Adaptive Density-Based Localization Algorithm Using Particle Swarm Optimization and DBSCAN Clustering Approach

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Abstract: Wireless Sensor Network (WSN) is a self-directed distributed wireless system independent, low-cost, power deficient. Localization is an important requirement in WSN for chasing and investigating identified data. In maximum appliances of WSN, the data without its area data has no importance. Provided the hardware restrictions and physical atmosphere where the sensors ought to function, along with recurrent alternations in-network prototype and its density, the algorithm needs to be developed to attain a vigorous and energy effective communicating methodology. In this regard, this paper suggested an algorithm for the adaptive behavior of wireless sensor networks. The complete methodology is implemented in two modules i.e. clustering the complete wireless network depending on the density using the Density-based spatial clustering of applications with noise (DBSCAN)approach and estimating the un-localized nodes within each cluster using Particle Swarm Optimization (PSO) based location estimation algorithm. The performance of the suggested methodology is supported using NS2 Simulator. The results inferred that the proposed methodology has a superior packet delivery ratio, advanced energy efficiency, network throughput, and less data packet ratio relative to present localization approaches.

Keywords:WSNs, Localization, Density-based localization, PSO, DBSCANAlgorithm, Clustering Approach.

1. Introduction

The field of wireless cellular networks has seen an enormous change lately because of the consistent development sought after for inclusion and higher information rate. The immense and exponential rise in computational and interactive technologies has led to the exponential rise in the evaluating tools like cell phones,laptops,GPS, andPDAs mechanisms which are turning out to be more inexpensive, more moveable, dispersed, and reduced in dimension. These devices are attained afundamentalpart of our everyday life.WSN is a self-directed distributed wireless network self-regulating, low-cost, power deficient, and tiny sensing nodes that are randomly deployed known as sensor nodes in addition to the server node known as base station [1]. Every node comprises computational elements, interacting elements, a power resource, and a certain additional sensor based on its usage and atmosphere. Upon deploying, these nodes arrange within themselves and generate a network that characteristically comprises numerous hundreds of sensor nodes in turn. These nodes are employed to control the neighboring atmosphere for a certain event and propel the sensual information to the base station which is called a sink[2,3,4].Nodes are positioned randomly in WSN and the exact position of the node can't be determined. This is a vital research study in WSN[5].To quote RTOs like fire mishaps conditions helping the firefighter salvage groups to discover their positions, course through a structure during in crisis circumstances and to impart the area data to an external controlling unit.

The localization procedure is essential for WSNs and is employed for numerous sensor network appliances. Whenever any sensor tool is placed in an untidy and tough environment, the global positioning system(GPS) could be inoperable at this place and localization is essential for attaining the position knowledge of every tool. Fundamentally, the localization system includes the referring nodes that have their position and the unknown nodes that do not have their position. Depending on this knowledge of the referring nodes, sensor nodes could attain their position through employing the ranging methods [6].Numerous localization approaches are being suggested in the last two decades to specify the position of a sensor node. Localization or Evaluation of the topographical position of sensor nodes is a significant infrastructural issue in the development and deployment of WSN. Manual localization is feasible in smaller networks where sensor nodes do not travel. In bigger moveable networks, automatic node localization is needed [9]. As discussed in [7, 8, 10, 11], the usage of GPS for localization issue is not practicable, appropriate, and realistic outcome, since GPS is not reachable as it takes a massive quantity of power, which is a restricted source in WSNs, and price, dimension constrictions of GPS restricts the reputation of sensor nodes

The deployment of WSNs suffers from restrictions about complex circumstances like the specified zone of network and the deficiency of system alignment. The restricted organization of nodes could make the network density extremely uneven which in turn could truly damage the efficiency of localization. The illustrative issues in WSN have broadcast hurricane [12] and localization failure. If the nodes are thickly deployed in the network, the multi-hop localization methodology rises the flooding information and makes the interaction dispute and collision in the localization approach [12]. On the other hand, the single-hop localization methodology minimizes the communication issue owing to the recurrent information. Nevertheless, whenever the referring nodes are sparse, the single-hop localization might generate an issue in the localization method.

