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EAPSO_GSA: Energy Aware Routing using Hybrid PSO and Gravitational Search Algorithm in Wireless Sensor Networks

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Abstract:
Demand of wireless communication system is increasing rapidly. Wireless Sensor Networks (WSNs) have gained huge attraction due to various real-time applications such as health monitoring, sensitive area monitoring, catastrophe supervision, etc. These networks are not so high in power resource so energy conservation is very crucial aspect here. Moreover, such networks are deployed in unattended and harsh atmosphere where power sources cannot be replaced. Hence, prolonging the network lifetime is a tedious task for these networks. Recently, energy ware routing and efficient cluster head (CH) selection techniques have been introduced to mitigate these challenges. In this work, we have focused on energy aware CH selection and routing to enhance the lifetime of network. To achieve this, we present a combined model using PSO i.e. particle swarm optimization and GSA i.e. gravitational search algorithm for CH selection. We compare the performance of proposed approach with existing techniques. The experimental study demonstrates that the presented scheme improvises the efficiency of network with respect to energy utilization, life of the network, and packet delivery ratio.

***Keywords**: energy management, wireless sensor networks, cluster head.*

Introduction

Wireless sensor networks (WSN) have gained enormous attraction by the research community and industry due to their vast usages in daily life scenarios such as health monitoring systems, environment monitoring, and security surveillance, etc. [1]. Generally, these devices are powered by limited and generally irreplaceable power sources and arebuilt with tinycomputing units and wireless transceivers. Moreover, these networks are installed in harsh geographical locations where it becomes impractical to replace the sensor nodes [2]. Thus, prolonging thenetwork lifetime becomes a tedious task which can be achieved by reducing the power consumption in during various operations of WSN communication. Usually, data transmission and packet forwarding are the major source of energy consumption. Similarly, overheating, collision, listening and controllingthe overhead of packetsare included in list of energy consuming variables. Due to collision, packet will be corrupted and discarded due to this scenario, the packet retransmission takes place which consumes extra energy and degrades the network lifetime [3]. These issues are considered as the challenging issues for sensor networks.

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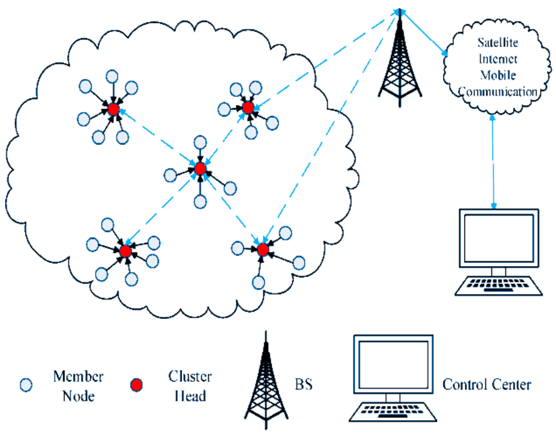

Fig.1. Data transmission using hierarchal routing

Efficient routing approaches play important role in WSNs for smooth transmission and long lasting network. For example, in health monitoring systems, the patient's data need to be transmitted accurately in a given time duration for appropriate diagnosis, such as in military, the information about opponent positions, objecttracking and target tracing need to be transmitted back to the army base stations, similarly, the WSNs are used for rescue system in natural disaster scenarios. Moreover, these networks can provide the information about civil infrastructure such as crack detection, structure defects and fire conditions [4]. These applications require reliable and promising routing to accomplish the desired data transmission task. To lengthen the life of a network, an energy efficient routing scheme is required. Similar to the energy consumption, packet delivery and network scalability are considered as challenging issue in these networks which can be addressed using efficient routing scheme [5] and hierarchal architecture [6], respectively. The hierarchal architecture divides the network into different layers where each node is allowed to perform different tasks. Clustering is the widely adopted hierarchal routing which divides network into multiple clusters which contains cluster head (CH) and ordinary node(ON). According to this process, the ordinary node collects the data and forwards to its corresponding cluster head, further, it delivers the collected information to the sink via hierarchal routing as depicted in figure 1. Various other routing schemes are also present which are categorized as node centric, data centric, source initiated and destination initiated which have some well-known routing schemes likeLEACH (Low energy adaptive clustering hierarchy), DD (Directed diffusion)and SPIN (Sensor protocols for information via negotiation). SPIN protocol is also considered as source-initiated protocol [7]. Furthermore, these routing protocols are divided into different categories based on network organization, protocol operations and route discovery as depicted in figure 2.

