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Lifetime Enhancement of Sensor Nodes Based On Optimized Sink Node Placement Approach

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Abstract

In Wireless Sensor Networks (WSNs), the sink node plays an essential task in which it collects or stores plenty of transmitted data from other sensor nodes. Optimal placements of sink nodes are a kind of procedure which enhances the network lifetime and minimize the energy consumption. Moreover, sink nodes contains additional resources like long-range antenna, powerful batteries, large memory and so on. Optimal placement of sink is considered as major problem in this work. So, an Enhanced Emperor Penguin Optimization (EEPO) is planned to place a lowest number of sink nodes in optimal locations to cover whole region. Initially, the sensor nodes are clustered using K-medoids algorithm to achieve this goal. After that, the sink nodes are optimally placed based on the EEPO algorithm. Moreover, the objective function is formulated to diminish the energy consumption and prolongs network lifetime. The proposed methodology (EEPO) is implemented using the Network Simulator (NS-2) tool. Moreover, the performance parameters like, packet delivery ratio (PDR), energy consumption, localization error, network lifetimeand running time are analyzed and compared against existing methodologies like Harris Hawks Optimization (HHO), Particle Swarm optimization (PSO) and Grey Wolf Optimization (GWO) algorithm. When compared to the recent techniques, proposed method achieves better network lifetime with specified number of rounds.

Keywords: *Wireless Sensor Networks, Multiple Sink Nodes, Enhanced Emperor Penguin Optimization Algorithm, Network Lifetime Enhancement, K-Medoids Clustering Algorithm.*

I. Introduction

Group of sensor nodes which have the capacity like sensing, computing and communication devices are named as WSNs. These kind of nodes also have low power and low cost capacities to recognize an event in a particular environment. Note that the specific environment may be a kind of any information technology framework or biological framework. The applications like medical telemetry, monitoring, tracking, data collection, and surveillance are performed by this network [1-2]. Control and activations are also performed by this sensor framework. Generally, these nodes are scattered in an exact region to measures a plenty of magnitude as indicated by the particular requirement of applications. But, the design of senor framework contains some limitations like energy consumption and network lifetime. Moreover, the sensors are designed with battery powered nodes [3].

Most of the researchers focused to design low energy consumed sensor nodes to improve the whole network lifetime. For wireless networks, replacing or recharging of battery is not possible because, these can cause limitations in the processing time as well as communication ranges [4]. So, various kinds of researches are done in this field to enhance the connectivity of whole network. Moreover, it depends on the amount of sensor nodes in each and every cluster in which the cluster head can manage the limited amount of sensor node at a time [5]. The data forwarding also performed by the nodes in each and every cluster to forward the information to cluster head [5]. The non-dominated solutions are obtained by the recent techniques in WSN to accomplish the optimal solutions. Moreover, the possible solution to enhance the network lifetime is to place the sensors in a best way [6-7].

Data security as well as reliability of sensor node is enhanced with the help of optimal sink node placement strategy. Also, energy consumption of whole system is reduced by this placement of sink node in an optimal manner. When compared to other sensor nodes, the sink nodes have some additional capabilities like higher transmission range, higher energy reserve and higher data processing capabilities [8-9]. Many of the researches are done in the field to place the sink node in optimal manner to enhance network lifetime [10]. In this paper, additional nodes are considered as sink nodes to avoid the faults in deployed network. This additional sensor node plays the role of sink nodes to achieve better data processing. Major goal of this paper is to minimize the usage of sink nodes [11-12] because, multiple sink node deployment is considered as NP-hard problem. Different kinds of algorithms are utilized to solve this problem in the fat few years. The deterministic algorithms not find any possible solutions to overcome this problem. So, many of the researchers use only the different kinds of heuristic and metaheuristics algorithm. Specifically, swarm intelligence algorithms, nature inspired algorithms are comprehensively used to find the correct solution. This kind of techniques achieved better placement of sink nodes in optimal manner [13-15].

The major contribution of our work is categorized as follows: Initially, we create an energy efficient sensor network model. After that, K-medoids clustering technique is utilized to cluster the sensor nodes. Finally, EEPO algorithm is proposed to place the sensor nodes in an optimal manner. In this algorithm, objective function is formulated to minimize the energy consumption as well as lifetime of the network.

Remaining sections are prearranged as follows: Section 2 exhibits literature review about the proposed work, an overall structure of the proposed system is labeled in section 3, an extensive explanation about experimental confirmation and execution estimations are debated in section 4, and section 5 portrays the conclusion of the proposed work.

II. Literature Review

An Improved Ant Colony Optimization (ACO) technique was suggested by Jin Wang et al. [16] for mobile sink nodes. So as to enhance energy efficiency, placement of sink node was considered as critical problem. So, the authors in this paper developed an improved ACO algorithm to find a best traversal path of mobile sink nodes. Moreover, the traditional ACO algorithm does not provide correct solution for this problem. So, an improved version of ACO algorithm was developed to solve this problem. The sensor node takes relatively long time for communication process. In order to enhance the proposed system, this work initially clusters the sensor nodes into diverse clusters and found the distance between cluster head nodes to perform other process. An optimal mobility route was find by the mobile sink node to commune with cluster node in the ACO algorithm after the calculation of distance.

For fault tolerant WSNs, Saunhita et al. [17] developed a Moth flame based optimized position of relay nodes. Nodes organized in the network may get smashed as a result of the difficult effects of hostile deployment environments. This makes loss of connectivity between sink node and sensor nodes. So, it was very essential to design a sensor framework without any kind of failure. When the sensor nodes were resource constrained, the single hop data communication model minimizes the network lifetime. Connectivity, fault tolerance and network lifetime may be enhances with the help placing a relay nodes in an optimal manner. This paper follows two phase implementation to place relay nodes. Mean shift algorithm was performed to cluster the sensor nodes in initial phase. Also, relay nodes were act as cluster heads. In second phase, the moth flame algorithm was developed to place the relay nodes to accomplish fault tolerance in fully connected network. When compared to other methods, proposed technique achieves better relay node placement in WSN.

Saunhita et al. [18] proposed a Bat Optimization algorithm to optimally place the relay nodes in a homogeneous WSN. The relay nodes were deployed in the homogeneous WSNs to enhance the network lifetime. These kinds of nodes were deployed to perform the data aggregation process. In this work, relay nodes were acted as cluster head. This paper studies four different kinds of meta-heuristic algorithms to perform the optimal node placement. The mobile sink node also collects information to maintain the latency. For informationcompilationpurpose, three mobile sink traversal techniques were simulated. From the simulation, it shows that the bat algorithm performs better sink node placement strategy.

