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Research paper

A Meta Heuristic Optimized Localization for Efficient Deployment of Nodes in Wireless Sensor Networks

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Abstract

The main issue in the Wireless Sensor Networks (WSN) comprises computing the sensor node positions (base stations) in order to obtain energy efficiency, coverage and required connectivity with as small number of nodes as possible. Whenever incidents take place in areas which do not have sufficient number of nodes, they are not noticed. Whereas, in places where there are more than required sensors, there is a lot of delay and congestion. Placing the sensor nodes strategically so as to obtain desired goals in throughput is one of the design optimization techniques. We explore a new heuristic called the fish swarm to determine the optimal solution for node deployment by making use of energy as well as Packet Delivery Ratio (PDR). Improvements have been experimentally shown over strategy that is randomly placed.

Keywords: *Wireless Sensor Network (WSN); Localization; Heuristic Optimization and Fish Swarm Optimization (FSO);*

1. Introduction

There are numerous sensors in a WSN that are dispersed across a geographical area. These nodes have a constrained storage, processing, sensing and communication abilities. They are also less costly and small in size .The application of WSN is in various areas such as health, commercial uses, military and environmental purposes. The location of sensors is more often than not, unknown as the node deployment is mostly arbitrary. Hence, an important problem in the WSNs is finding the physical locations of the sensor nodes [1].

Most of the algorithms that have been formulated for the WSNs are dependent on the assumption that the sensor nodes know their positions. Also, they are aware of the neighbouring nodes. There is a need for performing a localization method based on a local or a global co-ordinate system carefully as each measurement is rigidly connected to the sensor node locaion in the field. Also, certain WSN connected problems such as sensing coverage estimation, geographic routing or the procedures related to the sleep or the wake up of the nodes could enhance the requirement for obtaining the localization of the nodes. This is done by depending on the data regarding the location [2].

Supplying physical co-ordinates for all of the sensor nodes is the purpose of localization. For WSNs that are developed manually, the process of localization is quite simple. However, it gets complex for arbitrary deployment in unfriendly terrains or hazardous battlegrounds performed through procedures of aerial scattering from balloons, airplanes and guided missiles. These depend on specialized nodes that automatically determine their position. Known as the anchor or the beacon nodes, these are crucial to every technique of localization that occur inside the global co-ordinates.

Presently, the most expensive and sophisticated method is the Global Positioning System or GPS.GPS is suitable for outdoors in the absence of shelter. Though, since the nodes are expensive and are in huge quantities that are expensive. Need an establishment that is settled, the GPS is not viable for inexpensive and self-configuring sensor networks. It is impractical to connect GPS for each and every sensor node. As sensor nodes, in fact are installed by random bestrewing like the airplane, it is not possible to obtain the co-ordinates of a majority of them beforehand. Hence , a hot topic in WSN is the way in which the unknown nodes' position is to be obtained, which is also referred to as the problem of localization has become a popular subject in the area of WSN[3].

There are four types of localization- Distance based, known location based, angle based and proximity based.

Distance Based Localization- Hop distance between each node is used for node localization. For localization, it makes use of Distance Vector/ DV Hop propagation method or the DV propagation method is used.

Known Location Based Localization- The sensor nodes are aware of their locations beforehand. This can be obtained by using the Global Positioning System or by manual configuration. The latter can be performed using the with the aid of the Global Positioning System device. When there are no reference nodes for localization, the GPS devices are better. The accuracy is also better with a standard deviation of 4-10 m [4].

Angle Based Location- This makes use of the received signal angle or AOA- Angle of Arrival for finding out the distance. These are mostly used in the base stations as the method needs special and expensive antennas.

Proximity Based Localization- Here, the Wireless Sensor Network has many clusters and every cluster contains a CH or a Cluster Head which comprises a Global Positioning Sensor device. Every node can find the neighbouring location by using Bluetooth, Infrared etc.

