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Fuzzy Logic based Efficient Data Aggregation Scheme for WSN with Mobile Sink

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Abstract:

To develop an energy-efficient practical algorithm to aggregate data in a WSN is a widely acceptable problem in the literature. Generally, data aggregation is performed by the cluster heads (CHs), and CHs transmit this aggregated data to the sink. These CHs can deplete their energy rapidly during this period. The proposed scheme is a fuzzy-based reinforcement-learning technique for selecting data aggregator nodes in a WSN with a mobile sink. Virtual grid construction divides the network into uniform cells. Furthermore, a fuzzy logic-based reinforcement-learning algorithm selects a data aggregator node for each cell. Establishing a virtual backbone network of CHs initiates the mobile sink's movement along a predefined, relatively optimal path within the network. Experimental results after the implementation reveal that the presented scheme improves the stability of the network and increases its overall lifetime.

Keywords: Mobile sink, network lifetime, reinforcement learning, virtual grid, WSN

1. Introduction:

WSN has been a primary research area for decades for monitoring applications. Still, sensor network nodes contain very restricted resources such as storage, speed, and power (Kulkarni et al., 2010). The sensor node's lifetime completely depends on its energy. This energy of the node is used to aggregate environmental data. It transmits directly to a neighboring node or sink (Ozdemir, S. & Xiao, Y., 2009). By minimizing the total data transfer between nodes, the WSN's lifetime can be extended. Sensor nodes rely entirely on batteries for power, which may not be recharged or replaced due to their placement in challenging areas. By optimizing the power usage of these nodes, we can reduce rapid energy exhaustion and enhance the network's functional time (Yu et al., 2009).

WSN applications, utilized for investigation and surveillance, often generate significant redundant data (Xu et al., 2010). In literature, some cluster approaches are used for the aggregation of this extensive and wide range of data (Jesus et al., 2014). An efficient data aggregation scheme is required to control the network's data and improve energy conservation (Al-Karaki et al., 2009). After combining the sensor node's data, redundancy removal is carried out to reduce the amount of data transfers towards the sink node (Maraiya et al., 2011). A selected number of nodes participate in data transmission towards the sink in a good aggregation scheme (Aslam et al., 2011).

Several algorithms are used for data aggregation in WSN (Sanjay et al., 2020; Han et al., 2015; Zhu et al., 2015), including "fuzzy reinforcement learning-based energy-efficient data gathering (FR-EEDG)" and "tree grid-based data gathering algorithm (TCBDGA)". The issue with the current methods is that data aggregation is the responsibility of the CHs. As the same CHs communicate the accumulated data toward the sink node either directly or indirectly, they drain out energy soon. As a result, a high-node density network reduces the network's lifetime and maximizes the consumption of energy (Mishra, S. & Thakkar, H., 2012). These methods are also not suitable for mobile sinks. To address the issues stated above, we create a data aggregation strategy that is energy-efficient and appropriate for WSNs with mobile sinks.

Here, a data aggregation scheme is proposed to use energy efficiently. This scheme is applied on a virtual grid-based WSN with a mobile sink (MS). It uses fuzzy reinforcement learning technique for aggregating the data. A virtual grid is created by dividing the network area into K clusters of equal size. Then a virtual backbone network is constructed in this scheme that consists of all the elected CHs. The proposed scheme uses a fuzzy inference system for the selection of the data aggregator nodes by considering algebraic connectivity (AC), neighborhood overlap (NOVER), and distance of a node from the current CH as the parameters. Finally, the data aggregator node is selected by using the reinforcement learning algorithm. The aggregator node accumulates data within the cluster and transmits accumulated data to the CH of the cluster. Over the virtual backbone network, CHs report this data to the mobile sink. Sink mobility incurred the route re-adjustment cost, but the virtual backbone network minimized this cost. For collecting the data periodically from the network area, this scheme selects a predefined path for a mobile sink that reduces the re-adjustment cost and helps in an improvement of the network lifetime.

