



MULTIPLE MOBILE ANCHORS BASED LOCALIZATION USING PARTICLE SWARM OPTIMIZATION (PSO) FOR WIRELESS SENSOR NETWORKS

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ABSTRACT

In Wireless Sensor Network (WSN), though several works have been done on localization using mobile anchors, they cause huge delay in localization of the network since the mobile anchor has to cover the entire network. It will be difficult to provide maximum coverage to the entire network, without considering the visiting schedule of the mobile anchor node. In this paper, multiple mobile anchor based localization technique using Particle Swarm optimization (PSO) is proposed. PSO is used to determine the trajectory of the mobile anchor nodes which is based upon the node density and the distance between the nodes in the network. The mobile anchor nodes broadcast packets to the visited sensor nodes depending on the PSO visiting schedule. The non-localized nodes on receiving the packets, calculate the estimated distance between each of the mobile anchors and using trilateration method, they are localized. From the simulation results, it is proved that localization delay and energy consumption are reduced with increased packet delivery ratio, when compared to the existing approach.

Keywords: *Wireless Sensor Network (WSN), Particle Swarm Optimization (PSO), Mobile Anchors, Localization*

1. INTRODUCTION

The continuous development in the field of communication networks has led to the emergence of a new technology, Wireless Sensor Networks (WSNs) for monitoring the physical world [1]. It is made up of some small sensor nodes which are distributed in an area and also collects information from their environments [2]. The collection of this low-powered sensors dynamically form a network in the absence of any underlying infrastructure support [3]. The sensors are used to sense the data from the environment, process the data, and to transmit the data to the base station directly or in multi-hop fashion [3]. The sensing modality of each node is capable of communicating over wireless channel [1]. Here each sensor could monitor only its region and the collected data is send to the sink node. The ability to correlate collected data in time and in space can be considered as the potential of WSNs [4]. WSN can be deployed for a variety of tasks like detection, recognition, localization and tracking of objects or events of interest [5]. It can be used in a wide range of application like battlefield surveillance, environment or health monitoring and disaster relief operations [5]

Localization is defined as the identification of the sensor node's position in a sensor network. The accuracy of the localization technique is highly desired in any wireless sensor network [6]. The network includes a small number of anchor nodes. The position of these nodes is already known using GPS or are manually configured. The other nodes which don't know their own position are called unknown nodes. Trilateral method can be used to figure the location when an unknown node knows three or more than three anchor nodes' position information [7]. Localization is a fundamental service as it is important to many applications like target tracking, intruder detection, environmental monitoring where the location information of the node is necessary. It is also relevant to many network main functions like routing, communication, cluster creation, network coverage, etc. [4].

Localization algorithm is designed to find sensor location information for the WSN. The protocols are divided into two based on the type of information required for localization. They are namely range-based and range-free protocols. In range-based technique, special hardware is used for estimating the distance between anchors and

sensors. Hence it becomes expensive for large networks. In range free technique, the anchor informs other sensors about its own position by message passing. Hence the complexity is reduced [8]. Some of the aspects taken into consideration while designing or choosing a localization algorithm are limited resources, number and density of nodes, network topology, existence of obstacles or terrain irregularities, types of signal used and node mobility [4].

1.1 Need for Localization

Some of the advantages of localization are:

- **Localization enables the efficient routing:** In a sensor network, large number of nodes needs to communicate at a very short distance. The data collected by a node has to be sent to the central unit through several other nodes. Multi-hop routing is used to communicate the information. Hence it is necessary to have nodes of the same locality and to know their relative position with respect to their neighbors. Thus localization is very important.
- **Localization provides the power saving:** In the scenarios like pollution monitoring, the neighboring sensor nodes of the sensor network having same data which are not different from each other. Hence to save power the data from the neighboring nodes are combined. The combined and reduced data set is used for communication in order to conserve the power. The location information is necessary for the local data fusion. It shows the significance of localization.
- **Localization assists in the applications like target tracking:** In target tracking the range, speed and the direction of the target is needed to be determined. The sensors are deployed in region which sense the sign & from the moving target its range, direction, and speed can be monitored. Hence the location of the sensor nodes is necessary to calculate the global orientation of the target.
- **Localization useful in locating the source of the data:** In event based sensor networks, the nodes are normally in sleep mode, the nodes awake only on the occurrence of an event. The data sensed and transmitted by the nodes requires a location stamp and hence localization is necessary [9].

