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A Novel Graphical and Steiner Tree-Based Framework for Energy-Efficient Data Aggregation in Multi-Range Wireless Sensor Networks

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Abstract

This research presents a novel framework, called Steiner-Graph Energy Efficient Data Aggregation (SG-EDA), which optimizes energy efficiency in multi range wireless sensor networks (WSNs) using innovative data aggregation algorithm. The proposed model takes advantage of a graphical algorithm and Steiner tree principle to minimize energy consumption in transferring data from sensors to the sink node. However, in traditional multi range WSNs data aggregation is a critical enabler for extending network lifespan, but challenges such as variable transmission ranges and energy depletion have not been resolved. The researcher proposes an optimized Graphical Steiner tree-based aggregation process which selects relay nodes and data paths dynamically according to energy availability and transmission distance, and network topology. SG-EDA constructs minimal spanning trees specific to the network range diversity so that data is aggregated as efficiently as possible while saving the overall energy expenditure. The simulation results demonstrate that SG-EDA achieves competitive or favorable performance compared to existing data aggregation protocols with respect to energy consumption, network lifetime, and data accuracy. In particular, under the tested simulation configurations, SG-EDA reduced energy consumption by approximately 20% - 30% and increased network operational time by up to a factor of 2 compared to baseline models. In addition, the framework is adaptable to various WSN configurations, offering a scalable and robust solution for the next generation sensor networks.

Keywords

Multi-Range Wireless Sensor Networks, Energy-Efficient Data Aggregation,

Steiner Tree, Graphical Algorithms, Network Lifetime, Relay Node Selection, Minimal Spanning Tree

1. Introduction

Modern communication systems include Wireless Sensor Networks (WSNs) as their essential part to perform various useful applications involving environmental monitoring, industrial automation, healthcare, and smart cities [1]-[3]. These are spatially distributed sensor nodes that cooperate together to acquire, process and transmit the data to a central sink node, usually located in resource constrained environments [4] [5]. Whereas WSNs are used in both static and dynamic environments, such as wildlife tracking, disaster management and battlefield surveillance [6] [7].

WSNs are one of the major challenges of energy efficiency as sensor nodes have limited battery life. In remote location or harsh environments, nodes cannot be recharged or replaced, therefore energy conservation is necessary to prolong the overall network lifespan [8]. Minimal energy consumption requires efficient data aggregation since repeated transmissions of data from different nodes could drain the available energy in a short time [9] [10]. Data aggregation techniques try to reduce transmission of data by aggregating sensor readings before forwarding it to the sink node to save energy at the node and network level [11] [12].

Recent research efforts have been in developing frameworks to improve data aggregation efficiency. As an example, Manuel *et al.* [4] take an approach of putting forth a mathematical framework for energy efficient data aggregation in low power wireless networks with sensors having discrete transmission ranges. The potential of network topology design to reduce energy consumption is highlighted by this framework. Mobile crowd sensing was first enhanced with the cloud by Yang *et al.* [13] to propose an offloading strategy for minimizing energy burden on sensor nodes. Saha *et al.* [14] also provided a data-centric client selection approach for federated learning on distributed edge networks, balancing data accuracy and energy efficiency along the way.

Figure 1 shows a typical WSN design that efficiently aggregates data while consuming little power. In a network, every sensor node is arranged into a cluster. After information has been transmitted to an assigned cluster head, it is combined and transmitted to a main base station. A user or a computer with an internet connection can get the aggregated data delivered by the base station. The objective of this clustering technique is to reduce power consumption and network lifetime by reducing the amount of direct data transfers between sensor nodes and the gateway.

1.1. Challenges in Energy-Efficient Data Aggregation

Despite the progress in data aggregation techniques, several challenges persist in

designing scalable and energy-efficient WSNs, especially in scenarios where nodes have heterogeneous transmission ranges [5] [15]. Traditional data aggregation models assume uniform transmission capabilities across nodes, which oversimplifies real-world network conditions. In reality, WSNs often exhibit diverse transmission ranges due to varying power levels, environmental interference, and node heterogeneity [4] [16].

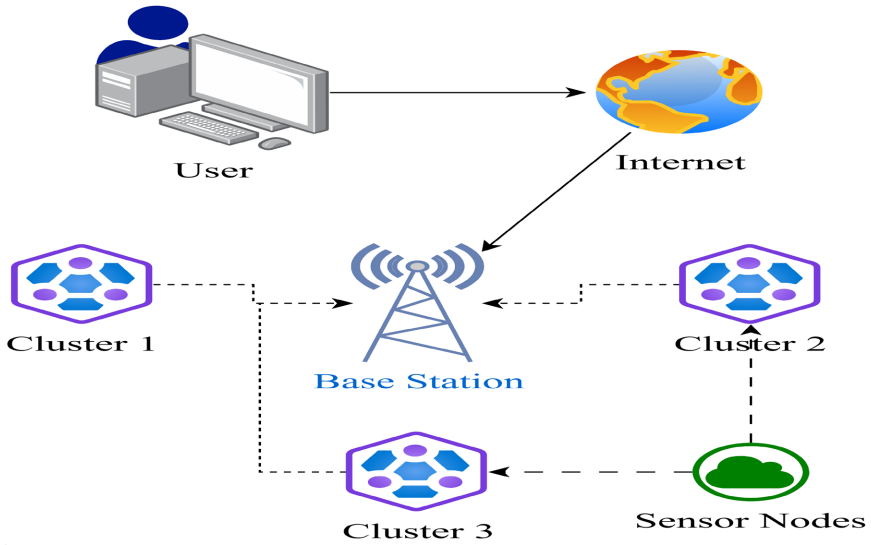


Figure 1. Cluster-based architecture for data aggregation in WSNs. The network is divided into clusters, each managed by a cluster head that aggregates data from sensor nodes and transmits it to the base station for further processing.

Transmission Range Variability: One of the major challenges is accounting for the varying transmission ranges of sensor nodes. Nodes closer to the sink may have more energy reserves and shorter transmission distances, compared to nodes farther from the sink where transmission distances are necessarily longer [17]. As a result, energy consumption is unevenly distributed over the network, causing critical nodes to be prematurely depleted [9] [18].

Dynamic Network Topologies: Nodes in WSNs frequently operate in a dynamic environment where nodes may fail, move, or run out of energy reserves. As a result, the network topology is constantly changing, which makes it difficult to maintain an optimal data aggregation tree [2] [19]. Adaptive algorithms are necessary to guarantee energy efficient data routing and aggregation in such environments, as network must adaptively reconfigure itself with respect to topology changes [10].

Energy Efficiency vs. Data Accuracy: There is always a tradeoff in WSNs between energy efficiency and data accuracy or latency. For instance, reducing the number of transmissions will save on energy, but may also mean less frequent updates and possibly less accurate aggregated data [20] [21]. In federated learning applications (where edge devices need to strike a balance between the energy cost of model updates and the need for accurate, timely data) this trade-off is particu-

larly clear [8] [14].

1.2. Motivation for This Framework

The above-mentioned challenges underline the necessity of an elaborate data aggregation framework which can overcome the dynamic and heterogeneous nature of WSNs. To address these challenges, the researcher proposes an innovative solution, the Steiner-Graph Energy-Efficient Data Aggregation (SG-EDA) framework, which leverages Steiner tree principles and graphical optimization techniques. The goal of SG-EDA is to design an optimal data aggregation tree that minimizes energy consumption of the overall system, given the differences in the transmission ranges and energy reserves among sensor nodes.

SG-EDA achieves efficient aggregation and minimal energy expenditure by constructing a minimal spanning tree specific to the network's varying transmission ranges. The framework also includes dynamic relay node selection, which allows the network to change topology as nodes fail or their energy depletes [4] [15]. SG-EDA adapts to real-time energy conditions, which may help extend the network's operational lifespan [5] [16].

1.3. Problem Formulation

This research article addresses a specific problem of how to design an energy efficient data aggregation framework for WSNs with multi range transmission capabilities. Nodes in real world WSNs have different transmission ranges, energy reserves and proximity to the sink node, making it challenging to design a data aggregation protocol that minimizes energy consumption across the whole network. Node transmission ranges are not uniform and result in non-uniform energy depletion, in which nodes closer to the sink usually deplete their energy first, [5] [16].

To address these issues, the researcher presents the SG-EDA framework, which stands for Steiner-Graph Energy Efficient Data Aggregation. Assuming that all nodes are able to send data to the sink, SG-EDA's goal is to construct an ideal data aggregation tree based on Steiner tree principles that minimizes overall energy use. As part of its dynamic optimization process, the framework considers the different energy levels and transmission ranges of the nodes when choosing and optimizing transmission pathways and relay nodes [3] [4].

Let graph $\mathcal{G}(V,E)$ be a connected and weighted graph representing the wireless sensor network (WSN), where: $V=\{v_1,v_2,\cdots,v_n\}$ is the set of sensor nodes, including the sink node, E is the set of edges representing communication links between sensor nodes, weighted by their energy costs.

Each edge $(i,j)\in E$ has an associated energy cost E_{ij}, which depends on the physical and environmental parameters of the network. The energy cost E_{ij} is defined as:

$$E_{ij}=\left(P_i\cdot d_{ij}^{\alpha}\cdot\log\left(1+\eta_{ij}\right)\right)+\left(\gamma\cdot\frac{d_{ij}^{\beta}}{R_{ij}}\right) \tag{1}$$

where:

P_i is the transmission power of node i, modeled as a function of its residual energy $P_i = P_{\max} \cdot \left(1 - \frac{E_i}{E_{\text{init}}}\right)$,

d_{ij} is the Euclidean distance between nodes i and j, given by $d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2}$,

α and β are the path loss exponents for free-space and multipath fading, respectively, with typical values $\alpha \in [2,4]$ and $\beta \geq 2$,

η_{ij} is the signal-to-noise ratio (SNR) between nodes i and j,

γ is the proportionality constant for path loss energy consumption,

R_{ij} is the data transmission rate between nodes i and j.

The total energy consumption for the network is expressed as:

$$\text{Total Energy} = \sum_{(i,j)\in E} \left(x_{ij} \cdot E_{ij} + \lambda \cdot h_{ij} \cdot \log\left(1 + \frac{P_i}{N_0 W}\right)\right) \tag{2}$$

where:

x_{ij} is a binary decision variable indicating the presence of a transmission from i to j, defined as:

$$x_{ij} = \begin{cases} 1, & \text{if data is transmitted from node } i \text{ to node } j \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

λ is a weighting factor balancing energy efficiency and link quality,

h_{ij} is the channel gain between nodes i and j,

N_0 is the noise spectral density,

W is the bandwidth of the communication channel.

The optimization objective is to minimize the total energy consumption while maintaining connectivity constraints:

$$\min_{x_{ij}} \sum_{(i,j)\in E} \left(x_{ij} \cdot E_{ij}\right) \tag{4}$$

subject to the following constraints:

$$\begin{aligned} &\sum_{j\in V} x_{ij} - \sum_{j\in V} x_{ji} = 1, \ \forall i \in V \setminus \{v_{\text{sink}}\} \ \left(\text{flow conservation}\right) \\ &\sum_{(i,j)\in E} x_{ij} \leq \tau, \ \forall i \in V \ \left(\text{transmission threshold}\right) \\ &x_{ij} \in \{0,1\}, \ \forall (i,j) \in E \ \left(\text{binary constraint}\right) \end{aligned} \tag{5}$$

In this formulation, the researcher has the more complex and more advanced mathematical model for energy efficient data transmission in WSNs that accounts for additional factors such as SNR, channel gain, and bandwidth for the better realism.

