

Deployment For Optimal Coverage In Wsns: Pb3c Based Approach

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ABSTRACT

It is a basic human instinct to explore and understand nature and the development of science and technology. With the advancing science and technology the urge to investigate has further increased (Alias et al., 2009), (Ibrahim et al., 2013). For the effective supervisory control, sensing plays one of the most important roles. To understand the physical world, various sensors such as chemical sensors, gas sensors and electronic sensors have been invented (Chapman et al., 2010). With the advent of wireless sensor networks (WSNs) the field of command, control and communication has experienced a paradigm shift. A WSN is a collection of densely populated low power nodes that are usually deployed for monitoring, surveillance and control applications (R.S et al., 2002). WSNs have found a wide spread application in automatic area monitoring in military, industry, agriculture, health monitoring in remote areas, environmental disaster detection or prevention and the very common automatic movement of escalators. Such sensors have been deployed in a physical space ranging from human body to international borders of nations. In this paper research work was intended to Sensor node deployment for optimal coverage: This objective is focused on searching, analyzing and selecting different approaches for node deployment to optimize the coverage area with the given number of network nodes.

INTRODUCTION

Wireless Sensor network replicated with different features has become popular in the field of monitoring and surveillance. The whole globe is expected to come under the surveillance of wireless sensor networks along with the use of internet. This is called Internet of Things (IOT). IOT is expected to cover whole world in the span of next 15 years (Eksin et al., 2006). WSNs has

vast number of applications such as defense (military), smart space, environmental application, transportation, homeland defense etc (A.E et al., 2004), (Kumar et al., 2016).

When the deployment area becomes large, network deployment becomes a challenge (Passarella et al., 2009). The harsh conditions and changing environment of the area makes this deployment more complex (Ozkarahan et al., 2007) (Kumar et al., 2003). To find out the appropriate locations of the mobile sensors software computing techniques are more suitable. In the previous chapter three optimization technique BB-BC (Erol, O. K., & Eksin, I. 2006), 3PGA (Kumar et al., 2016) and Genetic Algorithm (Malanie, M. 1999), were applied for deployment.

There are many applications where BB-BC optimization theory was successfully applied (Khehra et al., 2015; Kumbasar, T. et al., 2008; Kripka, M., & Kripka, R. M. L. 2008; Bhalla, P. 2013; Tahershamsi, A. 2012) However it was observed that for higher dimensional problems the algorithm did not perform well. At times, it was found to be trapped in the local minima (Woehrle et al., 2009).

This paper discusses application of parallel BB-BC (PB3C) global optimization technique to the optimal deployment of WSNs. Section 2 of this paper introduces the multi-population PB3C approach and section 3 presents results and discussion of simulation. Section 4 compares the performance with other three approaches. Section 5 draws the conclusions.

2. PARALLEL BB-BC APPROACH

Parallel BBBC was proposed by Shakti Kumar et al. PBBBC is multi-population based nature inspired computing algorithm. The parallel search has considerably improved the convergence rate of PB3C as compared to BB-BC. PBB-BC approach has been presented below.

Parallel Big Bang Big Crunch (PB3C) based Deployment Approach

begin

Randomly generate initial 'NP' population each of size 'PS'. Every individual consisting of 'NG' genes. NG here represents the 'n' number of sensors each represented with (x, y) coordinates. Thus each individual (candidate solution) consists of NG, (x,y) coordinates.

while not TC

for j = 1: NP

Compute the fitness value of all the candidate solutions of j^{th} population. In our problem fitness value is the overlapping area amongst the sensor nodes as computed by equations 3.4 and 3.6 as given in section 3.3 of chapter 3 of this paper. Overlapping areas need to be minimized in order to maximize the overall covered area.

Compute the Centre of mass using equation 1.

$$x^{\rightarrow c} = \frac{\sum_{j=1}^N \left[\frac{1}{f^j} x^{\rightarrow j} \right]}{\sum_{j=1}^N \frac{1}{f^j}} \quad (1)$$

Best fit individual can be chosen in place of center of mass;

Sort the population from best to worst based on fitness (cost) value;

Select local best candidate $l_{\text{elite}}(j)$ for j^{th} population;

end

From amongst “N” l_{elite} candidates select the globally best g_{elite} candidate;

for j =1: NP

With a given probability replace a gene of $l_{\text{elite}}(j)$ elite with the corresponding gene of global best g_{elite} candidate

end

for all NP populations

for j =1: PS

for k =1: NG

Calculate new candidates around the elite by adding or subtracting a small random number whose value decreases as the iterations elapse using equation 2;

$$x_{\text{new}(j,k)} = l_{\text{elite}(j,k)} + (1 * \text{rand}) / m \quad (2)$$

/* ‘m’ is the number of iteration */

/* $x_{\text{new}(j,k)}$ is the new candidate solution */

end

end

end while

end

3. RESULTS AND DISCUSSION OF SIMULATION

The proposed approach was simulated on a core i7@2.5GHz processor with 8GB RAM based computer running on Windows 7 platform.

