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Olfactory Apis Search Optimization Enabled Optimal Node Localization for Energy-Efficient Data Transmission in IoT Assisted Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) provides an efficient approach for remote monitoring and management of the system, especially in adverse environments. Such WSN networks are comprised of sensor nodes for sensing and transmitting the collected information to the Base Station (BS) for certain applications over the internet. Hence, the energy level of the sensor nodes is depleted with time during the data transmission, which affects the entire communication and the lifetime of the WSNs. Hence, the dead nodes are required to be localized for persistent communication as well as enhancing the lifetime of the network. Hence, the Olfactory Apis Search (OAS) optimization enabled optimal node localization is developed in the research that utilizes the information-sharing characteristics of apis, and olfactory sensing characteristics of both vespid and coleopteran for determining the location of the dead nodes that are required to be replaced with new nodes. The developed optimization determines the unknown location of the dead nodes with information on the exact location of the anchor nodes. Further, effective Cluster Head (CH) selection and routing are performed to attain efficient data transmission between the sensor nodes and the BS. The performance of the developed OAS optimization enabled node localization is measured in terms of RMSE as 0.573, RSSI -48.226 dBm at the 50th round for the simulation area 100x100m2, and RMSE as 0.587 and RSSI as -53.19dBm for the simulation area 200x200 m2.

Keywords: *Wireless sensor networks, Node localization, Cluster head, routing, base station.*

1. Introduction

WSNs are utilized for remotely monitoring the processes and forwarding the collected data to a central location for analyzing the process for extensive applications. WSN offers the merits of technological developments for satisfying sophisticated communication as well as the needs and specifications of computer technologies. Additionally, WSN is the most reliable and practical technology for real-time applications [1] [2]. WSN comprises randomly distributed tiny sensor nodes to monitor and gather data regarding the environment to acquire the necessary information [3][4]. By choosing the best location for the sink node, the energy consumption of the network is reduced which eventually increases the network's lifetime. Therefore, it can be inferred that the position of the sink node and the distribution of nodes have an impact on the energy of WSNs [5]. Additionally, node localization is needed to notify the incident's origin and help with routing, sensor queries, and network coverage problems [6][7]. Hence, node localization is one of the important factors that must be considered for the WSN to Localization schemes are categorized into anchor-based or anchor-free, centralized or distributed, GPS-enabled or GPS-free, stationary or mobile sensor node-based,fine-grained or coarse-grained, range-based, or range-free models. The known position of nodes supports locating the unknown node positions in an anchor-based scheme [11].Conversely, anchor free scheme determines the node's relative position rather than the absolute position [12]. In a centralized scheme [13], the position of nodes is computed by the sink node, which transfers the information to other network nodes. Sensors in a distributed scheme, assess each position independently and communicate with anchor nodes directly [14][15]. Despite this, the network administrator has no control over the sink node position, as modifying the position to minimize the rates of energy consumption is a difficult undertaking [16]. Multiple works are established as an optimization theme to be resolved by metaheuristic algorithms to address the localization of sink nodes[17]. Further, these approaches have attained success in handling the challenging optimization issues associated with different domains[18],[19]. Different optimizations such as ant colony optimization (ACO) [20], particle swarm optimization (PSO) [21], and so on are utilized for node localization. Further, metaheuristic algorithms possess excellent robustness, high nonlinearity in resolving the issues associated with various conditions, and possessing

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the merits of broad applicability, as well as easy alteration [22,23,24] [25]. However, there is still an enormous gap that insists on the need for exploring efficient metaheuristic algorithms for node localization [26]. Conventionally, most of the approaches are concentrated on employing the space distance constraint in conjunction with single objective optimization to resolve the localization issues of sensor nodes. Additionally, these techniques have significantly improved in terms of computational time as well as accuracy. However, because of the ranging errors, the single-objective function lags in addressing the primary factor affecting the geometric topology constraint. Hence, the problem insists on modeling the node localization as a multi-objective optimization problem for solving the constraints [27]. Range-based localization requires distance between sensor nodes to evaluate the position of the node followed by utilizing geometrical procedures such as multilateration and angulation, to calculate the node location. Additionally, range-free localization techniques require topological for evaluating the node localization. However, the range-based algorithms are not cost-efficient, the algorithms are more accurate than range-free algorithms [28]. Some range-based schemes involve Angle-of-Arrival (AoA) [29], Time Difference of Arrival (TDoA) [30], Time of Arrival (ToA) [31], Received Signal Strength Indicator (RSSI) [32][33][34] and acoustic energy [35]. The key objective of the research is to develop optimal node localization for enhancing the lifetime and energy efficiency of the WSN. Hence, in this research, the position of unknown nodes is determined with the known position of anchor nodes utilizing the OAS optimization. Further, the OAS optimization localizes the dead nodes concerning the localization error and remaining energy in the nodes. Hence, the dead nodes are replaced with the new nodes and the clustering is performed in which the CHs collect the data from the corresponding cluster members and utilize the efficient adaptive incorporated FABC and Beetle-based routing for transmitting the data to the BS.

- Olfactory Apis Search optimization (OAS): The proposed OAS optimization is developed by integrating the information-sharing characteristics of apis, and olfactory sensing characteristics of both vespid and coleopteran to reach the best solution. The algorithm offers the merits of high convergence speed, reduces exploitation and exploration problems, and lesser complexity for reaching the best solution.

