Optimization of routing in wireless sensor network in terms of energy usage and QoS,using Hybrid PSO and Golden Eagle algorithms

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Optimisation du routage dans le réseau de capteurs sans fil en termes de consommation d'énergie et QoS, à l'aide de l'algorithme Hybrid PSO et Golden Eagle

Amirmasoud SOLTANZADEH

RÉSUMÉ

Les WSN ont transformé les capacités de surveillance et de suivi dans de nombreux domaines en améliorant les réseaux de communication et de calcul. Ces réseaux, constitués de petits nœuds de capteurs qui transmettent des données à une station de base centrale, sont considérablement affectés par des ressources énergétiques limitées, ce qui peut raccourcir leur durée de vie opérationnelle. Cette étude est unique car elle propose un protocole de routage innovant et économe en énergie, une nouvelle approche pour relever ce défi. L'objectif principal est de créer un modèle de routage optimisé basé sur des clusters, améliorant ainsi l'efficacité énergétique et réduisant les retards et les nœuds morts dans le réseau.

Pour y parvenir, un clustering avec l'algorithme k-means est utilisé, suivi d'une sélection efficace des têtes de cluster à l'aide de la mutation PSO. Cette méthode robuste garantit l'optimisation des têtes de cluster appropriées. Par la suite, le routage entre les têtes de cluster est optimisé à l'aide de l'algorithme Golden Eagle (GEO), avec une comparaison de référence avec le protocole de routage LEACH-CR. L'algorithme Golden Eagle est utilisé ici pour choisir avec sensibilité les chemins de communication, rendant l'échange d'informations plus efficace tout en consommant moins d'énergie.

Pour surmonter les lacunes susmentionnées des protocoles de routage économes en énergie précédents qui n'ont pas réussi à fournir une solution optimale pour diverses applications et conditions énergétiques de manière efficace, ce travail de recherche vise à établir un nouveau protocole de routage efficace. Le protocole proposé est minutieusement testé via des simulations Matlab approfondies afin de mesurer les nœuds morts, le débit du système, la consommation d'énergie et le délai du réseau. Le processus de validation donne l'assurance et montre que le protocole a obtenu de meilleurs résultats que le protocole de routage LEACH-CR en termes d'utilisation de l'énergie et de durée du réseau.

Cet article a mis en œuvre la méthode de regroupement quantitatif, de sélection de tête de cluster et de routage de l'algorithme Golden Eagle présenté par rapport à LEACH-CR et a prouvé que la méthode présentée peut améliorer l'utilisation de l'énergie et la durée de vie du réseau de capteurs sans fil. De tels types d'études générales, habituelles dans les conditions multi-débits, multi-services et multi-applications, sont censés améliorer les performances et la fiabilité des réseaux pour un certain nombre d'applications pratiques.

Ainsi, cette recherche élargit la base de connaissances des WSN en fournissant une approche intégrée et efficace du problème de l'efficacité énergétique. En intégrant le clustering avec k-means, en sélectionnant les têtes de cluster avec mutation PSO et en utilisant l'algorithme Golden Eagle pour le routage, le protocole suggéré pourrait améliorer l'utilisation de l'énergie et, par conséquent, l'utilisation pratique et la longévité des réseaux de capteurs sans fil.

Mots-clés: Réseaux de Capteurs Sans Fil, Efficacité Énergétique, Protocole de Routage, Algorithme Golden Eagle, Algorithme Génétique, Durée de Vie Opérationnelle, Regroupement, Chefs de Cluster, Simulation, Matlab

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ABSTRACT

WSNs have transformed monitoring and tracking capabilities in numerous areas through grooming communication and calculating networks.These networks, consisting of small sensor nodes that transmit data to a central base station, are significantly affected by limited energy resources, which can shorten their operational lifespan. This study is unique because it proposes an innovative energy-efficient routing protocol, a novel approach to addressing this challenge. The main objective is to create an optimized routing model based on clusters, thereby improving energy efficiency and reducing delay and dead nodes in the network.

To achieve this, clustering with the k-means algorithm is employed, followed by the efficient selection of cluster heads using PSO mutation. This robust method ensures the optimization for suitable cluster heads. Subsequently, the routing between cluster heads is optimized using the Golden Eagle algorithm (GEO), with a benchmark comparison against the routing protocol LEACH-CR. The Golden Eagle algorithm is used here to sensitively choose communication paths, making information exchange more efficient while using less power.

To overcome abovementioned shortcomings of the previous energy efficient routing protocols which failed to provide optimal solution for various applications and energy conditions effectively, this research work aims to establish a new efficient routing protocol. The proposed protocol is thoroughly tested via extensive Matlab simulations in order to measure the dead nodes, the system throughput, energy usage and network delay. The validation process gives the assurance and this shows that the protocol has performed better as compared to the LEACH-CR routing protocol in energy utilization and network duration.

This paper implemented the quantitative clustering, cluster head selection, and routing method of the presented Golden Eagle algorithm compared with the LEACH-CR and proved that the presented method can enhance the energy utilization and life of the wireless sensor network. Such types of general studies usual to multi-rate, multi-service and multi-application conditions are believed to enhance the performance and reliability of the networks for a number of practical applications.

Thus, this research extends the knowledge base of WSNs by providing an integrated and effective approach to the energy efficiency problem. By integrating clustering with k-means, selecting cluster heads with PSO-mutation, and using the Golden Eagle algorithm for routing, the suggested protocol could enhance energy utilization and, therefore, the practical use and longevity of wireless sensor networks.

Keywords: Wireless Sensor Networks, Energy Efficiency, Routing Protocol, Golden Eagle Algorithm, Operational Lifetime, Clustering, Cluster Heads, Simulation, Matlab

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LIST OF ABBREVIATIONS

BS	Base Station
CR	Current Route
FF	Fitness Function
PSO	Particle warm optimisation
GEO	Golden Eagle Optimization
LEACH-CR	Low-Energy Adaptive Clustering Hierarchy with Crossover Routing
NR	New Route
SN	Sensor Node
WSN	Wireless Sensor Network

INTRODUCTION

In this thesis, our objective is to ensure the development of an energy-aware routing protocol and its assessment. Our goal is to significantly enhance the network's durability and ensure efficient and reliable data transmission in WSN. Our work not only covers the energy aspects but also the energy placement in such a way that the life cycle of the network is elongated as much as possible by reducing the occurrence of dead nodes. Our work aims at developing a new algorithm so as to bring enhancement to quality services in WSN.

Overview of WSN

Wireless sensor networks (WSNs) originated in the late 1970s through the 1990s, primarily developed for military purposes despite limited computing capabilities. This decade was paired with customers' increased concern with WSNs or the popularity of technologies, like MICA motes, involving power, various paths, and data fusion. Thus, WSN applications expanded significantly in different fields within the years post-2000, particularly in environment, agriculture, and health sectors.

Continuing the evolution in the second decade of the twenty-first century, WSNs proceeded to a development phase that integrates computing solutions and shifted to the cloud facilities to become the backbone of IoT.This period witnessed the appearance of new protocols such as Zigbee and LoRa that testified to extended prospects in smart cities and industrial uses. As the world enters the 2020 and beyond WSNs is expected to progress in the following aspects: AI and ML in WSNs, increased security measures that must be applied, shift towards energy scavenging, and the existence of new and improved communication technology 5G.

Wireless Sensor Network also commonly referred to as WSN is a system made up independent sensors meant to track different physical and or environmental factors such as heat, sound and pressure etc. Integrated with each other, these sensors help transfer the collected data over the network to the base unit for processing. The network is constructed from 'nodes' in which beneath every one of the it is possible to incorporate one or many sensors. Such nodes are generally very small and inexpensive, however, strength lies in the ability to add several thousands, or possibly millions of such nodes.

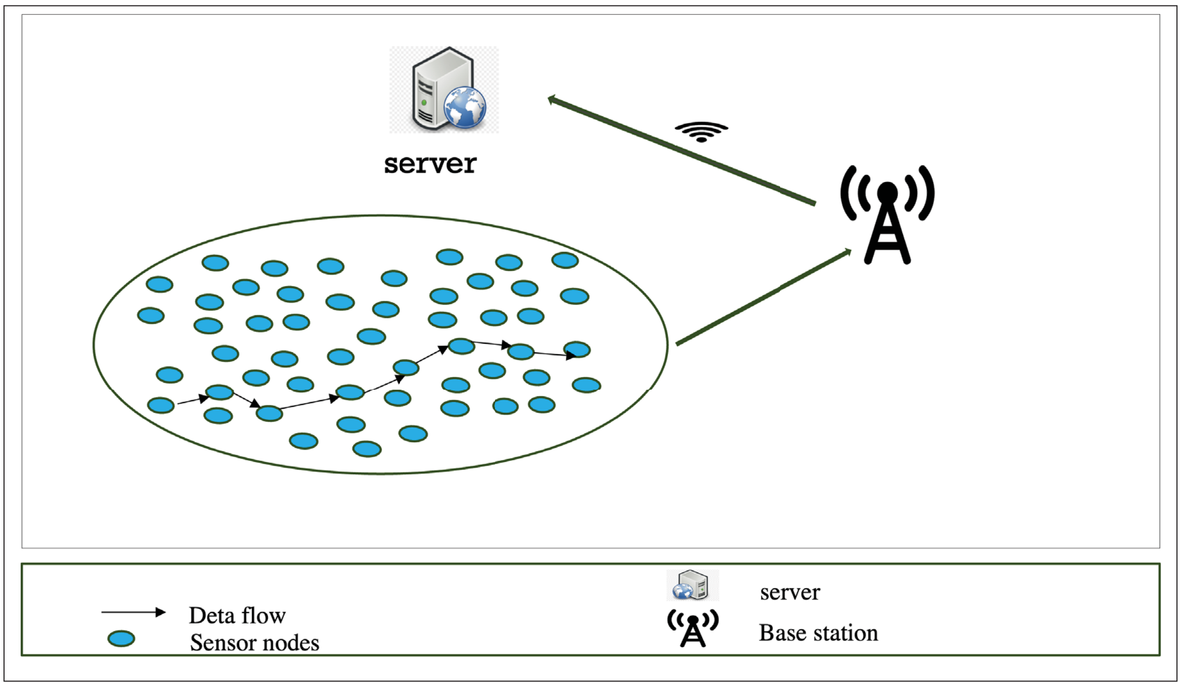

Figure 0.1 Wireless sensor network structure

Components

Wireless Sensor Networks (WSNs) are consisted of some sensors attached in a network to the other nodes to assist in data gather process. Topology of WSNs is associated with the organization of such sensor nodes and also their dynamic communication pattern which in actuality brings out the liveliness of the network. This topology encompasses essential components such as cluster heads, the sink, and the base station, each fulfilling a specific function within the network:

1. Sensor Nodes: WSN in its definition can be said to refer to a system that comprises of various sub-parts which are useful in the collection of data from the surrounding area. Such

collected data may be temperature, picture, voice, and any other depending on the need and intention of the network. These components commonly known as sensor nodes are generally described by low processing capability and energy supply.

2. Cluster Heads: In WSNs there are, of course, different topologies used and these clustering algorithms such as LEACH are used. In this topology the sensor nodes are divided in to groups called clusters and one or more than one nodes are chosen as the cluster head. In this hierarchical cluster, the data collection among various nodes is usually coordinated by the CH, and data could well be preprocessed, for example, reduced or compressed until an extraction of redundancies is made before forwarding of the data on to the sink or base station of a higher network protocol. This efficient data processing is one of the major activities of the cluster head and, therefore, makes the system more efficient in the WSN.
3. Base Station: The base station, a cornerstone of a sensor network, is a robust computing system with significantly more energy resources than the sensor nodes. Its primary function is to gather data from the network. However, its capabilities extend beyond data collection. The base station is capable of performing large and intricate calculations and processing of data and offers a glimpse of the kind of capability of this technology. It also represents an intermediary layer, while being interfaced with either the sensor network or end-users and other networks, like the Internet.

Based on this, it can be concluded that the general structure of WSNs comprehends the nodes that collect the data and send it to the leaders of the corresponding clusters. At this level, it is the individual heads of each of the clusters that receive this information and subsequently, they calculate the summary of the data in addition to passing it to the sink. Based on the collected data transmitted through the sink, data is used at the base station.This also assists in organising this efficiently as prevent the benchmark of total power consumption in the network because the many sensor nodes are not always transmitting.

Features

Features are the essential qualities of Wireless Sensor Networks (WSNs), showcasing their primary strengths and capabilities. These attributes, including efficiency, resilience, and adaptability, are crucial for practical applications. In the following sections, we will thoroughly explore the key features that contribute to the robustness and versatility of WSNs, explaining their importance in different scenarios.

1. Low Power Consumption: WSNs emphasize low power consumption to maintain prolonged operation in remote or challenging environments.
2. Scalability: WSN architectures are designed to be scalable, allowing for the seamless integration of additional nodes without logistical or operational burdens.
3. Self-Organization: Upon deployment, WSN nodes can automatically organize themselves into a functional network structure, reducing the need for manual configuration.
4. Fault Tolerance: WSNs can maintain functionality despite node failures or network disruptions, ensuring robustness and fault tolerance.
5. Adaptability: WSNs can modify their behaviour based on data conditions, such as adjusting sampling rates, to enhance efficiency and responsiveness.

Applications

Wireless Sensor Networks (WSNs) are widely utilized across various domains, leveraging their capabilities to enhance processes and collect crucial data for informed decision-making. Here are some examples of practical applications of WSNs:

1. Environmental Monitoring: Wildlife tracking, forest fire detection, and air as well as water pollution monitoring.
2. Military Applications: Security check, detecting incursions and observing the state of the conflict zone.
3. Healthcare:Patient observation and administration of medication.
4. Industrial Monitoring: Supervising the state of equipment and managing the procedures.
5. Agriculture: These are for instance estimation of the degree of wetness of the soil, feeding of the animals and adopting appropriate farming practices, and caring for the farming implements respectively.

Challenges

In the WSNs field, numerous challenges must be tackled to enhance their effectiveness and reliability. These challenges span technical, operational, and security aspects, among others. Below are some of the primary challenges faced in the deployment and management of WSNs:

1. Energy Conservation: Measures that help to decrease energy consumption should be regarded as the priority since they might increase the battery usage duration of the nodes.
2. Security: Preserving data accuracy and confidentiality is crucial especially in the areas of defense and medical applications. Positive controls that can protect data from being accessed or interfered with by unauthorized people should be provided.

3. Data Overload: Effective mechanisms are necessary to handle and process large volumes of data generated within Wireless Sensor Networks (WSNs). This helps to prevent overload and ensures timely data analysis.
4. Interoperability: Establishing standards and protocols is crucial for enabling seamless communication and collaboration among various types of WSNs, ensuring compatibility and interoperability across different networks.

WSNs are extensively acknowledged subsystems of IoT system due to the miniaturization and energy efficiency solutions, which improved WSN functionality and utilization.

Problem Statement

Wireless sensor networks' acting influences added power consumption, quality of service, and the network's lifetime, leading to multiple challenges. Battery-powered sensor nodes, often placed in remote and demanding environments, need energy-efficient mechanisms to prolong the lifespan of WSNs. Traditional routing protocols frequently fail to meet the increasing requirements of this domain, calling for innovative routing solutions that cater to WSNs' specific attributes. In addition to energy conservation, factors such as transmission lag and data transmission speed are critical for optimizing WSN performance. Tackling these complex challenges necessitates a holistic approach, considering various factors impacting network effectiveness and reliability.

