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Ant Lion Optimizer based Multi-sink Placement in Wireless Sensor Networks

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***Abstract* –Wireless Sensor Networks (WSN) are essential for creating security and military applications. The sensor network collects data from the actual site and sends it to the base station. The handling of resources is a more important task for the data transmission process. Topology control is a more efficient method of managing resources in data communication.Multi-sink placement is one of the topology control techniques to reduce energy consumption and lengthen the network lifetime. In this study, Ant Lion Optimization (ALO) is proposed to place proper sink placement locations. This methodology was designed by utilizing the hunting technique of ant lions. When calculating the energy efficiency of sensor networks, distance and hop count are taken into account.The experimental results demonstrate better results when the BFA and GWO procedures are compared. The suggested method decreases network delay and energy use while also extending network lifetime.**

***Keywords :*Wireless Sensor Networks, Multi sink placement, Ant Lion Optimization, Hop count,Energyutilization.**

I. INTRODUCTION

Wireless Sensor Network (WSN) develops the sensing environment with low-power wireless motes for emerging and advanced technological applications. The specialized hardware and communication protocols are more expensive for deploying sensor node applications. In most instances, WSN is involved for time-sensitive applications such as patient monitoring, health monitoring and forest fire detection. The computation and communication processes are restricted to the sensor nodes. The sensor nodes are very difficult to replace or recharge and the sensor nodes are limited by the battery.

The placement of the sensor nodes is random, and their precise locations are unknown. The topology must be planned and managed carefully for handling the resources in the wireless sensor network. The arrangement of various sinks is one of the key strategies for regulating the topological area. It is the base station's responsibility to gather and process the data.A sink node has more energy than the other sensor nodes.

The proper sink location is identified for efficient resource management of the network. The ideal placement of the sink increases network lifetime while consuming the least amount of energy. The illustration of multiple sink placements is shown in figure.1. The problem of where to place multiple sinks can be resolved using bio-inspired algorithms.

An organization and society are transitioning to the digital era in preparation for the data explosion [14,15,16]. As the complexity of the analysis rises, it becomes harder to extract information from the explosion of data.Bio-inspired algorithms are intelligent and learn from and adapt to the biological organism. Finding suitable solutions necessitates the use of intelligent techniques.

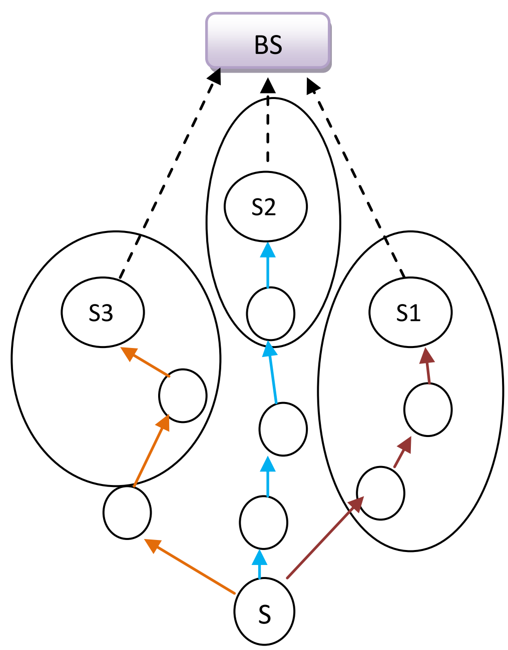

Fig.1Identification of multiple sinks

One of the key strategies in the algorithm with biological inspiration is called Ant Lion Optimization (ALO). The way that ant lions hunt has been used to develop this technique. The primary purpose of this methodology is to identify the best locations for the sinks on the candidate list. For minimizing the typical end-to-end delay and lowering typical energy consumption, the appropriate sink positions are found.

The paper includes the following contributions:

i) To formulate the placement issue for multiple sinks in a wireless sensor network.

ii) To use the Ant Lion Optimization (ALO) algorithm to pinpoint where the sink should be placed in the WSN.

iii) When the average energy delay and average end-to-end delay with BFA and GWO algorithms are taken into account, the results of the proposed technique are better.