- OAS optimization enabled optimal node localization: The significance of the research relies on developing the optimal node localization based on position estimation utilizing the OAS optimization concerning the multiobjective function, localization error, and remaining energy constraints for enhancing the lifetime and energy efficiency of the WSN nodes.

- The arrangement of the article involves: Section 2 describes the overview of recent works on node localization, and Sections 3, and 4 provide an interpretation of the detailed procedures associated with OAS optimization enabled optimal node localization, Section 5 involves the results analysis. Finally, Section 6 serves as the conclusion of the research.

2. Literature review

In this section, a review of the related works is made, which assists the researchers in formulating noteworthy contributions. Sheetal N. Ghorpade et al.[27]presented an optimal sensor node localization technique utilizing grey wolf optimization(GWO)in which the optimization is employed for optimizing the localization error. The distance and topological constraints are involved in the objective functions. Multi-objective GWO was utilized for determining the optimal solution and the technique attained high efficacy in localization of the unidentified node as well as minimizing the anchor nodes. However, the technique has a low convergence speed that limits the performance.Yedida Venkata lakshmi et al.[2]contributed a chan algorithm and hybrid PSO for node localization. The node localization problem is represented as a maximum probability distribution function, 2D and 3D coordinates related to the unknown nodes are determined utilizing the TDoA integrated with the Chan algorithm. The method offers high localization accuracy utilizing the two-hybrid localization PSO as well as reducing the error value to a minimal distance. However, the method works well in the case of small areas and large node densities.

S. Umamaheswari.[15]presented a hybrid Optimization method for energy efficiency that addressed the issues associated with node localization. The hybrid optimization method utilized the PSO for achieving optimal localization of nodes and GWO was utilized for obtaining the shortest path for energy-efficient data transmission. The method incorporated the cloud module for enhancing the characteristics of energy management. Additionally, the method minimized packet loss, and route failures, and enhanced the network lifetime. However, the computation cost was the drawback that evolved with the hybrid optimization.

Pudi Sekhar et al.[7]developed a group teaching optimization algorithm(GTOA) that addressed the node localization issues. The method in which the coordinate points of the unknown nodes are found with the GTOA evaluates the position of nodes with the anchor nodes. The GTOA employs the Euclidean distance for evaluating the fitness function that computes the nodes' localization. Further, time synchronization as well as scheduling strategies can be integrated to boost the efficacy of the approach in the future.

Rong Tan et al.[4]presented a distance mapping algorithm that determines the node position utilizing the distance and estimation matrix with the linear transforming function. The localization can be determined effectively with the integration of a genetic algorithm (GA), that offers high accuracy and low energy consumption. However, the method found difficulty in determining the node location due to the lack of a preset trajectory. Hence, the method can be enhanced by integrating path planning and predicting strategies in the future.

Essam H. Houssein et al.[26]developed a Harris Hawks optimization (HHO) enabled localization in which the Primis shortest path approach was utilized to reconfigure the network by creating effective data transmission lines. Additionally, the approach demonstrated a reduction in topology construction time when compared to other equivalents that formed the advantage of the model.

Visalakshi Annepu and A. Rajesh.[23] developed an artificial bee colony(ABC) algorithm for localization, in which the approach optimized the flying height over the localization accuracy and then expressed the localization as the least square optimization problem utilizing the optimal height. The least-square localization was determined to be a better alternative for the RSSI that reduced the localization error.

Jianpo Li et al.[20] developed an enhanced parallel compact CSO (PCCSO)for hop node localization. The PCCSO offered the merits of enhancing the local search along with saving memory space. The PCCSO was adopted over DV-Hop localization in WSN and offered high localization accuracy along with the merits of less localization error, memory saving, and reduced time complexity compared to other algorithms concerning the DV-Hop.

2.1. Challenges

- The DMA method found difficulty in determining the node location due to the lack of a preset trajectory that required integrating path planning and predicting strategies in the future [4].

- The method had limited performance due to the lack of time synchronization as well as scheduling techniques that require development in the future [7].

- The group teaching optimization method in which the high computation cost is due to the hybrid optimization that limited the performance of the model [15].

- If the network size differs, the parameters involving the number of sensor neighbors served by the sink node, residual energy, and the distance between the sensor nodes will vary correspondingly in the HHO-based method [26].

- Optimization attempts to determine an optimal solution concerning all the controlling parameters is a complex task and requires exhaustive calculations which insists on the need for developing an optimization with reduced complexity in the future [34].

3. Problem statement

The major challenge exists in RSS-based localization as the signal level indicator to estimate the distance of the dead nodes localization in the WSN is a complex task. Further, improving the localization accuracy is of paramount significance to decrease the effects of noisy distance measurements. Hence the proposed optimal node localization overcame the challenges by utilizing the OAS optimization for determining the location of the dead nodes concerning the multi-objective function designed using the localization error, RSS, and remaining energy in the nodes.

The RSS evaluation that follows the log-normal channel model is expressed as,

$$RSS(d_R) = P_T - PL(d_o) - 10\alpha_o \log_{10}\frac{d_R}{d_o} + X_\sigma$$

(1)

where X_σ denotes the noise in RSS, which is a zero mean Gaussian random variable, $PL(d_o)$is the signal power loss, $d_R$is the distance between the unknown and the anchor node.

