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Research Article

Computational Intelligence based WSN lifetime extension with maximizing the disjoint Set K-Cover

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Abstract: In this work-life enhancement of wireless sensor network has been considered through discovering the large 'K' number of disjoint set covers. Each disjoint set sensor covered all the targets. Hence rather than keeping active all the sensor nodes, only activating the sensors of a cover while keeping other covers sensors in sleep mode can increase the life span by K fold approximately. This approach also provides the saving of energy and time by eliminating the processing of redundant information from sensors. Evolutionary computation-based computational intelligence approach, Genetic algorithm, and Differential evolution have been applied over the different configurations of the sensor network. A local operator has also integrated to make the solution feasible. The facility of integer encoding of solution in the Genetic algorithm has given the benefit in finding more number of disjoint covers in compared to Differential evolution which carried the solution exploration fundamentally over continuous value region.

Keywords: WSN, lifetime enhancement, disjoint K-Cover, Genetic algorithm, Differential evolution

1. Introduction

Wireless sensor networks (WSNs) have shown significant advantages in a range of applications, including frontline control, environmental analysis, traffic management, animal tracking, and home applications. As it is not always practicable to replace the battery of sensors, a crucial technology for multiple applications involving long-term and low-cost management, in other words, the basic need of a WSN, is the network lifespan, also known as the duration of the operation. Non - renewable sensor batteries have compelled the creation of methodologies for extending network lifespan, which has emerged as one of the most important and daunting issues in WSNs. As a result, enhancing network lifespan is an important research subject in WSNs. Several approaches can be used to extend the lifespan of WSNs by focusing on data collection, routing, system location, topology management, and device monitoring. A subset of devices in a heavily deployed WSN will already solve coverage and connectivity problems. Only the sensing coverage issue needs to be addressed, as it has been shown that network communication with active sensors in full coverage is assured by enabling each sensor's interaction range to be at least twice as long as its sensing range. The coverage issue is important in a WSN because it determines how well sensors detect or track a region of interest. The coverage issue in a WSN is important because it determines how well a sensor-based or monitored region of interest is controlled or tracked, and the system management approach that regulates the devices' sleep/wakeup operations has shown promise. In general, sensors are randomly dropped from planes to the target site. In addition, most sensors have two modes of operation: active and sleep. When a sensor is in active mode, it consumes a lot of energy to carry out all of its tasks, such as sensing, computation, and connectivity A sensor in sleep mode, on the other hand, consumes little energy and can be awakened at a predetermined working interval to perform maximum operations. Whenever a subset of sensors in the region has adequately covered the target region, other sensors in the region may be scheduled to be in the sleep mode to save energy; thus, if there are a greater number of subsets, the WSN's lifetime will be greatly increased. To put it differently, expanding the number of fully covered subsets is an even more direct way to increase network lifetime. The dilemma of calculating the maximum number of complete cover subsets is challenging since each subset must have complete coverage of the target area, and the WSN will satisfy the surveillance challenge with only one subset of sensors operating at any given time. In a WSN, this problem is known as the disjoint set covers problem or the SET k-cover problem, and it has a nondeterministic polynomial total complexity (NPC).

The paper carried the information of literature survey in section 2 while problem definition has given in section 3. The applied methodology has been proposed in section 4 and simulation results have given in section 4. The conclusion has given at the end.

2. Literature Survey

Wireless sensor networks (WSNs) are considered to be extremely energy-constrained, and the lifespan of each network sensor is highly dependent on the node's battery power. As a result, network lifespan has become a major focus of WSN studies. Although several energy-efficient protocols have been suggested to extend network lifetime, different concepts of network lifetime have also been used for the various scenarios and protocols. The time to the first sensor node failure is commonly used to describe the lifetime of a sensor network, which appears to be overly pessimistic in many envisaged deployment scenarios. [1] presented a comparative analysis of WSN protocols focused on different network lifetime concepts as critically as possible, as well as consideration of the ramifications of these metrics and their applicability in measuring the efficacy of WSN data distribution schemes. [2] provides a review of recent advances in WSNs, including their implementations, design limits, and lifetime prediction models. Two Linear Programming (LP)-based algorithms were proposed in [3] to investigate the effect of collecting multiple critical nodes on WSN lifetime using numerical evaluations. The results showed that capturing several critical nodes in a WSN significantly reduces network lifespan. The work in [4]investigated the issue of expanding the lifetime of complex heterogeneous WSNs with EH sensors to improve the total WSN lifetime. This problem was described as determining the maximum number of covers, each of which is a component of all sensors, such that all targets can be tracked by these sensors. As this case for static WSNs is shown to be NP-complete, the problem at hand is also NP-complete. As a result, the work first mathematically models the problem before applying the harmony search algorithm with multiple populations and local search (HSAML) with dynamics, heterogeneity, and EH sensors. Routing is critical in wireless sensor networks for the deployment and management of an effective and adaptive network. Ensuring effective routing necessitates a growing reliance on optimized energy utilization and dependable resource management of all sensor nodes and the overall sensor network. [5] proposed an adaptive and complex multi-criteria routing protocol to extend the life of the network. The clustering approach has also been shown to increase or extend the existence of WSNs. Attempts have been made in [6] to build a clustering model with optimal cluster head selection while taking into account four main parameters such as energy, delay, distance, and security. In addition, for selecting the best CHs, proposes a new hybrid algorithm, firefly replaced position update in dragonfly, that combines the concepts of dragonfly and firefly algorithms. [7] addressed the issue of increasing WSN coverage efficiency while optimizing the number of DSCs Thus, in the sense of the WSNs design challenge, the key contribution is to transform the concept of a single-objective DSC problem into a multi-objective problem (MOP) by adding a competing objective to be optimized. Scheduling sensors into a maximum number of disjoint sets have been modeled as a disjoint set covers (DSC) problem, which is a well-known NP-hard optimization problem, in the literature. [8] addressed the issue of determining the maximum number of fixed covers while taking into account a more practical sensing model to account for variability in the sensors' target-coverage reliability. Investigations also resulted in the implementation of a basic multi-layer genetic algorithm (GA), the key component of which is to endorse the selection of a minimum number of sensors to be allocated to a maximum number of set covers. Because of the complex design of wireless sensor networks (WSNs) and the various potential cluster configurations, determining an optimum network arrangement on the fly is a difficult task. [9] suggested a genetic algorithm-based, self-organizing network clustering (GASONeC) approach to solve this problem, which provides a basis for dynamically optimizing wireless sensor node clusters. The idea of extending the lifetime of a homogeneous WSN is to prevent nodes from depleting energy before others. [10] presented a clustering model for WSN applications in diverse environments One approach to reducing network energy consumption is proper cluster head selection. The most prevalent routing algorithm is the low-energy adaptive cluster hierarchy (LEACH), wherein the cluster head is selected based on a predefined threshold. A routing protocol based on supercluster head election using fuzzy logic in three layers (SCHFTL) is proposed in [11], in which a supercluster head is elected from among the cluster heads. Sensor density can be increased by randomized deployment. [12] spoke about how to extend the network lifespan of WSNs. It can be enhanced by keeping the sensors in different set covers. Sensors were either working or sleeping at a certain point in time. Sensors can only track targets in active mode and be programmed as an optimization issue with Maximum Set Covers. A greedy-based heuristic for sensor deployment and scheduling was proposed to maximize or improve WSN network lifetime. In [13], the Optimal Mobility based Data Gathering approach (OMDG) with Time-varying Maximum Capacity Path Routing protocol (TMCP) was proposed, where CHEF was used for clustering and several dynamic sinks were used to gather the gathered data inside the cluster to minimize waiting time. The collected data was sent to the cluster head to extend the existence of the WSNs.