Range based localization: Based on the range, the localization is performed. This range can be computed using Time of Arrival (ToA), Received Signal Strength (RSSI) or Time Difference of

Arrival (TDoA). In ToA and TDoA, timing is used for range calculation whereas in RSSI, when the receiver transmits the signal strength corresponding to the sender, based on the strength of the signal, the sender calculates the distance. in ToA and TDoA, synchronization of time is a significant factor.

The localization algorithms can be spited into two categories depending on the requirement for measuring the true distance between the nodes. They are Range Free and Range Based. The former employ estimated in place of metrical distance for node localization [6] whereas the latter have to actually calculate the exact distance between the neighbouring nodes and use this data for performing localization.

Approximate Point in Triangle Test (APIT), coordinate and DV-hop are used in range-free localization algorithms .In the former, given 3 anchor nodes, an unknown nodes' position can be determined in case it lies within the triangle that is made of the three anchors. Here, numerous APIT tests are performed by every sensor node with various permutations of distinct anchor nodes thereby reducing its location as the intersecting triangles' centre of gravity wherein the node is. The co-ordinates here are free of GPS as there are no anchors, there is an absence of reference frame information in localization. After it obtains the distance to neighbour nodes and the distances between neighbour nodes, each node makes itself coordinate origin to establish a local reference frame. Then, it communicates with the nearby nodes for extending local reference frame.

There are two main classes of localization algorithms-The centralized and the distributed algorithms. The former collate the needed data in a central base station. After they process this information, they locate the sensors and communicate the resulting locations back to the corresponding nodes. The superior precision and removal of superfluous calculations in each node is the best advantage of these algorithms. However, the communication expense in a distributed algorithm is lesser as each sensor determines its location depending on local data autonomously [7].

As the WSNs are scalable as well as complex, there is a need for using distributed localization algorithms that are implemented on a single sensor node instead of on a central base station. Localization is performed by every target with inappropriate distance measurements from or more nearby anchors or settled nodes. Over the earlier methods, these are the advantages of the proposed methods [8]-

- The precision of localization is far better.
- The process of localization is iterative. i.e. nodes are settled in every iteration. Hence, there are more references in the transmission node that a node gets.This results in correction of errors arising due to flip ambiguity. Flip ambiguity refers to the situation that occurs whenever the references exist in proximity- collinear places.
- The location is independently estimated by every node. This makes it unnecessary to communicate with the central node that preserves energy and avoids congestion.
- Localization immunizes noise that is associated with the measurement of distances.

A collective behaviour of systems that are self-regulating and decentralized is denoted by SI or Swarm Intelligence .There are simple agents in the population of the system wherein there is an absence of a central control for regulating their behaviours. These basically lack intelligence and they only interact locally with each other as well as the surroundings for producing complex and intelligent behaviours. A problem can be solved by Meta heuristic approach that is exemplified by SI. For incorporating the swarm behaviour, a number of optimization algorithms have been modelled. Some of the well-known ones are Gravitational Search Algorithm (GSA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Intelligent Water Drops (IWD) that has been recently explored [9].

Yet another solution to the localization problem is the heuristic optimization [10]. A good and viable solution is close to optimal can be found using a heuristic approach. We can conclude that there is no solution or obtain a nearly optimal solution by making use of a well-designed heuristic method .The FSO algorithm has been proposed in this work? The FSO is easy to understand, robust and not

A heuristic global optimization method that depends on the population is the FSO algorithm. It is simple to comprehend, strong and is not impacted by the initial values. The performance of the algorithm is highly impacted by fish. The performance parameters include convergence speed and global search.

FSO algorithm in WSN localization has been proposed by this work. The related work in literature has been reviewed in Section 2. The methods used have been described in Section. The experimental results have been described in Section 4. The conclusion of the work is given in section 5.

2. Related Works

A new type of localization algorithm that combines the regression as well as the classification approaches was proposed by Ahmadi et al., [11]. This combined technique increases the previous method's localization precision, for which regression tree was used. This methodology depends on the choosing of 3 anchors which have the closest proximity to the target for testing phase and the formulation of the training set. Using the true measurements obtained in the office rooms, the performance is measured. It has been shown by empirical outcomes that the procedure for the selection of anchors gives rise to an enhanced precision visa vis the standard regression tree localization algorithm.