1.2. Issues in Localization of WSNs

- The shortest path is used for unavailable distance measurements in centralized localization algorithms such as the MDS

method. The shortest paths usually do not correlate well with their Euclidean distances in irregularly shaped sensor networks. Hence it leads to severe deterioration in the localization performance

- The GPS installation on each sensor node for location discovery is impractical due to its significant power consumption, cost and line-of-sight condition requirement. Also GPS receivers are susceptible to jamming and attenuations [10]
- The current generations of sensor nodes are smaller and cheaper. As a result the nodes have reduced memory and processing capacities and limited battery. In addition the nodes can only communicate with its local neighbors due to its short transmission range
- Some localization algorithm cannot be applied to low density WSNs as they cause considerable localization errors whereas the localization can be an expensive process using some algorithms in high density WSNs due to its high cost and high delay [4].
- Some of the localization algorithms the shortest path between a pair of nodes is calculated using the Euclidian distance. it is valid only if the shortest path is a straight line. This is not valid for network having concave topology as it gives distorted results. Some nodes gives good approximation whereas for others Euclidean distance differ significantly from the length of the shortest path. [4]
- The nodes positioned in the limits of the WSN area may not deal well localizing the nodes using some localization algorithm. Hence the distance information each nodes can obtain is less and with lower quality.
- The proposed localization solution have low accuracy in obstructed environment as the existence of obstacles obstruct the line -of -sight between the nodes. Signal reflection is caused by the obstacles and terrain irregularities which lead to wrong distance estimations. Both indoor and out door environments face this problem.
- Most solution uses radio signals to measure the distance between the nodes based on the received signal strength. It may cause low accurate or low reliable results as these signals are deeply affected by the environment either due to the presence of obstacles or multi-path phenomenon. The heterogeneity of the channel which depends on the propagation direction cannot be ignored; atmospheric condition like



temperature has less effect on the signal whereas rain can affect the signal.

- If the node distribution is sparse or non uniform the performance and accuracy of Ad hoc Positioning System gets deteriorated greatly [3].
- Localization for large scale mobile underwater sensor networks is very challenging due to adverse aqueous environments, non-negligible node mobility and large network scale.
- Localization schemes designed for static sensor network runs periodically to update the location results. Hence the communication overhead increases dramatically.
- Distributed localization scheme designed for small scale underwater acoustics network is not suitable for large-scale underwater sensor network because of their slow convergence speed and high communication overhead [11].
- Localization has not been studied extensively in three dimensional WSNs because of its complexity [6].

1.3 Need for Solution

This paper tries to answer the following problems:

- How to reduce the delay involved in the localization in case of single mobile anchor nodes.
- How to determine the optimum visiting schedule of the mobile anchor nodes such that maximum coverage is obtained with reduced computational overhead.
- How to reduce the energy consumption of sensor nodes involved in the localization process.

To solve the above problems, we propose a multiple mobile anchor based localization technique using Particle swarm optimization (PSO) technique for Wireless Sensor Networks (WSN). It consists of a set of three mobile anchor nodes for localization of the network.

Particle swarm optimization (PSO) is a popular multidimensional optimization technique. The strengths of PSO are ease of implementation, high quality of solutions, computational efficiency and speed of convergence [16]. PSO simulates the bird flock predatory behavior, each bird will be abstracted as a massless and sizeless particle to represent a candidate solution of the problem, the "particles" moves regularly and finds the optimal solution after a number of iterations in the solution space [17].

2. RELATED WORKS

Vibha Yadav et al [6] have discussed about a range free localization mechanism for WSN. It operates in a three dimensional space in this scheme. Here the sensor network is comprised of mobile and static sensor nodes. Mobile sensor nodes are equipped with GPS enabled devices so that their position at any instance can be known. The mobile nodes moving in the network space periodically broadcast beacon messages about their location. The messages are received by the Static sensor nodes as soon as they enter the communication range of any mobile node. The static nodes calculate their individual position on receiving the message based on the equation of sphere. When compared to existing approaches, the proposed scheme gains in terms of computational and memory overhead.

Hongyang Chen et al [8] have proposed a new cooperative localization scheme that can achieve high localization accuracy in mobility-assisted wireless sensor networks when obstacles exist. A convex localization algorithm has been presented to address the effects of non-ideal transmission of radio signals to consider the complex localization scenarios like the feasible set is empty. The localization accuracy is improved significantly even in the presence of mobile elements using the proposed cooperative localization scheme.