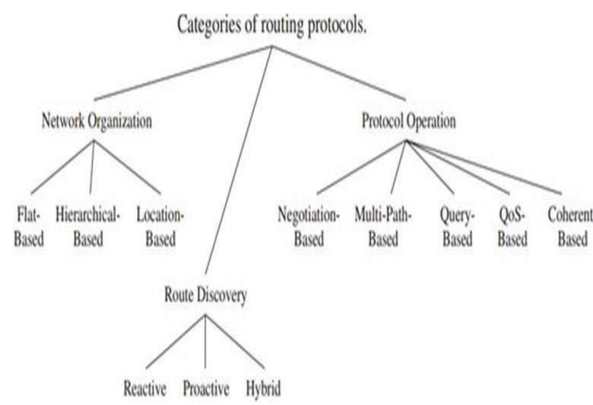

Fig.2. Categorization of routing protocols

Several routing schemes have been presented to enhance the performance of wireless networks for essential parameters like lifetime and packet delivery such as CREEP [8], CL-LEACH [9], ETARP [10], P-LEACH [11] and TERP [12] etc.Similarly, the artificial intelligence and optimization schemes are also adopted to improve the network performance such as Fuzzy Logic [13, 15], and evolutionary approach [14, 16], etc.Recent researches reported improvement in the network performance by using evolutionary optimization techniques. However, these networks suffer from various challenging issues in routing model such as efficient clustering, CHappointment, neighboring node selection and packet transmission. Along with this, the proper utilizationof energy and short life of network are well-known issues in WSNs. As discussed before, the data forwarding is one of the major sources of energy consumption, similarly, Brar et al. [17] reported that these clustering and CH head selection also consumes energy hence efficient clustering schemes is required. Furthermore, efficient routing can help to decrease the energy consumption.

Here, we work on improving the lifetime of network by developing a novel energy aware approach for clustering and multihop routing. Major offerings of the proposed approach can be listed as:

(a) Development of efficient model for node clustering and CH selection
(b) Development of multi-hop energy aware routing schemeto achievebetter packet delivery and prolong the life of network.

Remaining part of article is organized as: section II brieflydiscusses about recent techniques to improve the network lifetime, section III presents proposed approach for network lifetime maximization and improving the network throughput, section IV presents the comparative experimental analysis to show the improvementsby using proposed approach. Finally, section V presents concluding remarks of proposed model and future work notes.

1. Literature Survey

We reviewed several state-of-the-art works in the arena of WSN to improve the overall network performance with respect to network lifeenhancement and packet delivery ratio. Here, we discussed several clustering and multi-hop routingmechanismsbased on energy awareness models.

Ke et al. [18] focused on expandingnetwork lifeand developedNEACH (novel energy aware hierarchical cluster-based) routing protocol. Aim of this approach is reduction in the power consumption which is achieved using relay node selection process. In this work, the relay node is selected by formulating nonlinearprogramming and optimal solution is obtained using convex function. As discussed before, clustering plays important role in network lifetime. Based on this assumption, Huynh et al. [19] introduced energy efficient cluster orientedmultihoptransmission scheme to minimize the energy being consumedwhilepacket transmission and end-to-end lag in packet delivery. According to this process, first of all, selection of the cluster head is performed based on energy and end-to-end delay requirements. In the next phase, authors focused on inter-cluster routing and presented two cost functions as energy-cost function and end-to-end delay functions. In clustering process frequent changes in cluster head and number of clusters consumes excessive energy resulting in degrading network lifetime. Cengiz et al. [20] focused on this scenario and presented energy aware multi-hop routing protocol (EAMR) which uses fixed clustering. The EAMR approach is split into 2 stages, first is set-up stagewhere fixed clusters are formed and second, steady-state phase where sensor devices collects and does data transmission towards sinkthrough relay nodes. Similar to [20], Khan et al. [23] focused on energy awareness related issues in WSN and introduced Energy-efficient multistage routing protocol (EE-MRP) which performs clustering operation, CH selection and transmit the information to the sink via energy aware communication. This scheme reduces the re-clustering frequency using static clustering method.

Han et al. [21] presented WPO-EECRP method for energy aware data transmission in WSNs. Authors have focused on selecting appropriate CH in this approach and considered several parameters for CH selection such as remaining energy, sender and receiver path cost, neighborhoodaswell as no. of neighboring nodesby using weighting method.