To overcome the above-addressed issue, this paper suggested an adaptive density-based localization approach for WSNs. The suggested methodology regulates the broadcasting of position information through employing a DBSCAN clustering algorithm [13] and performs the localization estimation approach according to the node density using a naturally inspired PSO Algorithm. The irregular network density is cited through a density-based clustering algorithm and estimation of the localized nodes in each cluster is accomplished by the estimation algorithm using the PSO approach. B means of the suggested methodology, the nodes could minimize the communication overhead owing to the recurrent information whereas preserving the localization accurateness. Simulation work exhibited that the suggested methodology minimized the location error and communication overhead about the uneven network thickness. This overwhelms the network anomalies and improves the efficiency of localization.

2. Literature Survey

An encouraging methodology to localize arbitrarily deployed WSNs is to employ a single moveable beacon [24-27,30,31]. The approach by mobile beacon uses an anchor node with GPS to navigate through the area of interest. This anchor node broadcasts regularly the packets comprising their location, and unknown nodes evaluate their location employing the obtained packets. In [25], range assisted localization methodology is proposed where the sensor nodes calculate their location through performing the RSSI approach. In [27], suggesting a TDOA-aided localization policy using moveable anchors where the sensor nodes accomplish trilateration to evaluate its location.

In [24], a range-free moveable anchored aided localization policy depending on wireless connectivity constrictions is suggested to minimize the ambiguity of calculated sensor position. A Recurrent localization methodology is given in [28] depending on a moveable anchor strategy where the localization accuracy is gradually enriched every time a novel beacon message is attained from an anchored node. In [29], a novel range-aided localization strategy is given that includes a movement scheme with a less computational complexity of moveable beacon known as mobile beacon aided localization (MBAL). MBAL also employs RSSI for ranging to obtain the distance amongst nodes or amongst every node and a moveable beacon to support localization of entire nodes.

The optimization issues counted for Localization because of complexity and size features. To increase the complexity and for resolving optimization problems [14], Linear programming takes higher computation time. This enthused the optimization algorithms for WSN as these are strong and compelling [15]. From the most recent years, these methodologies got mainstream as they can undoubtedly changing the environment and have high effectiveness [16]. For finding the goal node's position, several algorithms have been used such as PSO [17], FA [18, 19],GA [20], GWO[21],etc. In WSN localization, the goal of the many optimization algorithms is to diminish the position estimation error.

3. The PSO Algorithm

PSO is an evolutionary computing methodology initially endorsed in [33] and was primarily envisioned for mimicking communal behavior, with a formalized depiction of the movement of creatures in a bird flock or fish school. The procedure was streamlined and was witnessed to have functioned as an optimizer. Book by Kennedy and Eberhart defines numerous theoretical facets of PSO and swarm intelligence. A wide spread review on PSO appliances are is made by Poli. PSO[34] is a computational approach that enhances an issue by recurrently attempting to augment a candidate solution regarding a specified measurement of quality. This approach is a famous biologically motivated methodology that is smeared to resolve numerous optimization issues in numerous domains comprising of machine intelligence, data mining, and robotics, and computer networks.

According to PSO, a swarm is denoted to numerous probable outcomes to the optimization issues, where every possible outcome is denoted with an individual particle. This approach intends to obtain the individual location that consequences in the finest estimation of a specified objective function. In the initialization procedure, every individual is provided with primary parametric arbitrarily and it hovered through the multiple dimension exploring the domain. In course of each iteration, every individual employs the data about its prior finest individual location and global finest location to increase the possibility of traveling towards a better outcome domain that would consequent in better fitness. Every individual movement is affected through its local finest known location and is likewise directed toward the best-known location in the exploring domain that is updated as best locations are discovered through other individuals. Whenever a fitness better compared to the individual best fitness is obtained, it would be employed to substitute the individual fitness and update its candidate result about the below-given equations.

This approach involves the intelligence and interaction of birds. The birds are capable of gaining knowledge f rom the experience of themselves and as well neighbor birds. Every bird (or say particle)takes values namely

- Present positionX_i,
- Local best valueP_i and
- VelocityV_i.

The objective function finds the particle positionP_g. Each particle updates its revise concerning the best particle using Eq(1) in the cluster.

$$New_{V_i} = \omega * V_i + c_1 * rand() * (P_i - X_i) + c_2 * Rand() * (P_g - X_i) \qquad (1)$$

Here $rand()$ and $Rand()$are arbitrary functions whose value is in the [0, 1]. Thec_1 andc_2 parameters are accelerationcoefficients or learning aspects and $\omega$is the inertia weight which is mostly employed to regulate the influence of earlier velocities of a particle on present velocity. Then the later part of the equation compares the particle's existing position to the finest position in local cluster and global cluster. The location of an individual using $latest\ V_i$is revised by Eq (2).

$$New_{X_i} = Current_{X_i} + New_{V_i} \qquad (2)$$

The value of$V_i$staysin the range of user-defined values of V_{max} $i.e. V_{max} \geq V_i \geq -V_{max}$ to regulate the consequence of the difference in velocity of the particle.

