Two Layers Stages Approaches for Lifetime Improvement in Wireless Sensor Network

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ABSTRACT

Node placement in the objective area is one of the most critical issues in wireless sensor networks and their deployment should be cost effective. The deployment cost depends upon the number of sensing devices deployed. Multi objective originations are real models for many complex engineering optimization problems. Multi-objective optimization problems may require a set of Pareto-Optimal points in the search space, instead of a single point. However, the WSN is a based on cluster, the cluster heads (CHs) absorb more energy due to extra work load of accepting the data aggregation, sense data and transmission of combined data to the base station. We proposed two layers stages approaches for lifetime improvement in wireless sensor network. We compare the performance of MOGA with DE with fitness function that has the objective minimizing the intra-cluster distance and optimize the energy consumption of network. We include a local development phase to the traditional DE for faster concurrence and better performance of our proposed algorithm. The experimental results determined the productivity of the proposed algorithm in terms of network life, energy consumption and connectivity.

Keyword: - *WSN, node deployment, multi-objective genetic algorithm, Differential Evolution, fitness function.*

1. INTRODUCTION

WSN are intelligent network application system that originally collect, integrate and transmit data. The latest technology developed achievement in microelectronic, network and communication. It was developed by military application like robotic exploration, health monitoring application, forecasting system, monitoring of human physiological data etc. For example the military area that can use WSN to monitor an activity. These sensor nodes sense it and send the information of base station by communicating with each nodes. Day by day use of WSN and the same time faces the problem of energy limitations in terms of limited battery lifetime. It consists group of low cost, low power, multifunctional and small size distributed sensor network. A WSN consists of sensor nodes that are able to perform sensing, computation and transmission. A WSN composed by hundreds or thousands of sensor nodes with shorter distance between adjacent nodes and low application data rate. It different types of wireless network such as Bluetooth, cellular network and wireless LAN. The sensor nodes is collect the local information of the process the data, target and send it to remote base station. The sink is connected to the internet. In the past decade, different kinds of evolutionary algorithm advanced to solve optimization problem such as genetic algorithm, ant colony optimization, particle swarm optimization algorithm, estimation of distribution algorithms, virtual annealing, differential evolution and cuckoo search algorithm, biogeography based optimization and artificial bee colony.

1.1 Node deployment

A WSN can be self-possessed of heterogeneous and homogeneous nodes that maintain the same or different statement and calculation capacity. The heterogeneous nodes consider, the lot of existing works search node placement in the circumstances of homogeneous WSNs. The most beneficial effects of homogeneity are less complexity and better manageability. Hence, homogeneous nodes in WSNs. These nodes can be deployed terminated a network in random or complete manner. Random node deployment is preferred in many application, possibly other deployments should be searched since unfortunate node deployment can raise the complexity of other problems in WSNs.

The rest of the paper is organized as follows. The related work is presented in Section 2. The Proposed work and the experimental results are presented in Sections 3 and 4 and we conclude our paper in Section 5.

2. RELATED WORK

(M.M. Ali, 2004) Proposed new versions of the DE algorithm, and also proposed some changes to the classical DE in order to improve its effectiveness and robustness. They introduced an auxiliary population of *NP* entities alongside the original population, a notation using sets is used – population set-based methods). (J. Sun, 2004) Proposed a combination of the DE algorithm and the assessment of distribution algorithm (EDA) that efforts to guide its search towards a promising area by sampling new solutions from a probability model. Based on experimental results it has been demonstrated that the DE/EDA algorithm outperforms both the DE and EDA algorithms. (A.K Qin, 2006) The proposed an extension of self-adaptive DE algorithm to solve optimization problem with constraints. The two control parameter F and CR are not compulsory to be pre-specified. (Ali M, 2012) Presented a modified differential evolution algorithm for solving multi-objective optimization problems. MODEA established the opposition-based learning for generating an initial population and the model of random localization in the mutation step.(O. Banimelhem, 2013) Proposed a genetic algorithm that was based on near optimal and finding optimal solution for Coverage Hole Problem. The author defines the situation when a group of sensing nodes do not work properly and do not sense the data and statement that it is a problem of hole in the network (Rakesh Kumar, 2013). Thus, the point of area coverage place an important role in sensor networks and there connectivity. (Y. Bendigeri, 2015) Proposed work was planned to concentrate on different placement of nodes like random, circular and grid based scenario of a network that was worked to save the energy consumed by the network on balance with sensor nodes and increase the network lifetime. Proved by energy utilization will be less with increase in network lifetime.

