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DAAG-SNP: Energy Efficient Distance and Angulation-Based Agglomerative Clustering for Sink Node Placement

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ABSTRACT Wireless Body Area Networks (WBANs) have significantly enhanced various aspects of human life, particularly in healthcare, fitness, entertainment, sports, and etc. In WBANs, the sensor nodes are placed in and around the body along with the sink node, which collects the physiological data from these sensors and forwards it for further processing. The placement of the sink node is one of the critical aspects in the design of WABNs as it affects both the energy efficiency and connectivity. To this end, this paper introduces a hybrid method called Distance and Angulation based AGglomerative Clustering (DAAG). DAAG, initially clusters the WBAN sensors using Distance and Angulation based k-Mean clustering. Afterward, Agglomerative Clustering is applied to determine the optimal placement of the sink node. The results of DAAG are compared with various machine learning and optimization approaches, including D-RMS (Distance based Random mean shift clustering), Reinforcement Q-Learning Approach (QL), Humpback Whale optimization (HWOA), Multi-Angulation (MA) and Closeness Centrality (CC). Given an initial energy, the results show that the DAAG exhibits superior performance in terms of latency, packet error rate (PER), and energy consumption. DAAG shows an energy consumption of only 1.51% outperforming QL, HWOA, MA, CC, and D-RMS along with an improved localization accuracy of 0.36 m.

INDEX TERMS WBAN, sink node placement, energy efficiency, optimization, machine learning, clustering, multiangulation, mean shift, Humpback Whale, Q-learning, packet error rate.

I. INTRODUCTION

WBAN comprises of sensor nodes that are placed in and/or around body to operate autonomously for collecting physiological data [1]. These sensors then transmit the data to a sink node, placed on the body, which collects and relays the information through gateways for health monitoring and medical study. WBAN architecture as shown in Figure 1 using a three-tier design, which includes Tier-1 for intra-BAN connections, Tier-II for inter-BAN connections, and Tier-III for connections outside of the BAN. The placement of sink node is one of the key challenges in WBAN as it directly influence network performance, in terms of latency, PER, network life time, and energy efficiency [2], [3], [4]. To improve network performance, various techniques have been proposed in the existing literature such as Particle Swarm Optimization (PSO) [5], Genetic Algorithm (GA), Q-learning [6], Ant Colony Optimization [7], Artificial Bee Colony Optimization [8], Hybrid PSO-GA [9], PSOBAN [10], Cuckoo Search [11], Grasshopper and DV-Hop [12], Opportunistic Energy-Efficient Routing with Load Balancing (OE2-LB) algorithm [13], and Optimized Cost-Effective and Energy-Efficient Routing Protocol (OCER) [14] to

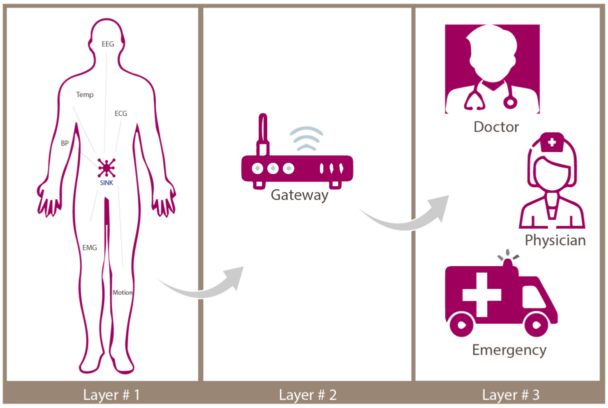

FIGURE 1. WBAN Architecture.

optimize sink node placement. The metaheuristic algorithms PSO, GA, Ant Colony Optimization, and Artificial Bee Colony Optimization have been adapted and applied to WBAN scenarios to optimize energy consumption, routing efficiency, and network lifetime. For example, the authors in [15] explored a comprehensive data routing approach that integrates a cluster routing protocol with a multi-objective particle swarm optimization (MO-PSO) based sink node placement. The suggested method uses a particle structure with three variables, the first two of which give the sink coordinates and the third of which specifies the cluster head node. The fitness of MO-PSO particles is estimated using a multi-objective fitness evaluation operator using the average bit error rate (BER) and network energy consumption recorded during a single data transmission loop. The created model develops into an ideal sink site that simultaneously reduces average BER and network energy consumption. Moreover, a lower BER results in a significant boost to the network throughput rate. Authors in [11] applied cuckoo search model that uses a fitness function to place the sink node. Table 1 shows related work on sink node placement. Distance-based, position & angle aware techniques have also been investigated to enhance the accuracy and efficiency of data transmission within WBANs [18], [19]. For example, in [20], the placement of the sink node on the body involves three distinct positions: waist (Location 1), upper limb (Location 2), and head (Location 3). This decision is motivated by the observation that the human legs frequently alter posture, leading to the choice of placing the central node on the head instead of the lower leg. The authors [21] explored an angle-based sink node placement. The positions of nodes are estimated based on the geometry of the network and the angles between nodes. The sink node's position is estimated by finding the intersection points of spheres created by the sensor nodes. In [22], authors examine the performance of three approaches, i.e.; Ad Hoc on-demand Distance vector, Ad Hoc on-demand Multi-path Distance vector, and Destination sequence distance vector for different mobility models where the sink is placed at a fixed position. Multi-path destination distance outperforms in terms of end-to-end delay, energy, and throughput. A novel 3D localization algorithm for Social Network Analysis (SNA) is introduced in [23], which focus on the concept of Closeness Centrality to form clusters and perform trilateration for accurate node localization.

Most of the earlier research in WBAN primarily focuses on either adopting a meta-heuristic model or some form of distance metric. Generally, the presence of a single sink node is both the scenarios often lead to performance trade offs. Since one of the main objectives in WBANs is to extend the network lifespan by effectively utilizing node batteries, we employ two additional cluster head sinks for the upper and lower body to balance the load on the sink node. Only nodes from the same cluster submit their sensed data and other information to the Cluster Head sink (CH-sink). The motivations behind using the two cluster head sinks are:

- When all sensor nodes submit data at the same time, there are increased chances of congestion occurring at the sink node.

- WBAN partially fails if just one of the CH-sink nodes goes down and completely fails if the main sink node goes down.

- More sensor nodes are needed for maximum body coverage, and if a clustering technique is utilized, it may burden a single sink node.

- When multiple sensor nodes communicate data at once, the performance at the sink node is compromised, resulting in a low delivery ratio.

To evaluate the presence of multiple CH-sinks in the WBAN design and ensure adequate coverage and connectivity within the network, We propose

- A novel Distance and Angulation based AGglomerative Clustering (DAAG) approach for efficient sink node placement that exploits the presence of two CH-sinks for sink node placement. This approach utilizes, angulation, distance metrics, and clustering to first create multiple clusters. The selection of two CH-sinks are carried out using AGglomerative clustering.
- Multiple distance and machine learning techniques for comparison. This include Distance-based Random Mean Shift Algorithm (D-RMS), Humpback Whale Optimization Algorithm (HWOA), Closeness centrality (CC) and Q-learning (QL) for a single sink node placement.
- The results of all these schemes are analyzed in terms of energy efficiency, residual energy, latency, PER and Mean localization error.

Definitions for commonly used abbreviations and acronym are provided in Table 2. This research article is organized as follows: In Section II, we explain our proposed technique, the Energy-efficient Distance and Angulation based Agglomerative clustering (DAAG), presenting its system model and comparative analysis with distance and angle based traditional algorithms. Section III presents the results and Analysis section. Finally, Section IV presents the conclusions drawn from the study.