We considered the 5 scenarios as shown in Table 1. For the first scenario, we consider a 100m ×100m marked area with 70 sensors each with arrange of 7 meters. For all other scenarios, we considered a sensor radio range of 14 meters. The various simulation parameters used for node deployment for optimal coverage are listed in the Table 2.

Table 1 Network Simulation Parameters

Scenario No.	Iteration	Sensors	Radius (m)	Area of Deployment (m ²)
1	2000	70	7	100×100
2	2000	70	14	200×200
3	2000	100	14	250×250
4	2000	160	14	300×300
5	2000	550	14	500×500

Table 2 Simulation Parameters

i). Number of Populations NP = 4
ii). Population size PS (Number of Individuals) = 5
iii). No. of genes in each Individual NG = No. of Sensors

For each scenario, we conducted 20 trials. Each trial was run for 2000 iteration. The minimum, maximum and average covered areas for 20 trials is given in the Table 3. Figure 1 represents the iteration versus covered area graph for scenario 4 (area 300×300 m²) & scenario 5 (area 500×500 m²) respectively.

Table 3 Performance of PB3C Algorithm

Scenario	Minimum	Average	Maximum
1	96.8924	97.8239	98.0443
2	96.1422	97.1463	97.9246
3	96.8523	97.3439	97.8462
4	97.2730	98.3962	98.9662
5	91.2461	92.0682	92.5245

For $100 \times 100 \text{ m}^2$ network area Parallel BB-BC was able to give an average coverage of 97.8239%. For $200 \times 200 \text{ m}^2$ network area with 70 sensors the average coverage area was observed to be 97.14 %. For $250 \times 250 \text{ m}^2$ marked area with 110 sensors the average covered area was observed to be 97.34%. For $300 \times 300 \text{ m}^2$ network with 160 sensors the average coverage area was observed to be 98.3962% for $500 \times 500 \text{ m}^2$ network with 450 sensors the average covered area in 2000 iteration was observed to be 92.0682%.

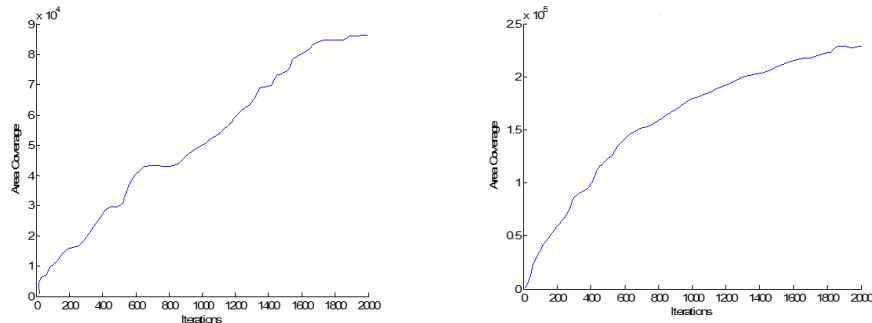


Figure 1 Iteration versus Covered Area of $300 \times 300 \text{ m}^2$ and $500 \times 500 \text{ m}^2$ respectively

Figure 1 shows the area covered versus iterations by PB3C based deployment in network scenario of $300 \times 300 \text{ m}^2$ by 160 sensors and area covered by 550 sensors in $500 \times 500 \text{ m}^2$ area respectively.

4. PERFORMANCE COMPARISON

In order to compare the performance of PB3C algorithm with respect to 3 other algorithms we simulated the performance of all the four algorithms with same scenario and same number of sensors. All approaches were run for same number of 2000 iterations. The minimum, maximum and average covered areas for 20 trials were recorded and given in Table 4. The simulated covered area performance of GA, 3PGA and BB-BC and PB3C are placed in Table 4 for comparison.

Table 4 Comparative performance

Scenario	Algorithm	Minimum	Average	Maximum	Ranking as per average covered area
1	GA	92.8501	94.5294	95.6151	1. PB3C
	3PGA	96.1520	96.6965	97.4155	2. 3PGA
	BB-BC	96.2033	96.3760	96.9275	3. BB-BC

