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Optimal Routing-Clustering Aware of Energy Consumption in Wireless Sensor Networks based on Deep Tree Learning

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ABSTRACT

Presently, the application of Wireless Sensor Networks (WSNs) poses challenges across various domains, with the most prominent being the energy consumption of sensor batteries. Sensor nodes, dispersed in diverse geographical environments for their designated purposes, rely on batteries for data collection. The deployment of sensor nodes induces energy losses during data collection and transmission, particularly in routing data, which demands substantial energy. To tackle this issue, clustering is employed either before or concurrently with routing. This article explores the implementation of clustering-routing alongside sleep and wake scheduling in sensor nodes to effectively conserve energy. The study introduces the optimal OCADR (Constrained Anisotropic Diffusion Routing) protocol, enhancing it with the DAVL (Deep Adelson-Velskii and Landis) tree rotation clustering algorithm. The research reveals that this innovative approach offers improved scheduling in terms of sensor nodes' sleep and wake time compared to prior methods. Moreover, it efficiently transmits packets to the base station through the head clusters. The initial energy allocation was 50 Joules, and after simulation using this method, only 22 Joules were consumed, leaving 28 Joules for network survival an advancement surpassing earlier methodologies.

1. INTRODUCTION

A number of studies have addressed the need for energy-efficient routing protocols in Wireless Sensor Networks (WSNs) [1-4]. These protocols are crucial for maximizing the lifetime of sensor nodes, which are limited by energy, storage capacity, and computing power. The review by Chaudhary (2014) [1] specifically focuses on hierarchical-based routing protocols, while Poonia (2011) [3] compares various energy-efficient routing protocols and highlights the importance of distributing energy dissipation throughout the network. Bhushan (2017) emphasizes the need for secure and energy-efficient routing protocols, particularly in the face of resource constraints and security attacks [4]. These studies collectively underscore the significance of energy-efficient routing protocols in addressing the energy consumption challenges in WSNs.

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A range of studies have explored energy conservation in wireless sensor networks (WSNs) through various techniques. Sadouq (2014) proposed a clustering-based framework that dynamically reconfigures the network to optimize energy consumption and extend network lifetime [5]. Ruperee (2014) [6] focused on reducing energy consumption by processing data at the node level using Delta Modulation, while Gopika (2020) conducted a comparative study of cluster-based protocols for energy conservation [7]. Zairi (2012) introduced a self-scheduling algorithm that considers remaining energy to determine which nodes should enter sleep mode, effectively extending network lifetime [8]. These studies collectively highlight the importance of energy conservation in WSNs and the potential of different approaches to achieve this goal.

2. LITERATURE REVIEW

Wireless Sensor Networks (WSNs) are composed of sensor nodes that are responsible for collecting and transmitting data to a central location. One of the most significant challenges in WSNs is energy consumption, as the sensor nodes are often powered by batteries with limited capacity. To address this challenge, researchers have focused on developing energy-efficient routing and clustering protocols to prolong the network's lifetime. In recent years, deep tree learning and metaheuristic optimization techniques have gained attention in the design of energy-efficient routing and clustering protocols for WSNs. This literature review aims to synthesize and integrate the latest research findings on optimal routing-clustering aware of energy consumption in WSNs based on deep tree learning and metaheuristic optimization [9-12].

Zhu et al. (2021) proposed a deep reinforcement learning approach for UAV trajectory planning in WSNs to minimize energy consumption. Their work demonstrates the potential of deep learning techniques in optimizing routing decisions to reduce energy consumption [13]. Additionally, Yun and Yoo (2021) developed a Q-learning-based data-aggregation-aware energy-efficient routing protocol for WSNs, highlighting the applicability of reinforcement learning in optimizing routing decisions while considering energy efficiency [14].

Xue et al. (2023) introduced a hybrid cross-layer routing protocol for WSNs based on the Harris-Hawk optimization algorithm [15]. Their study showcases the effectiveness of metaheuristic optimization algorithms in designing energy-efficient routing protocols for WSNs. Furthermore, Revanesh and Sridhar (2021) proposed a trusted distributed routing scheme for WSNs using blockchain and metaheuristic-based deep learning techniques, emphasizing the potential of metaheuristic approaches in enhancing the security and energy efficiency of routing protocols [16].

Shanmugam and Kaliaperumal (2021) presented an energy-efficient clustering and cross-layer-based opportunistic routing protocol (CORP) for WSNs [17]. Their work demonstrates the significance of cross-layer optimization in developing energy-efficient routing protocols for WSNs. Moreover, Subramani et al. (2022) introduced a multihop routing protocol for IoT-assisted WSNs, emphasizing the importance of energy-aware clustering and routing in IoT-enabled WSNs [18].

Cherappa et al. (2023) proposed energy-efficient clustering and routing protocols for WSNs using the Antlion Swarm and Firefly Optimization algorithms, showcasing the effectiveness of hybrid optimization algorithms in designing energy-efficient protocols [19]. Additionally, Padmanaban et al. (2023) developed a hybrid ANFIS reptile optimization algorithm for energy-efficient inter-cluster routing in IoT-enabled WSNs, highlighting the potential of hybrid optimization techniques in enhancing energy efficiency [20].

Han et al. (2022) introduced an energy-aware and trust-based secure routing protocol for WSNs using an adaptive genetic algorithm, emphasizing the significance of trust-based mechanisms in enhancing the security and energy efficiency of routing protocols [21]. Furthermore, Zachariah and Kuppusamy (2021) proposed a hybrid approach to energy-efficient clustering and routing in WSNs, highlighting the importance of integrating multiple optimization techniques to achieve energy efficiency [22].

