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A Swarm Intelligence Based Coverage Hole Healing Approach for Wireless Sensor Networks

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Abstract

In the WSN network, nodes are always deprived of battery and can't be in operation for a long time. Some nodes may die sooner than others, creating a void in the area. Our work in this article covered this hole area efficiently with the introduction of a novel hybrid optimization algorithm. Our algorithm makes the locally converging particle swarm optimization to a global optimization algorithm by ensembling it with the Gravitational search algorithm. The perturbation in this algorithm is also reduced by logistic chaotic mapping. The current solution has detected the holes and healed them with additional redundant nodes. The Delaunay triangulation method detected the number of holes with the improved algebraic approach. The results are validated by extensive experimentation with different sensing range and node's density. Our method seems to perform well than state of the art schemes. We have also shown that increasing the redundant nodes, more coverage can be achieved.

Keywords: WSN, ROI, PSO, Chaotic, GSA.

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1. Introduction

Wireless Wireless Sensing Network (WSN) has wide applications in the monitoring of physical environments. It contains lots of sensor nodes for the collection of information and events. All the sensors cover the region of interest (ROI) and obtain adequate monitoring information. The coverage in WSN can be classified in the three categories area coverage, barrier coverage, and target coverage. The coverage of ROI maximizes via area coverage, the set of target cover in the target coverage and barrier coverage deal with the probability of unidentified penetration via a sensor network. Few sensor nodes lack in proper operation due to their random deployment and energy exhaustion of nodes. These die soon and create a coverage hole. That area remains out of sensor nodes' communication range. These coverage holes affect the entire performance of WSN. The events detection ability and network reliability are directly affected by the coverage holes induced in WSN. The coverage holes problem in WSN belongs to the optimization of assets available in the area. The coverage holes cannot be eliminated from WSN, and their number will increase if not provide any solution. For smooth and efficient sensor network, the detection and healing of coverage holes must be required. The avoidance of coverage holes is infeasible, so the scheme which provided accurate coverage holes detection and repaired them in a short period has practical importance.

In previous years many researchers have suggested solutions on coverage holes detection and restoration [1-11]. The coverage optimization problem discussed with different coverage models which provided the sensor sensing capacity [1]. An RSSI approach was proposed for the coverage holes detection and recovery process in [2]. Author simplified the ellipse model of WSN using RSSI based sensor localization approaches. However, an RSSI approach faces some issue in specific applications like an infeasible solution in animal monitoring. A crucial intersection point (CIP) based localized method proposed in [3] for identification of coverage holes and perpendicular bisection based position estimation technique provided coverage holes restoration. It required minimum sensor nodes for the restoration of coverage holes.

Some methods used the computational geometry like Voronoi [4] and Delaunay triangulation [7, 10, 18,and 20] for the coverage holes identification. A Distributed Voronoi based Cooperation (DVOC) method was proposed for the K-coverage holes detection and restoration. The k-coverage target area provided the robustness to WSN [4]. Li et al. provided a tree and graph scheme for the identification of sensor node holes in ROI. It recognizes the shape, size, and position of coverage holes [5]. A deep Branch-and-Cut algorithm was used for the coverage holes reduction in C-RAN. It achieved complete coverage holes detection with an increment of convergence time and reduced internal disturbances. An adaptive routing based approach is used for coverage hole detection in [38]. Delaunay triangulation approach applied for the graph formation in triangle shape [7]. A hybrid optimization algorithm SAPSO proposed for the restoration of moving nodes in the coverage holes areas. It provides the global search as well as the local solution of unconstrained coverage holes detection problem in WSN[8]. An active contour model-based approach used for the coverage holes detection and PSO optimization implemented for the coverage recovery phase. The healing process provided efficient leverage mobility to evaluate mean coverage rate and motion distance among the sensor nodes of WSN [9]. The Delaunay triangulation[18] based distance-vector hole determination (DVHD) and Gaussian curvature-based hole determination (GCHD) with Gauss-Bonnet theorem used for the coverage hole identification. DHVD is a weighting model which identifies the boundaries of the holes with distance among two nodes [10]. A CHDR algorithm proposed for the coverage hole detection and repair in-network disconnection [11].

In [12], the deployment of static sensor scheme was proposed for the identification of an unseen target in free space condition. PSO and time cumulative probability curves estimated the best position of the sensors. The Monte Carlo simulation proposed in [13] for the deployment of static sensors. The residual energy concept used to detect the coverage holes in [14] and evaluated the life expectancy of processing nodes. In the WSN network, some routing protocols are available. The holes can be formed in the routing and coverage portion. In [16] both coverage and routing hole detection were proposed using graph symmetry. A Ranging Multidimensional Scaling (RMSD) implemented for the coverage hole detection [17]. It provided the distance among all the senor nodes included the holes with Time of Flight (TOF). The accurate distance is achieved by using CLF (coverage aware and link correlation balance) scheme, which identified the boundary of the holes. In [19] the author used the WHD (Wireless Sensor Hole Detection) algorithm for the calculation of hole area in WSN. The Grid algorithm partition the ROI in balanced cells and their location provided the coverage hole boundary. A hybrid network consists of both fix and the dynamic sensor was studied in [20].Geometrical approach - Delaunay triangulation used for the detection of coverage holes in hybrid WSN. In [21] Cat swarm Optimization (CSO-WT) Wavelet Transform approach was proposed for the sensor deployment in 3D WSN. CSO provided better coverage performance than the other optimization algorithm used in 3D WSN. The Voronoi and Delaunay triangulation approach proposed for the coverage hole detection and restoration of an ellipse model[22]. A random mobility model proposed in [23] for the coverage hole detection with geometrical approaches.

In real time test bed it is very challenging to identify the coverage hole. The realization of coverage hole is explained in [37] with the help of test bed. The swarm intelligence based approaches provide a better solution in different applications like healthcare monitoring [31, 32, 34, and 35], supply chain management [33] and thermal analysis. The Analogous Particle Swarm Optimization (APSO) [31] and Parallel Particle Swarm Optimization (PPSO) [35] approaches act as the cloud computing environment for optimal selection of virtual machine (VM) to process a medical demand. The optimal selected VM is used to predict kidney disease. The execution time of APSO is 1 second, which is less than the existing approach. A survey is presented for the diagnosis of a chronic disorder of humans via nature-inspired optimization algorithms. Various algorithms like Ant Lion Optimization (ALO), Ant Colony Optimization (ACO), Glow-Worm Swarm Optimization (GSO), Artificial Bee Colony (ABC) and Firefly Algorithm (FA) are presented for the diagnosis of a chronic disorder in human [32]. All these nature-inspired schemes are also proposed for the diagnosis of fatal disease [34]. A state of art literature review of supply chain management (SCM) by swarm intelligence (SI) is presented in [33]. An Integrated PSO (iPSO) algorithm is used to compute the heat losses of the thermal receiver tube [36]. The SI based approaches provided efficient outcomes than other nature-inspired optimization algorithms.

We propose a novel hole healing approach based on the hybrid Chaotic PSO GSA optimization algorithm. The papers form [24-27] reflected the Chaotic PSO used for different applications. In [24] the overall convergence improved by update the value of r1 and r2 in PSO chaotically. The addition of chaotic nature by logistic mapping in the current position of the swarm and update it with the usual formula [25, 27]. In [26] algorithm generates the initial swarm chaotically using logistic mapping and add chaotic disturbance in gravitational constant of GSA to update the best position of redundant nodes.