3. PROPOSED WORK

Two layers are proposed including node deployment and cluster head. Node deployment is layered with the multi-objective genetic algorithm. Clustering is layered by Differential Evolution.

3.1 Multi-objective optimization problem

Most optimization problems logically have some objectives to be realized and normally they conflict with each other. In general, a multi-objective optimization problem can be represented as:

min F(x) = (f1(x), f2(x), ..., fk(x))T

Subject to the p equality constraints:

hi(x)=0, i=1,2,……p

And the m inequality constraints

gi(x)≤0, j=1,2,…....m

Where k is the number of objective functions fi: Rn>R. We call x=[x1,x2,….,xn]T the vector of decision variables. A solution is said to be Pareto Optimal if it is not control by any other solution in the solution spaces. A Pareto optimal solution cannot be developed with respect to any objective without falling at least one other objective. Therefore, a practical approach to multi-objective optimization is to investigate a set of solutions (the best-known Pareto set) that represent the Pareto optimal set as much as possible. There are three conflicting goals.

1. The best-known Pareto front should be as close possible as to the true Pareto front. Ideally, the best-known Pareto set should be a subset of the Pareto optimal set.
2. Solutions in the best-known Pareto set should be equally distributed and different over of the Pareto front in order to provide the decision maker a true picture of trade-offs.
3. The best-known Pareto front should capture the whole spectrum of the Pareto front. This requires investigating solutions at the extreme ends of the objective function space.

3.3 Multi-objective Genetic algorithm

The multi-objective genetic algorithm was presented by Fonseca and Fleming in 1993. GA solves most of the multi-objective optimization problems. A genetic single-objective GA can be modified to find a set of various non-dominated results in a single run. The crossover operator of GA may achievement structures of good

solutions with respect to different objectives to create new non-dominated solutions in new parts of the Pareto front. Most multi-objective GA do not want the user to prioritize and weigh objectives. Therefore, GA has been the most popular heuristic approach to multi-objective design and optimization problems.
MOGA was the first multi-objective GA that easily used Pareto-based position and niching techniques organised to inspire the search toward the true Pareto front while maintaining variety in the population. Therefore, it is a good example to establish how Pareto based Ranking and fitness sharing can be integrated in a multi-objective GA.

Algorithm of MOGA

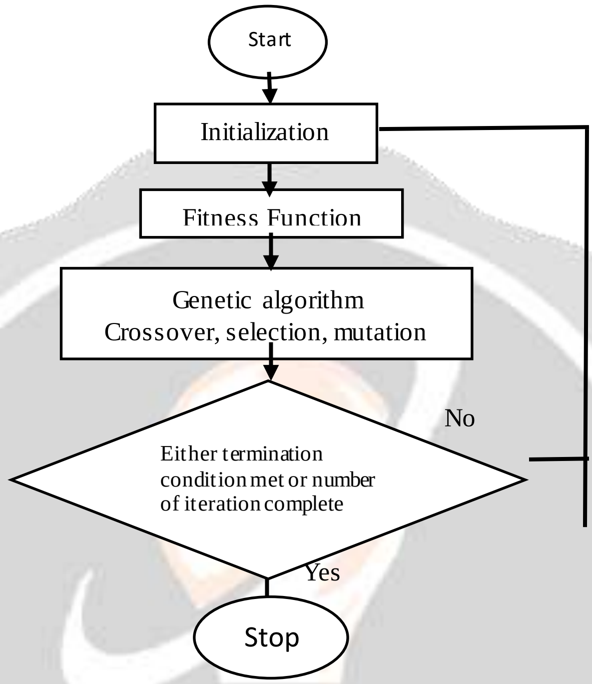

Fig. 1 Flowchart of MOGA

3.4 Fitness function

The main objectives of MOGA is to prolong the network lifetime of the WSN by taking care of the energy consumption and connectivity.

