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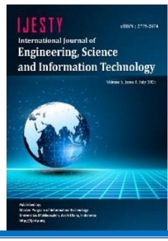

Swarm Intelligence-Based Performance Optimization for Wireless Sensor Networks for Hole Detection

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Abstract

Extensive research into maintaining coverage over time has been spurred by the growing need for wireless sensor networks to monitor certain regions. Coverage gaps brought on either haphazard node placement or failures pose the biggest threat to this objective. In order to identify and fix coverage gaps, this study suggests an algorithm based on swarm intelligence. Using both local and relative information, the swarm of agents navigates a potential field toward the nearest hole and activates in reaction to holes found. In order to spread out effectively and speed up healing, the agents quantize their perceptions and approach holes from various angles. The need for wireless sensor networks to monitor certain areas has grown, leading to many studies on maintaining coverage over time. Random node deployment or failures create coverage gaps, which pose the biggest threat to this objective. A swarm intelligence-based approach is proposed in this paper to identify and fix coverage deficiencies. Even with Their encouraging performance and operational quality, WSNs are susceptible to various security threats. The security of WSNs is seriously threatened by sinkhole attacks, one of these. In this research, a detection strategy against sinkhole attacks is proposed and developed using the Swarm Intelligence (SI) optimization algorithm. MATLAB has been used to implement the proposed work, and comprehensive Models have been run to assess its effectiveness in terms of energy consumption, packet overhead, convergence speed, detection accuracy, and detection time. The findings demonstrate that the mechanism we have suggested is effective and reliable in identifying sinkhole attacks with a high rate of detection accuracy.

Keywords: *Swarm Intelligence, Sinkhole Attacks, Detection Accuracy, Wireless Sensor Networks, Artificial Intelligence.*

1. Introduction

A subset of artificial intelligence (AI) is known as swarm intelligence (SI), or Bio-inspired computing in general. It was initially used in creating cellular robotic systems and has since been acknowledged as a developing field. Such SI-based algorithms are becoming increasingly popular for several reasons, chief among them being the flexibility and adaptability they provide. A subset of artificial intelligence (AI) is known as swarm intelligence (SI), or bio-inspired computation in general. It was initially used in creating cellular robotic systems and has since been recognized as an emerging field. Such SI-based algorithms are becoming increasingly popular for several reasons, chief among them being the flexibility and adaptability they supply. The algorithms' principal traits that have produced a great deal of attention and identified numerous Applications include their ability to learn on their own and their flexibility in response to external changes.

High-end application fields include image processing technologies, planetary motion sensing, navigation control, interferometry, micro-robot control, and the diagnosis and management of malignant tumors. There aren't many articles on swarm intelligence because it's still a relatively new field of study, except for a few widely used methods that have been overused. Therefore, the author's goal is to provide a review that addresses a few carefully chosen algorithms for swarm intelligence and their potential application.

