



A fault-tolerant dynamic graph attention network for energy efficient routing and reliability in wireless sensor networks

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Received: 24 May 2024 / Accepted: 11 January 2026

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Abstract

Wireless Sensor Networks (WSNs) face challenges such as dynamic environmental conditions, energy constraints, and fault occurrences, necessitating adaptive and resilient routing strategies. This paper introduces Fault-tolerant Dynamic Graph Attention Network (FDGAN), a comprehensive methodology designed to address these challenges. In the network modeling phase of the FDGAN, the sensor nodes are initialized with unique identifiers, and fundamental characteristics are defined, forming the basis for subsequent analyses. Graph construction employs different matrices, providing a robust representation of the WSN's topology. The FDGAN consists of the embedding layer, attention mechanism, neighbourhood aggregation layer, multi-head attention layer, and output layer. The embedding layer captures crucial node attributes, such as residual energy, node location, and connectivity information, forming the foundation for subsequent computations. The attention mechanism dynamically assigns attention coefficients, allowing the network to focus on relevant nodes during computations, contributing to dynamic adaptation, fault tolerance, and energy efficiency. The neighbourhood aggregation layer computes weighted feature aggregation from neighboring nodes, incorporating adaptive dynamic graph updates and position modules to enhance fault tolerance. The multi-head attention layer captures diverse information through independent attention computations, optimizing routing decisions and sleep scheduling. The output layer aggregates outputs for predicting fault-tolerant, energy-efficient dynamic routing paths. FDGAN's adaptability is further exemplified during fault handling processes, where the attention layer adjusts coefficients based on fault-related features, prioritizing resilient pathways. Overall, FDGAN presents a promising

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solution for addressing challenges in WSNs, offering adaptability, fault tolerance, and energy efficiency to enhance network performance and reliability.

Keywords WSN · Fault tolerant routing · Message passing · Graph attention network · Data aggregation

1 Introduction

In recent years, WSNs have become increasingly important in a variety of fields. They are now an essential piece of technology for many different fields, including surveillance, healthcare, environmental monitoring, and industrial automation (Mohamed et al. 2018). Concerns have been raised about how well energy resources are being used in different WSN applications due to the restricted power supply of sensor nodes. As a result, energy-efficient dynamic routing has emerged as a prominent research area to tackle this challenge (Mohemed et al. 2017).

The rapid proliferation of WSN applications has demanded the expansion of energy-efficient dynamic routing mechanisms. Traditional static routing schemes are ill-suited for dynamic network environments where node failures, changes in traffic patterns, and varying network topologies are common occurrences (Zhang et al. 2014). Energy efficiency has become a critical requirement due to the need for a prolonged lifetime of network and mitigated costs for maintenance. The implementation of dynamic routing strategies in WSNs allows for adaptation to changing conditions, optimization of energy, and prolonging the alive nodes in the network (Robinson et al. 2020).

Despite its significance, energy-efficient dynamic routing in WSNs presents several challenges. Firstly, the resource-constrained nature of sensor nodes (Joshi and Younis 2016), including limited processing power, memory, and battery capacity, imposes constraints on the routing protocols. Efficient utilization of energy resources while maintaining acceptable network performance becomes a balancing act. Secondly, the inherently unreliable and dynamic nature of wireless communication in WSNs (Mahmood et al. 2015) introduces challenges such as node mobility, link failures, and interference, which must be addressed to ensure trustworthy and effectual routing. It is a daunting task to choose the best routing method for a particular WSN deployment (Chan et al. 2020; Habibi et al. 2015). There is a wide range of existing routing algorithms, each with its advantages and disadvantages. The selection process must consider factors such as network size, node density, traffic patterns, reliability requirements, and scalability. Balancing energy efficiency, network performance, and fault tolerance while adapting to dynamic network conditions poses significant challenges in choosing an optimal routing strategy (Sharma et al. 2019; Faheem et al. 2017; Rault et al. 2014; Ding et al. 2015).

Given the challenges identified, the objective of research work in energy-efficient dynamic routing is to develop novel routing protocols and algorithms that can optimize energy consumption, enhance network reliability, and extend the overall network lifetime (Bandur et al. 2019). The scope of such research encompasses the design, analysis, and evaluation of routing strategies that address the specific requirements and challenges of WSNs. The need for this research arises from the increasing demand

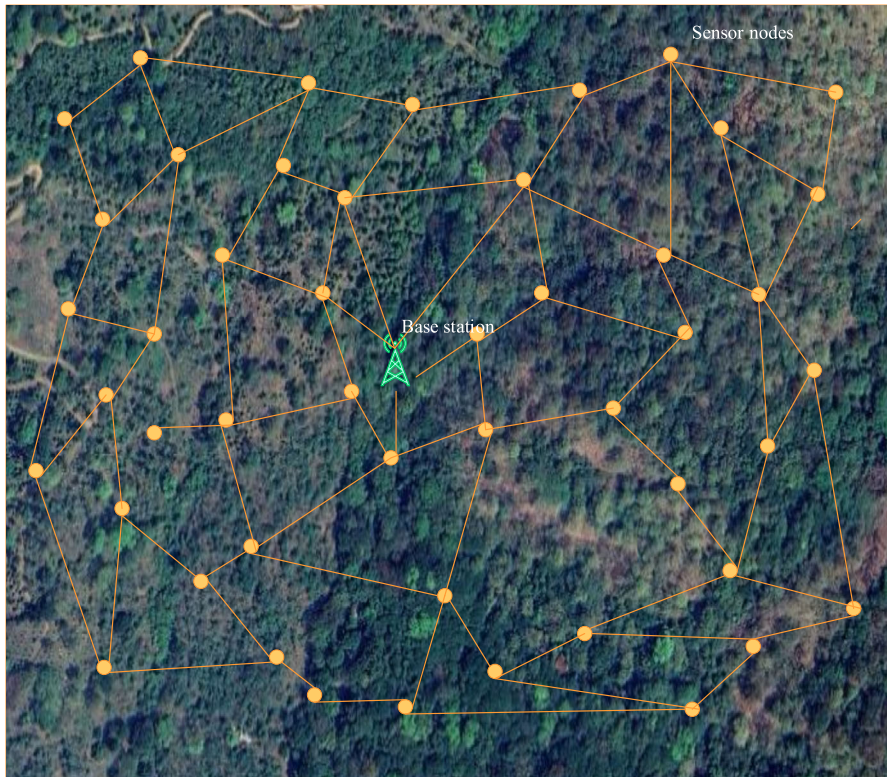


Fig. 1 Illustration of sensor nodes deployment in WSN

for energy-efficient and reliable WSNs in various application domains (Aslam et al. 2016; Guo and Zhang 2014). An illustration of sensor node deployment is depicted in Fig. 1.

Several existing routing algorithms have been proposed for energy-efficient dynamic routing in WSNs. Examples include Low Energy Adaptive Clustering Hierarchy (LEACH) (Singh et al. 2017; Mohapatra and Rath 2019), Threshold-sensitive Energy Efficient sensor Network protocol (TEEN) (Ge et al. 2018), and Stable Election Protocol (SEP) (Naeem et al. 2021; Behera et al. 2019). These algorithms employ a variety of methods, like clustering, data aggregation, and adaptive sleep scheduling, to reduce energy consumption and increase the lifespan of the network.

Despite the advancements in routing algorithms for WSNs, several challenges still need to be addressed. These challenges include efficient handling of node failures, adapting to dynamic network topologies, mitigating interference and congestion, achieving load balancing, and ensuring fault tolerance. Additionally, the proper selection of dynamic routing strategies in real-world scenarios remains a challenge due to the need for customization and optimization based on specific application requirements (Nayak et al. 2021; Al Aghbari et al. 2020; Sarkar et al. 2016; Kaur and Kumar 2020; Hammoudeh and Newman 2015). Therefore, an energy-efficient dynamic routing is

crucial for the successful deployment of WSNs in various applications. Overcoming the challenges associated with energy constraints, and dynamic network conditions, and selecting optimal routing strategies are essential for achieving efficient and reliable network operations. The goal of current research is to design new routing protocols for WSNs that will optimize energy usage, improve network performance, and lengthen the overall network lifetime. Therefore, we have proposed the FDGAN that introduces a holistic methodology to tackle challenges in WSNs. The key contributions of this paper can be summarized as follows:

- The FDGAN employs an embedding layer that captures crucial node attributes such as residual energy, node location, and connectivity information. This layer forms the basis for subsequent computations in the FDGAN protocol.
- The attention mechanism dynamically assigns attention coefficients to nodes based on specific parameters, enabling the network to focus on relevant information during subsequent computations. This adaptability contributes to dynamic adaptation, fault tolerance, and energy efficiency.
- The FDGAN introduces a neighbourhood aggregation layer that computes the weighted aggregation of features from neighboring nodes. This layer incorporates an adaptive dynamic graph update mechanism for energy-efficient data transmission and position modules to enhance fault tolerance.
- Multiple attention heads allow the model to capture diverse information about each node independently. CH selection and error-free dynamic message passing optimize routing decisions and sleep scheduling, contributing to fault tolerance.
- The output layer aggregates outputs from multiple attention heads, forming a comprehensive representation for predicting fault-tolerant, energy-efficient dynamic routing paths. The layer's adaptability during fault handling processes enhances the overall robustness of the FDGAN.

2 Related works

In the contemporary era, there have been numerous research on data routing in WSN. Here, we give a brief overview of a selected few of the currently used techniques and how they work:

Qabouche et al. (2021), proposed the combination of clustering with the multi-hop routing techniques called as the Hybrid Energy Efficient Static routing protocol (HEESR). Here, the network is divided into several levels and for each level the gateways or independent nodes (INs) acts as routing agents to transmit collected data. In each round, the protocol selects INs from various CHs and the inactive nodes are made as dormant nodes. HEESR incorporates two key processes: advertising and path selection. During the advertising process, nodes declare their capability to function as CHs, allowing the protocol to identify suitable candidates for routing. Once the CH is selected, the clustering process is initiated. Subsequently, in the path selection process, the protocol predicts the next hop for data routing and stores the relevant details in the routing table to facilitate efficient data transmission. However, energy

loss occurs in selecting the pre-determined INs and also this static method is ill-suited for the dynamic environments with changing network conditions.

Sharma and Tomar (2021), introduced a protocol called Multitier Random Deterministic Energy efficient Clustering (M-DEC) along with a dynamic deployment strategy. Here, the multi-tier deterministic factor divides the nodes into advanced-intermediate, normal, advanced and intermediate types for easier analysis. The protocol focuses on selecting CHs based on the lasting energy factor. During each iteration, the CHs broadcast their priority to the network's cluster members, allowing them to be aware of the CHs lasting energy levels. The CHs are then examined to determine if the same node can remain as a CH or whether it requires a new CH. The M-DEC protocol, however, causes high energy loss among nodes due to the ill-suited election probability factor.

The research conducted by Shyjith et al. (2021) focused on addressing CH selection in a WSN using two techniques: Rider Cat Swarm Optimization (RCSO) and Optimized Sleep-awake Energy Efficient Distribution (O-SEED). In this, RCSO determines the CH selection dynamically to pass the data. Here, the finest CH was determined by a threshold value computed using factors such as delay, energy, and distance. Once the CH was selected, O-SEED algorithm is employed to transfer the data from the CH to the Base Station (BS) using the. Here, the nodes go to the sleep state with an increase in the distance from the BS. The lasting energy of the nodes was continuously updated until all the data was successfully transmitted. However, the tracing mode of RCSO increases the number of active nodes and significantly causes high energy dissipation. This indicates a potential issue with the network's node longevity or stability.