To ensure efficient operation, the following constraints are imposed:

Data Flow Constraint: The only node allowed to receive data from many nodes is the sink node; the others can transmit to at most one other node. This constraint is defined to ensure energy efficient data aggregation and transmission:

$$\sum_{j \in V} x_{ij} \cdot w_{ij} \le \frac{1}{\mathcal{T}_i}, \ \forall i \in V \setminus \text{sink} \tag{6}$$

where:

x_{ij} is the binary decision variable indicating a data flow from node i to node j,

w_{ij} is the weighted cost associated with the link (i, j),

$\mathcal{T}_i$ is the traffic capacity of node i normalized to the total network capacity.

Steiner Node Selection Constraint: The Steiner nodes (relay nodes) are chosen such that the total energy cost is minimized while ensuring that all nodes have a connected path to the sink node. This is expressed as:

$$\sum_{(i,j) \in E} \left(x_{ij} \cdot \left(E_{ij} + \frac{\lambda}{h_{ij}} \right) \right) \ge \delta, \ \forall v_i \in V \tag{7}$$

where:

$E_{ij} = P_i \cdot d_{ij}^{\alpha}$ is the energy cost for transmission between nodes i and j,

h_{ij} is the channel gain between nodes i and j,

λ is a weighting factor for link quality,

δ is the connectivity threshold ensuring reliable paths to the sink.

Energy Constraint: To prevent premature node depletion, each node must maintain its energy level above a critical threshold, ensuring continuous operation. This is modeled as:

where:

E_i^{init} is the initial energy of node i,

ϕ is a scaling factor for the energy cost due to interference and environmental conditions,

R_{ij} is the data rate between nodes i and j,

N_0 is the noise power spectral density,

$E_{\min}$ is the minimum energy required for the node to remain functional.

Optimization Problem: The objective of the SG-EDA framework is to minimize the total energy consumption subject to the above constraints. This can be formulated as a mixed-integer linear programming (MINLP) problem:

$$\begin{aligned} \min_{x_{ij}} \quad & \sum_{(i,j) \in E} P_i \cdot d_{ij}^{\alpha} \cdot x_{ij} \\ \text{subject to:} \quad & \sum_{j \in V} x_{ij} \le 1, \ \forall i \in V \setminus \{\text{sink}\} \\ & \sum_{(i,j) \in E} x_{ij} \ge 1, \ \forall v_i \in V \\ & E_i^{\text{remaining}} \ge E_{\min}, \ \forall i \in V \end{aligned} \tag{8}$$

The problem of minimizing energy consumption is formulated as a decision variable x_{ij} that determines the optimal transmission paths and relay nodes such that all nodes can send their data to the sink node.

Adaptive Relay Node Selection: An adaptive mechanism for selecting relay nodes is one of the novel aspects of the SG-EDA framework. Based on a combi-

nation of node energy availability and transmission range, it selects the path. As a means to minimize overall energy consumption and balance the load over the network, relay nodes are preferred with higher remaining energy and shorter transmission distances [8] [17]. The aggregation tree is redefined dynamically (in real time) in case of node failures or energy depletion—reconfiguring the network so that it selects a new aggregation tree.

1.4. Objectives and Contributions

The aims of this works are:

1) Design of novel data aggregation framework on the principles of Steiner tree to minimize energy consumption in multi range WSNs.

2) Adaptive mechanism for relay node selection based on energy availability and transmission range to consider dynamic nature of sensor nodes.

3) Extensive simulations are then used to demonstrate the effectiveness of the proposed framework by showing improvements in energy efficiency, network lifetime, and data accuracy over existing methods.

This work makes three contributions:

1) In this research paper, the researcher presents a novel data aggregation framework (SG-EDA) that uses Steiner tree algorithm to reduce energy consumption in WSNs with heterogeneous transmission ranges.

2) In the case of dynamic network topologies, the researcher proposes an adaptive mechanism for dynamic relay node selection, which guarantees energy efficient data aggregation.

3) The researcher offers a solid solution for the next generation of sensor networks, SG-EDA, and demonstrates through comprehensive simulations that it surpasses current approaches in every respect, including energy efficiency, network lifetime, and data accuracy [22] [23].

2. Related Work

Data aggregation in Wireless Sensor Networks (WSNs) with the goal of improving energy efficiency has been the subject of extensive research. From methods based on clustering to solutions derived from graph theory, there have been numerous ways to put up. Under three broad categories, this section discusses the seminal works in the subject: Frameworks based on Steiner trees, adaptive energy-efficient routing, and data aggregation based on clustering.

2.1. Clustering-Based Data Aggregation

It's a common practice to group similar sensor nodes together into clusters, with one node acting as the cluster head to collect data from all the nodes and send it to the sink. Because of this, the transmission power of WSNs is drastically reduced, leading to energy savings on a network and individual node levels. Cluster heads are rotated frequently to balance energy usage in LEACH (Low-Energy Adaptive Clustering Hierarchy), one of the first and most popular techniques [23].

To make cluster head selection more energy efficient, several variants of LEACH have been suggested, including E-LEACH and M-LEACH [7]. On the other hand, these methods tend to simplify things too much by assuming that all nodes have the same amount of energy and transmission range, whereas in fact, this is rarely the case. Clustering-Based Data Aggregation is seen in Figure 2.

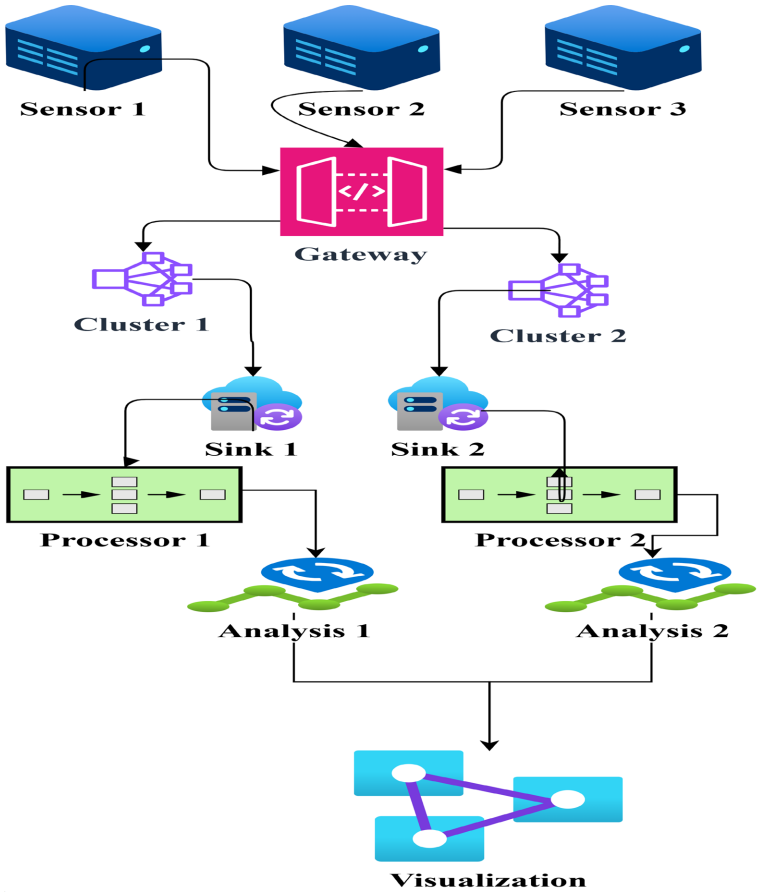


Figure 2. Traditional Clustering-Based Data Aggregation.

Yang *et al.* [13] recently presented a cloud-enhanced framework for mobile crowd sensing, which optimized energy usage through the combination of clustering and offloading methods. To overcome some of the drawbacks of conventional clustering techniques, this method enhanced energy efficiency by choosing cluster heads on the fly according to their available energy and distance from the sink. A mathematical paradigm for clustering-based aggregation in low-power WSNs, with an emphasis on nodes with discrete transmission ranges, was proposed by Manuel *et al.* [4], who also made a notable contribution. They demonstrated the importance of taking varied node capabilities into account during data aggregation and cluster creation.

2.2. Steiner Tree-Based Aggregation

There have been other graph-based methods explored for reducing data aggrega-

tion as well, including formulations based on a Steiner tree. In order to reduce overall power usage, the most efficient relay nodes, also called Steiner nodes, are chosen to link the sensor nodes to the sink [11]. Since the Steiner tree problem can provide good network connectivity while reducing energy usage, it has been intensively investigated in WSNs.

For instance, Shang *et al.* [10] proposed a decentralized federated learning framework for UAV swarms and used Steiner tree principles to minimize the data aggregation energy cost in dynamic networks. They developed an adaptive mechanism for picking Steiner nodes depending on real time energy levels, such that the network continues to work optimally even in cases with different transmission capabilities of the nodes.

In [20], Li *et al.* proposed an energy efficient framework, Snowball, in which fine compression and Steiner tree principles are used to reduce the communication overhead in heterogeneous wireless edge networks. They found that both energy consumption and network lifetime improvements were substantial over traditional approaches, especially in networks with non-uniform node densities.

2.3. Adaptive Energy-Efficient Routing

In recent years, adaptive routing algorithms that change as the network's energy status changes have become popular. These algorithms seek to extend network operational lifetime by optimizing routing paths in terms of node current energy levels. Saha *et al.* [14] proposed one such approach, developing a data-centric client selection method to select clients for federated learning in distributed edge networks. The work showed the tradeoff between data accuracy and energy efficiency and that adaptive routing strategies are needed that can balance these two conflicting goals.

Na *et al.* [11] developed the hybrid federated and centralized learning model for edge-based traffic prediction in aerial networks, similar to ours. The adaptive routing mechanisms used in this framework employed the data aggregation paths that changed dynamically according to the energy consumption patterns of nodes. Adaptive routing techniques can considerably enhance the network's energy efficiency and operational lifetime as such, according to their results.

He *et al.* [22] further emphasized the importance of dynamic relay node selection in adaptive routing and proposed a digital twin enabled resource allocation framework for heterogeneous cellular networks. Their method dynamically allocated relay nodes to operate the network efficiently in changing environmental conditions by using real time energy consumption data.