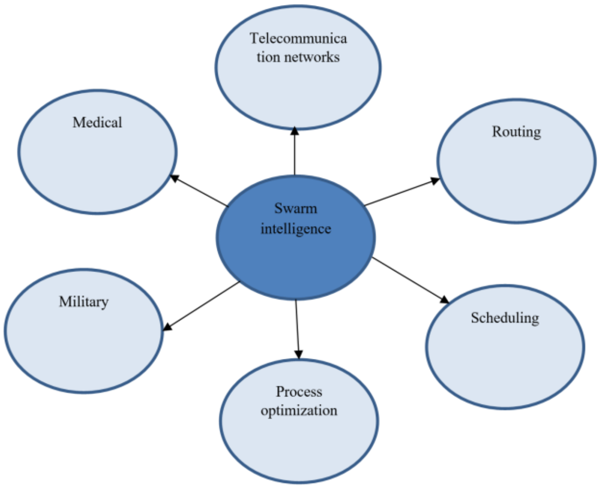

Fig 1. Application of Swarm Intelligence

Swarm intelligence has gained prominence recently due to the growing prevalence of NP-hard issues, in which it is almost impossible to find a worldwide optimum in a real-time environment in Figure 1. There are frequently an unlimited number of possible answers to such situations. Identifying a workable solution within time limitations become essential in these conditions. SI is useful for tackling nonlinear design issues with practical applications in practically every field of science, engineering, and industry, encompassing data mining, optimization, business planning, computational intelligence, bioinformatics, and industrial applications.
This paper's remaining sections are arranged as follows: An overview of WSN characteristics is given in Section 2, along with a comparison of the benefits and drawbacks of WSNs. The features of the intelligent optimization algorithms and the classification techniques are thoroughly explained in Section 3. An overview of the use of swarm intelligence optimization algorithms in various WSN domains is given in Section 4. This paper is summarized and concluded in Section 5.

2. Literature Review

The ideal or best options among the workable answers for a particular the issues are found using optimization techniques. Single and multivariable functions can be solved using a variety of optimization approaches, either with or without constraints [4]. Optimization Methods can be created using a variety of approaches, such as swarm intelligence, genetic algorithms that discover the optimal local solution from a given population, artificial annealing that is inspired by the process of metallurgical annealing, linear and non-linear programming, and more.
The hole quality determines the two models' prediction and efficacy. In drilling, the roundness inaccuracy in the hole is commonly employed as a gauge of hole quality [5]. Maximum circles with radii defined as the hole's inner and outer radii are inscribed within and outside the hole profile to calculate the roundness error. Roundness error is the difference between the hole's inner and outer radii. For every cutting condition, a high-resolution microscope took pictures of every drilled hole before the drill breaking, and the digitizer software tool calculated the outside and inner radii of each hole.
To this end, we provide a method that combines two traditional clustering techniques (K-means and fuzzy C-means) with swarm intelligence (SI) based optimization algorithms, namely seeker optimization (SO), ABC, ant colony optimization (ACO) [6], and PSO. By selecting image clusters with improved optimal centroids—which may be global optimum centroids—it significantly increases the accuracy of psoriasis lesion detection. The starting solution for the SI algorithms to refine the centroids and increase the likelihood of convergence to the global optimum centroids is the centroids derived by traditional clustering techniques.
Numerous hypotheses have been used in the literature to address the WSN deployment issue. By determining the best trade-off, some of the suggested methods aim to concurrently accomplish several competing goals [7]. Others were designed to simplify the challenge by making significant assumptions about the network and the area of interest. This oversimplification may lead to inaccurate assessments of deployed networks' performance. The usefulness of the suggested method has been assessed using a variety of matrices, including the Jaccard index, particularity, sensitivity, and accuracy, on a collection of 780 photos.

3. Methods

3.1 Swarm Intelligence Algorithms

The SI algorithms were created to investigate the fundamentals of basic individuals that can display sophisticated and intricate swarm optimization behaviors through swarm members' collaboration, organization, sharing of knowledge, and learning. The SI algorithms are categorized in Figure 2 based on their associated applications and historical development. More precisely, the SI algorithms were first put forth in the 1990s [8], and as of right now, their applications have been thoroughly studied and are comparatively developed. Bacterial Foraging Optimization (BFO), Artificial Fish-Swarm Algorithm, Artificial Bee Colony (ABC) Algorithm, and Firefly Algorithm are among the SI algorithms that were proposed between 2000 and 2010. Pigeon, inspired optimization (PIO), grey wolf optimizer (GW), and butterfly optimization algorithm (BOA) are some of the more recent and promising SI algorithms. The fundamental ideas of these popular SI algorithms are briefly discussed here.