2. Related Work

In a WSN with a significant number of nodes, the role of data aggregation became very important. Numerous schemes have been suggested in the literature for efficient data aggregation.

Xu et al. (2015) have proposed a "Hierarchical Sensor-Based Data Aggregation (HDACS)" method for WSNs. On the basis of cluster size, the approach establishes a number of compression thresholds, optimizing the amount of data transmitted at various levels of data collection. Based on simulation results, HDACS outperforms previous approaches in terms of signal recovery performance and offers considerable savings in energy.

A tree-based data aggregation method that makes use of approximation methods and NP-completeness to reduce energy expenses has been presented by Kuo et al. (2015). The overall energy cost of data transmission is reduced through the creation of a data aggregation tree. They discovered that in the worst situations, neither the Steiner tree approach nor the shortest-path tree algorithm performs well when relay nodes are taken into account. Simulations, however, suggest that a tree structure may be more energy-efficient than a non-tree structure for data aggregation that incorporates relay nodes.

The flow-based layer selection strategy for WSNs is a tree-structured data aggregation method that was proposed by Navaz, A. S., & Nawaz, G. K. (2016). Using the present flow of streams as a basis for layer selection and data transmission management, this scheme calculates the rate of flow of data streams at each layer. The method selects neighboring nodes in a layer randomly according to the energy exhaustion factor of nodes in neighboring layers.

To increase the effectiveness of data aggregation, a fuzzy logic-based scheme for distributed WSNs has been developed by Sert et al. (2018). Member nodes of each cluster deliver their sensed data to cluster heads (CHs) that subsequently aggregate sensed data. CHs transmit aggregated data to the sink by using the multi-hop CH transmission method, which can lead to the energy-hole problem. This protocol extends the network lifetime and demonstrates improved energy efficiency.

To improve packet delivery rates and shorten delivery times, Sharma et al. (2022) suggests a routing method for WSNs that makes use of reinforcement learning (RL). By efficiently balancing energy consumption across WSN devices, the suggested technique, known as ReLeC, contributes to increased scalability and network lifetime.

The TCBDGA algorithm has been introduced by Zhu et al. (2015) to increase the lifetime of WSNs with mobile sinks. This algorithm uses tree-based clustering for data collection. This approach builds clusters with parent and child nodes using a tree clustering procedure that depends on node weights. A rendezvous point (RP) is the root node found in any tree-based cluster.

3. Model Description

3.1 Network Characteristics

It is important to highlight the different sensor network assumptions before going into detail about our scheme. We presume the following network characteristics.

The homogeneous sensor nodes are positioned at random in the network area, and these nodes remain static. All these nodes also have information about their location. The adaptation of the transmission power of nodes depends on the distance of the node from communicating nodes. There are no resource limitations for the mobile sink, as it has unlimited power or energy. The MS periodically accumulates data from all CHs indirectly. When the MS moves along the internal edge of the clusters on the border of the network area, it communicates with the cluster heads of nearby clusters to collect data. For energy, the first-order radio model has been adopted (Nuruzzaman, M. T., & Ferng, H. W., 2016).

4. Proposed Scheme

To lengthen the network lifetime and optimize energy utilization, an energy-efficient data aggregation scheme is proposed, as shown in figure 1. This is achieved using virtual grid clustering combined with a fuzzy reinforcement algorithm. Initially, the sensor network is partitioned into grid cells or clusters. Once we divide the network area into clusters, we select the CHs. Initially, the node closest to the cluster's center is considered the CH for that cluster. After initial CH selection, a virtual backbone structure is established, and initial communication routes are set to handle data transmission between the clusters. Then, a data aggregator node is selected for each cluster using a fuzzy rules-based reinforcement learning algorithm, which evaluates three parameters: CH distance, number of overlapping nodes (NOVER), and aggregation capability (AC).

