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On Energy Hole And Coverage Hole Avoidance in Underwater Wireless Sensor Networks Using ABC Algorithm

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Abstract: Network lifetime plays an integral role in setting up an efficient wireless sensor network. The objectives of this thesis are: 1) To deploy sensor nodes at optimal locations such that the theoretically computed network lifetime is maximum 2) To schedule these sensor nodes such that the network attains the maximum lifetime. 3) A coverageaware sensor deployment scheme should be developed to ensure sufficient sensing coverage, and 4) to face of sensing node failures, a sensor self-organizing mechanism needs to be devised to efficiently recover the sensing void and restore the required sensing coverage. Since local repairs generally consume less moving energy and communication overhead than a global redeployment does, the sensor self-organizing mechanism should limit the network recovery/repairing locally to effectively reduce unnecessary.

Further, the nodes are scheduled to achieve this upper bound. This project uses artificial bee colony algorithm and particle swarm optimization for sensor deployment problem followed by a heuristic for scheduling. In addition, ANT colony optimization technique is used to provide maximum network lifetime utilization. The comparative study shows that artificial ACO performs better than bee colony algorithm for sensor deployment problem. The proposed heuristic was able to achieve the theoretical upper bound in all the experimented cases.

Keywords: UWSN, Sensor Deployment, Energy Hole, Sensor Scheduling, ABC algorithm, ANT Colony Algorithm, PSO algorithm.

I. INTRODUCTION

Wireless Sensor Networks have recently come into prominence because they hold the potential to revolutionize many segments of our economy and life, from environmental monitoring and conservation, to manufacturing and business asset management, to automation in the transportation and health care industries. The design, implementation, and operation of a sensor network requires the confluence of many disciplines, including signal processing, networking and protocols, embedded systems, information management and distributed algorithms. Since the sensor nodes can be deterministically deployed, the optimal deployment locations and the schedule are decided at the base station, prior to actual deployment. The existing method has two phases: sensor deployment and sensor scheduling. The nodes are initially deployed randomly.

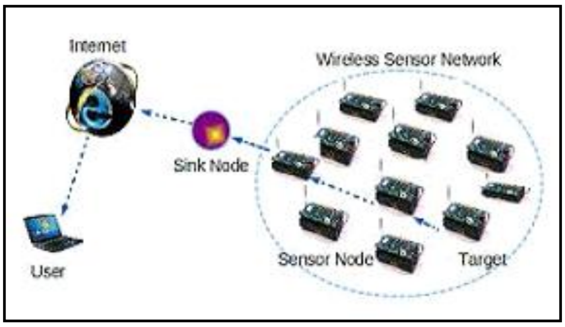

Fig 1.1 WSN Communication

Sensor coverage is important while evaluating the effectiveness of a wireless sensor network. A lower coverage level (simple coverage) is enough for environmental or habitat monitoring or applications like home security. Higher degree of coverage (k-coverage) will be required for some applications like target tracking to track the targets accurately or if sensors work in a hostile environment such as battle fields or chemically polluted areas. More reliable results are produced for higher degree of coverage which requires multiple sensor nodes to monitor the region/targets.

In some cases, for the same application, the coverage requirement may vary. For example, for forest fire detections, the coverage level may be low in rainy seasons, but high in dry seasons. An example of Q-coverage is video surveillance systems deployed for monitoring hostile territorial area where some sensitive targets like a nuclear plant may need more sensors cooperate to ensure source redundancy for precise data.

Both sensor deployment and scheduling are important to ensure prolonged network lifetime. Traditionally, the problems of sensor placement and scheduling have been considered separately from each other. A balanced performance is crucial for most applications. Different sensor deployment strategies can cause very different network topology, and thus different degrees of sensor redundancy. A good sensor deployment with sufficient number of sensors which ensures a certain degree of redundancy in coverage so that sensors can rotate between active and sleep modes is required to balance the workload of sensors.