4. Disjoint Set Cover Problem in WSN

If there is a finite set of target T, and a collection of subset S of disjoint type then finding the maximum number of subset such that for every cover C_i ($C_i \subseteq S$), every element of T belongs to at least one member of C_i, and for any two covers C_i and C_j ,Ci∩Cj=φ.

This problem has been proven to be $NP-Complete$.Figure.1 shows a WSN with five sensors and four targets. The relationship between sensors $S1 \dots S5$ and targets $T1 \dots T4$ is represented by a bipartite graph $G = (V, E)$ where $V = S \cup T$ and $e_{ij} \in E$ if $Si\ covers\ Tj$. Figure.2 represents the bipartite graph of the WSN in Figure. 1, where $S1 = \{T1\}, S2 = \{T1, T2\}, S3 = \{T2, T3, T4\}, S4 = \{T3\}\ and\ S5 = \{T4\}$. The maximum number K of disjoint covers in this example is two. They are $C1 = \{S1, S3\}\ and\ C2 = \{S2, S4, S5\}$. The aim of the SET K-COVER problem is to find the highest number of covers aligned with the maximum lifetime extension, which is equal to dividing the set of sensors into the maximum number of disjoint covers.

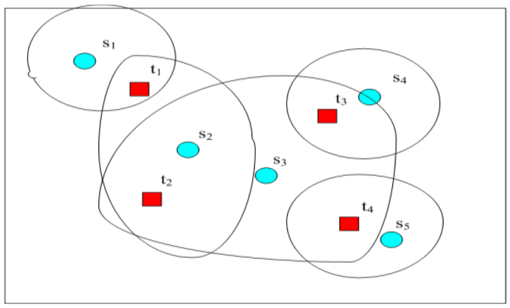


Figure. 1. Sample WSN deployment.

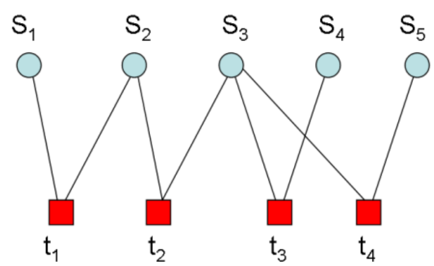
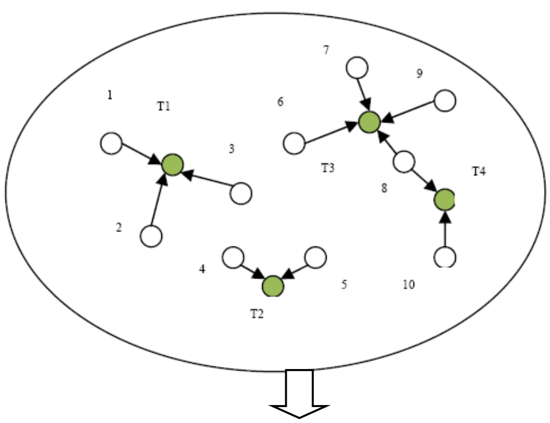


Figure 2. Bipartite graph of a sample WSN of Fig1

4.Applied Methodology

4.1. Solution Representation & Fitness value

In the construction of the solution representation, each sensor was assigned a unique integer number ranging from 1 to higher values up to the total number of sensors, and the solution was represented as a series of sensor numbers. In Fig.3, for four separate targets, the location of ten sensors, their target coverage, and the related solution representation and fitness estimate are shown in Fig3.



7	5	1	9	10	4	2	8	6	3
T3	T2	T1	T3	T4	T2	T1	T4,T3	T3	T1
1st Cover					2nd Cover				

Fig.3 : solution representation and fitness estimation for sensors and their covered target

Fitness of a solution is defined as the total number of developed disjoint cover hence in Fig.3 the defined solution {7,5,1,9,10,4,2,8,6,3} carried the fitness of 2 because there are 2 disjoint covers available.

4.2 Genetic algorithm with a locally corrected operator

In this work, the Genetic algorithm carried the more natural mechanism in creating the offspring by providing equal opportunities for every member has been applied. This process is different from the conventional form of GA where fitness-oriented priorities have provided in being of parents. Equal opportunities for every member to be a parent is more natural and provide the chance for better exploration. Two-point cross–over has been applied to explore the solution space while exploitation has been provided by the tournament selection process to obtain the population for the next generation. Fig.4 depicts the whole procedure. The initial population is determined by the random integer generator, which generates random integer values by permuting integer values from 1 to NS (NS: total number of sensors). Based on an equal opportunity, two random parents were chosen from the population, and offspring were produced by two-point cross-over. The offspring were further mutated through integer mutation strategy where the selected mutation position filled with randomly selected integer values in the range of [1, NS]. After mutation, there is a good enough chance that offspring may carry multi-locus characteristics in terms of placing the same sensor over different locations at the same time. Such a situation is not possible and the solution will become infeasible. To make the solution feasible, multi-locus position of sensors were corrected by placing the random selection of unavailable sensors in the present solution. Once the parent and offspring populations were the same size, they were grouped into a pool over which the tournament selection was used to determine the representatives of the next generation population. Finally, depending on the state of the termination, then the former population will be replaced by the next-generation population and the procedure will be replicated, or the final solution will be derived from the next-generation population.

