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Fractal Based Adaptive Routing Framework for Energy Efficient Environmental Monitoring in Smart Ecological Sensor Networks

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Abstract

The rapid expansion of Internet of Things (IoT) networks in smart environments such as smart cities, agriculture, and industrial monitoring has introduced significant challenges in energy-efficient communication. Existing routing protocols suffer from major limitations, including inability to handle heterogeneous node distribution, poor adaptation to topology irregularities, traffic congestion in dense regions, and unbalanced energy consumption, ultimately reducing network lifetime and stability. To overcome these issues, this study proposes a Fractal-Based Adaptive Routing (FBAR) framework that integrates fractal geometry principles into IoT routing design. The objective is to model multiscale network heterogeneity using Local Fractal Dimension and utilize it for adaptive routing decisions. The proposed method is implemented using a Python-based

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simulation environment, enabling scalable evaluation of IoT network behavior. The FBAR framework combines fractal topology analysis with energy-aware.
cluster-head selection and relay node optimization. Simulation results show that the proposed method achieves a fractal dimension of 1.47, indicating strong self-similar structure in the network. Traffic intensity is effectively controlled with a maximum value of 1.42 in dense regions, while energy variance among cluster heads is reduced to 0.019. Additionally, the proposed approach extends network lifetime to approximately 3871 rounds, significantly outperforming LEACH, HEED, and DEEC protocols. These improvements correspond to an estimated performance gain of more than 55–60% in lifetime efficiency. The results confirm that fractal-aware modeling provides a powerful mathematical framework for optimizing routing performance in heterogeneous IoT networks, making FBAR a scalable and energy-efficient solution for next-generation smart systems.

Keywords:
Energy efficiency; energy-aware routing; fractal-based routing; low-power iot networks; network lifetime; sustainable energy management; wireless sensor networks

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Introduction

This research supports Sustainable Development Goal 7 (Affordable and Clean Energy) by developing an energy-aware routing framework that reduces communication energy consumption, balances energy utilization among IoT nodes, and extends the operational lifetime of smart wireless networks. The Internet of Things (IoT) has revolutionized the sensing and communication infrastructures of the modern world by creating large-scale interconnections in the heterogeneous smart device world (Khan et al., 2025; Mowla et al., 2023). The IoT-based systems are used in many smart city monitoring, industrial automation, environmental sensing, health care, intelligent transportation system and precision agriculture applications (Singh et al., 2022; Zaman et al., 2024; Vrba, 2026). These applications are inherently time-sensitive and require constant sensing and dependable multi-hop wireless communications between energy-limited sensor nodes (Liu et al., 2025). Energy efficient routing is one of the most important issues that exists in the design of IoT networks, due to the limited battery power of most IoT devices and the fact that they are generally deployed in inaccessible environments (Kasturi et al., 2022; Dogra et al., 2022). If the routing-path is not optimized, the energy of nodes can be consumed quickly, packet loss can increase significantly and lifetime of the network can be shortened (Hussein et al., 2022).

Most of the traditional routing protocols like LEACH, PEGASIS, SEP, and RPL are based on probabilistic cluster formation or shortest path communication (Kumar et al., 2025; Wang et al., 2024). Though these solutions would be better than direct transmission methods in terms of communication efficiency, they usually assume that node distribution is uniform or random across the space. In actual deployments, however, the distribution of the IoT nodes is not always regular. Most sensing environments in the real-world feature dense clusters of sensors around assets to be monitored, sparse transition areas, and irregular placement due to environmental or infrastructural constraints (Damaševičius & Maskeliūnas, 2025; Acquaah & Kaushik, 2024). The resulting topologies are heterogenous, causing uneven traffic load and energy imbalance among relay nodes, which in turn may affect the routing performance (Elmonser et al., 2024). Fractal geometry offers a good mathematical model for irregular and self-similar geographical patterns (Arjunan, 2024; Nguyen et al., 2022). Generally, fractal dimension analysis is able to describe topology changes over a range of scales and thus represents a more robust measure of the complex distribution of nodes (El-Yaagoubi et al., 2024). This ability is the motivation behind the proposed Fractal Based Adaptive Routing (FBAR) framework which combines online fractal-dimension estimation with routing and cluster-head selection decision. The framework makes use of local fractal characteristics of nodes to detect irregularities in topology and dynamically adjust the routing behavior based on the distribution characteristics of nodes.

Most current energy-aware routing protocols for IoT networks make routing decisions based on local metrics such as residual energy, distance, degree and link quality (Kamruzzaman & Alruwaili, 2022). The methods are efficient for the network configuration with a homogeneous node distribution but do not consider the multi-scale structural heterogeneity of typical smart IoT systems such as smart cities, industrial monitoring and industrial sensing, environment monitoring, and precision agriculture. In such environments, sensor nodes are deployed arbitrarily which produces clusters of different sizes-dense areas and sparse areas that result in self-similar connections at various spatial scales (Cao et al., 2022). The conventional metrics cannot characterize this complex topology structure, which causes the same relay and cluster-head nodes to be repeatedly selected, thus the concentration of traffic, uneven energy distribution, the communication congestion, and failure of networks will occur. What's more, current routing schemes do not provide a quantitative method for describing network connectivity at multi-scales. Thus, the most important challenge is to propose a topology-aware routing strategy with the introduction of fractal topology analysis into routing decisions. Local fractal dimensions will be exploited to guide routing in heterogeneous networks for energy balancing and better communication and network life-time.

A number of studies have addressed the optimisation of routing and energy consumed by communication using heuristic and metaheuristic optimisation techniques in optimisation-based routing frameworks. Kamruzzaman & Alruwaili, (2022) proposed a Wireless Body Area Network (WBAN) based Energy Efficient Sustainable Network (EES-NOT) in context of Smart Grid and Renewable Energy Systems. The framework included Adaptive Scheduling Protocol for Energy Efficiency (ASPEE) and Secured Routing Protocol for Energy Efficiency (SRPEE) to enhance the throughput, network lifetime, overhead of transmission, latency and transmission rate. The proposed approach was 96.3% efficient in communication as compared with the existing methods. Cao et al., (2022) studied a Simultaneous Wireless Information and Power Transfer (SWIPT) enabled IoT network in which Hybrid Access Points (HAPs) cooperate in terms of energy. They jointly optimised the power allocation, time switching and energy cooperation using iterative optimisation and matching algorithms. The experimental results showed the improvement in energy efficiency and a decrease in the system energy consumption.

Sathish Kumar et al., (2022) presented a novel probabilistic connectivity optimisation framework for Wireless Sensor Networks (WSN) with IoT devices, which investigated the correlation between communication radius and the sensing coverage by employing mathematical probability theory. Compared to LEACH, ZTR and DSR protocols their approach increased their network connectivity and they consumed almost 40% less energy. The framework was, however, based mainly on communication radius modelling, and was not adaptive with regards to topology-aware routing in heterogeneous deployments. Han et al., (2024) introduced an enhanced Ant Colony Optimisation routing approach for Wireless Sensor Networks in IoT. They managed to optimize the concentration of pheromone and the probability of transferring it to find the energy-efficient communication paths, thereby enhancing the performance in terms of throughput, delay and dead-node reduction. The routing process, however, predominantly was based on the principle of shortest path optimization and lacked multi-scale topology awareness and adaptive spatial heterogeneity analysis.

Secure and energy balanced routing has also received a good deal of study in heterogeneous IoT communication environments. Nagaraju et al., (2022) presented a secure routing protocol for heterogeneous Wireless Sensor Networks (WSN) to optimize energy consumption by implementing Multipath Link Routing Protocol (MLRP), Hybrid-TEEN clustering and Ubiquitous Data Storage Protocol (U-DSP). The framework enhanced throughput, network lifetime, energy balancing, and data storage efficiency. It was not considered adaptive topology analysis nor irregular node-density characterization for routing decisions, though the study included secure communications and heterogeneous node management.

Albogamy et al., (2022) investigated real-time energy optimisation in sustainable smart homes using a Lyapunov Optimisation Technique (LOT). The proposed framework covered congestion management, battery energy storage management, integration of renewables, electric vehicle charging, HVAC (heating, ventilation and air conditioning) control and optimization of user comfort in the case of uncertain system dynamics. The algorithm ensured the stability of the virtual queues for energy storage scheduling, electric vehicle charging and indoor temperature control while reducing long-term energy cost and thermal discomfort. The results of the simulation showed a reduction of the average energy cost of about 20.15% without compromising user comfort requirements. The study mainly concentrated on energy scheduling mechanism and the framework didn't study wireless IoT sensor network communication-level routing optimisation.

Energy optimisation frameworks have also benefited from machine learning in intelligent resource management of IoT systems. Bagwari et al., (2023) proposed a Machine Learning based Enhanced Energy Optimisation Model (EEOM) for Industrial Wireless Sensor Networks. The proposed framework was based on knowledge-based learning to optimize the transmission energy, the idle-mode energy, and the sleep-mode energy consumption, while enhancing the reliability metrics of communication, like MCC, FMI, and critical success index. While the framework improved sustainability of industrial networks, it also increased the complexity of implementation and energy consumption of resource-limited IoT devices due to the excessive reliance on the energy-consuming computations of their machine learning.

Ahmed et al., (2022) presented a deep learning-based resource allocation method using Deep Neural Networks, Whale Optimisation and multi-objective optimisation based on Fireflies in cooperative IoT communication networks. The approach proposed increased the throughput, spectral efficiency, energy efficiency, network lifetime, and met the Quality-of-Service constraints. Although it was very effective in optimisation, it was not well suited to the computational requirements of low energy sensor nodes on the IoT, since it was based on deep-learning operations. Boutahri and Tilioua (2024) investigated machine learning-based optimisation of smart-building environments for thermal comfort and HVAC energy management, using Support Vector Machine (SVM), Artificial Neural Network (ANN), Random Forest (RF), and XGBoost (XGB) algorithms. Their research showed better prediction accuracy and better energy optimization, but their research focused primarily on smart-building energy prediction instead of communication-level routing optimization in IoT sensor networks.

