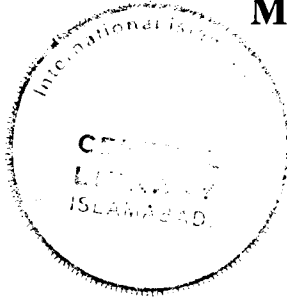


# Energy Efficiency Management in Wireless Sensor Network



**Muhammad Salman Qamar**



**15-FET/PHDEE/F18**

A Dissertation submitted to IIUI

in partial fulfillment of the requirements for the degree of

**DOCTOR OF PHILOSOPHY**

Department of Electrical and Computer Engineering  
Faculty of Engineering and Technology  
International Islamic University,  
Islamabad  
2024

Accession No. TH-26653 k.

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621-3822  
QAE

Wireless sensor networks

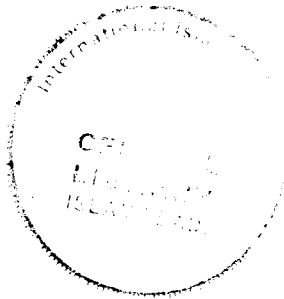
Energy conservation

Wireless communication systems - Energy consumption

Computer networks - Energy consumption

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DEDICATED TO

My Teachers,

Parents,

Brothers,

Sister,

Friends,

Wife,

and Kids

## CERTIFICATE OF APPROVAL

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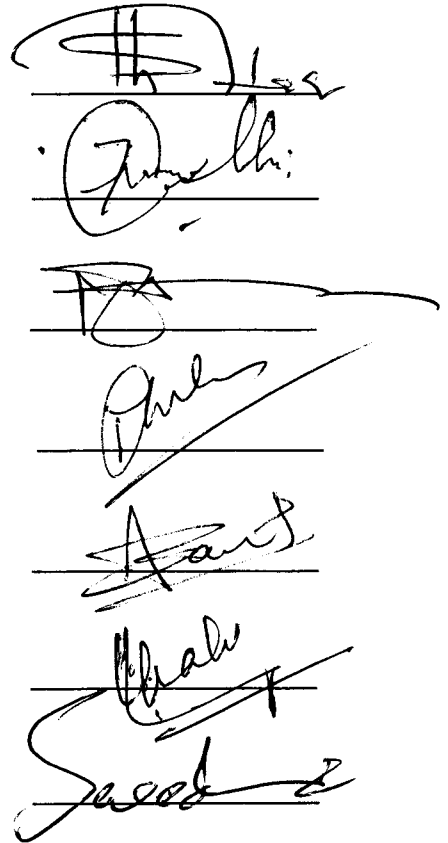
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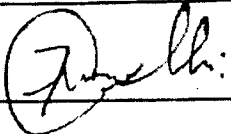
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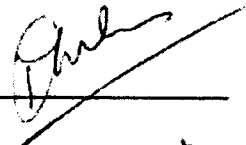


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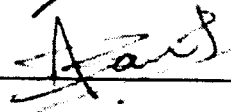
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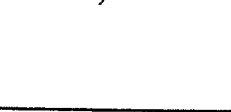


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## ABSTRACT

Wireless Sensor Networks (WSNs) consist of spatially distributed autonomous Sensor Nodes (SNs) designed to monitor and record environmental conditions, such as temperature, humidity, and pressure, and to relay the collected data to a central location through wireless communication. These networks leverage SNs equipped with sensing, processing, and communication capabilities, enabling various applications. Despite their versatility and widespread application, WSNs face several significant limitations that impact their performance and operational longevity. Therefore, the resource constraints and the unreliable nature of low-power links between sensor nodes pose significant challenges in the design of an efficient routing protocol. Failure of SNs in WSNs situated in hazardous environments such as forest fire surveillance, disaster management, battlefield exploration and, results in networks disconnectivity. As WSNs are increasingly deployed in larger and more complex environments, ensuring scalable and energy-efficient routing becomes even more critical. In many WSN applications (such as battlefield exploration and disaster management), the network environment is highly dynamic, with nodes moving or failing. There is a strong need for adaptive routing protocols that can adjust to changing topologies and maintain efficiency under such conditions. As data generation rates in WSNs increase (due to higher sensor density and more advanced sensing capabilities), reducing transmission overhead to prevent network congestion and energy wastage becomes a significant motivation. Optimized data aggregation and transmission methods should be explored. Many constructive solutions have been proposed in the literature, which have the capability to prolong the lifetime of WSNs through energy

management (EM) in an integrated manner by using reactive, proactive, and hybrid approaches.

The primary focus of the research dissertation lies on the development and implementation of energy-efficient routing protocols alongside optimization techniques within the context of WSNs. These optimized strategies are subsequently applied within WSN infrastructures to boost their efficiency and performance metrics.

Henceforth, the work investigates the usage of Mobile Sinks (MS) to address issues with energy consumption in WSNs within the context of energy-efficient routing. By strategically visiting pre-determined Rendezvous Points (RPs) instead of all Cluster Heads (CHs), the mobile sink strategy minimizes energy consumption and latency, improving network efficiency. Two innovative hybrid algorithms, "Reduced k-means based on Artificial Neural Network" (RkM-ANN) and "Delay Bound Reduced k-means with ANN" (DBRkM-ANN), are proposed to design efficient MS paths based on RPs. These algorithms optimize latency and delay-bound paths, ensuring network-wide coverage while maximizing efficiency.

Furthermore, to address overall energy efficiency and operational lifespan in WSNs, the LEACH-D protocol is paired with the Artificial Neural Network (ANN). This hybrid methodology optimizes battery Energy Consumption (EC) and extends transmission work time. Additionally, this scheme refines routing decisions and CH placement to reduce idle listening, thereby reducing EC and extending network lifespan.

Through extensive simulations and comparative analyses, the efficacy of these methodologies is demonstrated, showcasing substantial reductions in energy consumption and enhanced network efficiency across various performance indicators.

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- [1]. **MS Qamar et al.**, "A Novel Approach to Energy Optimization: Efficient Path Selection in Wireless Sensor Networks with Hybrid ANN" *CMC*, Vol.79, No.2, p. 2945-2970, 2024. **IF (3.1)**
- [2]. **M. S. Qamar et al.**, "Enhancing Energy Efficiency in WSNs with Hybrid LEACH-D and ANN" *IEEE Conference*, 2024 (**Accepted**)
- [3]. **M. S. Qamar et al.**, "Improvement of Traveling Salesman Problem Solution Using Hybrid Algorithm Based on Best-Worst Ant System and Particle Swarm Optimization," *Applied Sciences*, vol. 11, no. 11, p. 4780, 2021. (**IF 2.83**)
- [4]. Khurram Hameed, Wasim Khan, Armghan, Muhammad Asif, **Muhammad Salman Qamar**, Farman Ali\*, Md Sipon Miah, Mohammad Alibakhshikenari and Mariana Dalarsson "Far-Field DOA Estimation of Uncorrelated RADAR Signals through Coprime Arrays in Low SNR Regime by Implementing Cuckoo Search Algorithm" *Electronics*, 2022, **IF (2.690)**
- [5]. Farman Ali Ammar Armghan Fayadh Alenezi Ziaul Haq Abbas Asar Ali **Muhammad Salman Qamar** "Alleviation of Non-linear Channel Effects in Long-Haul and High Capacity Optical Transmission Networks" *International Journal of Communication Systems*, 2022 **IF (1.882)**
- [6]. Khurram Hameed; Shanshan Tu; Nauman Ahmed; Wasim Khan; Ammar Armghan; Fayadh Salman Alenezi; Norah Alnaim; **Muhammad Salman Qamar**; Abdul Basit; Farman Ali "DOA Estimation at low SNR through Coprime Arrays: An Innovative Approach by Applying Flower Pollination Algorithm" *Applied Science* **IF (2.679)**
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- [11]. Biological inspired, stochastic technique (PSO) for antenna array signal processing in RADAR communication system. K Hammed, SA Ghauri, **MS Qamar**, Journal of Sensors 2016 (Hindawi Publishing Corporation *Journal of Sensors* Volume 2016, Article ID 9871826) **IF (3.576)**
- [12]. An efficient TDMA-Based protocol using inter-relay displacement analysis IU Khan, U Ali, **MS Qamar**, I Ahmed *Science International* 28 (2) ,2016 **IF (1.852)**

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- [1]. **Muhammad Salman Qamar** et al, “Innovative Approaches for Energy Efficiency in WSNs: LEACH-D and ANN Integration” *IEEE Access*, (under review) 2024.

The research work presented in this dissertation is based on published paper 1 and accepted paper 2.

## ACKNOWLEDGEMENTS

*In the name of Allah (Subhanahu Wa Ta'ala), the Most Gracious and the Most Merciful, I express my gratitude for the strength and patience bestowed upon me to accomplish this research endeavor. Peace and blessings be upon His last Prophet Muhammad (Sallulah-o-Alaihihe-Wassalam) and all his Sahaba (Razi-Allah-o-Anhu), who devoted their lives to Dawah and the dissemination of knowledge.*

*I am sincerely thankful to my supervisor, Dr. Ihsan ul Haq, whose encouragement, motivation, and unwavering determination enabled me to complete my doctoral studies. He has not only been a guiding light in academia and research but also a role model for me and others in various aspects of life. I am also grateful for the invaluable support and guidance of Dr. Farman Ali during my research journey.*

*I am deeply appreciative of the continuous support from my colleagues and friends, Dr. Muhammad Fahad Munir, Dr. Adnan Anwar Awan, and Dr. Aimal Daraz, throughout these past years. I acknowledge the International Islamic University Islamabad, Pakistan, for their support and encouragement during my PhD studies. My heartfelt thanks also go to the departmental and university administration for their kind assistance.*

*I am profoundly thankful to my father, mother, brothers, and sister for their prayers, love, inspiration, and unwavering support throughout my life. I am especially grateful to my wife for her patience, cooperation, and encouragement at every stage of my PhD journey. Finally, I express gratitude to my children, whose innocent gestures have been a constant source of motivation for me.*

**(Muhammad Salman Qamar)**

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## LIST OF ABBREVIATIONS

<i>ANN</i>	Artificial Neural Network
<i>BS</i>	Base Station
<i>CHs</i>	Cluster Heads
<i>DBRkM</i>	Delay Bound Reduced k-means
<i>d</i>	Distance in meter
<i>d<sub>o</sub></i>	Threshold value of the distance
<i>DDR</i>	Data Delivery Ratio
<i>EM</i>	Energy Management
<i>EC</i>	Energy Consumption
<i>E<sub>r</sub></i>	Residual energy of a sensor node
<i>E<sub>threshold</sub></i>	Threshold energy of a sensor node
<i>E<sub>elec</sub></i>	The energy consumption of an amplifier to transmit or receive one bit
<i>ε<sub>fs</sub></i>	The energy cost of the amplifier to transmit one bit at one-hop
<i>ε<sub>mp</sub></i>	The energy cost of the amplifier to transmit one bit at multi-hop
<i>E<sub>i</sub></i>	Initial Energy
<i>LEACH</i>	Low Energy Adaptive Cluster Hierarch
<i>L</i>	Packet size
<i>MS</i>	Mobile Sink
<i>n</i>	Number of sensor nodes
<i>N<sub>br</sub>(i)</i>	One-hop neighbor set of any node <i>i</i>
<i>RPs</i>	Rendezvous Points
<i>RkM</i>	Reduced k-means
<i>SNs</i>	Sensor Nodes
<i>V<sub>n</sub></i>	Set of sensor nodes

$WSNs$	Wireless Sensor Networks
$x_i, y_i$	Location information of node $i$
$\delta$	Pause time of the mobile sink

## **CHAPTER 1. INTRODUCTION**

### **1.1 Introduction**

In an era dominated by the integration of persistent computing technologies, Wireless Sensor Networks (WSNs) emerge as a transformative paradigm, revolutionizing the environment of data acquisition, monitoring, and communication systems. WSNs are a specialized ad-hoc network class that employs autonomous sensors to collaboratively observe and transmit data across a targeted area. These networks find applications in diverse domains, spanning environmental monitoring, healthcare, industrial automation, and smart cities.

In the expanding landscape of Wireless Sensor Networks (WSNs), the pursuit of efficient Energy Management (EM) strategies is a fundamental imperative. As these networks find inescapable applications ranging from environmental monitoring to industrial automation, the need for prolonged operational lifetimes becomes paramount.

WSNs represent a nexus of interconnected nodes tasked with sensing, processing, and transmitting data in diverse environments. While these networks have demonstrated unparalleled utility, their effective deployment is contingent upon addressing the critical challenge of EM. The traditional LEACH protocol, a pioneering clustering algorithm, has long served as a cornerstone in mitigating energy consumption (EC) in WSNs. However, in the face of dynamic and unpredictable network conditions, adaptive, intelligent mechanisms are necessary to optimize energy utilization.

## **1.2 Evolution of Wireless Sensor Networks (WSNs)**

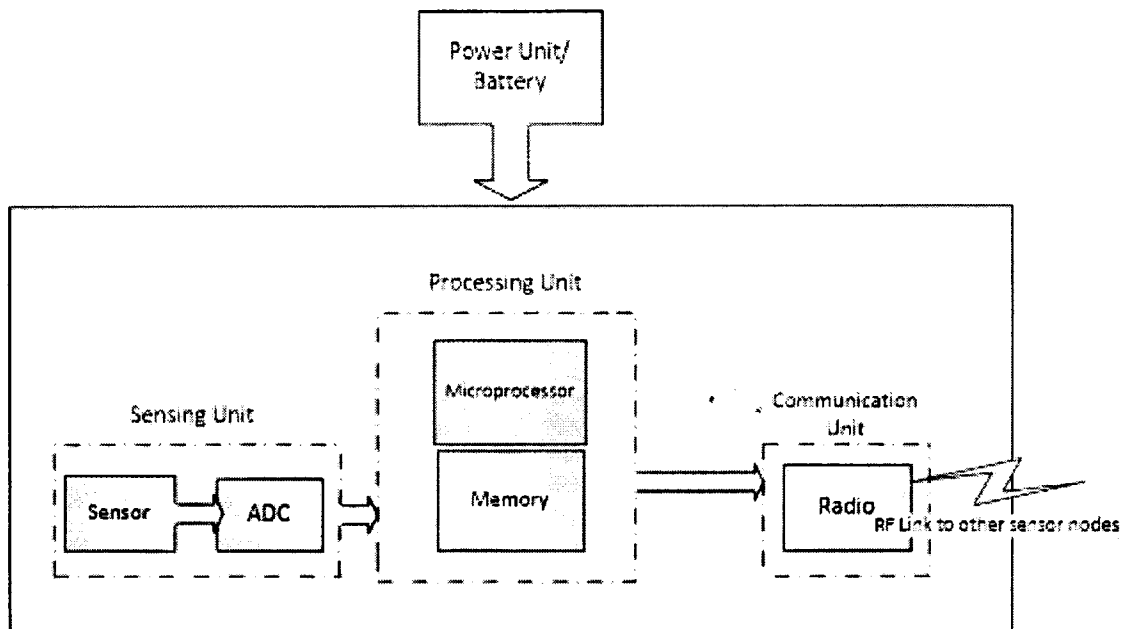
WSNs have emerged as a transformative paradigm in the landscape of information and communication technologies. The convergence of advancements in sensor technology, wireless communication protocols, and microelectronics has given rise to networks of autonomous, resource-constrained sensors capable of sensing, processing, and communicating data across diverse environments. WSNs find applications in numerous domains, ranging from environmental monitoring and healthcare to industrial automation and smart cities.

## **1.3 Structure of Sensor Node**

A typical sensor node comprises four main units: a sensing unit, a processing unit, a communication unit, and a power unit, as illustrated in Figure 1.1. The sensing unit detects specific areas using one or more electronic sensors connected to analog-to-digital converters (ADCs). These sensors monitor physical phenomena such as temperature, proximity, pressure, humidity, and seismic activity, generating analog signals. ADCs convert these analog signals into digital form, which are then collected by the processing unit.

The processing unit, equipped with a microcontroller or microprocessor, provides additional storage and utilizes various algorithms to manage sensor node coordination, configuration, medium access control, data routing, data aggregation, location, and network security. The communication unit uses a short-range radio for data transmission and reception via radio frequency links with other nodes. The power unit supplies energy to the sensor node, via a battery.

Additional devices may be integrated into the sensor node depending on specific application requirements. For instance, a global positioning system (GPS) unit can be added for location information. Sensor nodes may also be mounted on robots within a network to enhance functionality.



**Figure 1.1: Basic Sensor Node Layout**

These mounted nodes, or mobile nodes, navigate the network to perform tasks such as replacing failed nodes, fire extinguishing, collecting data from hostile areas, and gathering agricultural data. All components must be integrated into a compact, low-cost package, as high costs per sensor node make deploying large networks with hundreds of nodes financially impractical.

## **1.4 Key Characteristics of WSNs**

WSNs exhibit distinctive characteristics that differentiate them from traditional networks. Firstly, nodes in WSNs are typically resource-constrained in terms of processing power, memory, and, most critically, energy. This constraint demands the development of energy-efficient algorithms and communication protocols to extend the network's operational lifetime. Secondly, deploying nodes in WSNs is often in harsh and inaccessible environments, demanding robustness, self-organization, and adaptability to dynamic and unpredictable scenarios.

## **1.5 Application Domains of WSNs**

The versatility of WSNs manifests in a plethora of application domains:

### **1.5.1 Environmental Monitoring**

WSNs are employed for real-time monitoring of environmental parameters such as temperature, humidity, and pollution levels. These networks enable scientists to gather data on a large scale, facilitating a deeper understanding of climate patterns and ecological systems.

