International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Intelligent Triangulation based Sink Relocation and Energy-Equivalent Cluster based Routing for WSN assisted IoT

Naved Ahmed[1], Mona Quaisar[1] and Dr. Shraddha Prasad[2]

Submitted: 16/09/2023 **Revised**: 30/10/2023 **Accepted**: 14/11/2023

Abstract: Internet of Things (IoT) applications are made possible by wireless sensor networks (WSNs), which offer a seamless infrastructure for data collecting. The unequal energy usage and associated communication bottlenecks in large-scale IoT deployments, however, make efficient data routing and sink relocation difficult tasks. Our goalistoenhance network lifetime by minimizing energy efficiency. Many static sensor nodes form our network, along with a single mobile sink node. The proposed work includes 4 consecutive processes such as balanced clustered formation, Intra- cluster routing, inter-cluster routing, and Intelligent sink relocation. Firstly, we construct a network as Angle Separated Hexagon (ASep-Hex)divided by 6 parts by angle. A new Energy Equivalent Cluster Formation and Validation (E2CFV) method forms clusters in each sector and CH is selected by Fused Parameter (FuP). We introduce a novel approach namely Rule-based Balancing Degree (RBD) for validating formed clusters. Secondly, for intra-cluster routing, each cluster is a Hop-to-Hop Directed Acyclic Graph (H2H-DAG). Each node chooses the optimal parent for the CH based on Composite Criteria (Com-Criteria) after completion.Thirdly, the available best routes are learned from Tri-state Markov Chain Model (Tri-MCM). Then the generated routes are assessed by Quality Aware Assessment Model (QA2M). Fourthly, to identify candidate positions, a novel Intelligent Triangulation Method (ITM) is proposed. From the candidate positions, the optimal position is selected by Multi-Objective Spider Monkey Optimization (MOsMO) algorithm. The simulation, which uses the Network Simulator (NS-3.26), shows that the suggested work performs more than previous cutting-edge works.

***Index words**: Wireless sensor networks (WSNs), Angle Separated Hexagon (ASep-Hex), Rule-based Balancing Degree (RBD), Energy Equivalent Cluster Formation and Validation (E2CFV), Quality Aware Assessment Model (QA2M), Multi-Objective Spider Monkey Optimization (MOsMO)*

1. Introduction

Most recently, the field of microelectronics has expanded, assuming the initiative in the research and development of low-cost wireless sensor nodes, resource-constrained devices, and compact nodes. Many Internet of Things (IoT) applications that use wireless sensor networks (WSN) depend greatly on WSN [1-3]. One of the numerous IoT applications provided by WSNs is an intelligent parking system. Other IoT applications offered by WSNs include an industry wireless network, a healthcare surveillance structure, a border security tracking structure, and an animal surveillance system [4, 5]. The sensor nodes, actuators, RFID, and numerous other devices join to create a WSN-assisted IoT network (WSN-IoT) to achieve some shared objective. Contributing nodes in WSN-IoT allow physical objects to learn about a range of implemented network actual qualities, such as watching, tracking, and encountering, and to start an event with the aid of other devices [6]. Because of the severe environments in which sensors must function, the only part of a sensor's lifespan that can be modified are its power sources, which are either difficult to replace or recharge. This issue makes it difficult to integrate the WSN into the IoT, which drives up the price of new technologies. Consequently, a major challenge in the WSN-IoT is extended network lifetime. Therefore, a clustering strategy is utilized in the WSN to increase energy consumption and extend the network's lifetime. To save energy and extend the lifespan of the network by eliminating long-distance communication, the clustering protocol, in which the sensor nodes are separated into small clusters, is a successful approach [7, 8]. The WSN-IoT has several applications and enhances people's daily conveniences. The distributed network for different WSN-IoT systems may be static or dynamic based on the demands of the application. For instance, intelligent health monitoring systems and animal monitoring systems support dynamic networks whereas border surveillance and environmental monitoring support static networks. Nodes can easily shift from one site to another in a dynamic network. Together with the acceleration, halt period, and acceleration, the nodes' movement varies concerning time [9, 10]. To replicate user motion trends as a result, a variety of mobility algorithms have been proposed in the past, with varying results. After examining previously released research, we found that randomized waypoints and random paths are the most popular mobility models for modeling the wireless networks of WSN-assisted IoT. The node determines its destination in the random walk mobility

[1]*Reasearch Scholar, Jharkhand Rai University, Ranchi-835222*
[2]*Associate Professor, Jharkhand Rai University, Ranchi-835222*

model with no stopping period and randomized direction and speed [11-13].

The WSN-IoT networks have a significantly greater number of nodes and are dispersed across a larger area than WSN (mostly because of resource constraints). Therefore, conventional WSN techniques might not be viable in a scalable WSN-IoT network. To tackle the difficulties of network reliability and scalability, many studies utilized the cluster-based hierarchical framework [14–16]. The main focus of cluster-based routing systems is on the efficient Cluster Head (CH) selection and management of the cluster's remaining nodes. The nodes of the cluster send data to the CH to exchange information. The CH is in charge of gathering data from adjacent members of the cluster and transmitting it to the base station (BS) or other nearby CHs that are moving in that direction. Due to the added stress placed on CH, it uses more energy than usual nodes [17–18].

A. *Motivations and objectives*

Numerous current research projects have recently made efforts to identify the mobile sink node in the WSN context. However, various limitations occurred regarding energy consumption which reduces the performance of the WSN networks in the IoT Environment. The following list of issues serves as our motivation,

- **Optimal Cluster Formation and Balancing Energy Consumption**: In a WSN, each cluster has a CH that collects data from cluster members and transfers it to the base station or sink. The challenge is to find a cluster formation strategy that increases network longevity by evenly distributing sensor node energy usage. Balanced energy consumption reduces node failures, increases network lifetime, and enhances performance.
- **Efficient and Reliable CH Selection**: The operation of a WSN is based on the selection of compatible CHs. CHs manage cluster data transfer; hence they use more energy than ordinary nodes. An effective and reliable CH selection method that takes into account node energy levels, distance to the sink, and communication capabilities is required to distribute CHs throughout the network and maximize stability and energy efficiency.
- **Reliable and Timely Route Selection**: WSN data transport typically necessitates many hops from source to sink. Data integrity and network efficiency necessitate dependable paths with minimal latency and energy consumption. The aim is to create a route selection mechanism that quickly discovers robust and energy-efficient paths while minimizing processing overhead and assuring that the found routes can adapt to changes in network architecture.
- **Minimizing Energy Consumption During Sink Relocation and Improving Data Aggregation**: Sink relocation is critical in particular situations, such as when the original sink stops working or when network dynamics change. Energy consumption during sink migration must be kept to a minimum to avoid nodes consuming up all of their energy too quickly. Furthermore, the relocation technique should be designed to improve data aggregation, reduce redundant data transfer, and increase data collection efficacy.

In the presence of a mobile sink node, the data can be collected without much energy consumption. In addition, cluster formation, routing, and mobile sink relocation strategies can be presented to further improve energy efficiency. Thus, the major objectives of this research work are,

1. To design a WSN-IoT network with a mobile sink node to minimize the energy consumption
2. To improve network lifetime by mitigating energy consumption
3. To enhance data delivery efficiency in terms of the ratio of deliveries and delay

B. *Research Contributions*

The research concentrates on WSN/IoT systems with one mobile sink node and static sensor nodes. The major contributions of this research are listed as follows,

- A hexagonal network called ASep-Hex is constructed and it is divided into 6 sectors based on angle. E2CFV creates clusters in each industry. FuP selects the best CH.
- For intra-cluster routing, each cluster is constructed as equivalent H2H-DAG. After completion, each node selects the optimal parent towards the CH based on Com-Criteria. In this way, intra-cluster routing is carried out, and CH aggregates the data.
- At first, the available best routes are learned from Tri-MCM. Then the generated routes are assessed by QA2M which is formulated based on multiple important metrics such as Expected Transmission Count (ETX), delay, hop count, and bandwidth.
- To identify candidate positions, a novel Intelligent Triangulation Method (ITM) is proposed. From the candidate positions, the optimal position is selected by Multi-Objective Spider Monkey Optimization (MOsMO) algorithm.

C. Research organizations

The remainder of this document is divided into the following sections: The literature review of the prior work that is more relevant to our work is illustrated in Section II. The primary problem statements that are tackled in the existing works are presented in Section III. The research technique for the suggested work is presented in Section IV and includes a protocol, a mathematical representation, and a pseudocode. The experimental findings and a comparison of the suggested and current works are described in Section V. The suggested study is concluded in Section VI, which also provides plans for this research's future work.

2. Literature Survey

The author in [19] deals with the energy hole problem in WSN. Here the network is constructed with concentric circles and each circle is further divided into zones. Each zone is considered as a cluster and optimal CH is selected. To mitigate the energy hole problem, CH is not enabled in the first layer of the network. The aggregated data from the higher layer are transmitted to the sink node through any one of the nodes in the first layer. The author in [20] uses a hybrid CH selection mechanism for maximizing the network lifetime. The hybrid algorithm is formulated by Glowworm Swarm Optimization(GSO) algorithm and Fruitfly Optimization Algorithm (FOA). The authors have highlighted that the hybrid method performs better than existing CH selection methods. Further, the simulation shows a better network lifetime in the presence of optimal CH. IoT is an evolving paradigm that connects billions of smart sensors and devices to build a smarter world. WSN is integrated with IoT to extend its applications in smart cities, smart health care, transportation, and so on. Research [21], an energy-efficient WSN-IoT model is designed with a cluster formation approach. Two distinguished clustering models as an energy-aware model and a service-aware model.

The author in [22] combines WSN with IoT for the application of smart societies. For that, an energy-efficient fault-tolerant routing strategy is proposed and named a heterogeneous modified dynamic source routing (HCDSR) protocol. The setup phase, route determination phase, data transfer phase, and fault recovery phase are all included in the HCDSR protocol. Although the integration of WSN and IoT brings many real-time applications it also introduces many challenges. Particularly, energy efficiency is one of the major challenges in WSN-assisted IoT since billions of smart devices are interconnected. Authors in [23] present an energy management scheme based on a centroid-based routing protocol. This centroid-based protocol enables the ability of self-organization for sensor nodes. The authors have emphasized that the current LEACH protocol and its variants are not appropriate for an IoT setting.

