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QOS and Congestion Aware Routing Protocols with Data Aggregation Technique for WSN'S Assisted IoT

Manisha Chandrakar[1*], Dr. V. K. Patle[2]

[1]Research Scholar, PtRavishankar Shukla University, Raipur, C.G.*

[2]Associate Professor, Pt Ravishankar Shukla University, Raipur, C.G.

[*]Corresponding Author:Manisha Chandrakar[1*]

[1]Research Scholar, PtRavishankar Shukla University, Raipur, C.G.*

Email: [1]manishachandrakar00@gmail.com*

***Abstract*:** A wireless sensor network (WSN) has the potential to be a heterogeneous network, contingent upon its specific application. The energy constraint is a crucial concern within the field of WSN.In a WSN, the use of energy-aware routing protocols is crucial, however, those that just take into account energy parameters often struggle to effectively manage excessive energy consumption.The emergence of congestion in network nodes causes an increase in packet loss and energy usage. The routing algorithms should attempt to balance the load among the sensor nodes and maximize energy efficiency in order to extend the network lifetime.One of the best methods for agglomerating data across sensor nodes effectively is clustering. Frequent CH rotation in clustered networks is the key issue.In this study, we offer an energy-efficient data aggregation & congestion-aware routing method (EDCAR), which takes into account both energy optimization and congestion as two key characteristics during data aggregation in order to maximize network longevity, CH stability, and energy-efficient data aggregation.In this study, a method for choosing the cluster head of a WSN using the grey wolf optimization method is proposed. It takes into account a variety of criteria, including the node's energy level, degree, distance to the sink, distance within the cluster, and priority factor. In order to perform the efficiency requirements of a scalable WSN, collision-aware routing employing the seagull optimization method is also devised.Reduced energy usage at each node is achieved by the suggested collision-aware routing. When choosing congestion-free relays, the proposed seagull optimization method calculates fitness using queue length and network quality.The experimental data demonstrate that the proposed EDCAR scheme increases the network lifetime when compared to the current energy-efficient data aggregation systems.

Keywords: *WSN, Energy efficiency, Data aggregation, Congestion occurrence, Grey wolf optimization, Network lifetime.*

1. Introduction

The majority of tiny, affordable sensor nodes that make up WSNs are tiny [1]. The primary responsibility of the nodes is to produce various sorts of data and transfer them through single- or multi-hop data transmission methods to the Base Station (BS).Target tracking [2], combat monitoring, environmental monitoring, and other areas, where it is impractical to replenish the battery power of sensor nodes are only a few examples of where WSNs are utilized.As a result, the primary restriction in WSN that determines the network lifetime is the power consumption of sensor nodes.Sensing [3], computing and wireless communication are the three major functions of a sensor node. Communication in sensor nodes uses more power than sensing and processing combined.

Therefore, a variety of routing methods are implemented in WSN to reduce transmission to ultimately minimize power [4]. In a WSN, the base station, which is often in the center of the network, receives a flood of data from the sensor nodes. The data packet must travel a long distance if the sensor node is distant from the base station, which increases power consumption [5]. The bottleneck zone, which is a sensor area near the base station that experiences intense traffic, accelerates the battery drain on the node. As a result, the bottleneck zone's nodes experience quicker node death, which impacts network connection and longevity.

One of the effective and promising ways to increase energy efficiency is via clustering [6]. The CHs nearest the BS use more energy in multi-hop cluster-based WSNs. The CHs relay the data between other CH nodes in addition to collecting and delivering the data packets from its member nodes.This causes energy gaps and prompts network mortality in the CHs close to the sink because they exhaust their energy more quickly than those further away.Additionally, most known intra-cluster communication techniques involve member nodes of a cluster sending data directly to their respective CHs [7]. The nodes placed farther away from the CH need more energy to send their data packets since the energy consumption of member nodes relies on their transmission power.Consequently, when the distance between a member node and CH increases, so does the member nodes' energy consumption, with the result that the node that is the farthest away from CH runs out of energy faster than the others.

It is inefficient to use routing protocols that solely take energy into account [8]. A routing protocol is improved by employing more parameters in addition to energy efficiency. It is important to take into account different factors for various applications. Congestion control is one of the key variables.Network energy usage and packet loss increase when congestion occurs [9]. In networks, congestion may happen for a variety of causes. Lack of storage capacity in relay network nodes is one of the primary causes. A node experiences congestion when it gets more packets than it can handle, which leads to a large number of eliminated packets.Wireless sensor networks experienced congestion for much the same reasons. Congestion will develop, for instance, if many nodes opt to transmit packets utilizing a common media at the same time.

