Hybrid fuzzy logic and gravitational search algorithm based routing for wireless sensor networks

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ABSTRACT

Over the recent years, the wireless sensor network (WSN) has garnered significant attention from both researchers and the general populace. Its application in diverse environmental scenarios, including weather monitoring, temperature regulation, humidity tracking, and military surveillance, extends beyond conventional boundaries. WSNs consist of numerous nodes, each functioning as a sensor with the primary responsibility of data sensing. These nodes operate under constraints such as power, energy, efficiency, and deployment considerations. Moreover, the power and other resources cannot be replaced and renewed therefore prolonging the network lifetime has become the main aspect of WSNs. Energy aware routing play's important role to ensure the efficient data transmission with minimal power consumption and ensures the prolonged network lifetime. In this work, we focus on optimizing the routing process therefore we present a hybrid model which uses fuzzy logic for path identification and gravitational search optimization (GSA) for efficient path selection. The fuzzy logic considers energy consumption, residual energy, distance and delay parameters to identify the most suitable path for data transmission. The experimental analysis shows a significant improvement in network lifetime, delay an aspect delivery.

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1. INTRODUCTION

Recently, there has been a tremendous growth in utilization and development of wireless sensor network (WSN). The efficient utilization and adaption of these networks has sparked the development of economical and energy-efficient devices. These sensors incorporate signal processing devices and sensing equipment, offering diverse abilities for handling WSN nodes and facilitating seamless wireless communication in ideal network conditions [1]. Generally, these networks consist of several components such as device to sense the data, storage and power devices. These networks have been employed in various real-time applications such as disaster management, health monitoring, surveillance, and military applications [2]. The WSN is a type of which consist of several sensor nodes which accumulates the data from the deployed region and neighborhood and transmit the collected data to the sink node for further process. The sensor network helps to monitor the considered environment and converts it into user-understandable format. Nonetheless, cost of sensor nodes is very cheap, but they come with limited battery power, making them susceptible to energy constraints.

The primary challenge in WSN revolves around enhancing network lifespan [3]. In data gathering applications, each node assumes the responsibility of sensing and transmitting data packets to the sink node. The data aggregation process helps to minimize the energy consumption by aggregating the sensed data into single packet [4]. These networks are powered by a limited battery capacity therefore maintaining energy efficiency become the important aspect for these networks. Several methods have reported the importance of energy management in WSN to prolong the network lifetime. The sensor nodes perform two main tasks which are: (i) data collection from physical environment and (ii) data routing to neighbouring nodes and forward the data to base station (BS) [5]. Data collection task is performed based on the event occurrence but data transmission and routing play's important role. As discussed before, the WSNs are used in various real-time applications where obtained data is processed and analyzed to formulate the decision regarding event. Generally, the more number of sensor nodes can facilitate increased sensing and data collection accuracy however these nodes are equipped with limited battery capacity therefore maintaining efficient power utilization plays important role to increase the network lifetime [6].

When certain nodes within a network exhaust their energy supply, the network topology undergoes changes. The presence of too many inactive nodes can potentially render the network system paralyzed, disrupting its normal operation. Therefore, it holds significant importance for WSNs to develop routing protocols that achieve a balance in energy usage and efficiency, aiming to maximize the overall network lifespan [7], [8].

Hierarchical clustering protocols focus on improving the network lifespan by dividing the deployed network into multiple cluster [9], [10]. According to the clustering approach, the convolutional hierarchy (CH) is considered as pivotal part of the network which is responsible for collecting data from member nodes and transmitting the aggregated data to the BS. The other nodes present in the cluster are known as cluster members which communicate to their respective cluster head over short distance. Due to this arrange of communication minimizes the energy consumption in hierarchal routing. Several methods have been introduced to establish the communication between CH and BS which includes direct and indirect transmission methods where other nodes are used as intermediate nodes to facilitate the communication.

The term "network lifetime" typically refers to the duration until a certain ratio of nodes cease functioning for example the time where first node failure or the time until the last node failure [11]. This failure of the initial node, the network's stability experiences a sharp decline, leading to a considerable degradation in overall performance. The key to prolonging the network's lifespan lies in achieving equilibrium in energy consumption among nodes and enhancing energy efficiency. The routing mechanism plays crucial role to improve the network lifetime where collected data packets are transmitted in such a way that it consumes less energy. Figure 1 depicts the basic categorization of different routing protocols. Figure 2 illustrates a clustered WSN, showcasing the organized structure resulting from the clustering process.

