Energy Efficient Cluster Head Selection and Routing Algorithm using Hybrid Firefly Glow-Worm Swarm Optimization in WSN

Bharathiraja S[1*], Selvamuthukumaran S[2], and Balaji V[3]
[1] Department of Electronics and Communication Engineering, A.V.C.College of Engineering, Mannampandal, Mayiladuthurai.
[e-mail: bharathiavcraja@gmail.com]
[2]Department of Computer Applications, A.V.C.College of Engineering, Mannampandal, Mayiladuthurai.
[e-mail: smksmk@gmail.com]
[3]Department of Electronics and Communication Engineering, KCG College of Technology, Chennai.
[e-mail : balaji.phd.auc2008@gmail.com]
[*]Correspondingauthor:Bharathiraja S

Received March 8, 2023; revised June 2, 2023; accepted June 25, 2023; published August 31, 2023

Abstract

The Wireless Sensor Network (WSN), is constructed out of teeny-tiny sensor nodes that are very low-cost, have a low impact on the environment in terms of the amount of power they consume, and are able to successfully transmit data to the base station. The primary challenges that are presented by WSN are those that are posed by the distance between nodes, the amount of energy that is consumed, and the delay in time. The sensor node's source of power supply is a battery, and this particular battery is not capable of being recharged. In this scenario, the amount of energy that is consumed rises in direct proportion to the distance that separates the nodes. Here, we present a Hybrid Firefly Glow-Worm Swarm Optimization (HF-GSO) guided routing strategy for preserving WSNs' low power footprint. An efficient fitness function based on firefly optimization is used to select the Cluster Head (CH) in this procedure. It aids in minimising power consumption and the occurrence of dead sensor nodes. After a cluster head (CH) has been chosen, the Glow-Worm Swarm Optimization (GSO) algorithm is used to figure out the best path for sending data to the sink node. Power consumption, throughput, packet delivery ratio, and network lifetime are just some of the metrics measured and compared between the proposed method and methods that are conceptually similar to those already in use. Simulation results showed that the proposed method significantly reduced energy consumption compared to the state-of-the-art methods, while simultaneously increasing the number of functioning sensor nodes by 2.4%. Proposed method produces superior outcomes compared to alternative optimization-based methods.

http://doi.org/10.3837/tiis.2023.08.010 **ISSN : 1976-7277**

Keywords: Cluster head selection; Routing Algorithm; Wireless Sensor Network; Firefly Algorithm; Glow Worm Swarm Optimization.

1. Introduction

Numerous cutting-edge uses have been developed for WSNs, including monitoring and management of infrastructure and systems in the industrial and business sectors, as well as increased system awareness. The numerous tiny and energy-constrained sensor nodes that make up a WSN monitor and report on things like heat, temperature, motion, smoke, and pressure across an area. It is common practise to represent the dispersion of sensor nodes as a homogeneous Poisson point process. This is due to the fact that spreading out the sensor nodes uniformly across an n-dimensional space achieves the same results as using the configuration described. Given knowledge of the network's density, the Poisson point process model is a good approximation that may lead to interesting findings[1].

Data is gathered by sensors dispersed across a WSN and sent to centralised nodes, known as sinks. In an energy-constrained network like WSN, where nodes connect with each other via multi-hop broadcasts, sending data directly to sinks is inefficient. The fundamental disadvantage of multi-hop transmissions is the need to send several packets between connected nodes. Since the network's lifespan is directly proportional to the amount of energy each node has, this has a negative impact on the network's durability. Because of this, reducing energy usage is one of the biggest obstacles facing WSNs. Most researchers are focusing on topology management and network coding because they show the most promise for reducing power consumption and enhancing network performance[2].Cluster head selection and routing in wireless sensor network is shown in **Fig. 1**.

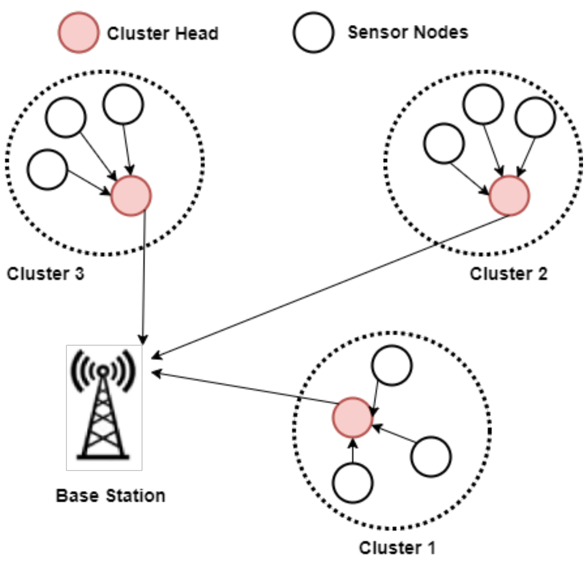

Fig. 1. Cluster head selection and Routing

Network coding is a type of forwarding architecture that dramatically increases multicast data transmission speeds[3]. This method treats packets as points in a vector space, and passes them along as the result of a linear combination with randomly chosen coefficients. By comparison to the more conventional store-and-forward method, this procedure lowers the energy requirements of WSNs [4]. Network coding is influenced by topology when the final nodes cannot linearly receive enough individual packets to reconstruct the original packets. It has been found that WSNs perform better when network coding and topology control are combined. With topology control framed as an optimization problem for maximising node transmission range, a number of centralised approaches have been proposed[5]. One of the drawbacks of the available combination methods is that the amount of time needed for computation to arrive at an optimal solution increase on an exponential scale in proportion to the number of sensor nodes. It is important to remember that the amount of time spent computing is a key part of major networks, and that the amount of time spent computing is limited in some real-world network scenarios. Furthermore, in order to achieve the necessary topology and simultaneously optimise specific objectives of the WSN, the centralised techniques described earlier need to gather information of the entire network in a centralised node. Therefore, in order to extend the lifetime of WSNs, it is necessary to propose a solution to distributed energy management that can make efficient use of the constrained power of battery-powered nodes while also accommodating the networks' inherently dynamic operating environment.