Research Objectives

Basically, this work aims at establishing and assessing an Energy Least Consumption (ELC) routing model to add more to enhancing the area of energy consumption issue in WSNs. This protocol assists in elevating the network's working time, lowering the energy scene, decreasing the contemplate, augmenting on the throughputs. By developing an optimized cluster-based routing model, this study seeks to advance WSN technology by offering a comprehensive solution that effectively balances energy efficiency with data transmission needs. By improving routing algorithms, this proposed protocol seeks to increase WSNs' durability and operational time, and in turn, the possibility of their continued use in many application areas.

It is important to note that this study does not cover scalability and security. The research primarily focuses on scenarios where energy limitations significantly impact the operation of network nodes.

Methodology Overview

These applications involve the necessity of WSNs, including environment monitoring and health care to obtain and transmit data. However, the current vegetation of the sensor nodes create a major problem with the sustainability and efficiency of such network. This limitation has been widely known to cause increased network delay and hence data latency and in the process, lowers the Quality of Service (QoS). Even though, numerous researches have been conducted to enhance energy consumption of WSNs, they often have to spend more time on addressing various tasks that stem from the diversity of corresponding network applications. Additionally, majority of the presented approaches have to solve a problem of the unequal energy distribution for the nodes of a sensor network to prevent the overall network failure at the initial state.To optimize these challenges, this thesis introduces a new routing protocol with novel approaches that uses AI algorithms for efficiency of energy resources in WSNs with improvement of QoS and longevity of the network. Thus, the further outlook of this solution is rather impressive, as this advance can dramatically change development of WSNs.

Contributions

This research marks a significant advancement in the development of energy-efficient routing protocols for WSNs, providing several noteworthy contributions:This research marks a significant advancement in the development of energy-efficient routing protocols for WSNs, providing several noteworthy contributions:These are several contributions that this research offers towards the improvement of optimal energy efficient WSNs routing protocols:

- Indeed, we continue our contribution with the propose a new routing protocol for WSNs with high energy efficiency. Specifically, the following algorithms were used to create this protocol, which is intended to consume the least power as well as prolong the network's life span.

- Among the interesting of our research is the utilization of k- means algorithm along with PSO mutation in order to achieve optimized clustering and selective cluster head which all are accompanied by the Golden Eagle algorithm for routing optimization. This approach, benchmarked against the LEACH-CR model, significantly enhances the efficiency of the network.
- In order to validate our theoretical findings, extensive experiments were conducted with the help of Matlab simulation tools and strictly monitoring such vital characteristics like energy dissipation, delay-time, attainable data rate, and node death.
- To ensure the effectiveness of our suggested model, it is compared with benchmark models, proving the efficiency and effectiveness of the proposed solutions. This research contains detailed analyses of the evaluations under several aspects, which provides the reader with a multifaceted understanding of the name model.
- Proposed solution of this work exhibit usefulness of applying the principles and concepts of WSNs in practice, improving energy utilization and progression of the networks, so contributing to the development of the reliable and efficient sensor networks.

Therefore, with the help of developed complex algorithms, detailed simulations and further comparative analysis, this work can be viewed as a promising base for the enhance of the Wireless Sensor Networks' energy characteristics and their performance. It creates a good platform for future research with an aim of improving WSNs in several fashions.

Thesis Structure

As a result of the structure followed in this thesis, It is developed in four chapters. Chapter 1 bridges the literature done in the past by carrying out a review on it and examining the existing studies. The kind of approach used in the research is discussed in the chapter 2 in addition to the objectives of the research, as well as the description on the design and simulation of the offered protocol of routing. Chapter 3 presents the developed protocol and actually performs the routing process of the network and the result shows the comparison made between the developed protocol and a benchmark routing protocol for the earnest result of the research. Moreover, since the thesis is divided into five chapters, the findings and implications are given in the last Chapter 4 of the entire writing.

CHAPTER 1

LITERATURE REVIEW

In this part, the attention is paid to the review of the most scholarly papers which describe the aspects associated with energy and quality of service in WSNs. In other works the idea is introduced of using routing algorithms with complex optimisation to save energy. Some among them include Alqarni et al. (2023), Deep Kumar et al. (2023), Ghawy et al. (2022), Al-Aboody, Al-Raweshidy (2016), Gantassi et al. (2021), Zhao et al. (2020), Tianshu Wang et al. (2017), Al-Shalabi, et Sh These are complex algorithms introducing

There is also existing work on the classification of clustering techniques to enhance the operation of networks. A few papers by Di Wu et al. (2021), Zamry et al. (2021), Nurfazrina et al. (2022), and Jin Wang et al. (2019) several work on how to cluster data to minimize energy usage and enhance the speed of communication in WSNs.

Furthermore, some research focuses on data compression techniques, which are crucial for saving energy and optimizing resource use in WSNs. Noteworthy contributions in this realm include the work by Wei Zhao (2015), which delves into robust data compression methodologies specifically for WSN environments. In the following sections, we describe these important studies in more details.

1.1 Routing algorithms with advanced optimization techniques

Alqarni et al. (2023) elaborated a work that incorporated the DDE algorithm and ACO in energy consumption for data collection in WSNs. The DDE technique is utilized here with an aim of generating the cluster heads and the routing nodes based on the various solutions generated concerning the residual power and distance to the network head so that the same message transmits minimum of times and in such a way that the whole nodes are used in such a way that they will be consumed equal energy.The ACO algorithm then provides structures for inter-cluster routing in a manner that mimics the ants' method of searching for the best routes in order to transport data through a network. This makes the DDE-ACO hybrid system to employ the use of bio-inspiration in providing the best path solutions and at the same time the best clustering processes. However, the approach is somewhat restricted because it employs the part of routing optimization strategies and the fixed number of models P possible for the SNs, which can hamper the advancement in the field of the innovative productions.

Deep Kumar et al. (2023) proposed an opportunistic routing protocol designed to efficiently manage resources, thereby extending the lifespan of a network and conserving energy in sensor nodes. This protocol of communicating data aims at improving the energy resources used in the transmission process. High power loads at nodes can become a problem in WSNs since node depletion directly influences the network's performance. The proposed model assesses candidate nodes for data transmission to reduce power consumption and enhance network longevity. The relevance of this model to the proposed scheme lies in its ability to optimize routing for data communication, thereby promoting balanced energy utilization in sensor nodes and extending the network's lifespan. However, a notable limitation is the potential complexity in accurately assessing candidate nodes in dynamic environments.

PSO was considered powerful for securing the optimal cluster head and path reliability concerning WSNs by Ghawy et al. (2022) and Xi Wang et al. (2020) while modelling like the birds' flocking or the fish schools' motion. PSO algorithms perform search operations for finding the better cluster heads so that the energy being consumed is less and the load is distributed in a better way.

While PSO shows a lot of promise over wireless sensor networks (WSNs), it is confronted by certain bottlenecks that keep it from complete adoption. The major challenge that comes along with the clustering modeling and the path routing complexity involves in the cases of scalable networks, such as large deployments. Subsequently, PSO algorithms have limited flexibility to dynamic network state, including node failures, and topology changes, thus affecting their ability to retain the best performance consistently. In the same manner PSO algorithms also get influenced by the settings of parameters which makes the optimization process more sophisticated and the performance results to the suboptimal level. In order to resolve the presented obstacles, continuous research initiatives have to be undertaken in the development of new optimization techniques and techniques involving hybrids, as well as tuning of the parameters to enhance scalability, adaptability, and efficiency of the PSO in WSN with dynamic scenarios.

Al-Aboody and Al-Raweshidy (2016) applied the new GWO algorithm considering the social heading and suing procedure of the gray wolves to deal with the energy-efficient routing problems in WSNs. Their Multi-Level Hybrid Clustering Routing Protocol (MLHP) use GWO to cluster the nodes and select the cluster heads based on the clusters' residual energy and other nodes distance hence accomplishes the hierarchical three levels of clustering.The fitness function accounts for the remaining energy level and intra-cluster distance in order to minimize power consumption. But there are still some issues in the GWO algorithm to improve for different conditions such as scalability, adaptability and robustness where there is a complex network environment and energy sources of different types are taken into consideration. Overcoming these difficulties is essential to enhance usage of GWO capabilities for the effective routing in the conditions of heterogeneous WSNs.

Wireless sensor networks, especially large-scale wireless sensor networks, may encounter various issues; Therefore, Gantassi et al. (2021) proposed the MDC-K protocol, which makes use of K-means clustering combined with the Mobile Data Collector (MDC). The intended goal of this protocol is to enhance certain QoS indicators including its lifetime, throughput, and delay alongside the elaboration of certain constraints. The MDC-K protocol uses K-means algorithm for clustering the data and MDC for transmitting the data that minimizes the distance of transmission between the clusters. Nevertheless, there is a serious limitation, which is the absence of the comprehensive strategy for the actualization of the delay minimization and network traffic reliability enhancement, which is critical for network throughput. Also there is a question related to balancing the transmission uncertainty on the one hand and the network strength on the other. Although the MDC-K protocol defines the solution to some of these issues, other algorithms might be required to solve all the challenges.

Another study involved the GWO, a meta-heuristic algorithm derived from the social behavior and hunting instinct of wolf; According to the recent work done by Zhao et al . As cited in Ren to et al., (2020) this algorithm is used in the optimization of the network path of WSNs. The GWO algorithm is evaluated with high performance in the route optimization; however, the conventional GWO is not sufficient to solve the challenges of HWSNs. Due to this limitation, the Heterogeneous Modified Grey Wolf Optimizer (HMGWO) algorithm has been proposed to enhance cluster selection in HWSNs. The HMGWO algorithm adapts a fitness scale to consider other objectives in influencing the decision some of which are; remaining power, distance from the base station and nodal density. It also explains why the prioritization of communication links try to achieve longer lifespans of the network and efficiency in energy consumption in non-homogeneous networks. Nonetheless, the current HMGWO algorithm has some limitations like scalability, flexibilities as well as its performance when applied to large and complex networks with the presence of different energy types.All these limitations must be demeaned so as to enable HMGWO to offer its best results with a view of enhancing routing and therefore reveal efficient performance in HWSNs. Wang et al., in (2017) proposed a genetic algorithm based routing for multi-hop networks with aim to minimize the load of the relay nodes for enhancing the network lifetime. The algorithm enhances the search quality through utilizing the optimal solution of one round as the new population for the other round. The method amalgamates clustering and routing into a chromosome and then determines total energy consumption while at the same time distributing the load among nodes. This approach leverages the computational efficiency of genetic algorithms to optimize routing and enhance energy efficiency. However, its effectiveness is limited by its application to single-hop data communication mechanisms, necessitating further improvements for broader applicability.

Al-Shalabi et al. (2019) proposed a genetic algorithm-based multi-hop route-finding method for WSNs, optimizing data communication and enhancing network lifetime. The algorithm employs a new fitness function to reduce energy utilization. However, it primarily addresses single-hop communication mechanisms, limiting its effectiveness for more complex network scenarios.

Shanthi et al. (2020) proposed a connection-oriented genetic algorithm to find the optimal energy efficient routes with participative crossover and mutation to attain feasible solutions. It gives the proposed model a bottom-up approach to look for energy-efficient routes using genetic algorithms in WSNs. But, it fails to provide support to the mobile sensor nodes to set up the optimal paths limiting its effectiveness for the dynamic networks.

load balancing strategy in WSN was proposed by Wang et al. (2020) with the help of chaotic genetic algorithm that enhanced the life of WSN. The algorithm determines the best cluster head and the most suitable path with the help of a single fitness function. While it does a good job of managing load and energy usage, it only concerns itself with finding the best path. However, the proposed model combines the optimal and the opportunistic routes using the Golden Eagle algorithm in order to improve the load balance as well as the network life cycle.

Roberts et al. (2022) introduced one innovative optimization algorithm called Golden Eagle Optimization (GEO) and its application in clustering and routing of WSNs with particular focus on the energy conservation. The means of searching the solution space is also borrowed from the movements of the golden eagles and here, GEO moves and explores for a better solution.

GEO is intelligent routing protocol algorithm used in the selection of the best cluster head. This may depend with the remaining energy and the number of relaying steps to the nodes that the packet has to pass through. Every GEO agent acts upon the problem of the CH and the fitness function tries to minimize energy and distance in the network. Thus, multi-objective aspect of the problem is well managed by GEO's fitness function to look for various solutions that represented different levels of compromise between objectives while looking for better solutions.

The next step is classifying all the visited area related data through the use of GEO. Meanwhile, enhanced shuffled frog leaping algorithm (SFLA) is used for the inter-cluster routing problem. SFLA assists in the shortest route to finding elect cluster heads querying to station base, making it more energy efficient and longer lifetime in the network. In the intra-cluster optimization, sensor nodes GEO that is used in the SFLA based way and for the inter-cluster routing, SFLA is used. The fact that this work combines two algorithms for the design of energy aware routing is clear indication of a novation in WSNs.

1.2 Clustering techniques

Di Wu et al. (2021) introduce LEACH-ABF as a significant advancement in addressing energy imbalances within Wireless Sensor Networks (WSNs). While the LEACH protocol initially introduced multi-hop transmission and reduced energy consumption, it suffers from limitations due to stochastic cluster head selection. This stochastic method can lead to asymmetrical peer distribution and varying power consumption levels among nodes, particularly problematic in large networks where it may result in memory storage and energy distribution issues. The dynamic nature of cluster head selection in LEACH contributes to higher overhead and vulnerability to environmental changes, such as structural fluctuations or node failures. These constraints pose challenges to scalability and hinder LEACH's ability to minimize energy consumption and extend network lifetime. To tackle these challenges, LEACH-ABF employs adaptive balancing techniques and optimized clustering processes, aiming to mitigate energy consumption issues in growing WSN deployments. By addressing these drawbacks, LEACH-ABF presents a more robust approach to energy consumption management in WSNs.

Zamry et al. (2021) highlight LEACH as a widely adopted low-energy adaptive hierarchical routing protocol for WSNs. However, they identify important drawbacks in its operation. LEACH relies on random selection of cluster heads, leading to unbalanced clusters and varying energy consumption among nodes. This stochastic principle can result in clusters of different sizes and underutilization of energy resources, especially in large WSN deployments. Additionally, dynamic cluster head selection introduces overhead and instability, particularly in environments with frequent topology changes or node failures, hindering LEACH's scalability and effectiveness in energy optimization. Despite its limitations, LEACH serves as a prototype for numerous routing protocols in WSNs. To address some of LEACH's shortcomings, Zamry et al. propose LEACH-CR (LEACH with Centralized Routing), a hybrid approach that combines centralized and distributed routing schemes. In LEACH-CR, sensor nodes within clusters select their leaders, while an inter-cluster head near the sink aggregates data. This hybrid model aims to balance energy consumption across nodes, mitigating imbalance issues observed in the LEACH network. However, LEACH-CR still faces challenges related to scalability and dynamic network interoperability.