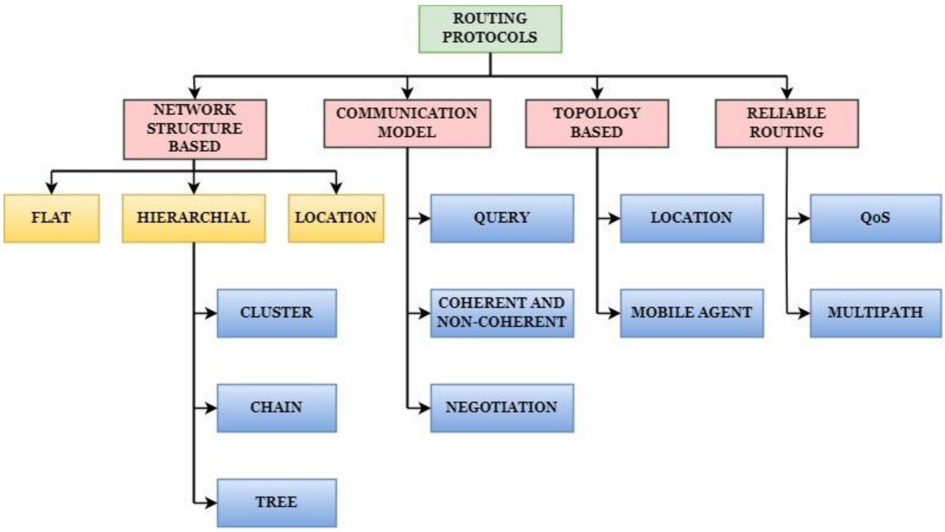

Figure 1. Routing protocols

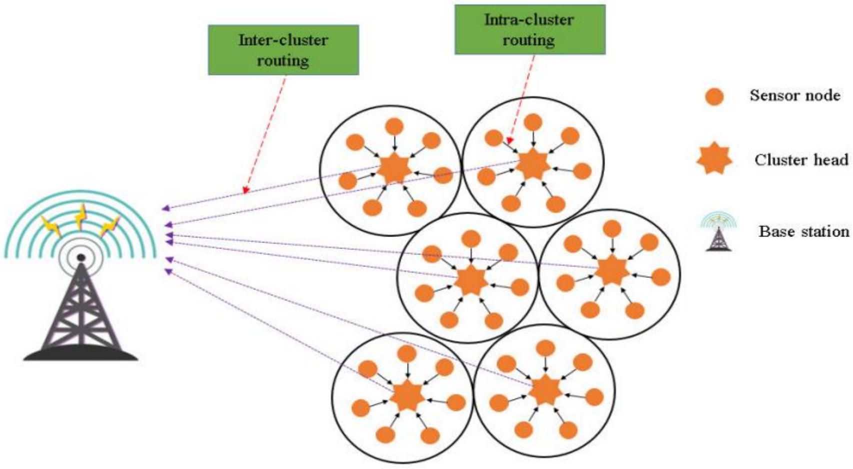

Figure 2. Clustering process in WSN

Several researches have been introduced based on this concept of hierarchal and clustering system such as LEAH-C-LEACH, TEEN, and APTEEN. However, energy consumption, complexity, flexibility and quality of service (QoS) remains challenging issue for these routing approaches. Current researches has adopted optimization and evolutionary methods to address the energy and QoS related challenges in WSN. These methods play crucial role to establish the energy efficient routing approach. In this context, several optimization strategies have been introduced such as swarm intelligence [12], ant colony optimization [13], [14].

Similarly, the load-balancing also plays important role to mitigate the energy consumption issues. Glowworm swarm optimization [15] was introduced to discover the optimal route for packet routing along with load balancing. Similarly, the grey wolf optimization (GWO) was also introduced for optimal cluster head selection in WSN [16].

Ezhilarasi and Krishnaveni [17] presented evolutionary multipath energy-efficient routing protocol (EMEER) approach to prolong the network lifetime by using evolutionary computation method. The specifics of WSN routing leveraging various optimization strategies were described by Al-Aghbari *et al.* [18]. The presented paper offers a thorough overview of the earlier research conducted in the field of WSN between 2010 and 2019. Attiah *et al.* [19] stated that due to the limited amount of energy available, each node's self-interest is to conserve its own energy. This can cause congestion, which raises latency and increases packet collisions. Eventually, this can accelerate the depletion of energy along certain pathways, reducing the network's lifespan. In the presented research, they model the route selection problem in a WSN as an evolutionary anti-coordination routing game and examine it from a game theoretic point of view. They determined the game's evolutionary stable strategy (ESS) and demonstrate that a greedy, or mutant, approach cannot overtake the resultant incumbent strategy. In addition, they developed the replicator dynamic of the suggested game to illustrate how the sensors behave while choosing routes. The replicator dynamics method demonstrates how the nodes adjust their strategies at each phase of the game until they arrive at a stable strategy (ESS) by learning from their strategic interactions.

Isabel and Baburaj [20] presented the combined model by using particle swarm optimization (PSO), fuzzy logic and greedy approach for to improve the QoS. Similarly, Song *et al.* [21] presented a hybrid model by using PSO and game theory model for clustering. On the other hand, a new approach was presented in [22] i.e., EEFCM-DE which uses energy efficient fuzzy C means with genetic algorithm to obtain the optimal routing path. Along with trust-based routing mechanism is introduced to incorporate security aspects along with QoS management [23].

The complete overview of this domain suggests that several methods have been discussed to improve the performance of WSN routing such as LEACH, PEGASIS, AODV, and optimization methods. However, these methods still face several challenges which are as follows:

- Energy efficiency: energy is a critical resource in WSNs, and routing protocols must aim to conserve and use energy in best possible manner to prolong network lifetime. This constraint often necessitates the development of energy-aware routing strategies to optimize energy usage across the network.
- Reliability and fault tolerance: WSNs are deployed in harsh and dynamic environments where nodes may fail due to various factors like hardware failures, environmental conditions, or malicious attacks. Routing protocols should ensure reliable data delivery despite node failures and network disruptions.

- Scalability: as WSNs may consist of thousands to millions of nodes, routing protocols must be scalable to accommodate large-scale deployments without sacrificing performance or efficiency. Scalability issues can arise due to the overhead associated with route discovery, maintenance, and data aggregation.
- QoS requirements: depending on the application, WSNs may have specific QoS requirements such as latency, throughput, and reliability. Routing protocols should be designed to meet these QoS requirements while optimizing energy consumption and network resources.

Despite numerous promising schemes, enhancing network lifetime and developing efficient routing remain challenging tasks that require attention. Some of the widely known issues are limited energy resource, non-uniform energy distribution, dynamic network condition, scalability, and communication overhead. Therefore, this work focuses on the aforementioned routing-related issues and introduces a novel routing scheme with the primary aim of improving system performance. The main aim of developing this improved routing approach is to improve energy efficiency, increasing network lifetime, adaptability to network dynamics and optimal path selection.

Rest of the manuscript is arranged in several sections. Section 2 presents the brief discussion about existing routing approaches. In section 3 demonstrates the proposed methodology for energy aware routing by using fuzzy logic and gravitational search method. Section 4 describes the experimental setup, outcome of proposed model and its comparative analysis with existing methods. Finally, section 5 presents the concluding remarks and future research direction in this field.