To address the above-mentioned problems, this paper introduces an energy efficient data aggregation and congestion aware routing strategy (EDCAR) to improve network lifetime, CH stability and data aggregation that uses less energy. For WSN, it employs cluster head selection approaches based on grey wolf optimization, taking into account variables such as node energy level, node degree, sink distance, intra-cluster distance, and priority factor. The seagull optimization algorithm is used for collision-aware routing, reducing energy consumption at each node. The algorithm uses queue length and link quality for fitness calculation to select congestion-free relays.

Contributions in this paper

- In IoT-based WSN, a hierarchical technique for data aggregation with consideration for congestion and energy efficiency is presented.
- Nodes with high energy and node centrality have greater advantages in the enhanced CH selection process, which favours them. By using this CH selection method, the likelihood of repeated CH selection is decreased.
- Selecting the data aggregation routing channel to CHs with the lowest cost while taking congestion and end-to-end delay into consideration.

2. Literature survey

Rani et al. [10] introduced MB-CBCCP protocol for IoT networks with WSN assistance.This method randomly chooses the next RNs from the nodes with the smallest distances, taking into account no distance-related criteria.As a result, there may be some RN overlap in different sensing areas. It results in increased RN engagement in that cluster. As a result, this results in increased system costs (caused by more nodes being chosen as RN) and wasteful resource consumption.The MB-CBCCP chooses the potential number of nodes as RNs beforehand, which is not ideal. Depending on the clusters' node densities, different clusters may have different numbers of RN selections.

Once again, it is divided into sets of g-size. These linked to these virtual infrastructure devices are known as in-line devices. The first-in-line device that encounters the device sends down the line its data, which is then kept by that device.An IoT device delivers data to the next-in-line device when it detects any data. A vertical request is sent to the virtual route by a hub whenever it needs data [11]. The first delivery is made by the aligned device along the line's path in both directions. The sensor devices that have the requested data send the data right away to the IoT hub after receiving the query.There are times when the number of queries sent exceeds the quantity of data. Data requests are sent across the network by LBDD via broadcasts [12].

A number of variations that enhance the performance of the LEACH technique are available.In using a set number of CHs in succeeding rounds and allocating CHs to clusters through a base station, Heinzelman et al. proposed LEACH-C [13]. In LEACH-F's setup phase, clusters only ever form once and last the whole network

[14]. In this arrangement, new IoT devices cannot connect to the network. By using single-hop communication, the network is managed by BS. Biradar et al. [15] suggestedamultihopLEACH, where the IoT hub serves as the root of an ideal multihop tree built amongst all CHs. Communication inside the network is handled through this route.Depending on the cluster size suggested by another version, MS-LEACH, one-hop and multi-hop communication is used for transmission by Qiang et al. [16]. Farooq et al. [17] suggested a MR-LEACH that separates the whole network region into layers based on the hop lengths between the cluster heads [17].

3. System Model

Radio Energy Model

In the experimental setup, the radio model operates by consuming energy for the operation of the radio-electronic components, such as the transmitter and power amplifier. Additionally, the receiver solely consumes energy for the operation of the radio-electronic components.As a result, the following energy will be used to send and receive k bit data:

$$E_{trans} = k(E_{ec} + E_{dis} * D)$$

$$E_{recv} = k(E_{ec})$$

E_{ec} Indicates the amount of electronic energy that is reliant on the coding, filtering, and spreading of the digital signal.E_{dis} D stands for the distance between the source and the destination and the energy expended during data transmission.

So, the total of the CH level energy used to aggregate the k bit data is as follows:

$$ECH_{agg} = E_{agg} * k * n$$

Here, $'k'$ how many bits are included in a package, $'n'$messages sent and received in number and E_{agg} is the energy required to send one data bit over a certain distance.

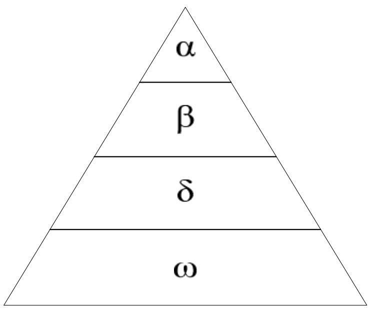
Proposed scheme

Grey Wolf Optimizer

The social structure and hunting habits of grey wolf packs served as the basis for the creation of the GWO algorithm. The population of grey wolves ranges from five to twelve on average. Wolves are classified into four categories: leader wolves (α), the second-best wolves (β), the third-best wolves (δ), and other wolves (ω), as shown in Figure 2. They decide how to hunt, when to relax, when to get up, and how to share food, among other everyday choices that affect α wolves.The primary responsibility of β wolves is to report to other α wolves about their performance in order to help them make judgments about their daily activity.δwolves are the followers of α and β wolves, mainly following the orders of α and β wolves, but can command the lower ω wolves. ωgenerally, wolves follow the directives of their superiors.