TABLE 1. Related work analysis.

References	Methods	Performance Metrics
[12] (2022)	Grasshopper and DV-HOP algorithm was proposed for node localization	Localization error
[16] (2020)	The optimal central node location is determined through analysis of the Reflection Coefficient (S11) of an antenna placed on the body, combined with the IEEE 802.15.6 CM3A path loss model between communicating nodes.	Path loss and link quality metrics (SNR), (BER), and (RSSI)
[17] (2022)	A sink placement scheme for WBANs, based on the Whale Optimization Algorithm (WOA), is devised to minimize node power consumption during data transmission while enhancing network stability, throughput, and latency.	Stability period, Residual Energy, Throughput, End-to-End Delay
[18] (2017)	locating the sink node between the hip and the chest.Assuming that the back, arms, and ankle have been implanted with transmitting sensor nodes	Network lifetime
[11] (2019)	An adaptive cuckoo search-based algorithm for relay node placement, aiming to minimize relay node cost, energy consumption, and achieve uniform load distribution, particularly in challenging optimization problems.	Energy-Consumption, Computation Time
[19] (2014)	Three placement algorithms for BNC considering distance awareness: Iterative BNC Placement Algorithm (DBP-I), Fixed BNC Placement Algorithm (DBP-F), and the Position-aware BNC Placement Algorithm (PBP).	Energy efficiency, Depletion time

TABLE 2. List of acronym and abbreviations.

Acronym	Definition
BER	Bit Error Rate
BNC	Body Node Coordinator
CC	Closeness Centrality
CH-S1	Cluster Head Sink 1
CH-S2	Cluster Head Sink 2
DAAG	Distance and Angulation based AGglometrative
DBP	Distance based Position
ECG	Electrocardiograph
EMG	Electromyography
HWOA	Humpback Whale Optimization
MA	Multi-Angulation
MSE	Mean Squared Error
PBP	Position aware Placement
PSO	Particle swarm Optimization
PER	Packet Error Rate
QL	Q-Learning
RSSI	Received Signal Strength Indicator
RMSE	Root Mean Squared Error
SNP	Sink Node Placement
WBAN	Wireless Body Area Network
WSN	Wireless Sensor Network

II. PROPOSED METHODOLOGY

In this study, we first implement various algorithms for sink node placement, including Random placement (D-RMS), Social Network analysis algorithm employing CC, Optimization algorithm (HWOA), Q-learning algorithm (QL), Computational geometry and positioning technique (MA). Additionally, we propose an energy-efficient clustering algorithm DAAG.

A. CLOSENESS CENTRALITY ALGORITHMS FOR SNP

In this algorithm, the sink node are placed strategically at multiple distinct locations. Subsequently, the closeness centrality for all sink nodes are calculated to determine the optimal (x, y) position. The resulting CC values are then arranged in descending order, and the node with the highest CC is designated as the sink node. To assess the effectiveness of the CC metric, the WBAN topology depicted in Figure 2 is considered. The algorithm's primary steps are listed below.

Step 1 (Sensor Nodes Deployment:) In the first step, multiple sink nodes strategically placed at different locations for the calculation of CC. To this end, We have considered three positions, i.e., arm, thigh, and abdomen.

Step 2 (Calculate Closeness Centrality (CC)): In the second step, CC is measured which is defined in [24] and quantifies the average distance between a node and every other node in the network, thereby identifying pivotal nodes within WBAN. The underlying idea is that a node migrating towards the network's center should exhibit the greatest distance from other nodes. The centrality value of a node in terms of proximity increases as its distance diminishes from the other nodes. In a connected system comprising of N nodes, the average shortest distance between a sink node and all other nodes in the network can be computed as shown in equation (1):

$$CC(i) = \frac{1}{n_i} = \frac{n-1}{\sum_{i \neq j} d_{ij}} \tag{1}$$

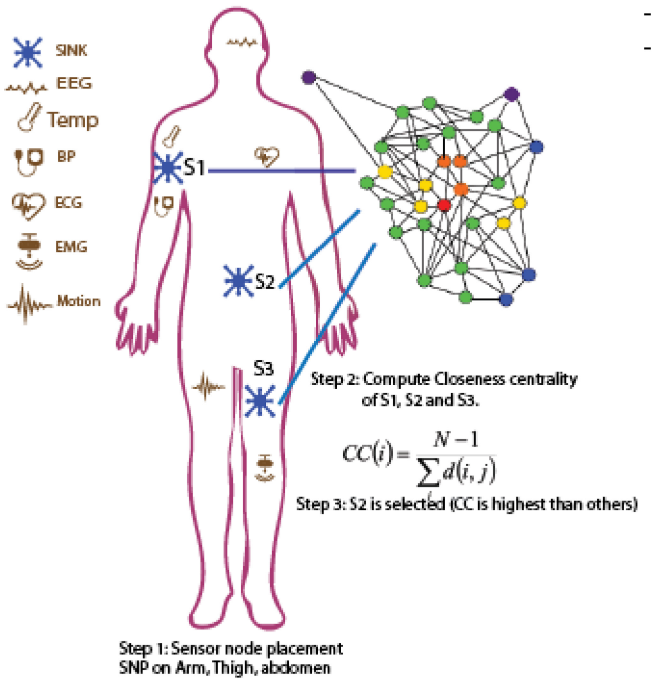

FIGURE 2. WBAN topology for Closeness Centrality of SNP.

Algorithm 1 Closeness Centrality for SNP

Inputs:
S_n: Sensor node position.
Random S_NP: AB_P: abdomen_position, A_P: arm_position, T_P: thigh_position.
Output:
S_NP: sink Node Placement.
Procedure:
Calculate distances from the sensor node to S_NP
Initialize distance [ ]
for each S_n in S_ns **do**
  Calculate distance from AB_P, A_P, T_P to S_n.
  Append distance to AB_P, A_P, T_P array.
end for
Initialize Closeness AB_P, Closeness A_P, Closeness T_P as 0.
for each distance **do**
  Update Closeness_C += 1 / distance.
end for
Display Closeness AB_P, A_P, T_P.
Print the highest closeness centrality score as SNP.
Display result:
  Print S_NP
End of Algorithm

The node n_i is closer to other nodes in the network if n_i is smaller and d_i defines the proximity centrality for node v_i. The equation is used to compute the CC of all three sink nodes (arm, abdomen, and thigh position).

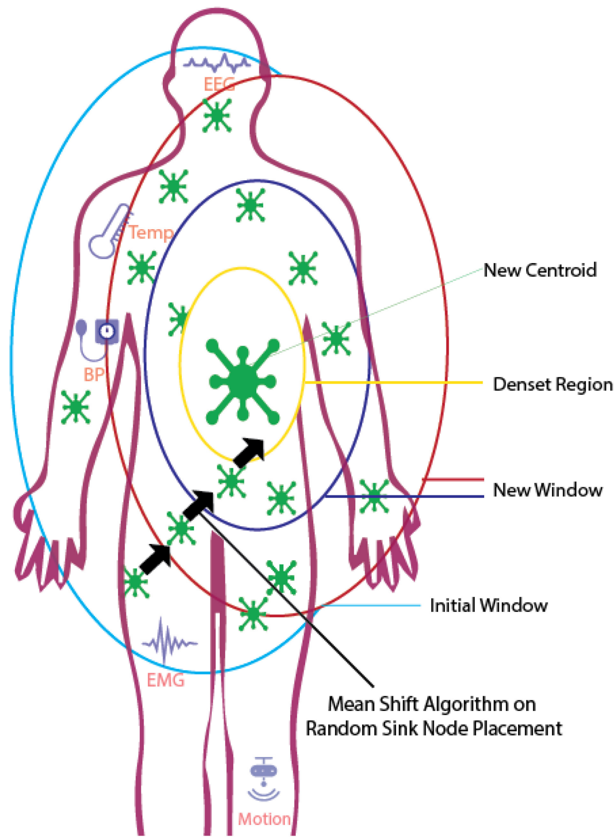

FIGURE 3. D-RMS for sink placement.