There are two fundamental issues related to the current bile beacon based range free localization method(1) The accuracy of localization is impacted by the irregularity with which the radio propagation varies .(2) The closer beacon broadcasting durations determine the precision of the estimation of position. These two issues were overcome by suggesting a Mobile Beacon (MOB) based range free localization method for WSNs by Singh & Khilar [12]. This in turn is based on the arc's analytical geometry. Cramer's rule has been used in this work. Here, the point of intersection of 2 perpendicular bisectors of the chords is considered as the sensor node's estimated position. It has been shown by the outcome of the simulation that, the suggested method shows better performance compared to the free localization algorithms that are existing.

A novel DV Hop localization algorithm was proposed by Kumar & Lobiyal [13].It enables localization without overly expensive communication costs as it does not require extra hardware. By computing the hop-size of the unknown nodes, the suggested methodology totally removes the communication from one of the steps .It also considerably decreases time consumed as well as the energy consumed. This is a very important improvement over DV-hop based methods. It utilizes the improvements for improvising the anchor nodes' hop size. It has been shown by experimental results that the presented algorithm performs greater compared to the DV-Hop algorithm and enhanced DV-Hop based algorithms across scenarios.

A new Non-Line-of-Sight (NLOS) identification algorithm based on distributed filtering to mitigate NLOS effects, including localization failures, was suggested by Pak et al. [14].The suggested algorithm dispenses the metrics among many local filters. The NLOS caused abnormal measurements are identified using distributed filtering and data association techniques. Thus it is possible to get rid if the negative effects. The Hybrid Particle Finite impulse response Filter (HPFF) was formulated for addressing the failures caused in the localization because of NLOS. The resultant HPFF that is a distributed method has the capability to detect failures and thus self-recover and thereby reset the algorithm. For showing the proposed algorithm's effectiveness, wide indoor localization simulations were performed using TOA metrics for various NLOS scenarios.

The target localization issue was accounted for Tomic et al, [15], in case of co-operative three dimensional Wireless Sensor Network. A hybrid system was utilized by the author. This system combines the measurements of distances and angles; these metrics of distance are extracted from RSSI and that of the angle from AOA information. The author derived a new non-convex calculator that derived its basis from Least Squares (LS) criteria. This was on the basis of range measurement model and simple geometry. It was shown that this calculator that was developed was viable for execution of distributed systems. This could be changed in to a convex one by making use of a Second-Order Cone Programming (SOCP) relaxation technique. It was also shown that, by following the Squared Range (SR) technique, the non-convex estimator that was developed can be changed into Generalized Trust Region Sub-problem (GTRS) framework.

The target localization problem was accounted for by Tomic et al. [16] in the cases of both co-operative and non-co-operative Wireless Sensor Networks. This was developed for the cases involving both the known and unknown Transmit Power (PT). A hybrid system was utilized by the author. This system combines the measurements of distances and angles; these metrics of distance are extracted from RSSI and that of the angle from AOA information. The author transformed the estimator into a convex problem for a co-operative WSN. He did this by the application of semi-definite programming relaxation methods. He also factored that, in cases where PT is not known, the generalization for suggested calculators is obvious .In cases of unknown PT, it was shown by the results of simulation that the novel estimators were not only robust but also exhibited superior performance. For non-cooperative localization, the novel estimators were shown to perform better than the existing ones. Also, superior performance under all considerations was shown by estimators in co-operative localization.

One of the most common localization approaches in WSN is the RSS based approach .Although under conditions of NLOS, this technique exhibits reduced precision of estimation, it is simple and inexpensive. The Pedestrian Dead Reckoning (PDR) uses Inertial Measurement Unit (IMU) for location tracking .For Wireless Sensor Networks, indoor localization algorithm based on RSS that was fused with the PDR location tracking was proposed by Cho and Kwon [17]. The goal is the compensation of the NLOS localization error making use of the PDR. This is done by simultaneously reducing the collated PDR error, in the Line Of Sight Conditions (LOS) by using localization method based on RSS.It was shown that the suggested technique considerably decreased the estimation errors in location in Wireless Sensor Networks . Large scale simulations seconded this.

