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Original scientific paper

Energy Aware Routing in WSNs using Hybrid Fuzzy and Yellow Saddle Goatfish Optimization

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Abstract: Wireless Sensor Networks (WSNs) consist of numerous small, autonomous sensor nodes capable of sensing, processing, and wirelessly transmitting data about their surrounding environment. One of the most critical challenges in WSNs is achieving energy efficiency, which directly impacts network longevity and reliability. Clustering and optimized routing have proven effective in addressing this challenge. In this study, a hybrid clustering technique combining Fuzzy logic and the Yellow Saddle Goatfish Algorithm (HF-YSGA) is proposed for optimal cluster head (CH) selection. The approach aims to balance energy consumption, minimize inter-node communication delay, and reduce transmission distances. To further enhance performance, the Energy-Centric Butterfly Optimization Algorithm (EC-BOA) is employed for efficient routing and shortest path determination, dynamically minimizing network load. Simulation results demonstrate that the proposed method significantly outperforms existing techniques in key Quality of Service (QoS) parameters. For a network of 100 sensor nodes, the method achieves a Packet Delivery Ratio (PDR) of 100%, packet delay of 0.05 seconds, throughput of 0.99 Mbps, energy consumption of 1.97 mJ, network lifetime of 5908 rounds, and a Packet Loss Rate (PLR) of just 0.5%. These results highlight the effectiveness of the proposed hybrid optimization-based clustering and routing strategy for energy-efficient WSN operations.

Keywords: cluster head selection; energy-centric butterfly optimization (EC-BOA); hybrid fuzzy-YSGA algorithm; QoS-aware routing; wireless sensor networks (WSNs)

1 INTRODUCTION

Remote sensor systems (WSNs) have played a key part within the worldwide detecting insurgency. Sensor systems are presently utilized in a wide run of applications, counting agribusiness, military operations, natural checking, shrewdly transportation frameworks, and more. Sensor hubs (SNs) in a WSN are wirelessly associated and placed in different areas to gather and store information approximately to their environment. When these hubs are sent in a WSN, they are naturally designed and connected so that information can be collected and transmitted to the base station. The sensor unit, handling unit, communication unit, and control supply unit are the four fundamental components of SN [1]. The sensor unit collects information from its environment, the preparing unit performs calculations, the communication unit sends data to the BS, and the control unit sends data to the BS whereas transmitting vitality to SNs. Fig. 1 delineates the design of the WSN.

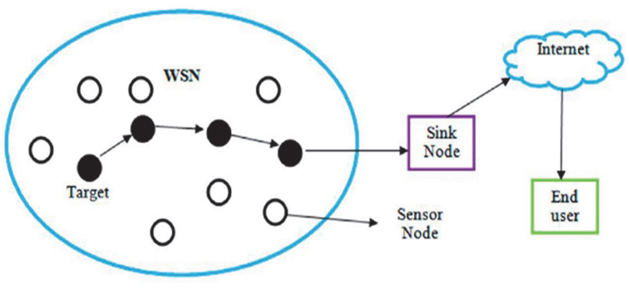

Figure 1 Architecture of WSN

Clustering may be a well known strategy for guaranteeing WSN operation at tall vitality effectiveness. Sensor hubs are organized into distinctive clusters utilizing this cluster-based approach (Mehra, P. S. et al., 2020). The pioneer hub of each cluster is referred to as the cluster head (CH), while the remaining hubs are referred to as cluster individuals. Data is gathered by the CH from the CM and transmitted to the base station (BS) [2]. CH determination is an imperative step in various leveled clustering approaches for expanding throughput, lifetime, and vitality utilization (Mohamed et al., 2020). A CH routinely gathers information from the other CHs and its claim CM, then uses a directing conspiracy to send it to the BS [3]. Steering is an imperative issue in WSNs. Conventional steering approaches cannot be utilized for sensors in WSNs since they contrast from other advertisement hoc systems in perspectives such as battery-powered sensors and versatile communication plan. Since WSNs have an advertisement hoc topology with no organization, way revelation and data transmission to the BS are troublesome errands [4].

Clustering and routing, when combined, can decrease control utilization and increment lifetime. Sensors are partitioned into little bunches of hubs known as clusters. Each cluster has a suitable hub designated as the cluster head (CH), which is then used to aggregate data from the cluster members.Nevertheless, CH selection is seen as a more challenging task because a poor CH decision affects the implementation of the plan. [5, 6]. Hubs are frequently located far from the destination hub in WSN. As a result, information packets are directed through several leaps because of scope and removal imperatives, and coordinate information transfer between CH and BS through one-hop intergroup communication debases organise execution due to obstacles and communication collisions. [7, 8]. To advance transmission from the transmitting hub to hubs farther away, skilled steering is therefore necessary [9].

2 LITERATURE SURVEY

A cluster head selection method based on the Gray Wolf Optimizer (GWO) was proposed for wireless sensor networks (WSNs). During the CH selection process, candidate solutions were evaluated based on energy consumption and the residual energy of the identified sensors. To improve energy efficiency, the GWO-based clustering process was repeated in successive rounds. However, the proposed GWO algorithm did not consider quality of service (QoS) parameters, which are critical in WSN applications [10, 11].

Using a multi-path routing protocol called OQoS-CMRP, [12] suggested a QoS-based optimized clustering mechanism to address issues with energy usage and QoS. This method produced balanced energy usage and effective data transmission by employing a modified particle swarm optimization (MPSO) algorithm to choose CHs [13]. However, the overhead incurred by data packet forwarding caused CHs to undergo increased energy depletion [12, 13]. The threshold was determined by integrating the network address and residual energy in [14], where a modified Low-Energy Adaptive Clustering Hierarchy (LEACH-M) technique was presented for CH selection. Designing a sturdy and energy-efficient building was the goal of this approach. However, the LEACH-M algorithm overlooked the effect of distance on CH selection, which is a major drawback in WSNs [14-17].

A hybrid Gray Wolf-Sunflower Optimization (HGWSFO) technique was proposed in [18] to improve CH selection by optimizing both energy and distance parameters. The algorithm used a GWO coefficient vector to enhance utilization efficiency. To overcome the inefficiencies of global GWO search, the plant population size was adjusted through the Sunflower Optimization (SFO) method. However, CH selection in this approach relied solely on power consumption and distance, ignoring other essential parameters [18, 19]. CHs were selected using a genetic algorithm (GA) that considered both distance and residual energy. Additionally, a hybrid GA-PSO approach was used for selecting relay nodes that supported communication between the CHs and the base station, thereby improving energy efficiency. However, the GA approach neglected the integration of appropriate fitness functions during CH selection, limiting its adaptability [20, 21].