Researchers are almost unanimous in their agreement that cluster-based techniques are the most effective strategies to reduce energy consumption in distributed WSNs [6]. The amount of data that needs to be transferred can be cut significantly thanks to clustering, and energy consumption can be more evenly distributed as a result. To provide further clarity, the data are accumulated after being received from nodes that are a part of a cluster. This is done in order to reduce the amount of data that needs to be transmitted to the sink nodes in order for the process to continue. In addition, designers can avoid some nodes from going hungry owing to a shortage of energy by rotating cluster heads. However, selecting appropriate cluster heads is a well-defined example of an NP-hard optimization problem that arises in wireless sensor networks. Because of this, energy-efficient clustering procedures in WSNs can be implemented using computational intelligence-based methodologies. Further, learning automata are thought to be a powerful method for handling systems with little data on their surroundings [7].

In this research, we employ clustering as a technique for optimal path selection based on firefly and glow-worm optimization. Our goals are to minimize the amount of time needed for computing and maintain a stable level of energy consumption. The remaining portion of this work is divided into sections as follows: Section II provides the gist of a survey conducted by a number of researchers Section III summarizes the process that was proposed, Section IV explains the Experimental Results of the proposed method. Finally, Section V Ends the paper with a list of cited references.

2. Related Study

Extending network longevity and optimising energy efficiency are two of the primary difficulties researchers face while studying WSNs. Therefore, it is essential to provide a low-power solution for the difficulties of cluster head selection, clustering, and routing protocols. WSNs, which typically use battery power in sensor nodes, have significant limitations due to the integrated processor, low-power radio, and insufficient memory that are present in each node. Most often, battery-operated sensor nodes are deployed in a hostile, unattended setting. So, the choice of how much power they get from their batteries is almost impractical because it limits how well the sensor nodes use energy. Transmission over WSN has been made more efficient by taking into account factors such as the cost, the amount of energy that is consumed, and the lifetime of the network. Many of the researchers came up with different ways to save energy and make the network last longer. To minimise energy loss and maximise network lifetime, an optimal clustering in circular networks (OCCN) approach was developed [8]with optimised parameters. The best configuration for a network with a base station (BS) at the centre included the number of clusters, their size, and their single-hop communication efficiency. As a result, the OCCN method can significantly lengthen the service life of a network. The most significant impact of this method is that it is not possible to maintain a constant level of energy loss patterns. This is because the behaviour of network energy loss is highly predictable.

Utilizing particle swarm optimization (PSO) and fuzzy clustering, a CH selection technique was developed [9]. Preliminary clustering was performed using fuzzy clustering, and the CH was chosen using extended PSO. Using this method, we were able to significantly reduce the number of dead sensor nodes in the network, effectively extending its service life. This approach has one major flaw: it can't be used for preliminary clustering to speed up calculations.A Fuzzy C means clustering algorithm for wireless sensor network was proposed by Su et al. [10], which divides nodes into groups of a fixed size. This strategy anticipated the best solution of CHs based on the density node to extend the lifetime of the network by considering the total energy loss across all nodes. The approach was successful in achieving a uniform spatial distribution of CHs and a uniform loss of energy across the network.

Though this technique successfully cut down on energy waste, the clustering methodology it employed is not well suited to the goal of wireless sensor network.

To lessen the drain on the network's power supply, Mirzaie et al. [11] devised a fuzzy-logic-based adaptive multi-clustering method (adaptive MCFL). By using this method, we were able to reduce the optimal number of CH selections and the repetition in the distribution of CH communications, resulting in a significant improvement in the sensor network's overall energy efficiency. The adaptive MCFL performed very well in terms of both energy efficiency and loss. Yu et al. [12] combine an energy-aware clustering technique with a cluster-based routing technique to create a cluster-based routing protocol for network, but they do not use a uniform node distribution. By controlling the amount of energy dissipated both within and across clusters, this routing technique was used to reduce the amount of power wasted while CHs communicated with one another. Thus, energy stability between sensor nodes increased network lifespan. In heterogeneous settings, lower-energy sensor nodes limited network lifetime, depleting higher-energy sensor nodes.

Intuitively better harmony search Gupta and Jha [13] presented the Cuckoo Search-based Clustering Protocol (HSCSCP) to maintain energy stability and extend network lifetime. For the purpose of ensuring that cluster heads are dispersed throughout the network evenly, a new HSCSCP with an innovative objective function was presented. Harmony search has been improved and integrated into routing to reliably distribute data packets between cluster heads and the sink. It eliminated uneven energy consumption across the network because sensor nodes closest to the sink may be inundated with traffic. It used energy-balanced node clustering to analyse routing between cluster nodes and the sink. SIWODE, a hybrid algorithm based on the self-adaptive invasive weed algorithm (IWO) and differential evolution algorithm (DE), has been suggested for continuous optimization [14]. HSCSCP outperformed state-of-the-art protocols in mean energy consumption, network longevity, and living and dead nodes. This clustering technique lacks scalability, reducing network performance.To resolve the conflict between increasing diversity and increasing intensity when choosing cluster leaders, Dattatraya and Rao [15] proposed a Hybrid Fruit Fly and Glowworm Search Optimization (GSO)-based Clustering Protocol (HFFGSOCP). This HFFGSOCP selected the cluster leaders by leveraging the effective dynamic exploration of GSO and the robust exploitation of Fruit Fly. The cluster head selection model was implemented to ensure long-term reliability and stable low power consumption. The cluster head selection process optimised for energy, latency, and distance to achieve optimal performance. The algorithm aimed to maximise energy efficiency while minimising delay by taking into account the estimated inter and intra-distance between sensor nodes and their respective cluster heads.

Hybrid Modified Artificial Bee Colony and Firefly Algorithm (HMABCFA) based Cluster Head Selection is proposed for the purpose of ensuring energy stabilisation, delay minimization, and inter-node distance reduction for the purpose of improving the network's lifetime [16]. This is done in order to avoid the frequent selection of cluster heads, which threatens the network's sensor nodes' ability to maintain a constant level of energy production. With a mean packet delivery rate of 23.21 and 22.83 percent, respectively, it was discovered to be superior to LEACH and GA in terms of improving the network lifetime.Longevity and throughput improvements in WSNs can be achieved with the help of an Energy Aware Cluster Routing Protocol (SOA-EACR) based on the Seagull Optimization Algorithm. During CH selection, the SOA-EACR ensures a healthy equilibrium between exploration and exploitation [17]. Methods based Fuzzy [18], Gaussian Regression[19] and Cyclic Grey Wolf Optimization [20] were developed. Traditional cluster head selection methods were found wanting in two key areas: energy dissipation and base station packet output.Maintaining the diversity and intensity rate during the cluster head selection process is an issue for most of the clustering procedures that have been presented to the literature. However, [21] most cluster head methods' inability to simultaneously handle energy stability and longevity decreases their scalability as the number of sensor nodes in the network grows. Few clustering approaches made an effort to thoroughly explore all of the factors that should be taken into account when choosing cluster leaders. The major contribution is as follows:

1. Cluster formation and cluster head selection using Firefly Optimization algorithm.
2. Following the selection of the cluster head, the Glow-Worm Swarm optimization technique is employed to determine the optimal path selection for routing.
3. Perform an experimental comparison of the suggested strategy with other existing approaches.