4. Design of optimal node localization utilizing the OAS optimization and multi-objective function in WSN

In the existing approaches, node localization is a challenging task to attain effective data transmission in the WSN. Hence, the developed method overcame the above challenge by developing an optimal algorithm for node localization. Initially, the nodes employed in the sensing environment collect the data related to the sensing environment and transmit the data among the different nodes in the network. During the transmission, the energy level of the nodes is depleted leading to node failure, which needs to be replaced using a new node. Thus, the newly placed node is localized concerning the anchor nodes built with the GPS. Further, the network nodes are split into clusters taking into account the number of network nodes. The nodes that receive the data record a minimal hop count and forward the message to the next node. Now, the hop size is calculated and the minimal hop count is evaluated. Then, the distance between the selected anchor node and the unknown node is determined. Hence the CH selection is utilized for determining the node with maximum energy that can be determined based on the OAS optimization and multi-objective function. Finally, the optimal location of the unknown node is located utilizing the OAS optimization algorithm concerning the

Multi-objective function designed using the localization error and remaining energy in the nodes. Further, the adaptive incorporated Fractional artificial bee colony algorithm (FABC)-based routing and Beetle-based routing perform the routing based on the intra-cluster distances for delivering the data packets via the CH to the BS for different applications. The proposed methodology for optimal node localization is represented schematically in Figure 1.

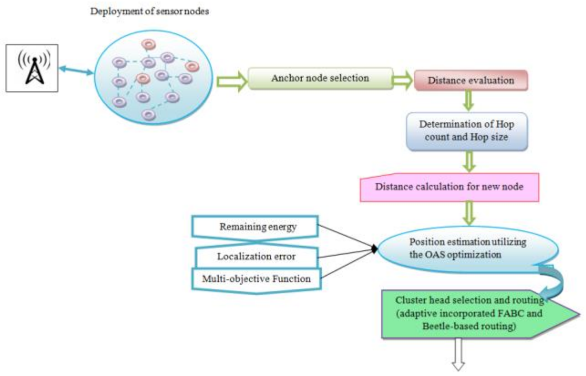


Fig.1. The proposed methodology for optimal node localization

4.1. Establishing the sensor network and anchor selection

Initially, the sensor nodes are deployed in the sensing environment to collect the data related to the specific phenomenon. During the process of data transmission, a few nodes lose energy over time due to battery depletion, and hence, new nodes are deployed for persistent data transmission. Let us assume that the WSN comprises the X anchor nodes and Y transmitter nodes or unknown nodes deployed in the sensing environment. Further, the space distance and geometric topology constraints are satisfied by the coordinates to form the unique topology of the OAS optimization-enabled optimal node localization model.

4.2. Distance evaluation

The nodes that transmit the data, record a minimal hop count and forward the message to the next node. The model involves a multi-objective function for determining the coordinates of the Y transmitter utilizing the anchor node's information. Initially, the ranging distance between the transmitter node and the anchor node is determined by the transmitter node utilizing the RSSI as well as the received signals from the anchor node. Additionally, every anchor node evaluates the distance from all the adjacent unknown nodes. The inter-node ranging distance d_i is evaluated as follows:

$$I_{au} = d_{au} + r_{au} \tag{2}$$

where d_{au} is the actual distance between the anchor node a and the unknown node u, r_{au} is the ranging error.

$$d_{au} = \sqrt{(l_a - l_u)^2 + (m_a - m_u)^2} \tag{3}$$

where (l_a, m_a) and (l_u, m_u) are the coordinate positions of anchor node a and unknown node u respectively. The expected distance $\overline{d_{au}}$ between the anchor node and the unknown node is

$$\overline{d_{au}} = \begin{cases} \sqrt{(\overline{l_a} - l_u)^2 + (\overline{m_a} - m_u)^2}, & \text{if } a \text{ is anchornode} \\ \sqrt{(\overline{l_a} - \overline{l_u})^2 + (\overline{m_a} - \overline{m_u})^2}, & \text{otherwise} \end{cases} \tag{4}$$

The ranging error r_{au} is the difference between the expected distance and the actual distance that can be formulated as,

$$r_{au} = \overline{d_{au}} - d_{au}$$

(5)

4.3. Determination of hop count and hop size

The nodes keep track of the hop counts during the transmission of data that ranges from the least number of hops to each anchor. Every anchor node floods the whole network with the global position and specifically, all nodes acquire the minimum number of hops with every anchor node. The hop size H_s is evaluated with the anchor node as follows,

$$H_s = \frac{\sum \sqrt{(l_a - l_u)^2 + (m_a - m_u)^2}}{\sum h_{\min}}$$

(6)

where the minimum number of hop count is denoted as h_m. Further, the selected anchor node's hop size is enhanced by the correlation factor υ as follows,

$$\upsilon = \frac{\overline{d_{au}} - d_{au}}{h_{\min}} \tag{7}$$

The correlation factor is employed to enhance the selected anchor node's hop size by integrating the factor with the previous hop size. Hence, the renovated distance D, between the unknown node and the selected anchor node is evaluated as follows,

$$D = (H_s + \upsilon) * h_{\min} \tag{8}$$

4.4. Position estimation utilizing the OAS optimization for optimally replacing the dead node with a new active node

The main intention of the proposed work relies on developing the optimal node localization based on position estimation utilizing the OAS optimization concerning the multiobjective function, localization error, and remaining energy constraints. The proposed OAS optimization is developed by integrating the information-sharing characteristics of apis and olfactory sensing characteristics of vespids and coleopterans to reach the best solution. The developed OAS optimization offers the advantages of high convergence speed, reduces the exploitation and exploration problems, lesser complexity involved in the design, and the ability to resolve the optimization issue in less time.

