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OPTIMIZATION OF ENERGY CONSUMPTION IN WIRELESS SENSOR NETWORKS USING ENERGY EFFICIENT SPHERICAL GRID ROUTING PROTOCOL

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Abstract

The primary factor influencing the wireless sensor network (WSN) is the energy consumption of the sensor node. One of the key factors influencing WSN energy consumption is the high power consumption and packet delivery ratio needed for WSN processing. The suggested Energy Efficient Spherical Grid Routing (EESGR) protocol reduces the node's energy consumption to meet the requirements. To choose the cluster heads, the WSN is clustered into a collection of nodes using the pillar k-means clustering method defined in the proposed protocol. One optimization algorithm inspired by nature, the ant lion, is used to create cluster heads for assessing energy consumption in WSNs. The behavior concept of the ant lion is utilized for choosing the best nodes for the selection of the cluster head. The multi-tier spherical grid routing proposed in the paper is used to grid the cluster head generated by the ant-lion optimization algorithm to evaluate the total energy consumed for processing the sensor network. The overall performance of this method is evaluated in Network Simulator 2 (NS2). The proposed method improves performance in throughput, end-to-end delay, packet delivery ratio, and energy consumption compared to the existing techniques.

Keywords: Ant Lion Optimization Algorithm, Multi-Tier Spherical Grid Routing, Network Simulator, Pillar K-means Clustering, Wireless Sensor Networks (WSN)

I. Introduction

Data networks use radio waves to connect devices like computers to the network. Networks use wireless data for the interconnection of nodes to handle the creation, reception, and transmission of information over communication channels to provide mobility. Wireless sensor networks have several advantages over wired networks, including easy access to network resources from any point within the service region, quick and affordable installation, and lower operating costs.

A WSN is a system consisting of autonomous sensors distributed spatially for monitoring physical or environmental constraints like pressure, sound, temperature, and so on, and to send their data to a specific important location through the network. Additionally, the modern networks also have the capability of enabling the control of sensor activity due to the bidirectional feature. In various applications relevant to the military, industrial, and consumer sectors, such as machine health monitoring and control, the implementation of WSNs has been utilized.

More power is consumed during sending and retrieving data, processing query requests, and forwarding queries to the neighbour nodes [XII]. The power dispersal occurs due to idle listening, retransmitting, overhearing, and overemitting [XI]. The protocol operations are used to maintain the data integrity, packet delivery, throughput, and packet drop ratio in the network [II]. The recent research approach on WSN is elaborated in the related work section 2, the EESGR routing protocol and its function are given in section 3. Sections 4 and 5 include the results and conclusion.

II. Related Work

Md Azharuddin and Prasanta K. Jana et al. proposed a PSO-based backend cluster with a fault tolerance scheme (PSO-BFT) to resolve the issue of hot-spot that is caused in the cluster-based WSNs due to the multihop communication [I]. The routing and clustering phases are involved in the algorithm. The distribution of traffic loads over the cluster heads (CHs) is made even in the routing phase, while in the clustering phase, all CHs will be monitored to prevent the earlier death based on the distributed scheme. The proposed method achieves good performance results in energy consumption, the number of dead gateways, the number of data packets received by the BS, the number of inactive sensor nodes, and network lifetime.

Walaa M. Elsayed et al. have presented the distributed self-healing approach (DSHA) that performs fault detection, repair, and diagnosis based on the cluster head and node levels [IV]. Resiliency and reliability are ensured with the successful detection of hardware failures and their diagnosis. The DSHA algorithm shows the improvement results in terms of network lifetime and fault tolerance based on the analysis of simulation results.

Khalid et al. have proposed a novel algorithm of cluster head selection known as modified centralized energy efficient distance (MOD-CEED), which is the modified CEED algorithm for WSNs [III]. Guangquian and Feng et al. have introduced a grid-based technique, heuristic tour planning (H-TOUR-P), for WSNs to avoid the obstacles in the schedule for mobile sinks [V]. The spanning graph is also designed for the mobile sink to find the shortest route to overcome the issues. The heuristic obstacle-avoiding algorithm is implemented using the cluster-based method for dispatching the mobile sink. The simulation results showed that the cluster-based technique provides the most feasible approach that provides a prolonged network lifetime.

