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Differential Evolution Meta-Heuristic Scheme for k-Coverage and m-Connected Optimal Node Placement in Wireless Sensor Networks

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Abstract: **A wireless sensor network (WSN) faces a wide range of issues, which includes coverage of the given set of targets under specified connectivity constraint. There is a need to monitor different targets in the sensor field for effective information communication to the base station from each wireless sensor node which monitors the target by maintaining required connectivity among them. The problem of ensuring every target covered by at least k sensors and each sensor directly communicate with m sensors is termed as k-coverage and m-connectivity problem in wireless sensor networks. As the wireless sensor nodes are battery driven and have limited energy, the primary challenge is to have an optimal placement of sensor nodes in the field of deployment to minimize energy consumption. The objective of this work is to deploy the optimal number of sensor nodes with k-coverage and m-connectivity constraints in an area of interest. In the last few years, many meta-heuristic algorithms have been proposed to solve different problems like clustering and localization in WSN. In this paper, we introduce a meta-heuristic based differential evolution algorithm to solve k-coverage and m-connectivity problem in WSN. The simulation result shows that the proposed meta-heuristic method out performs the genetic algorithm.**

***Keywords*:** Node placement problem, k-coverage, m-connectivity, Differential evolution, Wireless sensor networks**.**

I. Introduction

The recent development in communication technology has enabled the development of low cost, low power, tiny devices, which communicate through short distances. These devices consist of sensing, processing, and communicating components. The collaborative setting of these sensor nodes forms the WSN. It has seen a wide variety of applications like fire detection in a forest or home appliances, flooding, earthquake, health applications, tsunami detection, military application and surveillance applications. Variety of use in urban areas which include traffic monitoring, air pollution monitoring, precipitation monitoring in sewage, asset monitoring, temperature monitoring, power grid monitoring, water pipeline monitoring, geo-sensing applications, etc [3].

Wireless sensor networks are facing challenges due to the limited battery source, limited communication range, prone to failure by external events, and security threats [29]. The coverage problem plays a vital role in extending the lifetime wireless sensor networks. The coverage problem is centered around, how well sensors cover physical space in a deployed area [4]. The performance indicators for WSN are network coverage, network connectivity, network cost and network lifetime. In this context, coverage of targets and connectivity of sensors are two important performance indicators for WSN. The coverage problem can be classified into target coverage problem, where sensor required to monitor the set of specific locations in the region and area coverage problem, where each sensor required to monitor an area of interest.

The target coverage problem divided into simple, k-coverage and Q-coverage. In simple coverage, each target covered by at least one sensor, where as in k-coverage and Q-coverage each target is monitored by at least k sensors and each target t_j is covered by q_j sensors respectively, where $1 \leq j \leq n$ and n is a number of targets. It is also required to look into the connectivity aspects of WSN. Sensors are m connected if at least m sensors are in the transmission range of each other. Sensor node placement is one of the most sought challenges of WSN, where it finds optimal locations to place sensor nodes so that some design objective under given constraints must be satisfied [18].

Two types of sensor node placement are found in the literature called random deployment of sensors and deterministic deployment of sensors [18], [20]. A random deployment of the sensor might be the best choice whenever sensing field is hostile (e.g. disaster areas). In this type of deployment, some part of the sensor field may have a high density of sensor nodes, and also some other parts of the field may have low density. In deterministic deployment, optimal locations to place sensors are known in advance such that one or many design objectives of the network must be fulfilled [18].

Many heuristic (i.e., approximation) algorithms are proposed to solve target coverage problem like [5], [4]. Heuristic techniques are adopted to provide near optima solutions, whenever exact solutions are does not achievable. Thus, most of the real-world problems find solution by adopting meta-heuristic techniques that does require objective function and the domain of the variable instead of detailed information about domain space[26]. The Differential Evolution(DE) is a meta-heuristic technique used in many optimization problems. This algorithm is useful whenever other bio-inspired algorithm fails [2]. It takes a name from a differentiation operation which is used in the process of evaluation. The DE algorithm uses similar characteristics of the Genetic Algorithm (GA) such as mutation, crossover, and selection. The variants of DE, The varity of applications, and its advancement discussed in detail [22], [23], [27], [28]. More detailed technical information and discussion also available in [26]. The DE based technique used in solving the clustering problem in WSNs [1]. The authors in [24] adopted DE to place sensor node on different geometric shapes which minimize energy and increase the coverage area of the network. The best of our knowledge no researcher attempts to solve “k-coverage and m-connectivity” problem of WSNs using DE. The GA has limitation over DE in solving different combinatorial optimization due to its premature convergence. Therefore, in this paper, we propose a DE-based approach to solve “k-coverage and m-connectivity” problem of WSN and compared with the GA approach.

The remaining parts of this paper are organized as follows. Section II briefs related works on heuristic technique, meta-heuristic schemes for target coverage, “k-coverage and m-connectivity” problems of WSN. Section III summarizes about classical DE. Section IV presents assumptions and problem statement. The proposed DE based approach elaborated in Section V followed by results and discussion in Section VI. Finally, the paper concluded in Section VII.

II. Related Work

To solve the target coverage problem, authors in [5] discussed a heuristic which produces a disjoint sensor cover. The disjoint set covers the entire area, and only one of the disjoint is active at any given point of time. The algorithm achieves a significant improvement in energy saving by preserving coverage area. The authors in [4] adopted an approximation algorithm, where the lifetime of the network extended without considering a disjoint set; thus, a sensor node can present in more than one sensor cover, and also proved that the target coverage problem belongs to NP-Complete class.

