Towards Efficient Sensor Placement for Industrial Wireless Sensor Network

R. Pavithra, D. Arivudainambi
Department of Mathematics, Anna University, Chennai - 600025, India

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ABSTRACT

Industrial Wireless Sensor Network (IWSN) is the recent emergence in wireless technologies that facilitate industrial applications. IWSN constructs a reliable and self-responding industrial system using interconnected intelligent sensors. These sensors continuously monitor and analyze the industrial process to evoke its best performance. Since the sensors are resource-constrained and communicate wirelessly, the excess sensor placement utilizes more energy and also affects the environment. Thus, sensors need to use efficiently to minimize their network traffic and energy utilization. In this paper, we proposed a vertex coloring based optimal sensor placement to determine the minimal sensor requirement for an efficient network.

R. Pavithra,
Research Scholar, Department of Mathematics, Chennai - 600025, India
Email: pavithraravikumar94@gmail.com

1. INTRODUCTION

In today's competitive industrial marketplace, due to high cost, regular maintenance, and expensive communication cables, the traditional wired industrial monitoring and control systems are evaded and started focuses on cost-effective wireless automation systems to improve the process efficiency and productivity. The cost-effective wireless automation system is feasible with the help of Wireless Sensor Networks (WSNs), and this collaboration termed as Industrial Wireless Sensor Network (IWSN). IWSN consists of a set of sensor nodes installed on industrial equipment to monitor the critical parameters such as pressure, vibration, power quality, and temperature [5]. The sensed information of each sensor is transmitted wirelessly to the base station. The base station analyses the data and provides a warning if it notifies any problem in the system. The earlier notification helps in advance replacement or repair of the equipment before its efficiency drops or fails. Thus, the cost involved in the post effects of the equipment failure can be prevented and also prohibits the cost of maintenance of the hard-wired computing system and manual monitoring.

Some of the vital IWSN applications are as follows: The rolling machines at pulp and paper mills are expensive and complicated. The minor variations in the speed, temperature, or alignment of the rollers affect the quality or operation of the machine. Hence, to monitor the devices at some specific places, sensors are deployed, such that it provides immediate notification when there are minute changes in the data. In oil refineries, maintaining the temperature of pipes is essential, but it is also tedious to do manually. Thus sensors are utilized to monitor these pipes to maintain its temperature correctly and reduce the manual work.

Similarly, accessing the real-time tank inventory data through a wired computing system leads to a delay in retrieving it. Thus tank management systems in chemical inventories use the sensor to provide instant access to the data and also to determine the value hidden within the chain. Sensors are used in the industry to detect the fire and provide early warning. Deployment of sensors provides a significant impact on protecting the lives of millions of humans. Similarly, the chemical and biological sensors play a vital role in underground mining by sensing mine disaster signals and provides early warnings to improve the safety of underground production. This processed information transmits wirelessly to enable effective communication between the surface and subsurface and analyze collected data from sensors to enhance safety measures.

Similarly, many industries utilize sensors to monitor the specified targets (machines, pipes, etc.) to improve the industrial's efficiency [22]. Therefore, the replacement of sensors for cables contributes to flexibility and cost-effectiveness. Since these sensors are resource-constrained and low cost, excess sensor placement preferred for efficient coverage in IWSN. Each sensor requires more power to operate appropriately in the industrial application because of the inclusive of dust, dirt, smoke, and other contaminants. On the other hand, using excess sensors in IWSN consume high power and transmits high emission for data communication and network traffic. Therefore, the efficient utilization of a significant number of sensors is a fundamental issue for green networking [10] in IWSN. This problem referred to as the optimal sensor placement for the target coverage problem, where each target in the system must monitor by at least one sensor node such that the minimum number of sensors utilized. Although optimal sensor placement for target coverage problems extensively studied in WSN, little attention required for green computing in industrial environments.

Some of the prior works concentrating on optimal sensor placement are as follows: Astorino et al. [1] formulated mixed-integer non-linear programming for target coverage problems with directional sensors. Due to its NP-hardness, the authors introduced a Lagrangian relaxation model and also proposed heuristics algorithm to find feasible solutions. Authors in [2] proposed a heuristic algorithm with two phases; the first phase ensures target coverage, and the second phase provides sensor connectivity with mobility. The simulation results ensure its better performs when compared with other techniques. Craparo et al. [3] formulated a point coverage problem as a non-linear program and an integer linear program to locate sensors for maximizing the coverage. They have also proposed to divide the best sector algorithm for identifying the optimal position for each sensor.

Guo and Jafarkhani [6] modeled sensor deployment and energy efficiency problems as a constrained source coding problem and designed the Lloyd-like algorithm to provide efficient coverage with the constraint. The simulation results describe its efficiency. Guo et al. [7] proposed a simple deterministic deployment method, which divides the targeted area into grids, and the most suitable grid is selected to deploy sensors such that it provides efficient coverage and connectivity in the network. Authors in [8] proposed a biogeography-based optimization scheme for solving the target coverage problem and a differential evolution scheme adopted to determine the optimal sensor locations for achieving k-coverage and m-connectivity in the network. An improved genetic algorithm [9] is proposed for efficient target coverage, sensor connectivity, and scheduling and also formulated the problem as a linear programming problem.

A new heuristic algorithm [11] proposed for deployment and scheduling problems in WSN. Further, the proposed algorithm performs better when compared with ant colony optimization, artificial bee colony, and particle swarm optimization techniques. In [12], the cuckoo search optimization based mobile node deployment algorithm proposed for efficient target coverage in the network. The proposed algorithm finds it a set of the best location for the sensor deployment to obtain maximum target coverage in the system.