Step 3 (Determine Sink Node position): The algorithm calculates the CC for each sink node using equation (1), and then sort the results in descending order. The top-ranked node with the highest CC score is designated for the placement of the sink.

The algorithm calculates CC scores for predefined positions relative to the sensor nodes, selecting the position with the highest score as the optimal sink node placement, This to minimize communication distances in the sensor network for improved efficiency. Below is the pseudo-code of CC.

B. DISTANCE-BASED RANDOM MEAN SHIFT (D-RMS)

In the D-RMS scenario, the human body is assumed to be in a standing position. Multiple sink nodes are placed randomly on the human body. The D-RMS approach is applied to calculate the average of sink nodes. An example topology is provided in Figure 3.

Step 1: Compute the mean shift vector (given in equation (2)) for all randomly chosen sink nodes' positions. The mean shift vector indicates the direction of the most substantial increase in the density of sink nodes.

$$m(x) = \frac{\sum_{i=1}^{N} K\left(\frac{x \cdot x_i}{h}\right) \cdot x_i}{\sum_{i=1}^{N} K\left(\frac{x \cdot x_i}{h}\right)} - x \tag{2}$$

Algorithm 2 D-RMS for SNP

Inputs:
S_n: Fixed node deployment.
N_p: Random node placement.
Output:
C_C: Cluster Center
S_NP: Sink Node Placement.
Procedure:
Import libraries: *NumPy* & *MeanShift*.
Define Sensor Node Positions: *S_n*
Define Random Node Placement: *C_n*
Convert *N_p* list to array.
Apply Mean Shift clustering on *N_p*:
    meanshift = MeanShift()
    meanshift.fit(*N_p*)
Get cluster centers <- average positions:
    C_C = meanshift. *C_C*
Retrieve *S_NP*:
    average_S_NP = *C_C*
Display result:
    Print *S_NP*
End of Algorithm

Step 2: Adjust the starting point by displacing it in the direction of the mean shift vector.

Step 3: Iterate through Steps 1 & 2, until the starting point converges towards the highest density of sink node positions.

Step 4: The process is repeated by placing sink nodes randomly for each iteration to obtain the average sink node position.

Step 5: Finally, compute the distance of sensor nodes d_n from the selected SNP d_{sink} using Euclidean distance. The pseudo-code of the D-RMS technique is shown below;

C. MULTI-ANGULATION FOR SINK PLACEMENT

The MA technique is used for localization, where the positions of nodes are estimated based on the geometry of the network and the angles between nodes. The sink node's position is estimated by finding the intersection points of the circles/spheres created by the sensor nodes. In 2D, three intersecting circles will typically have exactly one intersection point, which is the estimated location of the sink node. To evaluate the performance of MA, we take into account the WBAN topology as shown in Figure 4. The algorithm's primary steps are listed below:

Step 1 (Sensor Node Placement): Define the positions of fixed sensor nodes. The body is in the standing position and six sensors (EEG, ECG, temp, bp, motion, and EMG) are placed on the human body to record data.

Step 2 (Calculate Bisectors of Sensor Nodes): Create a list to store information about the bisectors. Iterate through each sensor node and for each pair of sensor nodes, perform the following steps:

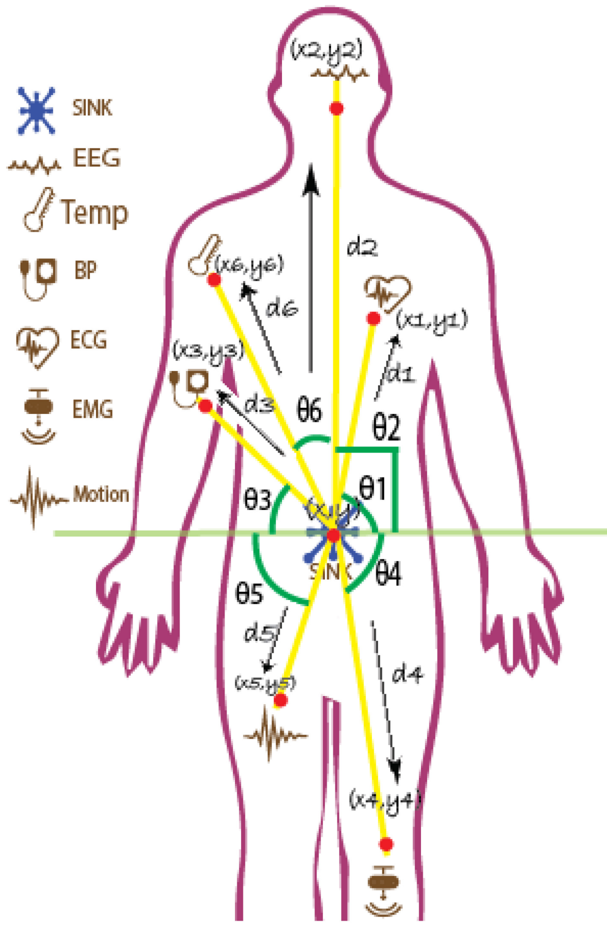

FIGURE 4. Multiangulation for sink placement.

a) Determine the slope (m) of the line segment connecting the pair of sensor nodes (Handle the case of a vertical line where the denominator is 0 appropriately).

b) Calculate the perpendicular slope ($m_{\perp}$) of this line segment (calculated in Step 2) by taking the negative reciprocal of the slope. If the line segment is horizontal, assign a tremendously large value to its perpendicular slope ($m_{\perp}$). Store the midpoint xy, and $m_{\perp}$ for each pair of sensor nodes in the bisector list.

Step 3 (Calculate the Centroid of the Bisectors): For each bisector in the bisectors list.

a) Add the x-coordinate of the bisector to $centroid_x$. Divide $centroid_x$ by the total number of bisectors to calculate the x-coordinate of the centroid.

b) Add the y-coordinate of the bisector to $centroid_y$. Divide $centroid_y$ by the total number of bisectors to calculate the y-coordinate of the centroid.

c) Display the calculated Centroid as "Best sink node Placement (x, y).

Below is the pseudo-code of the MA approach.

D. HUMPBACK WHALE OPTIMIZATION FOR SINK PLACEMENT

HWOA iteratively optimizes the placement of the sink node and utilizes a population of whales to explore the

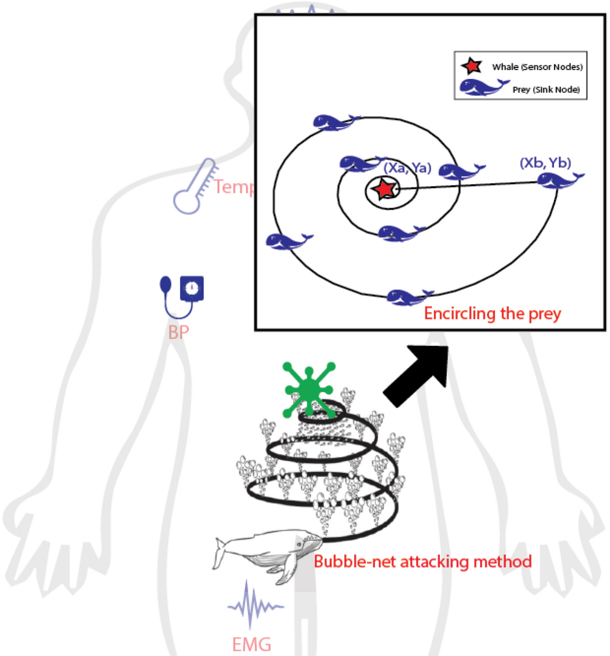

FIGURE 5. Humpback whale for sink placement.

search space, updating their positions according to the fitness function, i.e.; MSE, aiming to minimize the error. To evaluate the performance of HWOA, we consider the WBAN topology as shown in Figure 5. The optimization procedure involves the following steps,

Step 1: Define the number of iterations, population size, dimensions, and the lower and upper bounds for search space.