2. Hole Detection Problem Formulation

We focus on the coverage holes identification in WSN using the Delaunay triangulation (DT) techniques. This method is applicable for both 2D and 3D applications. The coverage model of nodes is also an important factor which differentiate the hole identification even by the same DT. In this research, we have used disk coverage model which is symmetrical in geometry and catalytically solves the problem analysis. Mathematically, it is a Boolean function for the distance between sensor and a point. The coverage by node s_i to a point p with sensing radius R_s in it is expressed as:

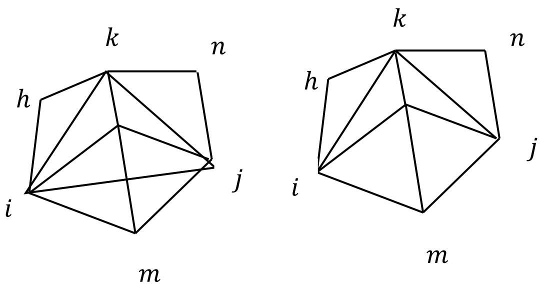
$$F\big(d(s_i, p)\big) = \begin{cases} 1, & if \;\; d(s_i, p) \le R_s \\ 0, & \quad otherwise \end{cases} \tag{1}$$

2.1. Delaunay Triangulation

A graph $G\,(V, E)$ represent the WSN, where $V \in v_1, v_2, \ldots\ldots, v_n$ reflects the group of nodes is called antennas and E shows the group of edges among the nodes. A subgraph is extracted from G by the composition of the adjacent triangle.

Related to the topology of WSN graph structure some important definition provided below;

- *Node Neighbor set (NNS)*-it is represented by $N_v(i)$, it includes the all one-hop nearest nodes, as shown in the figure 1 the NNS for nodes i and j;$N_v(i) = \{h, k, l, m, j\}$ and $N_v(j) = \{k, l, m, n, i\}$.
- *Edge Neighbor Set (ENS)*-it includes the common one-hop neighbors of two end nodes of an edge and represented by $N_e(e_{ij}) = N_v(i) \cap N_v(j) = \{k, l, m\}$ for figure 1(a)



(a) (b)

Figure 1. Original graph (a) and triangulated subgraph (b) using the set nodes and edges of WSN topology

- *Refined Edge Neighbor Set (RENS)*-it is represented by $R_e(e_{ij}) = \{v | v \in N_e(e_{ij})$ with Δ_{ij} not containing the node v', $\forall v' \in (N_e(e_{ij}) - v)\}$. RENS contains the subset of nodes with the ENS of edge.
- *Associated Edge Neighbor Set (AENS)*- it contains the node's edges among one of two end nodes of the edges and reflected as $A(e_{ij}) = \{e_{ik} | i \in \{i, j\} and\ k \in R_e(e_{ij})\}$
- *Equivalent Edges*- are those two edges which share the same AENS.
- *Weight*- the weight of the edges represented by$W(e_{ij})$, it indicates the number of triangle present in the graph.

The subgraph of G can be triangulated if the edges of subgraph containing the weights value 2. The triangulated graph reflected as Twhich the subgraph of original graph$G$, a triangulation edge present in the T called triangulation edge and an extra edge present in $G - T$. The edges of graph G containing the weights less than 2 are removed and each edge in AENS reduced the weight of edges by1. The subgraph obtained after the weight assumption contains the extra edges which removed for better subgraph observation. The extra edges or critical edges the weight more than 2 so they can be easily removed.

Algorithm for obtaining subgraph from the original graph G

1. *Initialization*-The edges of graph communicate with the nearby edges and figure out the local information like AENS, RENS, NNS, ENS, edges, weight, critical and equivalent edges.
2. *Edge removal*-After the initialization step removes the extra edges and critical edges from the subgraph itself with $Weight < 2$, or $Weight > 2$. It is an iteration process. If there is change in AENS the weights of the edges also update.
3. *Removal of extra and critical edges*- the length and weight of the edges more than two are removed.

We obtained the subgraph from the original one in which location of all nodes reflected in V is represented by $P \in p_1, p_2, \ldots\ldots, p_n$. The Delaunay Triangulation process divided as per two conditions reflected in equation 1 and 2.

2.1.1. Condition for Full coverage detection

Suppose a triangle developed by the three nodes $(v_i, v_j\ and\ v_k) \in V$ located at point$(p_i, p_j, and\ p_k) \in P$, with inside the circumcircle no other nodes available. The Euclidean distance among the nodes v_i and $v_j$reflected as d_{ij} with same distance from the other nodes. The acute triangle is completely covered if equation 2 condition is satisfied;

$$R_S \ge \frac{d_{ij} d_{jk} d_{ik}}{\sqrt{\left(d_{ij}^2 + d_{jk}^2 + d_{ik}^2\right)^2 - 2(d_{ij}^4 + d_{jk}^4 + d_{ik}^4)}} \tag{2}$$

In obtuse triangle case the fully covered condition is derive in equation 3

$$R_s \ge max\left\{\frac{d_{ij}^2 d_{jk}}{d_{ij}^2 + d_{jk}^2 - d_{ik}^2}, \frac{d_{ik}^2 d_{jk}}{d_{ik}^2 + d_{jk}^2 - d_{ij}^2}\right\} \tag{3}$$

2.2. Sensing Hole Detection

It is defined as the triangulation for group S of points inside the plane with no points of the S present in the circum circle of any triangle [23]. The full coverage using (DT) is achieved if all the triangles are completely covered by the three sensors radius which forms the vertices of the triangle. The coverage depends on the sensing rangeR_s to cover DT and nature of triangles: acute and obtuse. Following properties must be include in the DT.

- The outer boundary of DT is convex in nature which reflects the polygon shape.
- There is no sensor in a line and every node has the degree 2.
- There is no node present inside the circumcircle of every triangle.

The nodes are deployed in the network for the DT formation. The angular coordinate and relative position represented by $(d(i,j), \theta(i,j)$.The DT is framed with the help of vertices extracted with the algorithm of DT. Two adjacent triangles' common side is greater than twice of R_s, coverage hole exists there. Since our coverage model is based on disk modeling, so the hole area would also be circular. The isolated empty circle (IsEC) is formed after the hole existence. The radius of this IsEC is the difference of nodes' sensing range and circumradius of that triangle. Algorithm1 shows the process of hole detection.