Hongyang Chen et al [12] have presented a new cooperative localization scheme that can achieve high localization accuracy in mobility-assisted wireless sensor networks in the presence of obstacles. A convex localization algorithm has been presented to consider the complex localization scenario, namely, the feasible set is empty. It addresses the effects of non-ideal transmission of radio signals. An optimal movement schedule for Mobile Elements (ME)s have been developed to achieve a shortest path under expected localization accuracy.

Jongjun Park et al [13] have proposed a localization method using mobile anchor trajectory. The mobile anchor broadcasts its locations periodically. The sensor nodes pair them with RSSIs and estimate the trajectory of the mobile anchor. The locations of the sensor nodes are calculated using two different trajectories. The sensor nodes do not use any additional H/W devices.

Kuo-Feng Ssu et al [14] have described a range-free localization scheme using mobile anchor

points. Each anchor point was equipped with the GPS. It moves in the sensing field, periodically broadcasting its current position. The sensor nodes compute their locations using the obtained information. Here the sensor nodes do not need any extra hardware or data communication. Moreover, obstacles in the sensing fields can be tolerated.

Kezhong Liu and Ji Xiong [15] have presented a fine-grained localization algorithm for wireless sensor networks using a mobile beacon node. The algorithm uses RSSI for distance measurement. A GPS sender and RF (radio frequency) transmitter is attached to the beacon node and each stationary sensor node is equipped with a RF. The beacon node broadcasts its location information and stationary sensor nodes perceive their positions as beacon points. The location of the sensor node is computed by measuring the distance to the beacon point using RSSI.

From the literature review of existing works, we can say that, still there is need for multiple mobile anchor based localization scheme which answers all the problems listed in section 1.3.

3. MULTIPLE MOBILE ANCHORS BASED LOCALIZATION

3.1 Overview

The proposed technique uses PSO to determine the trajectory or visiting schedule of the three mobile anchor nodes based on the node density of the network.

Then based on the PSO based visiting schedule, when the three mobile anchor nodes traverse through the network, they broadcast packets which contain information regarding their id and location to the visited sensor nodes in the network. The unknown nodes having less received signal strength (RSS) value than the mobile anchor nodes on receiving the packet calculates the estimated distance between each of the mobile anchors to the unknown node. Each unknown node maintains anchor list having the anchor coordinates and estimated distance.

After that, Localization of the node is done using trilateration method. The unknown node will get two anchors from the list and localize them using trilateration method with the reference node. Reference node is the mobile anchor node having least distance to the unknown node.

The main advantage of the proposed solution is the usage of multiple mobile anchor nodes helps in reducing the delay due to the localization of the

network. Hence the localization of the network is carried out quickly. The PSO based approach for the visiting schedule of the mobile anchors enables it to traverse through the dense and sparse network with the same easiness. Hence the localization of both these networks is improved and the cost of localization is also reduced to a great extent.

3.2 Estimation of Node Density

A network consisting of several anchor nodes is considered and the local density is determined using the number of neighboring nodes. The node densities are classified into low, medium, and high. The ratio between expected hop distance and the transmission range for a particular local density is defined as the range ratio. The accuracy of the estimated hop-distance increases due to increase in number of categories at the cost of higher number of exchanged messages. Connectivity can be maintained using k number of neighbors in the wireless network.

Classification of density region depends on the number of neighbors. The region is identified as a low density region (L) when the number of neighbors is less than k . The region is identified as high density region (H) when the number of region reaches l . The region is considered as medium density neighbors (M) when the nodes are between k and l .

In the sensor network, reference nodes (RNs) contain a priori location information. The locations of other nodes are determined based upon the RNs.

In the sensor networks, when the hop-counts are propagated, the density awareness struggles to incorporate. Range ratio is represented as function of local density which is defined as the connectivity per unit transmission coverage. The RNs broadcast the hop-count and the nodes which hear the broadcast learn that they are one-hop neighbors of RN. Node's local density determines the distance associated with each hop. The hop-distances at different node densities are gathered together using range ratio λ .

If a node within hearing distance from RN finds that it has high local density, it stores the range ratio, $\sum \lambda_1 = \lambda_H$. On the other hand, if the node finds that it is located in medium or low density region, it maintains $\sum \lambda_1 = \lambda_M$ or $\sum \lambda_1 = \lambda_L$ respectively.

The gathered range ratio in the node gets forwarded to their neighbors. The process is repeated when the range ratio is lower than the existing value. Here the nodes uses their own local

density to estimate range ratio and are gathered for forwarding. The received packets are discarded when the range ratio is higher than the existing value. When all the RNs broadcast their range ratio the process goes to an end.