While the existing literature provides valuable insights into energy-efficient routing and clustering protocols for WSNs, there are several knowledge gaps and potential future research directions that warrant further investigation. First, there is a need for comprehensive comparative studies to evaluate the performance of deep tree learning, metaheuristic optimization, and hybrid optimization algorithms in designing energy-efficient routing protocols for

WSNs. Additionally, the integration of trust-based and secure mechanisms with energy-efficient routing protocols remains an open research area. Furthermore, the development of adaptive and self-organizing routing protocols that can dynamically adjust to the network's changing conditions is an important direction for future research.

In conclusion, the literature review underscores the significance of optimal routing-clustering aware of energy consumption in WSNs based on deep tree learning and metaheuristic optimization. The integration and synthesis of the provided research findings have shed light on the potential of advanced techniques in addressing the energy efficiency challenges in WSNs. Moreover, the identification of knowledge gaps and future research directions provides valuable insights for researchers and practitioners in the field of WSNs and IoT.

Overall, the literature review provides a comprehensive understanding of the current state of research on energy-efficient routing and clustering in WSNs and paves the way for future advancements in this domain.

The current article draws on some formulations from [23-27]. However, several routing protocols, including Constrained Anisotropic Diffusion Routing (CADR) discussed in [28], as well as some of the main and most challenging routing protocols discussed in [29], have been examined. [30] investigated energy-aware routing protocols and methods for optimizing them, while [31] provided a study on energy-aware hybrid routing protocols that select the best cluster heads in clustering. This article optimized hybrid routing protocols in terms of energy consumption using two algorithms: the Golden Eagle Optimization Algorithm (GEOA) and the Improved Grasshopper Optimization Algorithm (IGHOA).

3. PROPOSED METHOD

The proposed method uses a sleep-awake scheduling technique for WSN similar to the CADR protocol and the CADR-DAVL model. To eliminate CADR protocol gaps, a more optimal approach is required. A significant weakness of the protocol and the proposed method is the clustering around different sensor node movements, leading to re-clustering [21-25]. This clustering algorithm selects clusters and checks the node states (sleep and awake mode) to determine energy consumption while optimizing various quality of service criteria such as throughput, latency, bit error rate, signal-to-noise ratio, and high bandwidth. To address this gap, a new approach called the Adelson-Velskii and Landis (AVL) tree rotation clustering algorithm based on deep learning techniques is employed.

In this study, the energy consumption during each cycle can be estimated by analyzing the energy consumed by nodes when transmitting and receiving data. The first-order radio model is used to measure energy consumption. The energy required to transmit a one-bit packet between the transmitter and receiver at a certain distance can be defined by equation (1) [26, 27].

$$E_{TX} = \begin{cases} lE_{elec} + l\varepsilon_{fs}d^2 & .d < d_0 \\ lE_{elec} + l\varepsilon_{mp}d^4 & .d \geq d_0 \end{cases} \quad (1)$$

In this context, E_{elec} refers to the dispersed energy required by the transmitter or receiver circuit for each bit, while d represents the transmission distance. ε_{mp} and ε_{fs} signify the amplification energy ratios for open-space and multidirectional fading scenarios, respectively. The value of d_0, which serves as the threshold distance, is contingent upon both the amplification energy ratios and the particular environment. It can be represented as $d_0 = \sqrt{\varepsilon_{mp} / \varepsilon_{fs}}$. Furthermore, the energy required to receive one-bit data can be expressed as equation (2) [26, 27].

$$E_{Rx}(l.d) = lE_{elec} \quad (2)$$

The energy consumed for aggregating the data matches equation (3) [26, 27].

$$E_{Agg}(l.d) = lE_{DA} \quad (3)$$

In this context, E_{DA} refers to the energy required to transmit a single bit of aggregated data. It is essential to maintain a balance between the energy of sensor nodes in order to extend the network's lifespan. Limit the communication distance between clusters to the d_0 threshold and make sure that reduction in sensor-energy loss is achieved by using the vacuum model to decrease energy consumption within the cluster. When operating under a single-hop mode, the central hub (CH) can transmit data directly to the central station. If the central station is far from the monitoring area, the cluster head (CH) should utilize the multi-route attenuation model to mitigate energy boost losses. However, this model significantly amplifies the energy consumption of the central station. Therefore, the CH is more susceptible to energy drain and premature death than its constituent nodes, which ultimately diminishes the network's lifetime. Determining the optimal competition radius of the sprig and forming uniform and evenly distributed clusters is crucial for energy balance.

The competition radius of the sink candidate is referred to when a node broadcasts a candidate's CH message. Only nodes within the radius of the sensor network can receive the message from the CH candidate. In this context, the Adelson-Velskii and Landis (AVL) tree rotation clustering algorithm, using deep learning, presents an optimal graph-like tree that competes effectively. Its CH selection stage is capable of limiting the spatial distribution of CH by adjusting the competition radius. In single-hop mode, the major energy consumption task for sensor nodes is transmitting data to the central station. Therefore, the competition radius is the primary factor affecting the network's lifespan. Increasing the radius reduces the number of clusters, requiring more energy due to the enhanced signal strength required to transmit over longer distances.

