TELKOMNIKA Indonesian Journal of Electrical Engineering
Vol. 14, No. 3, June 2015, pp. 516 ~ 524
DOI: 10.11591/telkomnika.v14i3.7861

Wireless Sensor Networks Node Localization-A Performance Comparison of Shuffled Frog Leaping and Firefly Algorithm in LabVIEW

Chandirasekaran D*, T. Jayabarathi
VIT University, School of Electrical Sciences, Vellore, 632014, India
*Corresponding author, e-mail: chasan2k@gmail.com

Abstract

Wireless sensor networks (WSN) have become popular in many applications area including environmental monitoring, military and offshore oil & gas industries. In WSN the sensors are randomly deployed in the sensor field and hence estimation of the localization of each deployed node has drawn more attention by the recent researchers, It's a unique problem to identify and maximizing the coverage where the sensors need to be placed in a position so that the sensing capability of the network is fully utilized to ensure high quality of service. In order to keep the cost of sensor networks to a minimum, the use of additional hardware like global positioning system (GPS) can be avoided by the use of effective algorithms that can be used for the same. In this paper we attempted to use both the shuffled frog leaping (SFLA) and firefly algorithms (FFA) to estimate the optimal location of randomly deployed sensors. The results were compared and published for the usefulness of further research.

Keywords: *WSN, SFLA, FFA, localization, RSSI, ToA*

1. Introduction

Wireless Sensor Networks are distributed self-directed contain nodes which can senses and update the data's to the base station which are discussed in article [1]. WSN technology becomes popular in all areas of applications including military, medical, process and electronic industries due to its easy implementation and maintenance. The interest of research is to analyse the possibility of utilising it for process industries and hazard location is interest of research; howeverthe issues with WSN are the deployment of the nodes, localisation and energy aware clustering and an optimized solution required to do the same. Generally localization in WSN is done by equipping a Global positioning system (GPS) with each sensor node is to be done; however equipping a GPS with each sensor node is cost wise more expensive solution. Therefore an alternate solution need to be found to address the localization issues, which come out in the form of utilising the optimization algorithms for localization. The conventional optimization techniques are useful only for less number of nodes and requires more computational efforts with respect to the problem size .Hence an optimization method is required to overcome all these issues and currently our researchers has developed so many algorithms particularly based on the inspired characters from the natural living things. These Bio-inspired algorithms methods of optimization are computationally efficient compared to the conventional analytical methods; mainly the Shuffled Frog leaping algorithm (SFLA) andFirefly algorithms (FFA) are popular multi-dimensional optimization techniques. The features of these SFLA and FFA are easy implementation, more accurate solutions, computational efficiency and their fast convergence.

Formulation of work*:* A WSN consists of *N number of* nodes and thecommunicationrange between them is r, the nodes are distributed in the sensing field. The WSN is represented as the Euclidean graph $G = (X, Y)$, where $X= \{a1, a2. . .an\}$ is the set of sensor nodes. *_i, j_* ∈*Y*ij the distance between *ai* and *Xj*is*dij*≤ *r*. Unknown nodes are the set *V* ofnon-beacon nodeswhich location to be determined. Settled nodes are the set *S* of nodes that managed to estimate their positions using the localization algorithm.

Received February 10, 2015; Revised April 23, 2015; Accepted May 13, 2015

Given a WSN $G = (X,Y)$, and a set of beacon nodes B and their positions (xb, yb), for all $b \in B$, it is desired to find the position (xu, yu) of as many $u \in U$ as possible, transforming the unknown nodes into settled nodes S.

In the article [2] existing location awareness approaches is discussed, there is two techniques commonly employed, the first one isbased on distance or angle measurementand second iscombination of distance and angle. Received Signal Strength Indicator (RSSI) is the most popular method of measuring the node position by calculating the distance of nodes. Time of arrival (ToA) and Angle-of-Arrival (AoA), Triangulation and Maximum Likelihood (ML) estimation are the other methods. RSSItechnique is based on the receiving power andattenuation of radio signal exponentially with the increase of distance. In RSSI the distance can be calculatedbased on theloss in powerby comparing the theoretical model. Time based methods Time of Arrival (ToA) and estimates the distance by the difference of propagation time between two nodes with known velocity of signal propagation. Angle-of-Arrival (AoA) also known as Direction of Arrival (DoA) techniques calculates the position by geometric coordinates with the angle from where signals are received. As per as accuracy of determination is concerned ToA, and AoA methods are ahead RSSI, due to loss in radio signal amplitude by environmental factors. Triangulation technique is based on the direction measurement of the node instead of the distance measured in AoA systems. The node positions are determined by trigonometry laws of sinø and cosinø. Maximum Likelihood (ML) estimation calculates the position of a node by minimizing the differences between the measured distances and estimated distances. The localization in WSN is done in two phases, one is ranging phase and another one is estimation phase. The nodes estimates their distances from beacons (or settled nodes) using the signal propagation time or the strength of the received signal in the ranging phase. Due to noise accurate measurement of these parameters are not possible due to noise and hence the localisation algorithms uses these parameters may not be accurate. In the second phase, estimation of the position is carried out using the ranging information. This can be done either by traditional way of solving a set of simultaneous equations, or other way by using an optimization algorithm which minimizes the localization error.