The bat algorithm was suggested by Goyal & Patterh [18]. It is a Meta heuristic optimization algorithm. It had been developed to report the node localization accuracy in Wireless Sensor Networks. Utilizing the bacterial foraging strategies of Bacterial Foraging Optimization (BFO) algorithm, the current bat algorithm has also been modified. It has been shown, that by simulations, the new suggested algorithm functions better than the existing one. It helps in enhancing the success of localization along with robustness and fast convergence speed.

The distance among the anchor node like coach and the mobile sensor node like the bicycle in both indoor and outdoor environment was determined by Gharghan et al [9]. For estimating such distances there were two approaches that were considered. Conventional channel propagation model was considered for the first technique. This used Log-Normal Shadowing Model (LNSM). Hybrid Particle Swarm Optimization Artificial Neural Network (PSO-ANN) was used for the second approach. This was used for improving the estimation precision for the mobile node. The distance estimation precision in the hybrid PSO-ANN algorithm was considerably better than conventional LNSM technique without utilizing extra parts. The hybrid PSO-ANN algorithm had a mean absolute error of 0.022 for outdoor environment and 0.208 for indoor environment. In the indoor environs, the anchor node density’s effect was scrutinized. The summary of the related works has been shown in Table 1.

Table 1 Summary of Related Works

Authors	Techniques	Merits	Demerits
Ahmadi et al., [11]	Improved anchor selection strategy	Accuracy	Data acquisition
Singh & Khilar [12]	MOB	Better accuracy	Accuracy on position estimation and varying radio propagation irregularity
Kumar & Lobiyal [13]	DV-Hop algorithm	Lesser communication cost and reduces time and energy consumption	Time and energy consumption
Pak et al., [14]	HPFF and NLOS	Detecting failures and resetting the algorithm	Localization failure
Tomic et al., [15]	Cooperative 3-D WSN	Excellent performance	Target localization problem
Tomic et al., [16]	Non-cooperative and cooperative 3-D WSN	Excellent performance and robust	Target localization problem
Cho & Kwon [17]	RSS-based indoor localization algorithm	Reduce the location estimation errors	Location error
Goyal & Patterh [18]	Modified bat algorithm	Increasing localization success ratios and fast convergence speed but also enhance its robustness	The precision of node localization problem
Gharghan et al., [19]	LNSM and hybrid PSO-ANN	Improved the distance estimation accuracy	Distance estimation

3. Methodology

Typically, in traditional Wireless Sensor Network designs, the optimization objective is the most striking metric for evaluating performance. The other ones are regarded as optimization problem constraints. However, as they overstate the significance of the metrics to the disadvantage of the others, these optimization approaches with a single goal may be both unreasonable and unfair in WSN applications. A more realistic optimization is satisfying many objectives at the same time like shortest delay, longest network lifespan, highest consistency, maximum efficiency of energy and the balanced distribution of the remaining energy of the nodes or an exchange among the other goals. Correspondingly, for solving the issue stated, Multi-Objective Optimization (MOO) can be obviously accepted. This is because in case of realistic scenarios, it may be more regular [20].

For solving the varied Multi-Objective Optimization problems (MOPs) wherein the many objectives are subject to a set of constraints, these MOO algorithms gave been an area of interest for the researchers. But, it is not possible for many goals to reach their corresponding optima simultaneously. Hence, a single global optimal solution may be non-existent. This may be the best case scenario considering all of the objectives. However, there is a set of Pareto-optimal or non-dominated solutions generating a set of Pareto-optimal outcomes/objective vectors, which is called Pareto Front/Frontier (PF) or Pareto boundary/curve/surface. PF can be produced explicitly by a certain solution set. For this, the multiple objectives cannot be improvised without giving up on other goals. This set of non-dominated solutions or Pareto optimal set frame a focus of interest known as the Pareto-efficient set or Pareto Set (PS). This is mapped to the PF in the objective function space.