From the related literature, Nurfazrina et al. (2022) have provided a historical view of the development of LEACH-CR intended to further enhance the energy consumption in WSNs based on the conventional LEACH. Energy conservation is obtained through clustering and selection of the heads of the clusters, minimal broadcasting of the networks between the different nodes and the base station. As a distinct improvement in LEACH-CR protocols, the extension of Localized Evolution of Adaptive Clustering Hierarchy with Crossover Routing (LEACH-CR) Genetic algorithm technique is introduced. This approach introduces a smart way of analyzing and comparing different paths while maintaining optimal paths that consume less energy and eliminating the false shortcuts. While LEACH-CR also chooses cluster heads, it also finds the best path for data transmission and thereby improves the network and its duration. However, a notable drawback of LEACH-CR is its reliance on random cluster head election, which may negatively impact network performance by assigning nodes with high vitality to low-probability roles. Suboptimal cluster head selection can affect data management and routing efficiency, potentially leading to unnecessary energy consumption. Additionally, the scalability of LEACH-CR is limited by factors such as throughput reduction, packet loss, and decreased connectivity as node density and communication overhead increase. Addressing these constraints is crucial to maximizing the benefits of LEACH-CR in practical WSN deployments and ensuring its readiness for dynamic systems. In the context of the presented thesis, LEACH-CR serves as the benchmark model for evaluating energy-efficient protocols in WSNs.

In an attempt to solve the hot spot problem for the WSNs, Jin Wang et al. (2019) proposed a Power Efficiency Gathering Algorithm. They enhance the selection of routes that can minimize the energy used hence increasing the lifespan of the network and its latency. It employs threshold values to shut down highly active nodes when they are grouped with energy, and node’s transmission radius can be controlled effectively. Its practicality is demonstrated through a high level of routing and load balancing, which is necessary for energy-savings and system's durability in the context of the proposed protocol. Implementing this model involves routing data via neighboring nodes and offloading the sensor nodes (SNs), ensuring energy distribution across the network. However, this approach may not be universally applicable and is most effective in specific scenarios where threshold settings favor accuracy.

1.3 Data Compression Techniques

Wei Zhao (2015) proposed a method that enhances the data compression ratios in WSNs by establishing a reliable system that can be used for different WSN parameters. The effectiveness of this technique is well illustrated by the fact that the data sets used in this technique are real-life and encompasses all types of situations. The improvements are mainly attributed to the inclusion of a new data compression method because the previous methods had some drawbacks. This new approach is aligned with the end-to-end model and the energy region approach with the bandwidth compression to transfer data using the minimal amount of energy. It furthermore preserves energy and also increases the life of the network since the size of the traffic is reduced. This method is also highly useful in improving the network performance and durability where energy is limited in the nodes.

Summary

The literature review presented in this paper evaluates the current routing protocols and their application in expanding WSNs' energy efficiency and Quality of Service (QoS). However, there are still some materials that can be considered as problematic in this substantial field of study, which has a lot of works. Some of the difficulties that arise are the identification of the optimal parameters that affect energy consumption, problems of scalability in existing protocols, means for proper designation of cluster heads. Furthermore, new problems involving the emergence of clusters without a planned strategy and, therefore, non-uniform and dense filamentary pattern aggravate these problems. In order to address the listed challenges, this thesis focuses on targeting Energy efficiency in WSNs using Artificial Intelligence in proposing a new routing protocol.

CHAPTER 2

OBJECTIVES AND METHODOLOGY

Therefore, one of the objectives that were realised in this research is to propose a low energy routing protocol for WSNs. There are two significant challenges to be addressed: There is always energy overload in WSNs with several nodes and the loss of energy in data transmitted. These problems noted to lead to destruction of the nodes, in the early stages of the lifecycle of the network.

Nevertheless, the overall concept of the planned network is action-packed with the general plan – the diagrams of the data packets' movement and the clustering algorithm of the nodes of the sensors. Out of them, the network hierarchy of the formation of the clusters of the sensor nodes is one of the important components of this architecture. Each cluster possesses a cluster head and it is this head who has total control and management of all the nodes in that particular cluster and it is this head who is expected to pass the information to the base station.The means of conveying data are distinctly defined with the vision of reaching a point with information from the source with as much speed as possible and in a natural state. Additionally, if the network is dynamic, the architecture has procedures of formation of the clusters as well as alteration of network conditions that increases the rigidity as well as adaptability of a cluster. In summary, the system architecture discussed above provides a solution of focusing the WSN to improve its energy as well as the network.

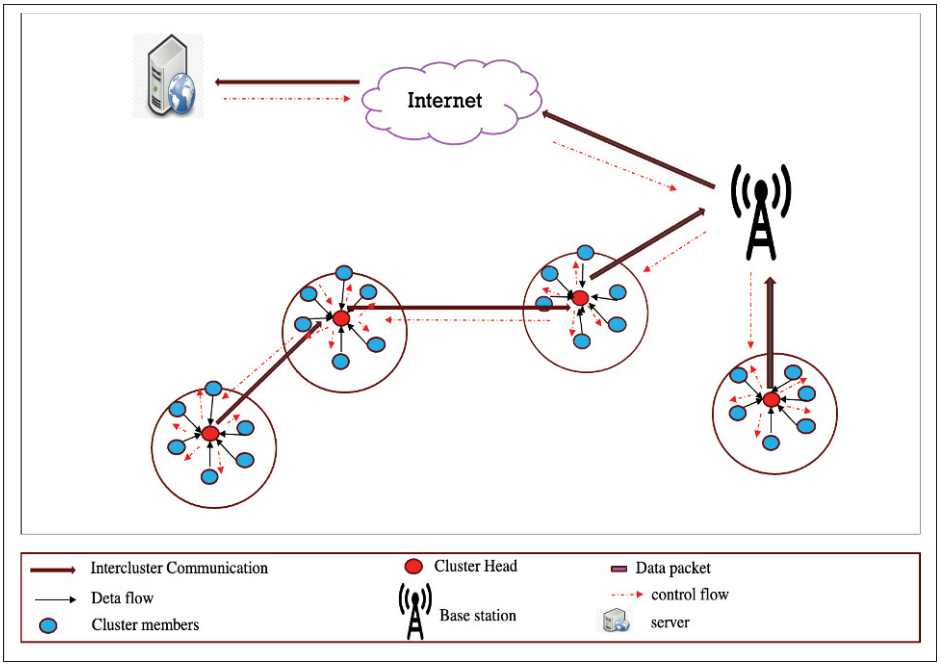

Figure 2.1 System architecture

2.1 Objectives

Among the remarkable objectives of this work is to describe and discuss some critical issues that are present in WSNs.In this case, energy is a priority. WSNs are constituted by decentralized sensors that are involved in the acquisition and transmission of information.Their applications are diverse and encompass environmental and health monitoring as well as industrial processes. Since these sensor nodes are usually small and are usually powered by batteries, energy management is a critical aspect of the design.

previous studies attempted to address the energy issue by coming up with he energy efficient routing protocols. these protocol use one or many algorithm to come up with the best path to use when transmitting data in the network.However, based on the finding of this research, these measures have not totally eradicated this problem. This loss can be attributed to the fact that the presented approach is general and does not presuppose the contention regarding the wide application of WSNs in different applications, and therefore the energy efficiency is not maximum in all applications.

In order to accomplish this goal, this paper aims at minimizing the energy consumption in the network while at the same time ensuring that the total energy consumption is fairly distributed among the nodes to enhance the node's lifetime and discourage the formation of dead nodes. Some WSNs have nodal energy consumption high, thus shortens its life cycle and the coverage and functionality of the WSN is reduced. Thus, one of the aims of the given research is to propose a clustering based routing protocol through which the load of sensor nodes would be evenly distributed.As a result, there is an opportunity for each node to become a bottleneck, and that is what the protocol attempt does not help and delays the network's death instead.

Therefore, it can be concluded that the primary aim of the present work surpasses the creation of a conventional energy-efficient routing protocol. It aims to find a solution that addresses these mentioned issues fundamentally and exclusively. Thus, through carefully choosing the routes whereby energy utilization would be optimally aligned to power consumption, the delivery of information, as well as the eradication of the current hitches in Wireless Sensor Networks, our research will enhance the data transfer rates. To formalize our sub-objectives, we define the following three optimization functions:To articulate our sub-objectives, the following three objective functions are formulated:

1) Minimization of Overall Energy Consumption (OEC)

In the present network, there is a need to decrease the average energy to carry out the transfer of data.

$$\min_{\text{C, H, R}} OEC = \sum_{i=1}^{n} E_i \tag{2.1}$$

where OEC is the energy consumption for each sensor node. This minimization is done over clustering selection (C), cluster head selection (H) and routing path selection (R).

2) Minimization of Energy Consumption Variance(ECV)

For ensuring balanced energy usage and network longevity, we want to minimize the the variance of energy consumption across the network.

$$\min_{\text{C, H, R}} ECV = \text{Var}(E_i) \tag{2.2}$$

where ECV is the energy consumption variance. This minimization process is performed over the clustering selection C, cluster head selection H, and the routing path R for the equal distribution of energy consumption and the reduction of dead nodes.

3) Minimization of Transmission Delay (DEL)

The aim and goal of this type of network is to bring down the mean delay of the network to the most optimum level. Chopnite total delay of the network and chopnite average time delay of a data packe in travelling from the initial node to the last node are defined as delay.

$$\min_{\text{C, H, R}} DEL \tag{2.3}$$

This minimization process is done over the clustering (C), cluster head selection (H), and routing path selection (R) to decrease time taken from sending node and receiving node.

2.2 Methodology

First, we formulate the multi-objective function to be minimised as a weighted sum of sub-objectives function defined in the previous section:However, before we proceed we transform the multi objective function to be minimised as defined in the previous section to a weighted sum of sub objectives function as follows:

$$F = \min_{\text{C,H},R}(C_1\text{OEC} + C_2\text{ECV} + C_3\text{DEL}) \tag{2.4}$$

For the above equation, C_1, C_2 and C_3 are weighting parameters with values between 0 and 1, and $C_3 = 1 - C_1 - C_2$.

As for the incorporation of other factors, we bring in the function of ETX(DEL) as it plays the role of improving the quality of transmission and increasing the dependability of the network to minimize transmission delay as described in section 2. 2. 1. 4. Then our multi-objective optimisation function is defined as:Then our multi-objective optimisation function is defined as:

$$F = \min_{\mathrm{C,H},R}(C_1\mathrm{OEC} + C_2\mathrm{ECV} + C_3\mathrm{ETX(DEL)}) \tag{2.5}$$

2.2.1 Model decomposition

In this section, we decompose the overall optimization problem for our Wireless Sensor Network (WSN) into three distinct steps. Each step addresses a specific aspect of the network's configuration and optimization, which are crucial for enhancing performance:

2.2.1.1 Step1: Clustering formation based on distance minimisation

Form clusters with minimize intra-cluster distance over clustering configuration

$$\min_{\mathrm{C}} \sum_{i=1}^{k} \sum_{j \in C_i} d(x_j, \mu_i) \tag{2.6}$$

where:

- k is the number of clusters,
- C_i is the set of nodes in cluster i,
- x_j is the position of node j,
- μ_i is the centroid of cluster i,
- $d(x_j, \mu_i)$ is the distance between node j and centroid μ_i.

In this step, we choose clustering selection by K-means algorithm, which is introduced in details in section 2.2.2.1

2.2.1.2 Step2: Cluster Head Selection Using Multi-Objective Optimization

Therefore, towards the definition of clustering head nodes, we apply the multi-objective function optimization we developed.

$$F = \min_{\mathrm{H}}(C_1\mathrm{OEC} + C_2\mathrm{ECV} + C_3\mathrm{ETX(DEL)}) \tag{2.7}$$

Constraints

$$\sum_{j=1}^{k} D_j \geq \alpha \tag{2.8}$$

$$\sum_{i=1}^{n} D_i \leq \beta \tag{2.9}$$

$$\sum_{j=1}^{k} (E_{\mathrm{cn}} + D_{\mathrm{no}_i} + D_{\mathrm{en}_i}) \leq \gamma \tag{2.10}$$

$$\sum_{j=1}^{k} \mathrm{ETX}_i \leq \delta \tag{2.11}$$

- the inequality or constraint (2. 8) where, D_j is the distance of between the cluster head nodes j and α is the minimum permissible distance of the inter-cluster. This seems to reduce the inter-cluster distances and this is inline with the propose outlined in the explanation.
- This contraint(2. 9),where D_i represent the distance of the nodes which are within cluster i and β is the maximum distance which is allowed between the head nodes of the particular cluster is used to control the distances between them as mentioned in the goal of avoiding the formation of multiple head nodes within cluster.
- The constraint (2. 10) mentioned the Maximum energy utilization of the nodes particularly the cluster headnodes represented as E_{cn} the number of nodes in a cluster represented as D_{no_i}

the energy variance of each cluster represented as D_{en_i} and the maximum energy threshold in the management of a node's energy resources and energy.

- This constraint (2.11),where ETX_i represents the ETX (Expected Transmission Count) for cluster head i, and δ limits ETX for managing packet transmission delays, is related to the packet transmission delays, which might not be explicitly defined in the equations but is indirectly implied through the energy consumption terms, especially when considering data transfer and communication delays.

PSO-mutation in this step is applied for selection of the optimization of the cluster heads that is discussed in section 2.2.2.2.

2.2.1.3 Step3: Routing between cluster heads based on distance and energy consumed

In this step, the routing paths among the CHs within the network are improved on with regard to the number of possible paths. The first task is to reduce the global distance and the global energy in addition to reviving the required communication with CHs. This involves two key considerations:This sounds like two factors that have to be taken into account:

1) Minimizing the total Distance Between Cluster Heads:

Shorter distances between cluster heads reduce the energy required for data transmission, leading to more efficient communication.This minimisation is done over routing path selection(R).

2) Minimizing Overall Energy Consumption:

This is because, by monitoring the minimum energy needed for the routing between the heads of the cluster, the lifetime of the whole network is also enhanced. The routing algorithm computes the distances of all the cluster heads and chooses paths that reduce the overall distance and energy use. This minimisation is done over routing path selection (R).

$$\min_{\mathrm{R}} \sum_{i=1}^{k} \sum_{j=1}^{k} (d(CH_i, CH_j) + OEC(CH_i, CH_j)) \tag{2.12}$$

Subject to:

$$d(CH_i, CH_j) \leq \beta \quad \forall i, j \in \{1, 2, \ldots, k\}$$

$$E(CH_i, CH_j) \leq \gamma \quad \forall i, j \in \{1, 2, \ldots, k\}$$

where:

- k is the clusters number,
- CH_i is the cluster head of cluster i,
- $d(CH_i, CH_j)$ is the distance between cluster head i and cluster head j,
- $E(CH_i, CH_j)$ is the energy consumed for communication between cluster head i and cluster head j,
- β is the maximum allowable distance between cluster heads to ensure efficient communication,
- γ is the maximum allowable energy consumption for communication between cluster heads.

We utilize the Golden Eagle algorithm for routing optimization which is described in Section 2.2.2.3.