Step 2: Mean Square Error (MSE) is defined as the fitness function. The mean square error (MSE), equation (3) is minimized by employing an efficient optimization algorithm:

$$MSE = \frac{1}{M}\sum_{i=1}^{M}\sqrt{(x-x_i)^2+(y-y_i)^2} \tag{3}$$

Step 3: Initialize the whale (sink) population with random positions within the search space and calculate the whale with the best fitness value.

Step 4: Let $\vec{X}_{\text{best}}(t)$ is the best fitness value defines the best sink node position determined using equation (4) and (5):

Encircling prey is the initial step to detect and encircle the best optimal position. $\vec{X}_{\text{best}}(t)$ define the best sink node position.

$$\vec{D} = \left|\vec{C}\cdot\vec{X}_{\text{best}}(t) - \vec{X}(t)\right| \tag{4}$$

$$\vec{X}(t+1) = \vec{X}_{best}(t) - \vec{A}\cdot\vec{D} \tag{5}$$

where t represents the current iteration. $\vec{D}$ is the distance vector between the position vector of the best solution $\vec{X}_{\text{best}}(t)$ at iteration t and the current position vector $\vec{X}(t)$. The term $\vec{X}(t+1)$ update the position vector of optimal solution for the next iteration $(t+1)$.

$$\vec{A} = 2\vec{a}\vec{r}_1 - \vec{a} \tag{6}$$

$$\vec{C} = 2\vec{r_2} \tag{7}$$

where, $\vec{a}$ is a scalar parameter that influences the exploration-exploitation balance in the algorithm, and $r1$ & $r2$ are the random vectors ([0, 1]) as shown in equation (6) & (7). The random exploration include the global space, whereas, the exploitation focuses on detailed search in promising areas [25].

Update the position and fitness of each whale.

a) Generate a random whale.
b) Update the position of the current whale.
c) Clamp the position within the search space bounds.
d) Update the fitness of the current whale.
e) Update the best position and best fitness.
f) Update the current whale's position in the population.
g) Display the best fitness value for the current iteration.
h) Display the final best position and best fitness value.

This iterative approach efficiently converges towards an optimal solution, enhancing the network's performance and resource utilization. Below is the pseudo-code of HWOA.

E. Q-LEARNING AWARE ROUTING STRATEGY FOR SNP

In the Q-Learning (QL) method, an iterative process is employed to choose actions, corresponding to sink locations, based on the current states of sensors. Rewards are calculated, taking into account factors such as distance and data quality, and a Q-Table is updated iteratively to facilitate learning optimal node placement. However, when one needs to choose a sink among the available sensor nodes (with fixed positions) the problem can be solved by simply using the round-robin method, and the maximum number of iterations to converge is equal to the number of sensor nodes. On the contrary, selecting one of the sensor nodes as a sink node can lead to compromised situations, where some of the sensor nodes in the network may have to rely on other sensors neighboring nodes to route their data to the sink. In this case, the problem cannot be solved simply by round robin method but also require routing considerations among the nodes.

To this end, we present a Q-Learning-based routing aware sink node placement scheme. Through multiple iterations, the algorithm identifies the best trade-off between the sink selection and routing distances by determining the Q-value for each sensor. To evaluate the performance of Q-Learning, we consider the WBAN topology as shown in Figure 6. The algorithm's primary steps are listed below:

Step 1 (Define Sensor Coordinates): Specify the coordinates of the sensor nodes. These coordinates represent the locations of the sensor placement in BAN.

Step 2 (Initialize Q-Table): We compute the distance matrix representing the Euclidean distances between all pairs of sensor nodes. This information will be used to define the rewards and update the Q-values.

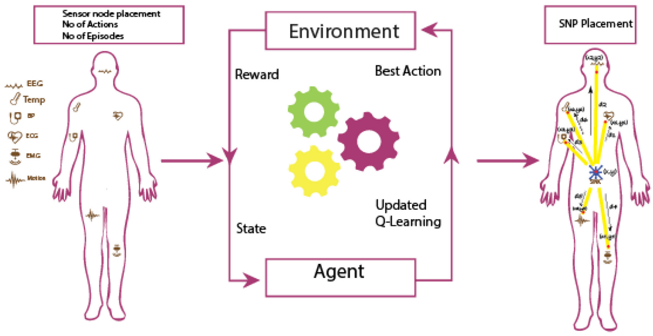

FIGURE 6. Q-Learning for Sink placement.

Step 3 (Q-Learning Algorithm): QL is applied to update Q-values as shown in equation (8) for each state-action pair in the Q-table. We iterate over each sensor node (state) and for each possible action (transition to another sensor node).

$$Q(s, a) \leftarrow Q(s, a) + \alpha\big(r + \gamma \max Q(s', a') - Q(s, a)\big) \quad (8)$$

Here r is immediate reward, γ is discount factor, $\max Q(s', a')$ is the maximum Q-value, α is learning rate lies between 0 to 1.

a) State-Action Selection: Select an action using Greedy policy with the highest Q-value for the current state. π represent the policy function, which maps states to actions. In the Greedy policy, the action a chosen for a given state s is the one with the highest Q-value, denoted as $Q(s, a)$ as shown in equation (9).

$$\pi(s) = \text{argmax}_a Q(s, a) \quad (9)$$

b) Calculate Reward: Calculate the immediate reward based on the selected action. The reward can be influenced by factors such as distance, data quality, or energy consumption. Here, we have chosen reward as the negative of distance between nodes $r = -\text{distance}(\text{state}, \text{action})$

c) Update Q-Table: First, identify the sensor node with the highest reward (maximum Q-value) and then apply action for each state in the Q-learning process to update Q-table.

Step 4 (Final Best Sink Placement): In last step, we identify the best placement for the sink node based on the occurrence frequency of sensor nodes in a given set of indices, we can express it mathematically in equation (10):

$$s^* = \text{argmax}_s \sum_{i \in I} \delta(s, i) \quad (10)$$

$\delta(s, i)$ is the indicator function, where s is the sensor node at index i and s^* represent most frequently sensor. Below is the pseudo code of the QL approach:

F. DAAG CLUSTERING FOR SINK PLACEMENT

DAAG technique integrates both distance-based and angulation-based methodologies for cluster selection within sensor networks. Initially, it employs K-means to determine cluster head positions, primarily focusing on distance metrics. Subsequently, angulation-based clustering is utilized to refine the cluster selections, taking into account angular information. Finally, the algorithm employs Agglomerative Clustering to compute optimal cluster positions, thereby enhancing network coverage and performance by leveraging both the distance and angular information. Specifically, in the DAAG algorithm, two sink nodes are selected instead of one, with the overarching goal of extending network lifetime and reducing overall energy consumption in WBANs.