The concept of Software Defined Networking and the intelligent optimisation frameworks for large-scale IoT communications have also been studied recently. Udayaprasad et al., (2024) suggested a cloud aided SDN based routing approach which combines the Genetic Algorithm, Particle Swarm Optimisation and the Artificial Bee Colony optimisation for large-scale Intelligent IoT networks. The framework enhanced the scalability of routing, scheduling of mobile sinks, load balancing, and energy management performance (Rahim, 2026). The simulation results showed that communication delay and energy consumption were significantly decreased and network life was enhanced. However, this framework was very much cloud-assisted SDN infrastructure and complex optimisation procedures, which added implementation overhead and made it less practical for distributed lightweight IoT deployments (Beken et al., 2026).

Previous IoT routing protocols are built on uniform node distribution and the use of computation expensive optimization, machine learning or cloud mechanisms which cannot fully take the multi-scale topology heterogeneity into consideration and is not suitable for energy constrained devices. Fractal-Dimension analysis is incorporated into the FBAR framework in both cluster head selection and inter-cluster routing to realize lightweight topology aware energy optimization.

The major contributions of this work are summarised as follows:

- Proposed a Python-implemented fractal-based routing framework for IoT energy optimization.
- Developed a mathematical relationship between Local Fractal Dimension and traffic intensity.
- Introduced fractal-aware cluster-head and relay selection mechanism for congestion control.
- Demonstrated significant reduction in energy variance and improved load balancing.
- Achieved extended network lifetime through topology-aware fractal optimization.

Network and Energy Model

Network Model

The proposed Fractal-Based Adaptive Routing (FBAR) framework considers a large-scale wireless Internet of Things (IoT) sensor network deployed within a two-dimensional square sensing region of side length L. The sensing field contains N homogeneous sensor nodes that are randomly distributed across the monitoring environment. Each sensor node is equipped with sensing, processing, and wireless communication capabilities, while all nodes are assumed to possess identical hardware characteristics, equal communication ranges, and the same initial battery energy E_0. A fixed Base Station (BS) is positioned outside the sensing field and is responsible for collecting aggregated information transmitted by cluster-head nodes. Since the base station is externally powered, its energy consumption is not considered within the network energy constraints.

Let the complete set of sensor nodes be represented in equation (1)

$$S = \{s_1, s_2, s_3, \dots, s_N\} \tag{1}$$

Where, s_i denotes the i^{th} sensor node within the network. The spatial position of each node is represented using Cartesian coordinates is expressed in equation (2)

$$s_i = (x_i, y_i) \tag{2}$$

Where, x_i and y_i represent the horizontal and vertical coordinates of sensor node s_i, respectively. The wireless communication topology of the IoT network is modelled as an undirected weighted graph is given in equation (3)

$$G = (V, E) \tag{3}$$

Where, Vrepresents the set of sensor nodes and Edenotes the communication links established among neighbouring nodes. A communication link exists between two sensor nodes whenever their Euclidean separation remains within the communication radius r_c. The Euclidean distance between two sensor nodes $s_i$and $s_j$is computed in equation (4)

$$d(s_i, s_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad (4)$$

Where, $d(s_i, s_j)$denotes the physical separation between nodes $s_i$and s_j, while $(x_i, y_i)$and (x_j, y_j)represent their corresponding spatial coordinates. Similarly, the distance between a sensor node and the base station is represented in equation (5)

$$d(s_i, BS) = \sqrt{(x_i - x_{BS})^2 + (y_i - y_{BS})^2} \quad (5)$$

Where, (x_{BS}, y_{BS})denotes the coordinate position of the base station. Assumptions are made in the design process such that all nodes within the network will not move from their initial location after deployment and will keep generating sensing data throughout the course of operation of the network. The wireless communication medium is assumed to be symmetric in the sense that two-way communication requires equal transmitting energy by each node.

To enhance the scalability and lower communication cost, the network is partitioned into several clusters. Each cluster consists of a cluster head node and some member nodes. The cluster head node is in charge of collecting the sensing information reported by the member nodes, compressing the redundant information, and transmitting the packets to the base station. Let the k^{th}cluster be represented in equation (6)

$$C_k = \{s_1, s_2, \dots, s_m\} \quad (6)$$

Where, $m$denotes the number of sensor nodes belonging to the cluster. The complete set of cluster-head nodes is expressed in equation (7)

$$CH = \{ch_1, ch_2, \dots, ch_K\} \quad (7)$$

Where, Krepresents the total number of active clusters within the sensing region. Because cluster-head nodes execute more communication and aggregation tasks, their depletion rate of energy will be faster compared to normal member nodes. Thus, balancing the cluster-head node selection process becomes imperative.

The neighbourhood relationship of a sensor node is defined according to communication range constraints. The neighbour set of nodes $s_i$is represented in equation (8)

$$\mathcal{N}(s_i) = \{s_j \in S \mid d(s_i, s_j) \le r_c,\ i \ne j\} \quad (8)$$

Where, $\mathcal{N}(s_i)$denotes all neighbouring nodes that can communicate directly with node s_i. The node degree of s_i, represented as δ_i, corresponds to the number of neighbouring nodes contained within its communication range. The average network connectivity degree is therefore expressed in equation (9)

$$\bar{\delta} = \frac{1}{N}\sum_{i=1}^{N} \delta_i \quad (9)$$

Where, $\bar{\delta}$denotes the average neighbour density across the sensing field. Higher node density improves communication reliability and routing flexibility but also increases packet collisions and energy consumption. Therefore, efficient routing decisions must carefully balance connectivity and communication overhead.

As per the proposed FBAR model, multi-hop communication is used to reduce energy consumption during the long-range data transmission process. In every transmission phase, the member nodes send out their sensed data to the respective cluster heads, who then compress the data before sending it on to the base station. The residual energy of sensor node $s_i$at transmission round $t$is represented in equation (10)

$$E_i(t) \quad (10)$$

Where, $E_i(t)$denotes the remaining battery energy available at node s_i. The total residual network energy at round $t$is computed in equation (11)

$$E_{total}(t) = \sum_{i=1}^{N} E_i\,(t) \quad (11)$$

Where, $E_{total}(t)$represents the cumulative remaining energy across all sensor nodes. Similarly, the average residual energy of the network is represented in equation (12)

$$\bar{E}(t) = \frac{1}{N}\sum_{i=1}^{N} E_i\,(t) \quad (12)$$

Where, $\bar{E}(t)$indicates the mean available energy per node at transmission round t. These energy metrics provide important indicators for evaluating routing efficiency, energy balancing capability, and network sustainability under varying deployment densities.

2.2 First-Order Radio Energy Model

The proposed FBAR framework is based on the first order radio energy model, which is used to estimate the energy dissipated during wireless packet transmission and reception during communication. In an IoT environment, wireless sensor networks (WSN) consume the most energy in their operations, due to the need for a lot of power to activate radio circuits, amplify received signals, modulate them, and travel through space. Thus, it becomes important to model the energy of the communication to be able to design energy-efficient routing strategies that can prolong the network lifetime. Figure 1 illustrates energy consumption during wireless packet transmission and reception.

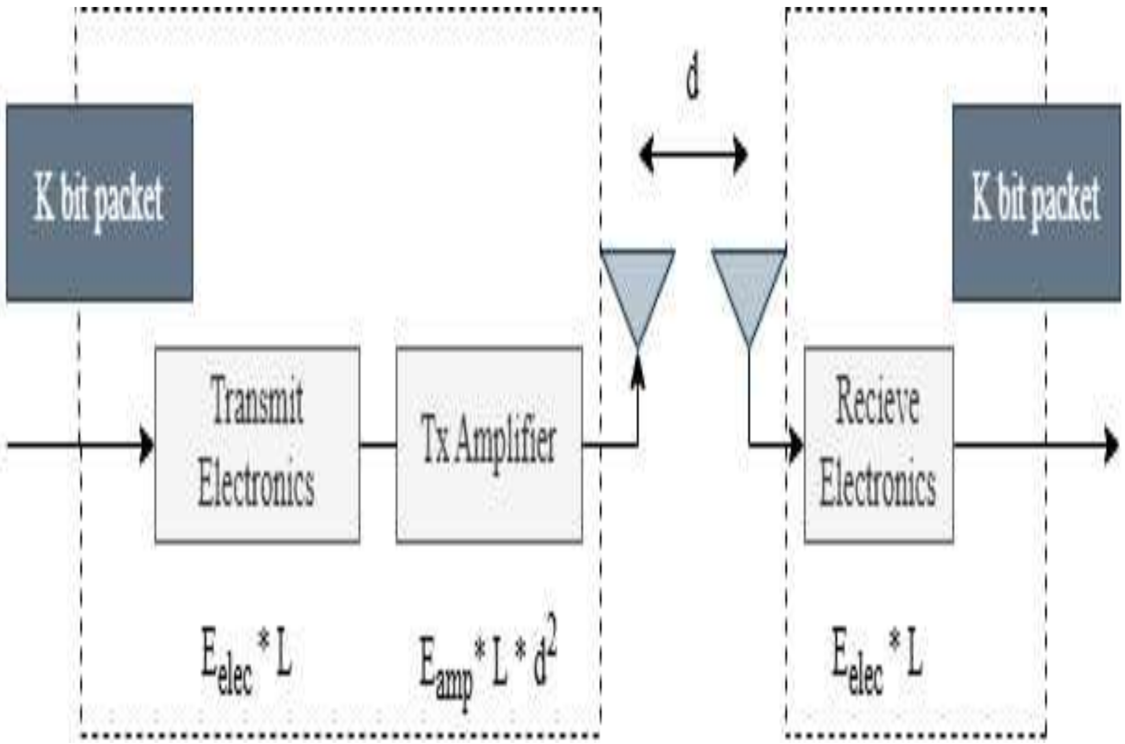

Figure 1. First-order radio energy model

According to the first-order radio model, the amount of energy for transmission depends on two factors, namely the size of packets and the transmission distance. There are two models considered when it comes to the propagation model in the communication scenario. These models include the free space and multi-path fading. The transmission energy required for sending a k-bit packet over distance $d$is expressed in equation (13)

$$E_{TX}(k,d) = \begin{cases} kE_{elec} + k\varepsilon_{fs}d^2, & d < d_0 \\ kE_{elec} + k\varepsilon_{mp}d^4, & d \geq d_0 \end{cases} \tag{13}$$

Where, $E_{TX}(k,d)$denotes the total transmission energy consumption, $k$represents the packet length in bits, E_{elec}denotes the energy dissipated by transmitter electronic circuitry, ε_{fs}represents the free-space amplifier coefficient, ε_{mp}denotes the multi-path fading amplifier coefficient, and $d$corresponds to the transmission distance between communicating nodes. The free-space model exhibits quadratic distance dependence, whereas the multi-path fading model exhibits fourth-order distance dependence due to signal scattering and fading effects.