2.2.1.4 Details of Step 2

1) Overall Energy Consumption(OEC) There are two general sections in the model of energy consumption in WSNs and neither section is exempt from evaluating and modeling the other. The amount of energy required to perform the clustering of the network of the current stage is as follows. Namely, in the first step, the respective CH node sends an informing message to all the nodes and allows other nodes to know that this node is CH node. Also, the change of the table of cluster nodes occurs and all nodes in the cluster receive the table with the changes. This table is sent to the nodes that are present within the cluster, and the amount of data that is transferred in this process is t bits. The energy dissipation of the cluster head node in case of transmission is given by the following equation.

$$E_{cn}(t, d_{cn}) = \begin{cases} t(E_{\text{elect}} + \epsilon_f d_{cn}^2), & \text{if } d_{cn} < d_0 \\ t(E_{\text{elect}} + \epsilon_m d_{cn}^4), & \text{if } d_{cn} \geq d_0 \end{cases} \tag{2.13}$$

Regarding this, E_{elect} show energy utilized by the cluster head node to transmit 1 bit of data, ϵ_f and ϵ_m represent energy to be consumed in signal amplifier per 1 bit of data to be transmitted in free space and multiple fading model respectively. As it is seen from Equation (11), d_{cn} gives the Euclidean distances of the current cluster's members to the CH node. The threshold for conversion between communication channel models is calculated using the following equation:The respective Transmission's Conversion Formula is calculated as follows:

$$d_0 = \sqrt{\frac{\epsilon_f}{\epsilon_m}}$$

Next, the node of the cluster receives the t-bit data and the table which has some correlation to the cluster from the CH node, after this node of the cluster send back t bit data to the CH node according to the same table for the identification purpose. In this process the energy dissipated by the nodes which belongs to cluster can be calculated by the below formula.

$$E_{\text{non-cn}}(t, d_{cn}) = \begin{cases} t(E_{\text{elec}} + \epsilon_f d_{cn}^2) + tE_{\text{elec}}, & \text{if } d_{cn} < d_0 \\ t(E_{\text{elec}} + \epsilon_m d_{cn}^4) + tE_{\text{elec}}, & \text{if } d_{cn} \geq d_0 \end{cases} \tag{2.14}$$

The total power consumption of energy for the CH node reception of data packets and accepting the CNs to transmit to them can be formulated as:

$$E_{\text{cn}}(n, d_{cn}) = tE_{\text{elect}} \times \left(\frac{N}{M} - 1\right) \tag{2.15}$$

Here, M is the number of cluster head node and N is the total number of members in the each of the cluster. Namely, the following equation is provided as the summation of the total energy consumption in the network in the clustering phase.

$$\text{OEC} = \begin{cases} \min\left\{tE_{\text{elec}} \times \left(\frac{N+2}{M} - 1\right) + t\epsilon_f d_{cn}^2 \times \left(\frac{N}{M} + 1\right)\right\}, & \text{if } d_{cn} < d_0 \\ \min\left\{tE_{\text{elec}} \times \left(\frac{N+2}{M} - 1\right) + t\epsilon_m d_{cn}^4 \times \left(\frac{N}{M} + 1\right)\right\}, & \text{if } d_{cn} \geq d_0 \end{cases} \tag{2.16}$$

2) Energy Consumption Variance(ECV) The variance of the network's energy consumption is divided into two components: Known as the d_{no} and the d_{en}. The dispersion of the number of nodes that are part of the cluster in the entire cluster d_{no} is as follows. Thus, it is logical to distribute the loads shared to each chosen cluster head based on the fact that the number of nodes in the cluster on average is higher when the value is reduced.

$$d_{\text{no}} = \frac{\sum_{i=1}^{m} (v_i - u)^2}{m} \tag{2.17}$$

The number of sensors in cluster i is represented by v_i, while u is the average number of member nodes in the cluster of the network. It is standard deviation of energy consumption for states within the groups of states defined by the clusters and is represented by d_{en}. The difference is as follows: A lower value of the metric will indicate that the consumption is spread out more evenly across the clusters. This variance is calculated using the following equation:This variance and all other calculations made to produce equations are stated below VI Var = [([X]2)/N] [X/N]2, where X = raw score, = population mean, N = total number of scores.

$$d_{\text{en}} = \frac{\sum_{i=1}^{m} (E_i - \bar{u}_e)^2}{m} \tag{2.18}$$

Where E_i is total energy consumed in the i- th cluster, and $\bar{u}_e$ is total energy used in all units of the cluster. In summary, the energy consumption balance of the network is using the following equation:Therefore, the supply of the energy used in the process of working of the network gives the following equation:

$$\text{ECV} = \min_{\text{H}} (d_{\text{no}} + d_{\text{en}}) \tag{2.19}$$

Therefore, for the desired goal of energy efficient WSNs, it is feasible to select a cluster head that improves service quality characteristics and the mentioned factors.

3) Transmission quality(ETX(DEL))

In WSNs, the efficiency of data transmission, often quantified by Expected Transmission Count (ETX), plays a crucial role in minimizing delays. ETX measures the energy cost associated with transmitting data between nodes and cluster head nodes. Nodes with lower ETX values indicate higher transmission quality, ensuring more reliable and energy-efficient data transmission.

Reducing ETX directly correlates to reducing delays in data transmission across the network. Lower ETX values signify improved transmission reliability, leading to faster and more efficient data delivery. By optimizing ETX metrics, we aim to enhance network performance, ensuring minimal delays and efficient data flow throughout the network.

By optimizing transmission quality, we can minimize transmission delays and ensure smoother and more efficient data transfer within the network.

$$\text{ETX(DEL)} = \min_{\text{H}} \sum_{i=1}^{n} \sum_{j=1}^{k} \left(\epsilon_e \times n_i \times d_{ij}^2 + (K-1) \times d_{jk}^2 \right) \tag{2.20}$$

Several parameters are used in the ETX formula; energy consummation constant (ϵ_e),; every node in every cluster (n_i); distance of nodes in every cluster (d_{ij}^2); total clusters number (K); and estimated distance between every cluster head node ($d_{jk},^2$).

2.2.1.5 Normalization of the parameters

This is because the manner in which we have used the parameters within the fitness function does not tally and besides the scale in which we have used these parameters also different.Thus, it can be seen depending on the different values of the parameters, it means that the parameter which is in the different scales with the greater value of the parameter has high weightage on the particles than the parameter which is having the lesser value of the parameter.Thus, the parameters and the correspondence of their values with those of definite range have to be changed and this is called normalization. Normalization intensifies the values of the parameters between 0 and 1 and other matters related to the scale of such parameters; the scale of such parameters does not affect results in a negative way; these are some extra problems that are linked to the scale of parameters.

Yes, it is crucial to note that in the scenarios where different parameters may have different units, normalization of data does not affect the weight determination for particles in any way because all parameters' values are normalized between 0 and 1 after normalization. Research has revealed that there are many approaches to normalization and among all such methods, Z-Score normalization can be considered to be rather popular. Among the normalization methods, the Z-Score method is selected in this research and it can be represented through the following equation (Saeed J. et al. , 2021).

$$\mathrm{data}_N = \frac{\mathrm{data} - \mathrm{mean}(\mathrm{data})}{\mathrm{std}(\mathrm{data})} \tag{2.21}$$

2.2.2 Algorithm Implementation

In this section, we explain the methods applied in the each of the steps mentioned in the optimization process, why the methods are chosen and how the methods fit in the steps in the mathematical model. The general approach to the implementation of the proposed methodology is described in the framework of three key stages depicted in Fig. 2. 2.

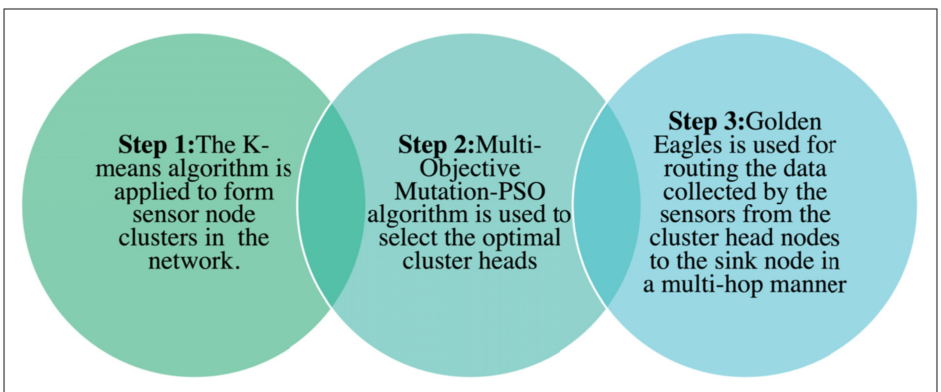

Figure 2.2 Critical steps of methodology

To begin with, using k-means clustering algorithm, we group the sensor nodes which have a close spatial relation or similarity in their operation hence providing us with the basic network structure. This algorithm is chosen because it helps in partitioning the nodes into clusters hence facilitating management and communication with the network.

Subsequently, the PSO-mutation algorithm is employed to select cluster heads within each cluster. This algorithm is preferred for its capability to optimize cluster head selection, ensuring that nodes with sufficient energy and strategic positioning are chosen. By selecting cluster heads effectively, we aim to balance energy expenditure across the network and mitigate the risk of premature node failure.

Thus, after town heads have been defined, routing between the heads is made using the results of the Golden Eagles algorithm. Hence, for the best routes setting, such an algorithm as the one chosen for the golden eagles' foraging is employed. They enable the right forwarding of the data packets from the sensor nodes to the base station using minimum delay and packets dropped.

In bench marking of this strategy we need to compare it with LEACH-CR model since it is recognized and has been bench marked in WSN. Hence, the comparison of the results with LEACH-CR is to establish an assessment in terms of effectiveness and performance of the proposed methodological approach to improve energy consumption and increase the network's lifespan. The reader will be told of these algorithmic steps and why these steps are considered when the subsequent sections are written because this section aims to state the method used in the research.

2.2.2.1 Step1: K-means algorithm

K-means clustering serves as a fundamental unsupervised machine learning algorithm employed in the proposed network architecture. This algorithm plays a pivotal role in partitioning sensor nodes into K clusters based on their similarity or proximity. Specifically adapted for WSNs, the K-means clustering process is instrumental in organizing sensor nodes into cohesive groups, facilitating streamlined data aggregation and routing. In WSNs, k-means clustering optimizes network efficiency and enhances performance by clustering nodes based on similar data readings or spatial proximity.This step corresponds to the minimization of the intra-cluster distance d_{nc} in the mathematical model, ensuring that nodes within each cluster are as close as possible to their respective cluster heads.

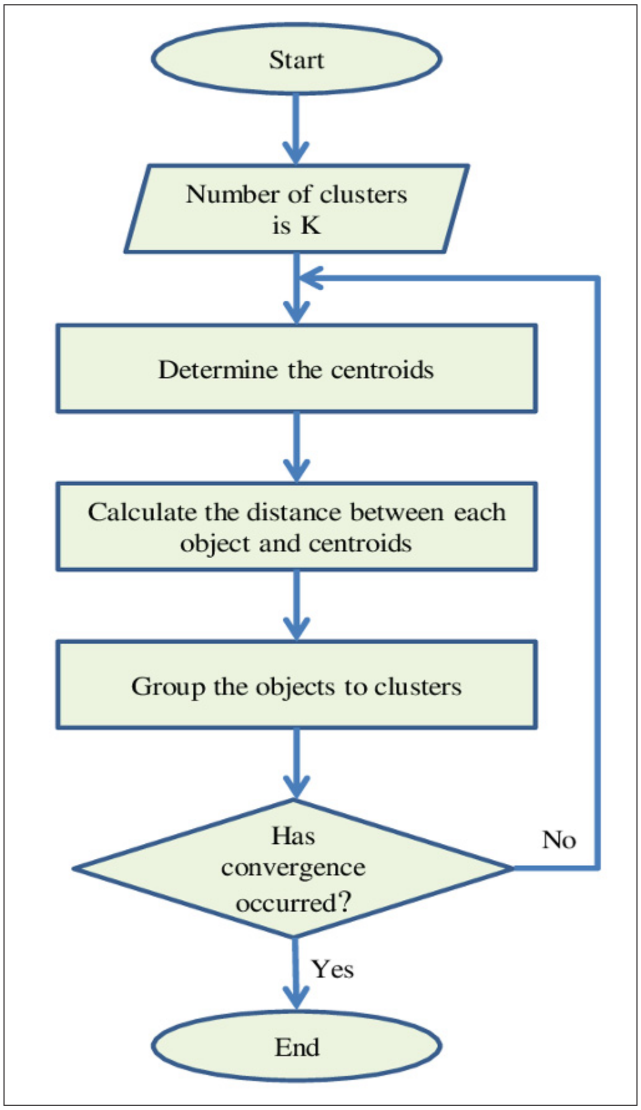

Figure 2.3 K-means algorithm flowchart

2.2.2.2 Step2: PSO-muation algorithm

It is equal to the multiple parameters objective function of the model which is represented by symbol F. Xi Wang et al. , in their publication of 2020, observed that to their understanding, PSO's basic idea was specifically developed, primarily to serve civil and computer sciences .

PSO is one kind of bionic algorithm formulating in base on the bird flock searching foraging behavior. Particles such as birds move all the time in the environment in search for the best place to be and hence can change their velocities constantly. They are suitable when there are multiple objectives of which some have to be met to various degrees. The mutation operation is introduced so as to enhance the PSO's exploration capability and not to converge simple and fast towards the local optima. The updated equations for the velocity vector (V_t) and position vector (X_t) of the i^{th} generation particle are shown in Equations (1) and (2):These new equations for V_t and X_t of the i^{th} generation particle are as follows Wang (2020):

Equation (1) is:

$$V_t(i+1) = wV_t(i) + C_1R_1(P_{t-\text{best}} - X_t(i)) + C_2R_2(G_{t-\text{best}} - X_t(i)) \tag{2.22}$$

Equation (2) is:

$$X_t(i+1) = X_t(i) + V_t(i+1) \tag{2.23}$$

Where w is the inertial weight that dictates the velocity of the next generation making a contribution with the previous generation by scaling. Acceleration constants are C_1 and C_2 which are both related to the factors of cognition and sociability. Hence R_1 and R_2 are two random numbers and each of them can be of the value between 0 1. In which $P_{t-\text{best}}$ = the best local position and $G_{t-\text{best}}$ = the best global position. The last, but by no means the least, parameter is t, which defines the number of dimensions of the search space in the given problem.

From Equation (2. 17) it can therefore be observed that there are three components in the velocity updating equation. The first of those is $wV_t(i)$, that includes momentum and translates to the ability of every particle in an organization to perpetuate the prior level of activity. Similarly, in the case of applying the flocking model, we have similar analogy as regarding the bird's desire to retain the velocity vector. The second term is the cognitive term defined as $C_1R_1(P_{t-\text{best}} - X_t(i))$ and it is proportional to the difference between the current best known position of the swarm

$P_{t-\text{best}}$ and the current position of the particular particle in the swarm $X_t(i)$. This can be taken as the particle memory which is defined as the decrease of the present position with reference to the best position known to the particular actor. In the elaboration of the bird example it just expanded on how much a bird can be affected by previous experience in searching for food. The last term of the equation is $C_2R_2(G_{t-true} - X_t(i))$ which is information sharing of the swarm regarding displacement of the particle i from the overall best solution discovered by the swarm. This depends with the awareness of the bird to the reports of the other birds regarding the found food. Hence, the physical meaning of C_1 and C_2 is the degree of flock birds' identification and participation in the exchange of social information at the intragroup and intergroup levels. The constants C_1 and C_2 can be tuned to set the level of influence of the cognitive term and information exchange, which in turn decide how much the particle shifts towards the best individual and global positions. Popsize determines the number of individuals involved in the search at any one time.

Again, the flow chart of the calculation process of one of the PSO methods is described below along with figure 2. 4 This is the point that the initial swarm of particles is identified upon the declaration of the values of the objective function and the related constants. Subsequently, the aim function is used to assess the fitness of the particle; it is evaluated against the current optimum and the best value found by the swarm. Also, the velocity and position of the particles are presented Euation 2. 22 and 2. 23.This cycle of calculation is performed until the convergence criterion is met Sometimes it may be required to point out that the choice of k defines the convergence pattern and the speed of convergence of this algorithm.