If $(n-1)$ th node is the previous node of (n) th node along a shortest multi-hop propagation path, then, the total range ratio accumulated by the (n) th node is

$$\sum \lambda_n = \sum_{i=1}^{n-1} \lambda_i + \lambda_n, \text{ where } \lambda = \lambda_L, \lambda_M, \text{ or } \lambda_H \quad (1)$$

The node has a higher probability of forwarding hop-count packets if the number of neighbors is higher. The nodes which are located at different directions and are close to transmission boundary receive the hop-count packet. The probability for the hop-distance to be closer to transmission range and at the direction that constitute shortest end-to-end path increases. The distance navigated becomes less than the transmission range when the number of neighbors is lower. The shortest end-to-end path is not provided for forwarding [18].

3.3 Estimation of Distance between Mobile Anchors

In this section, the Euclidian distance of one hop is estimated when an anchor node receives beacons from several other anchors. This is known as the correction factor. The equation (2) gives the correction factor handled by the anchor which is positioned at (x_i, y_i)

$$CF_i = \frac{\sum_j \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_j K_j} \quad (2)$$

Where K_j is the number of hops between the current anchor, positioned at (x_i, y_i) , and the anchor positioned at (x_j, y_j) . The location of the sensor node can be estimated using the first correction factor. The consequent correction factors are disregarded. The sensor nodes which are in the neighborhood of the anchors provide the correction factor. The probability grid is quoted once the sensor node receives the correction factor. The hop-count to the set of neighbors, anchor node's position, unit length of grid, and Euclidian distance estimate of one radio hop are the information contained in the sensor nodes at present.

Each node constructs the grid of arbitrary size which uses the position of at least three anchors and the unit length of the grid. The node density and the nodes in the network are specified for constructing

the grid of optimum size. Smaller grid sizes are adequate for higher densities of anchors in the network. The distances between the nodes are calculated as follows:

$$D = \frac{\text{Distance between grid point and anchor}}{\text{Correction factor}} \quad (3)$$

The computed D represents the distance, in hop count units, between the evaluated grid point and one anchor. [19]

3.4 Particle Swarm Optimization

Based upon the swarm intelligence, the particle swarm optimization (PSO) algorithm is proposed which solved the optimization problem in a search space. It also models and predicts the social behavior in the presence of objectives. It proves to be a stochastic, population-based computer algorithm which is based upon the swarm intelligence model.

The applications of swarm intelligence include social-psychological principles, approaches to social behavior and engineering applications. The fitness function is provided for evaluating the proposed solution. This communication structure or social network assigns neighbors for each individual for interaction.

The population of individuals is initialized and they are considered as random guesses at the problem solutions. These individuals are called the candidate solution or particles. In order to improve these candidate solutions, an iterative process is set. The fitness of the candidate solutions are evaluated by the particles and the information about the locations of best success are retained. This information is also available to their neighbors.

The locations of successful neighbors are also known. These successes guide the movements along with the populations converging at the end of a trial. This is used efficiently for a non-swarm approach. A candidate solution is given for each particle for optimization problem. The best position of the particle is judged by the particle itself. The neighboring particles determine the position of the best particle in its neighborhood. The global best particle is the best position in the neighborhood when the neighborhood of a particle is the entire swarm. This algorithm is named as gbest PSO. lbest PSO is used for smaller neighborhoods. The fitness function measures the performance of each particle and varies depending upon the optimization problem.



3.4.1 Estimation of Position and Velocity of the Particle

Each Particle in the swarm is represented by the following characteristics:

The current position of the particle

The current velocity of the particle

The population of the particles is used in the latest evolutionary optimization technique which is known as particle swarm optimization. In this algorithm, the particle corresponds to an individual and the position vector and velocity vector are updated by moving through the problem space.

$$V_i^{k+1} = wV_i^k + c_1 rand_1 \times (pbest_i - s_i^k) + c_2 rand_2 \times (gbest - s_i^k) \tag{4}$$

$$s_i^{k+1} = s_i^k + V_i^{k+1} \tag{5}$$

Where,

V_i^k is the velocity of i at iteration k ,

s_i^k is the current position of i at iteration k .

c_1 and c_2 are positive constants and $rand_1$ and $rand_2$ are uniformly distributed random number in $[0,1]$.