The threshold distance separating these two propagation conditions is referred to as the crossover distance and is expressed in equation (14)

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{14}$$

Where, $d_0$represents the critical communication distance at which the propagation model transitions from free-space attenuation to multi-path fading attenuation. When communication distances exceed d_0, transmission energy increases rapidly due to the fourth-power distance dependency, thereby motivating the need for energy-efficient multi-hop routing mechanisms.

The energy required for packet reception depends solely on receiver electronic circuitry because signal amplification is unnecessary during reception. The packet reception energy is therefore represented in equation (15)

$$E_{RX}(k) = kE_{elec} \tag{15}$$

Where, $E_{RX}(k)$ denotes the energy consumed for receiving a k-bit packet. This energy includes signal filtering, demodulation, decoding, and other electronic processing operations executed at the receiver node.

In cluster-based communications, the role of the cluster-head node is to carry out further data aggregation tasks, in order to avoid sending of redundant information collected from different member nodes. Data aggregation greatly helps to minimize packet transmission towards the base station. The energy required for aggregating data packets within a cluster is represented in equation (16)

$$E_{AGG}(k, M) = MkE_{DA} \tag{16}$$

Where, E_{DA} denotes the energy required for aggregating one bit of information and M represents the number of member nodes associated with the cluster head. Since cluster-head nodes simultaneously receive, process, aggregate, and forward multiple packets, their energy consumption becomes substantially higher than ordinary sensor nodes.

The total energy dissipated by cluster-head node s_i during a transmission round is therefore expressed in equation (17)

$$E_{CH}(i) = E_{AGG}(k, M_i) + (M_i - 1)E_{RX}(k) + E_{TX}(k, d_{i,BS}) \tag{17}$$

Where, M_i denotes the number of member nodes connected to cluster-head node s_i, and $d_{i,BS}$ represents the transmission distance between the cluster head and the base station. The first term corresponds to aggregation energy consumption, the second term represents packet reception energy from member nodes, and the final term denotes the transmission energy required for forwarding aggregated information toward the base station.

Similarly, the energy consumption of an ordinary member node is expressed in equation (18)

$$E_{member}(j) = E_{TX}(k, d_{j,CH}) + E_{RX}(k) \tag{18}$$

Where, $d_{j,CH}$ denotes the communication distance between member node s_j and its corresponding cluster head. Since member nodes generally transmit over shorter distances, their communication energy consumption remains significantly lower than cluster-head nodes.

The residual energy of sensor node s_i after transmission round t is updated according to equation (19)

$$E_i(t+1) = E_i(t) - E_{consumed}(i, t) \tag{19}$$

Where, $E_{consumed}(i, t)$ represents the total energy dissipated by node s_i during communication and processing operations at round t. The total network energy consumption per transmission round is therefore computed in equation (20)

$$E_{round}(t) = \sum_{i=1}^{N} E_{consumed}\,(i, t) \tag{20}$$

Where, $E_{round}(t)$ denotes the cumulative energy dissipated by all sensor nodes during round t. The average node energy consumption is represented in equation (21)

$$\bar{E}_{node}(t) = \frac{E_{round}(t)}{N} \tag{21}$$

Where, $\bar{E}_{node}(t)$ denotes the mean communication energy dissipated per node during network operation.

To evaluate communication efficiency, the packet-delivery energy efficiency metric is defined in equation (22)

$$EE_{PDR} = \frac{P_{success}}{E_{round}} \tag{22}$$

Where, $P_{success}$ denotes the number of successfully delivered packets during a transmission round. Higher values of EE_{PDR} indicate improved routing efficiency and reduced energy wastage during communication.

The energy balancing capability among cluster-head nodes is analysed using energy variance, which is expressed in equation (23)

$$\sigma_E^2 = \frac{1}{K} \sum_{i=1}^{K} (E_i - \bar{E}_{CH})^2 \tag{23}$$

Where, $\bar{E}_{CH}$ denotes the average residual energy of all cluster-head nodes. Lower variance values indicate balanced energy utilisation across cluster heads, thereby preventing premature node failures and improving network lifetime.

The cumulative energy depletion of the network is represented in equation (24)

$$E_{depletion}(t) = E_{total}(0) - E_{total}(t) \tag{24}$$

Where, $E_{total}(0)$ denotes the initial total network energy. The network survival ratio is further defined in equation (25)

$$SR(t) = \frac{N_{alive}(t)}{N} \tag{25}$$

Where, $N_{alive}(t)$ represents the number of operational sensor nodes remaining at transmission round t. The proposed FBAR framework minimises communication energy consumption through adaptive cluster-head selection, fractal-aware relay routing, balanced energy utilisation, and reduced control overhead, thereby significantly improving network sustainability, packet-delivery reliability, transmission efficiency, and operational lifetime in heterogeneous IoT deployments.

Fractal Characterisation of IoT Topology

In real Internet of Things scenarios, sensor nodes are not evenly distributed as in the ideal case. In practice, deployments are distributed in non-uniform ways due to environmental challenges, infrastructure limitations, sensing priorities, and non-uniform sensing needs. Dense concentrations of nodes typically grow around machinery or control units, and sparse distributions are found in peripheral monitoring areas in industrial monitoring systems. Likewise, smart-city sensing deployments are clustered around intersections, traffic hubs, and public utility areas, while agricultural IoT deployments have non-uniform distributions varying by irrigation regions, soil conditions, and crop-density variations. Spatial models for conventional routing protocols are typically uniform or Poisson, which are difficult to capture some characteristics of real-world networks, such as self-similarity and irregularity in the geometric arrangement of nodes. To overcome this, the proposed Fractal Based Adaptive Routing framework utilizes fractal geometry as a topology-characterisation mechanism which can model multi-scale spatial heterogeneity.

Fractal Geometry is the mathematical representation of irregular structure with statistical self-similarity at various scales of observation. There is a measure of a geometric distribution called the fractal dimension which is an indicator of how 'tightly' packed a structure is in the space around it. Fractal dimensions can take non-integer values, which are more representative of irregular spatial phenomena, as opposed to traditional Euclidean dimensions, which apply integer valued geometry. The fractal dimension can be used to quantitatively describe wireless IoT node clustering behaviour, topology irregularity, spatial fragmentation, and local density variation. Therefore, the routing decisions may be dynamically adjusted based on the geometric properties of the network, in addition to the residual energy or hop-count.

The proposed framework employs the box-counting method for estimating the fractal dimension of sensor-node distributions because of its computational simplicity and suitability for distributed IoT environments. Consider a sensing region of side length Lpartitioned into square boxes of side length ε. Let $N(\varepsilon)$represent the number of occupied boxes containing at least one sensor node. The relationship between the occupied region counts and spatial scale is represented in equation (26)

$$N(\varepsilon) \propto \varepsilon^{-D} \tag{26}$$

Where, $N(\varepsilon)$denotes the number of occupied boxes at spatial scale ε, εrepresents the side length of each observation box, and Ddenotes the fractal dimension of the node distribution. The proportionality shows that the number of occupied zones is a function of power-law scaling with the change in the observation scale. Network structures having high cluster formations tend to have low fractal dimensions while network structures with uniform distribution tend to have high fractal dimensions.

The theoretical fractal dimension is estimated using the logarithmic limit formulation expressed in equation (27)

$$D = \lim_{\varepsilon \to 0} \frac{\log N(\varepsilon)}{\log(1/\varepsilon)} \tag{27}$$

Where, Drepresents the box-counting fractal dimension, $N(\varepsilon)$denotes the number of occupied boxes corresponding to box size ε, and $\log(1/\varepsilon)$represents the inverse-scale logarithmic transformation. The equation quantifies the rate at which spatial complexity increases when the observation scale becomes progressively finer. Since practical wireless sensor deployments contain finite node populations and limited spatial resolution, the exact limit cannot be computed directly. Therefore, the proposed framework estimates the fractal dimension numerically using finite observation scales.

Assume that the sensing region is evaluated at $m$different box scales represented as $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_m$. For each scale, the number of occupied boxes is calculated. A logarithmic linearisation process is then performed by defining in equation (28) and equation (29)

$$X_q = \log\left(\frac{1}{\varepsilon_q}\right) \tag{28}$$

and

$$Y_q = \log N(\varepsilon_q) \tag{29}$$

Where, $X_q$represents the logarithmic inverse spatial scale corresponding to the q^{th}observation level and $Y_q$represents the logarithmic occupied-box count. The fractal dimension estimation problem therefore becomes a linear regression problem in which the slope of the fitted line corresponds to the estimated fractal dimension. The least-squares estimation of the fractal dimension is computed in equation (30)

$$\widehat{D} = \frac{m\sum_{q=1}^{m} X_q Y_q - \left(\sum_{q=1}^{m} X_q\right)\left(\sum_{q=1}^{m} Y_q\right)}{m\sum_{q=1}^{m} X_q^2 - \left(\sum_{q=1}^{m} X_q\right)^2} \tag{30}$$

Where, $\widehat{D}$ denotes the estimated fractal dimension, m represents the number of spatial scales used during analysis, X_q denotes the logarithmic inverse box size at scale q, and Y_q represents the logarithmic occupied-box count. This regression-based estimation reduces sensitivity to local fluctuations and improves robustness under irregular deployment conditions.