2. LITERATURE SURVEY

This section presents a brief discussion about existing methods of energy aware routing methods in sensor networks. Yadav and Mahapatra [24] introduced a hybrid optimization model for selection for energy aware cluster selection in WSNs. This method considers several criteria such as stabilization of energy, minimizing the distance between nodes, reducing the delay in data transmission. The final optimization model is termed cuckoo insisted rider optimization algorithm (ROA). This model is obtained by combining ROA and cuckoo search (CS) algorithms. Ibrahim and Ahmed [25] presented an energy-saving routing protocol for WSNs, considering energy levels, distance to BS, and data aggregation. It uses ant colony optimization and A* algorithms to optimize routes, improve energy utilization, and reduce communication costs.

Abasıkeleş-Turgut and Altan [26] reported that the issue of resource constraints in WSNs due to which these networks face issues or quick power depletion which becomes a crucial issue for long distance wireless communication. To address this, authors introduced a novel approach which performs two-level clustering mechanism named as intra-level and inter-cluster communication, dynamically determining second-level cluster coverage based on cluster head distance. Self-organized nodes designate clustering ranges, clusters, and heads without a central control mechanism, and static clustering reduces control messages generated by the system. This mechanism helps to reduce the overall energy consumption and improves the network lifetime.

Mehta and Saxena [27] focused on hierarchical WSNs because of their nature to monitor and track the events without human intervention. However, sensor nodes have short life spans, leading to battery drain and energy-hole problems. To preserve energy, precise clustering and path selection are essential. To address this issue, authors presented a sailfish optimizer and multi-objective clustering approach to achieve the optimal path for data transmission. A new fitness function is defined for CH selection in such a way that it minimizes the overall energy consumption resulting in reducing the dead node count. Later the SFO is used to obtain the most efficient path to ensure the appropriate data transmission.

Maheshwari *et al.* [28] focused on minimize energy consumption and maximize network lifetime in WSNs. The butterfly optimization algorithm (BOA) is used to select an optimal cluster head based on residual energy, distance to neighbors, BS, degree, and centrality. Ant colony optimization (ACO) is used to identify the optimal route between cluster head and BS. The BOA considers energy, node degree, centrality and distance to select the cluster head.

SureshKumar and Vimala [29] developed the E-ALWO algorithm which is an energy aware and trust-based routing technique. It integrates exponentially weighted moving average (EWMA) with ant lion optimization (ALO) and whale optimization algorithm (WOA). The model uses a CH to select the optimal route based on energy and delay constraints. The E-ALWO algorithm computes the optimal route based on factors like energy, trust, delay, and distance, and accepts the path with the highest fitness value.

Rezaeipanah *et al.* [30] presented an energy-aware cluster-based multi-hop routing algorithm that extends the network's lifetime by aggregating data in CHs and uniformly distributing energy among nodes. The algorithm ensures minimal energy consumption by balancing energy within the network. The proposed approach uses a combination of k-means and open-source development model algorithm (ODMA) for clustering and genetic algorithm for multi-hop routing. The clusters can be reformed during the routing procedure if needed. This approach ensures a balance of energy within the network.

Anandh and Baburaj [31] discussed the importance of energy aware data transmission to minimize the energy consumption and prolong the network lifetime. Therefore, authors introduced a hierarchical routing model where nodes are divided as outer level and inner level nodes where outer level nodes transmit the data to inner-level nodes. In order to optimize the performance, ant colony optimization method is also incorporated.

These methods have reported significant improvement in network lifetime however these methods still suffer from various challenges such as ACO algorithms may face scalability issues as the network size increases. The efficiency of ACO is influenced by factors like the number of nodes and the density of the network. BOA and ACO algorithms involve parameters that need to be tuned appropriately. Similarly, the ALO and WOA adds complexity which leads to additional overhead.

3. METHOD

This section presents the detailed description of proposed model for energy aware routing mechanism for sensor networks. The first subsection presents the basic details on network model and energy consumption model details, later, we present a hybrid objective model which considers several parameters such as energy, distance, delay, overhead, QoS and trust parameters to ensure the appropriate routing path. In next subsection, fuzzy logic, followed by optimization models are presented to obtain the best path.

3.1. Network model

This model assumes the numerous sensor nodes are deployed randomly in the given 2D geographical region. Moreover, we also assume that the sensor nodes are not aware of their positions, and each sensor node has homogenous characteristics. Figure 3 illustrates a graphical representation of the deployed network. The sensor nodes deployed in the system which are having limited power capacity while the BS possesses ample amount of energy to store, process and analyze the data.

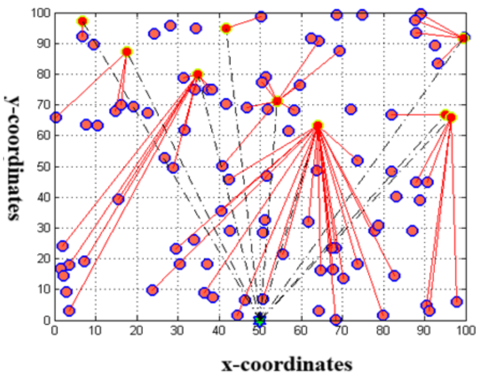

Figure 3. Wireless sensor network model

The network structure can be represented as a graph, denoted by $G(V, E)$, where V signifies the set of vertices, E characterizes the communication links between nodes. For example, $e(i, j) \in E$ represents a wireless link between node $i$and j. To establish this link, it is essential for the nodes to be within each other's transmission range. Let's consider that in the communication link represented by $e(i, j)$, where certain amount of data packet is transmitted from node i to j. This process of data exchange causes some amount of energy consumption, moreover, the radio hardware, radio electronics, and power amplifiers involved in the process also contribute to overall energy consumption. Figure 4 depicts the energy consumption process required to transmit the k bit data packet.