II. LITERATURE SURVAY

Yi Zou and Krishnendu Chakrabarty et al [1] describe The effectiveness of cluster-based distributed sensor networks depends to a large extent on the coverage provided by the sensor deployment. They propose a virtual force algorithm (VFA) as a sensor deployment strategy to enhance the coverage after an initial random placement of sensors. For a given number of sensors, the VFA algorithm attempts to maximize the sensor field coverage. A judicious combination of attractive and repulsive forces is used to determine virtual motion paths and the rate of movement for the randomly-placed sensors. Once the effective sensor positions are identified, a one-time movement with energy consideration incorporated is carried out, i.e., the sensors are redeployed to these positions. They also propose a novel probabilistic target localization algorithm that is executed by the cluster head. The localization results are used by the cluster head to query only a few sensors (out of those that report the presence of a target) for more detailed information. Simulation results are presented to demonstrate the effectiveness of the proposed approach.

Yunxia Chen et al [2] describe a **l**ifetime per unit cost, defined as the network lifetime divided by the number of sensors deployed in the network, can be used to measure the utilization efficiency of sensors in a wireless sensor network (WSN). Analyzing the lifetime per unit cost of a linear WSN, they find that deploying either an extremely large or an extremely small number of sensors is inefficient in terms of lifetime per unit cost. They thus seek answers to the following questions: how many sensors should be deployed and how to deploy them to maximize the lifetime per unit cost. Numerical and simulation results are provided to study the optimal sensor placement and the optimal number of deployed sensors.

P. Corke et al [3] describe a sensor network deployment method using autonomous flying robots. Such networks are suitable for tasks such as large-scale environmental monitoring or for command and control in emergency situations. They describe in detail the algorithms used for deployment and for measuring network connectivity and provide experimental data they collected from field trials. A particular focus is on determining gaps in connectivity of the deployed network and generating a plan for a second, repair, pass to complete the connectivity. This project is the result of a collaboration between three robotics labs (CSIRO,USC, and Dartmouth.)

Krishnendu Chakrabarty et al [4] describe a novel grid coverage strategies for effective surveillance and target location in distributed sensor networks. They represent the sensor field as a grid (two or three-dimensional) of points (coordinates) and use the term target location to refer to the problem of locating a target at a grid point at any instant in time. They first present an integer linear programming (ILP) solution for minimizing the cost of sensors for complete coverage of the sensor field. They solve the ILP model using a representative public-domain solver and present a divide-andconquer approach for solving large problem instances. They then use the framework of identifying codes to determine sensor placement for unique target location. They provide coding-theoretic bounds on the number of sensors and present methods for determining their placement in the sensor field. They also show that grid-based sensor placement for single targets provides asymptotically complete (unambiguous) location of multiple targets in the grid.

Pankaj K. Agarwa et al [5] describe the problem of covering a two-dimensional spatial region P, cluttered with occluders, by sensors. A sensor placed at a location p covers a point x in P if x lies within sensing radius r from p and x is visible from p, i.e., the segment px does not intersect any occluder. The goal is to compute a placement of the minimum number of sensors that cover P. They propose a landmark-based approach for covering P. Suppose P has ς holes, and it can be covered by h sensors. Given a small parameter $\varepsilon > 0$, let $\lambda := \lambda(h, \varepsilon) = (h/\varepsilon) \log \varsigma$. They prove that one can compute a set L of $O(\lambda \log \lambda \log (1/\varepsilon))$ landmarks so that if a set S of sensors covers L, then S covers at least $(1 - \varepsilon)$-fraction of P. It is surprising that so few landmarks are needed, and that the number does not depend on the number of vertices in P. They then present efficient randomized algorithms, based on the greedy approach, that, with high probability, compute $O(\tilde{h} \log \lambda)$ sensor locations to cover L; here $\tilde{h} \le h$ is the number sensors needed to cover L. They propose various extensions of their approach, including: (i) a weight function over P is given and S should cover at least (1 − ε) of the weighted area ofP, and (ii) each point of P is covered by at least t sensors, for a given parameter t ≥ 1.