3.1. Fish Swarm Optimization (FSO) Algorithm

A new method for searching global optimum is the FSO algorithm. This is the typical behavioural application in AI. It is an arbitrary search heuristic that depends on fish swarm behaviours that are simulated , which comprise swarming behaviour ,chasing and foraging behaviours. After constructing the artificial fish' non complex behaviour, on the basis of the local searching behaviours of the animals, it makes the global optimum appear at last. The FSO can help in not only searching the global optimums efficiently but also has a particular ability to adapt to the searching space [21].

Supposed the state vector of artificial fish swarm is $X = (x_1, x_2, ... x_n)$, where $x_1, x_2, ... x_n$ is status of the fish. Visual is the visual distance, the artificial fish occurs only in the inner radius of the circle to the length of the field of vision various acts. The food concentration in this position of fish is expressed as y = f (x), Where y is the objective function value. The distance between the artificial fish is $d_{i,j} = \| X_i - X_j \|$, i and j is a random fish. Step means the maximum step size of artificial fish. α is the degree of congestion factor [22].

Supposed X_v is the visual position at some moment. X_{next} is the new position. Than the movement process is represented as (1):

$$X_v = X_i + Visual \times rand(), \ i \in [0,n]$$
$$X_{next} = X + \frac{X_v - X}{\| X_v - X \|} \times step \times rand() \tag{1}$$

The artificial Fish's fundamental conduct is described as below:

Prey behavior: The fundamental conduct for food foraging. If the artificial fish' state is X_i, Select a state X_j within its sensing range randomly. If X_j superior to X_i , then move to X_j ; On the other hand, selected randomly state X_j . Then determine if the several times repeated forward conditions are to be met. In case the forward conditions are not still met , then move one step randomly in (2).

$$X_j = x_i + Visual \times rand()$$
$$if \ Y_i < Y_j, \text{ it goes forward a step in this direction.}$$
$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\| X_j - X_i^t \|} \times Step \times rand() \tag{2}$$

Swarm Behavior: Supposed the current state of artificial fish is $X_i(d_{i,j} < Visual)$, number of artificial fish is n_f , if $n_f < \delta$ indicates that the partners have more food and less crowded, if Y_c better than Y_i ,then go forward toward the center of the direction of the partnership, otherwise prey behavior in (3).

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\| X_c - X_i^t \|} \times Step \times rand() \tag{3}$$

Follow Behavior: Supposed the state of artificial fish is X_i , explore its optimal state X_{max} from Visual neighbors, the number of partners of X_{max} is n_f , If $n_f < \delta$ indicates that near distance have more food and not too crowded [23], further move to the front of X_{max} position; otherwise perform foraging behavior in (4).

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\| X_j - X_i^t \|} \times Step \times rand() \tag{4}$$

The pseudo code of FSO algorithm is shown in below:

$foreach\ AF\ i$

$\quad initialize\ x_i$

$endfor$

$bulletin = \arg\min_{X_i} f(X_i)$

$\text{Re}\ peat$

$\quad foreach\ AF\ i$

$\quad\quad Perform\ swarm\ behavior\ on\ X_i(t)\ and\ obtain\ X_{i,swarm}$

$\quad\quad Perform\ Follow\ behavior\ on\ X_i(t)\ and\ obtain\ X_{i,follow}$

$\quad\quad if\ f(X_{i,swarm}) \geq f(X_{i,follow}) then$

$\quad\quad\quad X_i(t+1) = X_{i,swarm};$

$\quad\quad else$

$\quad\quad\quad X_i(t+1) = X_{i,follow};$

$\quad\quad endif$

$\quad endfor$

$\quad if\ f(X_{Best-AF}) \leq f(bulletin)\ then$

$\quad\quad bulletin = X_{Best-AF};$

$\quad endif$

$until\ stopping\ criterion\ is\ met$

Here, the free moving conduct and the prey behaviours were regarded as a part of follow and swarm behaviours. This means that in case the artificial fish were not successful in performing a swarm and follow conduct, the prey conduct would be performed . In case, by executing swarm or follow conduct, the artificial fish is unable to perform prey behaviour, and in case a better position cannot be reached by implementing this, a free move conduct would be performed [24].