	PB3C	96.8924	97.8239	98.0443	4. GA
2	GA	95.8968	95.9604	97.7792	1. PB3C
	3PGA	96.4566	97.0852	97.3279	2. 3PGA
	BB-BC	95.3550	96.2761	98.0806	3. BB-BC
	PB3C	96.1422	97.1463	97.9246	4. GA
3	GA	95.2281	95.9854	96.8039	1. PB3C
	3PGA	96.6806	97.1556	97.7329	2. 3PGA
	BB-BC	94.6741	96.2411	97.4406	3. BB-BC
	PB3C	96.8523	97.3439	97.8462	4. GA
4	GA	95.2129	95.9635	96.5253	1. PB3C
	3PGA	95.6781	97.2031	97.5839	2. 3PGA
	BB-BC	95.8754	96.6961	97.5793	3. BB-BC
	PB3C	97.2730	98.3962	98.9662	4. GA
5	GA	84.2245	85.6050	85.9732	1. PB3C
	3PGA	89.3454	90.2070	91.1005	2. 3PGA
	BB-BC	85.2754	87.9243	88.7554	3. BB-BC
	PB3C	91.2461	92.0682	92.5245	4. GA

Figures 2(a), 2(b), 2(c), 2(d), 2(e) represent the min, mean and max values of the covered area under scenario 1, 2, 3, 4 and scenario 5 respectively.

From Table 4 one can observe that as far as the mean covered area is concerned PB3C based approach covers maximum area in all the scenarios. Followed by 3PGA, BB-BC and GA based approaches.