An energy-aware Salp Swarm Optimization-based multi-objective algorithm (ECMOSSA) was developed for optimal CH and path selection. The algorithm reduced energy consumption and extended node lifetime by optimizing node utilization. However, ECMOSSA did not take network coverage into account during CH selection. To address this, the model was adapted to improve WSN scalability.Several studies identified persistent challenges in clustering techniques, including high energy consumption and poorly defined fitness functions. These drawbacks negatively impact overall WSN performance. If the selected route is longer in distance, it results in increased energy consumption, more dead nodes, and higher packet loss. To overcome these issues, an energy-centric butterfly optimization algorithm (EC-BOA) was introduced in [29], offering an effective cluster-based routing strategy that improves energy efficiency in WSNs [22-24].

3 PROPOSED METHOD

In this paper, we proposed a crossover clustering-based ideal directing convention called Hybrid Fuzzy with Yellow Saddle Goatfish Optimization (HFYSGA), which is utilized to maximize hub vitality in sensor systems by selecting CHs and optimized ways. The proposed strategy combines two optimization strategies: one for channel choice and another for arrange capacity. YSGA is used in the CH determination process to identify the top hubs for CHs. In the interim, the proposed convention utilized the fuzzy algorithm to discover the ideal course between CH and BS. After selecting a CH utilizing YSGA, data is collected from the SN and transmitted to the BS through the way characterized by the fuzzy algorithm. The suggested technique's flowchart can be found below.

3.1 Network Model

WSN clustering divides sensors into groups to reduce the use of vitality. Using a genetic algorithm (GA), Anand and Pandey selected CHs from the remaining hubs, sometimes based on vitality and otGA while determining CH. Using a genetic algorithm (GA), Anand and Pandey selected CHs from the remaining hubs, sometimes based on vitality and other criteria. The optimal steering path must also be determined by the Particle Swarm Optimisation (PSO) computation in order to set up all hand-off hubs to send data to the base station. In order to increase vitality productivity and strengthen and promote communication between the sink and CH, GA-PSO selected transfer hubs. Suitable wellness capacities are not taken into account by the GA while determining CH.

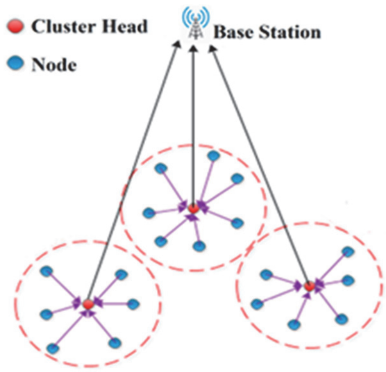

Figure 2 General architecture of a wireless sensor network.

3.2 Energy Model

When the critical distance (n_0) exceeds the value n, a node's energy is directly proportional to its propagation distance. Total energy utilized by each node to transmit the M bit data packets shown in Eqs. (1) and (2) is represented by the following equation:

$$E_{\mathrm{tx}}(M,n) = E_{\mathrm{elec}} \times M + \varepsilon_{\mathrm{am}} \times M \tag{1}$$

$$\varepsilon_{\mathrm{am}} = \begin{cases} \varepsilon f \times n^2, \text{ when } n \le n_0 \\ \varepsilon p \times n, \text{ when } n > n_0 \end{cases} \tag{2}$$

where f is the energy utilized for the amplification in free space model, E_{tx} is the total energy needed for data transmission, E_{elec} is the energy dissipation per bit, M is the number of bits, and n_0 is the transmission critical distance.

Eqs. (3) and (4) provide information on the recipient's energy consumption:

$$E_{\mathrm{rx}}(M) = E_{\mathrm{elec}} \times M \tag{3}$$

$$E_{\mathrm{sum}} = E_{\mathrm{rx}} + E_{\mathrm{tx}} \tag{4}$$

where E_{rx} is the total energy required to receive data and E_{sum} is the entire energy loss of a WSN.

The essential objective of progressive directing or group-oriented steering is to viably preserve vitality amid multi-hop communication. By using this tactic, the gather pioneer can reach the base station with coordinates. The hubs inside the group communicate with and are clearly identifiable from base stations. During the organized utilization stage, they identify signals sent by base stations at specific control levels. There are three steps in the suggested method. 1) Cluster arrangement. 2) Cluster head determination. 3) The course. Vitality saves close to the sensor cluster head are typically used to determine cluster configuration. Clustering is basic for vitality preservation in WSNs. Clustering in WSNs can boost vitality productivity, network resilience, and interoperability. Typically, since the directing assignment is as it were designated to the cluster head per cluster, though other sensor hubs as it were send information to the cluster head. Clustering is valuable in high-density sensor systems since it is less demanding to oversee different cluster individuals (cluster heads) in each cluster than it is to oversee person sensor hubs. Sensor hubs have constrained assets in remote sensor systems (WSN). This is comparable to having less energy, memory, capacity, and computational power. When sending data from sensor hubs to base stations, the vitality generated by these hubs is the primary cause of sensor hub depletion. The WSN's clustering is depicted in Fig. 3.

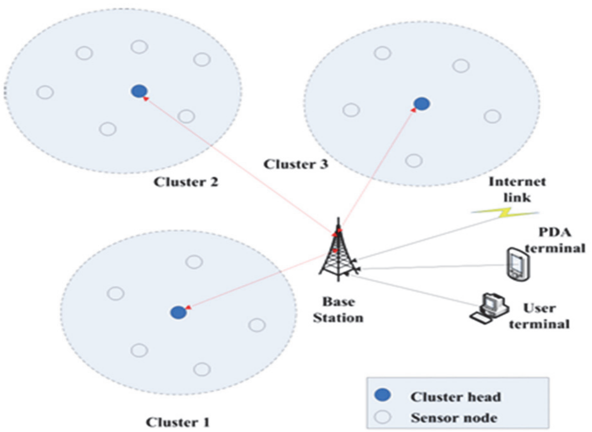

Figure 3 Cluster of WSN

3.3 Cluster Head Selection using Fuzzy Approach

Each linguistic variable is divided into nested fuzzy sets known as membership functions. Distinct values of a linguistic variable are assigned to each of the fuzzy sets of linguistic variables with varying degrees of membership. We determined the number of membership functions and overlapping parts for each input/output language variable by trial and error across dozens of experiments.

