GT-PSO- An Approach For Energy Efficient Routing in WSN

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Abstract
Sensor Nodes play a major role to monitor and sense the variations in physical space in various real-time application scenarios. These nodes are powered by limited battery resources and replacing those resource is highly tedious task along with this it increases implementation cost. Thus, maintaining a good network lifespan is amongst the utmost important challenge in this field of WSN. Currently, energy efficient routing techniques are considered as promising solution to prolong the network lifespan where multi-hop communications are performed by identifying the most energy efficient path. However, the existing scheme suffer from performance related issues. To solve the issues of existing techniques, a novel hybrid technique by merging particle swarm optimization and game theory model is presented. The PSO helps to obtain the efficient number of cluster and Cluster Head selection whereas game theory aids in finding the best optimized path from source to destination by utilizing a path selection probability approach. This probability is obtained by using conditional probability to compute payoff for agents. When compared to current strategies, the experimental study demonstrates that the proposed GTPSO strategy outperforms them.
Keywords
WSN, multi-hop routing, PSO, Game Theory.

1. Introduction

During last decade, there is a tremendous growth in technology. This technological growth has proliferated the communication technology including wireless communication. Wireless Sensor Networks (WSNs) are regarded as one of the fastest growing technologies which is enabled by recent sophisticated advancements in MEMS(Micro-Electro Mechanical System) and Wireless Communication Technologies [1]. Moreover, these networks are extensively used in diverse real time online and offline applications such as health monitoring, water quality monitoring, air pollution monitoring and natural disaster prevention [2, 3]. These Sensor Networks comprise of several tiny Sensor nodes which perform sensing, computation and networking capability. These sensor nodes facilitate end-user to measure and monitor the various types of phenomena in diverse environments. The sensing node is also known as source node, and the node which accumulates the data from all nodes and perform several required operations is referred as base station or sink node. The sensor nodes are accountable to aggregate the data and deliver it to base station [4].

The sensor nodes are equipped with inadequate resources pools such as range of sensing, communication range, battery power, limited storage and computation resources. Generally, these networks are meant to be working in the environment which are not easily accessible where battery replacement is a tedious task. Thus, maintenance of the power consumption is a critical component for these networks [5]. There are several tasks which consume energy such as data sensing, collection, aggregation and transmission. However, the exchange of data also consumes more energy when compared with other tasks in this communication. Similarly, packet collision, overhearing i.e. node transmits the packet which is assigned to other node, and idle listening are also identified as major source of energy waste. Due to collision, the packets get corrupted and these corrupted packets are discarded from communication thus packet retransmission is required which increases energy consumption. Moreover, due to limited communication or transmission range of these nodes, the data packets are transmitted to sink node via multi-hop communication. In order to obtain effective transmission, an efficient routing protocol is required which can focus on various aspects of data transmission and routing to improve the overall network performance. The efficient routing scheme includes several issues such as improving the network lifespan, self-organizing, route discovery for autonomous nodes, handling the random and complex environments and maintaining the multi-hop routing path.

The WSN routing protocols are broadly classified into two categories as flat and hierarchal routing protocols based on the architecture of the network. In flat routing protocols, nodes exchange the sensed data packet directly to base station where as hierarchal routing divides the deployed sensor nodes in to diverse clusters. Next, selecting the suitable cluster head is a tedious task which is designated based on their power levels and transmission range. This cluster head is accountable to collect the data from cluster members. Further, these cluster heads formulate a multi-hop routing path. the flat routing protocols face several issues such as energy, scalability and QoS in dense deployments. To overcome these issues, hierarchal routing schemes are widely adopted. Several techniques have been developed such as PEAL (Power Efficient and Adaptive Latency) to handle the latency and power consumption [6], energy aware

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clustering [7], LEACH [8], CL-LEACH [9], multi-stage routing protocol [10,11].

Current research community has adopted optimization and evolutionary computation as promising solutions to deal with energy efficient routing related issues. Several techniques have been developed based on optimization and evolutional approaches such as swarm intelligence based routing [12], Ant Colony Optimization (ACO) with hop count minimization [16] which presents a unique pheromone update strategy, improved routing using ant colony optimization [17], where it uses an heuristic function which considers node communication distance, direction of transmission and residual energy to find the optimal path, Glowworm swarm optimization is presented in [18] which performs load balancing and energy aware routing by applying pseudo-random route discovery and improved pheromone trail-based updating strategy, Grey Wolf optimization is introduced in [19] which uses Fractional Gravitational Search Algorithm (GSA) for cluster head selection and Tunicate swarm GWO for multipath routing [20] and many more optimization schemes [1]. Similarly, the evolutionary computation, rule based methods and learning based methods are also widely adopted for multi-hop routing such as in [20] authors presented EMEER to prolong the network lifespan which is based on evolutionary approach, in [21] authors presented a game theory based model with the help of evolutionary computing approach, in [22] a trust based routing scheme is developed which uses evolutionary particle swarm optimization, trust management by using fuzzy logic, and greedy mechanism for buffer sharing, a hybrid PSO and evolutionary game theory based model is presented in [23] which performs clustering and routing, EEFCM-DE [24] is an energy efficient Fuzzy C-Means based approach combined with differential evolution, genetic algorithm for distance-aware routing [13], evolutionary game theory based clustering [14] and many more [1]. In [25] fuzzy logic rule-based energy proficient clustering and data forwarding scheme is presented, in [26] authors introduced a hybrid model of fuzzy logic for CH selection and Emperor Penguin Optimization to discover the ideal route selection, in [27] a fuzzy logic-based approach is presented to proliferate the network lifespan which uses distance and residual energy to construct the fuzzy rules.