For an energy efficient sink node placement in WSN, Eva Tuba et al. [19] proposed a Brain storm optimization algorithm. Different conditions like energy preservation, reliability, distance and signal propagation were considered to place the sensor nodes as well as the sink nodes or base stations. In this paper, multiple sink nodes were placed optimally with advanced battery capacity. The normal sensors were placed statically in clusters around the sinks by considering energy efficiency as well as distance. The sink nodes were using gateways for communication purpose so, it was very essential to find the optimal positions. With different performance parameters, proposed method outperforms existing PSO algorithm in network lifetime.

In Large Scale WSNs(LSWSNs), Essam. H et al. [20] developed a HHO algorithm for optimal placement of sink node. LSWSN was collected of plenty of sensors which were dispersed in a particular area. The main goal of sink node was to process and examine the composed data from other sensor nodes. Moreover, this sink node acts as an administrator and a station among the sensors. Sink node determination in LSWSN was considered as one critical issue so; this paper developed a HHO algorithm to optimally solve the problem. Initially, to renovate the system, Prim’s shortest path algorithm was utilized to create smallest amount of communication paths startingfrom the sink node to other sensors.

A Cat Swarm Optimization (CSO) algorithm was suggested by Vaclav et al. [21] for sink node placement. This algorithm was developed to discover the correctposition of sink nodes in a fixed sensor node environment. After the determination of sink nodes, this greedy algorithm also utilized to create the data transmission paths for the sensor nodes. Yong Lu et al. [22] developed anArtificial Bee Colony (ABC) algorithm for mobile sink based path optimization policy. The energy consumption was more due to the mobility of sink nodes. Also, the performance of network model becomes very poor owing to the restriction of rapidity of sink mobile and extendedtime of data collection. So, this paper develops ABC algorithm to enhance the ability of data gathering process.

For mobile sink based WSN, XiaowenLv et al. [23] developed a Lifetime Optimization Algorithm (LOA). In this paper, the energy consumption of communication was calculated by the maximum capacity path routing technique. Moreover, genetic algorithm was utilized to alter the individuals to meet all constraints in the optimization model. The network lifetime got increased with the help of this LOA technique. For large scale WSN, Mohmmed et al. [24] developed a multi-objective whale optimization algorithm (MOWOA) algorithm. To diminish the energy consumption and to maximize the network lifetime, a new objective function was developed. PSO based clustering algorithm was developed by Jin Wang et al. [25] for mobile sink WSN. During the routing stage, PSO based clustering algorithm was performed. In this algorithm, cluster head was elected based on the position and residual energy of the sensor node.

III. Proposed Methodology

The network lifetime of sensor framework is enhanced based on the sink node's optimal assignment strategy. Also, it reduces energy consumption of the whole system. But, selection of multiple number of sink node is considered as one of the major issue in large scale WSN. So, this paper proposed anEEPO algorithm to optimally place the sink nodes. This algorithm is a recently developed algorithm which has a special mechanism to balance the exploration and exploitation phases. This algorithm optimally places the small number sink nodes to enhance the lifetime of whole sensor framework. Workflow of the proposed method is displayed in figure 1.

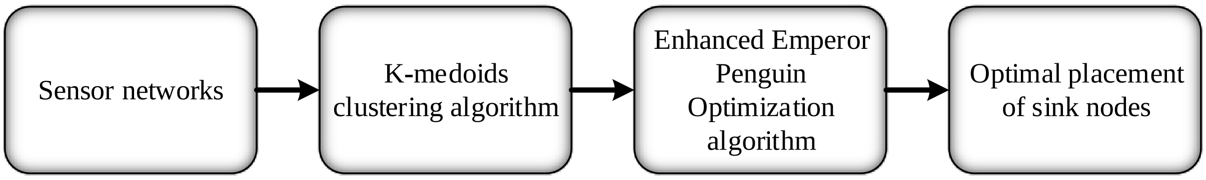

Figure 1: Work flow of proposed methodology

Initially, n numbers of sensors are evenly positioned in a particular region based on the memory and bandwidth. Major goals of these nodes are to transmit collected information to sink nodes. Each and every sensor nodes transmits messages to sink node in which it causes bottleneck to whole sensor framework. So as to evade this difficulty, the nodes are initially clustered using K-medoids clustering algorithm. After that, cluster heads are selected based on the some conditions like high residual energy and so on. The communication will be easier, when the sensor frameworks are divided into sub networks. After that, the EEPO algorithm is utilized to put the sink node in a best manner. In that algorithm, the objective function is formulated to place small amount of sink nodes to achieve better network lifetime.

A. Network Model

The system model is associated with plenty of sensor nodes. These are commonly divided into two categories. First one is cluster head and the final one is common node. Environment monitoring and transmitting sensed information to cluster head is the major role of these common nodes. Some parameters are used to elect the cluster head from common nodes. This receives the sensing information from the common node and sends those data to the sink nodes [26]. The network model of multiple sink WSN is given in the below figure 2.

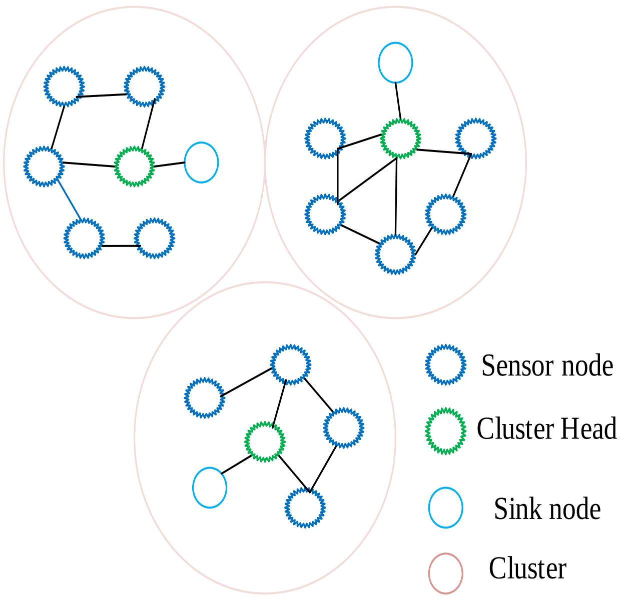

Figure 2 : System model of WSN

B. K-medoids Clustering Algorithm

This clustering algorithm is mainly used to decrease the energy consumption and to improve network lifetime. This algorithm is based on a universal clustering technique. By calculating the central circle mean points and residual energy, the iteration time is reduced by the optimized K-medoids algorithm.