Wendi Rabiner Heinzelman et al. used the LEACH protocol based on the random rotation of local base stations in the cluster for balancing the energy load among nodes [XV]. The amount of data transmitted to the base station can be reduced with data fusion and localization coordination. The results showed that the LEACH achieves reduced energy dissipation and enhanced network lifetime. Jin Wang et al. have proposed the EECDRA technique based on mobile sinks that select the cluster heads by considering the residual energy of a node [XIII]. The hot spot issue is tackled efficiently by using the cluster head rotation method.

Jin Wang et al. have proposed an improved energy-efficient ant colony optimization method for mobile sink (IACO-MS) in WSNs [XIV]. According to the node's residual energy, the cluster heads have been elected. The data are collected by the mobile sink based on the optimal moving trajectory, and communication is performed with CHs via short-range communication. Tarunpreet Kaur and Dilip Kumar et al. have proposed a particle swarm optimization using the unequal and fault-tolerance clustering technique (PSO-UFC) to overcome the fault tolerance and hot-spot problems [IX]. The multi-hop routing tree between master cluster heads and an optimum number of clusters is designed for balancing the inter- and intra-cluster communication. The PSO-UFC protocol provides better performance in network lifetime and power consumption.

Jiang Chang-Jiang et al. have proposed and evaluated energy balanced unequal clustering (EBUC) based on the PSO algorithm [VIII]. For the inter-cluster relay traffic, energy can be preserved by the cluster heads, and the problem of hot-spots can be restricted. The energy-aware multihop routing is adopted by EBUC for inter-cluster communication to minimize the energy utilization of CHs. The nodes' death speed is reduced, and the network lifetime is prolonged with this method.

Somaye Jafarali Jassbi and Elham Moridi et al. suggested a fault tolerance and energy efficient clustering (FTEC) technique for improving the fault tolerance and energy efficiency [VII]. The backend cluster is selected to enhance the fault tolerance, and the cluster head detects the faulty nodes based on the median weights. The improved data rate, enhanced energy efficiency, and improved detection accuracy are achieved by the FTEC algorithm more than the other algorithms.

Jianhua Huang et al. proposed the energy-efficient multi-hop routing protocol (EEMRP) to minimize the energy consumption by using grid clustering [VI]. This method optimizes the electoral method of nodes based on the location and the network area levels. The results indicated that the extended network lifetime and energy efficiency are achieved with this method. Divya Lohani et al. proposed the dynamic mobile agent approach based on data aggregation (EEDAA) that considers the network lifetime, energy efficiency, and end-to-end delay [X]. In a multihop sensor network, the decision for agent migration has been taken by this approach. The mobile agent is taking less time to return to the processing element by determining the most informative route. This approach achieves better performance results in terms of aggregation precision ratio, energy efficiency, and the lifetime of a network.

III. EESGR Protocol in WSNs

The proposed technique consists of clustering-based optimization and a spherical grid of sensor nodes for the verification of energy consumed in the WSN nodes. The pillar k-means clustering is used to cluster the network. The main function of this pillar, k-means, is to find the centroid of the cluster nodes. The ant lion optimization induces the work to find out the cluster head from the nodes by the matrix function in the optimization algorithm. It is an optimization method inspired by the food prey behavior of an ant lion, which is utilized to optimize the nodes for choosing the best node for the cluster head. The multi-tier spherical grid is used to evaluate the energy consumed by the sensor network for processing. The nodes are positioned in the grid to evaluate the energy utilized by the node when processing from source to destination. The grid operates by spherical motion for the processing of sensor nodes to reach from source to destination. The network simulator is used to evaluate the suggested work, and the performance is discussed.