Despite having several promising schemes, improving the network lifespan, developing efficient routing techniques remains as a challenging task. These issues need to be addressed. Thus, in this work the focus is on aforementioned routing related issues and developing a novel routing scheme. This approach has resulted in improvement of system performance with the help of following contributions:

- Particle Swarm Optimization (PSO) based solution to identify the optimal number of CHs and selection of CH is presented.
- Evolutionary game theory for multi-hop energy efficient routing path selection is presented. The path is evaluated based on the minimum Packet Error Rate(PER). To select the path, a conditional probability model is presented.

Rest of the document is systematized into following sections. Section II evokes the state-of-art routing algorithms, section III presents the proposed solution for optimization and game theory-based energy efficient routing, section IV presents the complete experimental setup, outcome of proposed approach and comparative analysis and section V describes the deducing observations and future scope in this research field.

2. Literature survey

In this section, a brief description about state-of-art techniques of various techniques related to minimizing the energy consumption by utilizing energy proficient schemes in WSN is presented. Currently the optimization procedures, evolutionary computing and machine learning based advanced computation techniques are widely adopted for routing. Moreover, multi-hop routing is quite significant in improvising the efficiency of WS, considering this, Al Mazaideh et al. [5] developed multi-hop routing algorithm with the help of compressive sensing and genetic algorithm. The compressed sensing helps to improve the data transfer where genetic algorithm is used to balance the energy efficiency. The multi-objective GA helps to reduce the mutual coherence and a greedy mechanism is used to divide the WSN into multiple paths which reduces load. Similar to this, Adnan et al. [15] developed clustering based multi-hop routing with the help of fuzzy logic. The fuzzy rules consider the distance between node and base station, remnant energy and concentration for CH selection. Based on the clustering concept, Rezaeipanah et al. [28] presented a new approach where clusters are re-formed during the multi-hop routing procedure to ensure the minimum energy consumption, minimum delay and maximum packet delivery. The re-clustering scheme is developed by combining Open-Source Development Model Algorithm (ODMA) and K-means. Moreover, this approach uses genetic algorithm for optimizing the clustering process. In [29] Arora et al discussed about the two types of cluster communications as inter and intra. Authors developed Energy-efficient Balanced Multi-Hop Routing Scheme (EBMRS). In this process a probability of selection metric is presented which is designed by considering numerous constraints like, residual energy, hop-counts and distance to base station. The intra-cluster communication follows the multi-hop process. Moreover, this scheme ensures the minimum distance between CHs which is used to maintain the balanced clustering process. Rajaram et al. [30] adopted fuzzy logic approach for routing and load balancing in WSN. Moreover, this approach presents a 3-tier multi-hop optimized routing scheme. Hamzah et al. [25] used fuzzy logic for CH selection where fuzzy rules are designed based on residual energy, position suitability, node deployment strategy, and distance from base station. Yong et al. [31] developed tree based multi-hop routing to optimize the energy consumption. According to this process, the nodes which are nearer to base station with higher residual energy, are selected to determine the CH set. In next phase, each cluster is partitioned into different regions where nodes which satisfy the CH eligibility conditions. Further, the CHs are selected based on their distance from base station.