3. Proposed Method

Clustering, Cluster Head(CH) selection, and optimization best path selection routing for data transmission are the three primary phases that are involved in the approach that has been developed. It emphasizes down on the issue of overcrowding close to the sink as the primary concern. We proposed a model called Hybrid Firefly Glow-Worm Swarm Optimization (HF-GSO) as shown in **Fig. 2**.

3.1 Network Setup and Energy Model

The network is a multi-hop network that is composed of the base station (BS) and the sink node (SN). In order to implement a random distribution of sensors, a Cartesian framework in two dimensions is used. Every sensor node includes a power source that does not support rechargeable batteries. Once they have been placed, sensor nodes are unable to change their location in any way. There is no difference between any of the sensors in terms of their capacity for communication or processing. There is no difference in the starting energies of any of the sensor nodes. The data can be diffused in either way through transmission lines between sensor nodes. Receiver gives power to radio electronics, and transmitter gives power to both radio electronics and power amplifiers. We use the multi-path fading model. According to the free-space model, the amount of energy lost is proportional to the square of the distance between the sender and the receiver, denoted by D^2. When D is larger than the cutoff, transmission failure occurs between the sender and the receiver. On the multi-path fading model, the amount of energy that is lost is written as DL. Thus, the amount of power required to transmit a packet containing n bits is given by equation 1,

$$E_c = \begin{cases} n * (E_{ec} + E_{rfs} * D^2), & D \leq d_0 \\ n * (E_{ec} + E_{mp} * Dh), & D \leq d_0 \end{cases} \tag{1}$$

E_{ec} is the SN simulation energy. The amplifier energy of a free space or multi-path fading model is determined by the distance between the sender and the receiver as well as the bit error rate that can be tolerated. Both E_{rfs} and E_{mp} indicate the amount of energy that must be expended in order to transmit a bit into free space over a multipath fading channel. The initial threshold value is obtained by equation (2),

$$D_0 = \sqrt{\frac{E_{rfs}}{E_{mp}}} \tag{2}$$

The equation (3) gives the amount of energy that is used up when receiving a packet containing n bits,

$$E_{rec} = n * E_{ec} \tag{3}$$

CH's data aggregation energy intake is calculated using equation (4),

$$E_{ag} = E_{eag} * n * m \tag{4}$$

Where m is the number of messages and E_{eag} represent amount of aggregated energy spent for one bit.

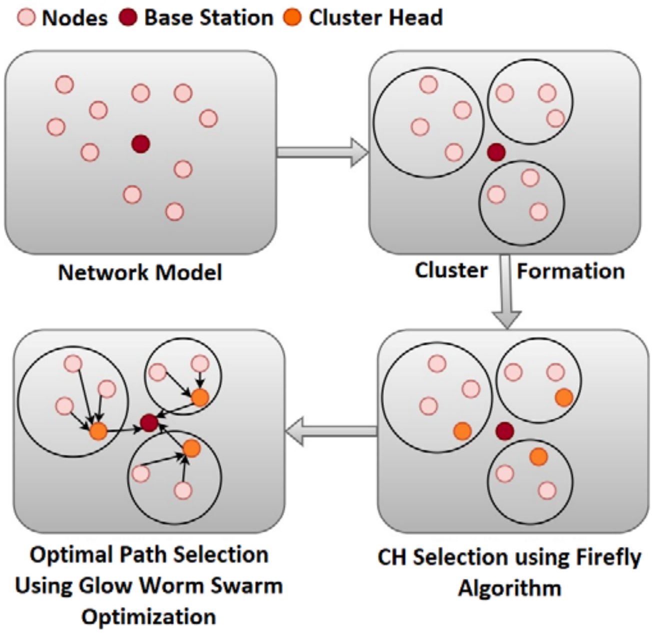

Fig. 2. Proposed HF-GSO Method

3.2 Cluster Formation and Head Selection using Firefly Algorithm

The Firefly algorithm is a member of the group of algorithms known as meta-heuristic algorithms. The algorithm has been framed using the flashing activity that is concerned with light. The primary goal of the firefly method is to determine the position of a particle that will produce the highest possible assessment in a specified fitness function. The fireflies are all regarded to be of the same gender. It doesn't matter that the fireflies are constantly switching genders; they still manage to attract one another. The attractiveness of the Firefly is inversely proportional to the distance from which one is observing it, and it diminishes as the brightness of the Firefly decreases. The intensity of the firefly's glow serves as the determining factor.

To calculate the light intensity at a distance d, uses the square law (Equation 5), where J_s is the light intensity coming from the source (Equation 6),

$$J = \frac{J_s}{d^2} \tag{5}$$

$$J = J_s \exp(cd^2) \tag{6}$$

The absorption coefficient is denoted by the letter C. It is believed that the subsequent Gaussian shape of the approximation will encourage the prevention of the singularity when distance is equal to zero. In the firefly technique, the attractiveness A is shown to be proportional to the brightness of the light source by Equation 7, where A_0 represents the attractiveness atd $= 0$.

$$A = A_0 \exp(-cd^m) \tag{7}$$

Distance between i^{th} and j^{th} firefly located in y_i and y_j respectively is given by Equation (8),

$$d_{ij} = \sqrt{\sum_{m=1}^{n} (y_{im} - y_{jm})^2} \tag{8}$$

Motion of attractiveness between i^{th} and j^{th} firefly is given by Equation (9),

$$y_{i+1} = y_i + B_0 e^{-vd^2}(y_j - y_i) + \gamma\varepsilon \tag{9}$$

Where B_0 is the attractiveness when distance is zero.