Moreover, two optimization parameters are also incorporated as weight coefficient $(W)$and neighbor communication range $(R)$for efficient clustering. In [22] Sajwan et al. focused on flat and hierarchal routing techniques and introduced hybrid approach using multi-hop communication. Initially, cluster headsareelectedwhere certain tasks are performed such as selecting CH, route discovery and route selection from nodes to CH and CH to sink. Their work has contributed in providing new method where the nodes which are placed more than d_0 distance are discarded during transmission.

According to Xu et al. [24] the conventional routing approaches propagate all over the WSN to ascertain the trustworthy nodes and routing path. However, this process requires extra energy to accomplish these tasks. In order to resolvethis problem, authors presented a new energy efficient region source routing (ER-SR)protocol. As per this approach, the devicethat contains the highest remainingenergy will be chosen as source node for routing. Later, source node source node computes the optimal routing path where partial nodes participate in communication to balance the energy consumption. Furthermore, distance-based ant colony optimization scheme is also incorporated to improve the routing. Similar to this approach, several techniques are present which utilize the optimization schemes for better routing. The traditional approaches use static sink node but, in some scenarios, dynamic sink node is required where static protocols fail to achieve the desired routing performance.Hence, Wang et al. [25] presenteda scheme that is based on particle swarm optimization (PSO) for clustering in WSN while considering dynamic sink node. To make CH selection, node's residual energy and position are considered as theprimary parameters. Similar to this, Mann et al. [26] introduced hierarchal routing approach using swarm intelligence approach. The complete model is divided into three phases as set-up phase using Bee clustering model, route discovery using Bee search and Data transmission phase using Bee Carrier model. These phases perform clustering, data routing and transmission tasks for the deployed WSN. Enxing et al. [27]demonstrated ant colony optimization (ACO) based scheme for routing to prolong the life of network. As per this process, the subsequent hop is chosenby considering the pheromone concentration on the path. This scheme shows low routing cost, data transmission using multipath model, and good adaptability helps to maintain balanced energy consumption to prolong the lifetime of network. Jiang et al. [28] also introduced a hybrid routing using ACO with minimum hop count during complete data transmission phase. This approach obtains optimal routing path along with minimum and balanced energy consumption in each node.

Fuzzy logic-based clustering schemes are also adopted widely in wireless networks to expand the life of the network. Al-Kiyumi et al. [29] proposed a decentralized energyconscious fuzzy logic oriented routing algorithm (DEFL) to form a power efficient network and maintain balance of energy in the network. Hamzah et al. [30] also presented fuzzy logic model for clustering. To choose the CH, authors have considered five parameters which are residualenergy, distance from base station, compacting, density, and location suitability.

2. Proposed Model

Here, we introducea novel solution to enhance the network's lifetime with the help of energy aware routing mechanism. As per the hierarchal routing concept, node clustering and cluster head selection are the primary task which have significant impact on network lifetime. After cluster head selection and cluster formation, we perform the multi-hop data transmission using cluster heads as relay nodes. This experiment is conducted for multiple rounds and finally the network performance is evaluatedby measuringnetwork lifetime, transmission delay, packet delivery, network throughput, etc.

2.1.System Model

In order to design the routing scheme, we consider a model which consist of n number of sensor nodes as $N_i(i = 1,2,3,4 \ldots .n)$. These sensory devices areplaced within $F \times F$two-dimensional area and remain static after deployment. Each sensor node can perform tasks like desired activity detection, data collection and communication ofdata in the deployed network region. Generally, these networks are deployed in unattended and harsh environment where power source for these networks cannot be replaced. According to this work, we consider a WSN scenario where cluster members (CM) sense the data when any event occurs and transmits theinformation to the CH and later, transmission of this information is performed to the sink. The sink node is always positioned towards the farthest position from the first cluster. Fig. 1 illustrates a sample model of network topology utilized in theproposed network. In this work, we organize the sensor nodes in various cluster where every cluster region has its own CH and other nodes are denoted as cluster members. Similarly, the neighbouring nodes can be reached using single-hop transmission with the help of transmission radius denoted as r_t

2.2.Energy Management

Here, we present the energy utilization model for the wireless sensor networks. The radio energy dissipation sensorcontains3elements for transmitting information, amplifying andreceiving information. The general energy dissipation model is depicted in figure 3.