The artificial bee colony algorithm was proposed [14] for sensor deployment under three categories of target coverage, namely, single coverage, K-coverage, and Q-coverage. Further, the deployed sensors scheduled using a heuristic algorithm for minimum energy consumption. Njoya et al. [15] proposed a multi-objective approach based genetic algorithm, referred to as a combined approach, for sensor deployment and disjoint set cover problem. The heuristic algorithm based on a genetic algorithm is proposed in [16] for target coverage in WSN to extend network lifetime. The algorithm selects the highest remaining energy nodes to cover the targets to avoid network failure and also removes redundant sensors to reduce the number of sensor nodes.

Differential evolution algorithm has proposed [17] to determine the optimal spot for the sensors in a 3D terrain. This algorithm obtained a feasible solution for the target coverage problem. Temel et al. [18] utilized the wavelet transform to get an initial set of positions for sensors. Further, to maximize its quality of coverage, a cat swarm optimization algorithm is used. Unaldi et al. [19] proposed a genetic algorithm based on wavelet transform for determining the optimal position for sensors in a 3D terrain under area coverage. It achieved maximum coverage with the minimum number of sensors when compared with the previous literature.

Wang et al. [21] proposed a novel particle swarm optimization based coverage control algorithm for energy-efficient coverage in the network. Area partition and charging discretization methods [23] proposed for sensor placement and scheduling. A mixed-integer linear programming model formulated for target coverage problems in [24] and three heuristic algorithms presented to deploy energy harvesting directional sensors in optimal spots. The result of the proposed algorithm achieves an equal success rate and solution quality. However, these deployment algorithms focused only on the effective utilization of the fixed number of sensors by determining their optimal spots. This method fails to monitor the entire targets in every scenario, because of the variation in sensor requirement due to the target's spatial coordinates, which leads to deploying excess sensors, in turn, affects the green network of IWSN. Hence, a generalized algorithm is needed, which not only optimizes the sensor position but also determines the actual requirement of sensors for the targets such that it avoids excess sensor deployment. No literature has focused on sensor requirements and its optimal spot for target coverage problem, to the best of our knowledge. Hence, Vertex Coloring based Optimal Sensor

Placement (VC-OSP) the algorithm proposed to determine them for efficient target coverage for the green network in IWSN.

The rest of the paper organized as follows: Section 2 deals with the target coverage problem, the quality of coverage, and the implementation of the proposed algorithm for determining the sensor requirement and its optimal position. Section 3 describes the efficiency of the proposed algorithm with a series of simulation results. Section 4 provides the conclusion.

2. PROBLEM FORMULATION

Consider a set of m targets in a fixed region A, as $T = \{T_1,\ T_2, \dots, T_m\}$. Let $S = \{S_1, S_2, \dots, S_n\}$ be the set of n sensors (n need to be determined), where $n < m$ and S_R be each sensor sensing range. Let (x_i, y_i) and (x_j, y_j) be the position of the sensor S_i and target T_j respectively. A target T_j is said to be monitored by the sensor S_i if and only if its distance between them is less than its sensing range and represented as

$$\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \leq S_R \tag{1}$$

where $1 \leq i \leq n, 1 \leq j \leq m$.

The coverage of the targets is represented as

$$\lambda = [\lambda_{i,j}] \tag{2}$$

where $\lambda_{i,j} = \begin{cases} 1, S_i\ monitors\ T_j \\ \ \ 0,\ otherwise \end{cases}; 1 \leq i \leq n, 1 \leq j \leq m$

The quality of target coverage in the network is obtained as follows

$$T_{cov} = \sum_{j=1}^{m} \left\lceil \frac{\delta_j}{n} \right\rceil;\ \delta_j = \sum_{i=1}^{n} \lambda_{i,j} \tag{3}$$

This paper focuses on maximizing the quality of target coverage in the network by deploying a minimum number of sensors in the predetermined spots. Even though various algorithms have proposed to enhance the quality of coverage, the problem still needs better solutions since the existing algorithms focus on the effective utilization of a fixed number of sensors to monitor the considered targets in the network. This method fails to monitor the entire targets in every scenario because of the variation in sensor requirement due to the target's spatial coordinates, as shown in Figure 1. Four targets considered in Figure 1 and its positions are varied and described in Figure 1 (a), (b) and (c) respectively. As in every optimal sensor placement algorithm, the number of sensors is assumed as two to monitor the four targets. By optimally deploying two sensors, four targets monitored of Figure 1. (a). Whereas the same two sensors are not sufficient to provide full coverage in Figure 1 (b) and Figure 1. (c) due to the target's spatial coordinates. Thus, finding optimal spatial coordinates for a considered set of sensors provides either excess coverage or insufficient coverage depending on the target's positioning. Hence, there is a need for a generalized algorithm, which not only optimizes the sensor utilization but also determines the sensor required for the target coverage in the network. Thus, the main objective of this paper is to determine, n in other words, the number of sensors required and its optimal spot such that it monitor m targets. Hence, Vertex Coloring based Optimal Sensor Placement (VC-OSP) the algorithm proposed to determine them for efficient target coverage in the network.