The following provides an outline of the primary processes involved in the suggested FCR approach for cluster head selection.

i. Set the initial state of the T particles so that they hold a randomly chosen eligible cluster head.

ii. Cost function computation for particles that have already been initialised. Determine the node with the shortest distance to the others and make it the head of the cluster. Enumerate the cost function using Eq. (10). Finally, the optimal pool is determined by maximising the cost function of the original population.

$$C_n = bc_b + (1 - b)c_a \tag{10}$$

Where b is the parameter value between 0 and 1 and functions c_a and c_b can be obtained by Equation 11 and 12 respectively,

$$c_a = e_1 * c_i^{dis} + e_2 c_i^{ene} + e_3 * c_i^{del} \tag{11}$$

$$c_b = \frac{1}{m}\sum_{i=1}^{m} \|n^x - B_s\| \tag{12}$$

Where B_s is base station, n^x is the cluster of nodes. e_1, e_2 and e_3 are the parameters of distance, energy and delay.

iii. Update the firefly population, cost function, and intensity. The updating model that has been provided is a switching function that moves between the random updating process and the traditional firefly algorithm. This function can be found in Equation (13) and Equation (14),

$$y_j = P_F + Q_F \tag{13}$$

$$\beta_1(k) = \begin{cases} 1; & \text{if } d > 0 \\ 0; & \text{otherwise} \end{cases} \tag{14}$$

Where

$$P_F = (1 - v)y_j^{FF} \tag{15}$$

$$Q_F = \rho \textstyle\sum_{k=1}^{n} \beta_1(k)\gamma_1(k)y_j^{rand}(k) \tag{16}$$

$$d = G(y_j^{rand}(k)) \tag{17}$$

v is a parameter given by,

$$v = \sum_{k=1}^{n} \gamma_1(k) \tag{18}$$

Based on the progress made by the updated fireflies, Equation (18) chooses whether to do a traditional update based on the firefly method or a random update. Using $\beta_1(k)$ and $\gamma_1(k)$, we can see the enhancements provided by the improved firefly Equation (14).

iv. The original Firefly should be swapped out for the updated Firefly if the intensity after updating is higher than the best pooling and continue from step 7.
v. If the new intensity is lower than the current best pool, then the function of the current best solution should be randomly adjusted and the intensity recalculated.
vi. In order to move on to the next step, it is necessary to repeat steps four and five for each cycle of N flies.
vii. After that, the newly created solutions are accessible, and steps (1-6) are repeated in order to determine the light intensity of each of the newly created solutions.
viii. Lastly, it needs to be ranked so that it can spot the best.
ix. Repeat the preceding procedures until the maximum number of iterations has been reached.

3.3 Optimal Path Selection using Glow-Worm Swarm Optimization

At first, each CH's neighbours receive the path information, which includes the node id, distance, and residual energy. The CH will then save the information in a routing database. To find out how to get from CH to BS. Each CH has a glow worm installed in it. Each glow-worm has its own adaptive neighbourhood, defined by a r_d^A and a fixed sensor range $r_s\left(0 < r_d^A \leq r_s\right)$ on both sides. A glow-worm will regard another glow-worm to be its neighbour if they are represented by the letters A and B, respectively. In the event if the Lucifer in level B is higher than A and it is also located inside the location series of A, the probability function for glow-worm A travelling towards glow-worm B is defined as follows:

$$P_{AB}(t) = \frac{l_B(t) - l_A(t)}{\sum_{k \in N_A(t)} l_k(t) - l_A(t)} \tag{19}$$

Here, at time t, the set of glow worm neighbours are denoting as $B \in N_A(t), N_A(t) = \left\{B: d_{AB}(t) < r_d^B(t); l_A(t) < l_B(t)\right\}$. The $d_{AB}(t)$ notation stands for the Euclidean distance between glow worms A and B. Glow-worm A corresponds to the adjustable neighbour choice denoted by $r_d^A(t)$. Each glow worm's neighbourhood range is then rationalised using the following criteria.

$$r_d^A(t+1) = m\ \left\{r_s, m\ \left\{0, r_d^A(t) + \partial(n_t - |N_A(t)|)\right\}\right\} \tag{20}$$

Here, ∂ is a constant parameter, and n_t is a constraint that limits the size of each neighbouring set. In a wireless-based communication system, the node that has the greatest potential for success is chosen to serve as a relay node along the path leading from CH to BS. However, in the periodic communication, the node with the lowest chance is the one that is chosen to act as the relay node.

4. Experimental Analysis

The performance evaluation of proposed method HF-GSO is carried out in MATLAB, and it is compared with the various existing algorithms that are currently available, Adaptive MCFL [11], SIWODE [14], HFFGSOCP [15], HMABCFA[16] and SOA-EACC[17]. **Table 1** contains a description of the parameters that were taken into account when carrying out the simulations.

Table 1. Parameters Used

Parameter	**Values**
Network deployment area	300m x 300m
Nodes	100-500
Clusters	Differs
Initial node energy	2 J
Network Energy	Varies based on the number of nodes
Packet size	10000 bits
Network Throughput	1 Mbps
Location	(0, 0)
Range of nodes	30-40m
Rounds	3500

For 100-500 nodes, clusters are formed based on the residual energy and distance. The node which is closer to the cluster is selected as cluster heads. The node density if gradually increased in terms of 50 from 100 to 500 and the performances are measured. Four clusters are formed in the experimentation and for each round the node density is alone increasedand cluster heads are kept same.

When the node density is increased, the cluster member for cluster head increases which increases the energy consumption of cluster heads while performing intra cluster communication. Due to this, the premature death of nodes will increase. Also, if the distance between nodes is same, the energy consumption will be high. Thus, to reduce the energy consumption of cluster head, the clustering radius is adjusted based on the network density. This will reduce the cluster size and avoids premature death of cluster heads and enhances the network lifetime.

The parameters used for performance evaluation are lifespan of a network, number of nodes alive, number of nodes dead, consumption of energy, throughput, and packet delivery ratio. Network Lifetime is the number of cycles, for time, throughout which the network can carry out its tasks. It indicates how many iterations into the job processing the field's nodes will perish. Sink nodes are nodes in a network that have sufficient energy to process the tasks that have been assigned to them, and the number of living nodes in a network is used to determine which sink nodes are present. The term "dead nodes" refers to sensor nodes in a network that are unable to carry out their functions because they lack the necessary amount of energy. The speed at which data is transmitted to the base station is referred to as the throughput, and this speed is independent of the number of nodes that are currently connected. The percentage of data packets that were successfully transmitted to the base station irrespective of the total number of nodes is referred to as the packet deliver ratio.