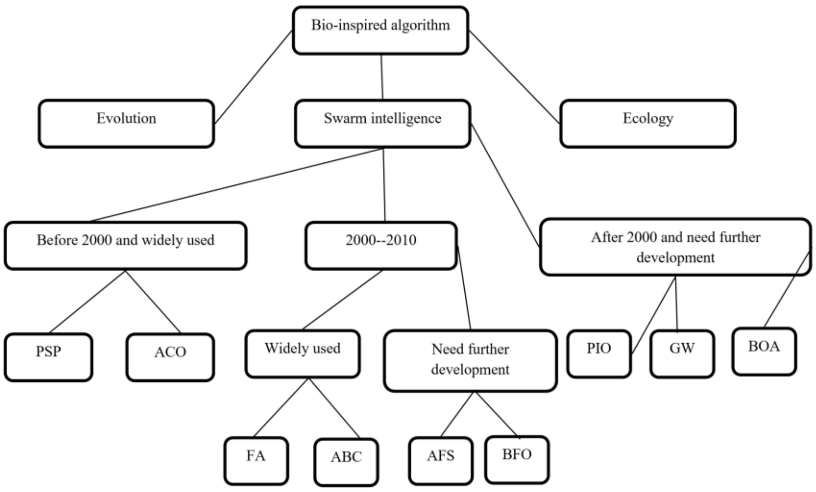

Fig 2. Taxonomy Of SI-Based Computation Algorithms

3.2. Particle Swarm Optimization

Kennedy and Eberhart introduced the PSO algorithm, a SI global random search method that mimics swarm and migration behavior during foraging. In the flock aggregation model, each person abides by the following guidelines: The flock as a whole flies to the destination after (a) avoiding collisions with nearby individuals, (b) matching individually in the area, and (c) flying to the center of the flock. Each optimization problem in the PSO has a particle, or bird, in the search space that could be the answer. Every particle travels at a speed that dictates its orientation and separations, and the optimal function determines each particle's fitness value. The particles then move through the solution space in pursuit of the current optimal particle. The basic PSO algorithm's flow chart is shown in Figure 3 [9].

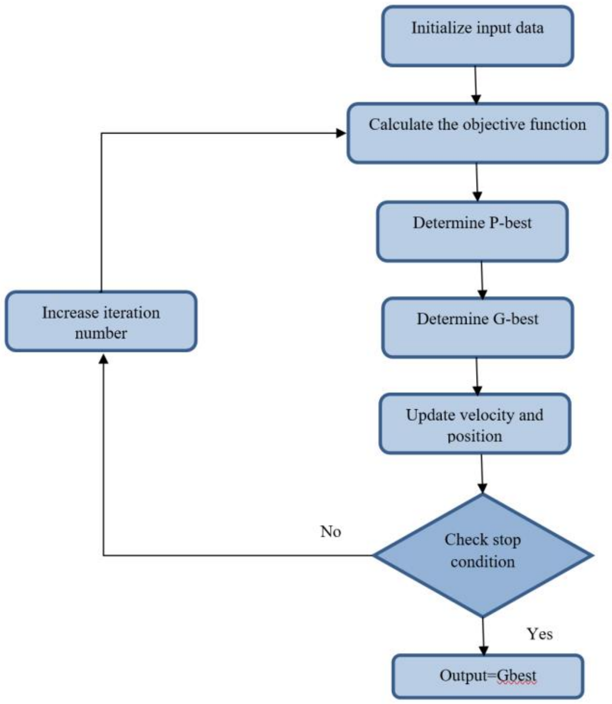

Fig 3. Flowchart of the PSO algorithm

The optimal position discovered by particle I, known as the individual extremum, is indicated by the Pbest [i] in Figure 3 [10]. The global optimal position determined by the entire particle swarm search is denoted by Gbest [i]. Step 5 involves updating the particle velocity using Formula (1) and updating the position using Formula (2).

$$\mathrm{V_{id}} = \omega \mathrm{V_{id}} + \mathrm{C_1} random(0,1)(\mathrm{Pbest_i} - \mathrm{X_{id}}) + \mathrm{C_2} random(0,1)(\mathrm{Gbest_i} - \mathrm{X_{id}}) \quad (1)$$

$$\mathrm{X_{id}} = \mathrm{X_{id}} + \mathrm{V_{id}} \quad (2)$$

The inertia factor in this case has a non-negative value. The ability to optimize globally increases with size, but the ability to optimize locally decreases with size. Two acceleration constants, C_1 and C_2, represent each particle's individual learning factor and social learning factor, respectively.