There have been several works on target coverage problem using many meta-heuristic algorithms. A multiobjective evolutionary scheme developed in [15] for prolong network coverage and lifetime, and also established a trade-off between these two issues, but connectivity issues have not considered in this scheme. The authors in [16] proposed a genetic algorithm (GA) technique for wireless sensor node placement with required coverage. But connectivity constraint not considered in their work. In [17] authors have discussed three coverage issues such as simple, Q-coverge, and k-coverage. In this scheme, the authors solved the coverage problem by designing cover optimization in the first phase, and M-connected optimization in the second phase. The main drawback of this algorithm is its high complexity. In [14] authors proposed an energy efficient technique for coverage and connectivity problem. In the proposed scheme, they are finding maximum disjoint sets of nodes for achieving required coverage and connectivity in the network. In [6] authors adopted the bio-inspired artificial bee colony scheme to solve the target coverage problem. In [7] a 2-connected target cover solution was proposed. In [8], the target coverage problem discussed with GA-based scheme, where authors selected the highest residual energy nodes in each generation to prolong the lifetime of the network. Harmony Search (HS)-based scheme for wireless sensor node placement proposed in [21]. The proposed scheme finds an optimal number of sensor nodes and also finds optimal locations to place sensor to maximize the coverage area of the field with minimum network cost. In [19] authors have proposed a solution for k-coverage of the network field by maintaining connectivity between the sensor nodes. In [25] a differential evolution based meta-heuristic technique is proposed for the target coverage problem in the wireless sensor network, and the scheme assigns an optimal disjoint set of sensors to targets. In [11], authors find cover set with minimum number of sensors to prolong the total network lifetime using GA-based approach. In order to achieve that, authors defined target coverage problem as maximum network life-time problem (MLP) and designed using the linear programming. Besides, authors in [12] developed genetic algorithms to identify the optimal positions to deploy sensor nodes in a way that the set of sensors covers the entire field and also ensures connectivity among them. The drawback of this technique is that crossover operation may produce an invalid offspring. This problem handled in [9], authors solved both coverage and connectivity problem using improved GA approach, where for a given a set of points, it finds the minimum number of potential positions to place sensor nodes to achieve k-coverage of targets and m-connectivity with other sensors. In [13] authors have proposed a Gravitational Search Algorithm (GSA)-scheme for wireless sensor node deployment in the network. This scheme provides l-coverage and n-connectivity in the WSN. The main drawback of GSA- scheme is that each wireless sensor sends sensed data to the base station directly, which in turn drains energy faster, and hence it degrades the performance of the network. Authors in [10] proposed a Biogeography-Based Optimization (BBO) scheme for solving the target coverage problem, where optimal sensors locations are computed for achieving k-coverage and m-connectivity of the given WSN. In this proposed work, differential evolution scheme adopted to solve the k-coverage and m-connectivity problem of the WSN.

III. Classical Differential Evolution

DE is a widely used evolutionary algorithm in many of the real-world applications. It is also used in diverse streams of engineering to solve a wide set of optimization problems. The algorithm is divided into four stages which include, initialization of population vector or chromosome, mutation, crossover, and selection. The algorithm. begins with a random population of specified size. Each vector is a solution to the optimization problem. The quality of individual vector determined using fitness value of that vector. Once the vectors are ready, the DE passes through, mutation, crossover, and selection process to obtain feasible solution vectors. Finally, depending on the fitness value best vector is selected as the best solution [2]. The various stages of classical DE is shown in Fig. 1

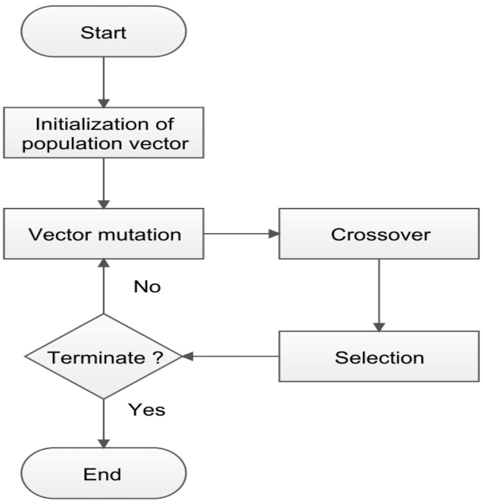


Figure 1. Flowchart of classical differential evolution

IV. Assumption and Problem Formulation

A. Assumption

In the proposed work, the WSN has modeled how targets are identified and are spread across an area of interest. A few candidate positions are predetermined to place sensors to sense the targets. We assume targets, candidate positions, and sensors are stationary. A wireless sensor node said to be covering a target if it is in its sensing range. Every sensor may cover one or more target. Data acquisition rounds are similar to technique proposed in [10]. Each sensor node forwards sensed data to the BS either directly or via other sensor nodes that are in its transmission range as shown in Fig. 2.

