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Research Article

A Hybrid Heuristic Model for Duty Cycle Framework Optimization

Kwabena Ansah, Justice Kwame Appati, Ebenezer Owusu, and Jamal-Deen Abdulai

Department of Computer Science, University of Ghana, Legon, Accra, Ghana

Correspondence should be addressed to Justice Kwame Appati; jkappati@ug.edu.gh

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This paper proposes a hybrid metaheuristic approach to optimize a duty cycle framework based on Seagull and Mayfly Optimization (HSMO-DC) Algorithm. This approach becomes crucial as current clustering protocols are unable to efficiently tune the clustering parameters in accordance to the diversification of varying WSNs. The proposed HSMO-DC primarily has two parts, where the first part takes care of the online cluster head selection and network communication using the seagull algorithm while the second part performs parameter optimization using the mayfly algorithm. The seagull is aimed at improving the energy distribution in the network through an effective bandwidth allocation procedure while reducing the total energy dissipation. Comparatively, with other clustering protocols, our proposed methods reveal an enhanced network lifetime with an improved network throughput and adaptability based on selected standard metric of performance measurement.

1. Introduction

Wireless sensor networks (WSNs) are formed out of several sensor nodes. These sensors are widely distributed. Through the collaboration of sensors, WSN has become an experimental paradigm for collecting information on a large-scale location [1]. WSN nodes are often battery-powered to reduce power consumption and outfitted with low-performance CPUs and tiny memory [2]. Because they are battery-powered, replacing their batteries is difficult, if not impossible. Furthermore, reducing the pace at which the node's energy is consumed is critical to obtain a more extended network lifetime [3]. Increasing the network lifespan and reducing packet delivery delays are two complex challenges for WSNs, which may be accomplished with the help of an energy harvesting method [4]. Sensor nodes must decide their sensed data rates to the base station (BS) to report the complete network information while reducing data redundancy in their sensed data reports to maximize the network lifespan [5]. Further, redundant data transfer is one of the most significant sources of high-energy dissipation, reducing the network lifespan [6]. In resolving some of these challenges, clustering has been demonstrated to be an efficient technique in terms of energy conservation, thereby boosting network lifetime. Implementing the cluster head creation and selection has enhanced the dependability and network life expectancy of WSNs [7]. Furthermore, nodes within its transmission range can get the code, but in practice, this approach uses a lot of energy from nodes and eventually reducing the network longevity. As a result, most networks do not always keep nodes active to preserve energy. Therefore, justifying the need to adopt a duty cycle based Wireless Senor Neworks [8].

The duty cycle is one of the most extensively employed energy-saving mechanisms in WSN, particularly at the medium access control (MAC) layer. Because the active duration is longer and more energy is spent when the MAC works at a high duty cycle, the duty cycle must be adjusted to match the MAC's strength to ensure appropriate data transmission while avoiding battery depletion [9]. In the same way, using the sensor node's duty cycle mode is an efficient technique to increase energy efficiency. Here, the nodes in the duty cycle mode wake up and sleep at regular intervals. The wireless receiving device is turned off while the node is in sleep mode, saving energy [10]. Because awake-state energy consumption is more than two orders of magnitude higher than sleep-state energy consumption, nodes are kept in the sleep state as much as possible to conserve energy [11]. Clustering is a hierarchical strategy initially employed in cellular networks, where mobile phones interface with fixed infrastructures to facilitate data flow [12]. The strategy allows bandwidth to be reused to increase system capacity and makes the network more stable when nodes move around [13]. The clustering approach in a WSN environment has the positive potentials to improve network performance by grouping nodes into clusters and assigning a leader to each cluster known as a cluster head (CH) [14]. In this kind of setup, cluster nodes transmit their data to the CH, aggregating it and sending it to the base station (BS) directly or through a multihop routing. Unfortunately, in a multihop routing, CHs closer to the BS are exposed to a high intercluster relay traffic load which exhausts their energy faster than other CH nodes [15, 16].

In an attempt to contribute to this domain of knowledge, a Hybrid Seagull Mayfly Optimization for Duty Cycle (HSMO-DC) was proposed for improved clustering. The first section of the proposed method focuses on selecting a cluster head and coordinating network interactions using the Seagull Optimization Algorithm (SOA). Next is the Mayfly Optimization Algorithm (MOA) used in the second phase to optimize critical parameters in SOA. The findings indicate that the hybridization of SOA with MOA into HSMO can enhance network performance and extend network lifespan in practically all network circumstances. In addition, our simulation shows that the proposed HSMO-DC is adaptable and works well over various network lifespan specifications. The main contribution of this study is the ability to hybridize SOA and MOA into unified novel algorithm to improve the energy lifespan of a network.

Finally, the organizations of this study are discussed in detail in subsequent parts. Section 2 discusses the findings and analysis of relevant existing work of the suggested model, outlined below. The recommended technique of the work is given in Section 3, and the work is experimented with and analyzed. The result analysis and comparative discussion of the study are covered in Section 4. The work's conclusion is shown in Section 5.

2. Literature Review

In this section, the existing method of the related work and their analysis is evaluated and described as follows. Now, in domain of wireless technologies, sensors and actuator nodes are installed to increase their battery lifetime. However, to achieve this objective, many recent methods have been developed to reduce battery consumption [17]. For instance, in the study of Draz et al., a Data Packet Forwarding Algorithm (DFPA) and Watchman Layer Update Mechanism (WLUM) were implemented [18] in WSNs to maintain energy efficiently. Also, Ramadan et al. presented a method of placing multisink nodes close to fog nodes that can save energy and facilitate coherent data transfer between WSNs and fog networks [19]. However, the crucial concerns of WSNs face are lowering energy usage and increasing network longevity. To support with this concern, High-Quality Clustering Algorithm (HQCA) is found as one of the most effective techniques for reducing energy consumption in WSNs. In the study of Baradaran and Navi, an HQCA was used to construct high-quality clusters. The HQCA approach employs a criterion for assessing cluster quality, which can enhance intercluster and intracluster distances while also lowering clustering error rates. The best cluster head (CH) is chosen using fuzzy logic and a variety of factors, including residual energy, minimum and maximum energy in each cluster, and minimum and maximum distances between cluster nodes and the base station [20]. The primary advantages of this approach are the high dependability, low error rate during the clustering process, independence of critical CHs, greater scalability, and exemplary performance in large-scale networks with a large number of nodes. Gaber et al. also introduced the external and internal criterion used to assess the validity of the clustering quality [21]. Another existing methodology to reduce energy consumption and increase the lifetime is the study of Han et al. which used the metaheuristic technique to create a clustering protocol (CPMA). The network lifespan is the primary factor in CPMA, which is divided into two components. The first section focuses on selecting a cluster head online and coordinating network interactions. The Harmony Search (HS) Algorithm was used to make the decision to decrease overall energy dissipation and smooth energy distribution across the network [22].