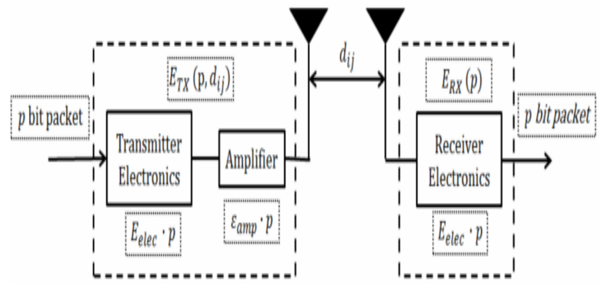

Fig.3. Energy dissipation model

The energy usage to transmit and receive the p-packet to j^{th} sensor node is computed as:

$$\mathcal{E}_{TX}(p, d_{ij}) = (\mathcal{E}_{elec} + e_{amp}).p$$
$$\mathcal{E}_{RX}(p) = E_{elec}.p \quad (1$$

Where d_{ij} indicates the path cost between node ii.e. sender to node$j$ i.e. receiver,$\mathcal{E}_{TX}$signifies the transmission energy and $\mathcal{E}_{RX}$signifies the energy dissipation during data reception, $\mathcal{E}_{elec}$ denotes the energy consumed by transceiver circuit, and e_{amp}indicates the energy usage of transmitter's amplifier. The amplification energy can be expressed as:

$$e_{amp} = f(x) = \begin{cases} e_{fs}.d_{ij}^2 for d_{ij} \leq d_{th} \\ e_{fs}.d_{ij}^4 for d_{ij} > d_{th} \end{cases}$$

Where $d_{th} = \sqrt{\frac{e_{fs}}{e_{mp}}}$, d_{th} denotes the threshold distance, e_{fs}indicates amplification energy in free-space, e_{mp}indicates the amplification energy in multi-path. According to the free-space model, the transmitter and receiver nodes uses direct line-of-sight (LOS) route from transmitting nodeto the receiving node, similarly, the multi-path model uses non-line-of-sight (NLOS). The energy consumed by cluster member is $\mathcal{E}_{CM}$ and energy consumed by cluster head is given as $\mathcal{E}_{CH}$that can be computed using eq. (3) and (4).

$$\mathcal{E}_{CM} = \mathcal{E}_{init} - \mathcal{E}_{TX}(p, d_{ij}) \quad ($$
$$\mathcal{E}_{CH} = \mathcal{E}_{init} - \mathcal{E}_{std}$$

$$\mathcal{E}_{std} = \mathcal{E}_{TX}(p, d_{ij}) + \mathcal{E}_{RX}(p) + \mathcal{E}_{DA}$$

$\mathcal{E}_{init}$ denotes the primary energy of the node, $\mathcal{E}_{std}$ denotes the typical energy usagefor any node to take part to choose the cluster head and $\mathcal{E}_{DA}$ signifies the usage of energy while performing data aggregation.

2.3.Proposed cluster head selection and energy aware routing

Here, we introduce the proposed system for cluster formation as well as energy aware routing. The proposed model consists of four phases as network deployment, nodeclustering, CH selection as well as transmitting data to the sink node. According to the proposed model, we deploy the sensory nodes in the predefined simulation space. The deployed networks are managed using network management control where control communication happens betweensensor nodes and base stations. After deployment, the base station broadcasts the communication initialization message to all nodes, the sensor devices respond to base station with initialization reply message. This message exchange helps to identify the present position and remaining energy related information of the devices. After deploying the network, we perform cluster formation process where entire network is split into multiple clusters. To achieve this, we consider Kmeans clustering approach where$K$ denotes the idealcount of cluster regions which is computed though eq. (4).

$$C_K = \sqrt{\frac{n}{2\pi}} \cdot \frac{F}{{d_{BS}}^2} \cdot d_{th}$$

Where $n$signifies the no. of wireless nodes, F denotes the size of network, d_{BS} denotes the average path cost between node and the sink, and d_{th} signifies threshold distance as mentioned in eq. (2). This approach of clustering is adopted from [31]. According to this process, we select center of the cluster randomly as C_1 and select another clustercenter C_2 where the distance between these two cluster centertoo uch higher than the r_ti.e. transmitting range of C_1, likewise, identify the third cluster as C_3 and distance between cluster should be maximum of themin$\left(d(C_3, c_1), d(C_3, C_2)\right)$. In this process, we compute the distance between initial cluster and sensor node based on Euclidean distance which can be computed as:

$$\boxed{d_{n-c} = \sqrt{\sum_{i=1}^{n} (P_i - P_C)}}$$

Where,P_i denotes the position ofi^{th}node and $P_c$symbolizes the position of node in the center of cluster. This method helps obtain the optimumcount of clusters. Further, we focus on the CH selection which has an important part in improving the network life.

