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

Priyanka R1 and Dr. K. Satyanarayan Reddy2,
1 Dept. of Information Science and Engineering, Cambridge Institute of Technology Bangalore, Affiliated to VTU
Belagavi (Karnataka), India
2Dept of Information Science and Engineering, Cambridge Institute of Technology Bangalore, Affiliated to VTU,
Belagavi (Karnataka), India

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 GT-PSO 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
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 evolutionary 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 improving 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 intra 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
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 \( G(\mathcal{V}, \mathcal{E}) \) 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.

![Wireless Sensor Network Model](image)
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.

Let \( d_{th} \) be the threshold distance, \( f_0 \) 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:

\[
E_{tx}(l, d) = \begin{cases} 
  l \cdot E_{elec} + l \cdot f_0 \cdot d^2, & d < d_{th} \\
  l \cdot E_{elec} + l \cdot mp \cdot d^4, & d \geq d_{th}
\end{cases}
\]

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

\[
E_{rx}(l) = l \cdot E_{elec}
\]

\( E_{elec} \) 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 Optimization 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:

\[
E_{CH_i} = E_{txA=πr^2} + E_{tx} + E_{dx} = (a \times l \times E_{elec}) + (a \times l \times E_{elec} + l \times mp \times d_{toBS})
\]

where \( E_{dx} \) is the energy consumption during data aggregation phase, \( a = \frac{N}{n} \) 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:

\[
d_{to\, BS} = \sqrt{x_i^2 + y_i^2}
\]

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:

\[
E_{cm_{ji}} = l \times E_{elec} + l \times f_0 \times d_{to\, CI(i)}^2
\]

The distance between CH and sink node is computed as:
\[ E(d_{BS}^2) = \int_0^M \int_0^M \left( x_1^2 + y_1^2 \right)^4 \rho(x_1, y_1) dx_1 dy_1 \]

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

\[ E(d_{CH}^2) = \int_0^M \int_0^M \left( x_2^2 + y_2^2 \right)^2 \rho(x_2, y_2) dx_2 dy_2 \]

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

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

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

\[ \frac{dE(E_{total})}{H} = 0 \]

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

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

1, otherwise

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

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 \( \epsilon \in (0,1) \)

\[ F_e = \mu_1 \times E_{residual\ CM} + \mu_2 \times D_{toCH} + \mu_3 \times H_{toBS} \]

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, \( \mu_1, \mu_2 \) and \( \mu_3 \) denotes the control parameters of the fitness function. The residual energy of cluster member (CM) can be computed as:

\[ E_{residual\ CM}(t) = E_{residual\ CM}(t - 1) - \sum_{i=1}^a \sum_{j=1}^{a-i} E_{CM_{ji}}(t) \]

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

\[ D_{toCH} = \sum_{j=1}^{a-i} d_{toCH_{ji}} \]

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

\[ H_{toBS} = \sum_{i=1}^a H_{toBS_i} \]
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 \( \epsilon \), respectively. The payoff of this types of games can be expressed as:

\[
w = \epsilon y + (1 - \epsilon)x
\]  

(15)

Here, we consider a large finite population where agents are playing pure strategy \( k \in K \) 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 the population which is using this fraction is denoted by a vector as \( x(t) = [x_1(t), ..., x_k(t), ..., x_K(t)] \). The expected payoff for this population is \( u(k, x) \) in the state \( x \), and the average payoff of population is \( u(x, x) = \sum_{k \in K} x_k u(k, x) \). 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:

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

(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 and base station is denoted as \( D \). Here, we consider a large finite population where agents are playing pure strategy \( k \in K \) and population of strategies total number of agents are 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 the population which is using this fraction is denoted by a vector as \( x(t) = [x_1(t), ..., x_k(t), ..., x_K(t)] \). The expected payoff for this population is \( u(k, x) \) in the state \( x \), and the average payoff of population is \( u(x, x) = \sum_{k \in K} x_k u(k, x) \). 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:

\[
\dot{x}_k = x_k \left[ u(k, x) - u(x, x) \right]
\]  

(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 have considered 100 number of sensor nodes deployed in 100x100m\(^2\) region. Each sensor node is capable to

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Network Area</td>
<td>100x100m(^2)</td>
</tr>
<tr>
<td>Number of nodes</td>
<td>100</td>
</tr>
<tr>
<td>Packet size</td>
<td>4000/bits</td>
</tr>
<tr>
<td>( \epsilon_{mp} )</td>
<td>0.0013pj/bit/m(^4)</td>
</tr>
<tr>
<td>( \epsilon_{fs} )</td>
<td>10pj/bit/m2</td>
</tr>
<tr>
<td>( E_{elec} )</td>
<td>50nJ/bit</td>
</tr>
<tr>
<td>Initial energy</td>
<td>0.5J</td>
</tr>
</tbody>
</table>

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 0.5 J. 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**

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>FND</th>
<th>HND</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEACH [15]</td>
<td>118</td>
<td>372</td>
</tr>
<tr>
<td>EAMMH [15]</td>
<td>164</td>
<td>416</td>
</tr>
<tr>
<td>EAUCF [15]</td>
<td>109</td>
<td>515</td>
</tr>
<tr>
<td>Fuzzy Logic [15]</td>
<td>353</td>
<td>610</td>
</tr>
<tr>
<td>Proposed GT-PSO</td>
<td>390</td>
<td>656</td>
</tr>
</tbody>
</table>

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](image)

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 300x300m² 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](image)