Shyjith et al. [32] suggested optimization-based approach for optimal and dynamic cluster head selection for WSN. This hybrid method is split into three stages as setup stage, data transmission, and measurement stage. In first stage, network parameters are initialized which includes energy and node mobility. In next stage, CH selection is performed with the help of Optimized Sleep-awake Energy-Efficient Distributed clustering. This distributed clustering uses a combination of Rider optimization and Cat Swarm Optimization. Moreover, the CH selection threshold value is obtained by analyzing the multi-objective restraints such as distance, energy and delay. In next stage data is transmitted to base station by using multi-hop communication. Lastly, the outcome of this approach is measured in terms of energy and network lifespan. Qabouche et al. [33] presented hybrid energy coherent static routing protocol to extend the lifespan of WSN. In this approach, nodes are divided into following categories such as cluster head and independent nodes or normal nodes. This approach combines the clustering and multi-hop routing technique. In each round, cluster formation, data collection and routing through gateways or independent nodes is performance and selects the cluster head dynamically where it introduces concept of dormant nodes. Koyuncu et al. [34] considered the agricultural monitoring using WSN and adopted existing Deterministic Energy-Efficient Clustering (DEC) protocol and modified it by combining multi-tier model. The cluster heads are designated based on the energy and location constraints of the node. Qureshi et al. [35] also focused on the application of WSN in the field of agriculture and introduced Gateway Clustering Energy-Efficient Centroid (GCEEC) routing protocol. This approach considers the centroid position of network for cluster head selection and considers gateway from each cluster. The gateway node is responsible for packets transmission to the base station. Xu et al. [36] explored the existing routing scheme of WSN and identified that optimization schemes can be considered as a promising solution to prolong the network lifespan. To achieve this objective, Energy-efficient Region Source Routing protocol (ER-SR) is developed where the nodes which are having higher residual energy are chosen as the source routing node with the help of distributed energy region algorithm. These nodes select the optimal routing path in such a way that it remains common for each source node. To abate the power depletion this scheme adopts the ant colony optimization algorithm. Han et al. [37] presented WPO-EECRP which is weight and parameter optimization for WSN. The cluster heads are designated based on several criteria like, residual energy, distance to neighbor nodes, distance from base station, and node degree. This scheme introduces a dynamic weight coefficient which helps to obtain the optimized clusters.

In this section, various routing techniques in the field of WSN has been discussed. Most of the techniques are focused on the optimization scheme where cluster head selection is considered as an important phase. However, packet collision remains a challenging task in this field and prolonging network lifespan is also considered as a challenging task.

3. Proposed GT-PSO model for routing

In this segment, the proposed resolution for energy proficient routing to mitigate the energy related issues and discussion on improvement strategies for wireless sensor networks has been illustrated. The complete section is arranged in three subsections as follows In first phase network and energy consumption modeling with various assumption is presented, in second phase optimization model is presented for cluster head selection, further, a novel multi-path routing mechanism is presented which is developed by using game theory approach.

3.1 Network and Energy Model

In this work, a WSN which comprises of heterogeneous sensor nodes and sink node or base station is examined. Figure 1 depicts the pictorial overview of network. The deployed sensor nodes are enabled with wireless connectivity and the base station or sink node have unlimited energy capacity. In this scenario, the nodes can be treated as sensor nodes which are accountable to collect the data and router nodes which are used for packet forwarding to the next hop or base station.

The network can be presented in the form of graph as $\mathcal{G}(\mathcal{V},\mathcal{E})$ where $\mathcal{V}$ represents the vertices set, $i \in \mathcal{V}$ which denotes the total count of sensor nodes and sink in the network and $\mathcal{E}$ denotes the set of edges which represents the communication link between nodes. Let us consider that $e(i,j) \in \mathcal{E}$ denotes the wireless connectivity link between nodes i and j. In order to establish this link, the nodes should be in the transmission range of each other.

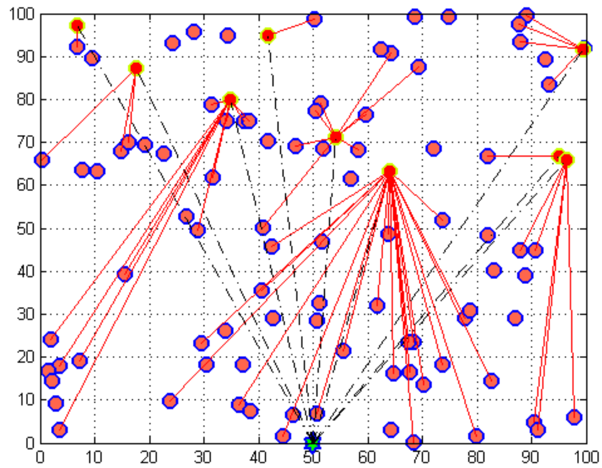

Figure 1 Wireless Sensor Network Model

Let us assume that in this communication link $e(i,j)$ node i transmits the data packet to node j. During this process of data exchange, the transmitter and receiver nodes consume some amount of energy. Moreover, radio hardware, radio electronics, and power amplifiers also consume energy.