PSO Algorithm for Location Estimation:

1. Initialize the population of particles using the centroid of anchor nodes (within the broadcasting range) as position and initialize its velocity by using Equation (3):

$$(x_i, y_i) = (\frac{1}{N}\sum_{i=1}^{N} X_i, \frac{1}{N}\sum_{i=1}^{N} Y_i) \qquad (3)$$

Here N is the number of anchor nodes inside the broadcasting range of each goal node.

2. Initialize the ω.
3. While t less than the highest number of iterations

a. The Minimization of the fitness function in WSN is given in Eq(4).

$$f(x,y) = \frac{1}{N}(\sum_{i=1}^{N}\sqrt{(x-x_i)^2 + (y-y_i)^2} - \widehat{d_i})^2 \qquad (4)$$

Here $N \geq 3$ are the beacon nodes interior to the range, (x_i, y_i) is the coordinates of beacon node within the range, and (x, y) is the coordinates of the particle

b. For particles 1to n

➢ Obtain the local best i.e. p_{best} of all particles using the evaluated objective function

c. End for

d. Obtain the global best i.e. b_{best} as the optimal-Fitness of entire particles from p_{best}

e. For particles 1to n

➢ Evaluate New Velocity of individual using Equation (1)

➢ Update the New location of individual using Equation (2)

f. End for

4. End While

5. Adaptive Density Aided Localization Approach

6.

A novel localization approach is suggested for irregularly deployed WSN in this section where the density of the network is not even. This localization approach is suggested in two modules such as the construction of clustering depending on the densities of the network which control the transmission of location messages and employed the localization estimation approach into each density-based clustered network using the PSO approach. The block diagram for the suggested localization approach is given in Figure1.

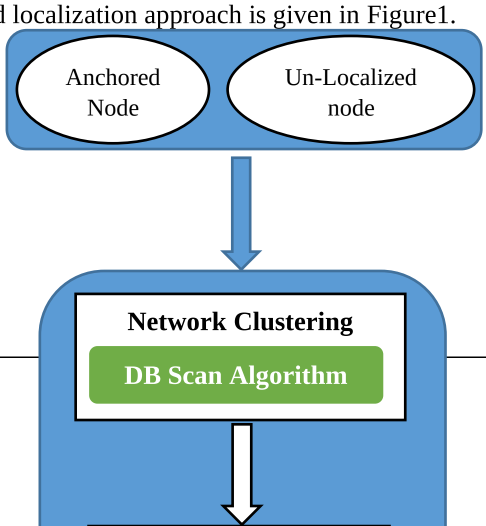

Figure1: Block Diagram for the Suggested localization approach

4.1 Density-Based Clustering of Wireless Network

Even though, lot of studies is carried on clustering methodologies, its application to sensor networks rise the following new requirements:

- ➢ Finding clusters with the random outline, as the clusters' structure in sensor networks might be no convex, sphere-shaped, linear, stretched out, etc.
- ➢ Good efficiency on very large networks, with considerably higher than merely a fewer hundred entities.

DBSCAN clustering algorithm is the foremost data mining approach which is an unsupervised learning task of accumulating the elements from a dataset into significant sub-classes.DBSCAN depends on a density-aided perception of groups. For every point p in a cluster, density in its ∈-neighborhood (the number of points situatedat a distance less than ∈ from p) has to exceedsome threshold $MinP$. This technique needs two input metrics (∈ and $MinP$) and assists the user in specifying an applicable value to them. This technique increases zones using sufficiently higher density into groups and finds the groups of arbitrary structure in databases. This approach also employs firm ideas for the explanation of groups, as to effectively know[9], as shown in Figure 2.