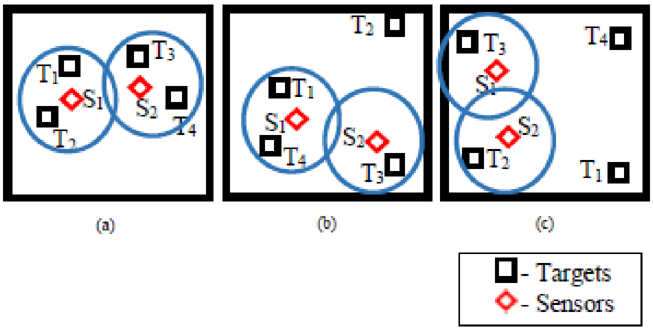

Fig. 1. Different requirement of sensors for varied target's position

3. RESULTS AND DISCUSSION

3.1. The ideology of VC-OSP algorithm

The VC-OSP algorithm proposed to determine the sensor requirement and its optimal spot to monitor all the targets in the network. As shown in Figure 1, the main reasons for the variation in the sensor requirement are the target's spatial coordinates and the sensor's sensing range. The proposed VC-OSP algorithm partitions the target set into the independent subsets in which each subgroup consists of a set of targets whose pairwise distance is less than the sensing range. In other words, the VC-OSP algorithm partitions the target set into sets, each group consists of a set of targets that are close to each other such that a common sensor is enough to monitor those targets. Then, the cardinality of such minimum independent subsets corresponds to the minimum number of sensors required to monitor the entire targets. Hence, to partition the targets, the VC-OSP algorithm utilizes the vertex coloring with the help of the graph, G. The Vertex Coloring Problem (VCP) assigns a minimum number of colors to the vertices of the graph, G such that no two adjacent vertices receive the same color. From the mathematical perspective, vertex colouring partitions the vertex-set of the graph into an independent subset comprising all the vertices of the same colour. Thus, vertex coloring is simply an intuitive way to represent the target set partition.

Let us consider a sample network to analyse the process of the proposed algorithm. Considered sample network in IWSN is of size $X \times Y$ units where X and Y in the real-time application be 1000×1000 square meters, 2000×2000 square meters or maybe 100×100 Acers. But, to consider a simple dimension sample network for easy explanation, the size of the region $X \times Y$ units projected to 10×10 units by considering the region as $\frac{10X}{X} \times \frac{10Y}{Y}$units. Let us consider a sample network of size 10×10 consist of ten targets whose coordinate points are $(3,5), (1,5), (2,4), (9,1), (4,5), (6,4), (2,10), (6,5), (10,5)$, and $(10,4)$. The sensing range of each sensor considered as three units. The objective is to determine the number of sensors required and its optimal spots to monitor these ten targets.

3.2. Construction of undirected graph for implementation of VC-OSP algorithm

The VC-OSP algorithm constructs an undirected graph $G = G(V(G), E(G))$ by considering targets as its vertex set and the adjacency made between the vertices (target T_i and target T_j) whose distance is greater than the sensing range. The reason for this adjacency is, for any graph, G in vertex coloring, the adjacent vertices receive different colors. Whereas in IWSN, the targets which are far away in other words that couldn't be monitored by the same sensor require additional sensors to monitor them. Hence, the edge set consists of the pair of targets whose distance is greater than the sensing range. Thus, each target receives different colors (sensors) using the vertex coloring technique.

The matrix representation of the adjacency of the targets is as follows

$$a = [a_{i,j}] \tag{4}$$

where $a_{i,j} = \begin{cases} 1, \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} > S_R \\ 0, \qquad\qquad otherwise \end{cases}$, $1 \le i \le m, 1 \le j \le m$ and (x_i, y_i) denotes the position of the target T_i

The VCP is NP-Complete because of determining the minimum number of colours required to colour all the vertices, which termed as the chromatic number, χ of a graph, G. But, this complex nature of VCP does not affect VC-OSP algorithm, since we aim to determine the minimum number of partitions whose cardinality, n should be less than m and not necessarily equal to χ. To achieve $n < m$, we assume that the constructed undirected graph should not to be complete. In other words, for any considered network, we assume that there exists at least one target T_i, for any other target T_j, whose distance is less than the sensor's sensing range. Mathematically, $\exists i$, for any $j \ni a(i,j) = 0$.

For the considered sample network, the adjacency matrix is obtained using equation (3) as

$$a = \begin{array}{c} \\ T_1 \\ T_2 \\ T_3 \\ T_4 \\ T_5 \\ T_6 \\ T_7 \\ T_8 \\ T_9 \\ T_{10} \end{array} \begin{array}{c} \begin{array}{cccccccccc} T_1 & T_2 & T_3 & T_4 & T_5 & T_6 & T_7 & T_8 & T_9 & T_{10} \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 \end{bmatrix} \end{array}$$

The undirected graph, G of the considered sample network as the vertex set, $V(G) = \{T_1, T_2, T_3, T_4, T_5, T_6, T_7, T_8, T_9, T_{10}\}$ and edge set, $E(G) = \{(T_i, T_j): a_{i,j} = 1\}$. Figure 2 represents the constructed undirected graph for the considered sample network.

