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ENHANCING ENERGY EFFICIENCY IN WIRELESS SENSOR NETWORKS: A HYBRID APPROACH INTEGRATING HF-GSO ALGORITHM, DVFS ALGORITHM AND DUTY CYCLING

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Abstract

Wireless Sensor Networks (WSNs) have expanded substantial attention owing to their wide variety of applications in various fields. However, energy consumption remains a critical challenge in WSNs, as the nodes are typically powered by limited battery resources. This paper addresses the energy consumption problem in WSNs by proposing a novel approach that combines the Hybrid Firefly Glow-Worm Swarm Optimization (HF-GSO) algorithm, Dynamic Voltage and Frequency Scaling (DVFS) algorithm, and the duty cycling technique. The HF-GSO algorithm stands employed for the selection of effective cluster heads and routing in WSNs. It leverages the collective behavior of fireflies and glow-worms to achieve optimal energy utilization and network performance. By incorporating HF-GSO, the proposed approach optimizes the formation of clusters, minimizing the energy consumption associated with long-distance communication and data aggregation. Additionally, the DVFS algorithm is integrated into the system to energetically regulate the voltage and frequency levels of sensor nodes. This adaptive scaling mechanism allows the nodes to operate at lower power levels during periods of low activity, effectively reducing energy wastage. The DVFS algorithm further contributes to energy efficiency without compromising the network's overall performance by scaling up the voltage and frequency only when necessary. Furthermore, the proposed approach utilizes duty cycling, a technique that enables the nodes to alternate between active and sleep modes. By effectively scheduling the node's active and sleep durations, duty cycling significantly reduces idle listening and idle transmission, minimizing unnecessary energy consumption. The usefulness of the proposed method is demonstrated through extensive simulations and performance evaluations. The results indicate notable improvements in energy efficiency, network lifetime, and overall system performance compared to existing approaches. In conclusion, this research paper gives a complete solution to the energy consumption problem in WSNs. By integrating the HF-GSO algorithm, DVFS algorithm, and duty cycling, the proposed approach achieves significant energy savings and extends the lifetime of WSNs, making it highly suitable for energy-constrained WSN applications.

Keywords:

Energy Consumption, Firefly algorithm, Glow Worm Swarm Optimization, Dynamic Voltage and Frequency Scaling, Duty Cycling, Wireless Sensor Networks

1. INTRODUCTION

Wireless Sensor Networks (WSNs) emerged as a leading technology that enables efficient monitoring and data collection in various domains. WSNs consist of a large number of small, cost-efficient sensor nodes prepared with sensing, processing, and wireless communication proficiencies. These sensor nodes are strategically positioned in a target area to collaboratively gather and communicate data to a base station or sink node. WSNs have increased substantial consideration due to their varied choices of applications in fields such as environmental monitoring, industrial automation, healthcare, smart cities, and precision agriculture, among others [1]. These networks offer unique advantages over traditional wired or centralized monitoring systems, including scalability, flexibility, cost-effectiveness, and the ability to operate in harsh and inaccessible environments. The fundamental objective of WSNs is to gather and communicate data from the sensor instrument to a base station for additional investigation and decision-making. Each sensor node within the network is responsible for sensing and gathering data from its surrounding environment, processing the collected information, and wirelessly transmitting it to the base station or other neighboring nodes for eventual delivery to the central station [2]. The Figure-1 below depicts a clear architecture of the WSN.

However, despite the promising potential of WSNs, they face several challenges, with energy consumption being a critical concern. Most sensor nodes in WSNs are typically powered by limited and non-rechargeable battery resources. Energy efficiency, therefore, plays a vital role in determining the network's overall lifespan and functionality. Prolonging the network's lifespan and optimizing energy consumption are crucial objectives in WSN research and deployment [3]. Efficient energy management in WSNs involves tackling various factors that contribute to energy consumption, such as sensing, processing, communication, and idle listening. Additionally, optimizing energy consumption while maintaining satisfactory network performance is a complex task due to the resource-constrained nature of sensor nodes [4].

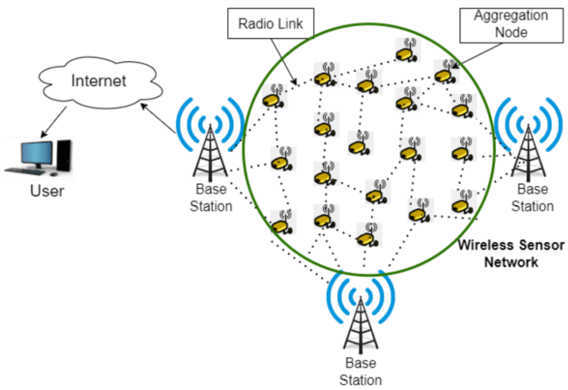

Fig.1. Architecture of WSN

The Hybrid Firefly Glow-Worm Swarm Optimization (HF-GSO) algorithm is a key component in our proposed approach for enhancing energy efficiency in WSNs. Inspired by the behavior of the fireflies and the glow-worms; HF-GSO aims to optimize cluster head selection and routing, thereby minimizing energy consumption associated with long-distance communication and data aggregation in WSNs [5]. The HF-GSO algorithm combines the strengths of both firefly and glow-worm swarm optimization techniques to achieve efficient cluster formation and routing. Firefly swarm optimization is known for its ability to find global optima by simulating the flashing behavior of fireflies. In this context, the fireflies represent the potential cluster heads in WSNs. They attract other nodes (non-cluster heads) in their vicinity based on their brightness, which is determined by the fitness of the solution they represent. This attraction encourages clustering and facilitates efficient data aggregation within each cluster [6, 7].

Glow-worm swarm optimization, on the other hand, focuses on optimizing the behavior of individual glow-worms to solve optimization problems. Glow-worms are attracted to brighter glow-worms in their vicinity, following the concept of positive feedback. This interaction enables the swarm to converge toward better solutions. In the context of WSNs, glow-worms represent the non-cluster head nodes and move toward brighter fireflies (potential cluster heads) to form efficient clusters. By combining these two optimization techniques, the HF-GSO algorithm leverages the collective behaviour of fireflies and glow-worms to achieve optimal energy utilization and network performance. The fireflies act as potential cluster heads, and the glow-worms dynamically adjust their positions based on the brightness of the fireflies, indicating their suitability as cluster heads [8, 9]. This mechanism facilitates the formation of clusters with balanced energy consumption and effective data aggregation. During the cluster formation process, the HF-GSO algorithm considers various aspects such as the residual energy of the sensor nodes, their proximity to the central base station, and mainly the communication cost. By considering these factors, the algorithm aims to select cluster heads that can efficiently collect and transmit data while minimizing energy consumption.