Due to sink mobility, the topology of the network becomes dynamic. Therefore, data communication routes must be updated with respect to the most recent position of the sink. In this scheme, only the CHs that make up the virtual backbone structure are required to update new routes toward the most recent mobile sink's location, as in VGDRA (Khan et al., 2014). As shown in figure 2(a), for collecting data periodically, the mobile sink moves at the inner edge of the clusters, which touch the outer border of the network area. To aggregate the data of clusters, an aggregator node is elected for every cluster that, after aggregating the data, sends it to the CH of its cluster. In the proposed scheme, the mobile sink accumulates data from the CHs of adjoining clusters of intersection points. When the mobile sink reaches an intersection point, it announces its presence to the CHs of adjoining clusters. These CHs, called Originating Cluster Heads, shares the information of the sink's presence with the rest of the CHs.

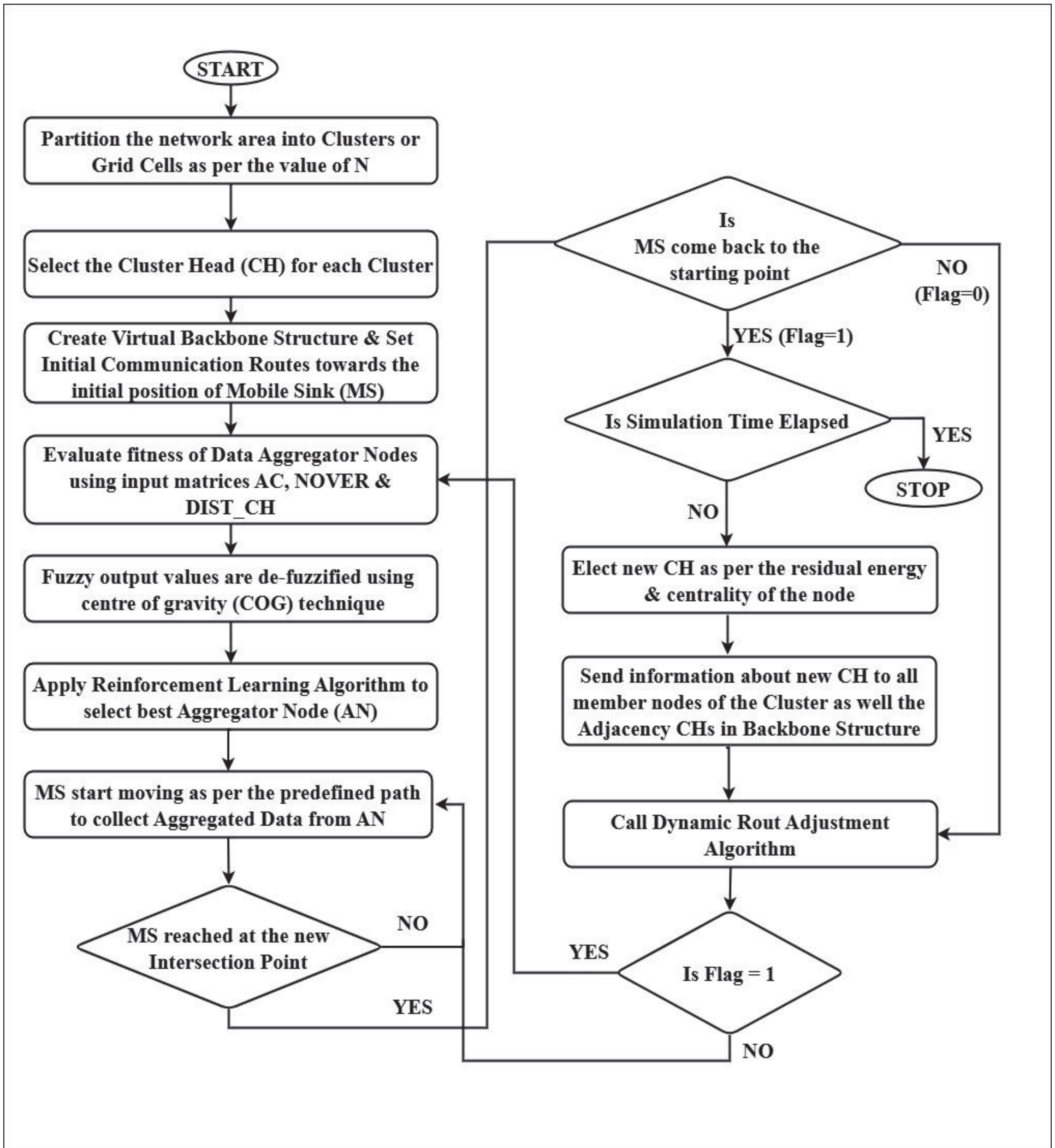


Fig. 1: Proposed virtual grid-based efficient data aggregation scheme.

These are four major steps taken by the proposed scheme.

- Virtual grid-based cluster construction and selection of CH are performed.