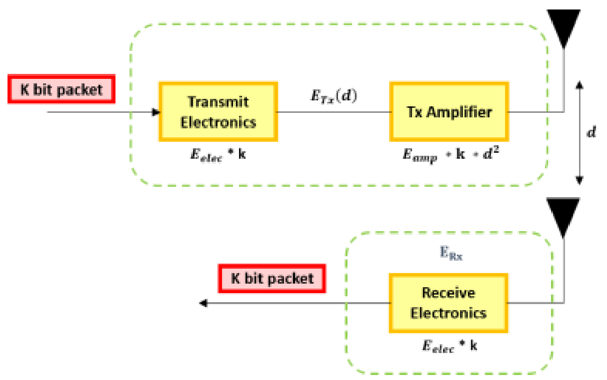

Figure 2 Radio model for free space

Let d_{th} be the threshold distance, f_s is the free-space model where power loss is d^2 and mp denotes the multipath fading where power loss is d^4. Thus, in order to transmit the l bit size of data over a distance d, the radio energy consumption for transmission phase can be expressed as:

$$E_{tx}(l.d) = \begin{cases} l.E_{elec} + l\varepsilon_{fs}d^2, & d < d_{th} \\ l.E_{elec} + l\varepsilon_{mp}d^4, & d \geq d_{th} \end{cases} \tag{1}$$

Similarly, the energy consumption to receive the transmitted data, the radio energy dissipation can be expressed as:

$$E_{rx}(l) = l.E_{elec} \tag{2}$$

E_{elec} varies according to modulation, filtering, digital coding and signal spreading. The free-space and multi-path amplifier energy varies according to the distance of receiver. Above given figure 1 depicts the radio model for free space scenario.

3.2 Overview of GT-PSO Model

In this work, minimizing this energy consumption for entire network to persist the network lifespan is achieved. The proposed GT-PSO methodology is an amalgamation of optimization and game theory-based approach. In first phase, PSO based strategy for cluster head selection is applied. In order to obtain the cluster head, the node must satisfy two conditions as follows: (a) The remaining energy of node should be greater than the average remaining energy of all nodes, and (b) Distance from sensor node to base station is more than the threshold distance.

After cluster head selection, game theory approach to obtain the most suitable end-to-end path for data transmission is applied. This optimal path is obtained by evaluating the Packet Error Rate (PER). Thus, the path which has less PER is selected as the multi-hop path to transmit the data to BS.

3.3 Optimizaiton Strategy for CH Selection

In WSN, the energy consumption performance is affected by several factors such as data volume, sensing duration, node distance and many more. Mainly, the distance between sensor node has the significant impact on energy consumption. This is known as compactness or deployment density of the nodes. Generally, the conventional clustering-based mechanisms use fixed number of Cluster Heads which may not be efficient for real-time and dynamic network environments. If a network contains more number of CHs, then cluster redundancy increases which leads to excessive power consumption by CH. In contrast, if the number of CHs is too low then the nodes which are placed at remote location, may not be able to find the appropriate cluster to join for communication. This leads to inaccurate monitoring and increased packet drop rate. During exchange of data, the nodes which are located in the range of BS, directly transmit the data to BS whereas the nodes which are out of the range of BS communication range use multi-hop communication routing path which is obtained by using game theory.

Let us consider that N amount of sensor nodes are installed in a 2-D terrestrial area of $M \times M$ for environment monitoring. According to proposed approach, the CH selection is performed. The CH performs numerous activities such as receiving the data, aggregating the received data and transmitting to next hop or base station. Thus, whole energy utilized by a CH can be expressed as:

$$\begin{aligned} E_{CH_i} &= E_{txA=\pi r^2} + E_{rx} + E_{dx} \\ &= (a \times l \times E_{elec}) \\ &\quad + (a \times l \times +l \times \varepsilon_{mp} \times d_{toBS}^4) \\ &\quad + (a \times l \times E_{da}) \end{aligned} \tag{3}$$

where E_{dx} is the energy consumption during data aggregation phase, $a = \frac{N}{H}$ signifies the total count of available nodes in cluster, l is the size of transferred data, E_{da} is the energy depletion during data aggregation, and d_{toBS} denotes the distance between CH and BS. This distance is computed as:

$$d_{to\ BS} = \sqrt{x_1^2 + y_1^2} \tag{4}$$

Similarly, the cluster members transmit the sensed data to CH. Here, we assume that the cluster members and CH are in the range of threshold distance. At this stage, the energy consumed by j^{th} cluster member in i^{th} cluster is computed as follows:

$$E_{cm_{ji}} = l \times E_{elec} + l \times \varepsilon_{fs} \times d_{to\ CH_{ij}}^2 \tag{5}$$

The distance between CH and sink node is computed as:

$$E(d_{to\ BS}^4) = \int_0^M \int_0^M \left(\sqrt{x_1^2 + y_1^2}\right)^4 \rho(x_1, y_1) dx_1 dy_1 = \int_0^M \int_0^M (x_1^2 + y_1^2)^2 \rho(x_1, y_1) dx_1 dy_1 \quad (6)$$