The proposed FBAR framework performs fractal estimation locally rather than globally. Each sensor node evaluates the spatial distribution of neighbouring nodes within a local observation radius r_f. Let $\mathcal{N}_i(r_f)$ denote the neighbourhood set associated with node s_i. The local neighbourhood is defined in equation (31)

$$\mathcal{N}_i(r_f) = \{s_j \mid d(s_i, s_j) \le r_f\} \tag{31}$$

Where, $d(s_i, s_j)$ represents the Euclidean distance between sensor nodes s_i and s_j, while r_f denotes the fractal-observation radius. This localised analysis allows routing adaptation according to regional topology characteristics instead of relying on global network statistics that may not represent local deployment conditions accurately.

The local node density surrounding sensor node s_i is represented in equation (32)

$$\rho_i = \frac{|\mathcal{N}_i(r_f)|}{\pi r_f^2} \tag{32}$$

Where, ρ_i denotes local node density, $|\mathcal{N}_i(r_f)|$ represents the number of neighbouring nodes within radius r_f, and πr_f^2 corresponds to the circular observation area. However, density alone cannot distinguish between regular and irregular spatial arrangements because different geometric structures may possess identical average densities. Fractal analysis therefore provides superior representation by incorporating multi-scale spatial behaviour.

The local fractal dimension associated with sensor node s_i is estimated using neighbouring-node occupancy distributions across multiple observation scales and expressed in equation (33)

$$\widehat{D}_i = \frac{m\sum_{q=1}^{m} X_{iq} Y_{iq} - \left(\sum_{q=1}^{m} X_{iq}\right)\left(\sum_{q=1}^{m} Y_{iq}\right)}{m\sum_{q=1}^{m} X_{iq}^2 - \left(\sum_{q=1}^{m} X_{iq}\right)^2} \tag{33}$$

Where, $\widehat{D}_i$ denotes the estimated local fractal dimension of sensor node s_i, X_{iq} represents the logarithmic inverse spatial scale associated with node s_i, and Y_{iq} denotes the logarithmic occupied-box count for the corresponding neighbourhood scale. Nodes located in highly irregular or congested regions generally exhibit larger fractal dimensions because occupied regions persist across finer observation scales.

To reduce estimation instability caused by transient neighbour fluctuations, the proposed framework introduces temporal smoothing using exponential averaging and expressed in equation (34)

$$\bar{D}_i(t) = \beta \widehat{D}_i(t) + (1-\beta)\bar{D}_i(t-1) \tag{34}$$

Where, $\bar{D}_i(t)$ denotes the smoothed fractal estimate at time instant t, $\widehat{D}_i(t)$ represents the current fractal estimate, and β denotes the smoothing coefficient satisfying $0 < \beta < 1$. This mechanism improves routing stability by suppressing abrupt topology fluctuations caused by temporary packet losses or mobility disturbances.

The variability of local topology can further be quantified through the neighbourhood fractal variance given in equation (35)

$$\sigma_{D_i}^2 = \frac{1}{|\mathcal{N}_i|}\sum_{s_j \in \mathcal{N}_i} \left(\bar{D}_j - \mu_{D_i}\right)^2 \tag{35}$$

Where, $\sigma_{D_i}^2$ denotes the fractal variance around node s_i, μ_{D_i} represents the average neighbouring fractal dimension, and $\bar{D}_j$ denotes the smoothed fractal estimate of neighbouring node s_j. Larger variance values indicate highly heterogeneous local topologies requiring adaptive routing decisions.

The proposed routing mechanism incorporates fractal analysis into cluster-head election through the Fractal Routing Weight. The routing weight associated with sensor node s_i is represented in equation (36)

$$FRW_i = \frac{\widehat{D}_i}{D_{max}} \tag{36}$$

Where, FRW_idenotes the Fractal Routing Weight of sensor node s_i, $\widehat{D}_i$represents the estimated local fractal dimension, and D_{max}denotes the maximum observed fractal dimension within the network. The normalisation process ensures that routing weights remain bounded within the interval $[0, 1]$.

The greater the fractal routing penalty weight, the higher the level of congestion in space and irregularity in topology in the particular region. Therefore, nodes existing in congested or irregular regions receive more routing penalties in cluster head election and relay selection. Such an approach helps avoid clustering in congested regions.

The proposed framework further defines a topology irregularity coefficient expressed in equation (37)

$$\Psi_i = \frac{\sigma_{D_i}}{\bar{D}_i} \tag{37}$$

Where, $\Psi_i$denotes the topology irregularity coefficient, σ_{D_i}represents neighbourhood fractal deviation, and $\bar{D}_i$denotes the average local fractal estimate. Larger values of $\Psi_i$indicate highly unstable neighbourhood structures that may cause excessive routing overhead and packet retransmissions.

To quantify neighbourhood self-similarity, the fractal consistency metric is represented in equation (38)

$$\Omega_i = \exp(-\Psi_i) \tag{38}$$

Where, $\Omega_i$denotes the local self-similarity consistency associated with node s_i. Regions with stable geometric structure produce larger consistency values, thereby favouring their participation in relay selection and cluster formation.

The fractal-aware cluster distribution probability is expressed in equation (39)

$$P_{CH}(i) = \frac{E_i(t)\Omega_i}{\sum_{j=1}^{N} E_j(t)\Omega_j} \tag{39}$$

Where, $P_{CH}(i)$denotes the cluster-head election probability of node s_i, $E_i(t)$represents residual energy at time instant t, and $\Omega_i$denotes fractal consistency. This formulation jointly considers energy availability and topology regularity during cluster-head selection.

The proposed mechanism for characterisation of fractals for routing has a positive effect on the routing efficiency, due to the ability of dynamically recognising heterogeneous regions and using this knowledge when making adaptation decisions for the network. Conventional single-scale density metrics can be inadequate for detecting locally clustered and globally fragmented deployments, while fractal analysis can detect spatial behaviour at multiple scales. As a result, the FBAR scheme can optimally balance cluster, alleviate congestion, mitigate packet re-transmissions, and stabilize energy consumption in irregular deployment of IoT. Figure 2 illustrates heterogeneous IoT topology, box-counting fractal analysis, and local fractal-dimension estimation. The extracted fractal characteristics guide topology-aware routing decisions, improving energy efficiency, connectivity, and network lifetime.

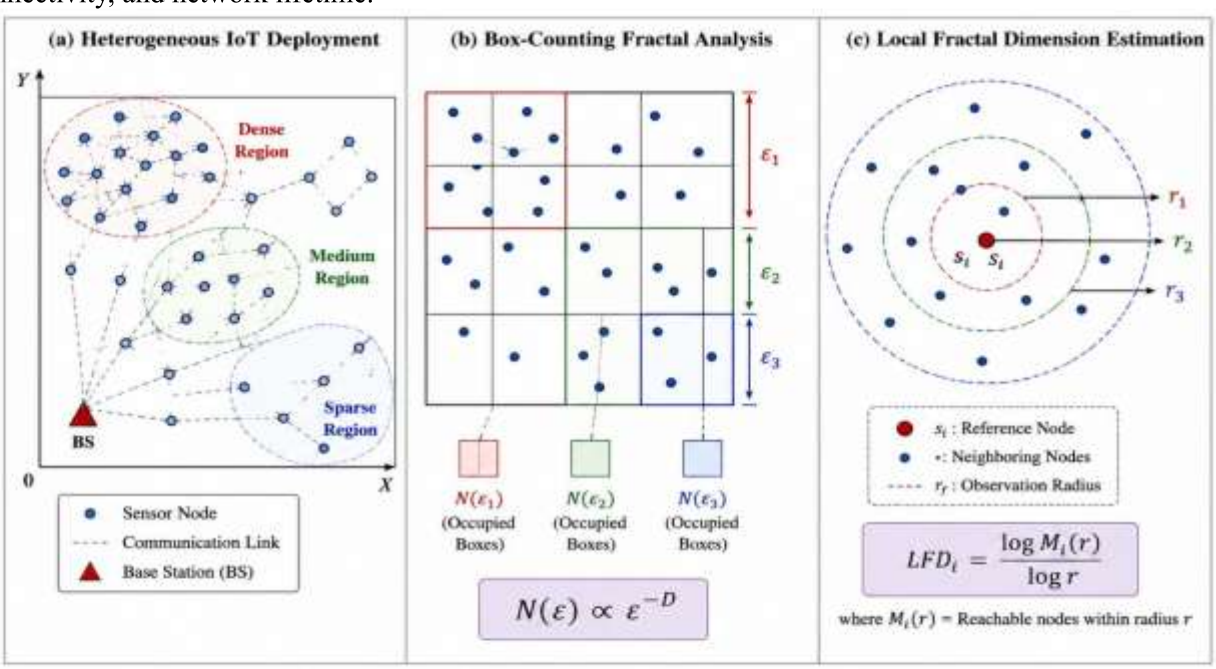

Fig. 2 Fractal characterisation of heterogeneous iot topology in the proposed fractal-based adaptive routing (FBAR) framework

(a) non-uniform sensor-node deployment exhibiting dense and sparse regions, (b) box-counting analysis for estimating the fractal dimension of the network topology, and (c) local fractal-dimension estimation around a sensor node using multi-scale neighbourhood observations

The computational complexity associated with local fractal estimation remains feasible for resource-constrained IoT devices because the box-counting operation is executed only within limited neighbourhood regions and at finite observation scales. Let $m$denote the number of box scales and $n_i$represent the number of neighbouring nodes surrounding sensor node s_i. The computational complexity of local fractal estimation given in equation (40)

$$\mathcal{O}(mn_i) \tag{40}$$

Which remains significantly lower than global topology-analysis approaches requiring complete network information. Therefore, the proposed fractal characterisation framework is suitable for lightweight embedded IoT environments with constrained memory, computation capability, and battery resources.