3.4.2 Optimization Function

Here the optimization function is calculated using the node density and the distance between the nodes.

$$f(\eta) = A \cdot \sum Di + B \cdot \frac{1}{\sum \lambda i} \tag{6}$$

Where λ represents range ratio and D is the distance between the nodes. A and B are the smoothing constants

The node density should be maximum and the distance should be minimum for the optimization function.

3.4.3 Weight Function

The inertia weight w weighting function in Eq (4), controls the momentum of the particle. The inertia weight can be dynamically varied by applying a scheme for the setting of the PSO, where w decreases over the whole run. The decrease depends on the start and end value of the weight given.

The Inertia term w , is provided with the below Eq (7) to make the convergence faster and easier.

$$w = w_{end} + (w_{start} - w_{end}) * \beta \tag{7}$$

where

$$\beta = \left(\frac{1}{1 + (\alpha x / x_{max})} \right)$$

w_{start} , Start value of the inertia weight

w_{end} , end value of the inertia weight

x , current iteration number

x_{max} , maximum iteration number

α , used to manipulate the gradient of the decreasing factor

The inertia term should linearly decrease in order to facilitate exploitation over exploration in later states of the search.

3.4.4 Visiting Schedule

Each particle represents a visiting scheduling scheme which uses n visiting schedules and m number of anchor nodes. x_i^k is the position value of

i_{th} particle with respect to n dimension and s_i^k is the sequence of tasks of i_{th} particle in the processing order with respect to the n dimension.

The position vector x_i^k has a continuous set of values

Then the operation vector r_i^k is defined as,

$$r_i^k = s_i^k \text{ mod } m. \tag{8}$$

The Initial population of particles is constructed randomly for PSO algorithm. The initialized continuous position values and continuous velocities are generated by the formula,

$$X_k^0 = x_{min} + (x_{max} - x_{min}) * r \tag{9}$$

$$V_k^0 = V_{min} + (V_{max} - V_{min}) * r \tag{10}$$

The flowchart for the scheduling algorithm is given. β is the iteration value and T_i is threshold for maximum number of iterations.[20]

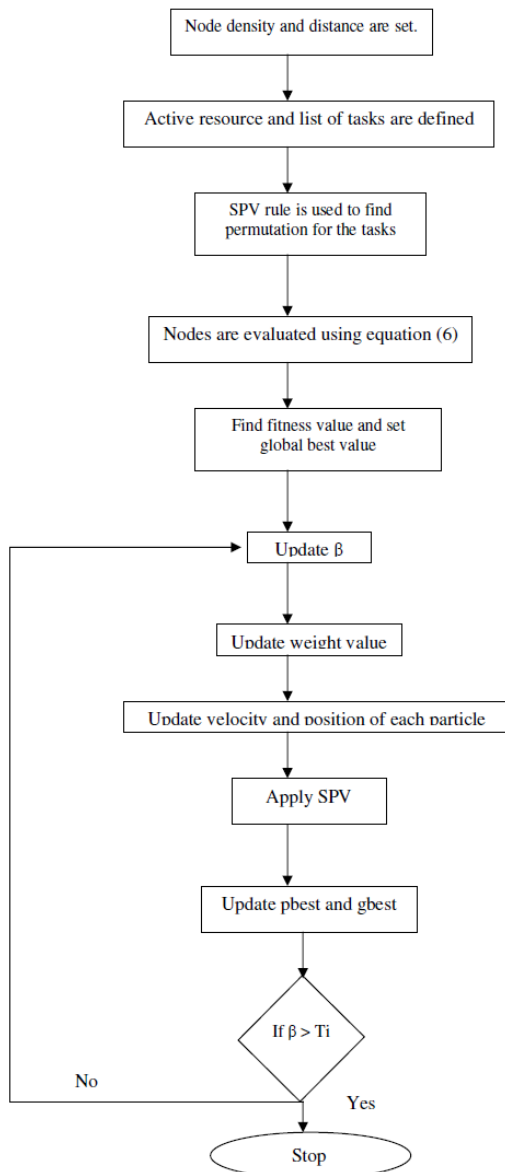


Figure 1: Flowchart For Scheduling

3.5 Localization using Trilateration

In this section, DV-hop algorithm is executed initially and the average distance per hop and anchor list for unknown nodes are accomplished. In DV-hop the position information is included in the packets which are generated by the anchor nodes. The numbers of hops away from the packets are denoted using a flag. In WSN, packets are broadcasted in the flooding mode. The hop number increases by one when they are transmitted by the relay nodes.