- A virtual backbone structure is established, and an initial communication route setup is performed to handle data transmission between the clusters.
- Reinforcement-learning based on fuzzy systems is modeled for aggregator node selection, which depends on three variables: AC, NOVER, and distance of CH from the node.
- Mobile sink moves on a predefined path and accumulates data from the CHs of adjoining clusters of intersection points.

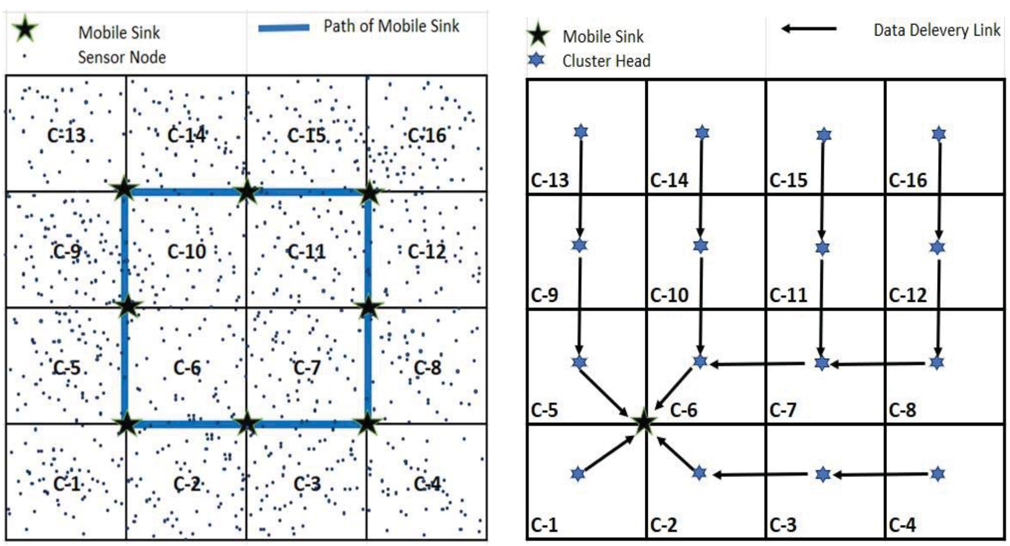


Fig. 2: a) Proposed path for the mobile sink. b) Initial route setup for grid cells.

4.1 Construction of Virtual Structure

For the virtual structure construction, the proposed method is using the scheme that is same as used in VGDRA (Khan et al., 2014). The network area is split into uniformly sized cells, or clusters. According to the total number of nodes that are present in the network area, the total number of clusters is determined.

This uniform division consequently improves network lifetime due to the uniform distribution of the workload on CH nodes. To distribute the network load, nearly 5% of the total nodes are selected as CHs (Heinzelman et al., 2002). After dividing the network area into clusters, CHs are selected. The node that is nearest to the cluster center is initially chosen to serve as the CH.