In brief, achieving an appropriate competitive radius result in a balanced energy consumption between clusters and intra-cluster communication overhead [23]. It is assumed that the monitoring area is a square region with sensor nodes M and N located at each end, yielding a node density of $\rho=N/M^2$. Assuming d_{CH} represents the eclipse competition radius and d_{toBS} represents the CH transmission distance to the central station, certain redundant nodes are programmed to sleep. The number of redundant nodes in the cluster is assumed to be the percentage of active member nodes in the cluster, as per member node $\sigma = 1 - V/(n-1)$. the active member node to the thread is set at l bits per round for simplicity. E_{toCH}, E_{re}, and E_{toBS} denote the energy consumed to transmit l-bit packets from the node to the header, the energy used by the CH to receive such packets, and the energy consumed to transmit l-bit packets from the CH, respectively. Furthermore, Equation (4) can be used to obtain the energy consumption of all active nodes within the CH's competition radius to transfer their collected data to the CH.

$$E_{toCH} = \sigma \int_{d_{CH}}^{0} 2\,\pi\, x \times \rho \times \left(lE_{elec} + l\varepsilon_{fs} x^2\right) dx = \sigma l \pi \rho \times \left(E_{elec} d_{CH}^2 + \frac{1}{2}\varepsilon_f d_{toBS}^4\right) \tag{4}$$

For every cluster, the energy expended regarding the tracked data received by members of the corresponding nodes in a cluster is approximated as the equation (5) [26, 27].

$$E_{re} = l \times (\pi r_i^2 \rho - 1) \times E_{elec} \tag{5}$$

The energy expended on data accumulation within it is computed using equation (6) [26, 27].

$$E_{Agg} = l \times \pi r_i^2 \rho \times E_{DA} \tag{6}$$

In addition, the energy expended by the CH to transmit data to the base station is calculated using equation (7) [26, 27].

$$E_{toBS} = lE_{elec} + l\varepsilon_{mp} R_i^4 \tag{7}$$

In this context, R_i represents the distance between the head and the base station. Thus, equation (8) can be utilized to calculate the total energy loss within a cluster, as per the aforementioned equations.

$$E_{cluster} = E_{toCH} + E_{toBS} + E_{re} + E_{Agg} = l\pi\rho r_i^2 (\sigma + \frac{1}{2}\sigma\varepsilon_{fs} r_i^2 + E_{elec} + E_{DA}) \tag{8}$$

Then, the average energy consumed by a single node in each cluster is computed using equation (9).

$$E_{avg} = \frac{E_{clutser}}{\pi r \rho_i^2} \tag{9}$$

The objective is to obtain the desired radius of competition, denoted as d_{CH}, by taking the derivative of formula (9), labeled r_i, as described in equation (10).

$$d_{CH} = \sqrt[4]{\frac{2\varepsilon_{mp}}{\sigma\pi\rho\varepsilon_{fs}}} d_{toBS} \tag{10}$$

According to equations (4) and (5), the optimal competitive radius of each node increases with its distance from the base station. Minimizing local energy consumption requires attention to the optimal competition radius of each node, allowing for the creation of an uneven hierarchical structure that is suitable for cluster-sensitive sensor networks. In the vicinity of the base station, the cluster distribution density will be relatively low. Cluster selection becomes effortless with the use of the rotational clustering algorithm of the DAVL tree. CH determination relies on a linear combination of probability selection and local competition. After finishing the operation, any node in the member position qualifies as a candidate. Initially, every node is designated as a common node and assigned a specific probability of being selected as a CH, based on its distance from the base station and its remaining energy. Nodes that are within close proximity to the base station have a higher likelihood of being chosen over nodes located further away. Therefore, the equation (11) [26, 27] may define performance.

$$CHs(i) = \alpha \times \frac{d_{\{max\}} - d_{toBS}(i)}{d_{\{max\}} - d_{\{min\}}} + (1 - \alpha) \times \frac{E_{res}(i)}{E_{init}} \tag{11}$$

In this context, $d_{\{max\}}$ signifies the farthest distance from the base station while $d_{\{min\}}$ signifies the nearest distance. a is a constant parameter. Each node obtains the probability of being CH to determine eligibility in the current CH cycle. Furthermore, nodes that are eligible change their position and calculate their desired competitive radius based on their distance from the base station. Other non-eligible nodes can conserve energy by disabling their wireless communication modules during the eligibility selection process. Additionally, eligible candidates must acquire information regarding their communication area's location and competition. Each CH candidate has a designated Neighborhood CH candidate table with the adjacent CHs' node ID, energy indicator, and remaining status. After selecting the Cluster Head (CH), the CHs disseminate a message that contains their identities and a list of member nodes, and then they wait for adjacent member nodes to join. Technical terms, such as CH and member node, will be explained when first used. Citations will follow a consistent format, and filler words will be omitted. Based on the strength of the received signal, non-CH nodes estimate the distances to their neighboring CHs and select the nearest member or cluster for location. This can decrease the energy usage of the clustered nodes for data delivery and also enable nodes in proximity to the base station to handle more load for transmitting or collecting data to achieve balanced energy consumption network-wide. Following this, the member nodes forward a message comprising of the node ID and the distance between the CHs to the CH. Upon receipt of this message from a non-CH, the CH applicant transmits an ACK message, simultaneously updating the cluster membership list.

The study's primary objective is to examine the optimal approach for sleep-wake scheduling with energy conservation. Sleep-wake scheduling is a distributed competitive mechanism that is founded on unequal clusters in WSNs. It relies on local decision-making to choose clusters while determining the radius of competition. To determine the competition radius of experimental clusters, the sleep-awake scheduling mechanism employs the residual energy and distance from the central station parameters. Technical abbreviations are explained in their first usage, and bias is avoided with objective language throughout. The structure is clear and concise, maintaining a consistent register, style, and formatting. Furthermore, it uses the DAVL tree rotational clustering algorithm to determine the optimal competition radius based on a probabilistic model that considers competition between CH candidates.