Several contradictory variables influence clustering efficiency, and to rectify this, Prince and Pragya presented a method that enables the nodes to work together to self-select the best CHs. To identify the optimal set of CHs from the various options that may efficiently meet the coordination criterion, several attribute decision-making approaches are applied [23]. However, to solve the drawbacks of some existing method of clustering, Kotary and Nanda used a moth flame optimization approach that minimizes the intracluster distance. The optimal moth position and accompanying fitness value (intracluster distance) are shared with surrounding nodes using a diffusion technique of cooperation [24]. Moreover, in solving the energy lifetime problems, Xu et al. presented a distributed energy region algorithm ER-SR to dynamically pick nodes in the network with the highest residual energy as source routing nodes [25]. As from early methods to reduce energy consumption through selecting the best CH, Dattatraya and Rao also presented Glowworm swarm with Fruit Fly Algorithm (FGF), which is the hybridization of Glowworm Swarm Optimization (GSO) and Fruit Fly Optimization Algorithm (FFOA) that helps to choose the best CH in WSNs [26].

More recently, there has been some good contribution to knowledge with the inclusion of additional power mode: thus deep sleep and hibernation mode. In the study of [27], a WSN for monitoring environment was implemented using the Selective Surface Activation Induced by Laser (SSAIL) technology. The study reveals distinct features and power capabilities of active mode, modem sleep mode, light sleep mode, deep sleep mode, and hibernation mode. In their observation, it was concluded that the deep sleep mode uses the least amount of energy making it the most preferred for Wi-Fi modules. Finally, the field of knowledge is the consideration of deep learning approaches to improve duty cycles as demonstrated in the study of [28]. In their study, a bidirectional long short-term memory model was proposed to predict future expected events while allocating the predictive sensors to the predicted event. However, to optimize the performance of the scheme to track missed and undetected events, the Q-learning algorithm was employed with promising results compared to conventional ML algorithms.

3. Research Methodology

3.1. Hybrid Seagull Mayfly Optimization for Duty Cycle (HSMO-DC) Protocol. A major complication in wireless sensor networks (WSNs) is congestion-free routing to minimize latency. Here, duty cycle management is becoming an essential process, where all the nodes are active, sleep, and preactive. In WSN, the member nodes only receive data when in the active state. The proposed HSMO-DC algorithm is developed to deal with duty cycle management for effective scheduling in terms of coverage and power. The HSMO-DC helps to form dynamic clustering in a WSN environment where all the sensors are deployed randomly. After the random deployment of nodes, the cluster head (CH) selection is determined to transfer data to the base station [16]. The HSMO-DC optimization algorithm is executed to select the active nodes in the network, and the rest of the nodes go to the sleep state. Moreover, the active and sleep nodes are determined by measuring the QoS value, such as node ID, bandwidth, and residual energy. In cases where the minimum energy of the active node is about to deplete completely, the sleep node gets awake ahead of time to ensure connectivity. Figure 1 shows the overview of the proposed model.

From Figure 1, the HSMO-DC algorithm forms a cluster with a corresponding cluster head by analyzing the QoS parameters of each node. The proposed model mainly relies on effectively managing the sensor network's lifespan by controlling energy consumption. The proposed model comprises four scenarios, i.e., base station at the top, bottom, left, and right. Figure 2 shows the left side scenario with left side cluster formation.

3.1.1. Information Exchange. In WSN, the entire nodes broadcast a QOS message, which is maintained in the Q-table. The N_i indicates each node, and its neighbor node is denoted as $NE(N_i)$, and this relative information is stored in the Q-table. The capability of the node (CoN) is determined using the following equation:

$$F_0 = \mathrm{CoN}_i = \sum_{N_j \in NE(N_i)} j. \tag{1}$$

Each node's CoN is analyzed with the delay time (D_T) which is evaluated with Eq. (2), where C and e are constant and exponential values, respectively.

$$D_T = Ce^{1/ND}. \tag{2}$$

D_T is the shortest node with the highest node degree [29]. In this study, the degree refers to the node with the maximum number of edges on the network. When the delay timer runs out, the node will send a message announcing itself as the cluster head, but if two nodes have the same latency, the node with the highest residual energy and sensing range is assumed to be the cluster head. The node's residual energy R_E can be formulated as

$$F_2 = R_E = I_n - (E_t + E_r), \tag{3}$$

where I_n, E_t, and E_r represents the node's initial energy, the energy used for transmission, and the energy used for reception, respectively. Apart from the initial energy, the transmission and reception energy are computed heuristically in the network. In subsequent sections of this study, CoN, D_T, and R_E will denote the bandwidth, delay, and residual energy, respectively.

(1) Formation of Cluster Head. CoN, ID, D_T, and R_E are the major parameters of the cluster activation message (CAM) to build the cluster. The node with maximum bandwidth, max residual energy, and minimum delay (QoS) is considered as the metric for the development of CH. The CAM will be transferred to all the neighbor nodes or cluster members (CM) to join the cluster. The CAM mainly helps to make the CM join into the specific cluster. As discussed earlier, the residual energy R_E, which always maintains a higher value for reliable nodes, will reduced to a certain level if the dynamic cluster formation (DCF) is executed. The DCF helps to appoint new cluster heads and clusters dynamically. Moreover, because the cluster head must span the whole network, DCF seeks to select the smallest number of nodes with the most neighbors. This contributes to the network's longevity as shown in Figure 3 with the left scenario data transmission in the CH (in yellow color) formation.