B. Problem formulation for node deployment

Let C denote the set of N candidate positions, $C = \{p_1, p_2 \ldots, p_N\}$ are predetermined locations on a field of interest and the set of m targets $T = \{t_1, t_2, \ldots, t_M\}$ are to be monitored. Then the objective is to select an optimal number of candidate locations to deploy wireless sensors such that it fulfills "k-coverage and m-connectivity" for a predetermined value of k and m.
Let C_{range} and S_{range} represents communication and sensing range of the wireless sensor nodes respectively.
Let $S(t_i)$, $T(s_i)$, and $C(s_i)$ represents set of sensor nodes monitors target t_i, set of target points monitored by sensor node s_i, and set of sensor nodes having direct communication range of sensor node s_i respectively.
Formally defined as follows,

$$S(t_i) = \{S_j \mid distance(t_i, s_j) \le S_{range}\}, \forall j\, 1 \le j \le P \quad (1)$$

$$T(s_i) = \{t_j \mid distance(t_j, s_i) \le S_{range}\}, \forall j\, 1 \le j \le M \quad (2)$$

$$C(s_i) = \{s_j \mid distance(s_i, s_j) \le C_{range}\}, \forall j\, 1 \le j \le P \quad (3)$$

To represent "k-coverage and m-connected" node deployment problem, and to define the coverage of targets, connectivity between senor nodes, and selection of final candidate position, we use variables t_{ij}, s_{ij}, and u_{ij} respectively. And formally defined as follows,

$$t_{ij} = \begin{cases} 1, if\ target\ t_i\ in\ the\ range\ of\ sensor\ node\ s_j \\ 0, \quad otherwise \end{cases} \quad (4)$$

$$s_{ij} = \begin{cases} 1, if\ sensor\ s_i\ in\ the\ range\ of\ sensor\ node\ s_j \\ 0, \quad otherwise \end{cases} \quad (5)$$

$$u_{ij} = \begin{cases} 1, \ if\ candidate\ location\ p_i\ is\ selected\ for \\ \quad node\ deployment\ \forall i\, 1 \le i \le N \\ 0, \quad otherwise \end{cases} \quad (6)$$

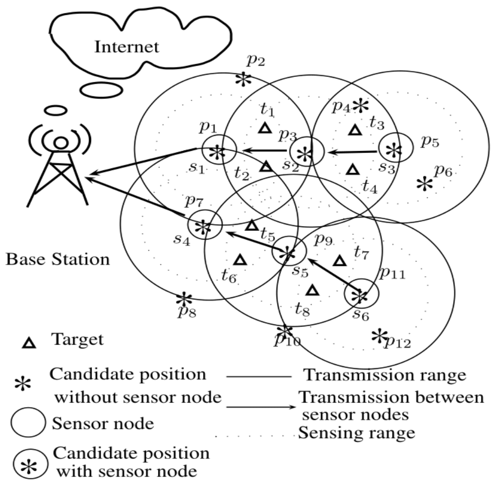


Figure 2. 2-covered and 1-connected wireless sensor network

Final LP-problem formulation from the Equation 4, 5, and 6 is expressed as follows

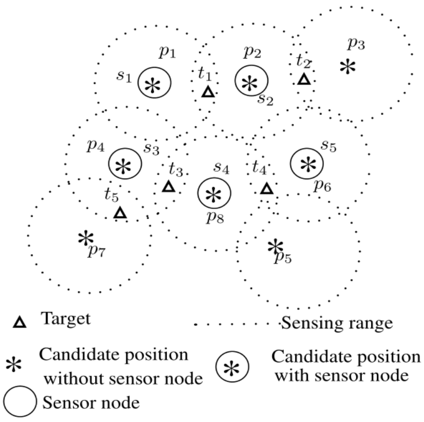
$$Minimize\ Z = \sum_{i=1}^{M} u_i \quad (7)$$

Subject to

$$\sum_{i=1}^{P} t_{ij} \ge k, \forall i\ 1 \le i \le M \quad (8)$$

$$\sum_{i=1}^{P+1} s_{ij} \ge m, \forall i\ 1 \le i \le P \quad (9)$$

a



b

Candidate Positions	p_1	p_2	p_3	p_4	p_5	p_6	p_7	p_8
Vector Values	1	1	0	1	0	1	0	1

Figure 3. a. A WSN with 5 targets and 8 candidates positions **b.** Vector representation

V. Proposed Differential Evolution-Based Algorithm

In this paper, we discuss k-coverage and m-connected wireless sensor node deployment in a wireless sensor network.
Definition 1: k-coverage and m-connectivity Problem
Let C denote the set of N candidate positions, $C = \{p_1, p_2, \ldots, p_N\}$ to deploy sensor nodes to cover M targets $T = \{t_1, t_2, \ldots, t_M\}$, find optimal sensor node placement positions so that,

1. Each target is monitored by at least k wireless sensor nodes, where $1 \leq k \leq M$.
2. Each wireless sensor node in C is in the range of at least m other nodes in C, where $1 \leq m \leq N$.
3. Minimize $\frac{P}{N}$, Where P is the obtained candidate locations to deploy sensor nodes, and N is the total number of candidate locations.

A. Vector encoding

In the proposed technique, each vector represented by an array of Boolean values. The length of each vector equals to the number of candidate positions on a target area. For a vector, the i^{th} entry value 1 to indicates a wireless sensor node is deployed on the i^{th} candidate location and the entry value 0 represents no wireless sensor node deployed at the i^{th} candidate location.

Illustration 1

Let a target based WSN with 5 targets $T = \{t_1, t_2, \ldots, t_5\}$ and 8 candidate positions $C = \{p_1, p_2, \ldots, p_8\}$ as shown in Fig 3a. The length of the vector is 8 as according to the number of candidate positions. Fig.3b represents a vector, where vector positions p_1, p_2, p_4, p_6 and p_8 have value 1, which indicates sensor nodes are deployed on candidate positions and vector positions p_3, p_5, and p_7 have value 0, which implies no sensor nodes placed on candidate position.