Furthermore, we incorporate the DVFS algorithm into our approach toward dynamically regulating sensor nodes' voltage and frequency levels based on the individual workload and power requirements, effectively optimizing energy consumption without compromising network performance. The DVFS algorithm exploits the fact that different tasks and processing requirements may vary in their intensity. Not all tasks require the same level of computational power, and therefore, nodes can operate at lower power levels during periods of low activity, leading to energy savings [10, 11, and 12]. By grading down the frequency and voltage level of the nodes during periods of low activity, the DVFS algorithm reduces the energy consumption of the sensor nodes while still maintaining the required performance. This reduced voltage and frequency levels result in lower energy dissipation, as the energy consumption of a digital circuit stands proportionate to the quadrangular of the source voltage and the frequency [13].

The DVFS algorithm continuously monitors the workload and processing requirements of each node in the WSN. It dynamically adjusts the frequency and voltage levels based on the current workload. When the workload decreases, such as during idle periods or low-demand tasks, the algorithm scales down the frequency and voltage level of the node, enabling it to operate at lower power levels [14,15]. During periods of high activity or increased processing demands, the DVFS algorithm scales up the frequency and voltage levels to ensure that the node meets the performance requirements. This adaptive scaling mechanism allows the nodes to dynamically optimize their power consumption based on the workload, effectively reducing energy wastage.

By intelligently adjusting the frequency and voltage level, the DVFS algorithm enables nodes to operate at an optimal power-performance trade-off. It prevents nodes from consuming excessive energy when their processing demands are low, thereby extending the overall network lifetime. The integration of the DVFS algorithm into our proposed approach contributes significantly to the energy efficiency of the WSN. It ensures that nodes operate at the appropriate power levels based on their workload, minimizing unnecessary energy consumption, and maximizing the utilization of available energy resources [16]. In wireless sensor networks, the sensor nodes remain installed in the environments where the event occurrences are sporadic, and continuous monitoring is not always necessary. However, traditional continuous listening by sensor nodes leads to significant energy wastage as they continuously monitor the environment, even during periods of inactivity. Duty cycling addresses this issue by allowing nodes to substitute between active and sleep modes, conserving energy during idle periods.

By defining appropriate duty cycles, nodes can synchronize their active periods with the occurrence of relevant events or data collection requirements. During the active period, nodes perform necessary sensing, processing, and communication tasks to fulfill their responsibilities within the network [17]. On the other hand, during the sleep period, nodes enter a low-power state where most of their functionalities are temporarily suspended, conserving energy. The importance of duty cycling lies in its ability to significantly reduce idle listening and idle transmission, two major sources of energy wastage in WSNs. When nodes continuously listen for incoming data or transmit data regardless of its relevance, it leads to unnecessary energy consumption. Duty cycling ensures that nodes only activate their listening and transmission capabilities when required, conserving energy during idle periods. In this research, we suggest a novel method to enhance energy efficiency in WSNs by integrating multiple techniques: the Hybrid Firefly Glow-Worm Swarm Optimization (HF-GSO) algorithm, Dynamic Voltage and Frequency Scaling algorithm and the duty cycling approach. We aim to minimize energy consumption while maintaining satisfactory network performance and extending the overall network lifetime.

In this paper, Section 2 comprehensively reviews related work on energy efficiency in WSNs. Section 3 briefs about the details of the proposed approaches, with the integration of the HF-GSO algorithm, DVFS algorithm, and duty cycling. Section 4 describes the experimental setup and provides the results and analysis. Finally, Section 5 completes this paper by pointing up the contributions, boundaries, and forthcoming research directions.

2. RELATED WORK

Rauber et al.[18] introduced new metrics to evaluate the outcomes and energy utilization of applications in the context of DVFS and thread parallelism. The concept discusses the impact of application program characteristics on hardware utilization, specifically focusing on frequency scaling (Dynamic Voltage and Frequency Scaling - DVFS) and thread parallelism in multi-core processors. The PARSEC benchmark suite and SPLASH-2 benchmark suite are used as application programs for investigation. PARSEC provides a diverse collection of applications running on chip multiprocessors, while SPLASH-2 is a shared suite for scientific studies. By combining frequency scaling and thread parallelism and introducing new evaluation metrics, the study seeks to gain insights into optimizing the outcomes and power efficiency of requests on multi-core processors. The choice of benchmark suites and hardware platforms ensures the study's relevance and applicability in the framework of modern computing systems.

Cheour et al. [19] discussed the significance of choosing the appropriate platform, specifically Field Programmable Gate Arrays (FPGAs), for image and video compression techniques in Wireless Sensor Networks applications. It is proved that the correct selection of image and video compression techniques, combined with the low power potential of FPGAs, can lead to significant improvements in energy consumption and computation time. The research specifically focuses on the low-consumption solutions offered by FPGA platforms. The utilization of low-power optimized FPGA-based solutions demonstrates notable improvements in the computation of various algorithms, particularly in terms of both processing speed and energy efficiency.

Yahia Benmoussa et al. [20] enhanced the power efficiency of video interpreters by effectively compounding Dynamic Voltage and Frequency Scaling (DVFS) with parallelism techniques. Initially, the researchers introduced an adaptive DVFS algorithm for energy-efficient mono-core decoding of H.264 videos. They utilize the metadata normalized by MPEG that provides crucial information about the upcoming workload. These metadata are processed through an adaptive filter to dynamically construct an accurate complexity model. This model is then used to calculate the minimal processor frequencies required for decoding video frames while ensuring that real-time constraints are met. The performance evaluations demonstrate that the proposed algorithm for mono-core decoding efficiently converges to an accurate complexity model within a short duration of less than 1 second. It is noted that the algorithm results in minimal overhead and achieves remarkable energy savings of up to 46 percent compared to the on-demand Linux DVFS governor.

Ruchi Dhall et al. [21] focused on IoT-based agriculture, aiming to enhance efficiency and produce in farm fields through real-time monitoring of agricultural parameters. The data collection process involves various sensors like soil, temperature and humidity sensors, air quality sensors, and video cameras mounted on drones. These sensors gather data, which is then aggregated at the base station and transmitted to a gateway. Microsoft's recent research on IoT-based precision agriculture identifies energy-efficient data aggregation as a significant challenge in such networks. In response to this challenge, the research proposes a duty cycling data aggregation algorithm (IDC) to improve the energy efficiency of the base station. The key feature of the proposed algorithm is its ability to reduce energy consumption, particularly during special events like cloudy weather, where energy conservation becomes crucial. To further optimize the network's reliability and lifetime, the research also introduces an efficient path selection approach based on residual energy parameters. This approach enables the network to intelligently choose paths that utilize nodes with higher residual energy, thereby extending the network's overall lifetime and reliability.