4.2 Virtual Backbone Structure Construction and Initial Route Setup

Following the initial CH selection, every CH broadcasts its new state to the nodes immediately surrounding it in the cluster and just a little bit outside of the boundary of the cluster. Nodes of any cluster may receive CH notifications from the CH of the same cluster as well as from the CH of other clusters also. Nodes associate themselves to the primary CH of the same cluster. Suppose member nodes receive notifications from the CHs of other clusters. In that case, they notify their primary CH about these secondary CHs. With the help of this information about secondary CHs, adjacency infrastructure is developed between the neighboring CHs. This mesh-like adjacency infrastructure is called virtual backbone structure. After the initial CH selection and virtual backbone structure establishment, the proposed scheme sets initial communication routes, as shown in Figure 2(b). If x and y are considered as dimensions of one cluster, then initially the mobile sink is located at the coordinates (x, y).

4.3 Selection of Data Aggregator Node

A data aggregator node (AN) is selected by using fuzzy rule-based reinforcement learning algorithms. This algorithm considered the distance of CH from the node and its link quality estimation metrics, including the number of overlapping nodes (NOVER) and aggregation capability (AC), as inputs for a fuzzy rule system. One direct measure that is frequently used to find out the quantity of neighborhood nodes that exist between the two connected nodes is called NOVER. The first node of the pair with the highest NOVER score is the one that is most likely to be chosen as an AN. The strength of link connectivity between the nodes is measured by a numerical value known as the AC of the node-link. Node-links with greater AC values have a better chance of becoming AN. IF-THEN rules are created using the fuzzy logic system for these metrics using a triangle membership function.

Input Metrics: AC, NOVER, and CH_DIS are the metrics that are utilized in the fuzzy rule system in order to determine whether or not the data aggregator node is suitable for assessment.

Fuzzification Step: The fuzzifier transforms crisp values of the input metrics into the corresponding linguistic variables and membership functions.

IF/THEN Rules Mapping: The Inference Engine maps the fuzzy values of AC, NOVER, and DIS_CH to predefined IF/THEN rules using a knowledge rule base. This mapping yields a fuzzy output value by ranking each sensor node's suitability to be a data aggregator node. Very poor, poor, unfavorable, acceptable, good, and very good are among the linguistic variables of the result. The fitness value is {very poor, poor, unfavorable, acceptable, good, very good} if AC is {weak, normal, strong}, NOVER is {low, medium, high}, and DIS_CH is {near, medium, far}.

Defuzzification: Using predefined output membership functions, fuzzy output values are de-fuzzified into appropriate numerical values. For this conversion, the center of gravity (COG) technique is used. Mathematically, COG is defined as follows:

$$x_{COG} = \frac{\int x\mu_A(x)\,dx}{\int \mu_A(x)\,dx} \tag{5}$$

Here 'x' is the sample element, 'A' is a fuzzy set, and the membership function of element 'x' is represented by $\mu_A(x)$ for the fuzzy set 'A'. The x_{COG} represents the evaluated de-fuzzified value.

4.4 Fuzzy-based Reinforcement Learning

The incorporation of the fuzzy-based reinforcement learning algorithm ensures proper selection of aggregator nodes. This algorithm assists in determining the suitability of a node for selection as an aggregator node. Cluster member nodes act as the learning agents, and the entire network is regarded as the environment. By exchanging beacon signals with one another, these agents learn about the environment. Every node selects a root node to facilitate data aggregation and transmission. Every node keeps a Q table to store the action values. Action values called Q-values are represented by $Q(s_t, r)$ help to decide whether a node r is the aggregator node or not in state s_t.