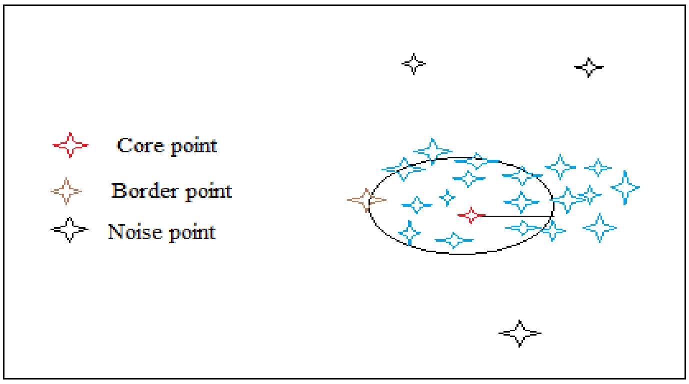

Figure2: Core, Border, and outlier for DBSCAN

<u>Determination of Minimum Number of Points</u>:

In Figure3, the intersecting element round the anchor nodes $s_1 = (x_1, y_1)$ and $s_2 = (x_2, y_2)$ are denotedass_{12} ands_{21}, and their coordinates are specified as :

$$x = \frac{x_2+x_1}{2} + \frac{(x_2-x_1)({r_1}^2-{r_2}^2)}{2d^2} \mp \frac{y_2+y_1}{2d^2}\sqrt{((r_1+r_2)^2-d^2)(d^2-(r_2-r_1)^2)} \quad (5)$$

$$y = \frac{y_2+y_1}{2} + \frac{(y_2-y_1)({r_1}^2-{r_2}^2)}{2d^2} \mp \frac{x_2+x_1}{2d^2}\sqrt{((r_1+r_2)^2-d^2)(d^2-(r_2-r_1)^2)} \quad (6)$$

Where the p_{12} x-coordinate relates to addition symbol in (5), and the consistent y-coordinate relates to subtraction symbol in (6). The distance amongst the anchor nodes are:

$$d(s_1, s_2) = \sqrt{(x_1-x_2)^2 + (y_1-y_2)^2} \quad (7)$$

Each un-localized node evaluates its distance from every anchor node such that it could obtain an indication from. This node could evaluate its location merely if it is in the dimension of three or more of these nodes. The meeting of the circles developed from entire evaluations of the un-localized node presents a group of points. If there are m anchor or localized nodes, they generate g groups. Here $g = \binom{m}{2} = \frac{m!}{2!(2-m)!}$. Thus the minimum number of points for clustering the network is given as $MinPts = g - 1$.

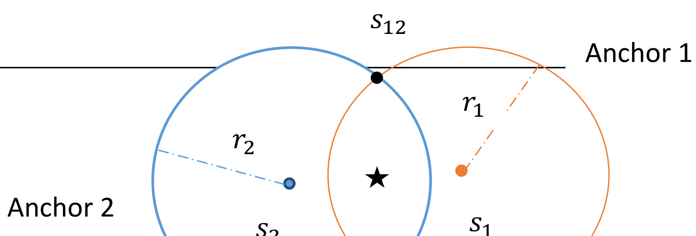

Figure3: Intersection of two anchor nodes

Determination of Epsilon (ϵ)

The $\in$ value is determined based on the number of minimum points i.e. $MinPts$ and the structure of the wireless network. The $\in$ values are defined as:

$$\in = \frac{\sum_{i=1}^{2g} \sum_{j>i \atop j=1}^{2g} d(s_i, s_j)}{g(2g-1)} \qquad (8)$$

Here $s_i$and s_j are the anchored node points considered for clustering the network. These measurements are employed to categorize the elements as core, border, or noise. The distance to the $MinPts$adjacentneighbor is evaluated for every element and is matched with $\in$. If this distance is lesser than $\in$, it is labeled as core point, else it is labeled as the border or noisy element. For non-core elements, if no elements within distance $\in$are core elements formerly it is a noisy element, else it is the border. Entire core and border points inside $\in$of one another are clustered into groups. The cluster with the highest number of elements is selected, and the remaining are rejected.

Algorithm for clustering the Network using DBSCAN Approach:

i. Select any anchored node as a random element p.
ii. Explore entire anchored and unanchored node points' density reachability from p about Epsilon and Minimum points.
iii. If p is a core anchored node, then a cluster is developed.
iv. If p is an unanchored border element then no element is reachable through density from p and the approach visits the subsequent element of the database.
v. This procedure continues till entire anchored and unanchored node elements are visited.

4.2 Localization Estimation Algorithm using PSO

Evaluating the position of the highest amount of goal nodes that are employing knowledge from the position of source nodes is the purpose of sensor node localization using PSO. The localization issue can be minimalized by PSO. These algorithms achieved good numbers on localization issues and benchmark functions [17]. The Meta-heuristics or naturally inspired optimization approach that is employed for the suggested methodology is the PSO Algorithm. This approach performs an enhanced location estimation with less complexity and more robustness.