Fractal-Based Adaptive Routing (FBAR) Framework

The Fractal-Based Adaptive Routing framework provides an intelligent routing mechanism which adapts cluster-head selection, relay-node formation and topology maintenance according to energy conditions and spatial topology irregularities. The traditional clustering protocols use the one-metric optimization approaches which typically result in the formation of imbalanced clusters and quick energy consumption in dense deployment areas. While routing in heterogeneous IoT environments should take into account node-energy availability, local topology characteristics, communication reliability, and relay accessibility, it is the node that is responsible for these decisions. Therefore, the proposed FBAR framework incorporates fractal-aware topology analysis at the adaptive routing decision level to gain benefits in terms of network lifetime, communication reliability, congestion balancing and energy efficiency.

The overall routing process starts with the discovery of the neighbourhood and the estimation of the local fractal dimension. Every sensor node, periodically sends out beacon packets that include residual energy, hop-count data, local fractal estimates, and link-quality data. This neighbourhood information is used in assessing candidate cluster heads by a combined scoring system. The chosen cluster-heads then form the inter-cluster forwarding paths in a fractal-aware manner with the adaptive re-clustering only occurring if any serious topology imbalance or energy degradation is detected. This is event driven routing adaptation, which is much lower than periodic re-clustering schemes in terms of unnecessary control overhead.

Fractal Topology Interpretation

The framework of FBAR presented here uses Local Fractal dimension (LFD) to capture the structural complexity of the IoT communication topology. Generally, most routing protocols use node degree to reflect local connectivity. It represents the number of neighboring nodes connected in communication range of nodes, but only reflects connectivity at a single spatial scale and gives no clue of the connectivity evolution in broader area.

Let $M_i(r)$denote the number of nodes reachable from sensor node $s_i$within an observation radius r. In a self-similar communication topology, the growth of reachable nodes follows a power-law relationship given in Eq. (41)

$$M_i(r) = Cr^{D_{f,i}} \tag{41}$$

Where, $C$is a proportionality constant and $D_{f,i}$represents the local fractal dimension associated with node s_i. The above equation indicates that connectivity expansion is governed by the fractal dimension and therefore depends on the topology structure surrounding the node.

Taking the logarithm of both sides' yields is formulated in in equation (42)

$$\log M_i(r) = \log C + D_{f,i} \log r \tag{42}$$

which can be rearranged in equation (43)

$$D_{f,i} = \frac{\log M_i(r) - \log C}{\log r} \tag{43}$$

The local fractal dimension therefore corresponds to the slope of the linear relationship between $\log M_i(r)$and $\log r$. Degree represents connectivity at a specific, fixed communication range while fractal dimension represents connectivity increase over multiple scales. Therefore, LFD gives a better representation of topological heterogeneity and self-similar communication networks.

The connection between the degree of nodes and their local fractal dimensions can also be shown by two nodes which have the same degree (i.e. Same number of neighbors). Both nodes can have the same degree but, as increase the observation radius around a node, the environment topology around it may change. Hence, the fact that nodes are identically degrees doesn't imply they are equally important for routing. With added connectivity scaling behaviour, the local fractal dimension helps distinguish the nodes with topological importance from normal nodes and provides more information about routing information not present in simple density metrics.

Similarly, the calculated fractal dimension also shows the properties of the topology region in terms of communication. Low value of fractal dimension means that the number of reachable nodes is slowly changing with the observation radius. Those regions have low density of connectivity and the routing choices are few, thus the communication distance will be long and the communication energy will be high. The average routing path length can be approximated in in equation (44)

$$L_i \propto \frac{1}{D_{f,i}} \tag{44}$$

Where, $L_i$denotes the expected path length associated with node s_i. As $D_{f,i}$decreases, communication paths become longer and routing efficiency deteriorates.

Conversely, larger fractal dimensions indicate rapid connectivity growth and strong local connectivity. However, excessively large values may cause routing traffic to concentrate around densely connected regions. The local traffic intensity surrounding node $s_i$is therefore modeled in in equation (45)

$$T_i = \kappa D_{f,i} \tag{45}$$

Where, $T_i$represents traffic intensity and $\kappa$is a scaling coefficient. Higher fractal dimensions generally attract a larger number of communication flows because dense regions offer numerous routing alternatives and relay opportunities.

The corresponding communication energy consumption is represented in in equation (46)

$$E_i = E_{TX} + E_{RX} + \lambda T_i \tag{46}$$

Where, $E_{TX}$and E_{RX}denote transmission and reception energy, respectively, and λcontrols the influence of traffic intensity on energy expenditure. Excessive traffic concentration therefore accelerates battery depletion and increases the probability of energy hotspot formation.

To balance connectivity and communication load, an optimal fractal operating region is defined. The topology efficiency associated with node $s_i$is expressed in in equation (47)

$$FTE_i = \frac{D_{f,i}}{1+|D_{f,i}-D_{opt}|} \tag{47}$$

Where, D_{opt}denotes the optimal fractal dimension corresponding to balanced connectivity and moderate traffic intensity. The topology efficiency reaches its maximum value when indicating that the node is located within a structurally favourable communication region.

$$D_{f,i} = D_{opt} \tag{48}$$

From the above reasoning, the node with extremely small fractal dimension may have sparse topology and long communication path, and the node with extremely large fractal dimension will have a tendency to produce congestion and energy hotspots. For the node whose fractal dimension approaches the optimum operation range, the topology connectivity and the route diversity is better, and the communication efficiency is still in the reasonable extent. Thus, the proposed FBAR selects cluster heads and relay nodes from those parts with optimal fractal characteristics in order to achieve the network topology to be able to reduce congestion and keep balanced energy consumption.

Cluster-Head Scoring Function

The selection of cluster heads is one of the most important operations in wireless IoT routing as they act as data aggregation, relay transmission, neighbour coordination, and topology management. The nodes in the cluster can become exhausted quickly and the network partitions due to unevenly distributed energy allocation when the cluster-heads do not have an even distribution. The proposed framework for FBAR is then a multi-objective cluster-head scoring function which takes into account the residual energy, fractal topology characteristics, hop distance and communication reliability.

The cluster-head suitability score associated with sensor node $s_i$is expressed in equation (49)

$$S_i = \alpha_1 f_E(i) + \alpha_2 f_F(i) + \alpha_3 f_H(i) + \alpha_4 f_L(i) \tag{49}$$

Where, $S_i$denotes the overall cluster-head score associated with sensor node s_i, $f_E(i)$represents the residual-energy contribution, $f_F(i)$denotes the fractal-routing influence, $f_H(i)$corresponds to hop-count priority, and

$f_L(i)$represents the communication link-quality contribution. The weighting coefficients $\alpha_1, \alpha_2, \alpha_3, \alpha_4$determine the relative influence of each routing parameter and satisfy the normalisation condition and stated in equation (50)

$$\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1 \tag{50}$$

The residual-energy contribution is designed to prioritise nodes possessing higher remaining battery capacity because such nodes can sustain cluster-management operations for longer durations. The residual-energy metric is defined in equation (51)

$$f_E(i) = \frac{E_i(t)}{E_{max}(t)} \tag{51}$$

Where, $E_i(t)$represents the residual energy of sensor node $s_i$at time instant t, while $E_{max}(t)$denotes the maximum residual energy observed within the local neighbourhood. Larger values of $f_E(i)$indicate stronger energy availability and therefore increase the probability of cluster-head selection.

The proposed framework integrates fractal topology awareness through the fractal-routing contribution function represented in in equation (52)

$$f_F(i) = 1 - \frac{\widehat{D}_i}{D_{max}} \tag{52}$$

Where, $\widehat{D}_i$denotes the estimated local fractal dimension associated with node s_i, while D_{max}represents the maximum observed fractal dimension within the network region. Nodes positioned in highly congested or irregular regions generally exhibit larger fractal dimensions and consequently obtain lower fractal scores. This mechanism prevents excessive cluster-head concentration within dense deployment zones and improves spatial load balancing across the sensing field.

Hop-count contribution is incorporated because shorter communication paths reduce transmission delay and energy expenditure during inter-cluster forwarding. The hop-priority metric is expressed in in equation (53)

$$f_H(i) = \frac{1}{HC_i + 1} \tag{53}$$

Where, HC_idenotes the minimum hop distance between sensor node $s_i$and the base station. Nodes located closer to the base station therefore achieve larger hop-priority values because fewer relay transmissions are required for data delivery.

Communication reliability is represented through the link-quality contribution function and it was given in equation (54)

$$f_L(i) = \frac{LQI_i}{LQI_{max}} \tag{54}$$

where LQI_idenotes the measured Link Quality Indicator associated with node s_i, while LQI_{max}represents the maximum observed link-quality value. Strong communication links reduce packet retransmissions, transmission delay, and communication overhead, thereby improving routing stability.

The optimal weighting configuration used in the proposed framework is expressed in equation (55)

$$\alpha_1 = 0.40, \alpha_2 = 0.30, \alpha_3 = 0.20, \alpha_4 = 0.10 \tag{55}$$

This configuration was determined empirically through extensive simulation analysis under varying network densities and topology conditions. Residual energy receives the highest contribution because energy sustainability represents the primary optimisation objective, while fractal-awareness receives the second-largest contribution because topology irregularity significantly affects routing balance and congestion behaviour.

The probability of sensor node $s_i$becoming a cluster head is subsequently represented in equation (56)

$$P_{CH}(i) = \frac{S_i}{\sum_{j=1}^{N} S_j} \tag{56}$$

Where, $P_{CH}(i)$denotes the cluster-head election probability and Nrepresents the total number of sensor nodes. This probabilistic mechanism ensures balanced cluster-head distribution while preserving adaptive routing flexibility.