Singh et al. (2021) designed a modified Genetic Algorithm (ModifyGA) to select CHs in WSNs and to exploit lifetime and energy efficiency. It incorporates a dynamic sensing range and defines the criteria for CH selection using the fitness function that deliberates the energy factor, node to sink distance, comparative bias and density. Here, the optimal solutions are found by simulating natural evolution where, the movement of sink persistently alters the gene structure of the chromosome. The concept of elitism is incorporated to preserve the best solution (fittest CH) found so far until a superior solution (best CH) emerges. Here, maximal energy is utilized within the cluster due to the low sensing range of CHs leading to node death at earlier instant.

Subramani et al. (2022), introduced a protocol for routing with Multihop Energy Aware Clustering (EACMRPMS) with mobile sink. Here, the Tunicate Swarm Algorithm (TSA) and Type-II Fuzzy Logic (T2FL) are applied for selection of CH and cluster assembly. In this, the tunicate's jet propulsion is used in TSA employing the swarming behaviour to cluster the nodes. The T2FL selects the shortest multi-hop routes to transmit the data to the sink. Moreover, an additional enhancement to the energy efficiency is achieved through the use of a mobile sink with a route adjustment scheme based on the path of the mobile node. However, the network lifetime may be constrained due to the rise of conflict among the search agent.

The Energy-Efficient Dynamic Adaptive State-based Scheduling (EDASS) scheme, introduced by Khan et al. (2022), aims to advance energy efficacy and persist the lifespan of a network. It involves nodes switching between different states (active, wait, sleep, and route) to facilitate dynamic data transmission. Initially, all nodes are

active and collect data through sensing. If the collected data is the same as the previous data, nodes enter sleep mode to conserve energy. Following a sleep cycle, an active node initiates a message broadcast to neighbouring nodes, signalling them to change to the active state. However, this system is susceptible to potential transmission faults when the nodes fails to sense the active cycle.

Narayan et al. (2023) proposed a method that combines Particle Swarm Optimization (PSO) and a Fuzzy based Energy Efficient Routing Protocol (E-FEERP) in routing to improve energy efficiency. PSO is used for clustering nodes, while E-FEERP determines the optimal path for data transmission. In this approach, PSO helps organize nodes into clusters by discovering the best solution based on a fitness function. E-FEERP then selects the most efficient route to pass on data between the CH and the BS. However, in E-FEERP data redundancy cause increase in the use of energy.

Satyanarayana et al. (2023) proposed a segregation model to improve fault tolerance and reliable coverage in data transmission within WSNs. The model consists of two stages: intra and inter-segregation. In the first stage, the network is initialized and divided into clusters. Here, relay nodes are considered as secure nodes. They are identified and separated from redundant and common nodes to participate in data transmission. The second inter-segregation stage involves transmitting data to the target node. Here, the fault-tolerance is achieved by increasing the coverage area through a coverage factor. This protects the network from intrusion of the invaders. However, it does not cover the attention area properly thus resulting in reduced fault tolerance.

Mohapatra and Rath (2020) introduced two novel algorithms: Uniform Energy Clustering (UEC) and Population-Based Clustering (PBC), designed to improve fault tolerance and prevent faults in WSNs. The UEC algorithm focuses on maintaining uniform energy levels among sensor nodes by distributing the workload evenly across clusters, thereby extending the network's lifetime and reducing energy depletion. In contrast, the PBC algorithm aims to prevent faults by optimizing the selection of CHs and ensuring effective communication paths. The paper outlines a communication model where intra-cluster and inter-cluster communications are facilitated through dedicated time slots, allowing for efficient data transmission between SNs and the BS1z. By simulating these algorithms and comparing their performance against established methods, the authors demonstrate significant improvements in fault handling and overall network efficiency, thereby contributing valuable insights for the deployment of robust WSNs in real-world applications.

The summary of various clustering and routing techniques is presented in Table 1.

3 Meta-analysis

The primary goal of this meta-analysis is to evaluate clustering and routing techniques used in WSNs, specifically focusing on:

- *Energy Efficiency* How well the methods optimize energy consumption, which is crucial in sensor networks due to limited power resources.

Table 1 Summary of different clustering and routing techniques

Author and year	Method	Deployment		CH selection parameters	Strengths	Limitations
		Static	Dynamic			
Qabouche et al. (2021)	HEESR	Yes	No	Threshold based upon residual energy	Static routing improves energy efficiency locally	Not suited for dynamic environments
Sharma and Tomar (2021)	M-DEC	No	Yes	Energy	Multi-tier clustering enhances CH selection	High energy loss due to election probability
Shyjith et al. (2021)	O-SEED, RCO	No	Yes	Energy, distance node mobility	Adaptive CH selection improves routing accuracy	Tracing mode increases energy dissipation
Singh et al. (2021)	ModifyGA	No	Yes	Node energy, node-sink distance, node density	Incorporates evolutionary optimization	Low sensing range increases intra-cluster energy
Subramani et al. (2022)	EACMRP-MS and TSA	Yes	No	Residual energy and distance	Mobile sink improves energy efficiency	Search agent conflicts reduce network lifetime
Khan et al. (2022)	EDASS	No	Yes	–	Energy conservation through state-based switching	Susceptible to sensing and transmission faults
Narayan et al. (2023)	E-FEERP	No	Yes	Energy, distance, node density, communication	Combines clustering with optimal path selection	Data redundancy increases energy consumption
Satyanarayana et al. (2023)	Segregation model	No	Yes	–	Improved fault tolerance through segregation	Reduced attention area coverage
Mohapatra and Rath (2020)	UEC, PBC	No	Yes	Equilibrium energy	Uniform energy distribution enhances fault tolerance	Limited scalability in dense networks

- *Network Lifetime* How the methods contribute to prolonging the network's operational time by minimizing node failures and optimizing data transmission.
- *Fault Tolerance* How effectively the methods handle node failures, communication interruptions, or environmental disruptions.
- *Dynamic Adaptation* How well the methods can adjust to changes in the network topology, node mobility, traffic patterns, etc.
- *Scalability* How the techniques perform when the number of nodes or network size increases.

By analyzing the key works in WSNs, the approaches are categorized based on the deployment type, clustering mechanism, and the specific attributes used for CH selection (such as energy, distance, or mobility).

3.1 Energy efficiency

HEESR and M-DEC both emphasize energy efficiency but use different methods. HEESR employs static routing, which is energy-efficient for local communication but fails to adjust to dynamic environments. In contrast, M-DEC dynamically adapts but suffers from high energy loss during CH selection. O-SEED and ModifyGA use energy-based CH selection, but the latter also faces intra-cluster energy dissipation due to a low sensing range. ModifyGA introduces evolutionary algorithms, but its low sensing range limits energy usage within the cluster, thus decreasing overall efficiency.

3.2 Network lifetime

The Mobile Sink approach in EACMRP-MS with TSA contributes to a longer network lifetime by adjusting paths based on sink mobility. However, this introduces conflicts among search agents that may reduce lifetime. On the other hand, EDASS and E-FEERP both propose methods to extend network lifetime through energy-efficient state switching and optimal path selection, respectively. However, EDASS suffers from potential transmission faults, which could hinder lifetime stability.

3.3 Fault tolerance

Segregation Models like the one proposed by Satyanarayana et al. introduce fault tolerance by separating redundant nodes and improving coverage, but this does not always ensure proper coverage in all regions. UEC and PBC maintain fault tolerance through uniform energy distribution and optimizing CH selection, which helps in handling faults effectively. E-FEERP also has a fault tolerance mechanism via optimal routing but suffers from data redundancy issues, which leads to excess energy consumption and increased fault vulnerability.

3.4 Dynamic adaptation

RCSO and O-SEED adapt dynamically by adjusting CH selection based on energy, distance, and node mobility. However, RCSO leads to high energy dissipation due to the active tracing mode. In contrast, M-DEC provides better dynamic adaptability through multi-tier clustering but may cause high energy loss because of its election probability, which is not well-suited for very large networks.

3.5 Scalability

HEESR performs well in smaller, static networks but struggles with scalability due to its reliance on static routing. This limitation restricts its performance in large or dynamic networks. ModifyGA and EACMRP-MS offer better scalability through their dynamic selection and mobile sink mechanisms but face trade-offs in terms of energy consumption and node management complexity.

After analyzing the strengths and limitations of each technique, the following patterns emerge:

- Energy Efficiency is a consistent goal across almost all methods, but there is often a trade-off between energy savings and network stability.
- Dynamic Adaptation is necessary to handle network changes (e.g., node mobility, varying traffic), but many approaches struggle with scalability and energy dissipation when nodes adapt frequently.
- Fault Tolerance is addressed by several methods, but issues such as data redundancy and improper coverage still persist.

The gaps identified are,

- Many methods like HEESR fail to scale in dynamic environments. While dynamic methods like RCSO and M-DEC scale better, they suffer from energy inefficiency and high operational costs.
- Adaptive algorithms are underexplored, especially for large networks where nodes frequently join/leave the network. Real-time adaptability remains a challenging area.
- Current methods often focus on energy and distance but miss out on using more complex parameters such as traffic patterns and inter-node communication dynamics, which could optimize both energy and network performance in real-time.

Based on the gaps identified, the proposed work focus on the following:

- Hybrid Approach for Energy Efficiency and Adaptability: A hybrid model combining static and dynamic routing that balances energy efficiency with scalability and adaptability.
- Enhanced Fault Tolerance: Propose a method to handle data redundancy effectively while ensuring proper network coverage and fault tolerance, especially in large-scale deployments.
- Adaptive Clustering Algorithms: Develop clustering algorithms that dynamically adapt to node mobility, energy states, and varying network conditions. This could

involve incorporating machine learning or other adaptive models for better scalability and efficiency.

- **Real-time Routing Optimization:** Introduce more advanced techniques for real-time path selection that take into account both energy levels and network conditions.

By addressing these gaps, the proposed work can advance the state of WSN routing and clustering techniques, offering a more energy-efficient, scalable, and fault-tolerant solution suitable for modern applications.

4 Proposed FDGAN for routing in WSN

The FDGAN methodology addresses WSN challenges such as energy efficiency, dynamic adaptation, network lifetime, and fault tolerance through a multi-step approach. In the initial network modeling phase, sensor nodes are initialized, and fundamental characteristics, including topology, node density, and energy constraints, are defined. Graph construction, utilizing connectivity matrices, sets the foundation. The FDGAN then employs an embedding layer to capture node attributes, an attention mechanism for dynamic attention coefficients, a neighborhood aggregation layer for weighted feature aggregation, and a multi-head attention layer for optimized routing and sleep scheduling. The output layer aggregates outputs for predicting fault-tolerant, energy-efficient paths. During faults, the attention layer adapts by adjusting coefficients, ensuring network resilience and prioritizing reliable pathways. The overall working of FDGAN is depicted in Fig. 2.

