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COVERAGE MAXIMIZATION MULTIOBJECTIVE IMMUNE GENETIC ALGORITHM FOR WIRELESS MOBILE SENSOR NETWORK

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Abstract— **Intelligent devices such as sensors are surrounding the people to provide safety and improve the quality of life in emerging situation. For better results sensors have to surveillance maximum possible area. Optimization as well as organization of resources of network is essential for ubiquitous communication. In present paper, multi-objective genetic algorithm for maximization of coverage during sensor deployment is conceived. This meta-heuristic approach is based on traditional genetic approach.**

Keywords— **WSN, GA, MIA, Senor Terminology**

I. INTRODUCTION

Wireless mobile sensor networks(WMSN) are networks with mobile nodes distributed spatially to monitor environmental and physical conditions likes sound, pressure, temperature, etc. in order to send data through network to destination[2]. The more sophisticated networks are two-directional. The creation of network is based on two basic criteria's as per requirement; a) to attain maximum area coverage, b) to prolong the sensing lifetime of each node. Mobile sensors are comprised of four building blocks: 1) Sensing Unit, 2) Processing Unit, 3) Power Unit, 4) Transceiver. Each unit consumes energy particularly while deploying mobile sensors, which need more energy to adjust their locations in order to maximize the coverage area[3]. There is compromise between energy consumption and area coverage. The sensor deployment is mostly deterministic but there are some area where manpower cannot reach to fix the positions of the sensors so mobile sensor in those cases are perfect. They can reposition themselves with their mobile facility. Initially mobile sensors are randomly installed but later relocation is done in order to achieve maximum area under surveillance.

In current paper, the multi-objective immune genetic algorithm is conceived. It leads to non-deterministic deployment as mobile sensors are capable to move in any direction. This strategy focuses on optimum placement of sensors so that maximum possible utilization of available recourses is achieved. The exact choice for position of mobile motes as per application necessity is tough. So, major issues in deployment are to install mobile sensor nodes in Region of Interest (ROI). ROI is area where there are more chances of favorable events occurrence, therefore detection must be needed. So, proposed algorithm will prolong lifetime as well as network coverage. Since, mobility itself demands energy from sensor's limited energy source. A deployment strategy should be circumspectly designed to impair energy consumption.

Abo-Zahhad et al. have been proved that immune node deployment algorithm is NP hard problem but novel approach is NP complete. This effort is distinct from earlier work on deployment algorithms. Proposed algorithm hybrid multi-objective immune genetic algorithm points at efficient deployment of mobile sensors for 2-D networks. Here sensors rearrange themselves on the basis of crossover and mutation in an adaptive manner.

II. MULTI-OBJECTIVE IMMUNE GENETIC ALGORITHM (MOIGA)

A. Assumptions:-

1. Each mobile mote is capable for covering circular area with radius R_s.
2. All mobile sensors have same communication range (R_c).
3. Obstacles inside sensing area can be examined by the sensor node itself.

B. BINARY SENSING MODEL: - The sensing model used here is a binary model, which is supposed to be covered as much as possible. This means that the area within the sensing range can be counted as covered with a probability of 1 and the area out of the sensing range will be set as 0 since it cannot be covered. The sensing field is considered to be m * n grids and each grid size is equal to 1. The coverage of the whole area is proportional to the grid points that can be covered. Considering the grid point G(x,y), the possibility that it can be sensed by a sensor node si(xi, yi) is described by;

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$$P(x,y,S_i) = \begin{cases} 1, & if\sqrt{a^2+b^2} \le R \\ 0, & otherwise \end{cases} \quad (1)$$

$$a = (x - x_i)^2 \quad (2)$$
$$b = (y - y_i)^2 \quad (3)$$

C. ALGORITHM: - Steps involved in algorithm MOIGA are as following:-

ANTIBODY POPULATION GENERATION

Finding the optimal positions of MSNs is important issue to improve the network coverage. Based on the collected information from sensor nodes, BS generates a population pool of ps positions' antibodies (PAs) by encoding the positions of nodes using the real coding representation. Each position antibody (PA) contains 2N genes. First N genes represent the x locations of nodes, and the next N genes represent the y locations of nodes.

EVALUATION OF OBJECTIVE FUNCTION

The goal of MIGA is finding the perfect positions of MSNs to maximize the covered area and minimizes the mobility cost determined by minimizing the uncovered area ratio o_1 as well as the moving distances all mobile sensor nodes o_2 for each PA the following:

$$Minimize(F(PA) = \alpha o_1 + (1-\alpha)o_2) \quad (4)$$

α is application dependent ($0 \le \alpha \le 1$) and signifies which factor is most crucial.

SELECTION

The roulette wheel selection [15] is working at immune based algorithms for antibodies reproduction. Its basic idea would be to determine the choice probability for every one sensor's position antibody (individual) compared to its fitness value (1/F(PA)) as with higher fitness values are more likely to be selected as the parent antibodies that generate offspring over the following step.