### **1.5.2 Healthcare**

In healthcare, WSNs contribute to the telemedicine paradigm by enabling continuous health monitoring, fall detection, and vital signs measurement. The seamless integration of sensors in wearable devices propels the development of personalized healthcare systems.

### **1.5.3 Industrial Automation**

WSNs play a pivotal role in industrial automation by providing real-time data on equipment health, facilitating predictive maintenance, and optimizing energy consumption. The implementation of Industry forces WSNs to create smart factories with enhanced efficiency and productivity.

### **1.5.4 Smart Cities**

The vision of smart cities relies heavily on WSNs to collect and analyze data pertaining to traffic flow, air quality, waste management, and other urban services. These networks form the backbone of intelligent urban planning and resource optimization.

## **1.6 Significance of Energy Management in WSNs**

The prevalent deployment of WSNs in remote and inaccessible environments, coupled with the inherent constraints on sensor node resources, underscores the critical importance of efficient energy management. The limited energy capacity of SNs poses a significant challenge to the prolonged operation and sustainability of WSNs. Unattended or inaccessible deployments necessitate that SNs operate on finite energy reserves for extended periods. Thus, the design and implementation of energy-efficient strategies become paramount for ensuring the longevity and effectiveness of WSNs.

This research holds significance in several dimensions. It contributes to the theoretical underpinnings of energy-efficient WSNs and offers logical insights applicable to real-world scenarios. By combining the robust clustering capabilities of LEACH with the predictive prowess of ANN, LEACH-D with ANN, Reduced k-means based on Artificial

Neural Network" (RkM-ANN) and "Delay Bound Reduced k-means with ANN" (DBRkM-ANN) for designing a fast, efficient, and most proficient MS path depending upon rendezvous points (RPs). This study ushers in a new era of self-adapting and intelligent WSNs, fostering sustainable and resilient networks.

### **1.7 Key Routing Issues and Challenges in Wireless Sensor Networks**

Developing a routing protocol in dynamic, energy-constrained networks is challenging. Various WSN characteristics influence the design. Key issues and challenges for WSN routing are discussed below:

- **Energy constraint:** Sensor Nodes (SNs) in Wireless Sensor Networks (WSNs) are powered by batteries, which impose significant energy limitations. A substantial amount of energy is consumed during data transmission, and additional energy is expended during route discovery and maintenance phases. The network's lifespan is directly linked to the total Energy Consumption (EC) by each node [1]. When a sensor node's energy falls below a critical threshold, it becomes nonfunctional, degrading network performance. Consequently, managing SN energy to maximize network longevity presents a substantial challenge for routing protocol designers.
- **Bandwidth constraint:** WSNs typically consist of numerous sensor nodes, complicating bandwidth allocation for each link. The route discovery and maintenance process necessitate broadcasting many control packets among SNs. Therefore, network bandwidth allocation depends on the number of links and their data transmission capacity [2].

- **Limited hardware constraint:** SNs are compact embedded devices with restricted processing and storage capacities. This necessitates the development of lightweight routing protocols that avoid complex computing procedures and functions, enabling efficient data processing and storage by the SNs [3].
- **Crowded center effect:** Data communication in WSNs follows a many-to-one pattern from source nodes to a sink. Each SN relays data to the sink via intermediate nodes in multi-hop environments. Nodes proximal to the sink handle a higher volume of data, thus consuming more energy and eventually depleting their power reserves. This phenomenon is known as the crowded center effect [4] or energy hole problem [5]. This leads to a partitioning between the sink and the source node in the network.
- **Node deployment:** Node deployment strategies vary depending on the application. Some scenarios necessitate structured deployment, while others require random deployment, often in hostile or unattended areas via aerial dispersal. The method of node deployment significantly impacts network performance [6].
- **Mobile node information:** Typically, SNs remain static post-deployment, but certain applications involve mobile nodes. Effective communication between mobile and static nodes necessitates accurate location tracking of mobile nodes. Additionally, some applications feature a mobile sink for data collection, requiring the routing protocol to inform nodes of the sink's location within the network [7].
- **Sensor node location:** Many applications, such as tracking, monitoring, and event detection, require precise geographical location information of SNs. Equipping each node with GPS is impractical [8]. Instead, nodes can determine their locations

using triangulation-based positioning and GPS-free methods. The routing protocol must facilitate location identification using these techniques [9, 10].

- **Scalability:** WSNs typically deploy many sensors within the target area, and the network size may expand during operation. The routing protocol must be designed to ensure node scalability does not adversely affect network performance [11].

In addition to these challenges, addressing energy constraints and mobile node information in WSNs is crucial. Detailed considerations for energy management and mobile sink management are outlined below.

### **1.7.1 Energy Management**

The routing protocol can employ various techniques to enhance energy efficiency and network longevity. Key energy management strategies include:

- **Energy model:** Implementing an accurate energy model for sensor nodes within the routing protocol can significantly enhance network performance [7]. A well-defined energy model provides precise estimates of the remaining energy in each node, facilitating straightforward monitoring and improving network lifetime.
- **Minimize the collision:** Ensuring data reaches the base station without interference is critical [2]. The routing protocol must guarantee that communication occurs in a congestion-free environment to avoid data retransmissions, negatively impacting the network's energy efficiency.
- **Minimize the control packet overhead:** Sensor nodes consume substantial energy during signal transmission [12]. Routing protocols must efficiently manage

neighbor information, route discovery, and maintenance by minimizing unnecessary control packet exchanges. Reducing control packet size can also decrease overall energy consumption.

- **Allow multi-hop communication:** Direct data transmission consumes more energy than multi-hop communication [13]. In direct transmission, nodes must maximize radio transmission power, increasing energy consumption. The routing protocol should facilitate multi-hop communication to improve energy efficiency.
- **Using the energy-aware MAC protocol:** SNs should switch to sleep mode when not sensing or routing to conserve energy [14]. An appropriate MAC protocol is essential for effective energy conservation in the network.
- **Load balancing:** In distributed environments, residual energy information is crucial. Using the energy model, each node calculates its residual energy [15]. The routing protocol must distribute workload efficiently, assigning more tasks to energy-rich nodes and reducing tasks for nodes with less residual energy, thereby enhancing energy efficiency.
- **Transmission range adjustment:** In WSNs, data often travels through intermediate nodes. During deployment, relay nodes are typically near the sender node. Adjusting transmission power based on the Received Signal Strength Indicator (RSSI) instead of using maximum power can reduce energy consumption and extend network lifetime [16]. This technique can reduce the EC and help to improve the network lifetime [17].
- **Data aggregation:** Aggregating similar data packets at specific points and sending aggregated data to the sink reduces network traffic [18]. This technique decreases

collisions and energy consumption, prolonging the network's lifespan [19]. Implementing data aggregation within the routing protocol is essential for maintaining network efficiency.

### **1.7.2 Sink Mobility Management**

Utilizing a mobile sink in Wireless Sensor Networks (WSNs) can reduce path length for data transfer, thereby decreasing latency and extending network lifetime. Additionally, it addresses the crowded center effect [4] or the energy hole problem [5]. However, incorporating a mobile sink (MS) increases the complexity of the routing protocol, as mobility introduces dynamic network conditions that differ from those applicable to static sinks. Sink mobility can be classified into the following categories:

1. **Controlled mobility:** This type of mobility follows a predefined schedule, where the next visit is determined based on the previous position and direction [20]. Controlled mobility can enhance network lifetime by impacting only specific network regions.
2. **Predictable mobility:** The position and timing of the sink's next visit are predefined, allowing source nodes to switch to sleep mode when the sink is outside their territory [21]. This predictability aids in energy conservation.
3. **Random mobility:** Unlike controlled mobility, random mobility does not rely on the previous location. Instead, it arbitrarily determines the next position and direction [21]. Managing random mobility is challenging as it affects a larger network area, preventing sensor nodes from switching to sleep mode and increasing energy consumption.

The choice of mobility pattern depends on the application to optimize energy efficiency. The routing protocol must manage sink mobility to minimize the affected area and reduce control packet flow. Additionally, involving a limited number of sensor nodes in sink management can enhance energy efficiency.

## **1.8 Motivation of the Research**

Wireless Sensor Networks (WSNs) are inherently multi-hop networks where data transmission relies on intermediate sensor nodes (SNs). The links between these SNs are prone to failure, which adversely affects the data delivery ratio and network reliability. This vulnerability underscores the critical need for robust routing techniques. As SNs are battery-powered, their energy resources are often irreplaceable in many applications. Once the energy is depleted, the SNs stop functioning, thereby compromising overall network performance. Consequently, designing energy-efficient routing techniques is imperative to prolong the network's lifespan and manage limited energy resources effectively.

One promising strategy to address energy consumption and latency in WSNs is the utilization of a mobile sink. By visiting a smaller number of nodes or pre-determined locations, known as rendezvous points (RPs), instead of all cluster heads (CHs), this approach can significantly reduce energy usage and delay. Additionally, employing weight functions and k-means clustering can enhance network efficiency and ensure comprehensive coverage. Furthermore, the introduction of the LEACH-D protocol, combined with Artificial Neural Networks (ANN), has the potential to improve the duration of transmission tasks. This methodology can ensure more uniform battery energy consumption across the network, thereby enhancing overall performance and reliability.

This research is driven by the need to develop advanced techniques that not only improve the reliability and efficiency of WSNs but also optimize energy consumption to extend the operational lifespan of the network.

## **1.9 Objectives of the Research**

To extend network longevity and optimize energy consumption (EC), implementing energy-efficient techniques within routing protocols is imperative. The objectives of this thesis are delineated as follows:

- i. Develop energy-efficient routing protocols to address limited energy resources in SNs.
- ii. Propose novel hybrid algorithms, for designing efficient MS paths based on RPs and utilize mobile sink (MS) strategies to mitigate EC through periodic network traversal.
- iii. Introduce another hybrid methodology, LEACH-D protocol paired with Artificial Neural Network (ANN), to address cluster distribution and CH rotation issues. Therefore, ensure balanced battery Energy Consumption (EC) and extend transmission work time through the LEACH-D algorithm and utilize ANN to optimize routing decisions, CH placement, and reduce idle listening, leading to substantial reductions in EC and extended network lifespan for WSNs.

## **1.10 Problem statement**

In WSNs, managing limited energy resources presents a significant challenge to ensuring efficient and reliable operation. SNs face constraints that necessitate strategies to mitigate EC issues. One effective approach to addressing these concerns involves utilizing a MS strategy, which involves periodic network traversal to reduce EC. Additionally, the

problem of multi-hop data collection with static sinks often results in high energy consumption within WSNs, further complicating the efficiency of data transmission.

Another challenge in WSNs is the issue of unequal cluster distribution, which arises from random CH rotation in traditional Low Energy Adaptive Cluster Hierarchy (LEACH) protocols. This randomness can lead to imbalanced energy consumption among nodes. To overcome this problem, a novel hybrid methodology combining the LEACH-D protocol with ANNs has been proposed. This approach addresses the issues of unbalanced battery energy consumption and inefficient CH rotation, effectively extending transmission work time and reducing idle listening, thereby enhancing the overall performance and longevity of the network.

### **1.11 Thesis Outlines**

The arrangement of the work presented in this thesis is as follows.

**Chapter 1** presents a conceptual outline of the whole thesis, consisting of background and motivation for problem identification and defining the Research Problem along with the Research Objectives and hypothesis.

**Chapter 2** provides a critical literature review, detailing the background and contemporary research, supported by reports and articles on relevant techniques and procedures.

**Chapter 3** details the research methodology, focusing on deploying a MS to address the issue of energy consumption via periodic network traversal. This study introduces two novel hybrid algorithms: "Reduced k-means based on Artificial Neural Network" (RkM-ANN) and "Delay Bound Reduced k-means with ANN" (DBRkM-ANN). These

algorithms are designed to optimize the MS path by determining rendezvous points (RPs) to enhance speed, efficiency, and overall performance.

**Chapter 4** explores methods for optimizing clustering tactics and energy-efficient routing protocols, which are covered in detail to improve the energy efficiency and operational lifetime of WSNs. This chapter presents a novel hybrid technique that combines an ANN with the LEACH-D protocol. The LEACH-D algorithm guarantees consistent battery EC while extending the duration of transmission activities. Simultaneously, the ANN plays a crucial role in coordinating the best routing choices and CH placement, which improves data aggregation and transmission procedures to reduce idle listening.

**Chapter 5** concludes the thesis by summarizing research outcomes, evaluating the achievement of objectives through comparative analysis with contemporary studies, and justifying the contribution. It suggests future research directions and enumerates publications resulting from this work.

## **CHAPTER 2. LITERATURE REVIEW**

### **2.1 Introduction**

Numerous researchers have made significant contributions to the development of routing protocols designed to optimize energy management in WSNs. This chapter gives a comprehensive review of the fundamental concept SNs, MS and routing protocols used for WSN. Mainly this chapter presents the critical reviews of the latest research work done in WSN along with their applications and shortcomings to different fields followed by a summary of the chapter at the end of the chapter.

### **2.2 Historical Background of WSNs**

The development of WSNs began in the 1950s with the US military's Sound Surveillance System (SOSUS), utilizing submerged acoustic sensors for seismic activity surveillance, some of which are still operational, explained by E. C. Whitman in [22]. In the 1980s, the Defense Advanced Research Projects Agency (DARPA) launched the Distributed Sensor Network (DSN) program to advance new technologies and protocols for sensor networks. Concurrently, the Advanced Research Projects Agency Network (ARPANET) initiated WSN research involving multiple institutions and industries explained in [14, 23]. In 1998, NASA's Sensor Web Project and Smart Dust Project furthered WSN development, aiming to create autonomous sensing and communication devices within a cubic millimeter. Early academic research in WSNs began around 1999 at institutions such as MIT, Berkeley, and the University of Southern California [6, 24].

### 2.3 Mobile Sink Mobility in WSNs

Several approaches aim to control MS mobility for effective data gathering in WSNs [25-29]. However, the management of MS mobility falls into two primary categories: random mobility [30] and controlled mobility [31]. While random mobility implementations are straightforward, they introduce unnecessary delays in data gathering [32]. In contrast, controlled mobility schemes establish the MS path based on predefined points or specific locations, often referred to as RPs explained by G. Xing *et al.*, [33]. In past studies researchers have encouraged planning a stationary MS path using RPs, with SNs randomly positioned in proximity to this path, as described in [34].

SNs are divided into two classes based on their proximity to the predefined path. The first class encompasses SNs within the communication range of the path, while the second class consists of the remaining SNs. SNs in the first class directly transmit data to the MS, while the second-class nodes relay their data through the first-class nodes. Nevertheless, these methods lack constraints on tour distance, rendering them unsuitable for delay-sensitive applications. In a study by Ghafoor *et al.* [35], the Hilbert curve was employed for designing an MS path in homogeneous WSNs. From this perspective, MS strictly approaches each SN, enabling one-hop communication for data gathering. However, this strategy results in a longer path, proving impractical for numerous critical applications.

The authors explain the method of multiple sinks following the predetermined routes in [36], but the MS tour length, which is critical for reducing data transmission latency, is neglected. Specifically for path establishment during MS path designing, in [37], H. Salarian *et al.*, present Weighted Rendezvous Planning (WRP), a delay-constrained technique, to address the issue. Based on the number of data packets provided and the SNs proximity to

the closest RP, WRP distributes weights to each node. However, the approach is not suited for large-scale Wireless Sensor Networks (WSNs) due to its significant time complexity of  $O(n^5)$ , where 'n' is the total number of sensor nodes. A Cluster-Based (CB) approach is proposed in [38] that uses binary search to find the minimal amount of RPs needed. In [39], authors discussed three mobile ad-hoc proactive and reactive routing protocols named DSDV, AODV and DSR, which work on the routing tables that are maintained at each node and find a route to a destination on demand whenever communication is needed but still carries complexity.

## 2.4 Energy-Efficient Protocols and Techniques

Efficient energy usage and network lifetime are the two main considerations in the design of WSN. Different research papers have been published on the improved performance of SNs in WSNs. To consider the transmission distance, transmission direction, and the role of ants in the search process, a method termed improved ACO-based routing is proposed in [40, 41]. However, this method is not suitable for in large-scale networks. An example of a routing strategy based on clusters that use type-2 fuzzy logic and an ACO algorithm presented by V. K. Alla and M. Mallikarjuna in [42] but still carries complexity. In order to preserve power, it is common practice to manage the power of SNs on a regular basis. G. Han *et al.*, In [43], introduced an adaptive duty cycling algorithm that considers data rates and traffic patterns to achieve maximum efficiency in terms of power usage. Nevertheless, duty cycling can introduce significant delays in data transmission. Comparable results in terms of energy savings were reported by Y. Liu *et al.*, in [44], who introduced a sleep scheduling method that dynamically modifies the sleep and active times

depending on network circumstances but this methodology can reduce the overall data throughput of the network.