In order to transmit a data size of l bits over a distance d, the radio energy consumption at this stage can be expressed as:

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

where d_{th} represents the threshold distance, $f_s$is used to represent the free space model, and mp represents the multipath fading where power loss is proportional to d^2 and d^4, respectively. On the other hand, a certain amount of energy is consumed while receiving the data transmitted data, the energy consumption in this phase can be expressed as:

$$E_{rx}(l) = l.E_{elec}$$

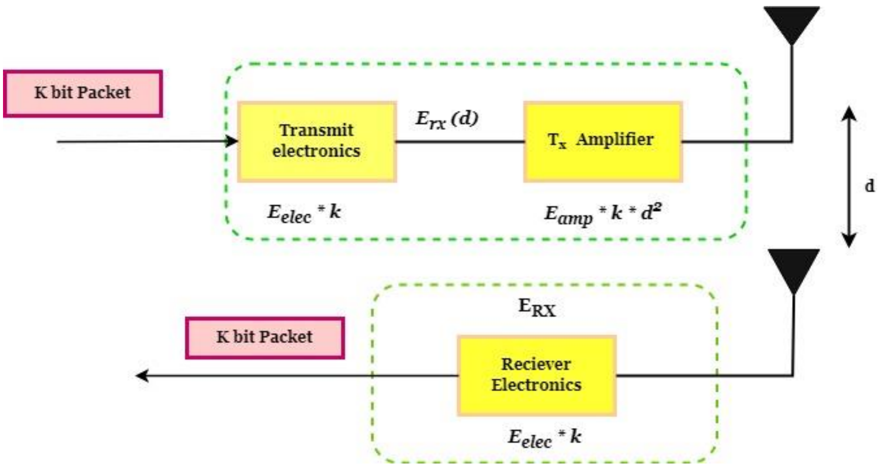

Figure 4. Radio model for free space

3.2. Parameters for efficient path selection and objective function

In this section, we describe the important factors considered to identify the routing path for energy aware data transmission.

(a) Energy

Energy plays a crucial role in determining the network's lifespan. As discussed before about absence of a power source therefore the battery cannot be replenished. However, transmitting information from all nodes to the BS demands extra energy. Additionally, the energy levels of nodes in the network are inclined to decrease during communication. $E(P_l)$ represents the energy of the l^{th} hop, and d signifies the number of hops in the multihop routing process which can be expressed as:

$$En = \frac{1}{D}\sum_{l=1}^{d} E(\rho l)$$

The overall, energy consumption can be obtained with the help of transmission energy and energy consumed during receiving the packets with the help in (1) and (2).

(b) Delay

Delay plays crucial role in time-constrained networks and has significant impact on the QoS. As the number of nodes are increased in the network, it impacts on the packet delivery time therefore total nodes required for packet transmission is considered as important parameter so that the overall delay can be minimized. The delay can be estimated as:

$$f^{delay} = \frac{d}{speed}$$

(c) Distance

The distance between sensor node affects the data transmission and network lifetime significantly. The distance can be estimated as:

$$f^{distance} = v \times t$$

(d) Residual energy

As discussed before the sensor networks suffer from the energy related issues therefore maintaining energy efficient communication becomes and important aspect. In this context, the residual energy has significant impact on the next hop selection, its capacity of data transmission and cluster head section. The residual energy can be calculated based on the initial energy and the energy consumed over time. It can be expressed as:

$$E_{res} = E_{initial} - E_{consumed}$$

The $E_{consumed}$ can be obtained by integrating the power consumption over time, as $E_{consumed} = \int_0^t P(t)dt$. With the help of these parameters, we defined an objective function which considers all parameters and the obtained function is further used for efficient path selection. The objective function for path selection is expressed as follows:

$$PathSelectioObjective = \min\left(\frac{1}{f^{energy}} + f^{delay} + f^{delay}\right) + \max(E_{res})$$

3.3. Path selection process

Optimum path selection technique is very crucial in any network as it helps network to save time and energy in data transmission. In wireless networks where the sensors have limited energy resource, these methods helps network to sustain for longer period of time. This section describes the complete process of optimal path selection for energy aware routing. The complete approach is described in below mentioned steps:

- Step 1: Initialize the simulation parameters: initially, all simulation parameters are assigned and network model is initialized based on the defined configurations.
- Step 2: Initialize the path selection parameters: in this stage, several important parameters related to path estimation are estimated such as energy, delay, residual energy and distance.
- Step 3: Initialize communication: in this stage, the model initiates the communication by selecting the source and destination nodes from the deployed sensors. Figure 5 demonstrates the sample representation of network deployment where S denotes the source node, D denotes the destination nodes and other sensor nodes are denoted by SN
- Step 4: Identifying the routing path: in this stage, we focus on finding the pack routing path from Sto D. according to this setup (Figure 5) total 11 paths are identified but all paths cannot be adopted for data transmission therefore, selection of most suitable path is the important factor. The list of identified paths is presented in Table 1.
- Step 6: Selection of optimal path: as discussed before, we obtain multiple routing path bit selecting the best path is an important criterion for energy aware routing therefore we present fuzzy logic based model for decision making process. The fuzzy logic process is described in next subsection.
- Step 7: Apply gravitational search algorithm (GSA): the previous stage facilitates the different paths to transfer the data packets but we incorporate GSA based optimization strategy to obtain the most suitable path for data transmission.