But there is not sufficient diversification to the PSO method Additionally, because of this, the algorithm may be trapped at the suboptimal solution. According to Figure 2. 4,thus as a consequence, M-PSO algorithm is regarded as an appropriate method in solving the above problem. However, the subroutine, mutation, may increase the degree of randomness of the algorithm and the search direction contrary to the PSO method. During the mutation process, a threshold condition was set as shown in Equation (2. 24):For the threshold condition within the mutation process, the following equation was described:

$$\text{threshold\_value} = \left(1 - \frac{i-1}{\text{maxgen}-1}\right)^{\frac{1}{\mu}} \tag{2.24}$$

where where, max(gen) is the maximum number of generations and μ is the mutation factor. In the earlier implementation, once a random number was less than the threshold value it used to go for the mutation program. Thus, a new position of lb and ub for each dimension t was randomly set. In Equations (2. 25) to (2. 28), by some algebraic calculation it is possible to obtain the boundary value. However, the new position continues if it is preferable over the earlier position of the involved employee.

$$\delta_{x-t} = \text{threshold\_value} \times (X_{\text{max}-t} - X_{\text{min}-t}) \tag{2.25}$$

$$\text{lb}_t = X_{i-t} - \delta_{x-t} \tag{2.26}$$

$$\text{ub}_t = X_{i-t} + \delta_{x-t} \tag{2.27}$$

$$[\text{lb}_t \quad \text{ub}_t] \in [X_{\text{max}-t} \quad X_{\text{min}-t}] \tag{2.28}$$

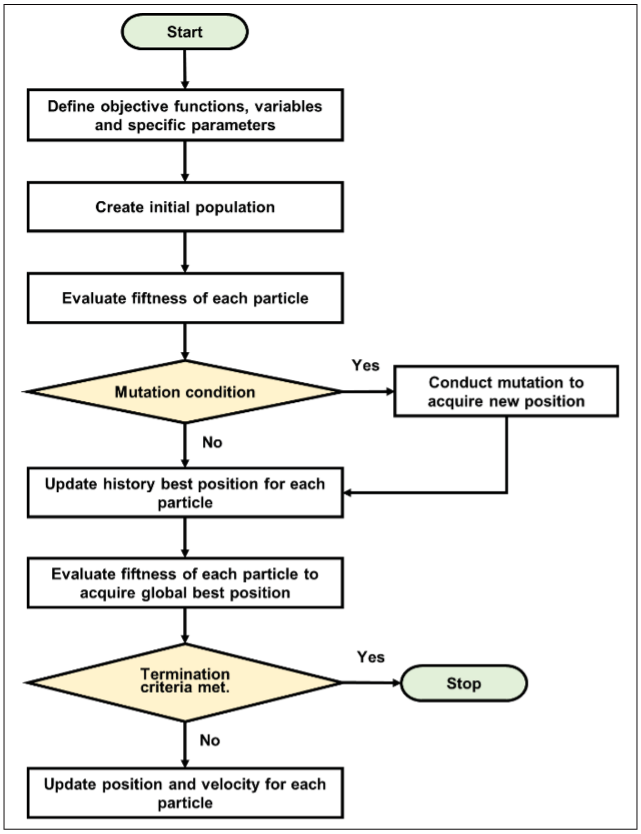

Figure 2.4 PSO-mutation algorithm

Integration of Item 1 and Item 2: Firstly, the formation of clusters and their creation is done through, k-means clustering formalism applies in this case. The next critical factor that arises after formation of clusters is the selection of the appropriate cluster heads which are involved in the process of data acquisition in the direction of the base station. The sink node then goes to choosing the best out of all the nodes/transmissions through probable analysis on the received data. Every of the energy consumption ratios for CHs and NCHs is calculated using the M-PSO algorithm. Accordingly, of the randomly generated cluster head, if the value is less than the threshold value it is a CH, else it is an NCH. The process of identification of clusters in the network is performed using PSO-mutation Algorithm that is implemented in the base station depending on the best probability to achieve the healthiest fitness values. If fitness function is better than the selections of CHs and NCHs, then the corresponding best choices are selected. This process is done until all the concerned selections are worked out to the best. In unison, the k-means clustering algorithm as well as the PSO algorithm improves the clustering process, as well as the election of heads of clusters in WSNs.

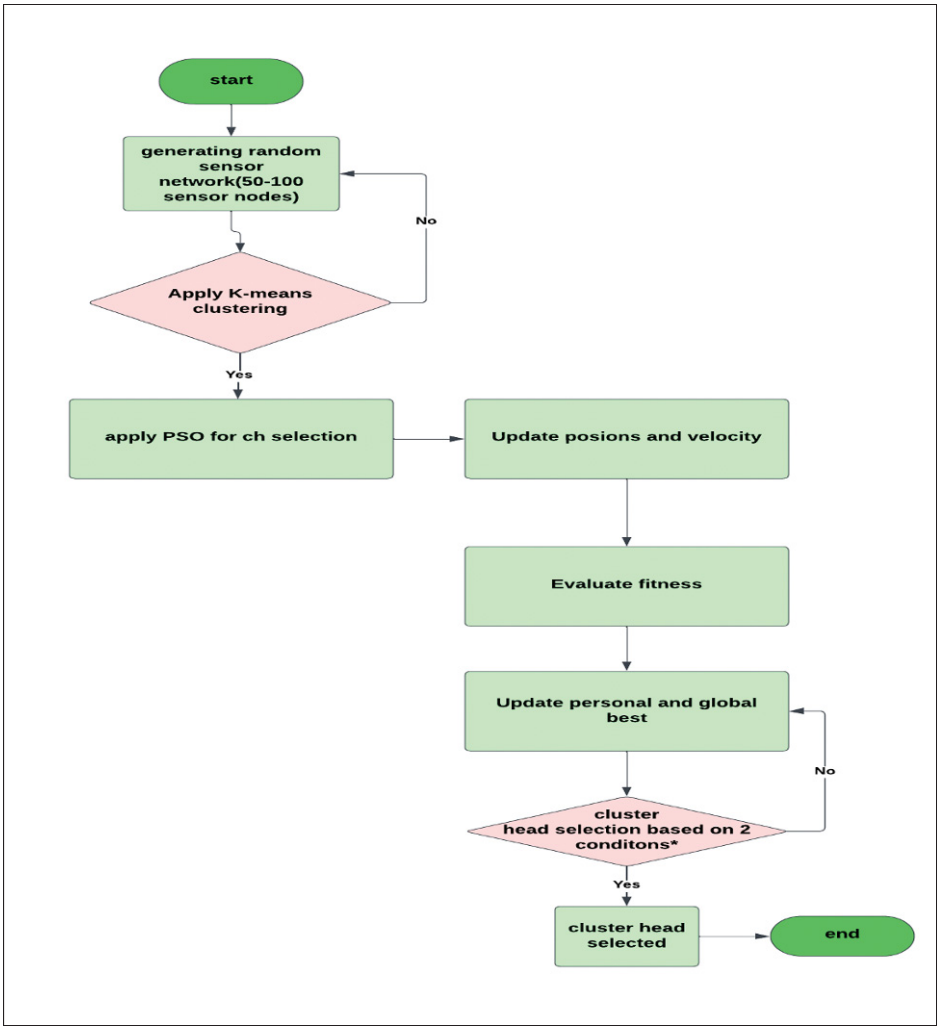

Figure 2.5 Clustering and cluster head selection based on k-means and PSO-mutation

The following is the flowchart exhibiting the consequence of the K-means algorithm and the Particle Swarm Optimization (PSO) to manage the network with 50 and 100 sensor nodes. This sequence is in concordance with the previous discussions made earlier, and at the same time shows the logical progression for the clustering and the subsequent selection of cluster head with the help of enhanced K-means and Particle Swarm Optimization.

2.2.2.3 Step3: Golden Eagle algorithm

This can be associated with distance between cluster heads $d(CH_i, CH_j)$ and another constraint that requires the condition of the residual energy E_{CH_i} to be greater than a certain value according to the discussed mathematical model. The model also introduced the Golden Eagle Optimization (GEO) algorithm for routing, and path optimization of the overlying sensor networks. What is similar to the hunting mechanism of the golden eagles is that GEO functions like an optimization algorithm in the natural environment ensuring that upcoming data transfer tasks are assigned equally among the nodes. It always evaluates and seeks to find the best course available taking into consideration the set goals and objectives such as; fuel consumption or delay in data transfer. The extracted GEO methodology from WSNs is based on the behavior of a golden eagle predatory hunt where the bird's velocity changes are of essence. Therefore, GEO lies down a novel approach of optimization in WSNs by allowing the candidate solutions to be explored through the process referred to as search and also exploiting the promising solutions. It can be referred to as a positive trend in the sphere as this approach can make WSN more efficient, effective, and extensible (Abdolkarim Mohammadi-Balani et al 2021).

As for this Algorithm, the routing between the source node and base station is intended to be chosen through the cluster heads. Here's a step-by-step explanation of the algorithm:Here is the illustration of how the viewed algorithm looks like:

1. **Exploitation Phase:** Optimizes available spots by selecting the best one iteratively.
2. **Fitness Function:** $F(D_i, E_i) = \frac{D_i}{E_i}$, evaluates efficiency based on distance and energy.
3. **Memory Matrix:** Stores parametric values, updated iteratively for decision-making and getting the most efficient result. $\mathrm{Mem}_{ij} = \mathrm{CHdist\_sink}(Pop\_Size, 1)$. CHdist_sink is initialized with each eagle's distance to the sink and updated based on the golden eagle iteration each time to get the most efficient results.
4. **Memory Max Selection:** Next hop is chosen based on the maximum value in the memory matrix. $\mathrm{CN}(E_i \cdot D_{ij}) = \{i \mid \mathrm{Mem}_{ij} = \max(\mathrm{CN}(E_i \cdot D_{ij}))\}$.
5. **Memory CH (Cluster Head):** Contains resource information, updated iteratively for optimization.

The critical steps of this algorithm is:

1. Initialize the population of golden eagles
2. Evaluate fitness function
3. Initialize population memory
4. Initialize p_a and p_c
5. For each iteration t
    a. Update p_a and p_c
    b. For each golden eagle i
        1. Randomly select a prey from the population's memory
        2. Calculate attack vector $\vec{A}$
        3. If attack vector's length is not equal to zero
            1. Calculate cruise vector $\vec{C}$
            2. Calculate step vector $\Delta\vec{x}$
            3. Update position
            4. Evaluate fitness function for the new position
            5. If fitness is better than the fitness of the position in eagle i's memory
            6. Replace the new position with the position in eagle i's memory

Figure 2.6 Pseudo-code of GEO

This continues with these steps and the selection of cluster head nodes for data transmission gets improved and improved until the energy of the nodes is depleted. The concept is to preserve the data flow path as close to optimal as possible by these criteria to extend and enhance WSN's life and efficiency.

2.3 Summary

The methodological chapter has revealed necessary and sufficient conditions on how the objective of this research study was accomplished. It starts with the definition of the research phase and other major activities that come with this phase are also defined accompanied by illustrations and figures with an aim of facilitating the understanding of the information presented. The same way, the chapter also categorizes the research objectives, hypothesis of the research with reference to the literature reviewed. This is followed by listing of how in the context of the above said proposed approach the energy consumption calculation model, the routing process and the network topology architecture functions. The major factors that have been anticipated in the process of the work are associated with the following components ; excessive and skewed energy consumption in WSNs.

This chapter begins with the implementation of the k-means algorithm for clustering, followed by PSO-mutation for cluster head selection. It's imperative to note that mutation amplifies the search space, aiding in the quest for a global optimal solution. There are subsequent sections that detail the implementation of Golden Eagle Optimization's routing algorithm, resulting in a comprehensive methodological framework designed to tackle the complexities of WSN energy efficiency.

CHAPTER 3

NUMERICAL RESULTS

Stress is given to the evaluation of the performance of the model that has been developed in this chapter within the framework of this study. It continues with the simulation environment, namely the tools applied and settings of the simulations. The simulation done on the aforementioned platform provides evaluation of the concerned model of the paper with respect to different scenarios and the findings of model based on total energy, delay, data rate and number of 'dead' nodes. In light of this, the benchmark and the proposed models are compared through two graphs each with regard to each of the evaluation parameters. However, in the contexts of assessing the result, it holds the degree of effectiveness of the specified model and the potential of its further advancements for enhancing the concerned network. Furthermore, this chapter includes the explanation of the results derived and the information about the cases where it achieve the energy efficient routing and the longevity of network. It also outlines the directions for the enhancement of the advised model and, simultaneously, it identifies the enhancing model chances and pitfalls. As such, the chapter justified the effectiveness of performance evaluation on the facet of improving the creation of better routing models; and the fact that such facets have to be given some consideration in order to receive the desirable outcome.

3.1 Simulations

Simulations for the proposed routing protocol were carried out using Matlab, with the benchmark being the already existing LEACH-CR. The first purpose was to compare the achievement of the energy density and the durability of the network targets using the model of choice with that of the baseline.

The measures taken to evaluate included operational lifetime, power usage, node exhaustion, data transfer rate, and delay. To display the results, graphs were used, and the axes of which denoted certain pieces of information.

3.1.1 Parameters

The decision on the selection of the simulation as well as setting of parameters is of the significance as These aspects influence the network in terms of efficiency and functionality in a rather profound way. Key parameters include network Length, energy usage parameters, distance of inter-node communication, energy values of data communication, transmitted power and received power, and packet sizes. Moreover, the factors such as distance between two devices actively participate in electromagnetic communication influences, explains and contributes to news and events updates or the information transfer process. and consequently it can be stated that this specific factors, or certain particular shapes of the traffic distribution have quite a strong impact.

According to Table 3. 1 Due to the random placement of the nodes, the monitored environment for this project is an open area of 100m by 100m with fifty to one hundred Sensor Nodes. It should be noted that the sensor nodes number is variable, depending on the studied situations. Variables that are not included in Price Index and Cost of Production, or the VaR risk highlighted in Table 3. Thus, for the 1's, the sites have been selected in line with the standard as explained in the literature. This means that the testbed is created with settings that are fit to replicate actual environment in order to enhance the realism of the findings that are achieved. On the other hand, as for the side of the simulation framework it employs such common parameters of WSN as density of nodes placement, energy and data rates.

Table 3.1 Parameter values for the simulations(behzad oveisi,2023)

Parameter symbols	Parametric Values
Network area in meter	100x100
The total energy of the nodes	2 joules
Data packet size in bits	500
Number of nodes	50 and 100
Etx (Transfering circuity energy consumption)	50x0.000000001
Erx(receiving circuitry energy consumption)	50x0.000000001
Efs (Energy used to amplify the signal)	10x0.000000000001
Eamp (amplifying circuitry energy consumption)	0.0013x0.000000000001
Data fusion Energy	5x0.000000001
Location of the base station	(50,50)
Data fusion ratio	0.7
Node mobility	fixed

3.2 Results

The simulations are conducted on Matlab platform for the proposed model with the help of parameters provided in the Table 3.1.