B. Initialization of the population vector

The scheme represents vector as follows. Each vector represents a selection of candidate positions to place sensors. The G^{th} generation of i^{th} vector having N components is indicated as $X_{i,G} = [x_{1,i,G}, x_{2,i,G}, x_{3,i,G}, \ldots, x_{N,i,G}]$

C. Derivation of fitness function

Our design objective is to obtain an optimal number of candidate locations from the set of candidate locations so that each target is k-covered and each wireless sensor node m-connected with other wireless sensor nodes for some predetermined values of k and m. We adopt the following parameters to design fitness function as described below

1. k-coverage of the targets (f_1)

To achieve k-coverage of a target, at least k wireless sensor node must monitor the target. So, we obtain the first objective of fitness function as follows,

$$Maximize\ f_1 = \frac{1}{M \times k} \sum_{i=1}^{M} CovCost(t_i) \quad (10)$$

Where M is number of target points and $CovCost(t_i)$ is defined as follows,

$$CovCost(t_i) = \begin{cases} k, & if\ |S(t_i)| \geq k \\ k - |S(t_i)|, & otherwise \end{cases} \quad (11)$$

2. m-connectivity of the sensor nodes (f_2)

To fulfill m-connectivity of the wireless sensor nodes, each deployed wireless sensor node required to maintain at least m-connectivity among other sensors. So, we define the second objective of the fitness function as follows,

$$Maximize\ f_2 = \frac{1}{P \times m} \sum_{i=1}^{P} ConCost(s_i) \quad (12)$$

Where P is number of selected candidates positions out of N candidate positions to deploy nodes and $ConCost(s_i)$ is defined as follows

$$ConCost(s_i) = \begin{cases} m, & if\ |C(s_i)| \geq m \\ k - |C(s_i)|, & otherwise \end{cases} \quad (13)$$

3. Selection of optimal candidate positions (f_3)

The main objective of our scheme to determine optimal candidate locations (P) so that each target point must satisfy k-coverage and each sensor monitor the target must fulfill m-connectivity with other sensors for a predetermined value of k and m. And hence we define the third objective of the fitness function as follows,

$$Maximize\ f_3 = \left(1.0 - \frac{P}{N}\right) \quad (14)$$

On the basis of individual objectives f_1, f_2, and f_3 we devise the final fitness function F as follows

$$Maximize\ Fitness\ F = w_1 \times f_1 + w_2 \times f_2 + w_3 \times f_3 \quad (15)$$

Where w_i is weight with $0 < w_i \leq 1,\ 1 \leq i \leq 3$ and $w_1 + w_2 + w_3 = 1$. The objective is to find the better vector having highest fitness value.

D. Mutation

We adopted DE/best/1/bin scheme [2] for mutation and crossover operation. For each vector of the population (called target vector), a mutation chromosome obtained through a DE mutation process. In this scheme, out of three chromosomes, the best chromosome and two random distinct chromosomes are selected which are different from current target vector. Let $X_{i,G}$, $X_{best,G}$ and $V_{i,G}$ are target, best, and donor vectors respectively. Then the mutation chromosome is obtained as follows

$$V_{i,G} = X_{best,G} + \mu \times D_{i,G} \quad (16)$$

where μ a scaling factor which lies in the interval [0.4, 1] [2]. We set μ as 1.0 and $D_{i,G} = X_{r,G} - X_{s,G}$ with $r, s \in [1, P]$, such that $r \neq s \neq best$. This classical mutation operation does not work for our scenario. This is because the subtraction of two components of the vectors gives a difference vector with negative values. Due to the fact that our vectors consist of 0 and 1, we adopted the scheme proposed in [1].

$$D_{j,i,G} = \begin{cases} 1 + X_{j,r,G} - X_{j,s,G}, & if\ X_{j,r,G} - X_{j,s,G} \leq 0 \\ X_{j,r,G} - X_{j,s,G}, & otherwise \end{cases} \quad (17)$$

Again, the same problem may occur at the time of addition operation. Therefore, donor vectors are generated as mentioned in [1].

$$V_{j,i,G} = \begin{cases} X_{j,best,G} + \mu \times D_{j,r,G} - 1, & if\ X_{j,best,G} + X_{j,r,G} > 1 \\ X_{j,best,G} + \mu \times D_{j,r,G}, & otherwise \end{cases} \quad (18)$$

E. Crossover

A trial vector $U_{i,G}$ is derived from the target vector $X_{i,G}$ and the donor vector $V_{i,G}$ as shown below

$$U_{j,i,G} = \begin{cases} V_{j,i,G}, & if\ rand() \leq C_r \\ X_{j,i,G}, & otherwise \end{cases} \quad (19)$$

where C_r is the crossover probability set to 0.2. To generate a j^{th} component of a trial vector, a random number obtained between 0 and 1. If the random number less than or equal to C_r, then we select j^{th} component of donor vector as j^{th} component of the trial vector; otherwise, it is selected from the target vector. The entire process of crossover is depicted in Fig. 4.