During a hunt, the prey's position is determined by wolves α, β and δ the remaining wolves determine how far apart they are from the prey before circling it. The formula used to determine the wolf's location is as follows:

$$\vec{X}^{t+1} = \vec{X}_p^t - \vec{A} \times \vec{D}$$



$$\vec{A} = 2 \times \vec{\alpha} \times \vec{r_1} - \vec{\alpha}$$

Fig 1. Grey wolf social hierarchy.

Where, $\vec{X}^{t+1}$ is the wolf's position in the $(t+1)^{th}$ iteration, $\vec{X}_p^t$ is the prey's position at the t^{th} iteration. $\vec{A}$is the convergence factor. $\vec{a}$gradually diminishes during the length of iterations from 2 to 0, and$\vec{r_1}$is an arbitrary vector with a [0, 1] range. $\vec{D}$is computed as follows to determine the distance away the wolves are from their prey:

$$\vec{D} = \left|\vec{C} \times \vec{X}_p^t - \vec{X}^t\right|$$

$$\vec{C} = 2 \times \vec{r_2}$$

where$\vec{X}_p^t$ and $\rightarrow$ $\vec{X}^t$position of the wolf and the location of the prey in thet^{th} iteration, $\vec{C}$the vectors of the coefficients, and $\vec{r_2}$is a random vector that ranges from 0 to 1.

The wolves in GWO that are closest to the prey are said to be the α, β, and δ. Additionally, they have the greatest hunting expertise, which allows them to find the target. Consequently, the following formula may be used to determine where the prey is.

$$\vec{X}_p^{t+1} = (\vec{X}_\alpha^{t+1} + \vec{X}_\beta^{t+1} + \vec{X}_\delta^{t+1})/3$$

where$\vec{X}_\alpha^{t+1}, \vec{X}_\beta^{t+1} and \vec{X}_\delta^{t+1}$where the α wolves, β wolves, and δ wolves are situated in the$(t+1)^{th}$ iteration, respectively. The locations of the other α wolves in the area of the prey will also be updated. Wolf fitness is the highest at the conclusion of the iteration periods. α Wolves are thus seen as the best way to fulfill the role.

According to GWO, all wolves are closest to their prey near the conclusion of the iteration, which is the ideal moment for the wolves to capture it.A node should be chosen as a neighbor node in a routing protocol if it has the minimum distance and aggregation cost. Since the BS is prey and the sensor nodes are wolves, this is how the suggested method works.

Proposed GWO-based CH selection approach

The data collecting, transmission, and reception procedures carried out by network nodes need energy. The CH nodes will use more energy than the other nodes in clustered networks since they transmit data, receive data from several sensor nodes, and aggregate the data gathered. For processing such activities, these nodes thus need more energy.It is necessary in this circumstance to pick CHs effectively. To increase the effectiveness of data aggregation, a consistent selection of CHs must be chosen.

The suggested GWO-based strategy is discussed in this section. The GWO-based approach involves three stages: Three steps are involved: initializing the wolves, calculating each wolf's fitness value, and updating the wolves' position and velocity.

Initialization of wolves:

Sensor node mappings to BS are used to represent each solution. The number of total sensor nodes determines the size of the solution. The approach offers a path for each node to get to the BS through network nodes that come after it.Initial random numbers are assigned to each sensor node $(R_{i,d}) = Rand(0,1)$where $1 \leq i \leq Ns$. Where, Nshow many initial solutions there are. A node number in the relevant solution is represented by the component d. It maps node$n_k$the BS from the next succeeding gateway in the routing routen_d, indicating that n_d sends data to n_k. The equation below represents the mapping of the routing route.

$$n_k = index(n_d, ceil\ (R_{i,d} \times |n_d|))$$

Where $index\left(n_d, \left(R_{i,d} \times n_d\right)\right)$the index of the nth node from is returned by the indexing function n_d. $ceil$ function computes the smallest integer of $\left(R_{i,d} \times |n_d|\right)$.