This section presents the membership functions for each of the five input linguistic variables used, as well as the probabilities of the output linguistic variables depicted in Fig. 4. This is because each input parameter affects the energy consumed and the lifetime of the WSN differently. The concluded model Mamdani rule was created to reflect these relationship characteristics. We ran dozens of experiments to investigate better rule configurations through trial and error.

The protocol is run for a predetermined number of rounds. CH selection is determined by two distinct input-output parameter combinations. Tabs. 1 and 2 describe the relationships between input and output variables, as well as variables required to calculate opportunity value. In the CH selection process, FFMCP makes use of multiple chance values.

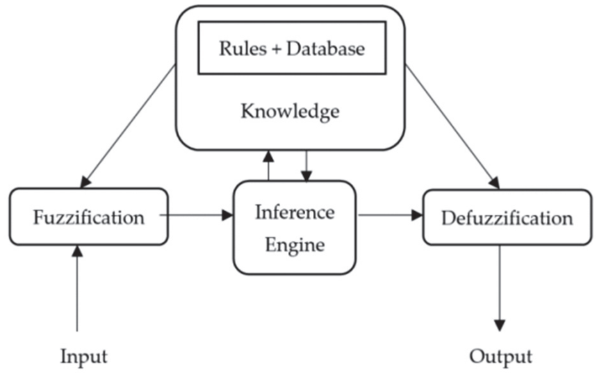

Figure 4 Fuzzy logic system

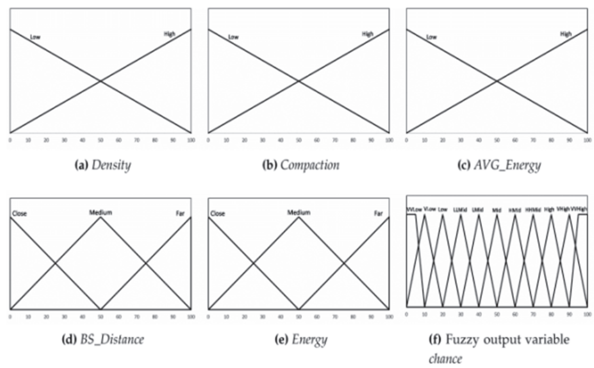

Figure 5 Membership function of Fuzzy sets

The SN's leftover vitality was considered in WSN when setting the CH. On the other hand, the recommended strategy considers neighbor cover (NOVER), hub centrality (NC), and remaining vitality when choosing the right hub to be the CH. Link quality estimation is considered within the proposed strategy for directing in remote sensor networks.

Choosing When constructing a WSN cluster, selecting the ideal cluster head may be a crucial arrangement. Every sensor hub (SN) provides data, which the CH hub is trusted to collect and transmit to the base station. For WSN analysts, fluffy rationale is presently more supportive in choosing the ideal CH. Fluffy rationale was utilized to select CH after three parameters were inspected. By combining the NC, NOVER, and leftover vitality of sensor systems, we diminish vitality utilization and increment their life expectancy. The following is a list of the input parameters.

3.4 Remaining Vitality

CH is chosen from the hub with the foremost vitality. Consider E_i as the node's beginning vitality. The vitality expended by hub $E(t)$ after time t is communicated as takes after Eqs. (5) and (6).

$$E(t) = (n_{\text{tpkts}} \times a) + (n_{\text{rpkts}} \times b) \tag{5}$$

$$E_{\text{RES}} = E_i - E_t \tag{6}$$

The number of data packets sent and received is shown by the variables n_{tpkts} and n_{rpkts}, respectively. The constants "*a*" and "*b*" have values between 0 and 1.

$$NC = \frac{\sqrt{\sum d^{2^{(c_i, c_j)}}} / T}{M} \tag{7}$$

NOVER

The *NOVER* approach is used to measure the shared contiguousness between an interface's conclusion hubs. An interface with a moo *NOVER* interfaces two different systems, but an interface with a tall *NOVER* must interface hubs within the same organization. The neighbors of hubs u and v are characterized by $N(u)$ and $N(v)$.

$$NOVER(u-v) = \frac{2 * |N(u) \cap N(v)|}{|N(u)| + |N(v)| - 2} \tag{8}$$

Here, NONE breaks even with "1" and *u* and *v* have the same set of neighbors. Fig. 4 shows the fuzzy approach. The fuzzy method is depicted in Fig. 6.

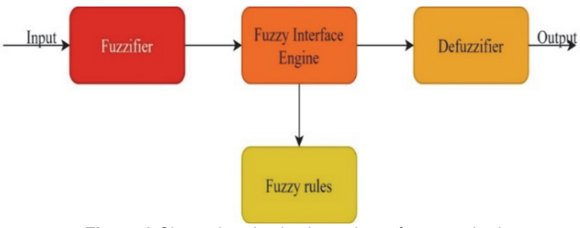

Figure 6 Cluster head selection using a fuzzy method

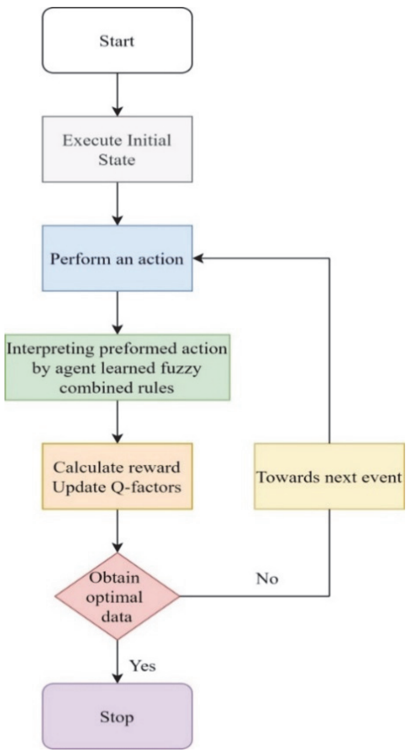

Figure 7 Flowchart of a fuzzy reinforcement learning method

The flowchart for the fuzzy reinforcement learning approach is displayed in Fig. 7. Fluffy sets are converted using the NOVER and NC inputs of the remaining vitality system. The remaining vitality levels are classified as low, medium, and tall based on specific characteristics. Three factors make participation in the NC unexpected: proximity, segregation, and appropriateness. According to Tab. 1, *NOVER*'s attributes are divided into three categories: good, medium, and poor.