The remaining sections are arranged as follows: The numerous sink placement techniques in WSN are described in Section II. Using the Ant Lion Optimization algorithm, Section III determines where the sink should be located in the WSN. Section IV provides the performance evaluation of the BFA, GWO, and ALO to choose the best location for multiple sinks. Section V presents the conclusion and suggested research.

II. RELATED WORKS

The various multi sink placement methodologies in wireless sensor networks are reviewed in the related works.Banka et al. developed PSO to place the sinks in the proper location. This method uses hop count and Euclidian distance to place the multiple sinks. This technique has improved the lifetime of networks. This algorithm can be improved for considering the energy consumption and end to end delay factor. [1].Jari et al. designed in order to improve network lifetime by addressing sink placement and any cast routing problems. Modified particle swarm optimization is utilized to identify the proper place of sink, and any cast routing designed using ACO. By using this technique, energy usage is decreased and network lifetime is increased. This algorithm is limited in terms of throughput and end to end delay between the sensor and base station [2]. SrinivasaRao et al. developed a gravitational search algorithm to identify the multiple sinks. For an effective design, this technique takes into account energy, data rate, and Euclidian distance. This method presented an optimal position for multiple sinks to extend the lifetime. This technique can be improved by considering the number of sink positions and number of cluster head percentage[3].

Singh et al. demonstrated different algorithms for improving sink node placement in the WSN. The PSO algorithm is utilized for placing the sink node in proper place, and the route is constructed using the artificial bee colony technique. This technique is utilized to improve network throughput and reduce the hop count. This technique can be improved by including node density, cluster head position variation and Network lifetime[4].Pardesi et al. developed the geographic sink placement method for increasing lifetime and lowering energy consumption. This technique is used for dividing the network into concentric circular rings. This method is utilized to identify the proper place of multiple sinks and also enhance their lifetime. This technique is to be improved for calculating the throughput and node density. The space and time complexity of the proposed methodology is to be addressed [5].

Zhao et al. have developed layer-based diffusion PSOto find the solution for solving sink and sensor placement.This algorithm is used to bind the sensors to a sink for finding the proper solutions. By using this method, the average residual energy is decreased and the network lifetime is extended.This technique has limitations for addressing the packet latency, throughput and average end to end delay[6].

Chatterjee et al. have demonstrated the distributed greedy algorithm for forming node-disjoint clusters on the basis of cluster diameter. With this approach, network lifetime is increased while node deployment costs are decreased. This methodology needs to be improved for large-scale sensor networks, average end to end delay and throughput [7].Bhattacharjee et al. have developed a lifetime-oriented method for determining the proper position. This method has utilized to reduce energy consumption and prolong the network lifetime. This methodology can be improved for calculating the hop count, number of sinks and node density [8]. The Harris' Hawks Optimization (HHO) method was created by Houssein et al. to locate the best placement for multiple sinks. This approach lowers energy use and increases network lifetime by reconstructing the transmission path from sink to sensor nodes using Prim's algorithm. This algorithm need to be improved for network lifetime, number of sinks, hop count and throughput[9].

Hanh et al. have developed the k-means algorithm for generating the groups. The sensor nodes are located in a suitable position for achieving the target coverage. For network connectivity, the greedy and spanning tree approaches are used. This methodology utilizes the minimum nodes required to ensure the connectivity and target coverage by using multi-sink. This algorithm can be improved for considering the coverage and connectivity parameters, network lifetime and node density [10].Sajid et al. have presented the distributed algorithms for deploying the sinks in the optimum positions. The sink positions are directly connected to the fault tolerance level and indirectly related to the network latency and transmission range. This algorithm can be improved for the network lifetime, packet latency and average end to end delay [11]. Masdari et al. have suggested a distributed fuzzy logic algorithm for independently selecting a sink node in congestion situations. This algorithm balances the load and also prevents congestion. This algorithm needs to be improved for considering the multiple mobile sinks, network lifetime and average hop count[12]. The algorithm for positioning the base station at the backbone centroid, or theoretical centre, of the graph was proposed by Snigdh et al.[13]. This approach reduces the number of hops needed to reach the sink. This method extends lifetime while reducing energy consumption and delay. This methodology can be improved for node density, packet delay, and transmission range.