Communication and data transmission in WSNs requires significant power consumption, which can limit the network's lifetime. To address this issue, various clustering routing protocols have been proposed to reduce energy consumption and enhance the network's overall lifetime. Salem et al. [22] Presented a practical implementation of an unequal clustering-based fuzzy logic algorithm using the Pan Stamp NRG 2.0 sensor node. The main objective is to analyze the actual performance of the network under real-world conditions. The algorithm is designed to optimize the energy consumption of nodes, increase their lifetime, and efficiently manage the packets transmitted within the network.

Radha et al. [23] addresses several major challenges in wireless sensor networks (WSN), namely false data detection, intrusion detection, and coverage rate. To overcome these challenges, the research suggests the use of scheduling in media access control (MAC) with gateway and relay nodes to improve the network's performance. The Firefly algorithm is presented in this research as a dynamic scheduling technique that results in better throughput and latency in WSNs. Furthermore, pipelined scheduling for linear sensor networks is proposed, offering improved efficiency in data transmission and processing. The research also highlights the importance of heuristic configuration, which addresses the issue of overhearing in WSNs. Moreover, node power-based MAC is introduced as a solution to control the power consumption of individual nodes, thereby optimizing the overall energy usage in the network.

Sheikh et al. [24] addresses the issue of path loss in wireless sensor networks and its impact on the signal strength from the transmitting node to the receiving node. Path loss, a critical factor in WSN, can be evaluated using stochastic, deterministic, or empirical methods. However, optimizing transmission power, reliability, and data rate in the presence of path loss remains a challenging task for WSNs. This research highlights the significance of selecting an optimum modulation scheme that can minimize errors and enhance the reliability of the WSN and it also presents a new approach that relates the path loss of the WSN to M-ary modulation schemes. Specifically, a critical comparative analysis is conducted for M-ary Frequency-Shift Keying (FSK) and M-ary Phase-Shift Keying (PSK) modulation schemes in a given scenario. The performance of these two schemes is analyzed for both the free space earth model and the plane earth model.

3. PROPOSED WORK

3.1 NETWORK SETUP

The network setup in this research consists of a multi-hop architecture comprised of a base station (BS) and the sink node (SN). The network is deployed in a two-dimensional Cartesian framework to facilitate a random circulation of sensor nodes. Each node is equipped with a power source that does not support rechargeable batteries. Once the nodes are placed, their positions remain fixed throughout the network operation. There are no variations in communication or processing capabilities among the central sensor nodes with the starting energies of the nodes being equal.

3.2 ENERGY MODEL

To analyze the power utilization in the sensor network, energy model stands established by considering the communication of data packets. The power consumption for sending a packet is in need of the distance among the sender node and the receiver node and is formulated based on a free space prototype and a multipath diminishing model.

In free space model, energy distributed for the transmission of a data packet containing '*n*' bits is specified by Eq.(1)

$$E_c = n*(E_{ec} + E_{rfs}.D^2) \quad (1)$$

where E_c represents total energy consumption, E_{ec} is the SN simulation power, E_{rfs} denotes the power needed to send one bit into the free space, and the D represents the distance among the sender and receivers. The term $E_{rfs}.D^2$ indicates the energy loss comparative to the quadrangular of the distance.

In multipath diminishing prototype, the power spent by communicating a data packet is modified to account for the effects of multi-path fading. The energy loss is now represented by DL and the equation for energy consumption becomes:

$$E_c = n*(E_{ec} + E_{mp} + D_h) \quad (2)$$

where E_{mp} represents the power required to communicate one bit over the multi-path fading channel, and D_h represents the multi-path fading distance.

The initial threshold value D_0 is calculated based on the ratio of E_{rfs} and E_{mp} as shown below:

$$D_0 = \sqrt{}E_{rfs} / E_{mp} \quad (3)$$

This threshold value helps determine the transmission success or failure between the sender and the receiver. The power spent for getting a data packet containing *'n'* bits is specified by the equation:

$$E_{rec} = n*E_{ac} \quad (4)$$

This equation indicates that the energy utilization for reception is straightly proportionate to the bit size of the data packet. Furthermore, the data aggregation energy intake for the cluster heads is computed by the following equation:

$$E_{ag} = E_{eag} * n * m \quad (5)$$

where E_{eag} represents the amount of aggregated energy spent for one bit, and m represents the number of messages.

3.3 IMPLEMENTATION OF THE DVFS ALGORITHM

The Dynamic Voltage and Frequency Scaling algorithm is implemented to optimize power consumption by dynamically adjusting the voltage and frequency levels of the microcontroller in the WSN. The algorithm aims to find the optimal operating point that minimizes power consumption while meeting the desired performance metrics. The Fig.2 below shows the architecture of the proposed work which combines the HFGSO, DVFS and duty cycling algorithm.

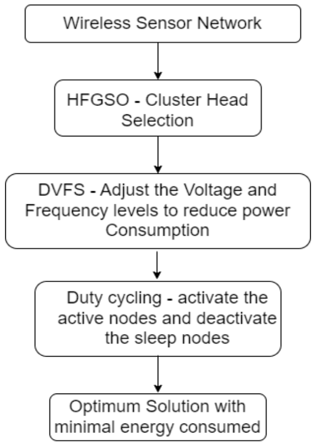

Fig.2. Proposed Architecture in WSN

3.3.1 Power Consumption Components:

The power utilization of the microprocessor in a WSN can be separated into three main components. The *Static Power (Pstatic)* component represents the power dissipated when the microprocessor is in an inactive or dormant state. It is mainly caused by reverse-biased diodes and outflow currents. The low-threshold outflow current and the gate outflow current are the primary factors contributing to static power consumption. The *Dynamic Power (P dynamic)* component is associated with the charging and discharging of capacitors during the execution of instructions. It is determined by the switching activity, supply voltage, switched capacitance, and clock frequency. Dynamic power utilization can be condensed by decreasing the clock frequency. *Short Circuit Power (P short circuit)* component caused by the current flow when substituting from the source voltage to the ground. It is comparable to the switching activity and source voltage.