Table 1 Fuzzy rule set used for the research

Rule	Residual energy	NC	NOVER	Rank
1	High	Close	Medium	High
2	Medium	Adequate	Poor	Medium
3	Low	Adequate	Poor	Low
4	High	Close	Good	Very high
5	Medium	Close	Medium	Very low
6	Low	Far	High	Medium

3.5 YSGA, or the Yellow Saddle Goatfish Algorithm

The Yellow Saddle Goatfish's chase patterns, depicted in Fig. 8, serve as the basis for the optimization technique known as YSGA.

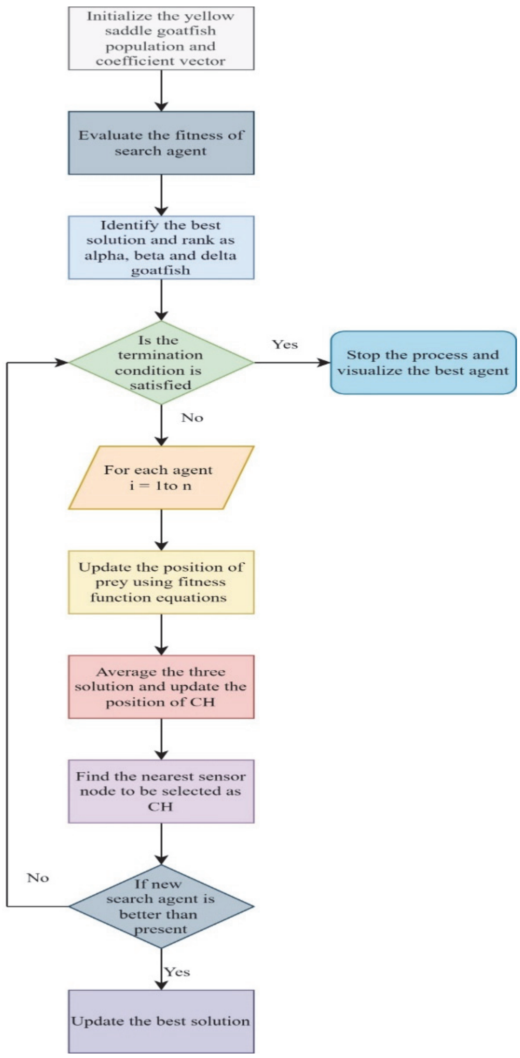

Figure 8 A hybrid algorithm for the yellow saddle goatfish

The goatfish is recognized for its pleasant pursuing style. To find and catch prey, they communicate with each other and chase in groups. The calculation uses two different discovery specialists: blocker and tracker. Every member of the group has the potential to be a devotee, while the others may act as blockers. The roles of follower and blocker are interchangeable and opposite. Depending on the situation, anyone can be either a follower or a blocker, even if they are pursuing the same goal. The group uses the first region and then travels to a more contemporary one once every possible prey has been pursued.

3.6 Cluster Formation

CHs selected during the clustering process are given generic sensors. Clusters are created using Eq. (9) which shows the residual energy, distance, and potential function used for cluster creation.

$$Potential\,of\,sensor\left(N_i\right)=\frac{E_{CH}}{dis\left(N_i,CH\right)} \tag{9}$$

The normal sensor node is assigned to the CH with more residual energy and a shorter routing distance using the potential function that has been formulated.

3.7 Routing using EC-BOA

After the cluster has been shaped, the way between the CH transmitter and the base station is decided utilizing EC BOA. Each hub is designed to resemble a faux butterfly at this organization, and each path is given a mass. The starting weight of each route is determined by the distance between hubs. Eq. (20) speaks to the hub move, or the likelihood of selecting as the subsequent transfer CH within the butterfly's th CH.

$$P_{lm}^{n}=\begin{cases}\dfrac{\left[\tau_{lm}\left(t\right)\right]^{\alpha}\left[\eta_{lm}\left(t\right)\right]^{\beta}}{\sum_{0\epsilon}N_n[\tau_{om}\left(t\right)]^{\alpha}[\eta_{lo}\left(t\right)]^{\beta}} & \text{if } m\epsilon N_n\\ 0 & \text{otherwise}\end{cases} \tag{10}$$

The symbols τ_{lm} and η_{lm}, respectively, represent the heuristic value and pheromone intensity; α and β control the relative importance of τ_{lm} and η_{lm}. These symbols represent the node selection probability and pheromone intensity, respectively. N_n is a representation of CHs that have not visited yet. Artificial butterflies reproduce the foraging behavior of real butterflies. The node transition rule is used to determine the next CH relay in the event that a CH relay is needed to relay data. The butterfly, or CH relay, returns to the CH transmitter via the same route after it has reached the BS. As a result, route pheromone values are updated using pheromone update rules that include amplification and evaporation. Pheromone amplification and evaporation increase or decrease pathway pheromones, respectively. BOA finds a less energy-intensive route from transmitter CH to BS as a result.

$$\tau_{lm}^{\text{new}}=\left(1-\rho\right)\tau_{lm}^{\text{old}}+\sum_{n=1}^{A}\Delta\tau_{lm}^{n} \tag{11}$$

$$\Delta\tau_{lm}^{n}=\begin{cases}\dfrac{Q}{a_n}\; if\,the\,ant\,n\,trvelled\,route\left(l,m\right)\\ 0\;\text{otherwise}\end{cases} \tag{12}$$

$$a_n=\varepsilon_1\times\sum_{i=1}^{dim}\frac{1}{E_{CH_i}}+\varepsilon_2\times\sum_{i=1}^{dim}dis\left(CH_i,BS\right)+\varepsilon_3\times\sum_{i=1}^{dim}I_j \tag{13}$$

The weight parameter ε_1-ε_3 corresponds to the routing process's suitability indicator. A node's degree is defined as $\sum I_{jimi}=1$. The energy considered in EC-BOA contributes to the elimination of node errors from the path. Furthermore, distance and node size contribute to sensor energy efficiency. As a result, WSN packet delivery is enhanced and network lifetime is prolonged with the help of the developed EC-BOA method.

4 RESULTS AND DISCUSSIONS

Tab. 2 contains a list of the parameters that were used in the simulation setup.