3.3. Hole Detection Problem Formulation

We concentrate on identifying coverage gaps in WSNs by applying Delaunay triangulation (DT) methods. Applications in both 2D and 3D can use this technique. Even by the same DT, the coverage model of nodes is a crucial component that distinguishes the hole identification. We employed a disk coverage model in this study, which solves the problem analytically catalytically and has symmetrical geometry. The distance between a sensor and a point is expressed mathematically as a Boolean function [11]. The coverage of a point pp with sensing radius Rs in it by node si is written as follows:

$$F\big(d(s,p)\big) = \begin{cases} 1, & if \;\; d(s,p) \leq Rs \\ 0, & otherwise \end{cases} \qquad (1)$$

3.4. Delaunay Triangulation

The WSN is represented by a graph $G\ (V, E)$, where $V\ \in v1, v2, \ldots.., vvnn$ reflects the group of nodes known as antennae, and E displays the group of edges among the nodes. Based on the composition of the adjacent triangle, a subgraph is taken from G.

Some crucial definitions pertaining to the topological of WSN graph structures are given below;

1. **The Node Neighbor Set (NNS)** is represented by $Nv(i)$, and it contains all of the one-hop nearest nodes. Figure 1 illustrates the NNS for nodes $ii\ akr$, lk, ll, mm, mm, mm, rn, ii.
2. **Edge Neighbor Set (ENS)** In figure 1(a), it is represented as (eij) = (ii) ∩ (jj) = {k, l, m} and contains the common one hop neighbors of two end nodes of an edge.

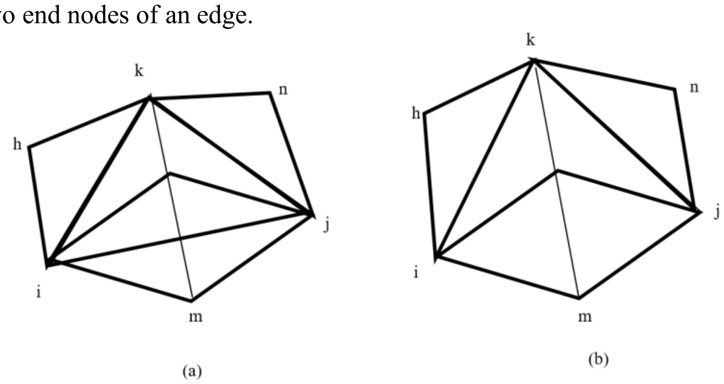

Fig 3. Delaunay Triangulation

3.5 A Brief Description of Algorithms for Swarm Intelligence Optimization

Fig 4. The Swarm Intelligence Optimization Algorithm's Framework Diagram

A novel evolutionary computational method known as the swarm intelligence bionic optimization algorithm has been investigated, drawing inspiration from the cooperative and competitive behavior of gregarious creatures. Multiple-purpose optimization, data classification, data aggregation, pattern recognition, biological system modeling, process planning, signal processing, robot control, decision support, simulation, system identification, and so forth are some of its application areas. Swarm intelligence adaptive optimization is a new technique for optimization computation. A kind of heuristic search method that improves a given objective based on group action is called the swarm intelligence optimization algorithm. The main features of the swarm intelligence algorithm are

1. Robustness and strength. If one member of the group fails, it won't impact the group's solution to the problem; in other words, it won't impact the situation as a whole because the members are dispersed and there is no centralized control.
2. Simple and straightforward to put into practice. There are easy things that any person can do.
3. Good scalability. Each person has a limited capacity for perceiving information.
4. Strong self-management. Individual contact is the cause of the group's complicated behavior.
5. It may exhibit distribution and parallelism properties.