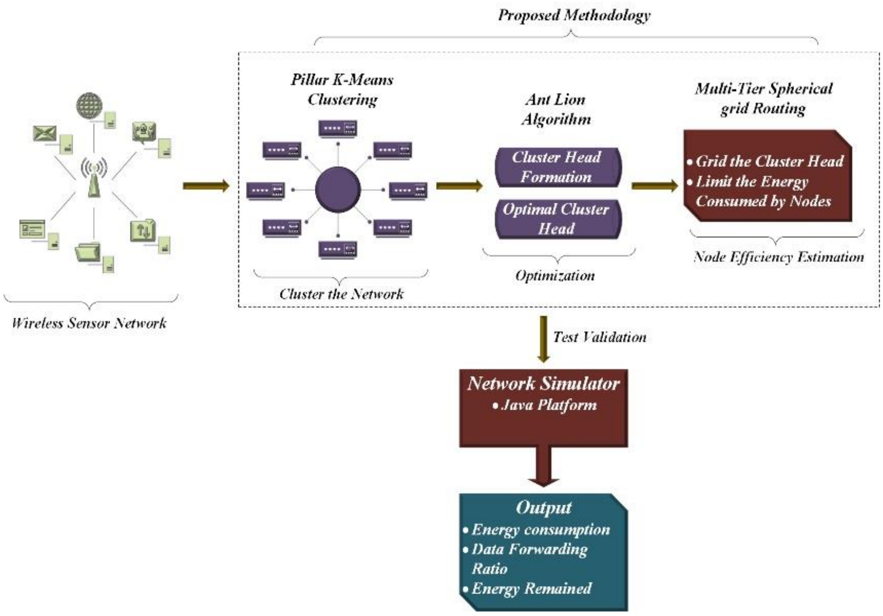

Fig. 1. Architecture of Proposed Technique

The architecture shown in Figure 1 demonstrates the step-by-step flow of the proposed methodology, which consists of pillar K-means clustering, the ant lion optimization algorithm to select the cluster head, and multi-tier spherical grid routing for evaluating the energy consumption. The NS2 (Network Simulator) is used in the proposed work to test and validate the energy calculation in the nodes.

Step 1: K-means Clustering

Clustering is the process of quantization of vectors, and it is originally practiced in signal processing, which has created popularity in clustering in data mining. The k-means clustering process clusters the n number of nodes into clusters.

a. Factors Considered in Clustering Process

Limiting Energy Consumption: The clustering process is mainly carried out in wireless sensor networks to limit the overconsumption of energy by the nodes in sending and forwarding data over the networks. The cluster will classify the energy-efficient nodes and consider them as optimal cluster nodes in the wireless sensor networks.

Network Node Lifetime: The lifetime of a node is attained by limiting the energy consumed by the nodes in the sensor networks.

Limited Abilities: The size of energy stored in the node will limit the capability of nodes in the network, and the cluster technique can share the resources by limiting the abilities of certain nodes.

Requirement of Application: The network application is one of the concerned factors in clustering. When designing a cluster algorithm, the efficiency and flexibility of applications are considered to adapt to various requirements in networking.

Step 2: Pillar K-means Clustering

The Pillar K-means clustering is initialized to cluster n number of nodes into various segments. Let Q={q_i} where {i=(1,2,…f)} be the f-dimensional vector attributes and the input of data is defined as {x_i= (1…n)}. The pillar k-means clustering separates the input node x_i into k partitions as clusters 'S' with input cluster range {c_i=(1…K)}. The cluster member is H $\in$ x_i and in the range $H_i = \{H_{ij} | j = 1 \cdots n(c_i)\}$ where n(c_i) is the member for c_i. Each cluster node has a center point $G = \{g_i | = 1 \cdots k\}$. The pillar K-means cluster creates the first cluster center at random. The centroid of a cluster can be evaluated by using equation 1 by giving input {x_i=(1…n)} into 'S' with minimum distance d(x_i, c_i).

$$S_i = \frac{1}{n_i} \sum_{j=1}^{n(x_i)} H_{ij} \in c_i \tag{1}$$

Where S_i is the optimal cluster centroid, x_i is the no. of input nodes, H_{ij} is the member set of the input cluster, and ci is the new cluster.

Equation 2 explains how to update the cluster's position.

$$\frac{S^t - S^{t-1}}{S^t} < \omega \tag{2}$$

Where ω is the threshold in updation and $S^t$is the iteration of the cluster.

Step 3: Ant Lion Optimization Algorithm

It is based on the ant lion's food-prey strategy and is inspired by nature. By optimizing the prey to acquire the best results, this algorithm mimics the ant lion's prey search. By classifying the food prey from its trap, the ant lion hunts its prey.

The prey is categorized as a random walk, and it is shown in equation 3.

$$Y(r) = [0, cusum(2c(r_1)-1), cusum(2c(r_2)-1), \cdots\cdots, cusum(2c(r_n)-1)] \tag{3}$$

where 'cusum' is the cumulative sum, n represents the maximum no. of iterations, c(r) is a stochastic function, and 'r' is the step of the random walk, and it is shown in equation 4.

$$c(r) = \begin{cases} 1 & if \quad randm > 0.5 \\ 0 & if \quad randm \leq 0.5 \end{cases} \tag{4}$$

The matrix given in equation 5 describes the position of nodes.

$$M_{Node} = \begin{bmatrix} N_{1,1} & N_{1,2} & \cdots & N_{1,n} \\ N_{2,1} & N_{2,2} & \cdots & N_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ N_{n,1} & N_{n,2} & \cdots & N_{n,d} \end{bmatrix} \tag{5}$$

where n and d represent the no. of nodes and node variables, respectively.