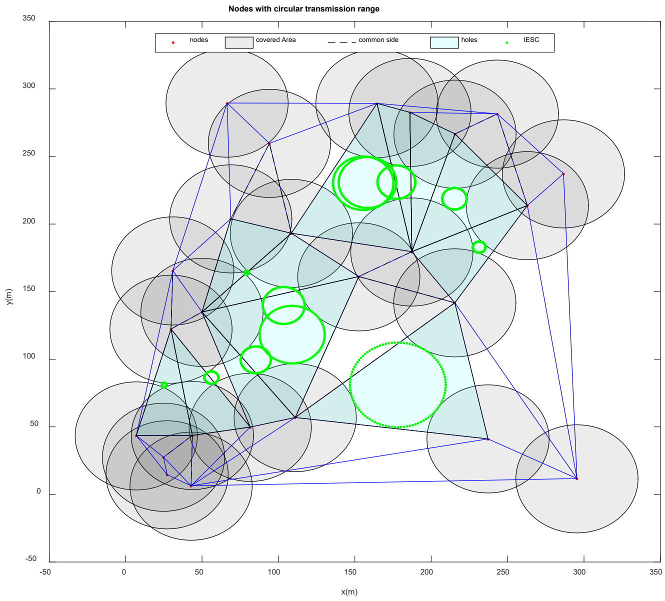


Figure 2. Coverage holes area by advanced DT

Algorithm 1. Coverage hole detection process in WSN network

Input: WSN sensor nodes$\Rightarrow \boldsymbol{V_n}$, $\boldsymbol{sensing\ range} \Rightarrow \boldsymbol{R_s}$
Output: number of holes $\Rightarrow \boldsymbol{N_{hole}}$, IsEC radius $\Rightarrow \boldsymbol{R_e}$

1. Initialize $\boldsymbol{N_{hole} = 0}$
2. Deployed the nodes in an area by gaussian distribution $\boldsymbol{f(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}}$
3. Formulate the Delaunay triangle for deployed nodes $\boldsymbol{D_n}$.
4. For $\boldsymbol{i = 1: D_n - 1}$
5. For $\boldsymbol{j = i + 1: D_n}$
6. If ($\boldsymbol{D_i}$, $\boldsymbol{D_j}$ are neighbors) && ($\boldsymbol{D_{i_{\overline{ab}}} \equiv D_{j_{\overline{ab}}}}$)
7. Calculate the length of common side $\boldsymbol{D_{i_{\overline{ab}}} \Rightarrow (d_{i_{\overline{ab}}})}$
8. If $\boldsymbol{d_{i_{\overline{ab}}} > 2 * R_s}$
9. $\boldsymbol{N_{hole} = N_{hole} + 1}$
10. $\boldsymbol{R_{e,ij} = R_s - D_{i,j,circumradius}}$
11. End if
12. End if
13. End for
14. End for

2.3. Coverage Hole Size Estimation

The empty green circles in figure 2 represent the holes. The hole's coverage area calculation is not the inscribed circle area as due to circular sensing range, part of hole could be covered [5]. So, the hole area is a measure of the inscribed circle area of a triangle. This concentric circle has the radius n times lesser than R_s. The distance of circumcenters (d_{ij}) of two adjacent DTs is less than the total radius of both then the hole area is defined as:

$$S_{ij} = \begin{cases} \pi R_i^2 + \pi R_j^2 - 2\left(R_i^2\theta_i - R_i d_{it} \sin\theta_i + R_j^2\,\theta_j - R_j d_{jt} \sin\theta_j\right) & \forall\, d_{ij} < (R_i + R_j) \\ \pi R_i^2 + \pi R_j^2 & \forall\ d_{ij} == (R_i + R_j) \end{cases}$$

Where S_{ij} is the hole area between i^{th} and j^{th} triangle with the corresponding radius R_i, R_j. The pseudo code for coverage area calculation is expounded in algorithm 2.

Input: n DTs, $\boldsymbol{R_s}$
Output: total coverage hole area $\boldsymbol{A_{hole}}$
1. Initiate the coverage hole $\boldsymbol{A_{hole}} = \mathbf{0}$
2. For $\boldsymbol{i = 1\ to\ n-1}$
3. For j= $\boldsymbol{1+1\ to\ n}$
4. Calculate the distance $\boldsymbol{d_{ij}}$
5. If $\boldsymbol{d_{ij} < (R_i + R_j)}$
6. $\boldsymbol{S_{ij} = \pi R_i^2 + \pi R_j^2 - 2\left(R_i^2\theta_i - R_i d_{it}\sin\theta_i + R_j^2\,\theta_j - R_j d_{jt}\sin\theta_j\right)}$
7. Else
8. $\boldsymbol{S_{ij} = \pi R_i^2 + \pi R_j^2}$
9. End if
10. End for
11. End for
12. $\boldsymbol{A_{hole} = \sum S_{ij}}$

Algorithm 2. Pseudo code for Coverage hole area estimation

3. Coverage Hole Healing

Proposed DT managed to get the coverage hole area with number of holes. The mitigation of these sensor nodes considered the redundant nodes [1] which remain idle or in sleep mode while other sensor mates work. These redundant nodes add into vertices of sensor tree as a new subset $V_d \in v_{1d}, v_{2d}, \ldots\ldots, v_{kd}$, to mitigate or reduce the coverage holes. We assumed these nodes have the moving capability and change the WSN graph dynamically to get optimal positions. The nodes deployment has previously attracted the researchers and measure research on it lie around making the process energy efficient. However, we are dropping this idea in this paper and focusing on the mitigation of holes only. V_ds are optimally deployed to ensure we get maximum coverage. We formulated the problem as to minimize the number of holes (N_{hole}) and coverage area (A_{hole}). We used Gaussian distribution function for the sensor nodes deployment which is which is $f(x|\mu,\sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}}e^{\frac{-(x-\mu)^2}{2\sigma^2}}$. Here $\mu = 0$ and $\sigma = 1$. It distributes them randomly in the predefined geographical area. Due to that, the disk coverage area of V_i, the hole area might show a different picture than number of holes present. The Figure 2 shows detected number of holes with advanced DT. The gaussian distribution system is responsible for this variation in holes' areafor each coverage hole. With the current nodes' deployment, the figure 2 has 12 different sized holes.

1. We adapted the swarm optimization method to deploy the V_d optimally to cover up holes. A hybrid Particle Swarm Optimization with chaotic Gravitational Search (PSOCGSA) Algorithm is proposed for this purpose. We formulated the objective function as
2. $argmin(w_1 \times N_{hole} + w_2 \times \sum_{i\in(1,N)} A_{hole,i}$ (4)
3. Here w_1, w_2 are random weights $\in (0,1)$.

3.1 Proposed Optimization Solution

Every optimization algorithm is stochastic in nature and two primary processes: exploration and exploitation, completes the optimization. In the exploration phase, search space is explored to its maximum and exploitation phase try to find the possible best solution quickly. The balance between these two phases is very difficult due to randomness in optimization and every optimization algorithm differs here. The particle swarm optimization (PSO) has the limitation of prematurely convergence and it doesn't explore the available search space due to more dependency on the local best positions of swarms. Previously researchers had improved the PSO global nature by introducing chaotic mapping in the current position in every iteration [24]][25][26][27]. They also focused on updating the values of random constants r_1, r_2 chaotically. Researchers in [28] also removed the initial positions' random perturbation in PSO by chaotic search space mapping. The chaotic initialization in PSO adds the advantage in the exploration phase and allows exploring the more directional search space but it still terminates prematurely as the exploitation phase is still not guided. The proposed solution take advantage of the Gravitational Search Algorithm's exploitation strength in the chaotic PSO to look for the best solution.