One of the most effective strategies to address the problem of energy consumption in WSNs is the use of mobile sinks. This study designs the network using a movable sink node to increase energy efficiency. Here the authors in [24] perform cluster formation in the presence of a mobile sink node to further improve energy efficiency. A finite state machine that uses the Markov model for achieving state transitions determines the function of the sensor node. The author in [25] proposes that optimal routing is performed in the presence of a mobile sink node. Here optimal path selection is performed for sink moving. This optimal path for the sink node is selected based on the hop counts and data generation rate. The main objective of this work is to improve aggregation efficiency in the network by relocating the mobile sink optimally. This mobile sink relocation procedure optimizes the network's energy effectiveness. The summary of the literature survey was presented in Table I.

Table I Summary Of Literature Survey

References	Aim	Algorithm or Model used	Disadvantages
[19]	This paper deals with the energy hole problem in WSN	Sector- based Energy-Efficient Hierarchical Protocol (SEHP)	Without cluster heads on the first layer, the network may not fully leverage the nodes' capabilities. This could lead to network hotspots and limited durability.
[20]	This paper uses a hybrid CH selection mechanism for maximizing the network lifetime	GSO and FOA	The algorithm's effectiveness and applicability may decrease as network size increases due to the optimization process's complexity.
[21]	Energy	Service and energy-aware	Computational complexity and memory utilization may

	efficientWSN-IoTmodelisdesignedwitha clusterformationapproach	clustering model	not be fully addressed, which could affect their practicality in resource-constrained WSN-IoT devices
[22]	A fault-tolerant routing scheme that is energy efficient.	heterogeneous modified dynamic source routing (HCDSR) protocol	HCDSR protocol phases like fault recovery and dynamic route identification may increase control message overhead.
[23]	Energy management scheme based on the centroid-based routing protocol	The energy-efficient centroid-based routing protocol (EECRP)	As IoT devices multiply, the centroid-based routing protocol and energy management system should be carefully reviewed for scalability.
[24]	A mobile sink node is incorporated into the network design to increase energy efficiency.	EnergyEfficientClusteringScheme(EECS)	Sensor nodes must follow and connect to the mobile sink, which may require frequent handoffs and communication overhead, reducing network efficiency.
[25]	Improve aggregation efficiency in the network by relocating the mobile sink optimally	Proactive Routing Protocol	Frequent path recalculations and sink relocation may result in additional routing overhead, increasing network congestion and communication delays.
[26]	attain a better quality of service (QoS)	neuro-fuzzy based routing algorithm	Executing256rulesforclusterformationincreasestime consumption
[27]	WSN cluster head selection for IoT applications	Low Energy Adaptive Clustering Hierarchy (LEACH) protocol	For optimal CH selection, focusing on just residual energy is ineffective
[28]	Efficient routing algorithm in WSN-IoT network	CLEARMaxT	Initialpathsetupbeforeclusterformationisnotnecessarybut bandwidth is a consuming process.
[29]	Multisensor data fusion (MDF) strategy to achieve energy efficiency in the WSN environment	Adaptiveneuro-fuzzyinferencesystem(ANFIS)	HereinPSOalgorithmisusedtotraintheANFISwhichdegradestheroutingefficiency
[30]	Optimal routing in WSN for IoT applications	Energy Efficient Survival Path Routing (SPR)	Networkmanagementiscriticalanditintroduceshotspotproblemsinthe network
[31]	Secure and energy-efficient routing model for	Threshold-TDMA (TTDMA)	Routeselection byexecuting125fuzzyrulesincreases thetime consumption

	WSN assisted IoT.		
[32]	To optimize the sink relocation problem	Improved ant colony optimization (IACO) algorithm	ACOalgorithmisrelativelyslowandconsiderslimitedmetricsforsink relocation
[33]	WSN-IoT systems with dynamic clusters	Secure Deep Learning (SecDL)	Vulnerabilities in a system can compromise the entire network.
[34]	A routing protocol is developed to enhance data transmission over the selected route	Energy-efficient Deep Belief Network (DBN)	For its resilience to node failures, communication disruptions, and mobility.
[35]	Cluster-based routing protocol for WSN networks with IoT support	Energy-efficient protocol	Managing more clusters may raise communication overhead and computational complexity, reducing protocol efficiency.
[36]	Three-layer hybrid clustering improves lower-layer head selection, reducing node control packet exchange constraints and improving network efficiency	Hybrid Hierarchical Clustering Approach (HHCA)	All nodes start with the same energy level in this situation. Thus, using a normal node as the grid head increases energy use for those nodes.

The author in [26] presents a neuro-fuzzy-based routing algorithm for energy-efficient routingand cluster formation in WSN-based IoT. The objective of this work is to attain a better quality of service (QoS). The neuro-fuzzyrules are formulated to enable energy-efficient cluster formation. Convolutional neural network (CNN) is utilized in the neuro-fuzzy model. The considered parameters are CH energy, the distance between the sink, the distance between the node, and the CH degree. Here, energy level determines CH and many parameters determine cluster formation. Thus, improper CH selection leads to an imbalance in cluster formation. The author of [27] discusses the option of cluster head in WSN for IoT app development. The optimal CH selection process has been incorporated into the authors' improved LEACH protocol. Here, taking into account the nodes' residual energy level, the ideal CH is chosen. Although this solution enhances the LEACH protocol, the hotspot problem is still a difficult challenge. For the best CH selection, relying solely on residual energy is ineffective. Using a WSN-IoT network, the author [28] provides a productive routing algorithm. Here initially a path is defined for each node for to enable data transmission with the sink node. This path set-up phase is initiated by a sink broadcasting message. Then the network is divided into multiple clusters and CH is selected randomly. For CH rotation, residual energy level is considered. Here a randomselectionofCHisnotefficienttoaggregatethedatafro mallsensornodes. Initialpathsetupbeforeclusterformationisnotnecessarybutba ndwidthis a consuming process. The author in [29] introduces a multi sensor data fusion (MDF) strategy to achieve energy efficiency in a WSN environment. This fusion technique Here fuzzy logic is designed for optimal CH selection by considering residual energy, node density, aggregation efficiency, historical throughput, and distance with Base Station (BS). For optimal routing, the network parameters are fused by ANFIS. Link bandwidth, centrality, latency, immediate channel status data, packet loss ratio, or signal-to-noise ratio are taken into account for routing data.

Here in PSO algorithm is used to train the ANFIS which degrades the routing efficiency. The author of [30] focuses on WSN applications for IoT that require optimum routing. For selecting the best route, a resilient path-based routing method has been put forth. Multiple criteria, such as the link's SNR, survivability factor, and congestion level, are used to conduct routing. The ratio between the minimal amount of remaining energy that is accessible at each node along the path and the total amount of energy used for transmission along that line is known as the survivability factor. In the study, network management is crucial and hotspot issues are introduced. In [31], the author provides a safe and energy-efficient routing paradigm for WSN-assisted IoT. Here the network is designed with sensors, coordinators, mobile sink, IoT gateway, and IoT users. At first, IoT users are authorized using a biometric authentication mechanism. Then sensed data is aggregated by the coordinator in threshold-TDMA (TTDMA) manner. To ensure data security, the sensed data is encrypted by RSA, and the authentication code is generated by the SHA-1 algorithm. Optimal route selection is performed by type-2 fuzzy logic. Then the selected optimal routes are validated to ensure path reliability. Route selection by executing 125 fuzzy rules increases the time consumption. The author in [32] designs an IACO algorithm to optimize the sink relocation problem. Initially, the network is clustered and CH is elected based on the residual energy level of the nodes. Further, inter-cluster routing is performed by considering distance metrics. The optimal sink position is determined by the distance value and residual energy level. Here ACO algorithm is relatively slow and considers limited metrics for sink relocation. Inter-cluster routing based on distance metrics is not efficient and leads to huge packet loss in the network. A novel SecDL approach is created by the author in [33] to dynamic cluster-based WSN-IoT platforms. To maximize energy efficiency, a network is constructed using bi-centric hexagons and mobile sink techniques. In this suggested architecture, an energy-efficient deep belief network (DBN) based routing protocol is developed to enhance data transfer across the selected route.

The author in [34] represents the reinforcement learning (RL) technique used to group the nodes in the entire network into clusters at first and distribute rewards to the nodes that are a member of each cluster. The CH required for efficient transmission of data is then selected using the Mantaray Foraging Optimization (MRFO) method. The data is transmitted to the sink node via the selected CH using an efficient deep-learning technique. For WSN-IoT capability, a cluster-based routing technique has been put out [35]. The cluster-based routing algorithm is known as the energy-efficient protocol because it aggregated data under the CH and minimizes data transmissions to the gateway's node. Three-layer-based cluster creation was used in the construction of the hybrid hierarchical cluster approach (HHCA) [36]. The choice of a regular node as the grid head responsible for managing the CHs is not the best one, as it results in increased energy usage for those specific nodes.

3. Problem Statement

This section summarizes the explicit existing works and their accompanying WSN solutions. Furthermore, the research remedies for the stated concerns are provided in this study.

Specific Problem Definition: The Fuzzy Energy-Efficient Clustering and Immune-Inspired Routing (FEEC-IIR) system for WSN- IoT systems was introduced in research [37]. An energy-efficient clustering algorithm called the adaptive fuzzy multi-criteria decision-making approach (AF-MCDM), which combines the fuzzy AHP and TOPSIS protocol, is used to identify the best cluster head. The key variables that can affect the choice of cluster heads are considered to be the node location, QoS impact, and energy status, each of which has several sub-criteria. To improve the reliability of data delivery, a route optimization technique inspired by the immune system is applied. The problems encountered in those approaches are listed below,

- Large time is required to execute fuzzy AHP and fuzzy TOPSIS algorithms which enhances time consumption for CH selection
- Hierarchical network design leads to hotspot problems due to energy consumption for sink nearer nodes
- This introduces huge data loss since route selection considers a single metric only

This study presents a special ring partitioning-based MAC (RP-MAC) technique to create an energy-efficient WSN using a mobile sink node. Energy efficiency is influenced by the clustering phase, MAC scheduling phase, data aggregation phase, and routing phase. A weighted Voronoi diagram (WVD) method starts the clustering step by giving each node a weight value. By permitting new RP-MAC scheduling in each cluster, energy consumption from idle listening is reduced. The RP-MAC protocol is used to ensure collision-free data transmission throughout the network. A two-fold data aggregation (TFDA) technique is recommended for the data aggregation phase to minimize the number of transfers. The problems associated with this work are,

- HCSO-based hop-by-hop selection increases energy and time consumption
- Intra-cluster routing considers distance metric only and the current characteristics are not considered.
- To build an energy-efficient trajectory for the MS, we first give a Linear Programming formulation for the problem that was done in [39]. Following that, suggest a multi-objective particle swarm optimization (MOPSO)-based algorithm. The algorithm is provided with a successful multi-objective fitness function and an effective particle

encoding scheme. For each particle, we apply Pareto dominance in MOPSO to determine the local and global optimal guides. Sink relocation in predefined rendezvous points (RPs) is not an intelligent decision which results in a large waiting time

- The network characteristics are changed over a while. Without consideration of current characteristics, the sink relocation imbalances the energy consumption
- When a node nearer to the current RP has lower energy, then it experiences higher energy consumption.