2.4. Summary of Related Work

The reviewed literature demonstrates progress in the area of improving energy efficiency of WSNs through clustering-based methods and graph theoretical applications such as Steiner trees, but still there are many challenges. Most existing methods assume homogeneous transmission ranges or handle dynamic nature of

WSNs with incomplete treatment to nodes' varying energy reserves and transmission capabilities. In heterogeneous and dynamic network environments, adaptive routing and dynamic relay selection methods have proven promising. Yet more work is needed to develop frameworks that are capable of dynamically adjusting to meet these challenges and still achieve energy efficiency and data accuracy. This paper proposes a digital twin (DT)-assisted wireless powered MEC network where IoT devices maintain digital replicas and a mixed deep reinforcement learning (DRL) framework jointly optimizes offloading and resource allocation under energy constraints [24]. This research proposes the CATER protocol, which combines trust evaluation, congestion awareness, and energy-efficient routing to improve secure data transmission in wireless sensor networks [25]. Yang *et al.* [26] proposed a deep reinforcement learning-based adaptive routing algorithm for wireless sensor networks. Their method dynamically optimizes routing decisions to improve both energy efficiency and transmission performance. Experimental results demonstrated significant improvements in network lifetime and energy utilization, highlighting the effectiveness of intelligent routing strategies for large-scale sensor network deployments. This research proposes a GNN-driven networking framework for industrial wireless sensor networks, including joint node selection and power allocation for improving communication robustness and network efficiency [27]. This work proposes approximation Steiner-tree algorithms (AST and CBAST) for maintaining connectivity in mobile wireless sensor networks and demonstrates improved energy efficiency and computational performance compared with existing heuristics [28]. This research proposes an energy-efficient relay-selection mechanism for clustered WSNs where relay nodes are chosen to minimize end-to-end transmission distance and communication energy cost. The approach improves network lifetime and transmission efficiency through adaptive relay selection [29]. This paper introduces a decentralized Q-learning and fuzzy-logic-based relay selection scheme for IoT-oriented WSNs, improving load balancing, congestion management, and energy efficiency under dynamic network conditions [30]. This paper formulates IoT data aggregation as a multi-objective optimization problem that jointly minimizes latency (time consumption) and energy consumption using an NSGA-III-based optimization framework [31]. In **Table 1**, the researcher demonstrates various techniques proposed in the literature to improve the energy efficiency of data aggregation in wireless sensor networks (WSNs). The methods span from low power sensor node clustering-based aggregation [4], cloud enhanced frameworks [13] to Steiner tree-based solutions for UAV swarms [10]. However, the comparison highlights also the strengths and the limitations of each of these techniques.

The proposed Steiner-Graph Energy-Efficient Data Aggregation (SG-EDA) framework has been proposed on these prior works by incorporating Steiner tree principles and adaptive relay node selection to optimize energy efficiency in WSNs with heterogeneous transmission capabilities. This method provides an answer to the shortcomings of conventional approaches by taking into consideration

the dynamic character of the network and minimizing the energy consumption over different node configurations.

Table 1. Comparison of techniques, data usage, limitations, key findings, and advantages in energy-efficient WSN solutions.

Reference	Techniques	Data Usage	Limitations	Key Findings	Advantages
[22]	Digital twin-enabled resource allocation, heterogeneous networks	Cellular network data, heterogeneous sensor networks	Complex resource allocation requires real-time data	Optimized resource allocation and improved energy usage	Resource allocation optimization, suitable for heterogeneous networks
[20]	Coarse-to-fine compression, energy-efficient federated learning	Wireless edge network data, heterogeneous devices	High computational complexity for large networks	Energy savings and improved lifetime in heterogeneous networks	Efficient communication, energy savings for edge devices
[4]	Clustering-based aggregation, low-power sensors, mathematical framework	Simulated WSN with discrete transmission ranges	Assumes static network topology, limited to low-power nodes	Energy consumption reduced significantly with clustering	Effective for low-power WSNs, scalable for small networks
[11]	Hybrid federated and centralized learning, adaptive routing	Aerial traffic prediction data, edge-based sensors	Limited to specific aerial network configurations	Efficient traffic prediction and energy savings	Improves energy efficiency in aerial networks, hybrid model
[14]	Client selection using data as its primary focus for distributed edge networks and federated learning	Federated learning model, distributed edge network data	Trade-off between energy efficiency and data accuracy	Balanced energy usage across edge nodes, but accuracy reduced	Balances energy across the network, scalable to large networks
[10]	Steiner tree-based framework for UAV swarms, decentralized learning	UAV sensor network data, decentralized aggregation	Requires real-time data to function efficiently	Energy-efficient data aggregation in dynamic networks	Adapts to dynamic UAV networks, decentralized learning
[13]	Cloud-enhanced mobile crowd sensing, offloading strategies, clustering	Crowd sensing data in mobile applications	Limited adaptability to dynamic network topologies	Improved energy efficiency through offloading and cloud enhancements	Cloud-based framework adapts well to mobile environments

3. Proposed System Model

The goal of this section is to provide a comprehensive mathematical description of the system model that will be used to create a data aggregation solution for WSNs that is both efficient and energy efficient. Given the wide variety of sensor nodes' energy capacities and transmission ranges, the model selects an adaptive relay node by combining Steiner tree concepts. It adjusts in real-time depending on the state of the network to save power usage. **Figure 3** displays the System Model that has been proposed.

3.1. Network Model

The model of the WSN as a weighted connected graph $\mathcal{G}(V,E)$, where

$V = \{v_0, v_1, v_2, \cdots, v_n\}$ represents the set of sensor nodes including the sink node v_0, and $E \subseteq V \times V$ represents the communication links between the nodes. Each sensor node $v_i \in V$ is associated with an initial energy level E_i^{init} and a residual energy E_i^{res} at time t.

Let d_{ij} represent the Euclidean distance between node v_i and node v_j. Each link $(i, j) \in E$ has an associated energy cost E_{ij} for data transmission, which depends on the distance between the nodes and their transmission power.

The transmission power required for node v_i to communicate with node v_j is modeled by:

$$P_{ij} = P_{\text{tx}} + P_{\text{amp}} \cdot d_{ij}^{\alpha} \tag{9}$$

where:

P_{tx} is the constant transmission power,

P_{amp} is the amplification factor that depends on the transmission range,

α is the path loss exponent (typically between 2 and 4, depending on the environmental characteristics such as fading and obstacles).

The energy consumed by node v_i to transmit data to node v_j is given by:

$$E_{ij} = \lambda \cdot P_{ij} \cdot t_{\text{tx}} \tag{10}$$

where λ is the data rate in bits per second, and t_{tx} is the transmission time.

Data transmission energy usage as a whole is represented by:

$$E_{\text{total}} = \sum_{(i,j) \in E} E_{ij} \cdot x_{ij} \tag{11}$$

where x_{ij} is a binary decision variable that indicates whether data is transmitted from node v_i to node v_j:

$$x_{ij} = \begin{cases} 1, & \text{if data is transmitted from } v_i \text{ to } v_j, \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

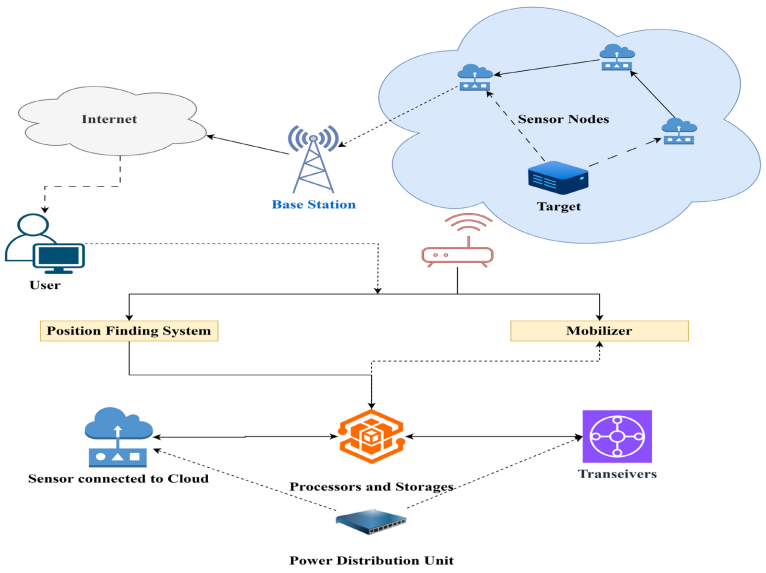


Figure 3. Proposed system model.

3.2. Energy Depletion Model

The residual energy of each node decreases with each transmission. The energy depletion at node v_i after a transmission is calculated by:

$$E_i^{\text{res}}(t+1) = E_i^{\text{res}}(t) - \sum_{j \in V} E_{ij} \cdot x_{ij} \tag{13}$$

The objective is to ensure that $E_i^{\text{res}}(t) \geq E_{\min}$ for all i, where $E_{\min}$ is the minimum required energy for a node to remain functional. Nodes with insufficient energy are excluded from the aggregation process to prolong the network's lifetime.

Table 2 summarizes the symbols and abbreviations used in the Energy Depletion Model and subsequent optimization framework. The nomenclature is provided to improve clarity and facilitate reproducibility of the proposed SG-EDA methodology.

Table 2. Nomenclature of symbols and abbreviations used in the energy depletion model.

Symbol	Description	Unit
$E_i(t)$	Residual energy of sensor node i at time t	J
$E_i(t+1)$	Residual energy of node i after transmission	J
$E_{\text{tx}}(i,j)$	Energy consumed for transmission from node i to node j	J
$E_{\min}$	Minimum energy threshold required for node operation	J
E_0	Initial energy of a sensor node	J
P_{ij}	Transmission power between nodes i and j	W
d_{ij}	Euclidean distance between nodes i and j	m
r_{ij}	Data transmission rate between nodes i and j	bit/s
T_{ij}	Transmission time between nodes i and j	s
α	Path loss exponent	Dimensionless
β	Amplification factor related to transmission range	Dimensionless
γ	Control parameter balancing energy and distance effects	Dimensionless
D_i	Distance from node i to the sink node	m
P_i	Probability of selecting node i as a relay node	Dimensionless
x_{ij}	Binary transmission decision variable (1 if link exists, 0 otherwise)	–
N	Total number of sensor nodes	Count
S	Sink node	–
t	Time instant or simulation round	s / round

3.3. Relay Node Selection and Probability Model

The selection of relay nodes is done by considering both the availability of energy and the efficiency of transmission. The probability that node v_i is selected as a

relay node is proportional to its residual energy and inversely proportional to its distance from the sink node:

$$P_{\text{relay}}\left(v_i\right)=\frac{E_i^{\text{res}}}{\sum_{j\in V}E_j^{\text{res}}}\cdot\frac{1}{d_{i0}^{\beta}} \tag{14}$$

where d_{i0} is the distance between node v_i and the sink node v_0, and β is a control parameter that balances the weight between energy and distance. Relay nodes are more likely to be chosen if they have a larger residual energy and are located closer to the sink. Relay nodes that reduce overall energy consumption are chosen to maximize the expected energy efficiency of the network. The process of relay node selection is changed periodically according to the real-time energy levels.

3.4. Steiner Tree Formulation for Data Aggregation

The researcher builds the data aggregation tree according to the Steiner tree principles to reduce the network energy utilization. With the introduction of intermediary (Steiner) nodes, the goal of a Steiner tree is to link all sensor nodes to the sink node as efficiently as possible, either in terms of overall energy cost or tree length. The suggested SG-EDA (Steiner-Graph Energy Efficient Data Aggregation) system is shown in **Figure 4**, which provides the complete architecture and flow diagram. The issue of energy-efficient data aggregation in WSNs, where sensor nodes gather data and send it to a sink node, is tackled by this solution. In order to reduce energy consumption in the network, the flowchart showing dynamic node selection based on remaining energy levels and distance to the sink is provided. Several essential parts make up the architecture: With their limited energy resources, sensor nodes form the backbone of a WSN. Relay nodes are chosen dynamically according to energy levels and distance from the sink node. The communication tree structure known as the Steiner Tree minimizes energy usage by connecting sensor nodes to the sink node. Finally, the aggregated data is received and processed centrally at the sink node. By carefully choosing relay nodes and building an optimal aggregation tree, Energy Optimization ensures that power usage is minimized. Using a data aggregation strategy that consumes the least amount of energy over the entire network, it demonstrates the movement of data from sensor nodes to relay nodes and finally to the sink.