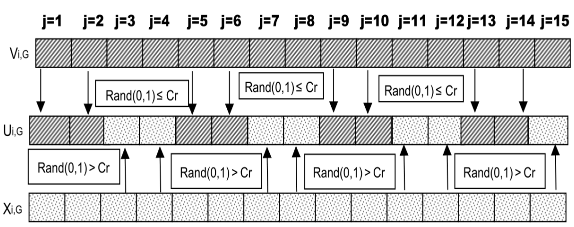


Figure 4. Crossover operation

F. Selection

The selection process determines the chromosome survives for the next generation, either target chromosome or trial chromosome. Both of these chromosomes are evaluated to find fitness values. The target vector $X_{i,G}$ is compared with the trial vector $U_{i,G}$ and one with the lowest fitness value is selected for the next generation as shown below

$$X_{i,G+1} = \begin{cases} U_{i,G}, & if\ fitness\,U_{i,G} \geq fitness\,X_{i,G} \\ X_{i,G}, & otherwise \end{cases} \quad (20)$$

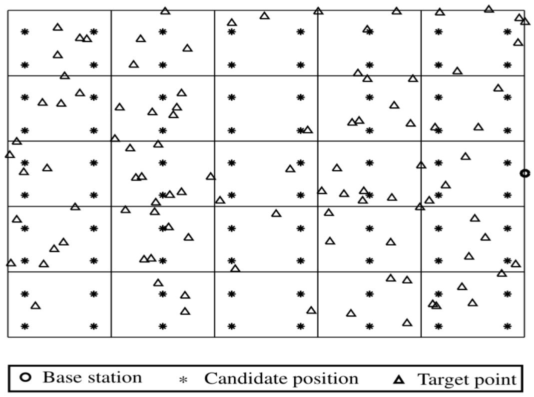


Figure 5. The first scenario, where candidate position are on a grid

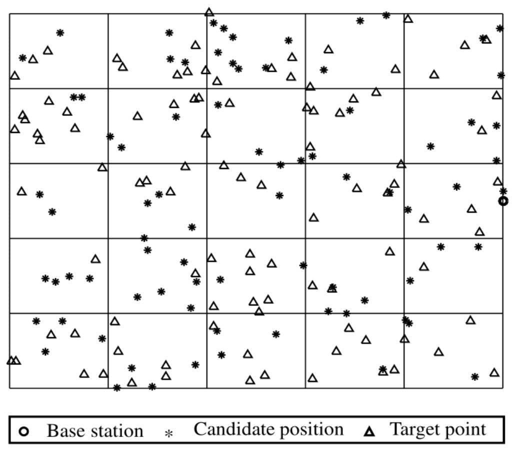


Figure 6. The second scenario, where candidate position are random

Illustration 2

Consider a wireless sensor network with 5 candidate positions to place sensors $C = \{p_1, p_2, \ldots, p_5\}$ and 4 targets $T = \{t_1, t_2, \ldots, t_4\}$ as shown in Fig. 7. An optimal node placement shown in Fig. 7a, which obtains a vector(chromosome) as shown in Table 2a and Table 2b. The integer 1 in the cell indicates selection, the integer 0 indicates non selection, and the symbol '-' indicates operation not applicable for the cell. The variable $CovCost(t_i)$ and $ConCost(s_i)$ represents coverage cost of targets and connectivity cost of sensors respectively.

The fitness value of vector computed using the Eq. 15 is given by,

$F_1=w_1\times f_1+w_2\times f_2+w_3\times f_3$, where $w_1=0.3,\ w_2=0.3,\ w_3=0.4$

and $f_3=1.0\text{-}P/N=1.0\text{-}3/5=0.4$.

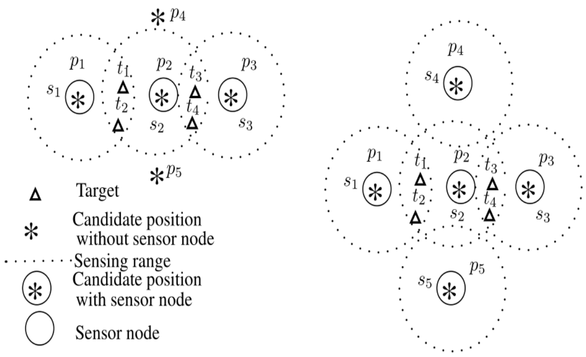
$F_1=0.3\times 1+0.3\times 1.3+0.4\times 0.4=0.85$, here f_1 and f_2 are taken from Table 2a and Table 2b respectively. The Table 3a and Table 3b represents a vector with an extra sensors node placement as shown in Fig. 7b. The fitness value of vector computed using the Eq. 15 is given by,

$F_2=w_1\times f_1+w_2\times f_2+w_3\times f_3$, where $w_1=0.3,\ w_2=0.3,\ w_3=0.4$

and $f_3=1.0\text{-}P/N=1.0\text{-}5/5=0.0$.

$F_2=0.3\times 1+0.3\times 1.6+0.4\times 0.0=0.78$, here f_1 and f_2 are taken from Table 3a and Table 3b respectively.

Since our objective is to maximize fitness function, the vector whose fitness value $F_1=0.85$ is better than the vector whose fitness value $F_2=0.78$.



a b

Figure 7. 2-coverage and 1-connected network scenarios **a.** optimal number of placed wireless sensor nodes and **b.** unnecessary and extra placed

Parameters	**Values**
Size of the network	300×300
Location of the sink	300,300
Number of target points	100
Number of potential positions	100-400
Sensing range	15
Communication range	30
Maximum Iteration	100
Population Size	100
Crossover Probability	0.2
Mutation factor(μ)	1.0

Table 1. Simulation parameters.