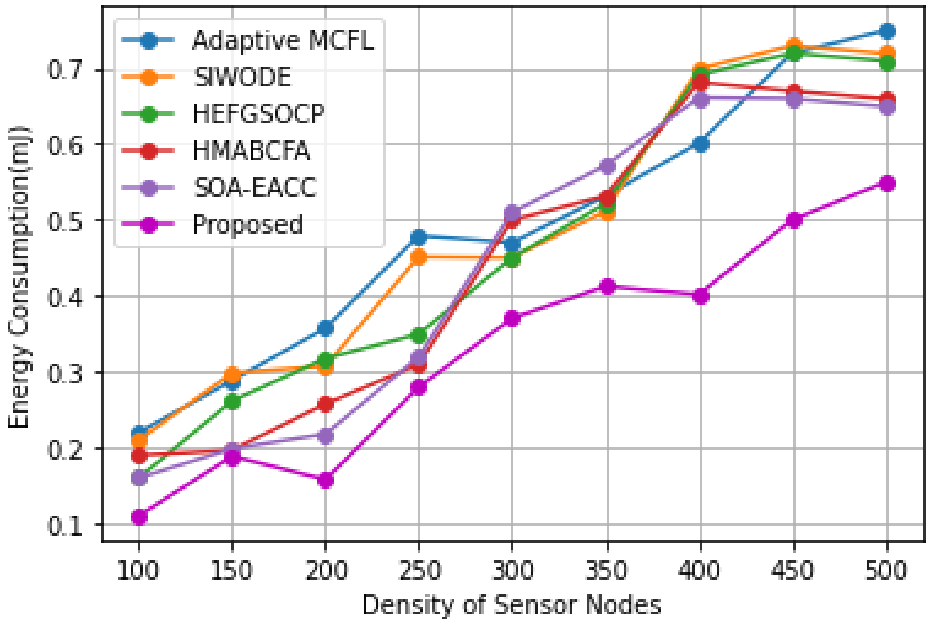

Fig. 3. Comparison of Energy Consumption with Other Methods

Fig. 3 presents a graph of the amount of energy that was consumed. Because of the usage of firefly-based uneven clustering and glow-worm swarm optimization in our work with wireless sensor networks (WSN), the proposed solution uses the least amount of energy possible. The proposed method takes into consideration a quantity of energy that is significantly less than that of other schemes. The strategy that was proposed produced the lowest energy consumption when compared to other approaches that are currently being used. The Adaptive MCFL strategy makes use of a significant quantity of the available energy. As the size of the network grows, so does the average rate of energy consumption. The graph shows that the proposed approach outperformed the others in terms of the average amount of energy used. Energy consumption in the existing schemes is relatively higher than the proposed scheme. The suggested technique uses up to 0.54 joules of energy for 500 nodes, while the Adaptive MCFL, SIWODE, HEFGSOCP, HMABCFA, and SOA-EACC based schemes each use 0.74, 0.71, 0.70, 0.64, and 0.65 joules of energy. The proposed technique reduces energy consumption by 20.9% compared to the baseline algorithm for 500 nodes.

Fig. 4 depicts the effectiveness of the network over its lifetime. As the number of nodes in a system grows, so does its performance and longevity. The proposed method outperformed all others tested too far. Using existing methods such as Adaptive MCFL, SIWODE, HEFGSOCP, HMABCFA, and SOA-EACC, the lifetime of the system is computed for varying numbers of nodes. The network lifetime is lowest with the Adaptive MCFL and SIWODE method. The proposed strategy outperforms alternative schemes in terms of network longevity. It is clear from the graph that the suggested method greatly enhances network lifetime performance.