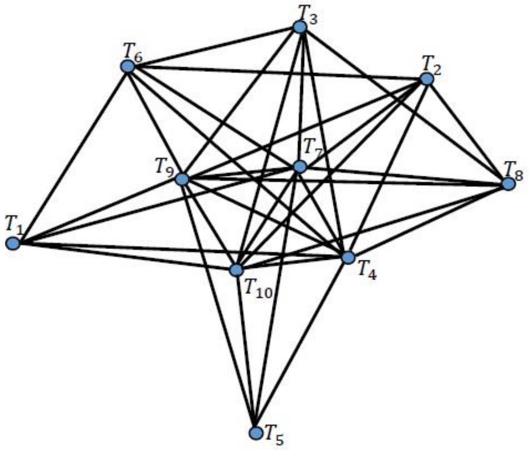

Fig. 2. The constructed undirected graph for the sample network

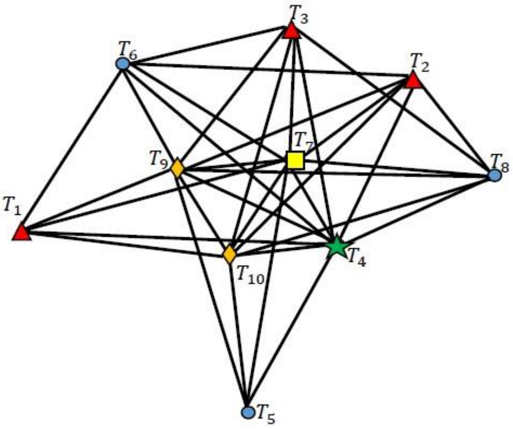

Fig. 3. Vertex coloring of the constructed graph

3.3. Assigning colors for the constructed undirected graph using VC-OSP algorithm

The proposed VC-OSP utilizes a sequential coloring algorithm [13] to provide vertex coloring for the constructed graph, G to partition the target set. Initially, the vertex set reordered concerning its neighbour vertices, and each vertex color assigned as zero. From the reordered vertex set, the algorithm considers each vertex to determine its neighbouring vertices and colors assigned to it and represent it as $neigh$ and $cneigh$ respectively. This process helps to find the maximum number of colors, mc utilized till previous iterations. Now, to assign color for the considered vertex, the algorithms check to reuse the colors assigned termed as availability of the colors, $avail$ using $setdiff(1{:}mc, cneigh)$. If $avail$ is zero, then algorithm assigns $mc + 1$ color for the considered vertex otherwise assigns minimum numbered color from the $avail$. This process iterated until colors assigned for each vertex. Each color assigned for each vertex partitions the vertex set into independent subsets. The cardinality of those independent subsets is the number of sensors required to monitor the entire targets.

For the considered sample network, the neighbouring vertices of each vertex listed in Table 1. The degree of the vertices mentioned in Table 1 represents the cardinality of neighbouring vertex set. The reordered vertex set concerning degree of vertices is $V(G) = \{T_4, T_7, T_9, T_{10}, T_6, T_2, T_3, T_8, T_1, T_5\}$. The proposed algorithm initially assigns color 'zero' for each vertex from the reordered vertex set. The sequential vertex coloring algorithm used for proper numeric coloring for the vertices and its process described in Table 2. Figure 3 shows the vertex coloring of the constructed undirected graph using the VC-OSP algorithm. From Figure 3 it is clear that the VC-OSP algorithm assigns five different colors namely red triangle, green star, blue circle, yellow square and orange diamond for the vertices $\{T_1, T_2, T_3\}$, $\{T_4\}$, $\{T_5, T_6, T_8\}$, $\{T_7\}$, $\{T_9, T_{10}\}$ respectively. Thus, the target set partitioned into five independent subsets with respect to its colours, and the cardinality of the independent subsets are the number of sensors required to monitor the targets. Thus, for the considered sample network, five sensors are sufficient to monitor ten targets.

Table 1. Neighboring Vertices of Each Vertex

Vertices	Neighboring Vertices	Degree of the Vertices
T_1	$T_4, T_6, T_7, T_9, T_{10}$	5
T_2	$T_4, T_6, T_7, T_8, T_9, T_{10}$	6
T_3	$T_4, T_6, T_7, T_8, T_9, T_{10}$	6
T_4	$T_1, T_2, T_3, T_5, T_6, T_7, T_8, T_9, T_{10}$	9
T_5	T_4, T_7, T_9, T_{10}	4
T_6	$T_1, T_2, T_3, T_4, T_7, T_9, T_{10}$	7
T_7	$T_1, T_2, T_3, T_4, T_5, T_6, T_8, T_9, T_{10}$	9
T_8	$T_2, T_3, T_4, T_7, T_9, T_{10}$	6
T_9	$T_1, T_2, T_3, T_4, T_5, T_6, T_7, T_8$	8
T_{10}	$T_1, T_2, T_3, T_4, T_5, T_6, T_7, T_8$	8

Table 2. Vertex Coloring Using Sequential Coloring Algorithm

Vertex	Neighboring vertices	Color of neighboring nodes	Maximum colors used	Available color	Color assigned
T_4	$T_1, T_2, T_3, T_5, T_6, T_7, T_8, T_9, T_{10}$	0	0	-	1
T_7	$T_1, T_2, T_3, T_4, T_5, T_6, T_8, T_9, T_{10}$	9	1	-	2
T_9	$T_1, T_2, T_3, T_4, T_5, T_6, T_7, T_8$	0, 1, 2	2	-	3
T_{10}	$T_1, T_2, T_3, T_4, T_5, T_6, T_7, T_8$	0, 1, 2	3	3	3
T_6	$T_1, T_2, T_3, T_4, T_7, T_9, T_{10}$	0, 1, 2, 3	3	-	4
T_2	$T_4, T_6, T_7, T_8, T_9, T_{10}$	0, 1, 2, 3, 4	4	-	5
T_3	$T_4, T_6, T_7, T_8, T_9, T_{10}$	0, 1, 2, 3, 4	5	5	5
T_8	$T_2, T_3, T_4, T_7, T_9, T_{10}$	1, 2, 3, 5	5	4	4
T_1	$T_4, T_6, T_7, T_9, T_{10}$	1, 2, 3, 4	5	5	5
T_5	T_4, T_7, T_9, T_{10}	1, 2, 3	5	4, 5	4

3.4. Determining the optimal spots for the sensors

As each independent subset requires one sensor to monitor them, the positioning of the sensor again depends on the position of the targets of each subset. The VC-OSP algorithm identifies the position of each target from each subset and determines its mean position for the optimal positioning of each sensor. In other words, the x-coordinate and y-coordinate of the sensor say S is the sum of the x-coordinates and y-coordinates of each target of an independent subset divided by the cardinality of the independent set respectively, and represented as follows

$$\bar{x}_s = \frac{(x_1 + x_2 + \cdots + x_t)}{t}, \bar{y}_s = \frac{(y_1 + y_2 + \cdots + y_t)}{t} \tag{5}$$

where $1 \le t \le m, 1 \le s \le n$; (x_i, y_i) and $(\bar{x_i}, \bar{y_i})$ denotes the position of the target T_i and sensor S_i respectively.