Initially, n amount of sensors is clustered into k clusters and the cluster count is already known. Here, X_{ij} mentions the j^{th} variable of node i in which

$(i = 1,..., n; j = 1,2,....., p)$. Euclidean distance is considered as a measure in this algorithm. Euclidean distance among node i and j is given by

$$d_{ij} = \sqrt{\sum_{a=1}^{p} (X_{ia} - X_{ja})^2} \quad i = 1,2..., n; j = 1,2,...., n \quad (1)$$

There are three stages are presented in this method.

Step 1: Initial medoid selection

1.1 Based on the Euclidean distance, compute the distance among each pair of nodes.

1.2 The following equation is used to compute v_j for object j:

$$v_j = \sum_{i=1}^{n} \frac{d_{ij}}{\sum_{l=1}^{n} d_{il}} \quad j = 1,2,....., n \quad (2)$$

1.3 The value of v_j is sorted in an ascending order. Initial medoids are selected based on the smallest value of n number of nodes.

1.4 Initial cluster is obtained by assigning each and every node to the nearest.

Step 2: (Medoids Updation) locate a new medoids of each and every cluster which minimize entire distance to other node in its cluster. New medoids is replaced with the current medoids in every cluster.

Step 3: Node assignment to medoids.

3.1 The cluster result is obtained by assigning each and every node to the nearest medoids.

3.2 The sum of distance from every node to their medoids iscomputed. When the sum is equal to previous one then stop the process. Or else go backside to step 2.

When updating the medoids, this clustering algorithm runs like a K-means clustering technique [27].

Selection of Cluster Head

The cluster head selection of sensor node is performed based on the minimum distance and maximum residual energy.

Distance

The given below expression is used to calculate the distance among cluster node and sink node. Here, (N_u, N_v) mentions the distance among the normal node and sink node.

$$dist(N_u, N_v) = \min \sqrt{(x_{n_u} - x_{n_v}) + (y_{n_u} - y_{n_v})} \quad (3)$$

Here, n_u is nodes in cluster and n_v is mobile sink node and $dist$ mentions a distance between nodes and sink node.

Residual Energy

The available power for the node is mentioned by x_i, and amount of nodes for cluster i depends on $RP(x_i)$. Maximum $RP(x_j)$ means more energy power and more steady power. Thus the node with maximum $RP(x_i)$ is extremely likely to be selected as a cluster head and able to support network lifetime for a long time.

$$EP = \max RP(x_i) = \sum_{x_j \in cluster_i} EP_{xj} \quad (4)$$

Where, the amount of nodes in cluster i is mentioned as x_i and EP_{xj} is the residual energy of the node x_j [28].

C. EEPO Algorithm for Optimal Sink Node Placement

Main aim of this EEPO [29] algorithm is to optimally place the sink nodes in an exact position to enhance the lifetime of the network. Huddling behavior of Emperor penguin is used in the EEPO algorithm and the objective is to attain the effective agent. This algorithm randomly generates the huddle boundary and computing the energy consumption of sink node around the huddle boundary. Distance between sensor and sink node is also calculated in which it will gives further exploitation and exploration. Finally, the correct location of sink node is calculated based on the best optimal solution which is obtained from the algorithm.

a) Generate huddle boundary for WSN constraints

Randomly initialize the node parameters and algorithm parameters in initial stage. In this stage total population and maximum iteration ranges are considered. The sink nodes have atleast some clustered sensor nodes as neighbouring nodes. In this algorithm, we have considered coverage rate, connectivity rate and energy threshold value as WSN constraints.

The energy model of WSN is taken from [30]. Transmission consumption and reception consumption are two main parts in this energy consumption model. The given below expression (5) mentions the transmission energy consumption value.

$$e_{Tx}(a,d) = \begin{cases} a.e_{elec} + a..\varepsilon_{fs}.d^2 & if\ d^2 < d_0 \\ a.e_{elec} + a..\varepsilon_{mp}.d^4 & if\ d^2 \geq d_0 \end{cases} \quad (5)$$

Here, the energy consumption of transmitter and receiver circuit is denoted as e_{elec}. The amplification coefficient for multi-path and free space model is mentioned as ε_{fs} and ε_{mp} respectively. Moreover, the given below expression is utilized to compute the threshold value d_0.

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (6)$$

Energy usage of reception unit is represented by the reception consumption. So, the given below equation (7) is utilized to measure the energy consumption.

$$e_{rx}(a) = a.e_{elec} \quad (7)$$

Capability of Coverage Area

The coverage ratio is an important index to calculate the coverage rate of monitoring region in WSN network model. In a sensing area with s_i as the center, a radius of r_i if the region a point within the range of s_i perception, so this point is called the coverage of s_i. The coverage area formula is given as follows:

$$C = \frac{Z_{ri}}{A} \quad i = 1,2,....,n \quad (8)$$

Here, A mentions the total area.

Connectivity Rate

Network nodes sensing perception, sensing and communication to the quality of service is measured by this network connectivity rate. The given below equation is used to compute the connectivity rate.

$$C_{rate}(s_i) = \sum_{j=1}^{n} E_{ij}, \quad j = 1,2,....,n, \quad j \neq i \quad (9)$$

Here, E_{ij} mentions the communication edge between nodes.

Based on the above constraints, the given below expression explains the huddle boundary of the nodes.

Huddle boundary constraints $H(b) = \begin{cases} C, & (r_i) \neq 0 \\ C_{rate}, & C_{rate} = 1 \\ e_{elec}, & d = d^0 \end{cases}$

(10)

The constraints are used to label the randomly generated clustering boundary of sensor nodes.

b) Determine the energy conservation of sink node based on huddle boundary

The sink node makes the huddle boundary as base to consume energy and to exploit the position of the sink node in an exact location. This is mathematically modeled based on the given below equation. This phase is responsible for both exploration and exploitation process for sink nodes with different locations. The position around the huddle Y' is computed as equation (11),

$$Y' = \left(Y - \frac{\max\ i}{b - \max\ i} \right); Y = \begin{cases} 0, & if\ \ r > 1 \\ 1, & if\ \ r < 1 \end{cases}; \quad (11)$$

Where, present iteration is denoted as b, radius is r, maximum number of iterationis mentioned by $\max\ i$ and the best result is mentioned at Y.