Jing LI et al [6] describe a sensing coverage is a fundamental problem in sensors networks. Different from traditional isotropic sensors with sensing disk, directional sensors may have a limited angle of sensing range due to special applications. In this paper, they study the coverage problem in Directional Sensor Networks (DSNs) with the rotatable orientation for each sensor. They propose the Optimal Coverage in Directional Sensor Networks (OCDSN) problem to cover maximal area while activating as few sensors as possible. Then they prove the OCDSN to be NP-complete and propose the Voronoi-based Centralized Approximation (VCA) algorithm and the VORONOI-based Distributed Approximation (VDA) algorithm of the solution to the OCDSN problem. Finally, extensive simulation is executed to demonstrate the performance of the proposed algorithms.

III SENSOR DEPLOYMENTMETHODOLOGY

Hundreds to several thousands of nodes are deployed throughout the sensor field. They are deployed within tens of feet of each other. The node densities may be as high as 20 nodes / m3. Deploying a high number of nodes densely requires careful handling of topology maintenance. Pre-deployment and deployment phase: Sensor nodes can be either thrown in as a mass or placed one by one in the sensor field. They can be deployed by dropping from a plane, delivered in an artillery shell, rocket, or missile, and placed one by one by either a human or a robot. Post-deployment phase: After deployment, topology changes are due to change in sensor nodes position, reach ability (due to jamming, noise, moving obstacles, etc.), available energy, malfunctioning, and task details. Redeployment of additional nodes phase: Additional sensor nodes can be redeployed at any time to replace malfunctioning nodes or due to changes in task dynamics. Sensor nodes are densely deployed either very close or directly inside the phenomenon to be observed. Therefore, they usually work unattended in remote geographic areas. They may be working in the interior of large machinery, at the bottom of an ocean, in a biologically or chemically contaminated field, in a battlefield beyond the enemy lines, and in a home or large building.

In a multi-hop sensor network, communicating nodes are linked by a wireless medium. These links can be formed by radio, infrared, or optical media. To enable global operation of these networks, the chosen transmission medium must be available worldwide. The wireless sensor node, being a microelectronic device, can only be equipped with a limited power source (< 0.5 Ah, 1.2 V). In some application scenarios, replenishment of power resources might be impossible. Sensor node lifetime, therefore, shows a strong dependence on battery lifetime. In this project used two types of sensor node deployments: random deployment and deterministic deployment. Random deployment is suitable for applications where the details of the regions are not known, or regions are inaccessible. An example of random deployment of sensor nodes would be in battlefield surveillance. In such a deployment, the most common way of extending the network lifetime is by scheduling the sensor nodes such that only a subset of sensor nodes that is enough to satisfy coverage requirement need to be active at a time.

In deterministic deployment, the details of the region will be known apriori and since a provision of deploying nodes at specific locations prevail, there exists two ways by which network lifetime can be maximized. One is at deployment phase and the other is at scheduling phase. Given a region with targets being monitored by sensor nodes, the upper bound of network lifetime can be mathematically computed. This information can be used for computing locations which would be appropriate for coverage to be satisfied as well as network lifetime to be maximum. Once the deployment locations are computed, sensor nodes can be scheduled to achieve the optimum lifetime. Sensor deployment and scheduling in this way contributes equally to extend the network lifetime. There are several ways of computing deployment locations. Bio-inspired algorithms prove to be effective for solving optimization problems.
In this project is use Artificial Bee Colony (ABC) algorithm to compute deployment locations. Apart from ABC algorithm, we also use a heuristic and PSO (Particle Swarm Optimization) to compute the deployment locations. Though the heuristic performs better than random deployment, it is not that good as ABC algorithm in maximizing lifetime. It is observed that ABC algorithm is robust than PSO algorithm for this problem. After computing the optimal locations, sensor nodes are scheduled using a heuristic so as to achieve the theoretical upper bound of network lifetime.

- It also extends the new algorithm to make it work in operative settings with time-varying and position-dependent coverage requirements.
- It extends a previously published algorithm based on virtual forces to accommodate heterogeneous sensors and prove important properties about this new algorithm.
- It demonstrates that it can be extended to deal with dynamically generated events or uneven energy depletion due to communications.