4.3 Differential evolution (DE)

To solve global optimization problems, the DE is now regarded as a powerful agent in evolutionary computation. The DE algorithm's population consists of NP individuals, each of which has a D-dimensional vector corresponding to the problem's D dimensions. DE uses mutations to generate a donor vector of dimension D after one generation for each vector. There are several methods for defining the donor vector. In this study, two separate methods were used: DE/rand/1 as defined in Eq (1) and DE/current to best/rand/1 as defined in Eq (2). The crossover operator was used to construct the trial vector in a probabilistic setting, as seen in Eq (3). CR is a crossover control parameter or element that exists between [0, 1] and represents the likelihood of generating parameters for a trial vector from the mutant vector. The integer index jrand is selected at random from the set [1, NP]. Then, as seen in Eq (4), a greedy selection operation chooses between the target and corresponding trial vectors to pick vectors for the next generation. The integer values were obtained via the rounding procedure.

$$V_i^{(G)} = X_{r1}^{(G)} + F * \left(X_{r2}^{(G)} - X_{r3}^{(G)}\right) \tag{1}$$

$$V_i^{(G)} = X_i^{(G)} + F * \left(X_{best}^{(G)} - X_i^{(G)}\right) + F * \left(X_{r1}^{(G)} - X_{r2}^{(G)}\right) \tag{2}$$

$$u_{ij}^{(G)} = \begin{cases} v_{ij}^{(G)} & if \quad rand(0,1) \le CR \quad or \quad j = j_{rand} \\ x_{ij}^{(G)} & otherwise \end{cases} \tag{3}$$

$$x_{ij}^{(G)} = \begin{cases} u_i^{(G)} & if \quad f\left(u_i^{(G)}\right) \le f\left(x_i^{(G)}\right) \\ x_i^{(G)} & otherwise \end{cases} \tag{4}$$

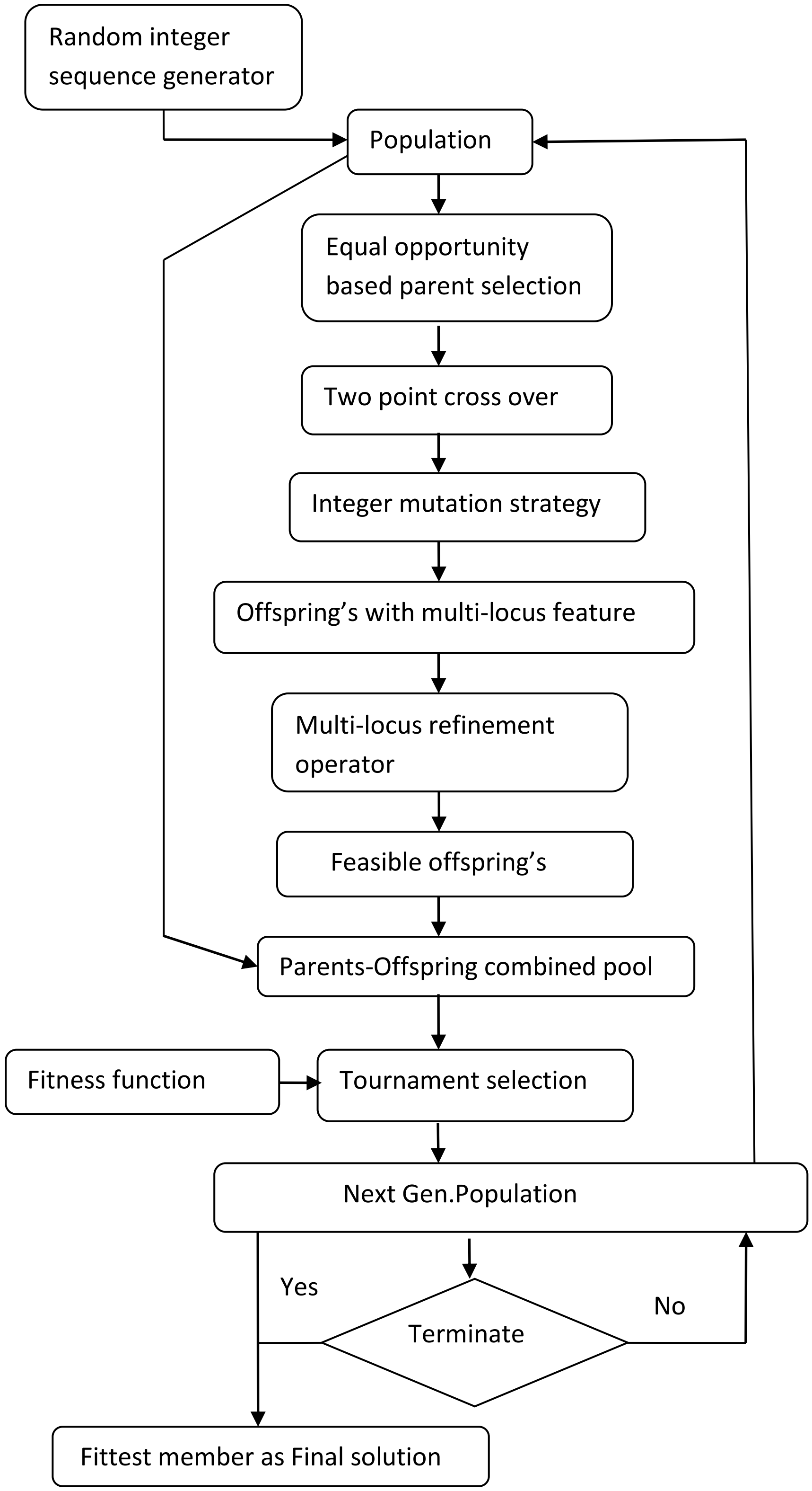


Fig.4. Proposed form of GA

4. Experimental Results

For different setup of simulated network of WSN, the proposed form of GA and DE have been applied. It is has been assumed that sensors were dropped randomly in 2D space and targets were fixed. Such condition has been simulated by assigning the random values of (x,y) coordinates for the sensors and targets. In the first stage, with help of Euclidean distance of each sensor to the targets, coverage matrix obtained which defined the converge of target by individual sensors. The formation of coverage matrix has shown in Fig. The whole simulation process has been setup under MATLAB environment.

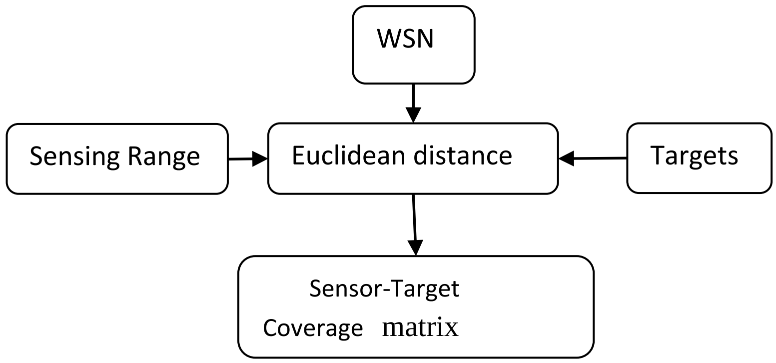


Fig.5

For the GA and DE, the population size has been considered as 100 and allowed number of generation was 100. The probability of mutation for GA has been considered as 0.1 while tournament size was 10% of the population. In the DE, the F value was 0.5 while CR was equal to 0.5.