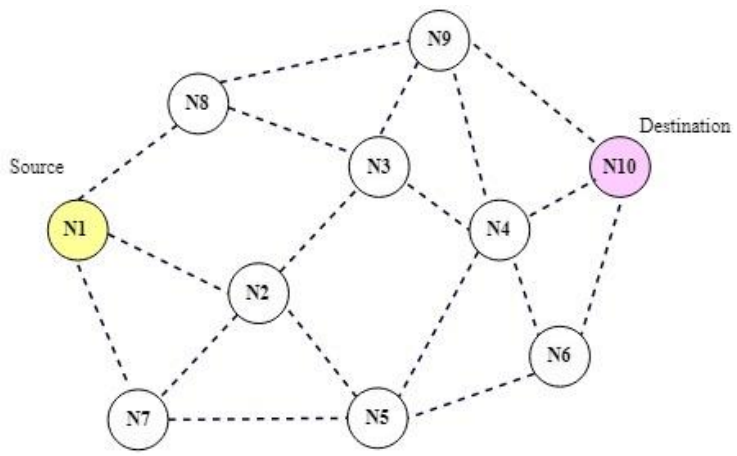

Figure 5. A sample network deployment with source, destination and sensor nodes

Table 1. Identified path form source to destination

Path number	Identified path
P 1	$SN_1 \rightarrow SN_2 \rightarrow SN_3 \rightarrow SN_4 \rightarrow SN_{10}$
P 2	$SN_1 \rightarrow SN_7 \rightarrow SN_2 \rightarrow SN_5 \rightarrow SN_6 \rightarrow SN_4 \rightarrow SN_{10}$
P 3	$SN_1 \rightarrow SN_7 \rightarrow SN_5 \rightarrow SN_6 \rightarrow SN_{10}$
P 4	$SN_1 \rightarrow SN_7 \rightarrow SN_2 \rightarrow SN_5 \rightarrow SN_4 \rightarrow SN_6 \rightarrow SN_{10}$
P 5	$SN_1 \rightarrow SN_7 \rightarrow SN_2 \rightarrow SN_5 \rightarrow SN_4 \rightarrow SN_6 \rightarrow SN_{10}$
P 6	$SN_1 \rightarrow SN_8 \rightarrow SN_2 \rightarrow SN_5 \rightarrow SN_{10}$
P 7	$SN_1 \rightarrow SN_8 \rightarrow SN_3 \rightarrow SN_9 \rightarrow SN_4 \rightarrow SN_{10}$
P 8	$SN_1 \rightarrow SN_8 \rightarrow SN_3 \rightarrow SN_4 \rightarrow SN_{10}$
P 9	$SN_1 \rightarrow SN_8 \rightarrow SN_3 \rightarrow SN_9 \rightarrow SN_{10}$
P 10	$SN_1 \rightarrow SN_2 \rightarrow SN_3 \rightarrow SN_9 \rightarrow SN_{10}$
P 11	$SN_1 \rightarrow SN_2 \rightarrow SN_3 \rightarrow SN_9 \rightarrow SN_4 \rightarrow SN_{10}$

3.4. Fuzzy logic

This section briefly describes the basic detail of fuzzy logic. It is a widely adopted mathematical concept in various real-time applications to handle the uncertainty and imprecision in decision making models. It focuses on performing computation based on "degree of truth" rather than following the Boolean logic concept. Basic process of fuzzy logic is explained below:

- Define variables: identify the input and output variables relevant to the model. These variables should be defined using linguistic terms, such as "Low", "Medium", and "High".
- Fuzzification: map crisp input values to the given fuzzy sets with the help of defined membership functions. The membership function helps to obtain the degree to which an input belongs to fuzzy set.
- Define fuzzy rules: in this stage, some rules need to be established based on the input and output variables. These rules are usually expressed in an "if-then" format.
- Inference: combine the fuzzy rules to derive fuzzy output sets. Various inference methods can be used, such as Mamdani or Sugeno. This step involves applying logical operations (AND, OR) to the fuzzy rule antecedents and generating fuzzy outputs.
- Aggregation: aggregate the fuzzy output sets obtained from individual rules to create a composite fuzzy output set. This step involves combining multiple rule outputs into a single, comprehensive output.
- Defuzzification: convert the fuzzy output set into a crisp output value. This is the process of determining a single output value that best represents the aggregated fuzzy information.

The fuzzy logic based models have been adopted widely in various applications of sensor networks such as adaptive sensing, fault detection, localization, QoS management, data fusion, and energy efficient routing. In this work, we have focused on routing in WSN because it enables adaptive routing decisions based on multiple parameters such as energy levels, link qualities, and traffic conditions. The adaptability of fuzzy systems allows the routing algorithm to respond to changing network conditions. The fuzzy logic model consists of several stages such as fuzzy rules, fuzzifier, defuzzifier, and inference. The fuzzy rules are formulated in such a way that it satisfies the objective function criteria. Table 2 shows the representation of fuzzy rules which are derived based on the energy, delay, distance and residual energy.

Table 2. Fuzzy rules for decision making process

Rule	Energy	Distance	Delay	Residual energy	Path
1	L	H	M	H	Good
2	M	L	H	H	Good
3	H	L	L	H	Excellent
4	M	L	H	M	Good
5	M	M	M	H	Excellent
6	H	L	L	M	Excellent
7	L	L	H	M	Worst
8	L	H	H	M	Worst
9	M	L	M	L	Good
10	H	L	H	L	Good

Once the decision is obtained then we apply GSA to find the optimal solution. A brief discussion of this algorithm is presented:

GSA is a nature-inspired optimization algorithm that simulates the gravitational forces between masses. GSA is used for solving optimization problems and is inspired by the law of gravity and the interactions between masses in the universe. In this work, we have presented a combined model by using fuzzy logic and GSA optimization methods. Algorithm 1 presents the proposed combined solution for this task.

Algorithm 1. Fuzzy logic and GSA for optimal routing
Step 1: Define fuzzy rules to evaluate each potential path based on the specified parameters:

$$F(Path_i) = \mu_1(D_i) \cdot \mu 2(RE_i) \cdot \mu 3(Dist_i) \cdot \mu 4(EC_i)$$

Step 2: Define appropriate fuzzy sets and membership functions (μ) for each parameter.
Step 3: Initialize GSA.
Step 4: Initialize the GSA parameters: N: number of masses (potential paths), G: gravitational constant, α: damping factor and $max\_iterations$: maximum number of iterations.
Step 5: Initialize masses for the potential path $Path_i$.
Step 6: Evaluate the fitness of each excellent path obtained from fuzzy logic:

$$Fitness(Path_i) = F(Path_i)$$

Step 7: Compute gravitational forces: calculate the gravitational force between each pair of potential paths based on their fitness values:

$$F_{ij} G. \frac{m_1 . m_2}{r_{ij}^2}$$

Step 8: Update velocity and acceleration parameters: update the acceleration and velocity of each potential path based on the gravitational forces:

$$\alpha_i = \frac{F_{net,i}}{m_i}$$

$$v_i = \alpha . v_i + a_i$$

Step 9: Update position: update the positions of potential paths based on the calculated velocities as:

$$path_i + Path_i + v_i$$

Step 10: Apply damping factor: incorporatea damping factor (α) to control the rate of convergence and prevent divergence.
Step 11: Revaluate the fitness:

$$Fitness(Path_i) = F(Path_i)$$

In Figure 6 illustrates the overall process of proposed optimum routing scheme. The proposed methodology includes integration of fuggy logic and GSA for rule based routing.