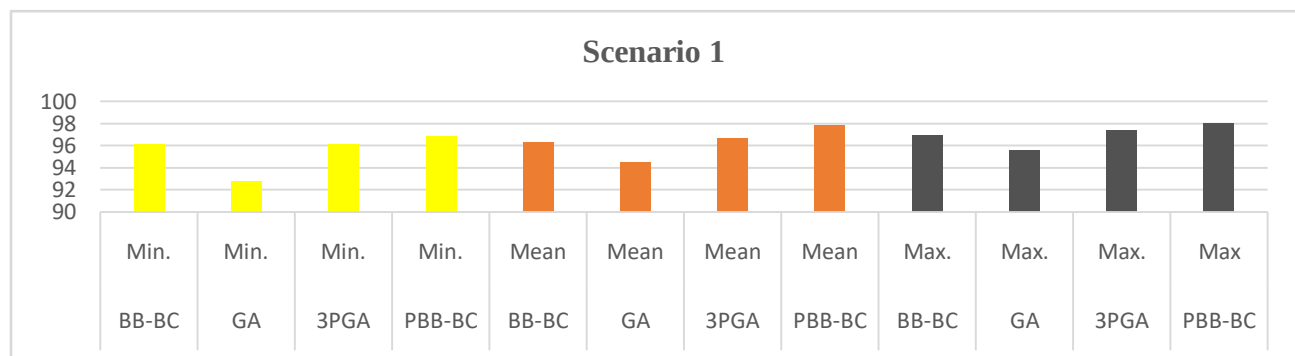


Figure 2 (a) Scenario 1

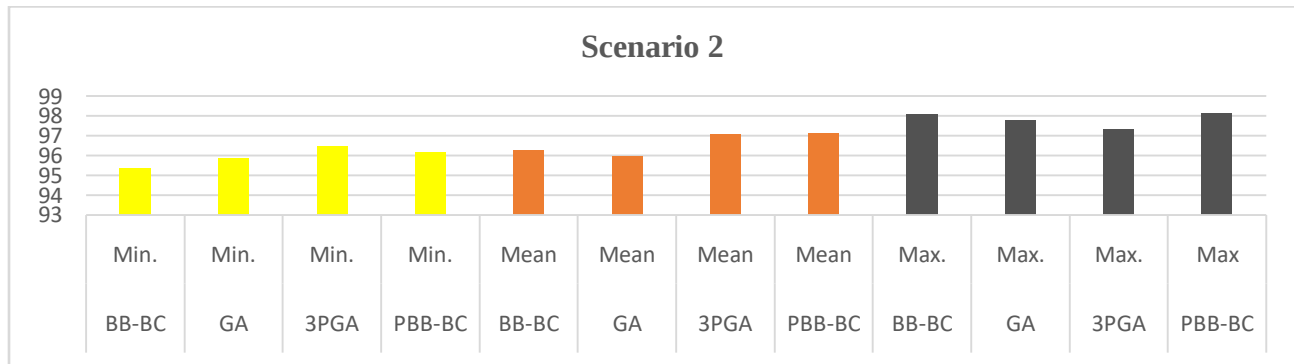


Figure 2 (b) Scenario 2

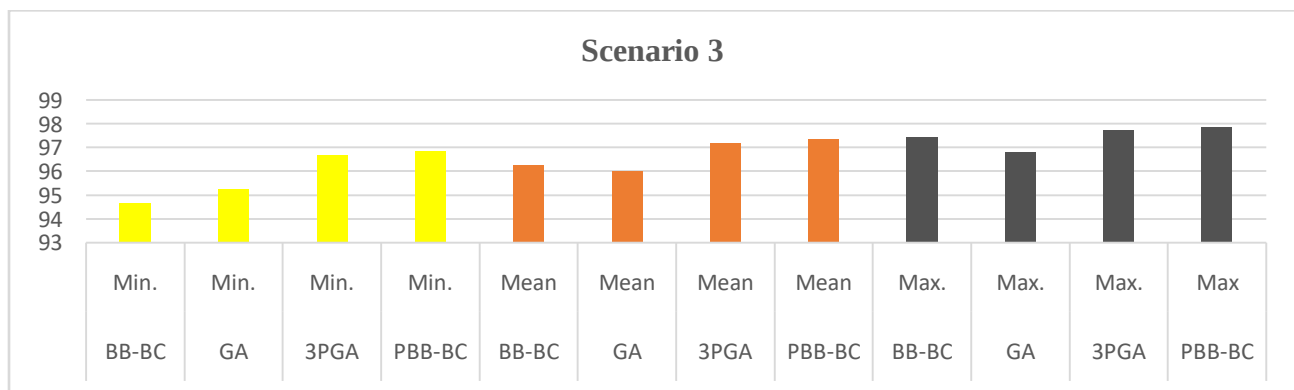


Figure 2(c) Scenario 3

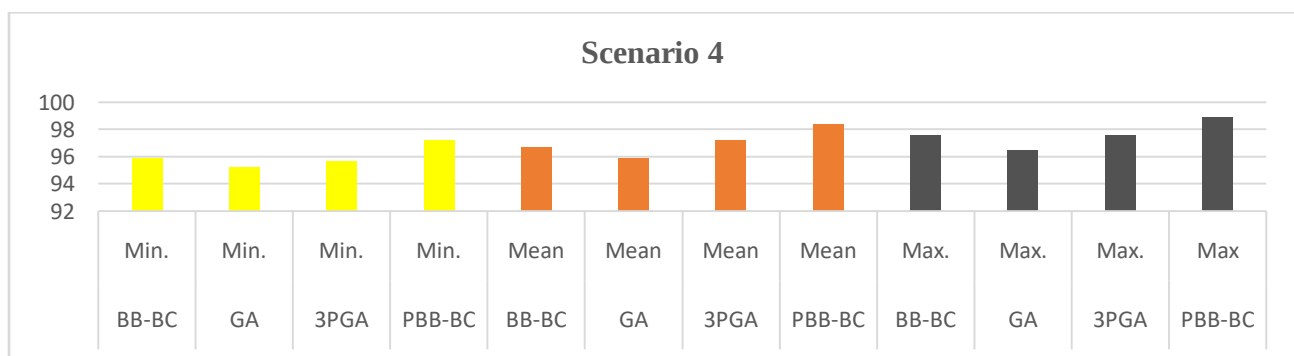


Figure 2 (d) Scenario 4

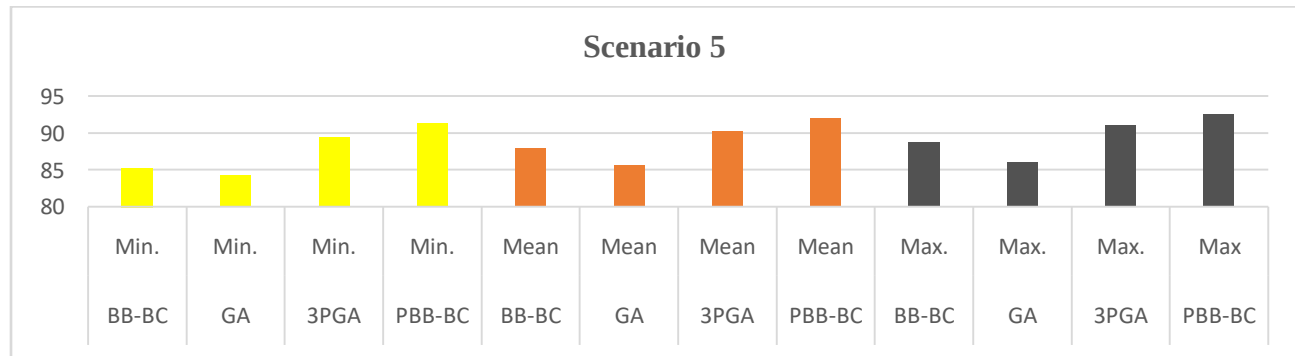


Figure 2 (e) Scenario 5

5. CONCLUSIONS

This Paper presented parallel BB-BC algorithm (PB3C) based new approach for WSNs deployment. PB3C is one of most recent nature inspired optimization algorithm reported in the literature. This is a multi-population algorithm with improved search and optimization capability than the simple BB-BC. The approach evaluates overlapping area and minimizes this overlapping, thus evaluating the maximal covered area for a given number of nodes.

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