Algorithm 3 Multi-Angulation for SNP

```
Input:
    S_n: sensor nodes
Output:
S_NP: sink Node Placement.
bisectors = Empty List
Procedure:
for each pair of S_n (S_1, S_2) in S_n do
    midpoint_x = (S_1[0] + S_2[0]) / 2
    midpoint_y = (S_1[1] + S_2[1]) / 2
    if S_2[0] - S_1[0] ≠ 0 then
        slope = (S_1[1] - S_1[0]) / (S_2[0] - S_1[0])
    else
        slope = Infinity
    end if
    if slope = 0 then
        perpendicular_slope = Infinity
    else
        perpendicular_slope = −1/ slope
    end if
    Append (midpoint_x, midpoint_y) and
    perpendicular_slope to bisectors
end for
centroid_x = 0
centroid_y = 0
for each bisector (b) in bisectors do
    centroid_x = centroid_x + b[0]
    centroid_y = centroid_y + b[1]
end for
centroid_x = centroid_x / Length(bisectors)
centroid_y = centroid_y / Length(bisectors)
Display result:
    Print S_NP
End of Algorithm
```

Step 1 (Sensor Node Deployment and Body Division): Fixed sensor nodes are positioned across the body in a standing posture to capture physiological data from various sensors such as EEG, ECG, Temperature, Blood Pressure, motion, and EMG. Additionally, the body is divided into two parts by determining the midpoint among these sensor nodes, facilitating effective data collection and analysis for biomedical applications.

Step 2 (Cluster Formation Using k-mean): In this step, we find the K centroids of the sensor nodes by using

Algorithm 4 Humpback-Whale for SNP

Inputs:
Define:
  n_i: number of iterations
  p_s & *d*: population size & dimensions
  u_b & *l_b*: lower and upper bounds for search space
  S_n: fixed sensor nodes
  F_F: fitness function (MSE)
  P_SS: Population within search space.
  B_P: Best position for an optimal solution.
  B_F: Best Fitness value.
  S_S: Search space.
Output:
S_NP: Sink Node Placement.
Procedure:
for iter = 1 to *n_i* **do**
  Update "a" and "a_2" for SS
  for i = 1 to *p_s* **do**
    position = population[i]
    Generate a random whale (R_W)
    Update the position of the whale using WOA eq:
    $d = |a \cdot \text{R\_W} - \text{position}|$
    $c = 2 \cdot \text{R\_vector}(num\_dim)$
    $distance\_to\_random\_whale = d \cdot \exp(b \cdot c) \; - 0.5 \cdot d$
    $updated\_position = \text{R\_W} - a2 \cdot \text{distance\_to\_whale}$
    Clamp the position within the search space:
    $updated\_position = (u\_p, \text{l\_b}, \text{u\_b})$
    Update fitness of current whale:
    $fitness = \text{F\_F}(updated\_position)$
    Update the best position and best fitness if the current whale's fitness is better than the previous best:
    if *fitness* < B_F **then**
      B_P = updated_position
      B_F = fitness
    end if
    Update the current whale's position:
    $population[i]$ = updated_position
  end for
  Display the B_F for current iter:
  print("Iteration:", iteration, "Best Fitness:", B_F)
end for
print("Final Best Position:", B_P)
print("Final Best Fitness:", B_F)
Display result:
  Print *S_NP*
End of Algorithm

Algorithm 5 Q-Learning for SNP

Input:
S_n: Sensor node deployment.
Define constants:
No_sensors
No_Actions
Episodes
Alpha, *Gamma*, *epsilon*
Output:
S_NP: sink Node Placement.
Procedure:
Define *S_n* & calculate distance
Initialize q_table with zeros
for episode = 1 to EPISODES **do**
  Set initial state to 0 and total_reward to 0
  while current state < `No_sensors` − 1 **do**
    Choose action using greedy policy
    Calculate reward based on distance
    Update q_table using Q-learning formula
    Move to the next sensor and update total_reward
  end while
  Print total_reward
end for
Find best_placement based on highest Q-values & reward.
Select sink_coordinates that occurs most frequently.
Display result:
  Print *S_NP*
End of Algorithm

conventional K-mean clustering as expressed in eq. (11):

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} A_{nk} \|x_n - c_k\|^2 \tag{11}$$

x_n is the position of n_{th} sensor, c_k is the centroid of cluster k. The mean for cluster k is n_k. An indicator variable determines whether or not to assign x_n to c_k. Assign each sensor node to a cluster and obtain the cluster head positions.

Compute the cluster heads using angulation-based K-means, where the angulation θ_i for each sensor node is calculated using Algorithm 3.

Step 3 (Dual Sink Selection Using Agglomerative Clustering): Multiple clusters have been selected for upper and lower body parts using steps (1) & (2). An agglomerative approach has been employed to select two sinks, namely CH-S1 and CH-S2. Agglomerative hierarchical clustering, a bottom-up method, begins with each object as a single cluster and progressively merges these individual clusters into larger ones until either all objects are within a single cluster or a predetermined termination condition is met.

a) Initially, each data point is treated as its own cluster, denoted as $C_i = x_i$ for $i = 1, 2, \ldots, N$, where C_i represents the cluster containing only data point x_i.

b) In each iteration, clusters are merged based on a proximity measure until a termination condition is met. Specifically, clusters C_i and C_j are merged if their distance $d(C_i, C_j)$ is minimal.

c) After merging clusters C_i and C_j, the distance matrix is updated to reflect the new distances between the merged cluster and the remaining clusters. This updating process is represented as $D_{ij} = distance(C_i, C_j)$, where D_{ij} is the updated distance between clusters C_i and C_j. Using an agglomerative clustering approach two cluster-sink heads $CH-S1$ and $CH-S2$ are selected for the upper and lower body portions.

III. RESULTS AND ANALYSIS

In the following, we present results for the techniques described in the previous section. Table 3 summarizes the

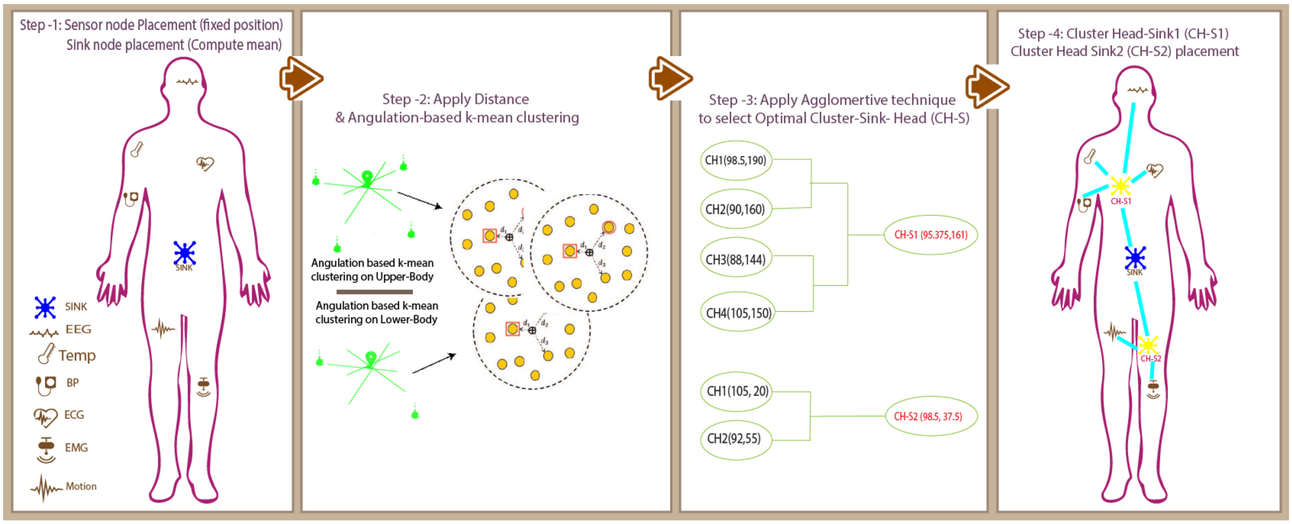

FIGURE 7. DAAG-Agglomerative Clustering Algorithm (Proposed).

