**Title:**

# Energy Hole Mitigation and Network Lifetime Maximisation in Shape-Varying 3D IoT-based Heterogeneous Wireless Sensor Networks

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# Abstract

The rapid expansion of IoT-based Heterogeneous Wireless Sensor Networks (HWSNs) amplifies challenges in energy management. These networks, comprising diverse devices deployed across varying terrains, are designed to efficiently collect data while ensuring complete coverage. However, achieving balanced energy consumption is critical to prevent energy holes, which occur when devices near base station deplete their energy at faster rate due to experiencing excessive transmission loads. Such imbalances lead to network instability and reduce operational lifespan. Existing energy hole mitigation techniques often fail to account for the diverse characteristics of heterogeneous devices, limiting their effectiveness and applicability. Furthermore, many of these approaches are tailored to specific applications or constrained by fixed network shapes, lacking the adaptability, scalability, and flexibility required for large-scale, dynamic IoT-based HWSNs. These limitations hinder their performance in managing the complex and diverse topologies encountered in real-world deployments.

This thesis aims to tackle these challenges by proposing novel methods to reduce energy consumption and balance it across resource-constrained heterogeneous devices. The proposed solutions focus on enhancing energy efficiency, extending network lifetime, and improving throughput, ensuring reliable data transmission from sensing nodes to the base station.

A critical focus is on deployment of the base station, is critical given the converge-caste nature of communication in HWSNs. An iterative algorithm is proposed to compute the overall network energy consumption for a set of alternative locations within a specified radius of the base station. While the iterative algorithm identifies the optimal deployment location, its computational complexity is addressed using a multi-criteria decision-making approach. The Technique for Order of Preference by Similarity to Ideal Solutions (TOPSIS) evaluates alternative locations based on their positive and negative contributions to energy consumption and balancing. This method improves network lifetime by 23.5% compared to central deployment techniques and adapts effectively to networks of varying shapes, including circular, square, cubical and spherical, in both 2D and 3D environments.

In the post-deployment phase, the distribution of heterogeneous resources across smaller network segments supports the design of an effective communication topology. Considering variations in network shape and spatial dimensions, this thesis proposes two fixed-shape

segmentation schemes-cubical and spherical segmentation, which cover the majority of network geometries. These schemes leverage the distribution functions of network parameters and integrate an unequal clustering method to ensure energy-balanced routing. However, the complexity of choosing the appropriate segmentation scheme for specific applications motivates the development of a novel shape-independent, data-traffic-based segmentation approach. To overcome this challenge, a novel shape-independent, data-traffic-based segmentation scheme is introduced. This scheme provides faster and more accurate insights into network parameter distributions, enhancing the unequal clustering algorithm. The integration of shape-independent segmentation improves network lifetime by up to 18.8% and reduces energy consumption by 61.4% compared to existing clustering methods.

Finally, coordinated and dynamic energy-efficient mechanisms for cluster head and next-hop relay node selection, along with rotation strategies, further enhance energy efficiency. These methods optimise both intra-cluster and inter-cluster communication by dynamically selecting energy-efficient cluster head nodes, rotating their roles, and identifying optimal next-hop relay nodes for inter-cluster communication. The integration of appropriate rotation mechanisms ensures balanced energy consumption across the network. The proposed routing techniques improve network throughput by 57.44% and increase energy efficiency by 17.63% compared to protocols such as Rotated Low-Energy Adaptive Clustering Hierarchy (RLEACH) and Cluster Routing Protocol using Fuzzy C-Means (CRPFCM).

The methods proposed in this thesis significantly extend network lifetime and optimise energy usage in IoT-based HWSNs. They provide a scalable and adaptable framework for energy management in complex, multi-parameter, and multi-level IoT-based HWSNs, offering potential applications in smart cities and other infrastructure systems.

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بِسْمِ اللَّهِ الرَّحْمَٰنِ الرَّحِيمِ

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Tamoor Shafique
2025

*Dedicated to my family…*

*Author's Declaration*

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

This thesis conforms to the university research regulations and represents my work.

The research findings are documented honestly and fairly, and work attributed to other researchers has been acknowledged and referenced.

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# Abbreviations

| | |
|---|---|
| **ADC** | **A**nalogue to **D**igital **C**onverter |
| **ANDT** | **A**ll **N**ode **D**eath **T**ime |
| **APSA** | **A**ffinity **P**ropagation-based **S**elf-**A**daptive clustering |
| **ARO-WSN** | **A**ppropriate **R**ank-**O**rder **WSN** |
| **BECHA** | **B**alanced **E**nergy **C**onsuming and **H**ole **A**lleviating |
| **BLOAD** | **B**alanced **LOA**d **D**istribution |
| **BS** | **B**ase **S**tation |
| **CCMAR** | **C**luster-**C**hain **M**obile **A**gent **R**outing |
| **CH** | **C**luster **H**ead |
| **CM2SV2** | **C**ircular **M**otion of **M**obile-**S**ink with **V**aried **V**elocity algorithm |
| **COCA** | **C**onstructing **O**ptimal **C**lustering **A**rchitecture |
| **DAC** | **D**igital to **A**nalogue **C**onverter |
| **DARE-SEP** | **D**istance **A**ware **R**esidual **E**nergy-efficient **SEP** |
| **DDEEC** | **D**eveloped **D**istributed **E**nergy **E**fficient **C**lustering |
| **DEACP** | **D**istributed **E**fficient **A**daptive **C**lustering **P**rotocol |
| **DEEC** | **D**istributed **E**nergy **E**fficient **C**lustering |
| **DE-SEP** | **D**istance and **E**nergy **A**ware **SEP** |
| **DGC** | **D**ata **G**athering **C**entre |
| **DR** | **D**ynamic **R**outing |
| **DRE-SEP** | **D**istance-based **R**esidual **E**nergy-efficient **SEP** |
| **DSP** | **D**igital **S**ignal **P**rocessor |
| **EA-BECHA** | **E**nergy **A**ware **B**alanced **E**nergy **C**onsuming and **H**ole **A**lleviating |
| **EAMMH** | **E**nergy-**A**ware **M**ulti-hop **M**ultipath **H**ierarchical |
| **EAUCF** | **E**nergy-**A**ware **U**nequal **C**lustering **F**uzzy |
| **EBCAG** | **E**nergy **B**alancing unequal **C**lustering **A**pproach **G**radient-based routing |
| **EDDEEC** | **E**nhanced **D**eveloped **D**istributed **E**nergy **E**fficient **C**lustering |
| **EESRA** | **E**nergy-**E**fficient **S**calable **R**outing **A**lgorithm |
| **EEUC** | **E**nergy-**E**fficient **U**nequal **C**lustering |
| **EEUSC** | **E**nergy **E**fficient **U**nequal **S**ector **C**lustering |
| **END-BE** | **E**nergy-balanced **N**ode **D**eployment with **B**alanced **E**nergy |
| **ETASA** | **E**nergy and **T**raffic **A**ware **S**leep-**A**wake routing |
| **FPGA** | **F**ield **P**rogrammable **G**ate **A**rray |

| | |
|---|---|
| **FPA** | **F**lower **P**ollination **A**lgorithm |
| **WSN** | **W**ireless **S**ensor **N**etwork |
| **HWSN** | **H**eterogeneous **W**ireless **S**ensor **N**etwork |
| **UWSN** | **U**nderwater **S**ensor **N**etwork |
| **IoT** | **I**nternet **o**f **T**hings |
| **IDC** | **I**nternational **D**ata **C**orporation |
| **MEMS** | **M**icro-**E**lectro-**M**echanical **S**ystems |
| **LEACH** | **L**ow **E**nergy **H**ierarchical **C**lustering **H**ierarchy |
| **LEACH-C** | **LEACH-C**entralised |
| **LEACH-EA** | **LEACH-E**nergy **A**ssociation |
| **LEACH-EC** | **LEACH-E**nhanced **C**entralised |
| **OPT-LEACH** | **OPT**imised **LEACH** |
| **HEED** | **H**ybrid **E**nergy-**E**fficient **D**istributed clustering |
| **ML-HEED** | **M**ulti-**L**evel **HEED** |
| **PEGASIS** | **P**ower efficient **E**nergy **GA**thering **S**ensor **I**nformation **S**ystems |
| **RF** | **R**adio **F**requency |
| **FND** | **F**irst **N**ode **D**eath |
| **FNDT** | **F**irst **N**ode **D**eath **T**ime |
| **GBK** | **G**rid-**B**ased **K**-means |
| **GTAB** | **G**ame-**T**heoretic **A**pproach for **B**alancing |
| **GWO** | **G**rey **W**olf **O**ptimisation |
| **HHO** | **H**arris' **H**awk **O**ptimisation |
| **HND** | **H**alf **N**odes **D**eath |
| **Homo-BR** | **H**omogeneous **B**alanced **R**outing |
| **ICSPC** | **I**mmune **C**lone **S**election-**B**ased **P**ower **C**ontrol |
| **IEECP** | **I**mproved **E**nergy **E**fficient **C**lustering **P**rotocol |
| **LND** | **L**ast **N**ode **D**eath |
| **MDC** | **M**obile **D**ata **C**ollector |
| **MLNM** | **M**ulti-**L**ayer **N**etwork **M**ode |
| **MOFCA** | **M**ulti-**O**bjective **F**uzzy **C**lustering **A**lgorithm |
| **MVO** | **M**ulti-**V**erse **O**ptimiser |
| **NRF** | **N**ominal **R**ange **F**orwarding |
| **ODTS** | **O**ptimal **D**istance based **T**ransmission **S**trategy |

| | |
|---|---|
| **PSO** | **P**article **S**warm **O**ptimisation |
| **QoS** | **Q**uality **o**f **S**ervice |
| **ROI** | **R**egion **O**f **I**nterest |
| **SCA** | **S**ine **C**osine **A**lgorithm |
| **SEHR** | **S**ector-based **E**nergy **H**ole **R**eduction |
| **SEP** | **S**table **E**lection **P**rotocol |
| **TEAR** | **T**raffic and **E**nergy **A**ware **R**outing |
| **TEEN** | **T**hreshold sensitive **E**nergy **E**fficient sensor **N**etwork protocol |
| **TOPSIS** | **T**echnique for **O**rder of **P**reference by **S**imilarity to **I**deal **S**olutions |
| **TSP** | **T**raveling **S**alesman **P**roblem |
| **TTDFP** | **T**wo-**T**ier **D**istributed **F**uzzy logic-based **P**rotocol |
| **UCR** | **U**nequal **C**luster-based **R**outing |
| **UCR-H** | **U**nequal **C**luster **R**outing with **H**eterogeneity |
| **VFEM** | **V**irtual **F**orce-**B**ased energy hole **M**itigating |
| **WOA** | **W**hale **O**ptimisation **A**lgorithm |
| **WSNEHA** | **W**ireless **S**ensor **N**etwork **E**nergy **H**ole **A**lleviating |

# Symbols

| | |
|---|---|
| $(x_i, y_i, z_i)$ | Coordinates of $i^{th}$ sensor nodes |
| $N$ | Total number of nodes |
| $(x_s, y_s, z_s)$ | Coordinates of sink node |
| $E_i$ | Initial energy of $i^{th}$ node |
| $d_{i,s}$ | Euclidean distance of $i^{th}$ node from sink node |
| $k$ | Number of bits in a packet |
| $E_{total}$ | Total energy consumption of the network |
| $E_{tx,i}$ | Energy consumption in transmission and reception for $i^{th}$ node. |
| $E_{residual,i}$ | Residual energy of node i |
| $\delta$ | Threshold for acceptable energy variance |
| $\alpha, \beta$ | Weighting factors for energy efficiency and balanced load distribution |
| $(x_{max}, y_{max}, z_{max})$ | Coordinates of boundaries of the network |
| $E_{\min}$ | Minimum value of energy range |
| $E_{\max}$ | Maximum value of energy range |
| $T_i$ | Initial value of data rate of $i^{th}$ sensor node |
| $R_i$ | Transmission range of the $i^{th}$ sensor node |
| $b$ | Path loss exponent |
| $d$ | Euclidean distance |
| $E_{elec}$ | Energy per bit for electronic circuitry |
| $\varepsilon_{fs}$ | Free space channel amplifier energy constant |
| $\varepsilon_{mp}$ | Muti-path channel amplifier energy constant |
| $E_{rec}$ | Energy consumption in reception |
| $(x_{s\_mean}, y_{s\_mean}, z_{s\_mean})$ | Mean of the coordinates of all the network nodes |
| $(x_{s\_alt(X)}, y_{s\_alt(Y)}, z_{s\_alt(z)})$ | Coordinates of alternative DGC locations |
| $\gamma$ | Search extent for alternative DGC locations |
| $F$ | Total number of alternative locations considered |
| $E_{CON1}$ | Array containing energy consumption values for each alternative location |

| | |
|---|---|
| $idx1$ | Set of index values of coordinates with minimum energy consumption. |
| $\left(x_{s_{Opt}}, y_{s_{Opt}}, z_{s_{Opt}}\right)$ | Coordinates of optimum location of DGC using iterative method |
| $E$ | set of initial energies of 'N' devices |
| $E_o$ | Minimum initial energy |
| $\beth$ | Energy heterogeneity factor |
| $o$ | Set of parameters with heterogeneous values |
| $\vartheta_o$ | Normalised value of heterogeneity parameter 'o' |
| $\theta_o$ | actual value of $o^{th}$ parameter |
| $\zeta$ | A matrix of normalised values for each parameter |
| $\zeta_p^+$ | Ideal positive solutions |
| $\zeta_p^-$ | Ideal negative solutions |
| $\aleph_p$ | Final rank of an alternative location |
| $\mathcal{N}$ | Set of sensor nodes |
| $\mathcal{L}$ | Network lifetime |
| $E_{Trans}$ | Energy spent in transmission operations |
| $d_{i,CH}$ | Euclidean distance between $i^{th}$ node and cluster head |
| $(a \times a \times a)$ | Dimensions of a virtual sub-cube in cubical segmentation |
| $l$ | Cubical network dimension |
| $Q$ | Set of all the virtual subcubes |
| $r_{max}$ | Maximum radius of the network |
| $\mu$ | Proportional factors for heterogeneity calculation |
| $\sigma$ | Resource multipliers used for the heterogeneity calculation |
| $E^j$ | Initial energy of $j^{th}$ type of heterogeneous node |
| $T^j$ | Data rate of $j^{th}$ type of heterogeneous node |
| $E_{network}$ | Total energy provision in the network |
| $T_{network}$ | Total data traffic in the network |
| $\kappa_i$ | Number of type-I sensor nodes |

# List of Published Work

**J01** Shafique, T., Gantassi, R., Soliman, A.H., Amjad, A., Hui, Z.Q. and Choi, Y., 2023. A review of Energy Hole mitigating techniques in multi-hop many to one communication and its significance in IoT oriented Smart City infrastructure. IEEE Access, vol. 11, pp. 121340-121367, 2023, doi:10.1109/ACCESS.2023.3327311

**J02** Shafique, T., Soliman, A.H. and Amjad, A., 2024. Data traffic-based shape independent adaptive unequal clustering for heterogeneous wireless sensor networks. IEEE Access, vol.12, pp.46422-46443, 2024, doi:10.1109/ACCESS.2024.3381520

**J03** Shafique, T., Soliman, A.H., Amjad, A., Uden, L. and Roberts, D.M., 2024. Node Role Selection and Rotation Scheme for Energy Efficiency in Multi-Level IoT-Based Heterogeneous Wireless Sensor Networks (HWSNs). Sensors, 24(17), p.5642, doi:10.3390/s24175642

# Chapter 1

# Introduction

This chapter provides an overview of the characteristics and constraints of heterogeneous wireless sensor networks (HWSNs), along with the trade-offs that can be applied to address these constraints. It establishes the motivation for focusing on the targeted research area and explores the various applications of HWSNs in the realm of the Internet of Things (IoT). Additionally, it explores the challenges associated with enhancing network lifetime and service delivery in these systems.

The chapter further outlines the aim and objectives of the research study, followed by a concise summary of the key contributions to knowledge achieved through this research. Finally, the organisation of the thesis is presented to provide a roadmap for the remainder of the document.

## 1.1 Background and Motivation

The proportion of the global population residing in urban areas has grown from 30% in the 1950s to 57% in 2023 and is projected to reach 66% by 2050 [1]–[3]. As the urban population continues to grow, the demand for modern, information-driven collaborative city systems requires robust and reliable connectivity. The IoT can serve as a fundamental basis for connectivity frameworks in contemporary urban cities, driving unified integration across diverse systems and enabling a diverse range of services, from real-time data analytics to enhanced urban living experiences. As IoT applications increase, the proliferation of connected devices continues to increase. According to Ericson's forecasts, the quantity of IoT-enabled devices will reach 5.5 B by 2027 [4]. This surge introduces the challenge of rising energy consumption in the data transmission and storage due to the vast number of connected devices. The International Data Corporation (IDC) predicts that IoT-connected devices will generate 79.4 ZB of data by 2025 [5].

In addition to the emergence of IoT, developments in micro-electromechanical systems (MEMs) enable timely and live access to real-time data. IoT integration in smart cities enables residents to experience intelligent living environments, including smart homes [6] and smart transportation [7], which often rely on numerous energy -constrained wireless devices deployed across vast areas [8]. A WSN is composed of multiple low-power microsensor nodes that cooperate to sense, process, and transmit environmental data [4]. Their affordability, quick deployment, and self-organising [10] nature make them highlight suitable for various applications, including marine data collection [11], pollution monitoring [12], smart agriculture [13], precision farming [13], disaster alerts [14], wild-life monitoring [15], and multi-level building data collection [16]. Integrating WSN with IoT does not necessitate a significant paradigm shift [17]. This integration enhances the service delivery, reduces cost, and improves quality of life [18] by enabling smart sensor networks with internet connectivity [17], [19].

Devices sharing information for collaborative services in smart cities vary in battery sources and data generation. They can obtain data about their surrounding environment either through physical mechanisms, such as hydraulic, pneumatic, or electromagnetic detection (e.g. resistive sensors), or from a distance using capacitive and inductive sensing mechanisms [20]. Some are deployed in hostile environments, while others are in resource-rich areas. Additionally, some devices are mobile, and others are stationary. There is a variety of parameters that determine heterogeneity among devices, including:

- ***Available Energy:*** Different devices may have varying levels of available energy.
- ***Communication Capabilities:*** Devices may differ in communication range.
- ***Storage Capabilities:*** The storage capacity can vary significantly among devices.
- ***Data Transmission Rate:*** Some devices support higher data rates than others.
- ***Network Roles:*** Devices may have specialised roles such as sensor nodes, cluster head nodes, gateways etc.
- ***Mobility:*** Devices can be stationary or mobile, with varying speeds.

These differences mean that some devices have higher energy availability, longer communication ranges, greater storage capacity, faster data transmission rates, different mobility characteristics, or specific network roles compared to others. Therefore, Heterogeneous Wireless Sensor Networks (HWSNs) represent an advanced and complex variant of traditional WSNs, characterised by diverse and dynamic parameters. Effective management of this heterogeneity is critical to ensure operation and integration within the broader infrastructures such as smart city.

Figure 1.1 illustrates an example of the overall infrastructure of IoT-based HWSN with energy heterogeneity. This infrastructure highlights the complexity and diversity of devices and their interactions within the network.

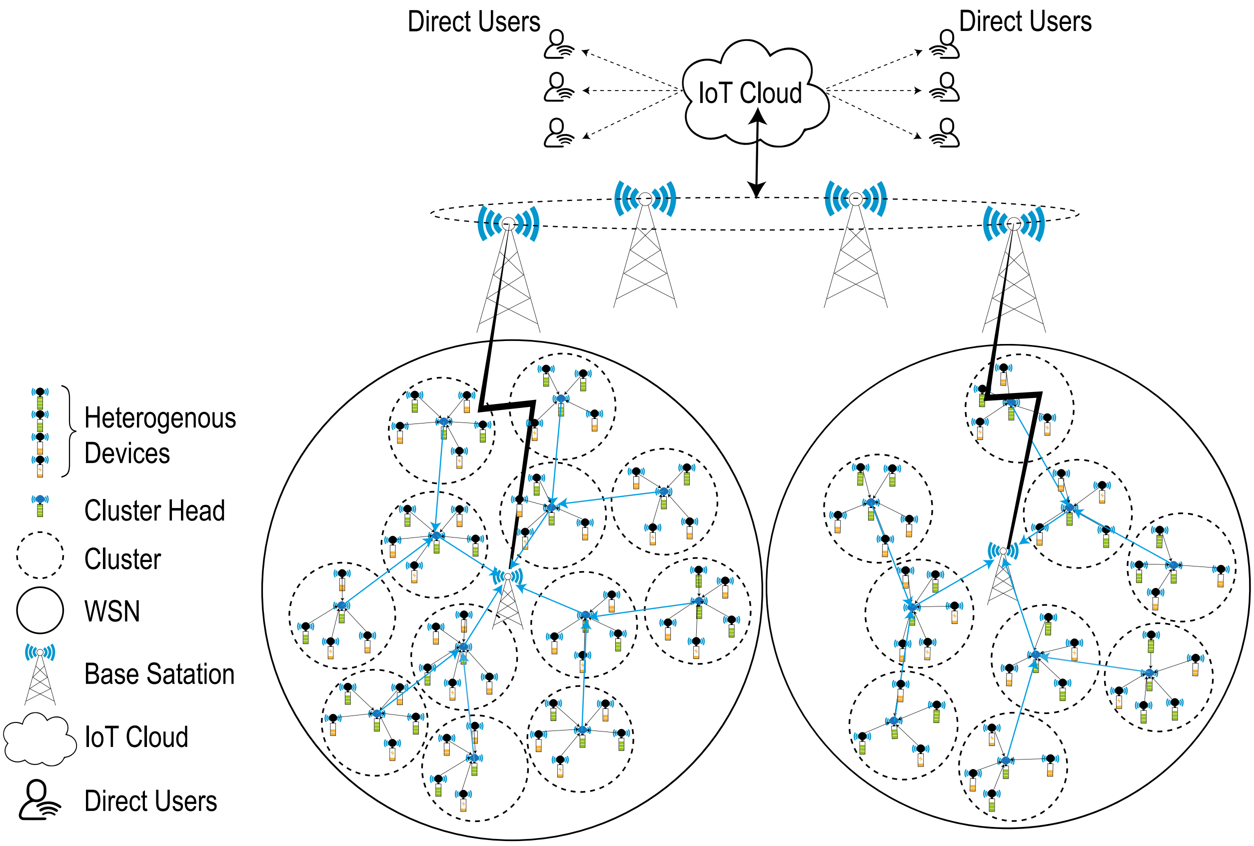



*Figure 1.1: IoT-based HWSN infrastructure.*

Real-time environmental data is collected by various sensors with heterogeneous attributes and communicated using clustered hierarchical routing to a base station [21]. The real-time data is accessed through the IoT cloud, facilitating streamlined service delivery in contemporary infrastructures like smart cities [22]. While IoT-based WSN systems are advantageous in operating autonomously within harsh and inaccessible environments [19], these conditions also pose significant challenges in terms of network longevity [23], primarily due to constraint of non-replaceable or non-rechargeable batteries [24].

The primary power source for a sensor node is typically an electrical battery [25]. Power consumption in a sensor node occurs across various functions, including sensing, processing, storage, and communication [26], with 90% of the overall energy consumed by the network's radio operations [27]. The challenge of prolonging network lifetime of IoT-based WSNs can be tackled by either enhancing energy supply for individual sensor nodes or optimising energy usage. Figure 1.2 illustrates that, beyond traditional techniques for extending battery life, approaches such as ambient energy harvesting [28]–[31] and wireless energy transfer [32], [33] have been developed to enhance energy availability at the sensor node. However, ambient energy is an inconsistent power source [34], and energy transference methods contribute to environmental noise.

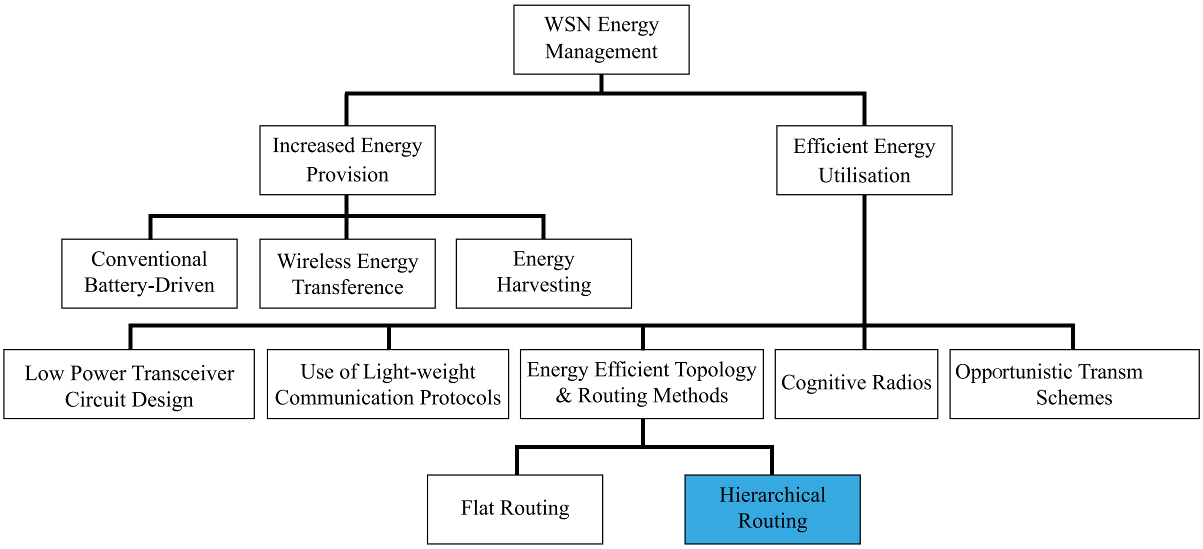



*Figure 1.2: Taxonomy of strategies for increasing network lifetime of WSN.*

Recent methods for reducing energy consumption in the radio operations of network nodes fall into several categories, including transceiver circuit design, transmission power control, lightweight protocols, opportunistic transmission schemes, cognitive radios, and energy-efficient routing [35] as shown in Figure 1.2.

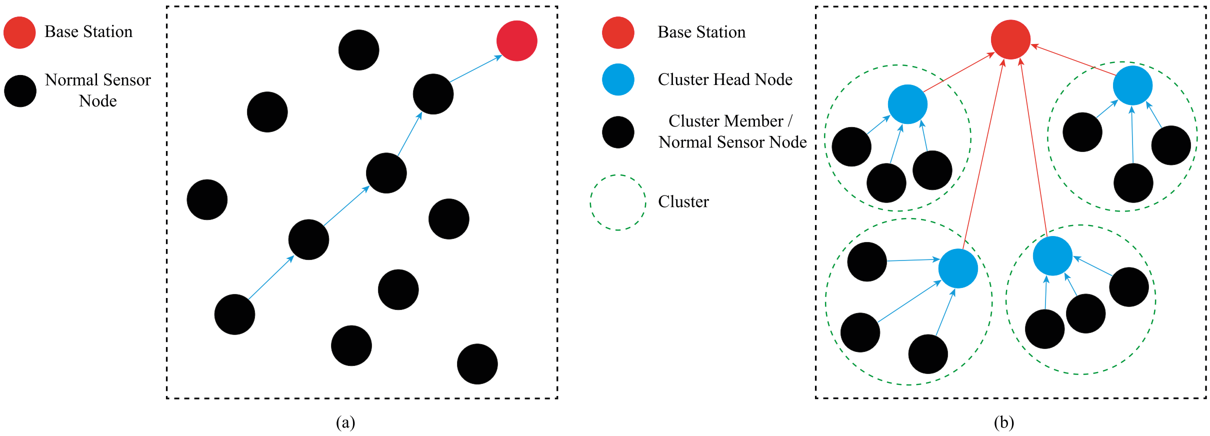



*Figure 1.3: Common routing topologies: (a) Flat routing; (b) Hierarchical routing [36].*

Typically, IoT-based WSN systems contain hundreds to thousands of sensor nodes. Besides sensing, these nodes primarily route sensed data to a base station. Energy-efficient routing is crucial for extending the total operational lifespan of WSN-assisted IoT. The taxonomy in Figure 1.2 categorises WSN routing protocols into two primary types: flat routing and hierarchical routing. In flat routing, (Figure 1.3a), all nodes have identical roles and perform as sensing and data transmission tasks to send data to the base station. These normal nodes communicate either directly with the BS or through multi-hop paths. However, given the large-scale deployment of nodes, flat routing proves to be inefficient in terms of energy consumption [36].

In contrast, hierarchical routing (Figure 1.3b) organises nodes into clusters, where each cluster is managed by a cluster head (CH), a more capable sensor node responsible for aggregating and forwarding data from normal sensor nodes within the cluster. This significantly reduces the total number of transmissions. Arrows in Figure 1.3b represent the direction of data flow from sensor nodes to CHs and ultimately to the BS.

Normal sensor nodes in this context are the low-power sensor nodes deployed for monitoring specific parameters (e.g., temperature, motion). CHs, have relatively higher energy or processing capacity and manage data routing and aggregation. The base station then collects the aggregated data for either local processing or forwarding to the IoT cloud. Hierarchical routing provides benefits such as scalability, extended network lifetime, reduced latency, and improved energy efficiency [36]. Therefore, as highlighted in Figure 1.2, techniques within hierarchical routing are further explored in this research.

Although hierarchical routing protocols for WSNs, are considered energy efficient, the converge-cast nature of multi-hop inter-cluster communication causes cluster-heads close to the base station to experience a higher transmission load, resulting in uneven energy distribution throughout the network. This imbalance results in the early failure of the CHs positioned close to the sink node, thereby limiting the network's lifetime [21]. Consequently, this inefficiency limits the effective use of available resources, leaving 90% of the initial energy unutilised by the end of network's lifespan [37], and negatively impacts network stability [38].

An extensive literature review of energy-saving and evenly distributed energy consumption strategies in IoT-based WSN suggests the following limitations:

***Real Heterogeneity:*** IoT-based WSNs can consist of sensor nodes with diverse heterogeneous capabilities, leading to development of IoT-based HWSNs [39]. Device heterogeneity can be characterised by various parameters, including available energy, communication capabilities, storage capacity, and other functional attributes of sensing nodes. The majority of the existing energy-efficient and balanced energy consumption schemes assume homogeneous networks [40]–[50]. Those schemes that do address heterogeneous network structures [51]–[54] do not fully exploit the multi-parameter and multi-level heterogeneous characteristics. Therefore, to develop an adaptable and scalable energy-efficient routing method, it is essential to extend heterogeneity consideration to multi-level and multi-parameters.

***Placement of the Sink Node:*** The placement of the base station (sink node) is crucial for energy-efficient and balanced network operation. Sensing nodes are typically placed either randomly or in a pre-planned manner within a region of interest [55]. Non-uniform deployment techniques [56] increase the device density from the outer to the inner sections of the network, resulting in more stable and efficient operation [57]. However, real-life applications such as sea surfaces, mountainous terrains, smart farming, and precision agriculture [46] impose significant limitations on the implementation of such schemes. These applications, feature varying terrains and remote locations, making controlled deployment challenging and sometimes unrealistic. Heterogeneous devices deployed in three-dimensional space must share transceivers for efficient data collection, but there is no standard mechanism for determining the optimal base station location [58]. Consequently, most of the existing network topologies place the sink node either at the middle of the network or on the boundary of the region of interest [8]. Therefore, determination of an effective location of the sink node is vital.

***Shape Independent Network Segmentation:*** IoT-based HWSNs can be two-dimensional or three-dimensional and can take any shape depending on the application [13], [59]–[61]. To maintain energy efficiency while ensuring balanced network operation, network segmentation is an effective method for obtaining information about the characteristics of heterogeneous nodes in smaller regions of the network. This approach helps determine both the cluster size and the selection of the cluster head for each successive cluster in a converge-cast communication process. However, most existing segmentation schemes are either two-dimensional [55], [62]–[64] or do not fully consider heterogeneous network parameters [45], [65]. Furthermore, these existing schemes are shape-dependent [66]–[70] and thus offer limitations in terms of scalability, adaptability, and flexibility.

***Unequal Clustering:*** Clustering is the one of the most effective and energy-efficient methods for transferring data packets from nodes to the base station [71]. However, equal clustering approaches [40]–[43], [51]–[54], [72]–[83] are unfair as they do not account for the dual responsibilities of CHs closer to the BS, which involve both aggregating and relaying data. Existing unequal clustering methods [44]–[47], [49], [50], [84]–[88] primarily focus on the cluster size, overlooking the number of nodes and the volume of heterogeneous data packets hosted by those nodes. Moreover, these methods typically employ shape-dependent fixed segmentation schemes and are limited to two-dimensional network structures. For a diverse network such as IoT-based HWSN with various applications, it is essential to have a shape-independent unequal clustering algorithm that truly balances energy consumption and extends the network's operational lifespan.

***Energy Efficient Cooperative Routing:*** For effective operation of an IoT-based HWSN, the selection of cluster heads should be made cooperatively with the next-hop in multi-hop inter-cluster communication. Most existing methods [9], [10], [19], [23], [89]–[91] lack cooperation between cluster head selection and rotation with the choice of relay nodes. Additionally, relay node rotation has not been collaboratively designed to fully enhance network lifetime and efficiently utilise available energy. Therefore, cluster head selection and rotation, as well as relay node selection and rotation, should be performed cooperatively to extend the network lifetime.

## 1.2 Trade-offs between parameters impacting balanced energy operation:

This study initiates with a comprehensive analysis and evaluation, supported by an extensive review of the literature on physical and natural phenomena that influence energy consumption and load balancing among devices. Through observations of network operations, it was identified that the following trade-offs can contribute to addressing the challenges encountered:

### *1.2.1 Sensing range and transmission distance*

Heterogeneous devices are considered to possess diverse characteristics, enabling them to collect environmental data through various physical mechanisms, such as hydraulic, pneumatic, or electromagnetic detection methods (e.g., resistive sensors) [20]. Alternatively, they can gather data from a distance via capacitive or inductive sensing mechanisms [20].

Energy expended by sensing devices in collecting information depends on their coverage range. In heterogeneous networks balanced energy consumption among such devices can be achieved by allowing maximum sensing range for devices near the sink node and minimum sensing range for devices towards the boundaries of the network. A balance in energy spent by devices can be achieved by working out an optimum trade-off between energy spent on sensing and transmission operation of each device.

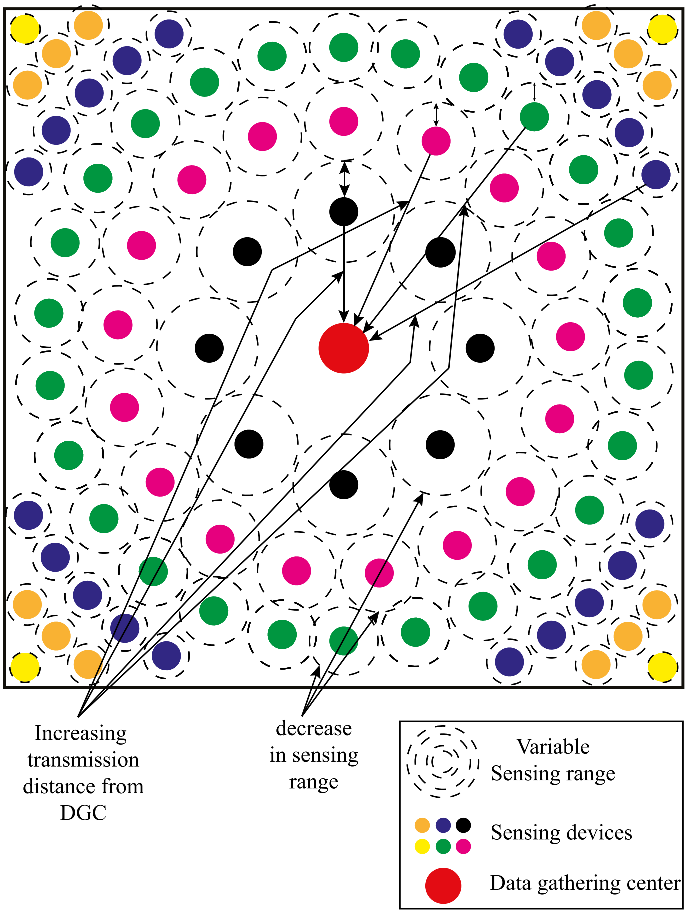



*Figure 1.4: The trade-off between sensing range and transmission distance of devices.*

Figure 1.4 illustrates how a reduction in sensing range, coupled with an increase in transmission distance from the base station, can be leveraged to achieve balanced energy consumption among nodes. This phenomenon is also observed in empirical studies, where nodes with limited sensing activity can conserve energy to support longer transmission paths [7].

However, since hierarchical routing applies a multi-hop communication of clustered devices the solution is not as simple as exploiting this trade-off. Though, sensing ranges if properly worked with the application of appropriate technique can reduce the formation of energy holes. A detailed investigation of this phenomenon was considered to achieve balanced energy consumption with increased network lifetime.

### *1.2.2 Next hop based on transmission data and distances*

Second phenomenon that balances energy consumption among devices with heterogeneous data rates is shown in Figure 1.5. Devices with less data to transmit can choose a next hop at further distance as compared to those with more data to transmit. This way a balanced energy operation allows devices to efficiently extend a network lifetime.

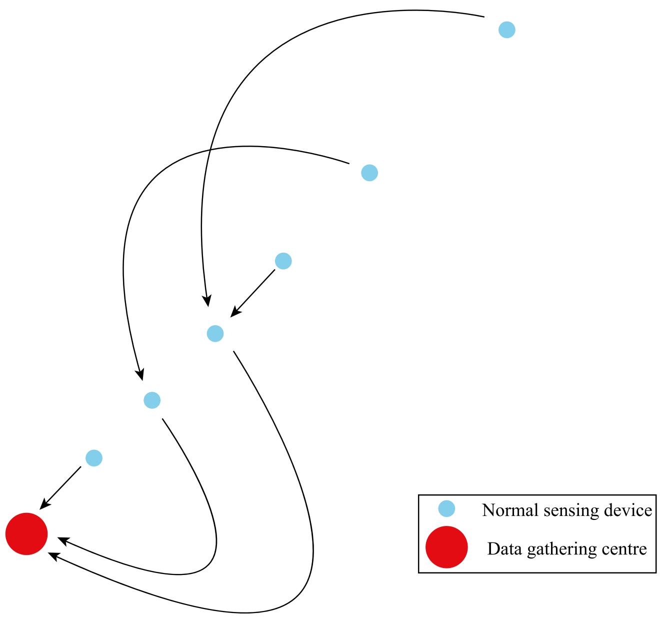



*Figure 1.5: The trade-off between transmission distance and data traffic on devices.*

Figure 1.5 illustrates that nodes with lower data loads can transmit over longer distances without disproportionately increasing energy consumption. This behaviour has been reported in prior WSN studies [53], where low-data nodes were empirically shown to sustain longer-range transmissions, contributing to balanced network performance and extended lifetime.

### *1.2.3 Transmission distance and accumulated data*

Thirdly, during multi-hop operation data accumulation increases on the devices closer to base station. The phenomenon shown in Figure 1.6 allows devices to achieve a balanced operation with a homogeneous data rate. If the distance vs data to transmit is worked appropriately it can assist in achieving balanced energy consumption. A proper management of this phenomenon in relation to the multi-hop communication can produce balanced energy operation of devices with heterogeneous data traffic.

As depicted in Figure 1.6, multi-hop data accumulation near the sink can lead to uneven energy drain. Simulation results in Chapter 5 confirm that controlling transmission distances based on traffic load enables energy balancing across nodes. This observation aligns with prior empirical work on hotspot mitigation in hierarchical WSNs [62], reinforcing the practical value of the trade-off.

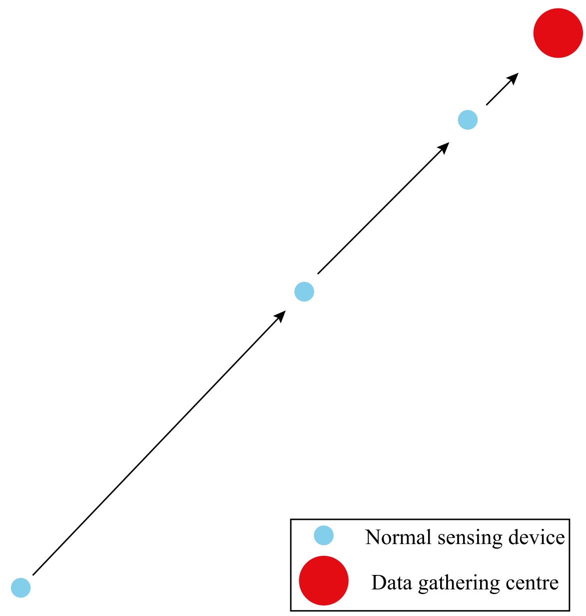



*Figure 1.6: Calculation of transmission distance based on heterogeneous data at different hops.*

### *1.2.4 Distance based unequal clusters for balanced energy consumption*

Hierarchical routing using unequal clustering is an effective routing method in terms of energy consumption. CHs gather data from the corresponding fellow nodes in a cluster and transmit to BS in a direct communication or through the next hop. Figure 1.7 shows unequal cluster boundaries based on distance from the base station. This phenomenon if worked appropriately not only achieves balanced energy operation of devices but extends the network lifespan due to efficient energy usage in multi-hop communication as compared to single-hop communication.

Figure 1.7 shows how adjusting cluster sizes relative to distance from the base station supports balanced energy use. Unequal clustering has been widely tested in literature [65], where increasing cluster size with distance has shown to reduce the burden on closer cluster heads.

Extensive literature review in chapter 2 summarises state-of-the-art techniques incorporating above mechanisms to achieve energy balancing and network lifetime. Limitations in adaptivity, scalability and stability of current hierarchical routing techniques have motivated this research. An integrated system approach to achieve balanced energy and flexible operation of devices is proposed in this research.

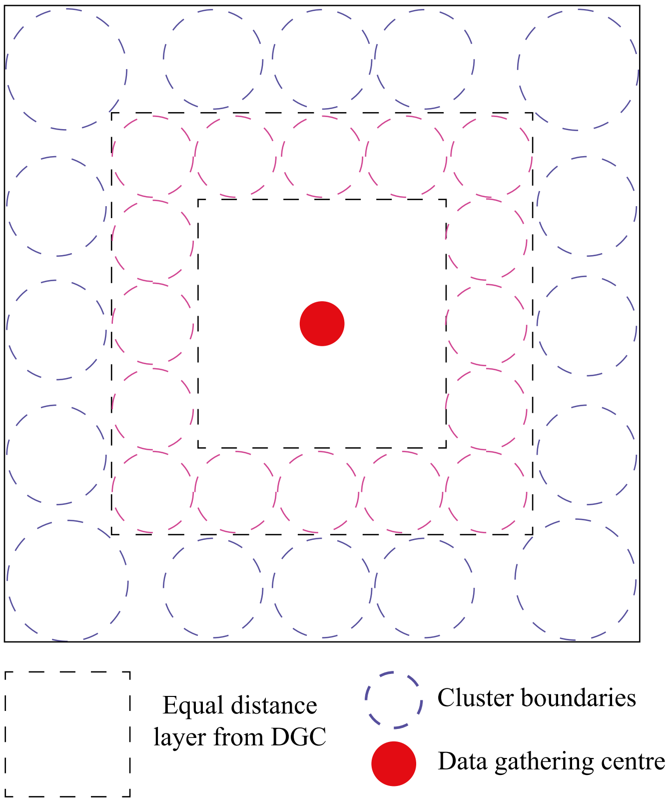



*Figure 1.7: Increase in cluster size relative to the distance from the base station.*

## 1.3 Problem Statement:

In large-scale IoT-based Wireless Sensor Networks (WSNs), especially those deployed in irregular or three-dimensional (3D) terrains, achieving balanced energy consumption across heterogeneous devices remains a persistent challenge. Sensor nodes deployed in such environments often differ in energy capacity, sensing range, data rate, and communication capability. Traditional routing and clustering techniques, which assume uniform node characteristics and simple 2D layouts, fail to scale or adapt effectively to these complex deployment scenarios. This leads to uneven energy consumption, formation of energy holes, and premature node failures, ultimately shortening network lifetime and reducing system reliability. Furthermore, existing methods often overlook the dynamic nature of heterogeneous networks, including spatial irregularity, diverse transmission demands, and variable node density. There is a critical need for an integrated, scalable, and shape-adaptive approach that optimises sink node placement, network segmentation, and energy-aware clustering and routing, in order to maximise network lifetime and maintain performance across varied deployment conditions.

## 1.4 Aim and Objectives:

### *1.4.1 Research Aim*

The main aim of this research is to investigate and address the challenges of maximising the network lifetime in Heterogeneous Wireless Sensor Networks (HWSNs), by developing an integrated energy efficient deployment, segmentation, clustering, and routing scheme. The proposed integrated scheme is expected to minimise the energy holes caused by uneven energy consumption, ensuring balanced energy usage, and enhance scalability and adaptability to meet the dynamic requirements of IoT-based HWSNs. The solutions are expected to support heterogeneous devices and variable data rates, providing a sustainable and energy-efficient framework for real-world IoT applications.

### *1.4.2 Research Objectives*

In order to achieve the research aim, and to address the gaps in knowledge, the following research objectives have been established:

- To conduct a critical literature review of existing balanced energy consumption techniques, network lifetime maximisation routing protocols and radio frequency (RF) energy estimation models to identify limitations in current methods.
- To examine the challenges in designing a shape-adaptive, energy-efficient, unequal clustering and energy-balanced routing schemes that maximises network lifetime of heterogeneous wireless sensor network.
- To design a technique for determining an optimal location of base station by analysing heterogeneous characteristics of sensor devices.
- To propose and develop three-dimensional segmentation schemes, specifically for cubical and spherical shaped networks, to support unequal clustering. These segmentation schemes are required to achieve a balanced energy and maximum lifetime routing in shape varying networks.
- To propose and develop a shape-adaptive network segmentation mechanism, that facilitates effective selection of cluster heads and manages device association in variable-shaped HWSNs.
- To develop a dynamic routing scheme that incorporates unequal clustering and enhances overall network lifetime, while ensuring scalability and adaptability for IoT-enabled HWSNs.

- To validate and benchmark the proposed techniques against state-of-the-art techniques and publish the findings through journal publications and a final thesis.

## 1.5 Research Contributions:

Throughout the development of WSNs for IoT-based applications, managing energy consumption while ensuring network scalability, adaptability, and longevity remains a persistent challenge. The complexity grows significantly in heterogeneous environments, where varying energy levels, data rates, and deployment terrains in three-dimensional space further complicate optimal sink node placement and routing efficiency. In addressing these critical challenges, this research introduces several innovative contributions, focused on improving the energy efficiency and overall performance of large-scale WSNs. The contributions of this research are outlined as follows:

- A new energy-efficient sink node placement technique has been developed, which evaluates all potential deployment locations within a defined radius of the network's centroid. It selects the optimal location based on minimum total energy consumption across direct and cluster-based transmissions. This contribution is detailed in chapter 3 of the thesis.
- The research addresses the computation complexity of sink node placement in heterogeneous wireless sensor network by formulating a multi-criterion decision making (MCDM) problem. The Technique for the Order of Preference by Similarity to Ideal Solutions (TOPSIS) was meticulously selected and adapted to accommodate the network's diverse characteristics-such as energy levels, distances, storage, data rates and computational capacity. By computing the positive and negative solutions, TOPSIS rigorously ranks each potential sink node location, ultimately pinpointing the most energy efficient position. This contribution is fully explored in chapter 3 of the thesis.
- Scalable and adaptable sink node deployment strategies have been proposed and validated using realistic scenarios across varying network scales and compared against metaheuristic alternatives. This contribution is presented in detail in chapter 3 of the thesis.
- Two novel 3D segmentation schemes i.e., cubical and spherical, have been introduced to enhance unequal clustering by incorporating centroid-based distribution of resources and traffic load. This contribution has been detailed in chapter 4 of the thesis.

- A data rate-based shape independent network segmentation scheme has been proposed. Centroid computation has been applied to the shape independent segmentation scheme to extend the adaptability and scalability of the balanced energy unequal clustering. This contribution is presented in chapter 4 of the thesis.
- An innovative method for identifying optimal relay regions has been introduced, combined with an energy-aware cluster head rotation mechanism that selects resource-rich relay nodes dynamically. This contribution has been explained in chapter 5 of the thesis.
- A novel approach is introduced to prolong network lifetime and improve energy efficiency in intra-cluster communication. This involves the creation of a flexible heterogeneity model for multi-parameter heterogeneous networks. Furthermore, a mathematical model is developed and incorporated into a new CH rotation algorithm, which optimises and balances energy consumption. These contributions ensure stable, energy-efficient network performance and sustainable operations. The details of the model have been shown in detail in chapter 5 of the thesis.
- A dynamic relay selection mechanism has been formulated, allowing adaptive role assignment based on real-time energy metrics to maintain inter-cluster energy balance. This contribution has been detailed in chapter 5 of the thesis.
- A relay role rotation algorithm has been developed to prevent early node depletion by distributing communication loads more evenly, thereby significantly improving network longevity. This contribution has also been presented in chapter 5 of the thesis.

## 1.6 Thesis Organisation:

The flow diagram in Figure 1.8 presents an overview of the thesis structure, beginning with the summary of research aim that already been defined in Chapter 1, and focuses on developing a cooperative deployment, clustering and routing scheme to improve network lifetime and stability by mitigating energy holes in heterogeneous wireless sensor networks (HWSNs).

The rest of the thesis is organised as follows:

Chapter 2 outlines the state-of-the-art energy hole mitigation techniques, highlighting limitations in existing sink node placement methods, clustering schemes, and routing methods, such as shape-specific segmentation, limited scalability, and limited heterogeneity consideration. These identified gaps lay the foundation for the subsequent research contributions.

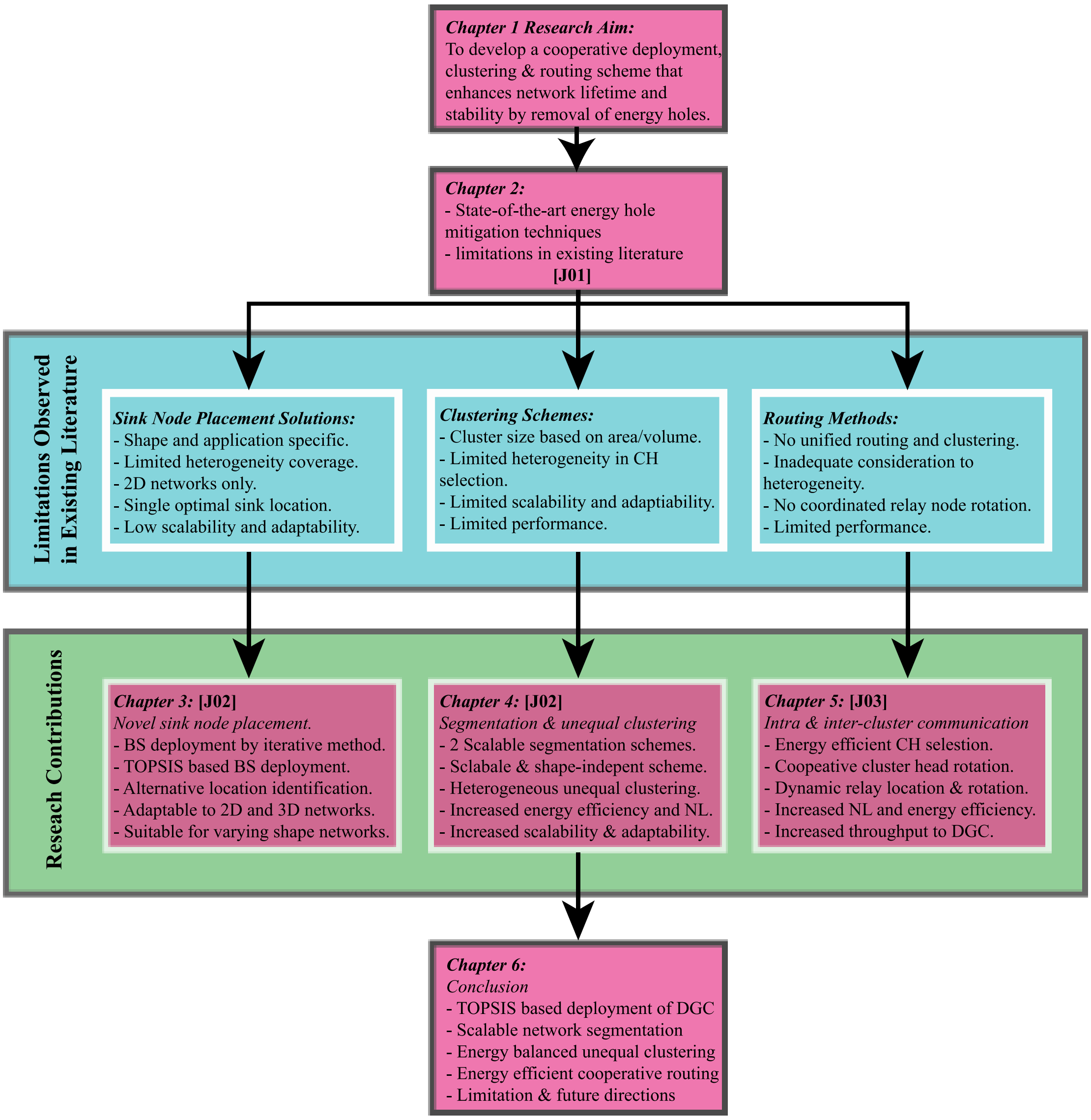



*Figure 1.8: Thesis structure and overview of research contributions.*

Chapters 3, 4, and 5 explain the core of the thesis, where each chapter addresses one of the critical issues from the literature review. Chapter 3 introduces a novel TOPSIS-based sink node placement strategy, focusing on alternative location identification and energy-efficient deployment suitable for various network shapes. Chapter 4 expands on segmentation and unequal clustering schemes, incorporating both fixed and shape-independent segmentation and addressing multi-level and multi-parameter heterogeneity to improve scalability and energy efficiency. Chapter 5 further contributes by optimising intra- and inter-cluster communication, introducing cooperative cluster head rotation and dynamic relay node identification and the role rotation, resulting in enhanced network lifetime and throughput.