For the considered sample network, the optimal spot for five sensors say $S = \{S_1, S_2, S_3, S_4, S_5\}$ is to be determined. To determine the position of the sensor, S_1 using (5) requires the position of targets T_1, T_2 and T_3 which are $(3,5), (1,5)$ and $(2,4)$ respectively. Using (5)

$$\bar{x}_1 = \frac{3+1+2}{3}, \bar{y}_1 = \frac{5+5+4}{3}$$
$$\bar{x}_1 = 2, \bar{y}_1 = 4.67$$

The position of the sensor, S_1 is $(2, 4.67)$. Similarly, the position of the sensors, S_2, S_3, S_4 and S_5 are obtained using (5) are $(9,1), (5.33, 4.67), (2,10)$ and $(10, 4.5)$. The corresponding coverage matrix and T_{Cov} using equation (2) and (3) are

$$\begin{array}{r|cccccccccc|} & T_1 & T_2 & T_3 & T_4 & T_5 & T_6 & T_7 & T_8 & T_9 & T_{10} \\ S_1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ S_2 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ \lambda = S_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ S_4 & 1 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 \\ S_5 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{array}$$
$$\delta = [1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 1 \quad 1]$$
$$T_{Cov} = 6$$

Thus, the VC-OSP algorithm determines the sensor requirement for the considered sample network as five and selected its optimal spot as $(2, 4.67), (9,1), (5.33, 4.67), (2,10)$ and $(10, 4.5)$ such that it monitors entire targets, as shown in Fig. 4. Hence, the VC-OSP algorithm determines the sensor requirement and also determines its optimal spot for efficient target coverage in the network.

4. PERFOMANCE EVALUATION

The performs of the proposed VC-OSP algorithm is evaluated by a series of simulations in 1000×1000 region using MATLAB. The main idea of VC-OSP is to identify the sensor requirement and its optimal position to monitor the targets such that T_{Cov} (indicates the number of targets covered by the sensors) attains maximum.

But, the VC-OSP algorithm determines the optimal spots for sensors depending on the target's positions this sometimes leads to the deployment of sensors over the targets (Like the positions of sensor S_1 and S_2 in Figure 4. Deploying the sensors over the targets in industrial applications may increase the probability of affecting the sensors due to its pressure, vibration, temperature, etc. in the system. Hence, to provide better optimal spots for the obtained set of sensors using the VC-OSP algorithm, the algorithm utilizes the existing algorithms such as random deployment, discrete Haar Wavelet transforms algorithm [6], and cuckoo search algorithm [4]. The results obtained are tabled.

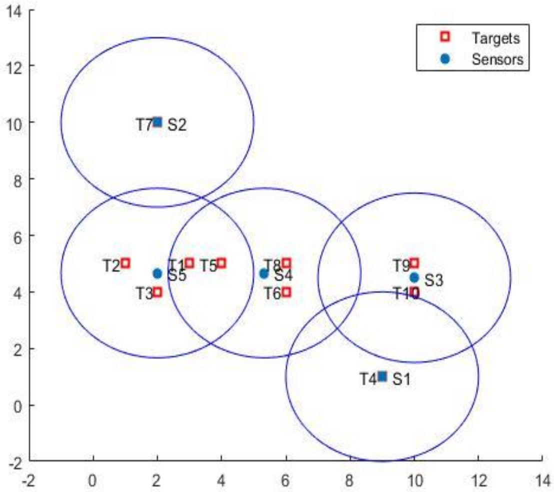

Fig. 4. The coverage of sensors using VC-OSP algorithm

Table 3 represents the estimated set of sensor requirements using VC-OSP with the variation in both targets and sensing range. The first column in Table 3 represents the variation in the targets from 100 to 250 with an increment of 25. The first row in Table 3 illustrates the variation in the sensing range from 55 to 85, with an increment of 5. The first entry of Table 3 means that the network requires 66 sensors to monitor 100 targets using the proposed algorithm with the sensing range of 55 units. Similarly, to survey 100 targets, the system requires 60, 57, 56, 54, 51, and 48 sensors with the sensing range of 60, 65, 70, 75, 80, and 85, respectively. Hence followed for other rows. Thus, Table 3 provides the sensors requirement using the VC-OSP algorithm for the considered set of targets in 1000×1000 region for the varied set of targets and sensing range.

Table 3. Number of Sensors Required for Varying Targets and Sensing Range Using VC-OSP

Targets	**Sensing range**						
	55	60	65	70	75	80	85
100	66	60	57	56	54	51	48
125	74	70	68	63	62	57	54
150	85	83	81	77	73	65	61
175	94	89	81	79	76	70	68
200	105	100	91	86	80	73	69
225	116	107	101	95	87	83	79
250	118	112	107	99	94	87	84

With the help of the obtained set of sensor requirements using the VC-OSP algorithm, the optimal spots determined using evolutionary algorithms and its corresponding quality of coverage (T_{Cov}) in the system also determined. Table 4, Table 5, Table 6 and Table 7 provides the estimated quality of coverage obtained under different conditions such as varying the targets set, sensing range, area, and sensor requirement respectively to evaluate the T_{Cov} in the system.