The total power consumption *(P total)* of the microprocessor can be demonstrated as the sum of these power components:

$$P_{total}=P_{static}+P_{dynamic}+P_{shortcircuit} \quad (6)$$

a) Static Power (P_{static}): The static power consumption is primarily influenced by leakage current. It can be represented as:

$$P_{static} = V_{DD}*I_{leak} \quad (7)$$

where V_{DD} is the source voltage and I_{leak} is the total leakage current.

b) Dynamic Power ($P_{dynamic}$): The dynamic power consumption can be computed using the following equation:

$$P_{dynamic} = a * cv^2 * f \quad (8)$$

where a is the switching factor representing the probability of substituting on any specific clock period, C is mentioned as the switched capacitance, V is the source voltage, and f is the frequency.

c) Short Circuit Power (P_{short}): The short circuit power is related to switching activity and supply voltage. It can be expressed as:

$$P_{shortcircuit} = T_{SC}*V_{DD}*I_{Peak} \quad (9)$$

where T_{sc} is the increasing time of input signal and I_{peak} is highest current.

3.3.2 Voltage and Frequency Scaling:

Dynamic Voltage and Frequency Scaling procedure adjusts both the voltage (V) and frequency (f) of the microcontroller. By reducing the source voltage, power consumption of the microcontroller can be significantly reduced. However, it is essential to ensure that the voltage remains above the minimum operating voltage to maintain reliable operation. The voltage scaling can be formulated as:

$$V_{new}=V_{min}+\Delta V*N \tag{10}$$

where V_{min} is the lowest operating voltage, ΔV is voltage step size, and N is the scaling factor.

The frequency scaling reduces the clock frequency of the microcontroller to decrease power consumption. The frequency can be modified based on the desired performance requirements and energy targets. The clock frequency scaling can be given as:

$$f_{new}=f_{max}-\Delta f*N \tag{11}$$

where f_{max} is the extreme clock frequency, Δf is frequency step size, and N is the scaling factor.

3.4 DVFS TECHNIQUE

The DVFS technique adjusts both the frequency and voltage of microprocessors to reduce power utilization. By operating microprocessors at a lower voltage and frequency while meeting the task deadline, significant power savings can be achieved. The objective of the DVFS algorithm in WSNs is to minimize power consumption while maintaining the required performance level and meeting the QoS (Quality of Service) requirements. The algorithm dynamically adjusts the frequency and voltage based on the workload and performance demands. The DVFS technique is applied using a power management module (PMM) that controls the essential voltage and frequency. PMM groups the voltage for the supply voltage supervisor (SVS) and the supply voltage monitor (SVM) based on the anticipated frequency of the microcontroller. The core voltage is adjusted to minimize power losses while ensuring stable operation. The DVFS algorithm continuously monitors the workload and performance requirements. Based on the workload, the PMM dynamically regulates the core voltage and frequency to a minimum level required to meet performance targets. This ensures optimal power consumption without compromising performance.

DVFS Algorithm:

Initialize the voltage V and frequency F.

While workload W is not completed:

a. Monitor the current workload metric W.

b. Analyze the workload and determine the required power consumption P(W).

c. If P(W) > P_target, increase the voltage and frequency levels.

d. If P(W) < P_target, decrease the voltage and frequency levels.

e. Check the SVM module to ensure the current voltage V_current is within the safe operating limits (V_min ≤ V_current ≤ V_max).

f. Adjust the voltage and frequency settings in the PMM module.

g. Measure the actual power utilization P_current.

h. Validate the performance metrics and adjust the voltage and frequency settings if necessary.

Terminate the DVFS algorithm when the workload is completed.

where, Workload: W, Power consumption function: P(W), Voltage: V, Frequency: F, Minimum voltage threshold: V_min, Maximum voltage threshold: V_max, Current-voltage level: V_current, Target power consumption: P_target and Current power consumption: P_current.

3.5 DUTY CYCLING ALGORITHM

The duty cycling algorithm is implemented to activate and deactivate the sensor nodes periodically, allowing them to enter sleep mode and conserve energy. The duty cycle determines the nodes' active time to sleep time ratio.

Let T_{total} remain the total period of time, and T_{active} be the active period of time. The duty cycle (DC) can be calculated as:

$$DC=(T_{total} / T_{active})*100 \tag{12}$$

where DC is expressed as a percentage.

The energy savings achieved through duty cycling depend on the duty cycle and power utilization in both active and sleep modes. By reducing active time and increasing sleep time, significant energy savings can be achieved. The duty-cycling algorithm is given as

Duty Cycling Algorithm

1. Initialization:
 - Set duty cycle parameters: Tac, Ts
 - Define target performance metrics and energy constraints
 - Initialize network topology, sensor nodes, and data collection
2. Workload Monitoring:
 - While (not termination condition):
 - Monitor workload and data traffic
 - Measure relevant metrics (e.g., R_data, λ_event)
 - Update workload information
3. Energy Consumption Analysis:
 - Analyze energy consumption patterns:
 - Calculate energy consumption in active and sleep periods
 - Assess energy consumption trade off based on duty cycle configuration
4. Duty Cycling Mechanism:
 - While (not termination condition):
 - Activate sensor nodes for Tac duration
 - Perform data sensing, processing, transmission
 - Put sensor nodes into sleep mode for Ts duration
5. Dynamic Duty Cycle Adjustment:
 - Calculate optimal duty cycle parameters:
 - Calculate optimal T_active_opt based on energy consumption and R_data
 - Calculate optimal T_sleep_opt based on energy consumption and λ_event - Adjust duty cycle parameters (Tac, Ts) based on optimal values
6. Performance Evaluation and Adaptation:
 - While (not termination condition):
 - Evaluate network performance metrics against desired targets

- Measure actual energy consumption and compare with expected values

- If necessary, adapt duty cycle parameters to maintain desired performance and energy constraints

7. Termination:

- Terminate algorithm when desired network performance metrics are achieved, or termination condition is met.

- Generate a summary report of the duty cycling process, including energy consumption, data transmission rates, and other relevant metrics

In this initialization step, we set the initial values for duty cycle parameters, such as active time (T_{ac}) and the sleep time (T_s) durations. These parameters determine when the sensor nodes should be active and when they should be in sleep mode to conserve energy. We also define the target network performance metrics and energy constraints to guide the duty cycling optimization process. Additionally, we initialize the network topology, sensor nodes, and data collection mechanism.

The workload monitoring involves continuously observing the workload and data traffic in the network. We measure relevant metrics like data transmission rate (R_{data}) or event occurrence rate (λ_{event}) to gain insights into the network's current workload. This information is periodically updated to reflect the changing workload conditions.