c) Distance between the Sink Nodes

Distance among the sink node and best obtained optimal solution is calculated after the generation of huddle boundary. The present value will be the best value which is close to the fitness value. Other sink nodes are also update their location according to present best global solution. The mathematical of this optimal solution is defined as in equation (12),

$$\overrightarrow{D_{sn}} = abs\left(\overrightarrow{S(L)}.\overrightarrow{Q(b)} - \vec{V}.\overrightarrow{Q_{sn}(b)} \right) \quad (12)$$

Here, distance between the sink node and best fitness agent is represented as D_{sn}, L and V is used to avoid the collision among the neighbour of two nodes, Q mentions the best optimal value, Q_{sn} denotes sink node's position vector, S is the social forces of sink node to move towards the direction of best optimal value. The L and V is evaluated as in equation (13),

$$\vec{A} = \left(M \times \left(Y' + P_{accuracy} \right) \times rand(0,1) \right) - Y' \quad (13)$$

$$P_{accuracy} = abs\left(\vec{Q} - \vec{Q}_{sn} \right) \quad (14)$$

$$\vec{V} = rand(0,1) \quad (15)$$

Where, M denotes the parameter movement that maintains distance between the searching node collision avoidance and value of M is given as 2. $P_{accuracy}$ is monitoring space accuracy by comparing the difference amongst the nodes. The function $S(\vec{L})$ is found out by given equation (16) as,

$$S(\vec{L}) = \left(\sqrt{k.e^{-b/l} - e^{-b}}\right)^2 \quad (16)$$

Control parameters are k and l for best exploration and exploitation, which is deceits in the ranges of [2, 3] and [1.5, 2]. Expression function is indicated as e.

d) Reallocation of sink nodes

The position of sink nodes is updated according to the best obtained optimal solution. In this stage, all sink nodes are optimally placed in an optimal location to improve the connectivity of network and lifetime. Given below expression is utilized to update next position of the sink node.

$$\overrightarrow{P_{sn}}(b+1) = \overrightarrow{P(b)} - \vec{L}.\vec{D}_{sn} \quad (17)$$

Sink node's next updated location is denoted as $P_{sn}(b+1)$. During the process of iteration, the sink nodes are optimally placed in correct location. If all sink nodes are allocated successfully or maximum iteration is reached, then the termination stage is take place.

Fitness Calculation:

The optimal placement of sink node is done by the considered the active neighbor nodes, energy rate are considered. Moreover, the sink nodes are optimally placed based on the given below objective functions.

$$F_1(x) = \frac{number\ of\ active\ nodes}{N_{neighbour}} \quad (18)$$

$$F_2(x) = \frac{1}{\sum_{i=1}^{N_{neighbour}} E_{neighbour}} \quad (19)$$

Here, the amount of node neighbor served up by sink node is mentioned as $N_{neighbour}$ and energy for every single sensor node for sink's neighbor is mentioned by $E_{neighbour}$. The average of neighbor node is mentioned in the first fitness function $F_1(x)$ is and the sink node that is chosen based on the sum of energy per group of nodes in which it is mentioned in second fitness function $F_2(x)$. The position vector x of every node is needed for both fitness function. The given below expression express the objective function.

$$\min\ F(x) = \frac{1}{\sum_{i=1}^{N_{neighbour}} F_1(x) + F_2(x)} \quad (20)$$

The pseudo code of the EEPO method is given in the below table 1.

Table 1. Pseudo Code of EEPO algorithm for sink node placement

Input: Parameter initialization, total iteration, number of sink nodes
Output: Optimal sink node deployment.

Begin
Initialize the node parameters like coverage ratio, connectivity ratio and energy as well as the maximum number of iterations.
Compute the fitness function for sink node using equation (20).
  for each sink node
    Initially determined the huddle boundary of sink node based on the equation (10)
  then
Calculate the energy conservation of sink node based on equation (11).
  end for
Calculate the distance between sink node using equations (12) to (16).
Update the position of sink node using equation (17)
Check this condition for every sink nodes using equation (11-17)
Compute the fitness function using equation (20).
Terminate the algorithm after the maximum (500) iteration.
Return the best optimal sink node position.

IV. Simulation Results and Discussion

The implementation of optimal sink node placement is simulated by NS-2 tool. Parameters like network lifetime, energy consumption, PDR, localized error, and running time are computed to illustrate the efficiency of the EEPO algorithm. Also, it is evaluated with modern algorithms like PSO, GWO and HHO. The optimal sink node placement of proposed methodology is given in figure 3.

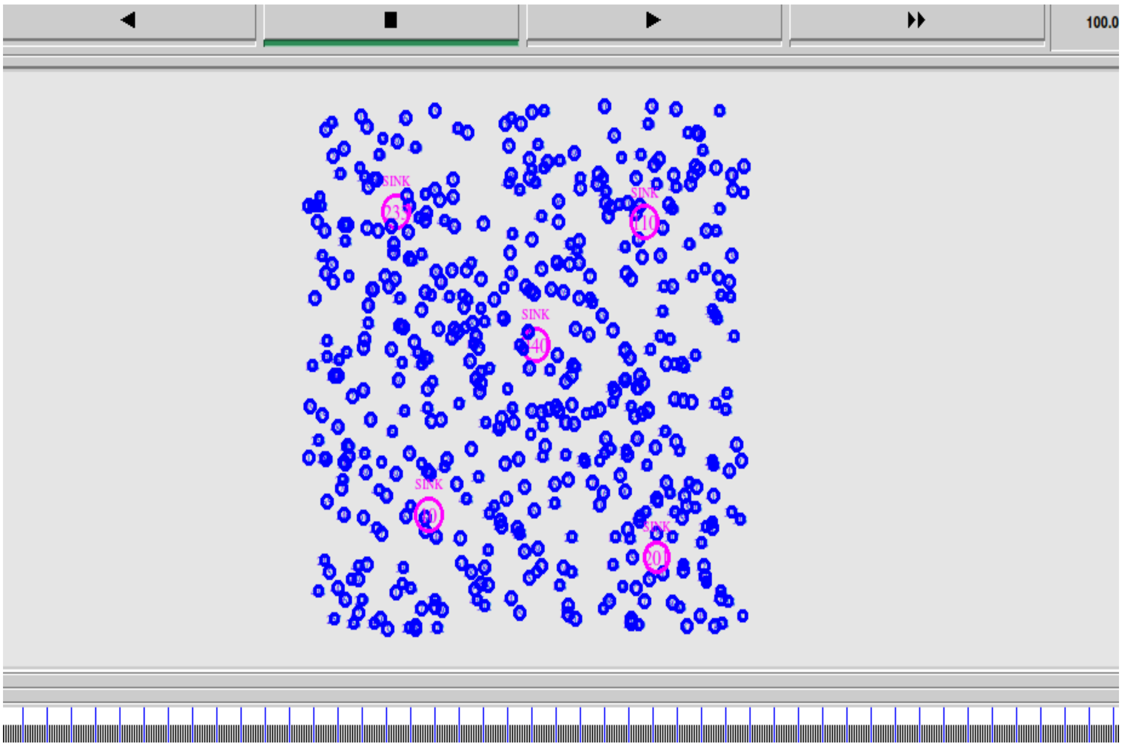

Figure 3 : Optimal placement of sink nodes

The figure 3 explains the optimal placement of sensor nodes. Here, total 500 nodes are taken to complete the process. Total 5 sink nodes are optimally placed to cover the whole network region.