To avoid repetitive cluster-head selection of the same sensor nodes, the framework introduces a cluster-head fairness factor represented in Eq. (57)

$$F_i(t) = \exp(-\omega n_i^{CH}(t)) \tag{57}$$

Where, $F_i(t)$denotes the fairness factor associated with node s_i, $n_i^{CH}(t)$represents the number of times node $s_i$has previously served as cluster head, and ωdenotes the fairness-control coefficient. Nodes repeatedly selected as cluster heads therefore receive progressively lower selection probabilities, thereby improving long-term energy balancing.

The final cluster-head election score is given in equation (58)

$$S_i^{final} = S_i F_i(t) \tag{58}$$

Where, S_i^{final} denotes the adjusted cluster-head suitability score after fairness correction. This mechanism prevents excessive energy depletion in specific sensor nodes and prolongs network operational lifetime.

Composite Inter-Cluster Routing Cost

Once cluster heads have been identified, the problem of effective communication between clusters is very important for data to be forwarded efficiently to the sink. Conventional shortest path algorithms are known to overburden particular relay nodes, resulting in fast depletion of their energy level. It is for this reason that the proposed framework for inter-cluster communication takes into account all these aspects in one go.

The routing cost associated with forwarding data from cluster head s_i to relay node s_j is represented in equation (59)

$$C(i,j) = \gamma_1 E_{TX}(k, d_{ij}) + \gamma_2 \left(\frac{1}{E_j(t)}\right) + \gamma_3 ETX_{ij} + \gamma_4 D_{ij} \tag{59}$$

Where, $C(i,j)$ denotes the composite routing cost between nodes s_i and s_j, $E_{TX}(k, d_{ij})$ represents the transmission energy required for sending a k-bit packet across distance d_{ij}, $E_j(t)$ denotes the residual energy of relay node s_j, ETX_{ij} represents the Expected Transmission Count associated with the communication link, and D_{ij} denotes the local fractal-topology cost.

The transmission-energy component is represented using the first-order radio-energy model and it was computed in equation (60)

$$E_{TX}(k, d_{ij}) = kE_{elec} + k\varepsilon_{fs} d_{ij}^2 \tag{60}$$

for short-range communication distances, while long-distance communication followed in equation (61)

$$E_{TX}(k, d_{ij}) = kE_{elec} + k\varepsilon_{mp} d_{ij}^4 \tag{61}$$

Where, E_{elec} denotes electronic circuitry energy consumption, ε_{fs} represents the free-space amplifier coefficient, and ε_{mp} denotes the multipath fading amplifier coefficient.

The Expected Transmission Count is estimated in equation (62)

$$ETX_{ij} = \frac{1}{p_{ij}^f p_{ij}^r} \tag{62}$$

Where, p_{ij}^f and p_{ij}^r denote the forward and reverse packet-delivery probabilities associated with the communication link. Larger ETX values indicate unreliable communication paths requiring additional retransmissions.

The fractal-routing cost associated with neighbouring cluster heads is represented in equation (63)

$$D_{ij} = \frac{\widehat{D}_i + \widehat{D}_j}{2} \tag{63}$$

Where, $\widehat{D}_i$ and $\widehat{D}_j$ denote the local fractal dimensions of nodes s_i and s_j. Relay paths traversing highly congested or irregular topology regions therefore receive larger routing penalties.

The weighting coefficients satisfy and formulated in equation (64)

$$\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 = 1 \tag{64}$$

Where, $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ determine the relative influence of transmission energy, relay energy availability, link reliability, and fractal topology awareness, respectively.

The optimal relay node is selected according to the minimum composite routing cost is expressed in equation (65)

$$s_j^* = \arg\min_{s_j \in \mathcal{R}_i} C(i,j) \tag{65}$$

Where, $\mathcal{R}_i$ denotes the candidate relay-node set associated with cluster head s_i, while s_j^* represents the optimal relay node. This routing strategy distributes communication load more uniformly across the network and prevents premature exhaustion of heavily utilised relay nodes.

Adaptive Re-Clustering Mechanism

The typical techniques adopted by existing schemes for clustering and re-clustering lead to high overheads since re-clustering takes place regardless of any changes in the topology condition. This results in increased packet collision, delay in communication, and unnecessary energy wastage. It follows that the FBAR model will employ an adaptive and event-driven re-clustering scheme where reconstruction is initiated when necessary.

The probability of re-clustering associated with sensor node s_i at time instant t is represented in equation (66)

$$P_{recluster}(i,t) = 1 - \exp(-\lambda_R[\Theta_E - E_i(t)]_+) \quad (66)$$

Where, $P_{recluster}(i,t)$ denotes the re-clustering probability, λ_R represents the re-clustering sensitivity coefficient, Θ_E denotes the residual-energy threshold, and $[\cdot]_+$ represents the positive-threshold operator defined in equation (67)

$$[x]_+ = \max(0,x) \quad (67)$$

When the residual energy $E_i(t)$ remains above the threshold Θ_E, the positive-threshold operator becomes zero, thereby suppressing unnecessary re-clustering operations. However, when residual energy falls below the threshold, the re-clustering probability increases exponentially, enabling rapid topology adaptation.

The global network-energy imbalance factor is represented in equation (68)

$$\Phi_E(t) = \frac{1}{N}\sum_{i=1}^{N}(E_i(t) - \bar{E}(t))^2 \quad (68)$$

Where, $\Phi_E(t)$ denotes the network-energy variance and $\bar{E}(t)$ represents the average residual energy of all sensor nodes. Larger variance values indicate severe energy imbalance requiring topology reorganisation.

Similarly, topology instability is quantified using fractal-variation analysis and it was stated in equation (69)

$$\Phi_D(t) = \frac{1}{N}\sum_{i=1}^{N}\left(\widehat{D}_i(t) - \bar{D}(t)\right)^2 \quad (69)$$

Where, $\Phi_D(t)$ denotes the fractal-topology variance and $\bar{D}(t)$ represents the average network fractal dimension. High topology variance indicates irregular cluster distribution and communication congestion.

The final adaptive re-clustering condition is represented in equation (70)

$$\Phi_E(t) + \eta\Phi_D(t) \geq \Theta_R \quad (70)$$

Where, η denotes the topology-sensitivity coefficient and Θ_R represents the global re-clustering threshold. Re-clustering is therefore triggered only when both energy imbalance and topology irregularity exceed acceptable operational limits.

This technique ensures that the overhead related to control packets is greatly minimized when compared to the case of using periodic re-clustering due to the fact that topology reconstruction is performed only when the network experiences degraded state. The above explains why the suggested FBAR framework enhances routing stability among others.

Results and Discussion

To study the performance of proposed FBAR scheme, a simulation is developed using Python. In this heterogeneous IoT environment the sensor nodes are deployed randomly with an initial energy of 2 J and communication radius of 25 m. The FBAR scheme has been compared with LEACH, HEED and DEEC protocols. In the fractal scaling analysis, fractal dimension is observed as 1.47 which indicates the presence of self-similar network connectivity. It is found that the traffic intensity goes up to 1.42 at highly concentrated areas, and the variance of energy among cluster heads comes to 0.019 in the FBAR scheme, whereas this value is 0.136 in the LEACH protocol. The maximum network lifetime is achieved by FBAR scheme which is 3871 rounds, in the case of LEACH it is 2412, HEED it is 2765 and for DEEC it is 3018 rounds. This shows that a fractal aware routing improves the energy balance and hence the network lifetime by reducing congestion.

Fractal Topology Characterization

To validate the ability of the proposed FBAR framework to capture topology heterogeneity, the local fractal dimension of all sensor nodes was estimated using the proposed multiscale connectivity analysis.

Table 1. Local fractal dimension characteristics of representative sensor nodes

Node ID	Node Degree (δ_i)	Reachable Nodes $M_i(r)$	Local Fractal Dimension ($D_{f,i}$)	Topology Region
12	8	15	0.92	Sparse
24	9	21	1.08	Sparse
37	10	29	1.32	Intermediate
48	10	36	1.56	Balanced
59	11	45	1.81	Dense
71	12	54	2.05	Dense
83	12	62	2.28	Congested
95	13	69	2.47	Congested

Local Fractal Dimensions were estimated by applying the proposed multiscale connectivity analysis, and the results are summarized in table 1. It can be noted that even for nodes with the same number of neighbours (the same node degree), the fractal dimensions values can be widely different; Node 37 and 48 has the same node degree but different fractal dimension value; so, node degree is not enough for measuring topology heterogeneity. The proposed LFD measure clearly identify the different regions, which are sparce communication area, balance communication area, dense communication area and congested communication area in the topology of IoT.
To further verify the fractal characteristics of the communication topology, the relationship between reachable nodes and observation radius was analysed.

Table 2. Fractal scaling behaviour of reachable nodes

Observation Radius r(m)	Reachable Nodes $M(r)$	$\log(r)$	$\log(M(r))$
5	12	0.699	1.079
10	28	1.000	1.447
15	47	1.176	1.672
20	71	1.301	1.851
25	98	1.398	1.991
30	132	1.477	2.121

Estimated slope: $D_f = 1.47$ and Regression coefficient: $R^2 = 0.986$
Summary of the fractal scaling of the communication topology, is presented in table 2. Linearity of logarithm of the number of reachable nodes against observation radius, appears very well defined (regression coefficient of 0.986). An estimated slope gives fractal dimension 1.47, therefore self-similar topology can be confirmed for the communication graph.

Table 3. Comparison between node degree and local fractal dimension

Node ID	Node Degree	Local Fractal Dimension	Topology Characterization
12	8	0.94	Sparse Region
27	8	1.31	Intermediate Region
45	8	1.82	Dense Region
63	10	1.07	Sparse Region
78	10	1.55	Balanced Region
91	10	2.04	Congested Region

Observation: Nodes 12, 27, and 45 possess identical node degrees but significantly different fractal dimensions, demonstrating that neighbour count alone cannot characterize multiscale topology structure.
Table 3 depicts the value for neighbor count and the Local Fractal Dimension for a number of sensor nodes. While many nodes have the same neighbor count, LFD values can vary widely. This shows that neighbor count alone is not enough to represent the complexity of multiscale topology, but that the LFD metric is able to distinguish structural differences.