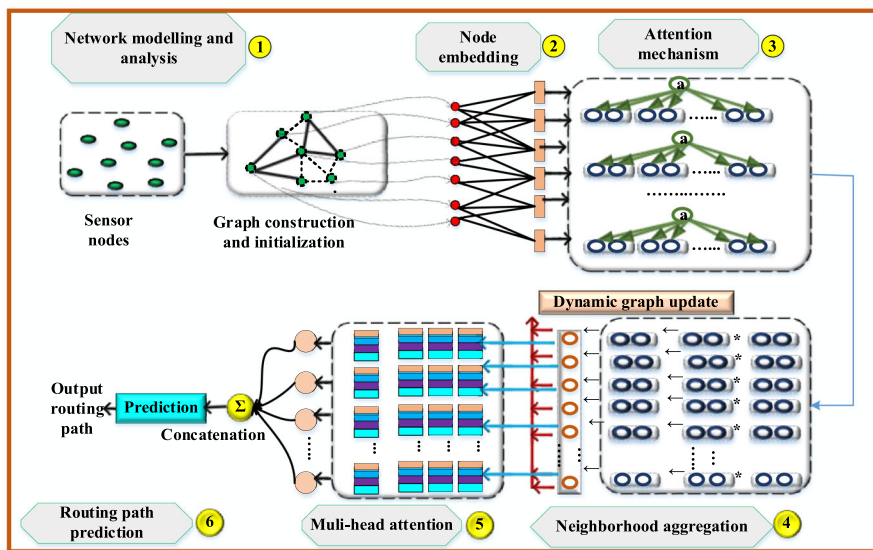


Fig. 2 Proposed FDGAN for fault tolerant dynamic routing in WSN

4.1 Network modeling

In the network modeling phase, the WSN is initialized with distinct identifiers and fundamental characteristics. Each sensor node is assigned a unique identifier, and the network's topology is established through a connectivity matrix based on Euclidean distances. The node density and energy constraints are defined, providing crucial metrics for subsequent analyses. Graph construction, utilizing connectivity matrices and mathematical structures like adjacency and degree matrices, forms a representation of the WSN. These structures set the groundwork for applying graph attention mechanisms and adaptive routing strategies in the FDGAN protocol, enhancing fault tolerance and energy efficiency.

4.1.1 Initialization

Let N be the total number of sensor nodes in the network, and i represent an individual node. In the initial phase of network modeling and analysis, the network is initialized by setting up sensor nodes with distinct identifiers and defining fundamental characteristics. Initializing sensor nodes with unique identifiers and defining their characteristics significantly enhances the network modeling phase in FDGAN by enabling clear node differentiation and accurate topology representation. Unique identifiers ensure distinct recognition of each node, avoiding ambiguity in operations like routing, connectivity establishment, and fault detection. Each sensor node i is assigned a unique identifier ID_i . Defining attributes such as location, residual energy, and connectivity provides the foundation for constructing connectivity matrices, adjacency matrices, and graph Laplacians, which are critical for graph-based computations. The network's topology is established through a connectivity matrix C , where $C_{ij} = 1$ signifies a connection between nodes i and j and $C_{ij} = 0$, if there is no connection such that $C \in \{0, 1\}^{N \times N}$. This connectivity matrix forms the backbone of the network topology, defining how data can flow between nodes. It is determined by their Euclidean distance (d_{ij}) within a specified transmission range tr .

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (1)$$

Here, (x_i, y_i) and (x_j, y_j) are the coordinates of nodes i and j respectively.

$$C_{ij} = \begin{cases} 1, & \text{if } d_{ij} \leq tr \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

The node density (ρ) representing the number of nodes per unit area, is calculated as N divided by the network area.

$$\rho = \frac{N}{Area} \quad (3)$$

Here, N is the total number of sensor nodes, and $Area$ is the total area of the network. Node density is a critical parameter as it impacts the network's coverage, connectivity, and overall performance. Higher density can lead to better coverage but may increase interference, while lower density might compromise connectivity.

Additionally, energy constraints E_i are defined for individual nodes, here E_i represents the initial energy available at the node. These constraints are crucial because sensor nodes typically operate on limited battery power. Efficient energy utilization is vital to prolong the network's lifetime and maintain its functionality over time. The initialization process, including topology definition using C , calculation of (ρ) and establishment of energy constraints E_i provides the foundational framework for subsequent analyses and optimizations. These parameters are essential for constructing an efficient and resilient WSN capable of addressing challenges such as energy consumption, fault tolerance, and scalability. This initialization facilitates dynamic adaptation to changes in topology, such as node failures or energy depletion, and contributes to fault tolerance by monitoring energy consumption and predicting potential faults. Additionally, it supports scalable and flexible network configurations, allowing easy integration of new nodes and customization of parameters like transmission range and node density to suit specific applications. These initializations also optimize routing efficiency by leveraging energy and connectivity data while enabling dynamic updates to maintain energy efficiency and fault tolerance.

4.1.2 Graph construction

In the process of graph construction during the network modeling and analysis phase, a graph G is formed to represent the WSN. The set $V = \{1, 2, \dots, N\}$ comprises sensor nodes, indexed from 1 to N . Utilizing the connectivity matrix C established during network initialization, the set of edges E is defined, where each non-zero entry in C corresponds to an edge between nodes such that $G = (V, E)$. The adjacency matrix is derived from the connectivity matrix created during the network initialization phase. This matrix represents the network's connections by indicating whether there is a direct link between two nodes. If a connection exists, the corresponding value is marked as one; otherwise, it is zero. The degree matrix is a diagonal matrix that shows the total number of connections for each node, with each diagonal entry representing the count of edges linked to a specific node. The graph Laplacian matrix is obtained by subtracting the adjacency matrix from the degree matrix. It serves as a crucial representation of the network's structure and connectivity. This matrix is instrumental in enabling advanced techniques, such as graph attention mechanisms and adaptive routing strategies, which are essential for creating fault-tolerant and energy-efficient wireless sensor networks. It supports efficient analysis of the network's topology and ensures robust communication even in challenging or dynamic conditions.

The adjacency matrix A is derived from E , such that $E = \{(i, j) | C_{ij} = 1\}$ capturing the connectivity relationships among nodes. Here, A_{ij} is 1 if there is an edge between nodes i and j , and 0 otherwise.

$$A_{ij} = \begin{cases} 1, & \text{if } (i, j) \in E \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

For a node i , the degree matrix is D , is a diagonal matrix where each diagonal entry D_{ii} is the degree of node i such that, $D \in \mathbb{R}^{N \times N}$. The degree of a node is the number of direct connections (edges) it has, calculated as:

$$D_{ii} = \sum_{j=1}^N A_{ij} \quad (5)$$

The degree matrix D reflects the degrees of individual nodes, and the graph Laplacian matrix L is computed as the difference between D and A .

$$L = D - A \quad (6)$$

The graph Laplacian matrix L plays a crucial role in representing the network's topology and connectivity. It encodes information about node connectivity and the structure of the network, enabling the analysis of various network properties, such as connectivity, clustering, and spectral characteristics. These matrices serve as foundational mathematical structures, providing a comprehensive representation of the network's topology and connectivity. The resulting graph G and its associated matrices lay the groundwork for subsequent steps in the FDGAN protocol, facilitating the application of graph attention mechanisms and adaptive routing strategies for fault-tolerant and energy-efficient WSNs.

4.2 Fault-tolerant dynamic graph attention network

In the FDGAN, the embedding layer captures node attributes, including residual energy and connectivity. The attention mechanism assigns coefficients, focusing on vital information. The neighbourhood aggregation layer aggregates features, dynamically updating the graph. The multi-head attention layer optimizes routing with CH selection and error-free message passing. The output layer synthesizes outputs for fault-tolerant, energy-efficient routing predictions. During faults, attention adapts, prioritizing resilient paths. FDGAN excels in adaptability, fault tolerance, and energy efficiency, promising enhanced WSN performance and reliability.

4.2.1 Embedding layer

In the FDGAN protocol, the process of node representation involves creating an initial embedding layer for each sensor node to encapsulate its fundamental characteristics. The physical location of each node, represented by its Cartesian coordinates, is integrated into this layer, allowing precise distance calculations essential for tasks like routing and cluster formation. Connectivity information is derived from the network's adjacency matrix, which indicates the communication status of each node with its neighbours, providing a clear picture of the node's local network structure. Residual energy, calculated as the difference between a node's initial energy and the energy consumed during operations, is another critical attribute included in this layer. These

elements such as residual energy, physical location, and connectivity details are combined into a comprehensive feature vector for each sensor node. This feature vector forms the initial embedding layer, which serves as the foundation for all subsequent computations in FDGAN. By capturing these essential attributes, the embedding layer ensures that the protocol has a detailed and dynamic representation of the network. This enables the FDGAN to make informed decisions regarding energy-efficient routing, fault-tolerant operations (Mohapatra & Rath 2020), and adaptive Cluster Head (CH) selection, ultimately enhancing the network's performance, reliability, and scalability.

In the second step of the FDGAN, the process of node representation is initiated to define the fundamental characteristics of each sensor node within the wireless network. Each sensor node i is characterized by its residual energy ($E_{residual_i}$) calculated as the difference between its initial energy (E_i) and the consumed energy.

$$E_{residual_i} = E_i - E_{consumed_i} \quad (7)$$

The physical location of each node, denoted as $L_i = (x_i, y_i)$ is considered, providing essential Cartesian coordinates for distance calculations. Connectivity information (C_i) is derived from the network's adjacency matrix, representing the communication status of node i with its neighbors.

$$C_i = [A_{i1}, A_{i2}, \dots, A_{iN}] \quad (8)$$

These attributes are collectively integrated into an initial embedding layer ($H_i^{(0)}$) forming a feature vector that encapsulates residual energy, node location, and connectivity details.

$$H_i^{(0)} = [E_{residual}, x_i, y_i, C_i] \quad (9)$$

The initial embedding layer captures essential attributes of each node, forming the basis for subsequent computations in the FDGAN protocol. The process of node representation involves creating a comprehensive feature vector for each sensor node, incorporating key parameters such as residual energy, location, and connectivity information.

4.2.2 Attention mechanism

The attention mechanism in the FDGAN protocol dynamically assigns attention coefficients to quantify the importance of nodes based on key metrics such as residual energy, connectivity information, and node location. Residual energy ensures that nodes with sufficient resources are prioritized, connectivity reflects the communication status between nodes using the adjacency matrix, and location considers physical proximity for effective communication. The process begins by representing each node with an embedding vector encapsulating these metrics, which is then transformed using learnable parameters (weight matrix W and bias vector b) optimized during training. A leaky ReLU activation introduces non-linearity, while a softmax function normalizes

the coefficients across a node's neighbors, ensuring their sum equals one. Using these coefficients, the mechanism aggregates feature from neighboring nodes by computing a weighted sum, emphasizing influential neighbors, and concatenates the aggregated features with the original node features for a refined representation. The coefficients adapt dynamically to real-time changes in metrics, allowing the network to focus on the most relevant nodes for routing, while also de-emphasizing faulty nodes during disruptions. This dynamic approach enhances energy efficiency, fault tolerance, and adaptability, ensuring robust and resource-efficient routing in the network.