3.1.1 Chaotic Mapping

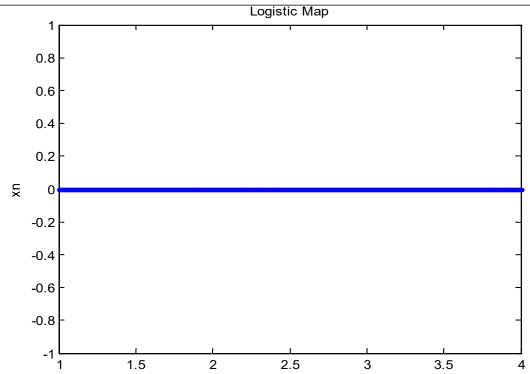
Chaotic maps generate the pseudo random numbers which are non-linear and ergodic in nature. Several chaotic maps like tent map, logistic map, Tchebychev map etc., are available but logistic map provides the randomness near the solution. It is a linear mapping with variable $x_n = rx_n(1-x_n), n = 0,1,2,3\ldots..$ The r is a system parameter $(0,4] and x_n \epsilon [0,1]$. The logistic mapping shows different behavior for different values of r.

The initialization response of swarms' population with $r \in (0,4]$ is listed in table 1. The logistic map failed to converge for $r > 4$ as x_n leaves the interval of 0 and 1. Figure 3 shows the stationary, periodic and complete bifurcation diagram for logistic map. Figure 3(a) and 3(b) shows the behavior of logistic mapping if the system parameter r is less than 1 and $3 \le \mathrm{r} < 1+\sqrt{6}$ respectively. For $0 \le \mathrm{r} < 1$, the swarm particles can't explore the area for foraging and die prematurely. Conclusively, redundant sensor nodes won't be able to heal the holes. The non-diminishing oscillatory behavior (figure 3(b)) also doesn't give any converging solution for optimal locations of redundant nodes. The chaotic behavior starts beyond 3.56994 and figure 3(c) shows the logistic mapping for a complete range of $\mathrm{r} \in (0,4]$. The area between $\mathrm{r} \in (3.54409,4]$ is the stable oscillations area and convergence in optimization can be achieved in this area. The solid lines in figure 3(c) point to the stable solution.

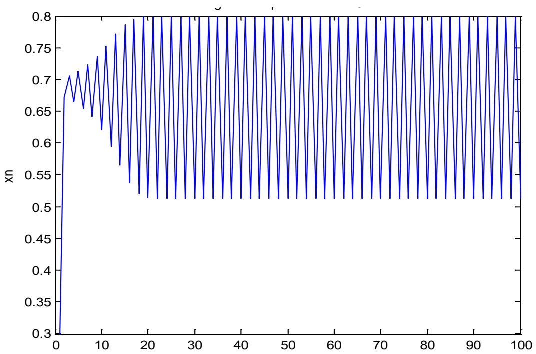
Table 1. Different behaviors of Logistic map for $r \in (0,4]$

Sr. No.	Value of r	Response

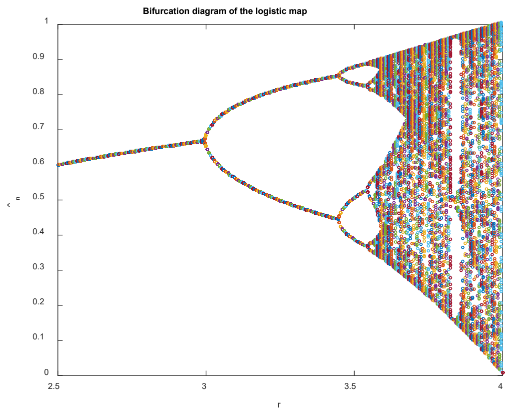
1	$0 \leq r < 1$	The solution terminates prematurely very soon irrespective of initial population
2	$1 \leq r < 2$	Solution will approach towards $\frac{r-1}{r}$,
3	$2 \leq r < 3$	Solution approaches towards $\frac{r-1}{r}$ again but oscillates around that value for some time and converges linearly.
4	$3 \leq r < 1+\sqrt{6}$	Solution oscillates permanently between two fixed values and stuck in non-decreasing solution.
5	$1+\sqrt{6} \leq r < 3.54409$	In this range, solution takes permanent perturbation between four values
6	$r > 3.54409$	At this, oscillations take for 8 values, then 16,32 etc.
7	$r = 3.56994$	This onset value and beyond this chaotic behavior starts. No more finite oscillations are visible. Large searching space can be exploited with slight variation in the initial populations.



(a): for $r = 0.5$



(b) for $r = 3.2$



(c) for $r \in (0,4]$

Figure 3. Stationary, periodic and bifurcation behavior of logistic mapping

3.2 Hybrid Particle Swarm Optimization with Chaotic Gravitational Search

The hybrid of optimization has several approaches as discussed in [30]. We have made the PSO, chaotic mapping and GSA as low level, co-evolutionary and heterogeneous hybrid method. It is low level and co-evolutionary as all the three approaches are combined into one and execute in parallel inside an algorithm instead of cascading of algorithms. Since these three methods are not same in nature, so proposed hybrid solution is heterogeneous. In our approach, PSO is used for exploration phase while GSA's strength of converging maturely is utilized at exploitation phase. The chaotic mapping introduces the pseudo randomness and perturbation at two levels: for the initial positions of swarms and to update the gravitational constant in GSA. The hybridization process is depicted in figure 4. Since the initial swarms in PSO are chaotically generated by logistic mapping, the chaos variable x_i^j ,$i = 1,2 \ldots N$ can be mapped into the searching space as

$$P_i^j = x_i^j\left(P_{max,j} - P_{min,j}\right) + P_{min,j} \tag{5}$$

Here $j = 1,2,..D$ for searching space dimension.

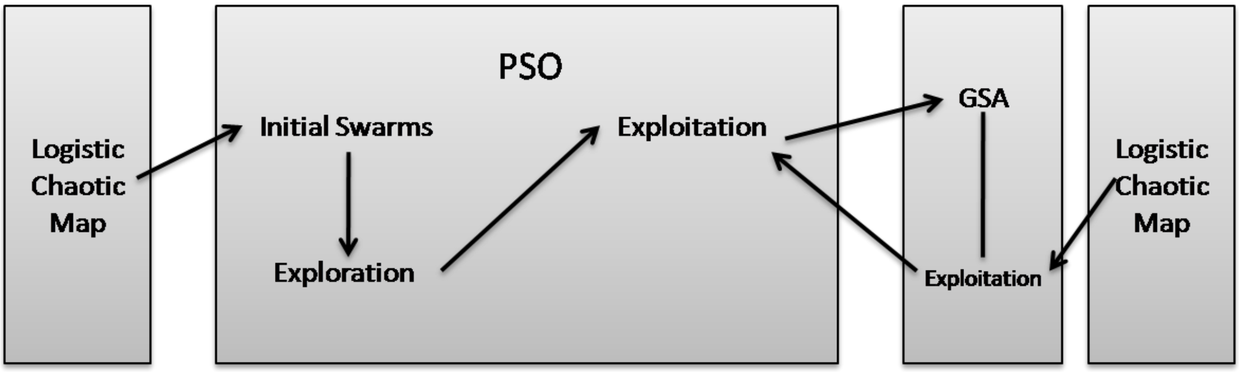


Figure 4. Low level hybrid process of PSO, chaotic mapping and GSA

It coverage holes healing problem, we have fixed number of redundant nodesV_d and objective is to deploy them to minimize the hole area as discussed in previous section. In actual we need to find the abscissa and ordinates of V_d. So, we have $D = 2 \times n_d$, where n_d is number of redundant nodes. $P_i^{j=1,2}$ is used to evaluate the equation 3. This fitness value if compared from previous local best value and winner has to take part again for global best calculation. The standard PSO updates the swarm's positions in exploitation step as