3.1.2. Convergence-Based Minimal Active Node Selection. The HSMO-DC approach is to find the most miniature set of active nodes in the clusters. Initially, the fitness feature $\mathrm{Fit}_f = \{\mathrm{CoN}_i, D_T, \text{and}\ R_E\}$ for every node's N_i is resilient and satisfying the neighboring node $NE(N_i)$ and the convergence condition defined in

$$\begin{aligned} NE(N_i) = \{ N_j \mid R_i + d(i,j) \le R_j, d(i,j) \\ \le R_j \ \text{AND}\ (R_i - R_j) \le d(i,j) \}, \end{aligned} \tag{4}$$

where N_i represents the source node, the N_j represents the destination node, the sensing range of N_i can be defined as R_i, and then N_j's sensing range is denoted as R_j. Specifically, the sensing range of R_i and R_j must be less than or equal to the distance between N_i and N_j. Considering this condition, the possibility of awake node redundancy can be reduced, and the prolonged sensor node's lifetime can be increased. Moreover, the weighted probability is a significant parameter

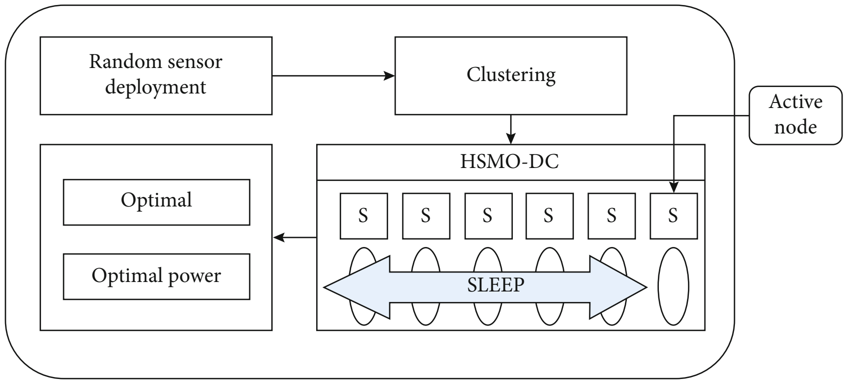

Figure 1: The proposed model.

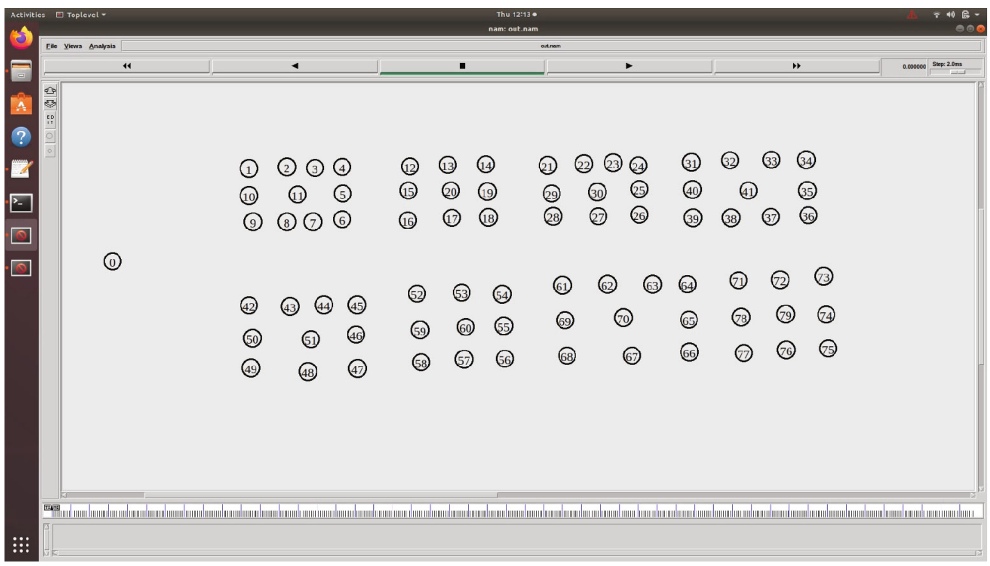

Figure 2: Illustration of the left scenario-based prestage cluster formation.

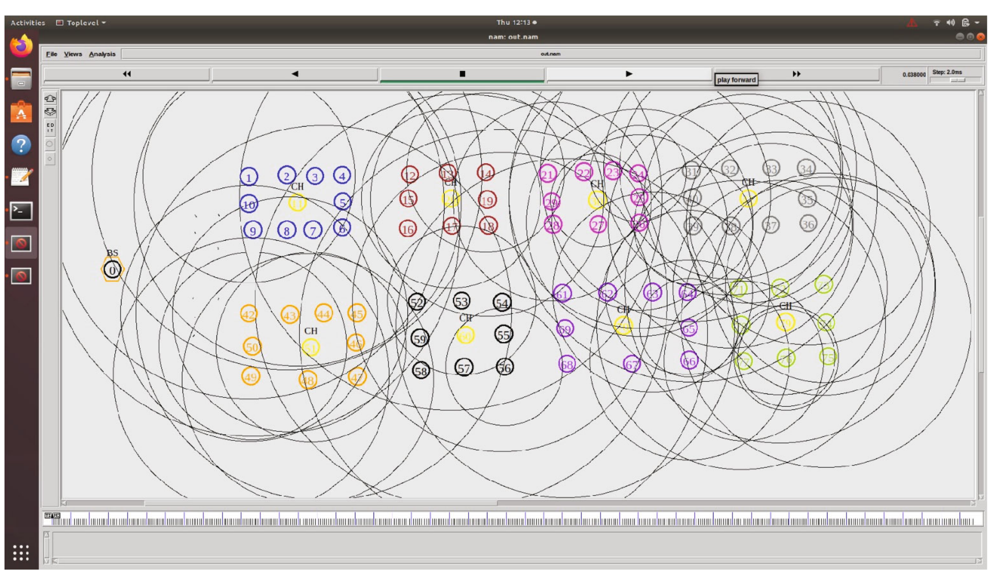

Figure 3: Data transmission with cluster head formation.