The attention mechanism in FDGAN calculates attention coefficients (α_{ij}) between nodes i and j , to quantify their relative importance based on key metrics: residual energy, distance to the sink, and connectivity. These coefficients determine how much influence a neighboring node j has on node i during feature aggregation, with higher weights assigned to nodes that are closer to the sink and have greater residual energy. (α_{ij}) between nodes i and j , is calculated using a function that takes into account the relevant parameters. Let $(H_i^{(0)})$ and $(H_j^{(0)})$ be the initial embedding layers of nodes i and j , respectively.

$$\alpha_{ij} = \text{soft max} \left(\text{LeakyReLU} \left(W \cdot [H_i^{(0)}, H_j^{(0)}] + b \right) \right) \quad (10)$$

$$\alpha_{ij} = \text{soft max} \left(\text{LeakyReLU} \left(W \cdot [[E_{\text{residual}_i}, d_{i,\text{sink}}, C_i], [E_{\text{residual}_j}, d_{j,\text{sink}}, C_j]] + b \right) \right) \quad (11)$$

Here, W and b are learnable parameters (weight matrix and bias vector) that are optimized during the training process. Here, $H_i^{(0)} = [E_{\text{residual}_i}, d_{i,\text{sink}}, C_i]$ The leaky ReLU activation function introduces non-linearity, and the softmax function normalizes the attention coefficients. Distance to the sink is derived from the node's physical location (x_i, y_i) . The Euclidean distance between node i and the sink node (with coordinates $(x_{\text{sink}}, y_{\text{sink}})$) is:

$$d_{i,\text{sink}} = \sqrt{(x_i - x_{\text{sink}})^2 + (y_i - y_{\text{sink}})^2} \quad (12)$$

This distance is incorporated into the embedding vector or used as a feature to influence the attention computation. Nodes closer to the sink (smaller $d_{i,\text{sink}}$) are preferred for routing to minimize energy consumption, as shorter paths require less transmission power. The attention mechanism prioritizes nodes with higher residual energy and shorter distances to the sink by learning to assign higher (α_{ij}) values to such nodes. During training, the weight matrix W and bias b are optimized to emphasize these features. For example, a node j with high E_j (more residual energy) contributes more to the aggregated features of node i , as it is more reliable for routing. A node j with a smaller $d_{j,\text{sink}}$ is favored, as it reduces the energy required for data transmission to the sink.

Once attention coefficients are calculated, the information from neighboring nodes is aggregated for each node by taking the weighted sum of their features.

$$F_{aggr_i} = \sum_{j=1}^N \alpha_{ij} \cdot H_j^{(0)} \quad (13)$$

This process allows each node to gather information from its neighbors with varying degrees of emphasis, determined by the attention coefficients.

The aggregated features are then concatenated with the original features of the node, forming an updated representation.

$$H_i^{(1)} = [F_{aggr_i}, H_i^{(0)}] \quad (14)$$

This updated representation captures the influence of neighboring nodes on the target node, providing a refined feature vector for subsequent steps. The process of dynamic sleep scheduling and error free message passing is presented in Fig. 3.

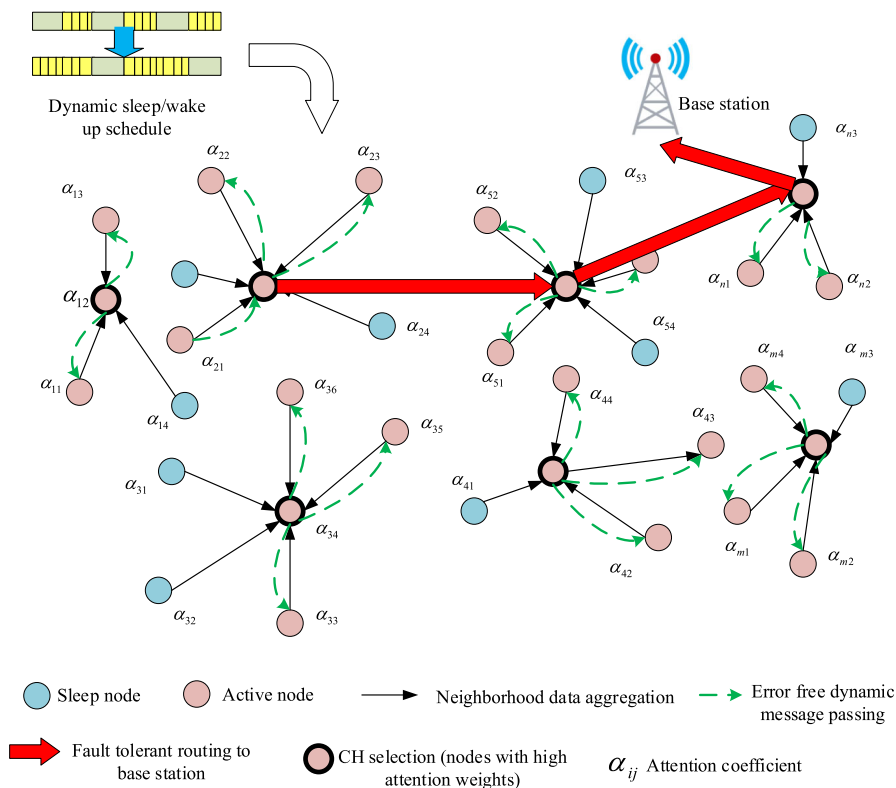


Fig. 3 Dynamic sleep scheduling and error free message passing in WSN

4.2.3 Neighbourhood aggregation layer

The data aggregation process within the FDGAN methodology involves a sequence of steps to enhance energy efficiency and fault tolerance in the WSN. Initially, attention coefficients, computed in the attention mechanism, are utilized to determine the relevance of neighboring nodes. Using these coefficients, the neighborhood aggregation layer calculates a weighted sum of the features from neighboring nodes, capturing their influence on the target node. This step results in the creation of an aggregated feature vector for each node. Subsequently, an adaptive dynamic graph update mechanism is employed to optimize the network topology. This mechanism assesses the aggregated features of nodes and dynamically modifies the adjacency matrix by determining the existence or absence of connections based on the function $f(F_{aggr_i}, F_{aggr_j})$, where F_{aggr_i}, F_{aggr_j} are aggregated feature vectors of nodes i and j respectively. This ensures that the connectivity adapts to the current state of the network, supporting energy-efficient data transmission. Additionally, a position module is integrated to prevent collisions by adjusting the transmission schedules and ranges of nodes. This module evaluates the physical locations of nodes in conjunction with their aggregated features to determine optimal transmission settings, mitigating interference and improving fault tolerance. The neighbourhood aggregation layer utilizes a weighted sum algorithm to compute the aggregated feature vector for each node, leveraging attention coefficients to prioritize contributions from more relevant neighbors. The aggregated feature vector (F_{aggr_i}) for each node i is computed by taking the weighted sum of the features of its neighboring nodes, as determined by the attention coefficients (α_{ij}) from (10).

$$F_{aggr_i} = \sum_{j \in \mathbb{N}_i} \alpha_{ij} \cdot H_j^{(0)} \quad (15)$$

An adaptive mechanism is introduced to dynamically update the graph structure based on the aggregated features. This dynamic update is intended to optimize the network topology for energy-efficient data transmission.

$$A_{ij}^{(t+1)} = f(F_{aggr_i}, F_{aggr_j}) \quad (16)$$

Here, $A_{ij}^{(t+1)}$ represents the updated adjacency matrix, and f is a function that considers the aggregated features of nodes i and j to determine the existence of a connection. This adaptation allows the network to dynamically respond to changes in connectivity requirements based on the features of the nodes.

To enhance fault tolerance, a position module is defined for each node to avoid collisions. The position module considers the physical locations of nodes (L_i) to adjust their transmission schedules and prevent interference.

$$tr_{dynamic(i)} = g(F_{aggr_i}, L_i) \quad (17)$$

Here, g is a function that takes into account the aggregated features and the node's location to dynamically adjust the transmission range, ensuring efficient communication while mitigating the risk of collisions.

The neighborhood aggregation layer not only facilitates the incorporation of information from neighboring nodes but also dynamically adapts the network's connectivity based on the aggregated features. The position module contributes to fault tolerance by considering the physical locations of nodes in the wireless sensor network, thereby improving the overall reliability of the system.

4.2.4 Multi-head attention

The multi-head attention layer in the FDGAN protocol is designed to capture diverse information about each node by utilizing multiple attention heads. Each attention head computes attention coefficients independently, allowing the model to attend to different aspects within the graph. The selection of CHs is then performed based on the remaining energy, location, and connectivity information, considering the attention weights assigned to the nodes. This layer is essential for making informed routing decisions and facilitating adaptive sleep scheduling.

For each attention head h , attention coefficients (α_{ij}^h) are computed independently for nodes i and j using the initial embedding layer $(H^{(0)})$. The leaky ReLU activation introduces non-linearity, and the softmax function normalizes the attention coefficients. Using (10), we get,

$$\alpha_{ij} = \text{softmax} \left(\text{LeakyReLU} \left(W_h \cdot [H_i^{(0)}, H_j^{(0)}] + b_h \right) \right) \quad (18)$$

Here, W_h and b_h are learnable parameters specific to the h -th attention head. This process allows different attention heads to focus on different aspects of the nodes features. CHs are selected based on the attention coefficients, residual energy, location, and connectivity information of nodes. The CH for node i is chosen based on the product of attention weights and node features, emphasizing nodes with higher attention weights.

$$CH_i = \arg \max_j \left(\alpha_{ij}^{(h)} \cdot [E_{\text{residual}_j}, x_j, y_j, C_j] \right) \quad (19)$$

The error-free dynamic message passing mechanism $m_p(\text{dynamic})$ is integrated for reliable communication. Nodes exchange information based on attention weights, adapting their connectivity dynamically for efficient data transmission. The attention layer also guides sleep scheduling decisions. Important or active nodes during sleep scheduling are identified based on attention weights, and dynamic sleep and wake-up schedules are adjusted accordingly. This integration ensures that the network adapts dynamically to changing conditions, conserving energy during idle periods and facilitating reliable communication through error-free message passing.

4.2.5 Output layer

The output layer in the FDGAN protocol plays a critical role in synthesizing and utilizing the information captured by multiple attention heads to predict a fault-tolerant, energy-efficient dynamic routing path. Each attention head processes network data to emphasize different aspects, such as energy efficiency, connectivity, and fault resilience. The outputs from these attention heads are either concatenated or averaged to form a comprehensive representation, enabling the model to consider diverse perspectives and capture complex patterns within the network. This aggregated information serves as the input to the final layer, where the predicted routing path is generated. Fault-tolerant mechanisms in the FDGAN protocol are seamlessly incorporated through dynamic attention coefficient adjustments, adaptive graph updates, and routing decisions tailored to handle fault conditions. During fault-handling processes, the attention layer plays a pivotal role by recalibrating attention coefficients based on fault-related features, such as node residual energy, connectivity, or observed anomalies. This recalibration is guided by a function that dynamically emphasizes or de-emphasizes node connections, ensuring that paths with higher reliability are prioritized for routing. The protocol integrates these adjusted coefficients to guide routing decisions, focusing on nodes or paths deemed more robust and capable of sustaining network performance despite faults. These fault-tolerant pathways are computed by aggregating diverse information captured by multiple attention heads, ensuring resilience in routing. Additionally, the adaptive graph update mechanism dynamically modifies the network's topology to address disrupted connections, optimizing connectivity and facilitating energy-efficient communication in the presence of faults. These mechanisms are specifically designed to address a variety of fault scenarios, including node failures due to energy depletion, connectivity losses from environmental interference, and transient faults that disrupt communication. By prioritizing resilient pathways and dynamically adapting to changes in the network, FDGAN ensures reliable data transmission and minimizes performance degradation under challenging conditions, enhancing the overall robustness of wireless sensor networks. The output layer in the FDGAN protocol serves the crucial role of aggregating information from multiple attention heads and generating the predicted fault-tolerant, energy-efficient dynamic routing path. The attention layer focuses on relevant nodes during fault handling processes, and the outputs from multiple attention heads are typically concatenated or averaged to form a comprehensive representation.