Candidate cluster heads (CHs) distribute information regarding their participation to neighboring nodes within the competition radius using the corresponding transmission power. The compMSG (Authentication, Authorization, and Accounting) message includes the candidate's ID and remaining energy. Upon receiving this message, the other candidate CHs record the candidate's CH ID in the CH table of their CH neighbors. Due to the varying sizes of the eligible candidates' competition radii, the ensuing scenarios may differ. Assuming that candidate i CH's competition radius exceeds that of candidate s header and j can receive the compMSG message from si. However, due to restricted si transfer range, si did not receive the compMSG message, and therefore remains unaware of the si CH candidate's existence. To acquire comprehensive data about nearby competitors, each candidate CH must estimate the transmitter's distance after receiving the compMSG message. If the candidate e-mail's radius exceeds the competition radius, the transmitter must reuse a compMSG message to obtain complete information and update the eligible neighbor e-mail list.

4. SIMULATION AND RESULTS

The study utilizes a MATLAB environment to conduct the simulation. The aim is to establish a structure for the sleep-awake network mechanism of the WSN with consideration of energy efficiency and quality of service criteria. The initial step requires configuring the WSN in accordance with the settings listed in Table (1).

Table 3. WSN settings

Number of sensor nodes	100
WSN scale (m^2)	100x100
Energy of each nodes (Joules)	0.5
Total Network Energy (Joules)	50
Network Runtime (sec)	500
Sink position (m^2)	50x50
Node probability selection for CH candidate	0.1
Alpha time for sensor node	0.2
Homogenous percentages of each node	0.1

At the beginning of the simulation, the sensor nodes are distributed randomly and settle in the initial environment. Figure (1) shows the initial placement of the sensor nodes.

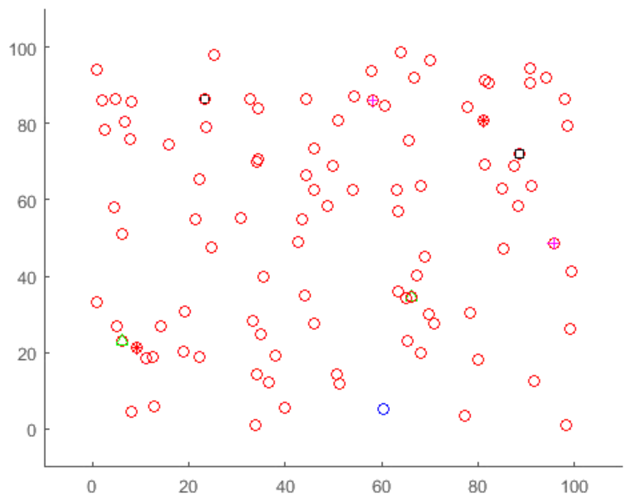


Fig. 1. Initial deployment of sensor nodes in the WSN environment

Figure 1 depicts the random placement of 100 sensor nodes with dimensions of 100×100 square meters. The first deployed nodes are red, while blue, purple, green, and black nodes are also present in the area and are likely to be selected as clusters. Subsequently, candidate CHs undergo initial clustering and selection, as shown in the output sample in Figure 2. It is important to note that the output may vary at different outputs due to the mobility of the sensor nodes.

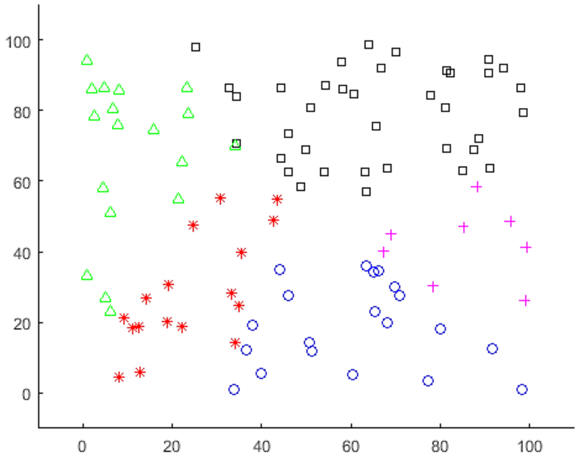


Fig. 2. Clustering and CH candidate selection

Based on Figure (2), it is evident that a total of 5 clusters or regions have been generated, with each cluster featuring the same node that was previously identified as a CH candidate in Figure (1) and is now represented by a different color block. The next step involves the consideration of the sleep-awake mechanism and a practical comparison of the two methods presented in references [23,24]. Notably, Figure (3) illustrates awake nodes, while Figure (4) depicts sleep nodes.