$P_i^{K+1} = P_i^k + v_i^{K+1}$ (6)

Where

$v_i(t+1) = w \times v_i(t) + c_1 \times rand \times (lbest - P_i(t)) + c_2 \times rand \times (gbest - P_i(t))$ (7)

v, represents the velocity of swarms. In the proposed solution the V_d are updated by adding the global nature of GSA in equation 6 as

$v_i(t+1) = w \times v_i(t) + c_1 \times rand \times acc_i + c_2 \times rand \times (gbest - P_i(t))$ (7)

Where acc_i is the acceleration in GSA for V_i. This acceleration is computed as

$$acc_i(t) = {F_i(t)}/{M_i(t)} \quad (8)$$

Where force , $F_{ij}(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t)+\varepsilon}(x_j(t) - x_i(t)$ (9)

$$\text{Normalized mass, } M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \quad (10)$$

$$\text{Mass, } m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad (11)$$

The gravitational constant computed as

$$G(t) = G_0 \times e^{(-\beta \frac{t}{t_{max}})} \quad (12)$$

$fit_i(t)$ is the fitness value calculated using equation 3 for each set of swarm's position. This is the exploration phase output which is fed into the exploitation phase. The minimum of this from a set of positions is the best value so far and maximum of this is worst value. This way the exploitation step of GSA is inherited into PSO to make it converge at a global solution.

The gravitational constant G in GSA is perturbed by logistic mapping to add the chaotic ergodicity and pseudo randomness in exploitation phase. In equation 10, G_0 and β are constants which are specified for particular problem. The $G(t)$ in our proposal is calculated as:

$G(t) = x_n \times (w_{max} - t \times (w_{max} - w_{min})/t_{max})$ (13)

Where x_n is the chaotic variable. It is made adaptive by multiplying with adaptive weights which changes in each iteration$t$.w_{max} and w_{min} are weights bounds. The system parameter r in logistic map is considered as 4 for best chaotic behavior from table 1. The pseudo code for the proposed hybrid optimization is shown in algorithm 3.

*Input:*searching space dimension D, WSN area limit, $\boldsymbol{n} \Longrightarrow$ $\boldsymbol{number\ of\ swarms}$, $\boldsymbol{t_{max}} \Longrightarrow \boldsymbol{maximum\ iterations}$

Output:$\boldsymbol{bestPosition}$ ⟹optimal $\boldsymbol{V_d}$'s best positions

1. Generate the initial swarms' positions $\boldsymbol{P_i^{j=1,2}}$ with logistic mapping as in equation 4
2. Initialize $\boldsymbol{gbestscore} = \infty$
3. For $\boldsymbol{t = 1: t_{max}}$
4. Check for WSN area constraints
5. Calculate the fitness value $\boldsymbol{fit_i(t)}$from equation 3
6. If $\boldsymbol{fit_i(t) < gbestscore}$
7. $\boldsymbol{gbest_i = P^{j=1,2}_{fit_{index}(t)}}$
8. Endif
9. $\boldsymbol{worst_i = \max(fit_i(t))}$
10. $\boldsymbol{best_i = \max(fit_i(t))}$
11. Calculate mass $\boldsymbol{M_i(t)}$using equations 9 & 10
12. Apply chaotic logistic mapping for gravitational constant $\boldsymbol{G(t)}$ using equation 12
13. Calculate force $\boldsymbol{F_{ij}(t)}$ and acceleration $\boldsymbol{acc_i(t)}$ using equations 8 and 7 respectively
14. Update the swarm's velocity by $\boldsymbol{acc_i(t)}$, $\boldsymbol{gbest_i}$ by equation 6 and add this to current position $\boldsymbol{P_i^k}$
15. $\boldsymbol{bestPosition = gbest_i}$
16. End for loop

Algorithm 3. Pseudo code for hybrid optimization PSOCGSA

4. Results Evaluation

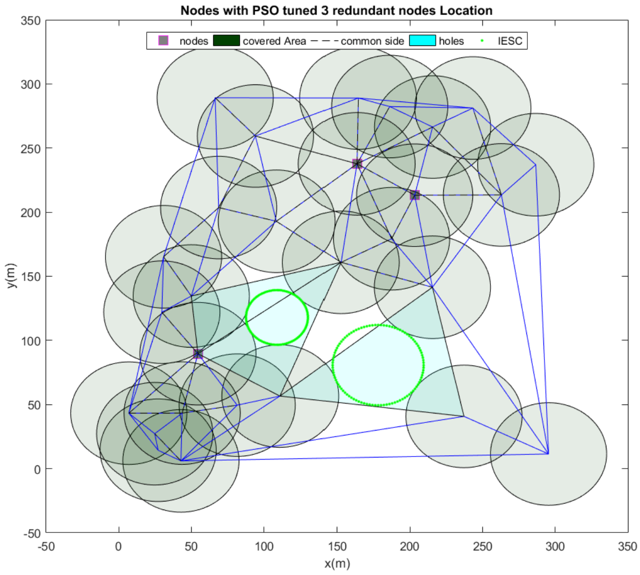
The simulation of the proposed approach is done in MATLAB for 25 nodes in the 300*300 square meter area. All nodes are assumed to have an omnidirectional antenna. Each node is able to transmit the signal in a 20 meter circular area. We also tested it for 9 and 11 meter sensing radius for the comparison with state of the art method. The proposed algorithm considered the 3,5,7,9,11 redundant nodes which heal the hole area. The two ray ground wave propagation model is considered for a simulation time of 150 ms. Testing is done with different number of redundant nodes. We evaluated the results on the criteria of number of holes and coverage hole area. Results are compared with the state of art PSO, CPSO optimization algorithms too. Without coverage hole healing, the nodes deployment is shown in figure 2. Since redundant nodes are initially idle, these are active only once coverage hole healing is required. This information is passed to these by main controlling station of WSN. The algorithm of control/active signal transmission to nodes and its effects on the network is out of scope of this paper. Before moving the V_ds, we assume the active status signal is already received and these are ready to move using random mobility model. Figure 5 shows the optimal positions of $V_{d=3}$ after PSO, CPSO and proposed PSOCGSA approach. For all three optimization algorithms, we have considered the 3 redundant nodes. The square box marker in the figure denotes the redundant nodes. The circular hole area after the positioning of redundant nodes is shown in the green colored circle in figure 5. In figure 5(a), the holes' area is more than holes in 5(b) and 5(c). This is due to PSO's premature termination nature which can't locate the better position of redundant nodes. After the CPSO optimization, the global nature of optimization has reduced the hole area as in figure 5(b) but the number of holes is 3. The proposed approach has overcome both limitations and reduced the hole area and hole number as in figure 5(c).

From this figure it is clear that number of holes are reduced with coverage area. Though the number of holes comparatively not reducing as per coverage area. Table 2 shows the comparative holes' number and hole coverage area for this case. In PSO and CPSO, the holes' number are more in CPSO but the coverage is reduced in CPSO than PSO. The size of holes in figure 5(b) is lesser than in 5(a). The proposed optimization solution is outperforming these two states of art optimizations and reduced the coverage area by 47% than CPSO and 57% than PSO.