for selecting an environment's active node. The weighted probability in Eq. (5) can be represented as w_p, which is to be considered in selecting a number of active nodes.

$$w_p = \frac{\text{fit}_f}{\sum \text{fit}_f}. \tag{5}$$

The active nodes are selected using the HSMO-DC algorithm for duty cycle management, initially based on the MF's gravity coefficient-based SOA. The exploration or migration strategy is considered when assigning the nodes, and this comes in three steps: collision avoidance, use of neighbor information, and best position. The collision avoidance strategy is incorporated for the optimal placement of nodes into a network environment which is achieved with the seagull-based optimal node deployment in

$$\overrightarrow{\text{Co}}_{\text{Node}} = \text{Ad} \times \overrightarrow{\text{Pos}}_{\text{Node}}(i), \tag{6}$$

where the $\overrightarrow{\text{Co}}_{\text{Node}}$ denotes the collision-free node allocation based on the node's current position and $\overrightarrow{\text{Pos}}_{\text{Node}}(i)$ is determined by incorporating the additional variable of the seagull "Ad" defined in Eq. (7). Moreover, "Ad" represents the movements of the nodes in the WSN environment or problem space. In addition, the "i" denotes the iteration in 0 to $\text{Max}(i)$ range.

$$\text{Ad} = f_c - \left(i \times \left(\frac{f_c}{\text{Max}(i)}\right)\right), \tag{7}$$

where f_c is the variable to control the frequency of the Ad in the interval $[0, f_c]$. Figure 4 shows the minimal active node selection.

3.1.3. Collect Neighbor's Data with Gravity Coefficient. This strategy helps to move the node towards the best neighbor as shown in

$$\vec{d}_e = g_c \times \left(\overrightarrow{\text{Pos}}_{b\text{node}}(i) - \overrightarrow{\text{Pos}}_{\text{Node}}(i)\right), \tag{8}$$

where $\vec{d}_e$ determines the current position of the $\overrightarrow{\text{Pos}}_{\text{Node}}(i)$ towards the current best node $\overrightarrow{\text{Pos}}_{b\text{node}}(i)$. The strategy of seagull is improved by incorporating the mayfly, specifically the gravity coefficient in range (0,1). Therefore, the balance between exploration and exploitation can be assured. Mathematically, the determination of the gravity coefficient is defined as

$$g_c = g_{\max} - \frac{g_{\max} - g_{\min}}{\text{Max}(i)} \times i, \tag{9}$$

where the $g_{\max}$ and $g_{\min}$ denote the maximum and minimum values, respectively. Likewise, the i and $\text{Max}(i)$ represent the current and maximum iterations, respectively.

3.1.4. Nodes Move towards the Best Solution. The nodes in the network update their position by determining the best solution based on the QoS value. At last, by analyzing collision-free node, the $\overrightarrow{\text{Co}}_{\text{Node}}$ and $\vec{d}_e$ are considered in updating the best position of the nodes. The $\vec{D}_e$ to determine the best new position is shown in

$$\vec{D}_e = \left\| \overrightarrow{\text{Co}}_{\text{Node}} + \vec{d}_e \right\|. \tag{10}$$

(1) Exploitation. In the exploitation phase, three parameters are considered, thus x, y, and z planes. Mathematically, these parameters are formulated in

$$x = r \times \cos(t), \tag{11}$$

$$y = r \times \sin(t), \tag{12}$$

$$z = r \times t. \tag{13}$$

The independent variable "t" is a random value defined between 0 and 2π while r denotes the spiral turn radius defined by

$$r = a \times e^{\beta t}, \tag{14}$$

where again the e represents the natural logarithm and a and β denote the shape of the spiral. Using Eqs. (10)–(13), the new position is updated with

$$\overrightarrow{\text{Pos}}_{\text{Node}}(i) = \left(\vec{D}_e \times x \times y \times z\right) + \overrightarrow{\text{Pos}}_{b\text{node}}(i). \tag{15}$$

At last, active nodes are determined, and data transmission is processed. Therefore, the active node will transmit the beacon message to all active neighbors and the cluster head. Most other nodes, except the active ones, are put to sleep. This is frequently used to minimize energy consumption. However, to prevent node failure, the sleep node must be set to wake up at a specific time.

3.1.5. Time Aware Sleep Node Scheduling. By tracking charge-discharge value with residual energy, node scheduling and putting extra sensor nodes to sleep are possible. If the battery is discharged, the neighboring sleep node wakes up before the active node sleeps. This results in lower energy consumption and a longer lifespan. Sleep, preactive, and active states exist in each node. In the sleep state, the node sleeps and uses very little energy. A node in the preactive state to the nearest active nodes will broadcast a beacon message while the active nodes continue to monitor their surroundings. The node enters the preactive state after waking up from its sleep state. The node will broadcast a hello message with a timer while in the preactive state. Active nodes within the sensing range send the reply message. Suppose the node receives the reply message with a sleep timer S_{time} before the timer expires, the node returns to sleep from preactive. The node enters the preactive state after S_{time} expires

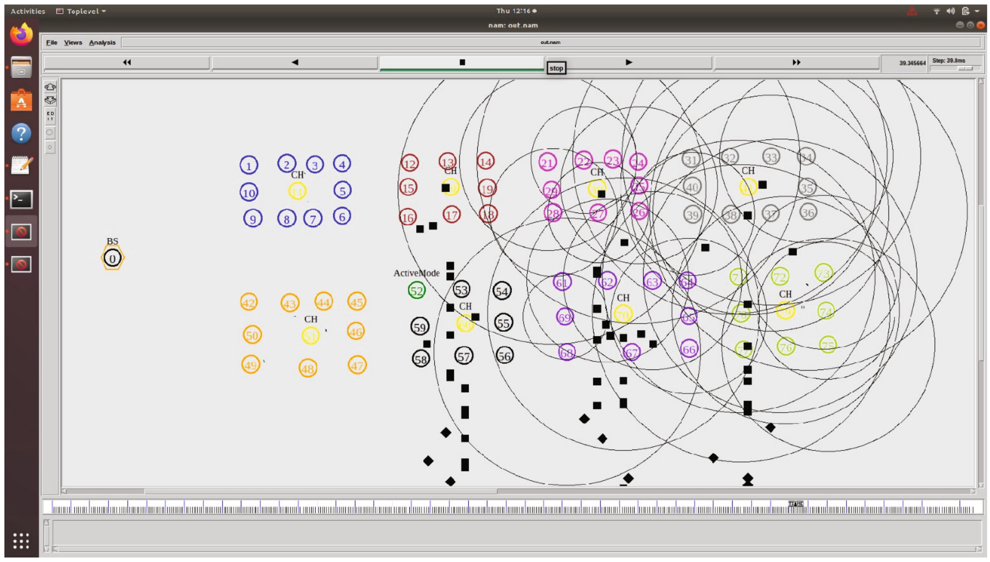

Figure 4: Minimal active node selection.

