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An Approach to Increase the Network Life Time of Wireless Sensor Network for Heterogeneous Node using Particle Swarm Optimization (PSO) Algorithm and Genetic Algorithm (GA)

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Abstract: *Wireless sensor networks (WSNs) have gotten a lot of interest from researchers in recent years because it plays an important role in a variety of applications. WSN's primary function is to process and transmit extracted data to remote destinations. A sizable number of sensor nodes are installed in the monitoring region. For research, it is imperative to deploy the fewest number of nodes necessary to maintain connectivity and full coverage. In addition to maximizing network lifetime, coverage and connectivity difficulties represented the primary concern to be taken into account in this survey. One of the key architectural challenges in creating a Wireless Sensor Network is maximizing the network lifetime (WSN). In recent years, numerous methods have been created to address this issue, such as network protocols, low-power data fusion algorithms, energy-efficient routing, and determining the ideal sink position. Putting out a clever deployment strategy for wireless sensor networks heterogeneous node deployment. Deployment of the nodes in a wireless sensor network is a difficult problem, Artificial intelligence (AI) includes number of techniques like Particle Swarm Optimization (PSO), Genetics Algorithms (GA), Ant Colony Optimization (ACO) etc. We employ the Particle Swarm Optimization (PSO) algorithm and Genetic Algorithm (GA) to discover the best placement of the heterogeneous nodes, hence lengthening the network lifetime. Artificial intelligence-based solutions aid in improving network lifetime & throughput. Direct and multi-hop routing protocols are the ones that were employed in this implementation. We found that the suggested solutions increase network lifespan compared to the initial lifetime by up to 140% after doing a number of tests. We contrasted GA and PSO by tracking lifespan and time to arrive at a solution, with the objective functions of the models being the inverse of a lifetime.*

Keywords: *PSO, GA, HETEROGENEOUS, WSN, Multi-hop.*

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I. Introduction

A wireless sensor network (WSN) is a collection of several energy-restricted nodes that monitor a range of activities. A sensor node is made up of a sensing unit, a CPU unit, a radio transceiver, and a power management unit [1]. Measured responses are delivered via a wireless channel to a communal sink by sensor nodes in response to changes in the physical or chemical environment. Nodes in a wireless sensor network are often energy-constrained, and their batteries cannot be refilled. A key factor for WSN is the network coverage. It refers to how effectively a network is keeping track of a specific area of interest. The sensing range of a node is frequently constrained. A node's sensing range is usually limited. It is deemed detectable if at least one node is located within the viewable field of view. A node will cover less space if it is positioned close to the area of interest's edge than if it is positioned in the core zone. The boundary or border effect is the name given to the effect. The reason is because when it is placed close to the border, some of its sensing area will be outside the region of interest [2].

Large geographic regions may be monitored at minimal cost and with high-quality using wireless sensor networks (WSNs). WSNs are often implemented as having a potentially large number of wireless sensor nodes that communicate over many hops [4, 5] with one or more sink or base stations. Wireless Sensor Network collect information from a physical environment. WSN's infrastructure is made up of low-cost sensors. The practical deployment of a WSN, which is made up of hundreds of thousands of physically embedded sensor nodes, is aided by improvements in small-scale computational devices. Radio signals allow the sensor nodes to communicate with one another. Sensing and computing equipment, as well as a radio transceiver and power components, are all included in a wireless sensor node. Following deployment, it is the responsibility of the sensor nodes to self-organize a suitable network architecture, which generally consists of multi-hop connections. Then, it is presumed that these sensor nodes are aware of the sink's position as the onboard sensors begin gathering interesting data that is sent towards a sink [6,7].