REPLICATION

Replication operation is applied to purchase better (pr * ps) PAs in line with the replication rate (pr) by sorting them according for their objective function values (F(PA)) in ascending order. Then, the initial (pr * ps) antibodies are selected to come up with offsprings.

CROSSOVER

Crossover is a genetic operator used to vary the programming of the chromosome or chromosomes within one generation with the next. It is usually analogous to reproduction and biological crossover, where genetic algorithms are based. Go over is an operation of taking a couple of parent solutions and to become a child solution from them.

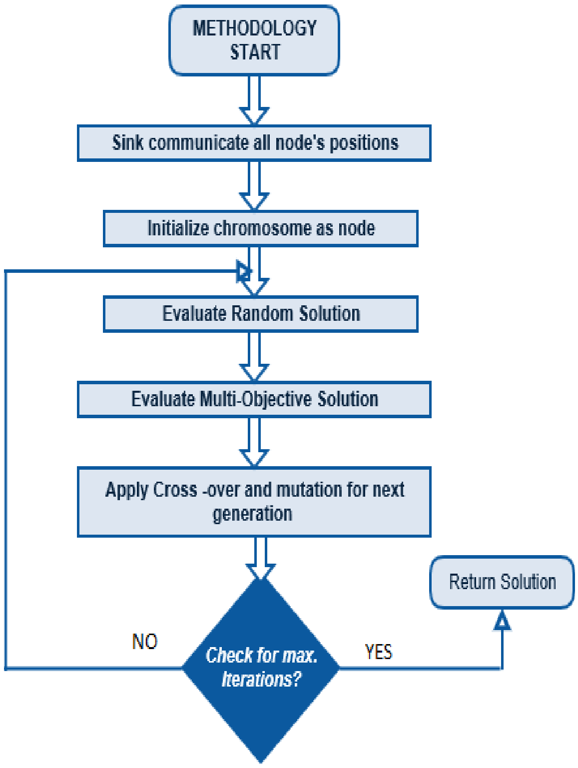

Fig.1: - Flowchart of MOIGA

MUTATION

The mutation operation is conceived from convex set theory to make exploration. Two genes available as one PA are randomly chosen to execute the mutation combination. For the PA = (P_1, P_2, P_3 ….., P_i,….,P_{2N}), if for example the genes P_i and P_k are randomly selected for mutation contingent on pm, the resulting offspring is PA' = (P_1,P_2,…., P'_i,….,P'_k,…..,P_{2N}). The new genes will be $P'_i=(1-\beta)P_i+\beta P_k$ and $P'_k=\beta P_i+(1-\beta)P_k$ respectively, where β=[0,1].

NEW ANTIBODY POPOLATION

Sort the current generation population in ascending order as per value of F(PA). First position will be acquired by antibody with minimum F(PA) and selected to construct the antibody population for the new generation.

STOPING CRITERIA

Till repetition occurs in F(PA) and positions of nodes are not changing for certain number of generations or specified maximum generation has been exceeded.

SIMULATION RESULTS

Ten tests has been conducted using Matlab 10.1 with different number of sensors. MIGA is compared here with immune node deployment algorithm. Maxgen= 200, P_h = 0.4, P_c= 0.4, α=0.9, R_s= 5

PERFERMANCE EVALUATION

Performance is analyzed on basis of area coverage , convergence speed, energy used by sensors and execution time.