Finally, Chapter 6 consolidates these contributions, concluding on the novel methods developed, including scalable network segmentation and cooperative routing, while suggesting future research directions to extend the applicability of these techniques.

# Chapter 2

# State-of-the-Art Techniques for Maximising Network Lifetime through Balanced Energy Consumption in IoT-based WSNs

## 2.1 Introduction

This chapter provides a comprehensive critical review and analysis of the cutting-edge techniques aimed at optimising energy consumption and extending network lifetime in WSNs, with a specific focus on IoT-based applications. As the IoT-based WSN become increasingly prevalent across wide range of fields, such as smart cities [92], smart homes [6], smart transportation [7], marine data collection [11], pollution monitoring [12], smart farming [13], precision agriculture [13], disaster alerts [14], wild-life tracking [15], and multi-floor building data collection [16], the need for energy-efficient data transmission within WSNs has grown. This need is particularly urgent in large-scale [8], heterogeneous [39], and dynamic environments.

The main aim of this chapter is to critically examine existing methods for balancing energy consumption and mitigating energy holes i.e., regions where network nodes deplete energy faster than others-while striving to extend overall network lifetime.

The review explores hierarchical routing techniques, such as Low Energy Hierarchical Clustering Hierarchy (LEACH) [40] and its variants, which utilise clustering to distribute energy usage across nodes. The advantages of variants of LEACH in reducing communication overhead and balancing load are discussed, alongside their limitations in heterogeneous environments [39] and large-scale deployments [8]. The probabilistic and chain-based routing techniques Hybrid Energy-Efficient Distributed clustering (HEED) [73] and Power efficient Energy Gathering Sensor Information Systems (PEGASIS) [75] are also evaluated which offer solutions to energy challenges but struggle with scalability and high latency, particularly in multi-hop communication scenario.

Emerging strategies have been classified in four major areas i.e., assisted node deployment, mobile sink deployment, unequal clustering, and energy-aware routing. While the protocols such as Balanced Energy Consuming and Hole Alleviating (BECHA) [93] and Energy Aware Balanced Energy Consuming and Hole Alleviating (EA-BECHA) [41] have demonstrated promising results with regard to energy savings and network stability, they often introduce additional complexity and computational overhead, which limits their applicability in resource-constrained networks.

Furthermore, the existing techniques are classified based on key device attributes, such as homogeneous vs. heterogeneous networks, inter-cluster communication (direct vs. multi-hop), and sink node mobility (stationary vs. mobile sink nodes). Advantages and limitations of each category have been presented. For instance, while multi-hop communication helps reduce energy consumption, it can result in an imbalance in energy usage across the network. Mobile sink strategies, though effective in balancing energy distribution, introduce increased latency and additional complexity in routing management.

Lastly, this chapter critically assesses the scalability, adaptability, and network topology (circular, square, and rectangular) of the existing techniques, offering insight into their generalisability for various IoT-based WSN applications. The key challenge remains in developing protocols that can effectively adapt to the dynamic and diverse requirements of IoT environments, while maintaining energy efficiency and ensuring network longevity.

## 2.2 Applications and Demands of Wireless Sensor Networks:

Advancements in microelectromechanical systems (MEMS) and communication technologies have made it possible for devices to communicate anytime, anywhere, with anyone, over any network or service [94]. Wireless sensors are essential components in IoT systems, enabling prompt and informed decision-making. Due to increasing applications of WSNs in larger infrastructures such as IoT and smart cities, the WSN market is anticipated to grow significantly, with a projected market value of USD 426.2 billion by 2030. This growth represents a compound annual growth rate (CAGR) of 18.3% between 2023 and 2030 [95]. As WSNs advance and expand, energy efficiency emerges as a critical concern. A key function of wireless sensors is transmitting collected date to a base station. Hierarchical routing through clustered sensor nodes has been identified as a highly energy-efficient approach data transmission.

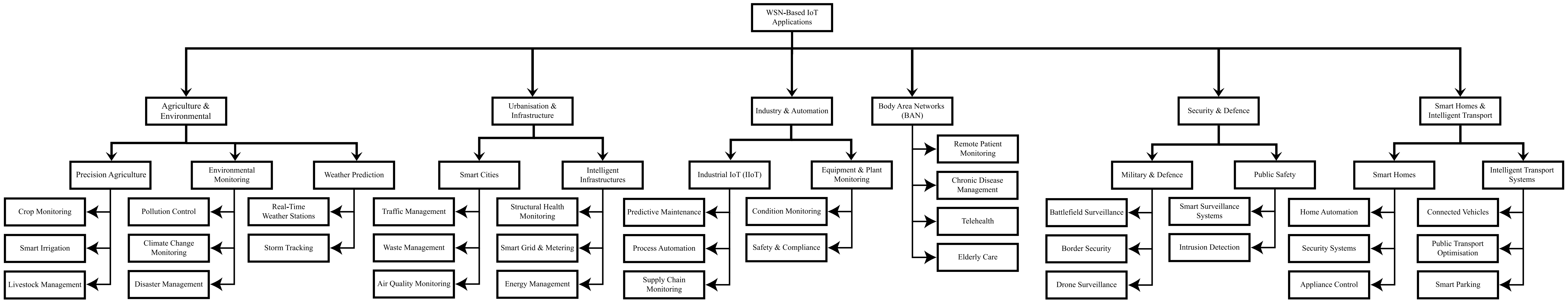



*Figure 2.1: Key applications of IoT-based wireless sensor network*

IoT-based WSNs and MEMs enable the design of cost-effective, compact, and multi-functional sensor nodes. These advanced nodes can integrate a variety of sensors, including thermal, seismic, acoustic, magnetic, infrared, and visual sensors, tailored to meet the specific needs of diverse applications [96]. As a result, IoT-based WSNs are capable of monitoring a wide range of environmental conditions, including pressure, humidity, temperature, direction, speed, noise levels, light intensity, and mechanical stress.

This adaptability makes IoT-based WSNs well-suited for a broad array of applications, including environmental surveillance, climate control, automated home systems, marine ecosystem tracking, incident management, and supply chain support. Figure 2.1 categorise the existing applications of IoT-based WSNs, highlighting some key usages.

The applications of IoT-based WSNs are diverse and encompass various domains. In the field of agriculture and environment, WSNs are used for precision agriculture [64], [97]–[100], environmental monitoring [101]–[104], and weather prediction [105]–[107]. Urbanisation and infrastructure applications include their integration into smart cities [108]–[113] and intelligent infrastructure [114]–[117], enhancing urban planning and sustainability. In industry and automation, WSNs play a critical role in supporting Industrial IoT (IIoT) [118]–[121] and monitoring equipment & plant operations [122].

In the healthcare domain, WSNs are employed in Body Area Networks (WBANs) to facilitate remote patient monitoring [123], chronic disease management [124], telehealth [125], and elderly care [126], contributing to more efficient healthcare delivery. In security and defence, they are pivotal for military operations [127]–[129], public safety, and crime prevention [130], [131]. Additionally, WSNs enhance the functionality of smart homes [132]–[134] and intelligent transport systems [135]–[137], improving daily life and transportation safety.

These applications demonstrate the versatility of IoT-based WSNs in addressing challenges across multiple sectors. Further details on their significant applications are provided in Appendix A.

### *2.2.1 Energy challenges in IoT-based WSN applications:*

The continuous expansion of IoT-based WSN applications in modern interconnected smart cities has led to a rapid growth in number of IoT devices. This surge introduces significant challenges in managing the energy consumption required to support these devices, especially within HWSNs. Ericsson projects that the IoT devices figure globally will total 5.5 billion by 2027 [4], while a study conducted by Farhan et al. suggests that this figure could rise to 24.1

billion by 2030 [138]. As the number of devices increases, the volume of data generated, transmitted, and stored, also rises, leading to a sizable increase in energy consumption.

The International Data Corporation (IDC) has projected that WSN-based IoT devices will generate an astounding 79.4 zettabytes (ZB) of data by 2025 [139]. This massive data influx demands substantial energy resources, not only for data transmission and storage but also for processing and managing information within WSNs. Balancing energy supply and demand in this scenario is particularly challenging because of limited energy resources available to sensor nodes, which are typically battery powered.

A critical issue in WSNs is energy imbalance, where certain nodes drain their energy much faster than others, leading to the creation of energy holes. These energy holes can result in network partitioning, reduced coverage, and ultimately a shorter operational lifetime for the network. Studies have shown that a significant portion of the network's initial energy remains unused by the time the network's lifetime ends, with up to 90% remaining in some cases [37]. This inefficiency underscores the need for optimised energy management strategies that ensure more balanced energy consumption across the network.

In addition to energy imbalance, the growing number of devices presents challenges in maintaining network stability. A network is considered stable if the time interval between the death of the first node and the last node is minimised [38]. However, as the number of devices and the volume of data increase, maintaining this stability becomes increasingly difficult. This situation necessitates advanced techniques that can adapt to varying network conditions and demands.

Given these challenges, energy management in HWSNs must prioritise the development of scalable and adaptable methods capable of handling the increasing number of devices and the corresponding data transmission demands. These methods should aim not only to extend network lifetime and increase throughput but also to enhance stability by preventing energy holes and ensuring a more balanced energy distribution among nodes.

The current literature presents various approaches to address these challenges, including clustering and routing techniques, energy harvesting, and mobile data collection strategies. However, there is still a pressing need for more comprehensive solutions that can seamlessly integrate these approaches, optimise energy consumption, and adapt to the diverse and dynamic environments in which WSNs are deployed.

## 2.3 Wireless Sensor Networks Architecture

As explored in the preceding sections, the rapid advancement of IoT-based HWSNs has led to their widespread application in several domains, ranging from agriculture and environmental monitoring to smart cities and industrial automation. However, the architecture of these networks remains fundamental to their functionality and efficiency, particularly in the context of energy management and network longevity.

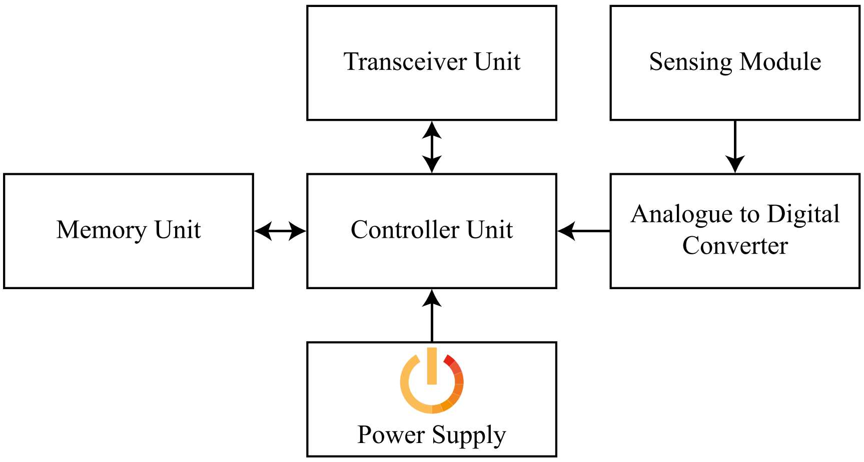



*Figure 2.2: Architecture of a typical wireless node.*

A typical architecture of a wireless sensor node, which forms the backbone of these networks, is shown in Figure 2.2. This architecture comprises of five fixed modules and one adjustable module, each playing a critical function in the operation of the wireless sensor node [140]. The fixed modules include a power supply, which can be a non-rechargeable or rechargeable battery depending on the deployment environment. The controller, another fixed module, manages the wireless sensor node's operations by processing data and overseeing both operational and maintenance tasks. Additionally, a memory module is incorporated based on the application's specific requirements, facilitating tasks such as data storage and algorithm implementation. For communication, the transceiver module enables the wireless sensor node to interact with other nodes and transmit sensory information across the network. The analogue-to-digital converter (ADC) converts analogue signals generated by the sensors into digital data that the controller can process. The adjustable module within the wireless sensor node is the sensing module, which is tailored specifically to the application at hand. These components collectively form the foundational architecture of a wireless sensor node, enabling it to perform its designated sensing and communication functions efficiently.

### *2.3.1 Power Supply:*

The power source is an essential component of any wireless sensor node and is often considered the heart of the system. It is responsible for providing the necessary energy to power all functions of the wireless sensor node. In some specific applications, such as measuring thermal heat in data centres, wireless sensor nodes may be powered with a continuous power source, ensuring uninterrupted operation [141]. However, in most cases, wireless sensor nodes are installed in remote or hard-to-reach locations where a continuous power source is not feasible. In these situations, the nodes rely on replaceable and rechargeable batteries.

The lifespan of these batteries is a crucial consideration during the development phase of a wireless sensor node. Ensuring an adequate power supply to support the node's intended sensing operations throughout its operational lifespan is essential, as frequent battery replacements can be both logistically challenging and costly. This requirement highlighted the importance of energy efficiency, which remains a critical and ongoing research challenge for wireless sensor nodes.

The power usage of a wireless sensor node is primarily driven by three main operations [142]:

- ***Sensing:*** Collecting data from the surrounding environment through various sensors.
- ***Data Processing:*** Processing the collected data, often within the node, before it is transmitted or stored.
- ***Communicating:*** Transmitting the collected data to other nodes or central systems.

Among these three operations, data transmission consumes the most significant (almost 90%) amount of battery power [27]. For example, the energy required to transmit 1Kb of data over a specific distance of approximately 330 feet is comparable to the energy required to execute 3 million instructions per second on a typical processor [143]. The batteries employed in these sensors are categorised according to the materials used in their construction, such as lithium-ion, nickel-cadmium, and nickel-metal hydride [144].

Additionally, some modern wireless sensor nodes are equipped with the capability to harvest energy from various environmental sources, such as Radio Frequency (RF) signals, solar power, and mechanical vibrations [32], [33]. However, these energy-harvesting technologies require additional electronics and are subject to the availability and variability of the energy source [145]. Despite these advancements, ensuring sufficient and efficient energy supply continues to be a major challenge in the design and deployment of sensor nodes, particularly in energy-constrained environments.

### *2.3.2 Controller Unit:*

The controller is often referred to as the central unit or "brain" of any wireless sensor node, as it is responsible for managing the functionality of the wireless sensor node. Its primary role is to process the data collected by the sensors and execute the various operations that the wireless sensor node performs. Commonly, a microcontroller is used as the controller within wireless sensor nodes due to its balance of functionality, cost, and power efficiency [146]. Microcontrollers are particularly well-suited to this role because they handle the relatively simple, yet critical, tasks of data processing and device control with minimal energy consumption. However, depending on the complexity and requirements of the application, alternative options such as Field Programmable Gate Arrays (FPGAs), Digital Signal Processors (DSPs), and microprocessors may also be employed. These alternatives offer varying degrees of processing power and flexibility, albeit often at the cost of higher power consumption and increased complexity.

### *2.3.3 Memory Unit:*

The memory unit within a wireless sensor node serves two primary functions: storing the data aggregated by the sensors and providing the necessary space for programming the device, including the implementation of algorithms. The specific memory requirements for a wireless sensor node are typically determined by the application it is intended to support. In most cases, the microcontroller used as the controller will come equipped with an onboard memory chip, which is sufficient for storing sensor data and handling programming tasks. Flash memory is commonly preferred for these purposes due to its combination of low cost and relatively high storage capacity. This allows the wireless sensor node to retain critical data and execute necessary operations without consuming excessive power or space. As such, the memory module is a vital component that ensures the smooth operation and reliability of the wireless sensor node, particularly in data-intensive applications.

### *2.3.4 Transceiver Unit:*

The transceiver module in a wireless sensor node is critical for enabling wireless communication, allowing the node to transmit and receive sensory information over the wireless channel. This capability is essential for the node to interact with other wireless sensor nodes and central systems within the network. The transceiver functions in four distinct modes: receive, transmit, idle, and sleep [140]. Advanced transceivers are often integrated with state machines that can manage these states automatically, optimising the node's energy consumption during different operational phases. However, it is important to note that the power consumption in idle mode is nearly the same as in receiving mode, which poses a challenge for energy efficiency. Significant power is also used when changing between different modes, further highlighting the need for innovative techniques to reduce power usage in transceiver operations [140].

### *2.3.5 Analogue to Digital Converter:*

Majority of sensors integrated into a wireless sensor node generate analogue signals in response to the physical phenomena they monitor. These analogue signals must be converted into a digital format to be processed by the controller. The Analogue to Digital Converter (ADC) serves this important function, acting as an interpreter between the sensor module and the controller unit. The conversion process is vital for ensuring that the data collected by the sensors can be utilised effectively within the wireless sensor node's processing and communication workflows. The efficiency and accuracy of the ADC directly impact the overall performance of the wireless sensor node, particularly in applications that require precise and reliable data interpretation.

### *2.3.6 Sensing Module:*

The sensing module is the main front-end component of a wireless sensor node and plays a pivotal role in the node's ability to interact with its environment. Sensors are responsible for detecting and measuring various environmental parameters, depending on the specific application for which the wireless sensor node is deployed. The types of sensors used can vary widely, ranging from temperature and humidity sensors to more specialised sensors such as those for detecting chemical concentrations or vibrations. The choice of sensors is entirely application-specific, meaning that the sensor module must be tailored to meet the needs of the particular use case. For example, in environmental monitoring applications, sensors might be selected to measure air quality, soil moisture, or water levels, while in industrial automation, sensors might be used to monitor machine vibrations or thermal emissions. These sensors generate the raw data that is essential for the node's operations, making them a key component of the wireless sensor node's architecture [140].

### *2.3.7 Observations on architecture:*

The architecture of a wireless sensor node is designed with efficiency and adaptability in mind, but the growing complexity and scale of WSN-based IoT applications pose significant challenges, particularly in energy management. As the applications of these networks expand, so too does the need for strategies that can maintain balanced energy consumption across all nodes.

Energy management in WSNs is critical, as it directly influences the overall network lifetime, particularly in large-scale IoT deployments where sensor nodes may be distributed across vast areas and often in difficult-to-reach locations. Ensuring that each node uses its available energy as efficiently as possible is paramount, as the ability to replace or recharge batteries in these environments is often limited.

## 2.4 Energy Management in IoT-Based WSN:

Building on the foundational architecture of WSN nodes and the critical role of energy management in IoT-based WSN applications, it becomes evident that the longevity and efficiency of these networks hinge significantly on how energy is consumed and conserved within each node. As discussed, the deployment of these sensor nodes across diverse and often challenging environments necessitates highly efficient energy utilisation strategies to ensure prolonged network operation and prevent premature node failure.

WSNs are a foundational technology for the Internet of Things (IoT) [147]. The surge in IoT applications has led to a corresponding increase in energy demands. One approach to mitigating increased energy consumption is through the implementation of lightweight routing and data aggregation protocols, specifically designed to limit energy usage within the WSNs themselves [147].

Each sensing node within a WSN consumes energy through sensing, processing, storing, and communication [26], with electrical batteries being the most common power source [25]. In large-scale WSN-assisted IoT networks, environmental factors and the physical layout of deployment areas make battery replacement or recharging highly challenging [38].

Efficient energy management is critical to extending the lifetime of these networks. Traditional approaches have focused on improving battery capacity, while recent advancements explore ambient energy harvesting [28]–[31] and wireless energy transfer [32], [33]. However, these methods face limitations, including the unreliability of ambient energy sources [34] and the potential interference caused by energy transfer.

Among energy-consuming operations, radio communication; encompassing data transmission and reception is the most power-intensive [148]–[150]. Recent research emphasises optimising energy consumption through techniques such as energy-efficient transceiver design, transmission power control, lightweight communication protocols, and energy-efficient routing strategies [35].

In IoT applications, WSNs often consist of numerous sensor nodes, ranging from hundreds to thousands. These nodes are responsible for sensing and routing data to a central gateway. Efficient routing is crucial for extending network lifetime. While flat routing protocols treat all nodes equally, they are less energy-efficient in large-scale networks [36]. Hierarchical routing protocols, which organise nodes into clusters with designated cluster heads, offer better scalability and energy efficiency [36]. However, challenges such as unbalanced energy consumption near sink nodes often lead to premature node death and energy holes, reducing network stability. Studies show that up to 90% of a network's initial energy may remain unused by the end of its lifetime [37]. A stable network minimises the time interval between the first and last node failures [38].

These challenges underscore the need for advanced energy management strategies that enhance network stability and optimise energy usage. The following sections explore innovative approaches to address these issues and improve the performance of IoT-based WSN systems.

## 2.5 Balanced Energy Routing in IoT-Based WSN

As outlined in the previous sections, energy management remains a critical challenge in WSN-based IoT, particularly in balancing the energy consumption of sensor nodes to extend network lifetime and ensure stable network performance. Hierarchical routing has emerged as one of the most energy-efficient approaches due to its ability to assign different roles to sensor nodes, allowing for more effective load distribution compared to flat routing protocols.

One of the foundational hierarchical routing protocols is the Low Energy Adaptive Clustering Hierarchy Protocol (LEACH) [40]. LEACH operates by dividing the network operation into rounds, with each round comprising a set-up phase for cluster organisation and a steady-state phase for data transfer. The randomised selection of cluster heads (CHs) in each round helps to distribute the energy load among nodes. However, despite its energy efficiency, LEACH suffers from several limitations: its random CH selection does not always ensure balanced energy usage, and its assumption of homogeneous node energy levels reduces effectiveness in heterogeneous networks. Furthermore, LEACH lacks support for multi-hop inter-cluster communication, which is essential in larger networks.

LEACH-Centralised (LEACH-C) was introduced to address some of these limitations by incorporating a centralised cluster formation process managed by the base station (BS) [72]. LEACH-C optimises the number of CHs per round, reducing the energy burden on sensor nodes. However, this centralised approach introduces new challenges, especially in large-scale networks where nodes farther from the BS may struggle to communicate their energy status, thus limiting the protocol's scalability. Another significant advancement was the Hybrid Energy-Efficient Distributed Clustering (HEED) protocol, which enhanced LEACH by selecting CHs based on residual energy and intra-cluster communication costs, allowing for more energy-efficient operation in heterogeneous networks [73]. HEED also introduced multi-hop communication, overcoming one of LEACH's primary limitations. However, the protocol's complexity increases the number of CHs, potentially leading to inefficiencies, especially in scenarios that require deeper hierarchies.

To provide a concise comparison of these foundational protocols, Table 2.1 summarises key features including the energy model used, clustering strategy, scalability, adaptability, and heterogeneity support.

*Table 2.1: Comparative Summary of Foundational Clustering-Based WSN Protocols*

| Protocol | Energy Model | Clustering Type | Scalability | Adaptability | Heterogeneity |
|---|---|---|---|---|---|
| **LEACH** | First Order Radio Model | Equal, Probabilistic | Moderate | Low | ✗ |
| **HEED** | Residual Energy + Communication Cost | Equal, Iterative | High | Moderate | ✗ |
| **DEEC** | First Order Radio Model + Residual Energy | Equal | High | High | ✓ |
| **SEP** | First Order Radio Model (2-Level Energy) | Equal | Moderate | Moderate | ✓ |
| **TEEN** | Threshold-based First Order Model | Hierarchical | Moderate | Low | ✗ |
| **PEGASIS** | Chain-based Radio Model | No Clustering | Low | Low | ✗ |

TEEN (Threshold-sensitive Energy Efficient sensor Network) introduces a reactive communication model where nodes transmit only when sensed values exceed certain thresholds. While this reduces energy consumption in event-driven applications, it limits adaptability in scenarios requiring regular updates. Power-Efficient Gathering in Sensor Information Systems (PEGASIS) [75], in contrast, creates a chain of nodes for sequential data forwarding, which reduces the number of transmissions but increases latency, making it less suitable for time-sensitive or large-scale networks.

Beyond these foundation protocols, several others have attempted to overcome their respective limitations. Cluster-Chain Mobile Agent Routing (CCMAR) [74] combines the benefits of clustering and chain-based routing. By employing mobile agents for data aggregation, it reduces the overhead and latency found in LEACH and PEGASIS [75]. However, mobile agents introduce new challenges related to fault tolerance, security, and implementation complexity, particularly in mission-critical applications.

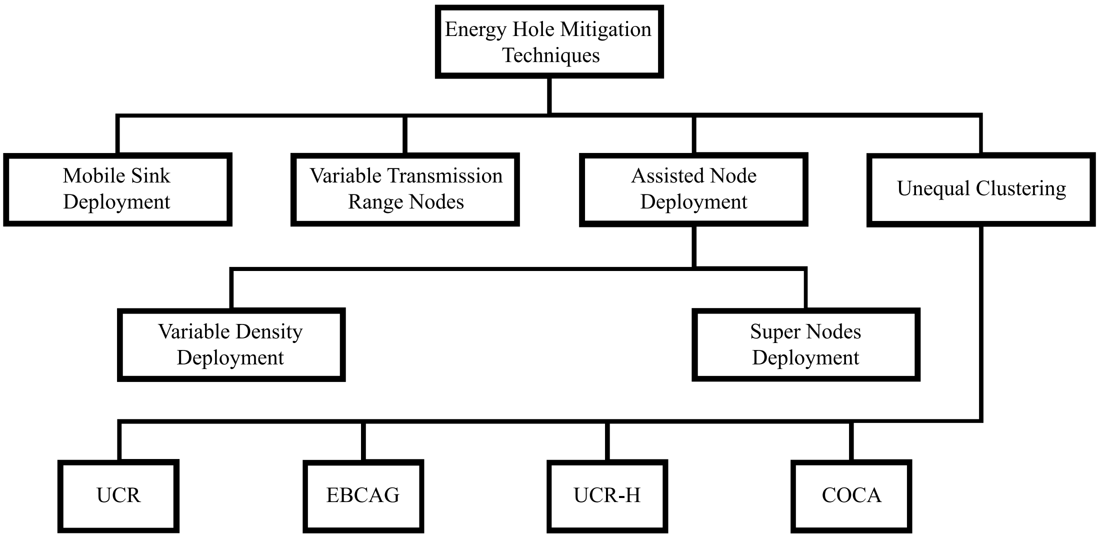



*Figure 2.3: Classification of existing Energy Hole Mitigation Techniques.*

In response to energy imbalance issues, the Wireless Sensor Network Energy Hole Alleviating (WSNEHA) algorithm utilises adaptive range adjustment to extend the network's lifespan by balancing energy usage among the devices closest to the BS [76]. However, WSNEHA's focus on the first-radius nodes leaves other regions of the network vulnerable to energy holes. The subsequent Balanced Energy Consuming and Hole Alleviating (BECHA) algorithm [93] and its enhancement, Energy Aware BECHA (EA-BECHA) [41], sought to address these limitations by distributing the load more evenly across the entire network. Despite these improvements, these algorithms remain limited in scenarios where low latency is required or where the network topology significantly deviates from the homogeneous circular model, such as in underwater sensor networks or strip-based network architectures.

To structure the discussion of these and other relevant techniques, Figure 2.3 provides a classification of existing energy hole mitigation strategies based on their underlying operational principles.

This section has outlined the progression of clustering-based routing techniques and their role in addressing energy imbalance in WSN-based IoT. Despite numerous advancements, existing methods often fall short in scenarios involving complex topologies, 3D deployments, and high heterogeneity, motivating the need for adaptive, scalable, and shape-aware solutions, as proposed in this research. Following sections address further classifications of energy hole mitigation techniques in hierarchical routing.

### *2.5.1 Mobile Sink Deployment*

In traditional multipoint-to-one point communication architectures of WSNs, nodes closer to the base station experience increased data relay loads, leading to uneven energy consumption and the development of energy holes. Mobile sink deployment strategies address this imbalance by dynamically altering the sink's position, thereby distributing the communication load more evenly across the network.

One such approach utilises a movable base station node with a virtual grid infrastructure, as proposed by Luo and Hubau [151]. In this approach the mobile sink traverses predetermined paths within the network, collecting data from sensor nodes systematically. This method effectively mitigates energy holes. However, maintaining up-to-date location information of the mobile sink introduces significant overhead and complexity. Continuous tracking demands additional energy consumption and can lead to increased latency, thereby potentially negating the benefits of balanced energy distribution.

To alleviate these challenges, Gu et al. [152] introduced the deployment of mobile forwarding nodes that works as intermediaries between sensor nodes and the sink. This approach simplifies routing protocols and reduces processing requirements on individual nodes. The introduction of mobile relays introduces some other issues, including increased system latency and additional energy expenditure for mobility management.

While mobile sink deployment strategies offer tangible benefits in balancing energy consumption, their practical implementation faces challenges related to increased latency, overhead in maintaining sink location information, and additional energy costs associated with mobility. These factors necessitate a careful trade-off analysis when considering mobile sink strategies for real-world WSN deployments.

### *2.5.2 Variable Transmission Range*

Another approach to achieving balanced energy consumption involves adjusting the transmission range of sensor nodes based on network conditions and data requirements. By dynamically modifying transmission power, nodes can optimise energy usage relative to communication distance and data volume.

The Balanced Load Distribution (BLOAD) scheme proposed by Li et al. [78] exemplifies this approach by dividing node data into small, medium, and large fractions, with each transmitted over calculated optimal distances. This method prolongs the network's stability period and overall lifetime by intelligently distributing communication loads. However, BLOAD assumes that all nodes can directly communicate with the sink, which is impractical in large-scale IoT infrastructures where nodes may be located far from the sink. Moreover, BLOAD's applicability is limited to specific network types, such as Underwater Sensor Networks (UWSNs), reducing its generalisability across diverse WSN scenarios.

Similarly, the super links-based data drainage scheme introduced by Ahmed et al. [153] employs devices with enhanced transmission abilities placed at key locations to facilitate hybrid, direct and multi-hop communication. While this enhances energy efficiency and reduces latency, deploying specialised nodes increases system complexity and cost, which may not be feasible in resource-constrained environments.

Variable transmission range techniques offer flexibility in managing energy consumption based on dynamic network conditions. However, their effectiveness is dependent upon network topology and scale. The requirement for all nodes to reach the sink node directly, or the need for specialised high-capacity nodes, limits the scalability and adaptability of these methods in heterogeneous and large-scale IoT deployments.

### *2.5.3 Assisted Node Deployment*

Assisted node deployment strategies aim to balance energy consumption by strategically placing additional nodes within the network to support data transmission and processing tasks. This method enhances network longevity by distributing workloads more evenly, particularly in areas prone to energy depletion.

One common technique involves deploying super nodes with higher energy capacities near the sink, as demonstrated by Huang et al. [154]. By dividing the network area into concentric coronas and populating inner regions with energy-rich nodes, the approach effectively mitigates energy holes and extends network lifetime. However, this strategy assumes control over node deployment locations, which may not be practical in all scenarios. Additionally, introducing heterogeneous nodes increases system complexity and leads to increase in cost.

Another variant that focused on increasing the density of homogeneous nodes near the sink, is Energy-balanced Node Deployment with Balanced Energy (END-BE) method, proposed by Liu et al. [155]. By calculating optimal node distributions across different network regions, END-BE achieves balanced energy consumption without relying on heterogeneous node capabilities. Despite its effectiveness, this increased node density can result in redundant data generation and potential communication interference, necessitating sophisticated data aggregation and coordination mechanisms.

Further, relay node deployment strategies, such as those proposed by Somasundara et al. [156], introduce dedicated relay nodes to assist CHs in data forwarding. While this reduces the burden on CHs and balances energy usage, it incurs additional deployment costs and complexity, potentially offsetting the energy savings achieved.

Assisted node deployment methods provide tangible improvements in energy distribution and network lifetime. However, their reliance on strategic and often complex deployment patterns, along with the increased cost and complexity of additional nodes, poses significant challenges. These approaches are best suited for applications where deployment control and resources are readily available and justified by the network's criticality and performance requirements.

### *2.5.4 Unequal Clustering*

Unequal clustering has emerged as a prominent approach to balancing energy consumption in WSNs. Unlike traditional uniform clustering methods, unequal clustering creates clusters of varying sizes, typically assigning smaller clusters to nodes closer to the sink. This design reduces the communication and aggregation burden on these nodes, thereby preventing premature energy depletion and extending overall network lifetime.

The Unequal Cluster-based Routing (UCR) protocol introduced by Li et al. [84] is a pioneering work in this domain. UCR employs an Energy-Efficient Unequal Clustering (EEUC) algorithm for topology management and utilises greedy geographic and energy-aware routing for inter-cluster communication. By forming smaller clusters near the sink, UCR effectively balances energy consumption and enhances network longevity. However, UCR's performance is limited in heterogeneous sensor networks, as it does not account for important factors such as transmission power variations, limiting its adaptability in more diverse and complex environments. The Energy Balancing Unequal Clustering Approach for Gradient-based Routing (EBCAG) proposed by Xie et al. [85] introduces a gradient-based method where clusters are formed based on the hop count to the sink. While EBCAG achieves improved energy efficiency and load distribution, it lacks a systematic approach for determining the optimal number of clusters (rings) and does not incorporate transmission power dynamics, thereby limiting its scalability and efficiency. The Constructing Optimal Clustering Architecture (COCA) by Yan et al. [86] further refines unequal clustering by dividing the sensor field into equal-sized square units and determining the optimal number of clusters based on energy consumption and load distribution metrics. Although COCA demonstrates superior performance compared to earlier protocols, its complexity and rigid structural requirements make it less practical for dynamic and irregular network topologies.

In addressing heterogeneity, protocols such as Stable Election Protocol (SEP) [51] and Distributed Energy Efficient Clustering (DEEC) [79] introduce multi-level energy considerations. SEP considers two types of nodes with different energy levels and adjusts the cluster head election probabilities accordingly. DEEC extends this concept by selecting cluster heads based on the ratio of residual energy to average network energy, accommodating multiple energy levels. While these protocols improve network stability and lifetime, they often penalise higher-energy nodes through repeated cluster head assignments, leading to early depletion. Moreover, many protocols fail to integrate unequal clustering principles, which limits their ability to fully balance energy consumption.

Recent advancements incorporate machine learning and optimisation techniques. For instance, the application of K-Means clustering algorithms prior to cluster head election, as seen in LEACH-K [46], improves cluster formation by ensuring nodes are close to cluster centroids, thereby reducing intra-cluster communication energy. Subsequent enhancements like LEACH-G-K [87] and MDC-LEACH-K [47] integrate grid-based clustering and mobile data collectors (MDCs) to further optimise energy consumption and quality-of-service (QoS) metrics. These protocols demonstrate significant improvements in energy efficiency and network performance; however, they introduce computational overhead and complexity that is not suitable for majority of WSN applications. Furthermore, intelligent MDCs based on the

Traveling Salesman Problem (TSP), as proposed in MDC-TSP-LEACH-K [49], [50], optimise data collection paths, reducing latency and enhancing energy efficiency. Despite their effectiveness, the reliance on complex optimisation algorithms necessitates higher processing capabilities and introduces scalability challenges in large-scale and dynamic networks.

Unequal clustering techniques offer scalable energy management for WSNs, but existing approaches are primarily suited to homogeneous or only energy-heterogeneous networks. These methods fail to consider other critical forms of heterogeneity, such as data rates, computational capacity, and storage. Furthermore, most methods are designed for two-dimensional networks, whereas real-world applications involve three-dimensional environments. This introduces challenges such as irregular node distribution and multi-plane communication. In the next section existing balanced energy communication techniques have been evaluated and categorised across a diverse criterion.

## 2.6 Evaluation of Existing Balanced Energy Communication Techniques

This section provides a critical analysis of the present balanced energy routing techniques used in IoT-based WSN applications, focusing on energy hole mitigation and network lifetime improvement. As illustrated in Figure 2.4, these techniques can be evaluated based on multiple criteria, including device-specific attributes (e.g., initial energy, transmission range, computational capacity), construction factors (e.g., dimensionality, network shape, node deployment etc.), Quality of Service parameters considered (e.g., network lifetime, overall energy consumption, scalability, adaptability, throughput, latency), and evaluation tools used (e.g., MATLAB, Network Simulator, OMNET++).

This section outlines the characteristics and limitations of existing balanced energy communication methods for WSNs, evaluated against the aforementioned criteria.

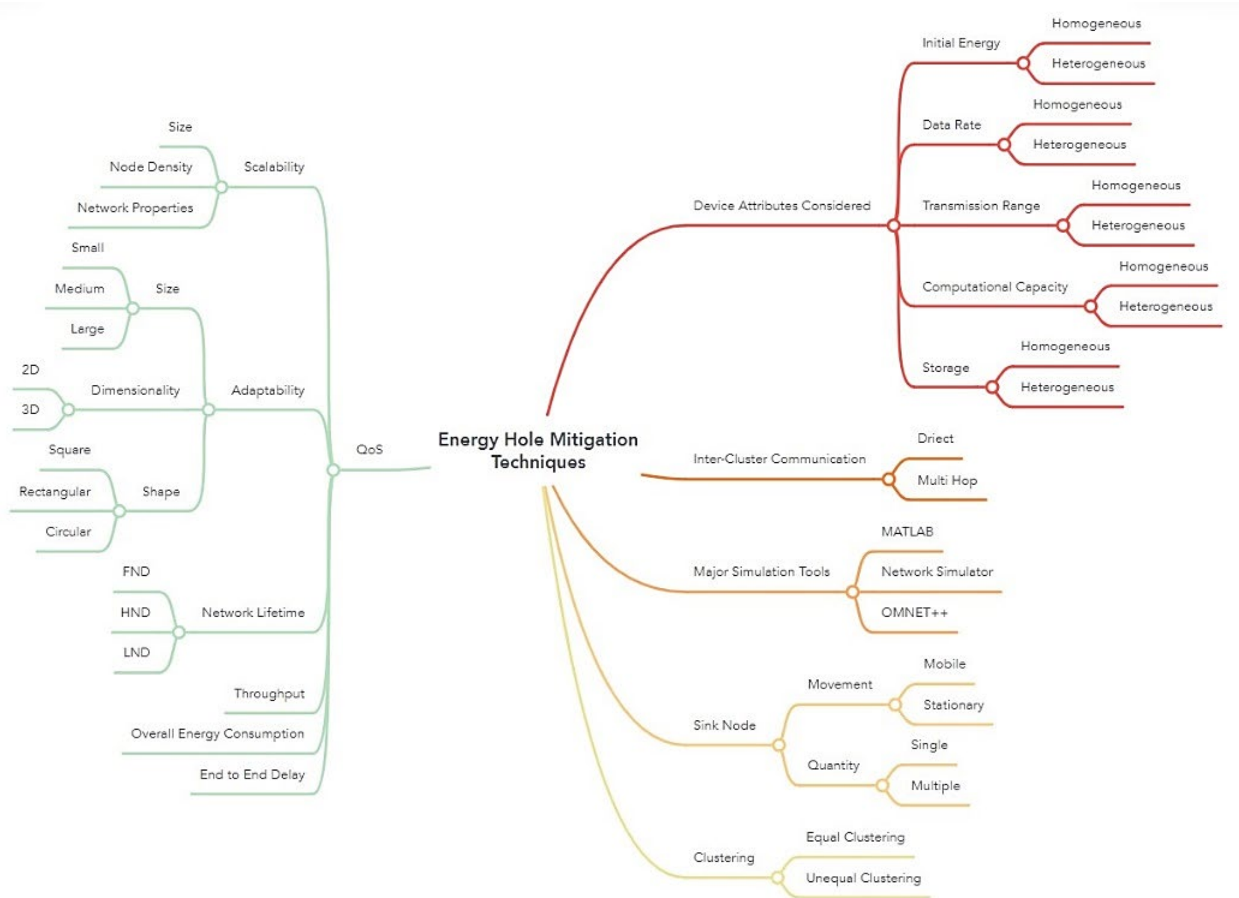



*Figure 2.4: Evaluation and categorisation of Balanced Energy Communication Techniques.*

### *2.6.1 Classification with Respect to Device Attributes*

Device attributes play a key factor in determining the effectiveness of energy hole mitigation techniques. The two primary classifications based on device attributes are homogeneous and heterogeneous approaches:

#### *i. Techniques for Homogeneous Networks*

Numerous energy hole mitigation techniques have been proposed, particularly for homogeneous networks where all nodes share the same characteristics, such as energy levels, transmission range, and processing capacities. These techniques typically assume that all sensor nodes have identical initial energy and performance capabilities, making the routing algorithms simpler to implement but less adaptable to real-world scenarios involving diverse nodes. Some of the key techniques for homogeneous networks are discussed below.

As discussed earlier LEACH [40] is a classical homogeneous protocol where all nodes are believed to possess the same initial energy. Each node has an equal probability of being selected as a CH, leading to uniform energy distribution across the network. While LEACH is simple to implement and achieves balanced load distribution by rotating the CH role among nodes, it has limitations due to its assumption of uniform initial energy. In heterogeneous networks, where nodes may have different energy levels, LEACH can lead to early node depletion. An extension of LEACH [40], LEACH-Centralised (LEACH-C) [72] overcomes the limitation of randomised CH selection by employing a central base station to organise clusters and select CHs based on residual energy. This results in more efficient CH selection and energy use. However, LEACH-C still assumes a homogeneous network and may struggle in larger networks where distant nodes have difficulty communicating with the base station. Hybrid Energy-Efficient Distributed Clustering (HEED) [73] improves upon LEACH by selecting CHs based on residual energy and communication costs, enabling it to work more effectively in homogeneous networks. HEED introduces multi-hop communication between CHs but is still limited to scenarios where all nodes share similar capabilities.

Cluster-Chain Mobile Agent Routing (CCMAR) [74] combines the cluster-based and chain-based approaches of LEACH and PEGASIS. While designed for homogeneous networks, it improves energy efficiency through deployment of a movable sink node for data collection. However, challenges such as fault tolerance and increased complexity limit its scalability in heterogeneous environments. The Wireless Sensor Network Energy Hole Alleviating (WSNEHA) [76] algorithm adjusts transmission ranges to balance energy consumption near the sink. While suitable for homogeneous networks, its limitation is that energy balancing only applies to nodes in close proximity to the sink, leaving distant nodes at a disadvantage. The Balanced Energy Consuming and Hole Alleviating (BECHA) [93] and Energy Aware BECHA (EA-BECHA) [41] algorithms improve upon WSNEHA by balancing energy consumption across the entire network, addressing energy holes in homogeneous environments. However, both still suffer from limitations in handling heterogeneous networks or varying network conditions.

Power-Efficient GAthering in Sensor Information Systems (PEGASIS) [75] uses a chain-based approach, where nodes communicate with their nearest neighbour, aggregating data along the chain to send to the sink. Designed for homogeneous environments, PEGASIS reduces energy consumption but suffers from high delays, particularly in large networks.

The Balanced Load Distribution (BLOAD) [78] improves network lifetime by dividing data into small, medium, and large packets and adjusting the transmission range accordingly. However, BLOAD assumes direct communication with the sink, limiting its applicability in large-scale IoT systems with distant nodes. Unequal Cluster-based Routing (UCR) [84] introduces unequal clustering sizes to minimise energy consumption for nodes near the sink. Although effective for homogeneous networks, UCR lacks adaptability to heterogeneous environments with varying energy levels across nodes. Energy Balancing Unequal Clustering Approach for Gradient-based Routing (EBCAG) [85] optimises cluster sizes based on hop count to the sink. It is ideal for homogeneous networks but struggle in scenarios requiring multi-level energy optimisation. Constructing Optimal Clustering Architecture (COCA) [86] divided the sensor field into equal-sized units, deploying more clusters closer to the BS to improve energy efficiency. COCA excels in homogeneous networks but is complex and challenging to implement in real-world environments with varying node capabilities.

Multiple Mobile Sink (MMS) [42] was designed for homogeneous networks with mobile sinks, effectively improving network lifetime but introducing additional complexity and delay. Mobile Data Collector (MDC) [81] and its Traveling Salesman Problem (TSP) variant MDC-TSP-LEACH-K [49], [50] enhanced the LEACH protocol by integrating a mobile data collector to gather data from CHs. These techniques are suitable for homogeneous environments, where the collector's mobility reduces energy consumption near the sink.

Techniques for homogeneous networks generally rely on the assumption that all sensor nodes share similar capabilities. This makes the protocols simpler to design and implement, but they may not be as adaptable to real-world applications, where nodes often vary in energy levels, communication range, and data processing power. The focus on homogeneous networks often limits scalability, adaptability, and performance in dynamic environments, such as IoT-enabled smart cities.

### *ii. Techniques for Heterogeneous Networks*

Heterogeneous wireless sensor networks (HWSNs) consist of sensor nodes that differ in their characteristics, such as energy levels, data rates, transmission ranges, and computational capacity. The diversity in these attributes allows for more adaptable and flexible network management but also introduces challenges related to fairness, load balancing, and energy consumption. This section critically examines techniques that address heterogeneity across various parameters.

***Heterogeneity Based on Energy Levels:*** In energy-heterogeneous networks, nodes possess different energy capacities. Some protocols exploit high-energy nodes to perform more demanding tasks, such as acting as cluster heads, but this can lead to early depletion of these nodes if not managed properly.

Stable Election Protocol (SEP) [51], introduces two levels of energy, normal and advanced nodes, and adjusts the probability of CH election based on the relative energy levels. It extends the stability of the network, but its limitation lies in the fact that advanced nodes are repeatedly chosen as CHs, which leads to early depletion.

Distributed Energy Efficient Clustering (DEEC) [79] was an improvement of SEP and selected CHs based on the ratio of residual energy to the average network energy, and supported multi-level heterogeneity . However, as with SEP, the repeated use of high-energy nodes as CHs can lead to imbalances in energy consumption. Developed DEEC, (DDEEC) [80] was built up on DEEC by adapting the election process once advanced nodes lost their energy advantage, mitigating the penalty on high-energy nodes . However, this still limits its flexibility in larger-scale networks. Enhanced DEEC, (EDDEEC) [52] introduced further multi-level heterogeneity by incorporating multiple types of nodes with varying energy levels and improving energy efficiency through better CH election strategies. However, it did not consider multi-hop communication, limiting its scalability in large-scale networks.

These protocols demonstrate the benefit of utilising high-energy nodes but need better mechanisms to prevent early depletion and consider multi-hop communication for more complex networks.

***Heterogeneity Based on Data Rates:*** In heterogeneous networks where nodes handle different data rates, protocols must consider the variable bandwidth demands placed on nodes. Nodes that process high data rates require more energy and processing power. Unequal Cluster Routing with Heterogeneity (UCR-H) [88] employs unequal clustering and accounts for nodes that handle varying data rates by dynamically adjusting cluster sizes and CH roles. It is effective in environments with diverse sensor data, such as smart cities, but lacks flexibility for other types of networks that demand higher transmission rates or lower latency. Moreover, LEACH-Energy Association (LEACH-EA) [157] and LEACH-Load Balancing (LEACH-EC) [157] protocols adapt to varying data rates by reducing energy consumption during CH election and balancing data handling between CHs and ordinary nodes. However, they do not account for nodes with significantly higher bandwidth demands.

Managing nodes with varying data rates remains a challenge in many-to-one communication schemes, and these protocols provide foundational methods but need further enhancement to support very high or very low data rates.

***Heterogeneity Based on Transmission Range:*** Nodes in a heterogeneous network may have different transmission ranges due to differences in antenna power, environmental factors, or node capabilities. Techniques that account for transmission range heterogeneity can optimise energy consumption by minimising long-range transmissions.

Grey Wolf Optimisation (GWO) [53] accounts for varying transmission ranges by allowing nodes with higher transmission power to act as relays for farther nodes, balancing energy consumption. However, the algorithm's complexity can hinder its scalability in very large networks. Energy and Traffic Aware Sleep-Awake routing (ETASA) [54] & Traffic and Energy Aware Routing (TEAR) [158] dynamically adjust routing paths based on residual energy and transmission capabilities, offering an energy-efficient solution for nodes with varying transmission ranges. However, like GWO, the computational requirements of these protocols may not suit smaller or simpler networks.

The key challenge for these protocols lies in managing the balance between short-range and long-range communication without introducing excessive overhead.

***Heterogeneity Based on Computational Capacity:*** Nodes with different computational capacities can manage different levels of data processing and decision-making tasks. Protocols must account for this heterogeneity by offloading intensive tasks to nodes with higher capacities.

LEACH-K [46] and LEACH-G-K [87] utilise K-Means clustering to minimise energy consumption and reduce computational load on less powerful nodes. Although effective, the use of clustering algorithms introduces added complexity, reducing their suitability for real-time or resource-constrained environments. MDC-LEACH-K [47] integrates mobile data collectors (MDCs) to reduce the data processing burden on nodes with lower computational capacity. It provides significant energy savings but introduces latency due to MDC movement.

Protocols in this category must carefully balance computational load to avoid penalising weaker nodes while ensuring efficient energy use in more powerful nodes.

***Heterogeneity Based on Storage Capacity:*** In HWSNs, storage capacity can vary significantly between nodes, which impacts how data is aggregated, buffered, and transmitted. Storage heterogeneity becomes a crucial factor when certain nodes are required to store larger volumes of data for longer periods, particularly in scenarios with delayed or intermittent communication opportunities, such as when mobile sinks or data collectors are employed.

Nodes with higher storage capacities can handle greater responsibilities in data aggregation and buffering, reducing the burden on nodes with limited storage. Conversely, nodes with smaller storage capacities may need to offload data more frequently, potentially increasing energy consumption due to additional communication overhead.

Storage heterogeneity is particularly relevant in networks where data generation is not uniform, such as environmental monitoring or smart cities, where specific nodes may gather more data based on their location or application requirements. Managing this heterogeneity requires protocols that can dynamically adjust storage responsibilities, ensuring that nodes with limited storage are not overwhelmed while also preventing bottlenecks in data collection and transmission.

Managing storage heterogeneity ensures that data flow is uninterrupted, even in networks with diverse storage capabilities. While techniques designed for energy and computational heterogeneity can indirectly address storage concerns, there is a need for more explicit mechanisms that consider storage as a distinct factor. Efficient storage management helps prevent data loss, reduce communication overhead, and balance the load across nodes with varying storage capacities. As WSNs continue to evolve in IoT environments, incorporating storage heterogeneity into routing and clustering protocols will become increasingly important, especially in applications that generate large volumes of data.

### *2.6.2 Classification Based on Inter-Cluster Communication*

In WSN-based IoT, inter-cluster communication can be broadly classified into direct and multi-hop communication. The choice between these two communication types plays a significant role in determining energy efficiency, data delivery rates, and overall network performance.

#### *i. Direct Inter-Cluster Communication:*

In direct inter-cluster communication, CHs send data directly to the base station without relying on intermediate CHs or relay nodes. This method simplifies the communication process, but it often results in higher energy consumption for CHs that are far from the BS, as the transmission distance is greater. Protocols that employ direct inter-cluster communication generally assume smaller network sizes or homogeneous energy models where all nodes can support such transmissions.

LEACH [40] and its variants like LEACH-C [72] rely on direct communication between CHs and the BS. While these protocols improve energy efficiency over flat routing, they still suffer from unbalanced energy consumption, as distant CHs drain their energy faster due to the longer transmission distances. PEGASIS [75], and other chain-based protocols use a form of direct communication where a leader node in a chain communicates directly with the BS. However, this approach may introduce delays and bottlenecks at the leader node, impacting overall network performance.

Direct inter-cluster communication can be beneficial in small-scale networks or when nodes are uniformly distributed with a limited number of CHs. However, in larger-scale networks, especially in heterogeneous environments, this approach can lead to energy imbalance, as CHs that are farther from the BS consume more energy. This ultimately shortens the network's operational lifetime and introduces latency in communication. The inherent limitations of direct communication highlight the need for more adaptive and scalable approaches, such as multi-hop communication, especially in IoT-based HWSN applications.

***ii. Multi-Hop Inter-Cluster Communication:***

In multi-hop inter-cluster communication, CHs relay data through other CHs or relay nodes before reaching the BS. This type of communication distributes load more evenly across the network and significantly reduces the energy consumption of CHs far from the BS, making it suitable for larger and more heterogeneous networks.

HEED [73], incorporates multi-hop communication between CHs and the BS. This protocol selects CHs based on residual energy and intra-cluster communication cost, and the use of multi-hop routing helps distribute the energy load across CHs. WSNEHA [76], BECHA and EA-BECHA [93],[41] also employ multi-hop communication to mitigate energy holes and balance energy consumption across the network. UCR [84] and COCA [86] use multi-hop communication, particularly in scenarios where clusters closer to the BS relay data for farther clusters, which helps achieve more balanced energy consumption. MMS [42] and MDC [81] protocols rely on multi-hop communication, supported by mobile data collectors (MDCs) to further improve energy efficiency and data transmission, particularly in large-scale networks.

Multi-hop inter-cluster communication provides significant advantages in large-scale networks and heterogeneous environments by reducing the energy burden on individual CHs and spreading the load across multiple nodes. This approach is particularly beneficial in IoT applications where energy efficiency and network scalability are critical. However, multi-hop communication introduces new challenges, including increased complexity in route management and the potential for higher latency, as data passes through multiple nodes before reaching the BS. Effective clustering and routing strategies must address these challenges to maintain a balance between energy efficiency, network longevity, and communication delays.

Direct communication tends to simplify the routing process but can lead to faster energy depletion in larger networks, while multi-hop communication enhances energy distribution but adds complexity to routing and data management. Protocols that incorporate multi-hop inter-cluster communication tend to be more suitable for heterogeneous networks where node energy levels and distances to the BS vary significantly. In contrast, direct communication is better suited for smaller networks with homogeneous energy models and fewer nodes.

### *2.6.3 Classification Based on Sink Node*

Sink nodes in IoT-based WSN play a critical role in data collection and routing decisions. The characteristics of the sink node, particularly its movability and the number of sink nodes used, significantly impact network performance, energy efficiency, and network lifetime. In this section, techniques are classified based on two criteria: (1) the movability of the sink node (mobile vs stationary), and (2) the number of sink nodes (single vs multiple).

#### *i. Classification Based on Sink Movability:*

Based on sink movability techniques can be divided as below:

##### *a) Techniques with Stationary Sink Nodes:*

Stationary sink nodes are fixed in a single position throughout the network's operational lifetime. Protocols using stationary sinks generally focus on efficient routing strategies to mitigate energy depletion in nodes closer to the sink, often leading to the formation of energy holes. While simpler to manage, stationary sinks can lead to uneven energy consumption, particularly in many-to-one communication scenarios.