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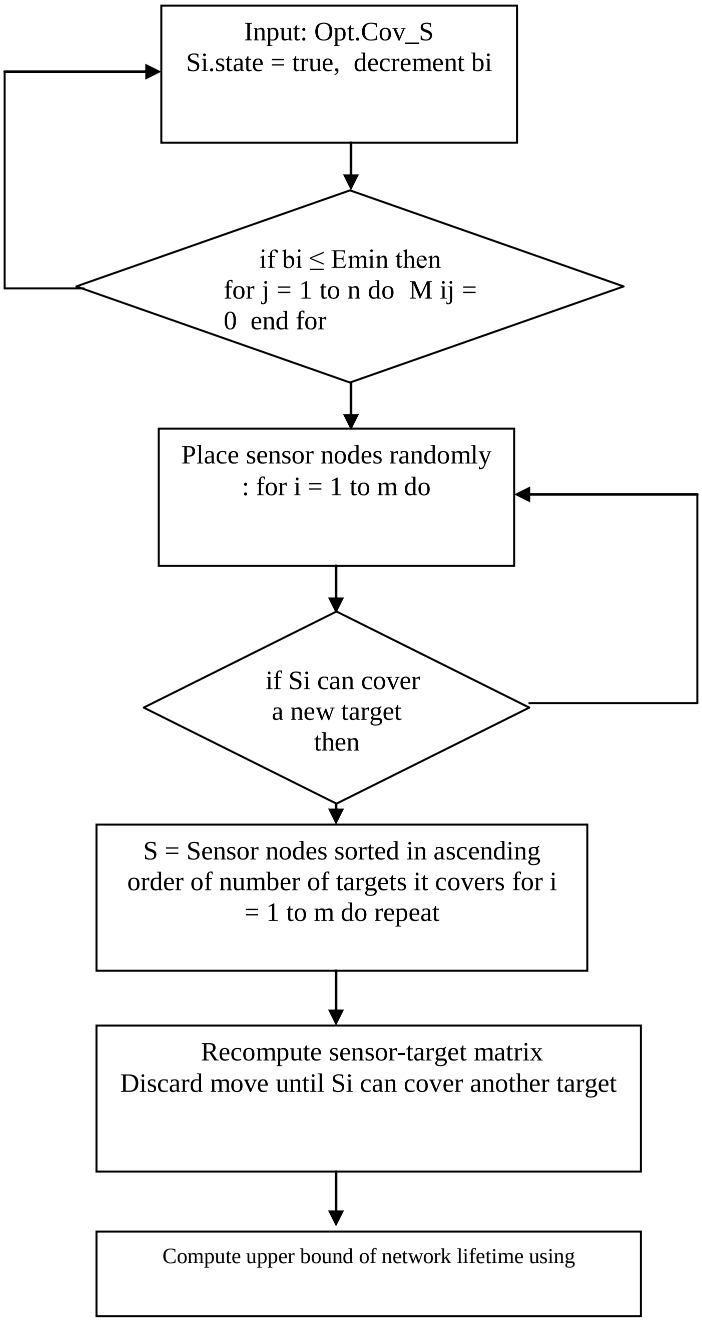
❖ Finally, by means of simulations, it shows that it provides a very stable sensor behavior, with fast and guaranteed termination and moderate energy consumption.
❖ It does not require manual tuning or perfect knowledge of the operating conditions, and works properly even if the sensor positioning is imprecise. The algorithm only requires loose synchronization and local communication.
❖ Because it converges quickly and does not require a priori knowledge of the deployment environment, it is also well suited for dynamic environments in which the sensing density requirements change over time

Heuristic for Sensor Deployment:
If any sensor node is idle (without monitoring any target), the node is moved to the least monitored targets' location. This is to ensure that all sensor nodes play their part in monitoring the targets. The sensor nodes are then sorted based on the number of targets it cover. The sensor node is placed at the middle of all the targets it covers. The next nearest target is identified and the sensor node is placed at the middle of all these targets. If it can cover this new target along with targets it was already monitoring, allow this move, and else discard the move.
This is done till the sensor node cannot cover any new target. At the end, upper bound is computed. The drawback of this approach is that it depends on the initial position of the sensor nodes. Though it may perform well for dense deployments, consistency cannot always be guaranteed.