Where $\rho(x_1, y_1)$ denotes the node deployment density. Similarly, we can obtain the distance between CH and base station as:

$$E\left(d_{to\ CH_{ji}}^4\right) = \int_0^M \int_0^M \left(\sqrt{x_2^2 + y_2^2}\right)^2 \rho(x_2, y_2) dx_2 dy_2 = \int_0^M \int_0^M (x_2^2 + y_2^2)^2 \rho(x_2, y_2) dx_2 dy_2 \quad (7)$$

Based on these energy consumption measurements, overall energy consumption of entire network as is computed as:

$$E_{total} = \sum_{i=1}^{H} \left(E_{CH_i} + \sum_{j=1}^{a-1} E_{CM_{ji}} \right) \quad (8)$$

In order to determine the optimal number of Cluster Heads we take the derivative of whole energy consumption as follows:

$$\frac{dE(E_{total})}{H} = 0 \quad (9)$$

At this stage, we adopt particle swarm optimization to learn the particle search operation of best result of last round which is denoted as l_{best} and the obtained learning weights are assigned to c_3 which is expressed as

$$v_{id}(t+1) = w \times v_{id}(t) + c_1 \times r_1 \times \left(p_{best}(t) - x_{id}(t)\right) + c_2 \times r_2 \times \left(p_{best}(t) - x_{id}(t)\right) + c_3 \times r_3 \times \Omega \times \left(l_{best}(t-1) - x_{id}(t)\right) \quad (10)$$

$$\text{Where, } \Omega = \begin{cases} 1, otherwise \\ 0,\ l_{best}(t-1) = p_{best}(t)\ or \\ l_{best}(t-1) = g_{best}(t), \\ x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \end{cases}$$

c_1 and c_2 are the learning factors, and c_3 is the newly introduced learning factor of previous best search l_{best}. In this approach, when l_{best} overlaps with local and global best solution then $\Omega = 0$. The particle position is updated based on p_{best} local best solution, g_{best} global best solution and l_{best} the global optimal solution obtained from last iteration. This stage generates the required optimal number of clusters. We consider remaining energy of cluster member (CM) node, distance between CM and CH and count of hops present in the path from CH to BS. To achieve this, we define a fitness function which covers all three parameters. This function is defined as:

$$F_t = \mu_1 \times E_{residual\ CM} + \mu_2 \times D_{toCH} + \mu_3 \times H_{toBS\ \mu_1+\mu_2+\mu_3=1} \quad (11)$$

where $E_{residual\ CM}$ denotes the residual energy of cluster members, D_{toCH} denotes the distance from CM to CH, H_{toBS} denotes the hop count to BS, μ_1, μ_2 and μ_3 denotes the control parameters of the fitness function. The residual energy of cluster member (CM) can be computed as:

$$E_{residual\ CM}(t) = E_{residual\ CM}(t-1) - \sum_{i=1}^{H} \sum_{j=1}^{a-1} E_{CM_{ji}}(t) \quad (12)$$

Where $E_{CM_{ji}}$ denotes the energy consumed by j^{th} CM node in i^{th} cluster at time t

D_{toCH} can be computed as:

$$D_{toCH} = \sum_{j=1}^{a-1} d_{toCH_{ji}} \quad (13)$$

Where $d_{to\ CH_{ji}}$ denotes the distance from j^{th}cluster member to i^{th} CH. Similarly, the hop count can be obtained as:

$$H_{toBS} = \sum_{i=1}^{H} H_{toBS_i} \quad (14)$$

Where H_{toBS_i} denotes the hop count from j^{th} CH to the i^{th} CH node. Here, we consider the distance parameter to transmit the data to the sink node. If the distance from CH exceeds the threshold distance, then multi-hop communication is performed otherwise the CH node directly transmit the data to BS.

3.4 Game Theory for Multihop Routing

The optimization scheme helps to obtain the optimal number of clusters and selection of cluster head. Selection of optimal path for multi-hop communication plays important role. Thus, multi-hop routing strategy using game theory is presented. In conventional game theory approaches, the rational player aims to maximize the payoff by selecting the strategy whereas in game theory, the games are played repeatedly by agents from a randomly drawn random population. This approach uses mutation and selection processes to improve the performance. The mutation process is used for refining the Nash Equilibrium and selection process is used to analyze the growth of sub-population. According to this selection process the subpopulation grows when it uses better strategies when compared with average strategies. Let us consider that initial population plays a pure or mixed strategy x which is known as incumbent strategy. In this let agents $\epsilon \in (0,1)$

play a different strategy y which is known as mutation strategy. Now, if we draw an individual from population then its probability of select incumbent strategy and mutant strategy is $1-\epsilon$ and ϵ, respectively. The payoff of this types of games can be expressed as:

$$w = \epsilon y + (1-\epsilon)x \quad (15)$$

Here, we consider a large finite population where agents are playing pure strategy as $k \in K$ where K denotes the set of strategies. We assume that at time t, $\lambda_k(t) \geq 0$ denotes the agents which are playing pure strategy k and population of agents is obtained as $\lambda(t) = \sum_{k \in K} \lambda_k(t)$. Similarly, let us consider that $x_k(t) = \frac{\lambda_k(t)}{\lambda(t)}$ denotes a fraction of agents which are using pure strategy k at a time t. Let us consider that the population which is using this fraction is denoted by a vector as $x(t) = [x_1(t), \dots, x_k(t), \dots, x_K(t)]$. The expected payoff for this population is $u(k,x)$ in the state x, and the average payoff of population is $u(x,x) = \sum_{k=1}^{K} x_k . u(k,x)$. We make assumption that the payoffs are proportional to the reproduction rate of each individual and inherits the strategy profile. With the help of this, we generate a model for population x_k as follows:

$$\dot{x}_k = x_k . [u(k,x) - u(x,x)] \quad (16)$$

$\dot{x}_k$ denotes the time derivation of x_k which shows that the population with better strategies grow and worse strategies shrink the population.

We adopt this model to achieve the most optimal path to convey the data from source to destination node. Here, we assume that the CH is not placed in the distance threshold range. The Cluster Head (CH) is denoted as source S and base station is denoted as D and total K number of paths are available which are denoted as strategies. total number of packets are denoted as $\lambda = \sum_{k \in K} \lambda_k$ which are considered as agents and λ_k denotes the packets which are following the path k. Based on this, the fraction of agents is obtained as $x_k = \frac{\lambda_k}{\lambda}$ are using each path and collected in the form of vector as $x = [\lambda_1, \dots, \lambda_2, \dots, \lambda_K]$.

Here, our main objective is to find the optimal flow vector as $\lambda = [\lambda_1, \dots, \lambda_k, \dots, \lambda_K]$ which transmit the information via path $k \in K$ with minimum PER. This condition can be expressed as:

$$0 \leq \lambda_k \leq \Lambda_k, k \in K \quad (17)$$

Λ_k denotes the path capacity

Generally, the agent nodes select best routing path to minimize the PER during transmission. Whenever, the model receives a lower value of PER for any specific path then it selects that path for routing otherwise it maintains the current routing path until next best PER value is obtained. This leads to revising the strategies of agents which depends on the current strategy and population state. We denote the average rate of employing any strategy as k as $r_k(x), k \in K$. In order to switch the strategy or path we introduce a probability factor. Let $p_k^l(x)$ is a probability to switch the path from k to path l. Thus, total number of agents which are switching their paths are $x_k . r_k(x) . p_k^l(x)$. Thus, the outflow from path k is $\sum_{l \in K, l \neq k} x_k . r_k(x) . p_k^l(x) = x_k . r_k(x)$ and inflow to path k is $\sum_{l \in K, l \neq k} x_l . r_l(x) . p_l^k(x)$. subtracting these in and out flows generates a derivation similar to the model as mentioned in (15), it can be expressed as:

$$\begin{aligned} \dot{x}_k = & \sum_{l \in K, l \neq k} x_l . r_l(x) . p_l^k(x) \\ & - x_k . r_k(x) . [1 - p_k^k(x)] \\ = & \sum_{l \in K} x_l . r_l(x) . p_l^k(x) - x_k . r_k(x) \end{aligned} \quad (18)$$

The process of an agent using strategy k depends on the attenuation A_k and A_l corresponding to path k and l. If the attenuation difference is positive i.e. $A_k > A_l$ then agents switch to the sampled strategy. The difference between A_k and A_l is obtained as random variable with a differentiable cumulative distribution function as $\phi: R \to [0,1]$. Here, we define a conditional probability function which is used by agent for switching the paths as:

$$\phi(A_k - A_l) = \Pr\{A_k - A_l > 0 | A_k > 0, A_l > 0\} \quad (19)$$

Based on this, the conditional probability of an agent who switches the strategy can be expressed as:

$$p_k^l(x) = \begin{cases} x_l \phi(A_k - A_l) \ \ if\ k \neq l \\ 1 - \sum_{i \neq k, i \in K} x_i \phi(A_k - A_i) \ \ if\ k = 1 \end{cases} \quad (20)$$

4 results and discussion

The outcome of proposed method and evaluation of the obtained performance with various state of art algorithms is demonstrated. The complete approach is implemented using MATLAB simulation tool. Below given table 1 demonstrates the parameters used in this simulation.