The above simulation is performed to evaluate the adverse realizations of the network in which the NPEP parameters are established depending of the rounds. A round is an iteration cycle that provides the activities of the network in different time intervals; it also contains set up phase in a network and stable phase in a network. In the first phase it involves the identification of the optimum clustering, which particular nodes should act as cluster head and which routing strategy should be followed in the current round, and in the second phase the node that has been identified as the current CH, using the optimum clustering and routing strategy, broadcasts information obtained from member nodes in its cluster through several phases to basestation. In each round, the network behaviour is described with reference to the data gathered by the SENs and the data sent towards the BS. The transmission of the data packets at the networks is done in cycles of each one of the phases of the protocol for the transmission. When calculating the cycles, the time each cycle takes is assumed to be one second and all ratios are in duty cycle, meaning that the number on top is the duration that the signal is high, the bottom is the time the signal is low. This means that all the activities within a cycle the where the sensor nodes collect data, forward data to the cluster heads, the cluster heads aggregate the data, and then forward to the base station happen within the same second.

The time between cycles (cycle time) is configurable by the operator in real-world applications, allowing adjustments based on needs (e.g., hourly or daily monitoring). In simulations, we typically set the cycle time to zero for simplicity and focus on the behavior within a single cycle.

The metrics of evaluating the simulation outcomes include the prerequisites like total energy utilization, node death rate, data transfer rate, and network delay. These metrics are gathered and retained at the end of several operating rounds to reflect the shift in the performance of the model between rounds.

It is also done using another model known as LEACH-CR model to compare the results from the simulation. This method is an extended version of LEACH protocol and it specifically focuses on improving the energy utilization in WSNs. It presents cooperative communication in which nodes within the cluster help each other in forwarding the data to the cluster head. This method cuts down the energy consumption because the load is evenly distributed across the nodes. The method chooses the cluster heads based on a probability distribution and it uses the cooperative communication to decrease the distance of transmission and energy consumption in order to enhance the performance of the network. The implication of the findings of this study are then presented, discussed and summarized in the last section of the study.

3.2.1 Clustering and choosing cluster heads

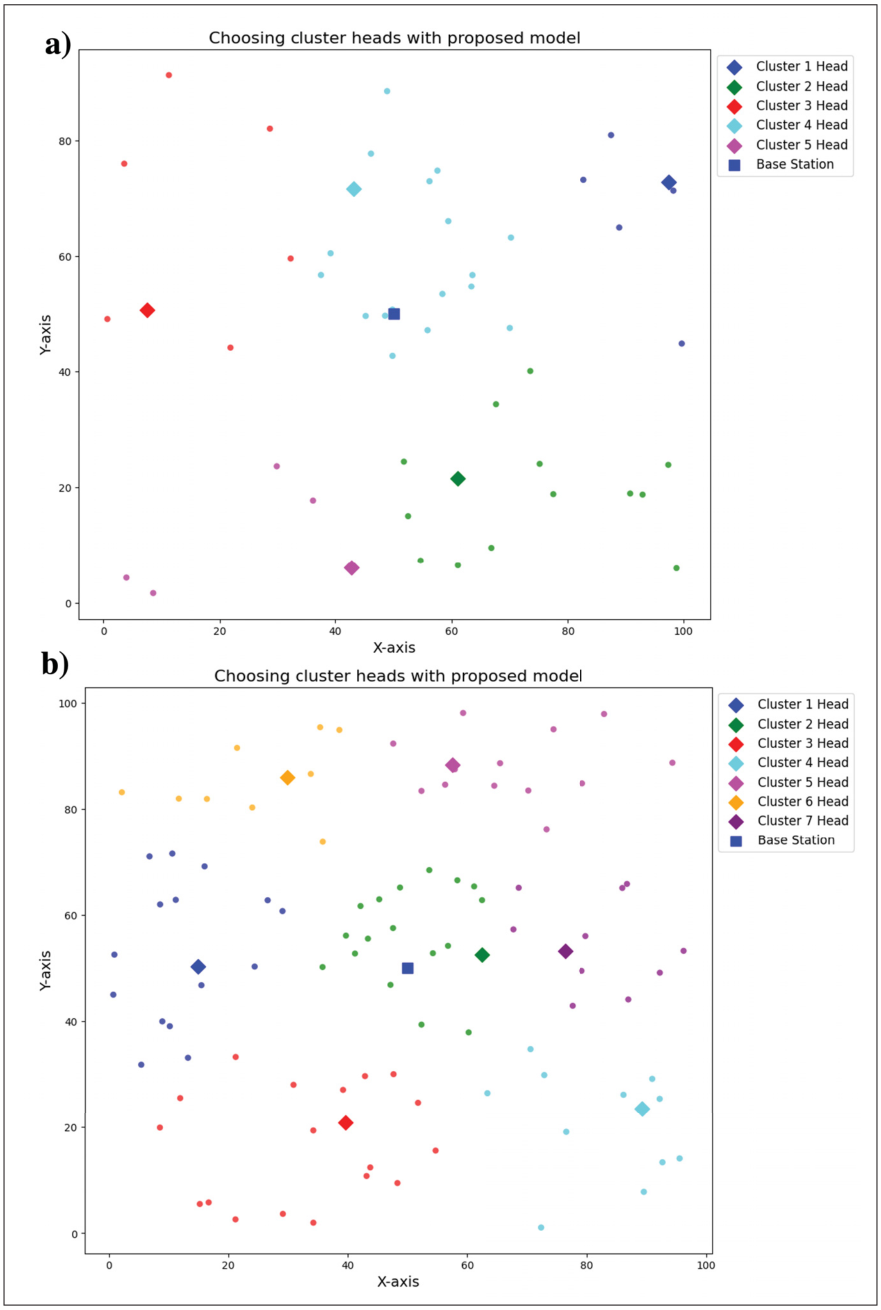

Figure 3.1 Choosing cluster heads with PSO-mutation for a) 50 nodes and b) 100 nodes

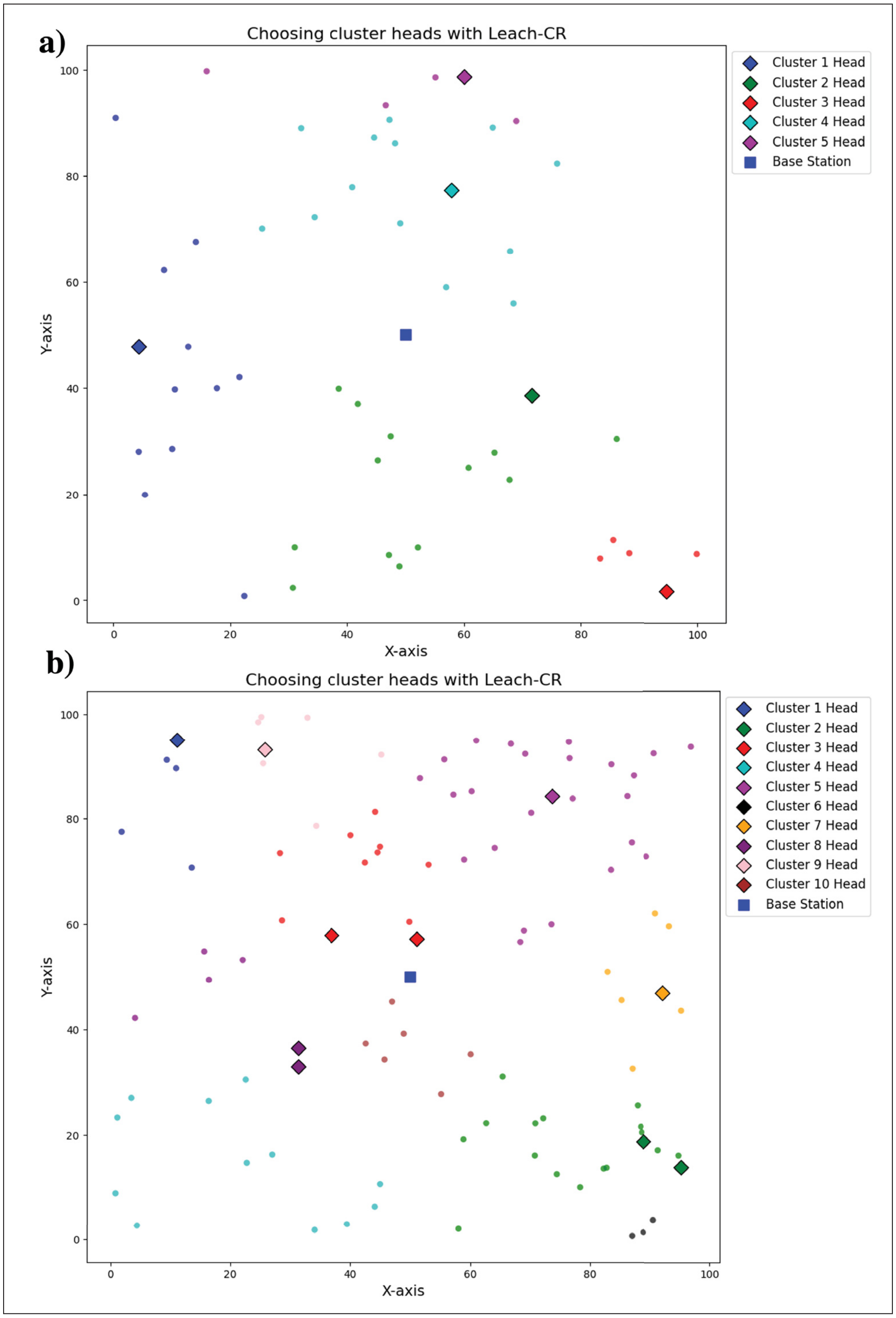

Figure 3.2 Choosing cluster heads with LEACH-CR for a) 50 nodes and b) 100 nodes

In Figure 3. 1, to justify the formation and the selection of the group head known as ‘cluster’, is the first one that’s why the proposed work includes k-means for the clustering aspect and PSO-mutation for the selection of the head of clusters. Figure 3. 1 a indicates that it is feasible to choose the heads of the clusters that are over 50 senor nodes and Figure 3 is also continued. 1 b describes the same procedure with only the number of sensor nodes raised up to 100.

In contrast, Figure 3. 2 is categorized as benchmark model which is LEACH-CR. This method is random in the manner it arranged the clusters and selected the cluster heads. Though this makes it easier, the random selection could at times lead to the choosing of unsuitable heads within the cluster. Figure 3. 2 a and Figure 3, 3 a b visually illustrate scenarios where some of the cluster head selections are poor or not well-made.

Thus, based on the findings presented in Figure 3 above, it can be posited that handicapped students are negatively targeted more often in their classrooms than non-handicapped students. 1 and 3. Therefore, following the evaluation made in section 3 in relation to the second criterion of the heuristic model of the proposed algorithm outperforms the benchmark significantly.

3.2.2 Energy Consumption Analysis

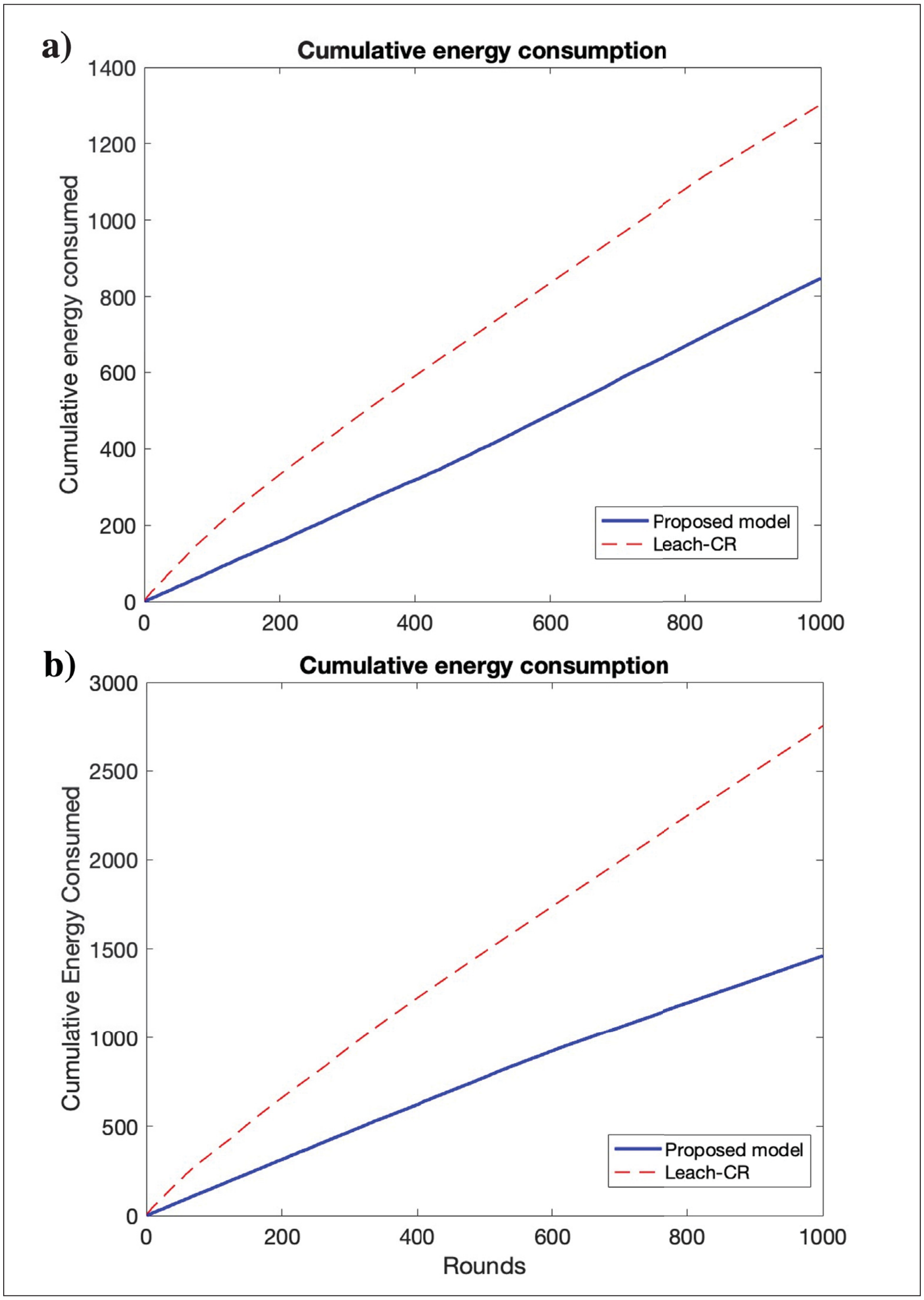

Figure 3.3 Cumulative energy consumption per round for a) 50 nodes and b) 100 nodes