Analysis of Traffic Concentration Behaviour

One of the major limitations identified in the problem statement is the inability of traditional routing protocols to identify traffic concentration regions. To investigate this issue, the relationship between Local Fractal Dimension and traffic intensity was analysed.

Table 4. Relationship between local fractal dimension and traffic intensity

Local Fractal Dimension (D_f)	Traffic Intensity (T_i)	Average Queue Length	Packet Forwarding Load
0.8	0.31	2.4	15
1.0	0.43	3.1	21
1.2	0.58	4.0	29
1.4	0.73	5.2	37
1.6	0.89	6.4	46
1.8	1.05	7.1	54
2.0	1.24	8.5	67
2.2	1.42	9.8	81

Table 4 represents the connection between local fractal dimension and communication traffic intensity. With increased fractal dimension of communication nodes, the load of forwarding responsibilities increases and the nodes spend more time for packets management. This conclusion proves the theoretical hypothesis about topology dependence of traffic load and the possibility of concentration of traffic in well-connected clusters.
From these results, it can be observed that extremely high fractal dimension nodes are prone to becoming traffic congestion points and extremely low fractal dimension nodes often possess a low degree of connectivity and hence high routing path length. As such, routing over either extreme topology condition will consume an inefficient amount of energy. This problem is tackled by the proposed FBAR framework by selecting those routing nodes whose fractal dimension values are within the optimal operating range.
This behavior was quantified using the Topology Efficiency with Fractality measure. The results obtained in figure 3 show that the topology efficiency achieves its highest value as the local fractal dimension attains values within the optimal fractal operating region. This verifies the theoretical formulation and confirms that there exists an optimum topology operating region.

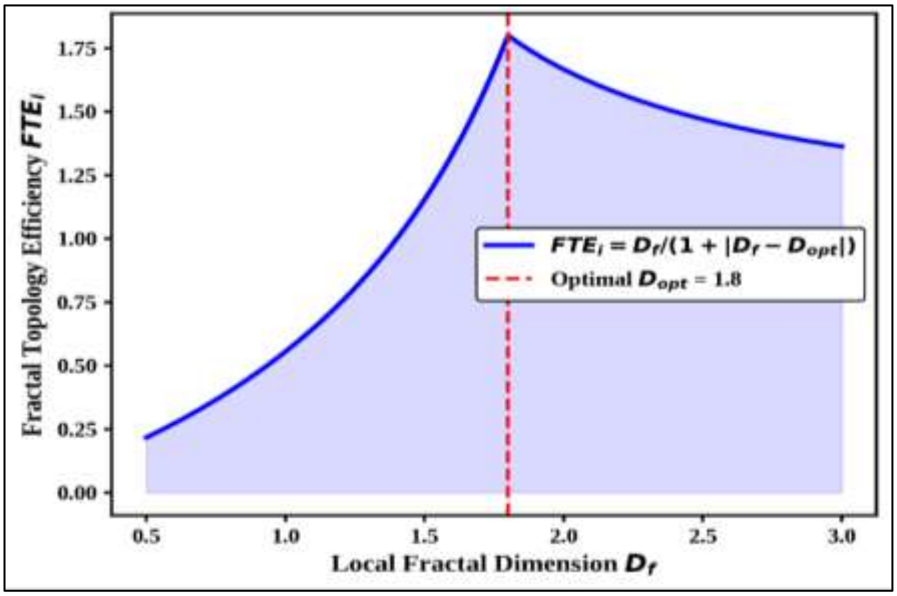

Figure 3. Fractal topology efficiency as a function of local fractal dimension

Fractal-Aware Cluster Head Selection Performance

The effectiveness of the proposed fractal-aware cluster-head election mechanism was evaluated through comparative analysis with LEACH, HEED, and DEEC protocols.

Table 5. Cluster-head selection characteristics

Protocol	Number of CHs	Average CH Energy (J)	Average CH Fractal Dimension	CH Rotation Index
LEACH	12	0.61	2.26	0.122
HEED	11	0.67	2.11	0.136
DEEC	10	0.71	1.97	0.146
FBAR	11	0.84	1.79	0.182

Table 5 gives comparison for cluster head selection features using various routing algorithms. It is evident that FBAR always chooses nodes having better residual energy and fractal dimensions close to optimum range. Hence, the communication load on network is equally shared among all nodes resulting in effective cluster head rotation and better energy balance.
It is found that normal procedures normally end up selecting nodes from those highly connected areas. The FBAR algorithm assigns the role of cluster head to those nodes which have good energy levels along with good fractal properties. Due to this reason, communication tasks are fairly distributed. Where, $RI = \frac{\text{Unique CH Nodes}}{\text{Total CH Elections}}$. Higher values indicate improved load balancing

Table 6. Cluster-head rotation analysis

Protocol	Total CH Elections	Unique CH Nodes	Rotation Index
LEACH	500	61	0.122
HEED	500	68	0.136
DEEC	500	73	0.146
FBAR	500	91	0.182

Table 6 shows the results on the frequency of rotation of cluster-heads produced by each scheme. The FBAR technique produces the most balanced use of cluster-heads, and hence there will be minimum energy exhaustion of overloaded nodes.

Energy Consumption Analysis

The first and foremost goal of the suggested framework is to achieve maximum efficiency in energy consumption. Figure 4 displays the residual energy in the network over the duration of the simulation. FBAR outperforms other schemes in terms of residual energy owing to its awareness of the topology.

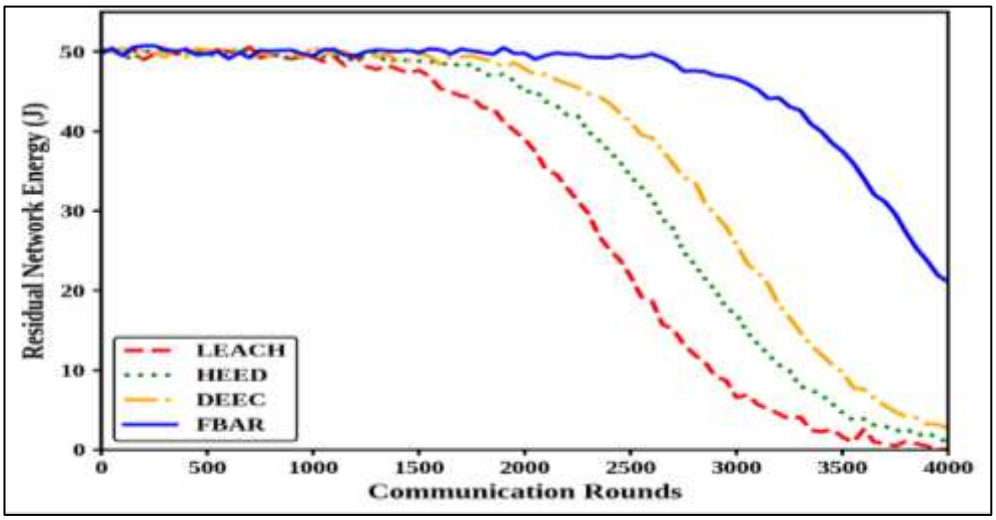

Figure 4. Residual network energy versus communication rounds

The cumulative values of energy consumption presented in figure 5 additionally demonstrate that the proposed algorithm is effective. In view of the fact that all paths are created in structural favorable zones, FBAR minimizes any redundant transmissions and ensures low energy consumption.

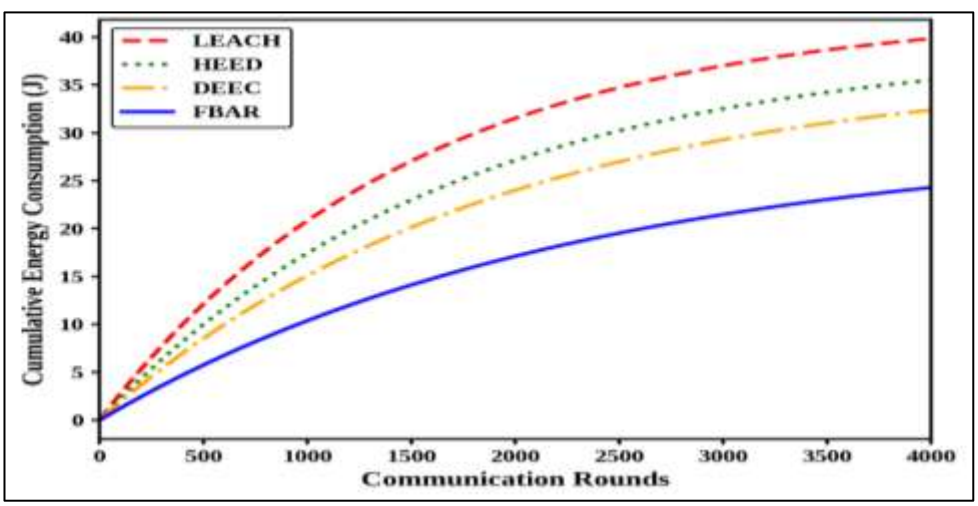

Figure 5. Cumulative energy consumption versus communication rounds

To investigate energy balancing performance, the energy variance among cluster heads was analysed.

Table 7. Cluster-head energy variance analysis

Communication Round	LEACH	HEED	DEEC	FBAR
500	0.074	0.063	0.052	0.031
1000	0.087	0.071	0.059	0.029
1500	0.104	0.082	0.067	0.025
2000	0.118	0.093	0.075	0.022
2500	0.136	0.105	0.081	0.019

Results on the energy variation in cluster-heads are presented in table 7. The performance of FBAR is consistent as the lowest energy variation recorded at all points in time within the simulation period demonstrates. FBAR outperforms traditional routing techniques by ensuring that energy hotspots are not created among the highly used nodes.