Targets	**Sensors**					
	p_1	p_2	p_3	p_4	P_5	**CovCost(t_i)**
	1	1	1	0	0	
t_1	1	1	0	-	-	2
t_2	1	1	0	-	-	2
t_3	0	1	1	-	-	2
t_4	0	1	1	-	-	2

$$f_1=\frac{1}{M\times k}\sum_{i=1}^{M}CovCost\left(t_i\right)=1$$

Table 2a. CovCost determination in optimal sensor node placement.

Targets	**Sensors**					
	p_1	p_2	p_3	p_4	P_5	**ConCost(s_i)**
	1	1	1	0	0	
p_1	-	1	0	-	-	1
p_2	1	-	1	-	-	2
p_3	0	1	-	-	-	1
p_4	-	-	-	-	-	-
p_5	-	-	-	-	-	-

$$f_2=\frac{1}{P\times m}\sum_{i=1}^{P}ConCost\left(s_i\right)=1.3$$

Table 2b. ConCost determination in optimal sensor node placement.

Targets	**Sensors**					
	p_1	p_2	p_3	p_4	P_5	**CovCost(t_i)**
	1	1	1	1	1	
t_1	1	1	0	0	0	2
t_2	1	1	0	0	0	2
t_3	0	1	1	0	0	2
t_4	0	1	1	0	0	2

$$f_1=\frac{1}{M\times k}\sum_{i=1}^{M}CovCost\left(t_i\right)=1$$

Table 3a. CovCost determination in unnecessary extra sensor nodes placement.

Targets	Sensors					
	p_1	p_2	p_3	p_4	P_5	**ConCost(s_i)**
	1	1	1	1	1	
p_1	-	1	0	0	0	1
p_2	1	-	1	1	1	4
p_3	0	1	-	0	0	1
p_4	0	1	0	-	0	1
p_5	0	1	0	0	-	1

$$f_2 = \frac{1}{P \times m} \sum_{i=1}^{P} ConCost\left(s_i\right) = 1.6$$

Table 3b. ConCost determination in unnecessary extra sensor nodes placement.

Algorithm V.1 The DE based k-coverage and m-connected algorithm for WSN

Input: Set of M targets, set of N candidate positions, values of k and m

Output: Set of optimal candidate positions with k-coverage and m-connectivity

// Generate initial population of size P
1. for $i = 1$ to P
2. Initialize each i^{th} individual
   // Using random function.

// Differential algorithm starts
1. for $itr = 1$ to $Max_{iteration}$
   // Generation
2. for each member vector of population $X_{i,G}$
3. Compute the fitness using Eq.15
4. Select best member vector $X_{best,G}$ using best fitness value.
5. Select two random number $X_{r,G}$ and $X_{s,G}$ such that $r, s \in [1, P]$ $r \neq s \neq best$ and set μ=1.0.
6. Perform mutation operation using Eq.18
7. Set crossover probability (C_r=0.2).
8. Perform crossover operation using Eq.19
9. Perform selection operation using Eq. 20
10. Obtain $Best_{fitness}$ and $X_{best,G}$

// Obtain optimal positions from $X_{best,G}$
11. Obtain selected candidate positions with k-coverage and m-connectivity.

VI. Experimental results

In this section, we discuss the simulation results of the proposed scheme. For simulation, we have used MATLAB R2017b and C programming language. In our experiment, we have considered two scenarios with random and grid deployment of sensors as shown in Fig. 5 and Fig. 6. We used the parameters mentioned in Table 1 to carry out simulations. A set of random and grid based wireless sensor networks generated within a field size of 300 × 300. The number of candidate positions varied from 100 to 400 in steps of 50; The 100 targets randomly placed on both the scenarios. The network is assumed be homogeneous, initial energy of each sensor 1J, and sensing range and communication range of each sensor 15 and 30 respectively. For our proposed approach, we considered a population of 100 vectors and 100 generations. We assumed a crossover rate (C_r) and scaling factor(μ) as 0.2 and 1.0 respectively.

The Fig. 8 shows performance comparison of different coverage and connectivity requirement for grid scenario. The Fig. 9 show comparison results of different coverage and connectivity requirement for random scenario. Both the scenarios show optimal selected candidate positions by satisfying k-coverage and m- connectivity demands of the wireless sensor networks. The Fig. 10 and Fig. 11 shows a comparison between DE-based approach and GA-based approach both in grid network and random network respectively, where we considered 100 and 300 as targets points and wireless sensor nodes respectively.

It can be noted that the proposed technique selects minimum number of candidate positions for deploying sensor nodes compare to GA-based scheme. It is also viewed that, selected candidate positions are more for random scenario compare to grid scenario, due to the reason that candidate positions are decided uniformly on a grid. The under performance of GA-approach over DE-approach due to premature convergence of GA-approach.

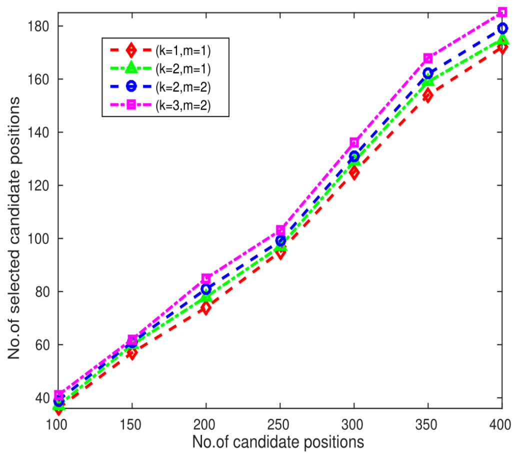


Figure 8. Performance comparison of DE-based scheme in terms of number of selected candidatelocations for grid scenario