Table 4 represents the T_{Cov} by varying the targets from 100 to 250 targets in 1000×1000 region with the fixed sensing range of 50 units. To compare the results of random deployment, DHWT algorithm, and cuckoo search algorithm, the target positions and the number of sensors utilized should be the same. But these algorithms do not determine the sensor requirement and randomly fix the value of n for target coverage. Thus, the VC-OSP algorithm utilized to determine the sensor requirement of sensors to monitor targets, and column 2 of Table 3 represents the obtained set of sensor requirements using VC-OSP. Column 3 to 5 of Table 3 shows the results of random deployment. Column 6 to 8 presents the results of DHWT columns 9 to 11 provide the results of the cuckoo search algorithm, and columns 12 to 14 describe the work of the VC-OSP algorithm. The minimum (Min.), average (Avg.) and maximum (Max.) T_{Cov} in Table 3 are obtained by executing the algorithm fifty times. Here, the average T_{Cov} of fifty experimental results is represented in percentage for easy understanding.

As depicted in Table 4, to monitor 100 targets, the sensor requirement obtained using VC-OSP is 74. By randomly deploying 74 sensors to monitor 100 targets for fifty times, the minimum T_{Cov} of random deployment is obtained as 21, the average T_{Cov} is 24.2% and the maximum T_{Cov} is 28. In DHWT, the minimum T_{Cov} is 31, the average T_{Cov} is 37.14% and the maximum T_{Cov} is 44. By using cuckoo search algorithm the minimum T_{Cov} is 56, the average T_{Cov} is 59.24% and maximum T_{Cov} is 59.24. Using VC-OSP algorithm the minimum, average and maximum T_{Cov} is 100%. Similarly, Table 4 provides the quality of coverage obtained for each varied set of targets with the determined sensor requirement using the VC-OSP algorithm. From Table 4, it is clear that the quality of coverage increases as the target set increases. The reason is, we have considered a large system (1000×1000 region) and less set of targets (eg. 100 targets) this leads to having scattered target position in the system. Hence providing the coverage for these targets with the determined bound for sensors is comparatively less when compared with a large set of targets (e.g. 250 targets). From the results, the T_{Cov} is achieved 100% using VC-OSP algorithm.

Table 4. Quality of Coverage by Varying Targets with The Sensing Range of 50 Units

TARGET	SENSOR USED (VC-OSP)	RANDOM DEPLOYMENT			DHWT ALGORITHM			CUCKOO SEARCH ALGORITHM			VC-OSP ALGORITHM		
		MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.
100	74	21	24.42	28	31	37.14	44	56	59.24	65	100	100	100
125	85	34	32.24	45	44	43.58	62	76	63.21	84	125	100	125
150	95	27	20.48	36	60	45.92	79	93	65.34	104	150	100	150
175	104	39	25.63	49	65	42.86	85	113	67.57	125	175	100	175
200	121	55	30.4	67	85	49.37	112	139	71.22	148	200	100	200
225	126	64	31.68	75	97	49.56	125	157	72.72	168	225	100	225
250	149	63	27.40	72	113	49.01	131	189	77.50	201	250	100	250

Table 5 provides the estimated T_{Cov} obtained by varying the sensing range, where the sensor requirement for each varied set of sensing ranges obtained using the VC-OSP algorithm to monitor 200 targets in 1000×1000 region. Here the sensing range is varied from 55 units to 85 units. Column 2 provides the obtained sensor requirement using the VC-OSP algorithm. The results of deploying sensors to monitor 200 targets executed fifty times, the minimum, average and maximum T_{Cov} are tabled in Table 4. The average T_{Cov} of random deployment, DHWT, cuckoo search, and VC-OSP algorithm are 24.25%, 48.87%, 75.91%, and 100% by deploying 110 sensors with the sensing range of 55 units in 1000×1000 region respectively. Similarly, the T_{Cov} is obtained and tabulated by increasing the sensing range. Here the VC-OSP algorithm performs better when compared with the random, DHWT, and cuckoo search algorithms. From the table, it is clear that as the sensing range increases, the T_{Cov} also increases. The reason is as the sensing range increases the number of targets monitored by a sensor increases thus it enhances the T_{Cov} in the system.

Table 5. Quality of Coverage by Varying Sensing Range to Monitor 200 Targets

SENSING RANGE	SENSOR USED (VC-OSP)	RANDOM DEPLOYMENT			DHWT ALGORITHM			CUCKOO SEARCH ALGORITHM			VC-OSP ALGORITHM		
		MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.
55	110	43	24.25	53	84	48.87	111	147	75.91	157	200	100	200
60	102	115	36.44	150	116	55.59	148	154	78.57	164	200	100	200
65	101	121	41.07	154	118	50.69	153	162	82.90	174	200	100	200
70	92	85	48.25	103	95	52.68	115	166	84.85	175	200	100	200
75	85	85	48.38	105	101	56.81	127	171	87.41	180	200	100	200
80	82	87	48.31	103	102	58.07	130	175	89.24	183	200	100	200
85	73	90	51.01	111	107	59.52	129	178	90.59	186	200	100	200