In the localization algorithm which uses iteration method, the nodes which are settled serve as beacons and theprocessof localization is continued until either all nodes are settled, or with no more nodes can be localized.

In this paper we dealt two bio-inspired optimization algorithms for node localization in a WSN. The first one is one is shuffled frog leaping algorithm (SFLA) which is detailed in article [3], and the other one isfirefly algorithm discussed in article [4]. Because of easiness in solving problem with more efficiency in multidimensional search nature these two algorithms are popular in the recent day’s research.

The paper is organized as follows: section 2discussed about the literature survey of previous research in WSN localization. Section 3 presents SFLA and FFA optimization algorithms used for localization in this study. Section 4 explains how the localization problem is approached using the above mentioned optimization methods. Section 5 about results and discussion based on the simulation work done and section6 presents conclusions and future possible research path.

2. Review of Related Work

Article [5] is a survey of localization systems for WSNs using bio inspired algorithms. An efficient localization system that extends GPS capabilities to non-GPS nodes in an ad hoc network is proposed in [6] using particle swarm optimization. Article [7] using shuffled frog leaping algorithm and firefly algorithm in article [8], in which anchors flood their location information to all nodes in the network and each dumb node estimates its location by trilateral method, also the localization accuracy is improved by measuring the distance between the neighbours. In article [9] the node localization is discussed using convex position estimation and then the semi-definite programming approach is further extended to non-convex inequality constraints in article [10]

WSN localization considered as a multidimensional optimization problem and evaluated though population-based techniques in recent days. The centralised localization techniques are discussed in article [11] and this approach requires a large number of beacons in order to localize all dumb nodes. In article [12] a genetic algorithm (GA) based node localization algorithm is presented which determines locations of all non-beacon nodes by using an estimate of their distances from all one-hop neighbours. Similarly in article [13] a two-phase centralized localization scheme that uses simulated annealing and GA is presented.

The advantage of distribute localization techniques over the centralised one is because of the complexity in nature and scalability issues present in centralised WSNtechniques. The distributed localization algorithms will be developed anddeployed on each individual sensor node instead of central base station adopted in centralised techniques. The target nodes localize based on distance measurement from the neighbouring beacons or already localised nodes. The case study done in this paper infers few features for in particular the localisation accuracy and the iterative method of localization ensures more number of nodes are localised in short span of time

3. Bio-Inspired Techniques – SFLA& FFAfor WSN Localization

Natural living organism provides rich source of ideas for computer scientists. The bio-inspired algorithms offer better accuracy and modest computational time.SFLAand FFA bio inspired algorithms are discussed in the following subsections.

3.1. Shuffled Frog Leaping Algorithm (SFLA)

Shuffled frog leaping algorithm is swarm intelligence based biological evolution algorithm. The algorithm simulates a group of frogs in which eachfrog represents a set of feasible solutions. The different memeplexes are assumed as different culture of frogs which are located atdifferent places in the solution space In article [14] and [15] in the execution of the algorithm, In order to form a group “F” frogs are generated and for a N-dimensional optimization problem, frog “i” of the group is represented asXi = (x1i; x2i; ...;xNi). Then based on the fitness values the individual frogs in the group are arranged in descending order, to determine Px the global best solution. The group is divided into m ethnic groups and each ethnic group includes n frogs by satisfying the relation F = m _ n. The ethnic group divided such thateach group will be in to their sub group like first group in to first sub group and second will be in second sub group and so on similarly frog m into sub-group m, frog m + 1 into the first sub-group again and so on, until all the frogs are divided the objective is tofind the best frog in each sub-group, denoted by Pb and worst frog Pw correspondingly. The iterative formula will bewritten as Equation (1) and (2):

$$D = rand() * (Pb - Pw) \tag{1}$$

$$Pnew_w = Pw + Di; \quad -Dmax \geq Di \geq Dmax \tag{2}$$

Where;

rand () represents a random number between 0 and 1,
Pb denotes the position of the best frog,
Pw denotes the position of the worst frog,
D represents the distance moved by the worst frog,
Pnew_w is the better position of the frog,
Dmax represents the step length of frog leaping.