To group the intermediate sensor/mobile nodes that are closer to both the sink node and the sensor node that is ready to send the data, the Energy and Distance aware Clustering Technique is introduced in the suggested study effort. To cluster the nodes in this case, the Weight K-means algorithm is used. The cat swarm optimization algorithm is used to execute optimal cluster head selection to maximize residual energy and bandwidth to ensure the successful transmission of data without node failure. This makes it easier to locate the sink node in the best possible location for resource optimization and better data transfer was done in [40]. The major problems are listed below,

- Implementation of k-means clustering needs prior knowledge (number of clusters) and unable to balance the energy consumption
- CSO-based CH selection is not optimal since it has convergence issues. Furthermore, CH selection by considering bandwidth and energy level is not sufficient for CH selection
- Sink relocation decision and position are not optimal but it needs to be optimized for energy-efficient network

The optimal cluster head in a routing protocol is energy-efficient in an IoT network. To extend the lifespan of the node, it is suggested that the Fractional Gravitational Search Algorithm (FGSA) be used to iteratively discover the optimum cluster head node. The cluster head node is selected by FGSA, referred to as multi-objective FGSA (MOFGSA), when using a variety of objectives, including distance, delay, connection lifetime, and energy.

- Here the introduction of energy holes is not considered which is a major cause of energy consumption
- GSO is relatively slow for even a single objective which means considering multiple objectives in GSO increases time consumption.

Research solutions: To solve the issues addressed by cutting-edge approaches, the Hotspot problem is mitigated in the ASep-Hex environment by deploying a mobile sink node. The network is managed by constructing ASep-Hex along with E2CFV-based cluster formation which balances energy consumption. Optimal CH is selected by FuP in which multiple metrics are combined for effectual CH selection. Route selection by H2H-DAG and Tri-MCM selects the optimal route for data transmission. Inter-cluster routing is performed by Tri-MCM and QA2M which considers multiple significant metrics. MOsMO algorithm is proposed with ITM for sink relocation which improves aggregation efficiency and energy efficiency without time consumption. Fig 1 illustrates the Overall Network Architecture.

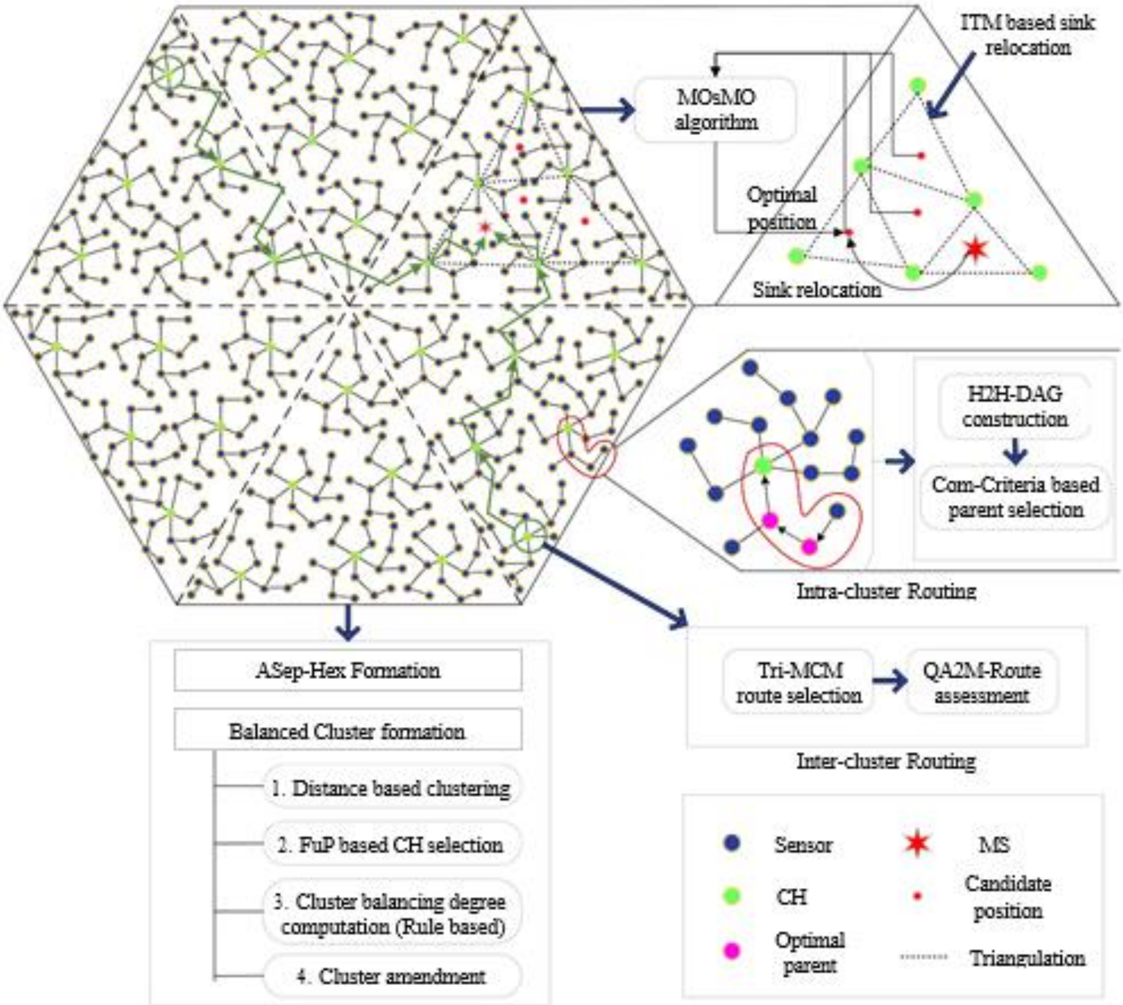

Fig. 1 Overall Network Architecture

4. Proposed Model

To overwhelm aforesaid problems, we propose a novel triangulation-based sink relocation process with joint cluster-based routing in WSN-IoT environment. Our goal is to extend the network lifetime by reducing energy consumption. This network is made up of several static sensor nodes and a single mobile sink node. For that, the following processes are performed:

- Balanced Cluster Formation
- Intra- Cluster Routing
- Inter-Cluster Routing
- Intelligent Sink Relocation

A. Balanced Cluster Formation

We construct the network as an Angle Separated Hexagon (ASep-Hex), that is divided into six sectors depending on angle and has effective data routing. The ASep-Hex can be divided into six sectors depending on angles, and by forming clusters within each sector, the network can achieve greater data aggregation and better network performance. This divide also makes it easier to assign a mobile sink (MS) visiting locations, facilitating effective data collecting.

Sensor Node Position: Let α_i , β_i be the position coordinates of the i[th] sensor node in the ASep-Hex network. Angle calculation: The angle θ_i for each sensor node can be calculated using the atan2 function, which provides the angle between the α- axis (positive x-axis) and the line joining the origin (0,0) and the sensor node (α_i, β_i)

$$\theta_i = \text{atan2}\,(\beta_i\,,\,\alpha_i) \quad (1)$$

The angle ranges for each sector are determined by dividing the Sep-Hex network into six equal sectors were represents in Table II.

Table II Sep-Hex Network Into Six Equal Sectors

Sector	**Degree**
1 st sector	$0^{\circ} \leq \theta_i < \pi/3$
2nd sector	$\pi/3 \leq \theta_i < 2\pi/3$
3rd sector	$2\pi/3 \leq \theta_i < \pi$
4th sector	$\pi \leq \theta_i < 4\pi/3$
5th sector	$4\pi/3 \leq \theta_i < 5\pi/3$,
6th sector	$5\pi/3 \leq \theta_i < 2\pi$

Each intersection point of the six equal sectors that make up the ASep-Hex is regarded as a visiting point (μ) for the mobile sink. Here, the threshold range (δ) is between 0-2π. By making one round of data collecting stops at each μ, starting with $\mu - 1$ and ending with $\mu - 6$, the mobile sink gathers sensing data. Sensor node (ϑ), (α_i, β_i). Pseudocode for ASep-Hex is mentioned as follows:

ASep-Hex Pseudocode

Initialize(ϑ), (α_i, β_i)θ_i

While($i < max$)

Calculate(ϑ), (α_i, β_i) for ASep-Hex using eq. (1)

If 0 <= θ_i<$\pi/3$, add ϑ to sector 1

Else if$\pi/3$<= θ_i< 2π/3, add the ϑ to sector 2

Else if$2\pi/3$<= θ_i< π, add ϑ to sector 3

Else ifπ<= θ_i<$4\pi/3$, add ϑ to sector 4

Else if$4\pi/3$<= θ_i<$5\pi/3$, add ϑ to sector 5

Else, add the sensor node to sector 6

- **End if**

- Update δ

- **End while**

The ASep-Hex network is formed and validated using the Energy Equivalent Cluster Formation and Validation (E2CFV) technique. This method's objective is to effectively group nodes in a way that enhances network performance and resource usage. E2CFV focuses on the Fused Parameter (FuP) to select the cluster heads and the Rule-based Balancing Degree (RBD) for cluster validation. Let us explain the stages one by one.

➢ *Stage 1: Cluster Formation with Distance Metric*

Clusters are initially created in this stage using a distance metric. Clusters are formed by gathering nodes that are relatively close to one another.

➢ *Stage 2: For Optimal Head Selection using FuP*

To select the optimal Cluster Head (η) for each cluster, a Fused Parameter (σ) is employed. The includes several essential variables, such as mean distance (υ), centrality factor(ϱ), node degree (φ), and energy level (ς). The following formula can be used to get the σ for the node i in cluster j within sector (τ)

$\sigma_{i.j,\tau} = \omega_1 . \varsigma_{i,\tau} + \omega_2 . \varphi_{\ i,\tau} + \omega_3 . \varrho_{i,\tau} + \omega_4 .\ \upsilon_{i,\tau}$(2)

➢ *Stage 3: Cluster Head Selection*

The node with the highest σ values in each cluster is chose as the η:

$\eta_{j,\tau} = \arg max_i\ \sigma_{i.j,\tau}$ (3)

➢ *Stage 4: RBD for cluster validation*

The RBD method is used to validate the clusters that have been constructed and ensure that energy consumption is balanced within each cluster. Utilizing a cluster's nodes' energy levels will allow us to determine the degree of balancing.The balancing Degree (ϕ) of cluster j in τcan be calculated as follows:

$$\phi_{j,\tau} = \frac{1}{|Cluster_{j,\tau}|} \sum_{i\epsilon cluster j,\tau} \varsigma_{j,\tau}$$ (4)

If $\phi_{j,\tau} < \delta_{\phi}$, the cluster has to be amended because it is unbalanced.