4. Results and Discussion

To test and execute the suggested algorithm, we created a MATLAB simulation environment for wireless sensor networks using the following setup. A 100 × 100 m square field makes up the network area, and the base station (BS) is situated in the central to the field. There are anywhere from 100 to 1000 sensor nodes. Nodes with distinct locations and identification numbers (IDs) are dispersed at random throughout the field. The transmission range of every sensor node that has been deployed is 10 meters. The specifics of the network's simulation parameters are shown in Table 1 [12].

Table 1. Network simulation parameters

Simulation parameters	Value
Network size	100 × 100 m2
Location of base station	(50,50)
Number of sensor nodes	100 - 1000
Number of cluster head nodes	10%
Transmission range	10 m
Initial energy	0.5 J
Buffer size	100 bytes
Size of packets from nodes to CH	200 bits
Size of packets from CH to BS	6400 bits
Clustering protocol	LEACH
Number of sinkhole nodes	1

Trial and error research was used to get the weight cutoff value. A CH node with a weight value of 0.86 is deemed suspicious, for instance, if a monitoring CH node assigns a weight value of 0.90 for a particular CH node and 0.86 for the next CH node. Therefore, depending on its global weight value, the monitoring CH node initiates the ABC method to determine whether or not this CH node is a real sinkhole attacker [13]. The simulation settings used for ABC are displayed in Table 2.

Table 2. ABC simulation parameters

Simulation parameters	Value
Number of decision variables (maximum)	100 - 1000
Number of decision variables (minimum)	1
Population size (colony size)	100 - 1000
Number of onlooker bees	100 - 1000
Number of iterations	10, 50, 100

This was anticipated as one observation node's local decision, which is subject to a high true negative error, determines the real sinkhole attacker. The average true positive rates obtained with various ABC algorithm iterations and without the ABC component are displayed in Figure 5.

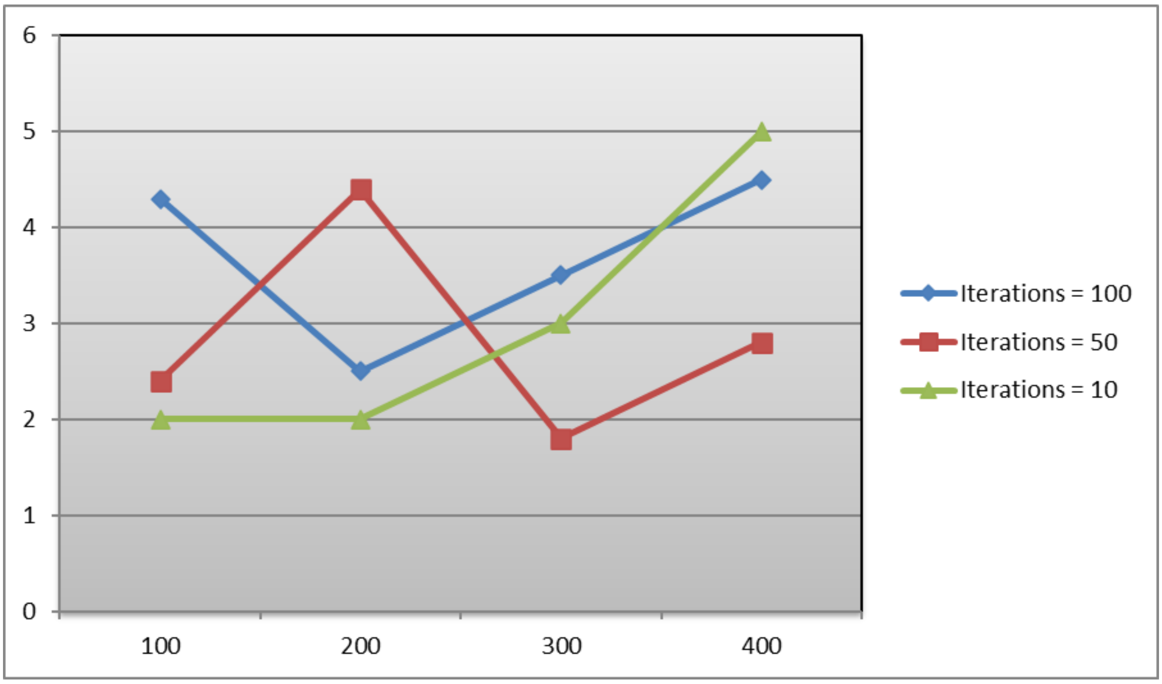

Fig 5. Average True Positive Rates with and without ABC and with varying numbers of ABC iterations