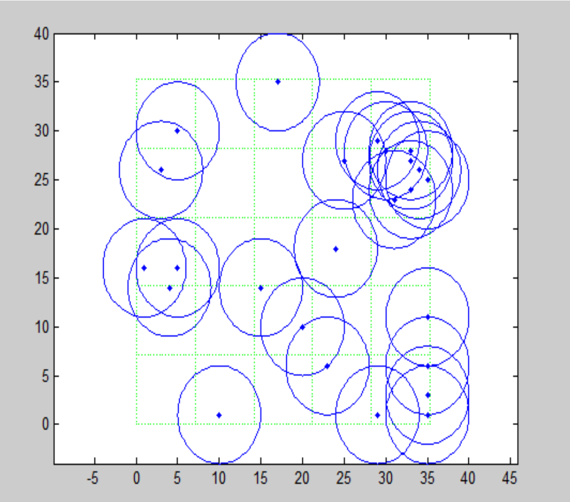

Fig. 2: -Initial Deployment

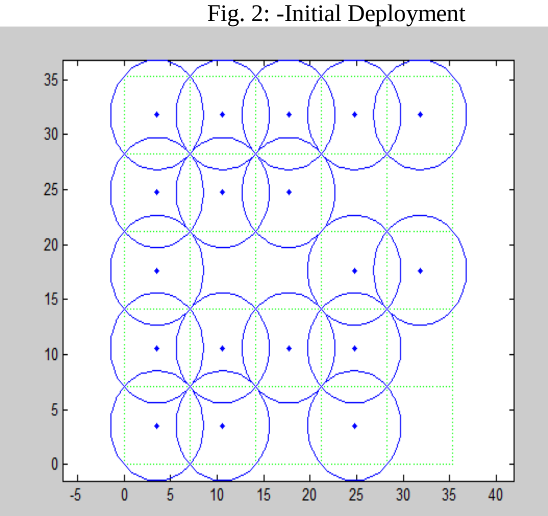

Fig.3: - Repositioning

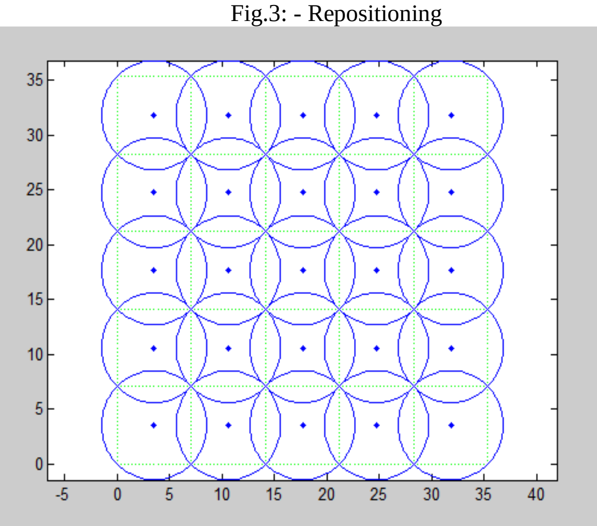

Fig.4: - Final deployment

Above figures depicts the initial random deployment then rearrangement of motes after applying MOIGA and final deployment which covers maximum sensing field.

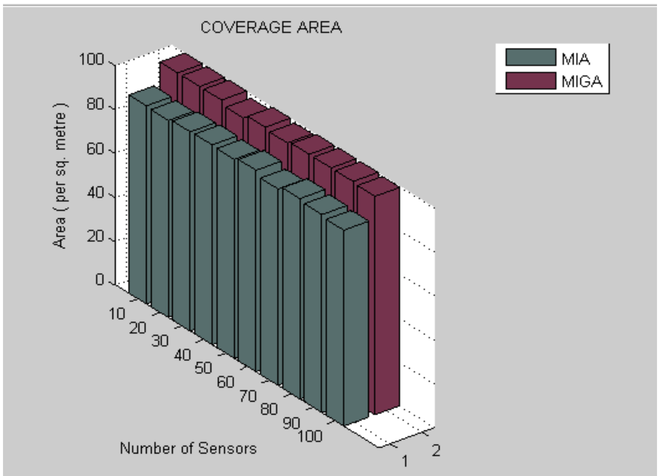

Fig.5: - Coverage area

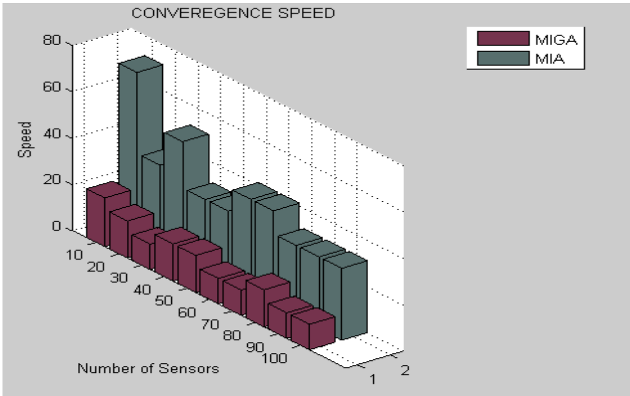

Fig.6: - Convergence Time

Fig. 5 and Fig. 6 demonstrates the improvement of MOIGA as compared to MIA. The coverage area of MOIGA is far better than MIA as average coverage area in MOIGA is 95% while in MIA is 87%. Convergence time in MOIGA is much less.

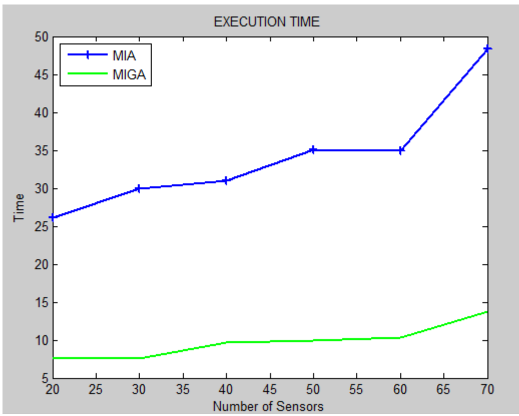

Fig.8:- Execution Time

III. CONCLUSION

Multi-objective immune genetic algorithm has depicted great results and also convergence speed is minimized to great extent. So MIGA helps mobile sensors to rearrange them with a meta-heuristic. So, from above analysis it has been shown that results of MIGA are much better than MIA.MIA take too long to reposition the sensors while MIGA do it in minimum time. Also coverage is maximized with MIGA.

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