Case1.

No. Of Deployed sensors	100
No. Of useful sensors	86
No. of Target	10
Sensing Range	20

Corresponding to define parameter a developed original network at the beginning has shown in Fig6 .As it is clear that there are some redundant nodes which doesn't cover any target hence discarded and final coverage matrix based network has shown in Fig7. and the coverage matrix has shown in Table1.It is clear from coverage matrix that all the included sensors in the network at least cover one target.

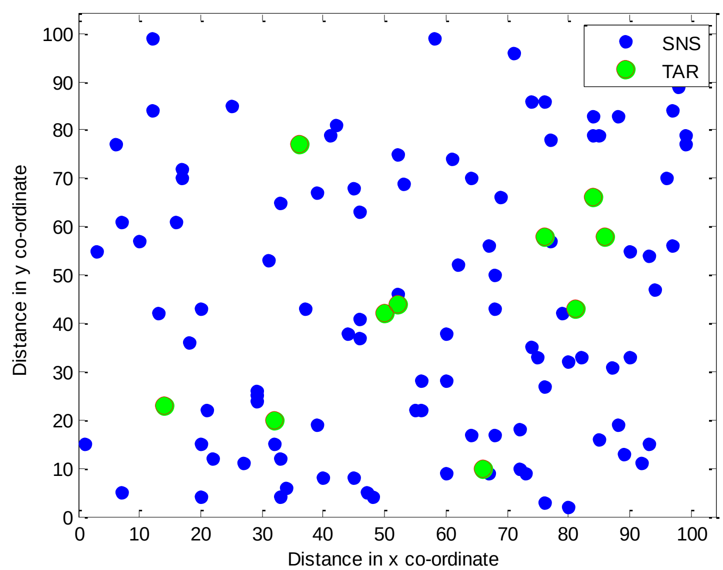


Fig.6. Raw network for the case 1

Sensor	Target 1	2	3	4	5	6	7	8	9	10	Sensor	Target 1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	1	1	0	0	0	0	46	0	0	0	0	0	0	1	0	1	0
2	0	0	0	0	1	1	0	0	0	0	47	1	0	0	0	0	0	0	0	0	0
3	0	0	1	1	0	1	0	0	0	0	48	0	1	0	0	0	0	0	0	0	0
4	0	0	1	1	1	0	0	0	0	0	49	1	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	1	0	50	0	0	1	0	0	1	0	1	0	1
6	0	0	0	0	0	0	0	0	0	1	51	0	0	0	0	0	1	0	1	0	1
7	0	0	0	0	0	0	1	0	0	0	52	1	0	0	0	0	0	0	1	0	1
8	0	0	0	0	0	0	0	1	0	0	53	1	0	0	0	0	0	0	0	0	0
9	1	0	1	0	0	0	0	0	0	0	54	0	0	1	1	1	1	0	0	0	0
10	0	0	1	0	0	0	0	0	0	0	55	0	0	0	0	0	1	0	0	0	0
11	0	0	1	0	1	1	0	1	0	1	56	0	0	0	1	0	0	0	0	0	0
12	1	0	0	0	0	0	0	0	0	0	57	0	0	0	0	0	0	0	0	1	0
13	1	0	0	0	0	0	0	0	0	0	58	0	0	1	0	0	0	0	0	0	0
14	0	0	0	0	0	0	1	0	0	0	59	0	0	0	0	0	0	0	1	0	1
15	0	1	0	0	0	0	0	0	0	0	60	0	1	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	1	0	1	0	61	0	0	0	1	1	1	0	0	0	0
17	1	0	0	0	0	0	0	0	0	0	62	0	0	0	0	0	0	1	0	1	0
18	0	0	0	1	0	0	0	0	0	0	63	0	0	0	0	0	0	1	0	1	0
19	0	0	0	0	0	0	0	0	1	0	64	0	0	0	1	0	0	0	0	0	0
20	0	0	0	0	0	0	1	0	1	0	65	0	0	0	0	0	0	1	0	1	0
21	1	0	0	0	0	0	0	0	0	0	66	0	1	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	1	0	0	0	67	0	0	0	0	0	0	0	1	0	1
23	0	0	1	0	0	0	0	0	0	0	68	0	0	0	0	0	0	0	0	1	0
24	0	1	0	0	0	0	0	0	0	0	69	0	0	0	1	0	0	0	0	0	0
25	1	0	0	0	0	0	0	0	0	0	70	0	0	1	0	0	0	0	0	0	0
26	0	0	1	0	0	0	0	0	0	0	71	1	0	0	0	0	0	0	0	0	0

1

Distance in y co-ordinate

27	0	0	0	0	0	0	1	0	1	0
28	0	1	0	0	0	0	0	0	0	1
29	0	0	0	1	0	0	0	0	0	0
30	0	0	1	1	1	1	0	0	0	0
31	0	0	0	1	0	0	0	0	0	0
32	0	0	0	0	0	0	0	1	0	1
33	1	0	0	0	0	0	0	0	0	0
34	0	0	0	1	0	0	0	0	0	0
35	0	0	0	0	0	0	1	0	0	0
36	0	0	0	1	1	0	0	0	0	0
37	0	0	0	0	0	0	1	0	0	0
38	0	1	0	0	0	0	0	0	0	0
39	0	0	0	0	0	0	1	0	1	0
40	0	1	0	0	0	0	0	0	0	0
41	0	0	0	0	0	0	0	1	0	1
42	0	0	1	0	0	0	0	0	0	0
43	0	0	0	0	0	0	1	0	1	0
44	0	0	0	0	0	0	0	0	1	0
45	1	0	0	0	0	0	0	0	0	0
72	1	0	0	0	0	0	0	0	0	0
73	0	0	0	0	0	0	0	0	1	0
74	0	1	0	0	0	0	0	0	0	0
75	1	0	0	0	0	0	0	0	0	0
76	1	0	0	0	0	0	0	0	0	0
77	0	0	0	0	0	0	0	0	1	0
78	0	0	1	0	1	0	0	0	0	0
79	0	0	0	0	0	0	0	1	0	1
80	0	0	1	1	1	1	0	0	0	0
81	0	0	0	1	1	0	0	0	0	0
82	0	0	0	0	0	0	0	1	0	1
83	0	0	0	0	0	0	0	1	0	1
84	0	1	0	0	0	0	0	0	0	0
85	0	0	1	1	1	1	0	0	0	1
86	0	0	1	0	1	1	0	0	0	0

Fig.7. coverage matrix based applied network for case1

Table1. Coverage matrix for the case1

The performance of GA and DE over 100th generation (last generation) against the 1st generation have shown in Fig.8. It is clear that at the beginning there were fitness varies from 4 to 6 cover while DE has developed 8 cover maximally while GA has discovered the 10 covers .The fitness convergence also has shown in Fig.9. The obtained final cover by DE and GA has been listed in Table 2 and can observe that with very few numbers of sensors all the targets can be covered. There were some unused sensors remaining in the case of DE which are not part of any cover can be reuse if needed.