LEACH [40], LEACH-C [72], and HEED [73] use stationary sink nodes, focusing primarily on clustering techniques to reduce energy consumption across the network. While LEACH and LEACH-C rely on probabilistic clustering, HEED introduces residual energy-based CH selection to better balance load distribution. WSNEHA [76], BECHA and EA-BECHA [93],[41] are designed to mitigate energy holes caused by stationary sinks by employing range adjustment strategies to prolong the lifetime of nodes near the sink. PEGASIS [75] uses a chain-based approach with a stationary sink node, which helps reduce the energy burden on nodes by enabling data aggregation before transmission to the sink.

Stationary sink-based techniques often result in energy depletion in nodes close to the sink, as they handle a disproportionate amount of data transmission. As these nodes die out, energy holes form, leading to network partitioning. While clustering and range adjustment techniques can alleviate some of the burden, these methods are less effective in large-scale or dynamic networks, where a more adaptive strategy is needed. The lack of sink mobility limits these protocols in terms of scalability and adaptability, especially for complex IoT environments.

***b) Techniques with Mobile Sink Nodes:***

In scenarios with mobile sinks, the sink moves within the network to collect data from sensor nodes, balancing the energy load by reducing the number of transmissions required from nodes near the sink. Mobile sink deployment reduces the formation of energy holes and extends the overall network lifetime. However, managing the mobility of the sink introduces additional challenges such as increased complexity in route management and potential latency.

MDC [81] and MDC-LEACH-K [47] use mobile data collectors (MDCs) to periodically move within the network, reducing the energy burden on CHs by acting as intermediary nodes between the sensor nodes and the stationary BS. This mobility helps distribute energy consumption more evenly. MMS [42] also incorporates mobile sink deployment to reduce the data transmission burden on nodes near the sink, extending network lifetime and improving overall energy efficiency. Cluster-Chain Mobile Agent Routing (CCMAR) [74] employs a mobile agent to aggregate data from CHs and transmit it to the mobile sink, reducing energy consumption but introducing challenges related to mobile agent deployment and fault tolerance.

The use of mobile sinks offers a significant advantage in balancing energy consumption, especially in large-scale WSNs and IoT applications. By periodically altering the sink’s location, these protocols prevent energy depletion in nodes close to the sink, thereby extending network lifetime. However, the benefits of mobile sinks come at the cost of increased latency and overhead due to sink mobility management. Furthermore, tracking the sink’s location requires additional energy, and ensuring consistent communication with the sink can be difficult in dynamic environments.

### ii. Classification Based on the Number of Sink Nodes

Many traditional protocols use a single sink node for data collection. While simpler in terms of routing management, single-sink networks often suffer from energy depletion in nodes closer to the sink due to the many-to-one nature of communication. This can lead to the formation of energy holes and uneven load distribution.

#### a) Techniques with Single Sink Node:

LEACH [40], LEACH-C [72] rely on a single sink for all data collection. Although LEACH introduces clustering to distribute the energy load, a single sink results in high energy consumption for nodes closer to the sink. PEGASIS [75] also uses a single sink with chain-based routing to minimise transmission costs, but the chain's leader still communicates directly with the sink, leading to energy imbalances. HEED [73], WSNEHA [76], BECHA and EA-BECHA [93],[41] all utilise a single sink, with varying techniques for mitigating energy consumption near the sink.

Single sink-based techniques are more suitable for small-scale networks where nodes are located near the sink. However, in large-scale networks, single sink nodes often lead to uneven energy consumption, particularly in many-to-one communication patterns. As a result, nodes near the sink drain their energy quickly, leading to energy holes and network partitioning. While some protocols introduce clustering and range adjustment methods to mitigate this issue, a single sink remains a limiting factor in terms of scalability and energy efficiency in larger IoT networks.

#### b) Techniques with Multiple Sink Nodes:

The use of multiple sinks helps distribute the energy consumption more evenly, as sensor nodes are able to communicate with the nearest sink, reducing the overall transmission distance and energy consumption. Multiple sinks also help to improve network scalability and reduce latency.

MDC-K [49] and MDC-TSP-LEACH-K [49], [50] employ multiple MDCs to gather data from sensor nodes, reducing energy consumption and improving network scalability. By using multiple mobile sinks, these protocols reduce the data transmission burden on individual nodes, particularly those near the sinks. COCA [86] uses multiple sinks to divide the network into optimal clusters, each with its own sink to ensure balanced energy consumption and reduce communication overhead.

The use of multiple sinks offers significant advantages in terms of energy distribution and network scalability. By reducing the communication distance for sensor nodes, multiple sinks help extend the network lifetime and mitigate energy holes. However, managing multiple sinks increases the complexity of the routing process, as sensor nodes must dynamically select the nearest sink, and inter-sink communication must be carefully managed to avoid data redundancy and network congestion. Multiple sink deployments are most effective in large-scale or highly heterogeneous IoT networks, where load balancing and energy efficiency are critical.

### *2.6.4 Classification Based on Clustering: (Equal vs. Unequal Clustering)*

Clustering is a key design parameter in hierarchical routing protocols. The size and number of clusters, as well as the method of communication between CHs and the BS, play critical roles in determining energy efficiency and network longevity.

One of the most important distinctions among clustering techniques is whether they use equal-sized clusters or unequal-sized clusters. Equal clustering is simpler and easier to manage, but it can result in energy imbalances, particularly in CHs closer to the sink, leading to faster depletion of these nodes and the formation of energy holes. To address this issue, unequal clustering techniques have been developed, where CHs closer to the sink manage smaller clusters to reduce the relaying burden, thereby balancing energy consumption across the network.

#### *i. Equal Clustering*

In equal clustering methods, all clusters in the network are of the same size, and CHs are typically selected based on a predefined criterion or probability. This clustering method is often favoured for its simplicity and uniformity in managing the network. However, it introduces significant challenges in energy balance since CHs near the sink often bear a disproportionate load of data transmission.

As one of the earliest and most widely adopted clustering protocols, LEACH [40] assumes equal-sized clusters and uses a probabilistic method to rotate CHs. While LEACH achieves energy savings by rotating CHs and distributing load, it does not account for the additional burden on CHs near the sink. LEACH-C [72] uses a centralised approach to form equal-sized clusters based on network topology and node energy levels, but similar to LEACH, it does not mitigate the extra load placed on CHs near the sink. HEED [73] selects CHs based on a combination of residual energy and intra-cluster communication cost, forming equal clusters.

It improves energy efficiency but still faces challenges with CHs near the sink depleting energy faster due to equal-sized clustering. Though primarily a chain-based protocol, Power-Efficient Gathering in Sensor Information Systems (PEGASIS) [75] can be viewed as forming equal clusters since each node takes turns acting as the leader. The equal workload does not account for variations in distance from the sink, leading to inefficiencies in larger networks. WSNEHA [76] and BECHA [93] use equal-sized clustering to balance energy consumption but are limited by the same challenges posed by CHs near the sink, particularly in terms of energy hole formation. DEEC [79] and its variants use equal clusters with the idea that CHs are selected based on their residual energy relative to the average energy of the network, but the uniform cluster sizes lead to similar issues with energy balance. LEACH-EA [157] also uses equal clustering and proposes an energy-aware mechanism for selecting CHs, but the basic clustering structure remains equal, limiting its effectiveness in addressing the energy hole problem.

Equal clustering methods are generally easier to implement and offer a straightforward way to manage CHs in IoT-based WSN applications. However, as these techniques do not consider the varying energy requirements of different parts of the network, they tend to create energy imbalances, particularly near the sink. CHs near the sink must relay more data, which results in their faster depletion, creating energy holes and reducing the overall network lifetime. Although techniques like LEACH-C and DEEC attempt to optimise CH selection to address these imbalances, the underlying equal clustering structure remains a limitation in more complex, large-scale networks. Future research should focus on integrating more adaptive clustering sizes or hybrid models to better balance energy consumption across the network.

### *ii. Unequal Clustering*

In unequal clustering, clusters closer to the BS are intentionally made smaller to reduce the burden on CHs that handle more data relaying. This approach helps in distributing the energy consumption evenly across the network and prevents energy holes from forming, particularly in scenarios where multi-hop communication is used.

UCR [84] is one of the pioneering protocols in unequal clustering, designed to form smaller clusters near the sink to reduce the relaying load on CHs. This significantly enhances the balance of energy consumption across the network and prolongs network lifetime. EBCAG [85] uses gradient-based clustering where cluster sizes vary based on their hop count to the base station. Closer CHs manage smaller clusters, which helps distribute energy consumption more evenly across the network. COCA [86] optimises the network by dividing the sensor field into square units, with the size of the clusters varying depending on their proximity to the sink. This results in balanced energy consumption and improves network scalability. LEACH-K [46] improves upon LEACH by integrating the K-Means clustering algorithm, which adjusts cluster sizes to ensure smaller clusters near the sink, thus reducing the workload on CHs and extending network lifetime. MDC-LEACH-K [47] further enhances energy efficiency by using a mobile data collector in conjunction with unequal clustering. The smaller clusters near the sink allow CHs to consume less energy, while the mobile collector gathers data more efficiently.

Unequal clustering offers a more advanced approach to addressing the energy hole problem in IoT-based WSN networks. By tailoring cluster sizes based on proximity to the sink, unequal clustering helps reduce the energy consumption burden on CHs near the sink, thereby extending network lifetime and improving energy balance. However, these methods introduce additional complexity in cluster formation and management, which can increase the computational burden on sensor nodes. Moreover, unequal clustering techniques are generally more difficult to implement in highly dynamic or large-scale networks where node mobility or variable data rates are significant factors. Despite these challenges, unequal clustering remains a highly effective strategy for improving the energy efficiency of IoT-based WSN, particularly in applications requiring long-term deployments and minimal maintenance.

### *2.6.5 Simulation Tools:*

To evaluate the performance of wireless networks, different simulation tools are commonly used. For researchers, it is useful to be familiar with the simulation tool that was originally applied to assess a particular technique. To assist with this, Table in Appendix B provides details on the simulation tools used during the initial evaluations of each method. MATLAB is widely regarded as the preferred tool for evaluating most techniques, particularly in comparison to other network simulators such as NS-1, NS-2, NS-3, and OMNET++. This preference for MATLAB arises from its ease of use and the availability of pre-configured functions [125]. Additionally, MATLAB simplifies the mathematical modelling of radio systems, making it easier to evaluate their performance.

### *2.6.6: Scalability and Adaptability:*

Energy hole mitigation techniques can be evaluated based on their ability to scale and adapt. As highlighted earlier, factors such as the distance between nodes and their size play a significant role in the overall network performance. While some techniques can efficiently balance energy consumption in smaller networks, they may not be suitable for large-scale deployments. In this section, these energy hole mitigation methods have been categorised with respect to scalability. Table in appendix B outlines that LEACH [40], LEACH-C [72], PEGASIS [75], SEP [51], ERNS-EEC [43], UDCH [159], ECUC [45], LEACH-EA [157], LEACH-EC [157], LEACH-K [46], LEACH-G-K [87], MDC-LEACH-K [47], MDC-K [49], and MDC-TSP-LEACH-K [49], [50] demonstrate scalability across various network sizes, while some techniques are limited to specific network sizes.

Besides scalability, the adaptability of routing techniques to different network geometries and multi-dimensional spaces is critical, especially given the varying needs of IoT-driven WSN infrastructures. A method that performs well in a network with a circular layout might not yield optimal results if the network's shape changes. Thus, the techniques are categorised based on the geometric shape and area they are optimised for. Techniques that perform well in square shape networks include LEACH [40], LEACH-C [72], HEED [73], CCMAR [74], SEP [51], DEEC [79], DDEEC [80], EDDEEC [52], MMS [42], GWO [53], SEHR [82], TEEC [43], UDCH [159], ETASA & TEAR [158], LEACH-EA [157], LEACH-EC [157], LEACH-K[46], LEACH-G-K [87], MDC-LEACH-K [47], MDC-K [49], (MDC-TSP-LEACH-K [49], [50]. Techniques such as PEGASIS [75], UCR [84], COCA [86], UCR-H [88], and MDC [81] are better suited for rectangular-shaped networks. Furthermore, methods such as WSNEHA [76], BECHA [93], EA-BECHA [41], BLOAD [78], EBCAG [85], WEMER [44], and ECUC [45] excel in circular-shaped networks.

Lastly, evaluating these techniques in three-dimensional node deployments is important, as many IoT-based applications operate in three-dimensional spaces. As such, Table in Appendix B also categorises these techniques according to the spatial dimensions they consider.

### *2.6.7 Evaluation of Existing Techniques on Network Lifetime and Stability:*

Network lifetime and stability are essential metrics for assessing energy hole mitigation techniques. Table in Appendix B compares these methods across various criteria, such as the round when the first node dies (FND) and the round when the last node dies (LND). A smaller gap between the FND and LND signifies better stability [38]. However, while stability is crucial for addressing energy holes, it should not come at the expense of the overall network lifetime. Additionally, network lifetime can be measured by the volume of data transmitted by the time of FND or LND, as different methods employ varying transmission bit rates. Some techniques assess performance based on the time from network startup to FND or LND rather than by the number of rounds.

As shown in Appendix B, the LEACH protocol [40] operates much longer than the minimum-transmission-energy routing protocol. Specifically, LEACH lasts 8 times longer before the first node dies (FND) and 3 times longer before the last node dies (LND). With an initial energy of 0.5J for homogeneous nodes, LEACH supports 932 rounds for FND and 1312 rounds for LND. When the initial energy is increased to 1J, LEACH can operate for 1848 rounds for FND and 2608 rounds for LND.

In LEACH-C [72], the authors evaluate network lifetime by measuring the number of data packets delivered relative to the number of active nodes. In this context, LEACH-C transmits 10 times more data despite having a shorter operational time than the Minimum Transmission Energy (MTE) protocol. The initial energy of network nodes is assumed to be 2J. LEACH-C is found to deliver about 40% more data per unit of energy compared to LEACH. The end-to-end delay is calculated based on the total number of nodes, the average number of hops to the BS, and the time required to traverse a single hop. This indicates that, within the same timeframe, LEACH-C can transmit more data than both LEACH and MTE.

HEED [73], a hybrid of hierarchical and chain-based routing methods, is particularly suited for large-scale networks. When evaluating performance in a $2000\text{m} \times 2000\text{m}$ network with each node having an initial energy of 4.0J, HEED achieves a network lifetime between 300 and 450 rounds on the FND scale. Similarly, CCMAR [74] shows a network lifetime of approximately 400 rounds on the FND scale. CCMAR uses 12.5% less energy compared to PEGASIS [75] and 60% less than LEACH. It also delivers a comparable number of packets to LEACH in 4% less time and to PEGASIS in 70% less time. In the case of PEGASIS, a series of experiments were conducted, with initial node energy randomly selected between 0.5J and 1J, and average results were presented for evaluation. The authors use two chain-based data transmission algorithms: the closest neighbour and the minimum total energy algorithms. The minimum total energy algorithm extends the lifetime by 15% to 30% on the FND scale compared to the closest neighbour method. In a network of 50 nodes, the energy consumption of the minimum total energy algorithm with linear chains is 10% that of the closest neighbour algorithm. However, when multiple chains are used, the energy consumption of the minimum energy algorithm is 40% that of the closest neighbour method. Due to the chain-based routing, significant end-to-end delay occurs in its operation

WSNEHA [76] uses a routing table to distribute the energy load evenly among network nodes located beyond the initial radius. When the first radius is set to 60m, WSNEHA leads to a 78% reduction in energy consumption and a 361.9% increase in network lifetime compared to scenarios without WSNEHA. BECHA and EA-BECHA, introduced by the authors in [93] and [8] further extend WSNEHA to reduce the formation of energy holes beyond the first radius. BECHA determines an optimal radius for WSNEHA to balance energy consumption among nodes, while EA-BECHA improves upon BECHA by integrating energy-aware routing along with the optimal radius. For example, when the radius is set to 10m, $0.9 \times 10^4$ bits are transmitted with an energy consumption of 6mJ. In contrast, at $r = 100$m, only $0.1 \times 10^4$ bits are transmitted with an energy consumption of 1mJ. EA-BECHA is more efficient, consuming 25% less energy than WSNEHA and achieving a 35% lower packet drop ratio.

BLOAD [78] measures network lifetime based on time intervals rather than the number of rounds. The First Node Death Time (FNDT) is 20 seconds, compared to 5 seconds in Nominal Range Forwarding (NRF) [160] and 10 seconds in Homogeneous Balanced Routing (Homo-BR) [161], when the initial energy is set to 1J. Similarly, the All-Node Death Time (ANDT) is 100 seconds for BLOAD, in contrast to 90 seconds for Homo-BR and NRF. However, when the initial energy of nodes is heterogeneous, Hetero-BR demonstrates 5% better stability compared to Homo-BLOAD [78].

UCR [84] employs unequal clustering to balance energy consumption across network nodes, albeit at the expense of increased overall energy use. EBCAG [85] further improves network lifetime and stability. Network lifetime in this context is evaluated based on the death of 5% of the nodes. With this criterion, in a network of 400 nodes, stability lasts for 35 rounds, but this reduces to 24 rounds when the network size increases to 800 nodes. Although overall energy consumption is not directly measured in these methods, the primary focus is on enhancing stability. COCA [86], another unequal clustering routing method, enhances network lifetime by 166% to 229% compared to UCR, depending on the network size, with an initial energy of 2J per node.

SEP [51] leverages heterogeneity to boost network stability, showing 8% to 26% better stability than LEACH, depending on the proportion of advanced nodes deployed. Similarly, DEEC [79] increases the number of heterogeneity levels and achieves a 20% improvement in network lifetime compared to LEACH. In DEEC, the first node dies in the 969th round, and the last node dies in the 5536th round of operation. DDEEC [80] further extends the network lifetime by 30% compared to SEP and 15% more than DEEC, with the first node dying in the 1355th round and the last node in the 5673rd round. EDDEEC [52] , another improvement upon DEEC, achieves a first node death (FND) in the 1717th round and the last node death (LND) in the 8638th round, when deploying 20 normal nodes with initial energy Eo, 32 advanced nodes with 2Eo, and 48 super nodes with 3.5Eo each.

In UCR-H [88], the FND occurs in the 1500th round, depending on the node density within the network. This method is particularly effective for balancing energy consumption in rectangular-shaped networks. WEMER [44] uses homogeneous energy nodes, with FND occurring in the 572nd round, HND in the 1128th round, and LND in the 1478th round. With an initial energy of 0.5J for all network nodes, WEMER demonstrates an average energy consumption of 0.042J per node.

MMS [42] with initial energy of 0.25J per node optimises energy consumption 19% in terms of FND and HND scales, with FND occurring at 409 rounds and HND at 482 rounds. Performance evaluation also reveals that after 200 rounds residual energy of the network is 14.38J for MMS, which is higher compared to LEACH (10.65J0), MOFCA (11.2J) [42] and OPTimised LEACH (OPT-LEACH) (13.945J). MDC [81] shows variations in network lifetime, with FND occurring between 6000 and 7000 rounds and LND between 8000 and 9000 rounds when the initial energy of each node is set to 5J. GWO [53] achieves FND in the range of 800-900 rounds and HND between 900-1100 rounds, depending on the number of sensor nodes in the network. The overall energy consumption is 250J lower for equal load and less than 230J for unequal load in a network of 100 nodes.

When the initial energy of 100 homogeneous nodes is set to 0.5J each, SEHR [82] demonstrates an FND of 597, compared to 403 in Dynamic Routing (DR), showing an improvement of 94 rounds. Similarly, SEHR achieves a 251-round improvement over DR on the LND scale. In ERNS-EEC [43], network lifetime is evaluated by the number of nodes remaining alive after 5000 rounds. While the technique performs sub optimally on the FND scale, it offers significantly lower energy consumption. After 1000 rounds, only 120 out of 1000 nodes are dead, and 31 nodes remain alive even after 5000 rounds. On the LND scale, the network lifetime achieved by this method ranges between 5000 and 6000 rounds.

Energy consumption in UDCH [159] is notably low. As detailed in Table in Appendix B, when the initial energy of homogeneous nodes is set to 0.3J each, the network remains free from energy holes even after the 700th round, when the total residual energy drops below half of the initial energy. On the FND scale, the network lifetime reaches an impressive 1220 rounds, while the LND is achieved at 1870 rounds. In the case of ETASA and TEAR, as proposed in [158] , the initial energy for each node is set to 0.5J for performance evaluation. The results show that after the 1500th round, the average residual energy of ETASA remains above 0.3J, whereas TEAR's residual energy is approximately 0.2J. The network lifetime across the FND, HND, and LND scales ranges between 1000 and 1030 rounds, 2400 and 2500 rounds, and 3990 and 4030 rounds, respectively.

ECUC [45] is a scalable approach that demonstrates a consistent increase in network lifetime across both small-scale (R=50m) and large-scale (R=200m) networks. In comparison to OCCN and DBS, network lifetime in ECUC is 22% longer for a 50m radius and 32% longer for a 200m radius compared to OCCN, and 16% longer and 25% longer than DBS for the same respective network sizes. In terms of energy consumption, ECUC reduces energy usage by 30% compared to OCCN and 28% compared to DBS.

In [157], two variations of LEACH are introduced: LEACH-EC for equal clustering and LEACH-EA for unequal clustering. While LEACH-EC does not show any improvement in network stability, LEACH-EA results in a 50% reduction in energy consumption compared to SEP and a 74% reduction compared to LEACH. Furthermore, LEACH-EA guarantees that the overall network lifetime reaches 4200, 5000, and 5000 rounds for 3, 5, and 7 clusters, respectively.

In [46], introduced two more variations of the LEACH protocol: LEACH-K, which incorporates K-Means clustering into the traditional LEACH approach, and LEACH-EC-EA [157]. LEACH-K demonstrates an overall energy consumption of 41.497J when K is set to 10, achieving an impressive stability of 1399 rounds. LEACH-EC-EA further improves upon this by offering substantial increases in network lifetime, with gains of 300%, 20%, and 82% over LEACH, the Threshold-sensitive Energy Efficient sensor Network protocol (TEEN), and SEP, respectively. LEACH-EC-EA achieves a network lifetime of 1600 rounds, significantly outlasting LEACH.

For a network of 100 nodes with an initial energy of 0.5J per node, LEACH-G-K [87] shows that even after 745 rounds, 50% of the energy remains, in contrast to LEACH and TEEN, which consume 50% of their energy by the 595th and 645th round, respectively. LEACH-G-K operates for 4528 rounds throughout its lifetime, with stability maintained for 352 rounds.

MDC-LEACH-K [47], which employs a movable data collector, demonstrates even greater stability, operating for as long as 2967 rounds. In terms of energy efficiency, MDC-LEACH-K outperforms LEACH, TEEN, and LEACH-K, maintaining an overall residual energy of 0.027J, while the other protocols are left with no remaining energy.

MDC-K [49] achieves a network lifetime of 5505 rounds when 100 nodes, each with an initial energy of 0.5J, are deployed in a 100m by 100m network. The stability period for MDC-K is 1992 rounds, with higher energy consumption compared to LEACH, TEEN, and LEACH-K. MDC-TSP-LEACH-K [49], [50], which integrates a mobile data collector using a travelling salesman routing algorithm, offers a stability period of 2000 rounds and a network lifetime of 7321 rounds. Its energy consumption is more efficient than that of LEACH, LEACH-K, TEEN, LEACH-G-K, and MDC-K.

### *2.6.8 Evaluation of Existing Techniques Based on Throughput*

Throughput, commonly measured as the number of successfully transmitted data packets within a given time frame, is a key performance metric in evaluating energy-efficient routing protocols in IoT-based WSNs. Higher throughput typically indicates efficient data transmission and a well-maintained network, while low throughput points to issues such as energy depletion, packet loss, or network congestion. Many of the existing hierarchical routing protocols are designed with energy efficiency in mind, but they also focus on maintaining a high throughput to ensure continuous and reliable data collection.

Hierarchical routing protocols, which form clusters of nodes with designated CHs, aim to optimise both energy consumption and throughput. Many of the hierarchical techniques focus on balancing load distribution across the network, which directly affects throughput. Several of the existing protocols have been evaluated on the basis of their throughput, as summarised in Table in appendix B. The techniques that perform well in terms of throughput typically employ strategies such as dynamic CH selection, the use of mobile data collectors, and multi-hop communication to reduce energy consumption and improve network performance.

LEACH [40] and LEACH-C [72] use hierarchical routing with a probabilistic method for CH selection. While LEACH delivers relatively modest throughput, its centralised variant LEACH-C offers an improvement in terms of the volume of data transmitted due to its more efficient cluster formation. However, both protocols can experience reduced throughput over time as nodes near the sink deplete their energy. CCMAR [74] and MMS [42] enhance throughput by incorporating mobile data collectors (MDCs) to assist with data transmission.

MDCs reduce the communication load on CHs and nodes, increasing the number of packets successfully transmitted over time. MMS optimises throughput through dynamic relay nodes in addition to CHs.

The use of mobile data collectors significantly boosts throughput in MDC-LEACH-K [47], MDC-K [49] and MDC-TSP-LEACH-K [49], [50]. MDC-LEACH-K delivers up to 27,865 packets per round, while MDC-K transmits 18,300 packets per round, and MDC-TSP-LEACH-K achieves 18,910 packets per round. These methods provide higher packet delivery ratios and are ideal for scenarios that require consistent data collection. WSNEHA [76] and EA-BECHA [93] use adaptive range adjustment and energy-aware strategies to maintain network performance. EA-BECHA, for instance, has a packet drop ratio 35% lower than that of WSNEHA, ensuring a higher packet delivery ratio and increased throughput. SEHR [82] delivers between $16\times10^4$ to $18\times10^4$ packets during the operation of the network. It focuses on energy efficiency through a multi-tier architecture that also contributes to improved data transmission rates.

UDCH [159] demonstrates strong performance, receiving 610,000 packets over 2,000 rounds. UDCH achieves high throughput by balancing the energy consumption across clusters and ensuring reliable data aggregation and transmission. Energy-aware hierarchical routing protocols aim to optimise both energy usage and data transmission by dynamically adjusting routing paths according to the remaining energy levels of nodes. COCA [86] and TEAR [158] incorporate energy-aware routing strategies to enhance network lifetime and throughput. COCA divides the sensor field into equal-sized square units, balancing the load distribution, which improves data transmission rates. Similarly, TEAR employs a traffic and energy-aware routing mechanism, ensuring higher packet delivery ratios over time. Grey Wolf Optimisation (GWO) [53] applies an enhanced shuffled frog leaping algorithm to distribute the load more effectively among CHs, leading to improved throughput in both equal and unequal load conditions. This protocol demonstrates enhanced load management and packet delivery, improving overall network performance.

Throughput is a critical factor in determining the efficacy of routing protocols in IoT-based WSNs. Techniques that incorporate mobile data collectors (e.g., MDC-LEACH-K, MDC-K) consistently outperform those that rely solely on CHs for data transmission, particularly in large-scale deployments. Mobile collectors reduce the burden on CHs and distribute communication tasks more evenly, which significantly increases the number of packets transmitted and received. Moreover, energy-aware routing techniques such as COCA, TEAR, and EA-BECHA demonstrate the importance of dynamic routing adjustments in maintaining high throughput. These protocols balance energy consumption with the need for efficient data transmission, extending network lifetime while ensuring the continuous flow of data.

However, many traditional hierarchical routing techniques (e.g., LEACH, PEGASIS) suffer from lower throughput due to the limitations of direct communication between cluster heads and the sink node. As CHs near the sink deplete their energy, throughput declines, particularly in large networks where distant nodes must expend more energy for data transmission. This highlights the importance of incorporating multi-hop communication and energy-aware mechanisms to sustain high throughput in heterogeneous and dynamic networks.

### *2.6.9 Evaluation Based on End-to-End Delay*

End-to-end delay refers to the total time taken for a data packet to travel from a source node to the sink or base station in a network. Minimising end-to-end delay is critical for time-sensitive applications in IoT-based WSN applications, such as industrial automation, healthcare, and disaster monitoring, where real-time or near-real-time data delivery is essential. The routing techniques discussed in the literature show varying degrees of efficiency in handling end-to-end delays based on their design, cluster formation, communication methods, and mobility models.

#### *i. Techniques with low end-to-end delay*

Techniques that focus on direct communication, optimal routing paths, and reduced hop counts generally result in lower end-to-end delays. These techniques are ideal for time-critical applications where rapid data transmission is paramount.

LEACH [40] and LEACH-C [72] rely on direct communication between CHs and the BS, they inherently reduce the number of hops and, consequently, the end-to-end delay. LEACH-C, which uses a centralised approach for cluster formation, further optimises the communication path and reduces delay. However, the randomness of CH selection in LEACH can sometimes result in suboptimal routing, leading to fluctuations in delay. WSNEHA [76] balances energy consumption and prolongs network lifetime while ensuring that delay remains relatively low. The adaptive range adjustment strategy used by WSNEHA minimises the distance data must travel, reducing delay, though its focus on first-radius nodes may lead to variations in performance across the network.

TEAR [158] is designed to optimise both energy efficiency and traffic, resulting in reduced end-to-end delays. By prioritising energy and traffic awareness in its routing decisions, TEAR minimises the number of hops, allowing for faster data transmission. This is particularly useful in environments where congestion might otherwise cause significant delays. MDC-LEACH-K [47] and MDC-TSP-LEACH-K [49], [50] employ mobile data collectors (MDCs) to gather and transmit data, reducing the number of hops and, thus, the end-to-end delay. MDC-TSP-LEACH-K leverages the Traveling Salesman Problem (TSP) to determine the optimal path for the MDC, further minimising delay. These techniques are well-suited for networks requiring both energy efficiency and low latency in packet delivery.

#### *ii. Techniques with Higher End-to-End Delay*

Techniques that rely on multi-hop communication, increased network density, or complex cluster formation algorithms often suffer from increased end-to-end delay. While these techniques may be more energy-efficient, the trade-off is typically longer delays, making them less suitable for real-time applications.

HEED [73] uses multi-hop communication for data transmission, which can result in higher end-to-end delays. Although HEED is energy-efficient, the additional hops between CHs and the BS increase the time required for data to reach its destination. EBCAG [85] is gradient-based routing protocol that assigns a gradient value to each sensor node based on the minimum hop count to the sink. While this technique is designed to reduce energy consumption, the multi-hop nature of the protocol increases the end-to-end delay, especially in larger networks.

Unequal clustering protocols like UCR [84] and COCA [86] distribute the communication load more effectively, but their reliance on multi-hop communication leads to longer end-to-end delays. The unequal-sized clusters in UCR help balance energy consumption but require more hops for data to travel through the network, increasing the delay.

GWO [53] uses an enhanced shuffled frog leaping algorithm to effectively distribute the load on CHs. While the algorithm helps in reducing energy consumption and prolonging network lifetime, the multi-hop communication in GWO contributes to higher end-to-end delays. The focus on load balancing rather than minimising hops adds latency to the system.

There is often a trade-off between energy efficiency and end-to-end delay in WSN-based IoT protocols. Techniques like LEACH, TEAR, and MDC-LEACH-K achieve lower delays by reducing the number of hops and employing direct communication, but this often comes at the cost of higher energy consumption, particularly for nodes near the sink. On the other hand, techniques that employ multi-hop communication, such as HEED and COCA, are more energy-efficient but incur longer delays due to the increased number of intermediate nodes involved in data transmission.

For applications where real-time data transmission is critical, protocols that focus on minimising delay through direct communication and mobile data collectors are preferable. However, for applications where energy efficiency and network longevity are prioritised over speed, multi-hop protocols can be more suitable, even if they introduce higher delays.

The choice of protocol depends heavily on the specific requirements of the IoT-based WSN application, with energy efficiency, delay tolerance, and network size all playing critical roles in determining the most appropriate routing strategy.

## 2.7 Classification of Existing Techniques based on Network Shape

The shape of the network plays a crucial role in determining the energy efficiency and scalability of IoT-based WSN applications. The network's geometric properties affect how routing protocols balance energy consumption among nodes and mitigate the formation of energy holes. This section categorises the existing balanced load routing methods based on the network shape-circular, square, and rectangular areas-and critically evaluates the advantages and limitations of each approach, as shown in Figure 2.5.

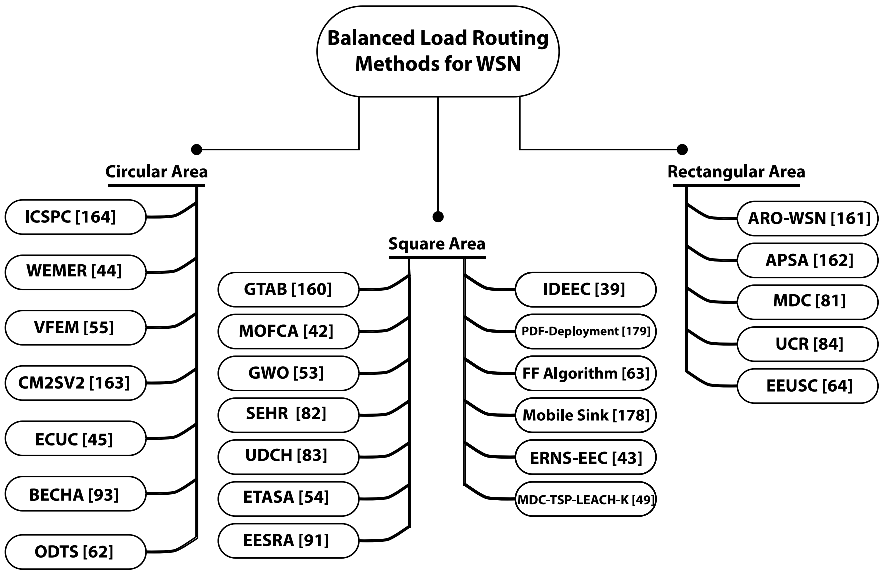



*Figure 2.5: Balanced Load Routing Methods for WSN Based on Network Shape*

### *2.7.1 Techniques for Circle Shape Networks*

Circular networks are commonly employed in applications where a centralised base station or sink node is located at the centre of the network, and data from sensor nodes is transmitted radially. Techniques optimised for circular networks often use corona-based segmentation to divide the area into concentric rings, allowing for more even distribution of energy consumption among nodes.

WEMER [11] segments the network into coronas, where unequal clusters are formed based on transmission distance. The merging of sectors when node energy falls below a certain threshold helps mitigate energy depletion, but it adds complexity to the cluster management process. The Virtual Force-Based Energy Hole Mitigating (VFEM) [55] method employs relay nodes within each annular region to evenly distribute energy consumption. While it enhances network lifetime, its reliance on relay node deployment makes it less adaptable to scenarios where node mobility or dynamic environments are present. Energy Efficient and Coverage Guaranteed Unequal-sized Clustering (ECUC) [45] uses optimal cluster ranges to balance energy and maintain network coverage. The drawback lies in its fixed sector angles, which reduce adaptability in scenarios where dynamic changes in network topology occur. The Balanced Energy Consuming and Hole-Alleviating Algorithm (BECHA) [41] uses multi-hop communication between corona segments to balance energy consumption and reduce energy holes. While effective for small-scale networks, BECHA may struggle with high latency in larger, more complex networks.

These circular network-based techniques demonstrate strengths in evenly distributing energy consumption, but they are often constrained by their assumptions of homogeneous node deployment and the need for controlled, static environments.

### *2.7.2 Techniques for Square Shape Networks*

Square and rectangular network topologies are widely used in urban, industrial, and agricultural applications, where networks are deployed in grid-like patterns. Balanced load routing methods for square areas often focus on sectoring or clustering nodes into groups based on their positions in the grid.

The Multi-Objective Fuzzy Clustering Algorithm (MOFCA) [42] leverages fuzzy logic and multi-sink configurations to achieve a balance in energy consumption. While effective in managing energy, the reliance on complex fuzzy logic mechanisms may introduce additional computational overhead for resource-constrained nodes. The Sector-Based Energy Hole

Reduction (SEHR) [20] protocol uses a three-tier architecture to balance load and enhance energy efficiency. However, its use of controlled, homogeneous node deployment limits its adaptability in heterogeneous environments. The Game-Theoretic Approach for Balancing (GTAB) [162] introduces energy harvesting techniques to supplement energy for high-energy nodes. However, GTAB penalises nodes with higher initial energy, which may lead to early depletion in nodes tasked with more intensive roles. MDC-TSP-LEACH-K [49] is a hybrid protocol that integrates MDCs with K-means clustering and Traveling Salesman Problem (TSP) optimisation to balance energy consumption and reduce latency. While highly efficient, the reliance on MDCs introduces additional mobility management challenges.

Techniques designed for square networks must account for the grid-like topology, which can introduce additional energy costs in communication. While several techniques address this with clustering and multi-hop communication, scalability and adaptability to varying node densities remain key challenges.

### *2.7.3 Techniques for Rectangular Shape Networks*

Rectangular and linear network topologies are common in specific IoT applications such as railway monitoring, agricultural monitoring, and pipeline surveillance. Techniques designed for these networks must handle longer communication distances and more dispersed nodes, which can lead to uneven energy consumption.

The Appropriate Rank-Order WSN (ARO-WSN) [163] method uses a combination of hierarchical and distance-based clustering to balance energy consumption across rectangular areas. This method works well for homogeneous networks but struggles to adapt to heterogeneous environments. The Affinity-Based Self-Adaptive Clustering (APSA) [164] method improves energy efficiency by using k-medoids clustering with affinity propagation. While it extends network lifetime, APSA is limited to homogeneous network deployments and lacks scalability in large-scale environments. The Energy Efficient Unequal Sector Clustering (EEUSC) [64] method divides the network into sectors, with nodes in each sector forming unequal clusters to balance energy. While effective, EEUSC may introduce energy imbalances if node density varies significantly across sectors.

Techniques for rectangular and linear networks must account for the elongated topology and the challenges of long-distance communication. Methods that rely on homogeneous deployments or static clustering may face difficulties in adapting to dynamic environments where node mobility or heterogeneity is present.

## 2.8 Limitations of Existing Techniques

The review highlighted several limitations and challenges associated with existing balanced energy routing techniques. Some major limitations are:

- Most of the techniques reviewed, including LEACH [40], HEED [73], and CCMAR [74], were found to perform well in small-scale networks but faced difficulties when scaled to larger networks. These techniques often fail to maintain network stability and efficiency when applied to networks with thousands of nodes, as is required in large-scale IoT applications.
- Adaptability remains a significant challenge. While unequal clustering techniques such as UCR [84] and BECHA [93] offer some adaptability to changing network conditions, most methods assume static network environments. This assumption limits their applicability in dynamic IoT environments where node mobility, energy levels, and data rates fluctuate frequently.
- Many techniques, including those based on LEACH [40] and PEGASIS [75], assume homogeneous network environments. However, many applications in IoT-based WSNs systems demand energy-efficient communication protocols that can adapt to networks with multi-parameter and multi-level heterogeneous devices. While some protocols such as SEP [51] and DEEC [79] address heterogeneity to some extent, they often penalise higher-energy nodes, leading to early depletion.
- Protocols that rely on multi-hop communication or mobile sinks, such as HEED [73], CM2SV2 [165], and MDC [81], tend to introduce higher latency, which can be problematic for time-sensitive applications. The balance between energy efficiency and low-latency operation remains an open challenge.
- The applicability of many techniques is limited by network shape considerations. Methods optimised for circular networks (e.g., VFEM [55], ICSPC [166]) may not perform well in square or rectangular networks, and vice versa. Additionally, most techniques are limited to two-dimensional network structures, whereas many real-world IoT applications require adaptability to three-dimensional network structures (e.g., in smart cities or underwater sensing).
- Despite advances in routing protocols, the problem of energy holes. Techniques such as BECHA [93] and WSNEHA [76] address energy holes to some extent but often at the expense of increased protocol complexity or reduced network lifetime.

### *2.8.1 Mapping of Research Gaps to Proposed Contributions*

To clarify how the gaps identified above are directly addressed by this research, Table 2.2 presents a comprehensive gap analysis. The table maps each major limitation of existing balanced energy routing techniques to the corresponding novel contributions proposed in this thesis.

*Table 2.2: Mapping Identified Research Limitations to Proposed Thesis Contribution*

| Identified Limitation / Research Gap | Reference | Corresponding Contribution | Chapter |
|---|---|---|---|
| Limited scalability of LEACH, HEED, CCMAR, etc., in large-scale networks | [40], [73], [74] | Scalable sink node placement and segmentation methods suitable for large-scale networks | Chapter 3 & 4 |
| Shape-specific designs (e.g., circular or square) that fail in irregular 3D deployments | [84], [93] | Cube-shaped, spherical, and shape-independent segmentation schemes for 2D and 3D deployments | Chapter 4 |
| Lack of adaptability to dynamic environments in most clustering techniques | [40], [51], [75], [79] | Dynamic routing and unequal clustering with CH rotation to adapt to changing energy and topology | Chapter 4 & 5 |
| Homogeneous network assumptions in many protocols; limited heterogeneity handling | [73], [81], [165] | Multi-level and multi-parameter heterogeneity model for adaptive clustering and routing | Chapter 5 |
| High latency introduced by multi-hop routing and mobile sink methods | [55], [166] | Delay-conscious relay selection and rotation schemes to balance energy and reduce transmission delay | Chapter 5 |
| Energy hole formation near the sink node remains unresolved or partially solved | [76], [93] | Optimal sink placement, relay region selection, and load-aware CH rotation to mitigate energy holes | Chapter 4 & 5 |

As illustrated in Table 2.2, this thesis addresses a range of longstanding challenges in energy-efficient routing and clustering for heterogeneous, large-scale, and three-dimensional WSN deployments. Each contribution is purposefully aligned with an existing limitation to ensure that the proposed solutions are both relevant and impactful. This alignment forms the foundation for the methods and models presented in Chapters 3 through 5.

## 2.9 Summary:

In this chapter, a comprehensive review and classifications of balanced energy routing techniques for WSNs in IoT-based applications were presented. The discussion emphasised the importance of energy efficiency and network lifetime. The chapter began by addressing the critical need for energy management in IoT-based WSNs. It highlighted that network longevity is primarily determined by the energy consumption of sensor nodes. Techniques for managing energy consumption through lightweight routing, energy harvesting, and efficient data aggregation were critically reviewed.

The literature review classified existing routing protocols based on a variety of parameters, including device-specific attributes, network topology, inter-cluster communication, sink node mobility, clustering techniques, and throughput. The protocols were also classified into homogeneous and heterogeneous based on parameters such as initial energy, data rate, transmission range, and computational capacity.

A classification based on the mobility of sink nodes was also explored. Mobile sinks, though efficient in balancing energy consumption across the network, introduce additional complexity and delay. The literature review also classified methods based on equal and unequal clustering. Unequal clustering techniques demonstrated significant advantages in load balancing but increased protocol complexity. Existing techniques were also found to be limited based on the shape of the network i.e., circular, square, and rectangular. These classifications underscore the adaptability challenges faced by most existing techniques, particularly when transitioning from two-dimensional to a third spatial dimension in the network.

The next chapter delves into key contributions towards energy-efficient base station deployment. The proposed methods aim to address the challenges of scalability, adaptability, and generalisability in existing data aggregation and transmission techniques, ensuring seamless and collaborative operations within IoT-enabled infrastructures, such as smart cities.

# Chapter 3

# Sink Node Deployment: Iterative and TOPSIS-Based Schemes

## 3.1 Introduction

The deployment of a base station (BS), also referred to as sink node, plays a pivotal role in the performance of WSNs, particularly in HWSNs-based IoT. As IoT-based WSN applications continue to expand in several areas, such as smart farming [13], precision agriculture [13], marine monitoring [11], and mountainous terrains, the need for scalable and energy-efficient routing becomes increasingly critical [22]. These environments often require adaptable strategies to ensure effective data collection and network longevity, especially when dealing with non-uniform device deployments across complex and varying terrains [56].

In traditional deployment techniques within WSNs, sensing devices are either randomly placed or arranged according to a pre-determined plan within a two-dimensional (2D) space. However, modern applications require three-dimensional (3D) deployment, which introduces additional challenges such as varying surface terrains and the lack of controlled deployment strategies [46]. This adds complexity to finding an optimal location for the data-gathering centre, as many existing methods assume the placement of sink node either at the centre or the boundary of the Region Of Interest [8]. Although these conventional approaches are effective in smaller networks with homogeneous nodes, they are inadequate for large-scale heterogeneous networks, where nodes differ in energy levels, data transmission rates, and computational capacities.

The primary challenge addressed in this chapter is the development of an efficient sink node deployment technique for HWSNs that is suitable for both 2D and 3D networks. The focus is on minimising overall energy consumption while ensuring the balanced energy usage and adaptability to diverse network topologies and heterogeneity. To address these challenges, this chapter proposes two novel sink node deployment methods that consider various network shapes and dimensions, as well as multi-parameter and multi-level heterogeneities. First approach develops an iterative algorithm that determines an optimum location of sink node from a set of alternative locations. To improve the computational complexities of iterative method the second method is proposed. This method incorporates the multi-criteria decision-making Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), enhancing network longevity and energy efficiency compared to the proposed iterative approach and other state-of-the-art deployment methods. The methods are tested across various prominent 2D and 3D network configurations, demonstrating that the TOPSIS-based deployment achieves 29.1% greater energy savings compared to existing approaches.

The structure of this chapter is as follows: Section 3.2 reviews existing network deployment schemes, and section 3.3 discusses the challenges and limitations in current sink node deployment approaches. Section 3.4 provides the problem formulation, employed models, and simulation setup. Section 3.5 details the proposed sink node deployment schemes, including an iterative method and the Technique for Order of Preference by Similarity to Ideal Solutions (TOPSIS) method. Section 3.6 presents the performance evaluation of the proposed methods. Finally, Section 3.7 summarises the chapter.

## 3.2 Existing Sink Node Deployment Methods

The deployment of sink nodes in WSNs plays a crucial role in maximising network lifetime and minimising energy consumption. Traditional hierarchical routing approaches assume a centralised sink node placement [142], [167], [168] or deployment outside the network boundary [163]. While effective in smaller, homogeneous networks, these approaches are inadequate for heterogeneous WSNs, where node capabilities vary, and balanced energy consumption becomes essential. In such contexts, centralised placements can lead to uneven energy distribution, creating energy holes that reduce network lifespan.

In response to these challenges, various optimisation algorithms have been developed, each with unique strengths and limitations. Techniques such as Particle Swarm Optimisation (PSO) [169], Flower Pollination Algorithm (FPA) [170], Grey Wolf Optimiser (GWO) [171], Sine Cosine Algorithm (SCA) [172], Multi-Verse Optimiser (MVO) [173], Whale Optimisation Algorithm (WOA) [174], and Harris' Hawk Optimisation (HHO) [8] have been used to address sink node placement issues by improving energy efficiency and balancing load. However, these approaches exhibit several limitations when applied to large-scale, heterogeneous networks.

The two foundational deployment models that are widely used in literature include central deployment of DGC (case i) [43], [44], [54] and DGC deployment at average coordinates (case ii) [16].

### *3.2.1 Case I: Central Deployment of DGC*

In Case I, the sink node is positioned at the centre of the network. This is a simple and widely used method, where placing the DGC at the centre of the network allows it to function as a natural hub for data collection.

For a 3D network, the rectangular coordinates $(x_s, y_s, z_s)$, representing the centre of the network for DGC placement can be mathematically determined as:

$$x_s = 0.5 \cdot x_{max}; \qquad y_s = 0.5 \cdot y_{max}; \qquad z_s = 0.5 \cdot z_{max}$$

Here, $x_{max} \times y_{max} \times z_{max}$ represents the volume of the 3D network. If the network is two dimensional, the third coordinate is omitted, and is reduced to $x_{max} \times y_{max}$.

For a 3D spherical network, the DGC location is at the centre of the sphere. Let $'r'$ be the radius of the spherical network. The DGC coordinates in a spherical deployment would simply be the centre point:

$$x_s = 0; \qquad y_s = 0; \qquad z_s = 0$$

assuming the origin is the centre of the spherical volume $\frac{4}{3}\pi r^3$. If the network is 2D, the omission of the third coordinate (z-coordinate), results in the volume reduction to $\pi r^2$. The central placement serves as the baseline technique for comparing the performance of more adaptable and optimised deployment schemes in diverse network configurations.

### *3.2.2 Case II: DGC Deployment at Average of Coordinates*

In Case II, the sink node is placed at the average location of all sensor nodes in the network. The DGC's coordinates are calculated by taking the mean of the coordinates of all $'N'$ sensor nodes, in each dimension. In a 3D rectangular or cubic network, the average coordinates $(x_{s\_mean}, y_{s\_mean}, z_{s\_mean})$ for the DGC location are calculated as:

$$x_{s\_mean} = \frac{\sum_{i=1}^{N} S_{ix}}{N}; \qquad y_{s\_mean} = \frac{\sum_{i=1}^{N} S_{iy}}{N}; \qquad z_{s\_mean} = \frac{\sum_{i=1}^{N} S_{iz}}{N}$$

Here, $S_{ix}$, $S_{iy}$, $S_{iz}$ are the coordinates of each sensor node $'i'$ in the network. For a 3D spherical network, the average coordinates are determined in the same way as in a 3D rectangular network. However, given that nodes are likely concentrated within the sphere's radius, this placement may lead to the DGC being closer to the densest region within the sphere.

In a 2D rectangular or square network, the third coordinate $(z_{s\_mean})$ is dropped and location is determined by the average coordinates $(x_{s\_mean}, y_{s\_mean})$ only. Similar is the case with 2D circular network where DGC is placed at the mean coordinates of all nodes, ideally close to the densest node region within the circle.

The average placement method allows the DGC to be centrally located based on actual node distribution, adapting to the spatial density of the network. It serves as a simple yet practical reference for comparing more advanced deployment schemes.

### *3.2.2 MCDM Techniques*

In multi-criteria decision-making (MCDM) scenarios for WSN-based IoT environments, several frameworks are available, such as AHP, VIKOR, ELECTRE, and SAW. Each method brings unique advantages and complexities, and selecting an appropriate method depends on the application's constraints and objectives.

AHP, relies on subjective pairwise comparisons and scales poorly with larger alternatives. Therefore, it is not fully deterministic and computationally efficient. AHP is Ideal for expert-driven decisions but unsuitable for real-time autonomous sensor networks due to reliance on subjective input and poor scalability. VIKOR, handles conflicting objectives well but introduces complexity through compromise solutions and regret measures, which can be computationally heavier. ELECTRE is Effective for qualitative or fuzzy criteria but involves complex outranking and threshold definitions, making it less adaptable to quantitative, lightweight deployments. SAW is easy to implement but lacks the ideal/anti-ideal framework, which is important for trade-off scenarios in multi-parameter routing and sink node deployment.

TOPSIS offer a favourable balance between computational efficiency, decision-making clarity, and real-world applicability in energy-constrained, heterogeneous WSNs. Other MCDM methods remain valuable for comparison and benchmarking in future work, particularly in scenarios requiring nuanced human judgment or conflict resolution.

## 3.3 Challenges and Limitations

Despite substantial advancements in sink node deployment techniques for wireless sensor networks (WSNs), existing methods exhibit following limitations, particularly in the context of large-scale, heterogeneous, 3D networks.

- Many traditional hierarchical routing techniques rely on a centralised sink node placement within the network or on deployment at the network boundary [142], [163], [167], [168] . While effective for small or homogeneous networks, these approaches are inadequate for completely heterogeneous WSNs. Such placements often lead to unbalanced energy consumption, that can result in the formation of energy holes, reducing network lifespan. Such approaches also lack flexibility, as they are not adaptable to varying network topologies and node characteristics.
- A critical shortcoming of many optimisation algorithms-such as Particle Swarm Optimisation (PSO) [169], Grey Wolf Optimiser (GWO) [171], and Flower Pollination Algorithm (FPA) [170], is their limited capacity to address heterogeneity within WSNs. These methods tend to treat nodes uniformly, neglecting variations in energy levels, data transmission rates, and computational capacities. As a result, they fail to fully exploit the heterogeneous nature of large networks, which can lead to suboptimal performance in terms of both energy efficiency and network lifetime.
- Most existing optimisation techniques have been designed for 2D network configurations, which limits their applicability in more complex, real-world deployments that require 3D spatial consideration. Techniques such as PSO [169] have demonstrated effectiveness in 2D deployments but fall short when applied to three-dimensional (3D) networks, which are increasingly necessary for applications such as IoT and smart cities. This lack of adaptability restricts their application in scenarios where nodes must be deployed across multiple layers or varying terrains.
- Many metaheuristic algorithms are primarily applied to small or medium-sized networks. Although some methods, such as Harris' Hawk Optimisation (HHO) [8], extend to larger networks, comprehensive evaluations for scalability in networks with thousands of nodes remain limited. This scalability constraint makes existing techniques insufficient for large-scale applications, such as those found in IoT-based WSNs, where thousands of nodes may be required to cover extensive areas.
- Existing methods are often designed with a specific application in mind, which restricts their generalisability to diverse use cases, such as IoT, smart cities, or

environmental monitoring. Algorithms like multi-objective Whale Optimisation Algorithm (WOA) [174] have been successful in specific applications but lack the flexibility required to be widely applicable across different WSN configurations and objectives.

Therefore, the limitations of existing sink node deployment methods underscore the need for more adaptable, scalable, and computationally efficient solutions. These limitations provide the foundation for the proposed methods in this chapter, which are designed to address these gaps by enabling dynamic, energy-efficient sink node placement that is valid in both two-dimensional as well as three-dimensional heterogeneous WSNs.

## 3.4 Problem Definition and System Model

This section presents the sink node deployment problem, aimed at maximising network lifetime and achieving balanced energy operation in 2D and 3D networks of varying shapes. The model addresses scalability and adaptability requirements in heterogeneous network environments.

### *3.4.1 Problem Definition*

In modern WSN applications, nodes are increasingly deployed in three-dimensional (3D) spaces to support applications in varied terrains such as forests, agricultural fields, mountainous regions, and sea surfaces, where controlled deployments are generally infeasible due to environmental constraints [46]. Consequently, sensors are often deployed in an ad-hoc or random manner, leading to irregular spatial distributions that complicate both sink node placement and routing processes. As shown in Figure 3.1, these environments demand unique configurations to support nodes that vary widely in energy capacities, data transmission rates, and computational capabilities. The heterogeneous characteristics of nodes within these environments further increase the difficulty of maintaining balanced energy usage and efficient network operation.