The outputs ($O^{(h)}$) from each attention head are typically concatenated or averaged to form a comprehensive representation. This allows the model to capture diverse information and perspectives from different attention heads.

$$O_i = \text{Concat}\left(O_i^{(1)}, O_i^{(2)}, \dots, O_i^{(H)}\right) \quad (20)$$

Here, H is the total number of attention heads. The aggregated outputs O_i serve as the input to the final layer, where the fault-tolerant, energy-efficient dynamic routing path is predicted. This prediction is based on the learned patterns and relationships captured by the attention heads throughout the network. The predicted routing path

$(R_{pr(i)})$ is computed as,

$$R_{pr(i)} = \arg \max(\text{Soft max}(W_0 \cdot O_i + b_0)) \quad (21)$$

The softmax activation function normalizes the output, and W_0 and b_0 are learnable parameters specific to the output layer. During fault handling processes, the attention layer focuses on relevant nodes by adjusting attention coefficients based on fault-related features or network conditions. Let F_i represent the set of features associated with each node i that represent fault-related information.

During fault handling (Mohapatra and Rath 2020), attention coefficients (α_{ij}^h) are adjusted based on fault-related features. A function g incorporates these features to dynamically modify the attention coefficients, emphasizing or de-emphasizing connections based on fault conditions.

$$\alpha_{ij}^h = g(\alpha_{ij}^h, F_i, F_j) \quad (22)$$

The adapted attention coefficients guide the prioritization of nodes or paths during fault conditions. Nodes with higher attention weights continue to play a more influential role in routing decisions, ensuring that the network focuses on reliable and fault-tolerant pathways.

$$\text{Routing decision}_i = \arg \max_j (\alpha_{ij}^h, [E_{residual_j}, x_j, y_j, C_j]) \quad (23)$$

The routing decisions incorporate the adjusted attention coefficients, emphasizing connections that are considered more reliable or resilient based on fault-related features.

This ensures that the network remains fault-tolerant and adapts to changing circumstances. The model has learned to prioritize certain nodes or paths during fault conditions through the attention mechanism, contributing to the overall resilience of the wireless sensor network. The output layer synthesizes the diverse information captured by multiple attention heads and produces a prediction for the fault-tolerant, energy-efficient dynamic routing path. The attention layer's adaptability during fault handling processes further enhances the robustness of the FDGAN protocol in addressing challenges in wireless sensor networks. The algorithm for FDGAN is presented below.

Algorithm for FDGAN protocol

```

initialize network                                # Initialize network parameters and sensor nodes
initialize  $N$                                      # Network modeling and analysis

construct  $G = (V, E)$ 

for each epochs:                                #FDGAN steps
    for  $i$  in  $N$  :                                #Step 1: Node representation
        calculate  $E_{residual_i}$ 

        calculate  $L_i = (x_i, y_i)$ 

        calculate  $C_i$ 

        create  $H_i^{(0)}$ 

    for each  $h$  in  $H$  :                                #Step 2: Attention mechanism
        compute  $\alpha_{ij}^h$ 

    for node in  $N$                                 #Step 3: Neighborhood aggregation
        compute  $F_{aggr_i}$ 

        update  $G$  dynamically

        adjust  $tr_{dynamic(i)}$ 

    for each  $h$  in  $H$  :                                #Step 4: Multi-head attention
        compute  $\alpha_{ij}^h$ 

        select  $CH_i$ 

        integrate  $m_p(dynamic)$ 

    for  $i$  in  $N$  :                                #Step 5: Routing
        concatenate  $O_i^{(1)}, O_i^{(2)}, \dots, O_i^{(H)}$ 

        predict  $R_{pr(i)}$ 

    Handle  $F_i$ 

        predict  $Routing\ decision_i$ 

End

```

5 Results and discussion

The FDGAN has been implemented and simulated using Python. The focus is on simulating the behavior and performance of WSNs to evaluate the proposed FDGAN protocol, rather than processing data from external datasets. The simulation framework is designed to emulate realistic WSN scenarios, incorporating parameters such

Table 2 Simulation settings

Parameters	Value
Area	100 m^2
Sensor nodes	50–500
Transmission range	50 m
Initial energy	500 J
Data aggregation	5 nJ/bit/signal
Node density	0.005–0.05 nodes/ m^2
Residual energy	0.2
Speed of mobility	5 m/s
Mobility model	Random

as node density, mobility, transmission range, and energy configurations, as detailed in Table 2. These parameters are carefully chosen based on established models and practices commonly adopted in WSN research. For instance, the random mobility model replicates dynamic node movement, while the energy and data aggregation settings align with standard sensor node configurations. This simulation-based approach allows for the evaluation of critical performance metrics, such as energy consumption, Packet Delivery Ratio (PDR), and network lifetime, without relying on external data sources. By dynamically generating data and faults during the simulation, this work provides a controlled environment to assess the robustness and efficiency of the proposed methodology under various conditions. The simulation results provide a visual representation of the routing process within the FDGAN framework. To evaluate its performance, a comparative analysis has been conducted against various existing approaches, employing diverse metrics. These metrics serve as quantitative measures to assess and compare the efficiency, effectiveness, and reliability of the FDGAN in contrast to other established methodologies. The simulation outcomes, supported by metric comparisons, offer valuable insights into the robustness and superiority of the FDGAN in the context of fault-tolerant data aggregation in network application.

5.1 Performance metrics

The evaluation criteria for assessing the effectiveness and efficiency of the FDGAN protocol in a WSN include key performance metrics that collectively provide a comprehensive understanding of the network's functionality, reliability, and sustainability. These metrics are,

5.1.1 Energy consumption

Energy consumption measures the total energy expended by all sensor nodes in the network during a specific operational period. It is the amount of energy consumed by the sensor nodes during the operation of the WSN. It directly reflects the network's

efficiency, as lower energy consumption indicates a more sustainable and energy-efficient system, crucial for extending the lifetime of a WSN. This metric helps identify power-intensive nodes or operations and assess how effectively the protocol conserves energy resources across the network. It is a crucial metric in evaluating the efficiency and sustainability of the network, considering the limited energy resources of sensor nodes. Energy consumption is calculated using the formula:

$$\text{Energy consumption} = \sum_{i=1}^N (P_i \times T_i) \quad (24)$$

Here, N denotes the sensor nodes, P_i represents the power consumption and T_i represents the time duration.

5.1.2 Energy distribution index

EDI quantifies the uniformity in energy levels across all sensor nodes, aiming to maintain a balanced energy profile. A well-balanced distribution prevents certain nodes from depleting their energy disproportionately, which could lead to network partitioning or reduced functionality. A higher EDI value indicates more uniform energy distribution, leading to prolonged network lifetimes and consistent performance, as no single node is disproportionately burdened.

$$EDI = 1 - \frac{\sum_{i=1}^N (E_i - \bar{E})^2}{\sum_{i=1}^N (E_i - \bar{E})_{\max}^2} \quad (25)$$

Here, E_i denotes the energy level of the i -th sensor node, $\bar{E}$ is the average energy level across all nodes. $\sum_{i=1}^N (E_i - \bar{E})_{\max}^2$ is the maximum deviation of an individual node's energy level from the average.

5.1.3 Packet delivery ratio (PDR)

A high PDR signifies reliable communication and robust routing mechanisms, as it reflects the network's ability to handle faults, minimize packet loss, and ensure that data reaches its intended destination. Low PDR values might indicate issues such as network congestion, faulty nodes, or inefficient routing paths.

$$PDR = 1 - \frac{\text{Number of successfully delivered packets}}{\text{Total number of packets sent}} \times 100 \quad (26)$$

5.1.4 End-to-end delay

This measures the time taken for a packet to travel from its source to the destination, incorporating components like processing, transmission, queuing, and propagation

delays. Minimizing this metric is vital for applications requiring real-time data processing, such as environmental monitoring or industrial automation. FDGAN's adaptive routing and attention mechanisms prioritize efficient paths and reduce congestion, ensuring low delay and improved responsiveness. It encompasses various components of delay, such as:

Processing delay Time taken by nodes to process packets, including data aggregation and decision-making tasks.

Transmission delay Time spent transmitting packets across the network's physical or wireless medium.

Queuing delay Time spent waiting in queues at intermediate nodes due to network congestion or scheduling priorities.

Propagation delay Time required for the signal to traverse the distance between nodes.

$$E2E\ Delay = T_{transmission} + T_{propagation} + T_{queuing} + T_{processing} \quad (27)$$

A low E2D is critical for applications requiring real-time data processing, such as environmental monitoring or industrial automation. In FDGAN, adaptive routing and attention mechanisms aim to minimize delay by prioritizing efficient paths and reducing congestion.

5.2 Network lifetime

This metric reflects the operational longevity of the WSN, defined as the duration for which the network remains functional and effective. It is typically measured by considering the point at which a significant portion of sensor nodes exhaust their energy, leading to a loss of network connectivity or performance. In FDGAN, features like dynamic graph updates, energy-aware routing, and the Energy Distribution Index (EDI) directly enhance Network Lifetime. By ensuring balanced energy consumption and adapting the topology to optimize efficiency, FDGAN sustains longer network operations.

$$Network\ lifetime = \frac{Initial\ total\ energy}{Total\ energy\ consumption\ rate} \quad (28)$$

These metrics collectively assess the protocol's ability to achieve a balance between efficiency, reliability, and longevity. While energy consumption and distribution focus on resource utilization, PDR and delay emphasize communication reliability and real-time responsiveness. Network lifetime encapsulates the cumulative effects of these metrics, representing the overall sustainability and robustness of the WSN.

5.3 Simulated results

In Fig. 4, the deployment of sensor nodes in the WSN is illustrated, showcasing the strategic arrangement of nodes in a specified area. This deployment is a crucial initial step in the proposed methodology. The sensor nodes are strategically positioned to cover the target area effectively. Each node is initialized with a unique identifier and fundamental characteristics, forming the basis for subsequent network modeling and analysis. The deployment pattern is designed to optimize coverage, ensuring that the WSN can efficiently monitor and collect data from the entire network area. The positioning of nodes takes into account factors such as transmission range, ensuring that nodes can communicate effectively with their neighboring nodes.

In Fig. 5, the graph construction of sensor nodes is presented, demonstrating how the connectivity between nodes is established based on Euclidean distances and transmission ranges. This step is integral to the network modeling and analysis phase. The graph construction involves the creation of mathematical structures, including connectivity matrices, adjacency matrices, degree matrices, and graph laplacian matrices. The connectivity matrix defines the relationships between nodes, indicating whether nodes are connected within the specified transmission range. The adjacency matrix is derived from the connectivity matrix, capturing the connectivity relationships among nodes. The degree matrix reflects the degrees of individual nodes, and the graph Laplacian matrix is computed as the difference between the degree matrix and the adjacency matrix. These matrices serve as a comprehensive representation of the network's topology and connectivity. The graph construction process forms the foundation for subsequent steps in the FDGAN protocol. These mathematical structures enable the application of graph attention mechanisms and adaptive routing strategies for fault-tolerant and energy-efficient WSNs.