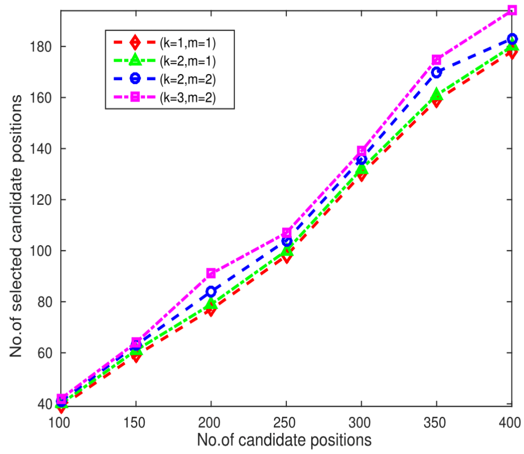


Figure 9. Performance comparison of DE-based scheme in terms of number of selected candidate locations for random scenario

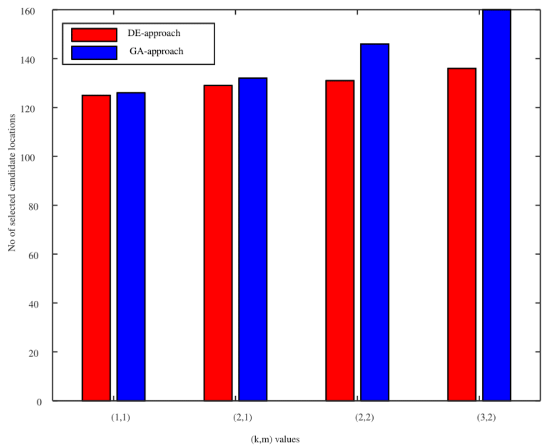


Figure 10. Performance comparison between DE-based scheme and GA-based scheme in terms of number of selected candidate locations for grid scenario

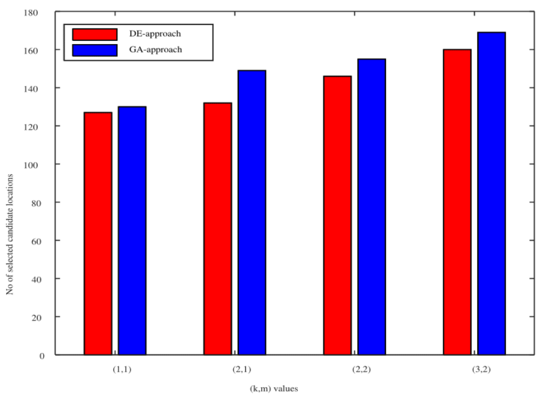


Figure 11. Performance comparison between DE-based scheme and GA-based scheme in terms of number of selected candidate locations for random scenario

VII. Conclusion

Most of the real world applications demand a high degree of connectivity and coverage of wireless sensor networks. In this paper, we have proposed a Differential Evolution based meta-heuristic technique for solving k-coverage and m-connectivity problem in WSN. The technique finds an optimal number of selected candidate positions for deployment of sensor nodes with specified k-coverage and m- connectivity demands of the wireless sensor network. We have adopted an efficient method to represent vectors of the population as well as for fitness calculation, then applied mutation, crossover, and selection operators to choose the best vector of the population. The steps of computing fitness values are illustrated. The simulations are performed by varying candidate sensor node positions and targets points along with coverage and connectivity specification. In addition, we have compared our proposed technique with a genetic algorithm based approach. The result confirms that the proposed approach is superior to the GA based approach.

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References

[1] Kuila, Pratyay and Jana, Prasanta K, "A novel differential evolution based clustering algorithm for wireless sensor networks", *Applied soft computing*, Elsevier, vol. 25, number 4, pp. 414–425, 2014.

[2] Storn, Rainer and Price, Kenneth, "Differential evolution a simple and efficient heuristic for global optimization over continuous spaces", *Journal of global optimization*, Springer, vol. 11, number 4, pp. 341–359,1997.

[3] Akyildiz, Ian F and Su, Weilian and Sankarasubramaniam, Yogesh and Cayirci, Erdal,"Wireless sensor networks:a survey", *Computer networks*, Elsevier, vol.38, number 4, pp. 393–422, 2002.

[4] Cardei, Mihaela and Thai, My T and Li, Yingshu and Wu, Weili: "Energy-efficient target coverage in wire-less sensor networks". In *INFOCOM 2005. 24th annual joint conference of the IEEE computer and communications societies,*IEEE,vol.3,pp, 1976–1984, 2005.

[5] Slijepcevic, Sasha and Potkonjak, Miodrag: "Power Efficient organization of wireless sensor networks", In *communication*, IEEE, vol. 2, pp. 472-476, 2001.

[6] Mini, S and Udgata, Siba K and Sabat, Samrat L, "Sensor deployment and scheduling for target coverage problem in wireless sensor networks", *IEEE sensors journal*, IEEE, vol. 14, number 3, pp.636-644, 2014.

[7] Panda, Bhawani S and Bhatta, Bijaya K and Mishra, Sambit Kumar: "Improved Energy-Efficient Target Coverage in Wireless Sensor Networks". In *International Conference on Computational*

Science and Its Applications, Springer, pp. 350–362, 2017.

[8] Singh, Deepti and Chand, Satish and Kumar, Bijendra and others: "Target Coverage Heuristics in Wireless Sensor Networks". In *Advanced Computing and Communication Technologies*, Springer, pp. 265–273, 2018.