Table 2. Simulation Parameters

Simulation constraints	Values
Size of the network	500x500m
Total sensor nodes	500
Energy capacity of every single node	10J
Node communication Range	100m
Node sensing Range	50m

The simulation parameters utilized in this work is listed in Table 2. Total 500 nodes are evenly scattered in a 500x500m area. The preliminary energy of every sensor node is set as 10J.Here pink color mentions the sink nodes and blue color mentions the sensor nodes.

Table 3. Performance comparison values

	Nodes	PSO	GWO	HHO	EEPO (proposed)
Localization error (%)	100	17.20	18.10	16.10	15.5
	200	18.70	16.80	15.70	15
	300	19.10	17.30	15	14.5
	400	16.10	17.50	16.0	15.55
	500	17.40	17.205	14.00	13.8
Packet delivery ratio (kbps)	**Number of rounds**	**PSO**	**GWO**	**HHO**	**EEPO (proposed)**
	100	1	1.5	2	2.57
	200	3.4	4.4	5.6	7
	300	4.2	7	9	10.7
	400	6	9.6	10.44	12.6
	500	9	10.32	13.5	15.5
Energy consumption (mJ)	**Nodes**	**PSO**	**GWO**	**HHO**	**EEPO (proposed)**
	100	0.4	0.45	0.4	0.39
	200	0.65	0.68	0.6	0.5
	300	0.8	0.7	0.75	0.68
	400	1	0.9	0.9	0.76
	500	1.5	1.4	1.3	1.21
Running time (seconds)	**Nodes**	**PSO**	**GWO**	**HHO**	**EEPO (proposed)**
	100	239.04	81.17	79.15	78.2
	200	239.42	275.73	271.11	269.5
	300	1330.27	600.07	550.91	530.6
	400	2130.81	1050.23	1000.99	980.78
	500	3330.82	1630.24	1560.87	1400.7
Network lifetime (%)	**Number of rounds**	**PSO**	**GWO**	**HHO**	**EEPO (proposed)**
	100	84	87	88.5	97
	200	83.45	86.57	87.5	96.6
	300	82	84	86	94
	400	80	82	85	92
	500	79.5	80	83	89.4

The performance comparison values of proposed and existing methodologies are presented in table 3.

Network Lifetime: The network lifetime is a significant feature in WSNs. Network lifetime is increased by the proposed method and this is the major outcome of the proposed method. Network lifetime is said to be good, when more amount of nodes are active during the last round.

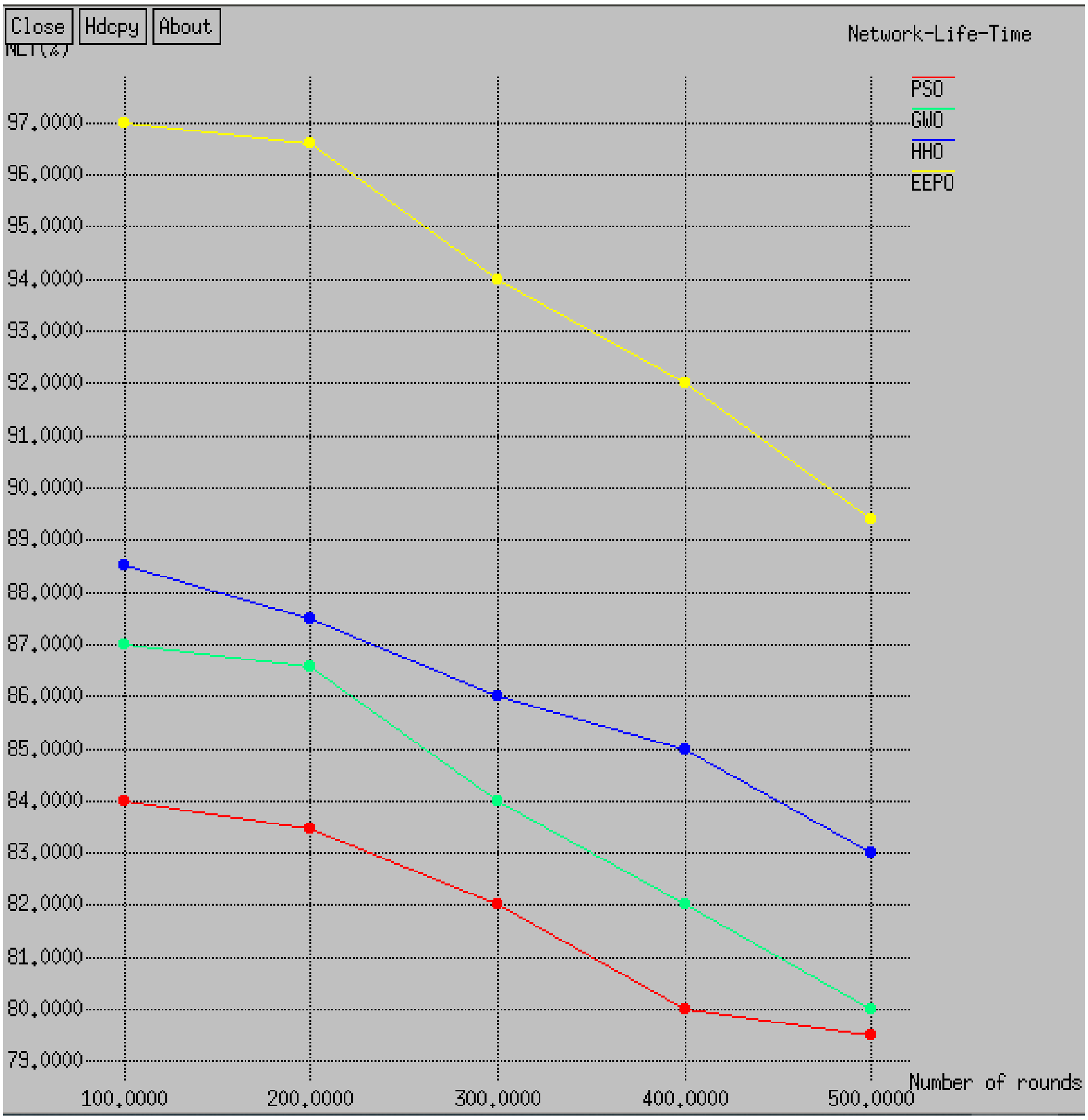

Figure 4 : Comparison of lifetime of the network

Comparison of network lifetime with number of round is displayed in figure 4. Also, it is evaluated with modern techniques like PSO, GWO, and HHO. It is clearly shown that the EEPO technique achieves 97% network lifetime in 100 rounds from the figure analysis.