again and sends the hello message to the nearest active nodes. If the preactive node does not receive a response message before the timer expires, it becomes active and senses the physical environment. S_{time} is calculated by mapping residual energy to the active node's battery discharge value [30]. In this study, Eq. (16) is used to calculate the battery voltage VOL_r with reference to residual energy:

$$VOL_r = (VOL_{max} - VOL_{min}) \times \left(\frac{h\%}{100}\right) VOL_{min}, \quad (16)$$

where VOL_{min} is the minimum operating voltage (0.9 V), VOL_{max} is the maximum operating voltage (1.4 V), and $h\%$ is the percentage of node's residual energy.

In applying the polynomial regression to the battery discharge value, S_{time} can be calculated from VOL_r using

$$S_{time} = a_1 + a_2 VOL_r + a_3 VOL_r^2 + a_4 VOL_r^3 + a_5 VOL_r^4 + a_6 VOL_r^5, \quad (17)$$

where a_1, a_2, a_3, a_4, a_5, and a_6 are the polynomial coefficients.

After S_{time}, the sleeping node should wake up earlier, before the active neighbor node's energy is completely depleted. The sleep node will awake within a certain period to reduce unnecessary wake ups. As a result, less energy is consumed, and the network's life expectancy is increased.

3.1.6. Optimal Connectivity Management. The goal of connectivity is to connect the nodes to meet the BS. To avoid data transfer disconnection, the nodes must be attached. To ensure connectivity, each active node (AN_i) sends a beacon message to all active nodes with three different transmission power levels (TPL). The TPL is maintained in the Q-table by all active nodes. The HSMO-DC algorithm evaluates each node based on the beacon message by extracting and verifying the node ID from the Q-table. In effect, the Q-table maintains in addition to the node ID, transmission power level (TPL), and R_E. If a receiver sends all three connection reply messages (CREP) of the same active node, it sends a CREP with the lowest TPL possible. If the sender has not received any CREP for a given time, it modifies the TPL value following Eq. (18) with TPL_3' being the older value of TPL_1.

$$TPL_1 = TPL_3' + 1, \quad (18)$$

where $TPL_3 = TPL_2 + 1$ and $TPL_2 = TPL_1 + 1$.

The CREP is again broadcast with a modified TPL by the requesting node. The HSMO-DC algorithm evaluates all the nodes. The discussed steps are reiterated until all nodes are linked with the lowest possible TPL. As a result, connectivity is guaranteed with minimal transmission power and secured with a low TPL while extending the network's lifetime. The coverage and connectivity are both of excellent quality. However, the lack of high-level coverage and connectivity is a serious problem. In this study, coverage with connectivity is supplied by optimal connectivity management, which spreads the network lifetime while using the least amount of transmission power possible. The overall flow of the proposed model is shown in Figure 5.

4. Result and Discussion

This section contains the results and discussions of the proposed and implemented methods for a hybrid metaheuristic approach to manage the network lifetime by providing an effective duty cycle-based method. The performance of the proposed HSMO-DC is evaluated and compared to current methods (in this study, it is CCBS). In addition, the

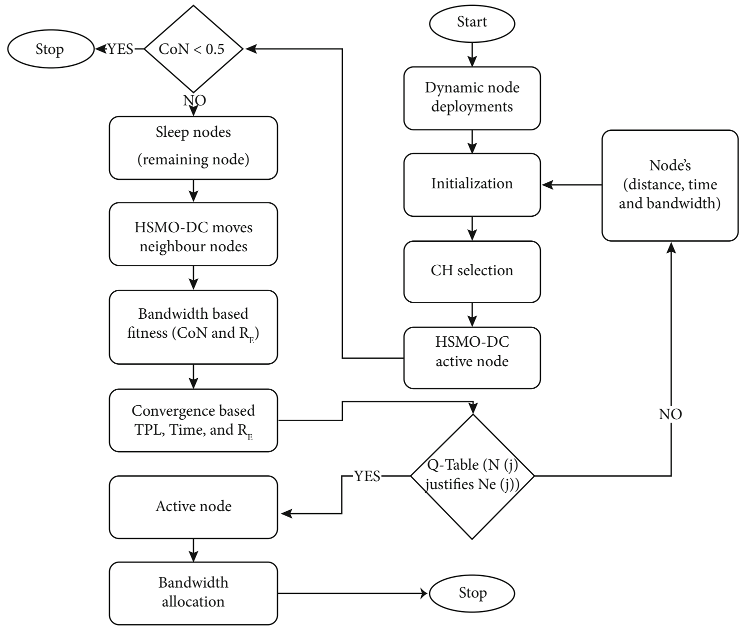

Figure 5: Flow chart of the proposed model.

implementation is done through NS2 stimulation. Standard metrics such Delay, Delratio, Energy, NLT, and Throughput values are computed and compared to CCBS method. These metrics are computed with Eqs. (19)–(23).