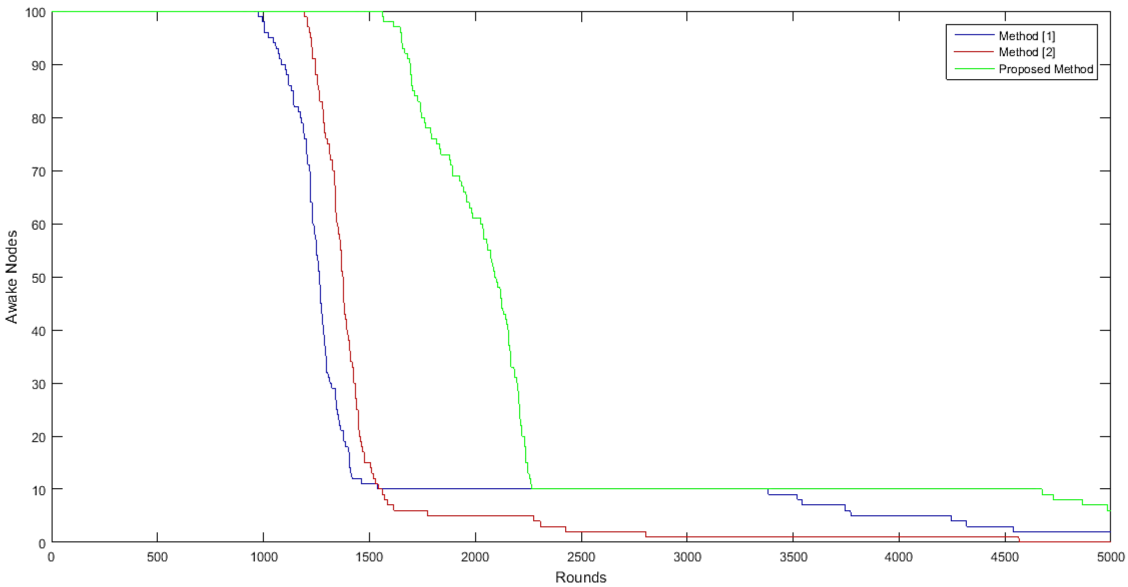


Fig. 3. Awake Nodes

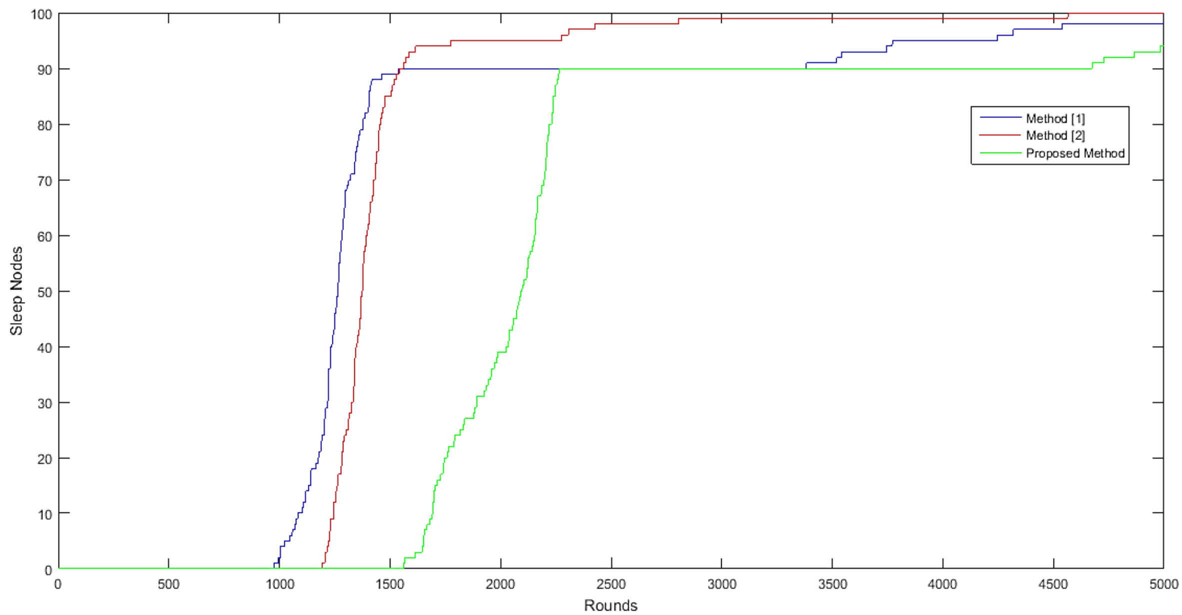


Fig. 4. Sleep Nodes

Figures (3) and (4) demonstrate the performance of the awakened and sleeping nodes in the sensor nodes after 5000 cycles or WSN execution time. Abbreviations: WSN = Wireless Sensor Networks. Figure (3) reveals that a wake-up time that results in lower energy consumption attains the lowest energy consumption of around 2200 rpm, i.e., 10 Joules of energy. This approach is more optimal compared to methods presented in [23,24]. According to Figure 4, the proposed WSN implementation requires 1550 rounds for the fall asleep time, which consumes less energy compared to the two methods outlined in [23,24]. The green diagram corresponds to the proposed approach, while the blue and red diagrams correspond to references [23,24], respectively. Next, we should compare the packets' transmission rate to the base station through the CH between the proposed approach and the two methods presented in [23,24]. The output of this comparison is shown in Figure (5).