TABLE 3. Model parameters.

Parameter	Value
d0(cm)	within 5cm range
PL(do)	49.81 dB
n	4.22
X	6.81 dB
f	0.402–0.405 GHz
ETX_elec	18.75 nJ/bit
ERX_elec	18.75 nJ/bit
E_init	0.5J
E_elec	100e-9
E_amp	50e-6
Overhead	80 bits
ACK/NACK	64 bits
Transmission power	-10dBm
Noise power	-100dB
Data Rate	800kbps
R/BN	2 bps/Hz

parameter values widely adopted in literature [26], [27], and [28]. We set the constants for the transmit power (P_T), data rate (R), and energy used by the transmitter ETX_{elec} and receiver electronics ERX_{elec} respectively [29], [30], [31]. According to the IEEE 802.15.6 standard, the maximum payload size is 2000 bits, and the maximum distance between WBAN nodes is 5 m [32].

A. BEST SINK POSITIONS OF D-RMS, ANGULATION, Q-LEARNING, WHALE, CLOSENESS CENTRALITY AND DAAG

Figure 8 shows the best sink placement using all the techniques. Here, the white diamond shows the sink placement that varies according to the algorithms, the red dots depict sensor positions that are fixed in all the scenarios, and the green triangle and blue square represent cluster Head sink positions. The final best position for sink node placement that we have computed using the D-RMS is: *(97.92,105.42)*, MA best position is: *(96.41,119.83)*, the best position of HWOA is: *(100,100)*, QL placement is: *(98.5,190)*, the best position of CC is: *(96.41,119.83)* and in DAAG two additional cluster head sinks, i.e.; $CH-S1$ *(95.38,161)* and $CH-S2$ *(98.50,37.50)* are positioned to support sink.

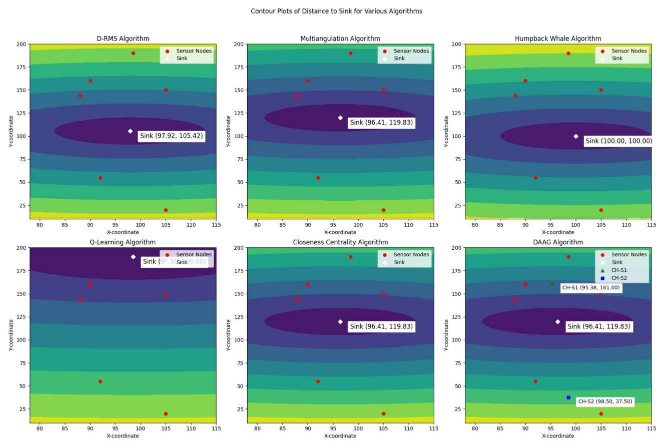

FIGURE 8. Best Sink Node Positions.

B. ENERGY MODEL

A radio model explains how much energy the sensor's electronic system uses. In our research, we selected the first-order radio model presented in [33], which is shown in Figure 9. The first-order radio model provides an analysis of the energy used by a sensor node during transmission or reception at each cycle. The radio has power control that only uses as much energy as necessary to reach the target audience [34].

The radio model defined in equations (12) and (13) explains the energy relations between the transmitter and

Algorithm 6 DAAG (HYBRID) for SNP

Part-I: Distance and Angulation based Clusters selection
Inputs:
S_n: Sensor node deployment.
n_C: no of clusters
C_h_p: cluster head positions
Output:
C_C: Cluster positions.
d_C_H: Distance Cluster Head.
A_C_H: Angulation Cluster Head.
S_CP: sink Cluster positions.
Procedure:
Use K-means with *n_C* and *S_n* as to compute *C_h_p*
Store the *C_h_p* in *d_C_H*
d_C_H
Create an empty list *C_h_p*
Make a copy of *S_n remaining_nodes*
for *i* in range(*n_C*)
Calculate the angulation of all nodes *remaining_nodes*
Find node Index with the farthest angle from origin
Append the position of node *C_h_p*
Remove the farthest node from *remaining_nodes*
return *A_C_H* Display result:
    Print *d_C_H* and *A_C_H*
Part-II: Cluster Head Selection using Agglomerative Clustering
Inputs: *S_n*: Sensor node deployment.
n_C: no of clusters
C_h_p: cluster head positions
d_C_H: Distance Cluster Head.
A_C_H: Angulation Cluster Head.
Outputs:
S_NP: sink Node Placement
S_CP: sink Cluster position
Procedure:
Define the array *S_n* containing the (x, y) coordinates of the sensor nodes
Define the variable *n_C* to specify the desired number of clusters
Implement the *distance_based_clustering* and *angulation_based_clustering* functions
Perform distance-based clustering using K-means and store the *C_h_p* in *d_C_H*
Perform angulation-based clustering and store the *C_h_p* in *A_C_H*
Calculate the optimal cluster positions using Agglomerative Clustering *d_C_H*
Store the optimal cluster position in *S_NP*
Display result:
    Print *S_NP*
End of Algorithm

receiver for delivering a data packet of size "n" across a distance of "d". ETX_{elec}

$$E_{TX}(n, d) = nETX_{\text{elec}} + nd^2 ETX_{\text{amp}} \tag{12}$$
$$E_{RX}(n, d) = nERX_{\text{elec}} \tag{13}$$

where (ETX_{elec} and ERX_{elec}) represent the energy lost per bit at the transmitter and the receiver, *Eamp* is the amplification factor, *Eelect* is the price of circuit energy used to send or receive a single bit of data, n represents the quantity of data

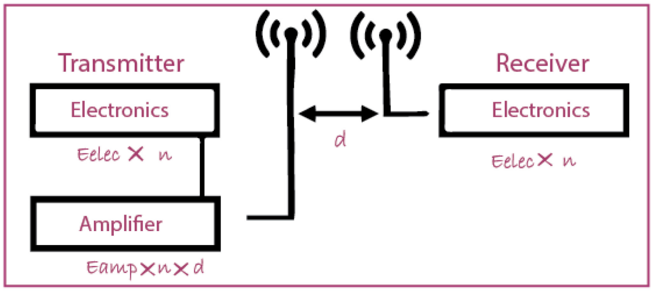

FIGURE 9. First Order Energy Model.

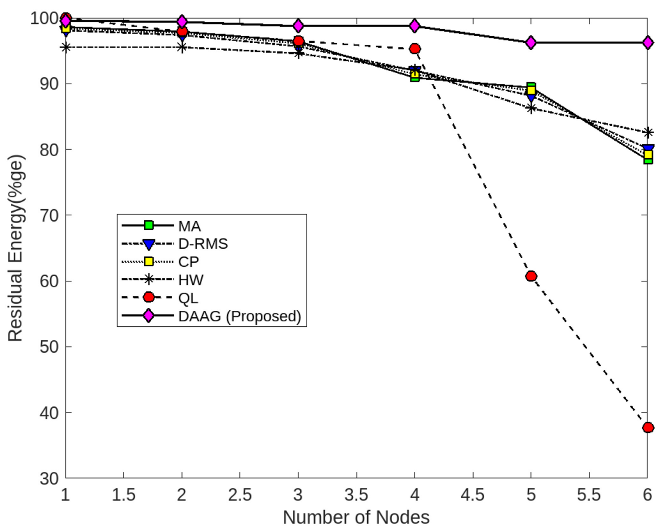

FIGURE 10. Residual Energy.

bits sent, and d is the separation between a sensor node and its associated sink node.