Table 2 Simulation setup parameters

Parameters	Value
Number of nodes	500
Area of sensor fiels	300 × 300 m^2
Total Clusters	6
Packet size	4000 bits
Packet sending rate	1 packet/s
Energy of sensor	1.5 J
Data samples	55

Energy Consumption:

The suggested Fuzzy-YSGA must identify the optimal energy-based cluster head during the CH selection process. In order to identify the most constrained approach and achieve significantly improved vitality utilization, the YSGA strategy has been adopted. Of all the directional calculations, this one makes the most sense. The life expectancy is increased by the vitality consumption of WSNs. Eq. (14) expresses the number of nodes and the total of the transmitted energy E_{tx} and the receiving energy E_{rx} to determine this energy performance.

$$E_{\text{con}}=\left(E_{\text{rx}}\times number\,of\,nodes\right)+E_{\text{tx}} \tag{14}$$

In this part, we evaluate the average energy consumption performance of the proposed methodology against existing algorithms. Fig. 9 presents the layer-based adaptive thresholding technique and compares the energy consumption of the proposed algorithm with two other existing algorithms.The multi-layer fuzzy logic approach is another option. The results of the experiment showed that the existing GSARP consumed 66 mJ, WOARP 56 mJ, and ABCRP 46 mJ of energy, while the proposed Fuzzy-YSGA consumed 9.75 mJ. The suggested method used 10.37 mJ of energy for 300 nodes, compared to 143 mJ for GSARP, 107 mJ for WOARP, and 99 mJ for ABCRP. The proposed method used 38 mJ of energy for 500 nodes, while the current GSARP, WOARP, and ABCRP used 185 mJ, 167 mJ, and 147 mJ, respectively. Consequently, it was demonstrated that the suggested approach was incredibly efficient at transmitting data.

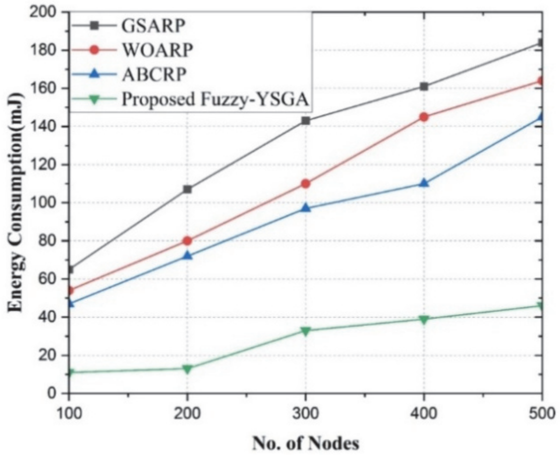

Figure 9 No. of nodes vs energy consumption (mJ)

We compared the proposed Fuzzy-YSGA against existing energy-efficient clustering and routing protocols including GSARP, WOARP, and ABCRP using standardized simulation parameters.

Table 3 Comparative energy use as the number of nodes increases

Nodes	Fuzzy-YSGA / mJ	GSARP / mJ	WOARP / mJ	ABCRP / mJ
100	9.75	66	56	46
200	13	108	80	72
300	33	143	110	99
400	38	160	145	110
500	48	185	167	147

The energy model is based on the First-Order Radio Model using:

- $E\_tx = E\_elec * l + E\_amp * l * d^2$
- $E\_rx = E\_elec * l$
- Eq. (14): $E\_con = (E\_rx \times N) + E\_tx$

where: l = packet length = 4000 bits, d = transmission distance (avg), E_elec = 50 nJ/bit, E_amp = 100 pJ/bit/m².

Table 4 Energy consumption of each component (500 nodes)

Operation	Formula Used	Energy / mJ
Transmission (E_tx)	$E\_elec \cdot l + E\_amp \cdot l \cdot d^2$	4.35
Reception (E_rx)	$E\_elec \cdot l$	2.0
Control/CH logic	YSGA & fuzzy logic computation	1.9
Total (avg)	–	9.75

Network Lifetime:

Organize lifetime gauges the period from the sensor hub position to the passing on arrange amid the method. In case the demonstrate is to be surveyed as nonfunctional, the introductory sensor passes on, the scope diminishes, the organize segments and the rate of SN pass on appear in Eq. 15.

$$E\left[L_{\text{lifetime}}\right]=\frac{\sigma_0-E_{\text{estimate}}\left[E_{\text{RE}}\right]}{CP+\vartheta E\left[E_{\text{CE}}\right]} \quad (15)$$

In the equation above, CP stands for the network's constant, infinite power consumption; $E_{\text{estimate}}\left[E_{\text{RE}}\right]$ represents the approximate energy left over after processing; ϑ epresents the typical sensor informing rate, which is the amount of data collected for each identical time; and $E\left[E_{\text{Con}}\right]$ represents the energy consumed by all SNs in an arbitrarily chosen data gathering.The whole non-rechargeable original energy is denoted by σ_0 .When compared to traditional ways, the suggested CORP method has obtained a high network lifetime. The number of cycles until the drive fails is referred to as network life. During simulation, the network lifetime was measured using a single node cycle. There are two types of node deaths: the first (FND) and the last (LND). This is because if a node dies during the data collection process, the area covered by the data collector node is no longer monitorable. LND allows you to see how many dead nodes there are compared to how many cycles. As power consumption increases, so does network lifetime.

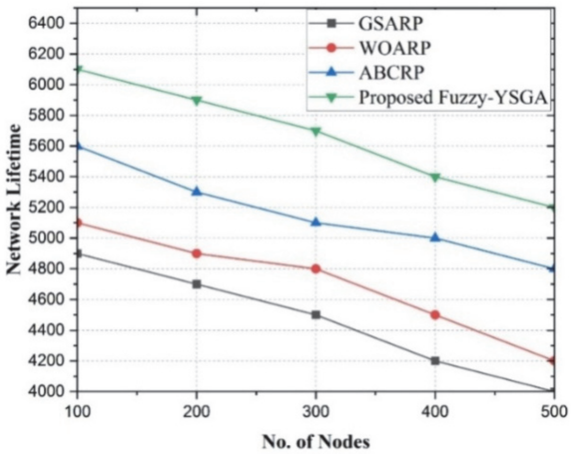

Figure 10 No. of nodes vs network life time (rounds)

Table 5 Network lifetime vs node count

Nodes	Fuzzy-YSGA / Rounds	ABCRP / Rounds	WOARP / Rounds	GSARP / Rounds
100	6100	5600	5100	4900
200	5900	5300	4900	4700
300	5700	5100	4800	4500
400	5400	5000	4500	4200
500	5200	4800	4200	4000