Every node must maintain a Q-value for each action and state. The present connection quality of the node is referred to as its state, and choosing to be a root node in order to maximize link quality with neighbor nodes is referred to as its action. The Q-table updates every five seconds. The mobile sink sends a beacon message, and all the unselected nodes update its Q-table. Each node initially sets its Q-value to 0. A node modifies its Q-value according to the following equation when it gets a beacon message from the mobile sink:

$$Q_m(s_t, r) = \lambda \times \ BQ(r, m) \ \times + \{R + \mu \times \max_{\mu \in N_r}(s_t + 1, \mu)\} \ + (1 - \lambda) \ \times Q_m(s_t, r) \qquad (6)$$

Here, BQ (r, m) represents the reception ratio of hello messages sent from mobile sink m to r. The left-handed Q-value notation $Q_m(s_t, r)$ indicates the current value, whereas the right-handed Q-value indicates the previous value. Nr indicates the number of nodes in the cluster, while s_t and s_t+1 represent the current and next states, respectively. $max_{\mu \in N_r}(s_t + 1, \mu)$ represent the maximum Q-value for a node r to be selected as an aggregator node. The value of the learning rate is considered 0.6, and the value of the μ discount factor is considered 0.8. The value of R called reward is calculated as:

$$R = \begin{cases} max(\frac{LQ_r}{LQ_{1r} \times |N_C|}, 1) & if\ m \in N_C \\ 0 & Otherwise \end{cases} \qquad (7)$$

Here, the set of active nodes in a given cluster is represented by N_C, LQ1r represents node 1's maximum attainable link quality, and the current node's computed link quality to the neighbor node is LQ_r. The reward is positive if good link quality is achieved by node r; otherwise, it is zero. Since obtaining the ideal Q function is difficult at first, performance optimization requires an iterative learning process.

4.5 Dynamic Routes Adjustment

As the sink is moving in the network area, network topology is dynamic, and data communication routes must be updated with respect to the most recent position of the MS. In the proposed scheme, only the CHs that make up the virtual backbone structure are required to update new routes toward the most recent position of MS, as in VGDRA (Khan et al., 2014).

As shown in figure 2(a), for collecting data periodically from sensor nodes, the mobile sink moves at the inner edge of the clusters, which touch the outer border of the network area. In the suggested scheme, the MS accumulates data from AN of adjoining clusters of intersection points. When the mobile sink reaches an intersection point, it announces its presence to the CHs of adjoining clusters. These CHs, called Originating Cluster Heads, share this information with the rest of the CHs.

5. Results And Comparative Study

The performance of the proposed strategy is evaluated by simulations conducted in MATLAB with N sensor nodes. The value of N varies from 100 to 600. The network field's area is measured at 200 x 200 m^2. Initially, the MS is located at the coordinates (x, y), where x and y are the dimensions of a single cluster. The proposed scheme has been compared with the existing "Topology-Control-Based Data Gathering Algorithm (TCBDGA)," "Fuzzy Reinforcement Learning-based Energy-Efficient Data Gathering (FR-EEDG) Algorithm," and "Grid Cluster-based FRS-RL (GCFRS-RL) Algorithm."

5.1 Packet Delivery Ratio (PDR)

PDR is a critical performance metric in WSNs. PDR measures the reliability and effectiveness of data transmitted by evaluating the ratio of received packets at the destination to the total number of packets transmitted by the source node. We use Equation (8) to determine PDR.

$$\text{PDR} = \frac{\text{Total number of packets received}}{\text{Total number of packets sent}} \times 100 \tag{8}$$

Figure 3(a) shows the evaluated results of PDR. Sensor nodes used in the experiment vary from 100 to 500 in number. The simulation findings indicate that an increase in the number of sensor nodes correlates with a drop in packet delivery ratio (PDR). We compare the proposed technique with alternative methods such as TCBDGA, FR-EEDG, and GCFRS-RL. The proposed technique outperforms alternative methods regarding PDR.