Table 2. Comparative analysis of detected coverage holes and coverage area after hole mitigation

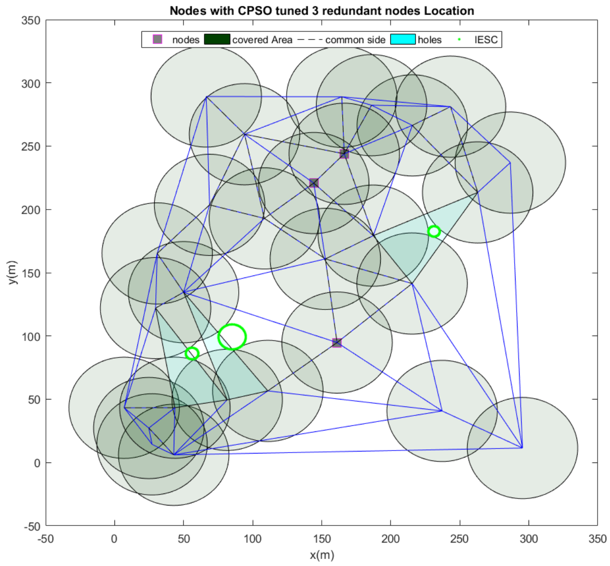
	Without healing	**PSO**	**CPSO[24]**	**PSOCGSA**
Number of holes (N_{hole})	12	2	3	2
Hole coverage area (A_{hole}).	179943.83	29014.38	23393.31	12358.08

The following pictures depict the coverge hole improvement through PSO, CPSO and PSOCGSA with three redundant nodes. it is clear that PSOCGSA performance is better than PSO and CPSO.

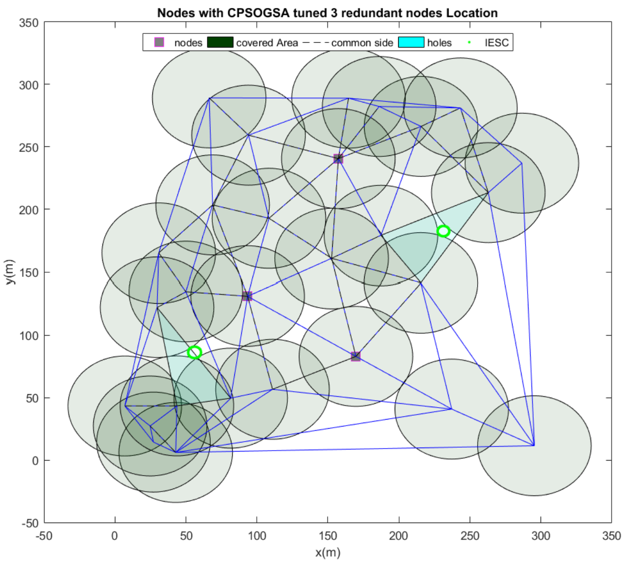


(a)

We also compared the convergence curve of these three optimization methods. Since the equation 3 is to be minimized, the lower the curve, efficient is the approach. Figure 6 shows the convergence curve comparison. The convergence curve validates the optimization process. Earlier is the termination to a saturation value; better is the optimization. Our objective is to minimize the hole area as well as the number of holes. The ordinate in figure 6 has the scale for objective function in equation 3. The proposed solution is converging at 21st iteration while others are taking more than it. The chaotic perturbation in the hybrid optimization has reduced the convergence time. Though due to stochastic nature of PSO the convergence curve may change in other trials yet in 10 trials test, we observed the improved convergence in proposed. The CPSO is converging at lower value than PSO but seems not attaining a minimum value even after 100 iterations. This is the measure drawback of CPSO [24] for the coverage hole healing.



(b)



(c)

Figure 5. Coverage hole's healing by (a) PSO (b) CPSO (c) PSOCGSA

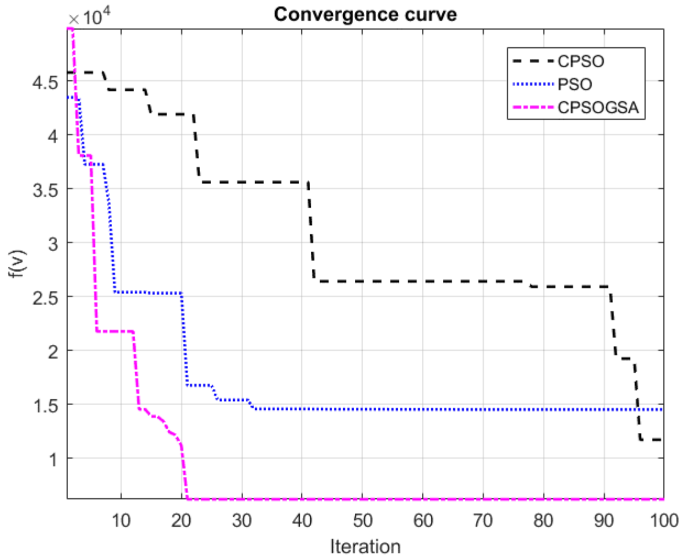


Figure 6. Convergence Curve Comparison for PSO, CPSO and PSOCGSA

We compared our approach with [23] which considered the redundant nodes which are already in active state in the network. Since, these are taking part in the communication, there energy might deplete to some extent already. This way the healed hole area will be again a hole soon. That paper has used the selection of redundant node on the basis of most surrounded nodes. Leaving that position will also create a new hole soon as to the one hop in data packet path is reduced and packets have to travel farther than original deployment. In table 3, we compared our solution with their results.

Table 3. State of art comparison with proposed approach

	Work in [23]		**Proposed Solution**	
	$R_s = 9m$	$R_s = 11m$	$R_s = 13m$	$R_s = 15m$
Hole area after healing	1.303	0	108.85	0
Number of Redundant nodes	7	9	6	6

In [5], extra redundant nodes are considered to heal the hole area which remain idle unless signaled.The coverage area is calculated by monte-carlo approach. They have distributed 1,000,000 points in the nodes' area and define the coverage area as ratio of all covered points to total points. We also followed the same approach to calculate the relative coverage area and compared with state of art [5] in table 4. The network is simulated for $100 \times 100m$ area for 80 sensor nodes with 10 m sensing range [5].

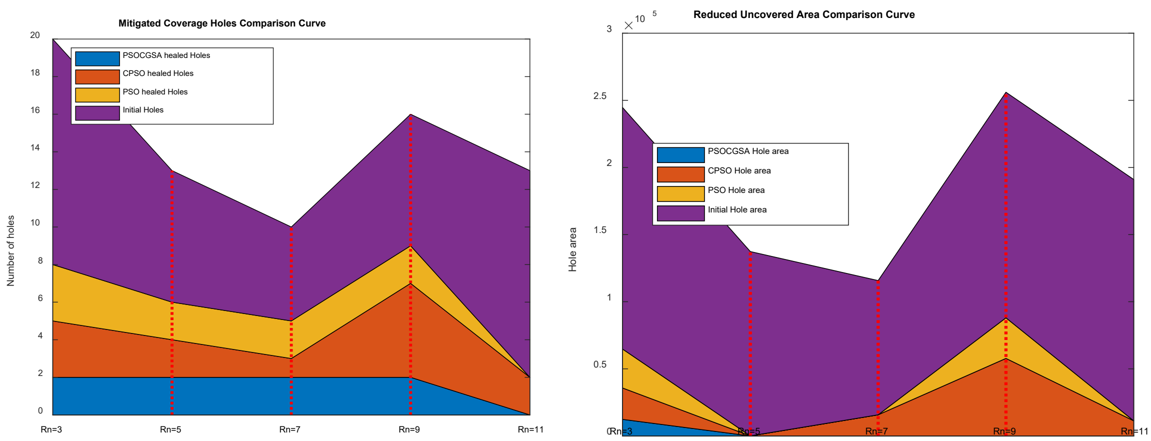
Table 4. Comparison of proposed solution with [5]

	LiW. et.al [5]	CPSO optimized	Proposed solution
Relative coverage area after healing	95.5%	97.06%	98.95%
Number of redundant nodes	11	11	9

From table 3 and 4, we are able to prove, the proposed solution can heal the hole area more efficiently upto 98% in left uncovered area from [23]. Whereas, with 22%lesser redundant nodes, our approach covered the 3.6% higher relative covered area.