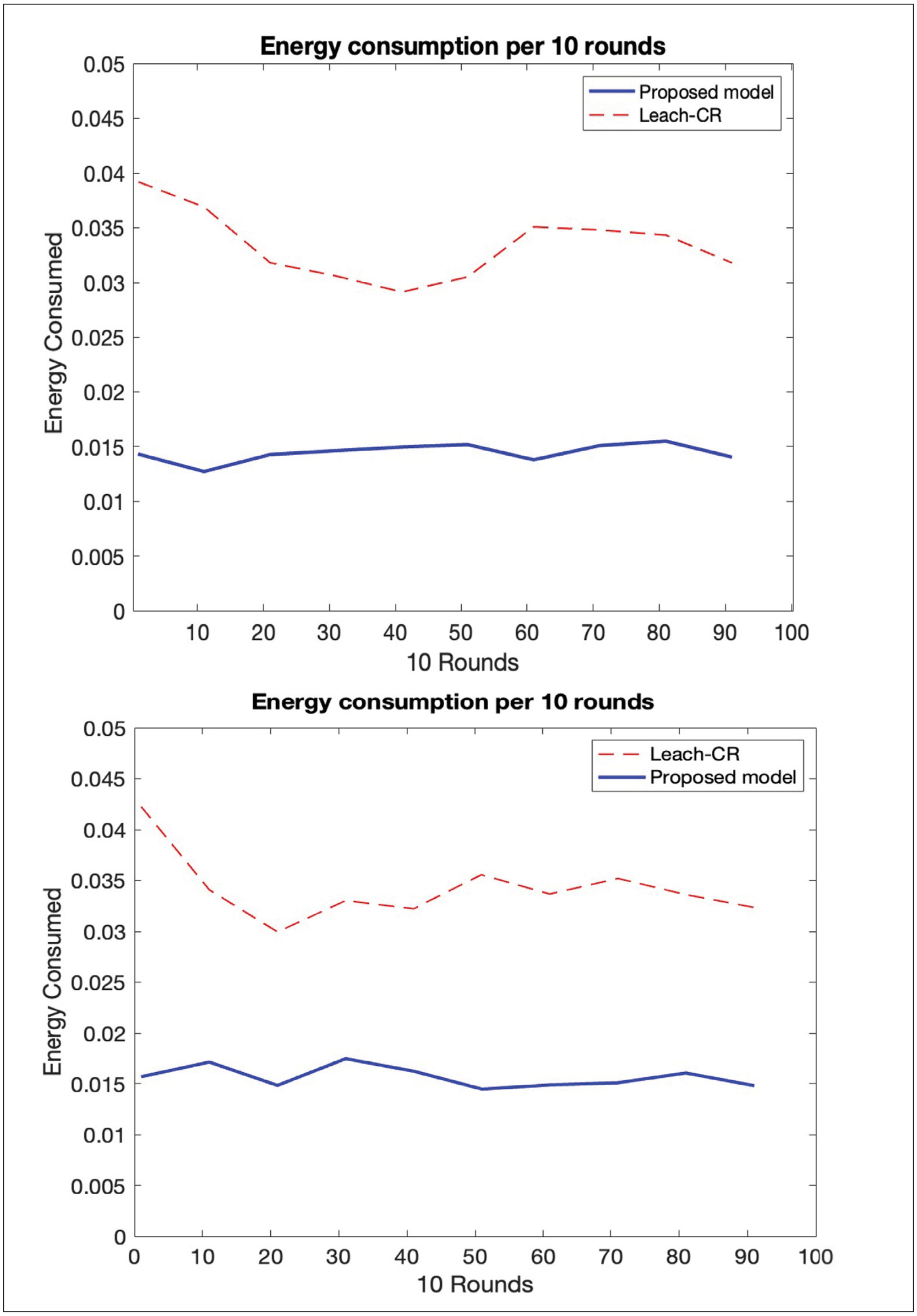

Figure 3.4 Energy consumption per average of 10 rounds for a) 50 nodes and b) 100 nodes

Figure 3.3 illustrates a comparative analysis between proposed routing protocol and the benchmark (LEACH-CR) concerning cumulative energy consumption vs operational rounds. In Figure 3.3 a, at round 997, the cumulative energy consumed is 1300, whereas in the proposed model, it is around 700. Similarly, according to Figure 3.3 b, at round 998, the cumulative energy consumed is 2700, while in the proposed model, it is around 1500.

Figure 3. 4 show the average energy requisite of the proposed model and benchmark model defined in (3) and (4) over ten iterations, as justified from the bar graph proving the efficiency of the benchmark model.

Overall, the proposed model demonstrates significant improvements in energy efficiency when compared with the benchmark model.

3.2.3 Dead Nodes Analysis

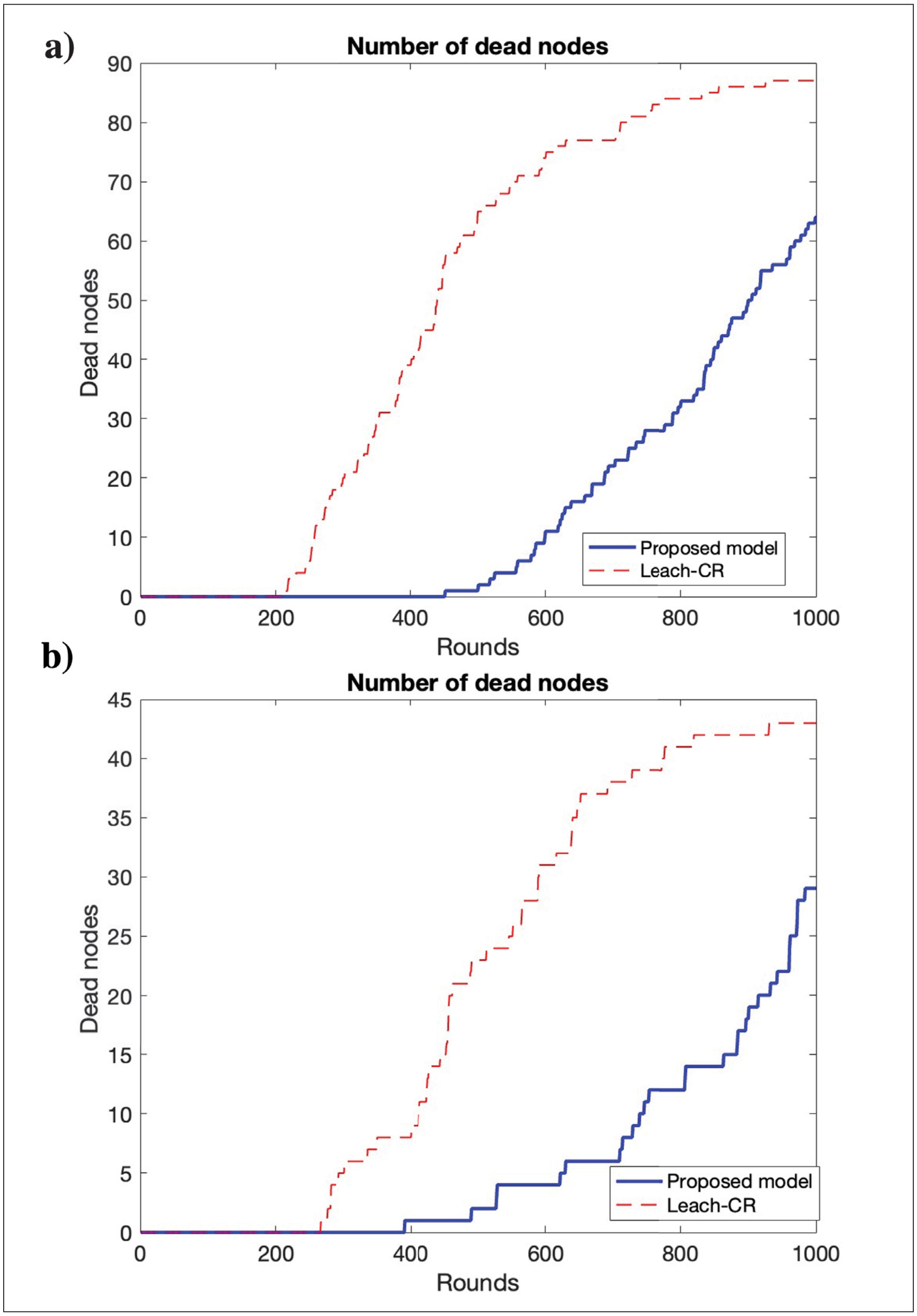

Figure 3.5 Number of dead nodes for a) 50 nodes and b) 100 nodes

In Figure 3.5, we see how many sensor nodes are dead due to lack of energy over rounds, comparing our proposed model with the benchmark model in tested scenarios. In Figure 3.5 a, with 50 sensor nodes, by round 998, the benchmark model has 45 dead nodes, while proposed model has only 21 dead nodes. Also, proposed model doesn't start losing nodes by around round 390, compared to round 300 for the benchmark model. According to Figure 3.5 b, with 100 nodes a similar trend is observed. By round 1000, the benchmark model records 88 dead nodes, whereas the proposed model demonstrates better performance, with only 43 dead nodes. Moreover, in the benchmark model the sensors start to inactive from round 200, whereas in the proposed model the sensor nodes start to die until round 360. In summary, the proposed model demonstrates superior performance compared to the benchmark model in this aspect.

3.2.4 Throughput Analysis

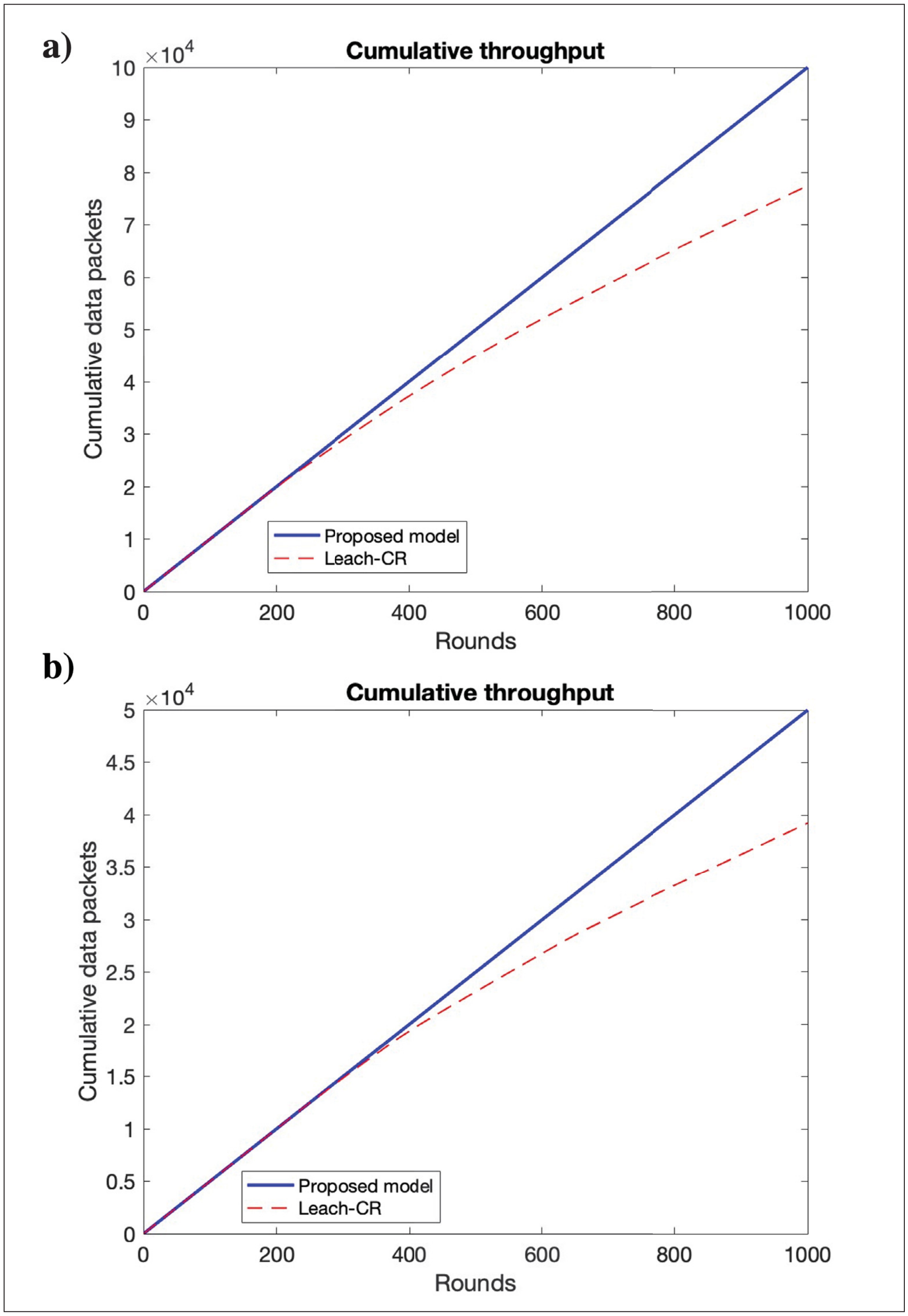

Figure 3.6 Cumulative throughput for a) 50 nodes and b) 100 nodes

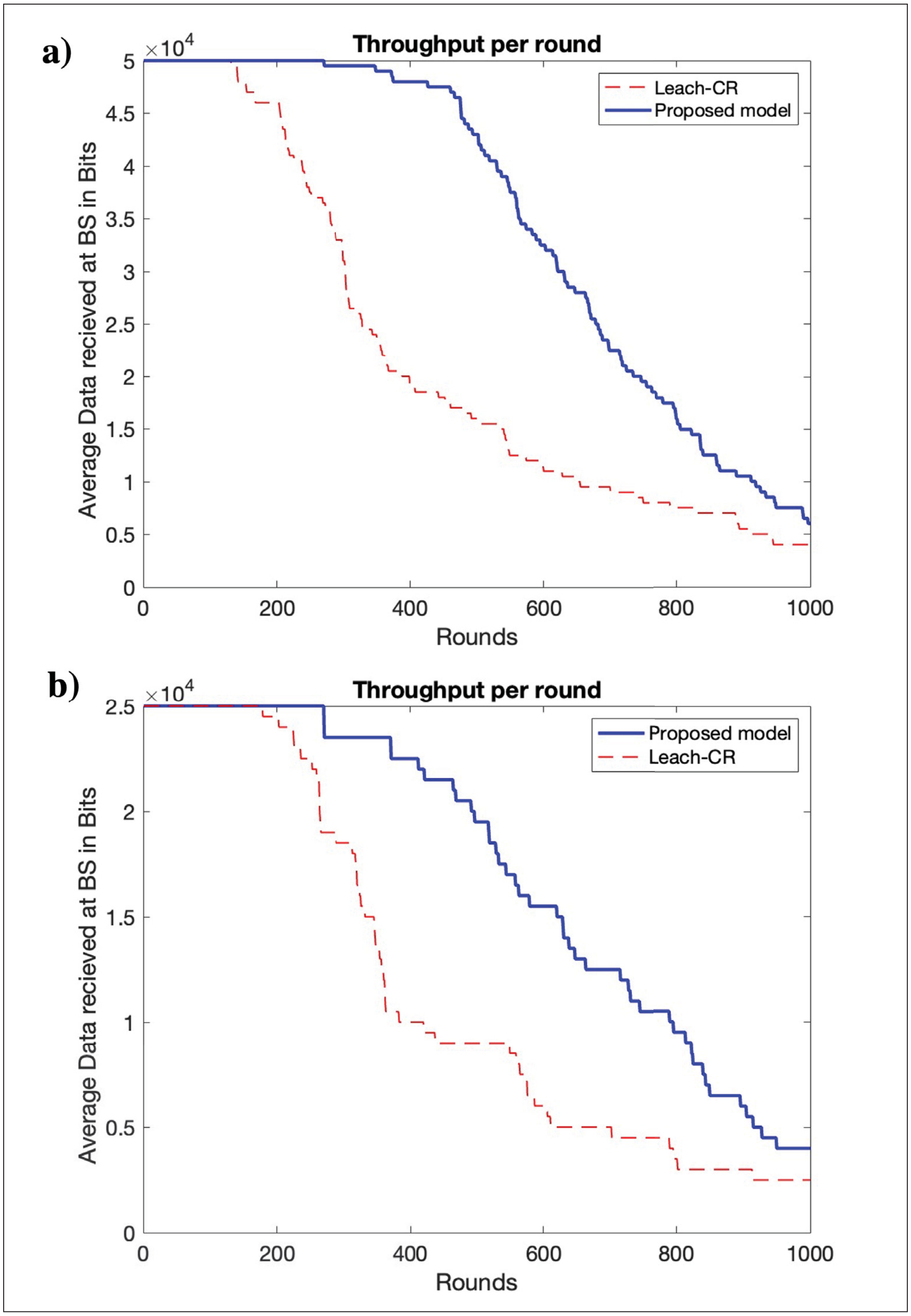

Figure 3.7 Throughput per round for a) 50 nodes and b) 100 nodes

Figure 3. 6 depicts the total amount of actual network through put against the number of rounds for the tested cases. The performance measure is defined as the number of data packets transmitted to the base station with respect to rounds. In Figure 3. 6 a, the benchmark model of send packets per thousand rounds was measured to be 75,983 packets. On the other hand the proposed model was able to forward a total of 98,800 packets in 1000 rounds. In Figure 3. 7 b , the benchmark model transmitted 49200 packets in 1000 round and the proposed model transmitted 38963 packets in 1000 round.