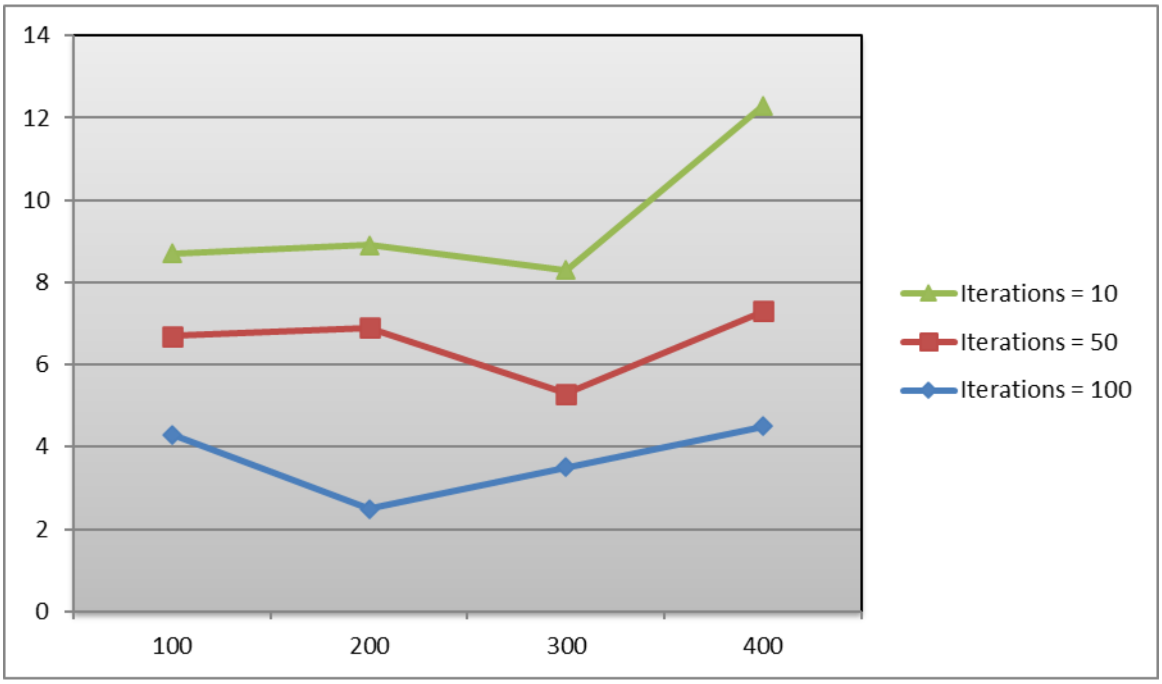

Fig 6. Average ABC Convergence Speed with Varying Iteration Count

As the network density rises, the ABC convergence speed also rises, as seen in Figure 6. This is due to the fact that as network density rises, ABC examines an increasing number of potentially harmful nodes.

5. Conclusion

We point out some of the work's shortcomings even if the goal was effectively accomplished. This paper is restricted to a system of stationary nodes for sensors, which might not be the case in every situation. Because of the dynamics of WSNs, the detection accuracy may be impacted. The suggested method can only accurately identify one sinkhole attacker node at a time. However, the detection accuracy percentage is likely to drop as the number of rogue nodes rises. This work can be expanded to include barriers in the nodes' route of communication in the following section of the research. These cause a sensor node's coverage area to fluctuate and produce holes with an anonymous shape.
For future use, the technique for identifying holes with unusual forms may also be taken into consideration.

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