(a) Cluster head appointment

In this subsection, we describe the proposed model for appointment of CH in the clustered sensor network. Main criteria for choosing CH isnode should have maximum remaining energy resource and should be closer to the base station than other nodes. However, due to iterative energy consumption, these two criteria may generate inaccurate results hence we define primary probability of sensor nodes to become the CH based on energy and distance of BS parameters. Thus, the probability of any node is calculatedvia:

$$E_{CH}(i) = \sum_{i=1}^{N} \wp_i(t) \;\; i = 1 \dots . k$$

$\wp_i$ is the probability of i^{th} node to be the CH, Let $l_i(t)$be the function which denotes that whether node has been chosen as CH in recent communication rounds i.e. if any node n is selected is cluster head then $l_i(t) = 1$ else $l_i(t) = 0$. Probability functionfor a node to be the CH at certain round $r$is:

$$P_i\,(t) = \begin{cases} \frac{k}{N - k * \left(r \bmod \frac{N}{k}\right)} : l_i(t) = 1 \\ 0 : l_i(t) = 0 \end{cases}$$

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However, due to frequent communication rounds, the node probability and CH selection becomes a tedious task, hence, for upcoming communication rounds we proposed a new objective function which is realized using particle swarm optimization scheme for optimal CHappointment. Generally, appointment of CH depends on the fitness function of the node. The presented fitness function considers two parameters such as energy consumption between sensor node and CH, and energy usage for data aggregation. The usage of energy between sensor nodes can be computed as:

$$E_1(j) = \sum_{n=1}^{N} \sum_{n_{k_j} \in C_k} \left\{ \frac{E_{k_j} - f(n_j, C_n)}{E_{max} - E_{min}} \right\} \times$$

$n_j$where $j=1,2,.....n$

The distance measurement can be expressed as:'

$$f(n_j, C_n) = \begin{cases} s^2(n_j, C_k), & if\ s(n_j, C_n) \leq d_0 \\ s^4(k_n, C_n), & if\ s(n_j, C_n) > d_0 \end{cases}$$

Where $s(C_n, k_n) = \min(n_j, C_n)\, \forall_k = 1,2,3, \dots .K$, similarly, the energy consumption between current cluster head and base station is computed as:

$$E_2(j) = \sum_{n=1}^{N} \left\{ \frac{E_{c_n} - g(C_n, BS)}{E_{max} - E_{min}} \right\} \times C_n$$

where $g(C_n, BS) = \begin{cases} d^2(C_k, BS), & if d^2(C_k, BS) \leq d_0 \\ d^4(C_k, BS), & if d\hat{}2(C_k, BS) > d_0 \end{cases}$.Thus, the total energy usedfor the transmission of the M bit data from sensor node to BS is:

$$\mathbb{E}(j) = E_1(j) + E_2(j) \quad ($$

Our goal is to reduce the total energy being consumed while communicationand improvise the life of network. On the other hand, we present CH-CH routing for efficient packet delivery and energy aware message transmission. To solve the energy wastage problem, we present particle swarm-based optimization scheme.

(b) Particle Swarm Optimization for energy aware routing

Here, we incorporate particle swarm oriented optimization scheme to mitigate the energy consumption issues. According to PSO model, we have predefined particles that are used to offer the solution for particular multi-dimensional problem. In PSO, the i^{th} particle of the given population can be represented as:

$$P_i = [X_{i,1}, X_{i,2}, X_{i,3}, \dots, X_{i,D}]$$

The PSO algorithm updates particle's position and velocity to obtain the optimal solution. This solution is provided using fitness function. The optimal solution is obtained using local best and global best position solutions which are denoted as P_{best} and g_{best}. The locationand velocity updates are achieved through:

$$V_{i,d}(\mathrm{t}) = (V_{i,d}(\mathrm{t}-1) \text{ x W}) + c1 \text{ x } \text{ r1 x } (X_{p^{best}\ i,d} - X_{i,d}(\mathrm{t}-1)) + \text{c2 x } \text{r2 x } (X_{g^{best}\ d} - X_{i,d}(\mathrm{t}-1)) \quad (1$$

Likewise, the location updates are calculated as:

$$X_{i,d}(t) = X_{i,d}(\mathrm{t}-1) + V_{i,d}(\mathrm{t}) \quad ($$

where $c1$ and $c2$ are two non-negative constants and the $r1$ and $r2$ are the 2arbitrary variables between 0 and 1. Keeping base as the PSO algorithm, authors proposed a routing scheme as presented in figure 2.