The matrix shown in equation 6 explains the fitness function for choosing the best cluster head node.

$$M_{OC} = \begin{bmatrix} f([CN_{1,1} & CN_{1,2} & \cdots & CN_{1,d}]) \\ f([CN_{2,1} & CN_{2,2} & \cdots & CN_{2,d}]) \\ f([CN_{n,1} & CN_{n,2} & \cdots & CN_{n,d}]) \end{bmatrix} \tag{6}$$

where f and CN are the objective function and cluster nodes, respectively.

$$M_{ClusterHead} = \begin{bmatrix} CN_{1,1} & CN_{1,2} & \cdots & CN_{1,n} \\ CN_{2,1} & CN_{2,2} & \cdots & CN_{2,d} \\ \vdots & \vdots & \ddots & \vdots \\ CN_{n,1} & CN_{n,2} & \cdots & CN_{n,d} \end{bmatrix} \tag{7}$$

where $M_{ClusterHead}$ represents the position matrix for cluster head, n and d are the no. of nodes and node variables, respectively.

Equation 8 is used to choose the best node for the cluster head.

$$Z_i^t = \frac{(Z_i^t - v_i) \times (b_i - s_i^t)}{(u_i^t - v_i)} + k_i \tag{8}$$

where v_i represents the minimum i^{th} variable of the random walk, s_i^t represents the minimum i^{th} variable in the t^{th} iteration, b_i represents the maximum i^{th} variable of the random walk, and u_i^t represents the maximum i^{th} variable in the t^{th} iteration.

a. Cluster Nodes updation

The cluster node updation is done by using equations 9 and 10.

$$s_i^t = CH_j^t + s^t \tag{9}$$

$$u_i^t = CH_j^t + u^t \tag{10}$$

where $s_i^t = s^t / R$ is the minimum variable in the t^{th} iteration, CH_j^t represents the position of the selected j^{th} cluster nodes in the t^{th} iteration, $u_i^t = u^t / R$ represents the maximum of all variables in the t^{th} iteration, and R represents the ratio calculated in the iteration.

$$R = 10^q \cdot \frac{t}{T} \tag{11}$$

$$q = \begin{Bmatrix} 1 & if & tm > & 0.1T \\ 2 & if & tm > & 0.5T \\ \vdots & & & \vdots \\ n & if & tm > & nT \end{Bmatrix} \tag{12}$$

where T represents the maximum iteration, tm represents the iteration, and q represents the iteration constant.

Cluster Head is selected by using equation 13.

$$CH_i^t = \frac{r_A^t + r_E^t}{2} \tag{13}$$

where r_A^t is the random walk in the t^{th} iteration, and r_E^t is the random walk chosen in the t^{th} iteration.

b. Fitness function

The fitness value for a sensor node (antlion) is derived as a function of the energy of the sensor node, the number of neighboring nodes of a sensor node, the cumulative distance between a sensor node and its neighbors, and the distance between the sensor node and the base station (BS).

For every ant and antlion, the fitness value is calculated. After the last iteration, the elite antlion/sensor node with the highest fitness value is chosen as CH, and its neighbors are added to the new cluster. Similarly, an antlion with the next highest fitness value assists in bringing the remaining sensor nodes into succeeding clusters. Equation 14 represents the fitness function (Fi) used in this technique to choose the cluster head.

$$Fi = \alpha_1 (\sum dis_{ij}) + \alpha_2 (E_{resid}(i) + \alpha_3 n_{neighb}(i) + \alpha_4 d_{i,Basest} \tag{14}$$

where α_1, α_2, α_3, and α_4 are the constants between 0 and 1, $(\sum dis_{ij})$ indicates the cumulative distance between node 'i' and its neighbors, $n_{neighb}(i)$ represents the

number of neighbor nodes for the node ‘i’ and $d_{i,Basest}$ indicates the Euclidean distance between the BS and node ‘i’.
The time complexity of this algorithm is typically O(It_{max} × N × D + OF_{cost}), where It_{max} is the maximum number of iterations, N is the number of ants and antlions, D represents the number of variables, and OF_{cost} is the cost of the objective function.