Energy Consumption: Most of the sensor nodes are driven by low energy resources and battery power so, it is very essential to reduce the energy consumption of the nodes to improve network lifetime.

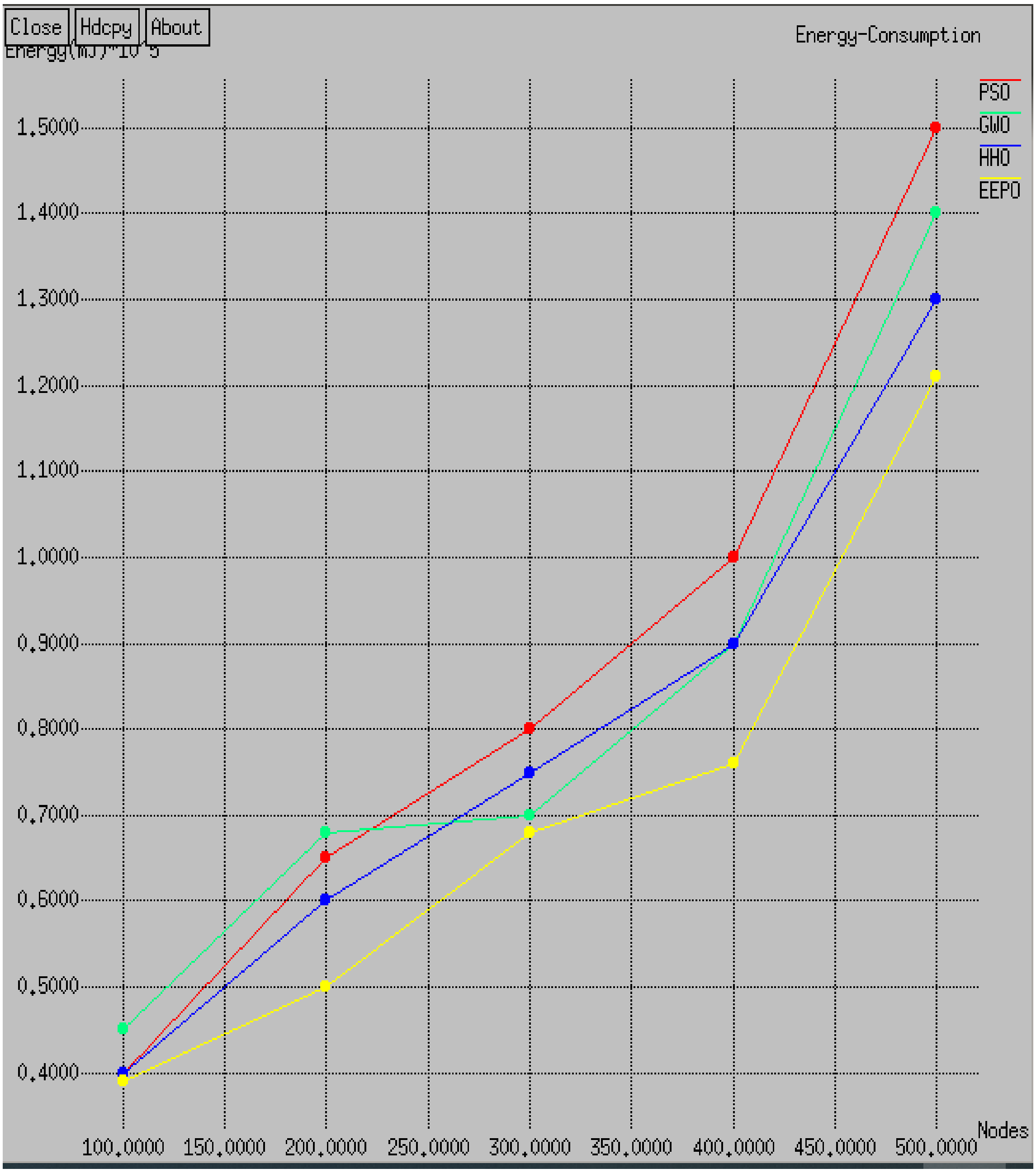

Figure 5 : Performance of energy consumption

Energy consumption with total amount of sensor node is demonstrated in figure 5. Also, it is judge against the modern techniques like PSO, GWO, and HHO. From the figure analysis, it is clearly shown that the EEPO technique utilizes less amount of energy for increasing size of the network.

Packet Delivery Ratio (PDR): Total amount data received by the total number of transmitted data is defined as PDR. For the recommended algorithm, the packet delivery ratio is calculated by,

$$PDR = 100 - \frac{total\,amount\,of\ received\ data}{Total\,amount\,of\ transmitted\ data}$$