In the SFLA algorithm execution, if the updated Pnew_w is in the feasible solution space m then the corresponding fitness value of Pnew_w will be calculated. If the resultant fitness value of Pnew_wis worse than the corresponding fitness value of Pw, then Pwwill replace Pb in Equation (1) andre-update Pnew_w. If there is still no improvement, then randomly generate a new frog to replacePw; repeat the update process until satisfying stop conditions

SFLA Algorithms steps:

1) Initialize groups and parameters such as group total number of particles N, total numberof frogs N1, number of sub-groups m, number of frogs in each sub-group and the updates within the sub group
2) Analyze the initial fitness values of the particles and save the initial best positions and best fitness values, then sort all N particles in ascending order as per the fitness values;

3) According to the sub group division rule sort the N frogs in ascending order and divide them into sub-groups.
4) Find out the best fitness individual Pb and the worst fitness individual Pwof each subgroup in frog group and also the group best individual Px
5) Progress the worst solution within a specified number of iterations based on equations (1) and (2).
6) According to the fitness value, arrange particles of the group in ascending order and re-mix the particles to form a new group.
7) If stop conditions are satisfied (the number of iterations exceeds the maximum allowable number of iterations or the optimal solution is obtained), the search stops, and output the position and fitness value of the first particle of the group; otherwise, return to step (3) to continue the search.

3.2. Firefly Algorithms (FFA)

Firefly algorithms (FFA) are developed based on the characters inspired from fireflies. The firefly species produces short and rhythmic flashes of light and the pattern of flashes is unique for each particular species. The basic motto of such flashes is to attract mating partners and search foods. The Female flies respond to male's unique pattern of flashing within the same species. As the distance increases the intensity of light decreases for any light emitting flies which strictly follows the inverse square law. When the air absorbs light then it becomes weaker and weaker as the distance increases. Luciferin is the terms used to denote the bio-luminescence from the body of the fireflies which is a light emittingcompound. The above behaviour of the fireflies made the researchers to develop an algorithm which is called firefly algorithms which serves as heuristic algorithm in computational intelligence.

In optimization problems, a firefly at particular location "x" has the brightness I of a firefly can have the relationship as $I(x) \propto f(x)$. The light intensity "I_r"varies with the distance "r" such that $I_r= I_0e^{-\gamma r}$ and also the light intensity is proportional to the attractiveness β such that $\beta = \beta_0 e^{-\gamma r2}$. I_0 and β_0 are the original light intensity and attractiveness constant at r=0 respectively. However, the attractiveness β is relative; it should be seen in the eyes of the beholder or judged by the other fireflies. Thus, it will vary with the distance rij between firefly i and firefly j. In addition, light intensity decreases with the distance from its source, and light is also absorbed in the media, so we should allow the attractiveness to vary with the degree of absorption. In the simplest form, the light intensity Ir varies according to the inverse square law $Ir = I_s r^2$ where $I_s$is the intensity at the source. For a given medium with a fixed light absorption coefficient γ, the light intensity I vary with the distance r.

The implementation of the firefly behaviour as described in article [16]. The algorithm was organised based on the following assumption (i) all fireflies are unisexual, which means one firefly will get attracted to all other fireflies. (ii) The attraction is proportional to their brightness and distance, hence for any two given fireflies the less bright one will try to attract brighter; however. (iii) If a firefly doesn't find a bright firefly than its own then it will move randomly. The following algorithms consider as brightness as objective function including the other associated constraints along with the local activities carried out by the fireflies.

Where,

i= i^{th} firefly, i 2 [1; n];
n= number of fireflies;
i- Max generation= count of the generations of fireflies (indicates iteration limit);
Ii= Magnitude of i^{th}firefly Light Intensity; depends on the objective function f (x);
$r_{i,j}$= distance between theith and j^{th} fireflies respectively.
f (xi) = objective function of i^{th}firefly, which is dependent on its location xi that is of d-dimension

Where d is the dimension of x in space that is also dependent onthe context of the firefly, iteration variable (t). Intensity or the brightness "I" is proportional to some objective function f(x) and the location update equation is given by (3).

$$Xi = Xi + \beta e^{[\gamma r2ij]}(Xj - Xi) + \alpha \in i \quad (3)$$

Where α is the step controlling parameter, r is the variable that brings about randomness, γ is the attraction coefficient, β is the step size towards the better solution, ∈ $\imath$is a vector of random number from Gaussian distribution and Xi, Xj are the firefly are the location information of the observing entity.