Step 4: Multi-Tier Spherical Grid Routing

It is the proposed routing technique carried out to evaluate the energy utilized by the sensor networks. The proposed routing technique can optimize the consumption of energy and thus promote an efficient model in the wireless sensor networks. The spherical coordinates induced in the grid routing are inspired from the position of the sphere, as shown in Figure 2.

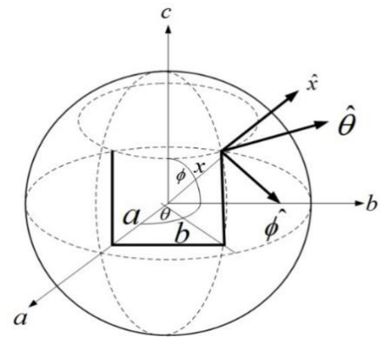

Fig. 2. Multi-Tier Spherical Grid Routing

Let’s take the sphere with the (a,b) plane from the axis points a with $0 \le \theta < 2\pi$, where ‘θ’ to be the horizontal angle in the (a,b) plane and ‘τ’ is defined as longitude in the axis, ϕ to be the polar angle with ϕ =90^0- λ where λ is the latitude from the positive *c*-axis with $0 \le \phi \le \pi$ and x to be the distance (radius) from the starting point. In spherical grid routing, the coordinates are mentioned as (x,θ,ϕ) respectively. The coordinates uses θ as the angle in the (a,b plane and ϕ as the angle out of that plane. The Cartesian equations are induced for the spherical coordinates of (a,b,c), and it is defined as

$$x = \sqrt{(a^2 + b^2 + c^2)} \tag{15}$$

$$\theta = \tan^{-1}\frac{b}{a} \tag{16}$$

$$\phi = \cos^{-1}\frac{c}{x} \tag{17}$$

where x $\in [0,\infty]$, $\theta \in [0,2\pi], \phi \in [0,\pi]$ and the inverse of the tangent function will be accurate quadrant for the (a,b) plane and expressed in terms of Cartesian coordinates as

$$a = x\cos\theta\sin\phi \tag{18}$$

$$b = x\sin\theta\sin\phi \tag{19}$$

$$c = x\cos\phi \tag{20}$$

For the determination of θ point of the quadrant should be considered, and it can be determined from the condition arctan(b/a) if the condition of a>0 and arctan (b/a+π) if a>0. If the value of $\theta = \pi/2$ then, a=0, b>0 and the value of θ=-π/2 then the condition a=0, b<0and the coordinates will be defined as

$$\phi = \arccos\left(c \Big/ \sqrt{\left(a^2 + b^2 + c^2\right)} \right) \tag{21}$$

Equation 21 is said to be a coordinate system for a spherical grid.

a. Route request

The size and number of grids depend on the requirements of the application and data size. Let L and R be the length of the grids and the distance of radio signal transmission. In this paper, let us assume D=[R/2$^{(1/4)}$] when the source node needs to be routed to the destination point without route data, the source node circulates the route request to the network. The route is done by covering the grid with a circular boundary from the source and the destination. The initial step starts with activating all the hosts and broadcasting a 'hello' message, and finding the grid head by black dots in the grid. If the grid head is selected, the remaining non-grid head hosts are set to sleep to conserve energy. The routing in the grid failed; another set of routing is initialized in the area for the route. If the grid receives a request packet, the grid head checks if it is in the area range. If the received packet is in the range, the grid ignores the packet, and it is not satisfied; it evaluates $G_{pred,}$ which predicts the nearby nodes. The remaining energy utilized for the node is low, so the remaining energy is lower than the energy predicted. Thus, the nodes in the intermediate section do not have sufficient energy to forward data packets. If the remaining node energy is higher than the predicted energy, then rebroadcasting of request packets cannot be performed, and the node reads the energy remaining in the node field of the route request and its routing table, and rebroadcasts the data to its nearby nodes. If the destination receives the request packets and checks if it is in the state of a grid head. If it is not the destination grid, warn before transmitting information packets to the nodes. Let the distance to the center be from the distance D, then the highest projection value in the grid will be

$$g = \frac{2rD^2}{D^2 + 4r^2} \tag{22}$$

where $r = D \Big/ \sqrt[2]{\theta}$, $\theta > 0$ then the projection value is estimated in the Equation 23.