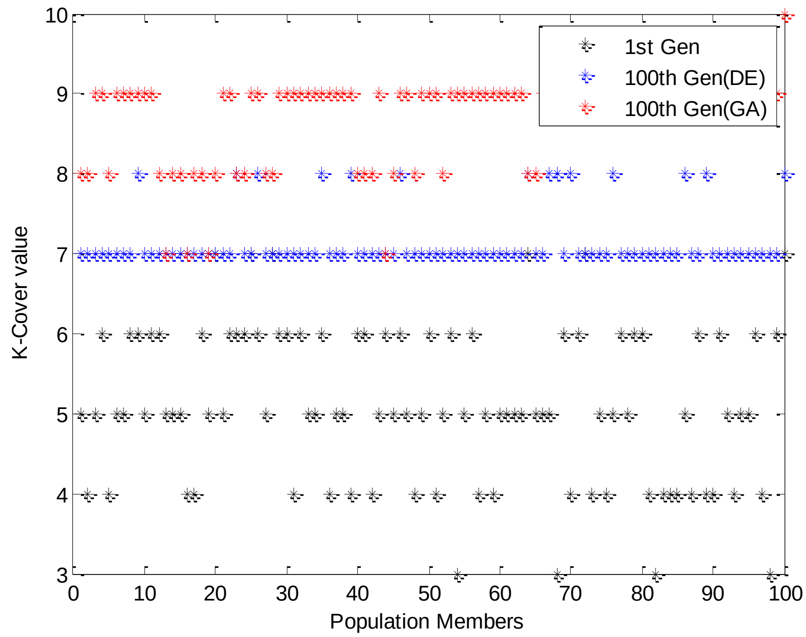


Fig.8. Population member fitness under different generation

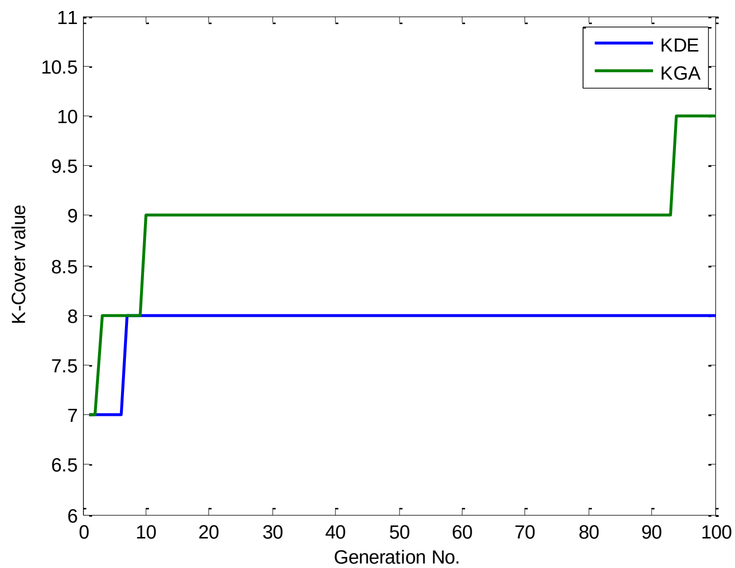


Fig.9. Best solution fitness convergence

Table.2 Discovered disjoint set

	DE	GA
K-Disjoint Cover	Sensor No.	Sensor No.
1	47 29 66 34 21 60 59 80 50 77 27	46 47 6 30 28 12 67
2	37 1 42 26 7 4 32 72 31 75 53 14 55 38 5	1 25 41 18 84 43 34 13 3
3	43 17 2 67 9 54 19 28	29 50 81 9 58 16 40
4	63 12 86 3 40 6 8	14 27 70 2 83 17 10 15 73 5 4
5	11 10 13 15 16 18	75 8 71 69 7 24 65 11
6	44 20 22 23 45 41 24 46 25 30	33 77 26 19 53 20 51 64 21 22 32 74 23 36
7	33 56 35 36 70 39 48 49 73 65 68 51	78 37 39 45 79 61 48
8	69 52 57 79 58 61 62 82 64 71 74	49 38 35 31 56 52 44 86
9		59 54 42 66 55 57 76 80 62
10		63 60 72 68 85 82
Unused Sensors	76 78 81 83 84 85	

Case2.

No. Of Deployed sensors	200
No. Of useful sensors	128
No. of Target	10
Sensing Range	20

For the case 2 there were more number of sensors have been considered in compared to case1 and remaining parameters were unchanged. The raw network and coverage matrix based network have shown in Fig.10 and Fig.11.The obtained coverage matrix has shown in Table3.