4.4.1. Inspiration

The information-sharing behavior of apis is often used to solve optimization problems related to efficient routing. The major advantages involve the utilization of an efficient search only around the best solution of the previous iteration to improve the exploitation along with high convergence speed. The apis comprise three groups involving the employer, onlooker, and scout. The potential solutions to an optimization problem are indicated as nectars, food sources [36]. Employer explores the existing solutions, and provides the information of neighborhood nectar source in the memory with a designated dance area in the hive; the onlooker acquires the information of the solution from the employers and selects one of the solutions; the scout is responsible for finding new solution nearer to the search space. Additionally, searching for the solution is enhanced by coleopterans that make predictions based on the sense received from the directions and move towards that direction [37]. Further, the vespids utilize the olfactory learning and photographic memory ability to memorize its hives boosting the efficiency of the search process for reaching the best solution [38].

Mathematical explanation of the OAS Optimization: The different stages involved in the OAS optimizer are explained as follows.

I. Representation of Solution: The solution of the OAS optimizer is initialized as S which comprises the best position of the nodes.

$$S = [U_{t+1}] \tag{9}$$

Phase I: Scout Phase: In the scout phase, the search agent searches for new access to the solution and locates the presence of the solution.

Case (i) $if\ K > 0.5\ and\ |G| > 1$

In this case, the adaptive parameter is greater than 0.5 and the alertness index G is greater than 1, in which the search agent searches beyond the search space. If the search agent finds the solution, then it will exploit the solution.

where $K = \frac{t-k}{j-C}$, in which j and k are upper and lower bands respectively, t represent the iterations and C denote the center boundary, K is an adaptive parameter.

The search agent searches for the solution in the nearby surroundings. Here the search agent continuously searches for the solution until it gets the best solution.

$$U_{t+1} = U_g(t) - G.\left|\psi U_g(t) - U(t)\right| \tag{10}$$

Where $G = (2R-1)b$ where R lies in the range $[0,1]$

$\psi = 2R$

$U_g(t)$ represents the global best position and $U(t)$ denotes the position at the t^{th} iteration.

II. Exploitation phase: The best solutions in the current population are significant for enhancing the convergence performance. The best solutions explored in the previous phase are employed to direct the movement of the current population and after getting the best solution, the search agent starts exploitation.

Case(ii) $if\ \ K \le 0.5\ and\ |G| \le 1$

In this case, the adaptive parameter is less than or equal to 0.5 and the search agent exploits the solution based on the global best solution as well as the personal best solution.

$$U_{t+1} = U_t + \varpi_1\left(U_g^{t-1} - U_t\right) + \varpi_2\left(U_p^{t-1} - U_t\right) \tag{11}$$

where $\varpi_1 = \frac{|U_g - U_t|}{|U_g + U_t|}$; $\varpi_2 = \frac{|U_p - U_t|}{|U_p + U_t|}$

where $t-1$ denotes the previous iteration of t.

III. Sensing phase: The search agent utilizes the sensing ability and moves towards the clockwise or anticlockwise direction where the strength of the solution sensing is high.

Case (iii) $if\ K > 0.5\ and\ if\ \ Q_p > K < 1$

In this case, the adaptive parameter is greater than 1. As the distance between the search agent and the solution changes that has the corresponding change in the search agent's direction.

where $$Q_p = \frac{[F(U_t)]^2}{[F(U_t)]^2 + [F(U_{t-1})]^2} \tag{12}$$

$$U^{t+1} = U^t - \phi^t q\, sign(E(z_1) - E(z_2)) \tag{13}$$

where z_1 and z_2 indicates the clockwise and anticlockwise values respectively. E represents the direction of the search.

$$z_1 = U^{t-1} - b^{t-1}q \tag{14}$$

$$z_2 = U^{t-1} + b^{t-1}q \tag{15}$$

Where b^{t-1} is the sensing distance of the solution at $(t-1)^{th}$ iteration.

$$\text{where } q = \frac{rand(e,1)}{\|rand(e,1)\|} \tag{16}$$

where q is a unit vector, $rand(\ )$ indicates the random orientation of the search agent, which $(e,1)$ is a matrix of $e \times 1$ dimensions.

$$\phi^t = \eta_1 \phi^{t-1} \tag{17}$$

where η_1 is a constant that determines the decay speed of the search step.

IV. Final phase: Additionally, the searching ability of the search agent increases with the distance from the solution and the memory ability of the search agent boosts the exploitation speed of acquiring the solution. The distance between the search agent and the solution is determined by using the following equation.