## 2.5 Data Aggregation and Compression Techniques

Data aggregation methods collect sensor data at intermediate nodes and provide a consolidated set of measurements to the BS to cut down on unnecessary data transfer. However, nodes responsible for data aggregation might deplete their energy faster than other nodes, leading to uneven energy consumption and potential network partitioning. In order to optimize energy usage by lowering the quantity of sent data presented by R. Chéour *et al.*, in [45] devised a dynamic data aggregation method that responds to changes in network circumstances. In addition, A. M. Hussein *et al.*, in [46] presented a compression-based strategy using wavelet modification to shrink data, reducing EC in WSNs but still carries complexity issues. Optimization of energy use in WSNs using ML and Artificial Intelligence (AI) methods has shown promising results. The study described by C. Zhao *et al.*, in [47] addressed the ideas of energy-efficient cluster head rotation and energy-balanced unequal clustering. It provided in-depth theoretical derivation and mathematical calculations grounded in the gradient concept to ascertain the optimal number of CHs, to equitably distribute energy consumption across the entire network topology. Nonetheless, by using energy-efficient head rotation technique, frequent CH rotations can introduce delays, as the network needs to re-establish routes and update tables, impacting real-time data transmission while applying energy-balanced unequal clustering method has more complex cluster formation issue. Q. Ding *et al.*, In [48] addressed, a Machine Learning-based routing system was controlled that dynamically adapted the routing pathways to balance energy use based on past data on node energy consumption but still brings complexity. AI algorithms were proposed by S.-H. Choi and S.-J. Yoo in [49], to

intelligently regulate the transmission power and duty cycle of nodes in order to maximize the WSNs' energy efficiency. Energy efficiency may be greatly improved with the use of effective topology management and routing protocols. A distributed topology control approach was introduced by B. Chen et al., in [50] to lessen energy consumption by dynamically adjusting the transmission power of nodes in response to changes in the network. Nevertheless, lack of a central coordinator can lead to issues like redundant transmissions or inconsistent network states. To optimize energy usage and extend network lifespan, the authors in [51] suggested a hybrid routing protocol combining LEACH with Ant Colony Optimization but Integrating ACO with LEACH requires careful design to ensure compatibility and effectiveness. This integration can be complex and may require significant modifications to the existing LEACH protocol. Energy harvesting methods use renewable energy sources to power WSNs, decreasing their reliance on battery-operated nodes. In [52], D. Lin *et al.*, suggested the study to employ social welfare theory to facilitate energy equilibrium during the CH selection process. Systematic social theory controls the CH election, and the best CH was determined using Atkinson's Inequality Measure but contains complexity of social dynamics and scalability issues.

## **2.6 Optimization Strategies in WSNs**

Optimization of energy use in WSNs through topology control and routing protocols is crucial. However, these strategies often involve trade-offs between efficiency and complexity. To maximize energy utilization, S. M. Antony *et al.*, in [53] presented a solar energy harvesting strategy that intelligently regulates the charging and discharging cycles of the energy storage unit. However, solar energy availability fluctuates with weather conditions, time of day, and seasonal changes, leading to inconsistent energy supply. Energy-efficient communication was also suggested by B. Priya and S. S. Manohar in [54]

via adaptive power management, in which nodes' transmission powers are dynamically adjusted according to connection quality and energy levels. Nonetheless, implementing these algorithms can be complex and computationally intensive, which might be beyond the capabilities of resource-constrained sensor nodes.

Cross-layer optimization methods reduce power consumption by capitalizing on communications across levels of a protocol stack. To reduce power consumption, A. Kumar *et al.*, in [55], suggested a cross-layer optimization framework that considers settings in the physical layer, the medium access control (MAC) layer and the network layer. Their findings showed that energy efficiency and network performance might be significantly enhanced. However, the need for additional communication between layers to share information can introduce extra overhead, which may partially offset the power savings achieved through optimization. A comprehensive investigation into energy-efficient strategies for static WSNs devoid of energy harvesting module was presented D. Lin *et al.*, in [56]. The power requirements of WSNs are greatly influenced by their MAC protocols. Using dynamic duty cycling and adaptive contention window modification was presented in [57], authors developed a MAC protocol that conserves power by minimizing idle listening and collisions. A similar contention-based MAC strategy was introduced by R. S. Cotrim *et al.*, in [58] to improve power consumption by reducing overhearing and contention but these methods can lead to scalability issues, making it difficult to apply for large scale WSNs.

S. Wang *et al.*, suggested in [59], an algorithm combining the advantages of a compressive sensing-based (CS-based) approach and a clustering strategy. Lemmas addressing the relationships between adjacent layers, the best cluster size, and the best location of CHs were extensively investigated, along with the supporting proofs. While CS

reduces the amount of data that needs to be transmitted, the computational overhead associated with encoding and decoding data can lead to increased energy consumption.

Energy optimization is greatly supported by topology control and routing protocols, which choose CHs, distribute energy consumption evenly, and allow for decentralized data processing. Rather than relying only on battery-operated nodes, WSNs may be fueled by renewable energy sources via energy harvesting methods explained by M. F. Mysorewala *et al.*, in [60]. Transmission power is constantly adjusted, and energy utilization is optimized using power management methods that considers both the connection quality and the available energy. However, the initial cost of implementing energy harvesting systems and integrating them into WSNs can be high. Additionally, the complexity of designing and maintaining such systems can increase the overall system cost and complexity.

Trained node types categorize ANN applications in WSN energy optimization. Some transmit raw data for off-network processing at a gateway connected workstation, simplifying deployment presented by F. Aliyu *et al.*, in [61]. Alternatively, well-endowed BS is trained to centralize data processing, reducing setup complexity. In clustered networks, cluster heads are commonly trained to enable data aggregation, streamlining the transmission of ANN results to the BS but still carries scalability issues.

The researchers, for instance, apply ANNs in order to classify farm animals' various kinds of behavior, such as strolling, grazing, lying down, and standing. Data is collected via accelerometers on neck-attached sensor nodes for each animal, with raw data relayed to the BS and subsequently to a user's workstation for ANN-based categorization. This system makes real-time monitoring of the animal's behavior possible, making it simpler to identify sick animals and increasing farm output. Frequent data sampling generates a substantial volume of packets, resulting in notable energy overhead on sensor nodes. Furthermore,

animals that behave in groups generate exponential traffic at relay nodes, which increases energy usage as explained by E. S. Nadimi *et al.*, in [62].

In [63], H. Soliman *et al.*, introduced a WSN coupled with an ANN for early forest fire detection. The WSN gathered environmental data encompassing temperature, light, and smoke, transmitting it to a pre-trained ANN within the BS. Data aggregation techniques were omitted to avert potential data ambiguity and associated risks. The system exhibited a commendable accuracy rate of over 93% in classifying fire incidents within 20 seconds while effectively ascertaining fire growth direction. However, the 20-second detection timeframe, influenced by the inherently noisy sensor node data, poses challenges. Enhancing sensor accuracy would incur elevated energy consumption.

To enhance both the responsiveness and energy efficiency of forest fire detection systems, as outlined L. Yu *et al.*, in [64], a clustered WSN was proposed, leveraging in-network processing methodologies explained in [65, 66] to predict fire outbreaks. Within the structure mentioned above, sensor nodes systematically collect data, including wind speed, temperature, smoke, and relative humidity. Subsequently, this data is dispatched to their CHs. These CHs employ ANNs within cluster to compute a weather index based on the received data. The weather index is then transmitted to a manager node via the BS. Users can receive real-time assessments of the threat level of forest fires and emergency reports for unexpected occurrences from this manager node. In the WSN, in-network processing significantly reduces communication overhead and saves energy. Nevertheless, this approach necessitates specialized cluster heads capable of managing the heightened data traffic within the cluster, and undertaking the computationally intensive ANN calculations.

## 2.7 Advanced Techniques and Emerging Challenges

ML and AI algorithms are increasingly being integrated into WSNs for tasks like anomaly detection, predictive maintenance, and adaptive routing. These techniques can optimize data processing, improve decision-making, and enable dynamic network management. Implementing ML and AI in resource-constrained sensor nodes is challenging due to the high computational power and memory required. Additionally, training ML models on sensor data can be data-intensive, potentially leading to increased energy consumption.

The development of the Energy Efficient Clustering (GEEC) protocol is aided by the game model for Cluster Head selection that is provided D. Lin and Q. Wang in [67]. Energy balance and longer network lifetime are achieved using the GEEC routing system, also known as clustering, which uses the evolutionary game theory idea. To increase WSN energy efficiency through balanced and decreased energy usage, D. Lin and Q. Wang in [68] introduces an energy-efficient clustering technique. A lemma addressing the dual-cluster-head process, which significantly reduces energy consumption during CH rotation, is introduced in the work. However, this protocol may face challenges when applied to large-scale networks. As the network size increases, the overhead associated with cluster formation and maintenance can grow significantly, potentially leading to inefficiencies and reduced performance. Table 2.1 enumerates several other studies focused on the comparing clustering and routing methodologies in WSNs.

**Table 2.1:** Comparison of Prior Studies on WSN Clustering and Routing.

Ref. No.	Applied Method	Objective performance Aspect	Major Outcome	Research drawbacks
[38]	Periodic Rendezvous Data Collection (PRDC)	Enhancing the solution to the clustering problem through recursive optimization. Reducing the communication distance between SNs.	A productive outcome of each phase	It limits the mobile element's tour length.
[69]	Routing algorithm using Mobile Sink	Calculating the most optimal path in the network	Computation of each node's coordinates values in WSN.	The results analysis are not convincing
[70]	Data gathering	A new approach towards data collection	Data gathering using a mobile collector	Static sink utilization does not enhances energy efficiency.
[71]	Fuzzy C-Means (FCM) protocol	Determining the optimal number distribution of cluster heads (CHs)	Enhances the network lifetime relative to the LEACH algorithm	The analysis results are not convincing compared to other methods except LEACH.
[72]	Bee-Sensor-C algorithm	A multi-path routing algorithm	Reduced the routing overhead	Not much comparison is shown from other methods.
[73]	Data Collection using Drone Tour selection	A drone with mobility capabilities is utilized as a mobile sink (MS) for data gathering and routing in WSNs.	Optimal drone trajectory for data acquisition and routing in WSN.	efficient data communication is not efficiently achieved.
[74]	A directional transmission-based, energy-aware routing algorithm	Energy-efficient sensor information collection system and dynamic source routing (DSR) protocols.	Finding the most energy-efficient routes	efficient data communication is not efficiently achieved.

[75]	HSA and PSO-based technique	To leverage the high search efficiency of HSA and the dynamic optimization capabilities of PSO in wireless sensor networks (WSNs).	Prolonged the network's lifetime	The analysis is limited exclusively to the selection of cluster heads (CH), without consideration of factors such as energy consumption and end-to-end latency.
[76]	Selection of CH based on PSO	Developing an optimized particle encoding and fitness evaluation methodology.	The proposed CH selection algorithm utilizes the residual energy of the nodes and their distance to the sink as key parameters.	Efficient data communication is not efficiently achieved.
[77]	CRO based clustering and routing algorithms	Developing a solution to energy hole problem	Remaining energy, network longevity, active node count, data packets received by the base station (BS), and convergence rate.	Factors like End-to-End Delay and PDR are not considered
[78]	Cuckoo search-based clustering technique and harmony search-based routing	Proposing a solution for the energy-balanced clustering and routing of nodes.	Estimating the AEC, active node count, inactive node count, and network longevity.	End-to-End Delay and PDR are not missing
[79]	An algorithm for real-time data collection involving multiple sinks in WSNs.	To address the data gathering problem in WSNs	Identified the optimal location of the sink using an approximation method. ratio.	Cost increases because of using multiple sinks
[80]	EAPC algorithm	Establishing an optimal data aggregation route and identifying an appropriate data collection strategy.	Decreasing energy consumption, enhance the network lifetime.	End-to-End Delay and PDR are not missing

## 2.1 Summary

The chapter discusses various methods to manage MS mobility in WSNs, distinguishing between random and controlled mobility. While random mobility is simple, it can cause delays, whereas controlled mobility, including techniques like Weighted Rendezvous Planning (WRP), offers more precision but can be computationally intensive. Energy-efficient protocols are explored, including the use of Ant Colony Optimization (ACO) and adaptive duty cycling, though these methods often involve trade-offs like increased complexity or transmission delays.

The review also covers data aggregation and compression techniques to reduce energy consumption, as well as the application of ML and AI for optimizing WSN performance. However, these advanced techniques face challenges such as high computational demands and potential delays.

The chapter concludes by summarizing the need for cluster-based algorithms to enhance WSN efficiency. Despite significant progress, challenges like scalability and computational overhead remain, necessitating further research for more innovative and scalable solutions in WSN optimization.

## CHAPTER 3. EFFICIENT PATH SELECTION IN WSN'S WITH HYBRID ANN

### 3.1 Introduction

The MS strategy in WSNs reduces energy consumption and latency by visiting a minimal set of nodes or pre-defined RPs rather than all CHs. CHs then communicate packets to adjacent RPs. This study's innovation lies in optimizing the shortest path to reach RPs. The MS concept is increasingly recognized for mitigating energy consumption issues associated with static sinks in multi-hop data collection scenarios.

This chapter introduces a novel approach for analyzing the energy efficiency of SNs in WSNs. The study proposes two hybrid algorithms: "Reduced k-means based on Artificial Neural Network" (RkM-ANN) and "Delay Bound Reduced k-means with ANN" (DBRkM-ANN). These algorithms aim to rapidly and efficiently determine the optimal Multi-Sink path leveraging rendezvous points (RPs). RkM-ANN prioritizes minimizing latency in MS paths, while DBRkM-ANN focuses on designing paths adhering to specified delay bounds. Both methods employ a weight function and k-means clustering for RP selection to enhance efficiency and ensure comprehensive network coverage. Furthermore, the study introduces a method for efficient data collection via MS scheduling. Extensive simulations and comparisons with existing algorithms validate the superior performance of the proposed methodologies across various performance metrics.

The key contributions of the study are summarized as follows:

- This research recommended two novel hybrid energy-efficient algorithms, RkM-ANN and DBRkM-ANN, to improve the design of RPs paths for MS to have more efficient WSN with less latency and the design of delay-bound paths the MS
- A unique strategy for finding the shortest path to reach RPs has been explored in the study by applying TSP methodology to overcome the revisit constraints of SNs.
- This research work explores energy consumption, end-to-end delay and network lifetime of WSN, which mainly emphasizes the importance of solving these problems for its efficiency.
- The proposed approach are powerful and enhanced versions. It decreases the energy consumption of SNs and prolongs WSN's lifetime.

We have analyzed a homogeneous WSN configuration, where SNs are distributed randomly across the selected area. The Sink, or data collection point, has been supposed to navigate the target region at a consistent rate. The physical constraints in this study are as follows.

- a. After deployment, each node remains stationary and uniquely identifies by a distinct ID.
- b. Nodes exhibit homogenous communication and processing capabilities, but heterogeneous battery energy levels.
- c. Data aggregation has been employed, compressing multiple data points into a single packet.
- d. Nodes work under a control mode based on distance power, ensuring uniform operation.
- e. The initial energy of nodes varies and is not rechargeable.
- f. Communication links between nodes are symmetric, resulting in even energy consumption and data transmission rates between nodes.

We have made several additional assumptions for our study.

**Communication Conditions:** Nodes communicate with each other if they fall within their respective communication ranges. All communication occurs wirelessly.

**Stationary SNs:** Once deployed, the SNs remain fixed in their positions throughout their operational lifespan.

**MS Break Time:** MS Break Time is the time in which MS collects data from the designated RPs. In this study, we only assume that the MS break time is sufficient to effectively gather data from the SNs.

**Network Functionality:** The network is considered operational until a specific percentage of the total SNs have depleted their energy.

**Energy Model:** The same energy model as mentioned in [81] is adopted in this research. Furthermore, no data retransmission methodology is assumed, and the transmission speed along MS's path remains constant.

These assumptions have been the foundational framework for our analysis of WSN's behavior and performance under specific conditions.

### 3.2 Mathematical Modeling

In developing the algorithms, we have used the following specialized terminology.

**Center (CR):** This point provides the primary reference center within the selected area. The mean values of the x- and y-coordinates of the deployed SNs are used to determine their coordinates. The Equation of the mean  $x_{CR}$  is

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$$x_{CR} = \frac{1}{n} \sum_{i=1}^n x_i \quad 1(a)$$

The mean value  $y_{CR}$  of the y-coordinates is

$$y_{CR} = \frac{1}{n} \sum_{j=1}^n y_j \quad 1(b)$$

**Hop Distance ( $H_D$ ):** Hop distance indicates how far an RP is from its nearest neighbor ( $n_{h_i}$ ) over one hop.

**Average Hop Distance ( $A_{HD}$ ):** An RP's  $A_{HD}$  is calculated by averaging the hop distances of its nearest neighbors. The mathematical expression is given below.

$$A_{HD_i} = \frac{\sum_{j=1}^{|O_{HN_i}|} D(c_i, n_{h_{ij}})}{|O_{HN_i}|} \quad (2)$$

Where:

$A_{HD_i}$  represents the Average Hop Distance for node  $i$

$|O_{HN_i}|$  is the number of one-hop neighbors of node  $i$

$D(c_i, n_{h_{ij}})$  is the distance between the node  $i$  and its  $j_{th}$  one-hop neighbor  $n_{h_{ij}}$

**Desired Distance Range ( $D_{DR}$ ):** A decrease in network lifetime is caused by selecting a route for an MS that is too distant or too close to the center of the target region. As a result, the MS's route should be selected such that it is between the two extremes of the intended space. This distance is called the Desired Distance Range, which can be written mathematically as,

$$D_{DR} = \frac{\sum_{i=1}^l D(C_R, EP_i)}{2l} \quad (3)$$

Where,

$D_{DR}$  represents the Data Delivery Ratio

$C_R$  represents central reference point within the selected area.

$E_{P_i}$  is the  $i_{th}$  endpoint.

$D(C_R, E_{P_i})$  is the distance between a central reference point  $CR$  and the  $i_{th}$  endpoint  $E_{P_i}$ .

$l$  indicates the number of extreme points.