In multi-hop communication, all the information is routed from one node to another until all the information reaches the sink. In this process of data transmission and reception, the sensor nodes spend a significant amount of their stored energy [8,9] An important design consideration is sensor deployment, which is often referred to as sensor positioning, deployment, layout and placement in the literature. "The deployment of a WSN has an influence on almost all of its performance indicators, including network longevity, sensor connection, and network's successful coverage," is how we'll use the term in this survey. In general, there are two types of WSN deployment techniques: random deployment and planned deployment. Sensors are often dispersed randomly (for example, using aircraft), leading to a stochastic dispersion of sensors; nevertheless, their concentration can be controlled to some extent. In some implementations where the field of interest is unreachable, for example disaster zones and live conflict zones, random deployment may be the only viable option. On the other hand, planned deployment is defined as choosing sensor locations to maximize one or more WSN design goals within the constraints of a specific application. Design goals frequently include optimizing network lifetime, minimizing power usage, and maintaining reliable network connections. Planned deployment is compatible with a huge range of WSN applications, as long as the RoI is available. Border patrol, facility access control, and architectural maintenance are all examples of this type of supervision. If the implanted sensors are mobile, it can even be done in unreachable RoI after a first random deployment.

In this paper, we offer a new categorization of the approaches and algorithms for planned deployment of WSNs which have been suggested in the research. The mathematical methodology utilized to model and solve the deployment issue is the basis for our categorization. Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are two separate mathematical methodologies described. It's important to note that the computational methods in our classification are heuristics and can provide less-than-ideal answers for the majority of WSN applications. Traditional deterministic optimization techniques that can produce optimum solutions, such linear programming, are useless for solving many planned deployment problems. This is due to the possibility of several design objectives, diverse WSNs, or a high proportion of sensor nodes in a context of pragmatic planned deployment. This shows that the time it takes to obtain optimal solutions for these issues using deterministic optimization methods, without applying any approximation methods, grows rapidly as their size expands.

The remains of the work are structured as follows: In Section II, the Literature Review of this research work. In Section III, give an overview of GA and PSO. In Section IV, Results and Discussion. The Conclusion is shown in the Section V of this research work.

II. Literature Review

A physically tangible definition of the Network Lifetime (NL) design objective can be formulated as the total amount of time during which the network is capable of maintaining its full functionality.

O. Banimelhem, M. Mowafi, and W. Aljoby [10] present a genetic algorithm aiming to resolve the problem of coverage holes in the network. The suggested technique determines the appropriate number and locations for mobile nodes after the first deployment of permanent nodes. A variety of metrics were used to assess the effectiveness of the genetic algorithm, and the simulation results show that this algorithm maximizes network coverage in terms of both the total number of extra mobile nodes and the coverage ratio.

K. J. Aval and S. Abd Razak [11] the goal is to investigate alternative multi-objective approaches to solving the problem of sensor deployment based on various parameters (coverage, scalability, connectivity, cost, lifetime, latency). The authors present numerous investigations utilizing particle swarms and genetic algorithms. In multi-objective case, they have also presented various simulation environments. There are two steps to the suggested simulation. The initial stage involves modeling the nodes' behavior and improving the outcomes up until convergence is reached. In the second stage, the results of a network simulation are fed in order to validate the found solution.

Hoesel et al. [12] proposed a cross-layer approach for jointly optimizing the MAC and routing layer in order to maximize the NL.2004 Kwon et al. discover the wireless sensor Network lifetime maximization problem, which considers the physical layer, the MAC layer and the routing layer.

Hu et al. [13] employed a genetic algorithm for achieving the maximum number of disjoint subsets of sensors for maximizing the NL, while providing full coverage for a specific target area.

Song et al. [14] have given two algorithms: centralized and distributed. For the deployment of deterministic nodes, the centralized algorithm is recommended. The radius of the entire area, the population, and other factors are used to create the transmission range list for each group. Nodes in each group transfer data in line with the transmission range list to prolong network lifetime. The distributed approach is suggested for non-deterministic node deployment, where the centralized algorithm is initially assumed to have created the transmission list. Now based on the values in the transmission range list, nodes in each group compute their energy consumption rate. This is done through consultation with the nodes of the adjacent groups by adjusting the transmission range for getting maximal network lifetime.