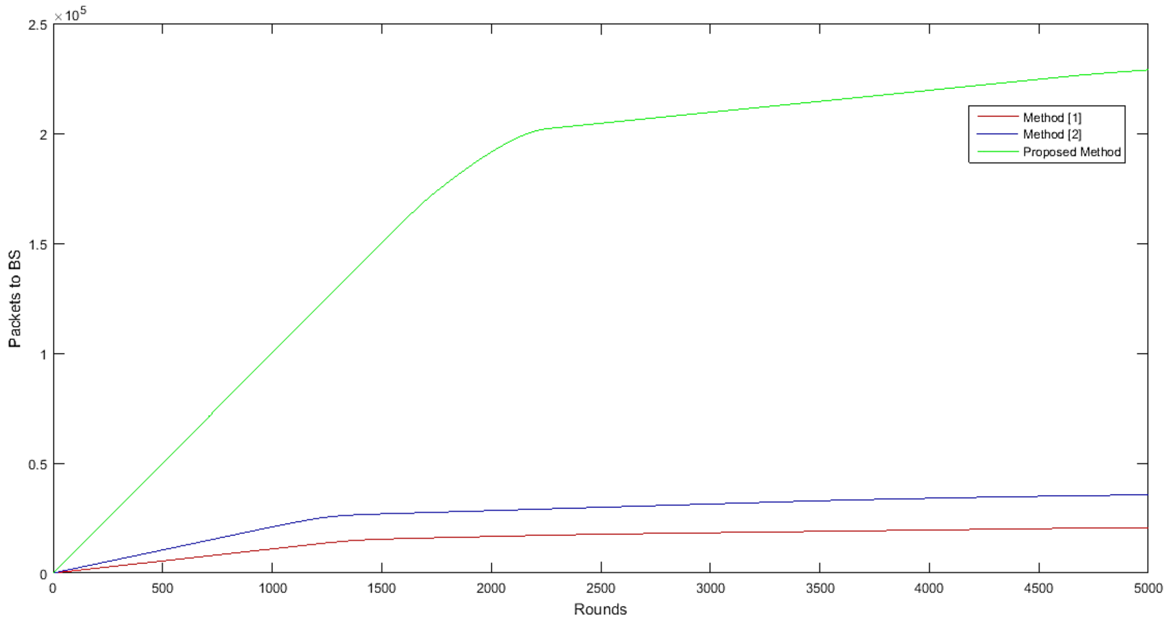
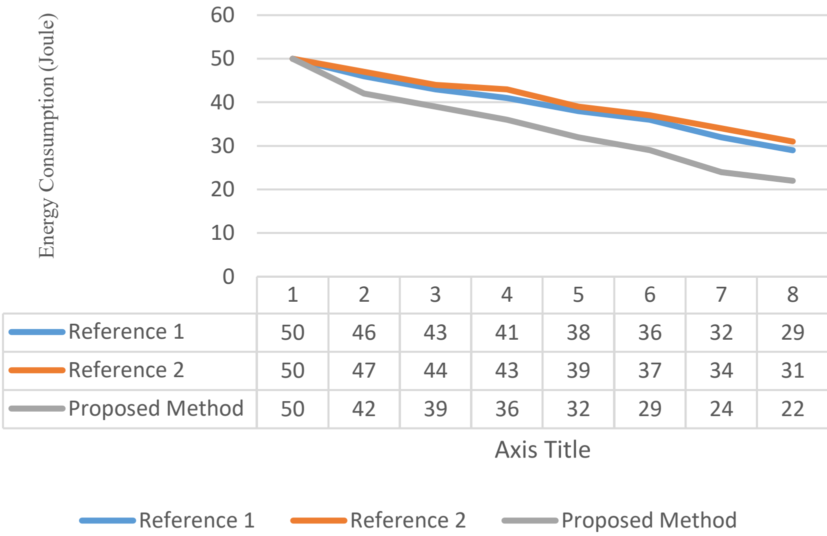


Fig. 5. Packets transmit rate to base station through CHs

Based on Figure 5, it is evident that the proposed approach utilizing the green diagram exhibits a superior capability for the sleep-awake mechanism of the sensor nodes. Additionally, this approach can acquire more information or data from the environment and transmit it to both the CHs and the base station. The findings reveal that the suggested method for transmitting data to the base database operates more efficiently than the two methods proposed in references [23,24]. Additionally, the energy consumption output comparison between the suggested method and the aforementioned methods is displayed in Figure (6).



	1	2	3	4	5	6	7	8
Reference 1	50	46	43	41	38	36	32	29
Reference 2	50	47	44	43	39	37	34	31
Proposed Method	50	42	39	36	32	29	24	22

Fig. 6. Energy Consumption

Based on Figure 6, the results display that within a 5000-second repetition cycle from the time of execution, the suggested approach utilizing 50 main energy consumes a mere 22 Joules while minimizing consumption in comparison to methods [23,24]. In contrast, approach [23] consumed 29 Joules with a remaining energy of 21 = 29-50 Joules. Similarly, the approach discussed in reference [24] had a total energy consumption of 31 Joules, with a remaining energy of 19 Joules, calculated as 31-50 Joules. In comparison, the proposed method only consumed 22 Joules of energy, resulting in a residual energy of 28 Joules, calculated as 22-50 Joules. This value can be compared to the other two approaches, which resulted in 21 and 19 Joules of residual energy, respectively. Additionally, the proposed method has shown to have 28 Joules of residual energy, which is an improvement between 7 and 9 Joules of energy consumption.

5. CONCLUSION

WSN has become one of the most promising technologies in use today. This type of network is capable of monitoring environmental conditions in a specific location and detecting changes in areas such as temperature, pressure, humidity, sound, intensity, vibration, and movement. WSN applications are extensively utilized in various sectors such as environmental monitoring, habitat monitoring, building monitoring, natural disaster monitoring, military applications, traffic monitoring, smart home monitoring, inventory management, industrial robotics, and medical applications. Medicine and health monitoring systems have implemented WSNs both scientifically and practically. WSNs may function as static or dynamic sensor nodes, or a combination of both. A Wireless Sensor Network (WSN) is composed of a multitude of sensor nodes that are utilized for data collection to generate meaningful results. Despite their value, these low-power devices possess limited computing and processing abilities. As such, a remote unit capable of computation is necessary to overcome this shortfall. Furthermore, these miniature devices have limited internal power reserves, such as a battery. They must have sufficient power to minimize power consumption while monitoring and collecting data to prolong battery life. Power usage and reduced data transmission rates are influenced by various network regions. Moreover, these networks involve multiple interconnected nodes engineered to detect, gather, process, and transmit task-specific information.