1. **Energy consumption:-** the energy among the dead nodes increased, consequently the connectivity among them detected to be loose.
2. **Connectivity:-** the connectivity among dead nodes found to be strong while energy supplied to them is comparatively very low.

4. Clustering Of Differential Evolution

DE is a stochastic and population created evolutionary algorithm that is commonly useful in solving many optimization problems. It contains of four steps, i.e., initialization of population vector, crossover, mutation and selection. DE initiates with randomly generated real valued population vectors of some predefined population size (says P). The vector are also known as genome or chromosome. The dimension D of all the vectors is equal. Each vector is calculated by a fitness function to judge the quality of the solution to the problem. Therefore, while designing clustering algorithm, one should take care not only the energy consumption of the CHs but also energy consumption of the sensor nodes to increase the network life time.

4.1 Fitness function

The main objective is to maximize the network life. This can possible only if we can make a balance of the lifetime of the cluster heads.
fitness= (remEnergy+(n-numCH) + (totalIC/n) + (totalBSD/n));
Where,

- remEnergy:- remaining energy holds the maximum value and denotes the amount of energy consumed by the active nodes through optimal deployment.

- numCH:- it denote that the number of Cluster Head should be minimum because it consume more energy.
- totalIC:- denotes total intra cluster distance should also be minimum because it consume less energy.
- totalBSD:- All nodes have minimum distance from the total base station.
- n is the total number of nodes.

5 EXPERIMENT RESULTS

We performed general experiment on the proposed algorithm using MATLAB tools. The experiments were performed with various number of sensor nodes ranging from 100m to 100m area. In the simulation run, we used following parameter values as shown in Table 1.

5.1 Simulation and Result

The experiments were performed with various number of sensor nodes ranging from 100m to 100m area. In the simulation run, we used following parameter values as shown in Table 1. The table 1 shows the inputs parameters for transmission of 4000 bits message over the network.

Table 1 :- Parameters of simulation

Parameter	Value
N (no. of nodes)	50
Area	100×100m
Einit	0.5J
Eelec	50nJ/bit
Efs	10pJ/bit/m^4
Eamp	0.0013pJ/bit/m^4
Eda	5nJ/bit
Packet Size	4000