Table 6 provides the estimated T_{Cov} obtained by varying the considered area from 700×700 square units to 1500×1500 square units. Column 2 of Table 6 provides the set of sensors required to monitor 150 targets with the fixed sensing range of 60 units for the various area using the VC-OSP algorithm. The results obtained by deploying these sensors categorized as the minimum, average and maximum T_{Cov} by executing random, DHWT, and cuckoo search algorithms fifty times tabulated in Table 6. The average T_{Cov} of random deployment, DHWT, cuckoo search algorithm, and VC-OSP are 75.54%, 76.09%, 88.46%, and 100% by deploying 68 sensors to monitor 150 targets in 700×700 region respectively. Similarly, the T_{Cov} is obtained and tabulated by increasing the considered region. From the table, it is clear that as the area increases the sensor requirement also increases while T_{Cov} decreases, even though the proposed algorithm achieves 100% coverage. The reason is, monitoring the fixed targets (150 targets) in larger regions, as stated before, the position of the targets tends to scatter over the area. The spread of targets increases the sensor requirement and deploying those sensors over the broader region with the fixed sensing range leads to decrease its T_{Cov}.

Table 6. Quality of Coverage by Varying Area to Monitor 150 Targets

AREA	SENSOR USED (VC-OSP)	RANDOM DEPLOYMENT			DHWT ALGORITHM			CUCKOO SEARCH ALGORITHM			VC-OSP ALGORITHM		
		MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.
700	68	98	75.54	129	99	76.09	128	130	88.46	139	150	100	150
800	71	95	69.60	116	88	66.62	115	119	82.48	131	150	100	150
900	79	82	64.13	107	84	63.96	109	112	77.62	122	150	100	150
1000	86	72	60.17	105	72	58.76	106	105	72.33	116	150	100	150
1100	94	69	55.77	94	66	55.57	106	99	68.61	108	150	100	150
1200	105	64	54.34	98	68	52.73	91	96	67.01	108	150	100	150
1300	100	59	48.36	84	56	46.25	89	87	60.10	96	150	100	150
1400	102	54	43.98	76	57	44.88	80	81	56.57	91	150	100	150
1500	115	40	42.13	78	54	44.01	77	79	55.32	88	150	100	150

For the above T_{Cov} estimations, the sensor requirement (n) for each experiment is determined using the VC-OSP algorithm. Thus, it is essential to check the T_{Cov} by considering the set of sensors less than and more significant than the determined n. This estimation could help us to realize the advantage of determining the sensor requirement using the VC-OSP algorithm before optimally deployed. Hence, each algorithm executed fifty times to calculate the minimum, average and maximum T_{Cov} for the sensor set less than, equal to, and more significant than the determined value n in 500×500 square units.

Table 7, Figure 5 and Figure 6 provides the performance evaluation of random deployment, DHWT, and cuckoo search algorithm with the varied set of sensor requirement ($< n, n, > n$). Column 2 of Table 6 shows the sensor requirement to monitor the mixed collection of targets in 500×500 regions with a fixed sensing range of 50 units. Using the VC-OSP algorithm, the sensor requirement to monitor 100 targets in 500×500 area with the fixed sensing range of 50 units obtained as 44. The average T_{Cov} to monitor 100 targets by randomly deploying sensors less than 44 sensors estimated as 48.38% whereas the average T_{Cov} by deploying 44 sensors (estimated sensor requirement using VC-OSP algorithm) is 72.04%. The result clearly shows the massive increase in T_{Cov} after determining the sensor requirement. Even though the average T_{Cov} of deploying sensors more excellent than 44 sensors is 72.96% (which is greater than the estimated sensor set T_{Cov}), excess sensor deployment leads to network traffic, increases the cost, and provides redundant coverage in the system. Hence, the T_{Cov} obtained by deploying the estimated set of sensors (minimum sensors) using random deployment provides better coverage than the varied collection of sensor requirements and thus for the other entities. From Table 7, it is clear that determining sensor requirements before deciding its optimal spot provides a better result by enhancing the T_{Cov} with minimum sensors. Similarly, the T_{Cov} is estimated by varying the sensor requirement for DHWT and Cuckoo Search algorithm, and represented in Figure 5 and Figure 6, respectively.

Table 7. Quality of Coverage by Varying the Sensor Requirement for Random Deployment

TARGETS	SENSOR USED (VC-OSP)	$< n$			n			$> n$		
		MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.	MIN.	AVG. (%)	MAX.
100	44	38	48.38	60	58	72.04	88	60	72.96	85
125	52	52	53.79	91	83	76.86	108	84	77.55	110
150	58	65	53.74	94	103	79.13	134	106	79.64	137
175	61	81	57.52	122	126	81.84	154	128	81.58	158
200	64	102	59.64	144	145	83.24	183	147	83.96	185
225	66	106	62.53	161	176	84.97	209	171	86.20	206
250	74	140	64.91	186	203	87.71	230	202	87.45	236