➢ *Stage 5: Amending clusters based on ϕ*

Reconsider the σ values for the unbalanced cluster's nodes using the eq. (2). Updated σ values should be used to reselect theηin eq. (3). Based on updated Cluster Head selections and balance factors, nodes may be moved to various clusters.

The RBD strategy is used iteratively to validate and modify clusters to establish efficient cluster architectures and balanced energy consumption in each ASep-Hex network sector.

B. Intra clustering routing

We present an energy-efficient routing algorithm to improve energy efficiency as wellasdatatransmissionrate. A cluster of sensor nodes, where one node serves as the η and other nodes are normal members, can communicate with one another using intra-cluster routing. The goal of the cluster is to improve the speed of data transmission and energy efficiency. Forintra-cluster routing, each clusterisconstructedasan equivalent **Hop- to-Hop Directed Acyclic Graph (H2H-DAG).** A graph without cycles is known as a directed acyclic graph (DAG), and it consists of nodes connected by directed edges. Each cluster in this scenario is represented by an H2H-DAG. This indicates that the cluster's nodes are set up so that communication moves from one node to the next in a directed, acyclic manner, ultimately reaching the η.Nodes within the communication range respond to each node's broadcast of their presence by clustering together. Within its cluster, each cluster head creates an H2H-DAG.

Com-Criteria for Optimal Parent Selection provides a technique for selecting the best parent node for each node toward the Cluster Head based on a set of Com-Criteria. The ideal parent node is chosen based on a combination of these parameters to enable effective energy use and data transfer. The particular composite criteria such as Residual energy in eq. (5), L1- Norm Minkowski Distance in eq. (6) and Link quality is as follows:

$$\gamma_i = \frac{\mho_i}{\mho_{max}} \quad (5)$$

Let $(\aleph_i, \rho_i)$ be the coordinates of the node i, and $((\aleph_\eta, \rho_\eta)$ be the coordinates of η Calculate:

$$\chi_i = |\aleph_i - \aleph_\eta| + \rho_i - \rho_\eta \quad (6)$$

Link Quality (ϖ_i) represents the node i's link quality to its parent η. Use the signal strength, SNR, or other pertinent parameters to determine ϖ_i.For γ, χ, and ϖ respectively, let $\mathfrak{A}, \mathfrak{B}, \mathfrak{C}$, and be the weighting factors. Calculate the com- criteria $\mathfrak{E}$ for node i:

$$\mathfrak{E}_i = \mathfrak{A} * \gamma_i + \mathfrak{B} * \chi_i + \mathfrak{C} * \varpi_i (7)$$

To identify the optimal parent nodes based on Com-Criteria, analyze the created H2H-DAG.

$$\mathcal{P} = \arg min_i(\mathfrak{X}_i) (8)$$

As the optimal parent, choose the node with the minimum composite criteria. Data transmission occurs along the directed edges of the H2H-DAG following the construction of the H2H-DAG and the selection of the $\mathcal{P}$using the $\mathfrak{X}$. Data from its child nodes are gathered and aggregated by the η. The efficiency of data collection and transmission within the cluster can then be maximized by processing, storing, or transmitting this aggregated data to higher-level nodes or sinks in the network. Here we introduce χ since it measures the accurate distance between two points. Intra-cluster routing is accomplished in this way and data is aggregated by η.

C. *Inter Clustering Routing*

The critical task of transferring the aggregated data to the specified sink node lies with the Cluster Head (CH) after the process of data aggregation inside a wireless sensor network. This assignment is completed by carefully choosing a route and focusing on the best route determination. The inter-cluster routing procedure, which is essential to this data transmission, involves the creation of the optimal routes and a subsequent evaluation of their quality. Finding the best routes to transfer the aggregated data is the main goal of the initial stage of this inter-cluster routing process. The Tri-state Markov Chain Model (Tri-MCM) is a customized model that is used to carefully find these best pathways. Low, moderate, and high energy states, which correspond to the remaining energy levels of individual sensor nodes within the network, are the three energy states that the Tri-MCM operates on. Relevant factors are included in this model, such as residual energy, packet transmission rate, and current buffer level. The Tri-MCM provides a thorough grasp of the potential paths that can be assessed as the "best" for data transmission by methodically examining and modeling the transitions between different energy states. A subset of an increasingly extensive Markov random process is a Markov chain. It is a Markov process, however, its state and time factors are discrete.

Let's consider the Markov process's s-parameter set is {Z, n$\in S\}$ is a discrete time domain S= 0.1, 2,….}. The set of discrete states D = d_1, d_2, d_3,..., corresponds to the state space Z_n , which contains all probable values. The following are some applicable definitions.A random method occurs $\{Z, n \in S\}$, The conditioned chance satisfies the following equations if for any integer n$\in S$ and any d_0, d_1,...,d_{n+1} ∈D:

$$\wp\{Z_{n+1} = d_{n+1} | Z_0 = d_0, Z_1 = d_1, \ldots, Z_n = d_n\} = \wp\{Z_{n+1} = d_{n+1} | Z_n = d_n\}. (9)$$

Then $\{Z_n, n \in S\}$ is known as the Markov chain. The definition of conditional probability in basic terms$\wp\{Z_{n+1} = i | Z_n = d\}$, calculates the probability that the framework will be situated in state 1 at time n and state i at time n + 1. As may be seen from the following formula, the conditional probability $\wp_{di}$ is:

$$\wp_{di} = \wp\{Z_{n+1} = i | Z_n = d\} (10)$$

It is known as the Markov chain's one-step transition chance $\{Z_n, n \in S\}$ at time n, where d, i $\in I$, as the transition probability. The transition probability $\wp_{di}(n)$ is typically dependent on time n, states d, and i. When $\wp_{di}(n)$ is independent of time n, it means that there is a static transition probability in the Markov chain.The Markov chain is considered to be homogeneous and is $\wp_{di}(n)$ recorded as $\wp_{di}$ if the transition probability $\wp_{di}(n)$ of the Markov chain $\{Z_n, n \in S\}$ is independent of n for each $\{Z_n, n \in S\}$.With the state space D= {1,2,…,} and let $\wp$ denote the matrix made up of the one-step transition probabilities $\wp_{di}$, According to the equation that follows,

$$\wp = \begin{bmatrix} \wp_{11} & \wp_{12} & \cdots & \wp_{1n} \cdots \\ \wp_{21} & \wp_{22} & \cdots & \wp_{2n} \cdots \\ \vdots & \vdots & & \vdots \end{bmatrix}. (11)$$

These one-step transition probability distributions of the system state have the following characteristics:

$\wp_{di} \geq 0, d, i, \in D$, (12)

$\sum_{i \in D} \wp_{di} = 1, d, \in D$.
(13)

The final value of I in the equation above is the sum of every probable state in the state space D. This characteristic demonstrates that the one-step transition probabilities matrix's aspect averages are all 1. The conditional probability of weighing is shown as follows:

$\wp_{di}^{(n)} = \wp\{Z_{b+n} = \text{i}|Z_b\}(\text{d,I} \in D, b \geq 0, n \geq 1)$. (14)

In the equation provided above, the Markov chain's n-step transition probabilities $\{Z_n, n \in S\}$, $\wp_n = (\wp_{di}^{(n)})$ is the Markov chain's n-step transition matrix, where $\wp_{di}^{(n)} \geq 0, \sum_{i \in D} \wp_{di}^{(n)} = 1, \wp(n)$is a random matrix as well.

Let $\{Z_n, n \in S\}$ be a Markov chain and$\wp_i = \wp\{Z_0,+\text{i}\}$ be $\{Z_n, n \in S\}$ initial probability. Let $\_\wp_s(0) = (\wp_\wp, \wp_2, \ldots)$ be the initial probability vector and $\{\wp_i = i \in D\}$ be the initial distribution of $\{Z_n, n \in S\}$.

The n-step transfer matrix $\wp(n)$ has the following characteristics for any integer $n \geq 0$, assuming that $\{Z_n, n \in S\}$ is the Markov chain:

$\wp^{(n)} = \wp\wp^{(n-1)}$, (15)

$\wp^{(n)} = \wp^{(n)}$(16)

In our strategy, we employ a three-state Markov chain model with two good states ($\kappa1$ and $\kappa2$) and one bad state (ψ). As a result, we are provided with the optimal paths. Residual energy$\mathcal{R}$, packet transmission rateT, and current buffer level $\mathfrak{B}$are all being worked on by the Tri-MCM represented in Fig. 2.

$$\wp = \begin{bmatrix} \wp_{11} & \wp_{12} & \wp_{13} \\ \wp_{21} & \wp_{22} & \wp_{23} \\ \wp_{31} & \wp_{32} & \wp_{33} \end{bmatrix} =$$

$$\begin{bmatrix} \wp_{\kappa1\kappa1} & 1-\wp_{\kappa1\kappa1} & 0 \\ \wp_{\kappa2\kappa1} & \wp_{\kappa2\kappa2} & 1-\wp_{\kappa2\kappa2}-\wp_{\kappa2\kappa1} \\ 0 & 1-\wp_{\psi\psi} & \wp_{\psi\psi} \end{bmatrix} (17)$$

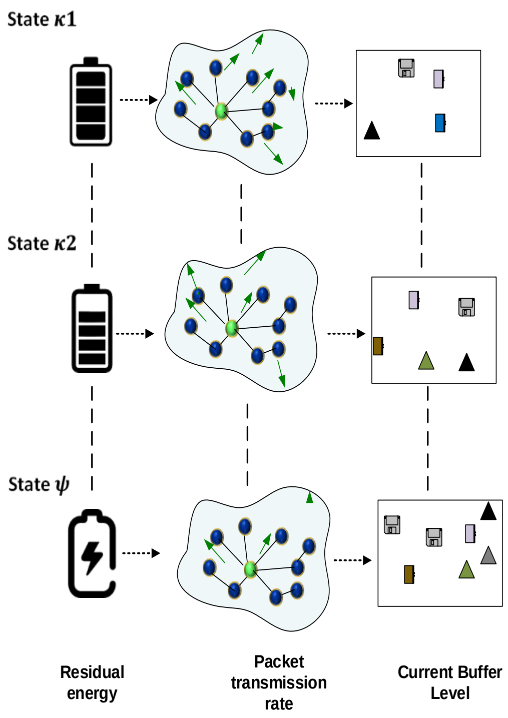

Fig. 2 Tri-state Markov Chain Model

- *State* $\kappa1$

A relatively high $\mathcal{R}$ is a sign that nodes have enough power reserves.