$$g = \frac{2r\theta}{(1+\theta)} \tag{23}$$

Consider the x and y in the spherical grid with projection, then

$$|xy| = (1+\theta)D(xy) \tag{24}$$

In wireless sensor networks, the nodes are transferred in a region 'R'. Let the spherical grid Sg with center 'O' and its coordinates be (0,0,0). The radius 'r' in the spherical grid is adjustable and assumes the sensor node is from the center to the destination at a distance 'D'. The criteria formed with two cases $r < D$ and $r \geq D$. At any point m(a,b,c) in R maps on the spherical grid. Then the position of m to the center can be evaluated by equation 25.

$$\psi = \sqrt{\left(a^2 + b^2 + c^2\right)} \tag{25}$$

If node (0,0,0) will be projected and forced to map to (0,0,r,0). D(xy) is the distance between the source and destination. Thus, the position can be evaluated by using equation 26.

$$D(xy) = |xy| = \left|\psi_x - \psi_y\right| \tag{26}$$

b. Packet Forwarding Ratio:

The data packet forwarding ratio represents the ratio number of data packets forwarded to the database to the packets formed by the source node.

$$P_R = \frac{1}{f}\sum_{F=1}^{e}\frac{H_F}{S_F} \tag{27}$$

Where F is the unique flow of data in source and destination, H_F is the flow of received packets, S_F is the flow of forwarded packets in networks, f is the total number of flows or transmissions, and P_R is the packet forwarding ratio in sensor networks.

c. Energy

Energy is calculated by using equation 28.

$$G_{TX}(m,D) = G_{elec} \times m + T_{amp} \times m \times l^2 \tag{28}$$

G_{elec}= energy consumed.
D= Distance between the cluster nodes
Tamp =Energy consumed by transmission Amplifier.
m=The no.of bits in data
l^2=Energy loss

$$G_{RX}(m) = G_{elec} \times m \tag{29}$$

Equation 30 gives the total energy consumption.

$$G_{Total} = \left\{G_{elec} \times m + T_{amp} \times m \times l^2\right\} + \left\{G_{elec} \times m\right\} \tag{30}$$

Equation 31 represents the multi-objective cost function C(P), which is a weighted sum of normalized component functions of energy, delay, and packet success rate.

$$C(P) = w_1(En) + w_2(N_d) + w_3(1-PDR) \tag{31}$$

where w_1,w_2 and w_3 are the weight coefficients.They sum to 1 ($w_1+w_2+w_3=1$).

d. Algorithm: EESGR Routing Protocol

Initialize the input number of cluster nodes and set the number of nodes to be (x_i=x_1… x_n). Initially, cluster the network and define a new cluster S_i for input (i=1.. k), then determine the cluster heads for i=1...n. If the initial iteration is complete, separate xi for i=1...n into clusters and update the position $d\left(x_i, X_i^t\right)$. Repeat the steps until the iteration convergence for each input finds the centroid and select the optimal as cluster heads. It is shown in Figure 3. From the set of nodes, select the node nearest to the centroid as the cluster head. The multi-tier spherical grid is implemented, and the nodes are positioned according to the spherical phenomenon $\psi = \sqrt{\left(a^2 + b^2 + c^2\right)}$. Find the set of nodes having more energy than E_{Total}.

```
Initialization the node input to random units, xi= x1....xn
Cluster the input nodes              // implement the Pillar
                                        K- means algorithm
For
        Input nodes, i= 1....n;

Repeat;                              // clustering the nodes
        Update matrix;                  // ALO algorithm
For
        Cluster centroid Si, i= 1....k;
        Update position (Si,xi),        // Pillar K -Means cluster

        Generate new cluster centroid 'Si'
Until;
    Iteration converges optimal value,
        Search nearest nodes,
If then
        Select the cluster head from nearby best nodes
Initialize grid routing
    Grid the CH to optimal value        // implement multi-tier
                                           spherical grid routing
Calculate the criteria
            //energy consumption; //data forward ratio;
                    //energy reserved by nodes;
Repeat;
        If criteria converges
End if
        Stop the criteria and plot the results.
```

Fig. 3. Pseudo code for Execution

IV. Results and Discussion

Table 1 shows the simulation parameters.

Table 1: Network Simulator Parameters

Parameters		
Type of Channel	:	Wireless
Radio Model	:	Two-ray ground
Deployment area	:	100m×200m
Base station location	:	(50,50)
Sending rate	:	1 packet/ sec
Initial energy in Joules	:	80
Routing Protocol	:	Multi-Tier Spherical Grid
Number of nodes	:	100
Packet size	:	1024 bit

IV.i. End-to-end delay performance of EESGR

Simulations are carried out for the proposed method, EESGR, and the existing methods EBUC, PSO-UFC, FTEC, and EEMRP for simulation time t(s) of 2s, 4s, 6s, 8s, and 12s, and the results of end-to-end delay are shown in Table 2 [11-14].