Our results with the different number of redundant nodes for same geographical area showed that the coverage area is reduced to approx. 99.8% by just 5 redundant nodes as in figure 7. In our simulation, we took 10 trials of every optimization and considered the best results. Figure 7 is plotted for nodes in area of $300 \times 300m$ with same sensing range.

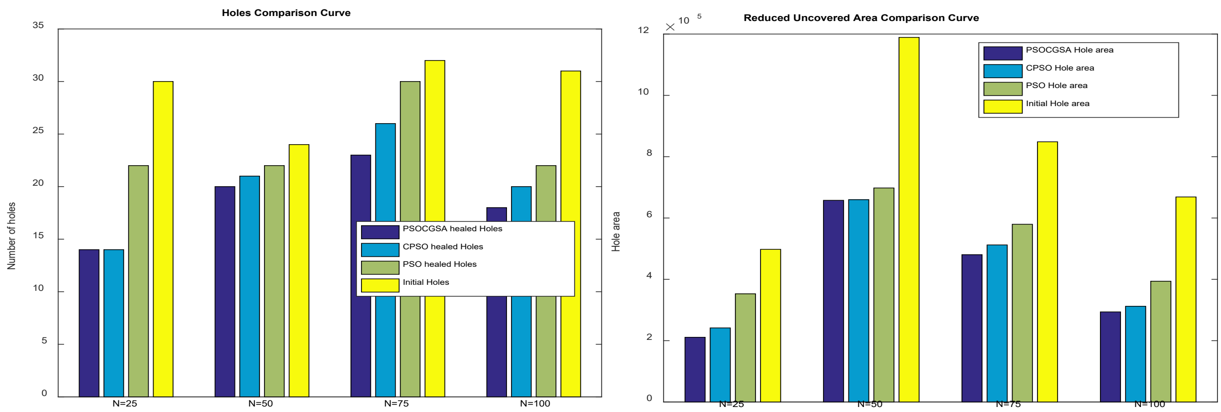
We also tested the algorithm for different nodes' density in the 500×500 area, considering 10% of the redundant nodes for healing. As the number of nodes increases, the number of holes also increases and so is the hole area. It follows the convention as shown in bar plot in figure 8 (a) & (b). Our optimization algorithm healed the area efficiently than others irrespective of nodes' density.



(a) (b)

Figure 7. Comparison of (a) number of detected holes (b) reduced uncovered area by PSOCGSA, CPSO, PSO, Initial cases

Since we have deployed the nodes randomly, the number of holes and hole area don't follow any convention as in figure 8. It also proves that the hole area can be different even if the number of holes is same as the case of 25 nodes in the geographical region. This is due to the different locations of holes in the network. This way, we can declare that our novel hybrid method outperforms the other schemes of hole healing in every condition.



(a)Number of holes vs number of Nodes (b) Hole Area vs number of nodes

Figure 8. Validation of proposed hybrid optimization for different number of nodes in the WSN area with 10% redundant nodes

5. Conclusion

In this work, we have dealt with the problem of hole coverage area detection and healing. An unprecedented hybrid optimization algorithm is proposed to heal the uncovered area. We have opted the stochastic way to deploy the redundant nodes in uncovered area to minimize it. Particle Swarm optimization is improved with the introduction of logistic map and Gravitational search algorithm. The exploitation phase of PSO is updated by GSA which itself is made pseudorandom by logistic map. Chaos is also introduced in initial positions' generations. The proposed scheme improved the coverage area upto 57% from PSO. Our scheme has over performed and gained a 3.6% improvement in covered area than the tree based approach by W. Li et.al and 98% from the advance Delaunay triangulation method by K. Lakshmi et.al. It has been shown that more hole area is covered with comparatively less number of redundant nodes.

In the next part of this research, this work can be extended for obstacle in the communication path of the nodes. Due to these, the coverage area for a sensor node may vary and creates the holes with anonymous shape. The method to detect the holes with irregular shapes can also be considered for further implementation.

References

[1]. Deng, Xianjun, Yalan Jiang, Laurence T. Yang, Man Lin, Lingzhi Yi, and Minghua Wang. "Data fusion-based coverage optimization in heterogeneous sensor networks: A survey." Information Fusion 52, pp. 90-105, 2019.

[2]. Zhai, Shuangjiao, Zhanyong Tang, Dajin Wang, Zhanglei Li, Xiaojiang Chen, Dingyi Fang, and Feng Chen. "Coverage hole detection and recovery in wireless sensor networks based on RSSI-based localization." In 2017 IEEE international conference on computational science and engineering (CSE) and IEEE international conference on embedded and ubiquitous computing (EUC), vol. 2, pp. 250-257. IEEE, 2017.

[3]. Verma, Manoj, and Sanjay Sharma. "A greedy approach for coverage hole detection and restoration in wireless sensor networks." Wireless Personal Communications 101, no. 1, pp. 75-86, 2018.

[4]. Qiu, Chenxi, Haiying Shen, and Kang Chen. "An Energy-Efficient and Distributed Cooperation Mechanism for k - Coverage Hole Detection and Healing in WSNs," IEEE Transactions on Mobile Computing 17, no. 6 pp. 1247-1259, 2107.

[5]. Li, W. and Wu, Y,"Tree-based coverage hole detection and healing method in wireless sensor networks', Computer networks, 103, pp.33-43, 2016.

[6]. Zhang, Yaqiang, Zhenhua Wang, Lin Meng, and Zhangbing Zhou. "Boundary region detection for continuous objects in wireless sensor networks." Wireless Communications and Mobile Computing, pp. 1-13, 2018.

[7]. Mharsi, Niezi, and Makhlouf Hadji. "A mathematical programming approach for full coverage hole optimization in Cloud Radio Access Networks." Computer Networks 150, pp. 117-126, 2019.

[8]. Zhouzhou, Liu, and Yanhong She. "Hybrid Wireless Sensor Network Coverage Holes Restoring Algorithm." Journal of Sensors, pp.1-10, 2016.

[9]. Yu, Xiaosheng, Ming Xu, Long Cheng, and Nan Hu. "A novel coverage holes detection and holes recovery algorithm in wireless sensor networks." In The 27th Chinese Control and Decision Conference (2015 CCDC), pp. 3640-3644. IEEE, 2015.

[10]. Ghosh, Pradipta, Jie Gao, Andrea Gasparri, and Bhaskar Krishnamachari. "Distributed hole detection algorithms for wireless sensor networks." In 2014 IEEE 11th International Conference on Mobile Ad Hoc and Sensor Systems, pp. 257-261. IEEE, 2014.