TABLE I :SIMULATION PARAMETERS FOR GT-PSO

Parameter	Value
Network Area	$100x100m^2$
Number of nodes	100
Packet size	4000/bits
ϵ_{mp}	0.0013pj/bit/m4
ϵ_{fs}	10pj/bit/m2
E_{elec}	50nJ/bit
Initial energy	0.5J

We have considered 100 number of sensor nodes deployed in $100x100m^2$ region. Each sensor node is capable to transmit the data packet of size 4000 bits where preliminary energy of each node is 0.5J. We measure the performance in terms of number of rounds vs First Node Dead[FND], number of rounds vs Half Node Dead[HND], First Node Dead for number of round vs varied network size, and number of round vs alive node. Below given table 2 shows the number of rounds where first and half nodes are dead.

TABLE II :FIRST AND HALF NODE DEAD

Algorithm	FND	HND
LEACH [15]	118	372
EAMMH [15]	164	416
EAUCF[15]	109	515
Fuzzy Logic [15]	353	610
Proposed GT-PSO	390	656

Depending upon this investigation, we obtained that proposed GT-PSO approach improves the lifespan of sensor nodes because the first dead node is obtained at 390th round whereas existing approaches reported their FND earlier rounds. Based on this experiment we obtained that the performance of proposed GT-PSO approach for FND is increased by 137.805% than LECH, 257.798% than EAUCF, and 10.48% than Fuzzy logic.

In the same way, we measure the outcome in terms of number of rounds, energy dissipation for FND and HND for varied network size. Below given figure demonstrates comparative analysis in terms of round for varied network size.

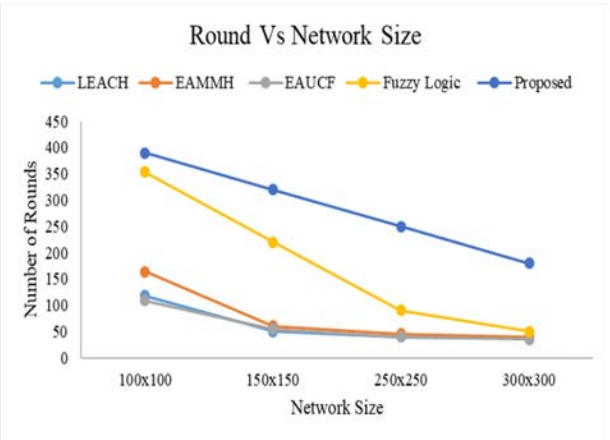

Figure 3. Round vs network size for FND

This experiment shows that as network size is increasing the existing approaches start running out of battery in less number of rounds such as fuzzy logic [15] scheme reported its FND in 50th round for a network size of 300x300m^2 whereas proposed GT-PSO approach reports FND in 180 round. Similarly, we evaluate the outcome of GT-PSO to obtain the HND performance as depicted in below given figure 4.

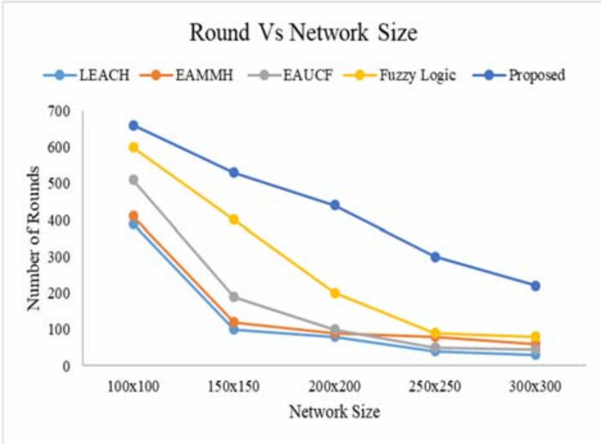

Figure 4 Round vs network size for HND

In this experiment also shows that proposed GT-PSO methodology attains better performance in terms of rounds completed until the half nodes are dead of the deployed network. The proposed approach requires 220 round for HND whereas fuzzy logic approach reported HND in 80 rounds. The obtained values are presented in below given table 3.

TABLE III :ROUND VS NETWORK SIZE FOR HND

Network Size	LEACH	EAMMH	EAUCF	Fuzzy	Proposed
100x100	390	410	510	600	660
150x150	100	120	190	400	530
200x200	80	90	100	200	440
250x250	40	80	50	90	300
300x300	30	60	45	80	220

The performance in terms of energy dissipation for varied network size for FND and HND is evaluated. Below given table 3 shows the comparative analysis for energy dissipation.