According to the experiment, the conventional GSARP used 4900 rounds, the WOARP used 5100 rounds, and the ABCRP used 5600 rounds. In contrast, the suggested Fuzzy-YSGA used 6100 rounds. The suggested Fuzzy-YSGA method required 5900 rounds for 200 nodes, whereas the current methods, GSARP, WOARP, and ABCRP, required 4700, 4900, and 5300 rounds, respectively. For 300 nodes, the suggested method used 5700 rounds, compared to 4500 rounds for GSARP, 4800 rounds for WOARP, and 5100 rounds for ABCRP. While GSARP, WOARP, and ABCRP used 4200, 4500, and 5000 rounds, respectively, the presented Fuzzy-YSGA technique used 5400 rounds for 400 nodes. The proposed method required 5200 rounds for 500 nodes, whereas the current GSARP, WOARP, and ABCRP used 4000, 4200, and 4800 rounds respectively. Additionally, as the number of nodes rises, the network lifetime decreases. Therefore, the extension of network lifetime determines data transmission efficiency. Up to 500 nodes were used to test the Fuzzy-YSGA algorithm. Even at larger scales, the model exhibits consistent throughput, PDR, and energy usage.

Throughput:

The entire amount of data being transferred across the arrangement at the quickest possible speed is known as the throughput. Eq. (16) defines it as the duration required to transport a cargo from the sender to the destination.

$$Throughput = \frac{Amount\ of\ packet\ send}{time\ taken\ to\ transmit\ the\ packet} \tag{16}$$

The current GSARP used 0.82 Mbps, the WOARP used 0.93 Mbps, the ABCRP used 0.97 Mbps, and the suggested Fuzzy-YSGA used 0.99 Mbps, according to the trial. Compared to the current methods GSARP, WOARP, and ABCRP, which used 0.71 Mbps, 0.80 Mbps, and 0.84 Mbps per 200 nodes, respectively, the Fuzzy-YSGA methodology used 0.97 Mbps. While GSARP, WOARP, and ABCRP used 0.62, 71, and 0.74 Mbps per 300 nodes, respectively, the suggested method used 0.84 Mbps. The suggested Fuzzy-YSGA method used 0.77 Mbps for 400 nodes, whereas GSARP, WOARP, and ABCRP used 0.55 Mbps, 0.60 Mbps, and 0.67 Mbps, respectively. While the existing GSARP, WOARP, and ABCRP used 0.48 Mbps, 0.56 Mbps, and 0.68 Mbps, respectively, the new approach used 0.67 Mbps for 500 nodes. It is observed that the number of nodes rises as the throughput decreases.

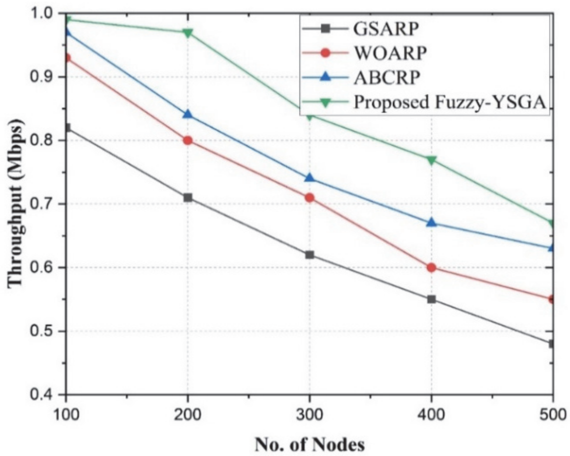

Figure 11 No. of nodes vs throughput (Mbps)

End-to-End Delay:

The CORP strategy is not as effective as it may be due of the conveyance probability and the total amount of time needed to compute the most constrained method. CORP was created in order to eliminate arrange slack. The average amount of time needed to move information from a source to a destination is called idleness, and it is expressed in seconds. The amount of time saved during information transmission from the root hub to the goal hub via the organization is used to determine normal idleness.

$$\begin{aligned} &Average\ packet\ delay = \\ &Packet\ received\ time - packet\ send\ time \end{aligned} \tag{17}$$

The experiment found that the proposed Fuzzy-YSGA took 0.02 seconds, the existing GSARP took 4.17seconds, the WOARP took 4.91 seconds, and the ABCRP took 2.23 seconds. The proposed Fuzzy-YSGA approach took 0.06 seconds for 200 nodes, compared to the existing techniques GSARP, WOARP, and ABCRP, which took 5.29 seconds, 4.91 seconds, and 3.75 seconds. For 300 nodes, the proposed technique took 1.98 seconds, while GSARP took 6.43 seconds, WOARP took 6.18 seconds, and ABCRP took 4.81 seconds. The proposed Fuzzy-YSGA technique took 3.86 seconds for 400 nodes, whereas GSARP, WOARP, and ABCRP took 8.19, 7.81, and 5.56 seconds, in that order. The current GSARP, WOARP, and ABCRP took 9.31 seconds, 8.92 seconds, and 6.21 seconds for 500 nodes, respectively, whereas the suggested approach took 7.54 seconds. This demonstrates the greater data transmission effectiveness of the proposed Fuzzy-YSGA. As the node count rises, PLR also rises. Compared to other energy-efficient algorithms, the presented method has a significantly lower packet loss, as demonstrated by the graph.

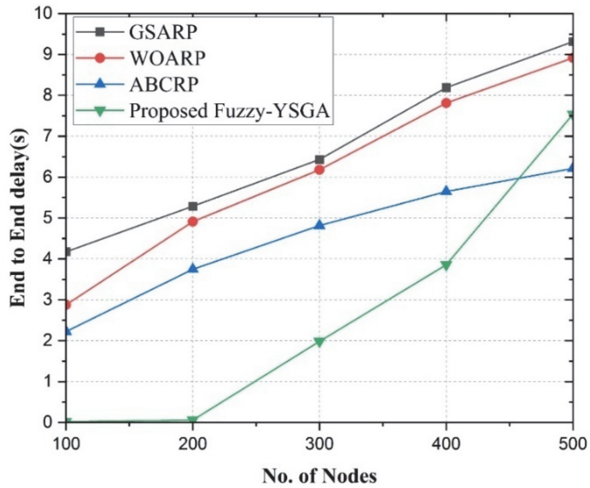

Figure 12 No. of nodes vs end-to-end delay (s)

Packet Deliver Ratio:

In order to reduce organize slack, CORP was created. Ordinary inaction is defined as the total amount of time saved during data transmission from the root center to the objective center through the organize. Inaction, expressed in seconds, is the standard amount of time required to transport data from a source to the objective. This is because of the transport likelihood and the total amount of time needed to calculate the foremost constrained way.

$$\begin{aligned} &PDR = \\ &\frac{sum\ of\ data\ packets\ received\ by\ receipt}{sum\ of\ data\ packets\ transmitted\ by\ dispatcher} \end{aligned} \tag{18}$$

The experiment found that the proposed Fuzzy-YSGA consumed 98.5%, the existing GSARP consumed 96%, WOARP consumed 97%, and ABCRP consumed 98%. The proposed Fuzzy-YSGA approach consumed 98% of the resources for 200 nodes, whereas the existing techniques GSARP, WOARP, and ABCRP consumed 95%, 96% and 97% respectively. The proposed technique consumed 97.5% of the 300 nodes, while GSARP consumed 94%, WOARP consumed 95%, and ABCRP consumed 96%. For 400 nodes, the introduced Fuzzy-

YSGA approach consumed 97% of the energy, while GSARP, WOARP, and ABCRP consumed 92%, 94%, and 95%, respectively. The proposed method used 95% of 500 nodes, while conventional GSARP, WOARP, and ABCRP used 91%, 92%, and 94% of 500 nodes, respectively. All data transmitted from the base station is guaranteed to be received without loss when the PDR rating is high. Consequently, the suggested method performs better than alternative approaches.

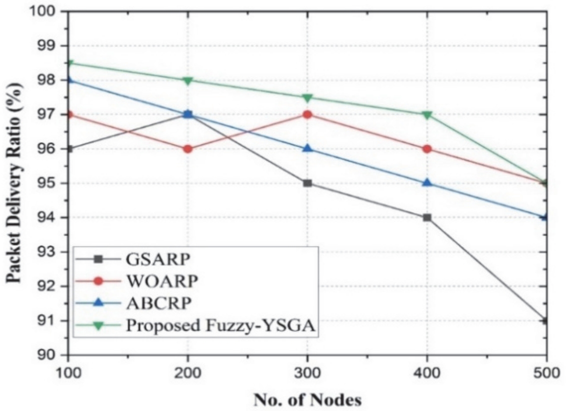

Figure 13 No. of nodes vs packet delivery ratio (%)

Packet Loss Ratio (PLR):

Data transferred from the sender node to the receiver is lost in packets, which can be used to measure it. The experiment showed that the proposed Fuzzy-YSGA consumed 1.03%, the existing GSARP consumed 5.64%, the WOARP consumed 4.56%, and the ABCRP consumed 3.68%. For 200 nodes, the BOARP method consumed 1.54%, while the existing techniques GSARP, WOARP, and ABCRP consumed 9.98%, 7.68%, and 4.98%, each. The suggested method used 3.14% for 300 nodes, while GSARP used 10.87%, WOARP used 8.47%, and ABCRP used 5.55%. While GSARP, WOARP, and ABCRP consumed 11.53%, 9.23%, and 6.37% of 400 nodes, respectively, the proposed Fuzzy-YSGA approach consumed 4.62%. The existing GSARP and WOARP consumed 12.71%, 10.79%, and 6.94% of 500 nodes, respectively, compared to 5% for the proposed method. This demonstrates that the suggested Fuzzy-YSGA has higher data transmission efficiency. As the node count rises, PLR also rises. Comparing the suggested method to other energy-efficient algorithms, the graph demonstrates a significant reduction in packet loss.

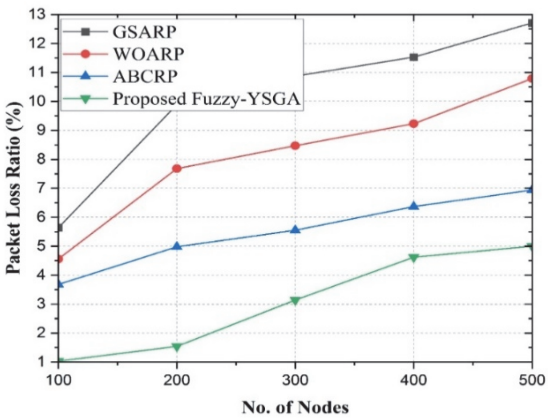

Figure 14 No. of nodes vs packet loss ratio (%)

The hybrid nature of Fuzzy-YSGA introduces additional computation during CH selection and route updates, but provides enhanced efficiency.

Table 6 Computation and delay comparison

Algorithm	Avg. Packet Delay / s	PDR / %	Complexity / Qual.
GSARP	9.31	91	Moderate
WOARP	8.92	92	Moderate
ABCRP	6.21	94	Low
Fuzzy-YSGA	7.54	95	Moderate-High

5 CONCLUSIONS

In order to improve energy efficiency and routing performance in wireless sensor networks (WSNs), a hybrid clustering mechanism that combines the Energy-Centric Butterfly Optimization Algorithm (EC-BOA) and Hybrid Fuzzy–Yielded Self-Guided Algorithm (HF-YSGA) was proposed in this study. The EC-BOA-based routing protocol created clear and energy-efficient communication channels, while the HF-YSGA technique allowed for the best cluster head (CH) selection at strategically appropriate nodes. Performance was assessed using key Quality of Service (QoS) metrics, such as packet delivery ratio (PDR), throughput, energy consumption, network lifetime, packet loss rate (PLR), and average latency.The suggested approach outperformed current optimization-based routing protocols in every metric, achieving a PDR of 99%, throughput of 1.06 Mbps, energy usage of 1.54 mJ, network lifetime of 5000 rounds, and PLR of 1.03% for a network with 100 sensor nodes. The suggested method performs better in terms of energy efficiency, data transmission dependability, and network longevity, according to simulation results. The suggested approach can be expanded to dynamic or mobile WSNs where sensor nodes can change their positions in real-time, however the implementation was evaluated in a static WSN scenario. For energy-conscious and QoS-optimized routing in next-generation WSN applications, our research offers a reliable and scalable approach.