Using this hop number from a node to any anchor node can be determined. In the same way, the anchor nodes compute their hops to other

anchors also. The receiver estimates its distance to the anchor node when the information is sent to the unknown node. The location of the anchor node is determined only after getting three or more estimated values from the anchor nodes.

Then the anchors are chosen such that unknowns will get two anchors out of the list. Then the two nodes are combined with a reference node and are localized by trilateration. The unknown nodes receive average distance per hop initially from the reference node. During iteration, the reference node becomes unknown node, the unknown node becomes known node for which the coordinate is computed in the previous step. Trilateration gives N results which are compared with the actual coordinate. The coordinates which has the smallest difference after iteration, is saved. Ultimately unknown nodes also determine their positions.

Based on the PSO based visiting schedule, when the mobile anchor nodes traverse through the network, they broadcast packets which contain information regarding their id and location to the visited sensor nodes in the network. The unknown nodes having less received signal strength (RSS) value than the mobile anchor nodes on receiving the packet calculates the estimated distance between each of the mobile anchors to the unknown node. Each unknown node maintains anchor list having the anchor coordinates and estimated distance.

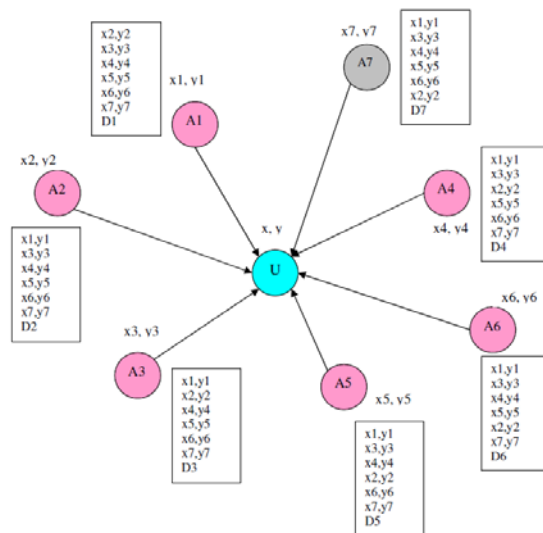


Figure 2: Trilateration

In this figure, initially we consider node U as the unknown node and it has seven anchor nodes around. We assume that U receives value from A7 initially. So, A7 is considered as reference node.

Each node consists of an anchors list which records all other node's coordinates and the estimated distances from them to U.

Node U randomly chooses two anchors from the other anchors and together with R to execute trilateration, records the result. Then we consider A7 as unknown node, and U as known node, and then execute trilateration again. Compare these results with A7's actual coordinate, pick out the one which is the nearest to the actual value, and send it to U. Therefore, U will understand which result is the best, and it's coordinate and the error will be recorded

Step 1: Initially the DV-hop algorithm is executed. The average distance per hop is computed and the unknown node save the value which they receive first and this is considered as the reference node. Each unknown nodes create an anchor list and the anchor's coordinates are recorded. The distance from it to these anchors are also recorded.

Step 2: Any two anchors out of the list for each time is chosen and localized by trilateration together with the reference node. Record the result. All the combinations should be included.

Step 3: Consider that D1 =4, D2 = 3, D3= 7, D4 = 6, D5 = 10, D6 = 9. Consider A7 as unknown node and U as known node, and displace A7 with corresponding Unknown node along with other two anchors to localize by trilateration.

Step 4: We will compare these coordinates' error at R with the formula below. The true coordinate is (x_r, y_r) , (x, y) is the estimate value in the computations:

$$\frac{\sqrt{(x_r - x)^2 + (y_r - y)^2}}{x_r + y_r} \times 100\%$$

Let P1, P2,P3, P4, P5 and P6 be the estimated positions from the other anchors A1,A2,A3,A4,A5 and A6 along with U. Pick out the value which with the least error, assumed to be P2.

Step 5: A7 will send the estimated co-ordinate of U with respect to P2 , to the unknown node U.

Therefore, U will know P2 is the best result, and it will consider P2 as its coordinate.

Each unknown node will obtain their Positions. [7]

Since multiple mobile anchor nodes are used, it reduces the delay due to the localization of the network. Hence the localization of the network is

carried out quickly. The PSO based approach for the visiting schedule of the mobile anchors enables it to traverse through the dense and sparse network with the same easiness.