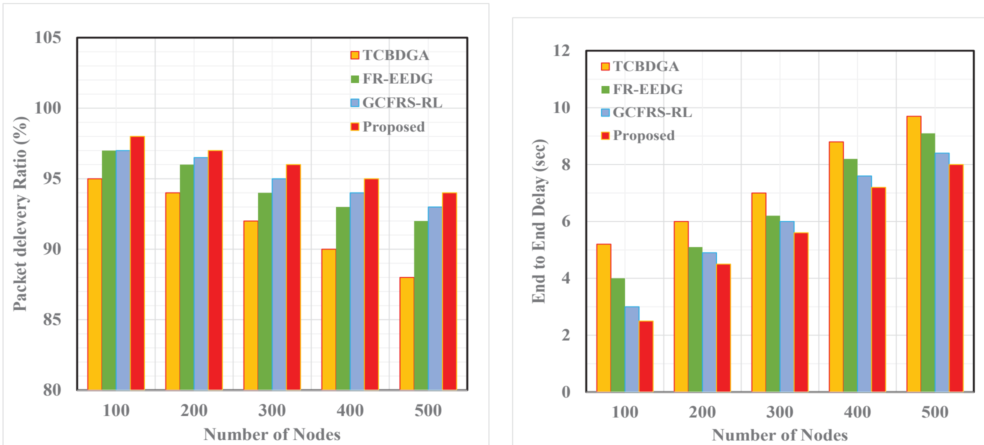


Fig. 3: a) Simulation results of PDR; b) Simulation results of end-to-end delay.

5.2 Route End-to-End Delay

In the context of a network, the term "end-to-end delay" refers to the length of time that is required to transport data from the source node to the destination node. Additionally included in it is the amount of time that was spent on both the reception and transmission of data packets.

$$End\_delay = d_{transmission} + d_{propagation} + d_{processing} + d_{queue} \tag{10}$$

Figure 3(b) illustrates the end-to-end delay. The findings indicate that the suggested method exhibits the lowest delay relative to the existing systems. The proposed strategy outperforms the alternative methods, as indicated by the simulation results.

5.3 Route Throughput

Throughput is the volume of data that is successfully delivered in a specific amount of time. It is a crucial indicator for assessing how well data is transmitted throughout the network.

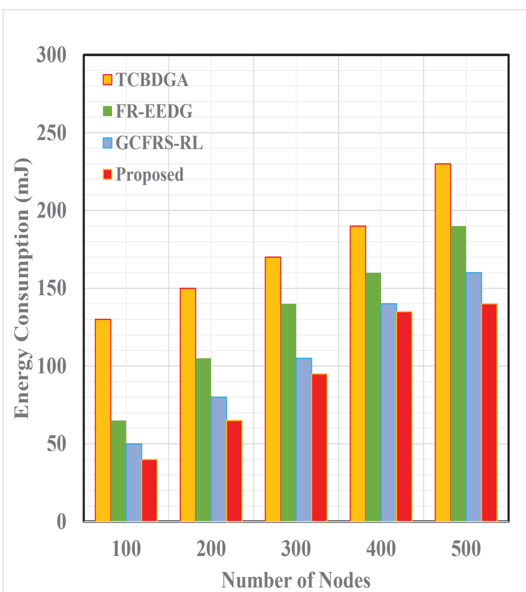
$$\text{Throughput} = \frac{\text{Packets successfully received} \times \text{Packet size}}{\text{Total time taken including delays}} \tag{11}$$

The evaluated results of throughput for the proposed scheme and various considered methods are shown in Figure 4(a). The simulation findings indicate that the proposed system surpasses the other three techniques in throughput for a network with 100–500 nodes. However, throughput diminishes with an increase in the number of nodes. The proposed strategy surpasses the other three methods for throughput, even in the case of a 500-node network.

5.4 Energy Consumption

The energy spent in the communication process significantly impacts the efficiency of data transmission and the overall performance of WSNs. Network lifetime and reliability are directly affected by the node's energy usage.

The total amount of energy used for different network sizes is shown in Figure 4(b). The proposed scheme consumes less energy than the other methods, as indicated by the simulation results. Networks with sizes of 100 to 500 nodes had been simulated for evaluating the energy consumption. The proposed scheme shows a consistent rise in energy consumption with an increase in node count.