Residual Energy: Residual energy is the difference between a node's initial energy and the energy used to send packets. In essence, it is the energy that is left over after the operation. Residual Energy (i.e., Eres, i) is represented by equation (14).

$$E_{res,i} = E_{init} - E_{consume,i} \tag{14}$$

Figure 10 shows the Residual energy of all techniques. Here, the x-axis shows the number of sensor nodes (EEG, ECG, EMG, Motion, BP, Temp) that are fixed in all scenarios. The average residual energy levels for various algorithms are as follows: QL at *81.34%*, HWOA at *90%*, MA at *91.94%*, CC at *91.95%*, D-RMS at *92%*, D-RMS exhibits an initial show residual energy of *91.49%*, which gradually increases after 50 iterations, stabilizing impressively at *92%* and DAAG at *98.48%*. It can be seen that the overall residual energy of DAAG is higher than all the other algorithms.

C. ENERGY CONSUMPTION

Energy consumption is a critical aspect that needs to be carefully managed. Energy is only used when sending and receiving packets in both modes; otherwise, no power is

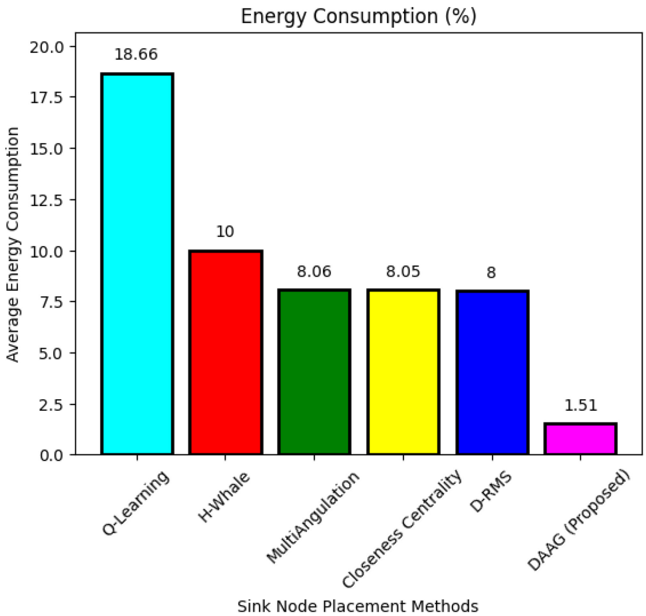

FIGURE 11. Energy Consumption.

consumed when the system is inactive or asleep [35]. Less energy is used in the transmission process when sensor nodes are closer to each other before data transfer. Since the distance between sensor nodes in a WBAN and the source of the signals to be monitored is typically less than 1 m significant energy savings can be achieved in a WBAN [36]. The power efficiency of individual sensor nodes directly affects their battery longevity. Strategic placement of sink nodes contributes to balanced energy consumption, ultimately extending the overall network lifespan by preserving the energy resources of individual nodes. It is evident that sending packets from source nodes to sink nodes will significantly increase the energy consumption of the WBAN. The sum of all wireless nodes' transmission and reception energy is used to represent overall energy consumption. ETX_{elec} and ERX_{elec} stand for the energy that the radio uses to power the circuitry in the transmitter and receiver, respectively. where;

$$E_{consume,i} = E_{transmit} + E_{receive} \tag{15}$$

where; ETX_{elec} is the total transmission energy and ERX_{elec} is the total reception energy. Figure 11 illustrates the average Energy consumption of all nodes. Results depict that the average Energy Consumption of QL is *18.66%*, MA and CC shows an *8.06%* and *8.05%* consumption level, and HWOA show a *10%* consumption level. Moreover, in the D-RMS case it is *8%*, whereas our proposed DAAG shows a *1.51%* energy consumption level.

D. LATENCY

The packet's latency is the interval between when it enters the input buffer of the node and when it is successfully received at the hub [37], [38].

$$\text{Latency} = \text{Prop}_{\text{delay}} + \text{Trans}_{\text{delay}} + \text{Proc}_{\text{delay}} + \text{Queue}_{\text{delay}} \tag{16}$$

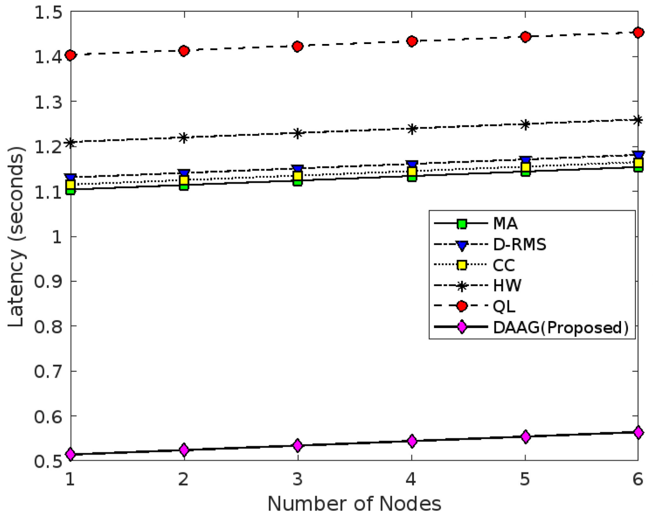

FIGURE 12. End-to-End delay of Techniques.

The packet delay of different packets from sensor nodes to the sink consists of queuing delay, transmission delay, and the ACK reception delay. The equation of delay is described by Equation (16).

Figure 12 shows the delay between sensor nodes and the sink node within the body area network. Here, we calculate the latency for each sensor separately and then analyze the worst-case scenario to identify the sensor with the highest latency to determine the maximum latency in our network. Our research findings show that our proposed DAAG has the lowest delay compared to all other algorithms. In a comparative analysis of the provided algorithms based on latency measurements, MA exhibits a latency of *1.10 sec*, RMS *1.13 sec*, and CC *1.11 sec*, indicating relatively consistent and predictable performance across these methods. On the other hand, HWOA exhibits slightly higher latency, i.e.; *1.21 sec*, suggesting a marginally slower processing speed, and QL has the highest latency of *1.40 sec*, making it more suitable for accuracy-focused applications with less emphasis on real-time responses. The DAAG algorithm stands out with the lowest latency of *0.51 sec*, making it an excellent choice for applications requiring minimal processing delay and real-time decision-making capabilities.

E. LOCALIZATION ACCURACY

Localization accuracy measures the average error between the estimated positions and the true positions of objects/nodes in a localization system. RMSE is a commonly used metric to assess the accuracy of a localization system. It quantifies the average error between the estimated positions and the true positions of objects. Numerous contributions to this problem, including [44], use RMSE to reflect

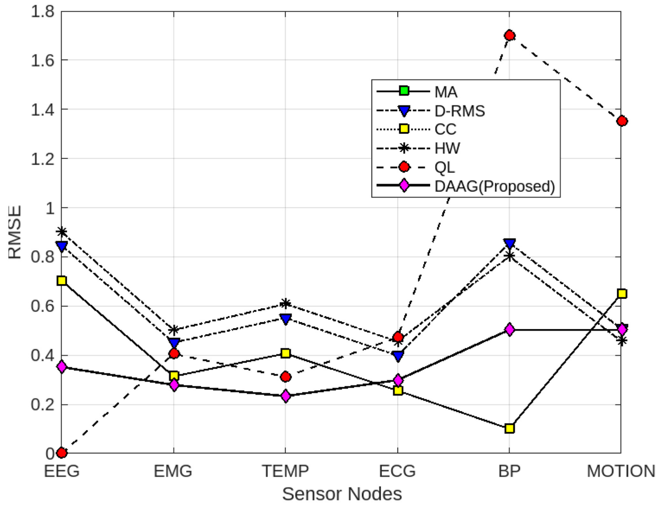

FIGURE 13. Localization Accuracy-RMSE.