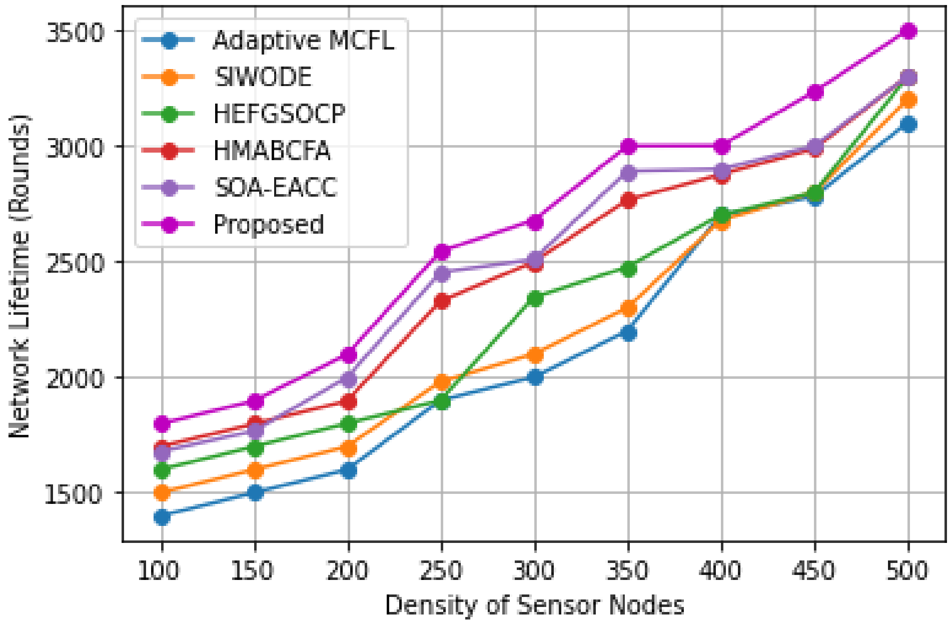

Fig. 4. Comparison of Network Lifetime with Other Methods

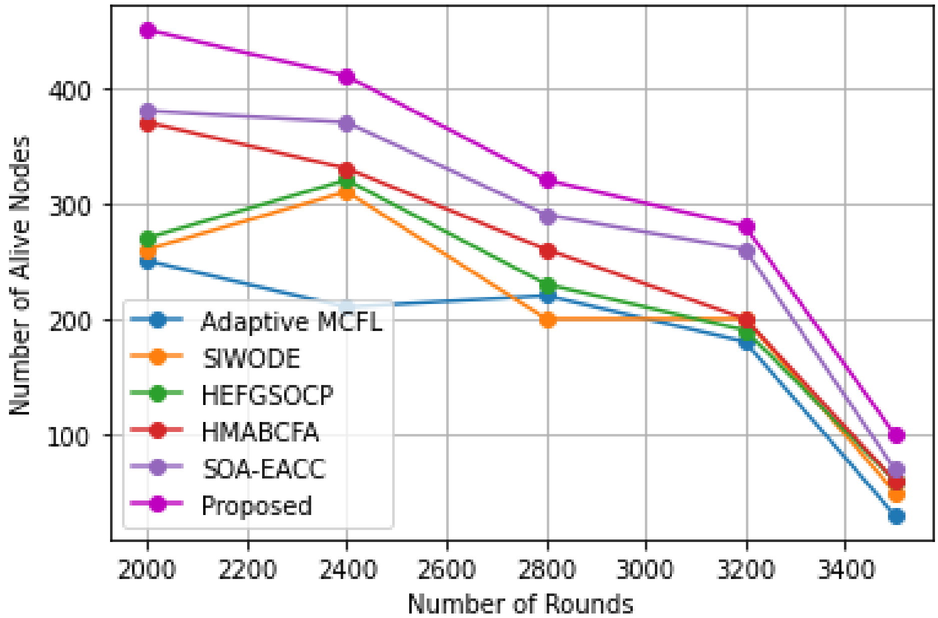

Fig. 5. Comparison of Alive Nodes with Other Methods

The number of sensor nodes that are still active during the processing of a set of rounds is shown in the **Fig. 5** The proposed solution finished all 3500 rounds and kept 100 nodes in an alive condition for the duration of the game. After 3500 rounds have been completed, the number of alive nodes for Adaptive MCFL, SIWODE, HEFGSOCP, HMABCFA, and SOA-EACC are, respectively, 40, 52, 60, 61, and 70. The proposed method yields around a 25.4% improvement in relation to 3500 rounds when compared to the other technique.

The proposed method lost fewer than 100 nodes after processing 2400 rounds, whereas other methods lost more than 100 nodes during this time frame (**Fig. 6**). This stands in contrast to the fact that network nodes are doomed to die while performing their functions. After 3500 rounds, the total number of SNs that have died due to the implementation of the recommended plan is 410. The suggested approach achieves a 5.1% improvement in comparison to 3500 rounds.

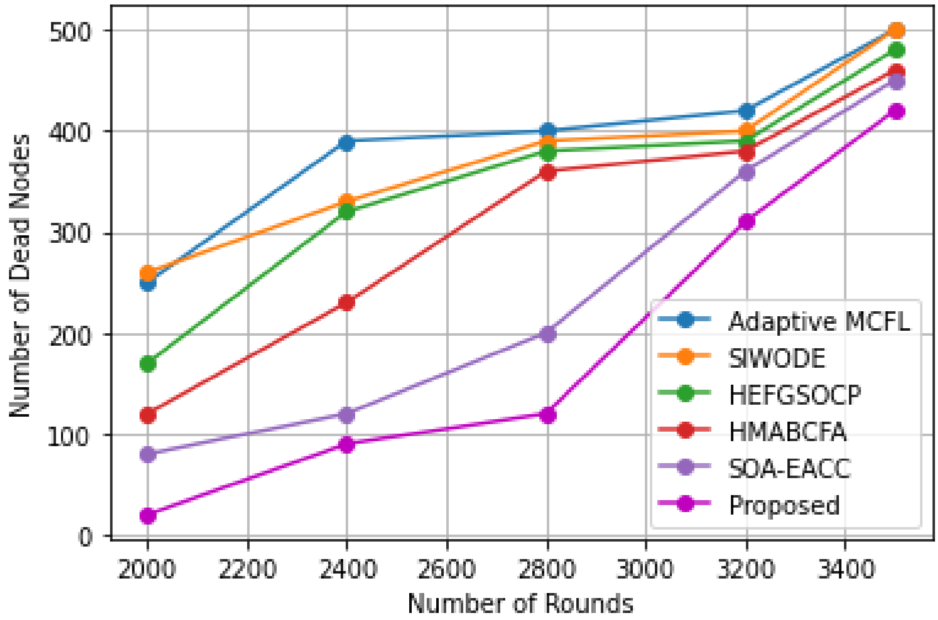

Fig. 6. Comparison of Dead Nodes with Other Methods

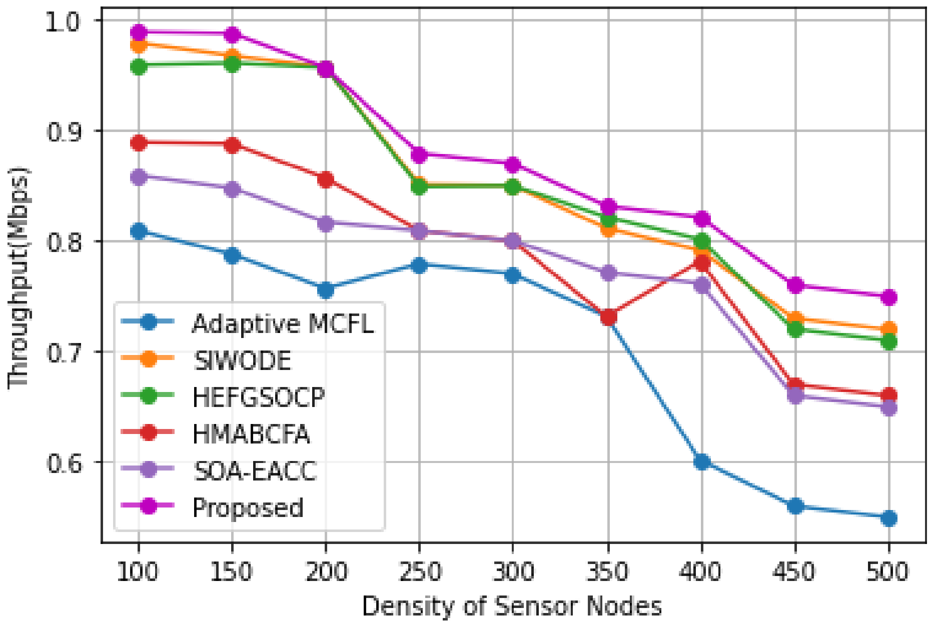

Fig. 7. Comparison of Throughput with Other Methods

Fig. 7 displays a comparison of the throughput of several methods. If you have between 100 and 500 nodes, the proposed method can transfer the data at a maximum of 0.98 Mbps and a minimum of 0.79 Mbps. The proposed method yields better throughput improvement in relation to 500 nodes when compared to the other technique.