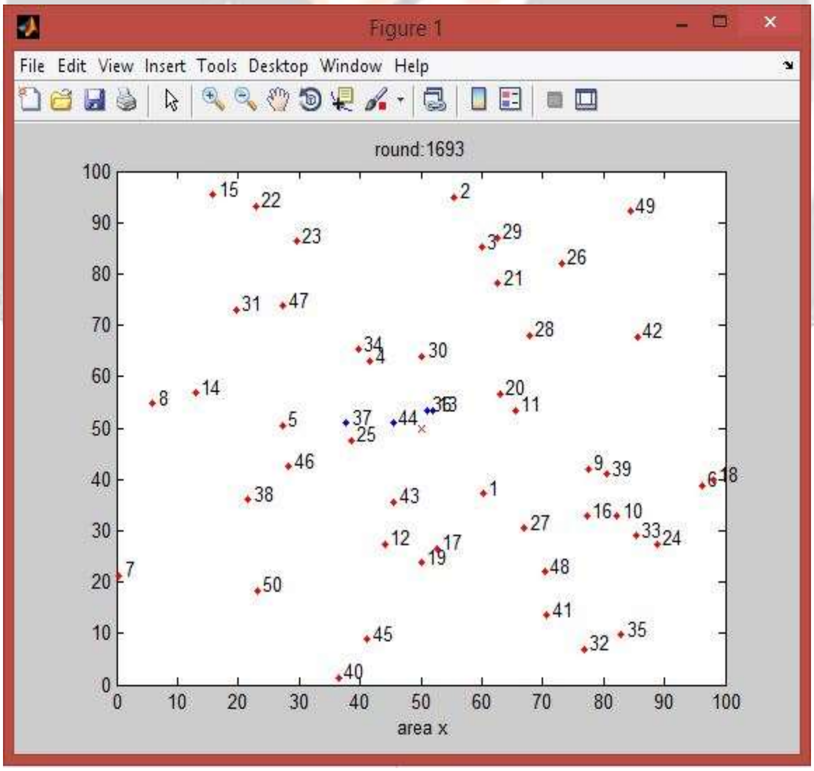

Fig. 1 Node Deployment

Fig. 1 Show the randomly deployment of nodes. As the number of round is increase the dead node is also increase. In this blue node represent the alive nodes and red nodes represent the dead nodes.

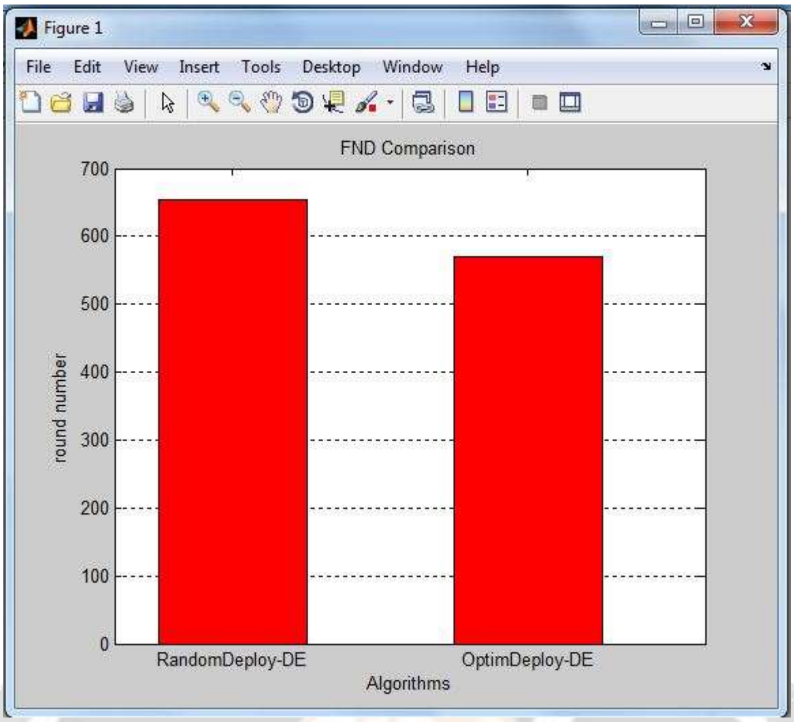

Fig. 2 FND comparison

(Fig.2) In case of FND the nodes of optimal deployed are dead early than the nodes of random deployed.