Delay. This is a dimensionless metric in a time-constrained WSN environment, and it is a crucial parameter for data forwarding.

$$\text{Delay} = \frac{\text{total produced time gap}}{\text{simulation time}}. \tag{19}$$

Delratio. It is the ratio of total packets delivered to total packets sent from the source node to the destination base station. This is also dimensionless.

$$\text{DR} = \frac{P_{\text{Received}} * 100}{\sum_{i=1}^{n} P_{\text{generated}\, i}}. \tag{20}$$

Energy. WSN nodes are small devices that run on batteries. As a result, an energy-efficient data aggregation strategy that maximizes network lifetime is critically defined in Eq. (21) with no dimension.

$$e = \frac{\sum_i^m E_{\text{consumed}}^i}{m\, E_{\text{initial}}}. \tag{21}$$

NLT. A key performance parameter in WSNs is network lifetime and is defined as the amount of time until the first sensor's energy runs out. This is measured in seconds.

$$\text{NLT} = \frac{E}{\left(1 - n_f\right)\left(r_1\left(\left(R\sqrt{1} - n_f\right)\right) + r_2\right.}. \tag{22}$$

Throughput. The number of packets per second received at the destination is measured by end-to-end network throughput. This is measured as bit/sec in this study.

$$\text{Throughput} = \frac{\text{total transferred bits}}{\text{simulation time}}. \tag{23}$$

The proposed and existing performance measures are captured in Figures 6–10.

Table 1 shows Delay, Delratio, Energy, NLT, and Throughput generated from nodes 20, 40, 60, and 80, respectively. It is observed from the table that, the proposed HSMO-DC, in terms of all the metric, however the proposed method is only efficient for larger sensor node. This, in essence, is not a drawback of the proposed method, as networks of this kind are deployed in quantity, rendering the proposed approach well-suited for practical applications. To give a better context to the values in Table 1, we have Figures 6–10.

In Figure 6, we have a graph of the delay metric comparing the proposed approach with the existing scheme based on the number of nodes. From the graph, our proposed method remains competitive to the existing system except for node 20 with a slight cooperation with the excising system. From this observation, one can conclude that the proposed method achieved lesser delay compared to the existing approach. In both cases, as the number of nodes increases, the delay is also increased.

A similar observation is noted for Figure 7 displaying the Delratio performance comparison of the proposed approach with the existing scheme based on the number of nodes. Again, the proposed method recorded a poor performance of 0.964434 at 20 nodes while the existing approach achieves 0.926988. However, after 25 nodes, the proposed method

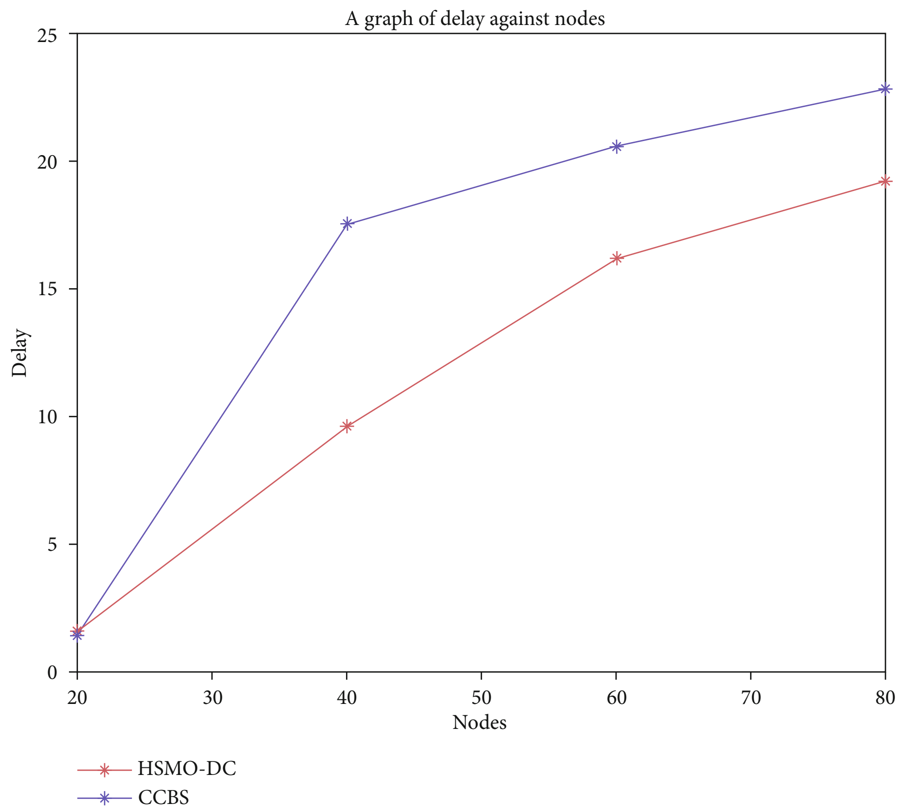

Figure 6: Delay plot for proposed and existing method.