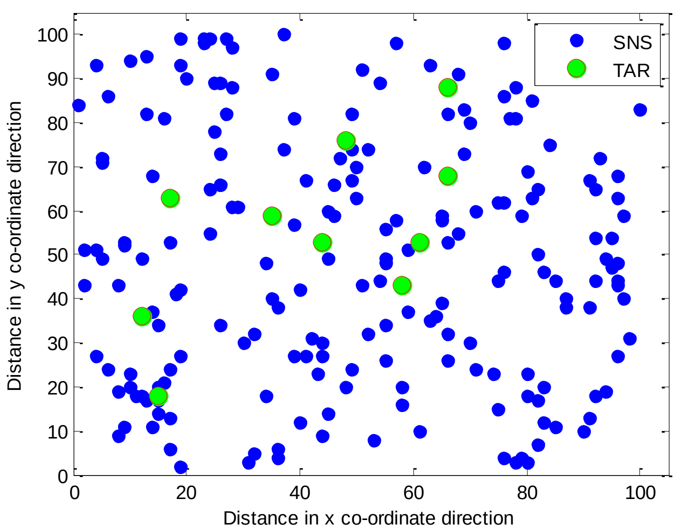


Fig.10. Raw network for the case 2

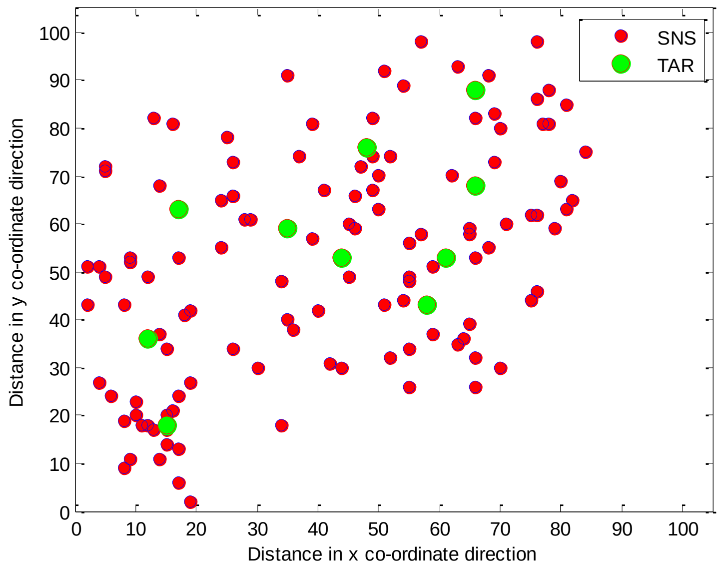


Fig.11. coverage matrix based applied network for case2

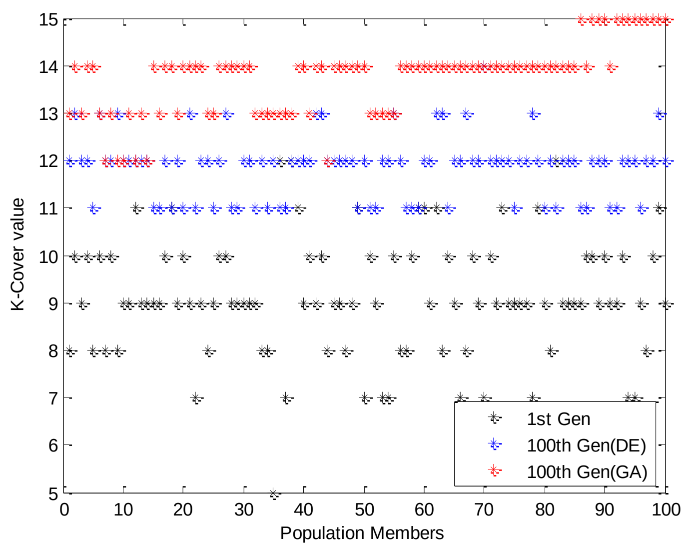


Fig.12. Population member fitness under different generation for case2

Table3. Coverage matrix for the case2

Sensor	Target 1	2	3	4	5	6	7	8	9	10	Sensor	Target 1	2	3	4	5	6	7	8	9	10
1	0	0	1	0	0	0	1	0	0	1	65	0	0	0	0	0	0	0	1	1	0
2	0	0	0	0	0	0	0	0	0	1	66	0	0	0	0	0	1	0	0	0	0
3	1	0	0	0	0	0	1	0	0	0	67	1	0	0	1	1	0	0	0	0	1
4	0	0	0	0	1	0	0	0	0	0	68	0	1	0	0	0	0	0	1	0	0
5	0	0	0	1	0	1	1	0	0	0	69	1	0	0	0	0	0	0	0	0	1
6	0	0	0	0	1	0	0	0	0	0	70	0	0	0	0	0	0	0	0	1	0
7	1	0	1	0	1	0	0	0	0	0	71	0	0	0	0	1	0	0	0	0	0
8	0	0	0	0	0	0	0	0	1	0	72	0	1	0	0	0	0	0	1	0	1
9	0	0	0	0	0	0	0	1	0	0	73	0	0	0	1	1	1	0	0	0	0
10	1	1	0	0	0	0	0	0	0	0	74	0	0	0	0	1	1	0	0	0	0
11	0	0	0	0	1	0	0	0	0	0	75	1	0	0	1	0	0	1	0	0	1
12	0	1	0	0	0	0	0	0	0	0	76	0	1	0	0	0	0	0	1	0	0
13	0	0	1	0	0	0	1	0	0	0	77	0	1	0	0	0	0	0	0	0	0
14	1	0	1	0	1	0	1	0	0	0	78	1	0	1	0	0	0	1	0	0	0
15	0	0	0	0	0	0	0	1	1	0	79	0	0	0	0	0	0	0	0	1	0
16	0	0	0	0	0	1	0	0	0	0	80	0	0	0	0	0	0	0	1	1	0
17	0	0	0	0	0	0	0	1	1	0	81	0	0	0	0	1	1	0	0	0	0
18	0	0	1	0	0	0	0	0	0	0	82	0	1	0	0	0	0	0	1	0	0
19	0	0	0	0	0	1	0	0	0	0	83	1	0	1	0	0	0	0	0	0	1
20	0	0	0	0	0	1	0	0	0	0	84	0	1	0	0	0	0	0	0	0	1
21	0	0	1	0	0	0	1	0	0	0	85	0	0	0	0	1	0	0	0	0	0
22	0	0	1	0	0	0	0	0	0	0	86	0	0	1	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	1	0	0	87	0	0	0	0	0	0	0	0	1	0
24	0	0	0	0	1	0	1	0	0	0	88	0	0	0	0	0	0	0	1	1	0
25	0	0	0	0	0	0	0	1	1	0	89	0	0	0	0	0	0	0	0	1	0
26	1	1	0	0	0	0	0	0	0	1	90	1	0	1	0	0	0	1	0	0	0
27	0	1	0	0	0	0	0	0	0	0	91	0	0	0	0	0	0	0	1	1	0