Existing approaches generally place the sink node at either the centre or boundary of the ROI [8]. While this approach is effective for small, uniformly deployed networks, it proves inefficient for large-scale, heterogeneous WSNs with non-uniform or 3D deployments. Neglecting spatial dimensions and energy consumption variations in non-uniform deployments can create "energy holes," where rapid energy depletion in certain areas drastically shortens network lifetime.

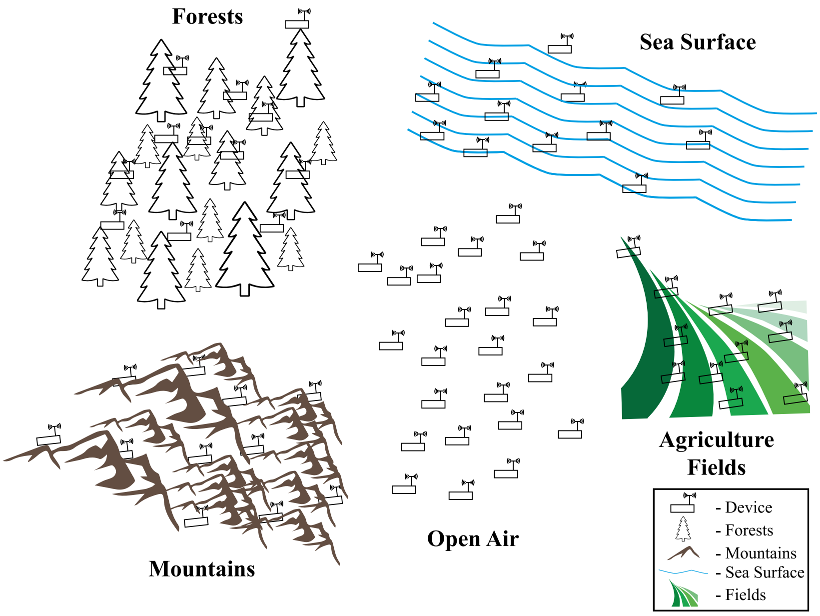



*Figure 3.1: Heterogeneous devices across networks with diverse terrains and shapes.*

Given these challenges, the primary goal is to determine an optimal location for sink node placement that minimises overall energy consumption, balances load distribution, and supports scalability and adaptability across diverse deployment conditions. It is required:

- To achieve energy efficiency by minimising the total energy consumption across all nodes by optimising the sink node's position. Since energy depletion rate varies across heterogeneous nodes, the deployment must consider factors such as transmission distance, node energy capacity, and frequency of communication to ensure efficient data relay operation to the sink node.
- To distribute the energy usage more evenly on nodes and prevent uneven energy consumption among nodes and avoid rapid depletion in specific regions.
- The deployment technique must be scalable to accommodate networks of various sizes and be adaptable to 2D and 3D topologies with non-uniform node densities.

Mathematically, the problem formulation can be described as:

Let $'N'$ be the number of sensor nodes in the network. $(x_i, y_i, z_i)$ represent the coordinates of the $i$th sensor node in a 2D or 3D space. $(x_s, y_s, z_s)$ represent the coordinates of the sink node to be optimised. $E_i$ denotes the initial energy of node $'i'$. $d_{i,s}$ represent the Euclidean distance between node $'i'$ and the sink node, calculated as:

$$d_{i,s} = \sqrt{(x_i - x_s)^2 + (y_i - y_s)^2 + (z_i - z_s)^2} \tag{3.1}$$

The primary objectives are:

1. To minimise the total energy consumption of the network. Where, energy consumed by the node $'i'$ for transmitting $'k'$ bits to the destination can be computed by the radio model [175], [176]. The total energy consumption $E_{total}$ can be given by:

$$E_{total} = \sum_{i=1}^{N} E_{tx,i} \tag{3.2}$$

   The objective is to minimise $E_{total}$ by choosing optimal $(x_s, y_s, z_s)$ values, thereby minimising average distances and energy usage.

2. To prevent the formation of energy holes and achieve a balanced energy consumption across the network, the variance in residual energy across nodes must be minimised. Let $E_{residual,i}$ represent the residual energy of node $'i'$ after data transmission. The balance constraint can be formulated as:

$$\max(E_{residual}) - \min(E_{residual}) \leq \delta$$

   where $'\delta'$ is a predefined threshold for acceptable energy variance among nodes, preventing rapid depletion in specific areas.

3. To ensure that $(x_s, y_s, z_s)$ is feasible within the ROI, covering both 2D and 3D layouts. This is represented as:

$$(x_s, y_s, z_s) \in \mathrm{ROI}$$

   where, ROI may vary based on network size and environmental conditions, ensuring scalability and adaptability across diverse applications.

   The multi-objective problem can be formulated as:

$$\min_{(x_s, y_s, z_s)} \left(\alpha \times E_{total} + \beta \times \left(\max(E_{residual}) - \min(E_{residual})\right)\right) \tag{3.3}$$

where $'\alpha'$ and $'\beta'$ are weighting factors for energy efficiency and balanced load distribution.

The formulation addresses the need for an adaptable and scalable sink node placement strategy that minimises energy consumption, balances load and accommodates diverse topologies and node heterogeneities. By considering these factors, this deployment approach is poised to extend network lifetime and enhance the performance of WSNs in real-world IoT applications across varied terrains.

### *3.4.2 System Model*

This section details the system model used in evaluating the proposed sink node deployment strategies, covering network structure, node characteristics, communication and energy models, as well as key assumptions and performance metrics.

#### *i. Network Structure*

The network is assumed to contain $'N'$ sensor nodes deployed within a predefined 2D or 3D Region Of Interest (ROI) for data collection and transmission to a base station.

Nodes are distributed randomly within the ROI to represent realistic IoT-based WSN deployment scenarios. The model supports scalable node densities, allowing adaptation for small- to large-scale networks.

For a 3D network, the ROI has dimensions $(x_{max}, y_{max}, z_{max})$. In 2D networks, $z$ is set to zero, and only $(x_{max}, y_{max})$ define the boundaries. This network structure is employed for testing and evaluation consistently across the rest of the chapters in this thesis

#### *ii. Node Characteristics*

Sensor nodes are heterogeneous, varying in energy levels, communication ranges, data rates, and computational capabilities, which are critical factors for optimising network performance. Each node $'i'$ is initialised with $E_i$, representing its unique initial energy, such that:

$$\sum_{i=1}^{N} E_i = E_{total} \tag{3.4}$$

Each element $E_i$ falls within a specified range:

$$E_{\min} \leq E_i \leq E_{\max}$$

The values of $E_i$ are randomly chosen while satisfying the above constraints. In a similar fashion the nodes generate data rate $T_i$, which may vary depending on the application. The nodes monitoring high-priority data (e.g. environmental hazards) may have higher $T_i$ values. In this case for testing, we have used a similar model for $T_i$ and $E_i$. Finally, each node $'i'$ has a specific transmission range $R_i$ and nodes with higher energy may be chosen to transmit at higher range than their other counterparts. These characteristics are also used consistently for the evaluation methods proposed in this thesis.

### *iii. Communication Model*

Nodes communicate either directly with the sink node (single-hop) or through intermediate nodes (multi-hop), depending on the distance $d_{i,s}$ between the sensor node $i$ and the sink node. For a node $i$ with coordinates $(x_i, y_i, z_i)$ and a sink node at $(x_s, y_s, z_s)$, the Euclidean distance is calculated as described by eq. (3.1).

The path-loss exponent $'b'$ varies depending on the environment:

- For free space, $b = 2$
- For multi-path fading environments, $b = 4$

The model switches between these based on the threshold distance $d_o$, which is calculated as:

$$d_o = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \tag{3.5}$$

where $\epsilon_{fs}$ and $\epsilon_{mp}$ are amplifier energy factors for free space and multi-path environments. This communication model is also employed consistently across to evaluate the results of proposed methods across the rest of this thesis.

### *iv. Energy Model*

The first-order radio model [177] is used to compute the energy consumption of each node for transmitting and receiving data packets. The energy consumed to transmit a $k$-bit packet over a distance $'d'$ is given by:

$$E_{Trans}(k, d) = \begin{cases} k \times E_{elec} + k \times \varepsilon_{fs} \times d^2 \ ; \ d < d_o \\ k \times E_{elec} + k \times \varepsilon_{mp} \times d^4 \ ; \ d \geq d_o \end{cases} \tag{3.6}$$

where

- $E_{elec}$ is energy per bit for electronic circuitry
- $\varepsilon_{fs}$ and $\varepsilon_{mp}$ are the amplifier energy constants for free space and multi-path models respectively
- $k$ is number of bits
- $d$ is Euclidean distance

Similarly, energy consumed to receive a $k$-bit packet is simply

$$E_{rec}(k) = k \times E_{elec} \tag{3.7}$$

Each node's radio adjusts its power output to the minimum required for transmission to the intended recipient, enhancing energy efficiency.

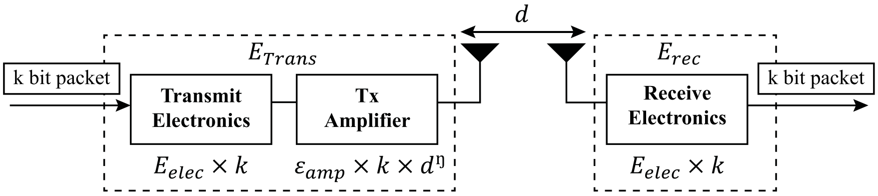



*Figure 3.2: First order radio model.*

The radio model of Figure 3.2 as well as the following assumptions are made while evaluating the performance of methods in this chapter and the rest of the thesis:

- There is a single base station.
- Nodes are assumed to be static after deployment.
- Data collection is periodic, with a defined interval that affects energy use and data transmission patterns.

## 3.5 Proposed Base Station Deployment Schemes

This section presents the proposed base station deployment schemes designed to address the challenges of heterogeneous WSN environments. These schemes focus on optimising both energy efficiency and balanced operation.

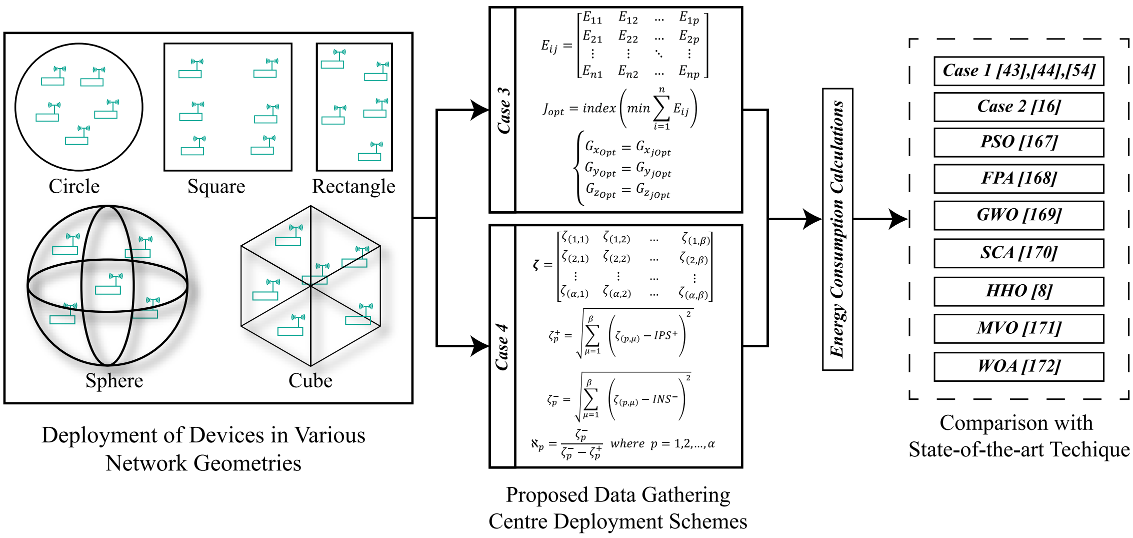



*Figure 3.3: Flow diagram for the proposed method.*

Figure 3.3 shows the overview of steps followed to evaluate the performance of proposed methods. Firstly, network is configured for main network shapes including circle, square, rectangular, sphere and cube. In second step applied deployment methods are applied, and corresponding energy consumption calculations are made. Finally, to validate the performance of proposed methods a comparison with the state-of-the-art deployment techniques is drawn.

### *3.5.1 Case III: Proposed Optimised Deployment of DGC (Iterative Method)*

In Case III, the DGC placement considers the fully heterogeneous nature of the network. Due to differences in node density and energy availability across the network, the optimal central point may not align with the geometric mean of node coordinates as explained in case II. Instead, this approach evaluates alternative DGC locations within a defined region around the mean coordinates, selecting the point that minimises overall energy consumption for data transmission, and balancing load across the network.

The mean coordinates $(x_{s\_mean}, y_{s\_mean}, z_{s\_mean})$ determined in case II, provide an initial approximation for the DGC placement. A spherical or cubic region with radius $'r'$ around the initial mean point $(x_{s\_mean}, y_{s\_mean}, z_{s\_mean})$ is defined, containing potential locations for the DGC. Each location within this radius acts as an alternative, allowing flexibility in identifying a more energy-efficient DGC position. The coordinates of each alternative DGC location $(x_{s\_alt(X)}, y_{s\_alt(Y)}, z_{s\_alt(z)})$ are generated as:

$$\begin{cases} x_{s_{alt(X)}} = \left(x_{s_{mean}} - \gamma\right) + \dfrac{X}{2} \\ y_{s_{alt(Y)}} = \left(y_{s_{mean}} - \gamma\right) + \dfrac{Y}{2} \\ z_{s_{alt(Z)}} = \left(z_{s_{mean}} - \gamma\right) + \dfrac{Z}{2} \end{cases} \tag{3.8}$$

where, $X, Y, Z = 0,1,2, \ldots, 2\gamma$ and $'\gamma'$ is a parameter controlling the search extent. For a 3D network, the number of alternative locations $'F'$, can be calculated as:

$$F = (2\gamma + 1)^3 \tag{3.9}$$

For each alternative DGC location $'f'$, the total network energy consumption is computed by evaluating the energy needed for data transmission between sensor nodes and their assigned cluster heads (CHs), as well as the energy required for CHs to communicate with the DGC.

The goal is to select the alternative DGC location that minimises overall energy consumption. Let $E_{CON1}$ be an array containing energy consumption values for each alternative, where:

$$idx1 = \arg\min_{i,j,k} E_{CON1}\,[i, j, k] \tag{3.10}$$

where $idx1$ is the set containing the index values of coordinates with minimum energy consumption. Therefore, the coordinates of the optimal DGC location can be given by:

$$\left(x_{s_{Opt}}, y_{s_{Opt}}, z_{s_{Opt}}\right) = \left(x_{s_{alt(i)}}, y_{s_{alt(j)}}, z_{s_{alt(k)}}\right) \tag{3.11}$$

***Proposed Algorithm 3.1:***

Algorithm 3.1 below outline the proposed procedure for the computation of optimal location of base station in an energy efficient manner using iterative method.

---

**Algorithm 3.1**: Location of base station based on minimum energy consumption.

---

**Require:**

The number of devices $'N'$ deployed within a network, their coordinates $(x_i, y_i, z_i)$ ; $i = 1,2,3, \dots, N$ of each sensor node, their heterogeneous initial energies denoted as $S_i^E$, their heterogeneous data rate denoted as $S_i^T$, radius $'r'$ from the point at mean of device coordinates in which alternative locations for the deployment of DGC are considered. Total number of clusters $'C'$. Total number of alternative DGC locations as; $f = 1,2,3, \dots, F$ and their coordinates in three-dimensional space using equations above.

**Ensure:**

$G_{(.)}^{Opt} \leftarrow \left(x_{s\_Opt}, y_{s\_Opt}, z_{s\_Opt}\right)$

1: $S_i^E \leftarrow E_o(1 + \beth)$

2: $S_i^T \leftarrow T_o(1 + \tau)$

3: for $i \leftarrow 1$ to $N$ do

4: for $j \leftarrow 1$ to $C$ do

5: if $(i \leftarrow index(j))$

6: $S_i^{type} = 'CH'$

7: else $S_i^{type} = 'NN'$

8: end if

9: $D_{ij} \leftarrow \sqrt{\left(S_i^x - G_j^x\right)^2 + \left(S_i^y - G_j^y\right)^2 + \left(S_i^z - G_j^z\right)^2}$

10: end for

11: $S_i^{cluster} \leftarrow argmin_{ij}(D_{ij})$

12: end for

13: for $i \leftarrow 1$ to $N$ do

for $j \leftarrow 1$ to $C$ do

if ($S_i^{type} = NN$ & $S_i^{cluster} = j$)

$E_{CON_i} \leftarrow Energy\ from\ i^{th}\ node\ to\ j^{th}\ CH$

elseif ($S_i^{type} = CH$)

$E_{CON_i} \leftarrow Reception\ energy\ from\ all\ members$

end if

end for

end for

for $j \leftarrow 1$ to $C$ do

for $f \leftarrow 1$ to $F$ do

$D_{jf} \leftarrow \sqrt{\left(S_j^x - G_f^x\right)^2 + \left(S_j^y - G_f^y\right)^2 + \left(S_j^z - G_f^z\right)^2}$

$E_{CON_{jf}} \leftarrow Energy\ from\ j^{th}\ CH\ to\ f^{th}\ location$

end for

$E_f = \sum_{j=1}^{C}(E_{CON_{jf}})$

end for

$Opt = arg\min_f(E_f)$

$\left(x_{s\_Opt}, y_{s\_Opt}, z_{s\_Opt}\right) \leftarrow \left(x_{s\_Opt}, y_{s\_Opt}, z_{s\_Opt}\right)$

The chosen DGC location minimises overall energy consumption within the network by considering a region around the mean coordinates. This method effectively balances energy use and reduces rapid depletion in specific areas. However, as network size and heterogeneity increase, the complexity of this approach also grows, given the expanded number of evaluated alternatives.

### *3.5.2 Case IV: Proposed TOPSIS-Based Optimised Deployment of DGC*

In Case IV, the optimal placement of the DGC is approached as a multi-criteria decision-making problem. This approach, based on the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), addresses the increasing computational complexity of energy-efficient deployment by incorporating multiple heterogeneous parameters, including device energy, data rate, device density, and distance. By integrating these criteria, this method provides a more adaptable and balanced solution for DGC placement, particularly in complex, heterogeneous networks.

Attributes for decision-making process can be determined by following mathematical representations.

Let $'E'$ represent the set of initial energies of $'N'$ devices, defined as:

$$E = \{E_1, E_2, \dots, E_N\} \tag{3.12}$$

where each device's energy $E_m$ is calculated as:

$$E_m = E_o(1 + ב) \tag{3.13}$$

Here, $E_o$ is the minimum initial energy, and $'ב'$ is a random number between 0 and 1, representing the heterogeneity in energy. Each device's data rate $T_m$ is also heterogeneous, following a similar formula, with values ranging from 1000 to 4000 packets.

Distances between potential DGC locations and each device are calculated based on candidate locations around the initial mean location, using eq. (3.8), above in Case III to generate a set of alternative coordinates within a defined radius.

***Multi-Criteria Decision-Making Process:***

The optimal DGC placement is treated as a multi-criteria optimisation problem with parameters measured on different scales. To standardise values, each parameter is normalised to a range $[0,1]$ using min-max normalisation:

$$\vartheta_o = \frac{\theta_o - \theta_{min}}{\theta_{max} - \theta_{min}} \tag{3.14}$$

where $\vartheta_o$ is the normalised value of parameter $'o'$, $\theta_o$ is the actual value, $\theta_{max}$ and $\theta_{min}$ are the maximum and minimum values for that parameter.

Let $'\zeta'$ be a matrix of normalised values for each parameter (e.g., energy, data rate, distance) across all alternative DGC locations:

$$\zeta = \begin{bmatrix} \zeta_{(1,1)} & \zeta_{(1,2)} & \cdots & \zeta_{(1,\beta)} \\ \zeta_{(2,1)} & \zeta_{(2,2)} & \cdots & \zeta_{(2,\beta)} \\ \vdots & \vdots & \ddots & \vdots \\ \zeta_{(\alpha,1)} & \zeta_{(\alpha,2)} & \cdots & \zeta_{(\alpha,\beta)} \end{bmatrix} \tag{3.15}$$

where, $\zeta_{(\alpha,\beta)}$ is the normalised value of the $\beta^{th}$ parameter of the $\alpha^{th}$ alternative DGC location.

Ideal Positive Solution (IPS) for parameters where a high value is preferred (e.g., initial energy, device density):

$$IPS^{+} = \max\{(\zeta_{(1,\mu)}), (\zeta_{(2,\mu)}), \dots, (\zeta_{(\alpha,\mu)})\}, \forall \ \mu \in \beta \tag{3.16}$$

Ideal Negative Solution (INS) for parameters where a low value is preferred (e.g., data traffic, distance):

$$INS^{-} = \min\{(\zeta_{(1,\mu)}), (\zeta_{(2,\mu)}), \dots, (\zeta_{(\alpha,\mu)})\}, \forall \ \mu \in \beta \tag{3.17}$$

The distance of each candidate DGC location from the ideal positive solution $(\zeta_p^{+})$ and the ideal negative solution $\zeta_p^{-}$ is calculated as:

$$\zeta_p^{+} = \sqrt{\sum_{\mu=1}^{\beta}(\zeta_{(p,\mu)} - IPS^{+})^2} \ where\ p = 1,2,3 \dots \alpha \tag{3.18}$$

$$\zeta_p^{-} = \sqrt{\sum_{\mu=1}^{\beta}(\zeta_{(p,\mu)} - INS^{-})^2} \ where\ p = 1,2,3 \dots \alpha \tag{3.19}$$

Each candidate location is ranked based on its relative closeness to the ideal solution, defined as:

$$\aleph_p = \frac{\zeta_p^{-}}{\zeta_p^{-} - \zeta_p^{+}} \ where\ \ p = 1,2,3 \dots \alpha \tag{3.20}$$

The location with the highest value of $\aleph_p$ is selected as the optimal DGC placement. However, if the location with highest rank value does not become available due to any deployment constraint the location with second highest rank value is considered as the most suitable deployment location.

In this method, equal weights are initially assigned to all decision criteria (i.e., energy, data rate, and distance) to provide a neutral, unbiased evaluation baseline. This approach is suitable when no expert input or application-specific priority is available. The equal weighting strategy ensures fair contribution from each parameter and avoids premature bias toward any single factor.

In future enhancements, alternative weighting schemes such as entropy-based weighting or expert-driven AHP could be integrated to reflect dynamic contextual needs. However, for this study, the equal-weight approach was adopted due to its simplicity, transparency, and computational efficiency, key factors for real-time, resource-constrained WSN environments.

In algorithm 3.2, the step-by-step procedure is presented using algorithmic language for clarity and precision.

***Proposed Algorithm 3.2:***

The procedure for determining the optimal location of the DGC using the multi-criteria decision-making technique TOPSIS is described below.

---

**Algorithm 3.2:** Optimal location for the deployment of base station using a multi-criterion decision making technique TOPSIS.

---

**Require:**

The number of devices $'N'$ deployed within the 3D network, the coordinates $(x_i, y_i, z_i)$ ; $i = 1,2,3, \ldots, N$ of each sensor node, their heterogeneous energies denoted as $S_i^E$, their heterogeneous data traffic denoted as $S_i^T$, radius $'r'$ from the point at mean of device coordinates in which alternative locations for the deployment of DGC are considered. Total number of clusters $'C'$. Total number of alternative DGC locations as; $f = 1,2,3, \ldots, F$ and their coordinates in three-dimensional space using eq. (3.8) as given in case III.

**Ensure:**

$G_{(.)}^{TOPSIS} \leftarrow \alpha \ with \max\{\aleph_p\}$

1: $S_i^E \leftarrow E_o(1 + \beth)$

2: $S_i^T \leftarrow T_o(1 + \tau)$

3: for $j \leftarrow 1$ to $C$ do

4: for $f \leftarrow 1$ to $F$ do

5: $D_{jf} \leftarrow \sqrt{\left(S_j^x - G_f^x\right)^2 + \left(S_j^y - G_f^y\right)^2 + \left(S_j^z - G_f^z\right)^2}$

6: end for

7: end for

8: $min\theta_{En} \leftarrow \min S_i^E$

$max\theta_{En} \leftarrow \max S_i^E$

$min\theta_{Tr} \leftarrow \min S_i^T$

$max\theta_{Tr} \leftarrow \max S_i^T$

$min\theta_{Dist} \leftarrow \min D_{jf}$

$max\theta_{Dist} \leftarrow \max D_{jf}$

Normalise $S_i^E$

Normalise $S_i^T$

Normalise $D_i^K$

for $i \leftarrow 1$ to $\alpha$ do

 for $j \leftarrow 1$ to $\beta$ do

  $\boldsymbol{\zeta} \leftarrow \zeta_{\alpha,\beta}$

  $IPS^{+} \leftarrow \max\{\zeta_{(\alpha,\mu)}\},\ \forall\ \mu \in \beta$

  $INS^{-} \leftarrow \max\{\zeta_{(\alpha,\mu)}\},\ \forall\ \mu \in \beta$

  $\zeta_p^{+} = \sqrt{\sum_{\mu=1}^{\beta}(\zeta_{(p,\mu)} - IPS^{+})^2}\ where\ p = 1,2,3 \ldots \alpha$

  $\zeta_p^{-} = \sqrt{\sum_{\mu=1}^{\beta}(\zeta_{(p,\mu)} - INS^{-})^2}\ where\ p = 1,2,3 \ldots \alpha$

  $\aleph_p = \frac{\zeta_p^{-}}{\zeta_p^{-} - \zeta_p^{+}}\ \ where\ \ p = 1,2,3 \ldots \alpha$

 end for

end for

return $\aleph_p$

---

The alternative DGC location with the highest rank $\aleph_p$ is selected as the optimal deployment site. If the top-ranked location is unsuitable due to environmental constraints, the location with the next highest rank is chosen as an alternative. This TOPSIS-based approach provides a computationally efficient method for multi-criteria DGC placement in complex, heterogeneous WSN environments.

## 3.6 Performance Analysis

In this section, the performance of the proposed sink node deployment techniques (iterative and TOPSIS-based) is evaluated and compared against traditional and state-of-the-art methods using MATLAB simulations. The evaluation is structured to demonstrate improvements in various QoS parameters, including network lifetime, energy consumption, and adaptability across different network shapes and communication models.

The following QoS parameters are used as evaluation metrics:

i. Network Lifetime
ii. Energy Consumption
iii. Balanced Network Operation
iv. Scalability
v. Adaptability

The simulations are performed over randomly distributed heterogeneous nodes in both 2D and 3D environments. This setup creates irregular topologies and clusters with varied node densities, representing real-world deployment in WSN-based IoT applications. Table 3.1 provides a summary of the key simulation parameters used throughout the experiments.

*Table 3.2: Simulation Parameters*

| Parameter | Value |
|---|---|
| Number of nodes | $100$ |
| Initial energy of nodes | $0.5\ to\ 2\ J$ |
| Packet size ($k$) | $1000 - 4000\ bits$ |
| Electronic circuitry energy ($E_{elec}$) | $50\ nJ/bit$ |
| Amplifier energy for free space ($\varepsilon_{fs}$) | $10\ pJ/bit/m^2$ |
| Amplifier energy for multipath ($\varepsilon_{mp}$) | $0.0013\ pJ/bit/m^4$ |
| Energy for data aggregation ($E_{da}$) | $5\ nJ/bit$ |

The simulation parameters listed in Table 3.1 are primarily based on the standard values defined by the first-order radio model. These parameters are consistently applied for experimental evaluations throughout the thesis beyond this chapter.

### *3.6.1 Energy-Efficient Deployment of DGC*

To evaluate the energy efficiency of the proposed DGC deployment techniques, experiments are conducted across four network shapes (3D cube, 3D sphere, 2D square, and 2D circle) and two communication models: direct and multi-hop communication using k-means clustering. In the below sub-sections, the results of these experiments are explained in detail.

#### *i. Direct Communication*

The total energy consumed per round was calculated for each deployment approach, including the DGC placed at the centre, at the mean coordinates, and as determined by the proposed iterative and TOPSIS-based methods.

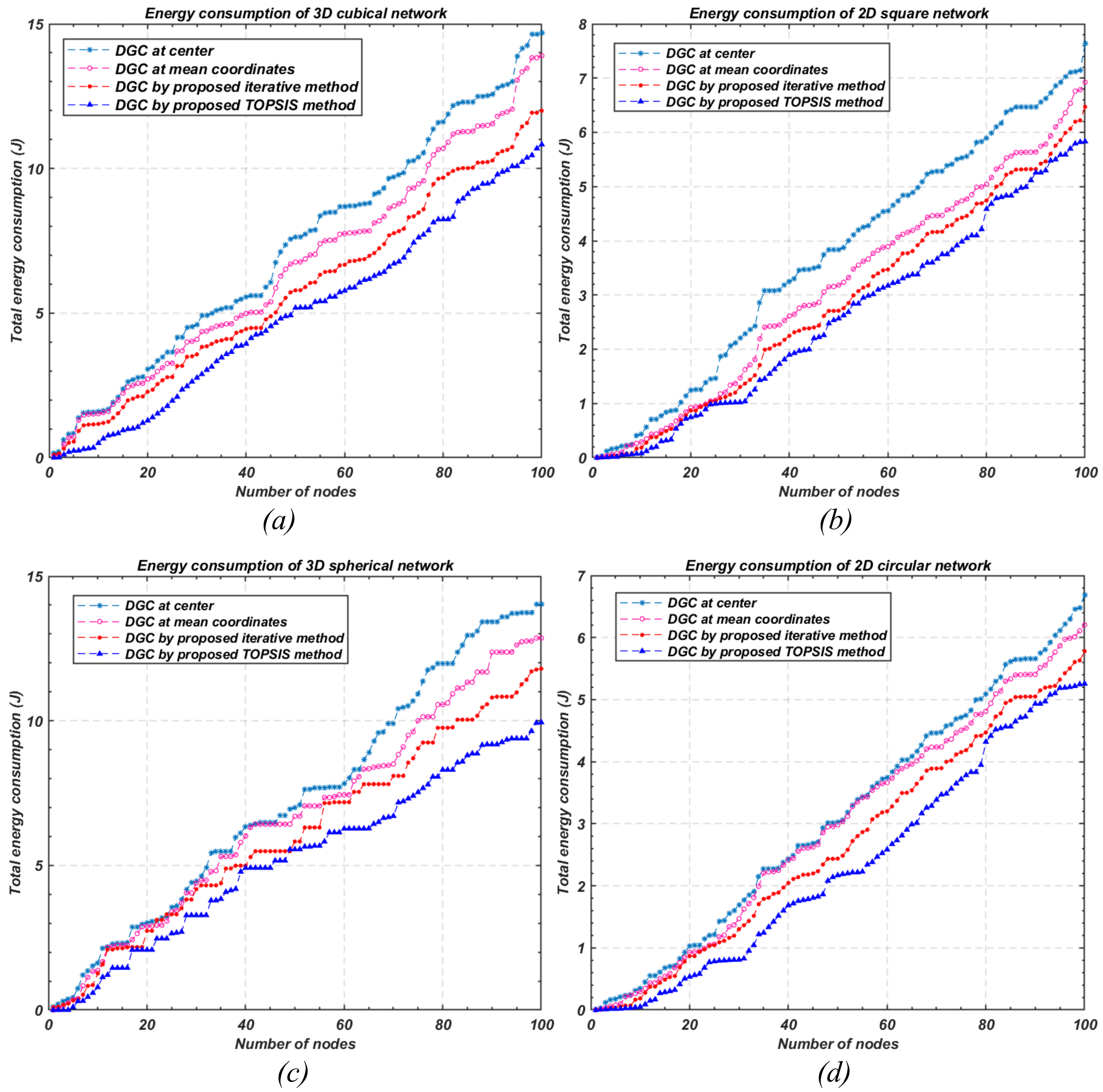



*Figure 3.4: Per round energy consumption of network (flat network); (a) 3D cubical network, (b) 2D square network, (c) 3D spherical network, (d) 2D circular network*

Figure 3.4 illustrates the energy consumption per round in a flat network across different shapes. The TOPSIS-based deployment consistently shows the lowest energy consumption, demonstrating the effectiveness of multi-criteria optimisation. Therefore, TOPSIS-based method achieves significant energy savings, with up to a 29.1% reduction in energy consumption compared to central DGC placement. This performance is particularly pronounced in the 3D sphere and 2D circle configurations.

Table 3.2 presents a summary of the total energy consumption for each approach in a flat network. The iterative method yields up to a 24.12% reduction in energy consumption, while the TOPSIS-based method achieves the most significant reduction of up to 29.1% as mentioned above.

*Table 3.3: Summary of Energy Consumption (J) Per Round (Flat Network)*

| Network shape | DGC at centre | DGC at mean coordinates | Proposed iterative method | Proposed TOPSIS method |
|---|---|---|---|---|
| **3D Cube** | 14.7 | 13.90 | 12.00 | 10.83 |
| **2D Square** | 7.64 | 6.92 | 6.47 | 5.83 |
| **3D Sphere** | 14.02 | 12.86 | 11.80 | 9.94 |
| **2D Circle** | 6.68 | 6.20 | 5.78 | 5.26 |

These results validate that the proposed methods adapt better to network shapes than traditional placements. In particular, the TOPSIS-based method's ability to weigh multiple parameters (e.g., energy, distance) results in more balanced and energy-efficient operation.

### *ii. Multi-Hop Communication with Clustering*

Energy consumption per round was also calculated for a clustered network using k-means clustering. Figure 3.5 and Table 3.3 show the energy consumption results. Both the iterative and TOPSIS-based methods achieve notable energy savings compared to traditional placements, with similar results in the clustered network.

While making specific comparisons with the central deployment of the DGC, the proposed iterative method achieves significant energy savings, reducing total energy consumption by up to 24.1%. Furthermore, the proposed TOPSIS-based deployment consistently outperforms all other deployment methods, achieving a reduction in energy consumption of up to 27.6%.

Similarly, the decrease in energy consumption compared to deploying DGC at mean location, as shown in the results of Table 3.3, is most pronounced with the proposed iterative method when tested in 2D square-shaped network, achieving a reduction of 13%. In contrast, the proposed TOPSIS-based deployment demonstrates its best performance in the square-shaped network, reducing energy consumption by up to 17%.

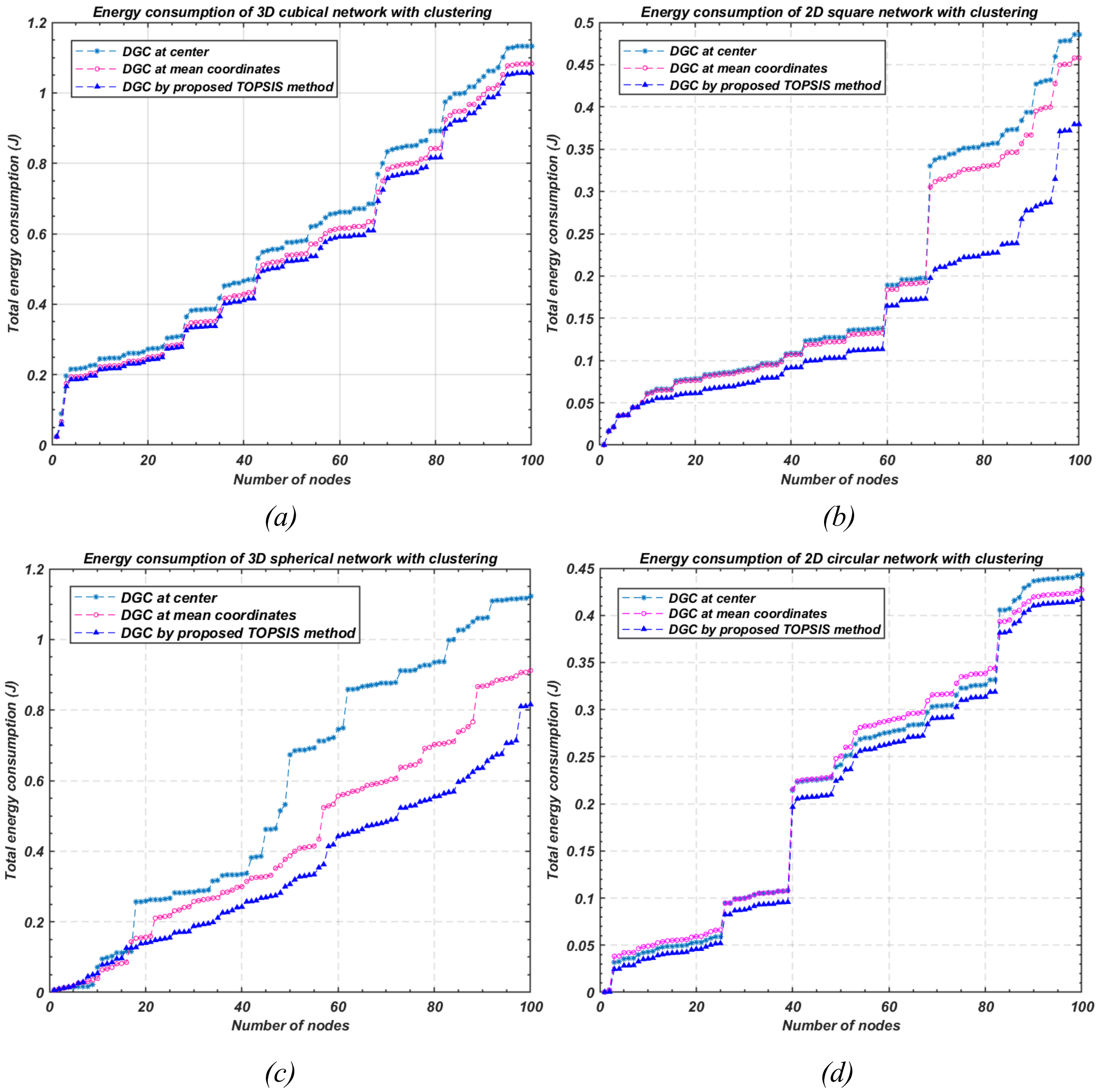



*Figure 3.5: Total energy consumption of network per round (Clustered network); (a) 3D cubical network, (b) 2D square network, (c) 3D spherical network, (d) 2D circular network*

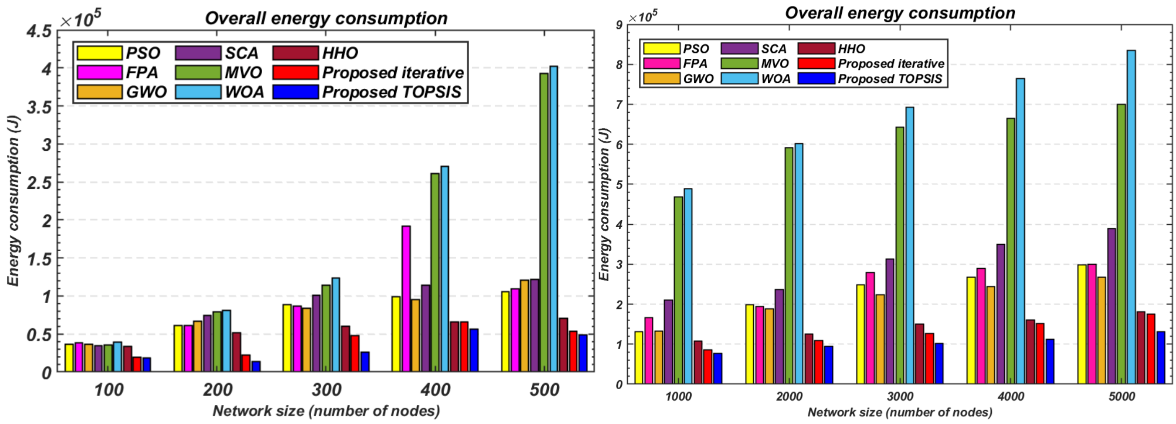
Table 3.3 concludes that the clustered network model benefits significantly from the proposed methods, with the TOPSIS method slightly outperforming the iterative approach, confirming its adaptability and effectiveness in multi-hop scenarios.

*Table 3.3: Summary of Total Energy Consumption (J) in Each Round (Clustered Network)*

| Network shape | DGC at centre | DGC at mean coordinates | Proposed iterative method | Proposed TOPSIS method |
|---|---|---|---|---|
| **3D Cube** | 1.13 | 1.08 | 1.05 | 1.05 |
| **2D Square** | 0.48 | 0.45 | 0.39 | 0.37 |
| **3D Sphere** | 1.12 | 0.91 | 0.85 | 0.81 |
| **2D Circle** | 0.44 | 0.43 | 0.41 | 0.41 |

### *3.6.2 Scalability and Network Lifetime*

To validate the scalability of the proposed methods, simulations were performed across a wide range of network sizes, from 100 nodes to 5000 nodes, reflecting real-world large-scale deployment conditions. To validate the proposed methods, their energy consumption was compared against seven cutting-edge algorithms (PSO [169], FPA [170], GWO [171], SCA [172], MVO [173], WOA [174], and HHO [8]) across different network sizes.




*(a)* *(b)*

*Figure 3.6: Comparison of overall energy consumptionacross different sink node deployment algorithms; (a) Small to medium scale networks (100 nodes to 500 nodes), (b) Large scale networks (1000 nodes to 5000 nodes)*

Figure 3.6 presents the energy consumption across network sizes ranging from 100 to 5000 nodes. Both the iterative and TOPSIS-based methods consistently exhibit lower energy consumption compared to all other algorithms, with the TOPSIS-based method achieving the most significant reductions. Notably, the energy efficiency of the TOPSIS-based method remains highly robust as network size increases, underscoring its scalability and effectiveness.

*Table 3.4: Comparison of the Total Energy Consumption in Advanced Sink Node Placement Methods*

| Nodes | PSO [169] | FPA [170] | GWO [171] | SCA [172] | MVO [173] | WOA [174] | HHO [8] | Proposed iterative method | Proposed TOPSIS method |
|---|---|---|---|---|---|---|---|---|---|
| **100** | 36911 | 38537 | 36446 | 34920 | 35820 | 39222 | 34101 | 19465 | 18056 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **200** | 60637 | 60957 | 67000 | 73931 | 79044 | 80569 | 51805 | 22163 | 13360 |
| **300** | 88115 | 87028 | 83732 | 100829 | 113868 | 123869 | 60224 | 47913 | 26462 |
| **400** | 98697 | 191788 | 94931 | 114198 | 260659 | 270659 | 66005 | 65439 | 56661 |
| **500** | 105190 | 109630 | 120544 | 121820 | 392475 | 402475 | 70233 | 53150 | 49022 |
| **1000** | 131419 | 165651 | 133185 | 209715 | 468689 | 488989 | 107456 | 85443 | 77260 |
| **2000** | 198464 | 194892 | 188526 | 236876 | 591674 | 601674 | 124777 | 109121 | 95262 |
| **3000** | 247826 | 279863 | 223074 | 313128 | 643032 | 693089 | 150659 | 127200 | 101427 |
| **4000** | 267899 | 289874 | 244088 | 349696 | 665284 | 764098 | 160659 | 151362 | 112426 |
| **5000** | 298755 | 299995 | 267896 | 389654 | 699978 | 834058 | 180999 | 175727 | 131303 |

Table 3.4 provides a detailed breakdown of the energy consumption for each algorithm across various network sizes. The results clearly highlight the superiority of the TOPSIS-based method in achieving the best energy savings. Additionally, the detailed summary of experimental outcomes demonstrates that while the iterative method also outperforms other state-of-the-art algorithms significantly, the TOPSIS-based method consistently delivers the highest energy efficiency.

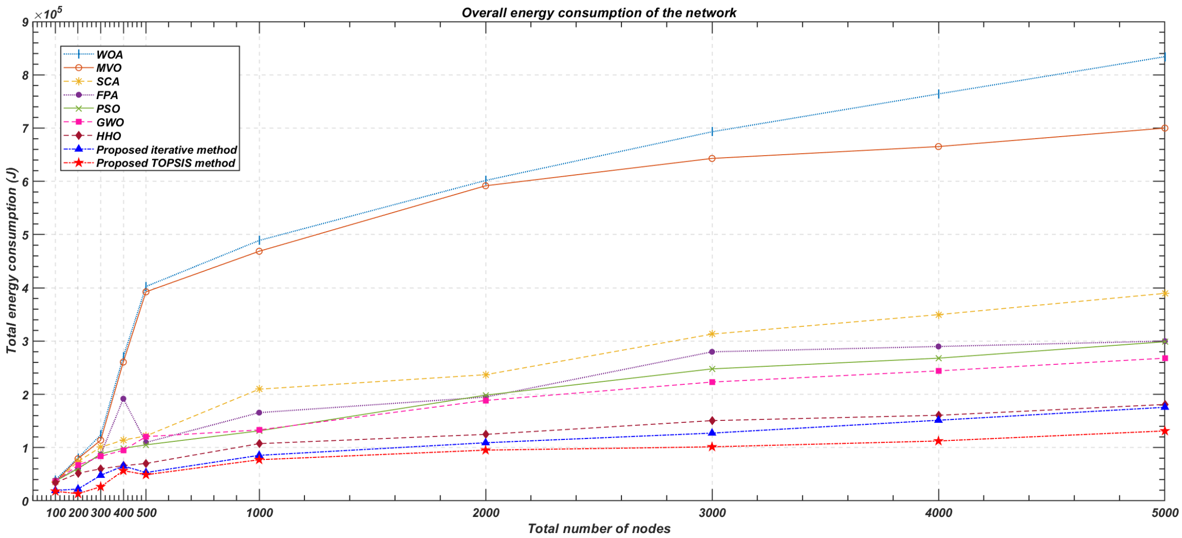



*Figure 3.7: Overall energy consumption of varying network sizes.*

Figures 3.6 and 3.7 provide a graphical representation of the energy consumption trends for all algorithms, reaffirming that the proposed iterative and TOPSIS-based methods consistently achieve lower energy consumption across various network sizes. The visual comparison further emphasises the consistent superiority of these methods, particularly in larger networks, where their efficiency becomes even more pronounced.

## 3.7 Summary

The results of experimental simulation indicate that the proposed methods achieve notable improvements in energy efficiency, adaptability, and scalability over traditional and state-of-the-art techniques. The TOPSIS-based method achieves the highest energy savings up to

29.1%, outperforming all other state-of-the-art methods. Both methods adapt well to larger network sizes, maintaining efficient energy usage. The proposed techniques perform reliably across various network shapes and communication models, validating their applicability in diverse WSN deployments. The proposed iterative and TOPSIS-based deployment techniques present significant advancements for energy-efficient sink node deployment, supporting more sustainable and long-lasting WSNs.

# Chapter 4

# Shape-Adaptive Network Segmentation and Unequal Clustering

## 4.1 Introduction

In this chapter, network segmentation is explored as a foundational aspect of adaptive clustering for heterogeneous devices operating in both two-dimensional and three-dimensional environments. Real-world deployments often feature networks of varying shapes influenced by environmental conditions, application requirements, and deployment constraints. To illustrate this diversity, Figure 4.1 presents a range of common network shapes evaluated using the proposed techniques, including 2D shapes such as circular, square and rectangular, and 3D shapes like spherical and cubical. This variety underscores the practical challenges and opportunities in adapting segmentation and clustering techniques to diverse real-world network structures.

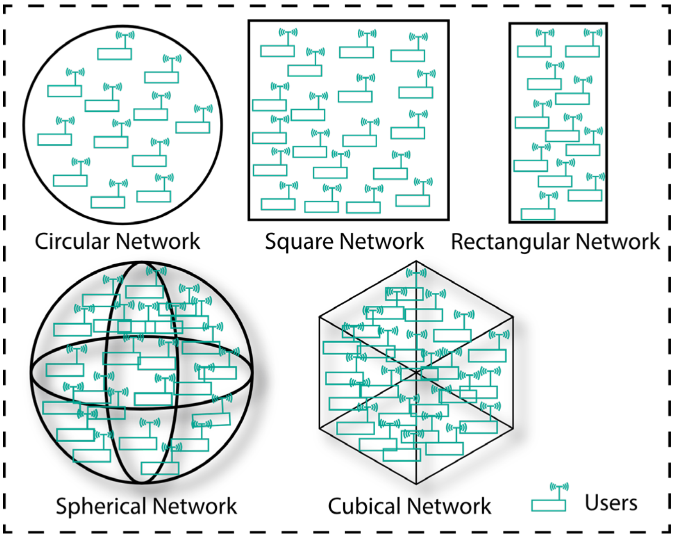



*Figure 4.1: Typical network shapes used in 2D and 3D environments.*

This chapter introduces segmentation and clustering techniques designed to optimise energy consumption and load distribution across diverse spatial configurations. The proposed strategies include fixed-shape segmentation schemes for specific network topologies and a shape-independent segmentation scheme for irregular or dynamic layouts.

For fixed-shape segmentation, circular/spherical networks are divided into concentric coronas and sectors, while square/cubical networks are divided into smaller squares or cubes. These methods facilitate localised cluster formation, enabling efficient data gathering and energy balancing. Recognising the limitations of shape-specific approaches, a shape-independent segmentation method is also proposed, segmenting the network based on data rate distribution rather than geometric constraints. This technique dynamically adjusts cluster head placement to balance energy consumption across nodes.

By incorporating multi-hop communication and optimising next-hop selection for inter-cluster data transmission, the proposed methods significantly enhance energy efficiency and prolong network lifetime. Simulation results confirm that the proposed shape-independent, data rate-based adaptive clustering method achieves up to 14.2% and 18.8% longer network lifetime as compared to Fuzzy Logic-based unequal clustering [142] and IUCR [65] methods, respectively. Additionally, the proposed shape-independent method reduces energy consumption by 61.4% compared to existing clustering techniques, demonstrating its effectiveness in large-scale, heterogeneous environments.

The structure of this chapter is as follows: Section 4.2 reviews existing balanced energy clustering schemes, and section 4.3 discusses the challenges and limitations in current balanced energy clustering approaches. Section 4.4 provides the problem formulation and system model. Section 4.5 details the proposed network segmentation schemes, including a proposed shape dependent and proposed shape independent segmentation schemes. Section 4.6 presents the performance evaluation of the proposed methods. Finally, Section 4.7 summarises the chapter.

## 4.2 Existing Hierarchical Clustering Techniques

In WSNs, efficient clustering and energy management are crucial for extending network lifetime and minimising energy consumption, especially in large-scale heterogeneous IoT applications. While hierarchical clustering effectively balances load and improves energy efficiency, it faces challenges in adapting to diverse network topologies and device heterogeneity. This section reviews notable clustering and energy-efficient routing techniques relevant to inform the development of adaptable and scalable solutions in heterogeneous WSNs.

LEACH protocol introduced a randomised rotation of CHs to spread energy consumption evenly across nodes [40]. While LEACH has been widely applied due to its simplicity, it assumes homogeneous node capabilities and is limited in scalability for large networks. LEACH-inspired approaches, such as IBRE-LEACH [70], address some of these limitations by incorporating node residual energy in CH selection, reducing the likelihood of premature node depletion. However, IBRE-LEACH and similar enhancements still perform inadequately in networks with high levels of heterogeneous parameters.

Fuzzy Logic-based clustering techniques, as explored in [142], use fuzzy parameters to select cluster heads based on node energy levels, distance to the BS, and other factors. This method provides adaptive clustering that can handle heterogeneity to some extent, improving energy balance and prolonging network lifetime. However, fuzzy-based clustering requires high computational power for continuous adjustments, which limits its scalability for large networks and makes it challenging to implement in resource-constrained WSNs.

Energy Efficient and Coverage Guaranteed Unequal-sized Clustering (ECUC) represent attempts to achieve balanced energy consumption in heterogeneous networks by varying cluster sizes and introducing adaptive CH selection based on location and energy levels [45]. However, the fixed clustering approach in ECUC is only suitable for circular networks.

Intra-cluster Unequal Clustering Routing (IUCR) [65] and Distributed Adaptive Particle Fuzzy Logic (DAPFL) [69] introduce adaptive clustering approaches that improve network stability in heterogeneous environments. IUCR applies unequal clustering to prevent energy holes by assigning smaller cluster sizes closer to the BS, effectively balancing energy distribution. DAPFL employs fuzzy logic to dynamically select CHs, enhancing adaptability to varying node characteristics. While both methods improve energy efficiency, they face scalability issues due to the computational complexity of CH selection and are less effective in handling diverse network shapes.

Hierarchical Hunter Optimisation Clustering with Fuzzy Rules (HHOCFR) [66] and Improved Harris Hawks Optimisation Fuzzy (IHHO-F) [68] represent recent advances in energy-efficient clustering for heterogeneous WSNs. HHOCFR uses fuzzy rules in a hierarchical clustering structure, optimising CH selection based on node attributes like energy and distance. IHHO-F extends the capabilities of HHO by integrating fuzzy logic for CH selection in multi-hop networks, enhancing load distribution and extending network lifetime. Despite their contributions, both HHOCFR and IHHO-F are computationally intensive, which limits their scalability for larger, dynamic networks with diverse topologies. The next section summarises the major challenges in existing clustering techniques.

## 4.3 Challenges and Limitations

Most existing clustering methods are constrained by assumptions of fixed network shapes, limited scalability, and uniform node characteristics, which reduce their effectiveness in real-world, dynamic 3D deployments. Following are the major concerns:

- Protocols for example LEACH [40] assume homogeneous nodes, which restricts their application in heterogeneous networks where nodes have varying energy levels, data rates, and roles, leading to inefficient energy management.
- Many methods, such as ECUC [45], rely on fixed network shapes such circular or square shaped networks for clustering. This limits their adaptability in three-dimensional or irregular layouts common in practical applications like urban and environmental IoT systems.
- Techniques for instance Fuzzy Logic-based clustering [142] and IBRE-LEACH [70] improve energy efficiency but lack scalability due to high computational requirements, making them challenging to implement in large, evolving networks.
- Advanced methods, including HHOCFR [66] and IHHO-F [68], enhance energy balancing but require significant computational resources, which limits their use in resource-constrained WSN nodes and increases operational costs.
- Many clustering methods do not sufficiently balance energy use among nodes, especially for cluster heads near the base station, leading to energy holes and reduced network lifetime.