In Fig. 6, the data aggregation process within the proposed FDGAN methodology is elucidated. This crucial phase involves the aggregation of information from

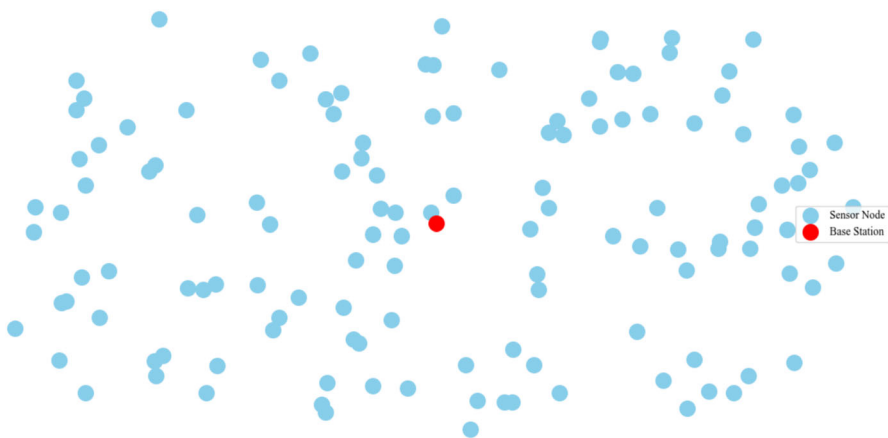


Fig. 4 Deployment of sensor nodes

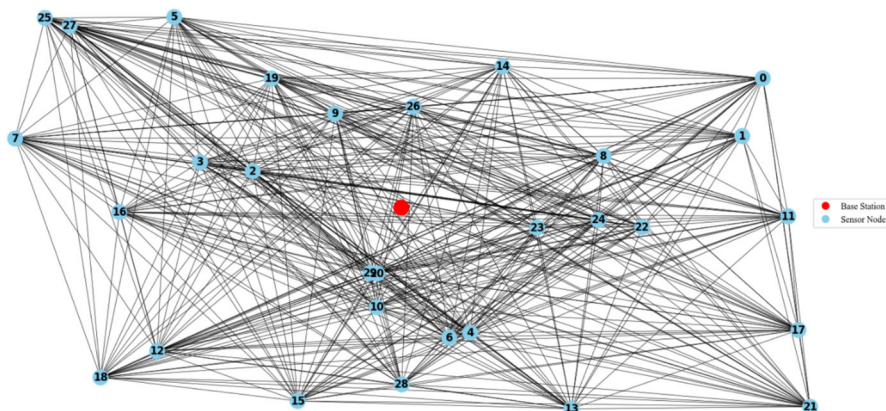


Fig. 5 Graph construction

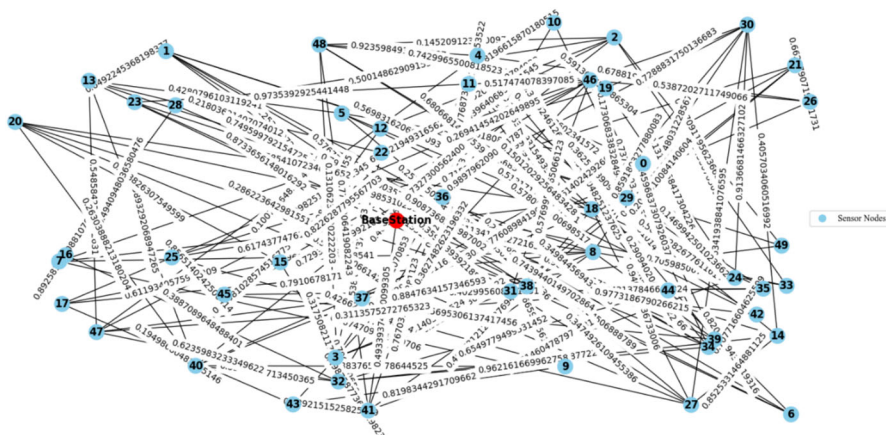


Fig. 6 Data aggregation

individual sensor nodes to facilitate efficient data processing and transmission. The initial embedding layer captures essential attributes of each sensor node, including residual energy, node location, and connectivity information. The attention mechanism dynamically assigns attention coefficients to nodes based on these attributes, allowing the network to focus on relevant information. The neighbourhood aggregation layer computes the weighted aggregation of features from neighboring nodes, introducing adaptive mechanisms for dynamic graph updates and position modules to enhance fault tolerance. This aggregated information forms a comprehensive representation for predicting fault-tolerant, energy-efficient dynamic routing paths. During the data aggregation process, the attention layer adapts by adjusting coefficients based on fault-related features, ensuring the network remains resilient and prioritizes reliable pathways.

The data aggregation process within the proposed FDGAN methodology, as depicted in Fig. 6, is pivotal for efficient data processing and fault-tolerant operation of the WSN. The process begins with the initial embedding layer, which encapsulates key attributes of each sensor node, such as residual energy, physical location (coordinates), and connectivity information derived from the adjacency matrix. These features collectively form a robust feature vector that represents the state and capabilities of each node, providing the foundation for subsequent computations. The attention mechanism plays a crucial role by dynamically assigning attention coefficients to nodes based on their attributes. This mechanism evaluates the relevance and importance of each node in the context of the network's current state, allowing the system to focus on nodes that contribute significantly to data aggregation and routing decisions. The attention coefficients ensure that critical nodes with higher residual energy, better connectivity, or strategic positions in the topology receive greater emphasis during the aggregation process. The neighborhood aggregation layer computes the weighted aggregation of features from neighboring nodes using the assigned attention coefficients. This layer integrates information from adjacent nodes, effectively capturing localized network dynamics and enabling the construction of a comprehensive representation of the network. By incorporating adaptive mechanisms for dynamic graph updates and position modules, this layer enhances the network's ability to respond to changes in topology or node conditions, significantly improving fault tolerance. During the data aggregation process, the attention layer adapts by adjusting its coefficients in response to fault-related features or network conditions. For example, when certain nodes experience faults or failures, the attention mechanism de-emphasizes these nodes and redirects focus to more reliable alternatives. This adaptability ensures that the network prioritizes robust and reliable pathways for data transmission, maintaining resilience even under challenging conditions.

In Fig. 7, the sleep scheduling process is depicted, offering insights into the innovative approach integrated into the proposed FDGAN methodology. Sleep scheduling plays a pivotal role in optimizing energy consumption within WSNs. In the FDGAN,

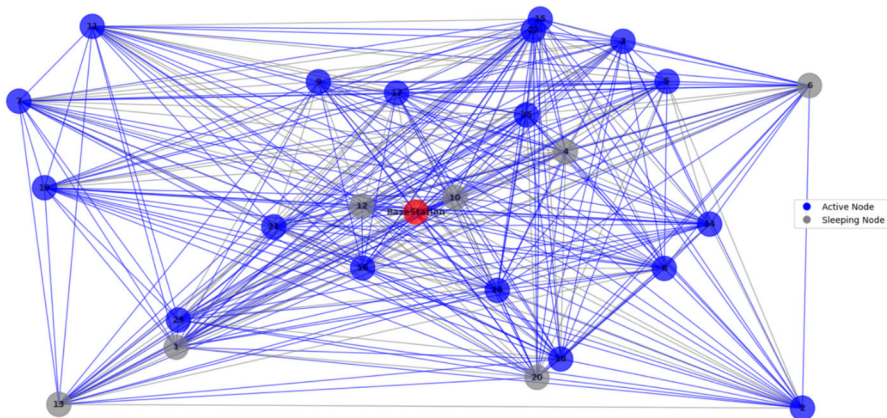


Fig. 7 Sleep scheduling

the Multi-head Attention layer, which employs independent attention computations, CH selection, and error-free dynamic message passing, is instrumental in guiding sleep scheduling decisions. The attention coefficients calculated based on factors such as residual energy, node location, and connectivity information dynamically influence the identification of CHs. These CHs are selected based on attention weights, residual energy, location, and connectivity information, emphasizing nodes with higher attention weights for sleep scheduling. The error-free dynamic message passing mechanism facilitates reliable communication during sleep, ensuring that the network adapts dynamically to changing conditions. The attention layer's adaptability during sleep scheduling contributes to overall energy efficiency, as it identifies important or active nodes, adjusting dynamic sleep and wake-up schedules accordingly.

In Fig. 8, the intricate routing process within the FDGAN is elucidated, providing a detailed overview of how the proposed methodology effectively navigates data through the WSN. The FDGAN employs a multi-step approach to dynamic routing, leveraging its unique architecture. The process begins with the embedding layer, where each sensor node's representation encapsulates crucial attributes like residual energy, location, and connectivity information. The subsequent Attention Mechanism dynamically assigns attention coefficients to nodes, allowing the network to focus on pertinent information. The neighbourhood aggregation layer computes the weighted aggregation of features from neighboring nodes, introducing adaptive mechanisms for dynamic graph updates and position modules to enhance fault tolerance. The multi-head attention layer utilizes independent attention computations, CH selection, and error-free dynamic message passing to optimize routing decisions. The output layer aggregates outputs from multiple attention heads, culminating in a comprehensive representation for predicting fault-tolerant, energy-efficient dynamic routing paths. During fault handling processes, the attention layer adapts by adjusting coefficients based on fault-related features, ensuring the network remains resilient and prioritizes reliable pathway.