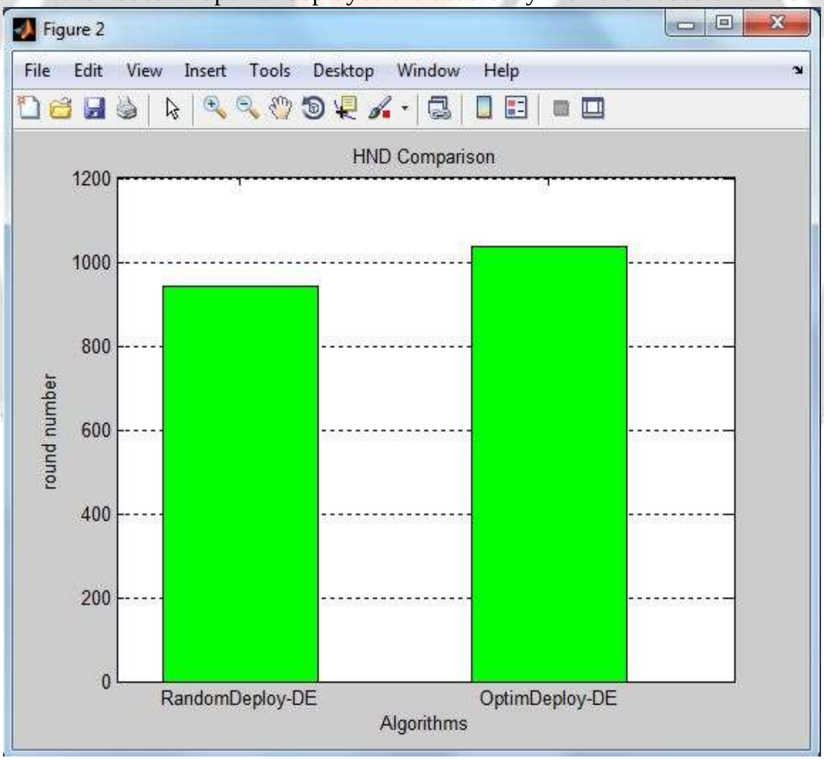

Fig 3. Half Node Death

(Fig. 3) Show the Half Node Dead I the network. Show that, In case of HND it was experiment found that the nodes of random deployed are dead early than the optimal deployed.

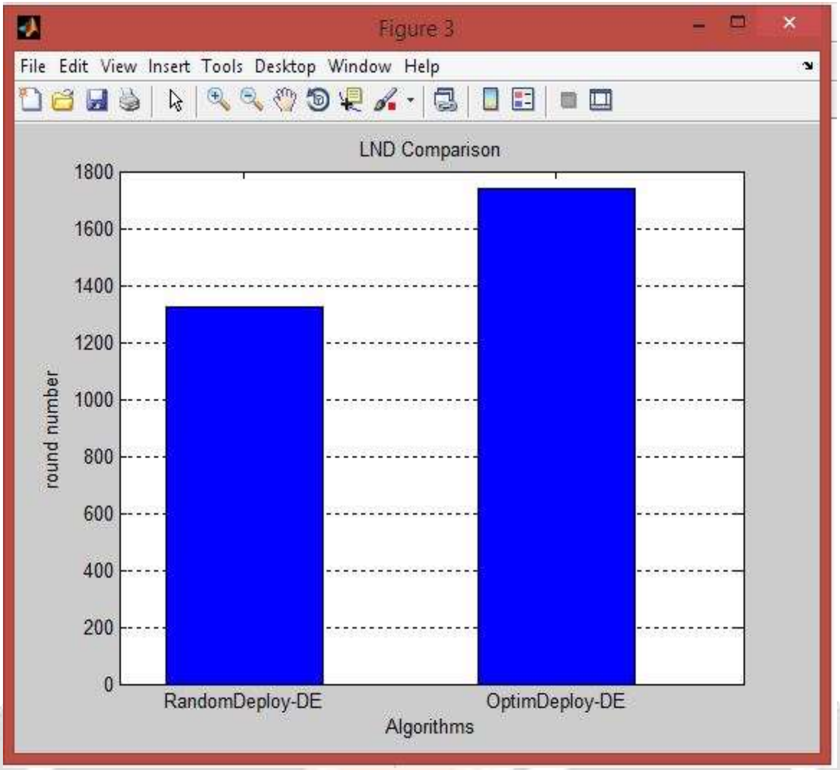

Fig.4 LND comparison

(Fig. 4) Random Deploy the Last Node Dead is in 1325 round but in Optimal Deploy nodes are dead in 1741 round. In case of LND the nodes of random deployed are dead early than the nodes of optimal deployed.