Input : set of generated cluster heads $\alpha = \{Ch_1, Ch_2, ..Ch_M\}$, PSO parameters, next hop and Hop count Output: optimal route R: $\alpha \rightarrow \{\alpha + Ch_{M+1}\}$
Step 1: Let the particles as $P_i, \forall_i, 1 \leq i \leq N_p$

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Step 2: for $i = 1\ toN_p$
(a) Compute the fitness as $F = Max\_Dist \times W_1 + Max\_Hops \times W_2$
(b) Find the personal best $P_{best} = P$
End
Step 3: find the global best (g_{best}) as $\{P_{best_k} | Fitness(P_{best_k}) = \min(Fitness(P_{best_k}))\}$
Step 4: Until the optimal condition achieved *do*
(a) $fori = 1{:}\,N_p$ do
(b) Update the particle's velocity and positions.
(c) Compute the fitness of current solution
(d) Find the $P_{best_i} = P_i$, i.e. if $Fitness(P_i) < Fitness(P_{best})$ then
(e) $P_{best_i} = P_i$
(f) End
(g) Find the $G_{best_i} = P_i$, i.e. if $Fitness(P_{best}) < Fitness(G_{best})$ then
(h) $G_{best_i} = P_{best_i}$
(i) end
(j) end
Step 5: Compute Next Hop cluster using G_{best}
Step 6: Stop

However, the existing schemes which are based on PSO, suffer from several issues such as time complexity to search the optimal solution, and sluggishconvergence that oftenpave way for premature solution discovery. These issues are addressed using proposed local search approach. In order to achieve this, we use gravitational search algorithm which helps to obtain the local best solution. The gravitational search algorithm is established on the Newton's theory which states that each particle attracts other particle with a force. The attraction force is inversely proportionate to the square of the distance and straightaway proportionate to the multiplication of the particle mass. In GSA we consider that the masses of particles are directly proportional to the fitness value. Because, heavier mass will have more attraction force and it becomes easy to obtain the global optimal solution. In GSA, we consider Nno. of agents that are deployed arbitrarily in a given subspace. During this process, the gravitational force by agent j on agent$i$ on time t is given as:

$$F_{ij}^d(t) = \left(x_j^d(t) - x_i^d(t)\right) \times \frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon} \times G(t) \qquad (1)$$

$M_{aj}(t)$denotes the active gravitational force of j, M_{pi} denotes the passive gravitational force of agent i, $G(t)$ gravitational constant at time t, R_{ij} indicates Euclidean distance between agent i and j, and ε is a small constant. The gravitational $G(t)$can be computed as:

$$G(t) = G_0 \times \exp\left(-\alpha \times \frac{iter}{maxiter}\right) \qquad (2)$$

α is descending coefficient and G_0 is the initial value, $iter$ denotes current iterations and $maxiter$ denotes maximum number of iterations. Similarly, the total force on the agent i can be computed as:

$$F_i^d(t) = \sum_{j=1, j\neq i}^{N} rF_{ij}^d(t) \qquad (3)$$

Where r is an arbitrary no. which is evenlydispersed between 0 and 1.

Further, we measure the acceleration of agent which is based on the force and mass. This can be computed as:

$$ac_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \qquad (4)$$

Where t denotes the time and $M_i$signifies the weightage of i^{th} agent. Thus, the updated velocity and positions of agents can be computed as:

$$v_i^d(t+1) = r_i \times v_i^d(t) + ac_i^d(t)$$
$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \qquad (5)$$

In order to improve the search operations, we incorporate gravitational search optimization with particle swarm optimization which provides the optimal solution for optimization to obtain the optimal solution. This combination helps to achieve the best solution for $gbest$ with the help of local search operations of GSA. The updated velocity using PSO and GSA can be given as:

$$V_i(t+1) = V_i(t) \times w + r_1 \times c_1^{'} \times ac_i(t) + c_2^{'} \times r_1 \times \left(gbest - X_i(t)\right) \quad (6)$$

$V_i$is the velocity of agent i, w is the weighting factor, r_1 random number and $ac_i(t)$ is the acceleration for agent i . Similarly, the particle positions can be updated as:

$$X_i(t+1) = X_i(t) + V_i(t+1) \quad (7)$$

According to the proposed combined approach, initially, all agents are initialized randomly and each agent is considered as candidate solution. In the next phase, the gravitational phase, gravitational constant, and other forces are computed and finally the acceleration parameter is computed. After computing the acceleration, the best solution must be updated in every iteration. This process is repeated until the optimal solution are obtained. The proposed method uses GSA as local search which reduces number of searches and provides optimal solution faster.