In the energy consumption analysis, we analyze the energy utilization forms in sensor network based on workload and data traffic information. We assess the energy consumed during the active and sleep periods to understand the overall energy tradeoff. This analysis allows us to quantify the relationship between energy utilization and the duty cycle configuration.

The duty cycling mechanism is responsible for controlling the active and sleep periods of the sensor nodes. During the active period, the sensor nodes are activated to perform tasks such as data sensing, processing, and transmission. Conversely, during the sleep period, the nodes are set into sleep mode towards conserving power and reducing unnecessary activity.

Dynamic duty cycling involves dynamically adjusting the duty cycle of the sensor nodes created on the workload analysis and energy consumption trade off. We calculate the optimal values for an active time (*T_active_opt*) and the sleep time (*T_sleep_opt*) using mathematical models to optimize the duty cycle.

$$T_{active\_opt} = \frac{\left(E_{\text{constraint}} * T_{\text{sleep}}\right)}{\left(E_{\text{active}} - E_{\text{sleep}} + \left(R_{Data} * E_{\text{active}}\right)\right)} \tag{14}$$

where,

E_{active}: Energy utilization per unit in active time.

E_{sleep}: Energy consumption per unit in sleep time.

R_{Data}: Data transmission rate.

$E_{constraint}$: Maximum allowable energy consumption constraint.

$$T_{sleep\_opt} = \frac{\left(E_{\text{constraint}} * T_{\text{active}}\right)}{\left(E_{sleep} - E_{active} + \left(\lambda_{event} * E_{\text{sleep}}\right)\right)} \tag{15}$$

where,

λ_{event}: Event occurrence rate.

By adjusting the duty cycle parameters (T_{active}, T_{sleep}) based on the calculated optimal values, we aim to achieve a balance between energy efficiency and desired network performance.

Performance Evaluation and Adaptation involves continuous evaluation of the network performance metrics against the desired targets. We measure the actual energy consumption and compare it with the expected values. If necessary, we adapt the duty cycle parameters to maintain the desired performance level and energy constraints. Fine-tuning of the duty cycle settings can be done based on real-time monitoring and analysis of the workload and network conditions. The duty cycling algorithm terminates when the desired network performance metrics are achieved or when a specific termination condition is met.

3.6 HF-GSO ALGORITHM

The Hybrid Firefly Glow-Worm Swarm Optimization (HFGSO) algorithm is designed to optimize the cluster head nomination process in the WSNs. It combines that principle of firefly algorithm and glow-worm swarm optimization to achieve efficient and effective cluster formation. The algorithm begins with an initialization step where parameters such as the number of fireflies, maximum iterations, and convergence threshold are set. The firefly inhabitants are randomly placed within the network, and their initial fitness values are calculated based on energy consumption, network connectivity, and other desired metrics. In the context of the HFGSO algorithm, a "firefly" represents an individual agent or entity within the population. Each firefly corresponds to a sensor node in the WSN is considered a potential candidate for being selected as a cluster head. The fireflies are used to simulate the movement and interactions of the nodes in optimization process.

The main loop of the procedure begins by iterating through each firefly in the population. The attractiveness of each firefly is calculated based on its fitness value and distance from other fireflies. Using this attractiveness information, the firefly's position is updated by moving towards more attractive fireflies while considering the distance between them. The fitness of the new position is evaluated, and if it improves the fitness, the firefly's position is updated accordingly. The algorithm then incorporates the Glow-Worm Swarm Optimization (GSO) mechanism to further enhance exploration. Each firefly serves as a source of light, attracting a population of glow-worms. The light intensity of glow-worms is being updated upon their fitness values, taking into account factors such as energy consumption and communication efficiency. The location of the glow-worms is being adjusted according to their light intensities and the attractive distances, favoring positions with higher light intensity. The fitness of the new positions is evaluated, and if it improves the fitness, the firefly's position is updated based on the position of the most attractive glow-worm.

The main loop continues till the extreme number of repetitions is grasped or conjunction is achieved. Convergence is determined by monitoring the change in the best fitness value. If the change falls below the predefined convergence threshold, the algorithm terminates. Once the iterations are completed, the cluster head selection phase begins. The final positions of the fireflies are analyzed, and the fireflies with the highest fitness values are selected as cluster heads. Other nodes are allocated to the appropriate cluster heads based on proximity and communication range. The network topology and cluster structure are updated accordingly to establish the communication hierarchy.

The HFGSO algorithm optimizes the cluster head selection process in WSNs by iteratively updating firefly positions based on attractiveness and incorporating the GSO mechanism for further exploration. The final selected cluster heads and network topology reflect an optimized solution based on energy consumption, network connectivity and other desired metrics.

The GSO returns various advantages such as it is better in handling multiple optima associated with a provided multimodal function. But it limits from several drawbacks such as poor in positioning the global optimum solution, falling into local optimum, slow speed to convergence, etc. Hence, to overcome the drawbacks of GSO, firefly algorithm is integrated into it and the so formed algorithm is referred as novel HF-GSO. This novel HF-GSO is better in handling local and global optimum solution and also speeds up the convergence process.

This novel HF-GSO works on the basis of random concept. If random number rand ≤, then the update takes place using the movement towards attractive firefly equation of firefly algorithm as in Eq.(15).

$$y_j(u+1) = y_j(u) + \beta_o e^{-\gamma s^2}(y_j - y_k) + \alpha\varepsilon_j \tag{15}$$

where, $y_j(u)$ shows a randomization parameter and $\beta_o e^{-\gamma s^2}(y_j - y_k)$ shows the result associated with the firefly s attraction; if β_o, then it appears to be a straight forward random movement. Otherwise, if random number rand≥ , then the update takes place using the movement of glow-worm's equation of GSO as in Eq.(16).

$$y_j(u+1) = y_j(u) + t * y_k(u) - y_{j\,/}\, y_k(u) - y_j \tag{16}$$

Here, the step size is shown by respectively. The pseudo code of proposed HF-GSO is shown in the below Algorithm.

Algorithm: HF-GSO

Start

Population initialization (clusters)

Parameter initialization such as firefly count, glow worm count, convergence threshold, and maximum iteration count.