Determination of each wolf's fitness value:

Regarding the node energy level, node degree, sink distance, intra-cluster distance, and priority factor characteristics that are involved in the solution, the fitness function evaluates its quality.Alpha, beta, and delta solutions should be updated after each iteration. In this case, our innovative fitness function is made to provide an effective routing route from each sensor node to the BS.

Energy level of the node: The following formula is used to compute the node's residual energy:

$$E_{res} = E_{total} - (E_C + E_T + E_R + E_A)$$

Here E_{total} is total energy, $E_C$data collecting involves the use of energy, $E_T \& E_R$correspondingly the energy used for transmitting and receiving data and $E_A$the data aggregation process uses energy.

$$RE = \frac{1}{M} * \sum_{i=1}^{N} E_{res}(N)$$

Node degree: -The intra-cluster communication becomes a dominating force when the network area is large.If a node is chosen as the CH regardless of how many nodes are nearby, it will be chosen because it is far away from the other nodes.The quantity of nearby nodes is thus taken into account to prevent such selection.

$$ND = \frac{D_{ij}}{NUM_c}$$

D_{ij} is used to indicate the separation between nodes i and j; NUM_c represents the total number of nodes in the cluster.

Node distance to CH: -The amount of energy a communicating node uses is determined by distance.Node energy consumption decreases with decreasing distance between node and CH.So that the average distance between the sensor nodes and CH might be decreased, the CH selection techniques take care of this parameter.

$$D_n = \sum_{i=1}^{N} \left(\frac{D_{(N-CH)}}{D_{AVG(N-CH)}} \right)$$

$D_{(N-CH)}$denotes the node's distance from the CH in terms of Euclidean distance, while, $D_{AVG(N-CH)}$The metric denotes the mean separation between a node and the cluster head.

Priority factor: The possibility of becoming CH increases as priority increases. For a node to serve as the cluster head, this factor regulates its durability and network stability.All nodes initially have the same value for this parameter. Additionally, this alters as the round progresses.The following equation yields it,

$$PF = \frac{1}{1 + TN}$$

Where, the node's total number of CH selections is represented by its TN value.

The proposed fitness function is formulated in the following equation

$$f = {}^{K}\!/_{(\omega_1 \times RE + \omega_2 \times ND + \omega_3 \times D_n + \omega_4 \times PF)}$$

where$(\omega_1, \omega_2, \omega_3, \omega_4) \epsilon [0,1]$ such that, $\omega_1 + \omega_2 + \omega_3 + \omega_4 = 1$ and $K$is a constant of proportionality.

Updating velocity and position of wolves:

Each wolf (solution) must update its location in accordance with the positions of the alpha, beta, and delta wolves in order to approach the prey (optimum solution).The best solution from the current iteration is the delta wolf, whereas the best solution from the prior iteration is the beta wolf. In the GWO-based method, the alpha wolf is the overall solution in the solution set.We use the average of the revised locations for alpha, beta, and delta wolves as indicated in the following equation to update the positions of omega wolves:

$$\vec{X}_p^{t+1} = (\vec{X}_\alpha^{t+1} + \vec{X}_\beta^{t+1} + \vec{X}_\delta^{t+1})/3$$

Finally, after assigning new places, all of the solutions are reevaluated using the fitness function.

Reliable intra-cluster routing

This study introduces collision-aware routing that reduces the extra energy consumption at each node in order to achieve more reliable data transfer in WSN. The proposed seagull optimization algorithm uses Queue length & link quality for fitness calculation to select congestion-free relays.

Seagull optimization (SOA) algorithm

This section provides a thorough description of SOA. The family Laridae, which includes seagulls, is widespread across the biosphere.Seagulls are among the many varieties of marine birds, and they have appealing qualities including a strong hunting drive and persistence.Because of their distinctive migrating and hunting behaviors, seagulls are considered intelligent birds.Because of their unique characteristics and rapid decision-making skills, seagulls are preferred over other freshwater and marine birds. The migrating and attacking phases of the seagull optimization technique are both crucial.

Routing Using SOA

Using the SOA, this phase identifies the source node to destination collision-free ideal transmission route. The creation of the routing route is optimized using SOA, employing the following fitness metrics, such as queue length and connection quality. The path generation method includes several stages, including representation, initialization, the calculation of the fitness function, and an iterative procedure. Here are the specifics of these procedures.