Kanimozhi et al. have suggested the ant-lion optimization to estimate the photovoltaic parameters of the single diode model. This approach is used to obtain a low root mean squared error. This methodology provides better results for analyzing the solar cell [19]. An unmanned aerial vehicles route can be planned using the dynamic adaptive ant lion optimizer, which was developed by Yao et al. With regard to accuracy and convergence speed, this algorithm performs better. [20].

Wang et al. have developed wavelet SVM and modified ant lion optimization to reduce the dimension of a hyper spectral image. This approach finds the optimal solution for classification accuracy and convergence level [21]. Kilic et al. have suggested an improved Ant-Lion optimizer to the tournament selection method for a single objective optimization problem. This algorithm provides good results in accuracy, CPU time, and optimality [22]. Mouassa et al. have developed the ant-lion optimization to find the efficient solution to the reactive power dispatch problem. In terms of both solution quality and the cost function for computation, this method works well for identifying the best solution[23].

From the literature review, ant lion optimization is applied for various applications. This optimization method is not applied formultiple sink placements in WSN. The authors have suggested the Ant Lion Optimization algorithm for locating the optimal position of the multiple sinks in WSN. This demonstrates the novelty of the paper.

III.EFFECTIVE MULTI SINK PLACEMENT IN WSN USING ANT LION OPTIMIZATION

A. Objective Function

An undirected graph, $G = (V, E)$, can be used to represent a wireless sensor network, where V indicatesthe nodes and Erepresents the edges.Let $d(V_0, V_1)$ be the distance among the two nodes$V_0$and V_1. If $d(V_0, V_1) <= TR$ where $TR$is transmission range.For solving problems involving the placement of multiple sinks, the Ant Lion Optimization algorithm is suggested. The primary goals are to decrease delay and average energy consumption. This can be indicated as:

$$\text{Minimize}_{i\in\{1..m\}}^{max} \{d_{end-to-end}\} \quad (1)$$

where,

$$d_{end-to-end} = g\,(c\_loc \mid s, r) \quad (2)$$

$$s = (s_{xi}, s_{yi}),\ i=1..n \quad (3)$$

$$c\_loc = (c\_loc_{xi}, c\_loc_{yi}), i=1..m \quad (4)$$

$d_{end-to-end}$is the end-to-end delay for the node, $s$represents the location of the nodes and c_loc represents the selection of the candidate locations for the m sinks, r is the routing protocol.

The Ant Lion Optimization is suggested to solve problems involving multiple sink placements. The primary goal is to lower average energy consumption and average end-to-end delays. The region of indifference is referred to as the sink, which can be located anywhere in the sensor network without altering the topology of the system. For gathering the group of potential locations, this method is used. One candidate location can represent each region, and the following equation can be used to calculate the total number of regions (NR).

$$NR = \sum_{i=1}^{sn+1} 2 * N_{ni} + 1 \quad (5)$$

Where N_{ni}denotes the number of neighboring nodes and sn represents the sensor nodes.

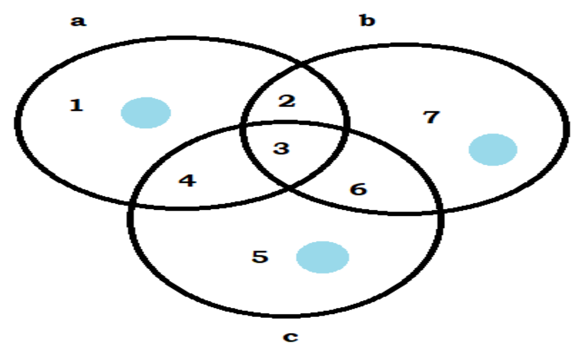

Fig.2 Region of indifference

A region of indifference is shown in Figure 2. The total number of regions is determined using the equ.5. There are 4, 6, and 7 regions in total for sensor nodes a, b, and c, respectively. The discretization process is used to determine the locations of the candidates.