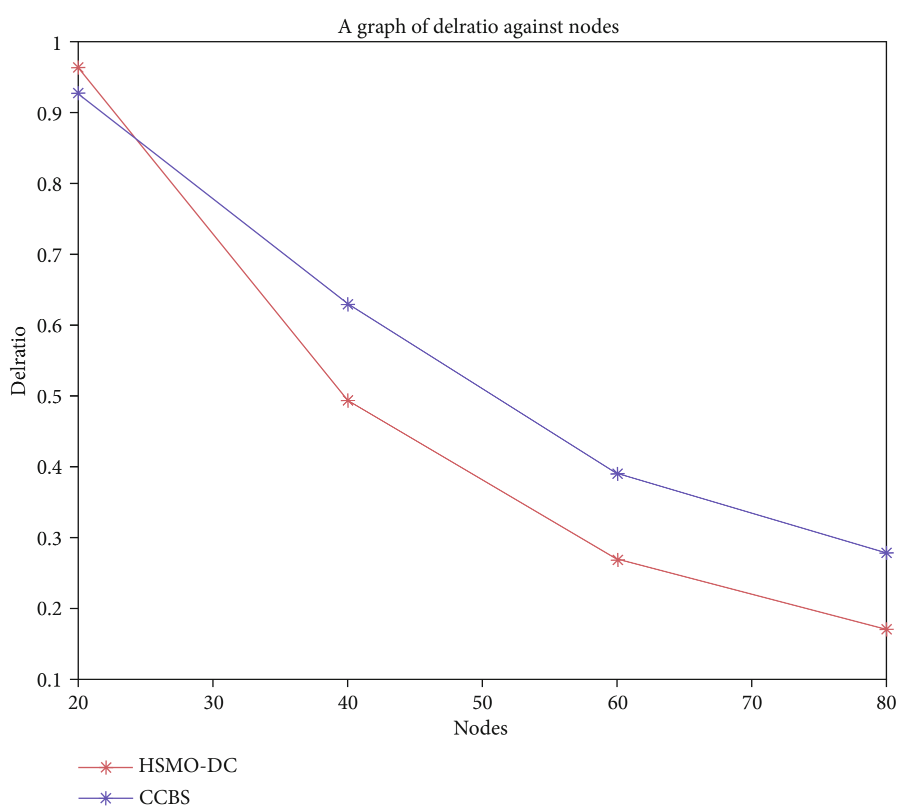

Figure 7: Delratio plot for proposed and existing method.

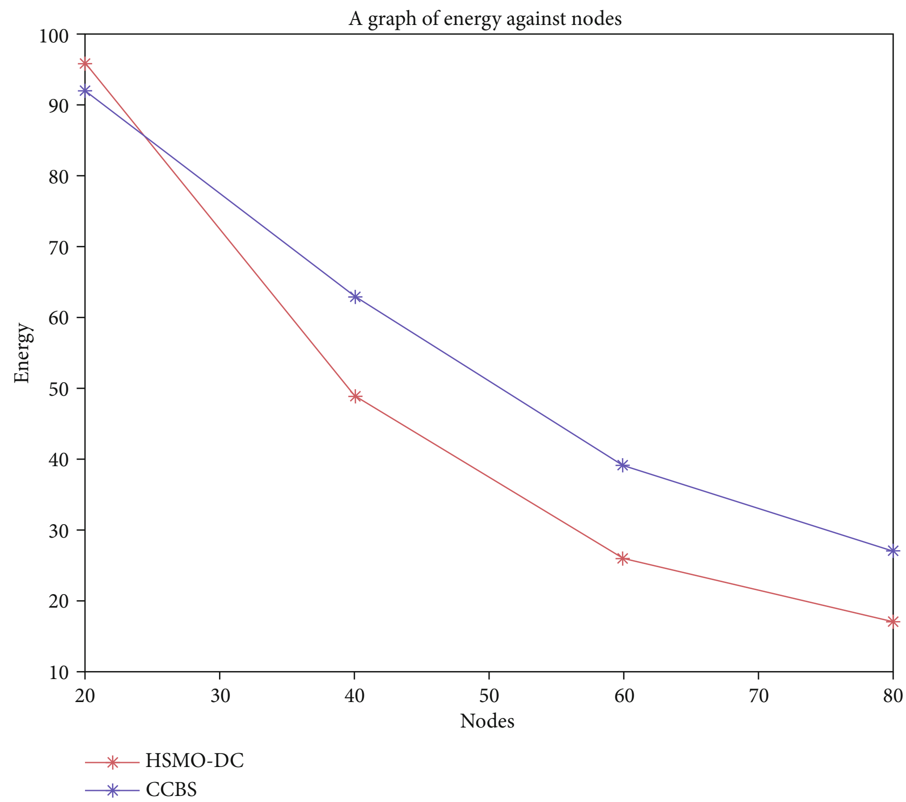

Figure 8: Energy plot for a proposed and existing method.

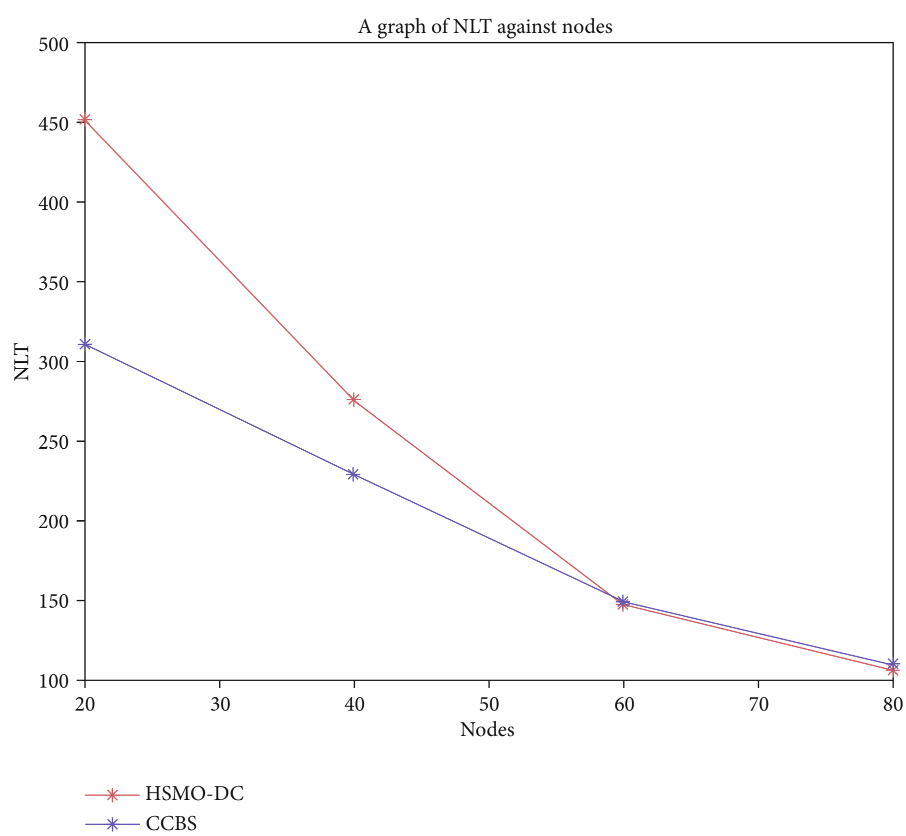

Figure 9: NLT plot for proposed and existing methods.