The Steps for the node localization for every goal node in WSN is given below:

1. T goal nodes and B source nodes are positioned arbitrarily in the sensor domain. Every source node has a broad casting range T_r. The localized nodes are considered as an anchor or a beacon in successive repetition to eradicate flip uncertainty.

2. Every goal node's distance$\widehat{d_i}$from every anchor node can be computed by$\widehat{d_i} = d_i + \eta_iand\eta_i$ is the computed noise in the dimension$(d_i \pm d_i(\frac{P_\eta}{100}))$ whichaffects the accuracy of the localization approach. The real distance can be computed by using Equation (9):

$$d_i = \sqrt{(x - x_i)^2 - (y - y_i)^2} \qquad (9)$$

Where (x, y)goal node's coordinates and(x_i, y_i) coordinates of anchor node.

3. The goal node that having$anchor\ node \geq 3$ within its broadcasting dimension is considered as a localizable node and shall be localized by PSO.

4. For every goal node, an optimal approach is implemented objectively as briefly described in section 3 using PSO Algorithm.

5. This naturally inspired PSO algorithm determines the ideal value (X, Y) after the extreme amount of repetitions.

6. Evaluate the mean localization error to determine the accuracy of localization as shown in Equation (10):

$$E_l = \frac{1}{N_L} \sum_{i=1}^{N} \sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2} \qquad (10)$$

where (x_i, y_i), (X_i, Y_i) are actual node position coordinates and estimated position coordinated and $N_L$representsthe count of localized nodes.

7. Iterate steps 2-7 till entire goal nodes attain localizability or no further goal nodes could be localized. The localization methodology efficacy depends on the assessed localization error and no. of un-localized nodesN_{N_L} where $N_{N_L} = M - N_L$. Localization accuracy is improved if E_l>N_L.

The amount of localized nodes rises as repetition increments. Any localized node can be employed as an anchor for the succeeding node which cuts the difficulty of flip uncertainty as more references are accessible for the localized node. Yet, this upsurges the time of computation.

5. Results and Its Analysis

The experimental result for the suggested adaptive density aided localization algorithm is carried out using an NS2 simulator. The goal of this experiment is to examine the energy efficiency, generated packets, packet loss, packet delivery ratio, received packet, and network through of the proposed methodology compared with the existing localization approaches. The proposed approach is compared with the existing density-based localization approach, adaptive density-based localization using fuzzy C-Means algorithm and with the location estimation approach without clustering the wireless network. The performance metrics employed for the investigation of localization estimation algorithms are localization accuracy, localization error, and localization time. The parametric description for the suggested approach is given in Table 1.

Table 1: Simulation Parameters

Parameters	**Values**
Simulation Period	80 ms
Coverage Area	1000*1000
Traffic Type	CBR
Agent Type	UDP
Number of Nodes	100 nodes
Routing Protocol	AODV
Initial Energy of node	100 J
No of Un localized nodes	10 nodes
Localized nodes	80 nodes
Cluster head nodes	10 nodes
Queue Type	Drop-Tail

In Addition to the existing, this paper also analyzed the performance of the PSO algorithm in the clustered network using dissimilar parametric values. The effectiveness of PSO-aided localization with diverse parametric values is analyzed and summarized in Table 2. The parameter values with less localization error are taken. To control the effect of the earlier velocities, the inertia weight is considered as the learning factor on the current velocity and the parameters. The n repetition simply that n times the position is revised to determine an ideal solution.

Table 2: PSO Algorithm with different Tuning Parameters

Parameters		N_L	E_L	T_L
ω	0.8	100	0.58	2.2
	0.3	100	0.72	2.3
$c_1 = c_2$	1.43	100	0.71	2.68
	1.98	100	0.63	2.54
n	30	100	0.73	2.12
	50	100	0.70	1.89
iterations	100	100	0.68	2.69
	150	100	0.57	4.63

Figures 4,5,6,7,8,and 9 represent the energy efficiency, generated packets, packet loss, packet delivery ratio, received packets, and throughput of the projected adaptive density aided localization algorithm relative to the present proposed methodologies. From Figure 4, it is inferred that the energy efficiency of methodology is advanced relative to the other existing approaches. From Figure 5, it is inferred that the generated packets of the network of the projected method are sophisticated when compared to the current methods. From Figure 6, it is inferred that the packet loss in the network of the proposed approach is less compared to the existing approaches. From figure 7, it is inferred that the packet delivery ratio of the projected method is sophisticated to the current methods. From figure 8, it is inferred that the received packets in the network of the projected method are sophisticated to the current methods. From Figure 9, it is inferred that the network throughput of the methodology is advanced than existing approaches.