Wireless sensor networks (WSNs) can be either static or dynamic, depending on the specific nodes. Dynamic networks with open nodes allow for nodes to freely join or leave the network, while static networks lack this feature. Static networks are more vulnerable to security breaches than dynamic networks. Cross-authentication is an essential part of dynamic networks, as it ensures secure communication. Additionally, the computations required in dynamic networks are larger than in static networks due to their ability to freely add and remove nodes. Due to the high energy consumption involved in clustering operations and the selection of CH during the sleep-awake technique, it is imperative to optimize WSN, which is exactly what the approach of this research aims to achieve.

The main innovations of this study are found in the heterogeneous cluster of the network where the sensor nodes are proposed to select the best cluster from the DAVL tree's rotational clustering algorithm. The residual energy of each sensor node in the WSN is calculated to attain a balanced network. The sensor node with the highest remaining energy is chosen as the optimal node for CH. As a result, our algorithm saves more energy and extends network lifespan while reducing computational complexity. Utilizing the DAVL tree rotational clustering algorithm establishes a dominant mode that functions as the network's backbone. Implementing this method minimizes data transfer latency ensuring reliable data transfer. The message is delivered to the end user with high speed, promising accuracy, energy efficiency, and reliability. Notably, these innovations are implemented in the context of WSN using the sleep-wake scheduling technique. The simulation in MATLAB illustrates that this proposed approach performs better in terms of energy consumption and quality of service criteria than previous similar methods.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

REFERENCES

[1] Chaudhary, R., Vatta, S., & No, P. (2014). Review paper on energy-efficient protocols in wireless sensor networks. IOSR Journal of Engineering, 4(02), 1–07.

[2] Kaur, T., & Kumar, D. (2019). Computational intelligence-based energy efficient routing protocols with QoS assurance for wireless sensor networks: a survey. International Journal of Wireless and Mobile Computing, 16(2), 172. doi:10.1504/ijwmc.2019.099043

[3] Poonia, R., Sanghi, A. K., & Singh, D. (2011). Energy Efficient Communication Protocols for Wireless Sensor Networks. International Journal of Computer Science and Information Technologies, 2(4), 1697–1699.

[4] Bhushan, B., & Sahoo, G. (2017, July). A comprehensive survey of secure and energy efficient routing protocols and data collection approaches in wireless sensor networks. 2017 International Conference on Signal Processing and Communication (ICSPC). Presented at the 2017 International Conference on Signal Processing and Communication (ICSPC), Coimbatore. doi:10.1109/cspc.2017.8305856

[5] Sadouq, Z. A., Mabrouk, M. E., & Essaaidi, M. (2014, October). Conserving energy in WSN through clustering and power control. 2014 Third IEEE International Colloquium in Information Science and Technology (CIST). Presented at the 2014 Third IEEE International Colloquium in Information Science and Technology (CIST), Tetouan, Morocco. doi:10.1109/cist.2014.7016654

[6] Ruperee, A., Nema, S., & Pawar, S. (2014, February). Achieving energy efficiency and increasing network life in wireless sensor network. 2014 IEEE International Advance Computing Conference (IACC). Presented at the 2014 IEEE International Advance Computing Conference (IACC), Gurgaon, India. doi:10.1109/iadcc.2014.6779314

[7] Gopika, D., & Panjanathan, R. (2020, February). A comprehensive study on various energy conservation

mechanisms in wireless sensor networks. 2020 International Conference on Emerging Trends in Information Technology and Engineering (Ic-ETITE). Presented at the 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE), Vellore, India. doi:10.1109/ic-etite47903.2020.285

[8] Zairi, S., Zouari, B., Niel, E., & Dumitrescu, E. (2012). Nodes self-scheduling approach for maximising wireless sensor network lifetime based on remaining energy. IET Wireless Sensor Systems, 2(1), 52. doi:10.1049/iet-wss.2011.0074

[9] Xu, Y., Jiao, W., & Tian, M. (2021). An energy-efficient routing protocol for 3D wireless sensor networks. IEEE Sensors Journal, 21(17), 19550–19559. doi:10.1109/jsen.2021.3086806

[10] Natesan, G., Konda, S., de Prado, R. P., & Wozniak, M. (2022). A hybrid Mayfly-Aquila optimization algorithm based energy-efficient clustering routing protocol for Wireless Sensor Networks. Sensors (Basel, Switzerland), 22(17), 6405. doi:10.3390/s22176405

[11] Shen, Z., Yin, H., Jing, L., Liang, Y., & Wang, J. (2022). A cooperative routing protocol based on Q-learning for underwater optical-acoustic hybrid wireless sensor networks. IEEE Sensors Journal, 22(1), 1041–1050. doi:10.1109/jsen.2021.3128594

[12] Del-Valle-Soto, C., Rodríguez, A., & Ascencio-Piña, C. R. (2023). A survey of energy-efficient clustering routing protocols for wireless sensor networks based on metaheuristic approaches. Artificial Intelligence Review, 56(9), 9699–9770. doi:10.1007/s10462-023-10402-w