4. SIMULATION RESULTS

4.1 Simulation Parameters

We evaluate our Multiple Mobile Anchor based Localization using PSO (MMAL-PSO) technique through NS-2 [21] simulation. We use a bounded region of 500 x 500 sqm, in which we place nodes using a uniform distribution. The number of nodes is varied as 50,100,150 and 250. We assign the power levels of the nodes such that the transmission range of the nodes varies from 250 meters to 400meters. In our simulation, the channel capacity of mobile hosts is set to the same value: 2 Mbps. We use the distributed coordination function (DCF) of IEEE 802.11 for wireless LANs as the MAC layer protocol. The simulated traffic is Constant Bit Rate (CBR).

The following table summarizes the simulation parameters used

No. of Nodes	50,100,150 and 200.
Area Size	500 X 500
Mac	802.11
Simulation Time	20,30,40 and 50 sec
Traffic Source	CBR
Packet Size	500
Transmit Power	0.660 w
Receiving Power	0.395 w
Idle Power	0.035 w
Initial Energy	15.3 J
Transmission Range	250,300,350 and 400 m
Routing Protocol	AODV

4.2 Performance Metrics

We compare the performance of our proposed MMALPSO method with the Mobile Anchor assisted node Localization (MAL) method [8]. We evaluate mainly the performance according to the following metrics:

Packet Delivery Ratio: It is the total number of packets received by the receiver during the transmission.

Average end-to-end delay: The end-to-end-delay is averaged over all surviving data packets from the sources to the destinations.

Average Energy Consumption: The average energy consumed by the nodes in receiving and sending the packets.

4.3 Results

A. Based on Nodes

In our initial experiment we vary the number of nodes as 50,100,150 and 200 with transmission range 250m and simulation time 50sec.

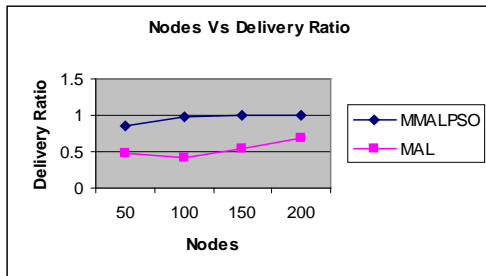


Figure 3: Nodes Vs Delivery Ratio

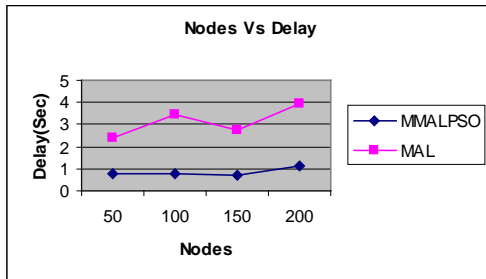


Figure 4: Nodes Vs Delay

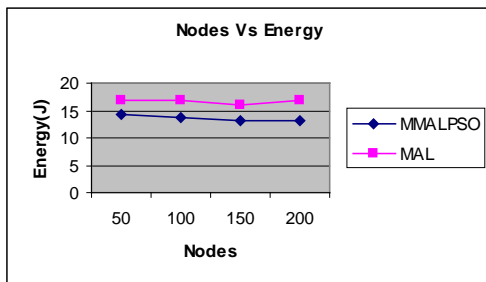


Figure 5: Nodes Vs Energy

Figure 3 show the Packet Delivery ratio occurred for both MMALPSO and MAL. As we can see from the figure, the delivery ratio is high for MMALPSO, when compared to MAL.

Figure 4 show the average end-to-end delay occurred for both MMALPSO and MAL. As we can see from the figure, the delay is less for MMALPSO, when compared to MAL.

Figure 5 show the Energy consumption for both MMALPSO and MAL. As we can see from the figure, the energy consumption is low for MMALPSO, when compared to MAL.

B. Based on Time

In our second experiment we vary the simulation time as 20, 30, 40 and 50 sec with 50 nodes.