These limitations underscore the need for adaptable, shape-independent clustering methods that can efficiently handle the diverse characteristics of large, heterogeneous WSNs. The following sections introduce novel techniques designed to address these challenges, improving energy efficiency, scalability, and network longevity in complex IoT deployments.

## 4.4 Problem Definition and System Model

This section defines the problem of segmentation and adaptive unequal clustering in HWSNs and outlines the system model that supports shape-independent, energy-efficient network operation.

### *4.4.1 Problem Definition*

In HWSNs, devices differ in energy levels, data rates, and transmission capabilities, leading to challenges in achieving energy-balanced clustering and preventing early energy depletion near the DGC. This is particularly important in large-scale and complex 3D deployments, where energy-efficient data collection is subjected to the network irregularities and topology variations. The goal is to propose adaptive segmentation and clustering methods that dynamically adjust to network shape and device heterogeneity, ensuring that CHs are optimally located to minimise energy consumption and maintain network stability.

Formally, let $\mathcal{N} = \{S_i | i = 1,2, \ldots, N\}$ represents a set of sensor nodes deployed in a two/three-dimensional region with coordinates $(x_i, y_i, z_i)$ (where $z_i = 0$ for 2D). Each sensor node $S_i$ has the following attributes:

- Initial energy $E_i$
- Data rate $T_i$
- Communication range $R_i$

The objective is to partition $\mathcal{N}$ into a set of clusters such that the overall energy consumption is minimised by dynamically adjusting cluster sizes on device proximity and residual energy as well as distance from the next hop.

The clustering scheme is expected to maximise network lifetime $'\mathcal{L}'$ by finding an optimal cluster configuration that meets the following objective function:

$$\mathcal{L} = \max \sum_{i=1}^{N} \frac{E_i}{T_i + E_{trans(d_{i,CH})}} \tag{4.1}$$

where $d_{i,CH}$ is the distance from node $'i'$ to its assigned cluster head $'CH'$, and $E_{trans}$ is the transmission energy.

### *4.4.2 System Model*

The system model and energy computation method utilised is consistent to chapter 3 as explained by eq. (3.2) in chapter 3.

## 4.5 Proposed Network Segmentations

This section introduces three segmentation techniques in HWSNs to achieve energy-efficient and adaptable clustering. By dividing the network into smaller, manageable segments, these methods facilitate efficient data routing and enable the adaptive selection of CHs in accordance with local device resources and network topology.

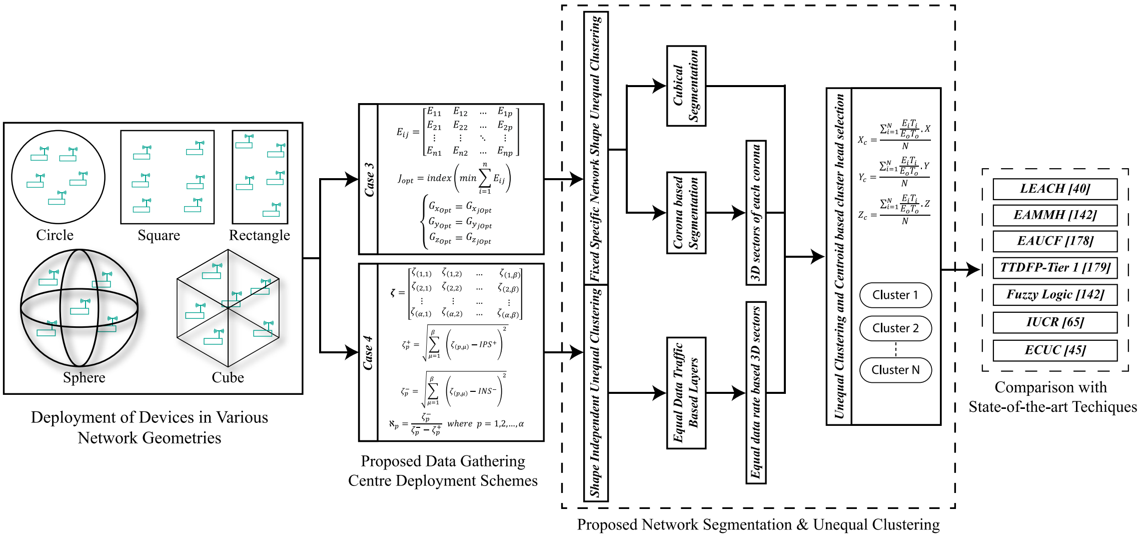



*Figure 4.2: Flow diagram of the proposed segmentation and unequal clustering methods.*

Figure 4.2 builds upon the deployment schemes introduced in chapter 3 (Figure 3.3), illustrating how proposed segmentation and unequal clustering schemes can be incorporated to enhance the network longevity and energy efficiency. The Figure 4.2 also highlights prominent clustering schemes used as benchmarks for performance comparison with the proposed methods.

The step-by-step logic for each proposed segmentation scheme is presented in Algorithm 4.1 (Cube-Based), Algorithm 4.2 (Spherical-Based), and Algorithm 4.3 (Shape-Independent).

### *4.5.1 Cube Shaped Network Segmentation*

In the cubical segmentation approach, the entire network is divided into $'N'$ non-overlapping, uniform virtual sub-cubes, each with dimensions $(a \times a \times a)$. This segmentation is effective in environments where the network structure resembles a cube/square or rectangular shape. For a network length $'l'$, the number of divisions along each dimension is calculated as $a = \frac{l}{q}$. Let $'Q'$ represent the set of all the virtual sub-cubes within the network, defined as:

$$\boldsymbol{Q} = \{Q_{hjk} \mid h, j, k = 1,2, \dots, q\} \tag{4.2}$$

Therefore, for a given virtual sub-cube $Q_{hjk}$, the boundary coordinates $(a_{h-1} \times a_{j-1} \times a_{k-1})$ and $(a_h \times a_j \times a_k)$ of the virtual sub-cube can be computed as:

$$a_{h-1} = \frac{h-1}{q} \times l \quad and \qquad a_h = \frac{h}{q} \times l$$

$$a_{j-1} = \frac{j-1}{q} \times l \quad and \qquad a_j = \frac{j}{q} \times l \tag{4.3}$$

$$c_{k-1} = \frac{k-1}{q} \times l \quad and \qquad c_k = \frac{k}{q} \times l$$

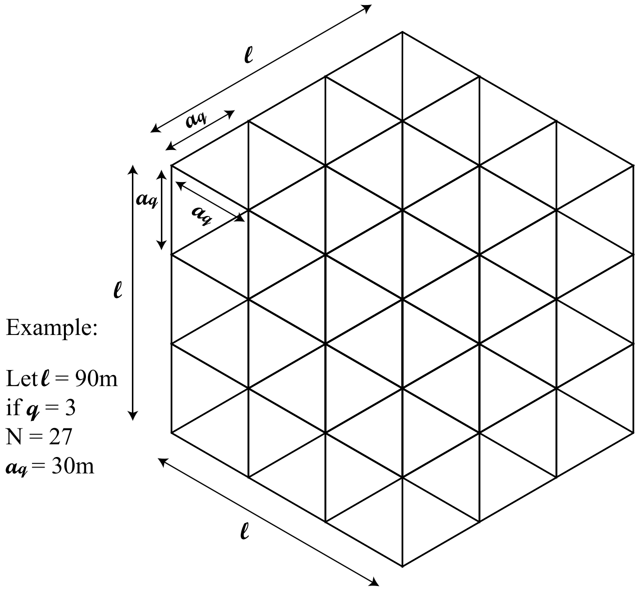



*Figure 4.3: 3D cubical network segmented into sub-cubes.*

Thus, $'\boldsymbol{Q}'$ represents a 3D matrix of dimensions $(h \times j \times k)$. For a sensing node $'S_{(m)}'$ where $'m'$ is a real number and $1 \leq m \leq n$.

$$\{\boldsymbol{S}_m \in Q_{hjk} \;\; \big| \; a_{h-1} \leq S_{hx} \leq a_h \; and \; a_{j-1} \leq S_{jy} \leq a_j \; and \; a_{k-1} \leq S_{kz} \leq a_k\} \tag{4.4}$$

Let $\boldsymbol{N}_{hjk}$ be 3D matrix that contains information about the number of nodes in each virtual sub-cube, such that:

$$N_{hj1} = \begin{bmatrix} N_{111} & \cdots & N_{1j1} \\ \vdots & \ddots & \vdots \\ N_{h11} & \cdots & N_{ij1} \end{bmatrix} \qquad for \; h, j = 1,2, \dots, q$$

$$N_{hj2} = \begin{bmatrix} N_{112} & \cdots & N_{1j2} \\ \vdots & \ddots & \vdots \\ N_{h12} & \cdots & N_{hj2} \end{bmatrix} \qquad for \; h, j = 1,2, \dots, q$$

.

.

.

$k = 1,2, \dots, q$

$$N_{hjk} = \begin{bmatrix} N_{11k} & \cdots & N_{1jk} \\ \vdots & \ddots & \vdots \\ N_{h1k} & \cdots & N_{1jk} \end{bmatrix} \qquad for \; h, j = 1,2, \dots, q$$

Segmentation offers the benefit of acquiring local information from various regions of the network, including density, data traffic, and energy levels. Let $'\boldsymbol{T}'$ be a 3D array that holds data rate information for each virtual sub-cube in the network, such that:

$$T_{hj1} = \begin{bmatrix} T_{111} & \cdots & T_{1j1} \\ \vdots & \ddots & \vdots \\ T_{h11} & \cdots & T_{hj1} \end{bmatrix} \quad for\ h, j = 1,2, \dots, q$$

$$T_{hj2} = \begin{bmatrix} T_{112} & \cdots & T_{1j2} \\ \vdots & \ddots & \vdots \\ T_{h12} & \cdots & T_{hj2} \end{bmatrix} \quad for\ h, j = 1,2, \dots, q$$

.

.

.

$$k = 1,2, \dots, q$$

$$T_{hjk} = \begin{bmatrix} T_{11k} & \cdots & T_{1jk} \\ \vdots & \ddots & \vdots \\ T_{h1k} & \cdots & T_{1jk} \end{bmatrix} \quad for\ h, j = 1,2, \dots, q$$

Similarly, $'E'$ is a $(h \times j \times k)$ array that contains information about the residual energies of devices within the corresponding virtual sub-cube.

Once the virtual sub-cubes-based segmentation is configured and information about the nodes in each virtual sub-cubes is gathered, a centroid is calculated for each sub-cube based on the distribution function. The selection of the cluster head is made based on the distance from the centroid. The number of cluster heads is determined by the distance of a virtual sub-cube from the base station, using geometric progression as follows: $NCH_1 = 1$; $NCH_2 = 2(NCH_1)$; $NCH_3 = 4(NCH_1)$ and $NCH_{\mathrm{N}} = 2^{\mathrm{N}-1}(NCH_1)$. Here, $NCH$ represents the number of CHs in each sub-cube, and N denotes the level of the virtual sub-cube based on its distance from the innermost sub-cube. The centroid of the distribution, based on the parameters of the devices in a sub-cube, is calculated using:

$$X_c = \frac{\sum_{i=1}^{N} \left(\frac{E_i T_i}{E_o T_o}\right) \cdot X_i}{N}; Y_c = \frac{\sum_{i=1}^{N} \left(\frac{E_i T_i}{E_o T_o}\right) \cdot Y_i}{N}; Z_c = \frac{\sum_{i=1}^{N} \left(\frac{E_i T_i}{E_o T_o}\right) \cdot Z_i}{N} \tag{4.5}$$

The number of CHs in each sub-cube is determined by a geometric progression based on the distance from the DGC, with $'NCH_{\mathrm{N}}'$ for the closest sub-cube and doubling for each subsequent level. This helps balance energy usage and supports hierarchical data transmission in large networks.

***Proposed Algorithm 4.1:***

The proposed algorithm for segmenting a cube-shaped network is presented below, illustrating the logical flow of this segmentation and corresponding unequal clustering method.

---

**Algorithm 4.1:** Cubical network segmentation scheme and cluster head selection based on centroid of distribution of devices in each parameter.

---

**Require:**

The number of devices $'n'$ deployed within the 3D network, their coordinates $(x_i, y_i, z_i)$ ; $i = 1,2,3, \dots, n$ of each sensor node, their heterogeneous energies denoted as $S_i^E$, their heterogeneous data traffic denoted as $S_i^T$. Total number of sub-cubes $'N'$ and length $'l'$ of each side of 3D network.

**Ensure:**

$S_{(.)}^{ch-subcube} \leftarrow devices\ with\ \min\left\{D_{C_{hjk}}^{i}\right\}$ & $\max\{E_{hjk}\}$

$l \leftarrow$ $length\ of\ each\ side\ of\ the\ network$

$N \leftarrow Total\ number\ of\ subcubes$

$q \leftarrow \sqrt[3]{N}$

for $i \leftarrow 1$ to $n$ do

    $S_i^E \leftarrow E_o(1 + ב)$

    $S_i^T \leftarrow T_o(1 + \tau)$

    for $h \leftarrow 1$ to $q$

        for $j \leftarrow 1$ to $q$

            for $k \leftarrow 1$ to $q$

                $a_{h-1} \leftarrow \frac{h-1}{q} * l$

                $a_h \leftarrow \frac{h}{q} * l$

$a_{j-1} \leftarrow \frac{j-1}{q} * l$

$a_j \leftarrow \frac{j}{q} * l$

$c_{k-1} \leftarrow \frac{k-1}{q} * l$

$c_k \leftarrow \frac{k}{q} * l$

if $(a_{h-1} \leq S_i^x \leq a_h)$

if $(a_{j-1} \leq S_i^y \leq a_j)$

if $\left(a_{k-1} \leq S_i^y \leq a_k\right)$

$N_{hjk} \leftarrow N_{hjk} + 1$

$T_{hjk} \leftarrow T_{hjk} + T_i$

$E_{hjk} \leftarrow E_{hjk} + E_i$

$X_{C_{hjk}} \leftarrow \frac{\sum_{i=1}^{N_{hjk}} \frac{E_i T_i}{E_O T_O} . X_i}{N_{hjk}}$

$Y_{C_{hjk}} \leftarrow \frac{\sum_{i=1}^{N_{hjk}} \frac{E_i T_i}{E_O T_O} . Y_i}{N_{hjk}}$

$Z_{C_{hjk}} \leftarrow \frac{\sum_{i=1}^{N_{hjk}} \frac{E_i T_i}{E_O T_O} . Z_i}{N_{hjk}}$

$D_{C_{hjk}}^i \leftarrow Distance\ of\ node\ in\ each\ cube\ to\ the\ centroid$

end if

end if

end if

end for

end for

end for

end for
for $h \leftarrow 1$ to $q$
    for $j \leftarrow 1$ to $q$
        for $k \leftarrow 1$ to $q$
            $D_{C_{min}} \leftarrow \min\left\{D^{i}_{C_{hjk}}\right\}$
            $E_{max} \leftarrow \max\{E_{hjk}\}$
            for $i \leftarrow 1$ to $n$
                if $\left(D_{C_{min}} \leftarrow D^{i}_{C_{hjk}} \ \&\& \ E_{max} \leftarrow E_i\right)$
                    $S_i^{type} \leftarrow CH$
                end if
            end for
        end for
    end for
end for
Return $S_{(.)}^{type}$

---

The proposed algorithm assesses the resources in various regions of a cube-shaped network and computes the centroid of distribution for each sub-cube. Devices with minimum distance to the centroid and maximum residual energy are selected as the CHs for their respective sub-cubes. The number of cluster heads in each sub-cube is determined based on the distance from the DGC. This approach ensures energy efficiency and promotes balanced network performance.

### *4.5.2 Spherical Shaped Network Segmentation*

For a spherical-shaped network, the network is segmented into $'q'$ non-overlapping concentric spherical coronas of equal volume, as depicted in Figure 4.4. The radius of each sphere from the origin can be computed as:

$$r_q = \sqrt[3]{\frac{3q}{4\pi}} \tag{4.6}$$

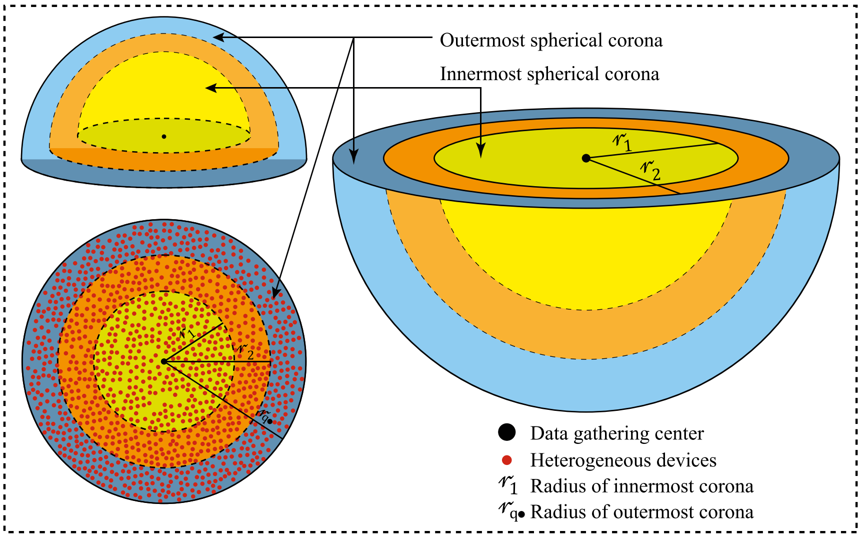



*Figure 4.4: 3D spherical network segmented into concentric coronas.*

The extend of each corona segment can be calculated as:

$$\mathcal{R}_q = r_q - r_{q-1} \tag{4.7}$$

The volume of each corona segment can be determined as:

$$V_q = \frac{4}{3}\pi\left[r_q^3 - r_{q-1}^3\right] \tag{4.8}$$

$'\mathcal{R}_1'$ represents the radius of the innermost spherical corona, as calculated using equation (4.7), where $\mathcal{R}_1 \leq Trans_{min}$ , and $Trans_{min}$ is the minimum transmission range. Let $r_m$ be the radius of $m^{th}$ corona. The condition for equal volume across each concentric corona implies that:

$$\frac{4}{3}\pi(r_m)^3 - \frac{4}{3}\pi(r_{m-1})^3 = \frac{4}{3}\pi(r_{m-1})^3$$

Thus $r_m$ can be calculated as:

$$(r_m)^3 = (r_{m-1})^3 + (r_{m-1})^3$$

$$r_m = \sqrt[3]{2} * r_{m-1} \tag{4.9}$$

Therefore, based on the maximum radius $r_{max}$ , which defines the boundary of the spherical network, the DGC calculates the volumes and boundaries of each spherical corona using equation (4.9) until it reaches $Trans_{min}$, the radius of first spherical corona.

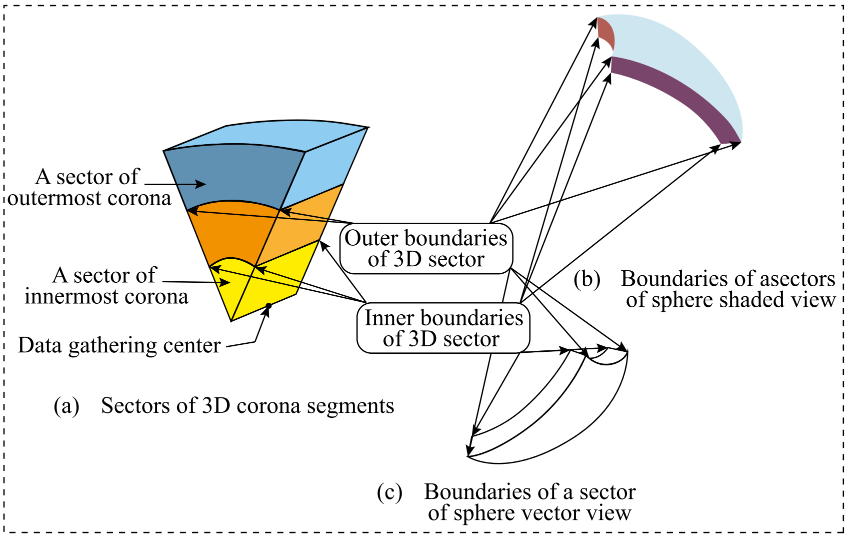



*Figure 4.5: Sectors of 3D coronas and their boundaries.*

The next step is dividing each corona segment into 3D sectors, as shown in Figure 4.5, and creating unequal clusters within each segment. The formation of sectors begins at the centre of the spherical network, and corners of each sector can be calculated using eq. (4.10).

Let $(G_x, G_y, G_z)$ be the centre of the sphere.

$$\begin{aligned} x_{\mathfrak{fgh}} &= r_{\mathfrak{f}} \cos(\varphi_{\mathfrak{g}}) \cos(\vartheta_{\mathfrak{h}}) \\ y_{\mathfrak{fgh}} &= r_{\mathfrak{f}}\, cos(\varphi_{\mathfrak{g}}) \sin(\vartheta_{\mathfrak{h}}) \\ z_{\mathfrak{fgh}} &= r_{\mathfrak{f}} \sin(\varphi_{\mathfrak{g}}) \end{aligned} \tag{4.10}$$

where $r_{\mathfrak{f}}$, $\varphi_{\mathfrak{g}}$ and $\varphi_{\mathfrak{h}}$ can be determined as:

$$\begin{aligned} r_{\mathfrak{f}} &= r_1, r_2, \dots, r_{max} \\ \varphi_{\mathfrak{g}} &= \left\{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi, \frac{5\pi}{4}, \frac{3\pi}{2}, \frac{7\pi}{4}, 2\pi\right\} \\ \varphi_{\mathfrak{h}} &= \left\{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi, \frac{5\pi}{4}, \frac{3\pi}{2}, \frac{7\pi}{4}, 2\pi\right\} \end{aligned} \tag{4.11}$$

Finally, the distribution centroid in each sector is calculated using eq. (4.5) and the device closest to the centroid with the highest energy is chosen as the cluster head.

***Proposed Algorithm 4.2:***

Proposed algorithm 4.2, explicitly applies unequal clustering in conjunction with spherical segmentation for a sphere-shaped network.

---

**Algorithm 4.2:** Spherical corona-based segmentation and 3D sectoring for unequal clustering and centroid based choice of cluster heads in sphere-shaped network.

---

**Require:**

The number of devices '$n$' deployed within the 3D spherical network, their coordinates $(x_i, y_i, z_i)$ ; $i = 1,2,3, \dots, n$ of each sensor node, their heterogeneous energies denoted as $S_i^E$, their heterogeneous data traffic denoted as $S_i^T$. Radius $r_{max}$ of spherical shape 3D network.

**Ensure:**

$S_{(.)}^{ch-sphere} \leftarrow devices\ with$ min $\left\{D^i_{c_{\mathfrak{fgh}}}\right\}$ and max $\{E_i\}$

$r_{max} \leftarrow$ maximum radius of network

$r_m \leftarrow$ Radius of $m^{th}$ spherical corona segment (It will start from $r_m \leftarrow r_{max}$)

if ($r_m < Trans_{min}$) do

  $r_m \leftarrow \sqrt[3]{2} * r_{m-1}$

  $m \leftarrow m + 1$

end if

for $i \leftarrow 1$ to $n$ do

  $S_i^E \leftarrow E_o(1 + ב)$

  $S_i^T \leftarrow T_o(1 + \tau)$

end for

$\vartheta_o \leftarrow 0$

$\varphi_o \leftarrow -\frac{\pi}{2}$

for $\mathfrak{f} \leftarrow 1$ to $m$

  for $\mathfrak{g} \leftarrow 1$ to 9

    for $\mathfrak{h} \leftarrow 1$ to 9

      $r_{\mathfrak{f}} \leftarrow r_m$

      $\varphi_{\mathfrak{g}} \leftarrow \varphi_{\mathfrak{g}} + \frac{\pi}{4}$

      $\vartheta_{\mathfrak{h}} \leftarrow \vartheta_{\mathfrak{h}} + \frac{\pi}{4}$

      $x_{\mathfrak{fgh}} \leftarrow r_{\mathfrak{f}} \cos(\varphi_{\mathfrak{g}}) \cos(\vartheta_{\mathfrak{h}})$

$y_{\mathfrak{fgh}} \leftarrow r_{\mathfrak{f}} \cos(\varphi_{\mathfrak{g}}) \sin(\vartheta_{\mathfrak{h}})$

$z_{\mathfrak{fgh}} \leftarrow r_{\mathfrak{f}} \sin(\varphi_{\mathfrak{g}})$

end for

end for

end for

for $i \leftarrow 1$ to $n$ do

for $\mathfrak{f} \leftarrow 1$ to $m$

for $\mathfrak{g} \leftarrow 1$ to 9

for $\mathfrak{h} \leftarrow 1$ to 9

if $(x_{\mathfrak{f}-1,\mathfrak{g}-1,\mathfrak{h}-1} \leq S_i^x \leq x_{\mathfrak{fgh}})$

if $(y_{\mathfrak{f}-1,\mathfrak{g}-1,\mathfrak{h}-1} \leq S_i^y \leq y_{\mathfrak{fgh}})$

if $(z_{\mathfrak{f}-1,\mathfrak{g}-1,\mathfrak{h}-1} \leq S_i^z \leq z_{\mathfrak{fgh}})$

$\mathfrak{N}_{\mathfrak{fgh}} \leftarrow \mathfrak{N}_{\mathfrak{fgh}} + 1$

$\mathfrak{T}_{\mathfrak{fgh}} \leftarrow \mathfrak{T}_{\mathfrak{fgh}} + 1$

$\mathfrak{E}_{\mathfrak{fgh}} \leftarrow \mathfrak{E}_{\mathfrak{fgh}} + 1$

$x_{c-\mathfrak{fgh}} \leftarrow \frac{\sum_{i=1}^{\mathfrak{N}_{\mathfrak{fgh}}} \frac{E_i T_i}{E_O T_O} . x}{\mathfrak{N}_{\mathfrak{fgh}}}$

$y_{c-\mathfrak{fgh}} \leftarrow \frac{\sum_{i=1}^{\mathfrak{N}_{\mathfrak{fgh}}} \frac{E_i T_i}{E_O T_O} . y}{\mathfrak{N}_{\mathfrak{fgh}}}$

$z_{c-\mathfrak{fgh}} \leftarrow \frac{\sum_{i=1}^{\mathfrak{N}_{\mathfrak{fgh}}} \frac{E_i T_i}{E_O T_O} . z}{\mathfrak{N}_{\mathfrak{fgh}}}$

$D_{c_{\mathfrak{fgh}}}^i \leftarrow Distance\ of\ nodes\ in\ each\ sector\ to\ centroid$

end if

end if

end if
end for
end for
end for
end for
for $i \leftarrow 1$ to $n$ do
for $\mathfrak{f} \leftarrow 1$ to $m$
for $\mathfrak{g} \leftarrow 1$ to 9
for $\mathfrak{h} \leftarrow 1$ to 9
$Distmin \leftarrow \min\left\{D^{i}_{\mathfrak{c}_{\mathfrak{fgh}}}\right\}$
$Ȩmax \leftarrow \max\left\{Ȩ_{\mathfrak{fgh}}\right\}$
if $\left(Distmin \leftarrow D^{i}_{\mathfrak{c}_{\mathfrak{fgh}}} \text{ \&\& } Ȩmax \leftarrow Ȩ_{i}\right)$
$S_{i}^{type} \leftarrow CH$
end if
end for
end for
end for
end for
Return $S_{(.)}^{type}$

---

The proposed segmentation method identifies the distribution of resources within each 3D sector of a spherical network and calculates the centroid of resource distribution in each sector. This centroid serves as a reference point for cluster formation within the sector. Devices located closest to the centroid and possessing the highest residual energy are selected as the cluster heads, ensuring efficient energy utilisation and effective communication.

Additionally, the number of cluster heads in each 3D sector is determined based on the distance of the sector from the DGC. This distance-based adjustment helps distribute the communication load more evenly across the network, enhancing overall energy efficiency and prolonging network lifetime.

### *4.5.3 Shape Independent Network Segmentation*

The proposed shape-specific unequal clustering techniques enhance network lifetime and balanced energy consumption but do not adapt well to networks with varying shapes. To overcome this limitation, a shape-independent unequal clustering algorithm is introduced. In this approach, the network is divided into layers based on equal transmission rates, rather than fixed geometric shapes.

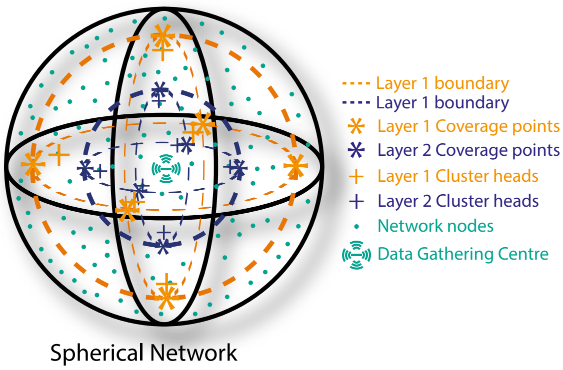



*Figure 4.6: Data rate-based segmentation with unequal cluster formation.*

Let $'D_i'$ represent the distance of the $i^{th}$ device from the base station located at $(G_x, G_y, G_z)$. Each device has heterogeneous initial energy levels and data traffic rates within a defined range. The DGC gathers information about the location, initial energy, and data rates of all devices. Based on this information, the devices are grouped into layers of equal data rates according to their distance from the DGC.

Figure 4.6 illustrates the layer boundaries for a 3-layer network structure. Starting with the outermost layer, the adaptive unequal clustering algorithm adds devices to the first layer, beginning with farthest device, until the total data traffic in the layer, $Ƭ_{L1}$, satisfies the condition $Ƭ_{L1} \geq \frac{\sum T}{4}$, where $\sum T$ is the total network traffic. The distance of last device from included in this layer defines the radial boundary of the layer 1. The algorithm continues to partition the network into concentric 3D layers, progressively grouping devices, until it reaches the innermost device located at $Trans_{min}$, the minimum transmission distance from the DGC.

Each layer is subsequently divided into eight sectors, ensuring an even distribution of data rates across them. Within each sector, a centroid of resource distribution is calculated, and devices with most available resources, that are closest to the centroid, are selected as CHs. The total number of CHs in each sector is determined based on corresponding layer number, ensuring energy consumption and efficient communication. The detailed operation of the shape-independent adaptive unequal clustering process is outlined in algorithm 4.3.

***Proposed Algorithm 4.3:***

The following is a detailed description of Algorithm 4.3, specifically developed for implementing shape-independent adaptive unequal clustering.

---

**Algorithm 4.3:** Adaptive unequal clustering for shape independent 3D network of heterogeneous devices.

---

**Require:**

The number of devices *n* deployed within any shape network, their coordinates $(x_i, y_i, z_i)$ ; $i = 1,2,3, \dots, n$ of each sensor node, their heterogeneous energies denoted as $S_i^E$, their heterogeneous data traffic denoted as $S_i^T$. The total number of layers of data traffic ɳ.

**Ensure:**

$S_{(.)}^{ch-dynamic} \leftarrow devices\ with\ \min\left\{D^i_{\text{ꞔꞘꞡꝧ}}\right\}$ & max {Ɇ$_i$}

1: for $i \leftarrow 1$ to $n$ do

2: $\quad S_i^E \leftarrow E_o(1 + \text{ב})$

3: $\quad\quad S_i^T \leftarrow T_o(1 + \tau)$

4: $\quad D_i \leftarrow \sqrt{(S_i^x - G_x)^2 + \left(S_i^y - G_y\right)^2 + (S_i^z - G_z)^2}$

5: end for

6: $I \leftarrow index(sort\{D\})$

7: Ƭ $\leftarrow T(I)$

8: $\text{Đ}_{L0} \leftarrow \max\{\text{D}\}$

9: for $i \leftarrow 1$ to $n$ do

if ($Ƭ_{L1} \leq \frac{\sum T}{4}$) do

    $Ƭ_{L1} \leftarrow Ƭ_{L1} + T(i)$

elseif ($\frac{\sum T}{4} \leq Ƭ_{L1} \leq \sum T$)

    if ($Ƭ_{L2} \leq \frac{\sum T}{4}$) do

        $Ƭ_{L2} \leftarrow Ƭ_{L2} + T(i)$

    elseif ($\frac{\sum T}{2} \leq Ƭ_{L2} \leq \frac{3\sum T}{4}$) do

        if ($Ƭ_{L3} \leq \frac{\sum T}{4}$) do

            $Ƭ_{L3} \leftarrow Ƭ_{L3} + T(i)$

        else do

        $Ƭ_{L4} \leftarrow Ƭ_{L4} + T(i)$

        end if

    end if

end if

end for

$\theta_o = 0$

$\phi_o = -\frac{\pi}{2}$

for $i \leftarrow 1$ to $n$ do

    for Ƒ ← 1 to 5

        for ɠ ← 1 to 9

            for ƕ ← 1 to 9

                $Γ́_{Ƒ-1} \leftarrow Đ_{L(Ƒ-1)}$

                $Γ́_{Ƒ} \leftarrow Đ_{LƑ}$

if ($Ƭ_{sec-ɠ} \leq \frac{\sum Ƭ_{Lɠ}}{8}$) do

$Ƭ_{sec-ɠ} = Ƭ_{sec-ɠ} + T(i)$

$ϕ_{ɠ} = ϕ_{ɠ} + +$

$\theta_{ƕ} = \theta_{ƕ} + +$

$ӽ_{Ƒɠƕ} = Γ'_{Ƒ} \cos(ϕ_{ɠ}) \cos(\theta_{ƕ})$

$ƴ_{Ƒɠƕ} = Γ'_{Ƒ} \cos(ϕ_{ɠ})\, sin(\theta_{ƕ})$

$ȥ_{Ƒɠƕ} = Γ'_{Ƒ} \sin(ϕ_{ɠ})$

end if

end for

end for

end for

end for

for $i$ ← 1 to $n$ do

for Ƒ ← 1 to 5

for ɠ ← 1 to 9

for ƕ ← 1 to 9

if ($ӽ_{Ƒ-1,ɠ-1,ƕ-1} \leq S_i^x \leq ӽ_{Ƒɠƕ}$)

if ($ƴ_{Ƒ-1,ɠ-1,ƕ-1} \leq S_i^y \leq ƴ_{Ƒɠƕ}$)

if ($ȥ_{Ƒ-1,ɠ-1,ƕ-1} \leq S_i^z \leq ȥ_{Ƒɠƕ}$)

$Ɲ_{Ƒɠƕ} \leftarrow Ɲ_{Ƒɠƕ} + 1$

$Ʈ_{Ƒɠƕ} \leftarrow Ʈ_{Ƒɠƕ} + T(i)$

$Ę_{Ƒɠƕ} \leftarrow Ę_{Ƒɠƕ} + E(i)$

$\text{ӽ}_{\text{ꞔ}_{\text{Ƒɠƕ}}} \leftarrow \frac{\sum_{i=1}^{\text{Ŋ}_{\text{Ƒɠƕ}}} \frac{E_i T_i}{E_O T_O} . \text{ӽ}}{\text{Ŋ}_{\text{ƒƑɠƕ}}}$

$\text{ƴ}_{\text{ꞔ}_{\text{Ƒɠƕ}}} \leftarrow \frac{\sum_{i=1}^{\text{Ŋ}_{\text{Ƒɠƕ}}} \frac{E_i T_i}{E_O T_O} . \text{ƴ}}{\text{Ŋ}_{\text{ƒƑɠƕ}}}$

$\text{z}_{\text{ꞔ}_{\text{Ƒɠƕ}}} \leftarrow \frac{\sum_{i=1}^{\text{Ŋ}_{\text{Ƒɠƕ}}} \frac{E_i T_i}{E_O T_O} . \text{z}}{\text{Ŋ}_{\text{ƒƑɠƕ}}}$

$D_{\text{ꞔ}_{\text{Ƒɠƕ}}}^{i} \leftarrow Distance\ of\ nodes\ in\ each\ sector\ to\ centroid$

end if

end if

end if

end for

end for

end for

end for

for $i \leftarrow 1$ to $n$ do

for Ƒ ← 1 to 5

for ɠ ← 1 to 9

for ƕ ← 1 to 9

$Distmin \leftarrow \min\left\{D_{\text{ꞔ}_{\text{Ƒɠƕ}}}^{i}\right\}$

$\text{Ę}max \leftarrow \max\left\{\text{Ę}_{\text{Ƒɠƕ}}\right\}$

if $\left(Distmin \leftarrow D_{\text{ꞔ}_{\text{Ƒɠƕ}}}^{i}\ \&\&\ \text{Ę}max \leftarrow \text{Ę}_{i}\right)$

$S_i^{type} \leftarrow CH$

end if

end for

75: end for

76: end for

77: end for

78: Return $S_{(.)}^{type}$

---

The next section presents the performance analysis of the proposed segmentation and unequal clustering techniques.

## 4.6 Performance Analysis

In this section, the performance of the proposed network segmentation and clustering methods is evaluated through MATLAB simulations. The analysis focuses on achieving energy efficiency, extending network lifetime, maintaining balanced energy operation, and ensuring adaptability across varying network shapes and device densities. Key metrics assessed include average residual energy, network lifetime across different densities and scales, scalability, adaptability, and overall energy consumption. Results confirm that the proposed methods provide significant improvements over existing clustering techniques.

### *4.6.1 Balanced Energy Operation of the Network*

The proposed unequal clustering technique is specifically designed to achieve the balance, ensuring that energy depletion is distributed more evenly among all nodes. Figure 4.7 illustrates the range of residual energies among network devices across multiple rounds. Initially, a significant disparity exists in energy levels due to variations in node locations and energy demands. However, as network rounds progress, these energy differences reduce, indicating a more balanced energy consumption pattern.

This outcome is attributed to the adaptive clustering approach, which dynamically adjusts cluster roles based on device energy and location, preventing nodes near the DGC from depleting prematurely due to high relaying loads. The simulation, conducted in a cubical network of $100 \times 100 \times 100\ m^3$, confirms that the proposed clustering technique mitigates energy imbalances effectively over time, extending network lifetime by minimising "energy holes" that could otherwise cause early network segmentation.

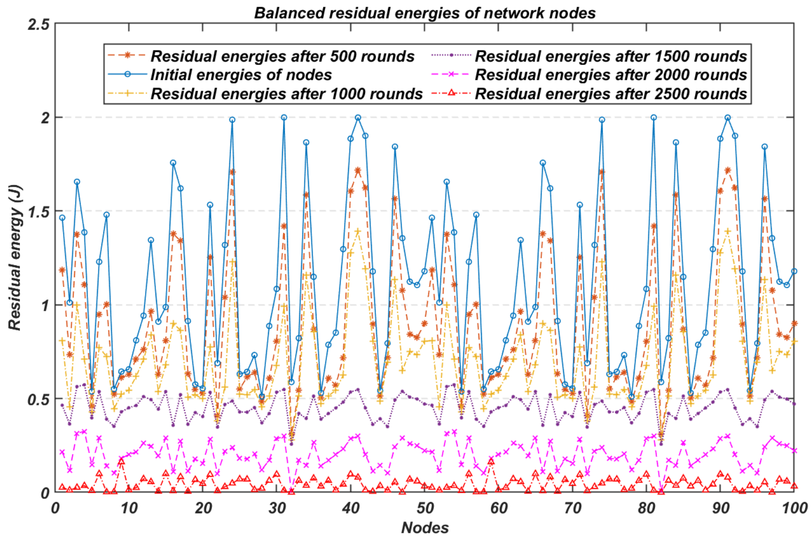



*Figure 4.7: Balanced residual energies of devices.*

For the spherical segmentation and unequal clustering strategy, Figure 4.8 further demonstrates balanced energy operation across node types, showing that energy consumption trends remain smooth and consistent for both normal nodes and cluster heads. The proposed algorithm achieves an even energy consumption profile, highlighting its ability to distribute energy demands across all nodes efficiently, regardless of their roles. This balance in energy usage not only prevents network segmentation but also ensures a longer and more stable network operation, supporting the overarching goal of extending network lifetime through balanced and energy-efficient clustering.

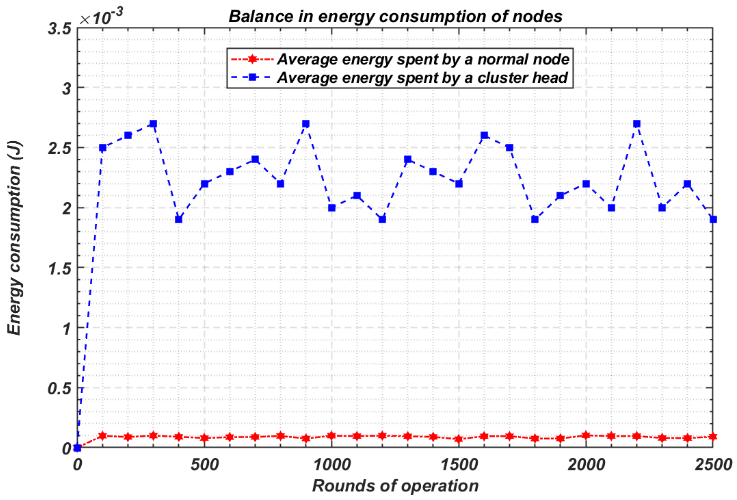



*Figure 4.8: Average energy consumption of the devices.*

### *4.6.2 Average Residual Energy*

This section assesses the performance of the proposed shape-independent adaptive clustering technique in terms of average residual energy across the network, aiming to evaluate its effectiveness in conserving energy over time compared to established clustering approaches.

For the experiment, 1000 devices were deployed in a 1000m × 1000m monitoring area, each initialised with 0.5J of energy (just to facilitate comparison with existing methods). The proposed adaptive clustering technique (Algorithm 4.3) was tested under the same simulation conditions as several benchmark protocols, including LEACH [40], Energy-Aware Multi-hop Multipath Hierarchical (EAMMH) [142], Energy-Aware Unequal Clustering Fuzzy (EAUCF) [178], Two-Tier Distributed Fuzzy logic-based Protocol (TTDFP) [179], and Fuzzy Logic-based Unequal Clustering [142].

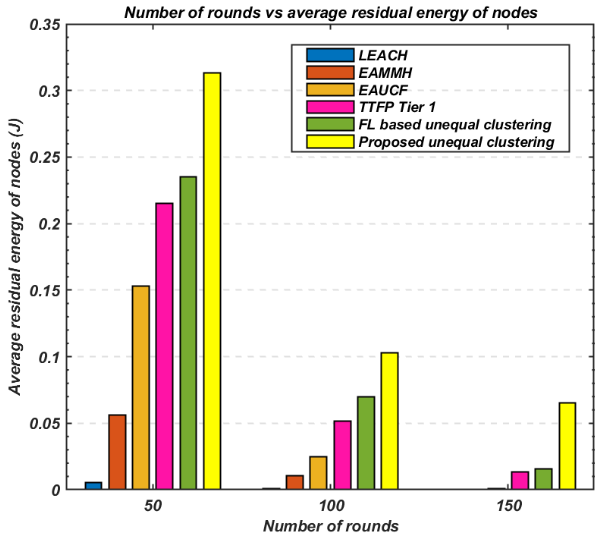



*Figure 4.9: Average residual energies of devices.*

Figure 4.9 illustrates the average residual energy of devices in the network after 50, 100, and 150 rounds. The results consistently show that the proposed shape independent unequal clustering method maintains higher average residual energy levels compared to the other techniques. This indicates that the adaptive clustering approach is more effective in conserving energy across a large-scale deployment. By preserving energy levels more efficiently, the proposed method enhances network lifetime and delays node depletion, which is critical in achieving extended and reliable network operation.

The consistently higher average residual energy achieved by the proposed method validates its effectiveness in enhancing energy efficiency and load balancing, especially in large-scale networks with varying energy demands and network densities.

### *4.6.3 Scalability and Improved Lifetime*

This section compares the scalability and network lifetime performance of the proposed adaptive unequal clustering method with existing unequal clustering methods, including Improved Unequal Clustering Routing (IUCR) [65] and Energy-efficient Coverage-guaranteed Unequal-size Clustering (ECUC) [45]. One key advantage of the proposed shape-independent method is its adaptability to different network sizes and densities, allowing it to consistently extend network lifetime across varying scales.

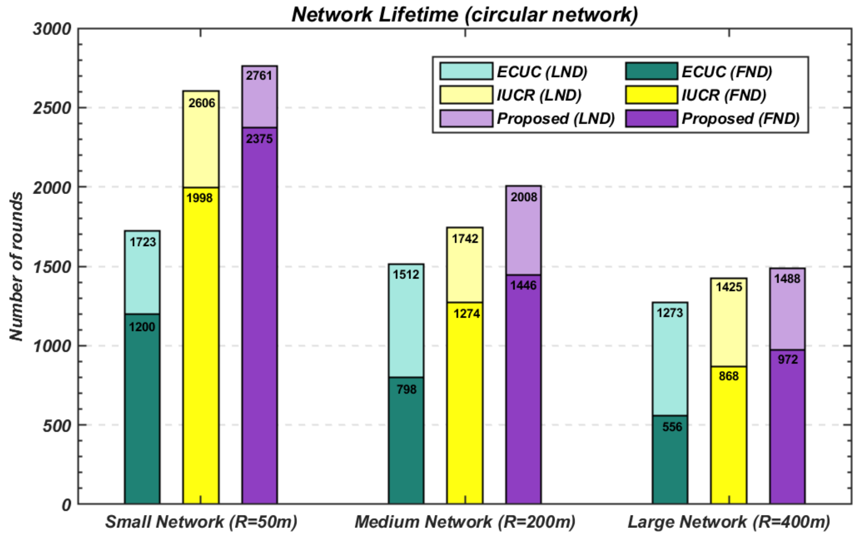



*Figure 4.10: Network Lifetime of different scale circular networks.*

Figure 4.10 presents the network lifetime achieved by the proposed shape-independent adaptive clustering method compared to IUCR and ECUC. The results are measured on three key scales: First Node Death (FND), Half Node Death (HND), and Last Node Death (LND). The proposed method consistently outperforms IUCR and ECUC on all three scales, confirming its effectiveness in enhancing network lifetime regardless of network size. This adaptability across varying network scales is critical in dynamic IoT-based WSNs, where node density and spatial distribution can fluctuate significantly.

Further results, shown in Figure 4.11, demonstrate the stability of the proposed method in handling different node densities. For a smaller network with 50 devices, the proposed method shows a notable improvement of approximately 45% over ECUC and 12% over IUCR in network lifetime. In a larger network with 300 devices, the proposed method achieves a 46% improvement over ECUC and a 10.7% improvement over IUCR, underscoring its scalability and efficiency in energy management even as network demands increase.

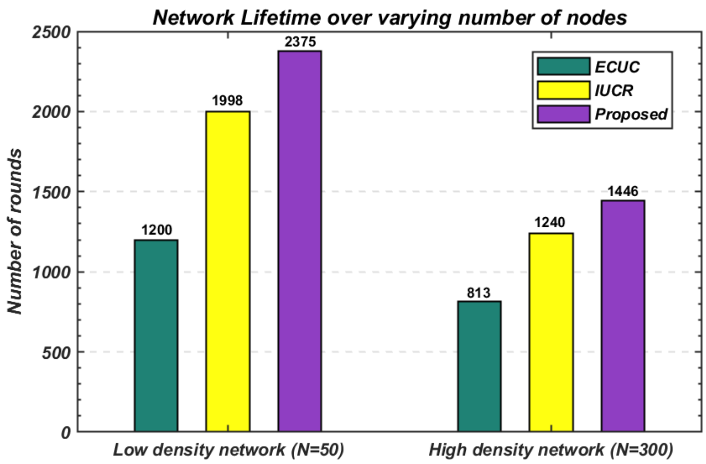



*Figure 4.11: Network lifetime under different devices densities.*

To assess adaptability across different network shapes, the proposed method was also tested against advanced techniques for square-shaped networks, including Harris Hawk Optimisation and Fuzzy Logic-based methods. Figure 4.12 compares the network lifetime of the proposed method with Harris Hawks Optimisation Clustering with Fuzzy Routing (HHOCFR) [66] , Harris Hawk Optimisation-based Unequal Clustering Routing Algorithm (HHO-UCRA) [67], Improved Harris Hawk Algorithm with Fuzzy (IHHO-F) [68], Distributed Clustering with Affinity Propagation and Fuzzy Logic (DAPFL) [69], and Improved Balanced Residual Energy LEACH (IBRE-LEACH) [70]. The results indicate that the proposed method significantly enhances network lifetime, achieving increases of 101%, 61%, 186%, 59%, and 24% on the FND scale compared to IBRE-LEACH, DAPFL, IHHO-F, HHO-UCRA, and HHOCFR, respectively. On the LND scale, the proposed method also outperforms these approaches by 45%, 29%, 13%, 41%, and 23%, respectively.

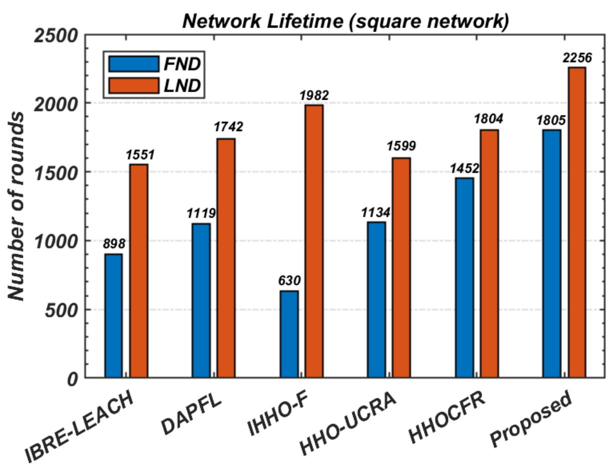



*Figure 4.12: Comparison in terms of network lifetime (FND and LND scales).*

These findings demonstrate that the proposed adaptive clustering method is highly scalable and adaptable, providing substantial improvements in network lifetime across diverse network shapes and densities. Its ability to maintain balanced energy consumption in various deployment scenarios underscores its utility for large-scale, heterogeneous IoT-based WSNs.

### *4.6.4 Adaptivity*

In this section, we compare the adaptivity of the proposed shape-independent unequal clustering method with shape-specific 3D unequal clustering schemes, namely cubical and spherical segmentation, evaluated through various deployment scenarios for the base station. Each segmentation approach is assessed across three different DGC placements: at the network centre, at the mean coordinates, and at the TOPSIS-determined optimal location. Figures 4.12 through 4.15 illustrate the results of network lifetime under each scenario, examining the First Node Dead (FND), Half Nodes Dead (HND), and Last Node Dead (LND) scales.

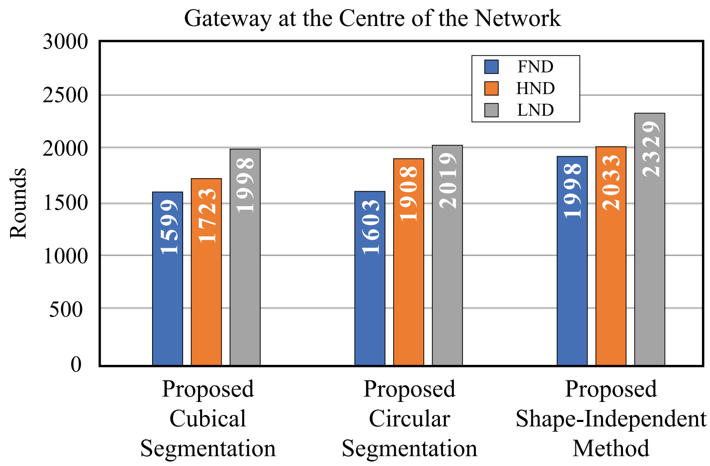



*Figure 4.13: Comparison of network lifetime in fixed and proposed shape-independent segmentations with unequal clustering method, with the gateway located at the centre of the network.*

Figure 4.13 displays the network lifetime comparison with the DGC placed at the centre of the network. The cubical segmentation scheme achieves 1599 rounds until the first node dies, 1723 rounds until half of the nodes die, and 1998 rounds until the network is entirely depleted. Spherical segmentation performs slightly better, with 1603 rounds until the first node dies and a complete network lifetime of 2019 rounds. In contrast, the adaptive shape-independent clustering scheme outperforms both by reaching 1998 rounds for the first node death (coinciding with the final round of cubical segmentation) and extending to 2329 rounds until full network depletion, demonstrating a substantial improvement in overall network longevity.

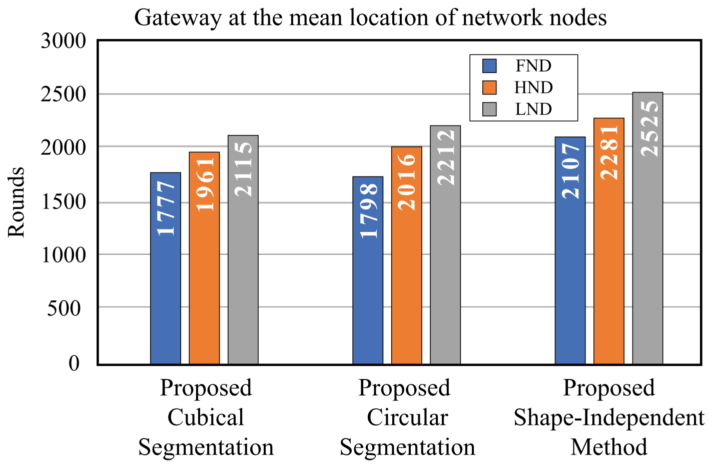



*Figure 4.14: Comparison of network lifetime between two fixed segmentations and the proposed adaptive unequal clustering method, with the DGC located at the mean position of the network.*

Figures 4.14 and 4.15 present similar findings for the mean-coordinate and TOPSIS-based DGC placements, respectively. Consistently, the proposed shape-independent clustering scheme shows superior adaptability, achieving longer network lifetimes across all DGC placements.