Firefly Algorithm Pseudo Code:

```
Begin
1:  Generate initial population of firefly's with location xi,
i = 1; 2; 3: n;
2:  Define objective function f (x), where x = (x1; x2; xd) T;
3: Generate initial population of fireflies xi , i = 1;2;3:::n;
4: Light intensity Ii of a firefly ui at location xi is determined by f (xi);
5: Define light absorption coefficient γ;
6: while(t < max generation) do
/*for all n- fireflies*/
7: for i=1:n do
/*for all n- fireflies*/
8: for j=1:i do
9: if (Ij> Ii) then move firefly i towards j in d-dimension
10: else
11: end for
12: end for
13: Attractiveness varies with the distance r via exp (-γr);
14: Evaluate new solutions and update light intensity;
15: end for
16: end while
17: Rank the fireflies and find the current best;
18: end
```

4. Problem Statement and Methodology

In WSN node localization the objective is to performestimation of coordinates of the distributed nodes to know their initial locations. If there is a maximum of N target nodes then using M stationary beacons whose know their locations then the location of unknown nodes will be determined. The following study approach is formulated for the localization of the same;

1) Initialize the sensors randomly
2) Initialize the beacons randomly
3) Calculate real distance ie the actual distance between the beacon and each deployed sensor nodes
4) Assign measured distance ie the distance obtained by the beacons using ranging techniques. This is done by adding noise to the real distance.
5) Find out how many sensors are within the transmission range of 3 or more beacons
6) For each sensor that can be localized SFLA and FFA are applied to minimize the objective function which represents the error function given by the Equation (4)

$$\sum_{i=1}^{n} \mathrm{ei} = \sum_{i=1}^{n} \left(\mathrm{Ri} - \sqrt{(\mathrm{xi}-\mathrm{xm})^2 + (\mathrm{yi}-\mathrm{ym})^2}\right))^2 \quad (4)$$

Here Riis the inexact ranging distance.
(xi, yi) is the corresponding beacon positions
(xm, ym) is the position occupied by the particle
"n" is the number of beacons having transmission coverage over that sensor.

7) The algorithms return the closest values of the coordinates (xm, ym) such that error is minimized.
8) The algorithm is then applied to the next sensor in range
9) The localized sensors are removed from the sensor list and now act as beacons
10) The localization error is computed after all the Nl nodes estimate their coordinates, it is the mean of squares of distances between actual node locations (xi, yi) and the locations (ˆxi, ˆyi), i= 1, 2 ...Nl is determined by SFLA or FFA. This is computed as Equation (5).

$$\mathrm{El} = 1/Nl \sum_{i=1}^{l} ((\mathrm{xi} - \widehat{xi})^2 (yi - \widehat{yi})^2) \quad (5)$$

11) All the steps from 3 to 9will be continued until either all unknown nodes get localized or no more nodes could be localized further. It is evident that the performance of the localization algorithm if observed from the valuesof N_{Nl} and El where N_{Nl} = N −Nl is the number of nodes that could not be localized. The lowervalues of N_{Nl} and El represent the better performance.

If the objective is to localize more number of nodes then the number of iterations steps, then the number of localized nodes increases. This increases the number of base references for already localized nodes. Firstly A node that localized using just three references in an iteration k may have more references in iteration k+1. Thus the chance of ambiguity is decreased. Secondly, the time required for localizing a node increases, if a node has more references in iteration k + 1 than in iteration k. The above issue is overridden in this performance study by limiting the maximum number of reference to six, which is arbitrarily chosen. The simulation is done using LabVIEW graphical user interface, the advantages of using LabVIEW can help for real time implementation in future scope of research.

Simulation is done in LabVIEW to understand the performance of WSN Localization. We chose 50 nodes as target to be localized and 10 beacons. The sensor field dimensionis considered as 100×100 square units and the transmission radius of beacon r = 25 units. The same simulation settings in LabVIEW for both the performance studies are made same and the results are presented.