Fitness calculation (considering network connectivity, energy consumption, and other desired metrics)

While

iter < iter_n

If rand≤$y_j(u+1) = y_j(u) + \beta_o e^{-\gamma s^2}(y_j — y_k) + \alpha\varepsilon_j$

Else

$y_j(u+1) = y_j(u) + \beta_o e^{-\gamma s^2}(y_j — y_k) + \alpha\varepsilon_j$

End if

iter=iter+1

End while

Return optimal solution (with consideration of network connectivity, energy consumption, and other desired metrics)

Stop

The combination of Dynamic Voltage and Frequency Scaling, duty cycling, and the Hybrid Firefly Glow-Worm Swarm Optimization (HFGSO) algorithm demonstrates significant effectiveness in refining the energy efficiency of WSN. Through leveraging DVFS, the system dynamically adjusts the frequency and voltage of sensor nodes, reducing power consumption during idle periods and optimizing energy usage based on task requirements. Duty cycling further enhances energy efficiency by periodically switching between active and sleep states, conserving energy during periods of inactivity.

Integrating the HFGSO algorithm into the optimization process enables efficient cluster head selection and network topology formation. By leveraging the attractiveness and movement principles of fireflies and glow-worms, the algorithm optimizes the positioning of cluster heads, resulting in balanced network load distribution and reduced energy consumption. The combined approach of DVFS, duty cycling, and HFGSO algorithm empowers WSNs with fine-grained control over energy usage, adaptive power management, and optimized network organization. This comprehensive approach leads to substantial improvements in energy efficiency, prolonging the network lifespan and enhancing the overall performance of WSNs.

4. EXPERIMENTAL ANALYSIS

The performance valuation of the proposed method HF-GSO with DVFS and Duty Cycling is worked out in MATLAB, and it is associated with the various current algorithms that are at present available, HBACS-HBACM [25], GA-CSO [26], DCC-IACJS [27] and FGS [28]. Below table Table-1 shows the parameters that are considered for carrying out simulations in Wireless Sensor Networks (WSNs).

Table.1.Parameters and their values for implementation

Parameter	Values
Network Size	100 – 500 nodes
Deployment Area	300m x 300m
Communication Range	30-40
Transmission Power	The power level used by nodes to transmit data.
Reception Power	-90dBm at the BER of 10^{-6}
Network Packet size	10000 bits
Sensing Range	30-40m
Data Rate	100-500Kbps
Traffic Pattern	Periodic traffic pattern
Initial Energy	2J
Simulation Time	The total duration of the simulation.
Throughput	1Mbps

To efficiently manage data transmission and energy consumption, WSNs often adopt clustering techniques. Cluster formation is a crucial process where nodes are organized into cluster groups, with one particular node selected as a cluster head (CH) which is the controller for combining and communicating data packets from its member nodes to the base station (BS).In this scenario, we will use the Hybrid Firefly Glow-Worm Swarm Optimization (HFGSO) algorithm to form clusters in a WSN with a range of 100 to 500 nodes. The HFGSO algorithm combines the strengths of the Firefly Algorithm (FA) and the Glow-Worm Swarm Optimization (GSO) algorithm to achieve efficient cluster formation.

To analyze the performance of WSNs with HFGSO, DVFS, and duty cycling algorithms, several key parameters should be considered. These parameters will help in evaluating the effectiveness and efficiency of the algorithms with regard to energy consumption, network lifetime, data delivery ratio and throughput.

Energy Consumption measures total energy used up by the network during simulation or operation. Network lifetime evaluates the lifespan of the WSN with different algorithms. It determines how long the network can operate before a significant number of nodes deplete their energy reserves. A longer network lifetime indicates that the algorithms effectively manage the energy resources of the nodes, resulting in extended network operation. Data Delivery Ratio calculates the percentage of effectively delivered packets of data with the totally sent packets. This metric provides insights into the algorithms' ability to transmit data effectively. Throughput assesses the total amount of data diffused effectively per unit of time. Higher throughput indicates efficient data transmission.

The proposed algorithm demonstrates superior effectiveness in energy consumption compared to HBACS-HBACM, GA-CSO, DCC-IACJS, and FGF algorithms, as evidenced by the graph presented. The Figure-3 indicates that the energy utilization of the proposed algorithm is significantly lesser than the supplementary algorithms, leading to extended network lifetime and improved energy efficiency while gradually escalating the number of nodes. The proposed algorithm reports the usage of 0.51 joules of consumed energy for 500 sensor nodes. The other algorithms HBACS-HBACM, GA-CSO, DCC-IACJS, and FGF report the consumption of 0.59, 0.6, 0.7 and 0.89 joules of energy, respectively. Our proposed algorithm decreases energy consumption by applying DVFS and Duty cycling algorithms.

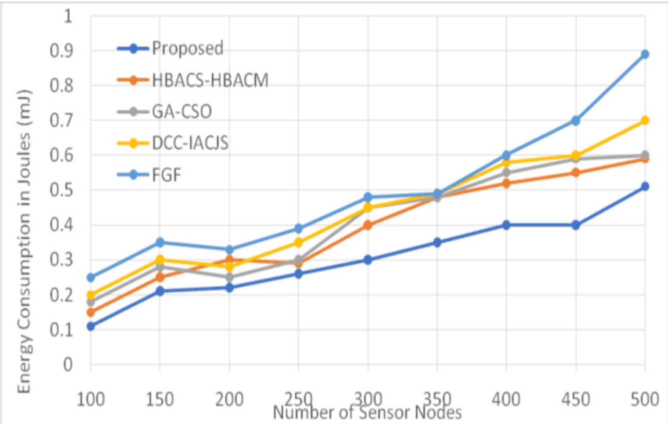

Fig.3. Comparison of Energy consumption measured from the other algorithms with the proposed algorithm

The suggested algorithm exhibits a significant advantage with regard to network lifetime compared to HBACS-HBACM, GA-CSO, DCC-IACJS, and FGF algorithms, as evident from the results. The Figure-4 below illustrates that the suggested algorithm consistently sustains a lengthier wireless sensor network's lifespan than the other algorithms, showcasing its superior energy efficiency and ability to prolong the WSN's operational duration. Upon varying network sizes, ranging from 100 to 500 nodes, the proposed algorithm maintains a consistent advantage, proving its scalability and robustness.