[13] Zhu, B., Bedeer, E., Nguyen, H. H., Barton, R., & Henry, J. (2021). UAV trajectory planning in wireless sensor networks for energy consumption minimization by deep reinforcement learning. IEEE Transactions on Vehicular Technology, 70(9), 9540–9554. doi:10.1109/tvt.2021.3102161

[14] Yun, W.-K., & Yoo, S.-J. (2021). Q-learning-based data-aggregation-aware energy-efficient routing protocol for wireless sensor networks. IEEE Access: Practical Innovations, Open Solutions, 9, 10737–10750. doi:10.1109/access.2021.3051360

[15] Xue, X., Shanmugam, R., Palanisamy, S., Khalaf, O. I., Selvaraj, D., & Abdulsahib, G. M. (2023). A hybrid cross layer with Harris-hawk-optimization-based efficient routing for wireless sensor networks. Symmetry, 15(2), 438. doi:10.3390/sym15020438

[16] Revanesh, M.., & Sridhar, V.. (2021). A trusted distributed routing scheme for wireless sensor networks using blockchain and meta-heuristics-based deep learning technique. Transactions on Emerging Telecommunications Technologies , 32 . http://doi.org/10.1002/ett.4259

[17] Shanmugam, R.., & Kaliaperumal, B.. (2021). An energy-efficient clustering and cross-layer-based opportunistic routing protocol (CORP) for wireless sensor network. International Journal of Communication Systems , 34 . http://doi.org/10.1002/dac.4752

[18] Subramani, N., Perumal, S. K., Kallimani, J. S., Ulaganathan, S., Bhargava, S., & Meckanizi, S. (2022). Controlling energy aware clustering and multihop routing protocol for IoT assisted wireless sensor networks. Concurrency and Computation: Practice & Experience, 34(21). doi:10.1002/cpe.7106

[19] Cherappa, V., Thangarajan, T., Meenakshi Sundaram, S. S., Hajjej, F., Munusamy, A. K., & Shanmugam, R. (2023). Energy-efficient clustering and routing using ASFO and a cross-layer-based expedient routing protocol for wireless sensor networks. Sensors (Basel, Switzerland), 23(5). doi:10.3390/s23052788

[20] Vazhuthi, P. P. I., Prasanth, A., Manikandan, S. P., & Sowndarya, K. K. D. (2023). A hybrid ANFIS reptile optimization algorithm for energy-efficient inter-cluster routing in internet of things-enabled wireless sensor networks. Peer-to-Peer Networking and Applications, 16(2), 1049–1068. doi:10.1007/s12083-023-01458-0

[21] Han, Y., Hu, H., & Guo, Y. (2022). Energy-aware and trust-based secure routing protocol for wireless sensor networks using adaptive genetic algorithm. IEEE Access: Practical Innovations, Open Solutions, 10, 11538–11550. doi:10.1109/access.2022.3144015

[22] Zachariah, U. E., & Kuppusamy, L. (2022). A hybrid approach to energy efficient clustering and routing in wireless sensor networks. Evolutionary Intelligence, 15(1), 593–605. doi:10.1007/s12065-020-00535-0

[23] Priyadarshini, R., & Sivakumar, R. (2018). Cluster head selection based on Minimum Connected Dominating Set and Bi-Partite inspired methodology for energy conservation in WSNs. Journal of King Saud University - Computer and Information Sciences.

[24] Wan, R., Xiong, N., & Nguyen The Loc. (2018). An energy-efficient sleep scheduling mechanism with similarity measure for wireless sensor networks. Human-Centric Computing and Information Sciences, 8(1). doi:10.1186/s13673-018-0141-x

[25] Zhang, W., Wang, J., Han, G., Zhang, X., & Feng, Y. (2019). A cluster sleep-wake scheduling algorithm based on 3D topology control in underwater sensor networks. Sensors (Basel, Switzerland), 19(1), 156. doi:10.3390/s19010156

[26] Qin, Z., Zhang, X., Feng, K., Zhang, Q., & Huang, J. (2015). An efficient key management scheme based on ECC and AVL tree for large scale wireless sensor networks. International Journal of Distributed Sensor Networks, 11(9), 691498. doi:10.1155/2015/691498

[27] Priyadarshini, R. R., & Sivakumar, N. (2021). Cluster head selection based on minimum connected dominating set and bi-partite inspired methodology for energy conservation in WSNs. Journal of King Saud University-Computer and Information Sciences, 33(9), 1132–1144.

[28] Shabbir, N., & Hassan, S. R. (2017). Routing protocols for wireless sensor networks (WSNs). In Wireless Sensor Networks - Insights and Innovations. doi:10.5772/intechopen.70208

[29] Jilbab, A., & Mohamed, E. H. (2020). Chapter 1 - Routing protocols for wireless sensor networks: A survey. In Advances in Ubiquitous Computing Cyber-Physical Systems, Smart Cities and Ecological Monitoring Advances in ubiquitous sensing applications for healthcare (pp. 3–15).

[30] Hemanand, D., Senthilkumar, C., Saleh, O. S., Muthuraj, B., Anand, A., & Velmurugan, V. (2023). Analysis of power optimization and enhanced routing protocols for wireless sensor networks. Measurement: Sensors, 25, 100610.

[31] Roberts, M. K., & Ramasamy, P. (2022). Optimized hybrid routing protocol for energy-aware cluster head selection in wireless sensor networks. Digital Signal Processing, 130(103737), 103737. doi:10.1016/j.dsp.2022.103737