Table 2: Comparison of end-to-end delay with EESGR

Method	End-to-end delay (ms)				
	t(s)=2s	4s	6s	8s	12s
EBUC	1.2781	1.4854	1.5219	1.7651	2.2563
PSO-UFC	1.1381	1.2854	1.3219	1.6251	2
FTEC	1.1135	1.2158	1.2966	1.5632	1.96
EEMRP	1.0956	1.1648	1.2548	1.5025	1.88
EESGR	**1.0481**	**1.1154**	**1.2419**	**1.4351**	**1.8**

From figure 4, it is decreased by 20.2%, 10%, 8.16% and 4.25% compared to EBUC, PSO-UFC, FTEC, and EEMRP, respectively, at a selected simulation time of 12s. At different simulation times, the proposed method operates efficiently with respect to existing techniques.

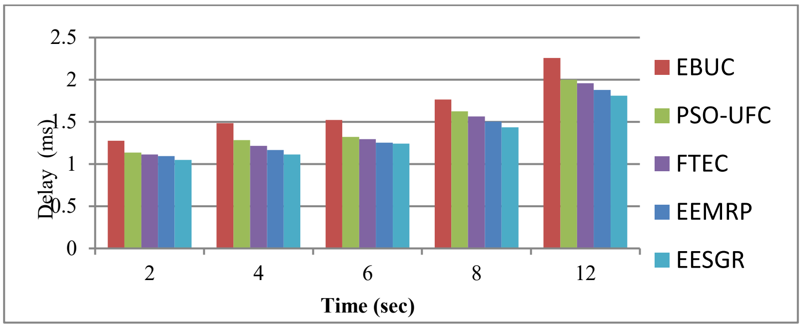

Fig. 4. Comparison of end-to-end delay with EESGR

IV.ii. Energy consumption performance of EESGR

Energy consumption values for the proposed method and the existing methods for simulation time t(s) of 2s, 4s, 6s, 8s, and 12s are noted in Table 3. The efficient CH selection is based on prioritizing the high-energy nodes.

Table 3: Comparison of energy consumption with EESGR

Method	Energy consumption (J)				
	t(s)=2s	4s	6s	8s	12s
EBUC	1.2281	1.3154	1.4219	1.5965	1.9563
PSO-UFC	1.1781	1.2854	1.3421	1.7765	1.8563
FTEC	1.1547	1.2389	1.3159	1.7106	1.8126
EEMRP	1.1126	1.1845	1.2649	1.6648	1.7729
EESGR	**1.0981**	**1.1354**	**1.2221**	**1.5965**	**1.7363**

The energy consumption of the EESGR is decreased by 11.2 %, 6.46 %, 4.21% and 2.06 % compared to EBUC, PSO-UFC, FTEC, and EEMRP, respectively, at a simulation time of 12s. Similarly, it is observed that the proposed technique works better at various simulation times. Comparison of energy consumption with EESGR is visualized in Figure 5.

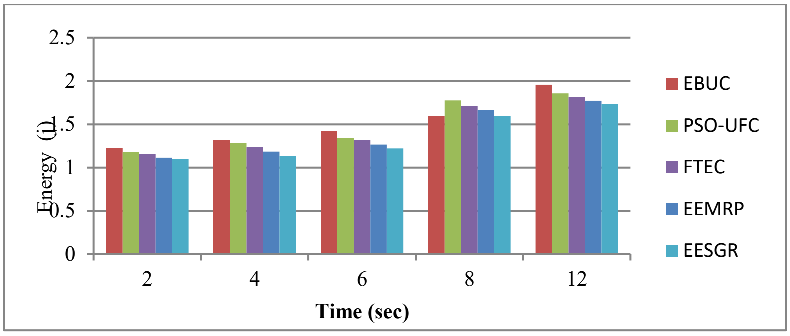

Fig. 5. Comparison of energy consumption with EESGR

IV.iii. Throughput performance of EESGR

Throughput values are given in Table 4 for the simulation times of 2s, 4s, 6s, 8s, and 12s. Throughput in the proposed method, EESGR is increased by 14.3%, 8.82%, 6.8% and 3.5% compared to the existing methods EBUC, PSO-UFC, FTEC, and EEMRP, respectively, at a selected simulation time of 12s.