Initialization of Seagull: A seagull is used to represent the likely answer to the SOA. According to the seagull population, there is a cluster head on the transmission route.The initialization of the SOA is expressed in the following equation, where the seagull's x and y coordinates are specific.

$$P_i = P_{i,1}, P_{i,2}, P_{i,3}, \dots . P_{i,d}$$

where$d$how many CHs are present in each transmission range, and$1 \leq P_{i,a} \leq d$the route's next CH is defined.

Fitness function:

The following are the parameters that were utilized in the route optimization:

Queue length (QL): -Queue length of a sensor node refers indicate how many packets the node has waiting to be sent. It is an important metric that indicates the congestion level and the efficiency of data transmission.As QL takes into account the congestion level of each node in the WSN-IoT, it is regarded as an important fitness metric when routing.

$$ql = \frac{R_{pkts}}{buffer}$$

Link quality (LQ): -The fading connection is often random and time-variant in wireless sensor networks. Retransmission takes place after the packets are incorrectly received by the recipient.The sensor node must use more energy during re-transmission. In order to achieve the necessary energy efficiency, the channel quality must be taken into account while controlling retransmission and energy usage. The formula below is used to determine the connection quality.

$$lq = \frac{RT_n - RT_{min}}{RT_{max} - RT_{min}}$$

Here, the RT_{max} andRT_{min} are, respectively, the maximum and lowest quantity of re-transmission from the nearby nodes. andRT_nrepresents the total number of times the node and its neighbours have sent data.

A single-objective fitness value is then created as illustrated below as a result of all the numerous objectives' fitness being in competition with one another:

$$fitness = \delta_1 \times ql + \delta_2 \times lq$$

where, $\delta_1, \& \delta_2$, are the 0.5-weighted weighted parameters, respectively.

Iterative Process: -The relay selection procedure is iterative and is as follows: the x and y coordinates of the next-hop CHs are sent to the seagulls when they are initially initialized with the routing route information.Based on the fitness metric, the best population of seagulls is determined among all of them. The remaining populations are updated depending on the best population (i.e., the optimum routing route) when the collision avoidance is completed.The seagulls' positions are also modified in accordance with the stage of exploitation. The locations are updated throughout this phase utilizing the optimal SOA solution. Last but not least, the suggested SOA offers the best route from the source CH to the destination node.

After determining the routing route using the SOA, the data packet transmission is started. Data is sent across the network through the node with reduced congestion using the collision-free route, which is created using the queue length.The value of the route is then determined using the transmitted and received packets and the connection quality. Therefore, the best collision-aware route for warning message delivery is chosen using these fitness values.

Energy analysis

Consider N to be the overall number of sensor nodes in the whole sensor area. There are k sensors in the cluster that is generated, hence there are k clusters in the separated area N/k. M bits of data are sent evenly by each sensor node. The energy necessary for transmission and reception'l' bits of data for distance $D_n$the sensor node is based on the Radio Energy Dissipation concept $E_{trans}\ (l,d)$ and $E_{recv}\ (l,d)$ respectively, such that

$$E_{trans}\ (l,d) = \begin{cases} lE_{ec} + l\varepsilon_{fs}d^2, & d \le d_0 \\ lE_{ec} + l\varepsilon_{mp}d^4, & d \ge d_0 \end{cases}$$

$$E_{recv}\,(l,d) = lE_{ec}$$

The route loss exponent n, where n is 2 for open space and 4 for multipath interference, determines the amount of energy needed for transmission.E_{ec}a single bit's energy consumption by the transmitter and receiver. 'd'how far apart the transmitter and receiver are. Here are the transmitter amplifier's energy requirements: ε_{fs},ε_{mp} depending on the exponent of the route loss. Considering that the sensor nodes aggregate data, the 'm'Data are combined into fewer total bits'h'. The model with centralized data aggregation (also known as Cluster Head) has the following energy consumption:E_{CD}. The suggested approach for doing data aggregation at the sensor node uses the following amount of energy:E_{SD}. The energy gainE_{gain} given a cluster, the result of the suggested approach is,

$$E_{SD} = m\left(E_{ec} + \varepsilon_{fs}d^2\right) + mE_{ec}$$

$$E_{CD} = h\left(E_{ec} + \varepsilon_{fs}d^2\right) + hE_{ec}$$

$$E_{gain} = E_{SD} - E_{CD}$$

$$E_{gain} = (2m-h)E_{ec} + (m-h)\varepsilon_{fs}d^2$$

Since there are N/kaggregations around the sensor. The suggested method's overall energy gain is indicated by

$$Total_{gain} = \left(\frac{N}{K}\right)E_{gain}$$

Algorithm

Initialize the Grey wolf population

For each node

$(r_{i,d}) = Rand(0,1)$where$1 \le i \le Ns$

End for

While $r < r_{max}$ do

For each search agent do

$f = {}^{K}\!/(\omega_1 \times RE + \omega_2 \times ND + \omega_3 \times D_n + \omega_4 \times PF)$