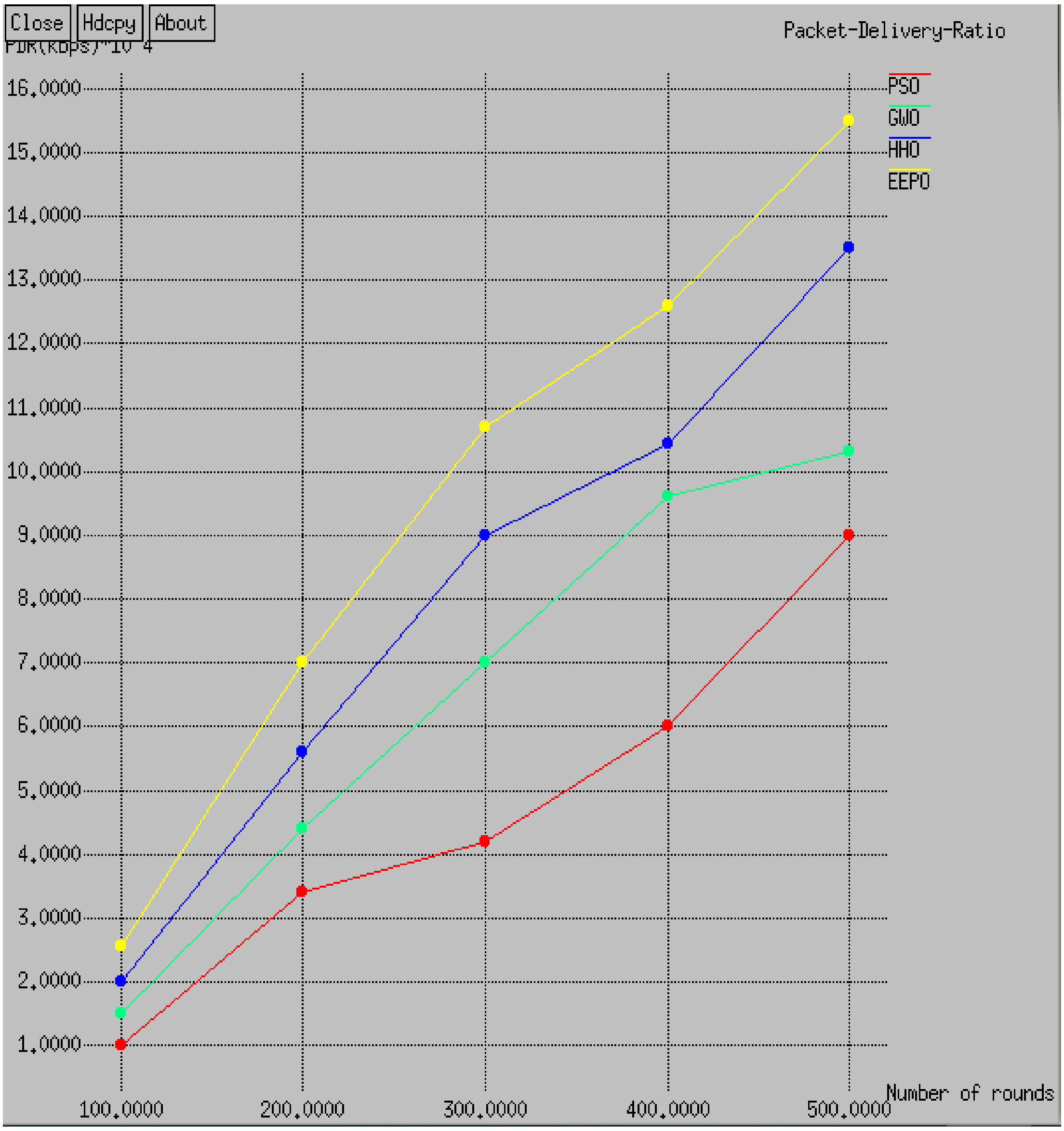

Figure 6 : PDR comparison

PDR comparison of proposed methodology is displayed in figure 6. Also, it is judge against the state-of-the-art techniques like PSO, GWO, and HHO. It is clearly exposed that the EEPO method achieves higher delivery ratio than other methods from the figure analysis.

Localization Error

The localization error performance of the EEPO and other algorithms are evaluated based on the given blow expression. The node's communication radius R_c is normally related to this localization error (LE). This is mainly utilized to estimate the performance of all nodes.

$$LE = \frac{\sqrt{(a'-a)^2 + (b'-b)^2}}{R_c} \times 100\%$$

Here, estimated coordinates of sink node is mentioned by $(a-b')$, real coordinates of sink node is mentioned by (x, y) and communication range of nod is mentioned by R_c. Minimize the localization error of sink coordinates is considered as one of the major goal of proposed method.