There is a fish population in the FSO with Cluster Head Algorithm wherein every fish comprises the cluster's centre position.In case the samples of clustering consider d-dimensional space, then, every fish (artificial) incorporates a position vector with n*d dimensions. In the novel method, each artificial fish moves with probability of p1%, based on the stored position in bulletin by (5):

$$\vec{X}_i(t+1) = \vec{X}_i(t) + ((\vec{X}_{Bulletin} - \vec{X}_i(t)) \times Rand(-1,1)) \tag{5}$$

Where, $\vec{X}_{Bulletin}$ is equal to the best found position by the algorithm and Rand function generates a random number in range of [-1, 1] with uniform distribution. According to (5), in case of generation the random number in range of [-1, 0], the new position of the artificial fish is away from bulletin position, which leads to explorer the distant regions by the artificial fish and escape from local minima. On the other hand, in case of generation the random number in range of [0, 1], the positions of the fish approaches the

bulletin which leads to increase convergence speed. So, using (5), a balance between density and diversity is obvious, which leads to establish a balance between exploration and exploitation [25].
In addition, another mechanism has been considered in the proposed method in order to increase convergence speed in clusters. As it was mentioned before, each artificial fish included n × d dimensional cluster centers. Since the nodes' clustering performs based on their position, and each node consists two components (X and Y geographical coordinates), the problem space for AFSA algorithm is a 2×n dimensional space. Position vector for each artificial fish in (6). Here $Z_{i,j}$ represents the dimension j from CH i.

$$\left(Z_{1,1}, Z_{1,2}, Z_{2,1}, Z_{2,2}, ..., Z_{n,1}, Z_{n,2}\right) \tag{6}$$

In the suggested method, the Fitness function that has been utilized is the sum of the distances within the clusters that is equivalent to the entire Euclidean distance between the Cluster Head that is the nearest and the nodes. In the 3rd method, a cluster head transforms itrs position with a P2% probability in every iteration. This Cluster Head is chosen randomly from a set of Cluster Heads. For changing the chosen cluster's position, firstlt, the nodes having their distances to the selected head lesser than the others are found. The head's novel position is equivalent to the determined nodes' centre position. Or, we can say that, the centre is equivalent to the determined nodes' mean position.
As discussed before, the fitness function regarded for the suggested technique is the sum of the distances between the clusters. However, as the cluster heads are chosen among the nodes, the process of clustering in Wireless Sensor networks is non- continuous. The suggested FSO algorithm, however, is used continuous problems as are most of the SI techniques. The artificial fish's movement is incorporated in the continuous form for solving this issue. But, these positions that are obtained using the heuristic are allocated to the node that is the closest post each movement. It is worthy of a mention that for preventing the perishing of the low energy nodes, firstly, the surviving nodes' average energy is computed and the selected node is the nearest one whose energy is greater than the mean energy. Determining the number of clusters in another important consideration.

Table *2* Percentage Failure

Anchor node density	Transmission range=10m	Transmission range=15m	Transmission range=20m
0.025	72	43	26
0.05	46	38	18
0.075	32	22	14
0.1	18	12	11
0.125	11	8	8
0.15	9	8	8
0.175	9	8	8
0.2	9	8	7

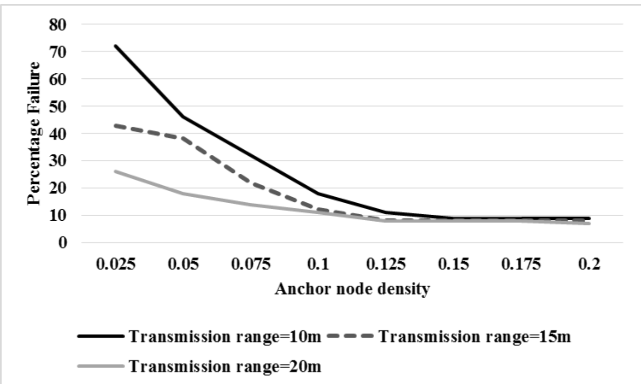

Fig. 2: Percentage Failure

The flow chat of FSO algorithm is shown as figure 1.