Update the best search agents α, β, γ

$\vec{X}_p^{t+1} = (\vec{X}_\alpha^{t+1} + \vec{X}_\beta^{t+1} + \vec{X}_\delta^{t+1})/3$

Calculate convergent factors $\vec{A}$

Update wolves' positions

End for

End while

Return α

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Relay selection using SOA

Initialization of Seagull

Fitness calculation

$$routing\ fitness = \delta_1 \times ql + \delta_2 \times lq$$

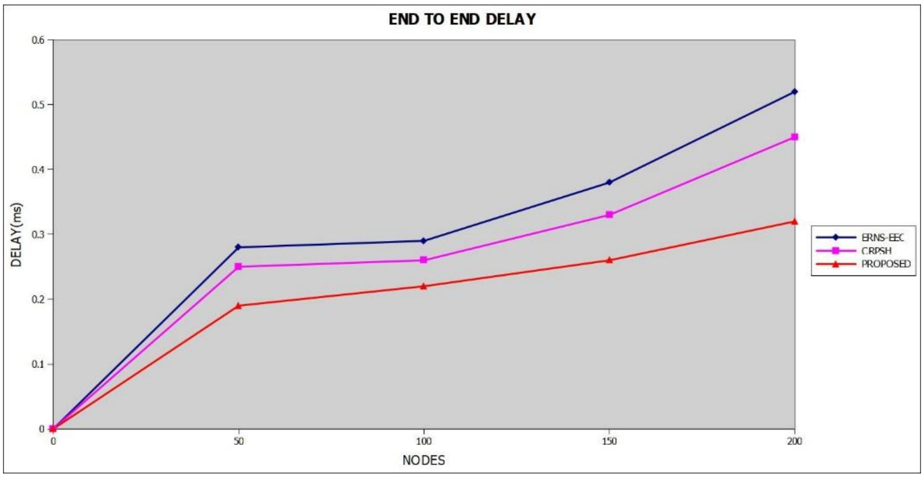
Update seagull positions

Data transmission

4. Results & Discussion

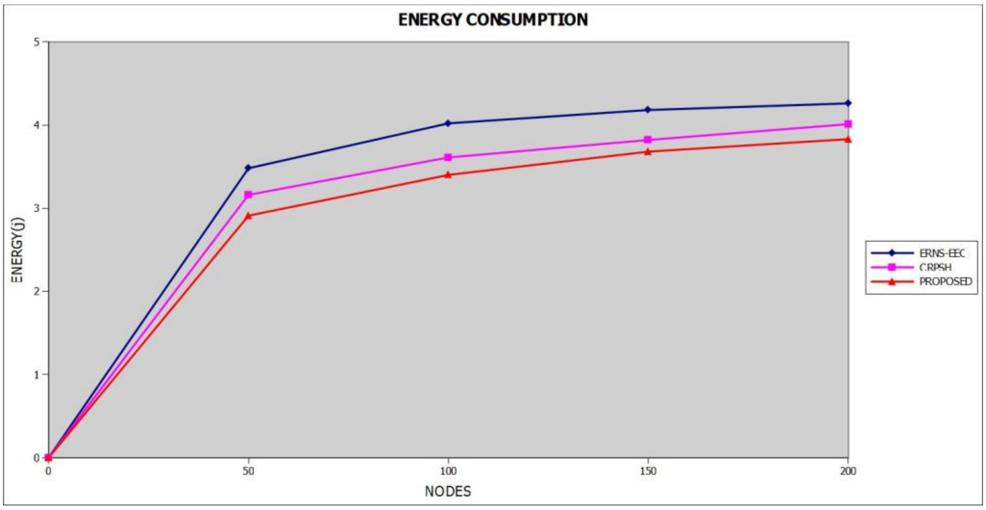
The suggested method is simulated in an area of 1000x500 meters with 50 to 200 mobile nodes in order to assess its efficacy. The starting energy of the sensor nodes, which are dispersed at random over a field, is set at 100 j. There are somewhere between 50 and 200 nodes in the network. Utilized as a traffic agent is CBR. Table displays the experimental parameter values.