Case(iv) $\quad else\ if\ \ K > 0.5\ and\ if\ \ Q_p < K$

In this case,

$$U_{t+1} = U_t + \gamma(U_g - U_t) + \kappa\vartheta_i \tag{18}$$

κ denotes the randomization parameter, ϑ_i is a vector of random noise, and γ indicates the stinging ability of the search agent.

$$\gamma = \gamma_0 e^{-v^{t+1}s^2} \tag{19}$$

where v denotes the experience of the solution and s indicates the distance between the solution and the search agent.

$$v^{t+1} = (1-\zeta_c)v^t + \zeta_c v^{t-1} \tag{20}$$

where ζ_c represents the flight length.

$$v^t = \begin{cases} (1-\zeta)v^{t-1} + \zeta\left|v^{t-1} - v^{t-2}\right|; & if\ \ fit\left(v^{t-1}\right) > fit\left(v^{t-2}\right) \\ v^{t-2} & ;\ otherwise \end{cases} \tag{21}$$

$$\zeta_c = \zeta_s \zeta_t \tag{22}$$

v^t indicates the experience of the solution at t^{th} iteration, ζ is a memory matrix.

$t-1, t-2$ represents the iterations at the previous and previous of previous iteration respectively.

$$U_{t+1} = U_t + \gamma_0 e^{-v^{t+1}s^2}(U_g - U_t) + \kappa\vartheta_i \tag{23}$$

Thus from the above hybrid methods improved search accuracy, exploitation speed as well as adaptability of path planning are obtained.

III. Fitness Re-evaluation: After performing the update rule, the fitness of updated solutions is measured thereby revealing the best solution.

IV. Termination: The iteration terminates by validating the condition and declaring the global best solution for updating the system.

The flowchart for the OAS optimization is depicted in Figure 2.

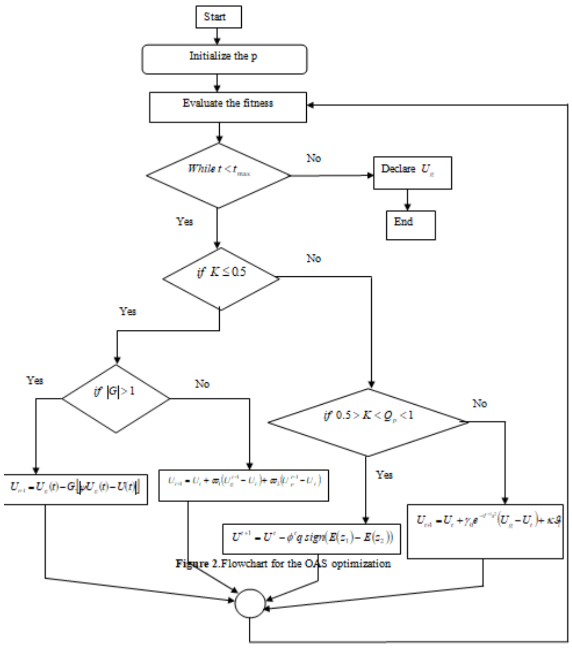


Fig. 2. Flowchart for the OAS optimization

4.5. Cluster head selection and routing

The CH selection and routing are performed utilizing the adaptive incorporated FABC-based routing and coleopteran-based routing. The optimal node localization is performed that extends the network lifetime for communication. Further, the CH selection and routing are performed for data transmission by determining the optimal CHs based on energy-related constraints like energy, delay, and distance. The clustering process acquires the energy utilization of the sensor nodes and the cluster nodes transfer the sensed data to their corresponding CH. The key purpose of the optimization methods in routing is to minimize the intra-cluster distances between CHs and the cluster members for efficient routing of the data packets.

4.6. Fractional Artificial Bee Colony routing and Beetle-based routing

The extension of traditional mathematics known as Fractional calculus(FC), makes use of the irreversibility and intrinsic memory attribute of FC to allow for the dynamic renewal of individuals through an evolutionary process. Additionally, the FABC algorithm is a stochastic algorithm motivated by the intelligent foraging characteristics of apis . To enhance the search for solutions in the predefined search space, ABC is altered with the mathematical concept, of fractional calculus. Hence, the integrated concepts can update the neighbor solution by utilizing the previous solution, and offer th advantage of decreasing the exploitation and exploration issues that the preceding solution in FABC provides the benefit of effective utilization of global information and is updated for each iteration. The multiple objectives utilizing the localization error and remaining energy in the nodes are embedded into the FABC algorithm.

5.1 Experimental setup

The proposed approach is simulated in the MATLAB tool with the simulation area of 100x100 and 200x200 operating in Windows 10, with 8 GB RAM for evaluating the performance.

5.2 Evaluation metrics

The metrics utilized for measuring the efficacy of the developed node localization approach are explained as follows

i)Root Mean Square Error (RMSE): RMSE is the difference between the population values predicted by the developed OAS optimization method and the actual values observed.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M} \left\| w_i - \hat{w}_i \right\|^2}{M}} \qquad (24)$$

where M denotes the total number of available data points, w_i is the actual observations, and the estimated prediction is denoted as $\hat{w}_i$.

ii)Received Signal Strength Indicator (RSSI): RSSI is the average of the squared magnitude of test samples in the linear scale and is evaluated as follows,

$$RSSI = 10 \times \log_{10}\left[\frac{1}{M}\sum_{i=1}^{M}\left(S_i(f)^2 + P_i(f)^2\right)\right] \qquad (25)$$

where the received samples quadrature as well as the in-phase components, are represented as $S_i(f)$ and $P_i(f)$ respectively, the total number of available samples is represented as M for individual RSSI, and the RSSI is measured in terms of dBm units.