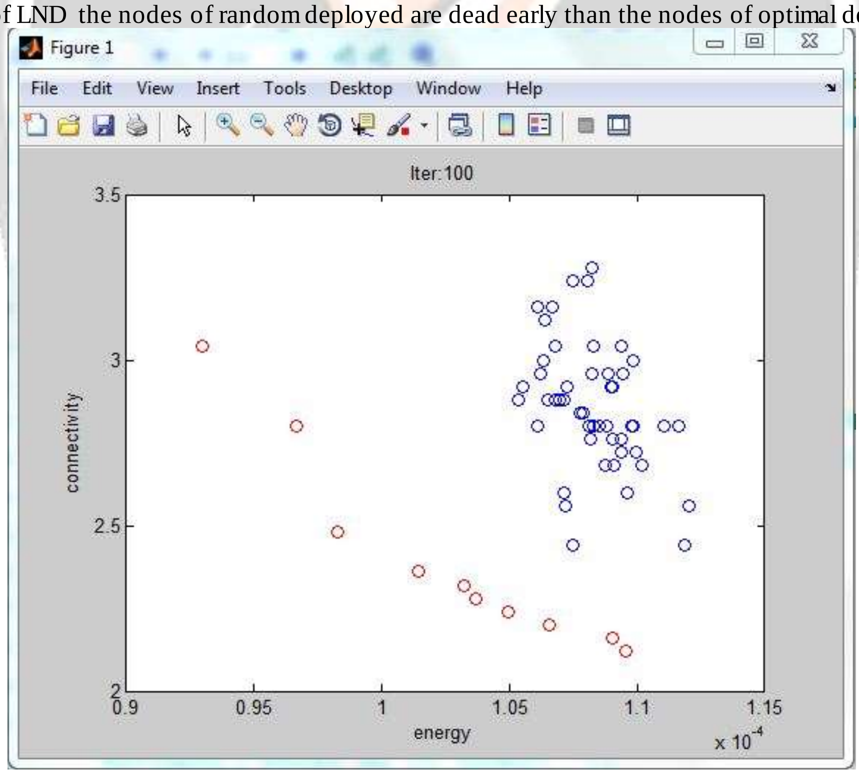

Fig.5 Comparison of energy and connectivity

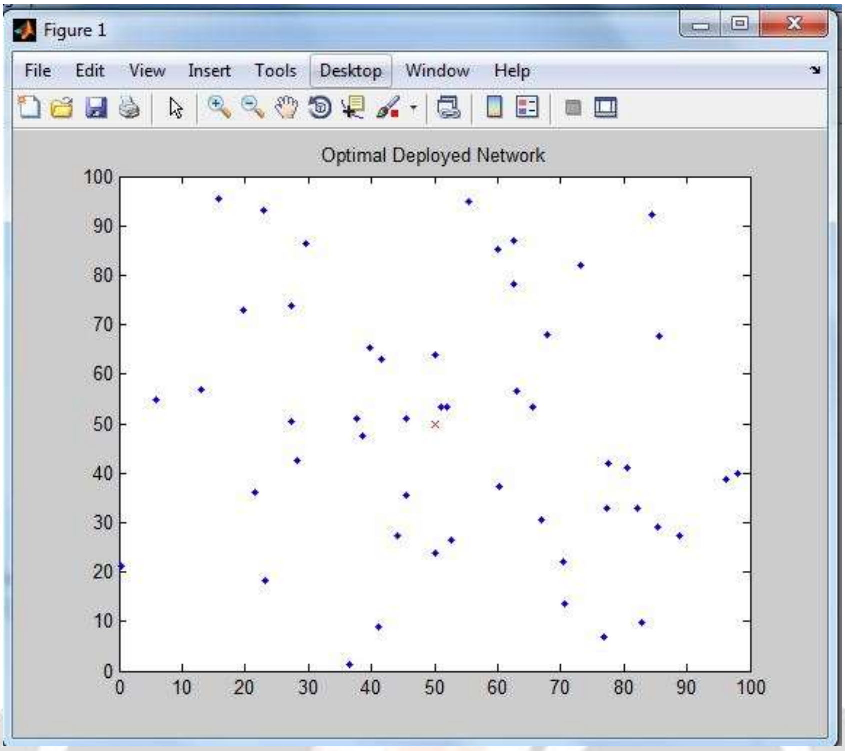

Fig. 6 Optimal Deployed Network

The100 nodes are scattered optimaly over the sensing field of 100*100 m^2 . The better result are obtained in optimal deployed in case of random deployed network as compared to the optimal deployed network as shown in fig. 4.4