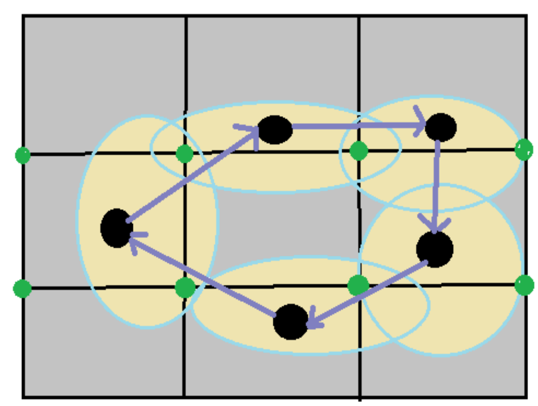

Fig. 3Grid size view of sensorfield

Figure 3depicts a grid-sized view of the sensor field.Regarding the distance between the sensors and the position of the grid, calculations are made. The calculated value is contrasted with the candidate location's distance from the origin and the sensor nodes' transmission range. The current node position must be listed in the candidate location if the prerequisites are satisfied. Finally, join every the grid points with comparable neighborhoods, and then select one node from that area. Utilizing the valueNR, the number of accepted grid points is assessed.The grid size is increased if the value is less than NR. In order to cover all the regions, this method is repeated.

B. Algorithm: Candidate Location Calculation

1) Read the sensor node position.
2) Find the regions NR for placing sink
3) Change the grid location of sensor.
4) Candidate position identified for every region.
5) For considering the sensor nodes n
   If the location of candidate is closer to the sensor node than the transmission range and closer to the origin than the radius,
   Increment the candidate location.

C. Ant Lion Optimization Algorithm

SeyedaliMirjalili[17,18] developed the ALO algorithm, which interacts between ants in traps and antlions. For this interaction,the ant moves to search the food in a random direction, and ant lions are allowed to hunt the ants using a trap.The ant's random walk$X(t)$ is depicted as:

$$X(t) = [0, cs(2 * r(t_1) - 1), cs(2 * r(t_2) - 1) \ldots \ldots . cs(2 * r(t_n) - 1)] \quad (6)$$

Where cs represents the cumulative sum, n denotes the maximum iteration, t represents the random walk and the function $r(t)$ is represented as:

$$r(t) = \begin{cases} 1 & if\ rn > 0.5 \\ 0 & if\ rn \leq 0.5 \end{cases} \quad (7)$$

wherern is a random number produced between [0, 1].The following matrix was used to represent the positions of ants.

$$M_A = \begin{bmatrix} A_{1,1} & \cdots & A_{1,d} \\ \vdots & \ddots & \vdots \\ A_{n,1} & \cdots & A_{n,d} \end{bmatrix} \quad (8)$$

This optimization uses the fitness function$M_A$and also to store all ant's value.

$$M_{OA} = \begin{bmatrix} f(A_{1,1} & \cdots & A_{1,d}) \\ \vdots & \ddots & \vdots \\ f(A_{n,1} & \cdots & A_{n,d}) \end{bmatrix} \quad (9)$$

Where M_{OA}represents the antsfitness, f is the fitness function, n is number of ant, $A_{i,j}$denotes the i^{th}ant in the j^{th}position.

The following matrix is utilized to represent the position of ant lions.

$$M_{AL} = \begin{bmatrix} AL_{1,1} & \cdots & AL_{1,d} \\ \vdots & \ddots & \vdots \\ AL_{n,1} & \cdots & AL_{n,d} \end{bmatrix} \quad (10)$$

Where M_{AL}represents the ant lions fitness, n is the number of ant lions, $AL_{i,j}$ represents the i^{th} ant lion in the j^{th} position.

The fitness used for optimization and also to store the value of all the ants.

$$M_{OAL} = \begin{bmatrix} f(AL_{1,1} & \cdots & AL_{1,d}) \\ \vdots & \ddots & \vdots \\ f(AL_{n,1} & \cdots & AL_{n,d}) \end{bmatrix} \quad (11)$$

Where M_{OAL}represents the fitness of ant lion.The min-max normalization is utilized to generate the ant's random walk.

$$X1_i^t = \frac{(X1_i^t - a1_i) * (d1_i - c1_i^t)}{(d1_i^t - a1_i)} + c1_i \quad (12)$$

Where $a1_i$ is the minimum value, $d1_i$ is the maximum value, $c1_i^t$ is the minimum value at t^{th}iteration, $d1_i^t$ is the maximum value at t^{th}iteration.The use of Ant Lion's traps modifies the ant's random walk. This can be represented by:

$$c1_i^t = antlion_j^t + c^t \quad (13)$$

$$d1_i^t = antlion_j^t + d^t \quad (14)$$

Where $antlion_j^t$ represents the j^{th}ant lion position at t^{th} iteration.