5.3.Performance evaluation

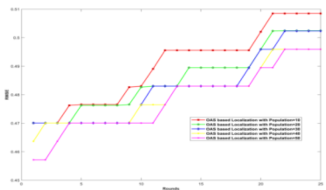
i)Performance evaluation for the simulation area 100 x 100:

The developed OAS-enabled node localization reaches the RMSE of 0.508 for the population of 10 and 0.495 for the population of 50 in the 25th round. The RMSE of the developed node localization is steadily improved from the initial population when the population size is increased in the simulation area of 100x100 which is depicted in Figure 3 a)

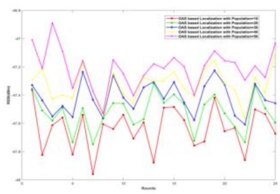
The RSSI of the developed method for the 25 rounds is depicted in Figure 3 b) in which the signal strength is steadily improved as the population increases from 10 to 50. The RSSI obtained by the developed approach is -47.673 dBm for the population of 10 and -47.032 dBm for the population of 50 respectively in the 25th round.

For the 50th round, the developed OAS-enabled node localization reaches the RMSE of 0.577 for the population of 10 and 0.539 for the population of 50 respectively. The RMSE of the developed node localization is steadily decreased from the initial population when the population size is increased from 10 to 50 in the simulation area 100x100 which is depicted in Figure 3 c)

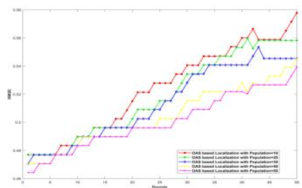
The RSSI of the developed method for the rounds up to 50 is depicted in Figure 3 d). For the 50th round, RSSI is -48.315 dBm for the population of 10 and -48.057 dBm for the population of 50 respectively, which shows that the signal strength is steadily improved as the population increases from 10 to 50.



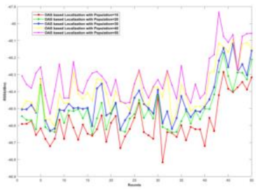
a)RMSE for 25 rounds



b)RSSI for 25 rounds



c)RMSE for 50 rounds



d)RSSI for 50 rounds

Fig.3. Performance evaluation for the developed method at a simulation area of 100 x 100 a)RMSE for 25 rounds b)RSSI for 25 rounds c)RMSE for 50 rounds d)RSSI for 50 rounds

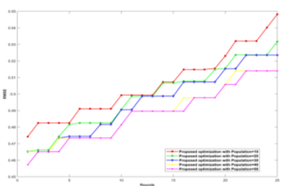
ii) Performance evaluation for the simulation area of 200 x 200

The developed approach attains the RMSE of 0.548 for the population of 10 and 0.513 for the population of 50 in the 25th round. The RMSE of the developed approach is steadily decreased from the initial population when the population size is increased in the simulation area of 200 x 200 which is revealed in Figure 4 a).

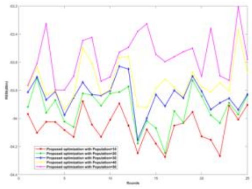
The RSSI for the corresponding rounds up to 25 is depicted in Figure 4 b), in which the signal strength is steadily enhanced as the population varies from 10 to 50. At round 25, the RSSI for the developed approach is -53.903 dBm for the population of 10 and -53.578 dBm for the population of 50 respectively.

The developed OAS-enabled node localization achieves an RMSE of 0.638 for the population of 10 at the 50th round and 0.608 for the population of 50 at the 50th round. The RMSE of the developed OAS-enabled node localization is steadily reduced from the initial population when the population size is increased which is demonstrated in Figure 4 c).

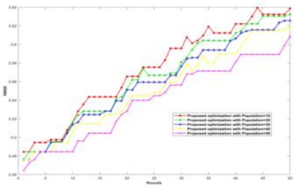
The corresponding RSSI for the rounds up to 50 is revealed in Figure 4 d), in which the signal strength is steadily improved from the population of 10 to 50. At round 50, the RSSI for the developed OAS-enabled node localization reaches -54.664 dBm for population 10 and -53.331 dBm for population 50 respectively.



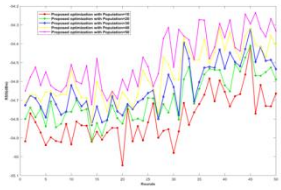
a)RMSE for 25 rounds



b)RSSI for 25 rounds



c) RMSE for 50 rounds



d)RSSI for 50 rounds

Fig.4. Performance evaluation for the developed method at a simulation area of 200x200

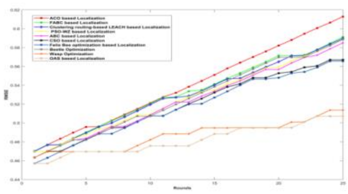
a)RMSE for 25 rounds b)RSSI for 25 rounds c)RMSE for 50 rounds d)RSSI for 50 rounds

5.4 Comparative evaluation

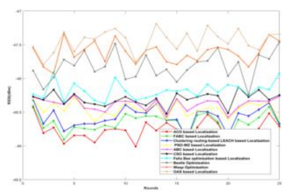
The performance of the proposed OAS optimization-enabled node localization is compared with the other traditional methods for node localization. The traditional methods involve Ant colony optimization(ACO)-localization [39], Fractional Artificial bee colony (FABC) -localization [40], Clustering routing-based LEACH-localization [36], Particle swarm optimization-based clustering (PSO-WZ)-localization[40], Artificial bee colony optimization(ABC)- localization [41], Chicken swarm optimization (CSO)- localization [42], Felis bee optimization-localization, Beetle optimization-localization[38], Wasp optimization-localization for 25 to 50 rounds in terms of the RMSE and the RSSI metrics.