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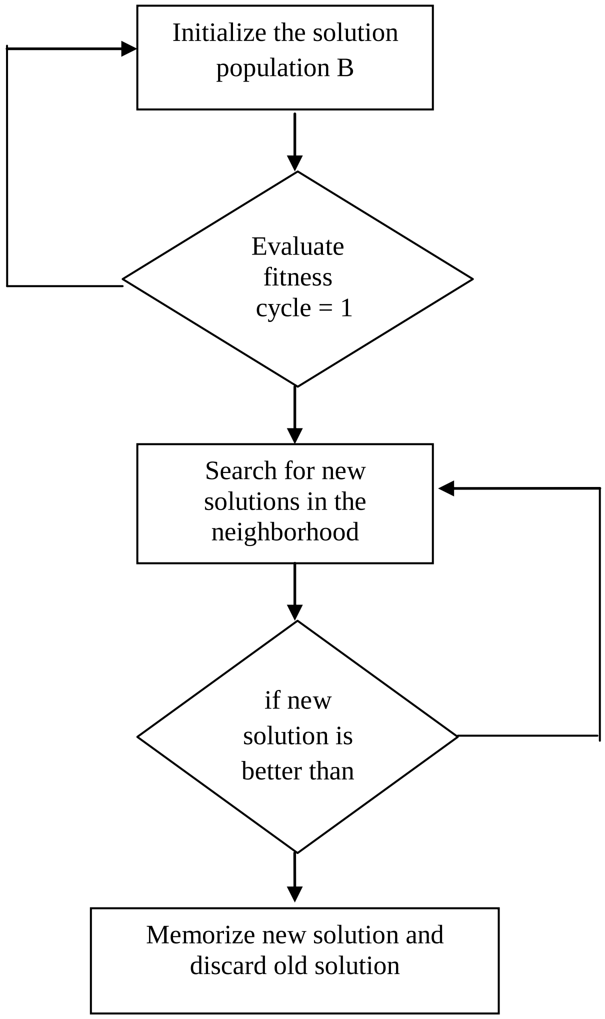
ABC algorithm
Artificial Bee Colony (EABC) Algorithm is an optimization algorithm based on the intelligent behavior of honey bee swarm. The colony of bees contains three groups: employed bees, onlookers and scouts. The employed bee takes a load of nectar from the source and returns to the hive and unloads the nectar to a food store. After unloading the food, the bee performs a special form of dance called waggle dance which contains information about the direction in which the food will be found, its distance from the hive and its quality rating. In the ABC algorithm, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. Therefore, the deployment of the sensors in the sensed area refers a food source (a solution) in the algorithm. The coverage rate of the network, i.e., total covered area, corresponds to the fitness value of the solution.

There are so many kinds of swarms in the world. It is not possible to call all of them intelligent or their intelligence level could be varying from swarm to swarm. Self-organization is a key feature of a swarm system which results collective behavior by means of local interactions among simple agents interpreted the self-organization in swarms through four characteristics. The positive feedback which promoting the creation of convenient structures. Recruitment and reinforcement such as trail laying and following in some ant species can be shown as example of positive feedback. Negative feedback: counterbalancing positive feedback and helping to stabilize the collective pattern. In order to avoid the saturation which might occur in terms of available foragers a negative feedback mechanism is needed. In the initialization phase, the population of food sources (solutions) is initialized by artificial scout bees and control parameters are set. In the employed bees phase, artificial employed bees search for new food sources having more nectar within the neighborhood of the food source in their memory. They find a neighbor food source and then evaluate its fitness. After producing the new food source, its fitness is calculated and a greedy selection is applied between it and its parent. After that, employed bees share their food source information with onlooker bees waiting in the hive by dancing on the dancing area.