3. Results and Discussion

This portion of article is all about proposed approach'sexperimental evaluation and result analysis. Here, we evaluate the efficacy of proposed model with the existing techniques. The outcomes ofproposed scheme is vetted againststandard techniques such as ER-SR,ER-RPL, PRD and MSGR schemes. The experimental parameters are adopted from [24] as presented in table 1.

Table 1. Simulation parameters

Parameter name	Parameter value
Network size	100mx100m
No. of nodes	100 ~ 300
Control Message size	25 bytes
Transmitter Electronics (E_{elec})	50 nJ/bit
Transmitter Amplifier (ε_{mp})	0.0013 pJ/bit/ m^2
E_0 (initial energy)	1J
Data packet size	512 bytes
Transmission Radius	20 m

According to the proposed model, we conducted an experimental analysis by considering a 2D area of 100mx100m where 100~300 sensor nodes are deployed randomly where each node has 20m transmission range. Each sensor node has initial energy as $1J$. With the help of these parameters, we repeated this simulation experiment for 50 times and obtained the average parameter to measure and compare the performance of projected model.

3.1.Performance measurement metrics

The performance of presented scheme is measured in terms of following parameters as described below:

- Energy Consumption: this is the crucial parameter for any sensor network where performance is measured by computing the overallpower consumption by a sensor node to send the information packet to the base station.
- Network Lifetime: Here, we measure the total no. of alive nodes until the simulation finishes.
- Packet delivery ratio: this is the measurement of total no. of packets that gets deliver successfully to the base station.
- End-to-end Delay: this is the measurement of time from packet generation to packet delivery.

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3.2.Experimental study

In this experimental analysis, we deploy 100 sensor nodes in the two-dimensional region where sink is positionedat the midpoint of the network.

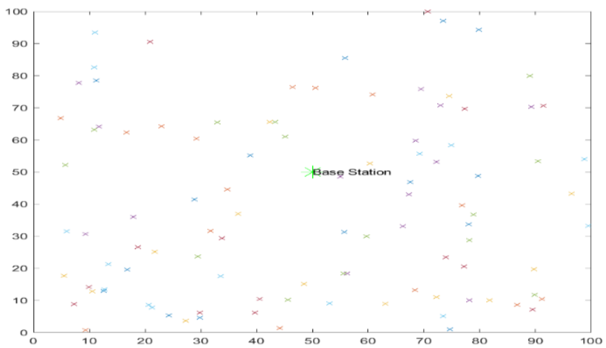

Fig.1 Sensor Node deployment

In the next phase, we perform clustering in which the complete sensor network is split into 7clusters and every cluster has a CH. In the next phase, we transmit the data from CH to the sink.

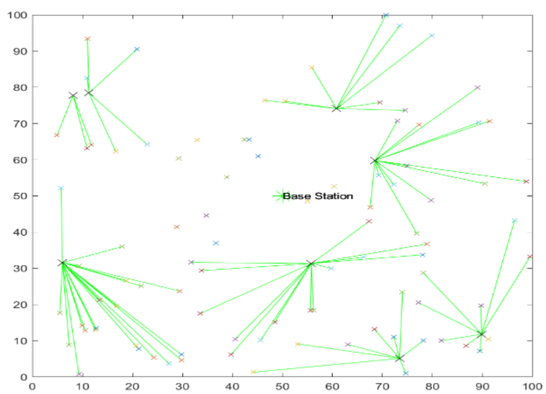

Fig.2. Clustering

We repeat thisproceduretill the timeevery sensor in the graphget dead or complete simulation iterations are finished. Lastly, we measure the efficiency of proposed model and evaluateits performance in contrast to existing techniques. Below given figure 3 shows a comparative analysis for 300 nodes where we have compared the energy consumption efficiency of proposed model in contrast with existing techniques.