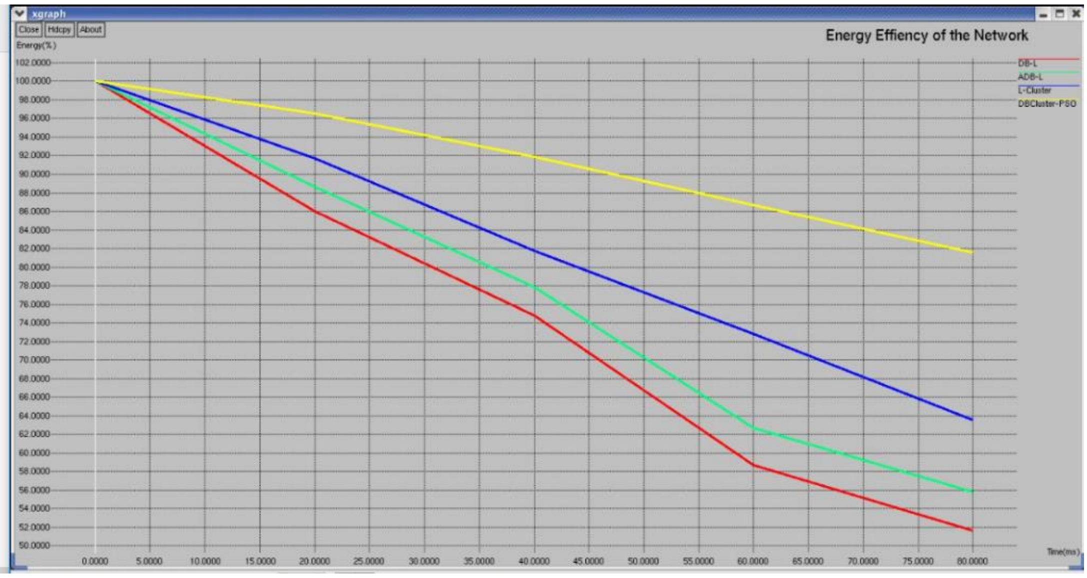

Figure4: Comparison of Energy Efficiency of the Network

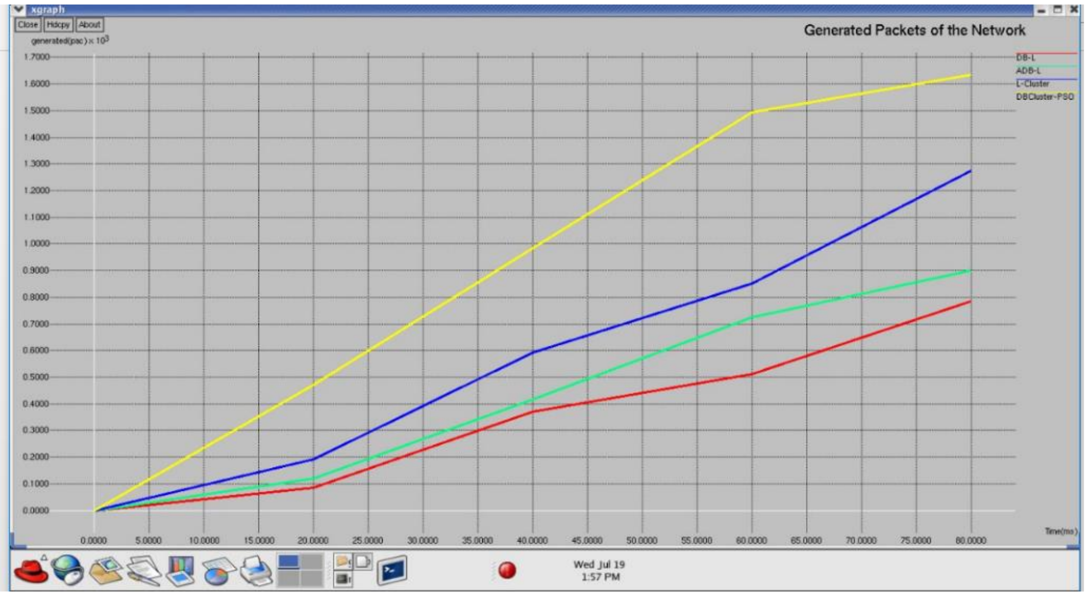

Figure 5: Comparison of Generated Packets of the Network

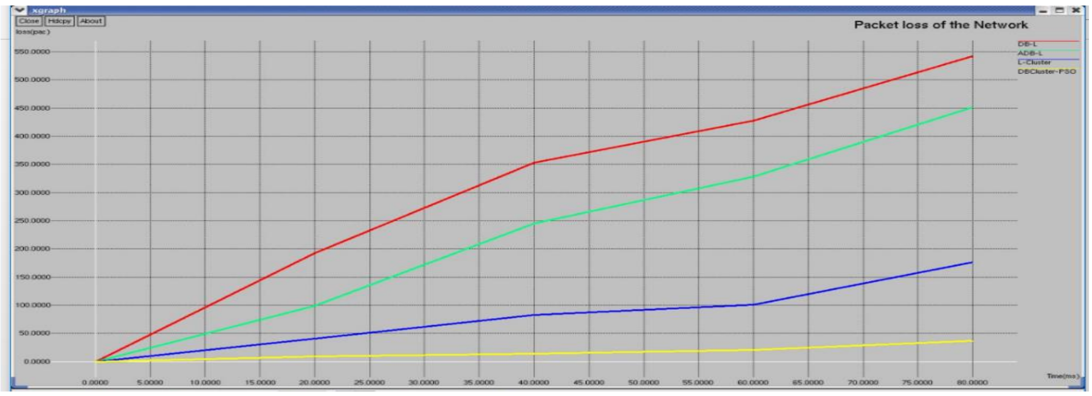

Figure 6: Comparison of data packet loss

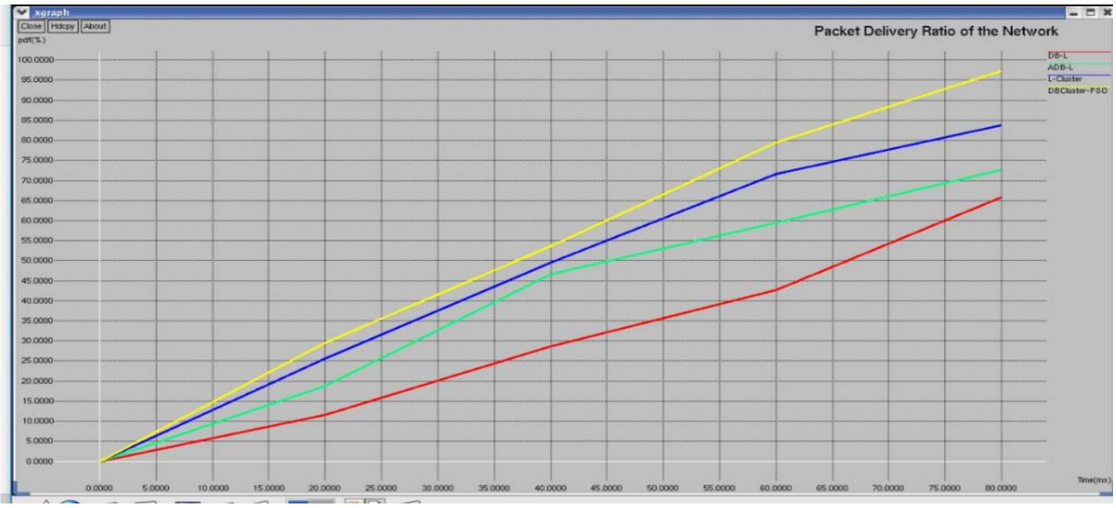

Figure 7: Comparison of Packet Delivery Ratio

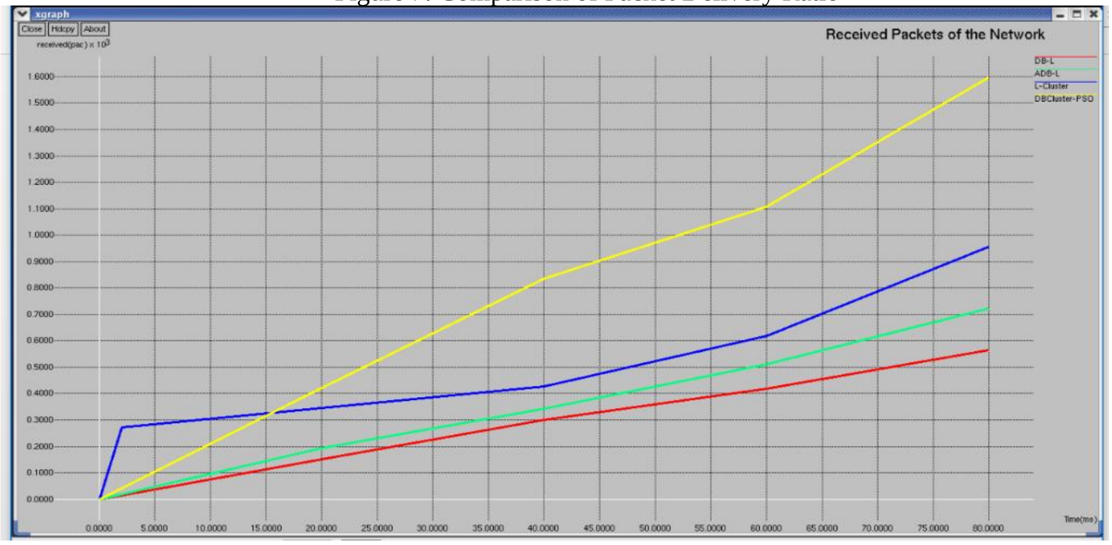

Figure 8: Comparison of Received Data Packets

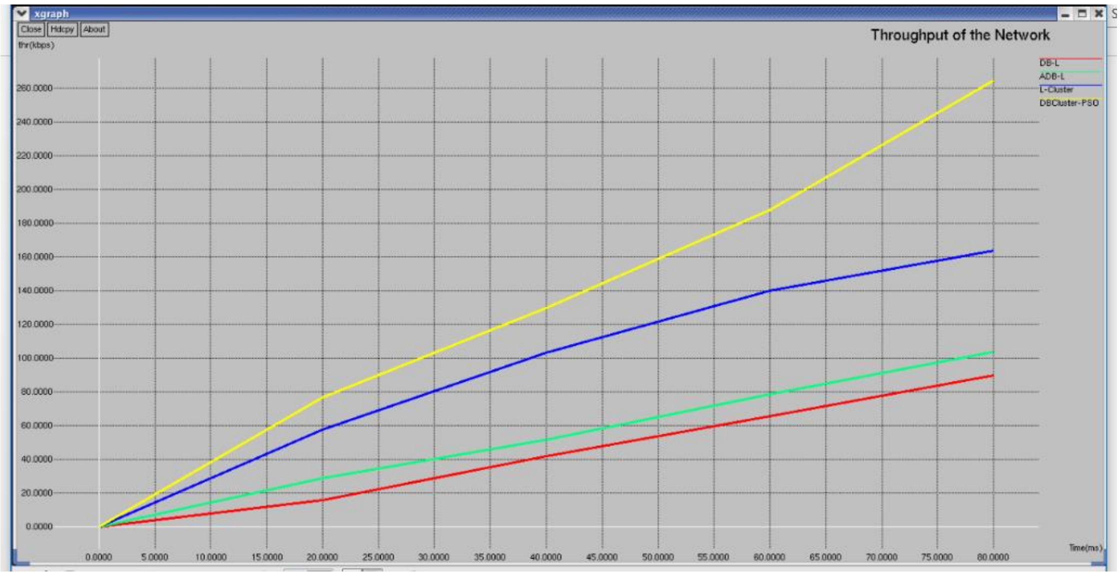

Figure 9: Comparison of Network Throughput

6. Conclusions

The complete methodology is implemented in two modules i.e. clustering the complete wireless network depending on the density using the DBSCAN approach and estimating the un-localized nodes within each cluster using PSO based location estimation algorithm. The performance of the suggested methodology is supported using NS2 Simulator .From Figure 4, it is inferred that the energy efficiency of methodology is advanced relative to the other existing approaches. From Figure 5, it is inferred that the generated packets of the network of the projected method are sophisticated when compared to the current methods. From Figure 6, it is inferred that the packet loss in the network of the proposed approach is less compared to the existing approaches. From figure 7, it is inferred that the packet delivery ratio of the projected method is sophisticated to the current methods. From figure 8, it is inferred that the received packets in the network of the projected method are sophisticated to the current methods. From Figure 9, it is inferred that the network throughput of the methodology is advanced than existing approaches.The results inferred that the proposed methodology has a superior packet delivery ratio, advanced energy efficiency, network throughput, and less data packet ratio relative to present localization approaches.

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