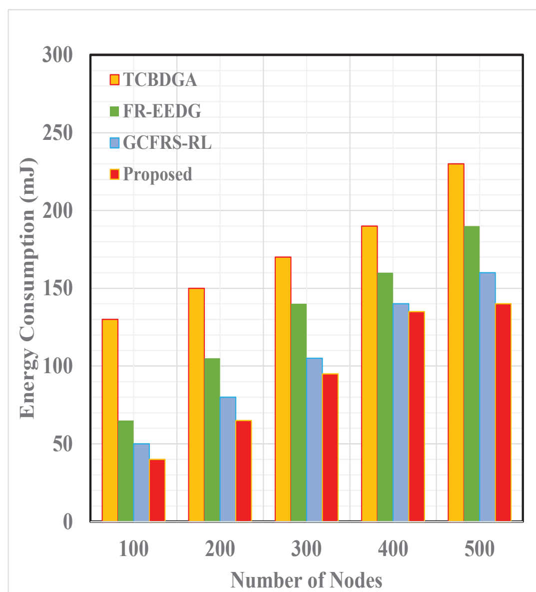


Fig. 4: a) Simulation results of throughput b) Simulation results of energy consumption

5.5 Network Lifetime

One important metric for assessing the effectiveness of WSNs is network lifetime. It denotes the duration the network may operate prior to the run out of energy in the first node. Figure 5 displays the simulation results for evaluating network lifetime. The findings indicate that, in comparison to other existing methods, the proposed scheme has a longer network lifetime. Among the methods under consideration, the TCBDGA method has the shortest network lifetime. Moreover, the network lifetime in every method reduces with an increase in nodes. The work load of the MS and the aggregator node is reduced as a result of sink mobility and the avoidance of duplicated data transmission. This results in a reduction in the amount of energy that is consumed and an improvement in the lifetime of the network.

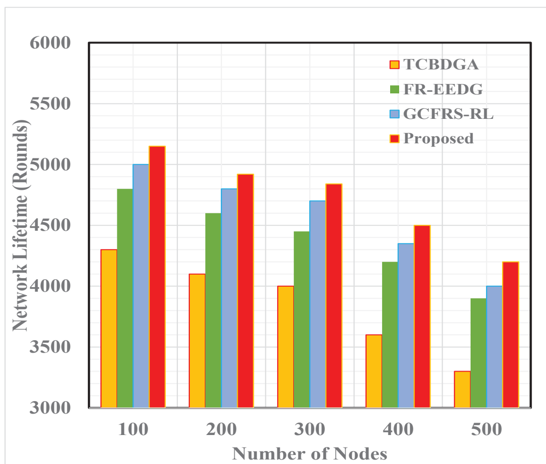


Fig. 5: Simulation results of network lifetime.

6. Conclusion

The suggested technique begins by partitioning the sensor network into uniformly spaced grid cells. Each grid cell is assigned a cluster head, who is in charge of transferring aggregated data to the mobile sink. Data aggregator nodes are in charge of accumulating data, which they subsequently provide on to the CH for further transmission. To pick the aggregator node within each grid cell, a reinforcement learning algorithm with a fuzzy rule system is used. In order to guarantee the selection of an ideal aggregator node, the proposed algorithm analyzes the following crucial parameters: AC, NOVER, and distance from CH. Furthermore, a mobile sink in the grid-clustered network architecture follows a comparatively small path so that it can directly collect the data from the four CHs of the adjacent clusters. The dynamic topology of the network is handled by streamlining the new routes towards the sink, which is required only for the CHs creating the virtual backbone structure. The efficacy of the proposed strategy is assessed based on end-to-end delay, throughput, energy consumption, network longevity, and packet delivery ratio (PDR). In comparison to existing schemes like GCFRS-RL, FR-EEDG, and TCBDGA, the suggested methodology consistently demonstrates enhanced performance across all metrics.

Conflict of Interest

The authors have not disclosed any conflicts of interest that are pertinent to the content of this article.

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