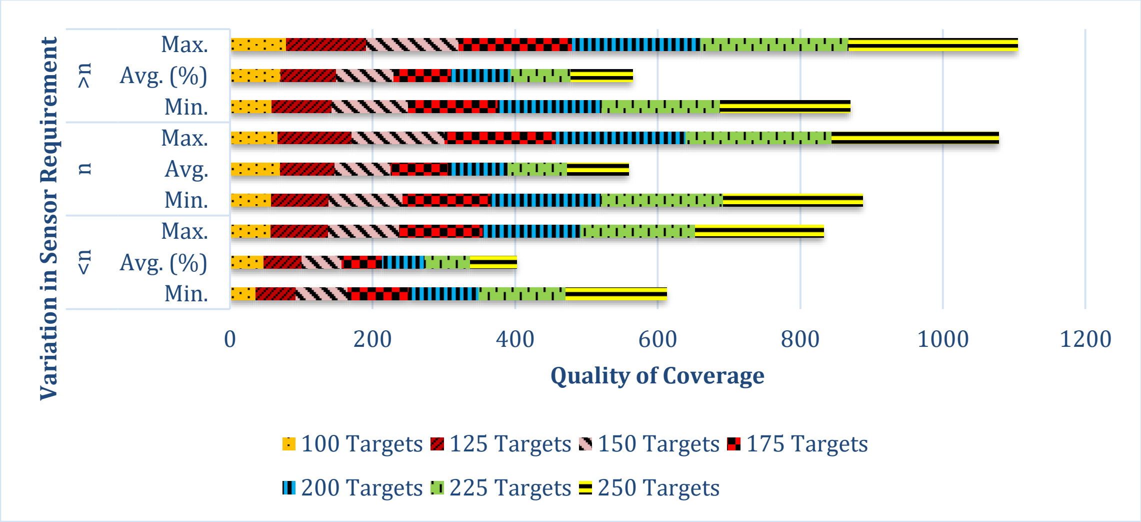

Fig. 5. Quality of coverage by varying the sensor requirement for DHWT algorithm

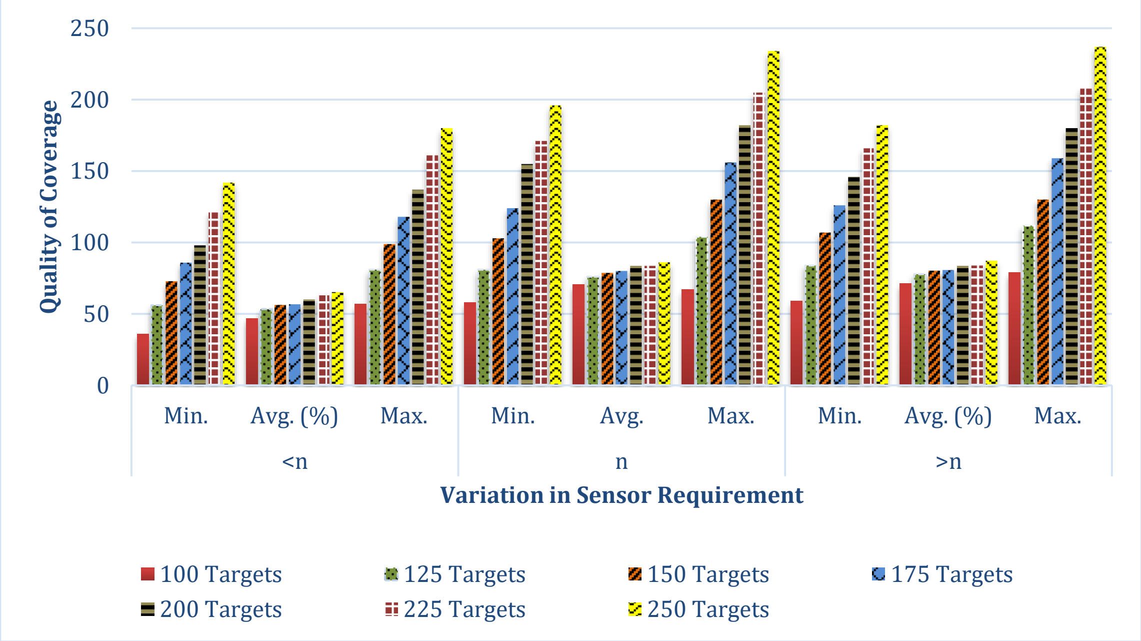

Fig. 6. Quality of coverage by varying the sensor requirement for cuckoo search algorithm

5. CONCLUSION

IWSNs play an enormous role in improving the productivity of industrial systems through controlling, monitoring, and maintaining the business processes. Even though IWSN is a rapidly developing area, few issues still annihilate its future exploration. The problems in IWSN are green computing, target coverage problems, network connectivity, optimal sensor placement, localization, security, and adaptability. This paper focuses on the target coverage problem by deploying the minimum number of sensors at the optimal spot for green IWSN. A simple Vertex Coloring based Optimal Sensor Placement (VC-OSP) algorithm proposed to address the above issue. The VC-OSP partitions the target set using a sequential vertex coloring algorithm to determine the sensor requirement and determines its optimal spot using the mean position of the targets in each subset. But, the VC-OSP algorithm determines the optimal spots for sensors depending on the target's parts. This method of finding positions sometimes leads to the deployment of sensors over the targets. Deploying the sensors over the targets in industrial applications may increase the probability of affecting the sensors due to its pressure, vibration, temperature, etc. in the system. Hence, to provide better optimal spots for the obtained set of sensors using the VC-OSP algorithm, the algorithm utilizes the existing evolutionary algorithms. The results obtained tabled. The simulation results clearly show that the better target coverage has achieved by each evolutionary algorithms since the sensor requirements predetermined before determining its optimal spots.

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BIOGRAPHY OF AUTHORS

R. Pavithra received her B.Sc. degree in Mathematics from University of Madras in 2014 and M.Sc. degree in Applied Mathematics from Anna University in 2016. She is currently working towards the Ph.D. degree in Anna University, Chennai. Her research covers wavelet analysis, algorithms, graph theory and wireless sensor networks. pavithraravikumar94@gmail.com

D. Arivudainambi is currently a Professor in the Department of Mathematics, Anna University, Chennai. He had been at University of Toronto, Toronto. His main research interests include network optimization, network models, queueing models with computer applications and communication systems. He is reviewer of many journals including IEEE, Elsevier, Springer and Wiley. He published many papers in reputed journals. He served as General and Technical Program Chair of numerous conferences. 2arivu@annauniv.edu