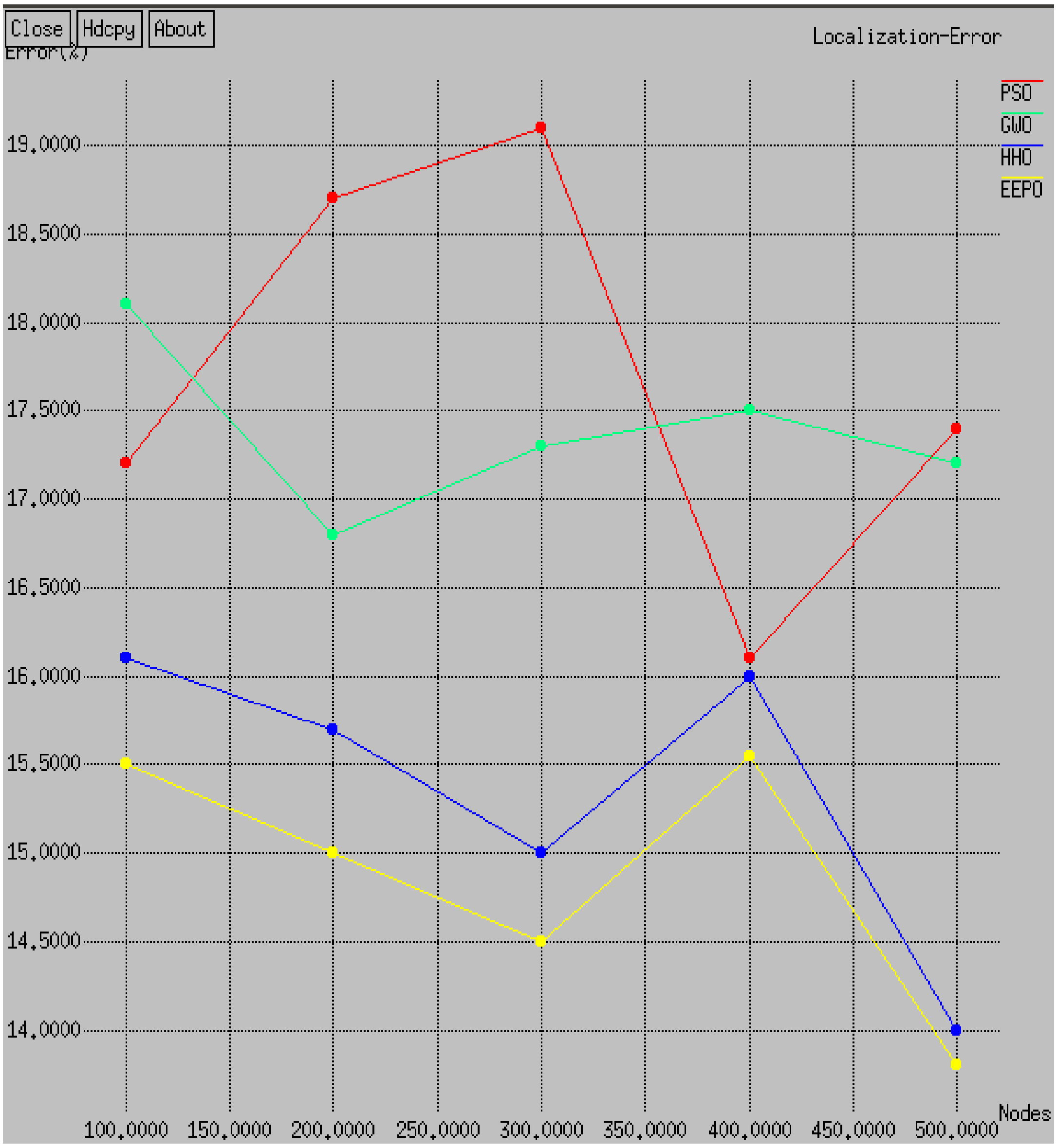

Figure 7 : Comparison of localization errors

Figure 7 shows the comparison of localization error percentage with number of nodes. Also, it is compared existing methods like PSO, GWO, and HHO. With respect to the increasing network size, the proposed algorithm consumes small localization error than any other methods.

Running time

Running time mentions the total time required by the network model to complete the optimal placement of sink nodes. It is measured in seconds. In this work, the time is computed against dissimilaramount of sensors.

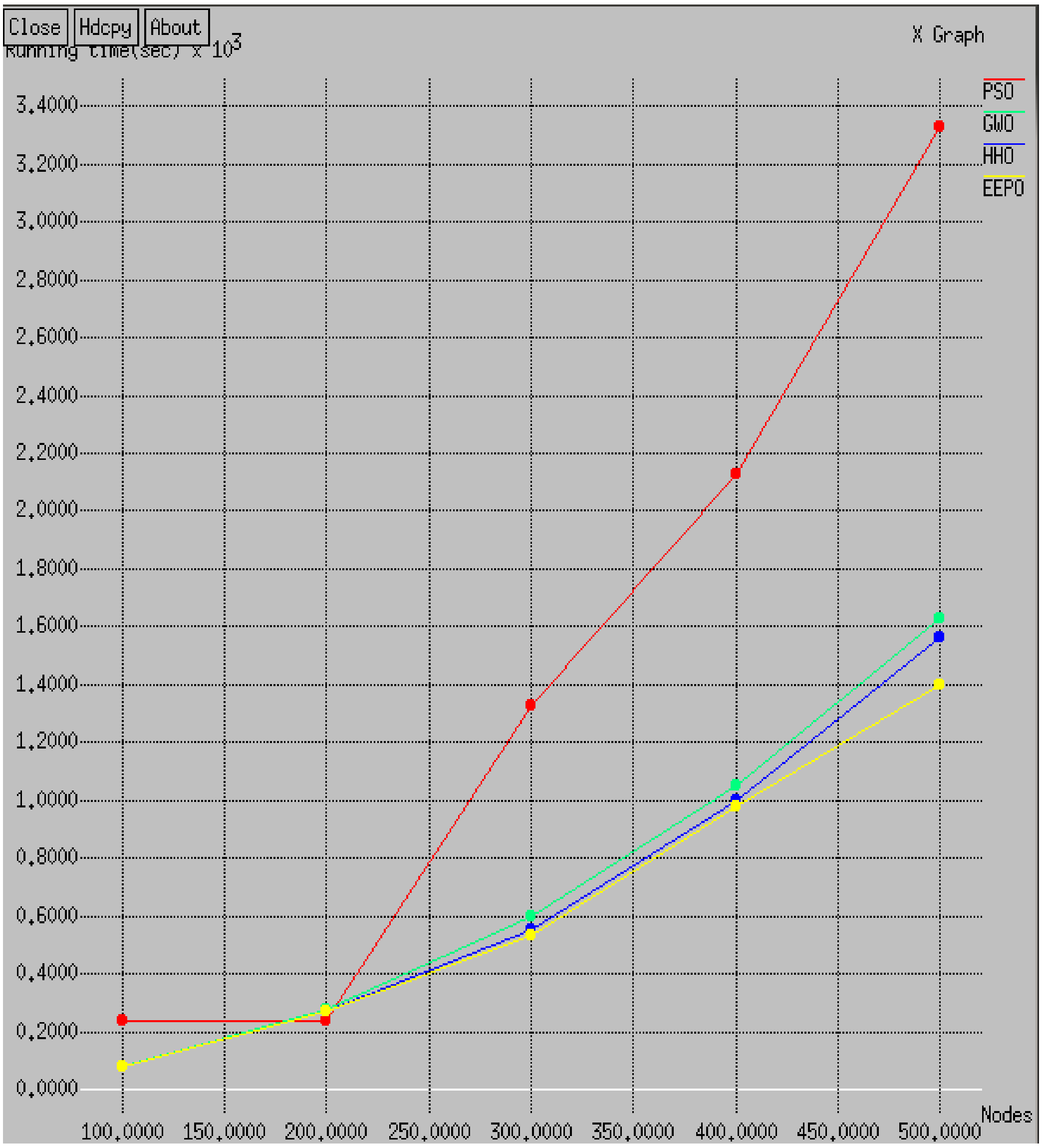

Figure 8 Comparison of running time

Running time comparison is displayed in figure 8. It is measured in terms of seconds. It is cleared that the proposed EEPO algorithm exceeds other modern methods in which they take more time to find the nearest sink node.

V. Conclusion

Placement of sink node in large scale WSN plays a crucial role in which it expands the lifetime of the deployed sensor nodes in a particular region. Different kinds of algorithms are used in the previous research, in which they can't provide accurate placement of sink node in a particular area. So, in our work, we proposed an EEPO algorithm to optimally place the sensor node so as to achieve enhanced network lifetime. Main aim of this EEPO algorithm is to place smallest amount of sensor nodes which connects whole network model to enhance lifetime of the network. Moreover, new objective function was formulated to enhance the network lifetime and to decrease energy consumption. To perform this process, the sensor networks are clustered using K-medoids clustering algorithm. After that, some conditions like distance and residual energy between nodes are utilized to compute the cluster head. Then, EEPO algorithm is utilized to perform the better sink node placement strategy. Moreover, the performance of EEPO algorithm is evaluated against with the recent techniques like PSO, GWO and HHO in terms of running time, network lifetime, energy consumption, localization error and PDR. Simulation result shows that our proposed EEPO algorithm achieves 97% network lifetime than existing methods to show the efficiency of the overall proposed system.

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