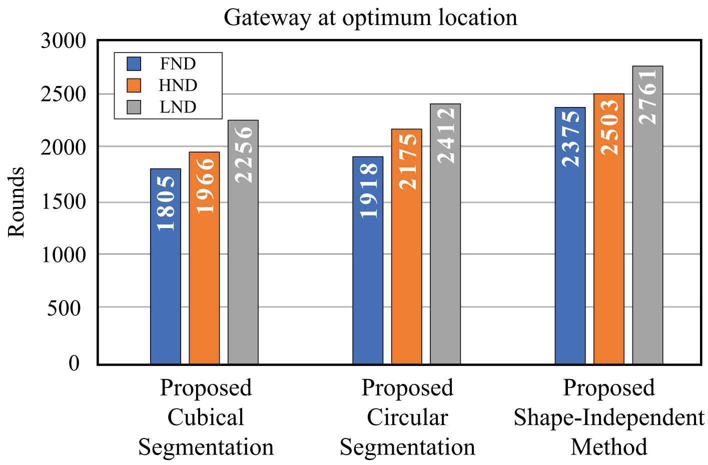



*Figure 4.15: Comparison of network lifetime between fixed segmentations and the proposed shape-independent unequal clustering method, with the gateway positioned at the TOPSIS-based optimal location.*

Figure 4.16 consolidates these findings, underscoring the adaptability of the shape-independent clustering scheme. This approach enhances network lifetime by approximately 32% and 27% compared to cubical and spherical segmentation, respectively, when combined with the TOPSIS-based DGC deployment. The results demonstrate that the proposed clustering method can dynamically adapt to various network shapes and deployment conditions, consistently improving network stability and energy efficiency across diverse configurations.

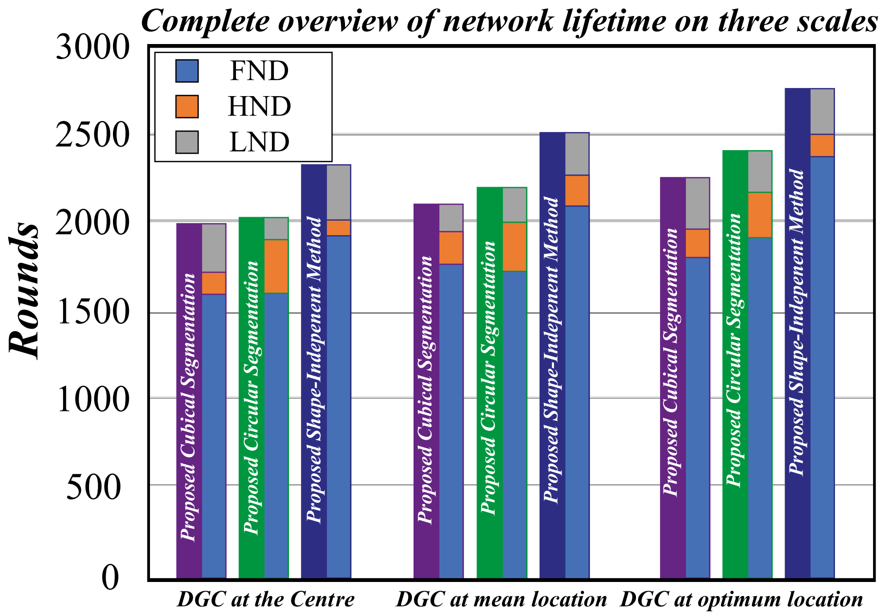



*Figure 4.16: Summary of results with fixed shape segmentations and shape-independent segmentations, followed by unequal clustering.*

### *4.6.5 Overall Energy Consumption*

This section presents a comparative analysis of the overall energy consumption achieved by the proposed shape-independent adaptive unequal clustering method against several state-of-the-art methods, including IBRE-LEACH [70], DAPFL [69], IHHO-F [68], HHO-UCRA [67], and HHOCFR [66], Fuzzy Logic based unequal clustering [142], IUCR [65], and ECUC [45]. The comparison, shown in Figure 4.17, demonstrates the energy efficiency of the proposed method over a simulation period of 1200 rounds.

As illustrated in Figure 4.17, the proposed method achieves significant energy savings over existing approaches, showing reductions in overall energy consumption of approximately 12.8%, 16.2%, 39.6%, 48.9%, 53.1%, 56.7%, 58.3%, and 61.4% compared to FL-based clustering, IUCR, ECUC, HHOCFR, HHO-UCRA, IHHO-F, DAPFL, and IBRE-LEACH, respectively. These substantial reductions in energy consumption highlight the efficacy of the proposed clustering method, which optimises energy utilisation by adapting dynamically to network heterogeneity and maintaining balanced energy use across nodes.

The proposed method's efficiency stems from its ability to adapt to various network shapes and node distributions while managing energy-intensive clustering and communication processes. By maintaining a balanced energy load across nodes, especially those closer to the

DGC, the proposed method minimises energy depletion, ultimately extending network longevity and reducing operational costs in large-scale heterogeneous networks.

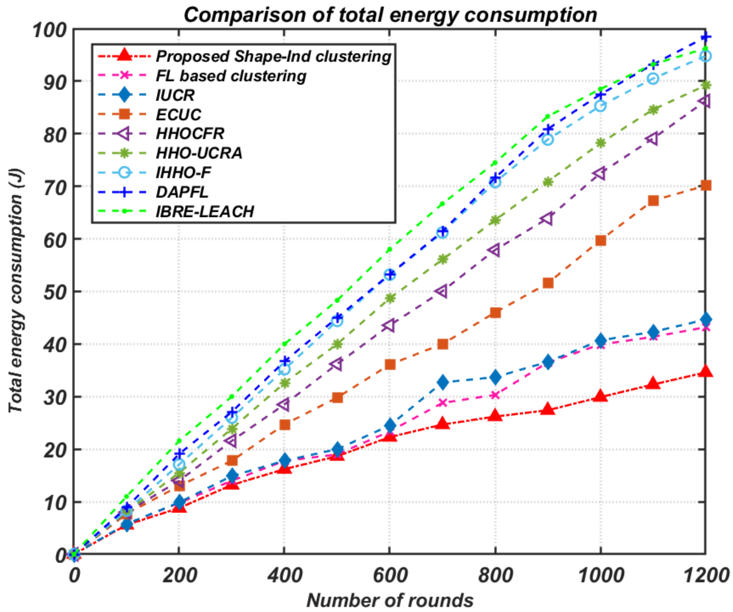



*Figure 4.17: Overall energy consumption of the network.*

## 4.7 Summary

This chapter explored energy-efficient data collection techniques in HWSNs, by leveraging hierarchical routing to achieve a balanced energy operation across the network. It began by defining the problem of segmentation and need for unequal clustering introducing two shape-specific segmentation schemes for 3D networks: cubical and spherical segmentation, which serve as foundational approaches for network segmentation and unequal cluster formation. Finally, a shape-independent adaptive unequal clustering technique was developed to enhance adaptability across various network shapes and dimensions.

The comparative evaluation shown in Figures 4.13 to 4.16 explicitly highlights the performance impact of increasing topological complexity, including both 2D (square, circular) and 3D (cube, spherical) environments, thereby validating the adaptability of the proposed segmentation and clustering techniques.

Simulation results demonstrated the substantial performance advantages of the proposed clustering techniques. The adaptive unequal clustering method notably reduced overall energy consumption, achieving savings of up to 12.8% compared to Fuzzy Logic-based clustering and 61.4% compared to IBRE-LEACH, showcasing its superiority over several state-of-the-art methods. Additionally, the proposed schemes consistently delivered results across varying network sizes and device densities, demonstrating their adaptability to diverse 2D and 3D network shapes.

# Chapter 5

# Energy Efficient Routing: Cluster Head and Relay Role Optimisation

## 5.1 Introduction

IoT-based WSNs often integrate nodes with varying capabilities, resulting in HWSNs, a more complex yet efficient variant of traditional WSNs [39]. The cluster head role selection and routing topologies are pivotal in extending the network's lifetime. Although, several cluster head rotation strategies have been developed [9], [10], [19], [23], [89]–[91]. These strategies aim to distribute the energy load by periodically changing the CH role among nodes. Static clustering methods [180], [181], [182] predefine cluster boundaries, whereas dynamic methods [40], [51], [72], [73], [79], [89], [183] adapt cluster configurations based on network conditions. Despite advancements, existing approaches face challenges, including the high energy consumption rate of CHs, inadequate consideration of device heterogeneity, and reduced network stability due to imbalances in energy consumption.

To address these challenges, this chapter proposes a novel energy-efficient routing scheme designed for IoT-based multi-level heterogeneous networks. The approach begins with the development of a versatile heterogeneity model and a mathematical framework to balance energy consumption within clusters, complemented by a new cluster head rotation algorithm to enhance sustainability and extend network lifetime. Additionally, a mathematical model identifies optimal relay regions by analysing resource distribution and energy costs, enabling dynamic relay node selection to prevent premature node failures and improve energy efficiency in inter-cluster communication. Finally, an innovative algorithm dynamically rotates relay roles among nodes within the identified optimal regions, ensuring balanced communication loads, significantly extending network stability, and prolonging the network's operational lifespan.

The structure of this chapter is as follows: Section 5.2 reviews existing CH rotation and balanced energy routing topologies, and section 5.3 discusses the challenges and limitations in existing approaches. Section 5.4 expands network structure and proposed heterogeneity model. Section 5.5 details the proposed intra & inter cluster communication schemes. Section 5.6 presents the performance evaluation of the proposed methods. Finally, Section 5.7 summarises the chapter.

## 5.2 Existing CH Rotation and Balanced Routing Methods

Clustering and routing approaches have significantly contributed to scalability and energy efficiency in WSNs, particularly in dynamic environments. Extending these methods to Internet of Things (IoT)-based HWSNs introduces additional challenges, such as managing multi-parameter heterogeneity and energy-efficient communication across large-scale networks. Numerous clustering protocols have been developed to address these challenges.

Early clustering protocols, such as Stable Election Protocol (SEP) [51], Distributed Energy Efficient Clustering (DEEC) [79], and their variants such as Developed Distributed Energy Efficient Clustering (D-DEEC) [80], Enhanced Distributed Energy Efficient Clustering (E-DEEC) [184], and Enhanced Developed Distributed Energy Efficient Clustering (ED-DEEC) [52], focused on distributing energy consumption evenly among nodes through probabilistic CH selection. These methods introduced energy heterogeneity by categorising nodes into normal, advanced, and super nodes. However, limitations such as static heterogeneity levels, high-energy penalties for advanced nodes, and frequent re-clustering reduced their efficiency.

Recent protocols have aimed to address these issues. Distance-Based Residual Energy-Efficient SEP (DRE-SEP) [185] and Distance Aware Residual Energy-Efficient SEP (DARE-SEP) [186] incorporated distance-aware clustering by factoring in node distance from the BS along with energy levels, enabling multi-hop communication to reduce energy consumption. Distance and Energy Aware SEP (DE-SEP) [187] further limited the number of CHs to optimise energy usage. While these advancements improved energy distribution, they remained constrained to specific heterogeneity levels and did not adequately address dynamic network conditions.

To accommodate multi-parameter heterogeneity in IoT-based HWSNs, protocols like Multi-Level HEED (ML-HEED) [188] and Improved Energy Efficient Clustering Protocol (IEECP) [19] introduced dynamic clustering mechanisms. ML-HEED extended HEED [29] by supporting up to six heterogeneity levels, demonstrating superior performance in terms of network lifetime and energy usage. However, frequent cluster reformation increased energy overhead. Similarly, IEECP employed back-off timers for CH rotation to avoid cluster overlap but focused solely on homogeneous networks.

The incorporation of fuzzy logic in clustering protocols, such as HEED-FL [189] and Singh's energy-efficient HWSN protocol [190], enabled dynamic CH selection based on multiple parameters, including node energy, distance, and density. However, these methods faced data loss issues when CH communication was interrupted and often lacked scalability for large-scale networks.

Recent works like RLEACH [191], CRPCM [192], [193], and EERPMS [193] emphasised energy-efficient routing by dynamically adjusting cluster sizes and employing multi-hop inter-cluster communication. RLEACH, an enhancement of LEACH, introduced relay nodes to optimise communication over long distances, effectively balancing energy consumption. CRPCM, combined clustering with relay-based routing to extend network lifetime, while EERPMS incorporated priority-based data transmission to reduce redundant energy usage. Despite these advancements, these protocols still face challenges in scalability, adaptability, and effective management of inter-cluster energy balance.

## 5.3 Challenges and Limitations

While significant progress has been made in clustering and routing protocols for HWSNs, several challenges and limitations persist:

- Many existing protocols, such as DEEC [79] and its derivatives [52], [80], [184] are limited to fixed levels of energy heterogeneity. Moreover, these protocols focus solely on energy heterogeneity, neglecting other critical parameters such as data rate, computational capabilities, and mobility. These static configurations fail to adapt to the dynamic nature of real-world IoT networks, where nodes often exhibit varying energy levels due to diverse tasks and resource requirements.
- Protocols such as ML-HEED [188] and ED-DEEC [52] necessitate frequent cluster reformation, leading to significant energy overhead. This not only reduces network efficiency but also accelerates the depletion of resources in energy-constrained environments.
- Existing methods, including HEED-FL [189] and CRPCM [192], [193], often overlook the energy burden on CHs due to inter-cluster communication. Without optimised relay node selection, cluster heads near the base station deplete their energy prematurely, creating energy holes.
- While some protocols, such as RLEACH [191] and EERPMS [57], demonstrate improvements in energy efficiency, they often lack scalability for large-scale networks

or adaptability to various deployment scenarios. This limits their applicability in diverse IoT-based HWSNs.

To address these challenges, this chapter proposes novel clustering and routing methods tailored to the unique demands of IoT-based HWSNs. These methods emphasise dynamic adaptability, multi-parameter heterogeneity management, and optimised energy balancing to enhance network performance and scalability. By overcoming the limitations of existing protocols, the proposed techniques aim to advance the state-of-the-art in energy-efficient HWSNs.

## 5.4 Network Structure and Heterogeneity Models

This section outlines the network structure and heterogeneity models employed for analysing and evaluating the proposed energy-efficient clustering and routing methods.

### *5.4.1 Network Structure:*

Figure 5.1 illustrates an m-level HWSN, where nodes with diverse functionalities communicate field data to a base station, which centralises and stores the information for access by authorised users. The term "m-level" refers to the varying range of resources and functionalities that nodes may possess, including sensing ranges, initial energy levels, mobility, computational capabilities, and data generation rates [39].

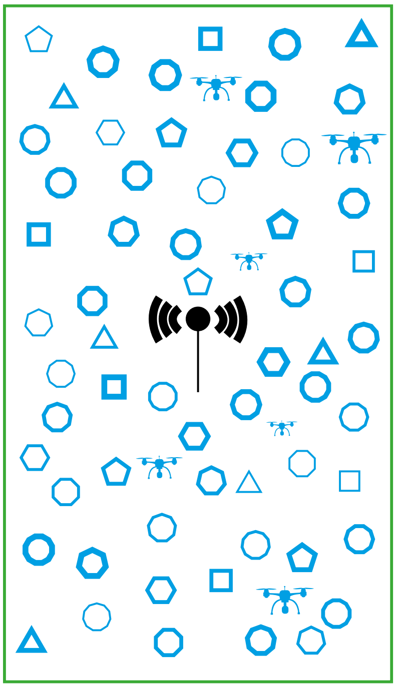


*Figure 5.1: Multi-parameter and multi-level heterogeneous WSN.*

Heterogeneity in sensor nodes provides a cost-effective solution to meet diverse application requirements, enhancing network performance and scalability. HWSNs can be categorised based on several attributes:

- **Energy Heterogeneity:** Nodes have different initial energy levels or employ replaceable batteries.
- **Computational Heterogeneity:** Nodes differ in processing power and storage capacities.
- **Link Heterogeneity:** Some nodes support longer-distance and more reliable communication links.
- **Data Rate Heterogeneity:** Nodes generate data packets of varying sizes and operate on different sensing schedules.
- **Mobility Heterogeneity:** Nodes may be stationary or mobile, with varying levels of mobility.

Among these, energy heterogeneity is fundamental, as link, computational, and data rate heterogeneities are often dependent on energy availability. Mobility heterogeneity adds another layer of complexity by introducing dynamic topology changes and energy challenges [39]. To ensure fair testing and evaluation of the proposed cluster head and relay node rotation schemes, a comprehensive heterogeneity model has been developed, providing a robust framework for performance evaluation.

### *5.4.2 Proposed Heterogeneity Model*

The proposed methods assume a multi-parameter heterogeneous sensor network characterised by the following attributes:

- Sensor nodes are deployed with varying energy levels and data rates, representing multiple levels of heterogeneity. These characteristics are confined to a given range to maintain a balance between functionality and resource constraints.
- All sensor nodes are stationary and remain fixed at their initial deployment locations throughout the network's operation.
- Nodes are capable of dynamically adjusting their transmission power levels to optimise energy usage and adapt to network requirements.
- Sensors periodically monitor the environment, and their data generation rates vary based on the nature of events or sensor node types.

- The BS is stationary, located at a fixed energy efficient position in the network, serving as the central hub for data aggregation and processing.
- The network topology can accommodate any number of sensor nodes and supports a variety of shapes and scales, enabling deployment in both regular and irregular environments.

To extend the concept of heterogeneity, the network is defined with $n$-levels of energy heterogeneity and $m$-levels of data rate heterogeneity, where $n, m > 0$ and $n, m \in Z^+$. The total number of sensor nodes, $N$, is divided among heterogeneous types based on proportional factors $\mu_1, \mu_2, \mu_3, \dots, \mu_n$ satisfying the equation:

$$\mu_1 + \mu_2 + \mu_3 + \cdots + \mu_n = 1 \tag{5.1}$$

$$\sum_{i=1}^{n} \mu_i . N = N \tag{5.2}$$

Consider, $\sigma_1, \sigma_2, \sigma_3$, and so forth as energy multipliers for nodes of types 1,2,3, and so on, following to the sequence:

$$\sigma_1 < \sigma_2 < \sigma_3 < \sigma_4 < \cdots$$

Here, $\sigma_1$ is assigned the value of 0, corresponding to nodes of type-1. Such that initial energy and data rate of the $j^{th}$ type of heterogeneous nodes can be found as $E^j = \left(E_0 + \sigma_j . E_0\right)$ and $T^j = \left(T_0 + \sigma_j . T_0\right)$ respectively. Where, $E_0$ and $T_0$ represent the initial energy and packet size type-1 nodes, respectively.

Therefore, the total network energy, $E_{network}$ and total data traffic in the network $T_{network}$ can be defined as follows:

$$E_{network} = \sum_{1}^{n} \mu_i . N . E^i \ and \ T_{network} = \sum_{1}^{n} \mu_i . N . T^i \tag{5.3}$$

Such that if $\kappa_i$ represents the number of type-$i$ sensor nodes, then:

$$\kappa_i = \mu_i . N \tag{5.4}$$

and

$$\sum_{i=1}^{n} \kappa_i = N \tag{5.5}$$

So, $E_{network}$ can be written as:

$$E_{network} = \kappa_1 . E^1 + \kappa_2 . E^2 + \cdots + \kappa_n . E^n$$

$$E_{network} = \kappa_1 . (E_0 + \sigma_1 . E_0) + \kappa_2 . (E_0 + \sigma_2 . E_0) + \kappa_3 . (E_0 + \sigma_3 . E_0) + \cdots + \kappa_n . (E_0 + \sigma_n . E_0)$$

Since $\sigma_1 = 0$

$$E_{network} = E_0[\kappa_1 + \kappa_2(1 + \sigma_2) + \kappa_3(1 + \sigma_3) + \cdots + \kappa_n(1 + \sigma_n)]$$

$$E_{network} = E_0(\kappa_1 + \kappa_2 + \kappa_3 + \cdots + \kappa_n + \sigma_2\kappa_2 + \sigma_3\kappa_3 + \sigma_4\kappa_4 + \cdots + \sigma_n\kappa_n)$$

$$E_{network} = E_0(N + \sigma_2\kappa_2 + \sigma_3\kappa_3 + \sigma_4\kappa_4 + \cdots + \sigma_n\kappa_n)$$

$$E_{network} = E_0(N + N\mu_2\sigma_2 + N\mu_3\sigma_3 + N\mu_4\sigma_4 + \cdots + N\mu_n\sigma_n)$$

$$E_{network} = NE_0(1 + \mu_2\sigma_2 + \mu_3\sigma_3 + \mu_4\sigma_4 + \cdots + \mu_n\sigma_n) \tag{5.6}$$

Similarly, $T_{network}$ can be written as:

$$T_{network} = NT_0(1 + \mu_2\sigma_2 + \mu_3\sigma_3 + \mu_4\sigma_4 + \cdots + \mu_n\sigma_n) \tag{5.7}$$

These formulations provide a scalable model for analysing networks with any level of heterogeneity.

The proposed models facilitate precise evaluation of energy consumption in heterogeneous networks, providing a foundation for optimising clustering and routing protocols. These models are essential for understanding and mitigating energy bottlenecks in IoT-based HWSNs. To quantify energy consumption in the network, this chapter utilises the radio energy dissipation model [177], applying equations (3.6)-(3.7) as introduced in chapter 3 to maintain consistency with the earlier chapters. This model accounts for energy costs associated with both transmission and reception, incorporating the effects of free-space and multi-path signal propagation losses.

## 5.5 Proposed Intra & Inter Cluster Communication Schemes

This section explains the proposed methodologies for enhancing energy efficiency, stability, and network lifetime in IoT-based HWSNs. The schemes are developed to address limitations in clustering, inter-cluster communication, and relay node selection by introducing novel approaches for cluster head rotation, inter-cluster communication, relay node selection, and relay node rotation. Following subsections elaborate the details of proposed schemes.

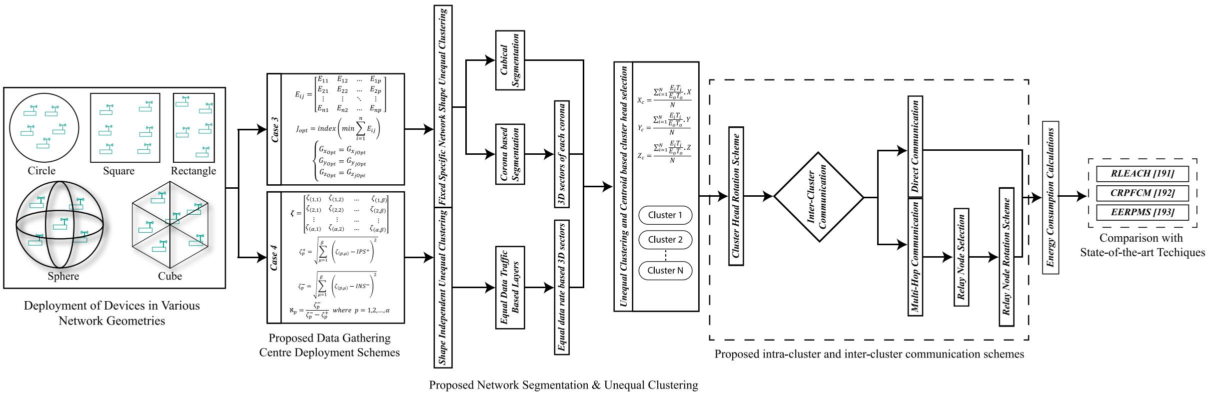



*Figure 5.2: Updated flow diagram of the proposed methods including proposed intra & inter-cluster communication methods.*

Figure 5.2 builds upon the deployment schemes presented in chapter 3 (Figure 3.3) and segmentation schemes proposed in chapter 4 (Figure 4.2), demonstrating how proposed intra-cluster and inter-cluster communication strategies can be integrated to extend the network longevity and energy efficiency. Moreover, Figure 5.2 highlights key routing topologies used as benchmarks for evaluating the performance of the proposed methods.

### *5.5.1 Proposed Cluster Head Rotation Scheme (Intra-Cluster Comm.)*

In HWSNs, energy consumption of sensor nodes varies due to differences in sensing mechanisms, leading to energy heterogeneity over time. Traditional CH rotation methods, designed for homogeneous networks, fail to account for these disparities, making them ineffective for heterogeneous environments. The proposed CH rotation scheme overcomes these challenges by optimising energy consumption and enhancing network stability through a well-coordinated rotation policy.

Figure 5.3 demonstrates the impact of CH role assignment on energy consumption and cluster lifetime. In the first scenario (Figure 5.3(a)), static CH assignment causes rapid energy depletion of the CH, leading to its premature failure after 250 cycles. In contrast, Figure 5.3(b) shows that rotating the CH role among nodes, extends the cluster lifespan to 328 cycles, with both nodes depleting their energy simultaneously, thereby maximising stability. When nodes have different initial energy levels, as shown in Figure 5.3(c), static role assignment results in suboptimal cluster lifetime. Figure 5.3(d) demonstrates that uncoordinated role rotation improves energy distribution but cannot fully optimise the cluster lifetime. Finally, Figure 5.2(e) illustrates that coordinated role rotation ensures balanced energy consumption, significantly enhancing both network lifespan and stability by minimising the time gap between node failures.

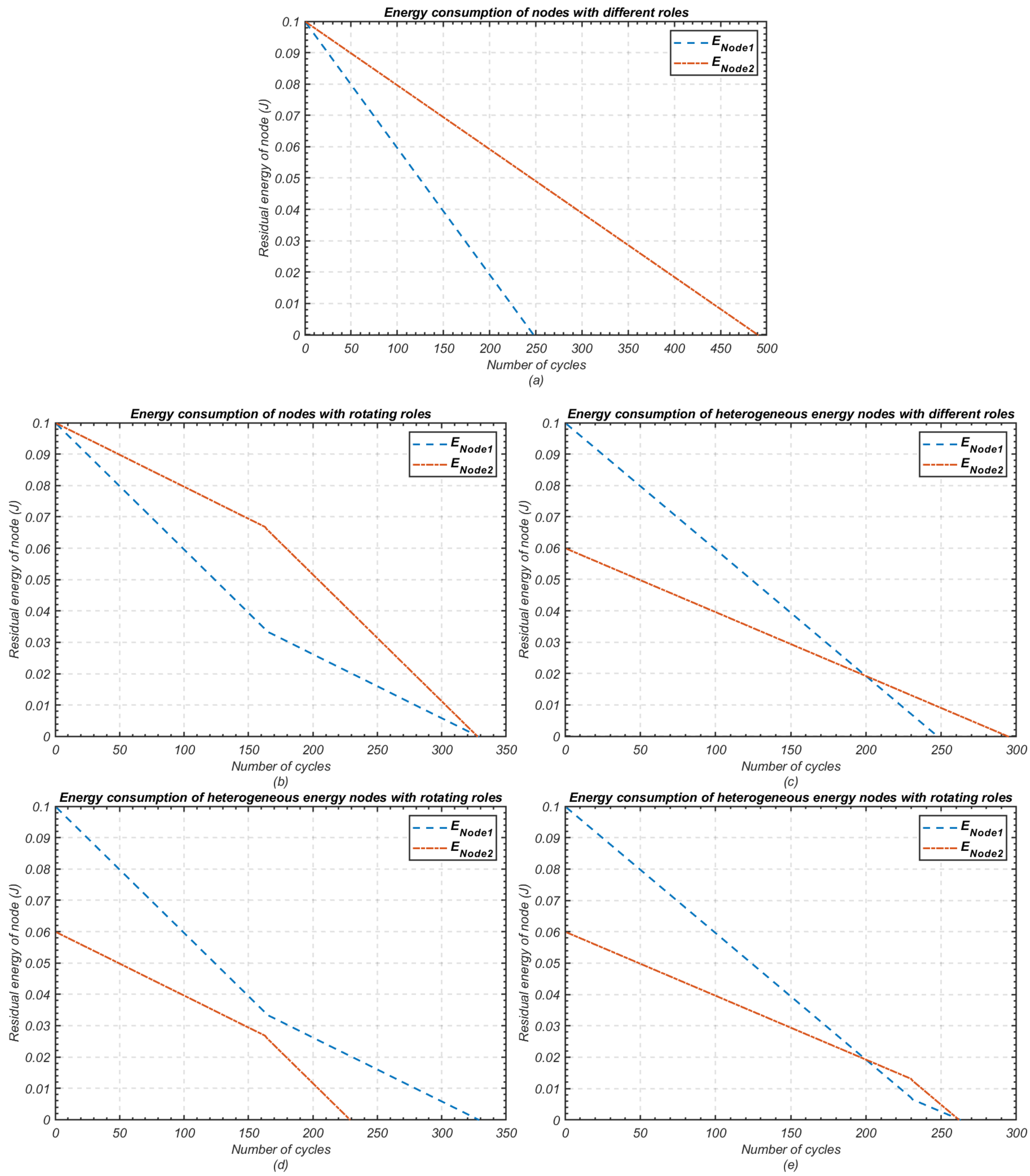



*Figure 5.3: Residual energy of nodes in a WSN under different role scenarios; (a) Homogeneous energy nodes with fixed roles; (b) Homogeneous energy nodes with rotating roles; (c) Heterogeneous energy nodes with fixed roles; (d) Heterogeneous energy nodes with uncoordinated role rotation; (e) Heterogeneous energy nodes with coordinated role rotation.*

Figure 5.4 further highlights the complexity of achieving energy efficiency in HWSNs with multi-parameter heterogeneity, where nodes have varying initial energies and data rates. Coordinated CH rotation, as depicted in Figure 5.4(c), balances the energy load and maximises network lifespan, even in large-scale networks with diverse characteristics.

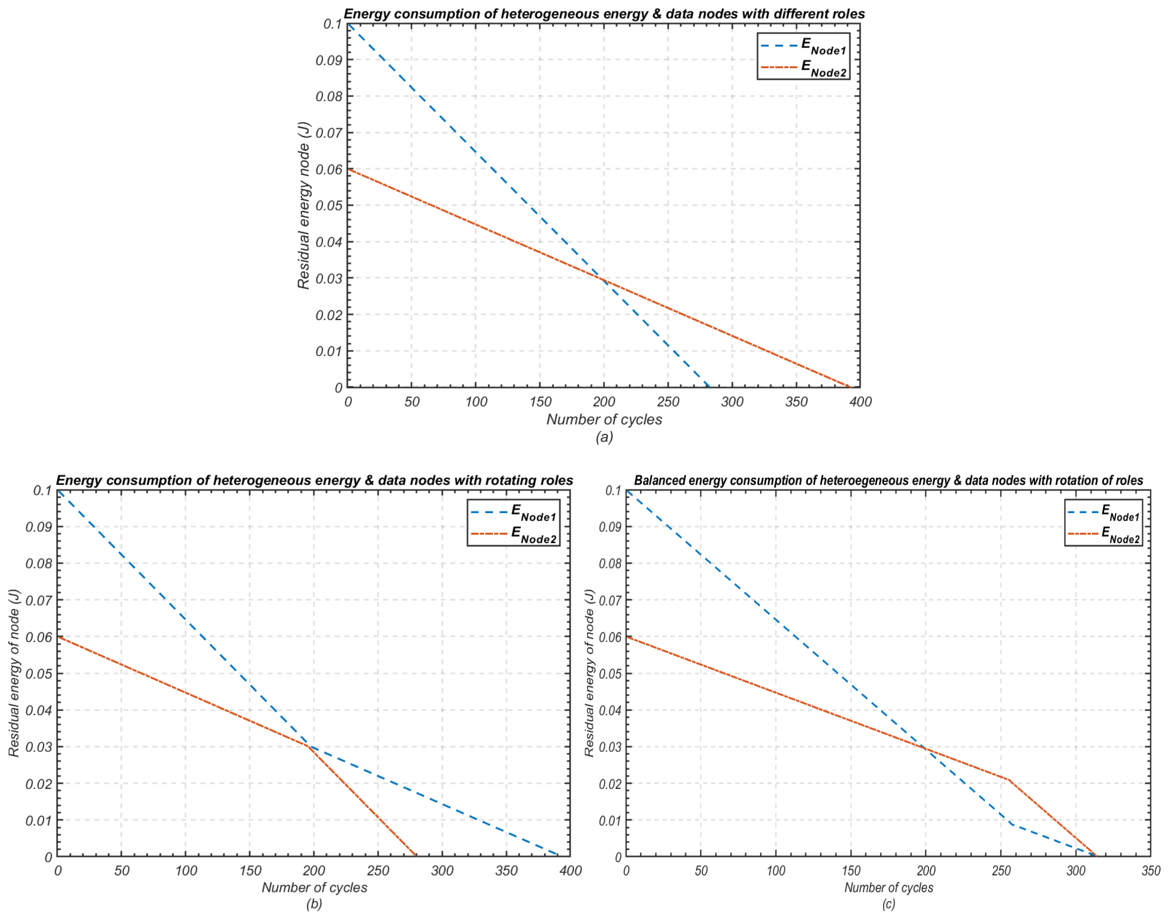



*Figure 5.4: Variation in the residual energy of nodes in a WSN with multi-parameter heterogeneity and role rotation; (a) Heterogeneous nodes with fixed roles; (b) Heterogeneous nodes with uncoordinated role rotation; (c) Heterogeneous nodes with coordinated role rotation.*

To achieve this, the proposed CH rotation scheme leverages on the BS to calculate pairwise distances $d_{ij}$ between all nodes within a cluster using Euclidean distances calculations as described by eq. (3.1) in chapter 3.

Here, '$d_{ij}$' represents the distance between the $i^{th}$ node and the $j^{th}$ node, as shown in Figure 5.5.

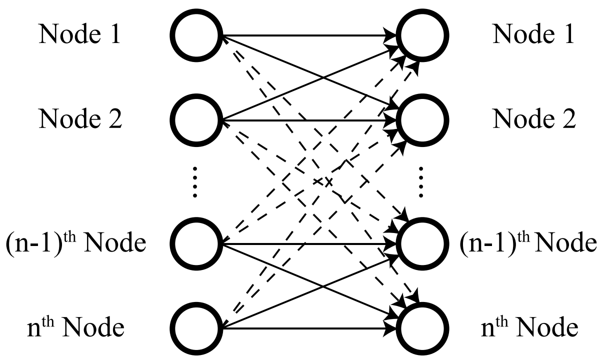



*Figure 5.5: Calculations of pairwise distances between each pair of nodes.*

Such that $'\boldsymbol{D}'$ is the array containing distance of each node from every other node in the cluster.

$$\boldsymbol{D}_{(i,j)} = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{bmatrix} \tag{5.8}$$

Based on the distance in array $'\boldsymbol{D}'$ BS calculates the expected energy consumption $e_{ij}$ for the transmission between each pair of nodes using equations (3.6) -(3.7).

Such that $'\boldsymbol{E}'$ is the array containing information about expected energy consumption for transmission between each node pair.

$$\boldsymbol{E}_{(i,j)} = \begin{bmatrix} e_{11} & e_{12} & \dots & e_{1n} \\ e_{21} & e_{22} & \dots & e_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ e_{m1} & e_{m2} & \dots & e_{mn} \end{bmatrix} \tag{5.9}$$

Then total expected energy consumption of the nodes in a cluster, while $j^{th}$ node is assumed to be a cluster head, is computed in next step.

$$E_T(j) = \sum_{i=1}^{n} e_{ij} \tag{5.10}$$

So, the average anticipated energy consumption when $j^{th}$ node is cluster head.

$$E_{avg}(j) = \frac{\sum_{i=1}^{m} e_{ij}}{n} \tag{5.11}$$

Therefore, the set of candidate cluster heads can be determined as:

$$\mathfrak{E} = sort(E_T) \tag{5.12}$$

$$\mathfrak{E} = \{\mathfrak{e}_1, \mathfrak{e}_2, \mathfrak{e}_3, \ \dots, \mathfrak{e}_n\}$$

The index of $\mathfrak{e}_i$ in $E_T$ can be determined using the following expression:

$$index(\mathfrak{e}_i, E_T) = \mathfrak{j} \tag{5.13}$$

Here, $\mathfrak{e}_i$ is an element in the sorted set $\mathfrak{E}$, where $E_T$ is the original unsorted set, and $\mathfrak{j}$ represents the index of element $\mathfrak{e}_i$ in the original unsorted set $E_T$. If $\mathbb{E}$ be the set of residual energies of each node.

$$\mathbb{E} = \{\mathbb{e}_1, \mathbb{e}_2, \mathbb{e}_3, \dots, \mathbb{e}_n\} \tag{5.14}$$

Therefore, index of the node with minimum residual energy is determined as:

$$index_{min}(\mathbb{E}) = \mathbb{i} \quad (5.15)$$

A node with minimum overall energy consumption continues to be cluster head until residual energy of minimum energy node drops below the mean of residual energies.

$$A = \jmath(\mathrm{i})\,, \quad \text{for i} = 1,2,3 \ldots \mathrm{n}$$

So, while $E_{(\mathbb{i},A)} \leq E_{avg}(A)$ & $\mathbb{E}(A) \geq \alpha * \max(\mathbb{E})$ the node with index '$A$' continues to be cluster head.

Nodes with minimal anticipated energy consumption are prioritised as CHs. A node retains its CH role until its residual energy drops below the network's average energy or a predefined threshold. The re-clustering factor $'\alpha'$ allows flexibility in tuning the frequency of CH role rotation, balancing stability and energy efficiency.

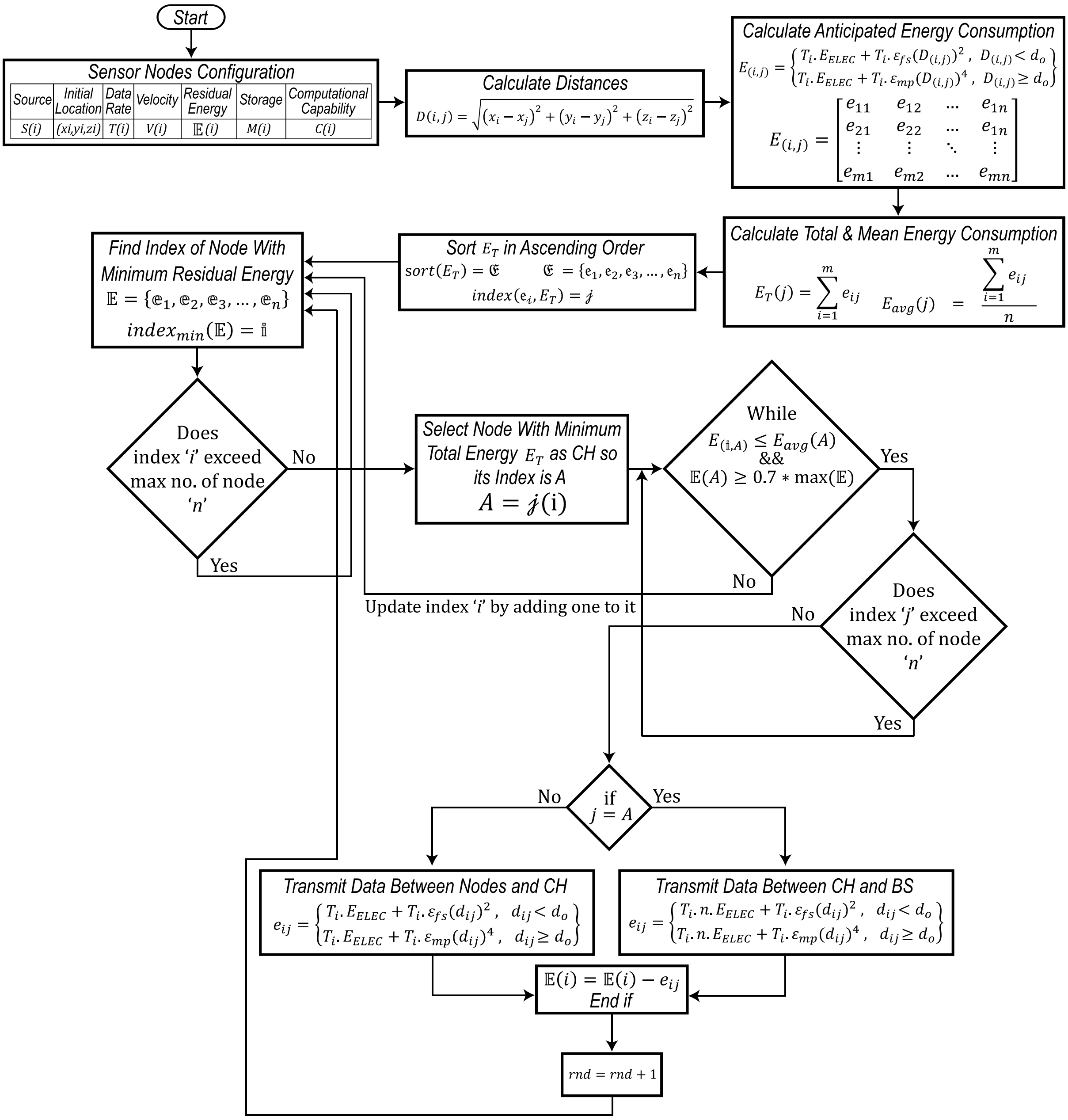



*Figure 5.6: Diagram illustrating the proposed cluster head rotation scheme.*

The operational flow is illustrated in Figure 5.6, and the detailed steps are outlined in Algorithms 5.1 and 5.2. These algorithms guide the dynamic rotation of CH roles, ensuring balanced energy usage and extended network lifetime. This method is particularly effective in environments with multi-level and multi-parameter heterogeneity, adapting to diverse network conditions while maintaining stability.

***Proposed Algorithm 5.1:***

Algorithm 5.1 outlines the sequence of events and operations performed by each sensing node within the network.

**Algorithm 5.1:** Sensing nodes

**Input:** Policy for the varying roles

**Output:** Data rate transmitted by each normal node in the network

1: round = round +1

2: Obtain policy for the varying roles of the node over the network lifetime from BS

3: **if** *node.role = Normal Node*

4: *Perform sensing operation and detect data*

5: **if** *change in the parameter value,* **then**

6: *Wake up communication module*

7: *send data to the Cluster Head*

8: **end if**

9: **elseif** *node.role = Cluster Head*

10: *keep communication module awake*

11: *receive data from members*

12: *send data towards base station*

13: **end if**

***Proposed Algorithm 5.2:***

The role rotation policy for nodes is determined through the series of operations outlined in Algorithm 5.2. This policy is centrally established by the Base Station during the network initialisation phase and is communicated to all participating nodes to ensure efficient operation throughout the network's lifetime.

**Algorithm 5.2:** Cluster Head Rotation (BS)

**Input:** Number of cluster member nodes '$n$', their initial locations $(x_i, y_i, z_i)$, heterogeneous fixed data rate $T_i$, and initial energies $\mathbb{E}_i$ of each sensor node.

**Output:** Role of each node over network lifetime ensuring balanced energy network operation.

**for** $i \leftarrow 1$ **to** $n$ **do**

  **for** $j \leftarrow 1$ **to** $n$ **do**

    $\boldsymbol{D}(i,j) \leftarrow \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 + \left(z_i - z_j\right)^2}$

    $\boldsymbol{E}(i,j) \leftarrow \begin{Bmatrix} T_i.E_{ELEC} + T_i.\varepsilon_{fs}.d_{ij}{}^2, & d_{ij} < d_o \\ T_i.E_{ELEC} + T_i.\varepsilon_{mp}.d_{ij}{}^4, & d_{ij} \geq d_o \end{Bmatrix}$

  **end for**

**end for**

**for** $j \leftarrow 1$ **to** $n$ **do**

  $E_T(j) \leftarrow \sum_{i=1}^{n} e_{ij}$

  $E_{avg}(j) = \frac{E_T(j)}{n}$

**end for**

$\mathfrak{E} \leftarrow sort(E_T)$

$\mathcal{j} \leftarrow index(\mathfrak{e}_i, E_T)$

**for** $rnd \leftarrow 1$ to $rnd_{max}$

  $\mathbb{i} \leftarrow index_{min}(\mathbb{E})$

  **for** $i \leftarrow 1$ **to** $n$ **do**

    $A \leftarrow \mathcal{j}(i)$

    **While** $E_{(\mathbb{i},A)} \leq E_{avg}(A)$ && $\mathbb{E}(A) \geq \alpha * \max(\mathbb{E})$ **do**

      **for** $j \leftarrow 1$ **to** $n$ **do**

        **if** $j = A$ **then**

          $e_{ij} \leftarrow \begin{Bmatrix} T_i.n.E_{ELEC} + T_i.\varepsilon_{fs}(d_{ij})^2, & d_{ij} < d_o \\ T_i.n.E_{ELEC} + T_i.\varepsilon_{mp}(d_{ij})^4, & d_{ij} \geq d_o \end{Bmatrix}$

        **else**

$$e_{ij} \leftarrow \begin{cases} T_i . E_{ELEC} + T_i . \varepsilon_{fs} (d_{ij})^2 , & d_{ij} < d_o \\ T_i . E_{ELEC} + T_i . \varepsilon_{mp} (d_{ij})^4 , & d_{ij} \geq d_o \end{cases}$$

$\mathbb{E}(i) \leftarrow \mathbb{E}(i) - e_{ij}$

**end if**

**end for**

**break**

**end for**

$rnd \leftarrow rnd + 1$

**end for**

---

Algorithms 5.1 and 5.2 work in conjunction on sensor nodes and cluster heads to facilitate the cluster head rotation and manage energy-balanced intra-cluster communication, ensuring optimal energy utilisation and extended network stability.

### *5.5.2 Proposed Inter-Cluster Communication Scheme*

Efficient inter-cluster communication is critical for energy optimisation in HWSNs. This section addresses the challenges associated with energy consumption during data transmission from CHs to the BS, particularly in large-scale networks. The proposed scheme evaluates the energy requirements of direct communication versus multi-hop inter-cluster routing and introduces a balanced energy strategy to enhance network stability and longevity.

#### *i. Direct Communication*

Let $'\mathcal{K}'$ represent the variable denoting the possible number of hops available between the outermost cluster head (CH) and the BS. Due to varying cluster sizes, the distances between these hops are varying and are represented by $r_1, r_2, r_{3,} \dots , r_{\mathcal{K}}$. The Energy consumed by outermost cluster head in communicating a message of packet size $'l'$ bits to the BS via direct communication can be calculated using first order radio model [21] as describted earlier.

$$E_{Direct} = E_{TX}(l, d = r_1 + r_2 + r_3 \dots + r_{\mathcal{K}}) \tag{5.15}$$

$$E_{Direct} = \begin{cases} E_{ELEC} * l + \epsilon_{fs} * l * d^2 \ if \ d \leq d_o \\ E_{ELEC} * l + \epsilon_{mp} * l * d^4 \ otherwise \end{cases}$$

Similarly, energy consumed during multi-hop inter-cluster communication can be computed as:

$$E_{Multihop} = \mathcal{K} * E_{TX}(l, d = {r_1}^2 + {r_2}^2 + \cdots + {r_\mathcal{K}}^2) + (\mathcal{K} - 1)E_{RX}$$

$$E_{Multihop} = \mathcal{K}\left[E_{ELEC} * l + \epsilon_{fs} * l * ({r_1}^2 + {r_2}^2 + \cdots + {r_\mathcal{K}}^2)\right] + (\mathcal{K} - 1)[E_{ELEC} * l] \quad (5.16)$$

To determine the requirement of inter-cluster multi-hop routing following the proposed method observes following two cases.

**Case 5.1: $d \leq d_o$**

If the overall distance $'d'$ between a cluster head and base station exceeds the threshold distance $'d_o'$ as defined by the radio model, then energy consumed during direct communication is given by:

$$E_{Direct} = E_{ELEC} * l + \epsilon_{fs} * l * d^2 \quad (5.17)$$

So, direct communication can be preferred in this case only if below condition is satisfied:

$$E_{Direct} < E_{Multihop}$$

$$E_{ELEC} * l + \epsilon_{fs} * l * d^2 < \ l\left[\left[\mathcal{K}E_{ELEC} + \mathcal{K}\epsilon_{fs}({r_1}^2 + {r_2}^2 + \cdots + {r_\mathcal{K}}^2)\right] + [\mathcal{K}E_{ELEC} - E_{ELEC}]\right]$$

$$d^2 < 2\frac{E_{ELEC}(\mathcal{K} - 1)}{\epsilon_{fs}} + \mathcal{K}({r_1}^2 + {r_2}^2 + \cdots + {r_\mathcal{K}}^2) \quad (5.18)$$

**Case 5.2: $d > d_o$**

However, if the total distance between a cluster head and base station is less than the threshold distance $'d_o'$ the energy consumed by direct communication is computed as:

$$E_{Direct} = E_{ELEC} * l + \epsilon_{mp} * l * d^4 \quad (5.19)$$

So direct communication requires less energy if:

$$E_{Direct} < E_{Multihop}$$

$$E_{ELEC} * l + \epsilon_{mp} * l * d^4 < \ l\left[\left[\mathcal{K}E_{ELEC} + \mathcal{K}\epsilon_{fs}({r_1}^2 + {r_2}^2 + \cdots + {r_\mathcal{K}}^2)\right] + [\mathcal{K}E_{ELEC} - E_{ELEC}]\right]$$

$$d^4 < 2(\mathcal{K} - 1)\frac{E_{ELEC}}{\epsilon_{mp}} + \mathcal{K}({r_1}^2 + {r_2}^2 + \cdots + {r_\mathcal{K}}^2)\frac{\epsilon_{fs}}{\epsilon_{mp}} \quad (5.20)$$

### *ii. Multi-Hop Communication*

If the network size is such that a multi-hop routing is energy efficient, Figure 5.7 highlights the problem of imbalanced load among cluster heads due to multi-hop inter-cluster routing. The cluster heads closer to base station are subjected to heavy relaying load in a large-scale network.

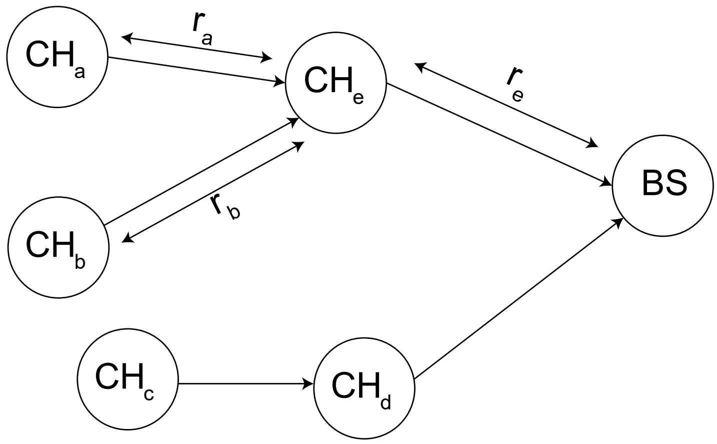



*Figure 5.7: Multi-hop inter-cluster data transmission to the base station.*

The proposed scheme examines the necessary conditions required to balance the load among cluster heads, aiming to enhance network lifetime and stability, as in the mathematical model below. Consider two cluster heads, $CH_a$ and $CH_b$, which are positioned at the same level within the network and manage an equal number of nodes $'a'$, with an identical data rate, $'l'$ assigned to them.

$$E_{a-TOTAL} = alE_{ELEC} + EDA + lE_{ELEC} + l\epsilon_{fs}{r_a}^2 \tag{5.21}$$

$$E_{a-TOTAL} = E_{b-TOTAL}$$

Let '$e$' be the number of nodes in cluster $CH_e$ so,

$$E_{e-TOTAL} = (a+b)lE_{ELEC} + elE_{ELEC} + EDA + lE_{ELEC} + l\epsilon_{fs}{r_e}^2$$

Therefore, the condition for balanced energy routing implies:

$$E_{a-TOTAL} = E_{e-TOTAL}$$

$$alE_{ELEC} + EDA + lE_{ELEC} + l\epsilon_{fs}{r_a}^2 = (a+b)lE_{ELEC} + elE_{ELEC} + EDA + lE_{ELEC} + l\epsilon_{fs}{r_e}^2$$

Since $a = b \neq e$

$$aE_{ELEC} + \epsilon_{fs}{r_a}^2 = 2aE_{ELEC} + eE_{ELEC} + \epsilon_{fs}{r_e}^2$$

$$\epsilon_{fs}{r_a}^2 = (a+e)E_{ELEC} + \epsilon_{fs}{r_e}^2$$

$${r_a}^2 = (a+e)\frac{E_{ELEC}}{\epsilon_{fs}} + {r_e}^2 \tag{5.22}$$

For balanced energy inter-cluster multi-hop routing the above condition must be met.

The proposed inter-cluster communication scheme evaluates direct and multi-hop routing options to minimise energy consumption. By considering network size, CH distances, and node heterogeneity, the scheme dynamically selects the optimal routing strategy. The inclusion of energy-balanced multi-hop routing further ensures uniform load distribution among CHs, extending network lifespan and improving performance in HWSNs.

### *5.5.3 Proposed Relay Node Selection Scheme*

Efficient relay node selection plays a pivotal role in enhancing the lifetime and energy efficiency of HWSNs. The proposed method distinguishes relay nodes alongside cluster heads CHs to optimise inter-cluster communication, particularly in large-scale networks with varying scales and device heterogeneity. This section details the novel relay node selection mechanism, which identifies energy-efficient relay nodes dynamically based on the network's spatial and operational constraints.

#### ***i. Energy Threshold for Direct Transmission***

To determine whether a relay node is necessary, the algorithm evaluates the condition $d \leq d_0^{min}$, where $d_0^{min}$ represents the minimum threshold distance for energy-efficient direct transmission. The threshold distance is computed as:

$$d_0^{min} = \sqrt[\gamma]{\frac{\varepsilon_o(\gamma)}{1 - 2^{-\frac{\gamma}{2}}}} \tag{5.23}$$

where:

- $\gamma \in \{2,4\}$ correspond to the free space $(\gamma = 2)$ or multi-path $(\gamma = 4)$ channel model,
- $\varepsilon_o(\gamma) = \frac{E_{ELEC}}{\varepsilon_{fs}}$ for $\gamma = 2$ and $\varepsilon_o(\gamma) = \frac{E_{ELEC}}{\varepsilon_{mp}}, \gamma = 4$.

If the distance between the ith cluster head $(CH_i)$ and the base station (BS) exceeds $d_0^{min}$, multi-hop communication is preferred, and relay nodes are selected. Figure 5.8 shows the Region Of Interest for the energy efficient selection of the relay node. As the distance between CH and the next hop increases the region for the selection of the relay node increases. The bigger region for the selection of relay node allows an increased set of alternatives for the selection of relay node, but it is not desirable from the perspective of increased energy consumption in long distant transmissions. Therefore, the proposed algorithm applies a stepwise synchronised procedure for the energy efficient network operation to extent network lifetime.