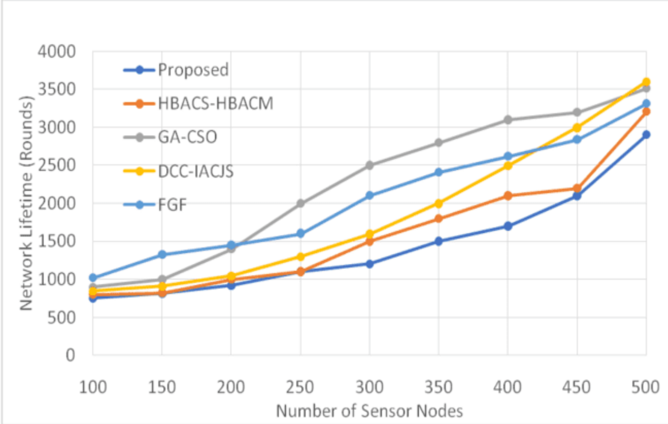

Fig.4. Comparison of Network lifetime measured from the other algorithms with the proposed algorithm

The proposed algorithm demonstrates a compelling advantage in data delivery ratio compared to other algorithms, signifying its superior performance in ensuring successful data transmission within the Wireless Sensor Network. The Fig.5 indicates that the proposed algorithm consistently achieves higher data delivery ratios when compared to competing approaches, making it a highly effective solution for consistent and effective data dissemination in WSNs. The suggested algorithm produces a data delivery ratio of 95.6% with 500 sensor nodes when compared with the HBACS-HBACM, GA-CSO, DCC-IACJS, and FGF algorithms. When working with 100 sensor nodes our proposed algorithm produces a data delivery ratio of 98.65%.

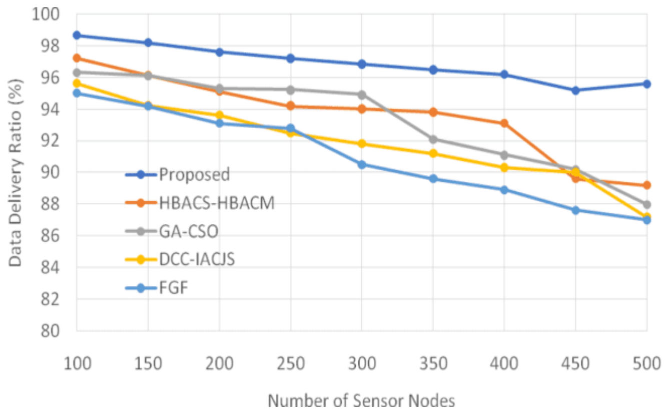

Fig.5. Comparison of Data delivery ratio measured from the other algorithms with the proposed algorithm

The proposed algorithm exhibits unparalleled throughput performance, surpassing all other algorithms in the comparison shown in Figure-6 below. The outcomes unequivocally demonstrate that proposed approach consistently achieves the highest throughput values, making it the optimal choice for maximizing data transfer rates and overall network efficiency in Wireless Sensor Networks. The suggested algorithm transmits the data at the rate of 0.98 Mbps in the case of 100 sensor nodes and gradually decreases up to 0.74 Mbps for 500 sensor nodes.

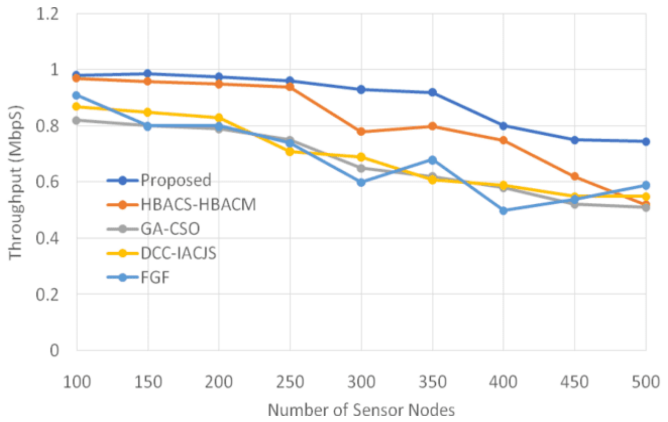

Fig.6. Comparison of Throughput measured from the other algorithms with the proposed algorithm

The Table.2 displays the comparison of proposed algorithm that comprise of a combination of HFGSO, DVFS and duty cycling algorithm with the other algorithms such as HBACS-HBACM, GA-CSO, DCC-IACJS and FGF. The performance of the suggested algorithm is measured by increasing the count of sensor nodes from 100 to 500. The table clearly states the outperformance of the proposed algorithm with the measured parameters.

Table.2. Performance metrics comparison with other algorithms

Algorithms	Energy Consumption (mJ)	Network Lifetime (Rounds)	Data Delivery Ratio (%)	Throughput (Mbps)
HBACS-HBACM	0.59	3210	89.21	0.9751
GA-CSO	0.60	3512	88.15	0.8213
DCC-IACJS	0.70	3601	87.20	0.8760
FGF	0.89	3310	87.00	0.9102
Proposed	0.51	2900	95.60	0.9852

5. CONCLUSION

In this research, we have presented a novel and innovative algorithm that combines the HFGSO algorithm with Dynamic Voltage and Frequency Scaling and Duty Cycling strategies to enhance energy efficiency, network lifetime, data delivery ratio, and throughput of the wireless sensor networks. Through comprehensive simulations and performance evaluations, we have demonstrated the significant benefits and superiority of the proposed algorithms compared to existing approaches. The proposed algorithm excels in energy efficiency, effectively optimizing the cluster head selection process through the HFGSO algorithm. By dynamically adjusting the voltage and frequency of sensor nodes using DVFS, the algorithm minimizes power consumption while maintaining data processing capabilities. Additionally, intelligent duty cycling strategies ensure energy conservation during idle periods, further extending the network lifespan. The scalability of the proposed system is noteworthy, as it maintains its advantage across different network sizes, accommodating both small and large-scale WSN deployments. This scalability, along with its robustness, makes the proposed algorithm suitable for diverse real-world applications. Our algorithm shows a substantial improvement in energy consumption by 20% and an improved data delivery ratio by 4% when compared with the existing approaches. The adoption of the proposed algorithm has the potential to revolutionize WSN performance, making it a key technology for the future of wireless sensor applications.

REFERENCES

[1] T. Abdellatif and M. Mosbah, "Efficient Monitoring for Intrusion Detection in Wireless Sensor Networks", *Concurrency and Computation: Practice and Experience*, Vol. 56, No. 2, pp. 1-13, 2018.

[2] Y. Dong, Y. Wang, S. Li, M. Cui and H. Wu, "Demand-Based Charging Strategy for Wireless Rechargeable Sensor Networks", *ETRI Journal*, Vol. 41, No. 3, pp. 326-336, 2019.

[3] J. Bhola, S. Soni and G.K. Cheema, "Genetic Algorithm based Optimized Leach Protocol for Energy Efficient Wireless Sensor Networks", Journal of Ambient Intelligence and Humanized Computing, Vol. 11, pp. 1281-1288, 2020.