T: Nodes in this state can send packets effectively at an appropriate pace.

$\mathfrak{B}$: Nodes contain a moderate amount of data scheduled for transmission.

- *State* $\kappa2$

$\mathcal{R}$: Like $\kappa1$, nodes in this condition have sufficient residual energy levels.

T: Nodes in this group can send packets, albeit at a slower pace than in $\kappa1$.

$\mathfrak{B}$: The buffer level may differ from $\kappa1$, indicating a different quantity of data queued.

- *State* ψ

$\mathcal{R}$: This state indicates that nodes' energy reserves have been significantly depleted, offering them less suited for data transmission.

T: Due to low energy levels, the transmission rate is likely to be impaired.

$\mathfrak{B}$: Due to their limited ability to send data, nodes may have a rather high buffer level.Then the generated routes are assessed by Quality Aware Assessment Model (QA2M) is used to evaluate and categorize the inter-cluster routing routes based on several crucial parameters such as Expected Transmission Count (ETX), delay, hop count, and bandwidth

Expected Transmission Count ($\mathfrak{T}$): The $\mathfrak{T}$ required for a packet to be properly received at its destination is an estimate. It considers both the possibility of an effective transmission and the probability of failure. A more dependable link is one with a lower $\mathfrak{T}$ value. $\mathbb{T}_{\mathbb{S}}$ refers to transmission success, and $\mathbb{T}_{\mathbb{F}}$ refers to transmission failure.

$$\mathfrak{T} = \frac{\mathbb{T}_{\mathbb{S}} + \mathbb{T}_{\mathbb{F}}}{\mathbb{T}_{\mathbb{S}}} \quad (18)$$

Delay ($\mathfrak{Q}$): A packet's delayis the amount of time it takes to get from one node to another. Propagation, transmission, and processing $\mathfrak{Q}$ are all included. Reduced latency is preferable with lower $\mathfrak{Q}$. $\mathfrak{V}$ indicates the propagation delay; $\mathfrak{Y}$ illustrates the transmission delay; $\mathfrak{Z}$ shows the processing delay.

$$\mathfrak{Q} = \mathfrak{V} + \mathfrak{Y} + \mathfrak{Z} \quad (19)$$

Hop Count ($\mathfrak{L}$): $\mathfrak{L}$ indicates how many intermediate nodes a packet must pass through to get to its final destination. In general, fewer hops result in less energy being consumed and faster transmission.

Bandwidth ($\mathfrak{S}$): The capacity of the link for transmitting data is referred to as $\mathfrak{S}$. Better performance and faster transmission rates are made possible by increased $\mathfrak{S}$.

D. Intelligent Sink Relocation

Sink relocation decisions are made once the energy level of related CHs has been depleted to a threshold level. To identify candidate positions, a novel **Intelligent Triangulation Method (ITM)** is proposed. Based on the locations of CHs, the ITM algorithm seeks to find potential sink relocation locations.Within a Wireless Sensor Network (WSN), the ITM seeks to locate potential locations for moving the sink. Based on the locations of three neighboring Cluster Heads (CHs), it uses triangulation to establish acceptable positions. As a starting point for sink relocation candidates, the centroid of the triangle formed by these CHs is used.

Step 1: Determine the Triangle's Centroid for CHs

It is possible to get the centroid of a triangle whose vertices are A (x1, y1), B (x2, y2), and C (x3, y3) using the following formulas:

$$C(x) = (x1 + x2 + x3)/3 \quad (20)$$

$$C(y) = (y1 + y2 + y3)/3 \quad (21)$$

Step 2: Modify candidate position to objectives

Modify the candidate location iteratively to maximize a variety of goals, including residual energy, distance, load, and connectivity level. Candidate position ($\mathfrak{P}$), Best position ($\mathcal{B}$). Pseudocode for ITM is represented as follows:

Pseudocode for ITM

function ITM (η1, η2, η3):
  Using $\eta 1$, $\eta 2$, $\eta 3$ determine the centroid $C(x)$ and $C(y)$
  Initialize the $\mathfrak{P}(x)$, $\mathfrak{P}(y)$ with $C(x), C(y)$
  Initialize the $\mathcal{B}(x), \mathcal{B}(y)$ with $\mathfrak{P}(x)$, $\mathfrak{P}(y)$
  Initialize $max_{iterations}$
Initialize $Convergence_{\ threshold}$
  for iterations in range ($max_{iterations}$)
    Calculate the objective values for $\mathfrak{P}(x)$, $\mathfrak{P}(y)$
Determine fitness level based on step 2.
    if the fitness score is higher than the prior best:
      Update the $\mathcal{B}(x), \mathcal{B}(y)$
    Else:
      If convergence is achieved:
        Break:
    Update $\mathfrak{P}$ depending on the optimization strategy
  Return $\mathcal{B}(x), \mathcal{B}(y)$
end

After computing the fitness score, the $\mathcal{B}$ is updated if the fitness score is higher than the prior best. If the fitness score is not higher, it checks for convergence and, if necessary, exits the loop. In each cycle, the algorithm updates the $\mathfrak{P}$ based on the optimization approach.

The SMO algorithm takes into account the process of locating food for spider monkeys (SMs). These activities can be divided into the social fission-fusion social structure (FFSS) of spider monkeys.

Initialization: Finding N random solutions is the first step. Then, the Spider Monkey Population (SMP) is divided into an agreed-upon number of groups, each represented by the letter $\mathfrak{N}$. A global leader who oversees all of the groups is then chosen, along with a local leader for every group. This optimization approach first establishes four parameters.

$$\mathcal{M}_{\mathfrak{a}\mathrm{b}} = \mathcal{M}_{\min b} + \mathcal{T}(0,1) \times (\mathcal{M}_{\max b} - \mathcal{M}_{\min b}) \quad (22)$$

Where $\mathcal{M}_{\max b}$ and $\mathcal{M}_{\min b}$ are limits of $\mathcal{M}_{\mathfrak{a}}$ in the b^{th} sector

$\mathcal{T}(0,1)$ is a random number between 0 and 1.

Local leader phase: At this time, the SMs will be receiving information from their neighbor as well as their local leader. As a result, their precise location will get updated. Below is a description of this procedure:

$\mathcal{M}_{new\mathfrak{ab}} = \mathcal{M}_{\mathfrak{ab}} + \mathcal{T}(0,1) \times \ell\ell_{hb} - \mathcal{M}_{\mathfrak{ab}} + \mathcal{T}(-1,1) \times (\mathcal{M}_{kb} - \mathcal{M}_{ab}$(23)

if $\mathcal{M}_{new\,\mathfrak{ab}}$ and $\mathcal{M}_{\mathfrak{ab}}$ represent a modified and old location for an SM, respectively. The $\ell\ell_{hb}$ symbol stands for the local leader of the h^th group in the b^th Dimension. $\mathcal{M}_{kb}$ represents the neighbor that is chosen at random.

*Global Leader Phase:*The SMs have another chance during this phase to update their positions and utilize their "fitness" to get to the "global optimum." The SMs may find motivation in their determination, neighbors, and global leader of the group. The following equation explains how the location is updated during this phase:

$\mathcal{M}_{new\mathfrak{ab}} = \mathcal{M}_{\mathfrak{ab}} + \mathcal{T}(0,1) \times g\ell_a - \mathcal{M}_{\mathfrak{ab}} + \mathcal{T}(-1,1) \times (\mathcal{M}_{kb} - \mathcal{M}_{ab}$(24)

where b=1,2, 3..., D signifies the index selected at random and $g\ell_a$ signifies the position of the global leader in the jth dimension. $\mathcal{M}_{\mathfrak{a}}$ modifies its position towards the probability. There are several ways to utilize fitness to determine the possibility of a particular solution, including:

$\wp k_a$=0.1($fitness_a/fitness_{max}$)×*0.9*(25)

*Local leader learning phase:*Since the global optimal is known, the method derives the local optimal and finds the local leader of the subgroups. By monitoring the threshold counter, this stage determines how often the local leaders update itself.

*Global leader learning phase:*By means of the phase's designation alone, it is aware that the global leader is present in the flocks and assesses whether or not it has updated its location to meet a specific threshold for additional actions.

Local leader decision phase: The SMs in the bevy will adjust the positions by following the sequence of the global leader or by arbitrarily establishing based on the rate of disturbance if the local leaders are not updated to a specific threshold during this phase. But equation (26) determines the update order.

$\mathcal{M}_{new\mathfrak{ab}} = \mathcal{M}_{\mathfrak{ab}} + \mathcal{T}(0,1) \times g\ell_a - \mathcal{M}_{\mathfrak{ab}} + \mathcal{T}(-1,1) \times (\mathcal{M}_{ab} - \ell\ell_{hb}$)(26)

*Global leader decision phase:*In the event of a "limit global leader," that is, global leaders do not update themselves to a specified threshold, the group as a whole fissions and fuses throughout this phase. The following is how MOsMO pseudocode is represented:

Pseudocode for MOsMO

Initialize the parameters of networks,η, Sink

Initialize the ITM and MOsMO parameters

While network conditions permit:

Monitor η energy levels.

If any CH energy reduces under the threshold:

Use ITM to determine $\mathfrak{P}$ for sink relocation

Initialize the SMP within $\mathfrak{P}$

Spilt into Spider Monkey into N groups

Select $\ell\ell$ and $g\ell$ in each group

For each generation (gen= 1 to $max_{generations}$)

For each SM in each group:

Update SM's location using the $\ell\ell$ in eq. (23) with $\mathcal{M}_{kb}$

Update the $g\ell$ in eq. (24)

Calculate the probabilities ($\wp k_a$) based on fitness in eq. (25)

For each group:

Update $\ell\ell$ using local leader phase

Update $g\ell$ using global leader phase

For each group:

If $\ell\ell$ counter does not reach the threshold, update positions using Eq. (26).

If $g\ell$ counter does not reach the threshold, update the positions

If the "limit global leader" condition is met, perform fission- fusion

Get optimal position from the Pareto front

Relocate the sink to the selected Optimal position

Intelligent Sink Relocation begins with setup and goes through energy monitoring, testing energy thresholds, and sink relocation. The algorithm then divides into two primary branches: the ITM and the MOsMO are represented in Fig. 3. Following the identification of candidate positions and the selection of the best position, the process concludes by improving aggregation and energy efficiency through sink relocation.