TABLE IV: ENERGY DISSIPATION

Network Size	Algorithm	FND	HND
100x100	LEACH	0.3032	0.0871
	EAMMH	0.2983	0.0738
	EAUCF	0.3587	0.0422
	Fuzzy Logic	0.2345	0.0551
	Proposed GT-PSO	0.2018	0.0425

Network Size	Algorithm	FND	HND
150x150	LEACH	0.3515	0.1362
	EAMMH	0.3576	0.1222
	EAUCF	0.4077	0.1187
	Fuzzy Logic	0.2548	0.0637
	Proposed GT-PSO	0.2170	0.0510
200x200	LEACH	0.3683	0.1237
	EAMMH	0.3934	0.1333
	EAUCF	0.4758	0.1371
	Fuzzy Logic	0.3202	0.0760
	Proposed GT-PSO	0.2891	0.0551
250x250	LEACH	0.4189	0.1246
	EAMMH	0.4380	0.1416
	EAUCF	0.4996	0.1424
	Fuzzy Logic	0.3733	0.1013
	Proposed GT-PSO	0.3052	0.0859
300x300	LEACH	0.3481	0.1468
	EAMMH	0.4362	0.1501
	EAUCF	0.4698	0.1584
	Fuzzy Logic	0.3830	0.1006
	Proposed GT-PSO	0.2215	0.0854

The energy dissipation experiment shows that the proposed approach consumes less energy for each experiment. Similarly, we evaluated the outcome of proposed approach in respect of network lifespan and packet delivery ratio as mentioned in [36]. Below given figure 5 depicts the network lifespan performance for varied number of nodes.

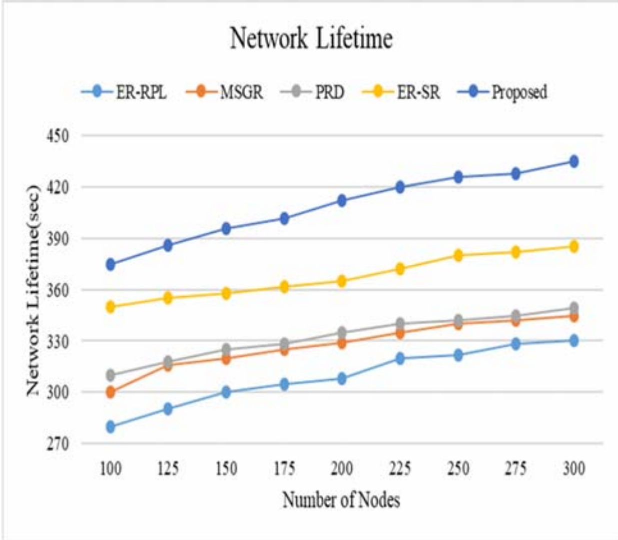

Figure 5 Network lifespan performance

In this investigation, the average network lifespan is obtained as 309.22s, 328s, 332.44s, 367.66s, and 408.88s using $ER-RPL$, $MSGR$, PRD, ER-SR, and Proposed approach respectively. This analysis demonstrates that the performance of proposed GT-PSO approach is increased by 32.22% than ER-RPL, 24.65% than MSGR, 22.99% than PRD, and 11.21% than ER-SR.

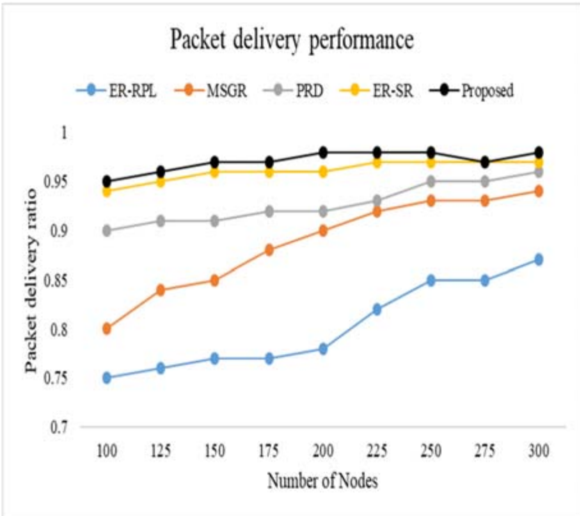

Figure 6 packet delivery performance

In figure 6, we analyze the packet delivery performance of proposed GT-PSO approach and compared it with existing scheme. The average packet delivery performance is obtained as 0.80, 0.88, 0.92, 0.96, and 0.97 using ER-RPL, MSGR, PRD, ER-SR, and proposed technique, respectively.

5 CONCLUSION

In this work, the network lifespan related issues is addressed. Thus, an energy aware routing for multi-hop communication is presented. In order to achieve this, a hybrid routing technique is developed where Particle Swarm Optimization and Game Theory approach is combined. The PSO is used for CH selection and identifying optimal number of CHs. The EGT(Evolutionary Game Theory) helps to find the most suitable path for multi-hop data transmission. We conducted an extensive simulation analysis and equated the outcome of proposed approach with other existing procedures. This comparative analysis shows that the proposed approach outperforms when compared with state-of-art techniques.

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