Parameter	**Value**
Network area	1000x500
Number of nodes	50 to 200
Transmission type	CBR
Initial energy	100j
Packet size	1024
Routing protocol	AODV
Packet interval	0.1ms



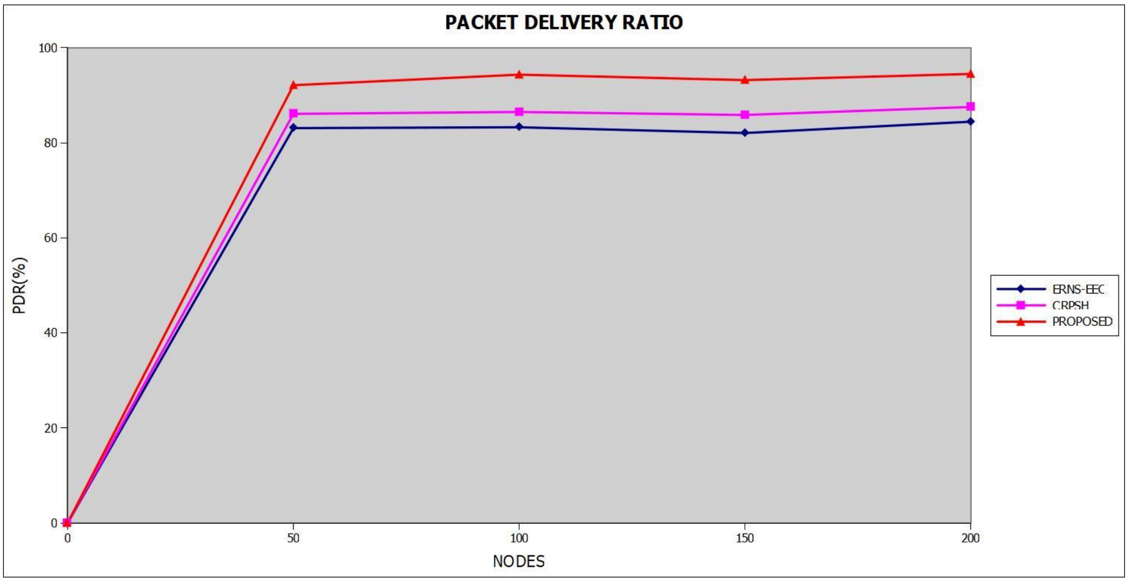
NODES	ERNS-EEC	CRPSH	EDCAR- PROPOSED
50	0.28	0.25	0.19
100	0.29	0.26	0.22
150	0.38	0.33	0.26
200	0.52	0.45	0.32

The simulation findings mentioned above show how to assess the suggested method's end-to-end delay time. The suggested relay selection system uses multi-factor selection to enhance the relay selection technique. It guarantees that only superior nodes are chosen for relay. The proposed relay selection scheme reduces delay by selecting low delay nodes using ql&lq parameters. End-to-end network latency is reduced as a result. In contrast to the suggested technique, the prior methods had higher average delays than the network's minimal average delay of 0.30ms.



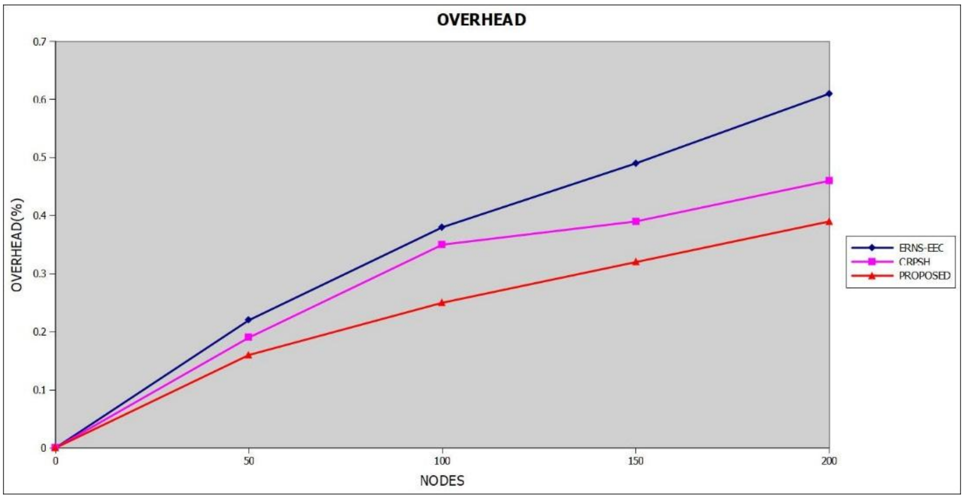
NODES	ERNS-EEC	CRPSH	EDCAR- PROPOSED
50	3.48	3.16	2.91
100	4.02	3.61	3.40
150	4.18	3.82	3.68
200	4.26	4.01	3.87

All network-related tasks need energy. At first, each node has a sizable quantity of energy available. During network activity, the energy is used.The effective selection of relay nodes in the suggested strategy greatly contributed to the reduction of undesired energy usage.The simulation results shown in the table above demonstrate that the suggested approach used much less energy than the earlier techniques.