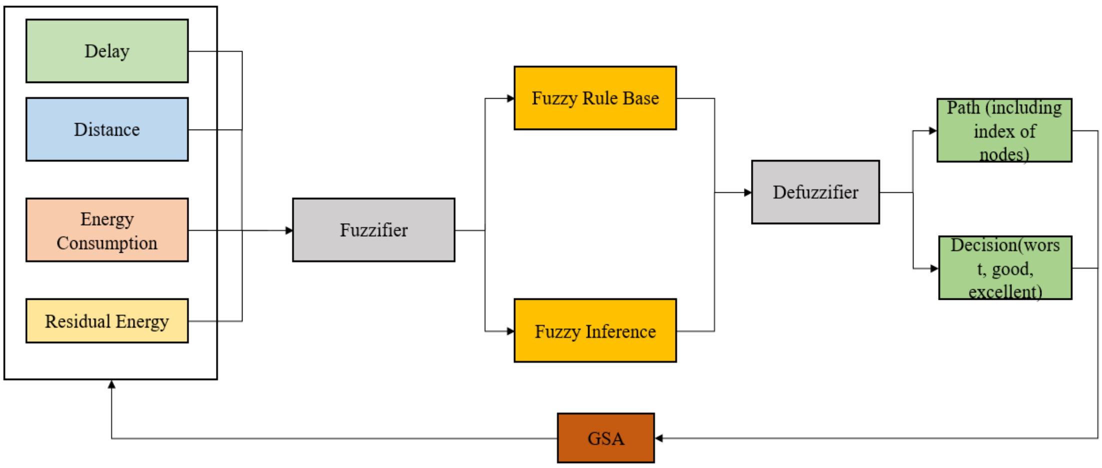

Figure 6. Combined fuzzy logic and GSA based model architecture for optimal routing

The fuzzy logic is based on the two main process which are fuzzification and defuzzification. In this work, we have employed this approach to identify the best suitable path for routing therefore this model considers, four different parameters namely delay, distance, energy consumption and residual energy. The fuzzifier uses fuzzy rules mentioned in Table 2 to perform the fuzzy operation. The obtained output is then processed through the defuzzification process. It generates the path which includes nodes with hop index along with their decision flag.

4. RESULTS AND DISCUSSION

This section demonstrates the outcome of proposed approach and compares the obtained performance with existing routing schemes. The first subsection presents the simulation setup and simulation parameter details, next subsection discussed the comparative performance analysis in terms of energy consumption, network lifetime, throughput end-to-end delay, packet delivery rate, packet loss rate, energy consumption for varied cluster size, CH selection time, and hop count.

4.1. Simulation parameters

The proposed model is implemented with the help of MATLAB 2018 simulation tool where total 500 number of nodes are deployed in the region of 500×500 m^2. The complete network is divided into 6 different clusters where each node has an initial energy of 0.1 J. Each node consumes 20.5 mW energy for transmission and 14 mW for receiving the data. The data is divided into numerous packets where packet size is considered as 512 bytes. Table 3 shows the considered parameters for simulation.

Table 3. Fuzzy rules for decision making process

Parameter name	Considered value
Number of nodes	500
Deployment region	500×500
Node distribution	Random
Total clusters	6
Initial energy	0.1 J
Tx energy	20.5 mW
Rx energy	14 mW
Packet rate	1 packets/s
Packet size	512 Bytes

4.2. Comparative analysis

In this section, we describe the outcome of proposed model and compare its performance with different existing methods. First of all, we measured the energy consumption performance for varied set of sensor nodes deployed. Figure 7 depicts the obtained performance for this experiment. According to this experiment the average energy consumption performance is reported as 1.2 mJ, 0.98 mJ, 0.568 mJ, 0.4 mJ, 0.36 mJ, and 0.198 mJ by using HEED, EECRP, GWO, CL-ALO, CL-HHO, and proposed approach, respectively. The detailed analysis for this experiment is presented in Table 4. This study shows that the increased number of nodes lead to increase the energy consumption however the proposed approach outperformed the optimization methods because of its robust path selection process.

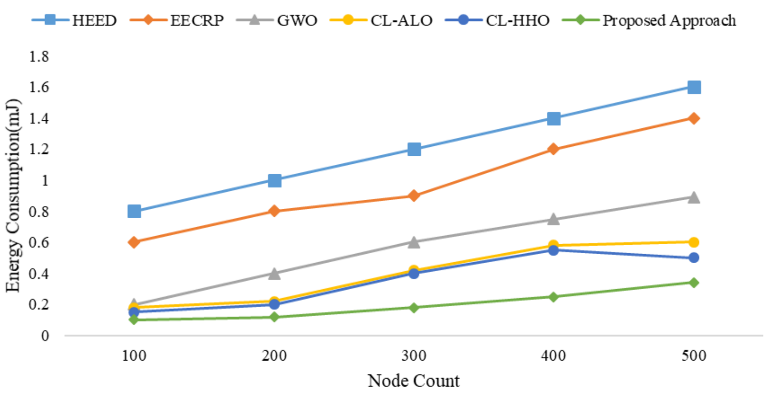

Figure 7. Energy consumption performance

Table 4. Energy consumption performance for each set of nodes

Nodes	HEED	EECRP	GWO	CL-ALO	CL-HHO	Proposed approach
100	0.8	0.6	0.2	0.18	0.15	0.1
200	1	0.8	0.4	0.22	0.2	0.12
300	1.2	0.9	0.6	0.42	0.4	0.18
400	1.4	1.2	0.75	0.58	0.55	0.25
500	1.6	1.4	0.89	0.6	0.5	0.34

In next stage, we measured the end-to-end delay performance for varied nodes scenario. The excessive delay represents the poor performance whereas the comparatively lesser delay shows the improve performance. Based on this, the average delay performance is reported in Figure 8 where the average delay is obtained as 7.4 s, 5.52 s, 5.24 s, 4.22 s, 3.46 s, and 3.1 s by using HEED, EECRP, GWO, L-ALO, CL-HHO, and proposed approach, respectively. The comparative analysis about end-end delay is presented in Figure 8. Table 5 shows the detailed outcome of this experiment. The proposed approach outperformed by reported the reduced average delay because of reduced packet collision and packet drop which helps to ensure the packet delivery without any delay.