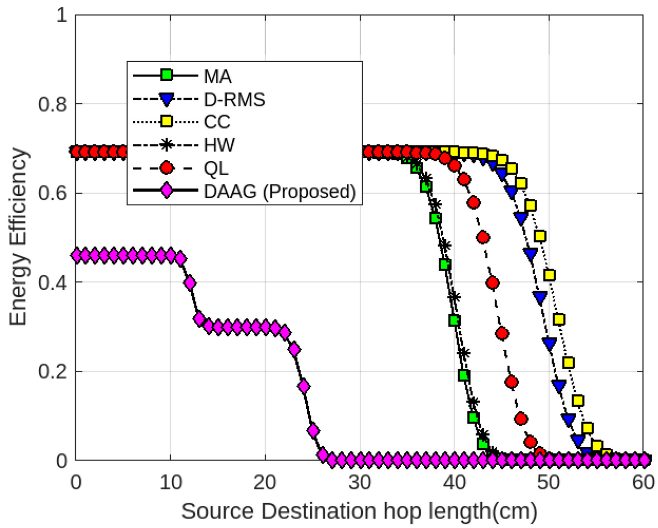

FIGURE 14. Energy-Efficiency.

localization accuracy. A lower RMSE value indicates higher accuracy, while a higher RMSE value indicates lower accuracy. RMSE can be expressed as shown in Equation (17).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|y(i) - \hat{y}(i)\|^2}{N}} \tag{17}$$

Figure 13 shows the localization accuracy of all algorithms. These RMSE values show that the D-RMS algorithm generally has moderate accuracy, with varying performance across different sensors. It performs best on ECG with an RMSE of *0.3983 m* and worst on the BP sensor with an RMSE of *0.8571 m*. The MA algorithm generally demonstrates moderate accuracy as well. It performs best on BP with an RMSE of *0.10019 m*, indicating higher accuracy, and worst on ECG with an RMSE of *0.2559 m*. The HWOA algorithm generally shows slightly lower accuracy compared to the previous two. It performs best on BP with an RMSE of *0.4561 m* and worst on EEG with an RMSE of *0.9001 m*. The QL algorithm shows perfect accuracy on EEG (RMSE = 0.0) but significant errors on BP and Motion sensors, with RMSE values of *1.7012 m* and *1.3516 m*, respectively. The CC algorithm's performance is similar to the MA algorithm, with RMSE values indicating moderate accuracy. The average Localization error of RMS is *0.601 m*, MA is *0.55 m*, HWOA is *0.620 m*, QL is *0.70 m*, CC is *0.55 m* and our proposed DAAG shows *0.36 m* which is better than all the other algorithms.

F. ENERGY EFFICIENCY

Let P_T be the output transmit power and ETX_{elec} represents the energy used by the transmitter electronics to send one bit. The term ETX_{data} is used to describe the total energy used by the transmitting node to send a data packet of size L bits as depicted in equation (18)-(19).

$$E_{TX\_DATA} = \left(E_{TX\_elec} + \frac{P_T}{,}R\right)(L+H) \tag{18}$$

where, R is the rate of data transmission. The energy used by the receiver electronics to receive and decode one bit will be denoted by the variable ERX_{elec}. The value of ETX_{data} which stands for the total energy used by the receiving node to receive and decode a data packet, can be written as follows:

$$E_{RX\_DATA} = \left(E_{RX\_\text{elec}}\right)(L+H), \tag{19}$$

Energy efficiency is defined as the ratio of the useful portion of the energy consumed to the overall energy consumed in a communication link between sender and receiver. It indicates the useful fraction of the total energy consumption.

$$\eta_{DC} = \frac{(1 - PER_{DC})xL}{x(L+H) + E_{TX\_ACK/NACK} + E_{RX\_ACK/NACK}} \tag{20}$$

The outcomes of energy efficiency of different techniques are shown in Figure 14. To compare the traditional one-hop techniques with our proposed DAAG-Clustering approach, energy efficiency is plotted against source-destination hop length. The findings support that the energy efficiency of all algorithms decreases with increasing source-destination distance.

G. PACKET ERROR RATE

Packet Error Rate (PER) defines the proportion of transmitted data packets that are incorrectly received or fail to arrive at their destination. It is a critical indicator of a communication link's dependability and quality. The following equation (21) is used to determine PER:

$$PER_{DC} = 1 - (1 - P_b)^{L+H} \tag{21}$$

Figure 15 shows the packet error rate versus source-destination distance for six different WBAN node placement algorithms. DAAG outperforms all other algorithms in terms of packet error rate, especially at longer distances. When the source and destination are in close proximity to each other (short distances), the signal strength between them

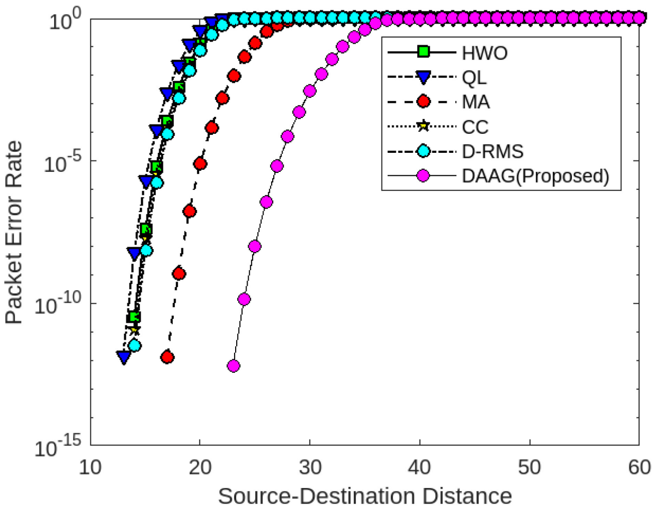

FIGURE 15. Packet Error Rate.

is strong and relatively stable. This often results in a low PER, meaning that a high percentage of transmitted packets are successfully received without errors. Regardless of the distance between the source and the destination, we find that the DAAG approach has a lower PER than other techniques.

IV. CONCLUSION

This work focuses on the significance of sink node placement in WBANs and the challenges associated with it, primarily focusing on energy efficiency and network lifetime. Six different techniques namely; D-RMS, MA, HWOA, CC the QL are discussed in this paper. DAAG outperforms other methods in several key aspects, including energy consumption, energy efficiency, PER, and localization accuracy. DAAG demonstrates superior performance in terms of average energy consumption (1.51%) and enhanced localization accuracy (RMSE of 0.36 meters) compared to other proposed techniques. These findings underscore the importance of careful sink node placement in WBANs, especially in healthcare applications where minimizing energy consumption during data transmission is crucial. The proposed DAAG approach appears to offer a more stable and effective solution in various scenarios, making it a promising choice for optimizing sink node placement in WBANs. In essence, the research suggests that through innovative techniques like DAAG, the design, and optimization of sink node placement in WBANs can contribute to improved network performance, energy efficiency, and the accuracy of physiological data collection, ultimately benefiting fields such as healthcare, fitness, sports, and entertainment.

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