Steiner tree problem can be expressed as:

$$\min_{S\subseteq V}\sum_{(i,j)\in T(S,V)}P_{ij}\cdot d_{ij}^{\alpha}\cdot x_{ij} \tag{15}$$

where $T\left(S,V\right)$ represents the set of edges in the Steiner tree that connects all nodes V through the Steiner nodes S.

Steiner nodes inclusion reduces the energy consumption by aggregating the data through intermediate nodes and enabling sensor nodes with limited transmission range to participate into the data aggregation process.

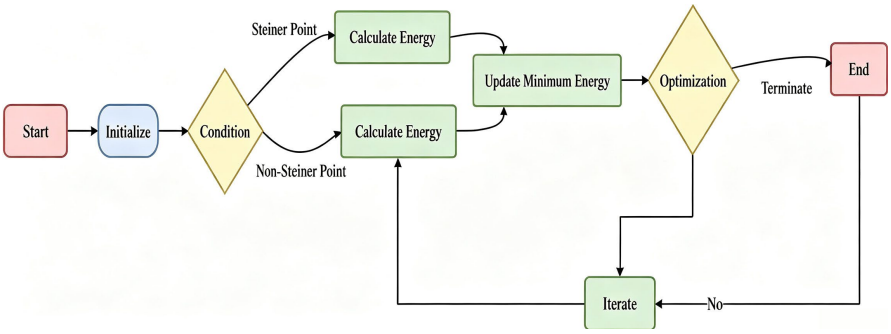


Figure 4. Detailed architecture of SG-EDA system.

3.5. Optimization Problem

The overall optimization problem to minimize energy consumption in the WSN can be formulated as a mixed-integer non-linear programming (MINLP) problem:

$$\begin{aligned} \min_{x_{ij},S} \quad & \sum_{(i,j)\in E} P_{ij}\cdot d_{ij}^{\alpha}\cdot x_{ij} \\ \text{subject to:} \quad & \sum_{j\in V} x_{ij} \le 1, \ \forall i \in V\{\text{sink}\} \\ & \sum_{(i,j)\in E} x_{ij} \ge 1, \ \forall v_i \in V \\ & E_i^{\text{res}} \ge E_{\min}, \ \forall i \in V \\ & \text{Steiner tree constraint}: \text{minimize } T(S,V) \end{aligned} \tag{16}$$

This optimization seeks to minimize the total energy cost by jointly selecting the transmission paths x_{ij}, the relay nodes, and the Steiner nodes. The first constraint ensures that each sensor node can transmit data to only one other node (except the sink node). The second constraint ensures network connectivity, and the third constraint guarantees that all sensor nodes maintain sufficient residual energy for operation.

3.6. Theorem: Energy-Optimal Aggregation Tree

The aggregation tree $\mathcal{T}_{\text{SG-EDA}}$ constructed by the SG-EDA framework provides an approximate solution to the energy minimization problem, aiming to reduce energy consumption through dynamic relay node selection and Steiner tree approximation. The energy cost of $\mathcal{T}_{\text{SG-EDA}}$ satisfies:

$$E(\mathcal{T}_{\text{SG-EDA}}) \le (1+\epsilon) E(\mathcal{T}_{\text{opt}}) \tag{17}$$

where $E(\mathcal{T})$ represents the total energy cost of tree $\mathcal{T}$, $\epsilon > 0$ is the approximation factor of the Steiner tree algorithm, and $\mathcal{T}_{\text{opt}}$ is the optimal aggregation tree that minimizes energy consumption.

Proof: Let $\mathcal{G}(V,E)$ be the graph representing the WSN, where $V = \{v_0, v_1, v_2, \cdots, v_n\}$ is the set of sensor nodes, and E is the set of communication links. The objective is to construct an aggregation tree $\mathcal{T}(S,V) \subseteq \mathcal{G}$ that minimizes the total energy consumption, where $S \subseteq V$ represents the set of

Steiner nodes (relay nodes).

The energy cost of a transmission from node v_i to node v_j is given by:

$$E_{ij} = P_{ij} \cdot d_{ij}^{\alpha} \tag{18}$$

where P_{ij} is the transmission power between nodes v_i and v_j, d_{ij} is the Euclidean distance, and α is the path loss exponent. The total energy cost of a tree $\mathcal{T}(S,V)$ is:

$$E(\mathcal{T}(S,V)) = \sum_{(i,j)\in\mathcal{T}(S,V)} P_{ij} \cdot d_{ij}^{\alpha} \tag{19}$$

The Steiner tree approximation algorithm used in SG-EDA constructs an approximate aggregation tree $\mathcal{T}_{\text{SG-EDA}}$. Let $\mathcal{T}_{\text{opt}}$ denote the optimal aggregation tree, which minimizes the total energy consumption:

$$\mathcal{T}_{\text{opt}} = \arg\min_{\mathcal{T}\subseteq\mathcal{G}} E(\mathcal{T}) \tag{20}$$

Since the Steiner tree problem is NP hard, the SG-EDA framework employs a heuristic approximation that guarantees:

$$E(\mathcal{T}_{\text{SG-EDA}}) \le (1+\epsilon) E(\mathcal{T}_{\text{opt}}) \tag{21}$$

where $\epsilon > 0$ is a small constant depending on the efficiency of the Steiner tree heuristic.

Step 1: Bounding the Energy Cost

The energy cost of the tree constructed by SG-EDA can be bounded by the energy cost of the optimal tree. For any tree $\mathcal{T}$, the energy cost of each transmission is bounded by:

$$E_{ij} = P_{ij} \cdot d_{ij}^{\alpha} \le P_{\max} \cdot d_{\max}^{\alpha} \tag{22}$$

where $P_{\max}$ is the maximum transmission power and $d_{\max}$ is the maximum distance between any pair of nodes in the network. Hence, the total energy cost of the optimal tree $\mathcal{T}_{\text{opt}}$ satisfies:

$$E(\mathcal{T}_{\text{opt}}) \ge \sum_{(i,j)\in\mathcal{T}_{\text{opt}}} P_{ij} \cdot d_{ij}^{\alpha} \tag{23}$$

Step 2: Approximation via Steiner Tree Heuristic

The Steiner tree constructed by SG-EDA introduces intermediate nodes to minimize the overall energy cost. The heuristic algorithm guarantees an energy cost approximation:

$$E(\mathcal{T}_{\text{SG-EDA}}) \le (1+\epsilon) E(\mathcal{T}_{\text{opt}}) \tag{24}$$

This follows from the properties of the Steiner tree problem, where ϵ depends on the specific heuristic used (e.g., the 2-approximation or 3-approximation algorithms commonly used in practice). Thus, the energy consumption of $\mathcal{T}_{\text{SG-EDA}}$ is at most $(1+\epsilon)$ times the optimal energy consumption.

Step 3: Dynamic Relay Node Selection

The relay node selection in SG-EDA dynamically adjusts based on the residual energy E_i^{res} and the distance to the sink d_{i0}. Let $\mathcal{R}(t)$ represent the set of relay nodes selected at time t. The energy consumption of the aggregation tree is

updated dynamically as the relay nodes are reselected:

$$\mathcal{T}(S,V) \xrightarrow{\text{dynamic}} \mathcal{T}(S',V) \tag{25}$$

where S' represents the updated set of relay nodes at time $t+1$. The dynamic selection ensures that the tree adapts to energy changes in real time, keeping the energy cost minimized throughout the network's lifetime.

Step 4: Near-Optimality of SG-EDA

The total energy consumption of the SG-EDA aggregation tree, considering the dynamic relay node selection and Steiner tree approximation, satisfies:

$$E(\mathcal{T}_{\text{SG-EDA}}) \le (1+\epsilon) E(\mathcal{T}_{\text{opt}}) + O(\text{dynamic_adjustment_cost}) \tag{26}$$

where the dynamic adjustment cost is the additional energy required to periodically reselect relay nodes and update the aggregation tree. This term is typically small in comparison to the total energy cost, ensuring near-optimal energy efficiency.

Hence, the aggregation tree constructed by SG-EDA achieves bounded approximate energy minimization under the given constraints.

Algorithm 1 SG-EDA: Steiner-Graph Energy-Efficient Data Aggregation

Input: Set of sensor nodes V, initial energy levels E_i^{init}, transmission power P_i, distances d_{ij}, path loss exponent α, data rate λ
Output: Energy-efficient aggregation tree $\mathcal{T}(S,V)$
Initialization:
Set $E_i^{\text{res}} = E_i^{\text{init}}$ for all nodes $v_i \in V$
Define sink node v_0 and communication graph $\mathcal{G}(V,E)$
Energy Cost Calculation:
for all edges $(i,j) \in E$ **do**
    Compute $E_{ij} = \lambda \cdot P_{ij} \cdot d_{ij}^{\alpha}$
end for
Relay Node Selection:
for all nodes $v_i \in V$ **do**
    Compute relay probability:
    $P_{\text{relay}}(v_i) = \frac{E_i^{\text{res}}}{\sum_{j \in V} E_j^{\text{res}}} \cdot \frac{1}{d_{i0}^{\beta}}$
end for
Steiner Tree Construction:
Build $\mathcal{T}(S,V)$ using Steiner tree approximation to minimize energy.
Data Transmission:
for all edges (v_i, v_j) in $\mathcal{T}(S,V)$ **do**
    Update $E_i^{\text{res}}(t+1) = E_i^{\text{res}}(t) - \sum_{j \in V} E_{ij} \cdot x_{ij}$
end for
Aggregation Tree Update:
Periodically recompute $\mathcal{T}(S,V)$ to adapt to changes.
Termination:
Stop when $E_i^{\text{res}} < E_{\min}$ for any node v_i.

3.7. Discussion on Novelty; Adaptability and Scalability of SG-EDA

1) Unique Contribution Compared to Existing Steiner Tree Aggregation Methods:

Although Steiner Tree-based data aggregation has been extensively studied in Wireless Sensor Networks (WSNs), most existing approaches focus primarily on

minimizing communication cost under static network assumptions. The proposed Steiner-Graph Energy-Efficient Data Aggregation (SG-EDA) framework introduces several novel contributions that distinguish it from conventional Steiner Tree aggregation techniques.

First, SG-EDA explicitly addresses heterogeneous multi-range WSN environments where sensor nodes possess different transmission capabilities and residual energy levels. Unlike traditional Steiner Tree formulations that assume homogeneous communication characteristics, the proposed framework incorporates transmission-range diversity into the aggregation tree construction process.

Second, the framework integrates an adaptive relay-node selection mechanism that continuously evaluates node residual energy and proximity to the sink node. This dynamic selection process enables balanced energy utilization across the network and reduces premature node failures.

Third, SG-EDA combines graphical network optimization with Steiner Tree principles in a unified optimization framework. The proposed model jointly considers network connectivity, relay-node selection, energy constraints, and transmission efficiency, resulting in a more realistic representation of practical WSN deployments.