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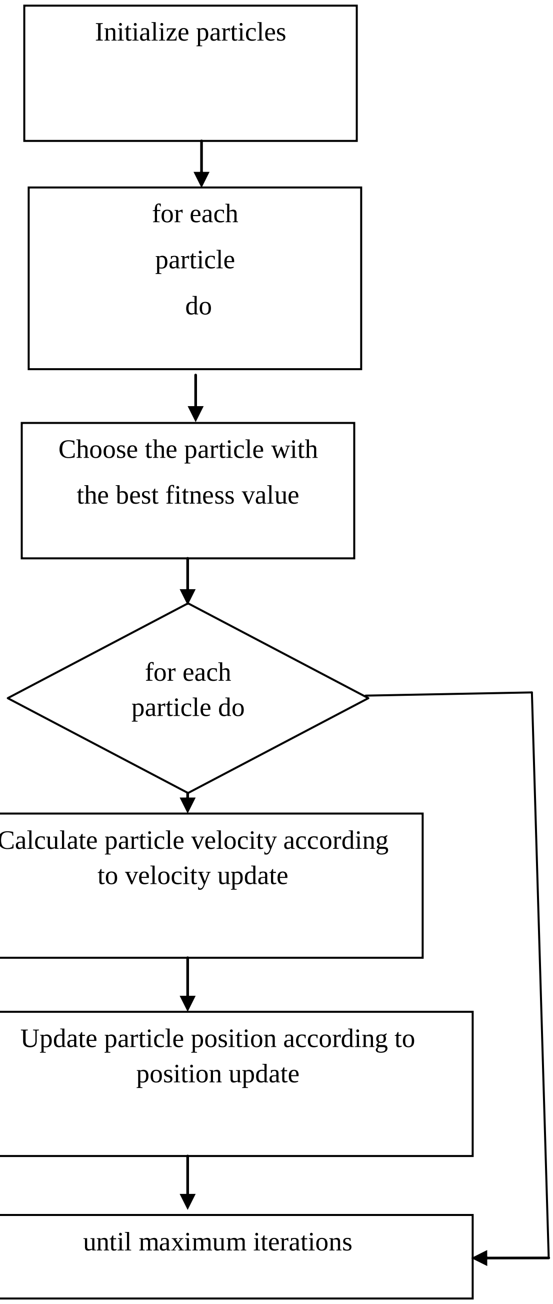
PSO Based Sensor Deployment:

Particle Swarm Optimization (PSO) consists of a swarm of particles moving in a search space of possible solutions for a problem. Every particle has a position vector representing a candidate solution to the problem and a velocity vector. Moreover, each particle contains a small memory that stores its own best position seen so far and a global best position obtained through communication with its neighbor particles.



IV EXPERIMENTAL RESULTS

The following **Table 4.1** describes experimental result for Heuristics, ABC, PSO algorithm and ACO algorithm in sensor deployment energy detection analysis. The table contains total number of wireless sensor node deployment and number of node count energy detection for Heuristics algorithm, number of node count energy detection for ABC algorithm, number of node count energy detection for PSO algorithm, number of node count energy detection for ACO algorithm details are shown.

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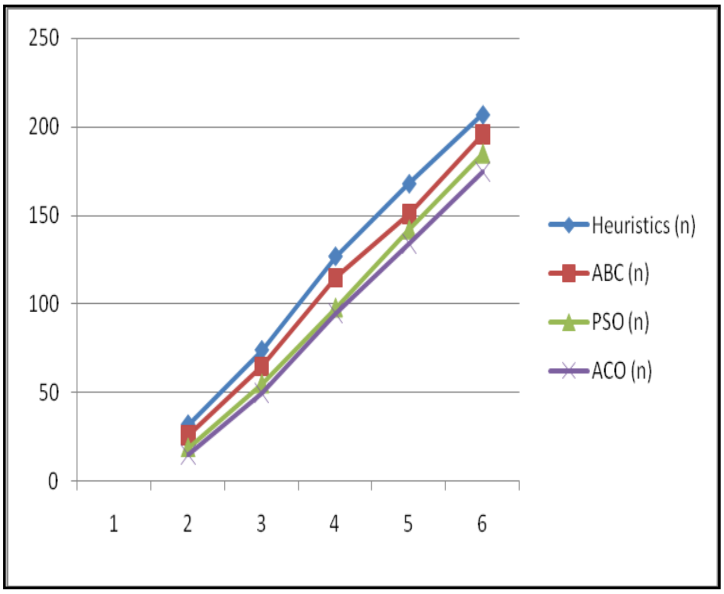
Table 4.1 Sensor Deployments Scheduling (Node Energy Detection)