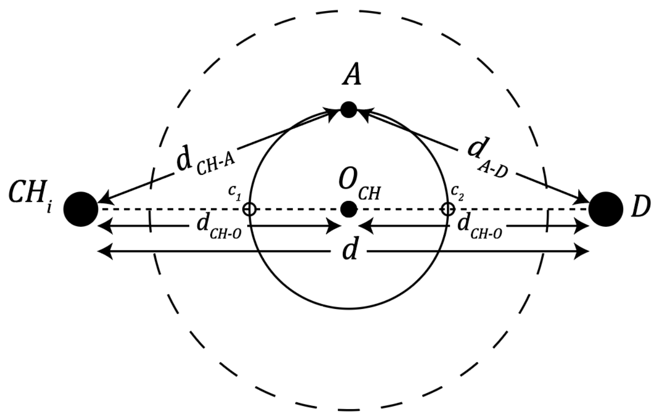



*Figure 5.8: Search region for relay nodes based on energy variation.*

Flow chart in Figure 5.9 further explains step-by-step procedure of the proposed method for balancing energy and maximising network lifetime in inter-cluster multi-hop communication. The proposed method starts from the farthest most cluster head and continues to calculate the number of hops for energy efficient transmission until it eventually reaches the closest relay options to the base station. The method ensures that it accounts for the fact that direct transmission from the closest relay candidates is energy efficient. The proposed relay node rotation scheme is inherently adaptable to varying network scales and heterogeneous configurations. By dynamically adjusting rotation frequency and relay selection criteria, the method maintains network stability and longevity across different IoT deployments.

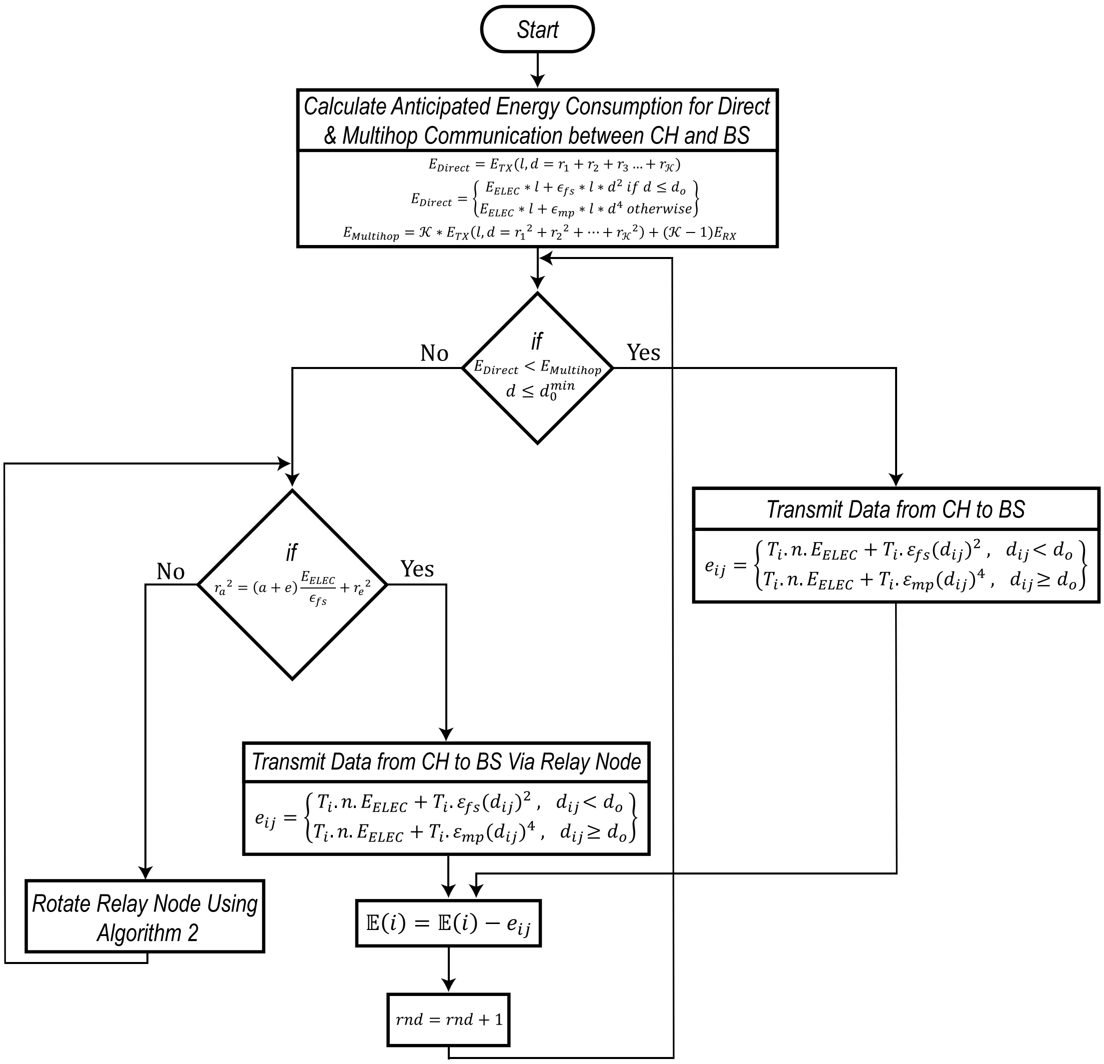



*Figure 5.9: Flowchart of the proposed relay selection and rotation strategy.*

***Proposed Algorithm 5.3:***

The procedure outlined in in algorithm 5.3 details the steps for energy-efficient relay node selection and dynamic rotation of relay roles among candidate relay nodes. This approach effectively balances energy consumption, thereby enhancing network stability and lifetime.

---

**Algorithm 5.3:** Relay Node Selection & Rotation Policy

---

**Input:** '$n$' number nodes, their locations $(x_i, y_i, z_i)$, heterogeneous fixed data rate $T_i$, and initial energies $\mathbb{E}_i$ of each sensor node, sensing region and its boundaries. Total number of cluster heads $\rho$ and total number of sensor nodes $N$.

**Output:** A policy for the selection of relay node for each cluster head to transmit its cluster data to the base station in an energy efficient and stable manner. A balanced energy transmission between nodes through timely and energy efficient rotation of relay nodes.

$d_0^{min} \leftarrow \sqrt[\alpha]{\frac{\varepsilon_o(\alpha)}{1-2^{-\frac{\alpha}{2}}}}$

**for** $i = 1$ **to** $\rho$ **do**

  $d_{CH_i-BS} \leftarrow d$

  **if** $d_{CH_i-BS} > d_0^{min}$ **then**

    *Compute the radius* $'A'$

    **for** $j = 1$ **to** $N$ **do**

      **if** $d_{ij} < A$ **then**

        $\mathcal{R}_{i-candidate} \leftarrow j$

        **While** $E_{(CH_i,j)} \leq E_{avg}(j)$ && $\mathbb{E}(j) \geq \alpha * \max(\mathbb{E})$ **do**

          *Continue to transmit data via relay node* $'j'$

          $\mathbb{E}(j) \leftarrow \mathbb{E}(j) - e_{j-BS}$

        **else**

          *Rotate relay role to next candidate*

        **Break**

      **end if**

    **end for**

  **else**

    *Transmit data via direct communication between* $'CH_i'$ *and* $'BS'$

    $E_{Direct} = \begin{cases} E_{ELEC} * l + \epsilon_{fs} * l * d^2 \ if \ d \leq d_o \\ E_{ELEC} * l + \epsilon_{mp} * l * d^4 \ otherwise \end{cases}$

    $\mathbb{E}(i) \leftarrow \mathbb{E}(i) - E_{Direct}$

  **end if**

  $rnd \leftarrow rnd + 1$

**end for**

## 5.6 Performance Analysis

This section evaluates the proposed techniques through MATLAB simulations, focusing on their performance in both intra-cluster and inter-cluster communication. The evaluation utilises several Quality of Service (QoS) parameters to determine the effectiveness and efficiency of the proposed methods. First a performance analysis of the proposed intra-cluster communication scheme has been completed in the subsection 5.6.1 followed by the performance analysis of proposed inter-cluster communication scheme in subsection 5.6.2.

The proposed inter- and intra-cluster communication schemes are evaluated using multiple performance metrics. These include:

- Network Lifetime, representing the operational duration until node failures;
- Residual Energy Trends, which reflect the cluster head (CH) energy depletion rate;
- Stability Period, indicating the energy balance among nodes;
- Energy Efficiency and Throughput, which indirectly account for clustering overhead and latency.
- These metrics collectively demonstrate the adaptability and scalability of the proposed methods in complex heterogeneous WSN environments.

### *5.6.1 Intra-Cluster Communication*

To analyse the performance of the proposed cluster head rotation method, simulations were conducted using the parameters outlined in Table 5.1. These parameters ensure the inclusion of multi-level heterogeneity in terms of energy and data packet size within each cluster. The heterogeneity model was applied to nodes in clusters with 3 and 5 members. However, the method can easily be scaled to clusters of higher nodes.

*Table 5.1: Simulation Parameters for Intra-Cluster Communication*

| Parameter | Value |
|---|---|
| Number of nodes | $3\ and\ 5$ |
| Range of heterogeneous initial energies of nodes | $(0.05 - 0.2)J$ |
| Total energy of nodes in a cluster | $0.5J$ |
| Range of heterogeneous packet size ($l$) | $(1000 - 8000)bits$ |
| Total data transmitted by nodes in a cluster | $20000\ bits$ |
| Electronic Circuitry ($E_{elec}$) | $50\ nJ/bit/m^2$ |
| Amplifier energy for free space ($\varepsilon_{fs}$) | $10pJ/bit/m^2$ |
| Amplifier energy for multipath ($\varepsilon_{mp}$) | $pJ/bit/m^4$ |

The simulation scenarios involve clusters where nodes are initialised with heterogeneous energy levels ranging between 0.05 J to 0.2 J, with total cluster energy normalised to 0.5 J to ensure a fair comparison. Additionally, nodes generate data packets of varying sizes, between 1000 bits and 8000 bits, such that the total data transmitted by all nodes in a cluster during one cycle equals 20000 bits. This configuration effectively represents real-world heterogeneous network conditions.

The energy dissipation model employed in the simulations integrates both free-space and multipath propagation models similar to chapter 3. Key performance metrics for intra-cluster communication include:

i. ***Residual Energy Analysis:*** The distribution and depletion of energy in the cluster are monitored to validate the efficiency of the proposed cluster head rotation scheme.
ii. ***Stability Period:*** The time interval during which no nodes fail in the cluster, indicating the balance of energy consumption.
iii. ***Network Lifetime:*** The time taken until all nodes in the cluster exhaust their energy, assessing the sustainability of the proposed method.
iv. ***Energy Efficiency:*** The total energy consumed per transmission cycle and the effectiveness of cluster head rotation in minimising intra-cluster energy consumption.

Subsections below analyse the inter-cluster communication and overall network performance.

### *i. Comparison of Residual Energy*

In this subsection, the energy-efficient operation of the proposed intra-cluster communication scheme is evaluated by comparing the residual energy of nodes achieved in proposed method against traditional rotation method. The primary goal of this experiment is to assess the effectiveness of the proposed cluster head rotation scheme in prolonging network stability and lifetime. Key metrics include the number of cycles before the first node's death, the convergence of energy usage among nodes, and the proportion of unused energy before cluster effectiveness diminishes.

Figure 5.10 illustrates the residual energy of nodes during intra-cluster communication in a cluster containing three nodes. Figure 5.10(a) represents the results from the traditional cluster head rotation method, while Figure 5.9(b) corresponds to the proposed rotation method. The traditional approach shows that the first node depletes its energy after only 194 cycles of operation, while the last node runs out of energy after 360 cycles. This discrepancy demonstrates a reduced stability period, as indicated by the considerable gap between the time of the first node's failure and the complete depletion of last node's energy.

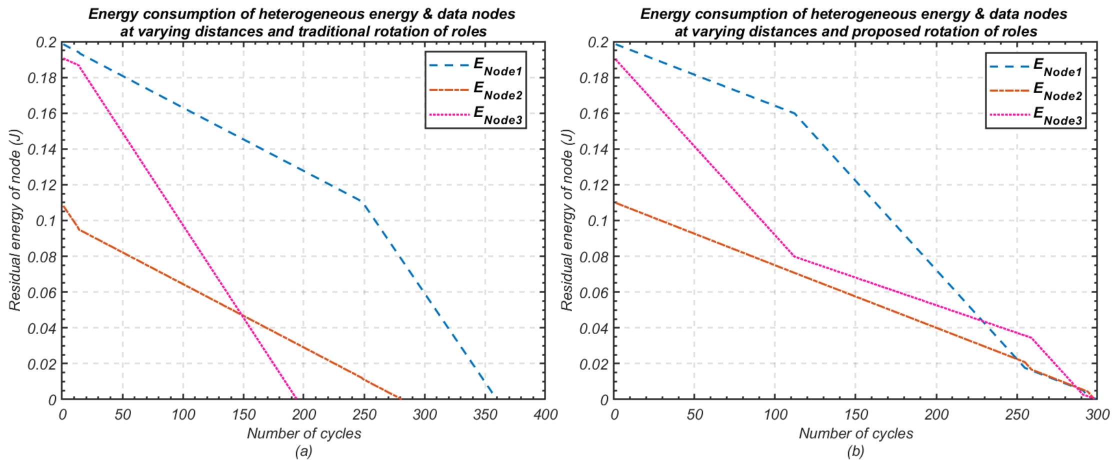



*Figure 5.10: Residual energy comparison using the proposed cluster-head rotation scheme and traditional method (n = 3); (a) Traditional rotation; (b) Proposed rotation.*

The proposed method achieves remarkable improvements as shown in Figure 5.10 (b):

- The first node's energy lasts until 298 cycles, a 53.6% increase in the stability period compared to the traditional method.
- The lifetime gap between the first and last node's energy depletion is minimised, showcasing a converging behaviour that balances energy consumption among nodes.
- The overall lifetime of the cluster is significantly extended, ensuring effective energy utilisation across all nodes.

Figure 5.11 shows per node comparison of the residual energy of each node in the cluster. It is evident that although there is a small decline in the lifetime of Node 1 (Figure 5.11(a)), a consistent rise in the lifetime of Nodes 2 and 3 (Figures 5.11(b) and (c)) has been achieved, which is a clear indication of the effective utilisation of available energy within a cluster.

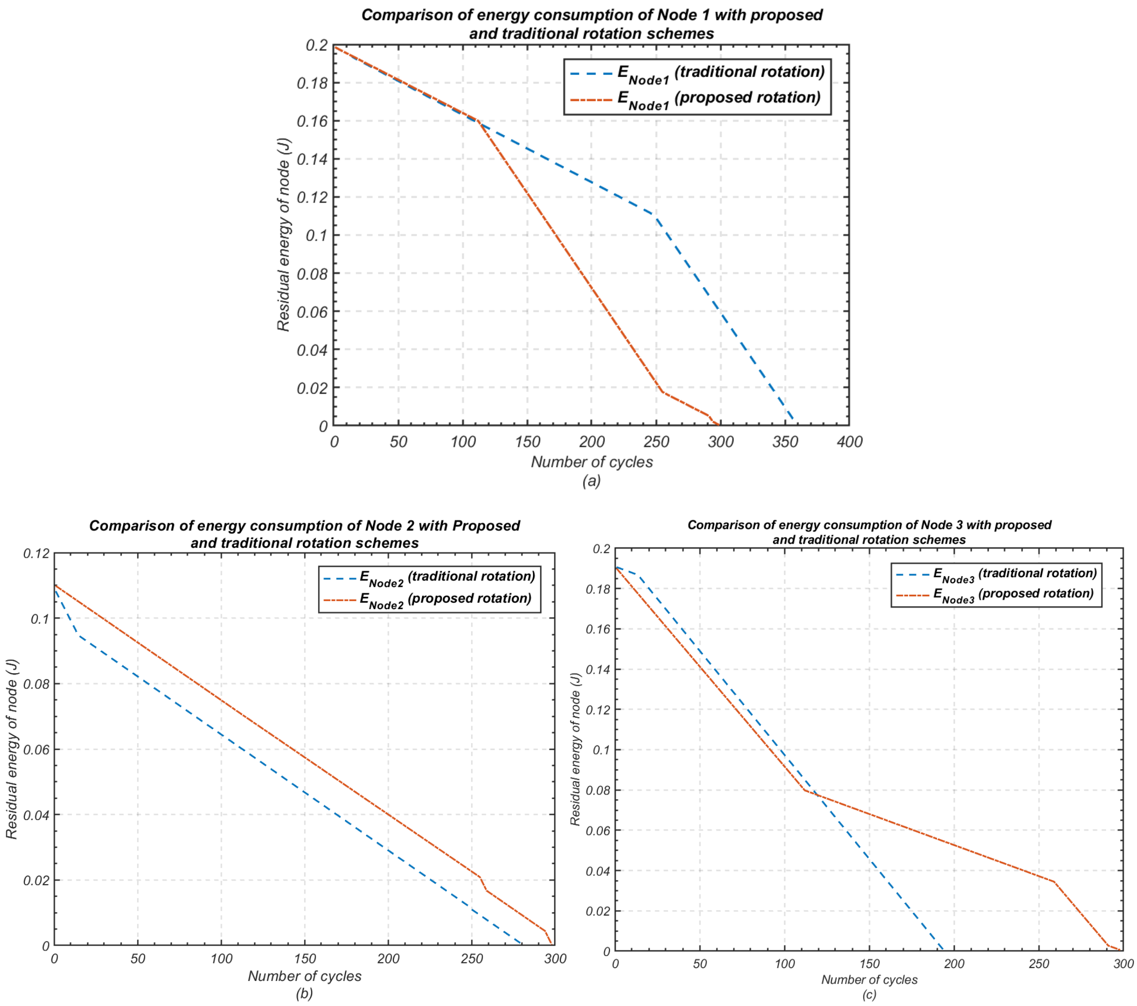



*Figure 5.11: Comparison of residual energies of each node; (a) Energy consumption of node 1; (b) Energy consumption of node 2; (c) Energy consumption of node 3.*

The scalability of the proposed scheme was validated by increasing the cluster size to five nodes, as shown in Figure 5.12. Consistent with the results observed for the three-node cluster, the proposed rotation scheme demonstrates improved energy balancing:

- The first node's depletion is delayed compared to the traditional method, ensuring a longer stability period.
- Convergence in energy usage among all nodes is maintained, even as the cluster size increases.

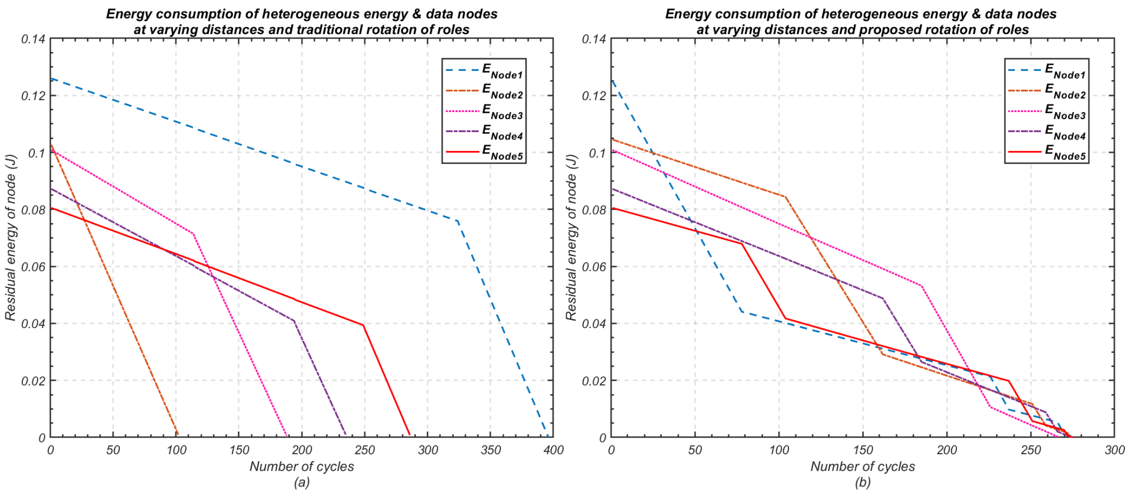



*Figure 5.12: Comparison of residual energy using the proposed cluster-head rotation scheme and traditional rotation (n = 5); (a) Traditional rotation; (b) Proposed rotation.*

This confirms the adaptability and scalability of the proposed method, making it suitable for larger clusters with diverse energy and data rate heterogeneity.

Similarly, Figure 5.13 shows a per-node comparison of the residual energy of each node in the cluster. A relatively small decrease in the lifetime of node 1 (Figure 5.13 (a)) results in significant gains in the lifetimes of node 2, 3, and 4 (Figures 5.13(b)-(d)). Node 5 also shows a very small decrease in network lifetime (Figure 5.13(e)), but the overall cluster lifetime is enhanced.

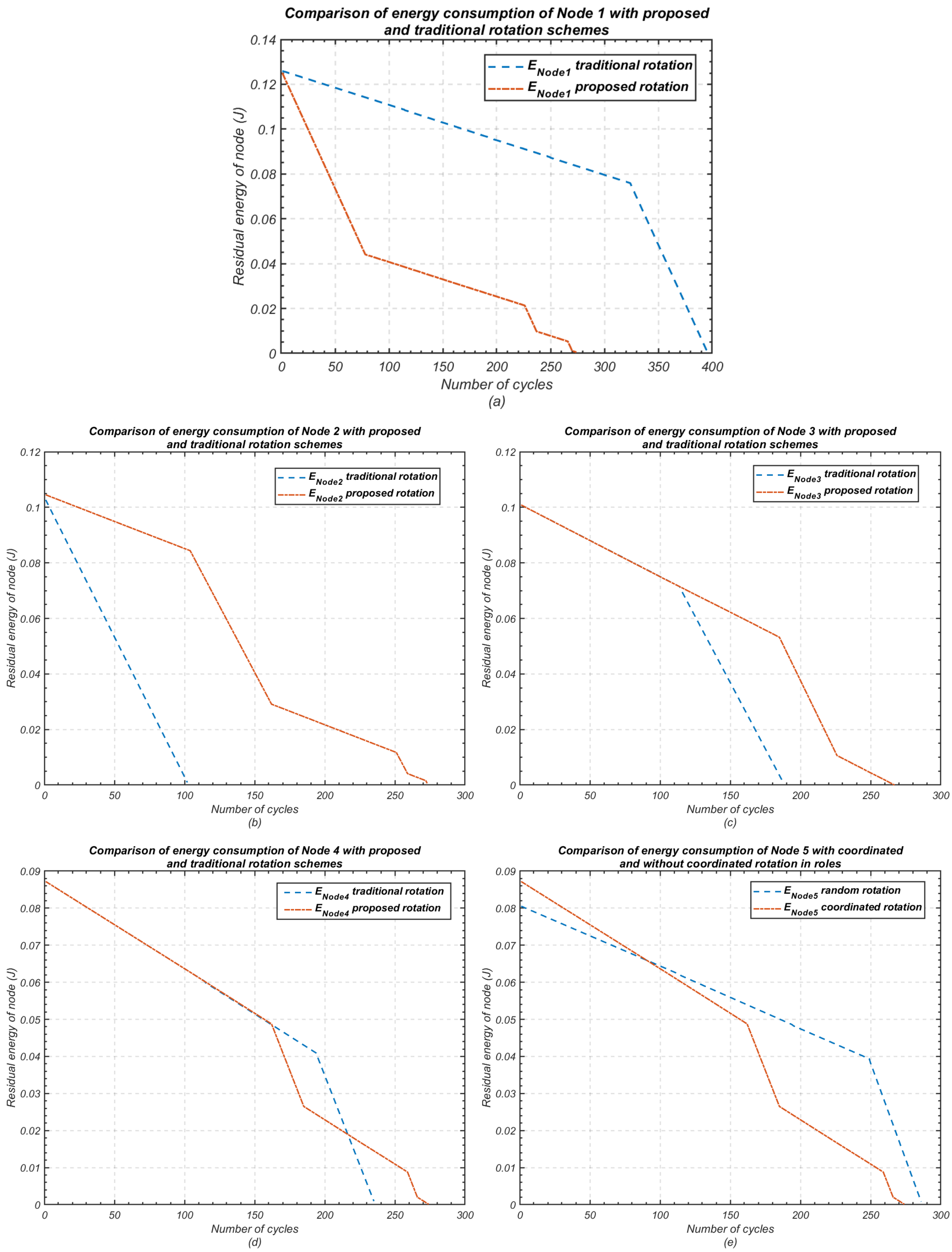



*Figure 5.13: Comparison of residual energy for each node using traditional and proposed rotation methods; (a) Residual energy of node 1; (b) Residual energy of node 2; (c) Residual energy of node 3; (d) Residual energy of node 4; (e) Residual energy of node 5.*

An important aspect of cluster efficiency is the proportion of unused energy when the cluster becomes ineffective, defined by the death of the first node. Figures 5.14 and 5.15 present comparisons of the average and total residual energy across nodes within the cluster for both the proposed and traditional rotation methods.

For a three-node cluster using the traditional method, 33.47% of the total initial energy remained unused by the time the first node depletes its energy after 198 cycles. The proposed method ensures more effective utilisation of the available energy, with reduced residual energy levels before the cluster becomes ineffective, highlighting improved energy balancing as shown in Figure 5.14 (a).

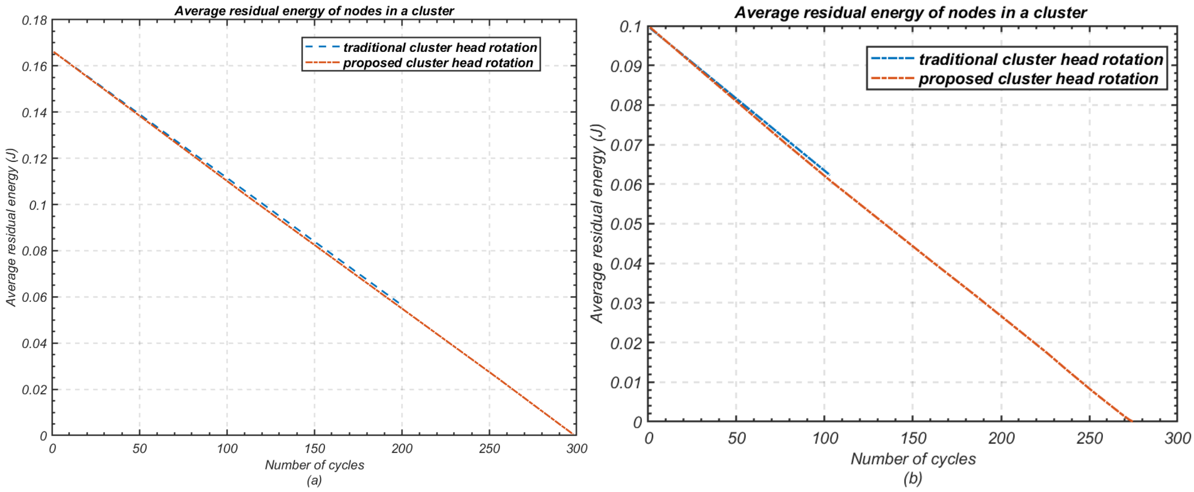



*Figure 5.14: Comparison of average residual energy of nodes in a cluster; (a) Nodes=3; (b) Nodes=5.*

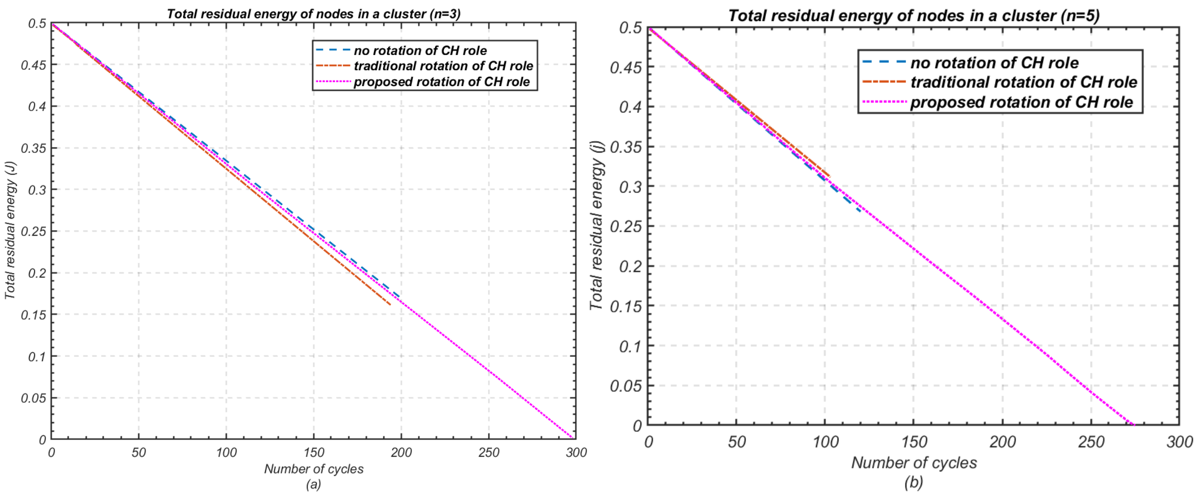



*Figure 5.15: Comparison of total remaining energy of nodes in the cluster; (a) cluster size = 3 nodes; (b) cluster size = 5 nodes.*

For a five-node cluster, the traditional method leaves 62.30% of the total average residual energy unused before the first node dies after only 103 cycles as shown in Figure 5.15 (b). The proposed method substantially reduces unused energy while extending the cluster's operational period, confirming the method's ability to balance energy consumption across all nodes effectively.

The proposed method increases the time to the first node's depletion by 53.6% in three-node clusters, significantly enhancing the network's stability period. It achieves similar energy utilisation improvements in five-node clusters, confirming the method's scalability to varying cluster sizes. The results validate the robustness and scalability of the proposed cluster head rotation method, ensuring consistent performance across heterogeneous and scalable IoT-based WSN.

By balancing energy consumption and extending stability, the proposed method addresses critical challenges in maintaining long-term and energy-efficient operation in heterogeneous WSNs. This analysis forms a strong foundation for exploring further performance improvements in inter-cluster communication and relay node utilisation.

### *ii. Average Energy Consumption*

Average energy consumption of nodes within a cluster is a critical parameter for ensuring the stable and efficient operation of the cluster. This subsection evaluates the performance of the proposed cluster-head rotation scheme in comparison with the traditional rotation scheme and a fixed cluster-head approach, where no role rotation is performed. The goal is to assess how effectively energy is utilised throughout the cluster's operation to maintain stability and prolong lifetime.

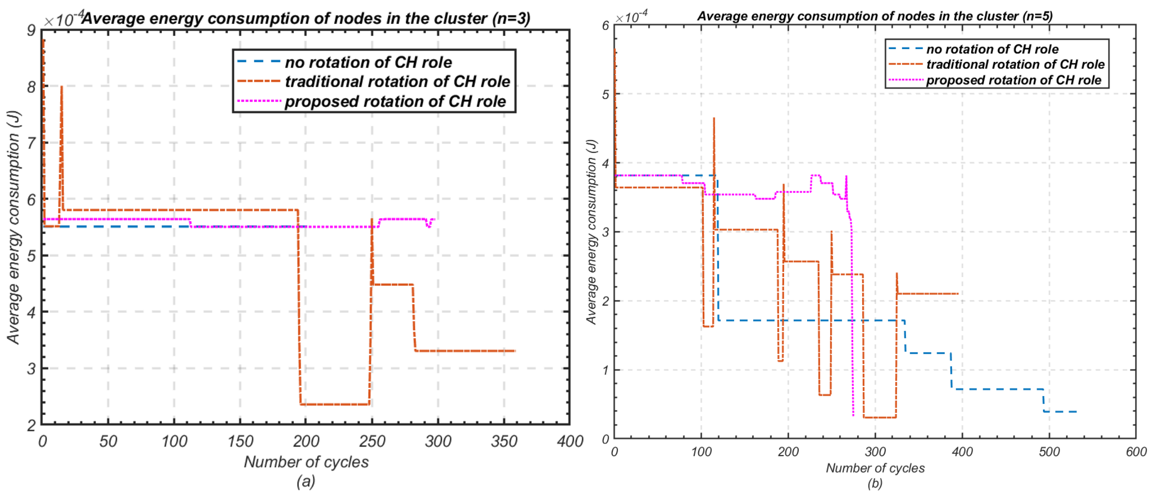



*Figure 5.16: Average energy consumption of nodes within a cluster; (a) Number of nodes n=3; (b) Number of nodes n=5.*

Figure 5.16 illustrates the average energy consumption of nodes in two different scenarios: a cluster with three nodes (Figure 5.16(a)) and one with five nodes (Figure 5.16(b)). The results demonstrate that the proposed cluster-head rotation scheme achieves a relatively stable energy consumption rate, effectively balancing the energy usage among all nodes in the cluster. This balanced consumption ensures that no single node is disproportionately burdened, thereby enhancing the cluster's overall stability and extending its operational lifespan.

In contrast, the traditional rotation scheme exhibits significant fluctuations in energy consumption across nodes, primarily due to early node failures. These failures not only disrupt the energy balance but also result in inefficient use of the remaining energy in the cluster. The erratic energy consumption patterns highlight the traditional method's inability to evenly distribute the workload, leading to reduced stability and shorter operational lifetimes for the cluster.

The fixed cluster-head approach, on the other hand, maintains a steady energy consumption rate during the initial phase of the cluster's operation. However, this method suffers from a critical limitation: once the first node dies, the cluster's energy efficiency drops dramatically. Unlike the proposed method, which adjusts the cluster-head role to balance energy usage, the fixed cluster-head approach fails to adapt to changing conditions within the cluster. Consequently, the remaining energy in the cluster becomes ineffective, as no further data throughput is transmitted to the base station after the first node's death.

### *iii. Throughput to the Base Station*

The effectiveness of a IoT-based WSN system is inherently linked to the amount of data collected and successfully transmitted to the BS. Throughput, serves as a critical metric for evaluating the performance of cluster-head rotation schemes in terms of data transmission efficiency and overall network productivity. In this subsection, the proposed cluster-head rotation scheme is compared against both the traditional rotation method and the fixed cluster-head approach to assess its impact on throughput under varying cluster sizes.

Figure 5.17 illustrates the throughput performance of the proposed method in comparison to the traditional and fixed cluster-head rotation schemes for clusters with three and five nodes. The results clearly demonstrate the superior efficiency of the proposed scheme in delivering data to the BS.

For a cluster with three nodes, as shown in Figure 5.17(a), the proposed method achieves a 50% increase in throughput compared to the fixed cluster-head scheme and a 7.1% improvement over the traditional rotation method. This significant enhancement underscores the proposed method's ability to efficiently utilise energy resources and balance the workload among nodes, ensuring that data transmission is maximised before the cluster becomes ineffective.

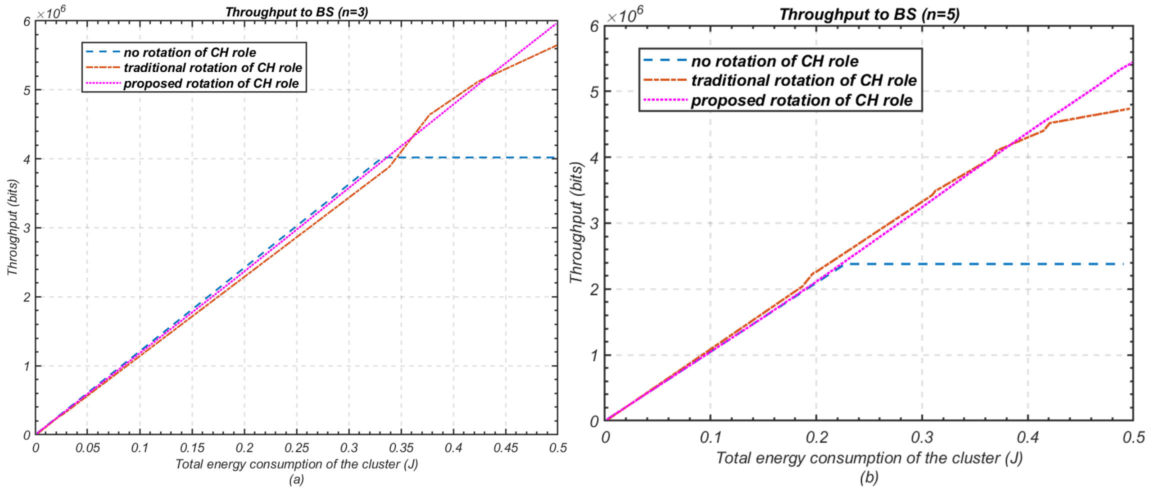



*Figure 5.17: Performance comparison in terms of throughput to BS against energy consumed; (a) Number of nodes = 3; (b) Number of nodes = 5.*

For a larger cluster size of five nodes, as shown in Figure 5.17(b), the performance improvements of the proposed scheme become even more pronounced. The method achieves a 125% increase in throughput compared to the fixed cluster-head approach and a 13% improvement over the traditional rotation scheme. These results emphasise the scalability of the proposed method, which maintains its effectiveness even as the number of nodes and heterogeneity within the cluster increases.

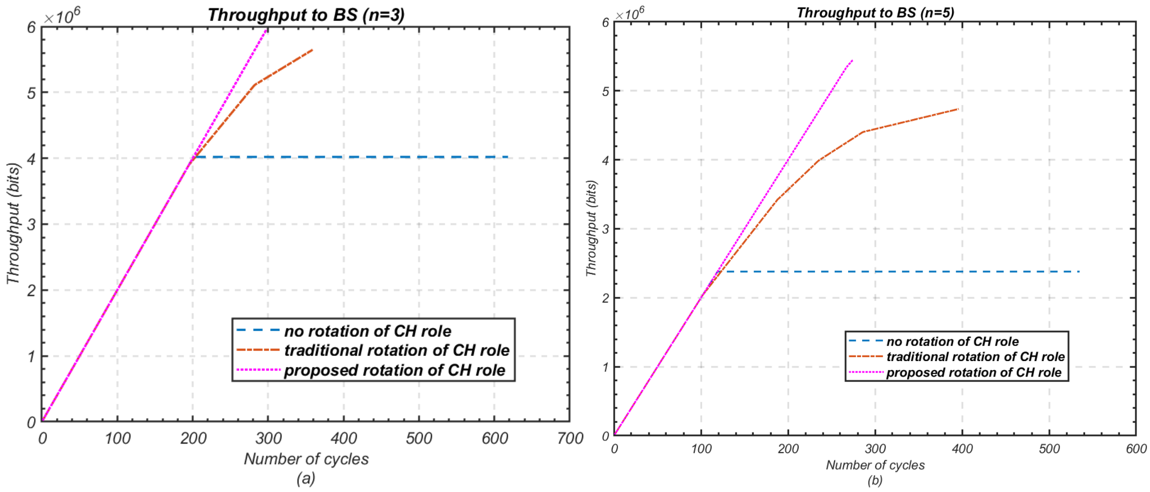



*Figure 5.18: Performance comparison in terms of throughput to BS against the network lifetime; (a) Number of nodes = 3; (b) Number of nodes = 5.*

Figure 5.18 further analyses throughput performance relative to network lifetime for clusters with three and five nodes. In both scenarios, the proposed method consistently delivers higher throughput throughout the network's operational lifespan.

For the three-node cluster, shown in Figure 5.18(a), the proposed scheme achieves a balanced throughput over the network's extended lifetime, ensuring that data transmission remains stable and efficient across the duration of cluster activity. By contrast, the traditional rotation and fixed cluster-head methods exhibit declining throughput over time, with the latter suffering from abrupt drops following the death of the first node.

In the five-node cluster, as shown in Figure 5.18(b), the proposed scheme maintains its throughput advantages, ensuring efficient energy usage and stable data delivery throughout the network's extended operational period. The fixed cluster-head approach, however, again fails to sustain meaningful throughput beyond the first node's depletion, highlighting its inefficiency in energy utilisation and resource management.

The proposed cluster-head rotation scheme significantly improves data transmission to the BS, achieving up to 125% higher throughput compared to the fixed cluster-head method and 13% greater throughput than the traditional rotation method in larger clusters. Moreover, the proposed method demonstrates robust performance across clusters of varying sizes, effectively adapting to increasing node heterogeneity and energy demands. Finally, unlike the fixed and traditional rotation schemes, the proposed method ensures consistent throughput over the network's lifespan, maximising data collection and transmission efficiency.

#### *iv. Network Lifetime Achieved by Intra-Cluster Communication*

The efficient utilisation of heterogeneous node resources is critical for extending the operational lifetime of WSNs, especially in small-scale networks where multi-hop routing may not be necessary for communication between CHs and the BS. This section evaluates the impact of the proposed cluster-head rotation method on the network's lifetime, with a focus on enhancing stability and balanced energy consumption among nodes. The analysis considers two cluster sizes: n=3 and n=5, comparing the proposed method against the fixed cluster-head and traditional cluster-head rotation schemes.

The performance of the proposed method in extending the lifetime of nodes within a cluster is illustrated in Figure 5.19. For a three-node cluster, Figure 5.19(a) demonstrates that without any rotation, the difference between the death of the first and last node is significant, resulting in imbalanced energy utilisation and reduced stability. Specifically, the fixed cluster-head approach exhibits a gap of 417 cycles between the first and last node's death, reflecting a lack of coordination in energy management.

The traditional rotation method reduces this gap to 165 cycles, offering moderate improvements in energy balancing. However, the proposed cluster-head rotation scheme significantly enhances performance by ensuring near-equal node lifespans. This demonstrates the method's capability to minimise energy disparities among nodes, leading to enhanced stability and a more balanced network operation.

For a larger cluster size (n=5), the results, as shown in Figure 5.19(b), exhibit similar trends. The fixed cluster-head method results in a 415-cycle difference between the first and last node's depletion, highlighting inefficient resource utilisation. The traditional rotation method reduces this gap to 294 cycles, while the proposed method achieves a difference of only 8 cycles, indicating almost uniform energy consumption across nodes.

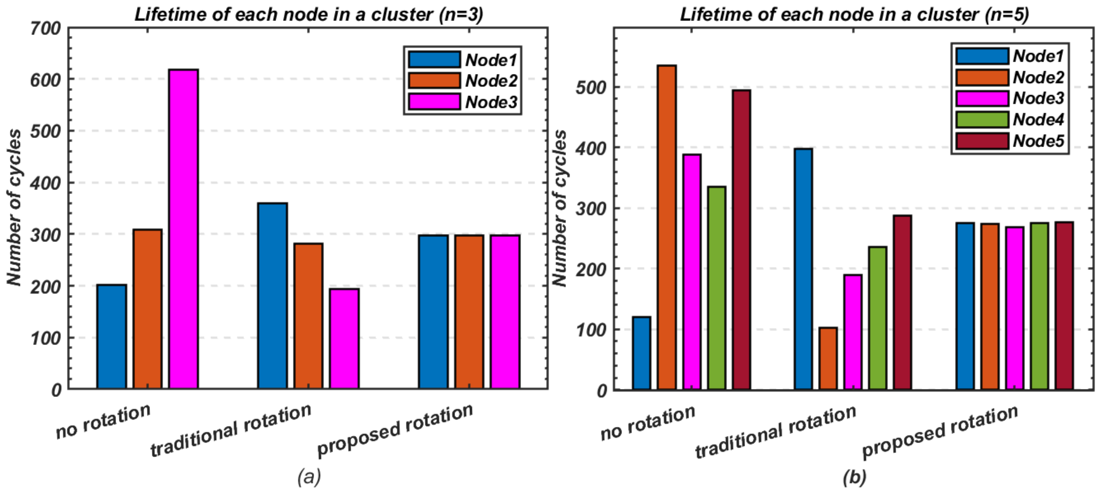



*Figure 5.19: Comparison of lifetime and stability; (a) Number of nodes = 3; (b) Number of nodes = 5.*

The overall cluster lifetime, measured in terms of the first node death (FND) and last node death (LND) scales, is summarised in Figure 5.20. The proposed method achieves notable improvements in extending the cluster's operational period on both scales, ensuring consistent performance throughout the network's lifetime.

For a three-node cluster, as shown in Figure 5.20(a), the proposed method extends the FND scale significantly compared to the fixed and traditional rotation schemes. This extension ensures that the cluster remains operational for a longer period before the first node depletes its energy, thus enhancing the network's reliability in real-world scenarios. The LND scale is similarly improved, with a more gradual decline in performance as nodes approach energy depletion.

In the case of a five-node cluster, depicted in Figure 5.20(b), the proposed method continues to demonstrate its robustness. The FND scale is extended significantly, ensuring that the network remains functional for a prolonged period. Additionally, the method maintains stability on the LND scale, further validating its suitability for heterogeneous IoT-based WSN applications.

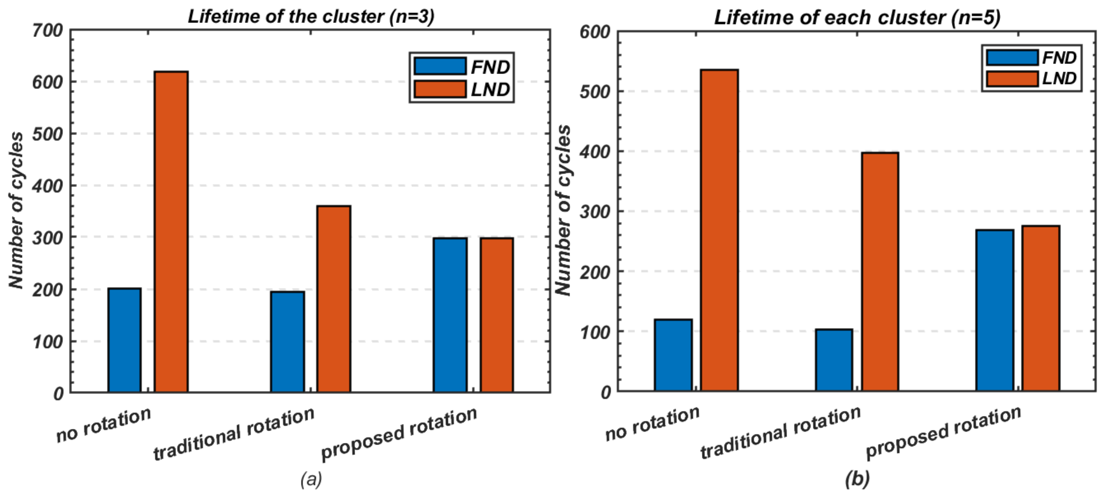



*Figure 5.20: Comparison of overall cluster lifetime on (FND) and (LND) scales; (a) Number of nodes = 3; (b) Number of nodes = 5.*

The proposed method achieves a nearly uniform node lifespan, reducing the gap between the first and last node's energy depletion to 8 cycles for n=5, compared to 294 cycles with the traditional rotation scheme and 415 cycles with the fixed cluster-head method. On both the FND and LND scales, the proposed method outperforms the fixed and traditional schemes, ensuring longer operational periods and stable performance. By balancing energy consumption among nodes, the proposed method extends the network's stability and maximises resource utilisation, addressing critical challenges in heterogeneous WSNs.

### 5.6.2 Inter-Cluster Communication

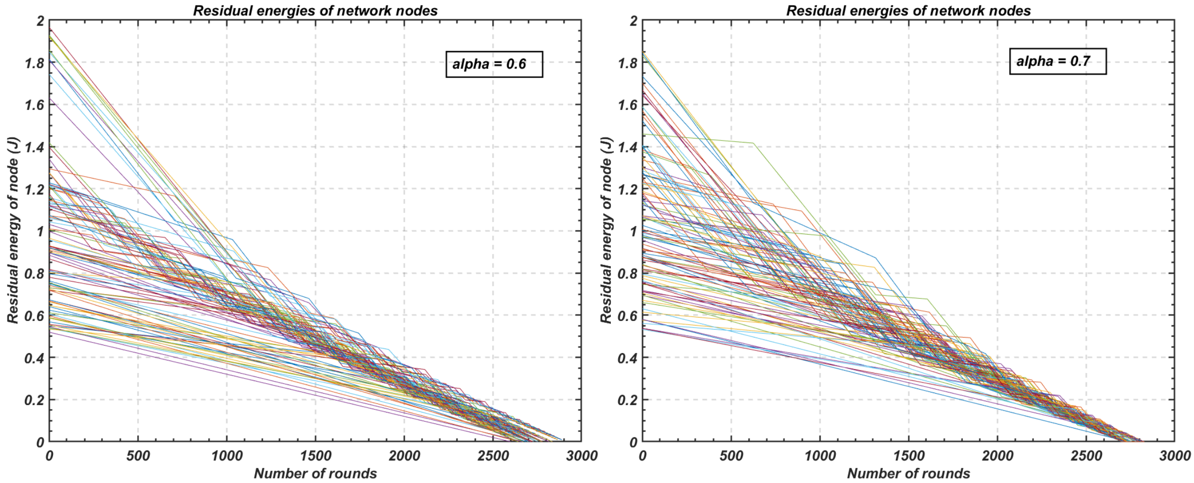
This section presents a detailed evaluation of the proposed inter-cluster communication scheme based on relay node selection and rotation. The experiments aim to validate the effectiveness of the proposed method in achieving a balanced energy operation and prolonging the network lifetime in IoT-based HWSNs.

Simulation parameters of Table 5.1 are used for the experiments to evaluate the performance of inter-cluster communication however, a complete network of 100 nodes is considered instead of only one cluster. Following subsections elaborate the performance evaluations of the proposed inter-cluster communication against the QoS metrics.

#### i. Network Lifetime and residual energy of nodes

To assess the performance of the proposed inter-cluster communication scheme, the network lifetime of each node was evaluated. The term network lifetime is defined as the number of rounds of operation before the first node depletes its energy First Node Death, (FND) and the last node depletes its energy Last Node Death, (LND). Here, a round refers to the complete cycle of sensing, intra-cluster communication to the cluster head, and inter-cluster communication from the cluster head to the base station via multi-hop routing. This section presents a sensitivity analysis of the α-reselection factor, which governs how frequently relay nodes are rotated. The analysis assesses its effect on network performance in terms of lifetime, energy distribution, and balance between stability and longevity.

The results of residual energy for all 100 nodes over the operational rounds are depicted in Figure 5.21. The analysis highlights the critical role of the proposed relay node rotation scheme in achieving balanced energy consumption across the network. Figure 5.21(a) shows when the value of $\alpha$ (the re-selection factor controlling relay node rotation frequency) is set to 0.6, the network achieves an FND at the 2602nd round and an LND at the 2890th round. The $\alpha$-factor allows dynamic adjustments to the frequency of relay node re-selection, enabling flexibility in balancing energy consumption. Although the network achieves a stable operation, there is a moderate difference between FND and LND scales, indicating potential room for further optimisation.




(a) (b)

*Figure 5.21: Comparison of residual energy of nodes with proposed relay node rotation scheme (a) alpha=0.6 & (b) alpha=0.7.*

Figure 5.21(b) shows that by increasing $\alpha$ to 0.7, significant improvements in stability and convergence of node lifetimes are observed. The network's FND rises to the 2703rd round, marking an increase in operational lifetime by over 101 rounds. Notably, the LND decreases slightly to the 2830th round, demonstrating a trade-off between stability and total network lifetime. This highlights the $\alpha$-factor's effectiveness in optimising network performance according to specific application requirements.

The proposed relay node rotation scheme ensures balanced energy consumption among nodes, as evidenced by the consistent residual energy levels across the network during the simulation. The rotation mechanism dynamically reassigns relay roles to nodes with higher residual energy, preventing premature energy depletion in critical nodes and extending the overall network lifetime. Additionally, the ability to adjust $\alpha$ provides a valuable tool for network administrators to balance stability and efficiency, depending on the application's demands.

The proposed scheme significantly improves the FND scale, extending the operational period of the network before the first node depletes its energy. This ensures reliable performance over extended durations. By increasing the $\alpha$-factor, the proposed method achieves higher stability, reducing the disparity in node lifetimes. This results in more uniform energy utilisation across the network. The method demonstrates scalability by effectively managing 100 nodes with diverse energy capacities and data rates. Its adaptability is highlighted through the $\alpha$-factor, allowing customisation for various deployment scenarios.

### *5.6.3 Overall Performance Evaluation*

This section provides a comprehensive analysis of the proposed methods in terms of their overall performance. The evaluation includes metrics such as the residual energy of the network, overall network lifetime, and throughput to the base station. The proposed cluster head rotation and balanced energy inter-cluster communication schemes are compared against state-of-the-art methods, namely RLEACH [191], CRPFCM [192], [193], and EERPMS [193]. The results demonstrate the significant improvements achieved by the proposed methods, underlining their effectiveness in addressing key challenges in HWSNs.

#### *i. Overall Residual Energy of the Network*

Cluster heads in WSNs often consume substantially more energy than normal nodes due to their additional responsibilities, including receiving, aggregating, and relaying data to the base station. This disproportionate energy consumption is further exacerbated in heterogeneous networks, where low-resource nodes may deplete their energy rapidly if selected as CHs. Additionally, in large-scale networks, the load imbalance caused by multi-hop inter-cluster communication further accelerates energy depletion in certain nodes.

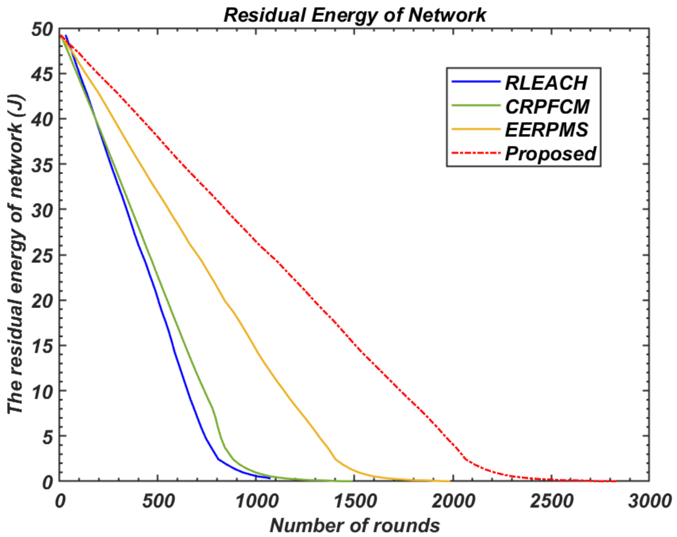



*Figure 5.22: Comparison of overall residual energy of the network.*

The proposed methods address these challenges by incorporating minimum energy consumption rate and resource-aware relay node selection. This means that the nodes with low energy consumption rates are prioritised for CH selection and nodes with higher energy reserves and favourable positioning are preferred for relaying tasks, ensuring balanced energy consumption.