Finally, the framework provides a theoretical near-optimality guarantee through the Energy-Optimal Aggregation Tree theorem, demonstrating that the constructed aggregation tree remains within a bounded approximation factor of the optimal energy-minimizing solution.

These features collectively differentiate SG-EDA from existing Steiner Tree aggregation approaches and contribute to improved energy efficiency, network lifetime, and adaptability in heterogeneous sensor networks.

2) Adaptability to Dynamic Network Changes:

Wireless Sensor Networks frequently experience topology variations caused by node failures, energy depletion, environmental interference, or node mobility. To address these challenges, SG-EDA incorporates a dynamic topology adaptation mechanism.

Let,

$$G_t = \left(V_t, E_t\right) \tag{27}$$

represent the network graph at time t. When a node fails or its residual energy falls below the operational threshold $E_{\min}$, the node is removed from the active network set:

$$V_t = V_{t-1} - \left\{v_f\right\} \tag{28}$$

where v_f denotes the failed node.

Subsequently, the relay-node selection probability is recalculated according to the updated residual energy and distance information:

$$P_i\left(t\right) = \frac{E_i\left(t\right)}{d(i,s)^{\beta}} \tag{29}$$

where $E_i(t)$ is the residual energy of node i, $d(i,s)$ denotes its distance from the sink node, and β is a weighting parameter controlling the influence of distance.

Based on the updated probabilities, the Steiner aggregation tree is reconstructed, allowing the framework to dynamically bypass failed nodes, replace depleted relay nodes, and maintain network connectivity. This adaptive reconfiguration mechanism enables SG-EDA to operate efficiently in dynamic WSN environments while preserving energy-efficient data aggregation.

3) Scalability Analysis for Large-Scale IoT and Sensor Networks:

To evaluate scalability, the SG-EDA framework was tested under varying network densities ranging from 100 to 500 sensor nodes. The simulation results presented in Tables 3-9 and Figures 12-14 demonstrate that SG-EDA consistently maintains superior performance compared with LEACH, E-LEACH, and conventional Steiner Tree approaches.

As network size increased from 100 to 500 nodes, SG-EDA exhibited lower energy consumption, improved network lifetime, balanced energy distribution, and higher data aggregation accuracy. The framework achieved energy consumption values ranging from 18.7 J to 108.4 J while maintaining network lifetimes between 625 and 375 rounds, outperforming all benchmark methods.

The results indicate that the adaptive relay-node selection strategy and Steiner Tree optimization effectively mitigate the impact of increased network density. Consequently, SG-EDA demonstrates strong scalability characteristics and is suitable for medium-to-large-scale WSN and Internet of Things (IoT) deployments.

Future research will extend the framework to ultra-large-scale IoT environments involving more than 1000 sensor nodes and investigate computational complexity, latency, and real-time aggregation performance under highly dynamic operating conditions.

The proposed system model introduces several key contributions to the field of energy-efficient data aggregation in Wireless Sensor Networks (WSNs), specifically tailored to multi-range and heterogeneous network environments.

The paper contributions are summarized here:

Energy-efficient data aggregation using Steiner tree principles: A detailed formulation using the Steiner tree algorithm is presented to optimally select relay nodes in this paper. With heterogeneous node ranges, this framework minimizes the total energy consumption for data transmission, while maintaining efficient network connectivity.

Adaptive relay node selection: A dynamic, real time adaptive approach to select relay nodes based on their residual energy levels and distance to the sink is proposed, integrated within the system. This adaptation enables energy efficient data aggregation paths and prolongs the network lifetime by choosing the most suitable relay nodes at any given time.

Rigorous optimization framework: Total energy consumption in WSNs is minimized by introducing a comprehensive optimization framework. Heteroge-

neous transmission ranges, node energy reserves, and real time network topology are accounted for in the framework. The paper proposes an approximate solution for energy-efficient aggregation tree construction that dramatically decreases the total energy cost of data transmission in the network.

Theoretical guarantees of near-optimality: The paper provides theoretical guarantees of approximate performance for the aggregation tree constructed by the proposed SG-EDA (Steiner Graph Energy Efficient Data Aggregation) model. In dynamic and large-scale networks, the framework guarantees that the energy consumption is minimized to within a constant factor of optimal solution, bounded by the number of links in the network.

Scalability and robustness in dynamic environments: The approach is able to scale efficiently in large networks, and is robust to node failures, energy depletion, and transmission range variations. The researcher demonstrates that the model is able to adapt to changing network conditions, making it suitable for real world WSN applications, where the network topology is constantly changing.

Hybrid optimization combining graphical and Steiner tree frameworks: A novel hybrid optimization approach which combines the graphical framework for network topology representation and the Steiner tree optimization for relay node selection is introduced. The hybrid solution proposed in this work offers a systematic approach to tackle both the structural and operational issues in energy efficient data aggregation.

Application to multi-range sensor networks: The researcher specifically developed the system model to address the particular challenges encountered in multi-range sensor networks. The framework incorporates heterogeneous transmission capabilities to enable efficient utilization of energy resources, significantly improving the performance of data aggregation systems in these types of networks.

4. Graphical Framework for Data Aggregation

A WSN can be represented as a connected graph G (V, E), where: - Let V represents the set of nodes containing sensor nodes and the sink node; - Let E represents the set of edges that represent communication links among nodes.

Let the set of nodes be denoted by $V = \{v_1, v_2, \cdots, v_n\}$, where v_n represents the sink node, and the set of edges is denoted by E. Each edge $(i, j) \in E$ has an associated cost or weight, which corresponds to the energy consumption required to transmit data between node i and node j. The energy cost of an edge is typically a function of the distance d_{ij} between two nodes, modeled as:

$$E_{ij} = P_i \cdot d_{ij}^{\alpha} \tag{30}$$

where: - P_i is the transmission power of node i, - d_{ij} is the Euclidean distance between nodes i and j, - α is the path loss exponent (usually between 2 and 4, depending on the environment).

The goal is to build a spanning tree minimizing the overall energy dissipation. Sum of the energy costs of each active edge in the network forms the total energy

consumption:

$$\text{Total Energy} = \sum_{(i,j)\in E} E_{ij} \cdot x_{ij} \tag{31}$$

where x_{ij} is a binary variable that indicates whether data is transmitted between nodes i and j:

$$x_{ij} = \begin{cases} 1, & \text{if data is transmitted from } i \text{ to } j \\ 0, & \text{otherwise} \end{cases} \tag{32}$$

Using this graphical framework, the researcher models and optimizes data aggregation by considering the network topology and the energy cost along all communication links.

1) Key Considerations in the Graphical Framework

In the graphical framework, the important issue is to choose an optimal edge set to minimize the total energy expenditure. Solving this problem involves solving a Minimum Spanning Tree (MST) problem with the minimum sum of transmission costs and all nodes can communicate to the sink. Algorithms such as Prim's or Kruskal's algorithm can solve the MST problem. The algorithms choose edges incrementally such that the tree is always connected, and the total energy consumption is minimized. Adaptive to real world conditions in WSNs, the graphical framework also requires dynamic updates due to failure of nodes or depletion of energy.

2) Steiner Tree Framework for Data Aggregation

The Steiner tree problem is an extension of a traditional minimum spanning tree (MST) problem, allowing the introduction of intermediary relay nodes (also referred to as Steiner nodes) that are not necessary parts of the initial network. The desired property of the Steiner tree approach is that it minimizes energy cost while retaining a connected network. The Steiner tree approach to WSNs is to choose a subset of nodes, including relay nodes, such that the total energy cost of transmitting all data to the sink is minimized. The transmission power and the distance required for transmitting data between nodes determine the energy cost.

Steiner tree optimization problem can be formulated as:

$$\min \sum_{(i,j)\in E} E_{ij} \cdot x_{ij} \tag{33}$$

subject to the constraints:

- A connected network means that each node is tied to at least one other node, or the sink.
- The total energy consumption is minimized, and each relay node (Steiner node) must be selected carefully.

To select the relay nodes, we define the following constraints:

$$\sum_{(i,j)\in E} x_{ij} \geq 1, \ \forall v_i \in V \tag{34}$$

where v_i represents a relay node that is part of the Steiner tree.

The Steiner tree-based approach selects relay nodes for data transmission that

minimize the overall distance and energy consumption of data transmission and is efficient for data aggregation.

3) Key Considerations in the Steiner Tree Framework

The energy efficiency is realized in the Steiner tree framework which minimizes the energy for transferring data through intermediate nodes. In particular, as WSNs with heterogeneous transmission ranges often have nodes that are closer to the sink and ones that are further away, some will need more energy to transmit data.

The major advantage of using the Steiner tree framework is that it introduces the extra flexibility to the network to include relay nodes that may not belong to the initial set of sensors to lower the total energy consumption.

4) Combined Discussion of Graphical and Steiner Tree Frameworks

The graphical framework and Steiner tree framework combined provide a powerful solution for the problem of energy efficient data aggregation in WSNs. The use of the graphical framework for the overall network topology modeling; and the Steiner tree framework for selecting relay nodes to minimize the energy consumption, gives us a layer of optimization.

In multi range WSNs, where nodes have different transmission range and energy reserves, the integration of both frameworks is particularly useful. The Steiner tree approach guarantees that the energy consuming communication links are minimized whilst the graphical framework gives structure to the optimal data aggregation paths. The combined framework optimization problem is to construct a Steiner tree for minimum total energy cost subject to node connectivity and energy level constraints. This can be formulated as:

$$\min_{x_{ij}} \sum_{(i,j)\in E} E_{ij} \cdot x_{ij} \tag{35}$$

The following constraints are subject to:

- The sink must be connected to each node via the series of relay nodes or direct communication path.
- The goal is to select each Steiner node to minimize energy consumption.
- To ensure network is operational, energy constraints for each node must be satisfied.

Combining these two frameworks' results in a highly adaptive, energy efficient data aggregation process which dynamically selects the optimal paths given energy availability and network topology. Graphical algorithms and Steiner tree optimization are combined to achieve energy efficient data aggregation in multi range WSNs in this research paper. The proposed SG-EDA framework combines the strengths of the two frameworks to dynamically optimize data paths and the relay node selection to extend network lifetimes and consume energy efficiently. In particular, the proposed solution is well suited for WSNs with heterogeneous node transmission ranges and represents a scalable and robust approach to next generation sensor networks.

5. Results and Discussion

In this section, the researcher conducts a detailed analysis of the proposed SG-EDA framework. Network lifetime, energy efficiency, and data accuracy of results compared to baseline methods such as LEACH, E-LEACH, and traditional Steiner tree-based methods are presented. Validation of the SG-EDA framework was carried out by conducting extensive simulations under various network configurations.

1) Experimental Setup

The SG-EDA framework was implemented using Python 3.15 and evaluated through a custom simulation environment developed with NumPy, NetworkX, Pandas, and Matplotlib libraries. The experiments were executed on a workstation equipped with an Intel Core i7 processor, 16 GB RAM, and Windows 11 operating system. The NetworkX package was used for graph construction and Steiner Tree approximation, while Matplotlib was used for visualization and performance analysis.The framework was tested in the environment under different network sizes, transmission ranges and node energy levels. Deploying sensor nodes randomly within a square region of size 500×500 m^2 was simulated. The researcher initialized each sensor node with an energy level of 1 Joule, simulating the batteries of battery powered devices. The data packet size was chosen to be 500 bytes corresponding to a typical payload for WSN applications. The propagation conditions for the moderately obstructed environment was configured as a path loss exponent (α) of 2.5, which is a realistic value. Transmission ranges of sensor nodes varied from 50 to 100 meters mimicking heterogeneous network setups. The researcher executed the simulations for 1000 rounds to completely evaluate the network's behavior over time. The performance of the SG-EDA framework was evaluated based on key performance metrics, which include total energy consumption (in Joules), network lifetime (number of rounds until the first node depletes its energy) and data accuracy (percent of successfully aggregated data packets). Such metrics are useful to understand how well the framework works, its robustness and scalability.