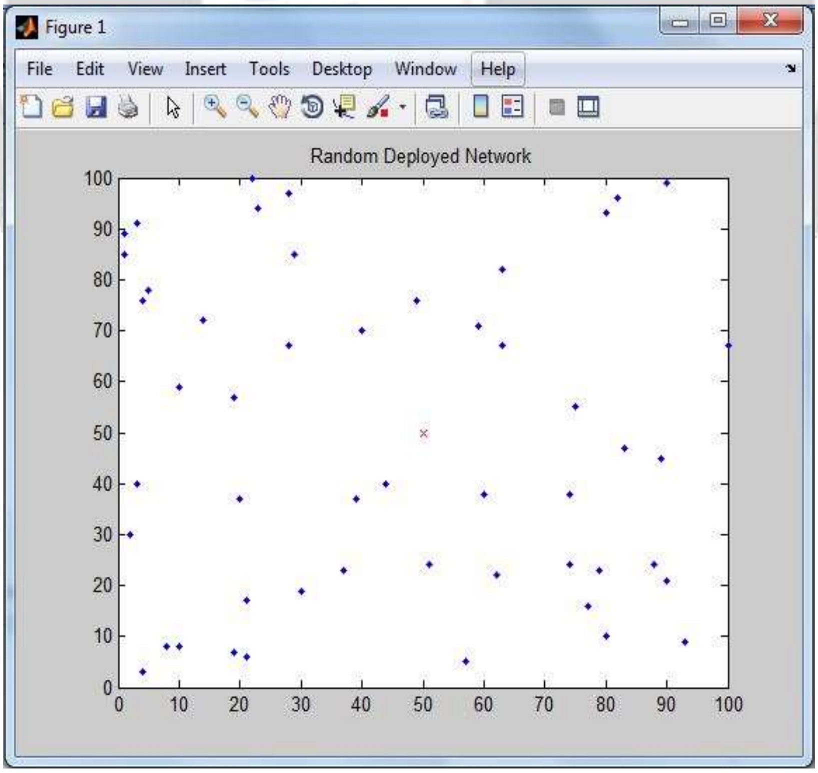

Fig 7 Random Deployed Network

The network model is consists of a multiple sensor nodes and a single base staiton. The100 nodes are scattered randomly over the sensing field of 100*100 m^2.

The better result are obtained in optimal deployed in case of random deployed network as compared to the optimal deployed network as shown in fig. 7.