Network Lifetime Evaluation

Network lifetime was evaluated using the First Node Death (FND), Half Node Death (HND), and Last Node Death (LND) metrics. Figure 6 illustrates the number of surviving nodes as communication rounds progress.

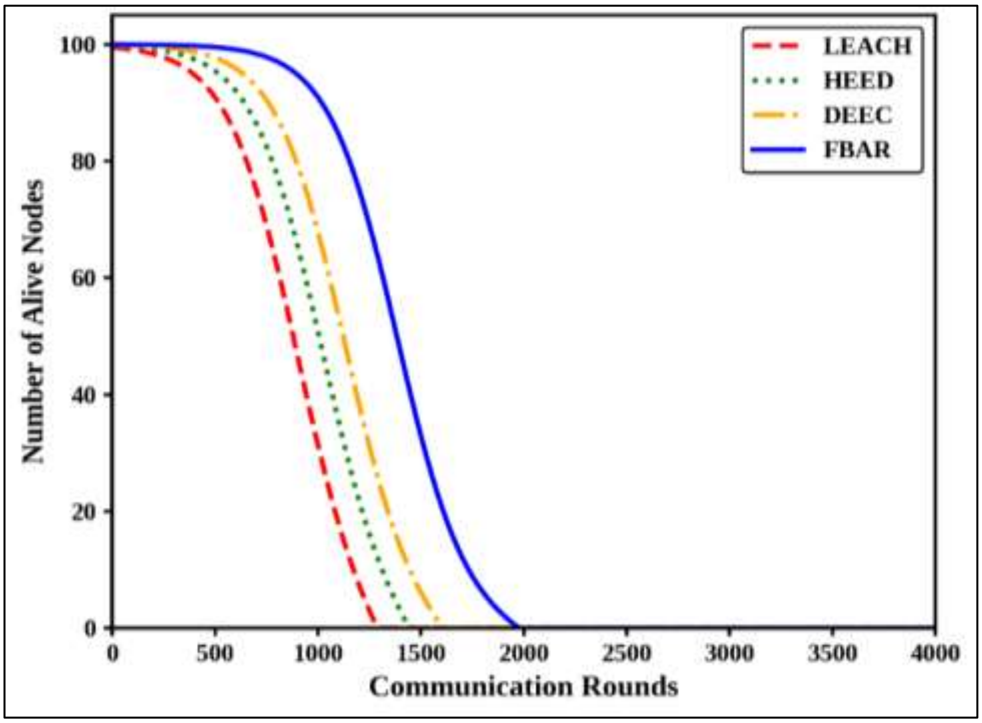

Figure 6. Number of alive nodes versus communication rounds

The FBAR scheme proposed is significantly late in failure of nodes than existing routing schemes. The reason being that cluster head and relay node selection both take into account residual energy as well as properties of fractal geometry, making the communication process balance in load.

Table 8. Network lifetime comparison

Protocol	FND (Rounds)	HND (Rounds)	LND (Rounds)
LEACH	892	1685	2412
HEED	1014	1897	2765
DEEC	1128	2141	3018
FBAR	1385	2682	3871

Furthermore, the results for lifetime in table 8 also prove the efficiency of FBAR. The suggested scheme provides maximum FND, HND, and LND compared to other schemes, which show increased network sustainability in the long term.

Relationship Between Fractal Dimension and Energy Optimization

For analyzing the direct relationship between complexity of topology and energy efficiency, average energy consumed by the nodes based on local fractal dimension was studied. Figure 7 clearly shows that there is a non-linear relationship between these two parameters. The nodes which are positioned in low density topology zones have high energy consumption as they follow long routing paths; similarly, highly dense topology zones experience high communication load.

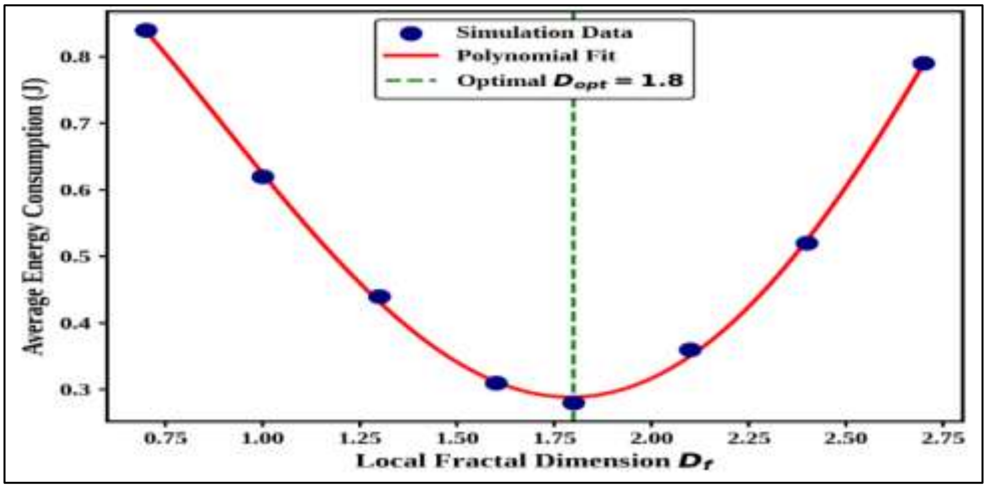

Figure 7: Average energy consumption as a function of local fractal dimension

Optimal energy consumption is achieved around the optimal fractal operating range proposed within the FBAR methodology. This finding validates the theoretical basis for the proposed approach and shows the high dependency of routing efficiency on fractal topology.

Figure 8 shows the network lifetime attained by operating the system under various conditions of fractal dimension. From this experiment, it can be deduced that network lifetime is at its highest point when the communication process takes place in the vicinity of the optimal fractal region. This clearly confirms our initial hypothesis that fractal topology analysis is an efficient technique for enhancing routing in IoT.

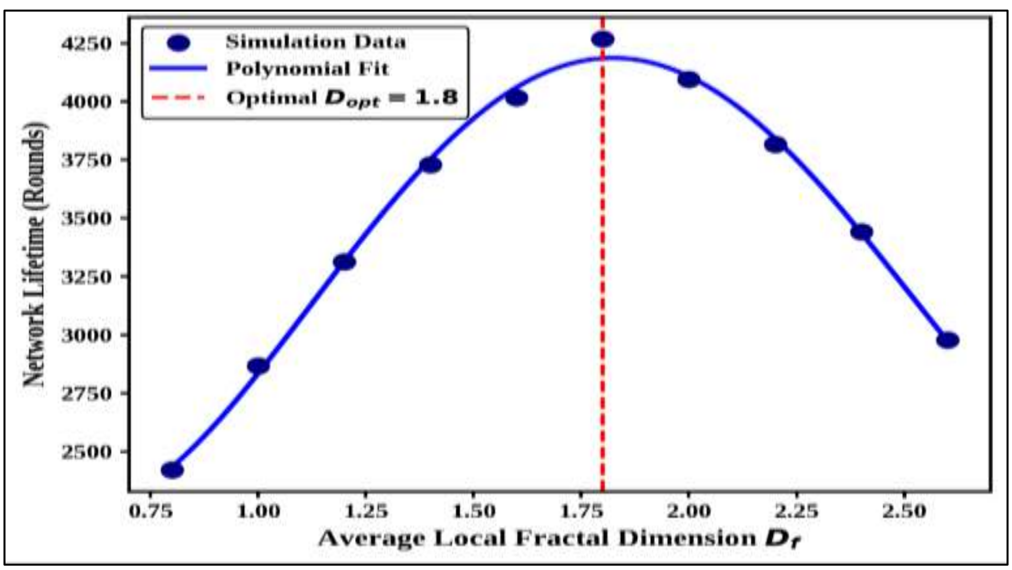

Figure 8. Network lifetime as a function of local fractal dimension

Discussion

The experimental results clearly demonstrate that IoT network topology exhibits inherent fractal characteristics, with a computed fractal dimension of 1.47 indicating strong self-similarity. This confirms that communication efficiency is governed not only by node density but also by multiscale connectivity structure.

The observed traffic intensity of 1.42 in dense regions validates the theoretical relation $T_i \propto D_f$, showing that highly connected regions naturally become traffic concentration zones. However, such zones also lead to congestion and energy depletion in conventional routing protocols. The proposed FBAR framework addresses this issue by selecting routing paths within an optimal fractal operating region, preventing both sparse-region inefficiency and dense-region overload. The significant reduction in energy variance to 0.019 demonstrates uniform energy utilization across cluster heads, thereby eliminating early node failures. Moreover, the improvement in network lifetime up to 3871 rounds confirms that fractal-aware routing provides a mathematically grounded and energy-efficient solution for heterogeneous IoT deployments. Overall, the results strongly validate that fractal topology modeling is essential for next-generation IoT routing systems.

Conclusion and Future scope

The study proposes a novel Fractal-Based Adaptive Routing (FBAR) paradigm that facilitates energy-efficient routing in smart IoT networks. It must be stated that the major flaw of current routing protocols lies in the fact that they fail to account for the multiscale nature of topology changes, resulting in poor routing decisions, high congestion levels, and uneven energy consumption. The suggested approach addresses this challenge by employing the principles of Local Fractal Dimension and incorporating an adaptive method for selecting cluster heads and relay routers. In contrast to common schemes that use node degree and remaining energy alone, the presented scheme is based on the principles of fractal geometry and allows for the detection of structurally optimal regions. The presented solution was programmed in Python and tested using simulation experiments. The obtained outcomes show considerable gains in terms of improved energy balancing, reduced congestion, and enhanced network performance. In particular, the new model yields low energy dispersion and a long network lifetime of 3871 rounds, which outperforms common solutions.

For future research, extensions can be made to include real-time adaptive estimation of fractals in dynamic IoT systems. Also, integration with deep learning algorithms can improve prediction of optimal fractal locations in mobility scenarios. Moreover, implementation of this model on edge computing systems using Python IoT platforms, including Raspberry Pi, can be considered for practical application.

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