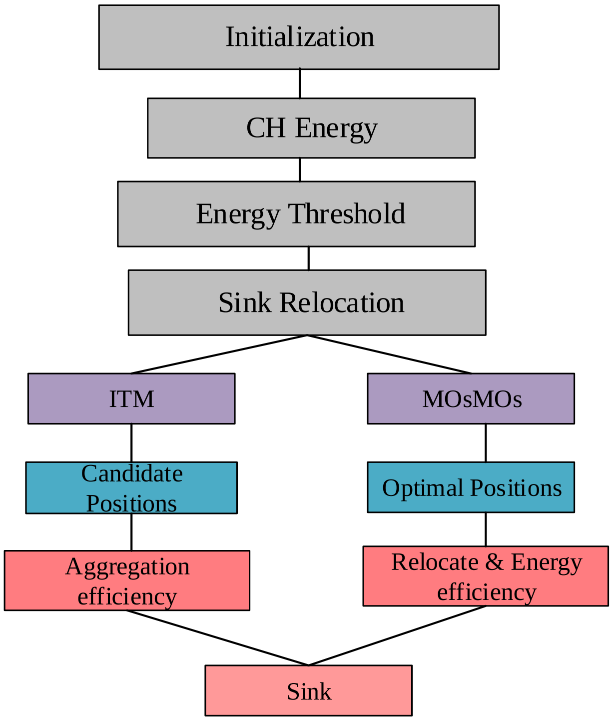

Fig.3 Intelligent Sink Relocation

5. Experimental Analysis

The experimentation findings of the suggested study methodology to assess performance are described in this section. There are three subsections such as simulation setup, comparison analysis, and the research summary make up this section.

A. Simulation setup

Network Simulator 3.26 (NS3) simulates the suggested research approach. This tool provides all the requirements needed to implement the suggested technique and has an effective network structure. Simulated habitats of $1000m\ x\ 1000m$ have been used to test the suggested approach. Various system Specifications are described in Table III. In table IV simulation parameters are represented.

Table III System Specifications

Software Specifications	OS	Ubuntu 14.04LTS
	Network Simulator	NS-3.26
Hardware Specifications	RAM	4GB
	Hard Disk	500GB

Table IV Simulation Parameters

Parameters		Descriptions
Network Parameters	No. of the sink node	1
	No. of. Sensor nodes	100
	Simulation area	$1000m\ x\ 1000m$
Transmission Slot parameters	Slot length	1040 bits
	Slot duration	8µs
	packet length	830 bits
Packet Parameters	Packet Size	1024
	No. of. Packets	~1500
	No. of. Retransmission	Max 5
	Packet interval	0.99s
	Data rate	280kbps
Energy Parameters	Initial energy	0.5J
	Transmission power	47J
	Receiving power	47J
	Data aggregation power	5J
	Battery power	3.3V
No. of. Run		1100
Simulation time		150s
Probability of node		0.1
Number of rounds		600
Duration of a single round		18s

B. Comparison analysis

In this sub-section, the proposed approach is compared with various existing approaches such as Power Efficient Cluster based Routing (PECR) [42], Fuzzy Grey Wolf Optimizer (FGWO) [43], and the Fuzzy rule-based Energy Efficient Clustering and Immune Inspired Routing (FEEC-IIR) method is performed to evaluate its performance. The evaluation i.e. validation is performed by considering the performance metrics such as the number of alive nodes, network lifetime, throughput, packet delivery ratio, and energy consumption respectively.

a) Number of nodes alive for simulation time

In the suggested network structure, we can use the following equation to explain the link between the number of alive nodes and simulation time:

$$\mathbb{N}(t)=\mathbb{N}_0-\frac{t}{\mathbb{T}_{avg}}\times\mathbb{N}_0\times\frac{\mathcal{E}_{consumed}}{\mathcal{E}_{initial}}$$

(27)

$\mathbb{N}(t)$ represents the number of nodes alive at the time (t); $\mathbb{N}_0$ presents the initial number of nodes (100 nodes); $\frac{t}{\mathbb{T}_{avg}}$ indicates the average lifetime of nodes (time till nodes die);

$\mathcal{E}_{consumed}$- energy consumed per unit time; $\mathcal{E}_{initial}$- initial energy of each sensor node.

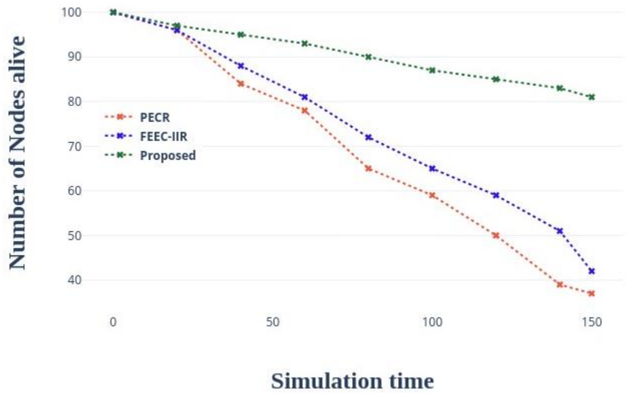

Fig.4 Comparison of Alive Nodes

The comparison of the number of alive nodes of the proposed work to the simulation time of several known methods such as PECR and FEEC-IIR approaches is shown in Fig.4. The number of alive nodes decreases as the number of simulation times increases. The suggested method reduces the number of alive nodes by 81 when n=100, whereas existing approaches such as PECR have 37 alive nodes when n=100, and the FEEC-IIR method has 72 alive nodes for the same n value. The suggested work's Intelligent Triangulation approach enhances the number of living nodes by lowering the energy consumption of the sensor nodes. The suggested work differs from the existing technique by 44 alive nodes for the PECR method and 39 nodes for the FEEC-IIR method.

b) Networklifetime

This statistic is used to calculate the sensor nodes' lifetime. The amount of time a sensor node is active until it runs out of energy is known as network lifetime.

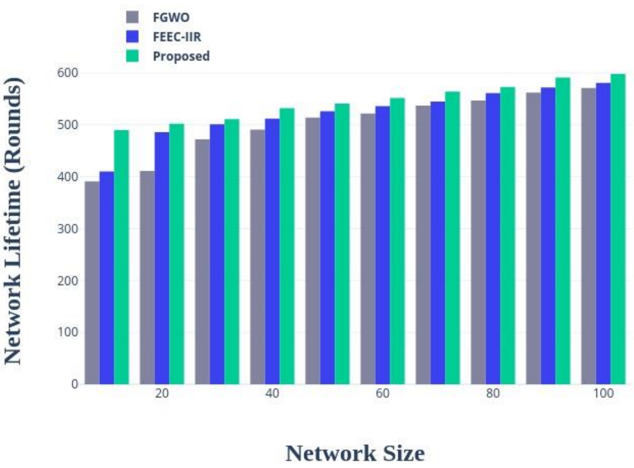

Fig.5 Network size vs Network Lifetime

The sensor node's active status is mostly determined by its power. It is denoted as 'ϑ_l,' which is written as follows:

$$\vartheta_l = \frac{K_j - \mathbb{w}_E}{\mathcal{N}_P + A_{\mathcal{E}}\mathbb{R}_e}$$
(28)

Where K_j indicates the network's beginning energy, $\mathbb{w}_E$ represents wasted energy, $\mathcal{N}_P$ represents continuous network power consumption, $A_{\mathcal{E}}$ represents average sensor reporting rate, and $\mathbb{R}_e$ represents expected reporting energy.

Fig 5 illustrates the comparison of the network lifetime of the proposed work to the network size with several existing works such as FGWO and FEEC-IIR methods.In the proposed system the network size in 10 the network lifetime in (rounds) achieves 502 and in 100 nodes it achieves 598. In the FGWO method in 10 nodes with 398 and finally in 100 nodes 546. FEEC-IIR in 10 nodes with 402 and 100 nodes 565.

Fig 6 illustrates the comparison of the network lifetime (rounds) of the proposed work with several existing works such as FGWO and FEEC-IIR methods. Network lifetime is evaluated in (rounds).It increases when an increase in network lifetime in rounds. The network lifetime of the proposed work is 625 at the final stage and approximately 425 in the initial stage. FGWO method has 361 of the network lifetimes in the initial and FECE-IIR method has 385 of network lifetime for the same value as the initial. The difference between the proposed and FGWO method is 44 and for the FEEC-IIR method, the difference is about 23.

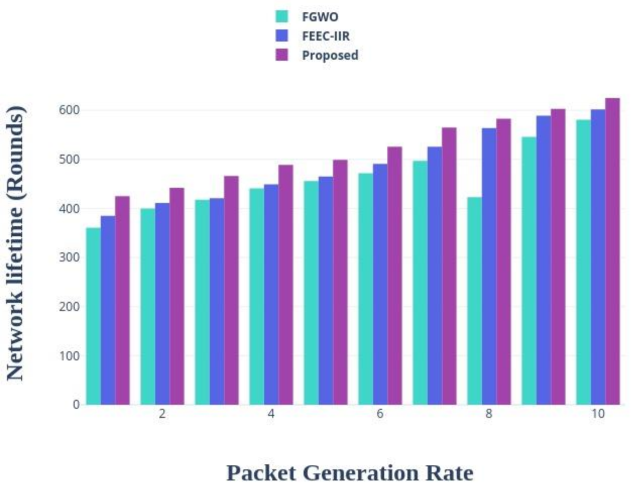

Fig. 6 Network lifetime vs Packet Generation rate

c) Throughput

The expression "network size vs. throughput" refers to a comparison of the physical size of a network, which is commonly quantified in terms of the number of nodes or devices, and throughput, which is the rate at which data can be transmitted over that network. This comparison seeks to comprehend how changes in network size affect data transmission capacity.

$\mathfrak{Y} = \mathfrak{K}.N^P$(29)

$\mathfrak{Y}$ presents the throughput; $\mathfrak{K}$ is a constant coefficient that determines the initial throughput; N represents the network size; P is an exponent that characterizes how the throughput scales with network size.

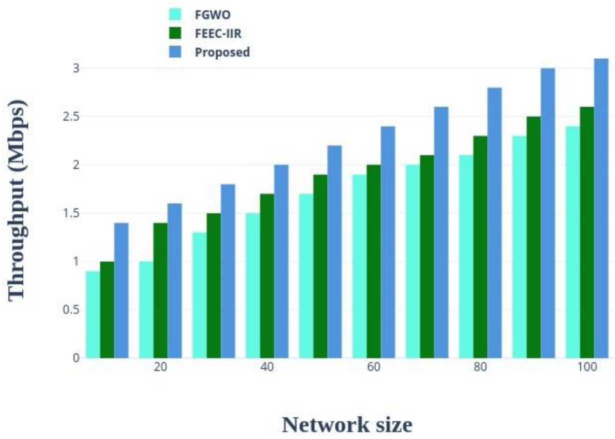

Fig.7 Throughput vs Network size

In fig 7 represents the throughput vs Network size when the network size increases the throughput also increases. In the proposed method the 10 nodes with 1.4 Mbps and in 100 nodes have 3.1 Mbps. In FGWO with 0.9 in 10 nodes and finally in 100 nodes the 2.3 Mbps. FEEC-IIR method in 10 nodes will 1Mbps and 100 nodes 2.5 Mbps.