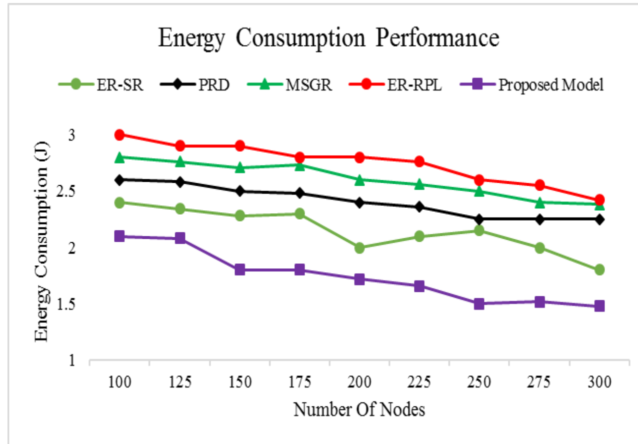

Fig.3. Energy Consumption performance comparison

As depicted in figure 3, the proposed approach reduces energy consumption when compared with existing techniques such as ER-SR, PRD, MSGR, and ER-RPL. The average energy consumption performance is obtained as 2.15 J, 2.40 J, 2.60 J, 2.74 J and 1.74 J using ER-SR, PRD, MSGR, ER-RPL and Proposed Model, respectively. As the count of nodes gets higher, the power consumption decreases because of proposed objective function which helps to find more number of optimal and reliable paths whereas existing techniques suffer from signaling overhead resulting in more energy consumption.

Figure 4demonstrates a comparative analysis with respect to lifetime where we have varied the count of nodes in each simulation and measured the overall life of network model. This figure shows that with the increase in nodes count, the network lifetime also gets increase due to variation in routing path and cluster head selection. Moreover, when number of nodes are less than the effective distance may be more than the distance threshold hence increasing node count affects the network lifetime performance.

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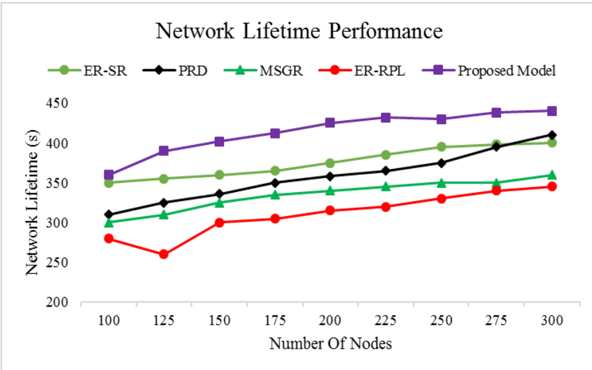

Fig.4. Network lifetime performance

According to this experiment, we obtained the average network lifetime performance as 310 s, 335 s, 358 s, 375.89 s and 414.33s using ER-RPL, MSGR, PRD, ER-SR and proposed approach, respectively. Proposed approach shows a significant improvement in network lifetime.

We have conducted another experimental analysis to measure the packet delivery performance .This experiment is also conducted using similar configuration as described in table 1. Figure 5 shows acomparative analysis for varied number of nodes.

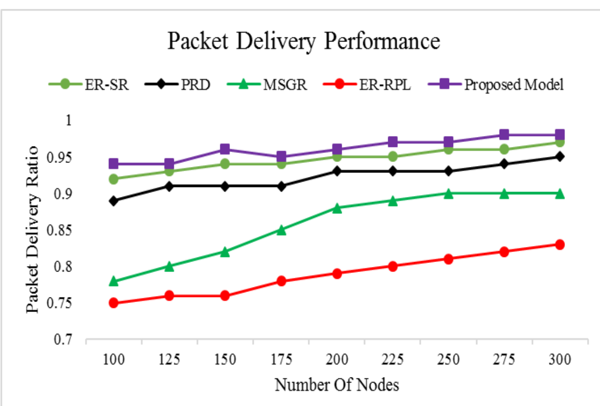

Fig.5. Packet delivery performance comparison

According to this experiment, we obtain the packet delivery performance as 78.88%, 85.78%, 92%, 94.67% and 96.11% using 33s using ER-RPL, MSGR, PRD, ER-SR and proposed approach, respectively. The comparative study shows that the presentedschemeachieves better resultswith respect to energy consumption, network longevity and packetdelivery when evaluated against the standardmethods.

4. Conclusion

In this paper, a novel approach is introduced to improve the network performance using meta-heuristic optimization approaches. According to proposed approach, we have presented cluster head selection and energy aware routing approach. To achieve this, we present PSO based optimization strategy for optimal cluster head selection. The PSO based approaches suffer from computational complexity to search the optimal solution hence we incorporate gravitational search algorithm-based model which reduces search operation. With the help of this, the optimal CH is selected and multihop routing is performed. We have conducted an experimental research and compared the performance of proposed schemeagainst other existing techniques. The experimental analysis illustrates that the presentedschemeattains better result.

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