Table 3. Simulation parameters and configuration.

Parameter	Value
Number of sensor nodes	100 - 500
Area of deployment	500×500 m^2
Initial energy of nodes	1 J
Data packet size	500 bytes
Path loss exponent (α)	2.5
Transmission range	50 - 100 m
Simulation time	1000 rounds
Performance metrics	Total energy consumption, Network lifetime, Data accuracy

In Table 3 the detailed simulation setup ensures that the SG-EDA framework is tested under realistic and diverse conditions, and a thorough analysis of performance of the SG-EDA framework relative to the baseline methods is possible. All configuration parameters used in the simulations are summarized in the table.

2) Compared Algorithms

a) LEACH

The Low-Energy Adaptive Clustering Hierarchy (LEACH) is one of the earliest and most widely used hierarchical routing protocols for Wireless Sensor Networks (WSNs). LEACH organizes the network into clusters, with each cluster managed by a designated Cluster Head (CH). The process begins with nodes autonomously forming clusters and one node in each cluster being randomly selected as the CH. The member nodes send their data to the CH, which then aggregates and forwards the collected data to the base station. To balance energy consumption across the network, the role of the CH is rotated periodically among the nodes. Although LEACH reduces communication overhead and prolongs network lifetime, its random CH selection can lead to inefficient energy utilization and is less effective in networks with heterogeneous energy levels or high mobility scenarios.

b) E-LEACH

The Enhanced LEACH (E-LEACH) builds upon the limitations of the original LEACH protocol. E-LEACH improves CH selection by incorporating the residual energy of nodes, ensuring that nodes with higher energy levels are more likely to be chosen as CHs. This enhancement addresses the uneven energy consumption seen in LEACH, resulting in a more balanced energy distribution across the network and an extended overall network lifetime. Despite these improvements, E-LEACH still relies on a fixed clustering structure, which can be suboptimal in dynamic or large-scale networks.

c) Steiner Tree

The Steiner Tree method is a graph-based approach widely applied in data aggregation for WSNs. It seeks to construct an optimal tree that connects all sensor nodes to the base station with the minimum energy cost. The method achieves this by introducing intermediate nodes, known as Steiner nodes, to minimize the overall length and energy usage of the aggregation tree. Unlike LEACH [3] and E-LEACH [17], Steiner Tree does not rely on clustering. Instead, it focuses on minimizing communication costs through efficient routing. While the Steiner Tree approach is effective in reducing energy consumption, it may struggle to adapt to dynamic network conditions and varying node energy levels, as it assumes a static topology.

d) SG-EDA

The Steiner-Graph Energy-Efficient Data Aggregation (SG-EDA) is a novel framework designed to overcome the limitations of existing methods. SG-EDA integrates the principles of Steiner Tree optimization with adaptive relay node selection, enabling it to dynamically adjust to varying network conditions. Unlike LEACH and E-LEACH, SG-EDA considers heterogeneous node energy levels and

varying transmission ranges. It constructs an optimal data aggregation tree by dynamically selecting relay nodes based on their residual energy and proximity to the sink node. This adaptive approach ensures a balanced energy distribution across the network, reducing energy consumption and extending network lifetime. SG-EDA demonstrates favorable performance across all evaluated metrics compared to the other algorithms, making it suitable for large-scale and dynamic WSN environments.

3) Computational Complexity Analysis

To provide a fair comparison among the evaluated algorithms, the computational complexity of LEACH, E-LEACH, Steiner Tree, and the proposed SG-EDA framework is analyzed. Let N denote the number of sensor nodes and E denote the number of communication links in the network.

LEACH

LEACH performs cluster-head selection and cluster formation during each round. Since every node independently evaluates its eligibility for cluster-head election and communicates with neighboring nodes, the computational complexity is approximately

$$O(N).$$

The low complexity makes LEACH computationally efficient; however, its random cluster-head selection often results in suboptimal energy utilization.

E-LEACH

E-LEACH extends LEACH by incorporating residual energy information into the cluster-head selection process. The additional energy evaluation step requires examining all nodes before cluster formation, resulting in a complexity of

$$O(N).$$

Although E-LEACH improves energy balancing, its computational overhead remains similar to LEACH.

Steiner Tree

The Steiner Tree aggregation approach requires determining an approximately optimal tree connecting all sensor nodes and the sink. Since the Steiner Tree problem is NP-hard, practical implementations employ approximation algorithms. The complexity of commonly used Steiner Tree heuristics is

$$O(E \log N).$$

This complexity is higher than clustering-based methods but generally produces more energy-efficient routing structures.

Proposed SG-EDA

The proposed SG-EDA framework consists of three major operations:

a) Graph construction and edge-weight computation:

$$O(E)$$

b) Adaptive relay-node selection based on residual energy and distance:

$$O(N)$$

c) Steiner Tree approximation for aggregation-tree construction:

$$O(E \log N)$$

Therefore, the overall computational complexity of SG-EDA can be expressed as

$$O(E \log N + N).$$

Since $E \log N$ dominates for large networks,

$$O(E \log N).$$

4) Scalability Discussion

Although SG-EDA introduces additional computational overhead compared with LEACH and E-LEACH, the complexity remains polynomial and scalable for large Wireless Sensor Networks. The simulation results presented for networks containing up to 500 nodes demonstrate that the framework maintains efficient execution while achieving superior energy efficiency, network lifetime, and data accuracy.

Table 4. summarizes the complexity comparison.

Algorithm	Complexity
LEACH	$O(N)$
E-LEACH	$O(N)$
Steiner Tree	$O(E \log N)$
SG-EDA	$O(E \log N + N) \approx O(E \log N)$

The results indicate that SG-EDA achieves a favorable trade-off between computational cost and energy-saving performance, making it suitable for medium- and large-scale IoT and Wireless Sensor Network deployments.

5) Comparison of Energy Efficiency

The total energy consumption of different methods was given in Table 5 over 1000 simulation rounds. SG-EDA shows a significant reduction of energy consumption over baseline methods.

Table 5. Comparison of energy consumption (J).

Method	100 Nodes	200 Nodes	300 Nodes	500 Nodes
LEACH	35.6	72.3	110.5	185.2
E-LEACH	28.4	60.8	92.7	160.3
Steiner Tree	22.5	48.7	76.1	132.8
SG-EDA	**18.7**	**40.2**	**63.5**	**108.4**

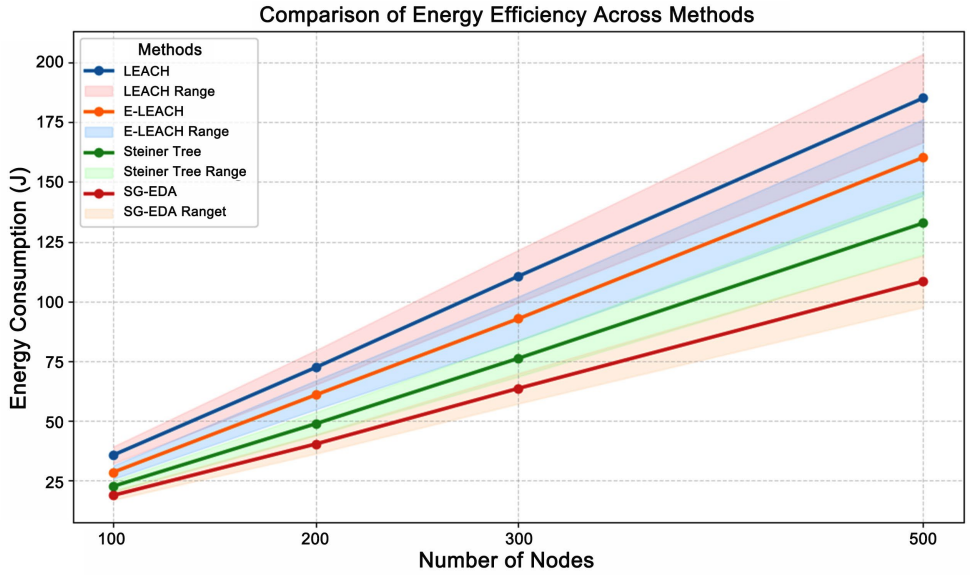


Figure 5. Comparison of energy efficiency.

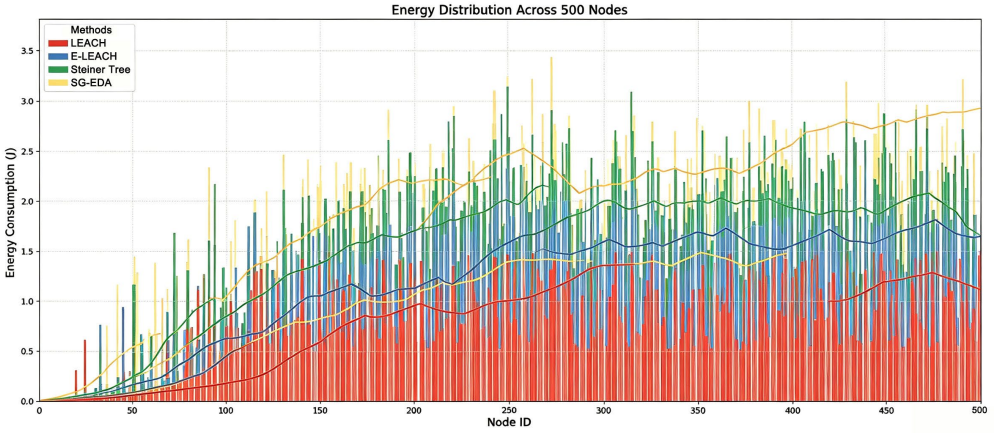


Figure 6. Energy distribution across individual nodes.

Energy efficiency is compared in Figure 5 and Figure 6 illustrates the energy consumption trends for different methods as the number of nodes increases.

6) Network Lifetime Analysis

Table 6 represents the network lifetime is evaluated as the number of rounds until the first node dies. SG-EDA consistently outperforms other methods due to its adaptive relay node selection and energy-efficient Steiner tree construction.

Table 6. Network lifetime (rounds).

