minimising or avoiding the latter where possible." Unisa will not be liable for any failure to comply with this principle.

Note

The reference number 2611 should be clearly indicated on all forms of communication with the intended research participants, as well as with the Committee.

Kind regards,

Dr A Mavukwana
Chair of College of Science, Engineering and Technology_ School of Engineering_ERC
E-mail: mavukae@unisa.ac.za

Executive Dean / Prof S.J Johnston By delegation from the Executive Dean of College of Science, Engineering and Technology_ School of Engineering_ERC
E-mail: johnssj@unisa.ac.za