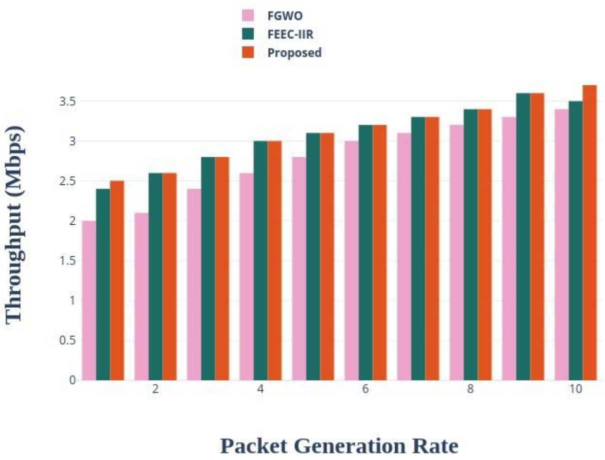

Fig.8 Throughput vs Packet Generation Rate

Fig 8depicts the throughput vs Packet Generation Rate. If the packet generation rate increases along with the throughput value it increases. In the proposed methods initially, the throughput with 2.5 Mbps, and finally the throughput is 3.7. In the FGWO method initially in 2 and finally it attains 3.4. In FEEC-IIR initially with 2.4 and finally it attains 3.6.

d) Packet delivery Ratio

The ratio of receiving all of the packets at the sink $(\mathcal{P}_d)$ to the total number of packets emitted from the sensor nodes $(\mathcal{P}_t)$. is known as the packet delivery ratio (PDR). The PDR of this approach is formulated as.

$PDR = \frac{P_d}{P_t}$(30)

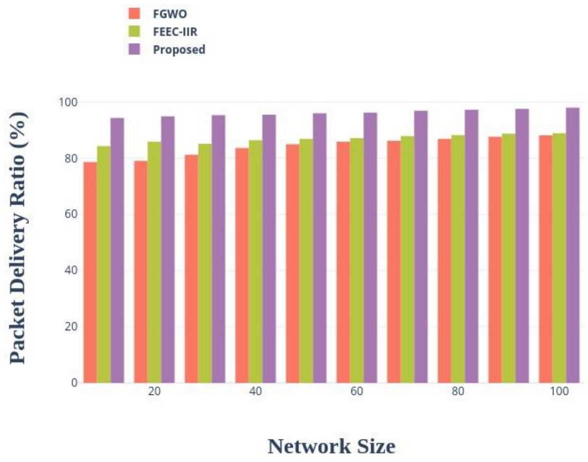

Fig.9 Network size vs Packet delivery ratio

Fig 9illustrates the comparison of the PDR to the network size among the suggested work and various existing works i.e. FGWO and FEEC-IIR. PDR increases when increasing the network size. In the proposed work, the PDR is increased by 98% when $n = 100$ and decreased to 94.3% when $n = 10$. Inter-cluster routing is performed by using **the Tri-MCM**algorithm for effective routing with high PDR. FGWO method has a PDR of 84% when $n = 100$ and the FEEC-IIR method is having 82% of PDR for the same n value. The suggested work's PDR is 10.3% higher than that of the FGWO approach and 12.3% higher than that of the FEEC-IIR approach.

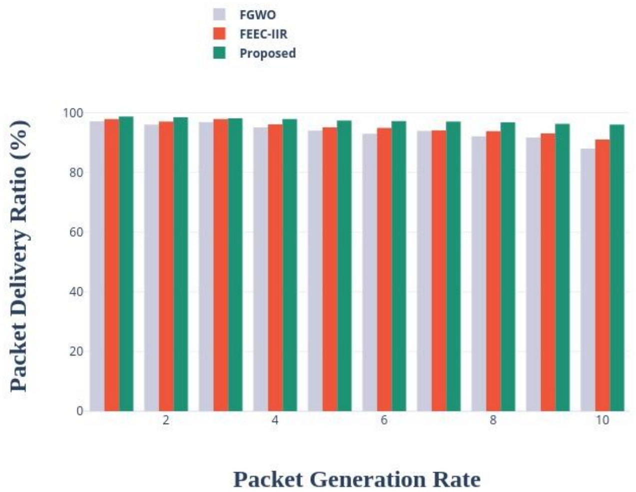

Fig. 10 Packet generation rate vs Packet delivery ratio

As the packet generation rate increases the packet delivery ratio decreases are representing in Fig 10. In the proposed method initially, it attains 98.7% and finally, it attains 96%. FGWO methods 97.1 initially and 88 in the final. FEEC-IIR method 97.9% initially and finally 91%.

e) Energy consumption

Energy consumption is defined as the amount of energy used for the sensor node in various states. It is calculated by the difference of total energy (E_T) to the residual energy (E_R) of the sensor node which is expressed as follows,

$$E_C = E_T = E_R (31)$$

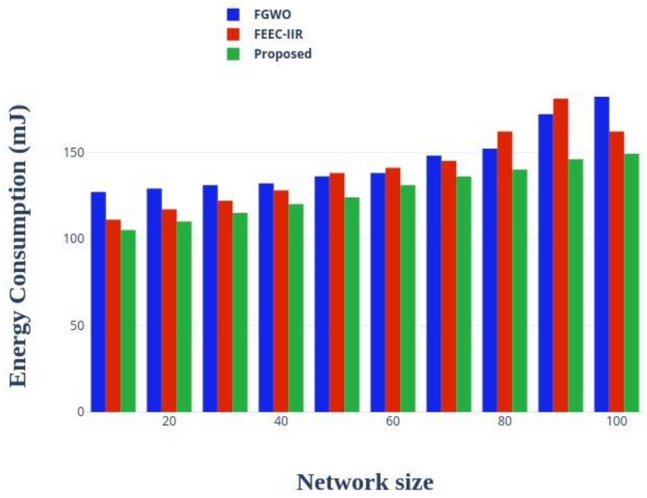

Fig. 11 Energy consumption vs Network size

Fig 11 indicates the comparison of energy consumption to the number of simulation rounds n among the proposed work and several existing works i.e. FGWO and FEEC-IIR methods. Energy consumption increases when increasing the number of simulation rounds. In the proposed work, the energy consumption is increased by 149mJ when $n = 100$ and decreased by 105mJ when $n = 10$. Energy-aware inter-cluster routing is performed by **the Tri-MCM** algorithm in the proposed work then the generated routes are assessed by **Quality Aware Assessment Model (QA2M)** which is formulated based on multiple important metrics such as Expected Transmission Count (ETX), delay, hop count, and bandwidth FGWO method consumes 182mJ of energy when $n = 100$ and FEEC-IIR consume 162mJ of energy for the same simulation rounds. The energy consumption of the proposed work is 33mJ decreased than the FGWO method and 1mJ decreased than the FEEC-IIR method.

C. Research Summary

In terms of the number of alive nodes, network lifetime, throughput, packet delivery ratio, and energy usage, the proposed work's performance is summarized in this part. These metrics are achieved by performing balanced cluster formation, intra-clustering routing, inter-cluster routing, and intelligent sink relocation. The numerical analysis of proposed and existing approaches is shown in Table V. The research highlights are listed as follows,

- The research introduces the E2CFV approach, which efficiently forms clusters in a hexagonal network topology by utilizing innovative criteria such as energy level, node degree, centrality factor, and mean distance. This tackles energy efficiency concerns by optimizing cluster head selection and certifying clusters using RBD.
- H2H-DAG is used for intra-cluster routing, providing optimal data aggregation within clusters. Tri-MCM improves communication efficiency between clusters, contributing to total network performance and throughput.
- ITM utilized to determine candidate spots reflects the company's dedication to optimizing network topology. MOsMO algorithm then chooses the best places to improve network coverage and connection.

Table V Numerical Analysis Of Proposed And Existing Methods

Performance metrics		PECR	FGWO	FEEC-IIR	Proposed
Number of nodes alive		37	-	42	81
Network lifetime (Rounds)	Network size	-	571	581	598
	Packet generation rate	-	581	602	625
Throughput (Mbps)	Network size	-	3.4	3.6	3.7
	Packet generation rate	-	3.4	3.5	3.7
Packet Delivery Ratio (%)	Network size	-	88.1	88.9	98
	Packet generation rate	-	88	91	96
Energy Consumption (mJ)		-	182	162	149

6. Conclusion

This research project proposes a comprehensive framework for improving the efficiency and performance of WSNs. It solves energy-efficient clustering, balanced cluster formation, optimum routing using Hop-to-Hop DAG and Tri-MCM, and intelligent node positioning utilizing ITM and MOsMO algorithms by proposing unique methods inside a hexagonal network design comprising 100 sensor nodes and a mobile sink. In conclusion, the discovery of novel approaches provided useful insights into the performance enhancements of WSNs. The suggested E2CFV approach has shown encouraging results across a variety of performance metrics, demonstrating its efficacy in enhancing network properties. The numerical results eloquently depict the study's accomplishments. Notably, the suggested method outperformed existing methods, resulting in 81 active nodes and a significant increase in the number of nodes alive. Furthermore, the suggested strategy increased network lifetime by 598 and 625 rounds under different packet generation rates. With both network size and packet generation rate in consideration, throughput increased significantly, reaching 3.7 Mbps. The proposed method's remarkable packet delivery ratio of 98% demonstrates its ability to assure dependable data transmission. Equally significant is the reduction in energy consumption, with the proposed approach demonstrating a significant decrease to 149 mJ. For future investigation the development of Quality of Service (QoS) aware routing algorithms that take into account elements like delay, dependability, and data priority in addition to energy savings. The network may cater to a broader range of application requirements and deliver more personalized services to different types of data traffic by improving routing paths to balance these diverse QoS measures. This could entail developing adaptive routing methods that modify dynamically in response to changing network conditions and QoS needs.

Reference

[1] Bharathi, R., Kannadhasan, S., Padminidevi, B., Maharajan, M. S., Nagarajan, R., & Tonmoy, M. M. (2022). Predictive model techniques with energy efficiency for iot-based data transmission in wireless sensor networks. *Journal of Sensors*, *2022*.