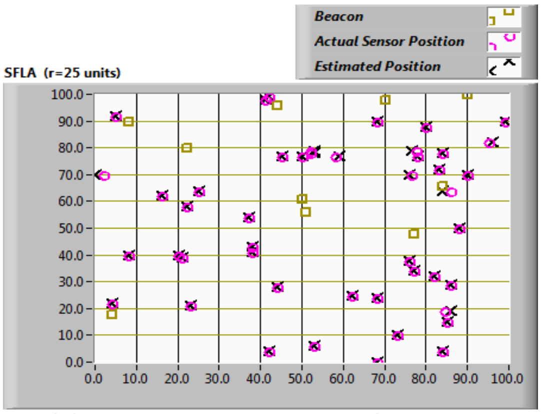
For both SFLA and FFA performance study, the parameters are: Population = 50, Iterations = 30. Particle positionslimits: Xmin=0 and Xmax=100.Total 30 trial experiments of SFLA based localization are conducted for Pn = 2 and Pn = 5. Average of total localization error El defined in (5) in each iteration in 25 runs is computed and the error is calculated.

5. Discussion on the Results

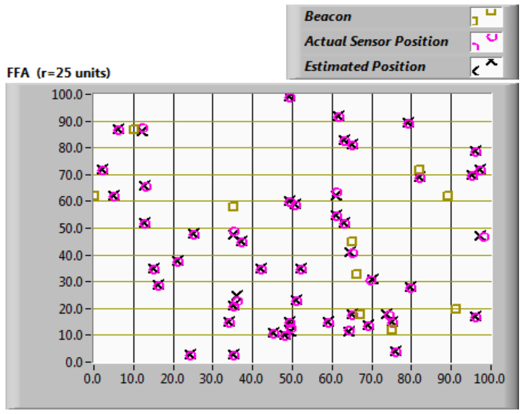
The two algorithms analysed here are stochasticand hence they do not produce the same solutions in all iterationsthough the initial deployment is same. That's why the results of multiple trial runs are averaged. In addition the initial deployment is random and hence the number of localizable nodes in each trialwill not be same. This affects the total computing time.

The coordinates of the estimated and actual locations of nodes as well as the beacons by SFLA and FFA in a particular trial run are shown in Figure 1. The initial deployment of nodes and beacons for SFLA and FFA based localization is the same in a trial run. Table 1 gives the summary of the various parameters obtained from the result of SFLA and FFA based localization algorithms. The performance of both the algorithms found fairly well in WSN localization. It has been observed that the localization accuracy is impacted by adding the Pn, percentage noise in distance measurement. It is also found that the average localization error in both SFLA and FFA is reduced when Pn is changed from 5 to 2. The performance metric doublet (N_{Nl},El) for FFA is less than that for SFLA, indicting superior performance of Firefly. However, computing time required for firefly is significantly more than that for SFLA, which is a weakness of FFA. In addition, the amount of memory required for FFA is more than that for SFLA. This clearly calls for a trade-off. A choice between SFLA and FFA is influenced by how constrained the nodes are in terms of memory and computing resources, how accurate the localization is expected to be and how quickly that should happen.

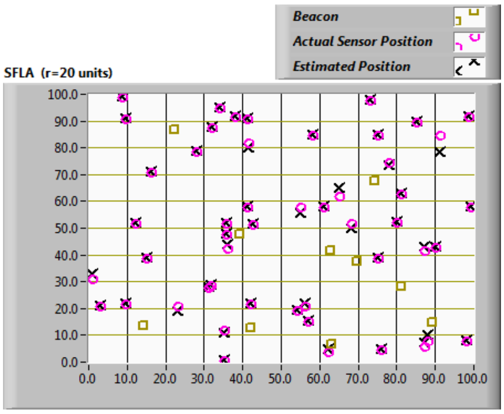
The effect of ranging distance error observations made in the first five trial runs out of the 50, are summarized in Table 1. This table depicts increasing Nl, the number of localized nodes in eachiteration. Table II shows the impact on the test results by varying the transmission radius. It is evident that the number of non-localized nodes increases when the transmission radius is made as 20 units from 25 units. It is also found that there is a correction of error due to flip of ambiguity from the Table 1. The average error is determined and shown in the Figure 2 with respect to beacons and the sensor nodes; from the results it is obvious that the SFLA performance looks better than the FFA. Also the increase in value of Ri indicates that the accuracy has been fairly improved.