Figure 5.22 illustrates the residual energy levels of the network after several rounds of operation. Compared to the benchmark methods, the proposed approach maintains significantly higher residual energy across the network. More precisely the proposed method achieves approximately 22% higher residual energy compared to EERPMS [193]. When compared to CRPFCM [192], [193] and RLEACH [191], the proposed method retains 38% and 45% more residual energy, respectively.

These results confirm that the proposed schemes effectively balance the load across the network, extending the operational period and maintaining higher energy reserves for prolonged functionality.

### *ii. Overall Network Lifetime*

The network lifetime is a critical performance metric for WSNs, often measured using the following scales:

- *First Node Death (FND):* The round in which the first node depletes its energy.
- *Half Nodes Death (HND):* The round in which half the nodes deplete their energy.
- *Last Node Death (LND):* The round in which the last node depletes its energy.

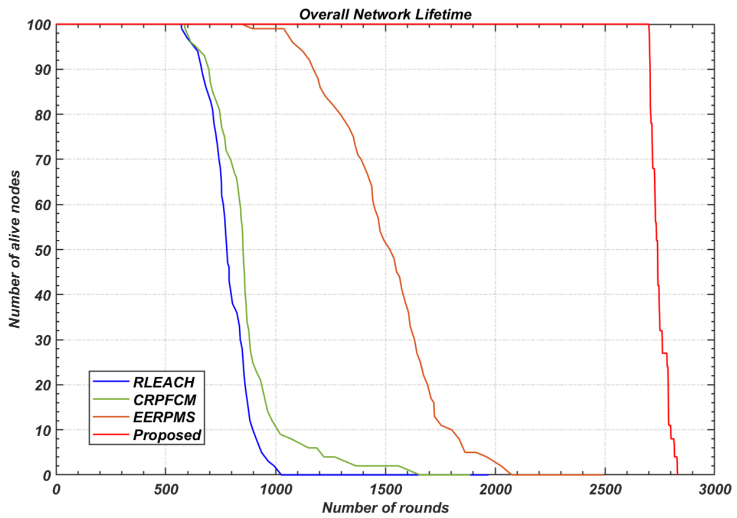
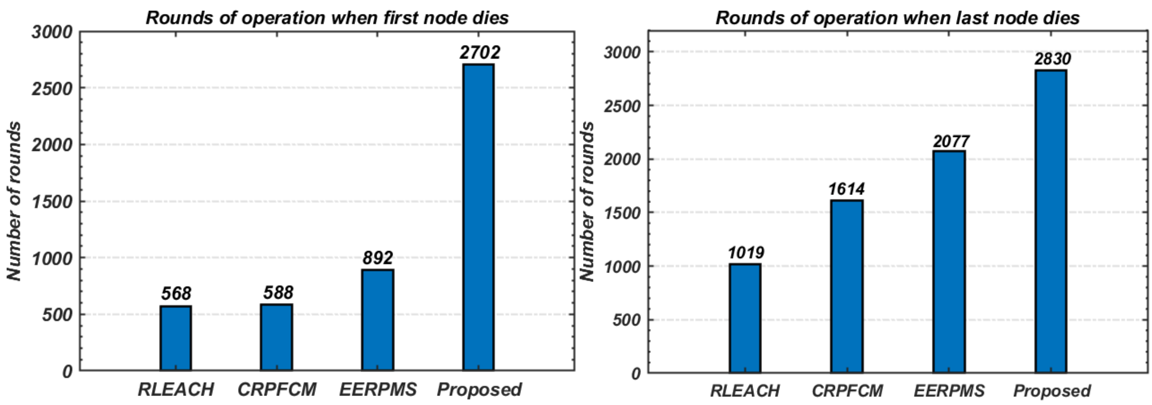



*Figure 5.23: Number of alive nodes vs number of rounds.*

Network lifetime is heavily influenced by energy consumption per round. Reducing this consumption extends the operational period before nodes become inactive. The proposed schemes achieve this by optimising intra-cluster and inter-cluster energy usage, particularly through the dynamic rotation of cluster heads and relay nodes.

Figure 5.23 illustrates the number of active nodes as a function of the number of operational rounds. The proposed methods demonstrate superior performance:

- *FND Scale:* The first node depletes its energy after 2682 rounds, representing an 18.7% improvement compared to EERPMS [193].
- *LND Scale:* The last node remains active until 3101 rounds, a 24.5% increase over CRPFCM [192], [193] and a 31% gain over RLEACH [191].




(a) (b)

*Figure 5.24: Comparison of overall network lifetime (a) FND scale (b) LND scale*

The results in Figure 5.24 further highlight that the proposed method delays FND by 21% and 28% compared to CRPFCM [192], [193] and RLEACH [191], respectively. The LND scale shows similar gains, with the proposed method consistently outperforming all benchmark methods.

These enhancements are attributed to the energy balancing strategies employed by the proposed schemes, ensuring uniform energy utilisation and prolonging network stability.

### *iii. Throughput to the Base Station*

In IoT-based HWSNs, throughput represents the amount of data successfully collected and delivered to the base station. High throughput is a critical indicator of a network's efficiency and effectiveness in energy utilisation. The proposed cluster head rotation and relay node rotation schemes prioritise data transmission efficiency, ensuring minimal energy wastage and maximising data delivery.

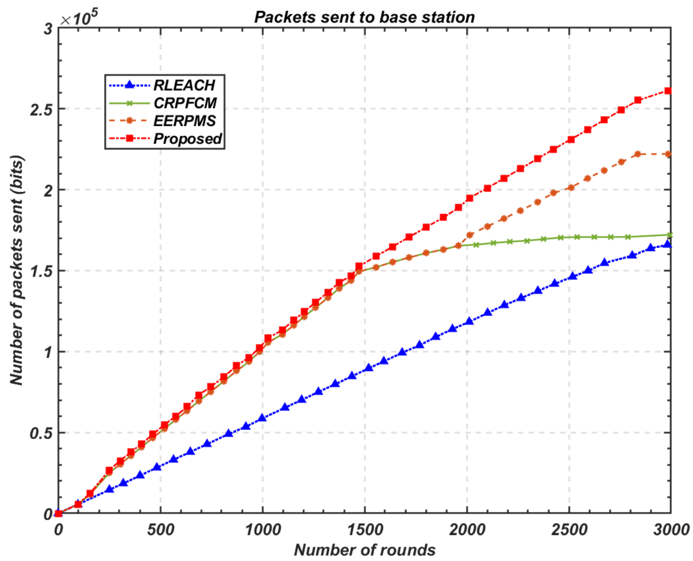



*Figure 5.25: Comparison of throughput to base station.*

Figure 5.25 compares the throughput achieved by the proposed methods with benchmark schemes. The results demonstrate remarkable improvements. The proposed method achieves a 17.63% increase in throughput as compared to EERPMS [193], 51.75% more data than CRPFCM [192], [193] and 57.44% improvement in throughput as compared to RLEACH [191].

These improvements are as a result of the energy-efficient routing and enhanced stability. Energy efficient routing is performed using optimised relay nodes and balanced load distribution that reduces energy wastage during data transmission and enhanced stability is achieved by prolonging operational period of nodes that continues data collection efficiently for the extended durations. The next section presents a summary of the proposed intra and inter cluster communication schemes.

## 5.7 Summary

This chapter introduced novel methods for balanced energy routing in IoT-based HWSNs, focusing on cluster head rotation, inter-cluster relay node selection, and relay node rotation. The proposed cluster head rotation method effectively balances intra-cluster energy consumption, ensuring enhanced stability and significantly extending network lifetime. The approach demonstrates adaptability to multi-parameter and multi-level heterogeneity scenarios, achieving superior performance compared to traditional and fixed cluster head rotation schemes.

The inter-cluster communication strategy introduced conditions for determining the energy efficiency of direct versus multi-hop communication, with an optimal relay node selection method ensuring balanced energy usage across nodes. Additionally, the relay node rotation scheme further improved network stability and throughput, outperforming state-of-the-art methods like RLEACH, CRPFCM, and EERPMS. The results validated the scalability, energy efficiency, and increased lifetime of the proposed techniques, highlighting their applicability to diverse IoT-based HWSN environments.

*Table 5.2: Overview of Proposed Relay Strategy and Popular Classical Routing Protocols*

| Routing Strategy | Energy Efficiency | Scalability | Routing Latency | CH Energy Balance | Suitability for HWSNs |
|---|---|---|---|---|---|
| MTE | Low | Low | Low | Poor | × |
| PEGASIS | Moderate | Low | High | Fair | × |
| Geographic | High (location-based) | Moderate | Moderate | Good | ✓(with extension) |
| Proposed Method | High | High | Moderate | Excellent | ✓ |

As shown in Table 5.2, the proposed relay strategy demonstrates higher energy efficiency and better scalability than MTE and PEGASIS, which suffer from limitations such as fixed paths and poor adaptability to energy heterogeneity. While geographic routing can be energy efficient, it typically relies on accurate location information, which may not always be feasible in all WSN applications. In contrast, the proposed scheme adaptively selects relay nodes based on multi-parameter metrics including residual energy and data traffic, making it more robust and responsive in heterogeneous and dynamic IoT environments.

This comprehensive evaluation lays a strong foundation for future work, including addressing mobility challenges to support robust and reliable connectivity in dynamic IoT-based sensor networks. The routing latency and communication overhead introduced as a result of multi-hop routing and relay rotation algorithms can also be reduced.

# Chapter 6

# Conclusions and Future Directions

## 6.1 Conclusions

The continued technological developments and diverse applications of wireless sensor networks have led increasing number of research communities to make effort and to contribute to this area. Due to the characteristics of sensing applications and the growing demands for data collection from environments with varying terrains, WSNs are usually deployed across multiple spatial dimensions such as 2D or 3D, and in various shapes. Sensor nodes are inexpensive resource constrained devices that consist of a sensor, embedded processor, limited memory, low power radio, and are normally powered by a battery. WSNs are inherently suffering from problems due to their resource constrained nature particularly while deployed in hostile environments. Regardless, of the environment energy efficient data collection by these sensor nodes is a primary quality of service criterion. Varying deployment spatial dimensions, shape requirements, and diverse resources on sensing devices introduce significant heterogeneity among these devices. The integration of Internet of Things (IoT) enables the collected data to be made available online, enhancing service delivery. This improves the quality of service for citizens but also adds complexity to system design. In particular, it raises challenges in ensuring energy-efficient operation and prolonging the longevity of such networks.

Moreover, the difference between the time when first node drains its energy and when last node drains its energy makes a huge impact on the effective performance and complete coverage of the wireless sensor networks. Consequently, lifetime enhancement is one of the key issues while designing deployment scheme to segmenting and clustering the network nodes and eventually while designing a routing topology for these WSNs with heterogeneous resources and accessibility to internet through IoT.

The following sections provide a summary of the research challenges, along with the proposed sink node deployment schemes, proposed network segmentation methods, proposed unequal clustering techniques, and proposed coordinated cluster head and relay node selection and rotation schemes, all aimed to enhance energy-efficient routing strategies.

### *6.1.1 Research Challenges*

IoT-based WSNs are essential in improving the quality of life in modern cities by enabling coordinated service delivery, made possible through timely access to relevant data shared across multiple applications. However, the varying sensing mechanisms and applications introduce significant challenges, as sensor nodes in these networks exhibit a wide range of inherent heterogeneities, including variations in data rate, sensing range, computational power and energy consumption. These disparities are further amplified by the distinct demands of each application, where sensing periods and data transmission tasks different considerably. Such heterogeneities necessitate a detailed and holistic consideration of multi-parameter and multi-level variations when designing deployment strategies and hierarchical energy-efficient routing schemes. The designs are required to not only account for the operational parameters of individual sensor nodes but also integrate these variations in a dynamic manner to optimise the network performance and energy utilisation.

Moreover, the deployment of heterogeneous devices across varying terrain surfaces, spanning both two-dimensional and three-dimensional spaces, introduces significant challenges due to the specific needs of different applications. Many protocols that assume a fixed network shape face substantial limitations in terms of adaptability, scalability, and stability, especially when confronted with the dynamic nature of real-world environments. The situation is further exacerbated when deployed in hostile environments that hinder the replacement or recharging of resources on these constrained devices, leading to rapid depletion of energy and inefficient operations. This becomes even more complex as network scale up, where variations in device capabilities and network structures introduce additional complexity. Therefore, a dynamic, flexible, and scalable routing topology that can adapt to the ever-changing network shapes and dimensions is required.

Moreover, due to varying scales of such networks, the protocols must first be able to make an efficient choice between direct and multi-hop communication. Determining the optimal cluster size is another critical issue to ensure balanced energy consumption, as cluster heads closer to base station may become overloaded due to additional relaying load from external cluster heads in multi-hop inter-cluster communication. Additionally, as resources within the network continuously change and are updated during operation, it becomes increasingly difficult to maintain optimal performance.  A flexible, scalable, and adaptive system is required to handle dynamic cluster head selection and rotation in different scenarios. Furthermore, not only is cluster head selection crucial, but the challenge extends to the next-hop relay node selection, as ensuring balanced energy consumption across both cluster heads and relay nodes is essential to maintaining network longevity.

In order to resolve the aforementioned research challenges within resource constrained IoT-based HWSNs, this study proposed energy efficient and reliable design solutions for collaborative sensing and communication schemes.

### *6.1.2 Energy Efficient Deployment of Base Station in Diverse HWSNs*

In this thesis, the problem of balanced energy consumption among network nodes while keeping maximum network lifetime has been explored in detailed. A thorough framework has been proposed to achieve the required goals of energy savings, network longevity, finally scalable, adaptable and flexible operation. First step in the framework was optimising the deployment of the BS in HWSNs. This was a fundamental challenge due to heterogeneous resources and varying communication costs of the network nodes. Firstly, an iterative method has been presented that determined an optimum location for the deployment of base station within a HWSN. Although the iterative method produces good results, the increased computational complexity of the iterative method adds a limitation to this method. Therefore, a multi-criteria decision-making technique, Technique for the Order of Preference by Similarity to Ideal Solutions (TOPSIS) was integrated to identify optimal location of the base station in diverse network scenarios. This approach accounts for energy consumption, distance, traffic load, and node density, providing a dynamic and adaptive solution for the BS deployment in heterogeneous environments.

The performance of both proposed methods was evaluated through MATLAB simulations. The results demonstrated that the proposed deployment methods significantly reduced energy consumption, with up to 25% improvement over central and average-coordinate deployments in both uniform and non-uniform topologies. This work laid a foundation for balanced network operation, ensuring equitable energy usage among nodes, which directly contributes to extended network lifetime and improved service reliability in large-scale IoT deployments.

### *6.1.3 Dynamic Shape Independent Network Segmentation*

Network segmentation was identified as a critical strategy for managing energy consumption in networks with varying shapes. The proposed segmentation schemes, which include cubed-shaped, spherical-shaped, and shape-independent approaches, provide scalable and adaptable solutions for partitioning large-scale networks. The cubed-shaped segmentation is particularly effective in in cube or square-shaped networks. The algorithm begins by determining the scale of the network, which then dictates how the network is divided into non-overlapping sub-cubes. By calculating the boundary coordinates of these sub-cubes, the algorithm can assess resource distribution within smaller segments of the network. In a similar way the proposed spherical segmentation is also a shape specific segmentation and is suitable for circular or spherical shaped networks. In spherical segmentation the network is segmented into equal sized coconut shaped circular segments and each segment is further divided into sectors. The boundary coordinates of sectors allow the algorithm to determine the distribution of nodes and corresponding resources within each segment.

The fixed shape approaches take into account that some resources contribute positively to the balanced energy consumption problem, while others have negative impact. To address this, the algorithms incorporate an unequal cluster head distribution strategy, which is based on resource distribution across different segments of the network.

Finally, to alleviate the shape dependency of segmentation schemes a shape-independent adaptive segmentation was proposed. This scheme considered the data traffic load to be transmitted as a foundation for the network to be segmented. Therefore, the network was divided into layers of equal data traffic and then divided into segments of equal data traffic. The proposed shape-independent adaptive segmentation, coupled with unequal clustering scheme, ensured consistent energy efficiency across various topologies, regardless of their geometric configurations.

Simulation results revealed that the adaptive segmentation and unequal clustering approach achieved an average energy savings of 18% compared to fixed geometric segmentation schemes, while maintaining uniform energy distribution. The segmentation also facilitated effective hierarchical clustering, directly impacting inter-cluster communication efficiency. By addressing the spatial heterogeneity inherent to real-world IoT-based networks, this research bridged a critical gap in existing segmentation techniques.

### *6.1.4 Energy Efficient Unequal Clustering*

The proposed hierarchical clustering techniques developed introduced unequal clustering methods tailored to the unique demands of HWSNs. The proposed unequal clustering method utilises a weighted calculation of node positions, where the cluster centroid is determined based on resource distribution, including energy and data rate. Specifically, the formulas for calculating the centroids in the x, y, and z directions take into account the energy levels and data rates of individual nodes in each cluster, with the weighting factors being adjusted according to the relative energy and data transmission capabilities of the nodes. These clustering strategies ensured balanced energy distribution within clusters, mitigating the "energy hole" problem that often arises near the base station. The proposed methods integrated dynamic cluster sizes, leveraging node attributes such as residual energy and data rates, to further enhance intra-cluster energy efficiency.

The simulations demonstrated that the proposed unequal clustering methods outperformed traditional approaches such as IUCR and ECUC. Specifically, the network lifetime on the First Node Death (FND) scale improved by up to 32% compared to state-of-the-art clustering protocols. Furthermore, the ability to dynamically adapt clustering to node heterogeneity and network scale ensured stable and consistent performance, underscoring the robustness of the proposed schemes.

### *6.1.4 Energy Efficient Dynamic Routing*

Routing in HWSNs was comprehensively addressed through the development of balanced energy intra cluster as well as inter-cluster communication schemes. The proposed methods encompassed cluster head rotation, relay node selection and rotation algorithms, which optimised the energy expenditure. These routing schemes were designed to dynamically balance load among nodes, accounting for varying levels of heterogeneity in energy and data rates.

The proposed methods introduced a versatile heterogeneity model and a comprehensive mathematical framework, forming the basis for evaluating the performance of networks with varying node capabilities. This model effectively addresses the complexities of energy distribution among nodes, ensuring efficient network operation. A novel cluster head rotation method is proposed which calculates the anticipated energy consumption within a cluster by considering each node as a potential cluster head. The node with the lowest overall energy consumption, provided its energy exceed predefined threshold, is selected as the cluster head.

Furthermore, the algorithm also incorporates a dynamic cluster head rotation approach. When a node’s residual energy falls below a dynamically adjusted threshold, based on the resources within the cluster, its cluster head role is reassigned. This process is driven by real-time energy consumption calculations and load balancing, ensuring that the network remains energy-efficient and that cluster heads are rotated effectively to prevent premature energy depletion.

Additionally, a dynamic approach was proposed to determine an energy efficient region for selecting the next-hop relay node. This method not only determines the optimal relay node based on energy consumption across the network, but also ensures that relay nodes are effectively utilised without overburdening any single node, thereby enhancing the network's energy efficiency and prolonging its operational lifetime.

The performance evaluation demonstrated that the proposed methods significantly outperformed benchmark algorithms such as RLEACH, CRPFCM, and EERPMS. The proposed relay node selection and rotation schemes extended the network lifetime on the FND scale by up to 18% and increased throughput to the base station by 17.63% compared to EERPMS, while delivering up to 57.44% more data than RLEACH. These results highlight the efficiency and scalability of the proposed routing solutions in addressing the unique challenges of HWSNs.

## 6.2 Research Limitations

Although the proposed schemes lead to significant energy savings and balanced energy consumption, the following aspect of this research requires further investigation.

- The varying sensing mechanisms in the proposed model could benefit from the integration of advanced energy harvesting methods, adding an additional layer of heterogeneity. While the current heterogeneity model can be extended to incorporate a wider set of heterogeneous parameters, doing so may introduce added complexity to the algorithms. This expansion would require further investigation and evaluation to ensure it does not compromise the efficiency and scalability of the system.
- This research primarily considers static sensor nodes, but modern sensor networks, including those with mobile nodes such as drones, present additional challenges. While not all sensor networks require mobility, this type of network could significantly contribute to delivering optimised services in smart infrastructures like smart cities. Adapting the proposed methods to effectively handle networks comprising both mobile and static sensors could present a new dimension to the work.

## 6.3 Future Directions

While the research presents comprehensive solutions to several critical challenges in IoT-based HWSNs, there remain opportunities for future exploration. The integration of mobile nodes is a promising area of research, as mobility introduces additional complexity in maintaining connectivity, stability, and energy efficiency. Future work could develop adaptive clustering and routing protocols tailored for networks with mobile nodes, ensuring seamless performance in dynamic environments.

The inclusion of energy harvesting techniques represents another potential avenue for enhancing network sustainability. By combining energy harvesting with efficient resource utilisation, future research can address the challenges of long-term operation in remote and resource-constrained environments.

Moreover, incorporating machine learning and artificial intelligence techniques can revolutionise HWSNs by enabling predictive analytics, adaptive decision-making, and real-time optimisation. This would allow for more intelligent and autonomous network operation, further improving scalability and adaptability.

Future work may also explore integrating terrain-aware or obstacle-aware models, such as smart buildings or forests, to assess the performance of the proposed methods under physical obstructions and signal propagation constraints.

Finally, real-world deployment and testing of the proposed methods in large-scale IoT applications, such as smart cities, precision agriculture, and disaster monitoring, would provide valuable insights into their practical applicability. Such deployments would also allow evaluation of robustness under real-time conditions, including unpredictable energy drain, relay node failure, and network congestion. Collaborations with industry stakeholders can help bridge the gap between academic research and real-world implementation, ensuring the resilience and scalability of these innovative solutions.

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# Appendices

# Appendix - A

Appendix A presents extended literature review on the applications of WSNs to highlight the significance of this area further.

## Wireless Sensor Networks: Applications and Demands:

Advancements in microelectromechanical systems (MEMS) and communication technologies have enabled not only people but also devices to communicate at any time, with anything or anyone, using any network and service [94]. Wireless sensors play a critical role in IoT systems, enabling flexible and informed operations. A key function of wireless sensors is the transmission of sensed data to a BS, and hierarchical routing using clustered sensor nodes has been proven to be an energy-efficient method for such data transmission.

Recent technological advancements have significantly transformed IoT-based WSNs, facilitating the development of cost-effective, compact, and multi-functional sensor nodes. These nodes can be equipped with various types of sensors, such as thermal, seismic, acoustic, magnetic, infrared, and visual sensors, depending on the specific application requirements [96]. As a result, IoT-based WSNs are capable of monitoring a wide range of environmental conditions, including pressure, humidity, temperature, direction, speed, noise levels, light intensity, and mechanical stress.

This adaptability makes IoT-based WSNs well-suited for a broad array of applications, including habitat monitoring, climate control, home automation, ocean observation, disaster management, and logistics support. Figure 2.1 in chapter 2, categorise the existing applications of IoT-based WSNs, with some key applications.

### *Agriculture & Environment:*

WSNs integrated with IoT technologies have revolutionised agriculture and environmental monitoring by enabling real-time data collection and decision-making. These advancements have significantly improved resource management, environmental sustainability, and productivity in both fields. Below are some of the key applications in agriculture and environmental monitoring.

### *i. Precision Agriculture:*

Precision agriculture is a significant application of WSNs integrated with IoT technologies. In this field, IoT-enabled sensors with diverse attributes are deployed across networks of various shapes and dimensions to monitor real-time parameters such as soil moisture, temperature, humidity, and nutrient levels [64]. These sensors allow farmers to optimise water usage through smart irrigation systems, enhance crop yields by providing timely data on soil conditions, and predict pest infestations, enabling preventive measures [97].

Key applications of IoT-based WSNs in precision agriculture include:

- ***Smart Irrigation:*** Sensors measure soil moisture levels and automatically adjust watering schedules to conserve water while maintaining optimal soil conditions for crops [98].
- ***Crop Monitoring:*** Continuous monitoring of environmental conditions provides insights into crop growth patterns and needs, leading to more efficient farming practices [99].
- ***Livestock Management:*** IoT devices track the health, location, and behaviour of livestock, reducing the risk of disease outbreaks and ensuring optimal care [100].

### *ii. Environmental Monitoring:*

Environmental monitoring using IoT-based WSNs has become crucial in tracking and mitigating the impacts of climate change and pollution. These systems provide real-time data on various environmental parameters, crucial for disaster management, pollution control, and climate change monitoring [101].

Key applications of IoT-based WSNs in environmental monitoring include:

- ***Pollution Control:*** IoT-enabled sensors can monitor air and water quality, providing critical data to help mitigate pollution in urban and industrial areas [103].
- ***Climate Change Monitoring:*** Long-term data collection on environmental parameters such as temperature, CO2 levels, and humidity helps in understanding the impacts of climate change and devising strategies to counteract its effects [102].
- ***Disaster Management:*** WSNs are deployed in disaster-prone areas to detect early signs of natural disasters like floods, wildfires, and earthquakes, enabling timely warnings and reducing the loss of life and property [104].

### *iii. Weather Predictions:*

The integration of WSNs with IoT technologies has significantly enhanced weather prediction capabilities. Distributed sensor networks collect localised weather data, improving forecast accuracy and enabling timely warnings of severe weather events [105].

The applications of IoT-based WSNs in weather prediction can be categorised into the following areas:

- ***Real-Time Weather Stations:*** These systems collect and transmit data on temperature, humidity, wind speed, and other weather-related parameters, contributing to more accurate and localised weather predictions [106].
- ***Storm Tracking:*** IoT networks are instrumental in tracking the development and movement of storms, providing critical data for early warnings and disaster preparedness[107].

## *Urbanisation & Infrastructure:*

The rise of smart cities and intelligent infrastructure is heavily dependent on the deployment of IoT-based WSN systems. These systems enable cities to become more efficient, sustainable, and responsive to citizens' needs. The following sections highlight key applications in this domain.

### *i. Smart Cities:*

Smart cities integrate IoT with urban infrastructure to enhance citizens' quality of life. IoT-based WSN systems play a crucial role by providing real-time data on traffic management, waste management, and air quality monitoring [108].

Key applications of WSN assisted IoT in smart cities include:

- ***Traffic Management:*** IoT sensors monitor traffic flow and provide real-time data to traffic control systems, reducing congestion and improving public transportation efficiency [109], [110].
- ***Waste Management:*** Smart bins equipped with sensors monitor fill levels and optimise waste collection routes, reducing costs and environmental impact [111].
- ***Utility Management:*** Sensors distributed throughout a city can continuously monitor water, electricity, and gas supplies [112], [113], providing data that helps effective utilisation of resources.

### *ii. Intelligent Infrastructures:*

Intelligent infrastructure refers to the use of IoT-enabled WSNs to monitor and manage critical infrastructure, such as buildings, bridges, and power grids. These systems enhance the safety, efficiency, and longevity of infrastructure [114].

Key applications include:

- ***Structural Health Monitoring:*** Sensors are embedded in buildings and bridges to monitor structural integrity and detect any signs of wear or damage, preventing catastrophic failures [115].
- ***Smart Grids & Metering:*** IoT-based smart grids manage the distribution of electricity more efficiently, while smart meters provide real-time data on energy consumption, enabling dynamic pricing and energy-saving strategies [116].
- ***Energy Management:*** IoT systems monitor and control energy usage in large buildings and industrial complexes, optimising energy consumption and reducing costs [117].

## *Industry & Automation:*

The industrial sector is experiencing a transformative shift through the implementation of Industrial IoT (IIoT) systems. These systems leverage WSNs to automate processes, improve operational efficiency, and predict equipment maintenance needs, among other applications.

### *i. Industrial IoT (IIoT):*

Industrial IoT (IIoT) integrates WSNs with IoT to enhance industrial operations, including predictive maintenance, process automation, and supply chain management. These systems improve efficiency and reduce downtime in manufacturing and industrial environments [118].

Key applications include:

- ***Predictive Maintenance:*** Sensors monitor the condition of machinery and predict when maintenance is needed, reducing downtime and extending the lifespan of equipment [119].
- ***Process Automation:*** IoT systems enable real-time monitoring and control of industrial processes, improving efficiency and reducing the need for human intervention [120].
- ***Supply Chain Monitoring:*** IoT devices track goods throughout the supply chain, ensuring transparency and optimising logistics [121].

### *ii. Equipment & Plant Monitoring:*

IoT-based WSN systems ensure that industrial plants operate efficiently and safely by providing real-time data on equipment condition and plant environments [122].

Key applications include:

- ***Condition Monitoring:*** Continuous monitoring of equipment health allows for timely maintenance, preventing unexpected breakdowns and production losses [122].
- ***Safety & Compliance:*** IoT sensors ensure that industrial plants adhere to safety standards and environmental regulations, preventing accidents and fines [122].

## *Health & Body Area Networks (BAN):*

In healthcare, WSNs integrated with IoT are transforming patient care through continuous monitoring, chronic disease management, and remote consultation. Body Area Networks (BANs) enable the real-time collection of health data, enhancing treatment effectiveness [125].

Key applications include:

### *i. Remote Patient Monitoring:*

Wearable sensors monitor vital signs such as heart rate, blood pressure, and glucose levels, transmitting data to healthcare providers for real-time monitoring and intervention [123].

### *ii. Chronic Disease Management:*

IoT devices help in managing chronic conditions like diabetes and hypertension by providing continuous data for timely treatment adjustments [124].

### *iii. Telehealth:*

IoT systems facilitate remote consultations and diagnostics, reducing the need for physical visits to healthcare facilities [125].

### *iv. Elderly Care:*

IoT-enabled devices monitor the health and safety of elderly individuals, enabling them to live independently while providing peace of mind to caregivers [126].

## *Security & Defence:*

In security and defence, IoT-based WSN systems are being deployed for real-time monitoring, surveillance, and early detection of potential threats. These technologies enhance both military and civilian security operations.

### *i. Military & Defence:*

IoT-based WSN systems are extensively used in military and defence applications, providing critical data for battlefield surveillance, border security, and detecting explosives and hazardous materials.

Key applications include:

- ***Battlefield Surveillance:*** IoT sensors are deployed in conflict zones to provide real-time data on enemy movements and environmental conditions, enhancing situational awareness [127].
- ***Border Security:*** WSNs monitor remote border areas, detecting unauthorised entries and providing early warnings to security forces [128].
- ***Drone Surveillance:*** Integration of IoT with unmanned aerial vehicles (UAVs) allows for enhanced surveillance capabilities in both military and civilian contexts [129].

### *ii. Public Safety & Crime Prevention:*

In public safety and crime prevention, IoT-based WSN systems monitor public spaces in real-time, and enhance law enforcement response times.

Key applications include:

- ***Smart Surveillance Systems:*** IoT-enabled cameras and sensors monitor public spaces for suspicious activities, helping to prevent crimes and ensure public safety [130].
- ***Intrusion Detection:*** WSNs detect unauthorised access to secure areas, triggering alarms and notifying authorities [131].

## *Smart Homes & Intelligent Transport:*

### *i. Smart Homes:*

The integration of IoT-based WSN systems in homes and transportation systems has ushered in a new era of automation and intelligence. These systems are pivotal in enhancing convenience, security, and efficiency in smart homes and intelligent transport networks.

Key applications include:

- ***Home Automation:*** IoT systems control lighting, heating, and appliances, optimising energy use [132].
- ***Security Systems:*** Smart cameras, motion detectors, and alarms provide real-time monitoring and protection of homes [133].

- ***Appliance Control:*** IoT devices allow homeowners to monitor and control home appliances remotely, improving energy efficiency [134].

### *ii. Intelligent Transport Systems:*

Intelligent transport systems (ITS) leverage WSN-based IoT technologies to optimise traffic flow, enhance vehicle safety, and improve public transportation.

Key applications include:

- ***Connected Vehicles:*** IoT enables communication between vehicles and infrastructure, improving road safety and traffic management [135].
- ***Public Transport Optimisation:*** IoT systems monitor public transportation networks, optimising routes and schedules to improve efficiency and reduce waiting times [136].
- ***Smart Parking:*** IoT-enabled sensors guide drivers to available parking spaces, reducing congestion and improving the efficiency of urban transportation [137]

The continuous expansion of IoT-based WSN applications in modern interconnected smart cities has led to an exponential increase in the number of IoT devices. This surge introduces significant challenges in managing the energy consumption required to support these devices, especially within HWSNs. According to Ericsson, the number of IoT devices worldwide is expected to reach 5.5 billion by 2027 [4], while a study conducted by Farhan et al. suggests that this figure could rise to 24.1 billion by 2030 [138]. As the number of devices grows, so does the volume of data generated, transmitted, and stored, leading to a substantial increase in energy consumption.

The International Data Corporation (IDC) has projected that WSN-based IoT devices will generate an astounding 79.4 zettabytes (ZB) of data by 2025 [139]. This massive data influx demands substantial energy resources, not only for data transmission and storage but also for processing and managing information within WSNs. Balancing energy supply and demand in this scenario is particularly challenging due to limited energy resources available to sensor nodes, which are typically battery powered.

A critical issue in WSNs is energy imbalance, where certain nodes deplete their energy much faster than others, leading to the creation of energy holes. These energy holes can result in network partitioning, reduced coverage, and ultimately a shorter operational lifetime for the network. Studies have shown that a significant portion of the network's initial energy remains unused by the time the network’s lifetime ends, with up to 90% remaining in some cases [37].

This inefficiency underscores the need for optimised energy management strategies that ensure more balanced energy consumption across the network.

In addition to energy imbalance, the growing number of devices presents challenges in maintaining network stability. A network is considered stable if the time interval between the death of the first node and the last node is minimised [38]. However, as the number of devices and the volume of data transmitted increase, maintaining this stability becomes increasingly difficult. This situation necessitates advanced techniques that can adapt to varying network conditions and demands.

Given these challenges, energy management in HWSNs must prioritise the development of scalable and adaptable methods capable of handling the increasing number of devices and the corresponding data transmission demands. These methods should aim not only to extend network lifetime and increase throughput but also to enhance stability by preventing energy holes and ensuring a more balanced energy distribution among nodes.

The current literature presents various approaches to address these challenges, including clustering and routing techniques, energy harvesting, and mobile data collection strategies. However, there is still a pressing need for more comprehensive solutions that can seamlessly integrate these approaches, optimise energy consumption, and adapt to the diverse and dynamic environments in which WSNs are deployed.

# Appendix - B

This appendix provides a comprehensive summary of the simulation environment, parameter settings, and performance metrics used across all evaluated techniques. The table included herein consolidates details such as the simulation tools employed (e.g., MATLAB, NS-2, OMNET++), network dimensions, node deployment strategies, transmission ranges, energy models, heterogeneity levels, and routing protocols. It also summarises the key performance indicators, including network lifetime (FND/LND), packet delivery ratios, energy consumption, and end-to-end delay. This information ensures full transparency and reproducibility of the experimental setup and enables meaningful comparisons across the reviewed techniques.

*Table: Evaluation of Existing Balanced Energy Communication Techniques*

| ***Clustering Method / Technique*** | ***Unequal Clustering*** | ***Multi-Hop Inter Cluster Comm.*** | ***Level of Heterogeneity*** | ***Penalty to Advance nodes*** | ***Deployment of nodes*** | ***Scalability*** | ***Sink Node (Stationary / Mobile)*** | ***Simulation Tool Used*** | ***No. of Sink Nodes*** | ***No. of CHs*** | ***Real-world /Simulation based*** | ***Network Lifetime*** | ***Packet Delivery Ratio*** | ***Energy Consumption*** | ***End to End Delay*** | ***Routing protocols*** | ***Transmission Range*** | ***Sensor Field*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***LEACH*** [40] | × | × | 0 | N/A | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | Initial energy=0.5J FND=932 LND=1312 Initial energy=1J FND=1848 LND=2608 | - | 4 to 8 times reduction as compared with MTE routing | - | Hierarchical (probability based) routing. | All nodes are assumed to be in communication range. | Square |

| ***Clustering Method / Technique*** | ***Unequal Clustering*** | ***Multi-Hop Inter Cluster Comm.*** | ***Level of Heterogeneity*** | ***Penalty to Advance nodes*** | ***Deployment of nodes*** | ***Scalability*** | ***Sink Node (Stationary / Mobile)*** | ***Simulation Tool Used*** | ***No. of Sink Nodes*** | ***No. of CHs*** | ***Real-world /Simulation based*** | ***Network Lifetime*** | ***Packet Delivery Ratio*** | ***Energy Consumption*** | ***End to End Delay*** | ***Routing protocols*** | ***Transmission Range*** | ***Sensor Field*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***LEACH-C*** [72] | × | × | 0 | N/A | Random | ✓ | Stationary | Network Simulator NS | 1 | Fixed | Sim | LEACH-C can deliver ten times more amount of data during network lifetime. | - | Initial energy=2J. LEACH-C delivers about 40% more data per unit energy than LEACH | More data in LEACH-C during a period as compared to LEACH and MTE | Hierarchical (probability based) | All nodes are assumed to be in communication range. | Square (100 × 100) |
| ***HEED*** [73] | × | ✓ | 0 | N/A | Non-Uniform | × | Stationary | MATLAB | Multiple | Fixed | Sim | - | - | - | - | Hybrid | Two nodes communicate using the same transmission power. | Square (2,000 × 2,000) |
| ***CMMAR*** [74] | × | × | 0 | N/A | Rand | × | Mobile | NS-2 | 1 | Fixed | Sim | FND = 400th round | - | 12.5% less than PEGASIS and 60% less than LEACH | 4% less than LEACH and 70% less than PEGASIS. | Cluster Chain Mobile Agent Routing | Variable i.e., $30m$ for $100m \times 100m$ and $50m$ for $500m \times 500m$ | Square ($100m \times 100m$) |
| ***WSNEHA*** [76] | × | ✓ | 0 | N/A | Rand | × | Stationary | MATLAB | 1 | Fixed | Sim | lifetime increased up to 361.92% when r=60 | - | Energy consumption decreased up to 78.35% | - | Routing Table based on the data send table | Variable (10m, 20m, 30m, 60m, 90m, 120m) | Circular ($500m$) |

| *Clustering Method / Technique* | *Unequal Clustering* | *Multi-Hop Inter Cluster Comm.* | *Level of Heterogeneity* | *Penalty to Advance nodes* | *Deployment of nodes* | *Scalability* | *Sink Node (Stationary / Mobile)* | *Simulation Tool Used* | *No. of Sink Nodes* | *No. of CHs* | *Real-world /Simulation based* | *Network Lifetime* | *Packet Delivery Ratio* | *Energy Consumption* | *End to End Delay* | *Routing protocols* | *Transmission Range* | *Sensor Field* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***BECHA & EA-BECHA*** [41], [93] | × | ✓ | 0 | N/A | Rand | × | Stationary | MATLAB | 1 | NA | Sim | BECHA: 13% and 100% more than WSNEHA and ECMSE.<br><br>FND=2*10^2 rounds<br><br>EA-BECHA: 58% and 166% more than WSNEHA and ECMSE | $r = 10, 9 \times 10^4$ bits of data are transmitted with energy dissipation 6 mJ. When $r = 100, 0.1 \times 10^4$ bits of data are transmitted with energy consumption 1mJ. EA-BECHA: In 500 rounds the packet drop ratio is 35% less than WSNEHA | EA-BECHA: 25% less than WSNEHA and 51% less than ECMSE | More latency as compared to WSNEHA. | Energy aware routing | Variable Transmission range | Circular $(250m)$ |

| *Clustering Method / Technique* | *Unequal Clustering* | *Multi-Hop Inter Cluster Comm.* | *Level of Heterogeneity* | *Penalty to Advance nodes* | *Deployment of nodes* | *Scalability* | *Sink Node (Stationary / Mobile)* | *Simulation Tool Used* | *No. of Sink Nodes* | *No. of CHs* | *Real-world /Simulation based* | *Network Lifetime* | *Packet Delivery Ratio* | *Energy Consumption* | *End to End Delay* | *Routing protocols* | *Transmission Range* | *Sensor Field* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***PEGASIS*** [75] | × | × | 0 | N/A | Rand | ✓ | Stationary | MATLAB | 1 | NA | Sim | In minimum total energy algorithm FND is15% to 30% more than closest neighbour algorithm. | - | Initial energy = 0.5 to 1J. Minimum total energy algorithm has consumption that is only 10% of closest neighbour algorithm. For multiple chains minimum total energy algorithm energy consumption is 40% of closest neighbour algorithm. | - | Two chain-based routing protocols have been proposed | - | Chain ( $Rectangular$) |
| ***BLOAD*** [78] | × | ✓ | 0 | N/A | Random | × | Stationary | MATLAB | 1 | Fixed | Sim | FNDT=20s as compared 5s and 10s in NRF and Homo-BR respectively ANDT of Homo-Bload=100s in comparison to 90s in Homo-BR and NRF.<br><br>Hetero-BR has 5% better stability than Homo-BLOAD | 10 Packets/s considered. Packet load distribution is done by the packet distribution table as a result of the weight mechanism. | Initial Energy = 1J Homogeneous scenario.<br><br>Energy consumption of BLOAD in heterogeneous scenario is more than Hetero-BR. | - | - | Adjustable transmission i.e., Three transmission ranges i.e., r, 2r and dtx | Circular ($1000m$) |

| *Clustering Method / Technique* | *Unequal Clustering* | *Multi-Hop Inter Cluster Comm.* | *Level of Heterogeneity* | *Penalty to Advance nodes* | *Deployment of nodes* | *Scalability* | *Sink Node (Stationary / Mobile)* | *Simulation Tool Used* | *No. of Sink Nodes* | *No. of CHs* | *Real-world /Simulation based* | *Network Lifetime* | *Packet Delivery Ratio* | *Energy Consumption* | *End to End Delay* | *Routing protocols* | *Transmission Range* | *Sensor Field* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***UCR*** [84] | ✓ | ✓ | 0 | N/A | Random | × | Stationary | MATLAB | 1 | Fixed | Sim | Residual energy of each node is balanced by unequal transmission load on cluster heads. | - | Higher overall energy consumption | - | Unequal clustered routing | Each sensor has adjustable power control capabilities. | Rectangular |
| ***EBCAG*** [85] | ✓ | × | 0 | N/A | Random | × | Stationary | MATLAB | 1 | Fixed | Sim | Until 5% of the nodes die. For a network of 400 nodes stability is 35 rounds and for a network of 800 nodes it is 24 rounds. | - | Overall energy consumption not given | - | Gradient-based Routing | - | Circular |
| ***COCA*** [86] | ✓ | × | 0 | N/A | Random | × | Stationary | NS-2 | 1 | Fixed | Sim | Network lifetime improved between 166 to 229 percent as compared to UCR for different network sizes. | - | Initial energy of each node = 2J | - | Energy aware routing | Maximum transmission range | Rectangular |

| ***Clustering Method / Technique*** | ***Unequal Clustering*** | ***Multi-Hop Inter Cluster Comm.*** | ***Level of Heterogeneity*** | ***Penalty to Advance nodes*** | ***Deployment of nodes*** | ***Scalability*** | ***Sink Node (Stationary / Mobile)*** | ***Simulation Tool Used*** | ***No. of Sink Nodes*** | ***No. of CHs*** | ***Real-world /Simulation based*** | ***Network Lifetime*** | ***Packet Delivery Ratio*** | ***Energy Consumption*** | ***End to End Delay*** | ***Routing protocols*** | ***Transmission Range*** | ***Sensor Field*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***SEP*** [51] | × | × | 2 Level | ✓ | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | Stable region of SEP is extended compared to LEACH by 8% to 26% depending upon the percentage of advanced nodes. | More than LEACH and FAIR. | - | - | Advanced Nodes are used. | - | N/A |
| ***DEEC*** [79] | × | × | Multi-Level | ✓ | Random | × | Stationary | MATLAB | 1 | Fixed | Sim | DEEC obtains 20% more number of round than LECH-E. FND=969 rounds LND=5536 rounds | More than LECH-E and SEP | - | - | Advance, and super nodes are used | - | Square ($100m \times 100m$) |
| ***DDEEC*** [80] | × | × | 2 Level | No | Random | × | Stationary | MATLAB | 1 | Fixed | Sim | 30% more lifetime than SEP and 15% more than DEEC in terms of FND. FND=1355 rounds LND=5673 rounds | - | - | - | Advance nodes are used for relaying most of data | - | Square ($100m \times 100m$) |

| ***Clustering Method / Technique*** | ***Unequal Clustering*** | ***Multi-Hop Inter Cluster Comm.*** | ***Level of Heterogeneity*** | ***Penalty to Advance nodes*** | ***Deployment of nodes*** | ***Scalability*** | ***Sink Node (Stationary / Mobile)*** | ***Simulation Tool Used*** | ***No. of Sink Nodes*** | ***No. of CHs*** | ***Real-world /Simulation based*** | ***Network Lifetime*** | ***Packet Delivery Ratio*** | ***Energy Consumption*** | ***End to End Delay*** | ***Routing protocols*** | ***Transmission Range*** | ***Sensor Field*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***EDDEEC*** [52] | × | × | Multi-Level | No | Random | × | Stationary | MATLAB | 1 | Fixed | Sim | FND=1717 rounds<br><br>LND=8638 rounds | More than EDEEC and DDEEC and DEEC | 20 Normal nodes having E0, 32 advanced nodes having 2Eo and 48 super nodes containing 3.5Eo | - | - | - | Square ($100m \times 100m$) |
| ***UCR-H*** [88] | ✓ | ✓ | Multi-Level | NA | Random | × | Stationary | MATLAB | 1 | Fixed | Sim | Roughly around 1500 rounds FND based on node density. | - | Balanced energy consumption among clusters in different units. | - | - | According to distance it is adjustable | Rectangular |
| ***WEMER*** [44] | ✓ | × | 0 | NA | Random | × | Stationary | MATLAB | 1 | Fixed | Sim | FND=582 rounds. HND=1128 rounds LND=1478 rounds | - | Initial Energy 0.5J. Average energy cost=0.042847J | High | Chain construction. | Threshold distance in a sector dth. | Circular |
| ***MMS*** [42] | × | ✓ | 0 | NA | Variable | × | Mobile | MATLAB | Multiple | Fixed | Sim | FND=409 rounds HND=482 rounds Total remaining energy in $200^{th}$ round is 14.387J which is more than LEACH (10.605J), MOFCA (11.228J) and OPT-LEACH (13.945J) | - | Initial energy is 0.25J.<br><br>Proposed method optimizes energy consumption 19% in terms of FND and HND scales. | - | Hierarchical routing supported by relay nodes and cluster heads | Each sensor can adjust strength of its transmission signal | Square ($200m \times 200m$) |

| ***Clustering Method / Technique*** | ***Unequal Clustering*** | ***Multi-Hop Inter Cluster Comm.*** | ***Level of Heterogeneity*** | ***Penalty to Advance nodes*** | ***Deployment of nodes*** | ***Scalability*** | ***Sink Node (Stationary / Mobile)*** | ***Simulation Tool Used*** | ***No. of Sink Nodes*** | ***No. of CHs*** | ***Real-world /Simulation based*** | ***Network Lifetime*** | ***Packet Delivery Ratio*** | ***Energy Consumption*** | ***End to End Delay*** | ***Routing protocols*** | ***Transmission Range*** | ***Sensor Field*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***MDC*** [81] | ✗ | ✗ | 0 | NA | Uniform | ✗ | Mobile | MATLAB | 1 | Fixed | Sim | Number of rounds when first node dies is between 6000-7000 and when last node dies are between 8000-9000 | - | Initial energy=5J. Due to transmission range and adjustable speed of MDC the network achieves less average energy consumption of a node. | - | Mobile Data Collector | Adjustable | 3D Rectangular |
| ***GWO*** [53] | ✗ | ✓ | 2 Level | NA | Random | ✗ | Stationary | MATLAB | 1 | Fixed | Sim | FND between 800-900 and HND between 900-1100 rounds depending upon the number of sensor nodes. | - | Less than 250J for equal load and less than 230J for unequal load with 100 sensor nodes. | - | Improved Shuffled Frog Leaping Algorithm (ISLFA) | - | Square ($50m \times 50m$) |
| ***SEHR*** [82] | ✗ | ✓ | 0 | NA | Variable | ✗ | Stationary | MATLAB | 1 | Fixed | - | FND=597 rounds LND=251 rounds better than that of DR. | Between $16 \times 10^4$ to $16 \times 10^4$ packets | - | - | 3-tier architecture is used for hierarchical routing. | - | Square ($100m \times 100m$) |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***ERNS-EEC*** [43] | ✗ | ✓ | 0 | NA | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | 31 nodes are still alive after 5000 rounds. It does not perform well on FND scale. Only 120 nodes are dead after 1000 rounds | - | Initial Energy=0.5J<br><br>Due to minimum energy consumption lifetime is between 5000-6000 rounds. | Average time per round is 0.04 seconds | Relay nodes-based routing | - | Square ($200m \times 200m/300m \times 300m$) |
| ***UDCH*** [159] | ✗ | ✓ | 0 | NA | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | FND=1220 rounds LND=1870 rounds | 610,000 packets received during 2000 rounds | Initial energy is 0.3J. Overall residual energy starts to drop below the half of initial energy from $700^{th}$ rounds. | - | - | - | Square ($200m \times 200m$) |
| ***ETASA & TEAR*** [158] | ✗ | ✗ | Multi-Level | NA | Random | ✗ | Stationary | MATLAB | 1 | Fixed | Sim | FND is between 1000-1030 rounds. HND is between 2400-2500 rounds. LND is between 3990-4030 rounds. | ETASA delivered slightly more number of packets as compared to TEAR | Initial lower bound energy 0.5J. Average residual energy of ETASA is more than 0.3J during $1500^{th}$ round while that of TEAR was close to 0.2J. | - | Traffic and Energy Aware Routing (TEAR) | - | Square ($100m \times 100m$) |

| ***Clustering Method / Technique*** | ***Unequal Clustering*** | ***Multi-Hop Inter Cluster Comm.*** | ***Level of Heterogeneity*** | ***Penalty to Advance nodes*** | ***Deployment of nodes*** | ***Scalability*** | ***Sink Node (Stationary / Mobile)*** | ***Simulation Tool Used*** | ***No. of Sink Nodes*** | ***No. of CHs*** | ***Real-world /Simulation based*** | ***Network Lifetime*** | ***Packet Delivery Ratio*** | ***Energy Consumption*** | ***End to End Delay*** | ***Routing protocols*** | ***Transmission Range*** | ***Sensor Field*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***ECUC*** [45] | ✓ | ✓ | 0 | NA | Uniform | ✓ | Stationary | OMNET++ | 1 | Fixed | Sim | 22% longer network lifetime than OCCN and 32% longer network lifetime than DBS in small scale network (R=50m) Whereas 16% and 25% longer lifetime than DBS and OCCN in large scale network (R=200m) | - | 30% reduction in energy consumption as compared to OCCN and 28% reduction as compared to DBS. | - | Energy-efficient and coverage-guaranteed unequal-sized clustering | Transmission ranges are considered to be adjustable. | Circular |
| ***LEACH-EA*** [157] | ✓ | × | 0 | N/A | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | 4200 rounds when number of clusters = 3 and 5000 when nc=5 and 5000 for nc=7000. | - | LEACH-EA shows 50% improvement as compared to SEP and 74% with respect to LEACH | | Both equal and unequal clustered routing is tried. | - | Square |
| ***LEACH-EC*** [157] | × | | | | | | | | | | | | | | | | | |

| ***Clustering Method / Technique*** | ***Unequal Clustering*** | ***Multi-Hop Inter Cluster Comm.*** | ***Level of Heterogeneity*** | ***Penalty to Advance nodes*** | ***Deployment of nodes*** | ***Scalability*** | ***Sink Node (Stationary / Mobile)*** | ***Simulation Tool Used*** | ***No. of Sink Nodes*** | ***No. of CHs*** | ***Real-world /Simulation based*** | ***Network Lifetime*** | ***Packet Delivery Ratio*** | ***Energy Consumption*** | ***End to End Delay*** | ***Routing protocols*** | ***Transmission Range*** | ***Sensor Field*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***LEACH-EC-EA*** [46] | ✓ | × | 0 | N/A | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | 1600 rounds as compared to 700 rounds for LEACH Lifetime gain LEACH 300% TEEN 20% SEP 82% | - | LEACH 105% SEP 43% TEEN 7% | - | - | - | Square $(100m \times 100m)$ |
| ***LEACH-K*** [46] | ✓ | × | 0 | N/A | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | Stability = 1399 rounds when K=10 | 30017 packets When K=10 | 41.497J when K=10 | 96.1602 when K=10 | - | - | Square $(100m \times 100m)$ |
| ***LEACH-G-K*** [87] | ✓ | × | 0 | N/A | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | Stability=352 rounds. Lifetime = 4528 rounds | 15292 packets | Initial Energy=0.5J/node Half of the energy (24.95J) is consumed in 745 rounds which was 595 rounds in LEACH and 645 rounds in TEEN. | 0.089 ms | Two scenarios first with LEACH and second with TEEN | - | Square $(100m \times 100m)$ |
| ***MDC-LEACH-K*** [47] | ✓ | × | 0 | N/A | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | Stability= 2967 rounds | 27865 packets | Residual energy =0.027J when rest LEACH, TEEN, LEACH-K has 0 energy. | 0.047 ms | mobile data collector | - | Square $(100m \times 100m)$ |
| ***MDC-K*** [49] | ✓ | × | 0 | N/A | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | Stability=1992 rounds Lifetime=5505 rounds | 18300 packets/round | High than LEACH, TEEN, and LEACH-K | 50,001 ms | Mobile Data Collector with LEACH | - | Square multiple simulations$(100m \times 100m)$ *to* $(1000m \times 1000m)$ |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ***MDC-TSP-LEACH-K*** [49], [50] | ✓ | × | 0 | N/A | Random | ✓ | Stationary | MATLAB | 1 | Fixed | Sim | Stability = 2000 rounds Lifetime=7321 rounds | 18910 packet/round | - | 35,16 ms | MDC with TSP | - | Square multiple simulations$(100m \times 100m)\ to\ (1000m \times 1000m)$ |