28	0	0	0	0	0	0	0	1	1	0	92	0	0	0	0	0	1	0	0	0	0
29	0	0	1	0	0	0	0	0	0	0	93	0	0	0	1	1	1	0	0	0	0
30	0	1	0	0	0	0	0	1	0	0	94	0	0	0	0	0	0	0	1	0	0
31	0	0	0	0	1	1	0	0	0	0	95	0	1	0	0	0	0	0	0	0	1
32	0	0	0	1	1	0	0	0	0	0	96	0	0	0	0	0	0	0	1	0	0
33	1	0	1	0	0	0	1	0	0	1	97	0	0	1	0	0	0	0	0	0	0
34	0	0	1	0	1	0	1	0	0	0	98	0	1	0	0	0	0	0	0	0	0
35	0	0	1	0	0	0	1	0	0	0	99	1	0	0	1	1	0	0	0	0	1
36	0	0	1	0	1	0	1	0	0	0	100	1	0	0	1	1	0	1	0	0	1
37	0	0	1	0	1	0	1	0	0	0	101	0	0	0	0	0	0	0	0	1	0
38	0	0	0	0	0	0	0	1	1	0	102	0	0	0	0	0	0	0	1	1	0
39	0	1	0	0	0	0	0	1	0	0	103	1	0	0	0	0	0	0	0	0	1
40	1	0	0	1	1	0	1	0	0	1	104	1	0	0	1	0	0	0	0	0	1
41	1	0	0	0	0	0	0	0	0	1	105	0	0	0	0	0	0	0	1	1	0
42	0	0	1	0	0	0	1	0	0	0	106	0	0	0	0	0	0	0	1	1	0
43	0	0	0	1	0	1	0	0	0	0	107	0	1	0	0	0	0	0	0	0	1
44	0	0	0	0	1	1	0	0	0	0	108	1	0	0	0	0	0	0	0	0	0
45	0	0	1	0	0	0	1	0	0	0	109	0	0	0	0	0	0	0	1	0	0
46	0	1	0	0	0	0	0	0	0	0	110	0	1	0	0	0	0	0	1	0	0
47	0	0	0	0	0	0	0	0	1	0	111	0	0	0	0	0	0	0	0	1	0
48	0	1	0	0	0	0	0	0	0	1	112	0	0	1	0	1	0	1	0	0	0
49	0	1	0	0	0	0	0	0	0	1	113	0	0	1	0	0	0	1	0	0	0
50	0	1	0	0	0	0	0	0	0	0	114	1	0	1	1	0	0	1	0	0	1
51	0	0	0	1	0	0	0	0	0	0	115	0	0	1	0	0	0	0	0	0	0
52	0	0	0	0	0	0	0	1	1	0	116	0	0	0	0	0	0	0	1	1	0
53	0	0	0	1	1	1	1	0	0	0	117	0	0	0	0	1	0	1	0	0	0
54	0	0	0	0	1	0	0	0	0	0	118	0	0	0	0	0	0	0	1	1	0
55	1	0	1	0	1	0	1	0	0	0	119	0	0	0	0	1	1	0	0	0	0

56	1 0 1 0 0 0 1 0 0 0	120	0 0 0 1 0 0 0 0 0 1
57	1 1 0 0 0 0 0 0 0 1	121	0 0 1 0 0 0 1 0 0 0
58	0 0 0 0 1 0 1 0 0 0	122	0 0 0 0 1 0 1 0 0 0
59	0 0 0 0 0 1 0 0 0 0	123	0 0 0 0 0 0 0 0 1 0
60	0 0 0 1 0 0 0 0 0 0	124	0 0 0 0 0 1 0 0 0 0
61	1 0 1 0 1 0 1 0 0 0	125	0 0 0 1 0 1 0 0 0 0
62	0 0 0 0 0 0 0 1 1 0	126	1 0 0 1 0 0 1 0 0 1
63	0 0 0 0 0 0 0 1 1 0	127	1 0 1 0 0 0 1 0 0 0
64	0 0 0 1 0 1 0 0 0 0	128	0 0 1 0 0 0 0 0 0 0

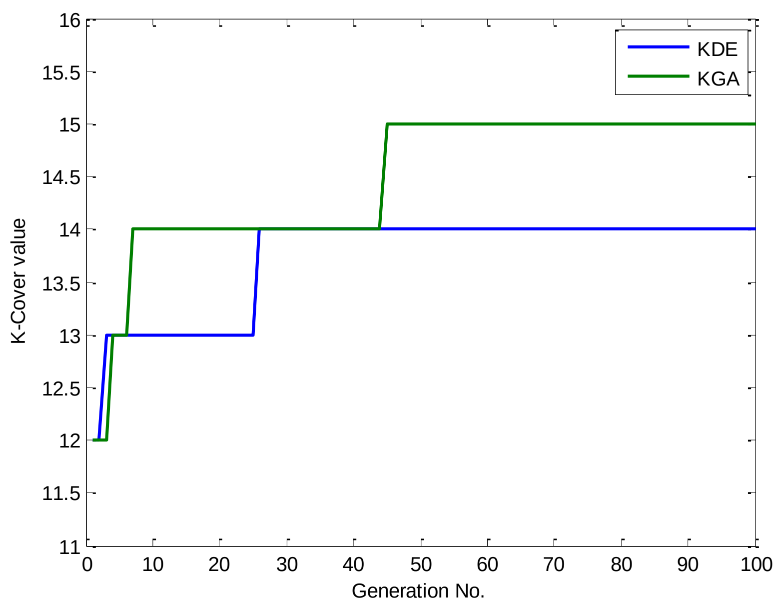


Fig.13. Best solution fitness convergence for case2

K-Disjoint Cover	Sensor No.
1	92 94 9 16 99 78 37 86 70 10
2	1 98 119 29 28 48 24 115 68 19 22 104
3	128 69 11 126 74 110 80
4	5 57 12 112 14 116
5	41 95 36 34 60 8 91 59
6	2 100 7 44 109 6 21 25 97 30
7	4 27 96 122 33 121 49 102 124 32
8	50 17 56 53 26
9	103 13 114 105 85 15 76 18 64

10	88 46 3 47 20 61 23 45 75
11	38 51 54 31 43 62 72 55
12	58 52 82 39 40 79 42 81
13	89 73 90 71 67 77 63
14	66 101 113 83 93 106 87 107
15	127 84 125 117 108 118
Unused Sensors	111 35 123 65 120

Table.4 Discovered disjoint set

As there were more number of sensors have been used so it was expected to have more number of disjoint covers. The fitness distribution by population members over different generation have shown in Fig.12 and observed that there was on average better fitness of population in the case of GA. The convergence characteristics have also shown in Fig.13 and observed that GA has given 15 disjoint cover while DE best evolution was 14 covers. It is also observed that there was faster evolution by GA in compared to DE. The final obtained disjoint cover by GA has shown in Table 4 where all 15 covers have in listed with their sensor members. Again unused sensors can be used if there is failure of any sensor in any cover and carried the same coverage as unused sensors have.

Case3.

No. Of Deployed sensors	500
No. Of useful sensors	442
No. of Target	15
Sensing Range	20