NODES	ERNS-EEC	CRPSH	EDCAR- PROPOSED
50	83.08	86.08	92.11
100	83.26	86.48	94.33
150	82.05	85.85	93.18
200	84.43	87.53	94.48

The percentage of packets that are successfully delivered to their intended location is known as the packet delivery ratio. PDR identifies the network's suitability for transmitting data.The packets were successfully delivered thanks to the selection of reliable relay nodes and effective data aggregation via effective relay nodes.The conventional approaches maintained their average PDR rates of 87% and 84%, respectively, whereas the suggested method increased PDR to a high of 94%.



NODES	ERNS-EEC	CRPSH	EDCAR- PROPOSED
50	0.22	0.19	0.16

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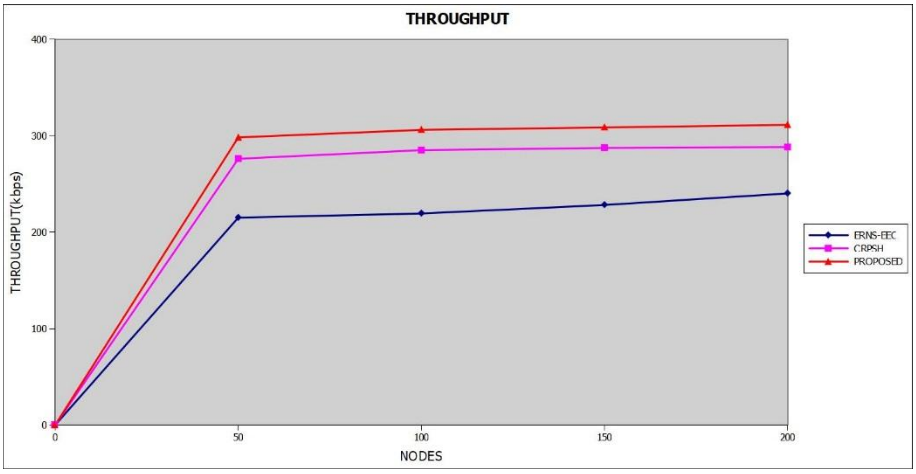
100	0.38	0.35	0.25
150	0.49	0.39	0.32
200	0.61	0.46	0.39

The number of control packets broadcast across the network during data transfer determines the overhead. The overhead reported on average using the suggested approach was 0.35, compared to the previous methods' overhead, which ranged from 0.46 to 0.60. The improved relay selection using SAO fitness estimation eliminates the inappropriate nodes and data dropping which leads to frequent route establishment. Therefore, the suggested technique maintains a minimal overhead.



NODES	ERNS-EEC	CRPSH	EDCAR- PROPOSED
50	215.09	276.08	298.25
100	219.34	285.05	306.08
150	228.18	287.35	308.56
200	240.18	288.21	311.3

Data transmission capacity between source and destination nodes is referred to as throughput. The transmission of a lot of data is ensured via high throughput.The table above demonstrates that the suggested technique outperforms current methods in terms of throughput rate.The suggested technique maintained an average throughput rate of up to 311 kbps throughout the trial, whereas the current methods maintained lower throughput rates.

5. Conclusion

This research presents an energy-efficient data aggregation & congestion-aware routing strategy (EDCAR) that takes into account both energy optimization and congestion as two key characteristics during data aggregation in order to maximize network lifespan, CH stability, and energy-efficient data aggregation. The improved CH selection strategy utilizes predicted remaining energy (PRE) & node centrality parameters for stable CH selection. For WSN, it employs cluster head selection approaches based on grey wolf optimization, taking into account variables such as node energy level, node degree, sink distance, intra-cluster distance, and priority factor. The seagull optimization algorithm is used for collision-aware routing, reducing energy consumption at each node. The algorithm uses queue length and link quality for fitness calculation to select congestion-free relays. The experimental data demonstrate that, when compared to the current energy-efficient data aggregation systems, the proposed EDCAR scheme increases the network lifetime.

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