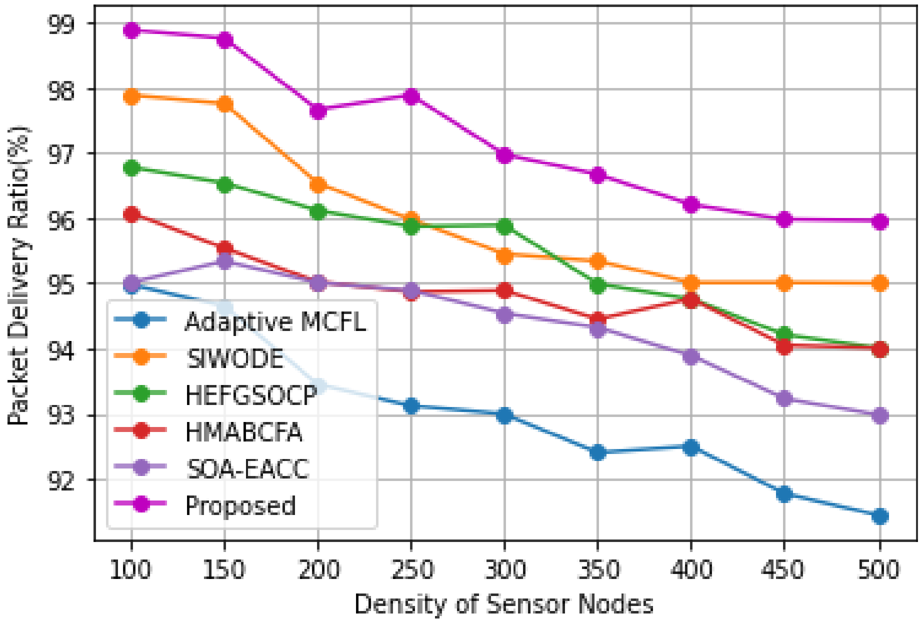

Fig. 8. Comparison of Packet Delivery Ratio with Other Methods

Fig. 8 illustrates the differences in the packet delivery rates achieved by the various methodologies. This demonstrates that the proposed routing strategy was successful in delivering the packets at a rate ranging from 95.96% with 500 nodes to 98.89% for 100 nodes.

Table 2. Comparison with Other Methods

Methods	Energy Consumption (mJ)	Network Lifetime (rounds)	Alive Nodes	Dead Nodes	Throughput (Mbps)	Packet Delivery Ratio (%)
Adaptive MCFL	0.74	3100	40	499	0.8089	91.44
SIWODE	0.71	3200	52	498	0.8789	93.00
HEFGSOCP	0.70	3298	60	480	0.9089	94.01
HMABCFA	0.66	3301	61	460	0.8998	94.20
SOA-EACC	0.64	3300	70	450	0.9543	92.98
Proposed	0.54	3499	100	420	0.9889	95.96

Table 2 shows how well the suggested method compares to those already in use, such as Adaptive MCFL, SIWODE, HEFGSOCP, HMABCFA, and SOA-EACC. The proposed method's performances are calculated and compared to other existing methods for varying numbers of SNs. Based on the data in the table, it is clear that the proposed strategy

outperforms the alternatives in every metric considered.

5. Conclusion

In this paper, an approach called Hybrid Firefly Glow-Worm Swarm Optimization (HF-GSO) is proposed. It solves the problem of the sensor nodes near the base station having a short battery life. The issue of low life comes about as a result of the heavy traffic movement that occurs between the numerous cluster heads and the sink. The cluster head selection approach utilised by the HF-GSO is derived from the Firefly Optimization algorithm and is known for its low impact on the environment. The Glow Worm Swarm optimization technique is utilised for the purpose of selecting the most efficient path from the cluster head to the sink node. The performance of HF-GSO is evaluated in comparison to other optimization-based routing methods that are currently in use. The proposed method improved performance by 20.9% in terms of energy consumption and by 2.4% in terms of the number of functional sensor nodes. There are substantial gains in energy efficiency, packet delivery ratio, and throughput with the proposed HD-GSO compared to the state-of-the-art.

Declaration

- Funding – The author did not receive support from any organization for the submitted work.

- Conflicts of Interest - The author has no relevant financial or non-financial interests to disclose.
- Ethics Approval – The paper is an original contribution of research and is not published elsewhere in any form or language.
- Consent Statement – All authors mentioned have contributed towards the research work, drafting of the paper as well as have given consent for publishing of this article.
- Availability of Data & Material – The author hereby declare that no specific data sets are utilized in the proposed work. The have also agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.
- Consent to publication – all authors listed above have consented to get their data and image published.
- Author’s contribution – Bharathiraja S– Research proposal – construction of the work flow and model – Final Drafting – Survey of Existing works – Improvisation of the proposed model; Dr.S.Selvamuthukumaran – Initial Drafting of the paper – Collection of datasets and choice of their suitability – Dr.V.Balaji--Formulation of pseudocode
- Code Availability – Since, future works are based on the custom codes developed in this work, the code may not be available from the author.
- The authors have no relevant financial or non-financial interests to disclose.
- No Humans or Animals were involved in the experimentation.

References

[1] N Antunes, G Jacinto, and A Pacheco, "Hop count distributions of the furthest and nearest distance routing protocols in mobile ad hoc networks," *SIAM Journal of Applied Mathematics*, vol. 75, no, 2, pp. 335–349, April 2015. Article(CrossRef Link)

[2] M.K Dermany, and M.J Nadjafi-Arani, "Mathematical aspects in combining network coding with transmission range adjustment," *IEEE Communications Letters*, vol. 23, no. 9, pp. 1568–1571, Sep 2019. Article(CrossRef Link)

[3] M.K Dermany, M Sabaei, and M Shamsi, "Topology control in network-coding-based-multicast wireless sensor networks," *International Journal of Sensor Network*, Vol. 17, No. 2, pp. 93– 104, March 2015. Article(CrossRef Link)

[4] M.Z Farooqi, S.M Tabassum, M.H Rehmani, and Y Saleem, "A survey on network coding: From traditional wireless networks to emerging cognitive radio networks," *Journal of Network and Computer Applications*, vol.46, pp.166–181, Nov 2014. Article(CrossRef Link)