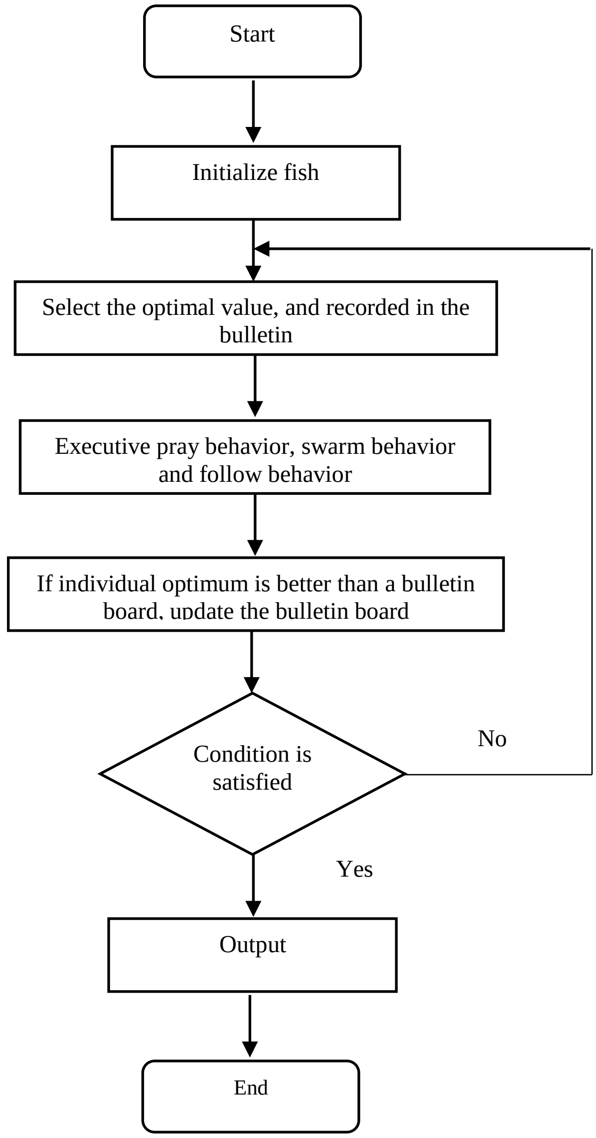

Fig 1 Flow chat of Fish Swarm Optimization (FSO) algorithm

4. Results and Discussion

In this section, the 500 number of nodes is used and the size of network is 100x100 m. The transmission range is 10m, 15m and 20m is used. Table 2 and figure 2 to 4 shows the percentage failure, localization error in meter and PDR using anchor nodes as CH.

From the figure 2, it can be observed that the transmission range=10m has higher percentage failure by 19.04% & 87.5% for 0.05 for anchor node density, by 40% & 48.27% for 0.1 for anchor node density, by 11.76% & 11.76% for 0.15 for anchor node density and by 11.76% & 25% for 0.2 for anchor node density when compared with transmission range=15m and transmission range=20m.