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**

<table>
<thead>
<tr>
<th>Network Size</th>
<th>LEACH</th>
<th>EAMMH</th>
<th>EAUCF</th>
<th>Fuzzy</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>100x100</td>
<td>390</td>
<td>410</td>
<td>510</td>
<td>600</td>
<td>660</td>
</tr>
<tr>
<td>150x150</td>
<td>100</td>
<td>120</td>
<td>190</td>
<td>400</td>
<td>530</td>
</tr>
<tr>
<td>200x200</td>
<td>80</td>
<td>90</td>
<td>100</td>
<td>200</td>
<td>440</td>
</tr>
<tr>
<td>250x250</td>
<td>40</td>
<td>80</td>
<td>50</td>
<td>90</td>
<td>300</td>
</tr>
<tr>
<td>300x300</td>
<td>30</td>
<td>60</td>
<td>45</td>
<td>80</td>
<td>220</td>
</tr>
</tbody>
</table>

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**

<table>
<thead>
<tr>
<th>Network Size</th>
<th>Algorithm</th>
<th>FND</th>
<th>HND</th>
</tr>
</thead>
<tbody>
<tr>
<td>100x100</td>
<td>LEACH</td>
<td>0.3032</td>
<td>0.0871</td>
</tr>
<tr>
<td></td>
<td>EAMMH</td>
<td>0.2983</td>
<td>0.0738</td>
</tr>
<tr>
<td></td>
<td>EAUCF</td>
<td>0.3587</td>
<td>0.0422</td>
</tr>
<tr>
<td></td>
<td>Fuzzy Logic</td>
<td>0.2345</td>
<td>0.0551</td>
</tr>
<tr>
<td></td>
<td>Proposed GT-PSO</td>
<td>0.2018</td>
<td>0.0425</td>
</tr>
<tr>
<td>Network Size</td>
<td>Algorithm</td>
<td>FND</td>
<td>HND</td>
</tr>
<tr>
<td>--------------</td>
<td>------------</td>
<td>-------</td>
<td>-------</td>
</tr>
<tr>
<td>150x150</td>
<td>LEACH</td>
<td>0.3515</td>
<td>0.1362</td>
</tr>
<tr>
<td></td>
<td>EAMMH</td>
<td>0.3576</td>
<td>0.1222</td>
</tr>
<tr>
<td></td>
<td>EAUCF</td>
<td>0.4077</td>
<td>0.1187</td>
</tr>
<tr>
<td></td>
<td>Fuzzy Logic</td>
<td>0.2548</td>
<td>0.0637</td>
</tr>
<tr>
<td></td>
<td>Proposed GT-PSO</td>
<td>0.2170</td>
<td>0.0510</td>
</tr>
<tr>
<td>200x200</td>
<td>LEACH</td>
<td>0.3683</td>
<td>0.1237</td>
</tr>
<tr>
<td></td>
<td>EAMMH</td>
<td>0.3934</td>
<td>0.1333</td>
</tr>
<tr>
<td></td>
<td>EAUCF</td>
<td>0.4758</td>
<td>0.1371</td>
</tr>
<tr>
<td></td>
<td>Fuzzy Logic</td>
<td>0.3202</td>
<td>0.0760</td>
</tr>
<tr>
<td></td>
<td>Proposed GT-PSO</td>
<td>0.2891</td>
<td>0.0551</td>
</tr>
<tr>
<td>250x250</td>
<td>LEACH</td>
<td>0.4189</td>
<td>0.1246</td>
</tr>
<tr>
<td></td>
<td>EAMMH</td>
<td>0.4380</td>
<td>0.1416</td>
</tr>
<tr>
<td></td>
<td>EAUCF</td>
<td>0.4996</td>
<td>0.1424</td>
</tr>
<tr>
<td></td>
<td>Fuzzy Logic</td>
<td>0.3733</td>
<td>0.1013</td>
</tr>
<tr>
<td></td>
<td>Proposed GT-PSO</td>
<td>0.3052</td>
<td>0.0859</td>
</tr>
<tr>
<td>300x300</td>
<td>LEACH</td>
<td>0.3481</td>
<td>0.1468</td>
</tr>
<tr>
<td></td>
<td>EAMMH</td>
<td>0.4362</td>
<td>0.1501</td>
</tr>
<tr>
<td></td>
<td>EAUCF</td>
<td>0.4698</td>
<td>0.1584</td>
</tr>
<tr>
<td></td>
<td>Fuzzy Logic</td>
<td>0.3830</td>
<td>0.1006</td>
</tr>
<tr>
<td></td>
<td>Proposed GT-PSO</td>
<td>0.2215</td>
<td>0.0854</td>
</tr>
</tbody>
</table>

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.

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.

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.

References


Prof. Priyanka R currently a Research Scholar at Cambridge Institute of Technology, Bangalore affiliated to VTU Belgaum. Her Research focus is on the area of Wireless Sensor Networks. She holds a B.E. degree in CSE from Visvesvaraya Technological University and a M.Tech degree in CSE from the Visvesvaraya Technological University. She is a life time member of Indian Society for Technical Education[ ISTE] and Institute for Engineering Research and Publication[ IFERP].

Dr. K. Satyanarayan Reddy currently working as Professor and Head of Information Science & Engineering, Cambridge Institute of Technology, Bangalore. His qualification includes Ph.D. in Computer Science (Dravidian University, Kuppam, AP), MTech in Computer Applications (Dept. Of CSE, ISM Dhanbad). He has worked as faculty in many Engineering Colleges. He has more than 25 Research Papers (National and International) in his credit and has chaired national and international conferences. Delivered Keynote address in few national level conferences.