The ALO algorithm is used to select ant lions based on their fitness value for catching the ants using the roulette wheel method. Based on their fitness value, ant lions are primarily used to generate the traps, and the ants move at random. Ant lions will shoot sand out of the centre of the pit when they detect an ant inside the trap.This can be represented as

$$c^t = \frac{c^t}{R} \quad (15)$$

$$d^t = \frac{d^t}{R} \quad (16)$$

Where R is ratio,c^t is the minimum value at t^{th}iteration, $d^t$is the maximum value att^{th}iteration.The updated position for catching the new prey requires an ant lion. This can be represented as

$$antlion_j^t = ant_i^t \quad if\ f(ant_i^t) > f(ant\ lion_j^t) \quad (17)$$

where$t$ indicates the current iteration, $antlion_j^t$ is the j^{th}ant lion at t^{th} iteration, ant_i^t represents the i^{th}ant at t^{th}iteration.

The top ant is identified and preserved as elite in each iteration. This can be represented as:

$$ant_i^t = \frac{R_{AL}^t + R_E^t}{2} \quad (18)$$

Where R_{AL}^t shows the random walk for antlion, R_E^t represents the random position of the elite, ant_i^tshows thei^{th}ant position of t^{th}iteration.

D. Flow chart

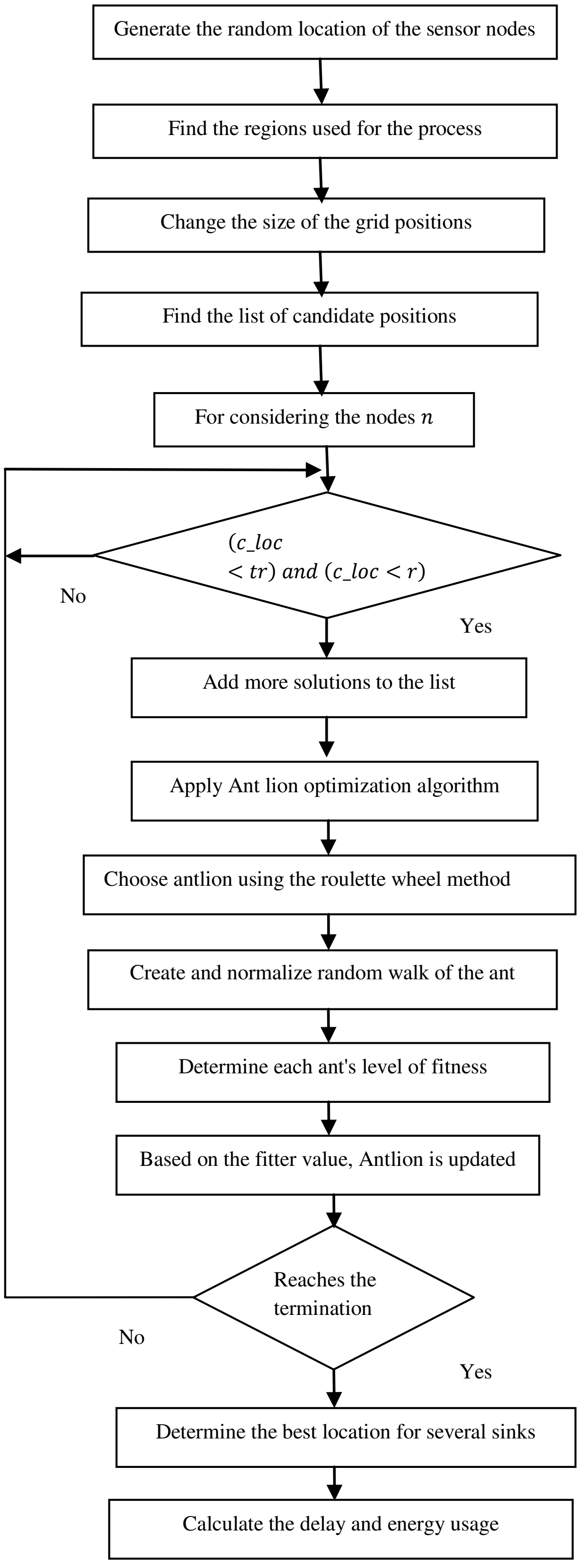

Fig.4 Flow chart for multiple sink placements using ALO algorithm

E. Multi sink placement using Ant Lion Optimization

Begin

On the basis of the candidate solution, the sink position is calculated.