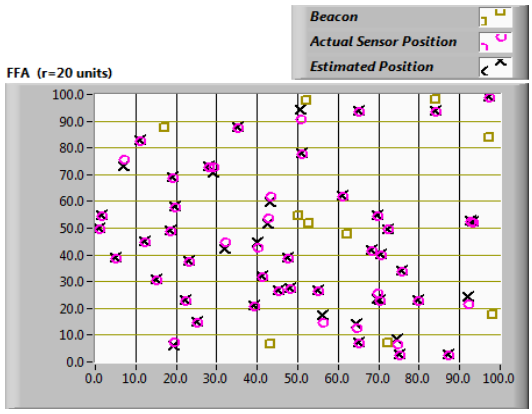
(a) Locations estimated by SFLA with r=25units&Pn=2



(b) Locations estimated by FFA with r=25units&Pn=2



(c) Locations estimated by SFLA with r=20 units &Pn=5



(d) Locations estimated by FFA with r=20units &Pn=5

Figure 1. Result of trial run of SFLA and FFA algorithms for the same deployment with N=50; M=10; and the sensor field range is 100x100 square units

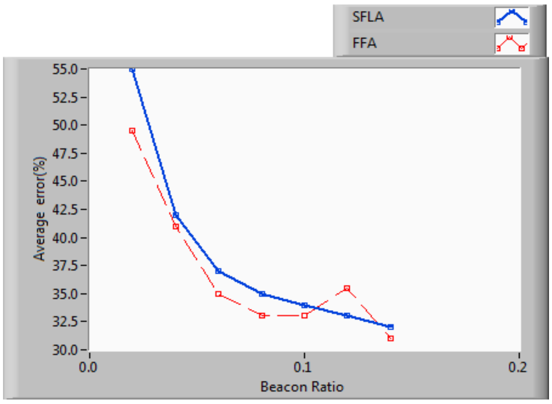
Table 1. Effect of ranging distance error of PSO and FFA (r=25 units)

Major Parameters	Percentage noise in distance measurement(Pn)			
	SFLA		**FFA**	
	2%	*5%*	*2%*	*5%*
Avg. no of non-localized nodes(N_{NI})	0.43	1.34	0.227	0.83
Avg. time taken*(s)	371.1	263.5	810.9	1121.5
Avg. localization error (El)	0.49	0.922	0.279	0.64

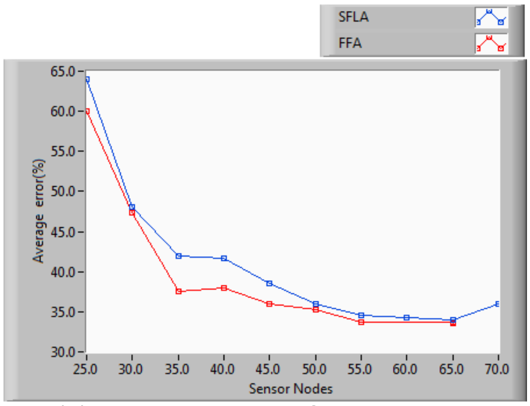
Table 2. Effect of varying the transmission radius (r) and Pn=2

Major Parameters	**SFLA**		**FFA**	
Transmission radius (r)	*20*	*25*	*20*	*25*
Avg no of non-localized nodes	1.4	0.41	1.23	0.28
Avg. time taken*(s)	631.8	589.7	940.4	1365.2
Avg. localization error	2.198	0.66	1.61	0.28

**All simulation are performed in the same computer*



(a) Average error Vs Beacon ratio



(b) Average error Vs Sensor nodes

Figure 2. Relationship between the average error with respect to the beacon ratio and sensor nodes

6. Conclusion

This paper has discussed SFLA and FFA, bio-inspired algorithms to find out the localised nodes of a WSN in a scattered and iterative method. The localization problem is considered as a multidimensional optimization problem and solved by the above mentioned population-based optimization algorithms. From the results obtained it was found that FFA offers less error value in comparison to SFLA but takes longer computational time to perform. We also ran the program with a smaller transmission radius and found that it leads to less number of nodes being localised. Although there is not vast difference in the errors offered by both the selection of what algorithms to use for localisation depends entirely on the hardware available to the user and the time constraints involved. This paper has also briefly presented a statistical summary of the results for comparison of both SFLA and FFA. Both thealgorithms are effective in their own way and can be further modified to suit the users need by changes in the program code to give even better results than what was obtained.

This work can be extended in many other directions, in a possible further study, both SFLA and FFAcan be used in centralized localization method so that to compare the localisation methods of centralized and distributed techniques, which can lead to solve energy awareness issue in WSN. Also it can lead a way to develop a hybrid algorithm by combining the advantages of both the algorithms.

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