### 3.3 Suggested Algorithms:

To acquire the possible RPs positions across the designated region of interest, the k-means clustering algorithm [82] supported by the proposed ANN utilizing the deployed SNs spatial coordinates has been used in this proposed work. Subsequently, to optimize this initial set of potential RPs the optimization objectives are as follows:

- a. Practically ensure every SN can be accessed with the least hop distance possible using one-hop communication.
- b. The selection of RPs is such that it shouldn't be too distant from or extremely close to the center of the targeted area.

This methodology has been constructed on the utilization of a weight function, which has been formulated through the following procedure.

#### 3.3.1 K-Means Clustering Algorithm

This section explains the fundamental k-means clustering algorithm. Its objective is to partition a given dataset into a predetermined number,  $k$ , of non-overlapping clusters. The k-means algorithm is widely researched and often yields satisfactory clustering outcomes. However, its primary drawback lies in the sensitivity to initial centroid values, leading to

varied cluster formations. The algorithm's computational complexity is notable, scaling proportionally with the product of data items, clusters, and iterations.

The algorithm comprises two phases: firstly, defining  $k$  centroids, each corresponding to a cluster, and subsequently assigning each data point to the nearest centroid based on Euclidean distance. Upon completing the initial grouping, centroids are recalculated to accommodate potential shifts due to newly included points. This iterative process continues until centroids stabilize, indicating convergence.

### 3.3.2 Weight Function

A weight function,  $W_t(i)$  has been created by carefully considering several factors that determine whether the possible location is appropriate for a RP. The following is a description:

**i) One-Hop Neighbors to a Potential RP Position:** To achieve comprehensive coverage of all SNs while minimizing the count of RPs, each RP must covers a substantial number of neighboring SNs. Therefore,

$$W_t(i) \propto |O_{HN_i}| \quad (4)$$

**ii) Distance to Desired Distance Range ( $D_{DR}$ ):** Experimental observation reveals that augmenting the parting between RP and DDR correlates with a rise in hop counts. Therefore, prioritizing the reduction of this distance is imperative.

$$W_t(i) \propto \frac{1}{\text{mod}(D_{DR}-D(C_R, C_i))} \quad (5)$$

Where  $i = 1, 2, \dots, n$ .

$W_t(i)$  is the weight assigned to node  $i$  at time  $t$ .

$D(C_R, C_i)$  represents the distance or some metric between the central reference point  $CR$  and node  $c_i$ .

**iii) Average Hop Distance:** The energy consumed during the transmission of a data packet is directly linked to the transmission distance, following a power-law relationship where  $2 < \alpha < 4$ . Therefore,

$$W_t(i) \propto \frac{1}{A_{HD_i}} \quad (6)$$

where  $i = 1, 2 \dots n$ .

Relating all the parameters explained from equations. (4) to (6), we get

$$W_t(i) = Z * \frac{|O_{HN_i}|}{\text{mod}(D_{DR} - D(C_R, C_i)) * A_{HD_i}} \quad (7)$$

Where “Z” represents the proportionality constant, Considering  $Z=1$ . We got,

$$W_t(i) = \frac{|O_{HN_i}|}{\text{mod}(D_{DR} - D(C_R, C_i)) * A_{HD_i}} \quad (8)$$

It is essential to note that within the weight function  $W_t(i)$ , these parameters are interconnected, with each potentially influencing the others. This interdependency arises due to the variation of these parameters across different value ranges. Consequently, to facilitate a consistent assessment, we normalize each parameter within the range of 0 to 1, employing the following methodology.

$$O'_{HN_i} = \frac{|O_{HN_i}|}{\max(|O_{HN}|)} \quad (9)$$

$$A'_{HD_i} = \frac{|A_{HD_i}|}{\max(A_{HD}A_{HD})} \quad (10)$$

$$D'_{DR_i} = \frac{\text{mod}(D_{DR} - D(C_R, C_i))}{\max(\text{mod}(D_{DR} - D(C_R, C_j)))} \quad (11)$$

$$W_t(i) = \frac{O'_{HN_i}}{D'_{DR_i} * A'_{HD_i}} \quad (12)$$

### 3.3.3 Proposed Artificial Neural Network (ANN) Algorithm

One type of Artificial Intelligence is ML and ANN is a subfield of ML. The human brain's biological neural networks serve as the inspiration for ANNs, which are computer models. The "neurons" of an ANN are just like the nodes in a network, and they process and send data. Energy prediction, data analysis, and decision-making are just some of the many uses for ANNs, many of which are used in WSNs [83].

ANNs are made up of nodes that are interconnected, called neurons, and are arranged in layers. Each neuron processes inputs and produces an output using weighted connections and activation functions. Predictions are made based on the patterns and correlations they learn from trained data.

Two primary types of ANN learning approaches are called supervised and unsupervised [84]. In this research, supervised ANN learning architecture is applied on WSN as shown in figure 3.1. A total of five WSNs in which each network contains sixty-four SNs called clusters. Each cluster includes one CH node containing the highest energy level that collects information from all the other nodes and forwards it to the next CH node of another cluster network, and at the end final data is transferred to the BS, which is using the architecture of ANN as a single-layer feed-forward neural network containing three layers. First are the

input layers, second are one or more hidden layers and the third is the output layer on each cluster.

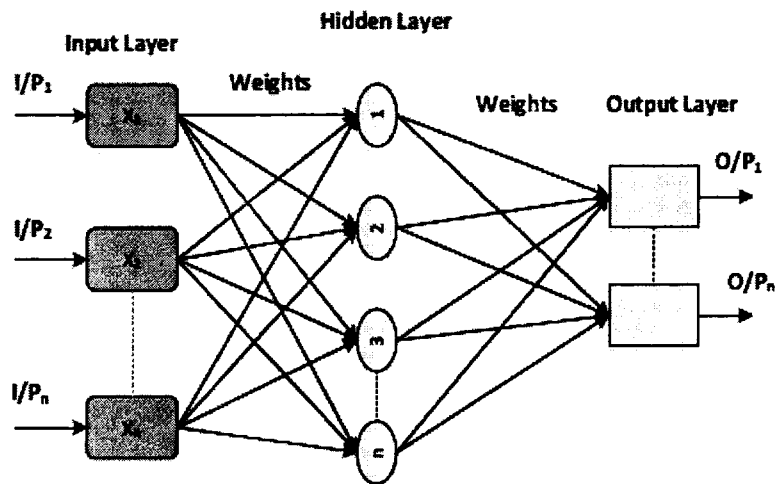


Figure 3.1: Supervised learning ANN Architecture.

### 3.3.3.1 Mathematical Modeling of ANNs

The mathematical equations governing the functioning of a feed-forward neural network can be described as follows:

#### *Input Layer:*

The input layer, also called Layer 1, consists of input features denoted as  $x_i$  (where  $i = 1, 2, \dots, n$ ). The input layer has  $n$  neurons, each representing one feature. The output of the  $i$ th neuron in the input layer (denoted as  $a_i^{(0)}$ ) is just the input feature itself. In this case, we have considered a **hundred** input layers and **sixty-four** neurons per layer.

**Hidden Layer:**

The hidden layer consists of  $m$  neurons, where  $m$  is the number of hidden units. Each neuron in this layer takes inputs from the input layer and produces an output using weighted connections ( $w_i^{(1j)}$ ) and an activation function ( $g$ ). The output of the  $j$ <sup>th</sup> neuron in the hidden layer ( $a_j^{(1)}$ ) is calculated as follows:

$$a_j^{(1)} = g(\sum_{i=1}^n (w_i^{(1j)} * a_i^{(0)} + b_j^{(1)})) \quad (13)$$

where:

$w_i^{(1j)} * a_i^{(0)} + b_j^{(1)}$  is the output of the  $j$ <sup>th</sup> neuron in the hidden layer.

$w_i^{(1j)}$  is the weight connecting the  $i$ <sup>th</sup> input feature to the  $j$ <sup>th</sup> neuron in the hidden layer.

$a_i^{(0)}$  is the output of the  $i$ <sup>th</sup> neuron in the input layer.

$b_j^{(1)}$  is the bias term for the  $j$ <sup>th</sup> neuron in the hidden layer.

**Output Layer:**

Layer 3, indicated as the output layer, comprises  $k$  neurons, where  $k$  indicates the number of output classes or regression outputs. Analogous to the hidden layer, each neuron within the output layer takes inputs from Layer 1 and produces an output utilizing weighted connections ( $w_j^{(2k)}$ ) and an activation function ( $g$ )

The ending result of the  $k$ <sup>th</sup> neuron in the output layer ( $y_s$ ) is calculated as follows:

$$y_s = h(\sum_{j=1}^m (w_j^{(2s)} * a_j^{(1)} + b_s^{(2)})) \quad (14)$$

where:

$y_s$  stands for the output of the  $k$ th neuron in the output layer (which represents the final anticipated outcome of the neural network's output layer.).

$w_j^{(2s)}$  shows the weight that connects the  $j$ th neuron in the hidden layer to the  $k$ th neuron in the output layer.

$a_j^{(1)}$  denotes the output of the  $j$ -th neuron in the hidden layer.

$b_s^{(2)}$  represents the bias term associated with the  $k$ -th neuron in the output layer.

$g$  shows the activation function applied element-wise to the weighted sum of inputs and biases.

The overall processing of forward propagation through the neural network involves calculating the output of each layer, in which the working input layer is initialized and proceeds through the hidden layer(s) to the output layer. The expected output result ( $y_s$ ) is then compared to the actual output during the training process to compute the loss, weights and biases are updated using an optimization algorithm to lessen the loss and increase the network's performance. This is known as back-propagation, and it is used to adjust the network's parameters iteratively during training to learn meaningful representations and make accurate predictions.

### ***Neuron Activation***

The activation of a neuron in an ANN can be calculated using an activation function and, in this study, we used the sigmoid function:

$$Activation = \frac{1}{1 + e^{-z}} \quad (15)$$

Here,  $z$  represents the weighted sum of inputs to the neuron.

WSNs often utilize AI algorithms for routing to optimize data transmission, reduce energy consumption, and improve network efficiency. This research uses ANN as an AI-based routing algorithm for WSNs. ANNs are part of the broader category of machine learning algorithms and are used in WSNs for routing by employing them as intelligent decision-making components to determine the most suitable routing paths based on network conditions.

In this dissertation, following scheme has been adopted to use ANN algorithms for WSN routing:

**1. Data Collection and Feature Extraction:**

We gather WSN data, including network topology, node status, node locations, energy levels, signal strengths, and historical routing data. After that, we preprocess and transform the data into a format suitable for input to the ANN.

**2. Applied Supervised Learning method:**

In this research we used a supervised learning setup, labeling the data instances with the desired routing outcomes. These labels represent the optimal routing paths or strategies.

**3. Data Preprocessing:**

Preprocess the data and then feeding into the ANN. This involved scaling features, handling missing data, and splitting the data into training and testing sets.

**4. ANN Architecture Design:**

A total of **one hundred** input layers have been used in this work, and then the number of neurons in each layer is initially considered as **sixty-four**, and sigmoid is the choice of the activation function.

The input layer typically receives data on network conditions, and the output layer provides routing decisions. The intermediate hidden layers process this information.

#### **5. Training the ANN:**

Train the ANN using the labeled data. During training, the network adjusts its internal parameters (weights and biases) using equations 13 and 14 to minimize the error between predicted routing paths and the labeled paths. The network learns to make routing decisions based on the input data and the labeled outcomes.

#### **6. Routing Decision:**

When a data packet needs to be transmitted from a source node to a destination node, the trained ANN is used to make a routing decision. Input to the ANN includes current network conditions, such as node locations energy levels.

The output of the ANN is a routing decision, specifying the next hop or set of nodes through which the data packet should be forwarded.

#### **7. Data Transmission:**

The data packet is transmitted through the nodes determined by the ANN's routing decision.

#### **8. Feedback and Learning:**

After data transmission, the ANN receives feedback on the success or failure of the routing decision. This feedback is used to update the ANN's parameters during online learning, further refining its routing decision-making capability.

---

## **Algorithm 1: Artificial Neural Networks (ANNs) for Energy Optimization**

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### **Step 1: Training the ANN Model**

- i. *Collecting a dataset of sensor node which are the inputs of ANN includes location, remaining energy, distance to the Base Station, and their corresponding energy consumption.*
- ii. *Preprocess the dataset by normalizing the input attributes.*
- iii. *Design the architecture of the ANN model, specifying the number of layers as 100 and neurons per layer as 64.*
- iv. *Assign the **sigmoid** activation function to the neurons within each layer using equation. (15)*
- v. *Split the dataset into two distinct sets: a training set and a testing set.*
- vi. *Train the ANN model using the training set, adjusting the weights and biases through back-propagation and gradient descent optimization.*
- vii. *Evaluate the trained ANN model using the testing set and measure its performance metrics (e.g., accuracy, mean squared error, etc.).*

### **Step 2: Energy Prediction and Optimization**

- i. *Deploy the trained ANN model to each sensor network.*
- ii. *Each sensor node periodically measures its attributes (such as remaining energy, distance to the base station, etc.).*
- iii. *Input the measured attributes into the ANN model to predict energy consumption.*
- iv. *If the predicted energy consumption is above a threshold, then perform energy optimization techniques, such as reducing transmission power, adjusting sleep/wake schedules.*
- v. *Implement the energy optimization techniques and update the node's energy consumption accordingly.*

### **Step 3: Repeat**

*Repeat Steps 2 and 3 periodically or whenever necessary.*

### **Outputs of ANN:**

*Optimal Cluster Heads*

*Efficient Routing Paths*

---

The proposed ANN architecture system was trained based on the energy consumption and delay of the nodes. We have pre-trained the ANN model based on a data set that includes the total number of nodes in the network, which is three hundred, the initial energy of each sensor node and intra-node distance and each node's threshold energy. Figure 4.2 shows the trained structure of ANN with Mean Square Error (MSE). If a node's communication energy delay falls below the specified threshold, it is considered a failed node. The system then selects a nearby node as a replacement communication node, integrating it into the communication path. Among the 64 contributing neurons, representing node properties such as energy and delay, inputs are given into the ANN's input layer. With a hidden layer comprising ten neurons, optimal performance was achieved. The output layer comprises 56 neurons, indicating eight failed nodes out of the original 64, demanding removal from the network. This approach saves node energy, thereby extending the network lifespan.

The degree of node density includes both sparse and dense in a WSN critically influences the performance of algorithms. Sparse networks challenge algorithms with connectivity and energy efficiency issues, requiring more complex solutions. Dense networks offer better connectivity and potential energy savings but introduce challenges like interference and overhead management.

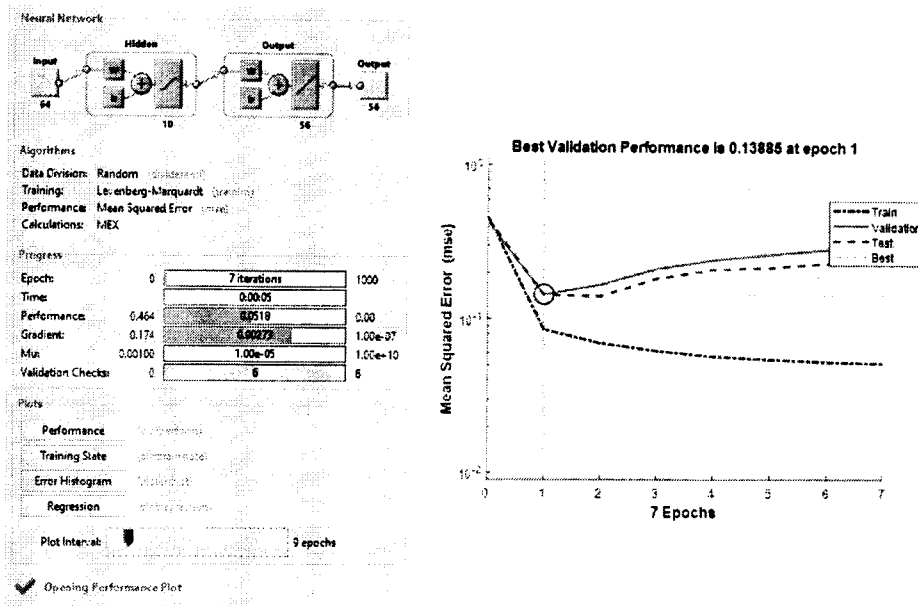


Figure 3.2: Trained ANN Structure I.

### 3.3.4 Proposed RkM-ANN Algorithm

The initializing of the set of potential positions for RPs, denoted as  $C$ , was done through k-means clustering algorithm using ANN. Subsequently, our primary objective is to minimize the count of potential RP positions while ensuring the coverage of every SN within a single hop communication range, thus optimizing hop distance and conserving energy.

To achieve this, we have employed the Reduced k-means hybrid with the ANN (RkM-ANN) algorithm, which operates as follows:

- During the iteration process of RkM-ANN, we systematically eliminate any potential RP position that covers at most one SN. This strategic elimination is geared toward energy conservation.
- Next, we calculate the weight of the remaining potential RP positions, subsequently selecting the one with the highest weight value.
- The chosen RP and all SNs covered by it, is then removed from consideration.

- d. This iterative process continues until the set C becomes empty.
- e. After the creation of the final set of RP placements, we used Christofides's heuristic to support the proposed method using the Traveling Salesman Problem (TSP) [41] algorithm to find the best route for the Mobile Sink (MS).

---

**Algorithm 2:** Proposed RkM-ANN Algorithm for RP Selection and Path Calculation for Mobile Sink (MS)

---

**Input:**

- *S* (Set of Sensor Nodes)
- *CTR* (Cluster Head to Threshold Rendezvous Point distance)
- *OHN* (One-Hop Neighbor Count Threshold)
- *MDD* (Maximum Desired Distance)
- *AHD* (Average Hop Distance)
- *k* (Number of Rendezvous Points to Select)
- Threshold level for each node (40%)

**Output:** Set of Rendezvous Points (RP's) and Path for the Mobile Sink (MS)

**Initialization:**

Initialize RP as an empty set:  $RP = \phi$

**Step 1:** Cluster Sensor Nodes and Initialize Rendezvous Points

Initialize set C for potential RP positions by k-means clustering using ANN with input parameters (*S*, *k*).