[11]. Feng, Xin, Xin Zhang, Jing Zhang, and Ali Ahmed Muhdhar. "A coverage hole detection and repair algorithm in wireless sensor networks." Cluster Computing, pp. 1-8, 2018.

[12]. Kashino, Zendai, Julio Vilela, Justin Y. Kim, Goldie Nejat, and Beno Benhabib. "An adaptive static-sensor network deployment strategy for detecting mobile targets." In 2016 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), pp. 1-8. IEEE, 2016.

[13]. Kashino, Zendai, Justin Yonghui Kim, Goldie Nejat, and Beno Benhabib. "Spatiotemporal adaptive optimization of a static-sensor network via a non-parametric estimation of target location likelihood." IEEE Sensors Journal 17, no. 5, pp. 1479-1492, 2016.

[14]. Zhang, Yunzhou, Xiaohua Zhang, Wenyan Fu, Zeyu Wang, and Honglei Liu. "HDRE: Coverage hole detection with residual energy in wireless sensor networks." journal of communications and networks 16, no. 5, pp. 493-501, 2014.

[15]. Jan, Naeem, Nadeem Javaid, Qaisar Javaid, Nabil Alrajeh, Masoom Alam, Zahoor Ali Khan, and Iftikhar Azim Niaz. "A balanced energy-consuming and hole-alleviating algorithm for wireless sensor networks." IEEE Access 5, pp. 6134-6150, 2017.

[16]. Arya, Anju, Amita Malik, and Sanjay Kumar. "A routing protocol for detecting holes in wireless sensor networks with multiple sinks." In Proceedings of the Third International Symposium on Women in Computing and Informatics, pp. 103-108. ACM, 2015.

[17]. Li, Qiyue, Baoyu Chu, Zhong Wu, Wei Sun, Liangfeng Chen, Jie Li, and Zhi Liu. "RMDS: Ranging and multidimensional scaling–based anchor-free localization in large-scale wireless sensor networks with coverage holes." International Journal of Distributed Sensor Networks 13, no. 8, pp. 1-17, 2017.
[18]. Li, Wei, and Wei Zhang. "Coverage hole and boundary nodes detection in wireless sensor networks." Journal of network and computer applications 48, pp. 35-43, 2015.
[19]. Koriem, S. M., and M. A. Bayoumi. "Detecting and measuring holes in wireless sensor network." Journal of King Saud University-Computer and Information Sciences, pp. 1-8, 2018.
[20]. Zhang, Guanglin, Chengsi Qi, Wenqian Zhang, Jiajie Ren, and Lin Wang. "Estimation and Healing of Coverage Hole in Hybrid Sensor Networks: A Simulation Approach." Sustainability 9, no. 10, pp. 1-15, 2017.
[21]. Temel, Samil, Numan Unaldi, and Okyay Kaynak. "On deployment of wireless sensors on 3-D terrains to maximize sensing coverage by utilizing cat swarm optimization with wavelet transform." IEEE Transactions on Systems, Man, and Cybernetics: Systems 44, no. 1, pp. 111-120, 2013.
[22]. Zhai, Shuangjiao, Zhanyong Tang, Dajin Wang, Qingpei Li, Zhanglei Li, Xiaojiang Chen, Dingyi Fang, Feng Chen, and Zheng Wang. "Enhancing received signal strength-based localization through coverage hole detection and recovery." Sensors 18, no. 7, pp. 1-23, 2018.
[23]. Joshitha, K. Lakshmi, and S. Jayashri. "A Novel Redundant Hole Identification and Healing Algorithm for a Homogeneous Distributed Wireless Sensor Network." Wireless Personal Communications 104, no. 4, pp. 1261-1282, 2019.
[24]. Wang, Lin, Xiyu Liu, Minghe Sun, Jianhua Qu, and Yanmeng Wei. "A New Chaotic Starling Particle Swarm Optimization Algorithm for Clustering Problems." Mathematical Problems in Engineering, pp. 1-15, 2018.
[25]. Yuan, Zhenglei, Liliang Yang, Yaohua Wu, Li Liao, and Guoqiang Li. "Chaotic particle swarm optimization algorithm for traveling salesman problem." In 2007 IEEE International Conference on Automation and Logistics, pp. 1121-1124. IEEE, 2007.
[26]. Dong, Na, Xing Fang, and Ai-guo Wu. "A novel chaotic particle swarm optimization algorithm for parking space guidance." Mathematical Problems in Engineering, pp.1-15, 2016.
[27]. Xu, Xiaolong, Hanzhong Rong, Marcello Trovati, Mark Liptrott, and Nik Bessis. "CS-PSO: chaotic particle swarm optimization algorithm for solving combinatorial optimization problems." Soft Computing 22, no. 3, pp.783-795, 2018.
[28]. Khalifa, Banafsj, Zaher Al Aghbari, Ahmed M. Khedr, and Jemal H. Abawajy. "Coverage hole repair in WSNs using cascaded neighbor intervention." IEEE Sensors Journal 17, no. 21, pp. 7209-7216, 2017.
[29]. Liu, Chen, Dingyi Fang, Zhe Yang, Xiaojiang Chen, Wei Wang, Tianzhang Xing, Na An, and Lin Cai. "RDL: A novel approach for passive object localization in WSN based on RSSI." In 2012 IEEE International Conference on Communications (ICC), pp. 586-590. IEEE, 2012.
[30]. E. G Talbi, "A Taxonomy of Hybrid Metaheuristic," Journal of Heuristics, vol. 8, no. 5, pp. 541-546, 2002.
[31]. Selvaraj, A., Patan, R., Gandomi, A. H., Deverajan, G. G., & Pushparaj, M. (2019). Optimal virtual machine selection for anomaly detection using a swarm intelligence approach. Applied Soft Computing, 84, 105686.
[32]. Gautam, R., Kaur, P., & Sharma, M. (2019). A comprehensive review on nature inspired computing algorithms for the diagnosis of chronic disorders in human beings. Progress in Artificial Intelligence, 1-24.
[33]. Soni, G., Jain, V., Chan, F. T., Niu, B., & Prakash, S. (2019). Swarm intelligence approaches in supply chain management: potentials, challenges and future research directions. Supply Chain Management: An International Journal.
[34]. Kaur, P., & Sharma, M. (2017). A survey on using nature inspired computing for fatal disease diagnosis. International Journal of Information System Modeling and Design (IJISMD), 8(2), 70-91.
[35]. Abdelaziz, A., Salama, A. S., & Riad, A. M. (2019). A Swarm Intelligence Model for Enhancing Health Care Services in Smart Cities Applications. In Security in Smart Cities: Models, Applications, and Challenges (pp. 71-91). Springer, Cham.
[36]. Moloodpoor, M., Mortazavi, A., & Ozbalta, N. (2019). Thermal analysis of parabolic trough collectors via a swarm intelligence optimizer. Solar Energy, 181, 264-275.
[37]. Shalu. & Malik, A., (2016). Realization of wireless sensor network through real time test bed, 3rd International Conference on Computing for Sustainable Global Development, IEEE.
[38]. Antil, P., Malik, A &. Kumar, S. Neighbor Adjacency based Hole Detection Protocol for Wireless Sensor networks, Procedia Computer Science, 79(2016), 866-874, Elsevier.