Ant and Antlion populations are initialized randomly

Fitness is calculated for ants and ant lions

Select the best ant lion from the ant lions

While the iteration is not reached

For each ant

By utilizing the roulette wheel method to choose the antlion.

Change the values for c and d in equ 15 and 16.

Equation 6 and 12 are used to create and normalize

random walk of ant

Using equ.18, adjust the position of the ant.

End for

Determine each ant's level of fitness.

An appropriate ant will take the place of Antlion using equ.17

Based on the fitter value, Antlion is updated and considered elite.

End while

Return elite

Find the optimal location for multiple sink placements.

Calculate the usage of energy and delay.

end

IV. SIMULATION MODEL

Over a surface area of 100 * 100 m^2, the sensor networks are positioned at random. The corresponding x and y values are considered for reading the position of the sensor nodes.For this simulation, two to eight sinks are taken into account. At the beginning, the energy of each sensor node is the same. The sink and sensor nodes are both fixed. Over a 16 m distance, the sensor nodes transmit the data at a rate of 19.2 kbps. Using the AODV protocol, the data is transmitted to the nearby sensor nodes. This protocol can quickly respond to topological changes and easily adapt to dynamic networks. The simulation parameters used for the experiment are shown in Table I.

A. Control parameters of ALO

For the purpose of choosing appropriate control parameters, Ant Lion Optimization performs well. Table II displays the ALO control parameters as well as those used in the experiment process.

Table I. Simulation Parameters

Parameters	Value
Number of sensor nodes	20 to 100
Number of sinks	2 to 8
Topology size	100*100m^2
Protocol	AODV
Transmission Range	250m
Simulation time	600seconds
Packet size	512bytes

Table II. Control Parameters of ALO

Parameters	Value
No of search agents	40
Maximum iterations	500
Number of variables	4
Upper bound	100
Lower bound	-100

B. Performance Metrics:

The following metricsutilized for finding the location for placing multiple sinks by using ALO.

• **End-to-end delay:**This phrase describes the time needed to transmit a packet from its source node to all of its sinks.

•**Energy consumption:**This represents the energy expended during the execution process.

C. Simulation Results

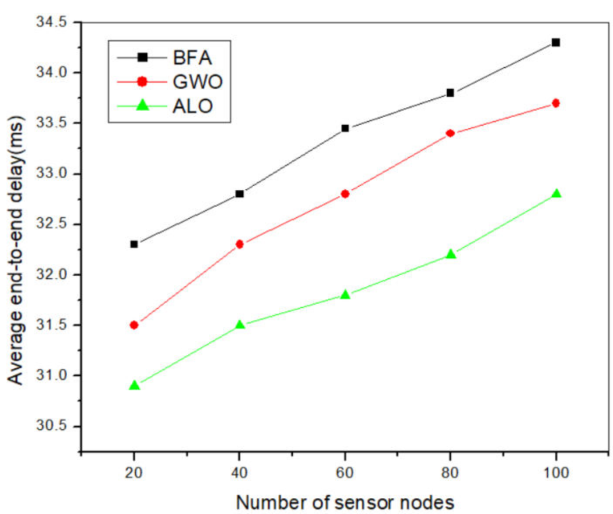

Fig.5.Sensor nodes vs average end to end delay

In figure.5 the average end-to-end delay is measured for varying the sensor nodes.Average end-to-end delay is considered for the time sensitive applications in WSN. The performance evaluation is measured with the BFA, GWO, and ALO algorithms. In comparison to other algorithms, the ALO algorithm uses the minimum average end-to-end delay values.The suggested methodology locates the sinks quickly in the optimal position.