**Step 2:** Rendezvous Point Selection Loop

Start a loop:

For each candidate RP position  $c_i$  in set C:

*Check if the indegree (number of connected nodes) of  $c_i$  is less than 1.*

*If true, remove  $c_i$  from set  $C$ .*

**Step 3: Check for Termination**

*If the size of set  $C$  becomes 0, exit the loop.*

**Step 4: Weight Computation and Selection**

*For each remaining candidate RP position  $c_i$  in set  $C$ :*

*Compute the weight  $W_t(i)$  using equation 12.*

**Step 5: RP Selection and Data Removal**

*Select the candidate  $c_i$  with the maximum weight from set  $C$ .*

*Add  $c_i$  to the RP set:  $RP = RP \cup c_i$*

*Remove the selected  $c_i$  from set  $C$ .*

*Remove every Sensor Node (SN) covered by  $c_i$  from set  $S$ .*

**Step 6: Traveling Salesman Path Calculation**

*After the loop concludes, call the Traveling Salesperson Problem (TSP) algorithm on set  $RP$  to obtain the optimal path for the Mobile Sink (MS).*

*End of Algorithm*

---

Using TSP, this algorithm determines the best possible route for the MS by continually selecting Rendezvous Points from a candidate set according to specified criteria.

RkM-ANN establishes one-hop communication for equal SNs distribution. Simulation results indicate that 96% of SNs lie within a one-hop distance of the selected RPs, even in unequal deployments. The remaining 4% of SNs achieve RP connectivity within 2 or 3 hops

through intermediary SNs. While RkM-ANN confirms energy-efficient Mobile Sink path formation, it lacks a guarantee for data delivery within a specified delay, a critical constraint for real-time applications. This constraint is addressed by the subsequent DBRkM-ANN algorithm, detailed below.

### 3.3.5 Proposed DBRkM-ANN Algorithm

The key objective of the proposed hybrid model is to search for a minimized set of RPs that allow the MS to gather information efficiently within a sufficient latency, reducing hop counts and distances for energy management. Similar to RkM-ANN, DBRkM-ANN begins with a k-means clustering with an ANN predefined set of potential RP positions. The algorithm initializes an empty set of RP and iteratively chooses a potential RP position with the largest weight to add to the set. Afterward, the Traveling Salesman Problem (TSP) algorithm [41] determines the shortest path. The algorithm iterates until the path length crosses the predefined delay limit. The pseudocode for this approach is presented below.

---

#### Algorithm 3: Proposed DBRkM-ANN

---

##### ***Input Parameters:***

- *S*: Set of sensor nodes (SNs)
- *CR*: Communication range
- *OHN*: One-hop neighbors
- *MDD*: Maximum Delay Duration
- *AHD*: Average Hop Distance
- *k*: Number of Rendezvous Points (RPs)

##### ***Output:***

- Set of RPs (RP)
- Path for Mobile Sink (MS)

##### ***Pseudocode:***

- i. Set  $RP$  as an empty set.
- ii. Apply hybrid model of  $k$ -means clustering ( $S, k$ ) using ANN to generate an initial set of potential  $RP$  positions and store it in  $C$ .
- iii. While the tourcost (path length)  $< D$

*Loop through each potential  $RP$  position ( $c_i$ ) in  $C$ :*

*If the indegree ( $c_i$ )  $< 1$*

*Eliminate  $c_i$  from  $C$ .*

*End If*

*End Loop*

*Loop through each remaining potential  $RP$  position ( $c_i$ ) in  $C$ :*

*Compute the weight of  $c_i$  using Equation 12 ( $W_i(i)$ ).*

*End Loop*

*Extract the potential  $RP$  position ( $c_i$ ) with the maximum weight from  $C$  and add it to  $RP$  ( $RP = RP \cup c_i$ ).*

*Remove the selected  $c_i$  from  $C$ .*

*Remove all SNs from  $S$  that are covered by the selected  $c_i$ .*

*If the size of  $RP$  is greater than 1:*

*Calculate the tourcost using the Traveling Salesman Problem (TSP) algorithm with nodes in  $RP$ .*

*End If*

*End While*

This procedure initiates an empty set of RPs and generates an initial set of possible RP places using  $k$ -means clustering using ANN.

Based on specified requirements, continuously picks possible RP places, calculates their weights, and adds them to the RP set. SNs covered by selected RPs are removed from the SN set  $S$ .

The algorithm executes until the tourcost (path length) exceeds its maximum delay duration (MDD).

Furthermore, using the nodes in RP, the TSP method is used to determine the MS path.

Note: The following pseudocode is based on the availability of specific functions (e.g., TSP, Equation 12, and indegree).

### **3.3.6 Proposed data gathering scheme**

The MS chooses a destination RP for each SN based on its corresponding distances after selecting the RPs. The decision of the nearest RP for each SN is important in order to ensure uniform energy distribution across the network. Following this assignment, MS initiates the broadcast Information Packet for the Rendezvous Points (IPR) to the whole network, encapsulating crucial information.

Upon reception of the IPR, SNs take its contents to establish their respective destination RP. With this information in hand, all SNs are now ready to transmit data to their designated RPs. The data gathering period is organized into different rounds, each involving the MS's traversal of the selected area to collect information. The MS sequentially visits the selected RPs for data retrieval from the SNs.

When SN falls within the communication range of its designated RP, it directly forwards its data to the MS. Conversely, if the distance is required, the SN utilizes its nearest SN as a

relay to facilitate data transmission to the RP. The MS approaches a specific RP and issues a polling message, denoting the RP's identifier. SNs intend to transmit data through when the data arrives at the RP, which then processes the received data and sends it to MS.

This process will continue until MS has successfully collected information from all the SNs assigned to each RP; then, it moves on to the next RP. Each SN is only responsible for saving its data using its buffer, which is one of the main advantages of suggested techniques. In comparison, information is kept in Data Storing Nodes (DSNs) that are one hop away from the RP in the traditional data collection architecture [85]. With the second approach, nodes two or more hops distant from DSNs have to relay their data to them, which enhances the possibility of data overflow, leading to data loss and retransmission.

### 3.3.7 Traveling Salesman Problem (TSP) Mechanism

The TSP involves the returning mechanism of a salesman looking for the smallest route to find food from specified cities and then returning to their initial city. For mathematical representation, one can use the entire weighted graph  $G = (N, A)$ , where  $N$  shows the number of nodes that stand for cities and  $A$  is the set of arcs that connect with  $N$ . The length of each arc, denoted by the symbol  $d_{xy}$ , is measured in units of this kind  $(x; y)$ . TSP involves determining the minimum possible Euclidean distance between any two nodes in the graph  $G$ . With symmetric TSPs, the distance between any two cities called nodes, denoted by  $d_{xy}$ , is equal to  $d_{yx}$  regardless of which way the arcs are traversed.

### 3.4 Experimental Results:

**Table 3.1: Simulation Parameters**

Simulation Parameters	Values
Area	200x200 m <sup>2</sup>
$E_l$ (Initial Energy)	3 J
Number of nodes (N)	300
$E_{elec}$ (Energy Consumption)	100nJ/bit
$E_{amp}$ (Multi-path model of transmitter amplifier)	0.001301pJ/bit/m <sup>4</sup>
$E_{fs}$ (Free space model of transmitter amplifier)	12pJ/bit/m <sup>2</sup>
The communication range of each SN	30-200m
D (Distance)	600m
L (Packet size)	5000 bits

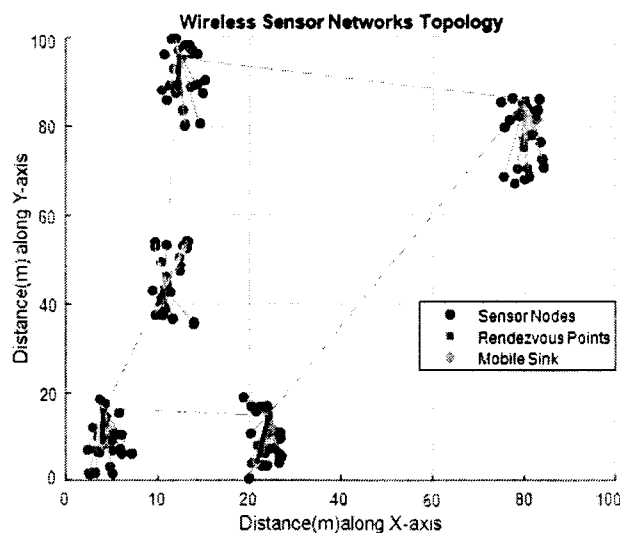
The proposed algorithms have been carefully evaluated through simulations conducted on MATLAB software (R2021a version) on Windows 8.1. The system employed for these simulations was equipped with 8 GB of RAM and featured a processor running at 2.5 GHz, housing an Intel Core *i-7* CPU. The assessment of these algorithms encompassed a range of network scenarios achieved by varying the number of SNs across a target area measuring 200 x 200 square meters (m<sup>2</sup>). Each SN was initially endowed with 3 Joules (J) of energy, and no energy limitations were imposed on the MS. The MS was assumed to move at a velocity of 4 m/s. The parameters investigated in this study are mentioned in Table 3.1. In our analysis, we have compared the RkM-ANN algorithm with a technique that generates  $q$  RP positions directly using straightforward k-means clustering using ANN, the traditional RkM [86] and K-means based algorithms, Region based Hierarchical Clustering for Efficient Routing (RH CER) [87] and Extended Multi-sink Placement and Anycast Routing (EMPAR) [88]. Furthermore, DBRkM-ANN was have compared with four existing

algorithms, namely the traditional DBRkM [86] technique, Weighted Rendezvous Planning (WRP) [37], location and energy-aware k-means clustered routing [89] and dual cluster-head energy-efficient algorithm [90].

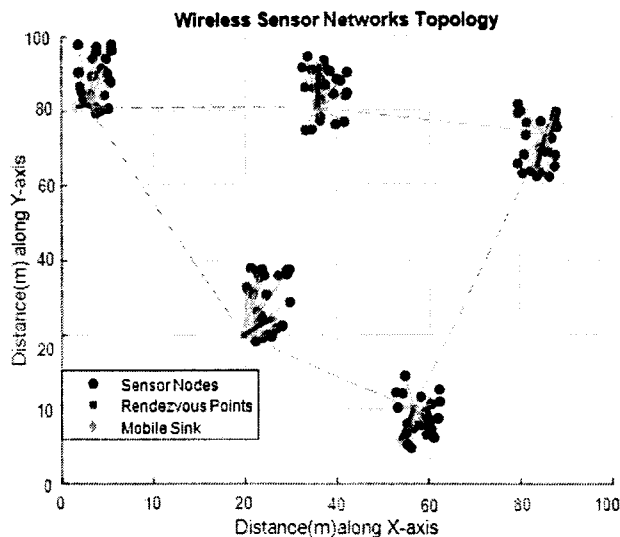
The results of these simulations were subjected to a comprehensive evaluation utilizing multiple performance metrics:

### 3.4.1 Result and Analysis of RkM-ANN

Figures 3.3 and 3.4 show the runtime scenarios of both the k-means-based ANN and RkM-ANN approaches. These scenarios were generated using a network configuration consisting of 20 SNs with a communication range denoted as "r" equal to 50 meters (m). In the graphical representations, the data broadcast pathways by the SNs convey their detected data to the RPs are mentioned with the green lines, while the purple dash line illustrates the trajectory of the MS to the RPs and the purple lines represent the connection path between the WSNs. It's important to note that this runtime scenario is visualized within a target area measuring 100 by 100 square meters ( $m^2$ ).



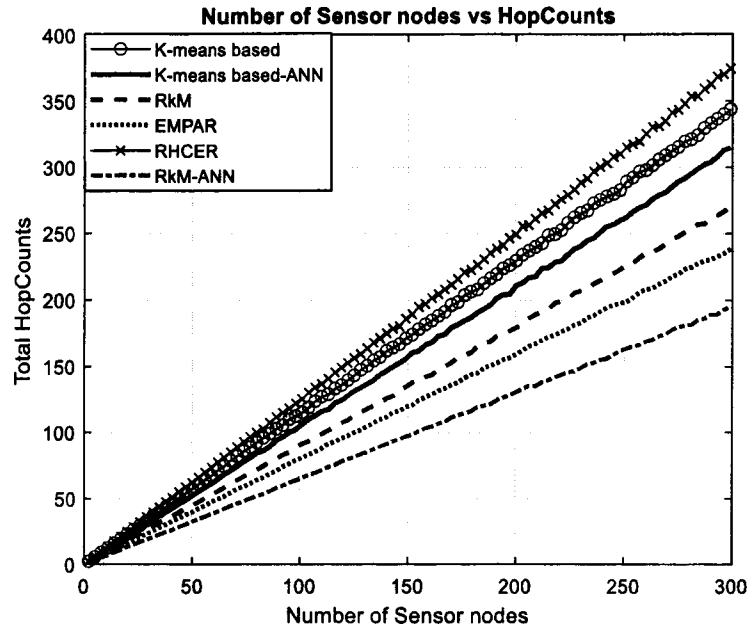
**Figure 3.3:** Experimental Scenario of k-means based-ANN Approach



**Figure 3.4:** Experimental Scenario of the RkM-ANN Approach

#### 3.4.1.1 Analysis of Hop Counts:

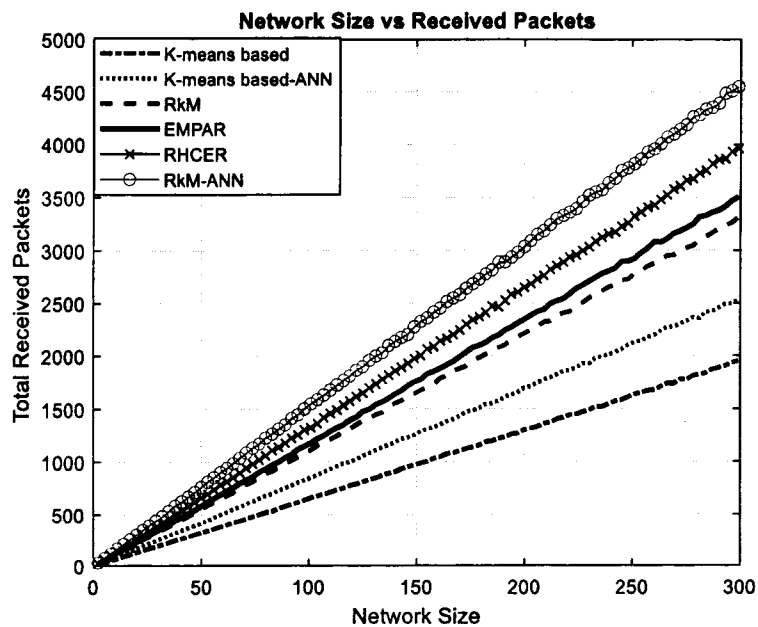
Figure 3.5 represents the performance analysis of total hop counts under varying node densities for the clustering techniques of K-means based, proposed K-means based-ANN, Reduced k-means (RkM), and proposed Reduced k-means with ANN (RkM-ANN). The figure vividly illustrates that approximately 96% of SNs are protected by designated RPs. This outcome is attributed to the algorithm's avoidance of RP placements covering only a single SN, resulting in about 4% of SNs communicating with MS through intermediary SNs. Notably, the total hop counts are significantly reduced compared to the simple k-means based approach with the proposed k-means-based-ANN algorithm model. In another proposed technique, RkM-ANN, potential RP positions with a higher number of one-hop neighbors are prioritized compared to the simple RkM approach.



**Figure 3.5:** Number of Sensor Nodes vs Number of Hope Counts

### 3.4.1.2 Analysis of Packets Received to BS:

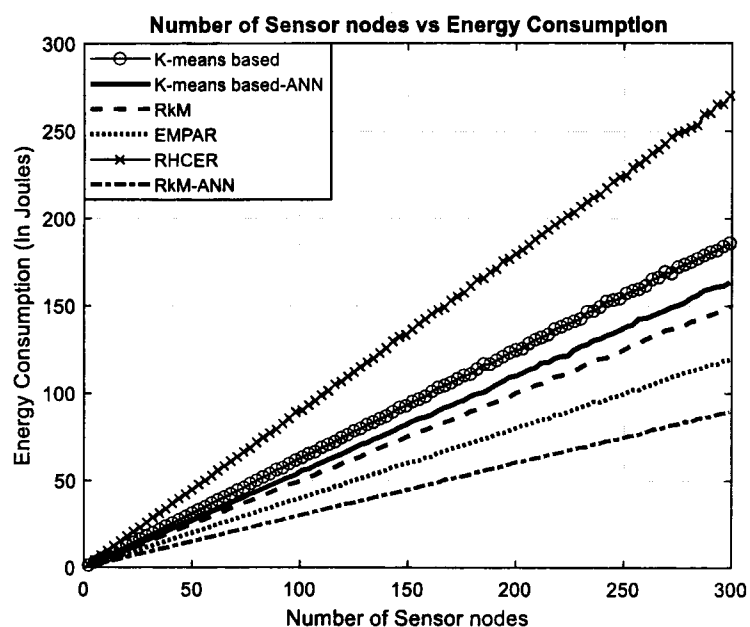
Figure 3.6 presents the total received packets to the BS, demonstrating that RkM-ANN outperforms the k-means based and k-means based-ANN and traditional RkM approach.