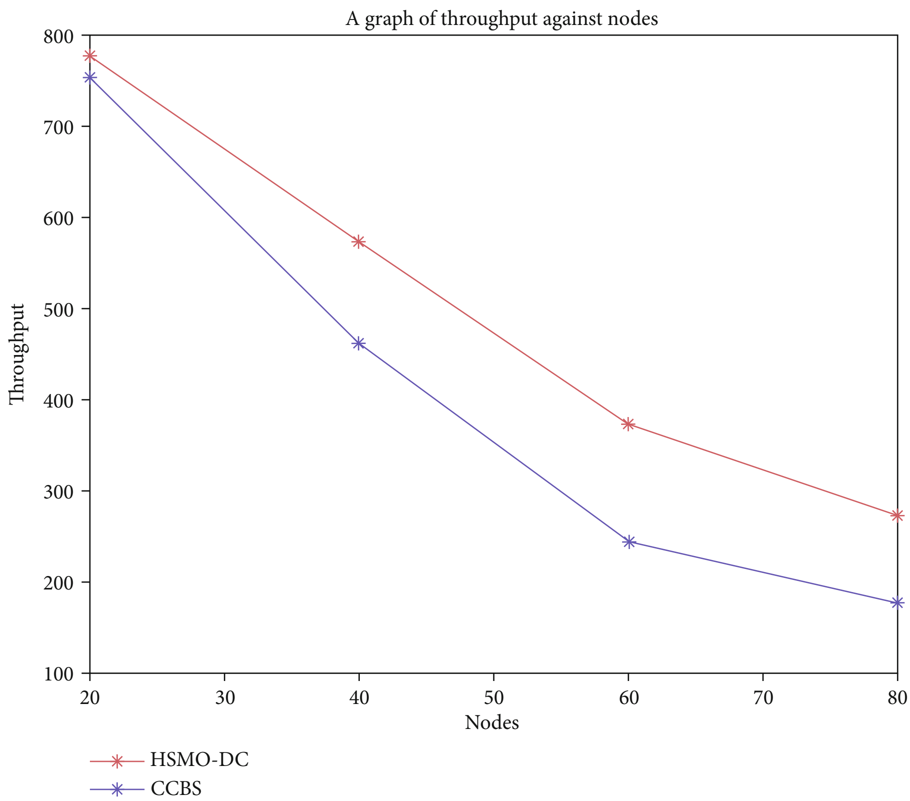

Figure 10: Throughput plot for proposed and existing method.

Table 1: Comparison of experimental results of proposed method with existing method (CCBS).

Node	Delay	Delratio	Energy	NLT	Throughput
The proposed method (HSMO-DC)					
20	1.543259	0.964434	96	452	777.650000
40	9.614474	0.494258	49	276	573.475000
60	16.197291	0.269553	26	147	373.116667
80	19.236650	0.171237	17	106	273.775000
Existing method (CCBS)					
20	1.444667	0.926988	92	311	753.850000
40	17.539263	0.630955	63	229	461.575000
60	20.612230	0.390439	39	149	245.500000
80	22.859480	0.278740	27	109	177.637500

regains its capability, demonstrating good performance over the existing method and affirming the robustness of the proposed approach. Despite this observation, one cannot be fully convinced of the performance of the proposed model without observing the other metrics in Figures 8–10.

Without the deliberate effort in repeating the same observation of Figure 7 into Figure 8, discussion on Figure 8 is skipped while focusing on an interesting observation noted in Figure 9.

Surprisingly, from Figure 9 showing the NLT performance comparison of the proposed approach with the existing scheme based on the number of nodes, an inverse observation was noted. From the graph, our proposed method rather did very well at node 20 to a little above node 50 with a close linear competing performance from node 60 and above. Despite the appreciable marginal performance of the existing system, it will be wrong for one to quickly conclude on a single metric with no prejudice to other relevant metrics. This slight difference is largely compensated for by the other four metrics which is mostly ignored in most studies that only reports on duty cycle longevity.

Finally, we have Figure 10 showing the throughput performance of the proposed approach based on the number of nodes. As has been the trend of observation, the proposed methodology in this case remains adept right from the minimum node of 20 and widening performance range till the maximum node of 80.

5. Conclusion

In this study, we proposed a Hybrid Seagull Mayfly Optimization for Duty Cycle (HSMO-DC) to reduce the total energy dissipation and improve smooth energy distribution across a wireless senor network. The incorporation of the Mayfly Optimization Algorithm (MOA) played the role of parameter optimization. The results show that the hybridization of SOA with MOA can improve network throughput and network lifetime under almost all network conditions over the benchmark algorithm thus CCBS with a good margin in most cases. All the results show that HSMO-DC is suitable and efficient for a wide range of WSN applications despite the competitive tire with the NLT metric as the node grows larger. In future studies, this study seeks to explore how to hybridize other swarm intelligence algorithms to further improve performance and also review their theoretical benefit in this domain of research.

Acronyms

AN: Active nodes
BS: Base station
CAM: Cluster activation message
CH: Cluster head
CM: Cluster members
CoN: Capability of the node
CPU: Central processing unit
CREP: Connection reply messages
DCF: Dynamic cluster formation
DFPA: Data Packet Forwarding Algorithm
FFOA: Fruit Fly Optimization Algorithm
FGF: Fruit Fly Algorithm
GSO: Glowworm Swarm Optimization
HQCA: High-Quality Clustering Algorithm
HS: Harmony Search
HSMO: Hybrid Seagull Mayfly Optimization
HSMO-DC: Hybrid Seagull Mayfly Optimization for Duty Cycle
MAC: Medium access control
MOA: Mayfly Optimization Algorithm
NLT: Network lifetime
QoS: Quality of service
SOA: Seagull Optimization Algorithm
TPL: Transmission power levels
WLUM: Watchman Layer Update Mechanism
WSNs: Wireless sensor networks.

Data Availability

No data was used for this study.

Conflicts of Interest

There is no conflict of interest among the authors.

Authors' Contributions

Kwabena Ansah was involved in conceptualization, data curation, investigation, methodology, and validation. Justice Kwame Appati was involved in formal analysis, supervision, investigation, and methodology. Ebenezer Owusu was involved in conceptualization, supervision, and validation. Jamal-Deen Abdulai was involved in formal analysis and supervision.

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