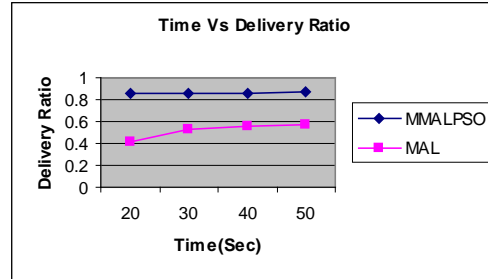


Figure 6: Time Vs Delivery Ratio

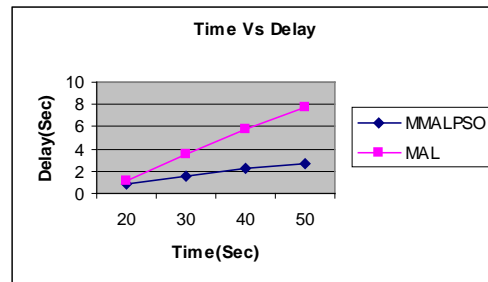


Figure 7: Time Vs Delay

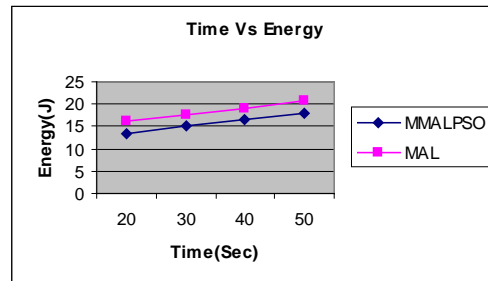


Figure 8: Time Vs Energy

Figure 6 show the Packet Delivery ratio occurred for both MMALPSO and MAL. As we can see from the figure, the delivery ratio is high for MMALPSO, when compared to MAL.

Figure 7 show the average end-to-end delay occurred for both MMALPSO and MAL. As we can see from the figure, the delay is less for MMALPSO, when compared to MAL.

Figure 8 show the Energy consumption for both MMALPSO and MAL. As we can see from the

figure, the energy consumption is low for MMALPSO, when compared to MAL.

C. Based on Transmission Range

In our third experiment we vary the transmission range as 250,300,350 and 400m with 200 nodes.

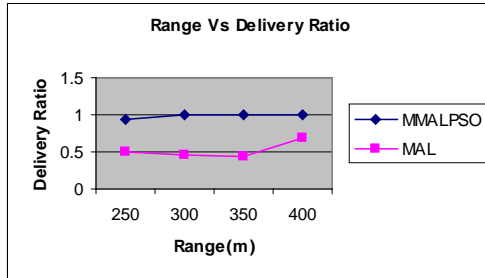


Figure 9: Range Vs Delivery Ratio

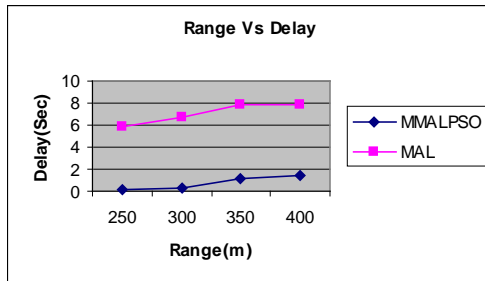


Figure 10: Range Vs Delay

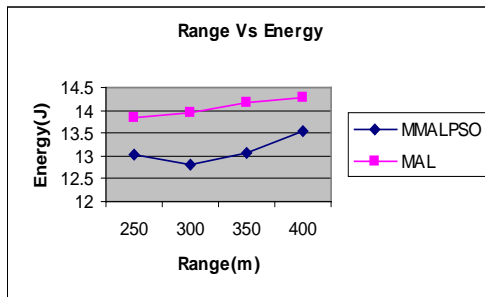


Figure 11: Range Vs Energy

Figure 9 show the Packet Delivery ratio occurred for both MMALPSO and MAL. As we can see from the figure, the delivery ratio is high for MMALPSO, when compared to MAL.

Figure 10 show the average end-to-end delay occurred for both MMALPSO and MAL. As we can see from the figure, the delay is less for MMALPSO, when compared to MAL.

Figure 11 show the Energy consumption for both MMALPSO and MAL. As we can see from the figure, the energy consumption is low for MMALPSO, when compared to MAL.

5. CONCLUSION

In this paper, we have proposed a multiple mobile anchor based localization technique using Particle swarm optimization (PSO) technique. PSO is used to determine the trajectory of the mobile anchor nodes which is based upon the node density and the distance between the nodes in the network. We consider three anchor nodes for localization. The mobile anchor nodes broadcast packets according to the PSO visiting schedule. It contains id and location to the visited sensor nodes. The unknown nodes having less received signal strength (RSS) value than the mobile anchor nodes on receiving the packet calculates the estimated distance between each of the mobile anchors to the unknown node. Each unknown node maintains anchor list having the anchor coordinates and estimated distance. After that, localization of the node is done using trilateration method. The unknown node will get two anchors from the list and localize them using trilateration method with the reference node which is the mobile anchor node having least distance to the unknown node. From our simulation results, we have shown that the localization delay is reduced since multiple mobile anchor nodes are used and the visiting schedule of the mobile anchors enables it to traverse through the dense and sparse network.

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