Table 3 Localization Error in Meter

Anchor node density	Transmission range=10m	Transmission range=15m	Transmission range=20m
0.025	0.44	0.42	0.38
0.05	0.38	0.34	0.32
0.075	0.34	0.31	0.21
0.1	0.32	0.29	0.28
0.125	0.28	0.25	0.22
0.15	0.26	0.22	0.21
0.175	0.24	0.22	0.21

0.2	0.24	0.21	0.21

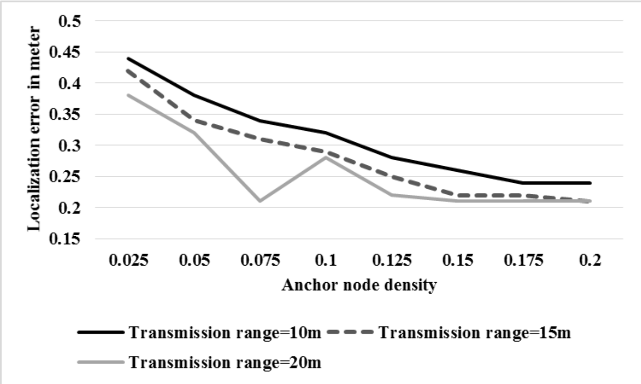

Fig 3 Localization Error in Meter

From the figure 3, it can be observed that the transmission range=10m has higher localization error in meter by 11.11% & 17.14% for 0.05 for anchor node density, by 9.83% & 13.33% for 0.1 for anchor node density, by 16.66% & 21.27% for 0.15 for anchor node density and by 13.33% & 13.33% for 0.2 for anchor node density when compared with transmission range=15m and transmission range=20m.

Table 4 Packet Delivery Ratio (PDR) using Anchors as CH

Anchor node density	Transmission range=10m	Transmission range=15m	Transmission range=20m
0.025	37.15	29.34	26.84
0.05	32.87	25.57	23.41
0.075	32.37	22.23	21.05
0.1	23.87	20.03	17.91
0.125	16.58	15.53	13.66
0.15	13.36	9.7	9.34
0.175	12.72	10.09	9.77
0.2	8.28	6.45	6.06

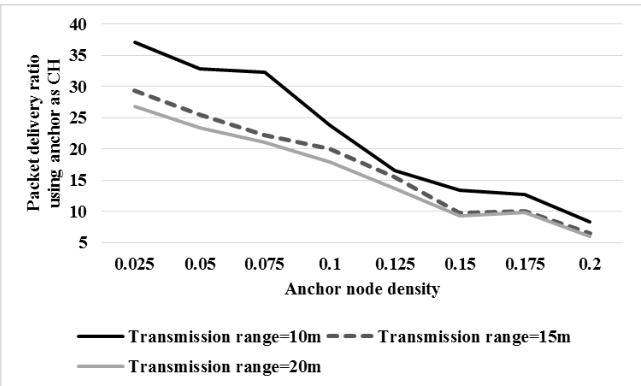

Fig 4 Packet Delivery Ratio (PDR) using Anchors as CH

From the figure 4, it can be observed that the transmission range=10m has higher PDR using anchors as CH by 24.98% & 33.61% for 0.05 for anchor node density, by 17.49% & 28.53% for 0.1 for anchor node density, by 31.74% & 35.41% for 0.15 for anchor node density and by 24.84% & 30.96% for 0.2 for anchor node density when compared with transmission range=15m and transmission range=20m.

5. Conclusion

In The wireless sensor networks, localization has posed to be a challenge . This is because of the arbitrary deployment of the wireless sensors in the network environment and the requirement for determining the location of the sensors .The heuristic based on FSO is one effective way of solving this issue. Even though the algorithm has a lot of benefits, the disadvantage is that, in low density networks, there is less of precision . With the increase in the network density, the processing time for localization proportionally increases. Here, in the current work, a new algorithm based on FSO for clustering has been suggested. By enhancing the balance between the local and the global searches, the efficiency of the FSO has been improvised in the suggested method. For enhancing the convergence speed in clustering issues, the base algorithm is added with a new technique. It has been shown by the results that the transmission range=10m has higher PDR using anchors as CH by 31.74% & 35.41% for 0.15 for anchor node density, by 24.84% & 30.96% for 0.2 for anchor node density , 24.98% & 33.61% for 0.05 for anchor node density, by 17.49% & 28.53% for 0.1 for anchor node density visa vis with transmission range=15m and transmission range=20m.

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