i) Comparative evaluation for the simulation area of 100 x 100:

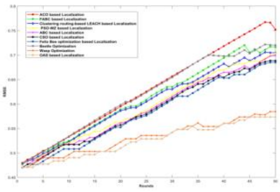
The developed OAS optimization enabled node localization attains the RMSE at round 25 is 0.507 which is decreased by 20.811% over existing ACO- localization technique, 16.564% over FABC- localization,16.247% over Clustering routing-based LEACH- localization, 16.010% over PSO-WZ-localization, 15.319% over ABC-localization, 11.785% over CSO- localization, 11.487 % over Felis bee optimization-localization, 16.043% over Beetle optimization-localization, 1.271 % over Wasp optimization-localization. The developed OAS optimization enabled node localization attains the RSSI at round 25 is -47.342dBm which shows 2.891% improvement over existing ACO- localization technique, 2.821% over FABC- localization, 2.804% over Clustering routing-based LEACH- localization,2.679 % over PSO-WZ-localization, 1.951% over ABC- localization, 1.909% over CSO- localization, 1.232% over Felis bee optimization-localization, 0.249% over Beetle optimization-localization, 0.213% over Wasp optimization-localization. Additionally, the developed method attains the RMSE at round 50 is 0.573 which is decreased by 31.134% over existing ACO- localization technique, 24.911% over FABC- localization, 22.903% over Clustering routing-based LEACH- localization, 22.857 % over PSO-WZ-localization, 21.940% over ABC-localization, 20.048% over CSO- localization, 19.457% over Felis bee optimization-localization, 25.580% over Beetle optimization-localization, 1.941% over Wasp optimization-localization. The developed attains the RSSI at round 50 is -48.226 dBm which shows 1.281% improvement over existing ACO- localization technique, 0.964% over FABC- localization, 0.736 % over Clustering routing-based LEACH- localization, 0.713 % over PSO-WZ-localization, 0.554% over ABC- localization, 0.280 % over CSO- localization, 0.230 % over Felis bee optimization-localization, 0.299% over Beetle optimization-localization, 0.265% over Wasp optimization-localization. The comparative analysis for the simulation area of 100 x 100 is depicted in Figure 5, which shows the developed method is superior in performance compared with other traditional methods.



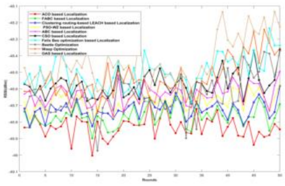
a)RMSE for 25 rounds



b)RSSI for 25 rounds



c) RMSE for 50 rounds



d)RSSI for 50 rounds

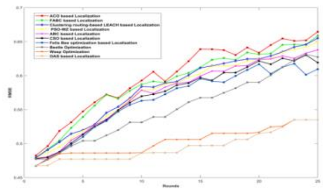
Fig. 5: Comparative analysis of the developed method for the simulation area 100 x100

a) RMSE for 25 rounds b) RSSI for 25 rounds c) RMSE for 50 rounds d) RSSI for 50 rounds

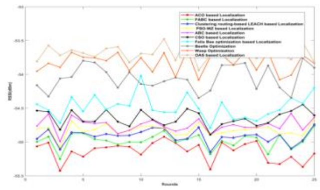
ii) Comparative evaluation for the simulation area 200 x 200:

The developed OAS optimization enabled node localization attains the RMSE at round 25 is 0.535 which is decreased by 24.202% over existing ACO- localization technique, 23.114% over FABC- localization, 22.445 % over Clustering routing-based LEACH- localization, 21.328% over PSO-WZ-localization, 19.203 % over ABC-localization, 15.718% over CSO- localization, 13.913% over Felis bee optimization-localization,17.241% over Beetle optimization-localization. The developed OAS optimization enabled node localization attains the RSSI at round 25 is -52.822dBm which shows 2.504% improvement over existing ACO- localization technique, 1.744 % over FABC- localization, 1.704% over Clustering routing-based LEACH- localization, 1.553% over PSO-WZ-localization, 1.510% over ABC- localization, 1.452% over CSO- localization, 0.697% over Felis bee optimization-localization, 0.144% over Beetle optimization-localization, 0.024% over Wasp optimization-localization. Additionally, the developed method attains the RMSE at round 50 is 0.587 which is decreased by 19.968% over existing ACO- localization technique, 18.883% over FABC- localization, 17.494% over Clustering routing-based LEACH- localization, 16.764% over PSO-WZ-localization, 16.124% over ABC-localization, 14.743 % over CSO- localization,14.590% over Felis bee optimization-localization, 17.482% over Beetle optimization-localization, 1.998% over Wasp optimization-localization. The developed attains the RSSI at round 50 is -53.190 dBm which shows 2.201 % improvement over existing ACO- localization technique, 1.674 % over FABC- localization, 1.620 % over Clustering routing-based LEACH- localization, 1.553% over PSO-