[2] Bayih, A. Z., Morales, J., Assabie, Y., & de By, R. A. (2022). Utilization of internet of things and wireless sensor networks for sustainable smallholder agriculture. *Sensors*, *22*(9), 3273.

[3] Gardašević, G., Katzis, K., Bajić, D., & Berbakov, L. (2020). Emerging wireless sensor networks and Internet of Things technologies—Foundations of smart healthcare. *Sensors*, *20*(13), 3619.

[4] Abdulwahid, H. M., & Mishra, A. (2022). Deployment Optimization Algorithms in Wireless Sensor Networks for Smart Cities: A Systematic Mapping Study. *Sensors*, *22*(14), 5094.

[5] Ahmed, S., Hossain, M. F., Kaiser, M. S., Noor, M. B. T., Mahmud, M., & Chakraborty, C. (2021). Artificial intelligence and machine learning for ensuring security in smart cities. In *Data-Driven Mining, Learning and Analytics for Secured Smart Cities: Trends and Advances* (pp. 23-47). Cham: Springer International Publishing.

[6] Shukla, A., & Tripathi, S. (2020). A multi-tier-based clustering framework for scalable and energy efficient WSN-assisted IoT network. *Wireless Networks*, *26*, 3471-3493.

[7] Kandris, D., Nakas, C., Vomvas, D., & Koulouras, G. (2020). Applications of wireless sensor networks: an up-to-date survey. *Applied system innovation*, *3*(1), 14.

[8] Altowaijri, S. M. (2022). Efficient next-hop selection in multi-hop routing for IoT enabled wireless sensor networks. *Future Internet*, *14*(2), 35.

[9] Hasan, M. Z., & Mohd Hanapi, Z. (2023). Efficient and Secured Mechanisms for Data Link in IoT WSNs: A Literature Review. *Electronics*, *12*(2), 458.

[10] Yagoub, M. F., Khalifa, O. O., Abdelmaboud, A., Korotaev, V., Kozlov, S. A., & Rodrigues, J. J. (2021). Lightweight and efficient dynamic cluster head election routing protocol for wireless sensor networks. *Sensors*, *21*(15), 5206.

[11] Hassan, A. A. H., Shah, W. M., Habeb, A. H. H., Othman, M. F. I., & Al-Mhiqani, M. N. (2020). An improved energy-efficient clustering protocol to prolong the lifetime of the WSN-based IoT. *Ieee Access*, *8*, 200500-200517.

[12] Chao, F., He, Z., Pang, A., Zhou, H., & Ge, J. (2019). Path optimization of mobile sink node in wireless sensor network water monitoring system. *Complexity*, *2019*, 1-10.

[13] Gulati, K., Boddu, R. S. K., Kapila, D., Bangare, S. L., Chandnani, N., & Saravanan, G. (2022). A review paper on wireless sensor network techniques in Internet of Things (IoT). *Materials Today: Proceedings*, *51*, 161-165.

[14] Jothikumar, C., Ramana, K., Chakravarthy, V. D., Singh, S., & Ra, I. H. (2021). An efficient routing approach to maximize the lifetime of IoT-based wireless sensor networks in 5G and beyond. *Mobile Information Systems*, *2021*, 1-11.

[15] Mahajan, H. B., Badarla, A., & Junnarkar, A. A. (2021). CL-IoT: cross-layer Internet of Things protocol for intelligent manufacturing of smart farming. *Journal of Ambient Intelligence and Humanized Computing*, *12*(7), 7777-7791.

[16] Lenka, R. K., Kolhar, M., Mohapatra, H., Al-Turjman, F., & Altrjman, C. (2022). Cluster-based routing protocol with static hub (CRPSH) for WSN-assisted IoT networks. *Sustainability*, *14*(12), 7304.

[17] Moussa, N., Hamidi-Alaoui, Z., & El Belrhiti El Alaoui, A. (2020). ECRP: an energy-aware cluster-

based routing protocol for wireless sensor networks. *Wireless Networks*, *26*, 2915-2928.

[18] Rezaeipanah, A., Amiri, P., Nazari, H., Mojarad, M., & Parvin, H. (2021). An energy-aware hybrid approach for wireless sensor networks using re-clustering-based multi-hop routing. *Wireless Personal Communications*, *120*(4), 3293-3314.

[19] SalehiPanahi, M., & Abbaszadeh, M. (2018). Proposing a method to solve energy hole problem in wireless sensor networks. Alexandria Engineering Journal, 57, 1585-1590.

[20] Dattatraya, K.N., & Rao, K.V. (2019). Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN. Journal of King Saud University –Computer and Information Sciences

[21] Abidoye, A.P., & Obagbuwa, I.C. (2017). Models for integrating wireless sensor networks into the Internet of Things. IET Wireless Sensor Systems, 7, 65-72.

[22] Muhammed, T., Mehmood, R., Albeshri, A., & Alzahrani, A. (2020). HCDSR: A Hierarchical Clustered Fault Tolerant Routing Technique for IoT-Based Smart . Societies.

[23] Shen,J.,Wang,A.,Wang,C.,Hung,P.C.,&Lai,C.(2017) .AnEfficient Centroid-Based RoutingProtocolforEnergyManagementinWSN-Assisted IoT. IEEEAccess,5,18469- 18479.

[24] Saranya, V., Shankar, S., & Kanagachidambaresan, G.R. (2018). Energy Efficient Clustering Scheme (EECS) for Wireless Sensor Network with Mobile Sink. Wireless Personal Communications, 100, 1553-1567.

[25] Mitra, R., & Sharma, S. (2018). Proactive data routing using controlled mobility of a mobile sink in Wireless Sensor Networks. Computers & Electrical Engineering, 70, 21- 36.

[26] Thangaramya, K., Kulothungan, K., Logambigai, R., Lavina, L.S., Ganapathy, S., & Kannan, A. (2019). Energy aware cluster and neuro-fuzzy based routing algorithm for wireless sensor networks in IoT. Computer Networks, 151, 211-223.

[27] Behera,T.M.,Mohapatra,S.K.,Samal,U.C.,Khan,M.S., Daneshmand,M.,& Gandomi,A.H. (2019). Residual Energy-Based Cluster-Head Selection in WSNs for IoT Application. IEEE Internet of Things Journal, 6, 5132-5139.

[28] Shah, S.B., Chen, Z., Yin, F., Khan, I.U., & Ahmad, N. (2018). Energyand interoperable aware routing for throughput optimization in clustered IoT-wireless sensor networks. Future Generation Comp. Syst., 81, 372-381.

[29] Kumar, S., Lal, N., & Chaurasiya, V.K. (2018). A forwarding strategy based on ANFISin internet-of-things-oriented wireless sensor network (WSN) using a novel fuzzy-based cluster head protocol. Annals of Telecommunications, 73, 627-638.

[30] Elappila,M.,Chinara,S., & Parhi,D.R. (2018). SurvivablePath Routingin WSNfor IoT applications. Pervasive and Mobile Computing, 43, 49-63.

[31] Jain, J.K. (2019). Secure and Energy-Efficient Route Adjustment Model for Internet of Things. Wireless Personal Communications, 108(1), 633-657.

[32] Wang, J., Cao, J., Sherratt, R.S., & Park, J.H. (2017). An improved ant colony optimization-based approach with mobile sink for wireless sensor networks. The Journal of Supercomputing, 74, 6633-6645.

[33] Sujanthi, S., & Nithya Kalyani, S. (2020). SecDL: QoS-aware secure deep learning approach for dynamic cluster-based routing in WSN assisted IoT. *Wireless Personal Communications*, *114*, 2135-2169

[34] Arya, G., Bagwari, A., & Chauhan, D. S. (2022). Performance analysis of deep learning-based routing protocol for an efficient data transmission in 5G WSN communication. *IEEE Access*, *10*, 9340-9356.

[35] Mishra, J., Bagga, J., Choubey, S., Choubey, A., & Gupta, K. (2021, February). Performance evaluation of cluster-based routing protocol used in wireless internet-of-things sensor networks. In *2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)* (pp. 1-10). IEEE.

[36] Ullah, M.F., Imtiaz, J., & Maqbool, K.Q. (2019). Enhanced Three Layer Hybrid Clustering Mechanism for Energy Efficient Routing in IoT. Sensors.

[37] Preeth, S., Dhanalakshmi, R., Kumar, R.R., & Shakeel, P.M. (2018). An adaptive fuzzy rule-based energy efficient clustering and immune-inspired routing protocol for WSN- assisted IoT system. Journal of Ambient Intelligence and Humanized Computing, 1-13.

[38] Movva,P.,&Rao,P.T.(2019).NovelTwo-Fold DataAggregationandMACScheduling to Support Energy Efficient Routing in Wireless Sensor Network. IEEE Access, 7, 1260- 1274.

[39] Kaswan, A., Singh, V., Jana, P.K. (2018). A novel multi-objective particle swarm optimization-based

energy efficient path design for mobile sink in wireless sensor networks. Pervasive and Mobile Computing, 46.

[40] Pushpalatha, A.M., & Kousalya, G. (2018). A prolonged network life time and reliable data transmission aware optimal sink relocation mechanism. Cluster Computing, 1-10.

[41] Dhumane, A.V., & Prasad, R.S. (2019). Multi-objective fractional gravitational search algorithm for energy efficient routing in IoT. Wireless Networks, 25, 399-413.

[42] Firdous, S., Bibi, N., Wahid, M., & Alhazmi, S. (2022). Efficient Clustering Based Routing for Energy Management in Wireless Sensor Network-Assisted Internet of Things. *Electronics*, *11*(23), 3922.

[43] Singh, J., Deepika, J., Sathyendra Bhat, J., Kumararaja, V., Vikram, R., Jegathesh Amalraj, J., ... & Sakthivel, S. (2022). Energy-efficient clustering and routing algorithm using hybrid fuzzy with grey wolf optimization in wireless sensor networks. *Security and Communication Networks*, *2022*.

[44] Dhabliya, D. (2021). Feature Selection Intrusion Detection System for The Attack Classification with Data Summarization. Machine Learning Applications in Engineering Education and Management, 1(1), 20–25. Retrieved from http://yashikajournals.com/index.php/mlaeem/article/view/8

[45] Miller, J., Evans, A., Martinez, J., Perez, A., & Silva, D. Predictive Maintenance in Engineering Facilities: A Machine Learning Approach. Kuwait Journal of Machine Learning, 1(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/113

[46] Raghavendra, S., Dhabliya, D., Mondal, D., Omarov, B., Sankaran, K.S., Dhablia, A., Chaudhury, S., Shabaz, M. Retracted: Development of intrusion detection system using machine learning for the analytics of Internet of Things enabled enterprises (2023) IET Communications, 17 (13), pp. 1619-1625.