**Figure 3.6:** Network Size vs Received Packets

### 3.4.1.3 Analysis of Energy Consumption:

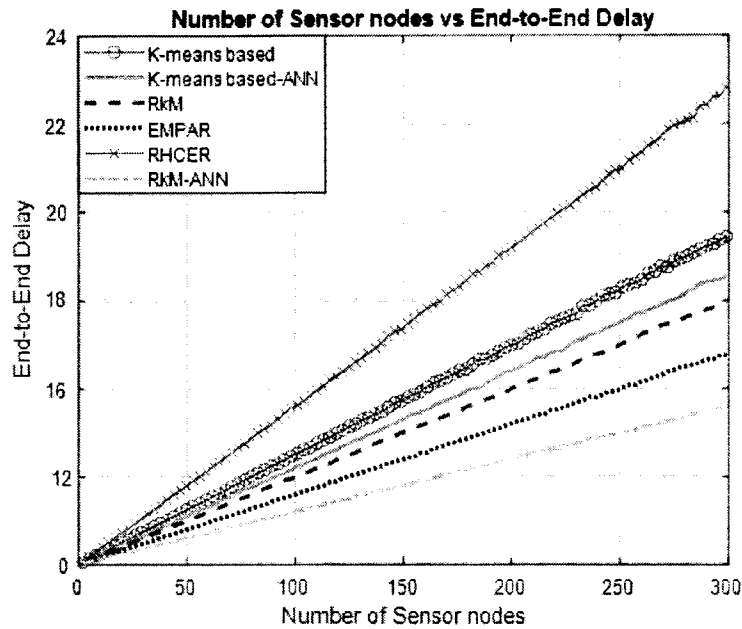
Figure 3.7 showcases the algorithms' performance in terms of energy consumption over various data collection rounds. Remarkably, RkM-ANN exhibits lower energy consumption than the RkM approach compared to the k-means-based and k-means-based-ANN approach.



**Figure 3.7:** Number of Sensor Nodes vs Energy Consumption

### 3.4.1.4 Analysis of End-to-End delay:

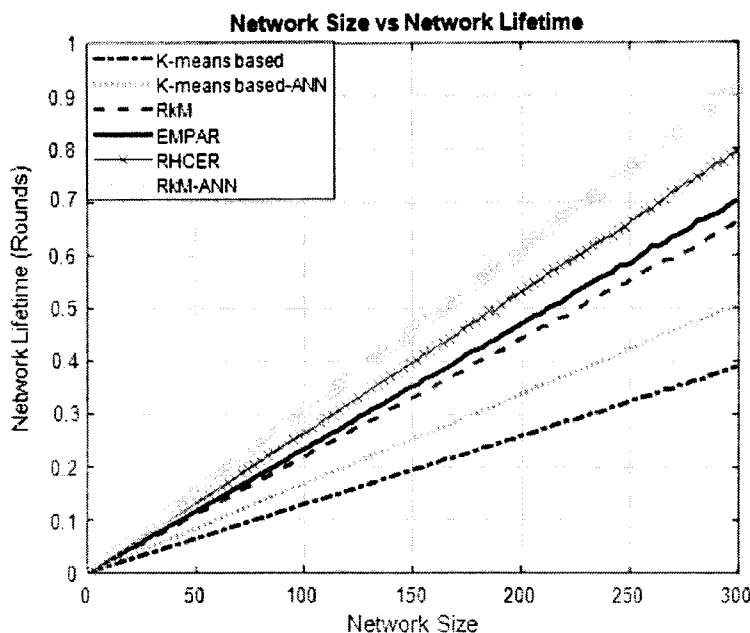
Figure 3.8 compares RkM-ANN, RkM, k-means based and k-means based-ANN concerning the total number of End-to-End delays. RkM-ANN outperforms the other three algorithms. This superiority can be attributed to the usefulness of the suggested weight function, which strongly emphasizes the reduction of End-to-End delay by choosing potential RPs with the highest in-degree.



**Figure 3.8:** Number of Sensor Nodes vs End-to-End Delay

#### 3.4.1.5 Network Lifetime:

The proposed technique intensely increased the network lifetime under varying node densities through the weight function. The program optimized the routing patterns based on the expected energy consumption, leading to effective data transfer. This was achieved with the use of the RkM-ANN algorithm. This enhancement provided consistent data collection and decreased network-wide data loss. Figure 3.9 represents the graphical analysis of Network Size vs Network Lifetime.



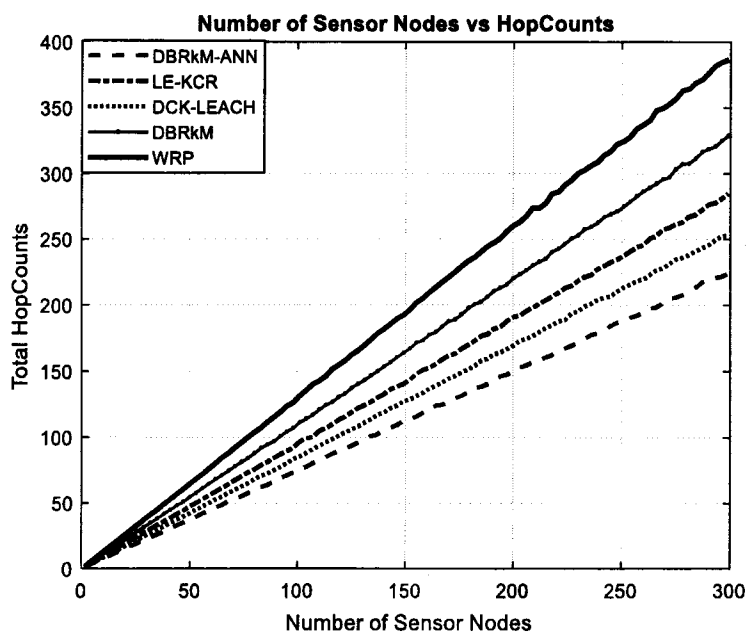
**Figure 3.9:** Network Size vs Network Lifetime

### 3.4.2 Results and Analysis of DBRkM-ANN:

In this section, different results are analyzed for various parameters that are considered in this study and compared with the existed methods such as LE-KCR [89], DCK-LEACH [90], DBRM [86] and WRP [86]. They are given below.

#### 3.4.2.1 Total Hop Counts:

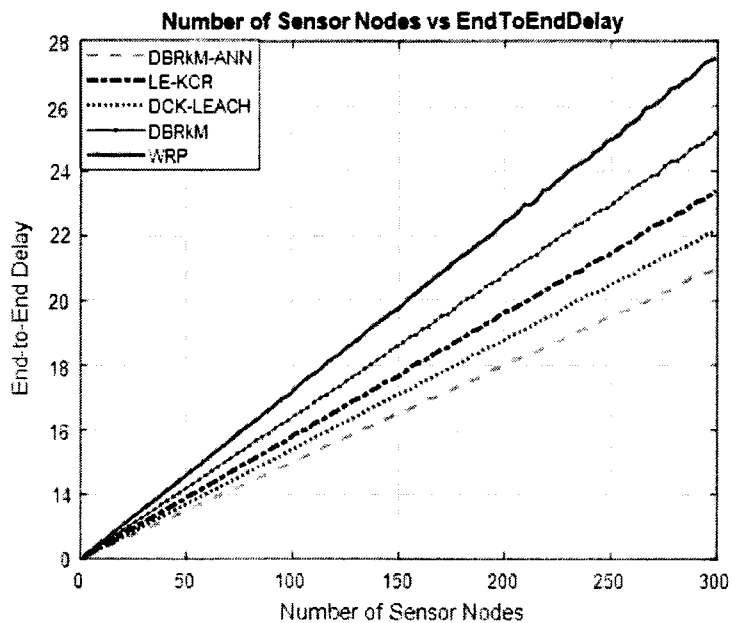
A comparison of total hop counts between DBRkM, WRP, LE-KCR, DCK-LEACH, and the proposed DBRkM-ANN is shown in Figure 3.10. DBRkM performs better, which is explained by the effectiveness of the proposed weight function. Equation (4) illustrates the function's priority of reducing total hop counts by selecting possible RPs with the highest indegree.



**Figure 3.10: Number of Sensor Nodes vs Hop Counts**

#### 3.4.2.2 Analysis of End-to-End delays:

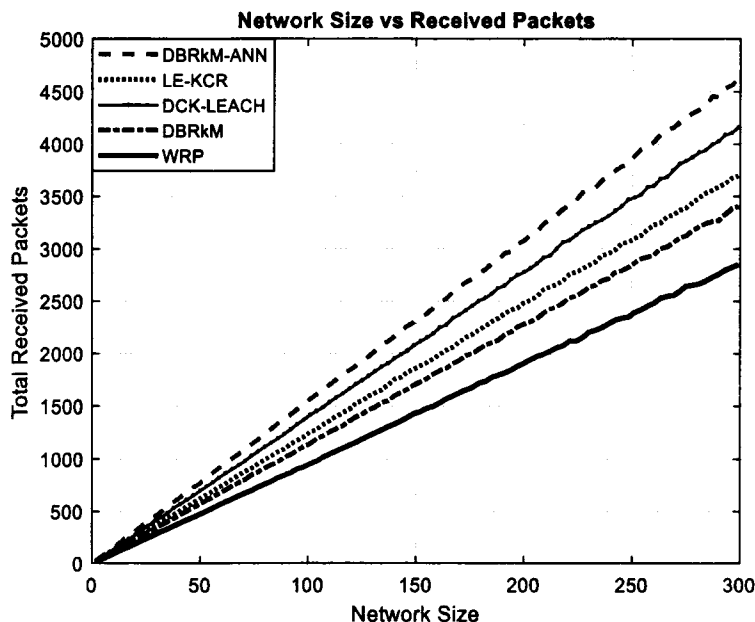
The number of End-to-End Delays is plotted in Figure 3.11, showcasing DBRkM-ANN's superiority over other algorithms. The proposed methodology has a lower number of end-to-end Delays than the other existing techniques.



**Figure 3.11:** Number of Sensor Nodes vs End-to-End Delay

### 3.4.2.3 Analysis of total received packets:

Figure 3.12 demonstrates the analysis of the proposed model DBRM-ANN regarding the number of received packets. The results indicate that the suggested technique performs better than the other two algorithms regarding the highest number of received packets.



**Figure 3.12:** Network Size vs Received Packets

#### 3.4.2.4 Energy Consumption:

The random deployment of 300 SNs in one single network as shown in figure 3.13. The energy of the network drops immediately as the data transmission initializes within the network. In this research, we have suggested the initial energy of the network is 3-Joules. According to the results after analysis, the network's energy usage rose in tandem with progress. However, less energy consumption was noted by reducing multi-hop route lengths, and the number of hops was counted when and the number of hops was counted using the hybrid approach. The DBRkM-ANN strategy was applied on WSN. As a result of the optimization of the network, less energy was consumed than in the case of the other existing methodologies.

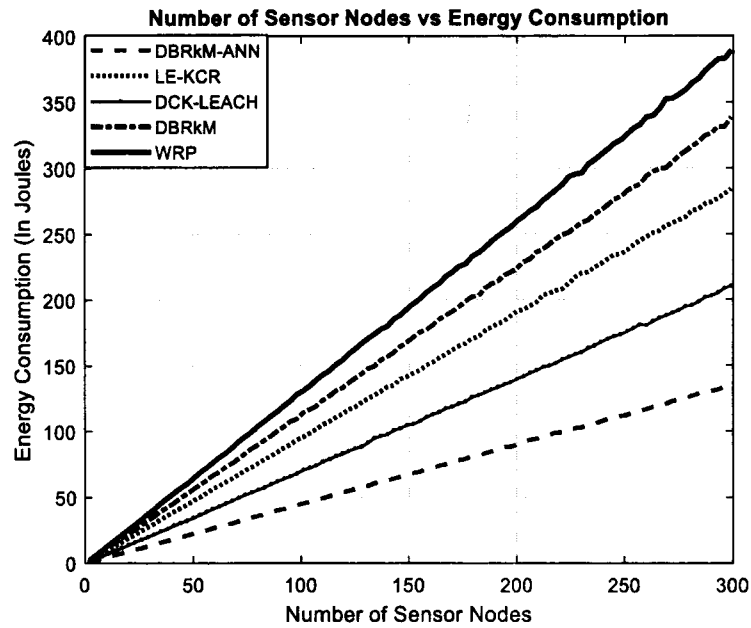
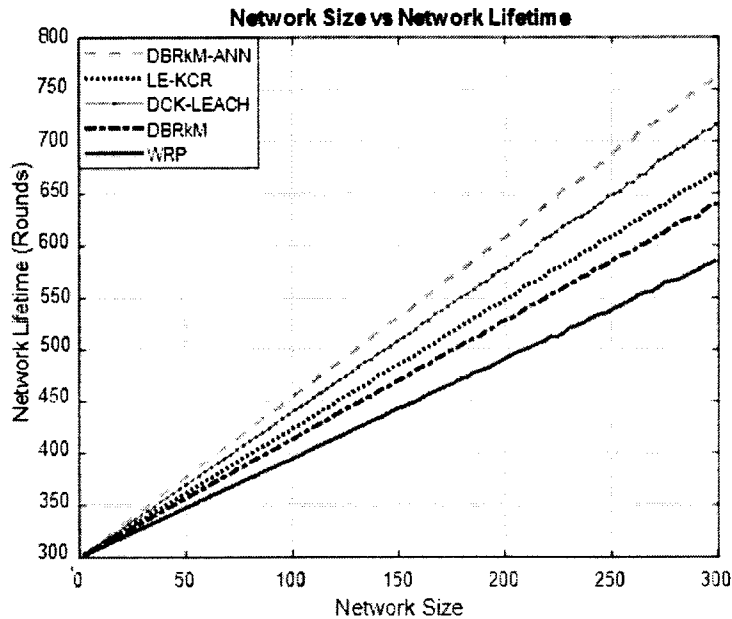


Figure 3.13: Number of Sensor Nodes vs Energy Consumption

#### 3.4.2.5 Network Lifetime:

The proposed technique “DBRkM-ANN” intensely increased the network lifetime under varying node densities through the weight function compared to WRP and traditional BDRkM algorithms. The program optimized the routing patterns based on the expected energy consumption, leading to effective data transfer. This enhancement provided consistent data collection and decreased network-wide data loss. Figure 3.14 represents the graphical analysis of Network Size vs Network Lifetime.



**Figure 3.14:** Network Size vs Network Lifetime

### 3.5 Summary

In this chapter, two hybrid algorithms, namely Reduced k-means with ANN (RkM-ANN) and Delay Bound k-means with ANN (DBRkM-ANN) are proposed which have been designed for the optimization of MS and improved path formation within WSNs. The simulation results have been compared with the existing protocols based on metrics such as total number of hop counts, energy consumption, and the number of received packets, end-to-end delay and network lifetime. It has been found that the proposed protocol outperformed the existing protocols.

Ensuring the real-time performance and robustness of the algorithms proposed in this thesis, especially considering the multiple objective functions involved, is crucial. Here are some strategies and examples to illustrate how these aspects can be addressed:

- i) In our proposed K-means based-ANN algorithm, parallel processing can be used during the initial clustering phase to speed up the assignment of nodes to clusters,

thereby ensuring that the clustering process does not delay real-time decision-making.

- ii) For the RkM-ANN model, employing an online learning approach can allow the ANN to adapt to new patterns and data points on-the-fly, maintaining real-time responsiveness.
- iii) The DBRkM-ANN algorithm can be designed to use a weighted sum approach for multi-objective optimization, where the weights are dynamically adjusted based on current network conditions to ensure robustness against varying scenarios.
- iv) In the K-means based-ANN approach, a fallback mechanism can be included where secondary cluster heads are designated to take over in case the primary cluster head fails, thus maintaining network stability and robustness.

By implementing these strategies, the proposed algorithms can achieve both real-time performance and robustness, ensuring they are effective and reliable under various network conditions.

However, despite the effectiveness of our proposed model, it presents several challenges. These include potential scalability issues when the network size increases, imbalances in energy consumption among nodes, and the computational overhead associated with integrating K-means clustering with ANN. Future research can address these challenges by employing more optimized techniques and advanced algorithms.

## **CHAPTER 4. ENHANCING ENERGY EFFICIENCY IN WSN'S WITH HYBRID LEACH-D AND ANN**

This chapter aims to enhance the operational lifetime and energy efficiency of WSNs. In WSNs, the constrained energy resources of SNs pose a significant challenge to maintaining efficient and reliable functionality. A cluster-based approach is elaborated upon in this chapter to demonstrate the improved efficiency of WSNs.

### **4.1 Introduction**

To improve WSNs operational lifetime and energy efficiency, this chapter explores methods that optimize energy-efficient routing protocols and clustering techniques. The suggested approach maximizes EC while preserving WSNs' overall effectiveness. A cluster-based mechanism called LEACH requires non-cluster head nodes to disable their radio frequencies until their designated time periods. However, the random CH rotation in traditional LEACH results in an unequal cluster distribution, which is an issue. We present a novel hybrid methodology called LEACH-D protocol paired with ANN to address this problem. The LEACH-D algorithm ensures balanced battery EC while extending the transmission work time. Meanwhile, ANN optimizes routing decisions and CH placement, refining data aggregation and transmission to reduce idle listening. Performance evaluation is conducted using a MATLAB simulator across nodes ranging from 100 to 500. Comparative analysis against existing methods through simulations demonstrates substantial reductions in EC and extended network lifespan for WSNs.

The major objective of the research is as follows:

- a. To minimize EC of nodes during data transmission.

- b. To improve the End-to-End delay of WSN.