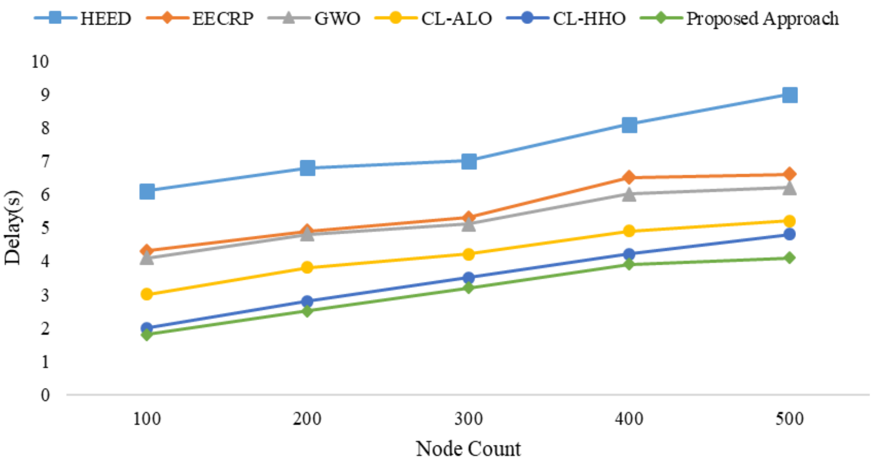

Figure 8. End-to-end delay performance

Table 5. End-to-end delay performance

Nodes	HEED	EECRP	GWO	CL-ALO	CL-HHO	Proposed approach
100	6.1	4.3	4.1	3	2	1.8
200	6.8	4.9	4.8	3.8	2.8	2.5
300	7	5.3	5.1	4.2	3.5	3.2
400	8.1	6.5	6	4.9	4.2	3.9
500	9	6.6	6.2	5.2	4.8	4.1

The energy consumption and delay has serious impact on the network lifetime therefore in next experiment we measure the network lifetime performance where network lifetime is evaluated in terms of total rounds. The average network lifetime is obtained as 3,480 rounds, 3,780 rounds, 4,180, rounds, 4,460 rounds, 4,800 rounds, and 5,260 rounds by using HEED, EECRP, GWO, L-ALO, CL-HHO, and proposed approach, respectively. The comparative analysis of network lifetime is depicted in Figure 9 where proposed model shows the improved performance when compared with the state-of-art models. The detailed performance is presented in Table 6.

In order to further evaluate the performance, we measure the network throughput performance for varied node scenarios. The obtained comparative analysis is presented in Figure 7 where average throughput performance is reported as 0.6, 0.656, 0.728, 0.792, 0.886, and 0.942 by using HEED, EECRP, GWO, L-ALO, CL-HHO, and proposed approach, respectively. Figure 10 depicts the obtained network throughput performance for varied existing and proposed model. The detailed performance is presented in Table 7.

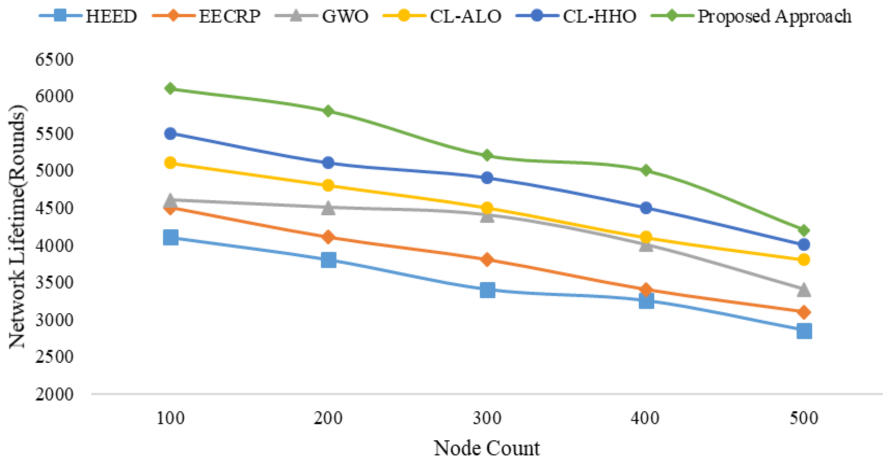

Figure 9. Network lifetime performance

Table 6. Network lifetime performance (rounds)

Nodes	HEED	EECRP	GWO	CL-ALO	CL-HHO	Proposed approach
100	4,100	4,500	4,600	5,100	5,500	6,100
200	3,800	4,100	4,500	4,800	5,100	5,800
300	3,400	3,800	4,400	4,500	4,900	5,200
400	3,250	3,400	4,000	4,100	4,500	5,000
500	2,850	3,100	3,400	3,800	4,000	4,200