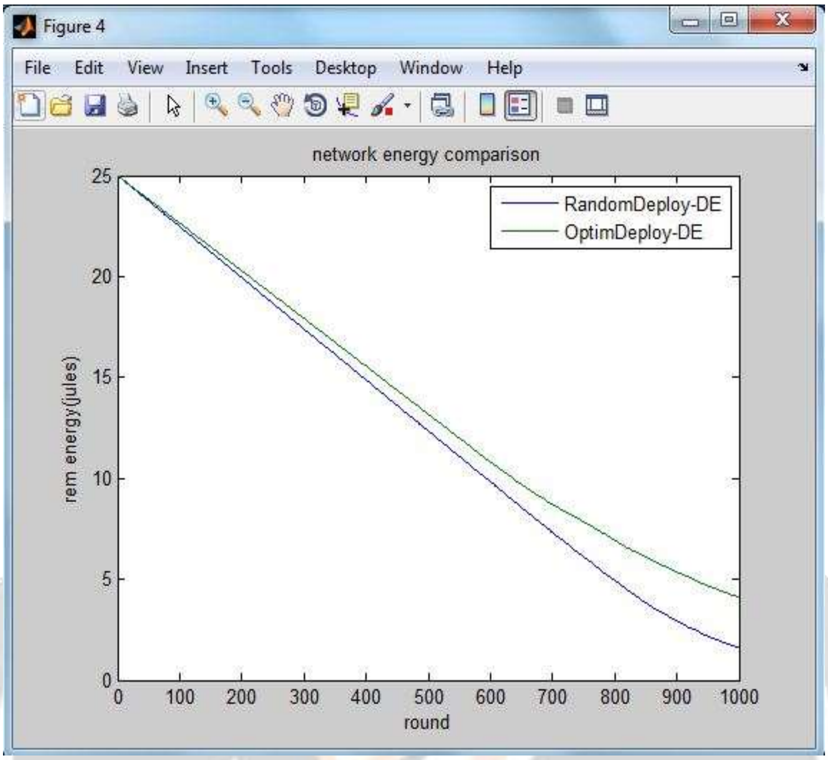

Fig. 8 Comparison in terms of Network Energy

Fig.8 the network energy consumption of both algorithm. Initially energy of network is 25J. We see that as the number of round increase the energy consumption of Random Deploy is more as compare to Optimal Deploy. Shows that the remaining energy of Optimal Deploy is more than Random Deploy. Hence the clustering using Random Deploy enhance the network lifetime as compared to Optimal.

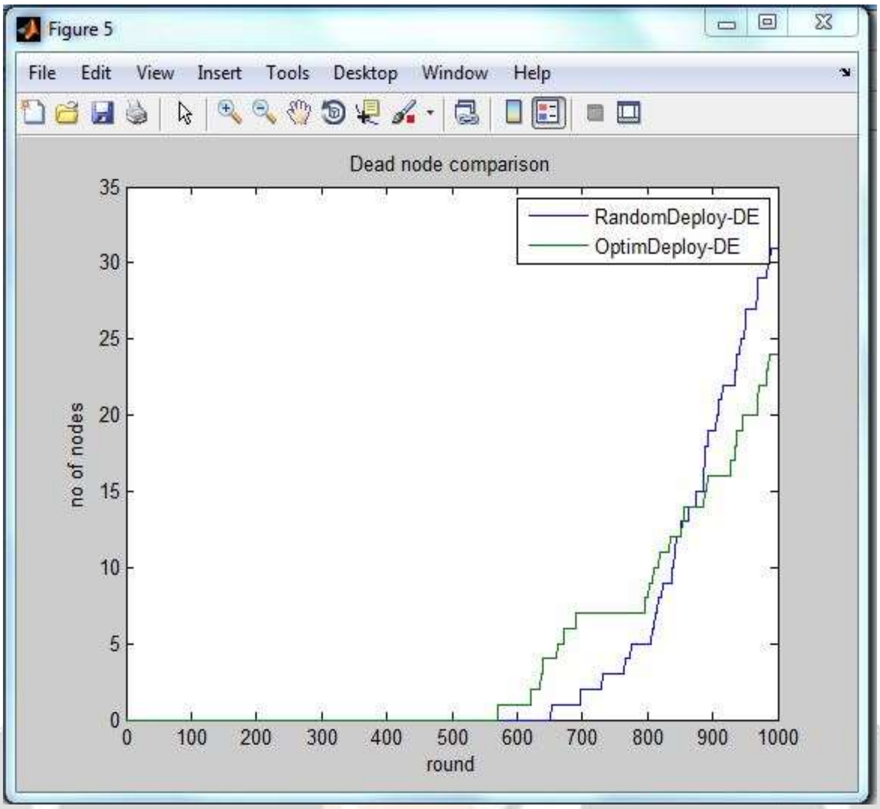

Fig 9. Comparison in terms of Dead node

Shows the comparison of the algorithm in terms of number of nodes. The Optimal Deploy DE performs better than the random deploy.

Our objective is not only to minimize the energy consumption of the network, but also maximize the lifetime. This is effectively achieved by taken care of the lifetime of the CHs that is essential for extending network life.

6. CONCLUSION

We have presented a two layers stages approaches for lifetime improvement in WSN. We have also derived an efficient fitness function takes care of energy consumption. The experimental results have shown than the proposed algorithm converges faster than the traditional DE and MOGA. We shows that it perform better than the exiting algorithm i.e, traditional random and optimal deployed in terms of energy consumption and number of dead nodes.

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