S.NO	NUMBER OF WSN NODE (n)	Heuristics (n)	ABC (n)	PSO (n)	ACO (n)
1	50	32	26	19	15
2	100	74	65	55	50
3	150	127	115	98	95
4	200	168	151	142	134
5	250	207	196	185	175



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The following **Table 4.2** describes experimental result for Heuristics, ABC, PSO algorithm and ACO algorithm in sensor deployment time interval analysis. The table contains total number of wireless sensor node deployment and number of node time taken for Heuristics algorithm, number of node time taken for ABC algorithm, number of node time taken for PSO algorithm, number of node time taken for ACO algorithm details are shown.

Table 4.2 Sensor Deployments Scheduling
(Time Interval Analysis)

S.NO	NUMBER OF WSN NODE DEPLOYMENTS(n)	Heuristics (ms)	ABC (ms)	PSO (ms)	ACO (ms)
1	50	0.025	0.022	0.018	0.015
2	100	0.036	0.032	0.029	0.024
3	150	0.046	0.042	0.038	0.032
4	200	0.056	0.050	0.044	0.039
5	250	0.072	0.068	0.065	0.061

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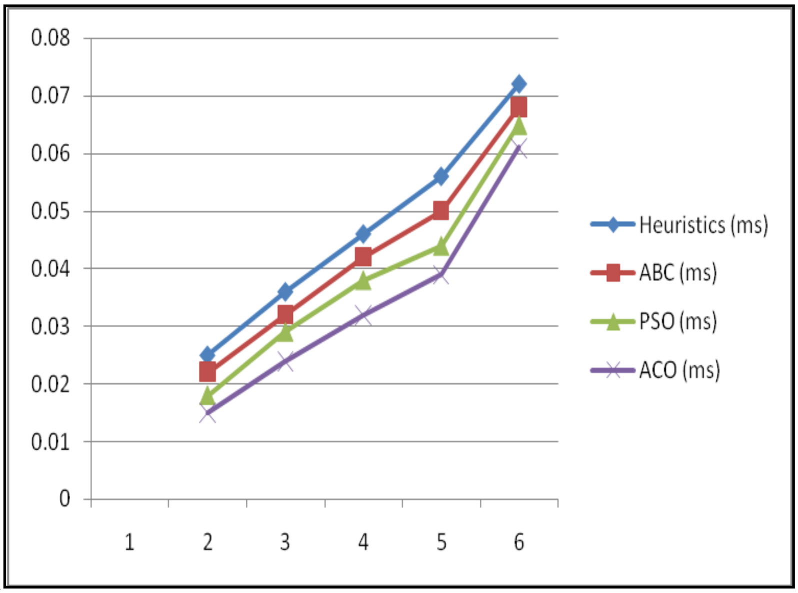

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V CONCLUSION

The ABC algorithm is applied to the dynamic deployment problem in WSNs within the scenario of mobile and stationary sensors, which is based on a probabilistic detection model. In this project is compute deployment locations for sensor nodes using artificial bee colony algorithm such that the network lifetime is maximum. Artificial bee colony algorithm performs better than PSO algorithm for this problem. In order to avoid the battery drain of all nodes at a time, sensor node scheduling can be done so that only minimum number of sensor nodes required for satisfying coverage requirement needs to be turned on.

The performance of the algorithm is compared with the PSO algorithm, which is a well-known swarm based optimization technique. In the simulations, a similar network scenario which is studied in the literature is tried to be used to make comparison. Simulation results show that the ABC algorithm obtains better deployments for WSNs than the PSO algorithm.

As a future work, study the usage and performance of the ABC algorithm not only in the dynamic deployment of WSNs, but also for other optimization issues like localization and routing. Further extension of this work is to use this technique with other format of sensor deployment. In future, study the related to establish a sophisticated mixing model for the extended sensor deployment with better color quality will be considered. For future work, plan to extend this method of deployment and scheduling for probabilistic coverage in wireless sensor networks.

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