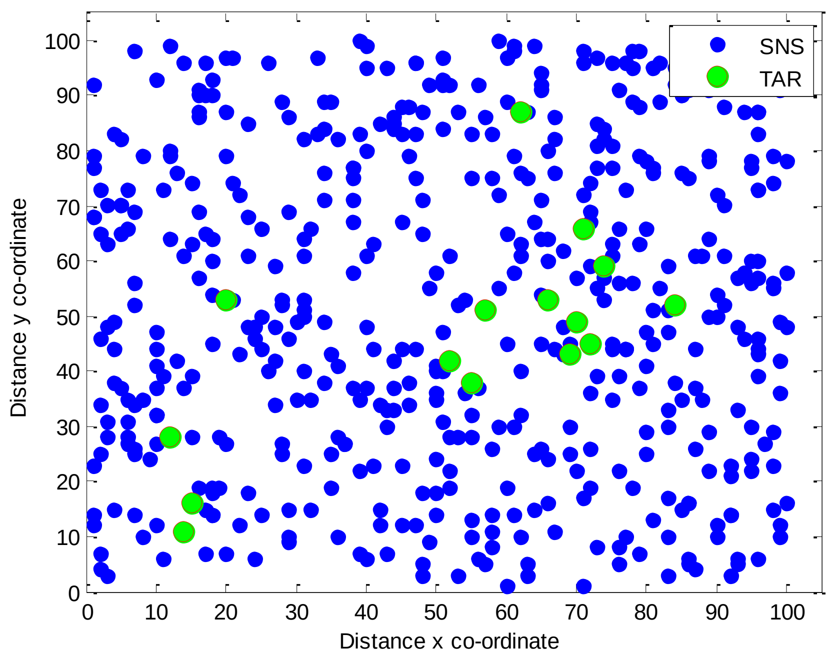


Fig.14. Raw network for the case 3

A large number of sensor 500 have been considered for a network carried 15 targets and its raw network as well as coverage matrix have shown in Fig.14 and Fig.15.As the number of sensors increased there are possibilities of more disjoint covers but at the same time discovering these covers is big challenge for the algorithms. Population fitness for different generation has shown in Fig.16 while convergence characteristics has shown in Fig.17. It can observe that again GA has shown better performance and have delivered 28 disjoint cover while DE has delivered 26 covers.

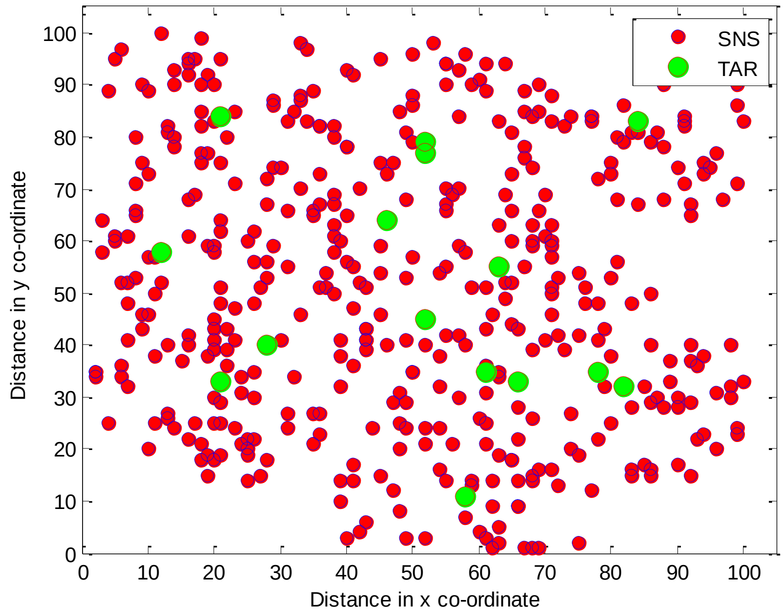


Fig.15. coverage matrix based applied network for case3

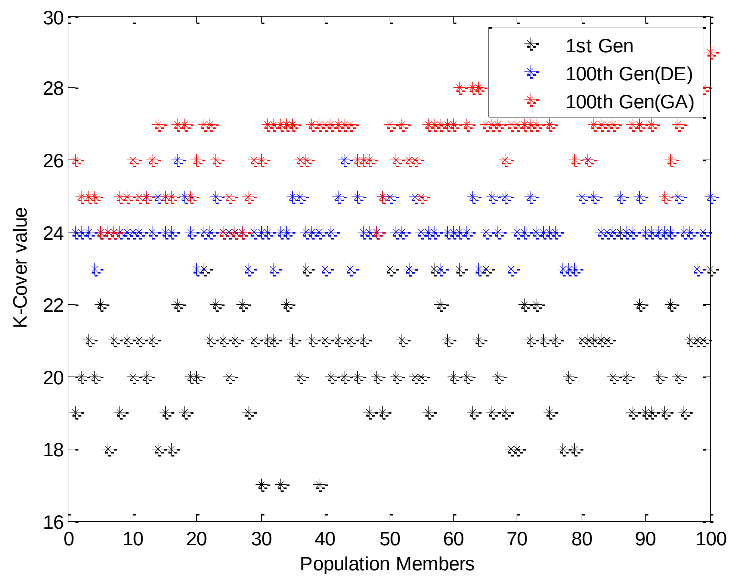


Fig.16. Population member fitness under different generation for case3

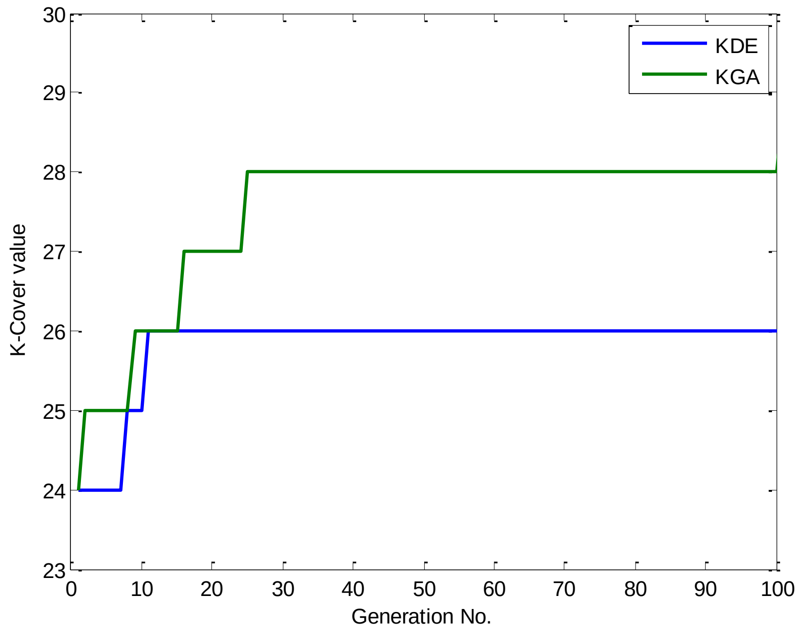


Fig.17. Best solution fitness convergence for case3

Conclusion

In most of the application where of WSN where placement of sensors were random and dropped large number of sensors, use of disjoint cover based solution can deliver the huge saving in the battery energy. Finding the disjoint covers are very difficult but heuristic based algorithm like GA has shown very satisfactory performances. The other benefit of direct integer coding in GA not only support for easy implementation but also free the error of transformation from continuous value to integer value. DE is very efficient over continuous search space but integer transformation has limited its efficiency. It is clear with simulation results that with very few number of sensors complete coverage can be done while keeping most of network sensors in sleep mode to save the energy.

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