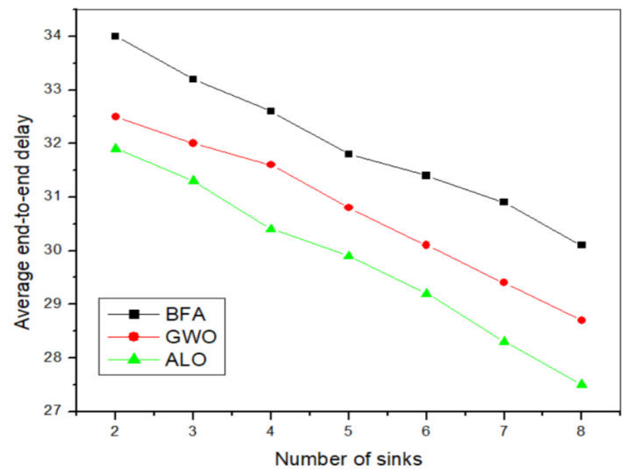

Fig.6number of sinks vs average end-to-end delay

When the number of sinks is increased from 2 to 8, Figure 6 displays the average end-to-end delay. The typical end-to-end delay will decrease as the sink count rises. Three different optimization techniques, such as BFA, GWO, and ALO, are considered for the analysis of the end-to-end delay. Comparing the ALO algorithm to the BFA and GWO algorithms, the end-to-end delay is decreased. The suggested method decreases the typical end-to-end delay for time-sensitive applications.

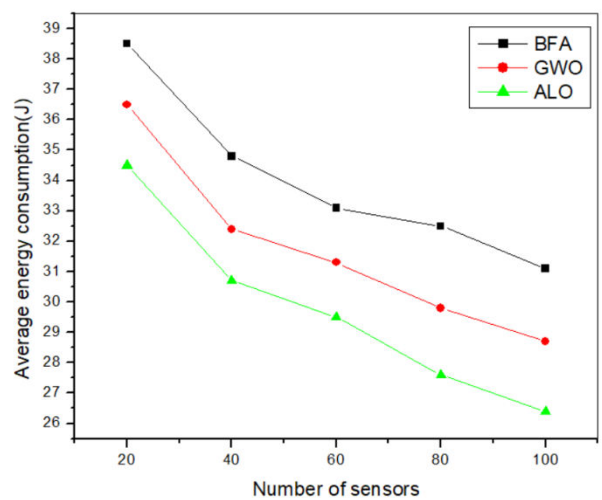

Fig.7 number of sensors vs average energy consumption

The measurement of energy consumption for various sensor nodes is shown in Figure 7. The primary factor in data packet transmission from source to destination and in extending network lifetime is energy. Different optimization algorithms, such as BFA, GWO, and ALO, are used to carry out this analysis. The ALO algorithm uses the least amount of energy possible to transmit data. The suggested methodology increases network lifetime while also consuming less energy.

Novelty in the proposed design should be established through a comparative analysis. Comparative analysis is performed with BFA, GWO and ALO algorithms.Table.IIIshows the average energy consumption and end-to-end delay for different algorithms. ALO shows the better results in average energy consumption and end to end delay.

Table III. Average energy consumption and end to end delay for various algorithms

Algorithm	Average Energy consumption(J)	Average end-to-end delay(ms)
BFA	31.1	34.3
GWO	28.7	33.7
ALO	26.4	32.8

Table IV shows the average energy consumption by identifying the number of sinks. The performance is analyzed with BFA, GWO and ALO algorithms. The proposed methodology shows the better results in average end to end delay.

Table IV. Average end to end delay for number of sinks of different algorithms

Number of sinks	BFA	GWO	ALO
2	34	32.5	31.9
5	31.8	30.8	29.9
8	30.1	28.7	27.5

The following points are considered as advantages of the proposed method. The implementation process is very easy and flexible. This methodology balances between exploration and exploitation. The limitation of the proposed methodology is given as follows: The method is executing the code for long time and also has a premature convergence.

V. CONCLUSION

In this study, Ant Lion optimizer is proposed to find the optimallocation for placing the multiple sinks. The proposed methodology have implemented in NS-2 and compared with BFA and GWO. Transmission range and distance between the sensor nodes are considered for evaluating the fitness function. The ALO identifies the proper candidate positions to minimize the average energy utilization and average delay. The proposed methodologygives better results when compared to BFA and GWO algorithms. The future scope of the work is as follows:

i) This work can be expanded by using a hybrid approach of meta-heuristics such as PSO or Firefly techniques to determine sink placement in a WSN.

ii) The proposed methodology can be extended for the mobile sensor networks.

iii) This methodology can be developed for addressing the coverage of the sensor networks.

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