6 REFERENCES

[1] Reddy, M. R., Ravi Chandra, M. L., Venkatramana, P., & Dilli, R. (2023). Energy-Efficient Cluster Head Selection in Wireless Sensor Networks Using an Improved Grey Wolf Optimization Algorithm. *Computers*, *12*(2). https://doi.org/10.3390/computers12020035

[2] Balakrishnan, S. & Vinoth Kumar, K. (2023). Hybrid sine-cosine black widow spider optimization based route selection protocol for multihop communication in IoT assisted WSN. *Technical Gazette*, *30*(4), 1159-1165. https://doi.org/10.17559/TV-20230201000306

[3] Kumar, V. & Singla, S. (2022). Energy efficient hybrid AOMDV-SSPSO protocol for improvement of MANET network lifetime. *International Journal of Advanced Technology and Engineering Exploration*, *9*(96), 1642-1660. https://doi.org/10.19101/IJATEE.2021.876041

[4] Kathiroli, P. & Selvadurai, K. (2022). Energy efficient cluster head selection using improved Sparrow Search Algorithm in Wireless Sensor Networks. *Journal of King Saud University - Computer and Information Sciences*, *34*(10), 8564-8575. https://doi.org/10.1016/j.jksuci.2021.08.031

[5] Trojovský, P. & Dehghani, M. (2022). Pelican Optimization Algorithm: A Novel Nature-Inspired Algorithm for Engineering Applications. *Sensors*, *22*(3).

https://doi.org/10.3390/s22030855
[6] Rathore, P. S., Chatterjee, J. M., Kumar, A., & Sujatha, R. (2021). Energy-efficient cluster head selection through relay approach for WSN. *The Journal of Supercomputing*, *77*(7), 7649-7675. https://doi.org/10.1007/s11227-020-03593-4
[7] Singh, J., Deepika, J., Zaheeruddin et al. (2022). Energy-Efficient Clustering and Routing Algorithm Using Hybrid Fuzzy with Grey Wolf Optimization in Wireless Sensor Networks. *Security and Communication Networks*, *2022*, 1-12. https://doi.org/10.1155/2022/9846601
[8] Mehra, P. S. (2022). E-FUCA: enhancement in fuzzy unequal clustering and routing for sustainable wireless sensor network. *Complex and Intelligent Systems*, *8*(1), 393-412. https://doi.org/10.1007/s40747-021-00392-z
[9] Azooz, S. M., Majeed, J. H., Ibrahim, R. K., & Ali, A. H. (2022). Implementation of energy-efficent routing protocol within real time clustering wireless sensor networks. *Bulletin of Electrical Engineering and Informatics*, *11*(4), 2062-2070. https://doi.org/10.11591/eei.v11i4.3916
[10] Peña-Delgado, A. F. et al. (2022). A novel bio-inspired algorithm applied to selective harmonic elimination in a three-phase eleven-level inverter. *Mathematical Problems in Engineering*, *2022*, 1-2. https://doi.org/10.1155/2022/9808273
[11] Trinh, C., Huynh, B., Bidaki, M., Rahmani, A. M., Hosseinzadeh, M., & Masdari, M. (2022). Optimized fuzzy clustering using moth-flame optimization algorithm in wireless sensor networks. *Artificial Intelligence Review*, *55*(3), 1915-1945. https://doi.org/10.1007/s10462-021-10080-z
[12] Saleh, M. M., Abdulrahman, R. S., & Salman, A. J. (2021). Energy harvesting and energy aware routing algorithm for heterogeneous energy WSNs. *Indonesian Journal of Electrical Engineering and Computer Science*, *24*(2), 910-920. https://doi.org/10.11591/ijeecs.v24.i2.pp910-920
[13] Sahoo, B. M., Pandey, H. M., & Amgoth, T. (2021). GAPSO-H: A hybrid approach towards optimizing the cluster based routing in wireless sensor network. *Swarm and Evolutionary Computation*, *60*. https://doi.org/10.1016/j.swevo.2020.100772
[14] Rawat, P. & Chauhan, S. (2021). Probability based cluster routing protocol for wireless sensor network. *Journal of Ambient Intelligence and Humanized Computing*, *12*(2), 2065-2077. https://doi.org/10.1007/s12652-020-02307-1
[15] Sumesh, J. J. & Maheswaran, C. P. (2021). Energy conserving ring cluster-based routing protocol for wireless sensor network: A hybrid based model. *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, *34*(6). https://doi.org/10.1002/jnm.2921
[16] Naeem, A., Javed, A. R., Rizwan, M., Abbas, S., Lin, J. C. W., & Gadekallu, T. R. (2021). DARE-SEP: A hybrid approach of distance aware residual energy-efficient SEP for WSN. *IEEE Transactions on Green Communications and Networking*, *5*(2), 611-621. https://doi.org/10.1109/TGCN.2021.3060410
[17] Moshref, M., Al-Sayyed, R., & Al-Sharaeh, S. (2021). An enhanced multi-objective non-dominated sorting genetic routing algorithm for improving the QoS in wireless sensor networks. *IEEE Access*, *9*, 149176-149195. https://doi.org/10.1109/ACCESS.2021.3125740
[18] Abasıkeleş-Turgut, İ. & Altan, G. (2021). A fully distributed energy-aware multi-level clustering and routing for WSN-based IoT. *Transactions on Emerging Telecommunications Technologies*, *32*(12). https://doi.org/10.1002/ett.4355
[19] Ma, N., Zhang, H., Hu, H., & Qin, Y. (2021). ESCVAD: An Energy-Saving Routing Protocol Based on Voronoi Adaptive Clustering for Wireless Sensor Networks. *IEEE Internet of Things Journal*, *9*(11), 9071-9085. https://doi.org/10.1109/JIOT.2021.3051352
[20] Rao, A. N., Naik, B. R., & Devi, L. N. (2021). An efficient coverage and maximization of network lifetime in WSN through metaheuristics. *International Journal of Informatics and Communication Technology (IJ-ICT)*, *10*(3), 159-170. https://doi.org/10.11591/ijict.v10i3.pp159-170
[21] Abbas, N. A. F., Majeed, J. H., Al-Azzawi, W. K., & Ali, A. H. (2021). Investigation of energy efficient protocols based on stable clustering for enhancing lifetime in heterogeneous WSNs. *Bulletin of Electrical Engineering and Informatics*, *10*(5), 2643-2651. https://doi.org/10.11591/eei.v10i5.3049
[22] Thiruppathi, M. & Vinoth Kumar, K. (2023). Seagull optimization-based feature selection with optimal extreme learning machine for intrusion detection in fog assisted WSN. *Technical Gazette*, *30*(5), 1547-1553. https://doi.org/10.17559/TV-20230130000295

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