[4] U.M. Durairaj and S. Selvaraj, "Two-Level Clustering and Routing Algorithms to Prolong the Lifetime of Wind Farm-Based WSN", *IEEE Sensors Journal*, Vol. 21, No. 1, pp. 857-867, 2021.

[5] J. Hou, J. Qiao and X. Han, "Energy-Saving Clustering Routing Protocol for Wireless Sensor Networks using Fuzzy Inference", *IEEE Sensors Journal*, Vol. 22, No. 3, pp. 2845-2857, 2022.

[6] A. Naeem, A.R. Javed, M. Rizwan, S. Abbas, J.C.W. Lin and T.R. Gadekallu, "DARE-SEP: A Hybrid Approach of Distance Aware Residual Energy-Efficient SEP for WSN", *IEEE Transactions on Green Communications and Networking*, Vol. 5, No. 2, pp. 611-621, 2021.

[7] Z. Qu, H. Xu, X. Zhao, H. Tang, J. Wang, and B. Li, "An Energy-Efficient Dynamic Clustering Protocol for Event Monitoring in Large-Scale WSN", *IEEE Sensors Journal*, Vol. 21, No. 20, pp. 23614-23625, 2021.

[8] W. Shi, W. Liu, T. Wang, Z. Zeng and G. Zhi, "Adding Duty Cycle Only in Connected Dominating Sets for Energy Efficient and Fast Data Collection", *IEEE Access*, Vol. 7, pp. 120475-120499, 2019.

[9] M. Wang and J. Zeng, "Hierarchical Clustering Nodes Collaborative Scheduling in Wireless Sensor Network", *IEEE Sensors Journal*, Vol. 22, No. 2, pp. 1786-1798, 2022.

[10] Y.D. Yao, X. Li, Y. -P. Cui, J.J. Wang and C. Wang, "Energy-Efficient Routing Protocol Based on Multi-Threshold Segmentation in Wireless Sensors Networks for Precision Agriculture", *IEEE Sensors Journal*, Vol. 22, No. 7, pp. 6216-6231, 2022.

[11] Y. Zhang and W.W. Li, "Energy Consumption Analysis of a Duty Cycle Wireless Sensor Network Model", *IEEE Access*, Vol. 7, pp. 33405-33413, 2019.

[12] N. Ajmi, A. Helali, P. Lorenz and R. Mghaieth, "MWCSGA-Multi Weight Chicken Swarm based Genetic Algorithm for Energy Efficient Clustered Wireless Sensor Network", *Sensors*, Vol. 21, No. 3, pp. 791-812, 2021.

[13] H. Ahmad and N. Kohli, "LBCM: Energy-Efficient Clustering Method in Wireless Sensor Networks", *Engineering and Applied Science Research*, Vol. 48, No. 5, pp. 529-536, 2021.

[14] W. Osamy, A.A. El Sawy and A. Salim, "CSOCA: Chicken Swarm Optimization-Based Clustering Algorithm for Wireless Sensor Networks", *IEEE Access*, Vol. 8, No. 12, pp. 60676-60688, 2020.

[15] J. Li, Z. Luo and J. Xiao, "A Hybrid Genetic Algorithm with Bidirectional Mutation for Maximizing Lifetime of Heterogeneous Wireless Sensor Networks", *IEEE Access*, Vol. 8, No. 4, pp. 72261-72274, 2020.

[16] Y. Zhang and Y.I. Wu, "Multiple Sources Localization by the WSN using the Direction-of-Arrivals Classified by the Genetic Algorithm", *IEEE Access*, Vol. 7, No. 8, pp. 173626-173635, 2019.

[17] D. Dutta, J. Sil and P. Dutta, "Automatic Clustering by Multi-Objective Genetic Algorithm with Numeric and Categorical Features", *Expert Systems with Applications*, Vol. 137, No. 4, pp. 357-379, 2019.

[18] T. Rauber, T. Runger and G. Stachowski, "Performance and Energy Metrics for Multi-Threaded Applications on DVFS Processors", *Sustainable Computing: Informatics and Systems*, Vol. 17, pp. 55-68, 2017.

[19] R. Cheour, S. Khriji, D.E. Houssaini, M. Baklouti, M. Abid and O. Kanoun, "Recent Trends of FPGA used for Low-Power Wireless Sensor Network", *IEEE Aerospace and Electronic Systems Magazine*, Vol. 34, No. 10, pp. 28-38,2019.

[20] E. Senn and J. Boukhobza, "Joint DVFS and Parallelism for Energy Efficient and Low Latency Software Video Decoding", *IEEE Transactions on Parallel and Distributed Systems*, Vol. 29, pp. 858-872,2019.

[21] R. Dhall and H. Agrawal, "An Improved Energy Efficient Duty Cycling Algorithm for IoT based Precision Agriculture", *Procedia Computer Science*, Vol. 141, pp. 135-142,2018.

[22] J.B. Salem, I. Kammoun and O. Kanoun, "Testbed Implementation of a Fuzzy based Energy Efficient Clustering Algorithm for Wireless Sensor Networks", *Proceedings of International Multi-Conference on Systems, Signals and Devices*, pp. 351-356,2019.

[23] S. Radha, G.J. Bala and P. Nagabushanam, "Scheduling and Adaptive Listening Approaches in MAC for WSN Applications: A Survey", *Journal on High-Speed Network*, Vol. 26, pp. 325-338, 2020.

[24] S.A. Sheikh, "*Implementation and Analysis of Energy Efficiency of Mary Modulation Schemes for Wireless Sensor Network*", Springer, 2019.

[25] J. Amutha, Sandeep Sharma and Sanjay Kumar Sharma, "An Energy Efficient Cluster based Hybrid Optimization Algorithm with Static Sink and Mobile Sink Node for Wireless Sensor Networks", *Expert Systems with Applications*, Vol. 203, pp. 1-28, 2022.

[26] A.J. Basha, S. Aswini, S. Aarthini and Y. Nam, "Genetic-Chicken Swarm Algorithm for Minimizing Energy in Wireless Sensor Network", *Computer Systems Science and Engineering*, Vol. 44, pp. 1-23, 2023.

[27] Yang Liu, Chaoqun Li, Yao Zhang, Mengying Xu, Jing Xiao and Jie Zhou, "DCC-IACJS: A Novel Bio-Inspired Duty Cycle-Based Clustering Approach for Energy-Efficient Wireless Sensor Networks", *Journal of King Saud University - Computer and Information Sciences*, Vol. 35, No. 2, pp. 775-790, 2023.

[28] Kale Navnath Dattatraya and K. Raghava 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, 2022.