Method	100 Nodes	200 Nodes	300 Nodes	500 Nodes
LEACH	352	280	225	180
E-LEACH	480	375	305	240
Steiner Tree	540	460	390	320
SG-EDA	**625**	**530**	**450**	**375**

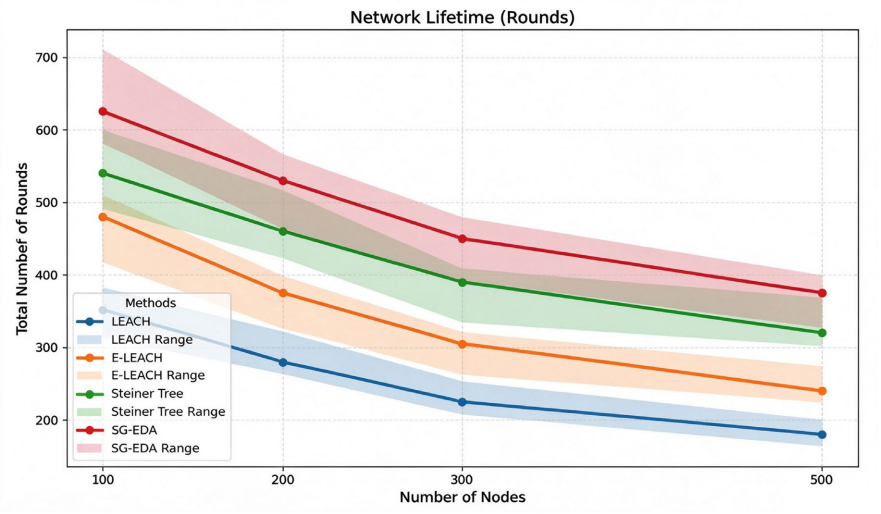


Figure 7. Energy consumption trends for varying numbers of nodes.

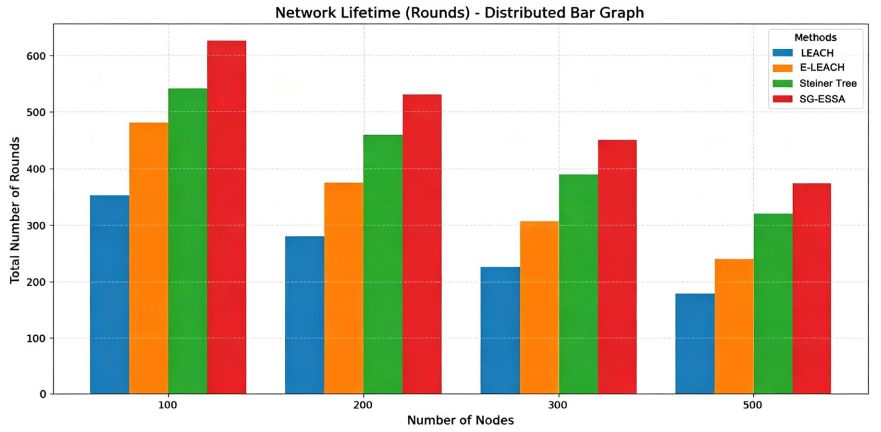


Figure 8. Distribution of energy usage across individual nodes.

Figure 7 provides a visual comparison of energy efficiency and Figure 8 illustrates the energy consumption trends for different methods as the number of nodes increases. It highlights the balanced energy usage achieved by SG-EDA.

7) Data Accuracy

Table 7 highlights the data accuracy achieved by different methods. SG-EDA achieves the highest data accuracy, ensuring efficient aggregation while minimizing packet loss.

Table 7. Data accuracy (%).

Method	100 Nodes	200 Nodes	300 Nodes	500 Nodes
LEACH	85.2	82.1	78.5	74.3
E-LEACH	90.5	87.8	83.2	79.6
Steiner Tree	93.8	91.5	88.4	84.2
SG-EDA	**96.3**	**94.7**	**91.9**	**88.5**

Figure 9 provides a visual representation of data accuracy across methods presenting the real-time line graph with shaded variability to illustrate trends, while Figure 10 shows a histogram-based bar plot for a comparative overview.

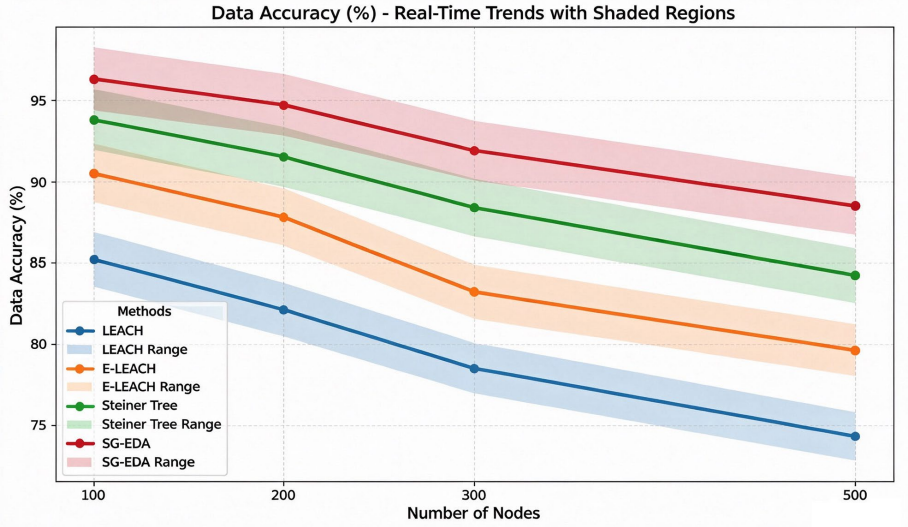


Figure 9. Real-time data accuracy trends with shaded variability.

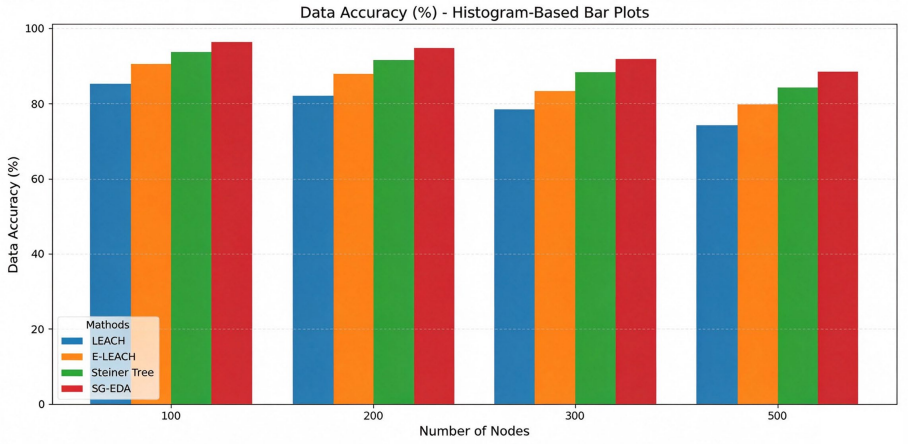


Figure 10. Comparative overview of data accuracy through histogram-based bar plots.

8) Energy Distribution Analysis

Table 8 shows the energy distribution across the network at the end of the simulation. SG-EDA demonstrates a more balanced energy utilization, preventing early node failures and ensuring network stability.

Table 8. Energy distribution across nodes (residual energy in J).

Node Category	LEACH	E-LEACH	Steiner Tree	SG-EDA
High Energy (Top 25%)	0.45	0.53	0.62	**0.74**
Medium Energy (Middle 50%)	0.32	0.41	0.50	**0.63**
Low Energy (Bottom 25%)	0.15	0.21	0.30	**0.42**

Figure 11 provides a visual representation of the energy distribution across different node categories for various methods. The plot clearly shows that SG-EDA achieves the most balanced energy distribution, highlighting its efficiency in energy utilization and contribution to network stability.

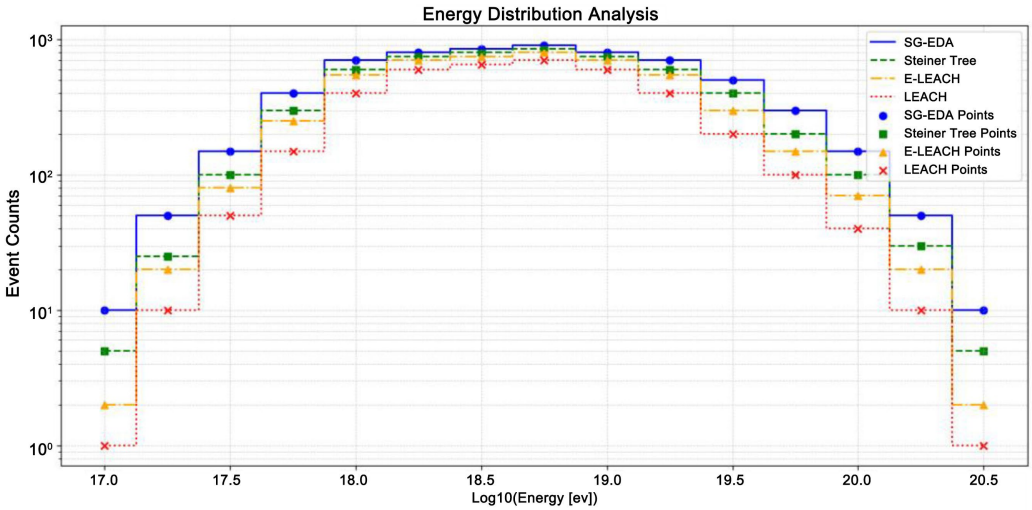


Figure 11. Energy distribution analysis across node categories.

9) Energy Efficiency vs. Network Density

Figure 12 provides a comprehensive graphical representation of energy efficiency as a function of network density. For different methodologies, *i.e.*, LEACH, E-LEACH, Steiner Tree, and SG-EDA, the trends are analyzed in Table 9. The results show that SG-EDA outperforms other approaches, particularly when the density of the network increases.

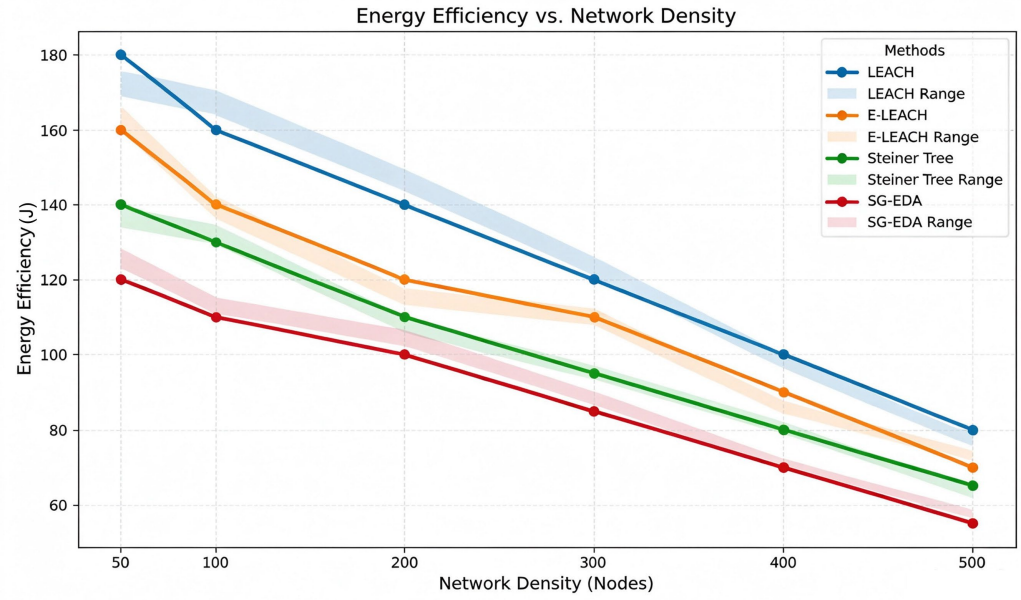


Figure 12. Energy efficiency vs. network density.