In Figure 3. 7 The throughput is labelled per round in the following figure. According to Figure 3. 7a, the overall throughput in our proposed model decrease from round 340 while the benchmark's one starts to reduce before that. Similarly, in Figure 3. 7b, which represents that from the round 350 the throughput is decreasing in the proposed model but in the benchmark it is starting the decrease from the round 150 and hence, it proved that the proposed is better. Therefore it can be ascertained that through putting forward the proposed model throughput has been enhanced and that is the enhancement of WSN based on it. Moreover, this throughput is the second one linked to appearing dead nodes in the network of CBR messages.

3.2.5 Delay Analysis

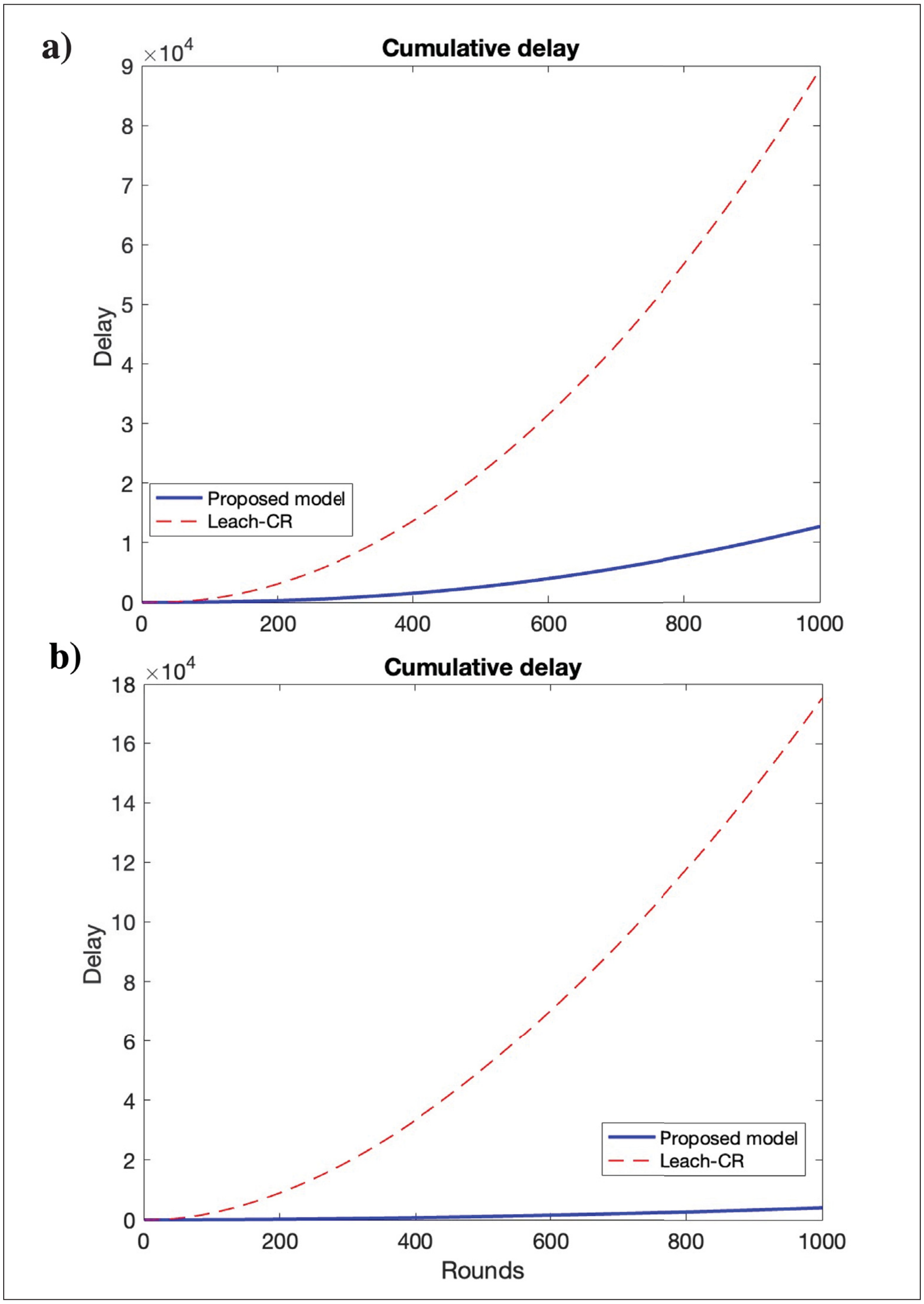

Figure 3.8 Cumulative delay for a) 50 nodes and b) 100 nodes

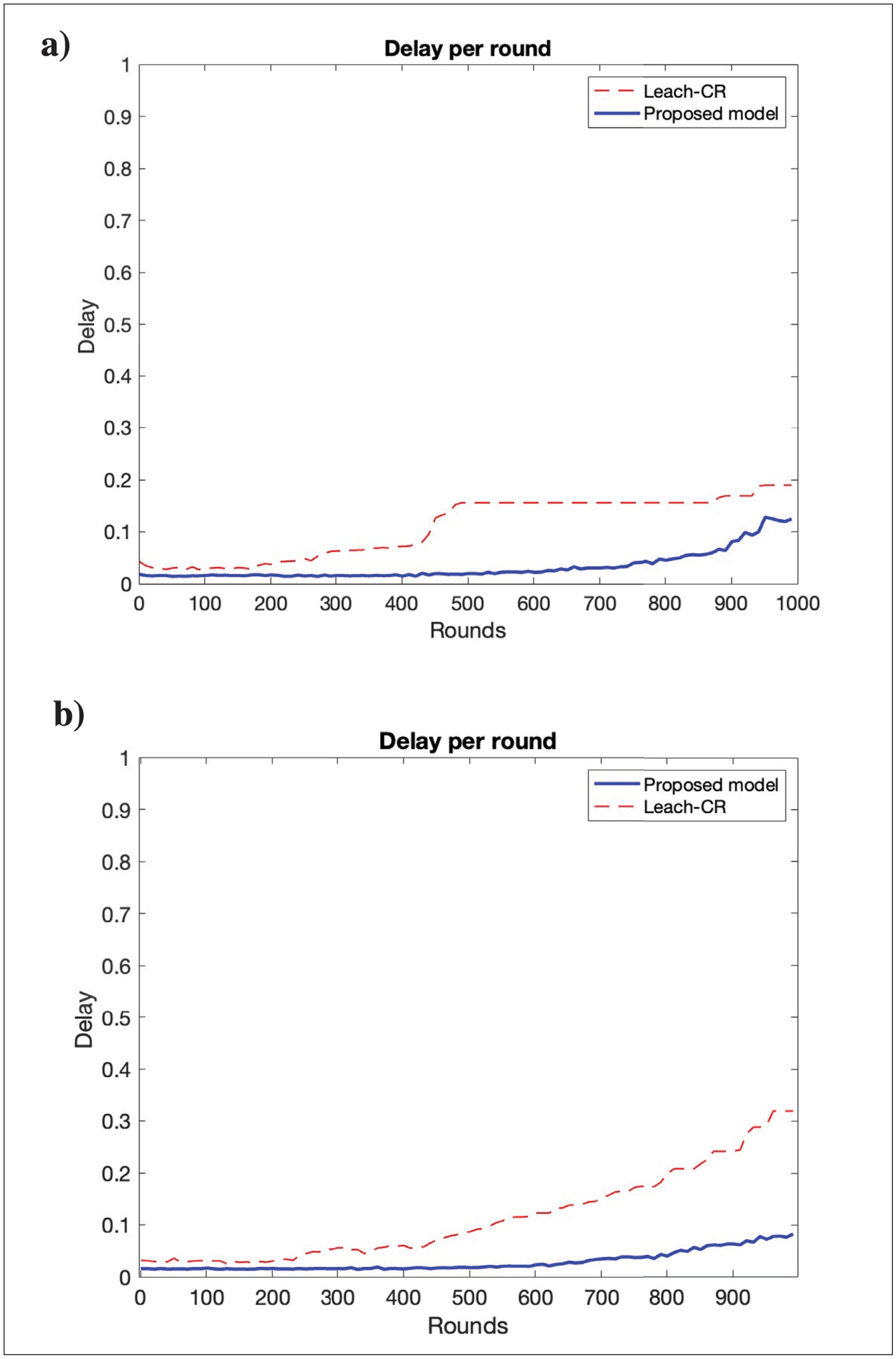

Figure 3.9 Delay per round (where each value is average of 10 neighboring rounds) for a) 50 nodes and b) 100 nodes

Figure 3.8 illustrates the cumulative delay in tested scenarios. In Figure 3.8 a, the cumulative delay steadily increases over 1000 rounds across the tested scenarios. For instance, by round 1000, the delay reaches 88655 in the benchmark model, whereas in the proposed model, it is notably lower at 11965, indicating the proposed model's superior efficiency in this metric.Similarly, in Figure 3.8 b, the delay continues to rise over 1000 rounds, with the delay reaching 172412 by round 1000 in the benchmark model, compared to only 3984.12 in the proposed model over 1000 rounds. Figure 3.9 illustrates the delay as a function of rounds (where each value is an average of 10 neighboring rounds to reduce high variability of the delay per round), demonstrating that delay in the benchmark model increases significantly once the number of dead nodes increases. Overall, according to Figure 3.8 and Figure 3.9, the proposed model provides lower delay in comparison to benchmark model.

3.3 Numerical results summary

Before providing an overview of the performance of the presented numerical results, it is crucial to emphasize that the analysis of our proposed model's outcomes is satisfactory within the WSN routing protocols domain. By selecting comparable standards and carefully comparing several factors the efficiency of the model was critically assessed to meet objectives of energy saving and network durability.

In particular the proposed model has demonstrated significant improvements across various performance metrics:However, the following has been found to have fairly good changes regarding the proposed model in terms of the performance index:However, the following has been found to have fairly good changes incomparison with the proposed model in terms of the performance index:

- The proposed model reduced energy usage by 52% in the 50 nodes network and by 65% in the 100 nodes' network.
- Additionally, it increased throughput by 21% in networks with 50 sensor nodes and by 44% in networks with 100 sensor nodes.

- Moreover, the proposed model reduced delay by 15,000 milliseconds in networks with 50 sensor nodes and by 19,000 milliseconds in networks with 100 sensor nodes.
- Furthermore, it decreased the number of dead nodes by 24 nodes in networks with 50 sensor nodes and by 45 nodes in networks with 100 sensor nodes.

Therefore, the findings of this paper demonstrate that the proposed model is drastically beneficial and applicable for enhancing the performance of WSNs and encourage the society to actively develop and apply actual performance improvement methodologies.

CHAPTER 4

CONCLUSIONS AND FUTURE WORKS

4.1 Conclusion

They can be applied to almost all the areas of CS and from the case studies the examples are vivid. However, under this issue, only the former has not been completely solved, that is, the energy restriction problem of the sensors. The crucial aim of this research is to help to develop the new energy efficient routing protocol for WSN that will successfully solve this problem with the help of new ideas and concepts and the analysis of the literature.

The given routing protocol acquire strength and, at the same time, nurtures data stability and the network's endurance in the durability checkbox. As far as the results of the comparison of the proposed protocol with the benchmark model of LEACH-CR, carried out in the framework of the simulation of this paper, it has also been shown how the sensor nodes, energy dissipation, and delay of the protocol have been represented. Favourable towards the WSN field and to the promotion of the prospects, this work aids on the enhancement of the standard and great communications that are significant to energy management and network existence.

Also, the proposed protocol has incorporated the following improvements in the design strategy of WSN routing protocols. The key contribution of this study include:

- Development of a Novel Protocol: Propose a proper routing protocol that consumes less energy for WSNs to improve the network's lifetime.
- Model Decomposition: Incorporation of k-means and PSO-mutation for clustering and cluster head selection, along with the Golden Eagle algorithm for routing optimization, in comparison to the benchmark model LEACH-CR, to improve network operational efficiency.
- Comprehensive Experiments: Conducted a lot of simulations using Matlab, the measurement criteria being energy used, delay, throughput and number of dead nodes.
- Benchmark Comparison: Supplementing this is a benchmarking exercise of the proposed model against the other benchmark models to show that the proposed model is better off. The

present research synthesizing the literature and looks into and covers a number of evaluation criteria and brought for the purpose of this study; a critical appraisal of the model.In addition to the detailed descriptions and the non-trivial comparative analysis, which connect the simulations and the complex algorithms, the present work offers not only the foundation for obtaining the improvements of the energy efficiency and the performance of the WSNs but it gives the foundation for obtaining further advancements also.Therefore, it offers enough prior information for the subsequent investigations dedicated to the improvement of WSNs.

In this work, the problem of energy efficiency in WSNs is recognized as critical and presents an original method of solving it. It provides a fresh approach of improving network characteristics and dependability to act as a guide for future works in this dynamic area.

4.2 Future Works

While the current study has successfully met its objectives, there are several potential directions for future research:Therefore, in detail, the nature of the present study has been described elaborately and for the said purpose and objective of the present study, it has to be limited but it can be expanded in the future studies as follows:

- **Algorithmic Evolution:**
  AI and machine learning are still young disciplines and there is always better algorithms that could be applied to increase WSN energy efficiency even more. This is because future work could refer to these algorithms as other or further to the Golden Eagle algorithm.
- **Holistic Optimization:** Besides the energy consumption, there is a possibility of future work to include other performance parameters that can be used to come up with a routing protocol that is efficient for use in most networks.
- **Practical Implementation:** While simulations are valuable, actual implementation of the protocol would offer the best proof of the utility of the protocol.
- **Adaptive Techniques:** Given that WSNs are usually characterized by flexibility in their working, there might be some advantages of using parameters through which the network can self-optimize in real-time.

- **Security Considerations:** Actually, it has been noted earlier that several WSNs are applied in sensitive regions; therefore, integrating security to the energy efficient routing algorithm could still be a valuable enhancement.

Therefore, through the following study, one can systematically identify the above mentioned areas and in the process enhance the energy efficient routing protocol in the future, which will go along way in the advancement of WSN. Hence, the outcomes of the present research are not only useful to address the modern concerns regarding energy efficiency in WSNs but also develop several new directions for the study and advancement.

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