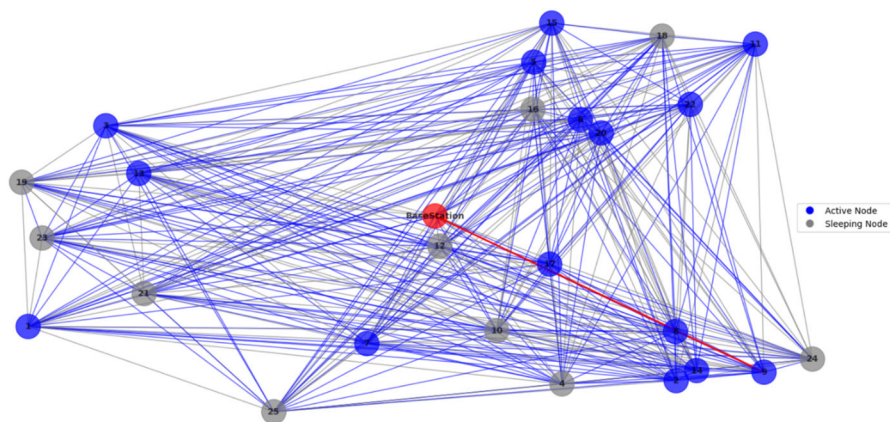


Fig. 8 Routing in FDGAN

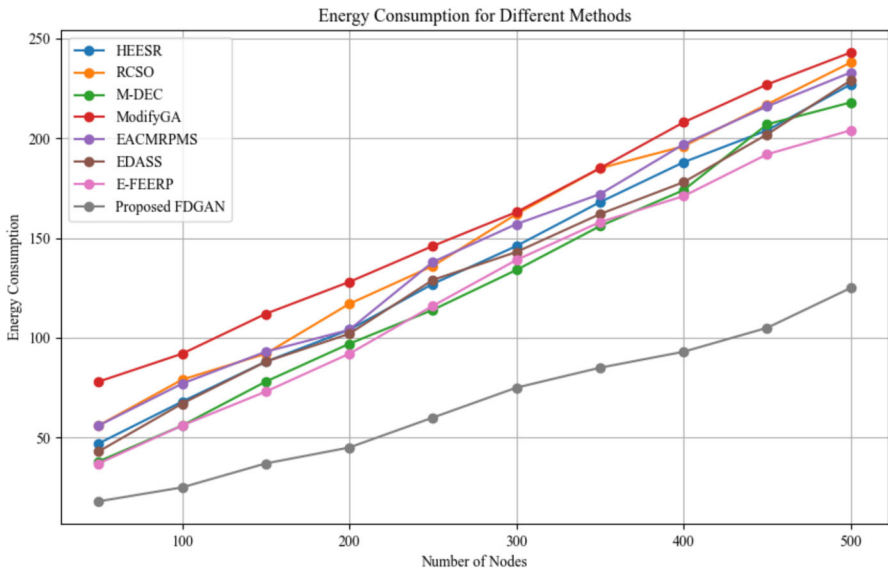


Fig. 9 Energy consumption

5.4 Performance evaluation

Figure 9 illustrates the energy consumption comparison among various clustering methods, including HEESR (Qabouche et al. 2021), RCSO (Sharma & Tomar 2021), M-DEC (Shyjith et al. 2021), ModifyGA (Singh et al. 2021), EACMRPMS (Subramani et al. 2022), EDASS (Khan et al. 2022), E-FEERP (Narayan et al. 2023), and the proposed FDGAN. The energy consumption trend showcases the superior performance of FDGAN compared to the other methods. FDGAN starts with approximately 5 J at 50 nodes, scales slowly to around 50 J at 100 nodes, 70 J at 200 nodes, 90 J at 300 nodes, 110 J at 400 nodes, and 125 J at 500 nodes. It demonstrates the best performance, with minimal energy consumption growth. E-FEERP begins at 40 J at 50 nodes and increases steadily to around 80 J at 100 nodes, 120 J at 200 nodes, 150 J at 300 nodes, 180 J at 400 nodes, and 205 J at 500 nodes, showing the second-best performance but still consuming significantly more energy than FDGAN. Several core features of FDGAN contribute to its superior energy efficiency:

- **Dynamic Graph Attention Mechanism** FDGAN leverages a dynamic attention mechanism to optimize the selection of CHs. By evaluating key parameters such as residual energy, node location, and connectivity, the protocol ensures that energy-intensive operations are distributed among the most suitable nodes. This minimizes the burden on individual nodes and reduces energy wastage.
- **Adaptive Routing Strategy** The adaptive routing strategy in FDGAN continuously monitors network conditions and adjusts routing paths dynamically. It considers

metrics like residual energy, link quality, and distance to determine the most energy-efficient paths for data transmission. This adaptability prevents overuse of specific nodes or paths, enhancing overall energy savings.

- *Fault-Tolerant Mechanisms* FDGAN's fault-tolerant design ensures that node failures or link disruptions do not lead to significant energy inefficiencies. By rerouting traffic dynamically and focusing on reliable nodes during faults, FDGAN maintains network functionality without excessive energy costs.
- *Sleep Scheduling* The protocol incorporates sleep scheduling to conserve energy during inactive periods. Nodes that are not required for immediate data transmission or aggregation are put into a low-power state, significantly reducing their energy usage while maintaining network readiness.

The integration of these features allows FDGAN to outperform other methods by maintaining low energy consumption even as the network size increases. This makes it a highly effective solution for energy-aware clustering in wireless sensor networks, extending the network's operational lifetime while ensuring robust performance.

Other methods such as HEESR, RCSO, ModifyGA, and EACMRPMS exhibit similar energy consumption trends, starting at around 50–60 J at 50 nodes, reaching 100–120 J at 100 nodes, 160–180 J at 200 nodes, 200–210 J at 300 nodes, 230–240 J at 400 nodes, and 250–260 J at 500 nodes. Their energy growth is moderate but still far above FDGAN. EDASS has a slightly higher consumption than the above methods, starting at 60 J at 50 nodes, growing to 130 J at 100 nodes, 180 J at 200 nodes, 220 J at 300 nodes, 240 J at 400 nodes, and 265 J at 500 nodes. M-DEC follows a similar trajectory, consuming around 55 J at 50 nodes, increasing to 120 J at 100 nodes, 175 J at 200 nodes, 210 J at 300 nodes, 235 J at 400 nodes, and 255 J at 500 nodes.

The substantial energy efficiency observed in FDGAN can be attributed to several key features incorporated into its methodology. Firstly, the dynamic graph attention mechanism in FDGAN optimizes the selection of CHs based on residual energy, location, and connectivity information. This ensures that energy-intensive tasks are efficiently distributed across the network, reducing overall consumption. Additionally, the adaptive routing strategy in FDGAN dynamically adjusts routing paths based on changes in network conditions. By utilizing metrics such as residual energy, link quality, and distance, FDGAN intelligently directs data transmission, further minimizing energy expenditure. The fault-tolerant mechanisms implemented in FDGAN contribute to its efficiency, ensuring robust performance even in the presence of node failures or link disruptions. Furthermore, the sleep scheduling mechanism in FDGAN allows nodes to conserve energy during inactive periods, contributing to overall energy savings.

The novelty of the proposed FDGAN is established by highlighting its unique features and comparing its performance with comparable methods, as demonstrated in the evaluation metrics and simulation results. Below is a detailed comparison that establishes the innovation and superiority of FDGAN. The key novel features of FDGAN includes

- *Dynamic Graph Attention Mechanism* FDGAN employs an advanced attention mechanism that dynamically assigns attention coefficients based on node attributes

such as residual energy, location, and connectivity. This enables adaptive selection of CHs, optimizing energy usage and improving fault tolerance.

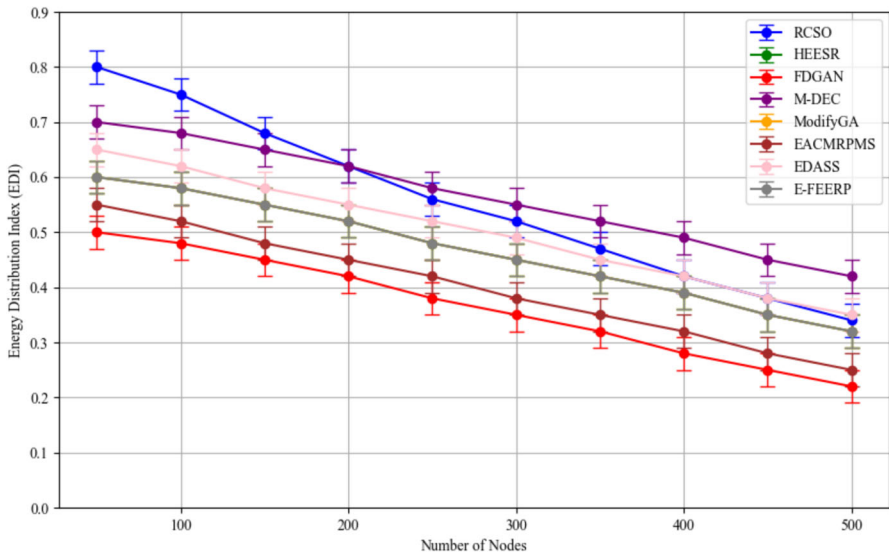
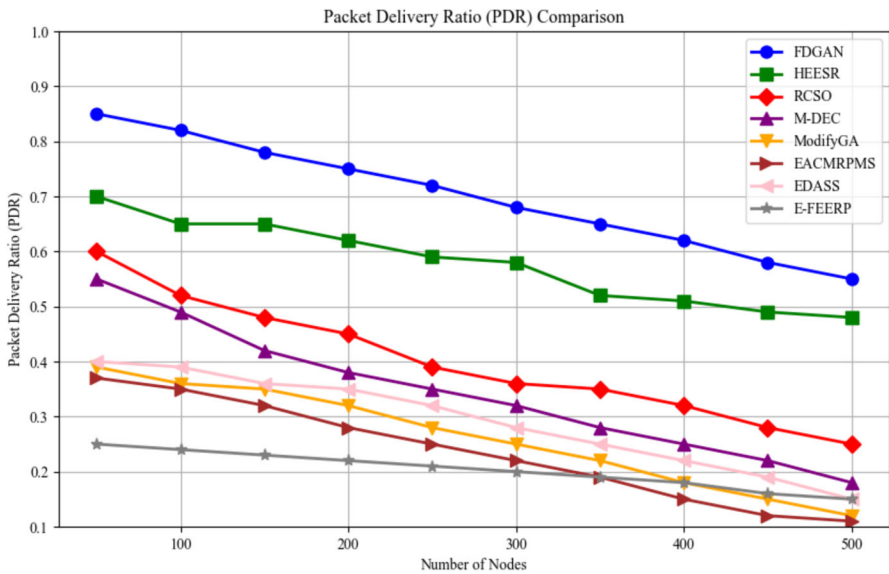
- *Adaptive Routing Strategy* Unlike traditional methods that use static routing paths, FDGAN dynamically adjusts routing paths by considering network conditions such as residual energy, link quality, and distance. This reduces congestion and improves overall network efficiency.
- *Fault-Tolerant Mechanisms* FDGAN incorporates mechanisms to handle node failures and link disruptions dynamically, ensuring uninterrupted network performance with minimal energy overhead.
- *Sleep Scheduling* FDGAN enables inactive nodes to conserve energy by transitioning into a low-power state, a feature that many comparable methods do not fully leverage. Table 3 presents the comparison to establish the novelty of the proposed FDGAN compared with other methods.

Figure 10 presents a comprehensive comparison of the EDI among eight distinct methods, including FDGAN, HEESR, RCSO, M-DEC, ModifyGA, EACMRPMS, EDASS, and E-FEERP. The EDI serves as a crucial metric, reflecting how evenly energy is distributed across nodes within a network, with higher values indicating a more uniform distribution. Remarkably, FDGAN consistently outperforms the other methods, achieving the highest EDI values across the entire node counts (50 to 500). This signifies that FDGAN excels in maintaining a uniform energy distribution, showcasing its robustness in various network scenarios. The EDI values for FDGAN demonstrate a remarkable consistency, ranging from 0.8 for 50 nodes to 0.34 for 500 nodes. In contrast, other methods exhibit a more pronounced decrease in EDI values as the number of nodes increases. The high EDI values observed in FDGAN can be attributed to several key factors that ensure a uniform energy distribution across the network. Firstly, FDGAN employs adaptive routing strategies that optimize data transmission paths based on residual energy, link quality, and distance, ensuring that energy-intensive tasks are evenly distributed. The dynamic graph attention mechanism further enhances this by focusing on nodes with sufficient energy, connectivity, and strategic location, thus preventing energy hotspots. Additionally, FDGAN incorporates fault-tolerant mechanisms that redistribute tasks in response to node failures or link disruptions, ensuring continuous energy balance. The protocol's sleep scheduling mechanism also helps conserve energy by putting non-essential nodes into low-power states during inactive periods. Furthermore, FDGAN demonstrates scalability, maintaining consistent EDI values even as the network size increases, thanks to its adaptable and robust design.