[9] Gupta, Suneet Kumar and Kuila, Pratyay and Jana, Prasanta K, "Genetic algorithm approach for k-coverage and m-connected node placement in target based wireless sensor networks", *Computers & Electrical Engineering*, Elsevier, vol. 56, pp. 544–556, 2016.

[10] Gupta, Govind P and Jha, Sonu, "Biogeography-based optimization scheme for solving the coverage and connected node placement problem for wireless sensor networks", *Wireless Networks*, Springer, pp. 1–11, 2018.

[11] Chand, Satish and Kumar, Bijendra and others, "Genetic algorithm-based meta-heuristic for target cover- age problem", *IET Wireless Sensor Systems*, Elsevier, vol. 8, number 4, pp. 170–175, 2018.

[12] Rebai, Maher and Snoussi, Hichem and Hnaien, Faicel and Khoukhi, Lyes and others, "Sensor deployment optimization methods to achieve both coverage and connectivity in wireless sensor networks", *Computers & Operations Research*, Elsevier, vol. 59, pp.11–21, 2015.

[13] Jehan, C and Punithavathani, D Shalini, "Potential position node placement approach via oppositional gravitational search for fulfill coverage and connectivity in target based wireless sensor networks", *Wireless Networks*, Elsevier, vol. 23, number 6, pp. 1875–1888, 2017.

[14] Liu, L and Hu, B and Li, L, "Energy conservation algorithms for maintaining coverage and connectivity in wireless sensor networks", *IET communications*, IET, vol. 4, number 7, pp. 786–800, 2010.

[15] Le Berre, Matthieu and Hnaien, Faicel and Snoussi, Hichem: "Multi-objective optimization in wireless sensors networks". In *Microelectronics (ICM), 2011 International Conference*, IEEE, pp. 1–4, 2011.

[16] Yoon, Yourim and Kim, Yong-Hyuk, "An efficient genetic algorithm for maximum coverage deployment in wireless sensor networks", *IEEE Transactions on Cybernetics*, IEEE, vol. 43, number 5, pp. 1473–1483,2013.

[17] Mini, S and Udgata, Siba K and Sabat, Samrat L, "M-Connected Coverage Problem in Wireless Sensor Networks", *ISRN Sensor Networks*, Hindawi Publishing Corporation, 2012.

[18] Wang, Bang, "Coverage problems in sensor networks: A survey", *ACM Computing Surveys (CSUR)*, ACM, vol. 43, number 4, 2011.

[19] Kalayci, Tahir Emre and Yildirim, Kasim Sinan and Ugur, Aybars, "Maximizing coverage in a connected and k-covered wireless sensor network using genetic algorithms", *International Journal of Applied Mathematics and Informatics*, vol. 1, number 1, pp. 123–130,2007.

[20] Deif, Dina S and Gadallah, Yasser, "Classification of wireless sensor networks deployment techniques", *IEEE Communications Surveys & Tutorials*, IEEE, vol. 16, number 2, pp. 834–855,2014.

[21] Mohd Alia, Osama and Al-Ajouri, Alaa, "Maximizing wireless sensor network coverage with minimum cost using harmony search algorithm", *IEEE Sensors Journal*, IEEE, vol. 17, number 3, pp. 882–896, 2017.

[22] Das, Swagatam and Suganthan, Ponnuthurai Nagaratnam, "Differential evolution: a survey of the state-of- the-art", *IEEE transactions on evolutionary computation*, IEEE, vol. 15, number 1, pp. 4–31, 2011.

[23] Das, Swagatam and Mullick, Sankha Subhra and Suganthan, Ponnuthurai N, "Recent advances in differential evolution an updated survey", *Swarm and Evolutionary Computation*, Elsevier, vol. 27, pp. 1–30, 2016.

[24] Céspedes-Mota, Armando and Castañón, Gerardo and Martínez-Herrera, Alberto F and Cárdenas-Barrón, Leopoldo Eduardo and Sarmiento, Ana María, "Differential evolution algorithm applied to wireless sensor distribution on different geometric shapes with area and energy optimization", *Journal of Network and Computer Applications*, Elsevier, vol. 119, pp. 14–23, 2018.

[25] Chandra Naik, D Pushparaj Shetty, "A Novel Metaheuristic Differential Evolution Algorithm for Optimal Target Coverage in Wireless Sensor Networks", In *Innovations in Bio-Inspired Computing and Applications*, Springer, vol. 939, pp. 83-92, 2019.

[26] Rajpurohit, Jitendra and Sharma, Tarun Kumar and Abraham, Ajith and Vaishali, A "Glossary of metaheuristic algorithms", *Int. J. Comput. Inf. Syst. Ind. Manag.* Appl, vol. 9, pp. 181–205, 2017.

[27] Das, Swagatam, Ajith Abraham, and Amit Konar. *Metaheuristic clustering*. Vol. 178. Springer, 2009.

[28] Fan, Qinqin and Yan, Xuefeng and Zhang, Yilian, "Auto-selection mechanism of differential evolution algorithm variants and its application", *European Journal of Operational Research*, Elsevier, vol. 270, number 2, pp. 636–653, 2018.

[29] Ranjan, Pratik and Om, Hari: "Computational Intelligence Based Security in Wireless Sensor Networks: Technologies and Design Challenges". In *Computational Intelligence in Wireless Sensor Networks*, Springer, pp. 131–151, 2017.

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