[5] D Jiang, Z Xu, W Li, and Z Chen, "Network coding-based energy-efficient multicast routing algorithm for multi-hop wireless networks," *Journal of Systems and Software*, vol. 104, pp.152–165, June 2015. Article(CrossRef Link)

[6] M Khalily-Dermany, M.J Nadjafi-Arani, and S Doostali, "Combining topology control and network coding to optimize lifetime in wireless sensor networks," *Computer Networks*, Vol. 162, pp. 106859, Oct 2019. Article(CrossRef Link)

[7] P.S Mann, and S Singh, "Energy efficient clustering protocol based on improved metaheuristic in wireless sensor networks," *Journal of Network and Computer Applications*, Vol. 83, pp. 40–52, April 2017. Article(CrossRef Link)

[8] Arghavani, Mahdi, Mohammad Esmaeili, Maryam Esmaeili, Farzad Mohseni, and Abbas Arghavani, "Optimal energy aware clustering in circular wireless sensor networks," *Ad Hoc Networks*, vol. 65, pp. 91-98, Oct 2017. Article(CrossRef Link)

[9] NiQingjian, Qianqian Pan, Huimin Du, Cen Cao, and Yuqing Zhai, "A novel cluster head selection algorithm based on fuzzy clustering and particle swarm optimization," *IEEE/ACM transactions on computational biology and bioinformatics*, Vol. 14, no. 1 pp. 76-84, Feb 2017. Article(CrossRef Link)

[10] SuShengchao, and Shuguang Zhao, "An optimal clustering mechanism based on Fuzzy-C means for wireless sensor networks," *Sustainable Computing: Informatics and Systems*, vol. 18 pp. 127-134, June 2018. Article(CrossRef Link)

[11] Mirzaie Mostafa, and Sayyed Majid Mazinani, "Adaptive MCFL: An adaptive multi-clustering algorithm using fuzzy logic in wireless sensor network," *Computer Communications*, Vol. 111, pp. 56-67, Oct 2017. Article(CrossRef Link)

[12] Yu Jiguo, Yingying Qi, Guanghui Wang, and Xin Gu, "A cluster-based routing protocol for wireless sensor networks with nonuniform node distribution," *AEU-International Journal of Electronics and Communications*, vol. 66, no. 1 pp 54-61, Jan 2012. Article(CrossRef Link)

[13] P Gupta Govind, and Sonu Jha, "Integrated clustering and routing protocol for wireless sensor networks using Cuckoo and Harmony Search based metaheuristic techniques," *Engineering Applications of Artificial Intelligence*, vol. 68, pp. 101-109, Feb 2018, Article(CrossRef Link)

[14] Zhao Fuqing, Songlin Du, Hao Lu, Weimin Ma, and Houbin Song, "A hybrid self-adaptive invasive weed algorithm with differential evolution," *Connection Science*, vol. 33, no. 4 pp. 929-953, April 2021. Article(CrossRef Link)

[15] Dattatraya Kale Navnath, and KRaghava Rao, "Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN," *Journal of King Saud University-Computer and Information Sciences*, vol.34, no.3, pp.716-726, March 2022. Article(CrossRef Link)

[16] J Sengathir, ARajesh, Gaurav Dhiman, S Vimal, C.A Yogaraja, and Wattana Viriyasitavat, "A novel cluster head selection using Hybrid Artificial Bee Colony and Firefly Algorithm for network lifetime and stability in WSNs," *Connection Science*, vol. 34, no. 1, pp. 387-408, Jan 2022. Article(CrossRef Link)

[17] S Sankar, RamasubbareddySomula, BalakesavareddyParvathala, Srinivas Kolli, and Srilatha Pulipati, "SOA-EACR: Seagull optimization algorithmbased energy aware cluster routing protocol for wireless sensor networks in the livestock industry," *Sustainable Computing: Informatics and Systems*, vol. 33, pp.1-13, Jan 2022. Article(CrossRef Link)
[18] Jayaraman Ganesh, and VR Sarma Dhulipala, "FEECS: fuzzy-based energy-efficient cluster head selection algorithm for lifetime enhancement of wireless sensor networks," *Arabian Journal for Science and Engineering*, vol. 47, no. 2, pp. 1631-1641, Feb 2022. Article(CrossRef Link)
[19] George Anna Merine, S.Y Kulkarni, and Ciji Pearl Kurian, "Gaussian Regression Models for Evaluation of Network Lifetime and Cluster-Head Selection in Wireless Sensor Devices," *IEEE Access*, vol. 10, pp. 20875-20888, Dec 2022. Article(CrossRef Link)
[20] Sarkar Amit, and TSenthil Murugan, "Analysis on dual algorithms for optimal cluster head selection in wireless sensor network," *Evolutionary Intelligence*, vol. 15, no. 2, pp. 1471-1485, June 2022. Article(CrossRef Link)
[21] J.S Manoharan, "Double attribute-based node deployment in wireless sensor networks using novel weight-based clustering approach," *Sādhanā*, vol.47, no.3, pp. 1–11, 2022. Article(CrossRef Link)

Mr.S. Bharathiraja is currently working as a Assistant Professor of Department of Electronics and Communication Engineering in A.V.C. College of Engineering and he is doing Ph.D. in Anna University in the field of Wireless Sensor Networks. He has 12 years of teaching experience. He is having life membership at ISTE and IAENG.

Dr.S.Selvamuthukumaranis currently working as professor of Computer Applications department at A.V.C. College of Engineering, Mayiladuthurai, Tamilnadu, India. He received his Ph.D. degree in computer Science in the year 2011. His area of interest includes computer vision, Data mining, Big data andwireless networks. Presently he is guiding research scholars in the field of Big Data and Wireless networks. He is a senior fellow member of CSI and ISTE.

Dr.V.Balaji is graduated With B.Tech degree in Electronics and Communication Engineering in the year 2003,M.Tech in Applied Electronics in 2007 and Ph.D.in the year 2014 from Pondicherry University, Bharath University and Anna University respectively. Currently he is working as Associate Professor in the department of Electronics and Communication Engineering at KCG College of Technology, Karapakkam, Chennai. He has 18 years of teaching experiences and has published more than 50 papers in the leading journals and conferences. His areas of interest are Wireless Networks, Image Processing, and Machine Learning. He is an Active member of IEEE, IAENG and IFERP.