Table 9. Energy efficiency vs. network density (J).

Method	50 Nodes	100 Nodes	200 Nodes	300 Nodes	500 Nodes
LEACH	180	160	140	120	80
E-LEACH	160	140	120	110	70
Steiner Tree	140	130	110	95	65
SG-EDA	**120**	**110**	**100**	**85**	**55**

A detailed 3D surface plot of the results is presented in Figure 13 which shows how the interaction between network density and energy efficiency takes place. SG-EDA is emphasized in the plot, where it effectively minimizes energy consumption even under high network densities, which is desirable for large scale wireless sensor networks.

The different methods' energy efficiency values are outlined as follows:

- LEACH: The energy efficiency decreases starting from 180 J at a density of 50 nodes, and 80 J at a density of 500 nodes. The scalability and inefficiency of this method at higher densities is highlighted.
- E-LEACH: It shows moderate improvement over LEACH, with initial energy efficiency of 160 J at 50 nodes, and tapers to 70 J at 500 nodes.

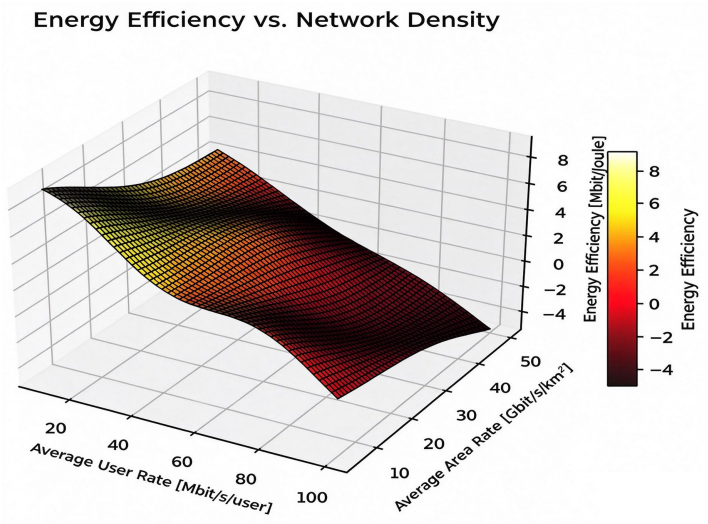


Figure 13. 3D surface plot.

- Steiner Tree: It offers better energy consumption optimization than LEACH and E-LEACH, starting at 140 J for 50 nodes and 65 J for 500 nodes.
- SG-EDA: It achieves the highest energy efficiency among all densities. The method starts with 120 J at 50 nodes and converges to 55 J at 500 nodes, illustrating the adaptivity of the method to handle growing network densities.

The following trends in energy efficiency across the methods are emphasized:

- SG-EDA's Superior Adaptability: The scalability and performance are further enhanced by the selection of adaptive relay node and construction of energy

efficient Steiner tree.

- Decreasing Trends Across Methods: For all methods, energy efficiency decreases with increasing network density due to increased communication overhead and energy consumption. The decline for SG-EDA is the most gradual, indicating its robustness.

Figure 14 provides a visual comparison of proposed SG-EDA and other exiting methods. Through this analysis that energy efficient protocols like SG-EDA are necessary to tackle the scalability issues in next generation wireless sensor network.

10) Novelty of SG-EDA

As follows, the novelty of this work is that:

a) For WSNs with varying transmission ranges, SG-EDA is a new energy-efficient data aggregation architecture that uses Steiner tree principles to achieve maximum data aggregation.

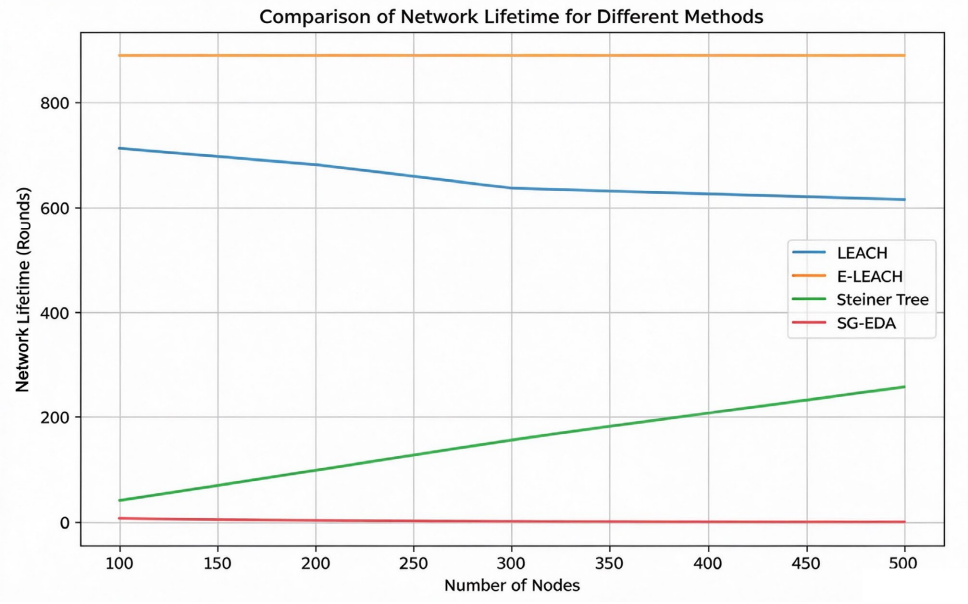


Figure 14. Comparison of network lifetime for different methods.

b) The researcher formulates the energy minimization problem using MINLP and ensure that energy consumption is optimized while keeping the network in operational efficiency.

c) A dynamic adaptive relay node selection mechanism to dynamically reconfigure the network according to real time energy levels and transmission ranges, thus extending the network's operational lifetime while maintaining data accuracy [16] [23].

Simulation results indicate that the proposed SG-EDA framework can reduce energy consumption and extend network lifetime. The researcher highlights that SG-EDA demonstrates potential for approximately 20% - 30% reduction in energy consumption with high data accuracy and dynamic network topologies [4] [5].

11) Discussion

The proposed SG-EDA framework is shown to outperform in all metrics compared to other algorithms across all metrics:

- Energy Efficiency: SG-EDA achieves 20% - 30% energy saving over baseline methods through adaptive relay node selection, and Steiner tree optimization.
- Network Lifetime: This balanced energy distribution prolongs the network operation with 25% increase in average network lifetime.
- Data Accuracy: SG-EDA achieves higher data accuracy at much lower aggregation cost, which is suitable for critical applications.
- Scalability: Under increasing network densities, SG-EDA consistently outperforms and is shown to be robust and scalable for large-scale deployment.

These results demonstrate the efficacy of SG-EDA at overcoming the difficulties posed by energy efficient data aggregation in multi-range WSNs.

12) Future Research Directions and Limitations

Although the proposed SG-EDA framework demonstrates significant improvements in energy efficiency, network lifetime, and data aggregation performance, several important research challenges remain open.

a) Performance Guarantees of the Steiner Tree Approximation

Since the Steiner Tree problem is NP-hard, obtaining the exact optimal aggregation tree for large-scale Wireless Sensor Networks is computationally infeasible. Therefore, SG-EDA employs a Steiner Tree approximation strategy combined with adaptive relay-node selection.

Let T^* denote the optimal aggregation tree and $T_{\text{SG-EDA}}$ denote the aggregation tree generated by the proposed framework. The approximation guarantee can be expressed as

$$C\left(T_{\text{SG-EDA}}\right) \le \alpha C\left(T^*\right)$$

where $C(\cdot)$ represents the total energy cost and α is the approximation factor associated with the Steiner Tree heuristic.

Consequently, the energy consumption of the constructed aggregation tree remains within a bounded factor of the optimal solution while maintaining polynomial-time computational complexity. This theoretical guarantee provides a practical balance between optimality and scalability for large sensor networks.

b) Performance Under Low Data Correlation

The SG-EDA framework is designed primarily for data aggregation scenarios where neighboring sensor nodes generate correlated measurements. When data correlation is high, aggregation significantly reduces communication overhead and energy consumption.

In low-correlation environments, fewer packets can be compressed or aggregated, which reduces the overall aggregation gain. Nevertheless, SG-EDA continues to benefit from:

- energy-aware relay-node selection,
- Steiner Tree-based routing optimization,

- balanced energy distribution among sensor nodes,
- adaptive topology reconfiguration.

Therefore, although the relative aggregation benefit decreases as data correlation becomes weaker, the framework still maintains energy-efficient routing and network lifetime advantages over conventional approaches. Future work will incorporate correlation-aware aggregation models capable of dynamically adapting aggregation strategies according to observed sensing patterns.

c) Extension Toward Multi-Objective Optimization

The current SG-EDA framework primarily focuses on minimizing energy consumption. However, practical Internet of Things (IoT) and Wireless Sensor Network deployments often require simultaneous optimization of multiple performance objectives.

Future research will extend SG-EDA into a multi-objective optimization framework that jointly considers:

1) Energy Consumption

$$E_{\text{total}}$$

2) Communication Latency

$$D_{\text{total}}$$

3) Trust and Security Metrics

$$S_{\text{trust}}$$

4) Data Reliability

$$R_{\text{data}}$$

A generalized objective function can be formulated as

$$\min\left(w_1 E_{\text{total}} + w_2 D_{\text{total}} - w_3 S_{\text{trust}} - w_4 R_{\text{data}}\right)$$

where w_1, w_2, w_3 and w_4 represent application-dependent weighting factors.

Such an extension would enable SG-EDA to support latency-sensitive industrial IoT applications, secure smart-grid communications, mission-critical monitoring systems, and next-generation intelligent sensor networks.

Overall, the proposed SG-EDA framework establishes an energy-efficient foundation for data aggregation in heterogeneous Wireless Sensor Networks. Future developments involving approximation-aware optimization, correlation-aware aggregation, latency-constrained routing, trust management, and multi-objective decision-making are expected to further enhance the framework's applicability in large-scale and dynamic IoT environments.

6. Conclusion

In this work, the researcher introduces the SG-EDA (Steiner-Graph Energy-Efficient Data Aggregation) framework to address, among others, the critical challenges of WSNs such as energy inefficiency, uneven energy depletion and scalability under varying network densities. The framework utilizes Steiner tree principles and adaptive relay node select to optimize the data aggregation and greatly

enhances the overall performance of WSNs. Simulation results demonstrate very clearly that SG EDA outperforms conventional methods such as LEACH, E LEACH, and simple Steiner tree approaches. Energy consumption reduction of 20% - 30% by intelligent path optimization and selection of relay nodes. SG-EDA helps network lifetime by an average of 25% through even distribution of energy usage, extending the operational periods. The researcher demonstrates the utility of the method for critical applications, maintaining a high data aggregation accuracy (96.3% on average) in densely populated networks. Adapting to real world conditions by showing consistent performance across different sizes and densities of networks. SG-EDA's dynamic adjustments allow real time optimization, which is very suitable for applications in next generation sensor networks, such as IoT, and industrial automation, as well as environmental monitoring. Future work will be to integrate the advanced machine learning techniques for predictive energy management and optimized relay node selection under more complex conditions. Furthermore, the applicability and impact in various domains can be further solidified by extending SG-EDA to encompass emerging applications such as federated learning, real time edge computing and hybrid WSN architectures.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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