As a result, the overall packet transfer to the BS is increased due to the SNs' lower energy demand. Most of the energy used by WSN is used for data transmission and reception, so it's important to develop an efficient clustering and routing system that resolves this problem.

After addressing the challenges, this work presents an updated version of the LEACH algorithm called LEACH-D, which includes two major components: the clustering and transmission phases. During the clustering phase, nodes are organized into clusters, and Cluster Heads (CHs) and Main Cluster Heads (MCHs) are chosen to use an improved threshold formula and a process known as "second clustering." In the transmission phase, the algorithm determines data transmission paths between clusters, from clusters to the BS, and develops a node multi-hop strategy.

The main contributions of this study are summarized as follows:

- This study discovers EC and delay problems in WSNs for their efficiency.
- This research offers a hybrid model of LEACH-D protocol with the ANN to address the energy optimization challenge.
- The LEACH-D algorithm was specifically created to address end-to-end delay and EC concerns in WSNs. Using clustering techniques, it successfully decreases delay times and EC during data transfer.
- ANN makes the optimal routing decisions and CH placement, refining data aggregation and transmission strategies to restrain idle listening.

- The simulation investigations support the algorithm's performance by improving transmission delay, energy efficiency, network longevity, and other performance measures.

## **4.2 Proposed Energy Consumption (EC) and Delay Model**

WSNs are comprised of SNs, communication devices, power supplies, and specialized applications. They enhance operations in remote areas by collecting and transmitting data. Nevertheless, WSNs encounter hurdles such as increased EC and delays, significantly diminishing their efficacy [91, 92]. To tackle these challenges, a new methodology is needed to accurately assess both challenges within WSNs.

### **4.2.1 Development of wireless EC model for WSN**

One of the most significant challenges in WSN is managing the EC of wireless sensors. The system experiences a significant increase in EC caused by the increasing number of devices and sensors. Insufficient node energy management leads to increased maintenance expenses and system latency, which have major financial consequences. It is important to implement high-efficiency devices and sensors, optimize system topologies for lower energy usage, and set up complex energy management protocols to address this problem. The integration of wireless EC models enhances the use of energy management algorithms by helping to calculate energy usage across various transmission methods.

A wireless EC model that analyzes SNs EC is presented in [93]. Wireless SNs' EC may generally be divided into three main categories: data processing, interaction, and communication accounting for the bulk of energy usage. The following formula is used to calculate the energy node when delivering  $l$ -bits of data to another node at a distance of  $d$ :

$$E_{TX}(l, d) = \begin{cases} l \times E_{elec} + l \times \varepsilon_{fs} \times d^2 & \text{if } d \leq d_0 \\ l \times E_{elec} + l \times \varepsilon_{mp} \times d^4 & \text{if } d > d_0 \end{cases} \quad (16)$$

$$E_{(l,d)} = l \times E_{elec} \quad (17)$$

Where  $E_{elec}$  shows the energy utilized at the transmitter or receiver and  $d_0$  is the minimum detectable distance. The Eq. given below in (18) is used to determine the threshold distance.

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (18)$$

In this case, the amplification energy in the free space model is represented as  $\varepsilon_{fs}$ , and the multipath model is  $\varepsilon_{mp}$ , respectively. The values of  $\varepsilon_{fs}$  and  $\varepsilon_{mp}$  depend upon the amplifier model of the transmitter.

The energy used by a SN while receiving  $l$ -bits of data can be written as:

$$E_R(l) = l \times E_{elec} \quad (19)$$

Hence, the calculation formula for the total EC of CHs and MCHs in each round of data transmission is as follows:

$$E = E_R(l) \times (N_{CH} + N_{MCH}) + E_{ag} + E_T(l, d) \quad (20)$$

Here,  $(N_{CH}$  and  $N_{MCH}$  represent the count of CHs and MCHs in this round, respectively.  $E_{ag}$  represents the energy used by each CH for aggregate member nodes, determined by the formula:

$$E_{ag} = n \times E_R(l) \quad (21)$$

#### 4.2.2 Development of Delay model for WSN

Here, network jamming, data overload, and inadequate data management are some of the

challenges WSN experience. These issues create delays in data transmission and processing. Network architecture optimization, edge computing integration, data volume reduction, and the use of efficient transmission algorithms are essential to minimize delays. These approaches improve the effectiveness of WSN, particularly in remote locations. To assess the performance of the transmission system, a delay model that specifies the timing of sensor node transmission including cluster formation, data transmission, and processing, is put forth. The energy consumption  $T(r)$  in each transmission round can be calculated using the formula below:

$$T(r) = T_{trans}(r) + T_{cluster}(r) + T_{BS}(r) \quad (22)$$

where  $T_{cluster}(r)$  denotes the duration taken by a node to establish a cluster in round  $r$ ,  $N_{max\ cluster}$  represents the maximum allowable members within the cluster during this round, and  $\tau_{cluster}$  signifies the cluster formation time coefficient:

$$T_{cluster}(r) = N_{max\ cluster} * \tau_{cluster} \quad (23)$$

$T_{trans}(r)$  signifies the time allocated by nodes for data transmission in round  $r$ . and  $T_{trans}$  representing the data transmission time coefficient:

$$T_{trans}(r) = d * T_{trans} \quad (24)$$

In this case,  $N_{thr}$  is the BS information processing power threshold,  $N_{BS}$  is the amount of data processed by the BS in this round,  $\tau_{BS_L}$  represents the processing time coefficient when  $N_{BS}$  exceeds than  $N_{thr}$ , and  $\tau_{BS_S}$  is the processing time coefficient when  $N_{BS}$  is less than or equal to  $N_{thr}$ .

$$T_{BS}(r) = \begin{cases} N_{BS} - N_{thr} \times \tau_{BS_L} + N_{thr} \times \tau_{BS_S} , & N_{BS} > N_{thr} \\ N_{BS} \times \tau_{BS_S} , & N_{BS} \leq N_{thr} \end{cases} \quad (25)$$

### 4.3 Simulation-Based Analysis of Cluster based LEACH-D Algorithm

#### Approach

Researchers presented clustering as an algorithm in [94] to enhance the performance of WSNs while reducing sensors EC. The proposed idea consists of organizing SNs into clusters, each with a CH who operates as an intermediary between the nodes and the BS. CHs collect data from other neighboring clusters and send it to the BS. This approach decreases the number of nodes communicating directly to the BS, minimizing sensor node EC and data transmission latency. Several clustering-based methodologies have been established in past studies, as shown in Table 4.1.

**Table 4.1:** Existed LEACH Protocols

Existed LEACH Protocols	Limitations
LEACH [95]	High communication cost
LEACH-C[96]	CHs selection can be from Low-energy nodes. Not appropriate for large-scale network
Q-LEACH [97]	Used only fixed Cluster formation Cannot add or remove nodes
LEACH-M [98]	If CHs are selected from high mobile nodes, then they rapidly change their position from one cluster to another.
V-LEACH [99]	If the energy of CHs becomes zero, the network disconnected.
CQ-LEACH [100]	Issue of network coverage balanced energy distribution for large networks
NR-LEACH [101]	The remaining energy of neighbor nodes is not considered.
I-LEACH [102]	Only dedicated to a small network

#### 4.3.1 Development of Delay model for WSN

The proposed LEACH-D algorithm has been developed using the classic LEACH algorithm. Contrary to its previous version, the initial LEACH algorithm failed to account for the precise positioning of CHs, which resulted in the early depletion of some CHs that

were in direct communication with the BS but were positioned at a distance. An extra CH clustering phase has been added to the LEACH algorithm after the first CH selection step, as part of the LEACH-D enhancement. During this phase, CHs are designated as relay nodes to help with data collection and transmission to other CHs. Below is further information about this improved algorithm:

"In the initial round, LEACH-D employs the same selection formula as the LEACH algorithm, as denoted by:

$$P(n) = \begin{cases} \frac{h}{1 - h \times (r \times \text{mod}(\frac{1}{h}))} & , n \in G \\ 0 & , \text{else} \end{cases} \quad (26)$$

In other rounds, LEACH-D uses the following selection formula:

$$P(n) = \begin{cases} \frac{h}{1 - h \times (r \times \text{mod}(\frac{1}{h}))} \times \frac{E_{i_{current}}}{E_{avg}} & , n \in G \\ 0 & , \text{else} \end{cases} \quad (27)$$

Within this network framework, the variable "h" denotes the probability of a regular node transitioning into a CH or MCH node. The symbol "r" signifies the on-going round, with "n" denoting the anticipated CH for this round. Additionally, "G" represents nodes that have not assumed CH roles over the preceding  $\frac{1}{h}$  rounds.  $E_{avg}$  shows the average energy left over the network during the initial phase (i.e., total remaining energy divided by the number of alive nodes).  $E_{i_{current}}$  denotes the current energy level of node i.

Starting with the next round of selections, the threshold estimation reduces the likelihood of a node with lower remaining energy being selected as CH by factoring in  $\frac{E_{i_{current}}}{E_{avg}}$ .

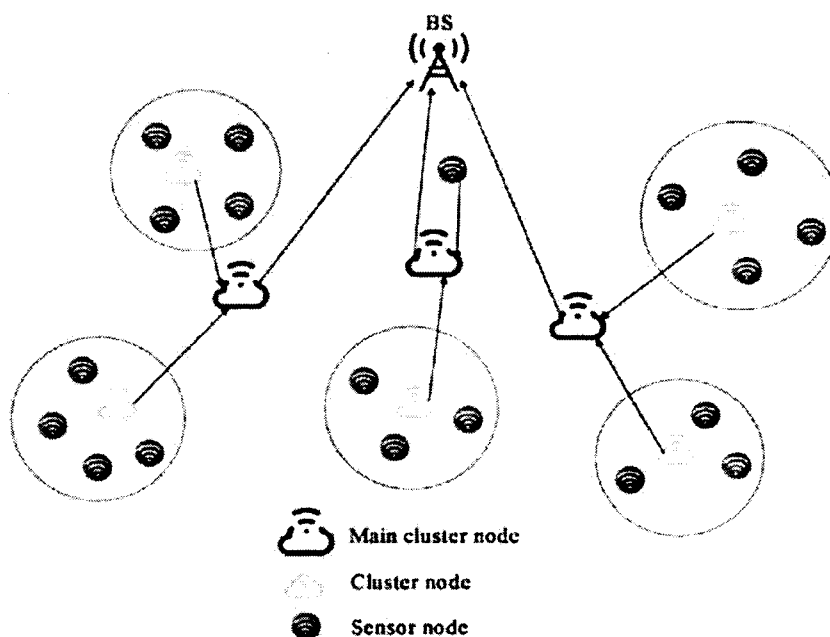
### 4.3.2 The clustering process

During the first clustering phase, the sensor network's nodes are given random values between 0 and 1. Nodes that have values less than  $P(n)$  are referred to as CHs. CHs coordinate gathering of data from other nodes in their clusters and send out "cluster formation request" messages containing information about their exact position and energy reserves. Regular nodes send a "consent" message with their ID, position, and remaining energy to the appropriate CH after identifying which cluster they belong to depending on signal strength and distance.

CHs are randomly re-assigned in the next rounds, and if their value is less than the threshold  $P(n)$ , MCHs are determined. By sending out a "cluster formation request" messages around the network, MCHs aggregate data from all CHs. Other CHs determine the power and distance to establish cluster connection and then send a "consent" message to the respective MCH to complete the cluster creation process. Nodes that receive numerous "request to form a cluster" signals choose the one with the highest remaining energy.

### 4.3.3 Data transmission process

During this phase, MCHs formulate TDMA (Time Division Multiple Access) schedules and sends them to controlled CHs. Concurrently, each CH creates a schedule for its nearby nodes. Subsequent data transfer adheres to the TDMA timings. This network's three-stage structure is explained in Figure 4.1, where MCHs initially communicate with the BS. Following data processing, CHs send processed data to MCHs, with common SNs collecting and sending environmental data to CHs at the end [103].



**Figure 4.1:** Architecture diagram of LEACH-D protocol

During the cluster formation phase, nodes that do not receive the "request to form cluster" message send an "ask for help" message across their transmission area, defining them as lonely nodes (LNs). LNs get "response" messages from neighboring regular SNs, which include the node's ID, remaining energy, cluster head ID, and location. LNs send a "consent" message with the node that has the shortest distance and most remaining energy. This repetitive approach maintains that all LNs form their clusters.

This transmission method confirms the equitable distribution of energy burden among network SNs, successfully reducing overall EC and mitigating early node depletion distant from the BS [104].

#### 4.4 Proposed Work

A distributed node network area of  $100 \times 100$  is created during the first stage. Node distribution varies randomly in the 0 to 100 range, resulting in varying closeness between

nodes, requiring the management of dense and remote nodes via establishing of head nodes within clusters. Clustering methods make it easier to manage large numbers of nodes.

The LEACH clustering approach has been used to group nodes into clusters, with cluster centers chosen based on node's minimal distance and residual energy. Each CH is then connected to the BS, which is located in the middle of the network area. The next goal is to create routes between source and destination nodes using the LEACH-D routing protocol. Data is transmitted from source nodes to the nearest CH, which transfers it to the BS, allowing transmission to the target node. Failed nodes or those with insufficient energy are recognized, causing communication delays or data loss. ANNs are used to overcome this issue. The ANN system is trained using node EC and delay. Nodes that fail to achieve the established requirements for EC and delay are classified as unsuccessful. Next, neighboring nodes are classified as communication nodes and added to the communication path. Figure 4.3 shows the pre-trained ANN structure and the MSE.

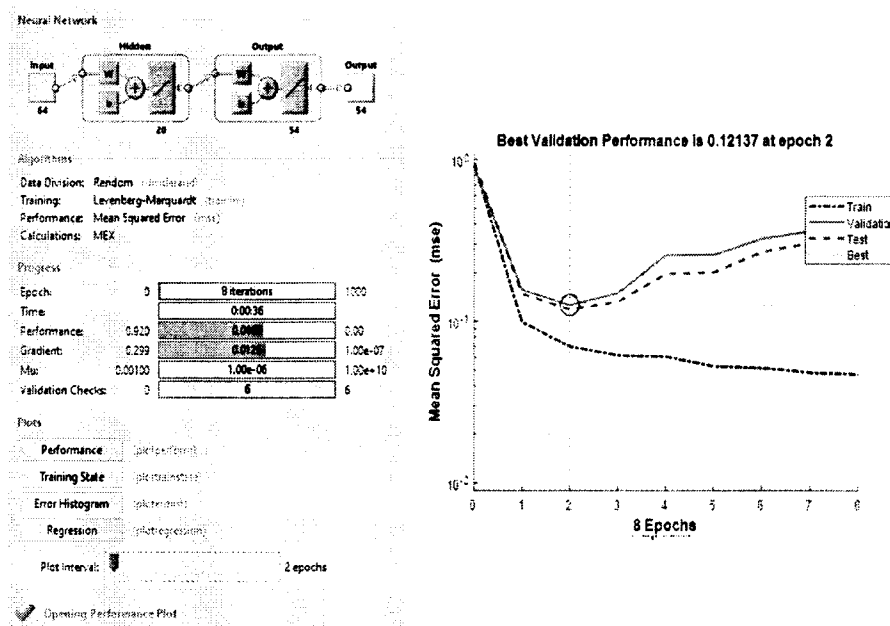
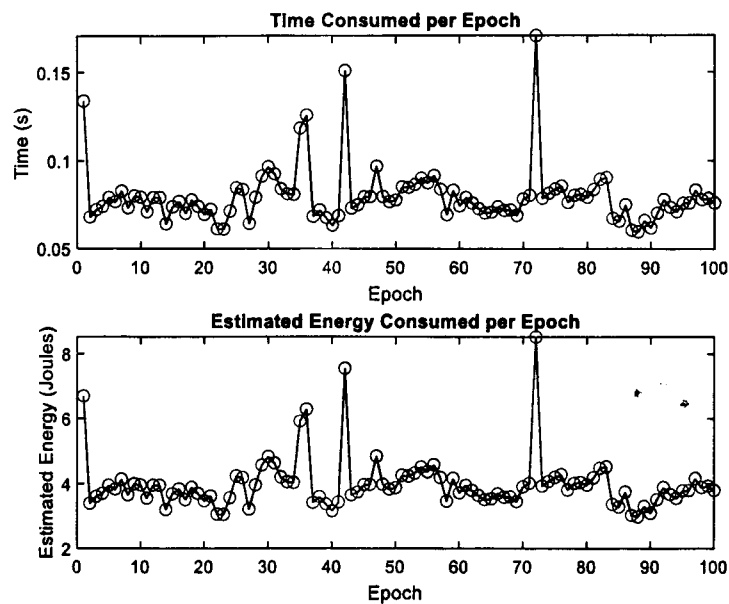


Figure 4.2: Trained ANN structure II

The trained structure demonstrates the involvement of 64 neurons in the routing process. Attributes like energy and delays are sent to the ANN's input layer. The hidden layer consists of twenty neurons, which results in better performance. At the output layer, 54 neurons identify the presence of 10 failed nodes out of 64, requiring their elimination from the network. This strategy saves node energy, which improves network lifetime. Figure 4.4 represents the energy and time consumed for training the neural network.



**Figure 4.3:** Analysis of Estimated Energy and Time Consumption

## 4.5 Results and Discussion

Energy efficiency in WSNs can be improved by applying the combination of LEACH-D protocol with ML methods. In this research, a topology of 100-500 static nodes were created. Considering the network area  $100\text{ m} \times 100\text{ m}$ , and the performance is based on 1000 independent iterations. The novelty of this research is that it explains the CH selection based on the ML algorithm in which LEACH-D-ANN is applied on WSN rather than to the traditional LEACH approaches. The training of ANN has been done based on the selection

of CH and the residual energy of the node. The final results demonstrate the significant superiority of the proposed approach when compared to previous studies.