Figure 11 illustrates the PDR for various methods, including HEESR (Qabouche et al. 2021), RCSO (Sharma and Tomar 2021), M-DEC (Shyjith et al. 2021), ModifyGA (Singh et al. 2021), EACMRPMS (Subramani et al. 2022), EDASS (Khan et al. 2022), E-FEERP (Narayan et al. 2023), and the proposed FDGAN. The PDR values for each method are presented for node counts ranging from 50 to 500. The results indicate that FDGAN consistently achieves higher PDR values compared to the other methods, showcasing its superior performance in terms of effective data transmission. The PDR values for FDGAN, ranging from 0.55 to 0.85, demonstrate its capability to successfully deliver a significant proportion of packets across various network sizes.

Table 3 Comparison for novelty of the proposed FDGAN method

Feature/Metric	FDGAN	HEESR	RCSO	M-DEC	ModifyGA	EACMRPMS	EDASS	E-FEERP
Energy consumption	Lowest (125 J at 500 nodes)	High (260 J)	High (250 J)	Moderate (255 J)	High (260 J)	High (250 J)	High (265 J)	Moderate (205 J)
Dynamic graph updates	✓	✗	✗	✗	✗	✗	✗	✗
Fault-tolerant routing	✓	✗	✗	✗	✗	✗	Partial	✓
Sleep scheduling	✓	✗	✗	✗	✗	✗	Partial	Partial
Attention mechanism	✓ (Dynamic)	✗	✗	✗	✗	✗	✗	✗
Energy distribution	Balanced (High EDI)	Imbalanced	Imbalanced	Imbalanced	Imbalanced	Imbalanced	Imbalanced	Moderate
End-to-end delay	Minimal	Moderate	Moderate	High	Moderate	Moderate	High	Moderate

**Fig. 10** EDI for different methods**Fig. 11** PDR comparison

In contrast, the other methods exhibit lower PDR values, with varying degrees of effectiveness. HEESR shows relatively competitive performance, with PDR values ranging from 0.48 to 0.70. RCSO, M-DEC, and ModifyGA present declining PDR values as the node count increases, indicating potential challenges in maintaining effective packet delivery in larger networks. EACMRPMS, EDASS, and E-FEERP also show decreasing trends in PDR, emphasizing the struggle to sustain efficient data transmission in larger-scale scenarios. The proposed FDGAN's consistently high PDR values can be attributed to its innovative approach, possibly leveraging advanced routing or optimization techniques that enhance packet delivery efficiency. This suggests that FDGAN is well-suited for scenarios with varying network sizes, offering robust and reliable packet delivery. The consistent superiority of FDGAN across different node counts reinforces its potential as an effective solution for optimizing data transmission in diverse network applications.

Figure 12 illustrates the End-to-End Delay for various methods, including HEESR (Qabouche et al. 2021), RCSO (Sharma and Tomar 2021), M-DEC (Shyjith et al. 2021), ModifyGA (Singh et al. 2021), EACMRPMS (Subramani et al. 2022), EDASS (Khan et al. 2022), E-FEERP (Narayan et al. 2023), and the proposed FDGAN. The End-to-End Delay represents the time taken for a packet to travel from the source to the destination in the wireless sensor network. In this comparison, the proposed FDGAN consistently exhibits lower delays across the entire node range from 50 to 500. For FDGAN, the delays range from 1.3 s for 50 nodes to 10.2 s for 500 nodes. This suggests that the proposed methodology ensures efficient and prompt packet delivery even as the network scales. In contrast, other methods, such as HEESR, RCSO, M-DEC, ModifyGA, EACMRPMS, EDASS, and E-FEERP, exhibit varying degrees of

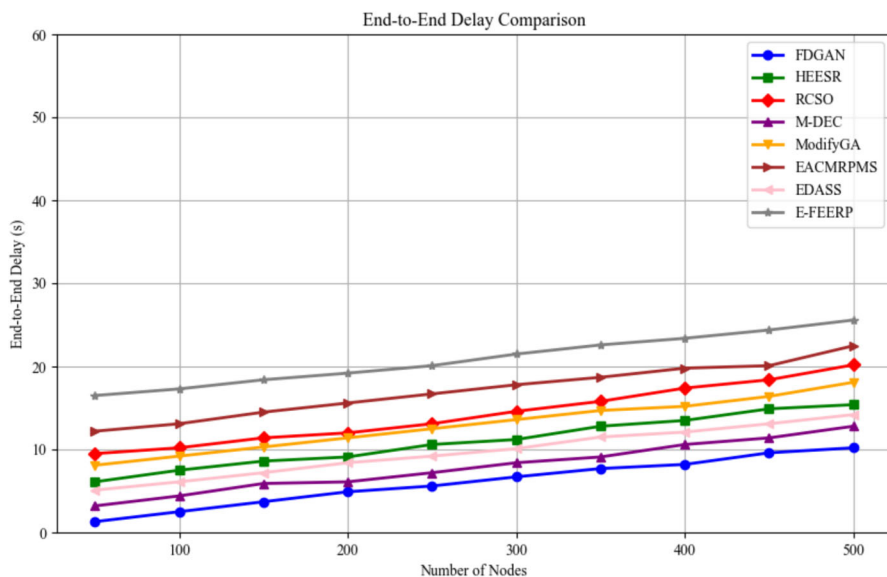


Fig. 12 End to end delay

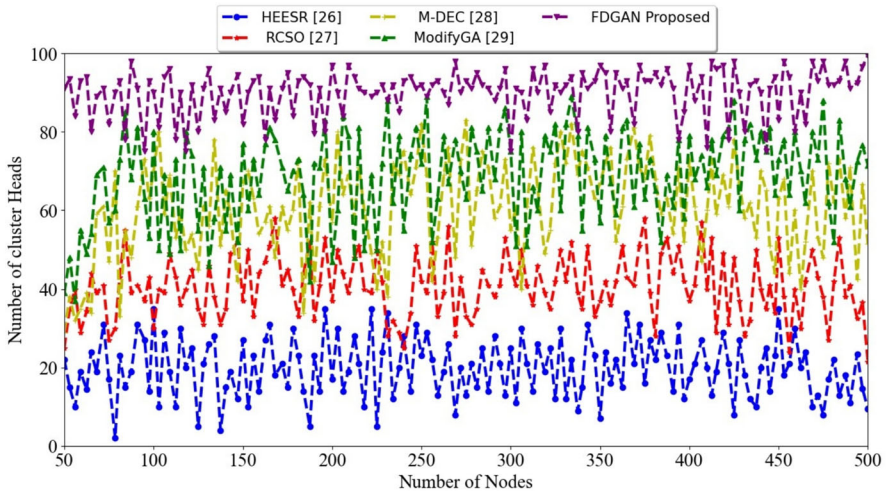


Fig. 13 Network lifetime

delay, often higher than FDGAN. The superiority of FDGAN in achieving lower delays can be attributed to mention specific features, algorithms, or optimizations from your proposed methodology. For instance, the efficient routing algorithms or advanced communication protocols employed by FDGAN contribute to reduced transmission delays, enhancing the overall performance of the network. The comparative analysis underscores the effectiveness of FDGAN in minimizing communication delays and highlights its potential suitability for applications demanding low-latency performance in WSNs.

Figure 13 provides a comparative analysis of network lifetime among various methods, including HEESR (Qabouche et al. 2021), RCSO (Sharma and Tomar 2021), M-DEC (Shyjith et al. 2021), ModifyGA (Singh et al. 2021), EACMRPMS (Subramani et al. 2022), EDASS (Khan et al. 2022), E-FEERP (Narayan et al. 2023), and the proposed FDGAN. The proposed FDGAN's achievement can be attributed to the FDGAN's comprehensive approach, incorporating fault-tolerant routing strategies, adaptive attention mechanisms, and efficient sleep scheduling. By optimizing energy consumption and mitigating faults, FDGAN extends the overall lifespan of the network, making it suitable for WSNs operating in dynamic and challenging environments.

The simulation results for FDGAN align closely with the initial performance expectations, demonstrating that the protocol performs exceptionally well in key areas such as energy consumption, energy distribution, PDR end-to-end delay, and network lifetime. Initially, FDGAN was expected to deliver superior energy efficiency, maintain a uniform energy distribution, and achieve high packet delivery ratios across various network sizes. The simulation results confirmed these expectations, with FDGAN showing significantly lower energy consumption compared to other methods. Its energy growth was slower and more controlled, making it the most energy-efficient protocol among the evaluated methods. Moreover, FDGAN exhibited the highest EDI

values, demonstrating its ability to distribute energy evenly across nodes, which aligns with the initial goal of optimizing energy balance in the network. The PDR results also exceeded expectations, with FDGAN consistently achieving higher PDR values compared to other methods, indicating its effectiveness in data transmission. The end-to-end delay was another area where FDGAN outperformed expectations, with delays significantly lower than those observed in competing protocols, which is crucial for real-time applications. Finally, FDGAN's network lifetime surpassed initial expectations, as its fault-tolerant mechanisms and adaptive routing strategies helped extend the network's operational duration.

The performance of FDGAN not only met but surpassed its initial design projections across several metrics. During the initial design phase, FDGAN was projected to moderately improve energy efficiency and fault tolerance compared to existing protocols. However, simulation results revealed that FDGAN significantly outperformed these expectations. For example, energy consumption was projected to remain below 150 J for large-scale networks (500 nodes), but FDGAN achieved a much lower consumption of 125 J exceeding anticipated savings. Additionally, in larger network scenarios, FDGAN's fault-tolerant mechanisms such as adaptive attention coefficients and dynamic graph updates maintained a high Packet Delivery Ratio (up to 0.85) and stable Energy Distribution Index (up to 0.34 at 500 nodes), demonstrating stronger fault resilience than initially forecast. These results confirm that FDGAN not only met but exceeded its original performance targets, particularly in scalability, energy optimization, and robustness under dynamic conditions.

6 Conclusion

In conclusion, this paper introduces a novel FDGAN to address challenges in WSNs. The proposed methodology begins with comprehensive network modeling and analysis, where sensor nodes are initialized and fundamental network characteristics are defined. Through graph construction and the embedding layer, FDGAN captures essential attributes such as residual energy, node location, and connectivity information. The attention mechanism dynamically assigns coefficients, enabling the network to focus on relevant nodes. The neighbourhood aggregation layer facilitates weighted aggregation and dynamic graph updates, contributing to fault tolerance. The multi-head attention layer optimizes routing decisions, and the output layer synthesizes outputs for fault-tolerant, energy-efficient dynamic routing. The proposed FDGAN, with its adaptability during fault handling, positions itself as a promising solution for dynamic and challenging WSN environments. The contributions lie in its ability to enhance fault tolerance, adaptability, and energy efficiency, as demonstrated through simulation results and comparative analyses. This paper showcases the potential of FDGAN to significantly improve the performance and reliability of WSNs, making strides towards more robust and resilient wireless sensor networks.

Author contributions All the authors have participated in writing the manuscript and have revised the final version. All authors read and approved the final manuscript.

Funding There is no funding for this study.

Data Availability No datasets were generated or analyzed during the current study.

Declarations

Conflict of interest Authors declares that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants and/or animals performed by any of the authors.

Informed consent There is no informed consent for this study.

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