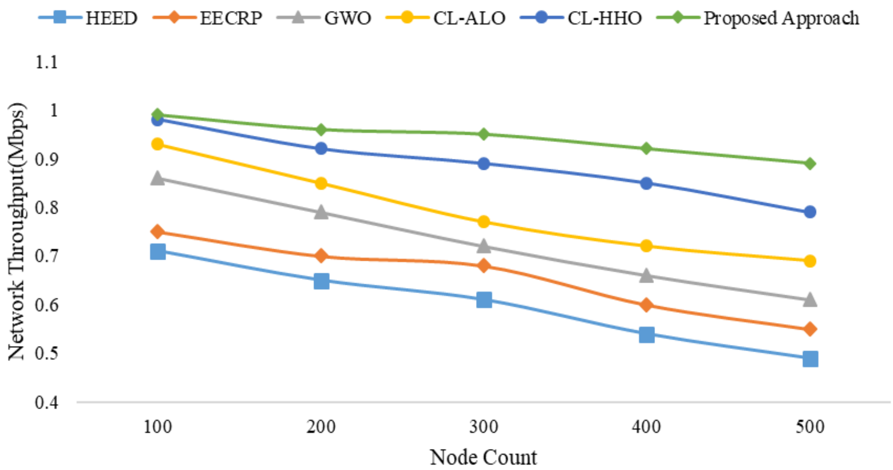

Figure 10. Network throughput performance

Table 7. Network throughput performance

Nodes	HEED	EECRP	GWO	CL-ALO	CL-HHO	Proposed approach
100	0.71	0.75	0.86	0.93	0.98	0.99
200	0.65	0.70	0.79	0.85	0.92	0.96
300	0.61	0.68	0.72	0.77	0.89	0.95
400	0.54	0.6	0.66	0.72	0.85	0.92
500	0.49	0.55	0.61	0.69	0.79	0.89

In next stage, we measure the packet delivery performance where the average packet delivery performance is reported as 93.14, 94.36, 95.4, 96.06, 97.26, and 98.06 by using HEED, EECRP, GWO, L-ALO, CL-HHO, and proposed approach, respectively. Figure 11 depicts the comparative analysis and Table 8 shows the detailed performance. Finally, we measured the energy consumption performance for varied number of clusters which is considered as an efficient solution to improve the network lifetime and ensuring the packet delivery for wider ranges. The obtained performance is presented in Figure 12 where average performance is reported as 1.2, 0.94, 0.852, 0.572, 0.372, and 0.244 by using aforementioned methods.

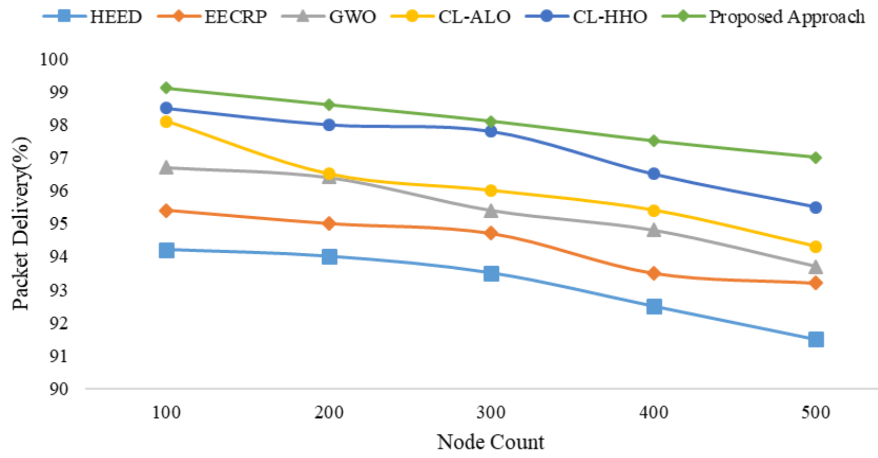

Figure 11. Packet delivery performance

Table 8. Packet delivery performance analysis

Nodes	HEED	EECRP	GWO	CL-ALO	CL-HHO	Proposed approach
100	94.2	95.4	96.7	98.1	98.5	99.1
200	94	95	96.4	96.5	98	98.6
300	93.5	94.7	95.4	96	97.8	98.1
400	92.5	93.5	94.8	95.4	96.5	97.5
500	91.5	93.2	93.7	94.3	95.5	97

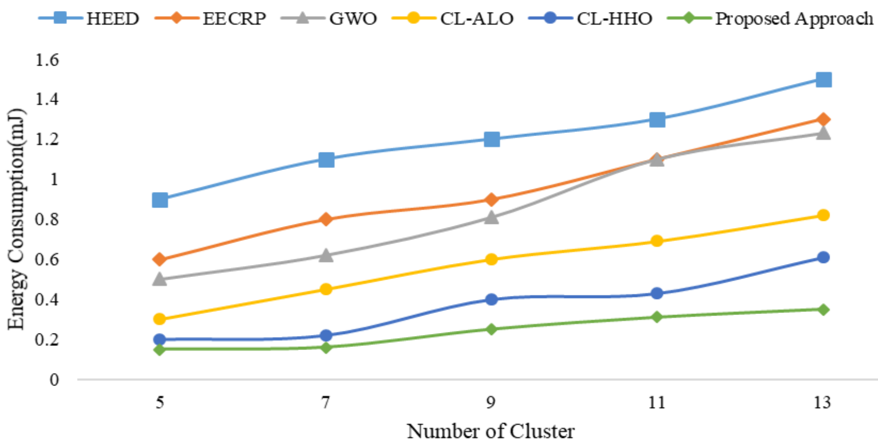

Figure 12. Packet delivery performance

5. CONCLUSION AND FUTURE WORK

This article focus on development of energy aware routing protocol for WSN to improve the network lifetime an ensure the better QoS. However, path identification faces several challenges therefore we present fuzzy logic based decision making solution approach which considers energy, delay, distance and residual energy to identify the suitable path. Further, a GSA optimization method is employed to identify the best path based on its fitness value. Integrating trust mechanisms and secure data transmission protocols into our proposed model can enhance the overall security and reliability of WSNs, providing an end-to-end solution for data communication. Additionally, exploring the scalability of our approach to larger network deployments and different network topologies could provide valuable insights into its practical feasibility in real-world scenarios. The experimental analysis shows that the proposed model is able to achieve better performance in terms of energy, packet delivery, throughput and delay. In future, this approach can be extended with trust mechanism and secure data transmission protocols to provide end-to-end solution for WSN.

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