Implementing the proposed energy-efficient routing method LEACH-D and ANN takes place in MATLAB 2021a version on the Windows 10.3 operating system with an Intel core i7 CPU and 8 GB of RAM. The primary determination of using matlab software is the simplicity with which mathematical operations can be performed and effective data analyses. The selected parameters are shown in Table 4.2.

Several performance metrics were assessed, including network size vs. energy consumption, network size vs. lifetime, End-to-End delay (EED), and packet delivery ratio (PDR), evaluating the method's effectiveness.

**Table 4.2: Simulation Structure**

Parameters	Area ( $m^2$ )	$E_t$ (Initial energy)	Number of nodes (N)	$E_{elec}$ (Energy consumption)	$E_{amp}$ (Multi-path model of transmitter amplifier)	$E_{fs}$ (Free space model of transmitter amplifier)	L (Packet size)
values	100x100	0.9 J	100-500	80 nJ/bit	0.001301 pJ/bit/m <sup>4</sup>	10 pJ/bit/m <sup>2</sup>	5000 bits

#### 4.5.1 Network Size vs Network Energy Consumption:

According to the experimental results, the network's energy usage increased as the network progressed. However, the speed of increase in energy consumption was slowed down when the hybrid approach of the LEACH-D-ANN strategy was applied to WSN. By dynamically adjusting the nodes' transmission power the ML-based energy optimization method

increased efficiency. As a result of the optimization of the network, less energy was consumed than in the case when the traditional LEACH strategy was used in existing articles. Figure 4.5 and Table 4.3 given below shows the Graphical and Numerical Analysis of Network Size vs Network Energy Consumption between LEACH, Q-LEACH, I-LEACH, LEACH-D and the proposed methodology LEACH-D-ANN.

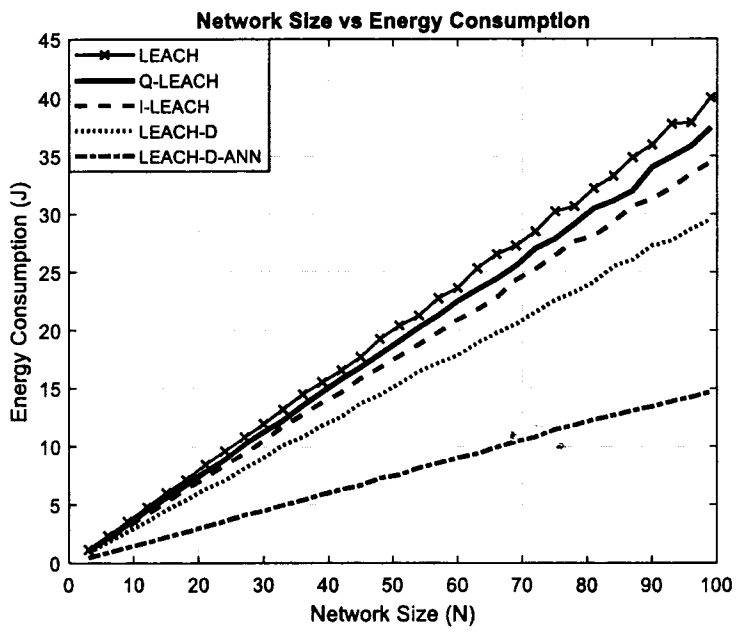


Figure 4.4: Graphical Analysis of Network Size vs Network Energy Consumption

Table 4.3: Numerical Analysis of Network Size vs Network Energy Consumption

Network Size (N)	Energy Consumption (J)									
	LEACH		Q-LEACH		I-LEACH		LEACH-D		LEACH-D-ANN	
	Number of Rounds (n)	Energy Consumption for n rounds (EC)	Number of Rounds (n)	Energy Consumption for n rounds (EC)	Number of Rounds (n)	Energy Consumption for n rounds (EC)	Number of Rounds (n)	Energy Consumption for n rounds (EC)	Number of Rounds (n)	Energy Consumption for n rounds (EC)
100	862	10%	913	10%	1366	10%	1589	10%	1799	10%
200	1360	20%	1686	20%	2167	20%	2486	20%	4828	20%

300	2465	40%	2798	40%	2958	40%	3288	40%	9351	40%
400	4062	60%	5986	60%	8532	60%	9188	60%	20698	60%
500	6965	80%	8225	80%	10589	80%	12582	80%	38496	80%

#### 4.5.2 Network Size vs Network Lifetime:

In the proposed simulation model, the numbers of nodes around 100 to 500 are distributed randomly to analyze network performance. The algorithms of the proposed hybrid model LEACH-D-ANN were evaluated with WSN. The results show that after applying the proposed LEACH-D-ANN model, 46592 rounds are observed compared with the traditional LEACH, Q-LEACH, I-LEACH, LEACH-D, TEO-MCRP [105] and PSO-ECSM [105] methods containing 22970, 27532, 23548, 34882, 29964, and 27631 rounds over 100 nodes network. Hence, it is observed that network lifetime increases by increasing the number of nodes as shown in Figure 4.6. Table 4.4 contains the numerical analysis of Network Size vs Network Lifetime.

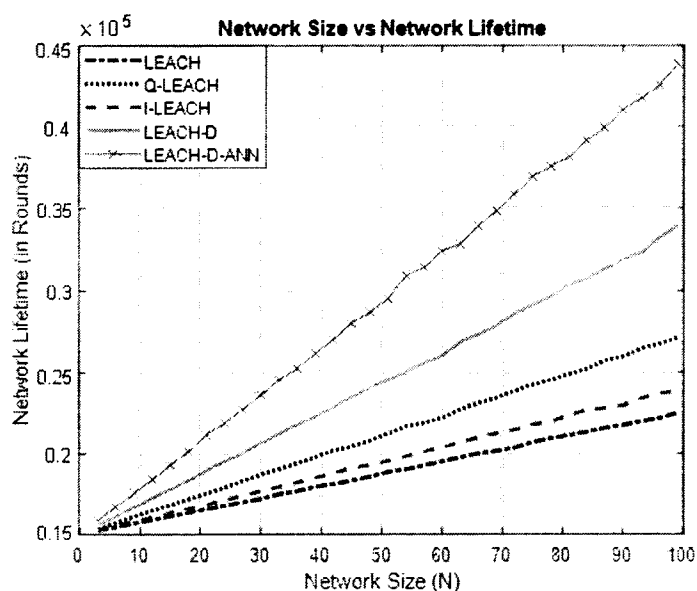


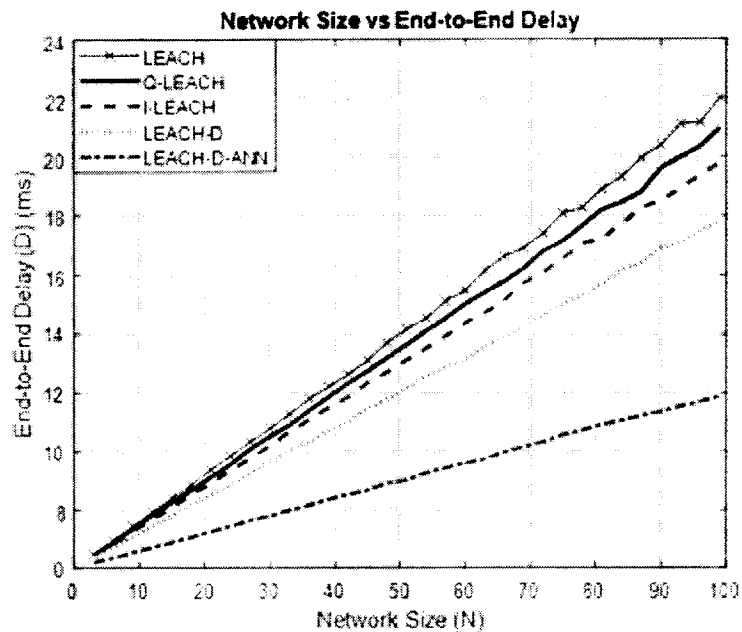
Figure 4.5: Graphical Analysis of Network Size vs Network Lifetime

**Table 4.4: Numerical Analysis of Network Size vs Network Lifetime**

Network Size (N)	Network Lifetime in Rounds (n)				
	LEACH	Q-LEACH	I-LEACH	LEACH-D	LEACH-D-ANN
100	22970	27532	23548	34882	<b>44592</b>
200	25072	29258	25687	36888	<b>49598</b>
300	28977	32589	28654	40682	<b>52099</b>
400	31776	36584	31559	43985	<b>56997</b>
500	33272	38654	33567	48282	<b>59098</b>

#### 4.5.3 End-to-End Delay (D):

The End-to-End delay of a packet denotes the time it takes to traverse from its source node to its ultimate destination, typically the BS. As the number of nodes within the network grows, the End-to-End delay tends to increase across all employed algorithms. End-to-End latency was lower when using the integrated method compared to the other existing ones. The proposed hybrid technique decreases packet delay and increases data transmission by optimizing routing choices and cutting power use. Figure 4.7 and Table 4.5 represent the Graphical and Numerical analysis of WSNs End-to-End Delay.



**Figure 4.6:** Graphical Representation of End-to-End Delay (D) in WSN

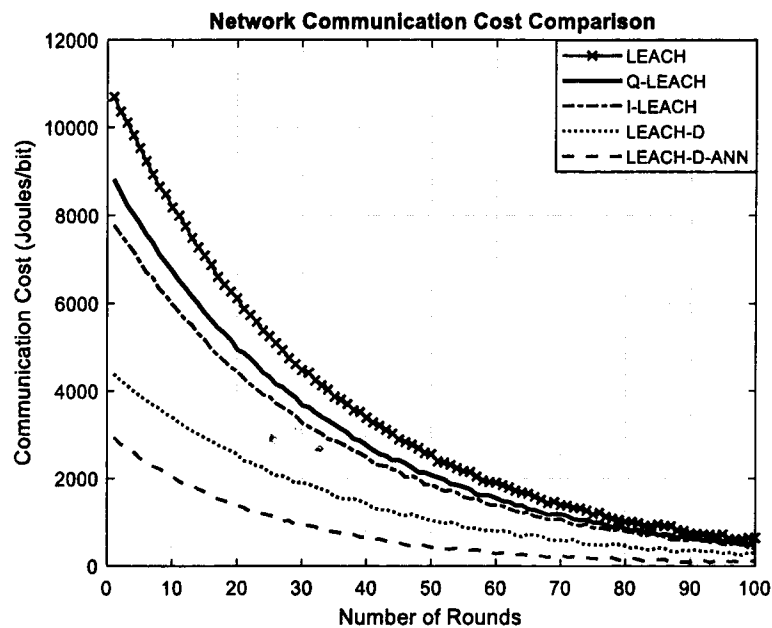
**Table 4.5:** Numerical Analysis of End-to-End Delay in WSN

Network Size (N)	End-to-End Delay (D) (in ms)				
	LEACH	Q-LEACH	I-LEACH	LEACH-D	LEACH-D-ANN
20	9.2	11	10.8	8.7	5.7
40	12.1	12	11.6	11	8.4
60	15.5	15.1	14.2	15.2	9.8
80	18.8	18.1	17.3	15.8	10.9
100	22.1	21	20	16.9	11.95

This study shows that minimizing energy usage in WSNs can be accomplished by combining the ANN approach with LEACH-D. This technique reduced energy usage and End-to-End delay while improving the packet delivery ratio (PDR), and the lifespan of the network.

#### 4.5.4 Network Communication Cost

Figure 4.8 presents the graphical analysis of the total communication cost incurred by the network, compared against various methodologies. This comparative evaluation highlights the proposed model's efficiency and performance metrics, demonstrating the lowest communication cost among the protocols analyzed.



**Figure 4.7:** Graphical Analysis of Network Communication Cost

The results show that minimizing energy usage in WSNs can be accomplished by combining the ANN approach with LEACH-D. This technique reduced energy usage and End-to-End delay while improving the lifespan of the network. Detailed comparison tables of the findings are shown in Table 4.6. The parameters which are being compared with previous techniques include Network Energy Consumption, Network Lifetime and End to End delay for hundred (100) network nodes.

**Table 4.6:** Comparison of the Numerical Analysis of proposed parameters in WSN with existing techniques

Parameters	Network Energy Consumption	Network Lifetime (rounds)	End-to-End Delay (D) (in ms)
LEACH-D-ANN (Proposed)	1799 (10%)	44592	11.95
LEACH-D	1589 (10%)	34882	16.9
Q-LEACH	913 (10%)	27532	21
I-LEACH	1366 (10%)	23548	20
LEACH	862 (10%)	22970	22.1
TEO-MCRP [105]	1246 (10%)	29,964	15.734
PSO-ECSM [105]	1056 (10%)	27,631	17.852

#### 4.6 Summary

In this chapter, we have proposed a novel algorithm to improve the lifetime of WSNs through efficient energy resource management to maintain communication for a longer duration of time. The simulation results illustrate LEACH-D-ANN as an evolutionary ML technique that rotates and dynamically assigns CHs to balance energy consumption among SNs. LEACH-D optimizes CH numbers and positions by utilizing ANN, which also improves data aggregation and transmission algorithms to reduce idle listening. Our hybrid method combines the energy uniformity and CH selection of LEACH-D with the route optimization of ANN to promote lower energy consumption, longer network lifetimes, and higher data throughput in WSNs. An experimental comparison with current approaches validates the effectiveness of our suggested model and demonstrates better WSN performance.

## CHAPTER 5. CONCLUSION AND FUTURE WORK

In this chapter, the proposed techniques are concluded based on the experimental results and structural analysis. Additionally, it offers guidelines for future research, encouraging scholars to apply or adapt the suggested methods across different engineering fields.

### 5.1 Conclusions

The conclusion drawn from the research work presented in the dissertation revolves around the successful development and evaluation of innovative methodologies to enhance energy efficiency and operational performance in (WSNs).

- The first contribution emphasizes introducing novel hybrid algorithms designed to optimize mobile sink paths in WSNs, thereby reducing energy consumption and latency. It presents two novel hybrid algorithms, namely RkM-ANN and DBRkM-ANN, designed to optimize of MS and improve path formation within WSNs. Both algorithms are planned to facilitate efficient MS path selection by considering many critical factors. These factors encompass maximizing one-hop neighbors, reducing average hop distance, and minimizing the distance between RPs and the most favorable distance from a reference point. While RkM-ANN establishes a path via one-hop communication, DBRkM-ANN employs a similar technique to construct a path while adhering to delay-bound constraints. Both algorithms are rigorously evaluated against existing counterparts, namely Weighted Rendezvous Planning WRP and traditional DBRkM algorithms. The study investigates the path to reach RPs by applying Travelling Salesman Problem (TSP) methodology to mitigate the revisit constraints of SNs across networks. The assessment encompasses various performance metrics, including the total number of hop counts, energy consumption,

received packets, end-to-end delay and network lifetime. The results conclusively demonstrate the superior performance of RkM-ANN and DBRkM-ANN across these metrics compared to existing methodologies, showcasing significant improvements in various performance indicators.

- The second contribution is the LEACH-D protocol coupled with ANN to address energy efficiency issues in WSNs, particularly focusing on cluster distribution challenges. The simulation results illustrate LEACH-D-ANN as an evolutionary ML technique that rotates and dynamically assigns CHs to balance energy consumption among SNs. LEACH-D optimizes CH numbers and positions by utilizing ANN, which also improves data aggregation and transmission algorithms to reduce idle listening. Our hybrid method combines the energy uniformity and CH selection of LEACH-D with the route optimization of ANN to promote lower energy consumption, longer network lifetimes, and higher data throughput in WSNs. An experimental comparison with current approaches validates the effectiveness of our suggested model and demonstrates the better WSN performance. The simulation performance evaluations demonstrate substantial reductions in energy consumption and extended network lifespan, reinforcing the effectiveness and practicality of the proposed LEACH-D algorithm. Collectively, these conclusions signify significant advancements in the field of WSNs, showcasing promising solutions for improving energy efficiency and operational longevity in sensor networks.

## **5.2 Future Work**

The useful guidelines for future research for interested scholars in this area are as follows:

- **Enhancement of Hybrid Algorithms:** Future work could involve further refining and enhancing the proposed hybrid algorithms for optimizing mobile sink paths in WSNs. This could include exploring additional optimization techniques, fine-tuning parameters, and conducting more extensive simulations to validate and improve their performance under various network scenarios.
- **Advanced Optimization Techniques:** There is potential for exploring and integrating more advanced optimization techniques into solving the Traveling Salesman Problem (TSP) within WSNs. This could involve investigating other metaheuristic algorithms, machine learning approaches, or evolutionary algorithms to optimize TSP arrangements further and improve overall network efficiency.
- **Optimizing Cluster Distribution:** Future research can focus on refining the LEACH-D protocol paired with ANN to address challenges related to cluster distribution in WSNs. This may involve developing more sophisticated algorithms or mechanisms to ensure a more balanced distribution of cluster heads and improve overall network performance.
- **Energy-Efficient Data Collection:** Another area for future work could be the development of innovative methods for energy-efficient data collection in WSNs. This may include exploring data aggregation, adaptive sampling techniques, or dynamic routing protocols to minimize energy consumption during data transmission and improve network reliability.
- **Real-World Implementation and Testing:** Further research could involve the real-world implementation and testing of the proposed algorithms and protocols in practical WSN environments. This would provide valuable insights into their

performance, scalability, and effectiveness in real-world scenarios, helping to bridge the gap between theoretical research and practical applications.

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