Table 4: Comparison of throughput with EESGR

Method	Throughput (kbps)				
	t(s)=2s	4s	6s	8s	12s
EBUC	0.4319	0.4854	0.5519	0.7065	0.7763
PSO-UFC	0.4719	0.5054	0.6019	0.7365	0.8263
FTEC	0.4988	0.5547	0.6628	0.7619	0.8519
EEMRP	0.5217	0.5973	0.6946	0.7894	0.8743
EESGR	**0.5619**	**0.6154**	**0.7219**	**0.8065**	**0.9063**

Figure 6 visualizes the comparison of throughput values for all methods. As the simulation time increases, the throughput increases symmetrically for all the methods.

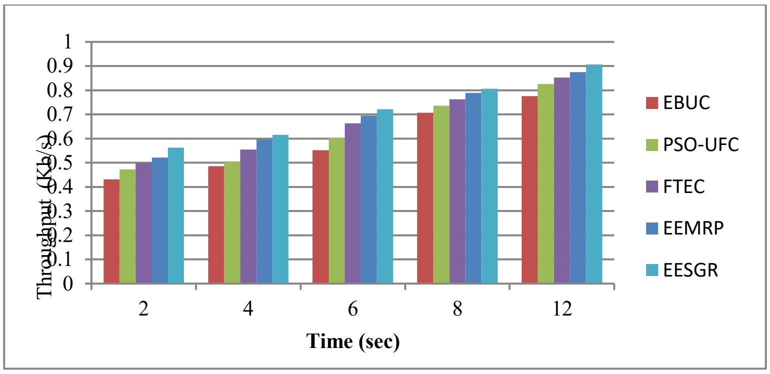

Fig. 6. Comparison of throughput with EESGR

iv. Packet delivery ratio performance of EESGR

Figure 7 depicts the impact of simulation time on PDR. Percentages of values for the proposed and the existing methods for simulation time t(s) of 2s, 4s, 6s, 8s, and 12s are given in Table 5.

Table 5: Comparison of packet delivery ratio with EESGR

Method	Packet delivery ratio (%)				
	t(s)=2s	4s	6s	8s	12s
EBUC	35.46	42.19	57.12	62.39	72.45
PSO-UFC	39.46	48.19	62.24	69.29	77.45
FTEC	42.12	52.69	66.37	72.95	81.26
EEMRP	45.69	55.68	69.48	77.15	85.26
EESGR	**47.65**	**59.9**	**75.43**	**80.12**	**88.56**

PDR is increased by 18.19%, 12.54%, 8.24 % and 3.72 % compared to the existing methods EBUC, PSO-UFC, FTEC, and EEMRP, respectively, at a selected simulation time of 12s. The EESGR is improved in terms of the delivery ratio compared to the other methods for other simulation times.

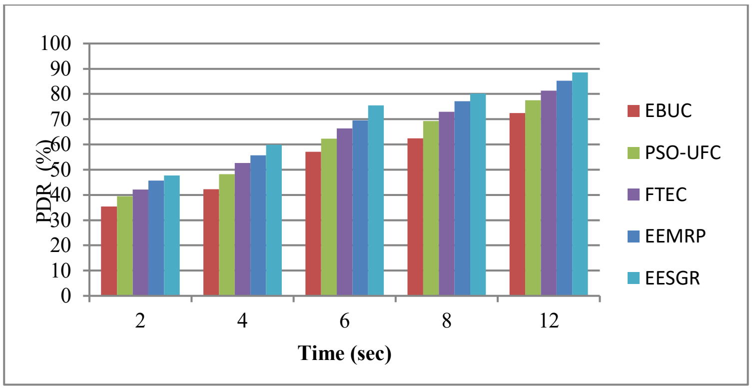

Fig. 7. Comparison of packet delivery ratio with EESGR

V. Conclusions

The proposed EESGR protocol can enhance the efficient usage of energy in the sensor networks. The energy is mainly utilized for the processing of nodes from the source to the destination. The cluster process proposed in this work classifies the network into a set of nodes. The ant lion optimization algorithm will choose the best node to find an optimized cluster head to evaluate the energy consumed in processing the WSN. An energy-efficient prototype is designed to reduce the energy utilized in the WSNs. The total process is evaluated by using NS2, and the performance is compared with the existing techniques.

Conflict of Interest:

There was no relevant conflict of interest regarding this paper.

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