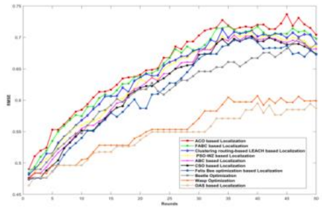
WZ-localization, 1.425% over ABC- localization, 1.359% over CSO- localization, 1.355% over Felis bee optimization-localization, 0.499% over Beetle optimization-localization, 0.153% over Wasp optimization-localization. The comparative analysis for the simulation area of 200 x 200 is depicted in Figure 6, which shows the developed method is superior in performance compared with other traditional methods



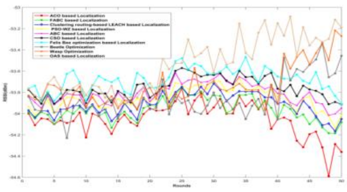
a)RMSE for 25 rounds



b)RSSI for 25 rounds



c) RMSE for 50 rounds



d)RSSI for 50 rounds

Fig. 6: Comparative analysis of the developed method for the simulation area 200 x200 a) RMSE for 25 rounds b) RSSI for 25 rounds c) RMSE for 50 rounds d) RSSI for 50 rounds

5.5. Comparative discussion

The performance of the developed approach is examined with the other traditional techniques for the simulation area of 100 x 100 and 200 x 200 is depicted in Table 1. The traditional methods utilized for comparative analysis had some limitations, in which the LEACH-based localization protocol found challenges such as random selection of CHs, uneven distribution of CHs, single-hop communication between CHs and BS, excessive energy consumption, and easy node death [36]. The ACO-enabled localization was found with limitations as the method does not maintain the network connectivity, increases power consumption, and requires more deployment cost [39]. The double path routing with FABC has not attained the potentiality as the nodes are scattered in big intervals concerning the energy and hence finding of multi-path to transmit the data was found to be a complex task [40]. Additionally, the CSO- localization required dynamic adjustment of the population in each group to update their velocity in a structured way [42]. The PSO-WZ technique utilizes a conventional method for aligning the particle within the boundary and requires tuning the model to adapt within the network [41]. However, the ABC optimization-based localization, in which the signal strength evaluated at the receiver is affected by the shadowing effect, and hence the evaluated distance concerning the RSS is found to be erroneous [37]. The beetle optimization enabled node localization had limitations with the randomness of node distribution, which made calculating the position a difficult process [38]. However, the OAS optimization enabled node localization approach overcame the drawbacks in the conventional techniques by employing the OAS optimization that evaluated the position of the dead nodes and replaced those nodes with new nodes that maintained the lifetime and energy efficiency of the network. Additionally, the method utilized an efficient routing mechanism that ensured effective data transmission between the nodes. From Table 1, it is evident that the developed approach contributed to low RMSE and high RSSI compared with other traditional methods.

Table 1. Compaartive discussion for the OAS optimization enabled node localization.

Methods	Simulation area 100x100				Simulation area 200x200			
	25 rounds		50 rounds		25 rounds		50 rounds	
	RMSE	RSSI(dBm)	RMSE	RSSI(dBm)	RMSE	RSSI(dBm)	RMSE	RSSI(dBm)
ACO- localization	0.612	-48.710	0.752	-48.844	0.664	-55.17	0.704	-54.361
FABC- localization	0.591	-48.677	0.716	-48.692	0.658	-54.761	0.697	-54.08
Clustering routing-based LEACH- localization	0.589	-48.669	0.704	-48.581	0.655	-54.74	0.689	-54.051
PSO-WZ- localization	0.588	-48.610	0.704	-48.57	0.649	-54.659	0.685	-54.016
ABC- localization	0.584	-48.266	0.699	-48.494	0.637	-54.635	0.681	-53.948

CSOlocalization	0.567	-48.246	0.688	-48.361	0.619	-54.604	0.673	-53.913
Felis bee optimizatin-localization	0.565	-47.925	0.685	-48.338	0.609	-54.198	0.672	-53.911
Beetle optimizatin-localization	0.588	-47.460	0.72	-48.37	0.627	-53.9	0.689	-53.455
Wasp optimizatin-localization	0.513	-47.443	0.584	-48.354	0.535	-53.835	0.598	-53.271
Proposed OAS optimizatin enabled node localizatin	0.507	-47.342	0.573	-48.226	0.535	-53.822	0.587	-53.19

6. Conclusion

In this research, OAS optimization is utilized for optimal node localization in WSN, which minimizes the localization error and enhances the energy efficiency in the WSN, resulting in reducing the cost and providing efficient routing for effective data transmission. The developed approach evaluated the location of unknown nodes with the known position of anchor nodes utilizing the OAS optimization. Further, the OAS optimization localizes the dead nodes concerning the localization error and remaining energy. Hence the dead nodes are replaced with the new nodes and the clustering is performed with the efficient adaptive incorporated FABC and Beetle-based routing for transmitting the data to the BS. The developed OAS optimization enabled node localization method attains RMSE of 0.573, RSSI of -48.226 dBm for the simulation area 100x100 and RMSE of 0.587, RSSI of -53.19 dBm for the simulation area 200x200.The experimental outcomes demonstrate that the developed method surpasses the traditional approaches by substantially minimizing the localization error and enhancing the lifetime and energy efficiency of the WSN.Further the energy efficiency of the developed approach can be enhanced by incorporating other advanced optimization approaches in the future.

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