Azad and kamruzzaman [15] Energy-balanced transmission range regulation policies are employed in WSNs to maximize network longevity. The authors considered a network architecture based on concentric rings, with the sink at the center. Firstly they have analyzed the traffic and energy usage distribution across nodes and found two attributes - ring thickness and hop size responsible for energy balancing. Based on the analysis, a transmission range regulation scheme is proposed for each node and determined the optimal ring thickness and hop size for maximizing NL.

Efthymiou et al. [16] have put out a probability-based balanced data propagation technique where a node chooses whether to deliver data straight to the sink or to disseminate it over many hops. Two forwarding method is used to choose the proposed probability value. The probability is calculated using two crucial parameters: network size and the distance between the node and the sink. The probability value is chosen so the average energy consumption per unit area for the entire network remains constant for the whole network ensuring energy balance. One major drawback of the proposed algorithm is that network Scalability is not supported.

Jarry et al. [17] have examined data collection and network lifetime maximization issues and demonstrated that balancing nodes' energy consumption results in the greatest possible network lifespan and data flow to the sink. Based on the analytical findings, the author suggested probabilistic online distributed routing algorithms for different network setups. A node calculates the possibility that a neighbor node will be selected to send its data as follows in one proposed probabilistic online distributed routing strategy: If a neighbor node consumes more energy than its immediate neighbors on average, the risk of this happening lowers. If a node detects that its own probability value is higher than that of its neighbors, it transmits its data directly to the sink; otherwise, it chooses the neighbor node with the lowest probability value to forward the data.

Olariu and Stojmenovic [18] have investigated network design recommendations for uniform node deployment that maximize lifetime and minimize energy hole. Although the two-ray model can avoid it, the uneven energy depletion caused by the energy hole is required for the free-space model. Additionally, they introduced the multi-path model with corona architecture design guidelines. They haven't examined the potential for uneven node deployment, though.

Changetal.[19] have proposed two node deployment strategies that are distance-based and density-based strategies, with an objective for balanced energy consumption among the nodes. The deployment positions of nodes in a distance-based strategy are chosen so that the nodes' neighbors towards the sink are positioned fairly close to each other. The density-based strategy partitions the network into a number of equalized zones, adjusts the density of nodes in each zone by controlling the switching mode as on/off and balances the load of each zone. Finally, the authors suggest a collision-free MAC scheduling approach to avoid energy waste due to data collisions and subsequent data retransmission.

Cardei and Cardei [20] have also suggested a heterogeneous node deployment technique to lengthen the lifespan of sensor networks. The authors define heterogeneous nodes as two types of nodes: resource-constrained nodes and resource-rich super-nodes. With the goal of extending network lifetime, they suggested two algorithms: integer programming based heterogeneous connected set covers (IP-HCSC) and distributed heterogeneous connected set covers (Distr-HCSC) with an objective of prolonging network lifetime. One sensor node and one relay node are made active at a time inside each set while the other nodes in the set are kept in sleep mode using the IP-HCSC algorithm for building the interconnected set covers. The Distr-HCSC algorithm was then developed by the authors after the technique was improved. The sensor node in each set with the largest residual energy is chosen to remain active, and the active relay node is chosen to be the node nearest to the active sensor node. Distr-HCSC is more scalable and adjusts to big and dynamic topologies better.

(Aslam, M., et al. 2012) [21] His research mostly focuses on how to expand routing protocols' functionality to lengthen their useful lives and how to enhance the quality of routing protocols for wireless sensor networks. Hierarchical routing protocols divide the entire network into multiple clusters. Each cluster has one node that follows the leading rule. In clustering routing systems, the cluster head is the only node that can connect with the base station. As a result of simply having to send to the cluster head, typical nodes' routing overhead is dramatically reduced.

Soe, K. [22] Target tracking sensor network lifetime is proposed to be increased by the system design and implementation architecture. The system aims to provide the ability for the sensing nodes in the network to follow the position of moving targets in a low-energy, energy-efficient manner and to increase the lifespan of a sensor network.

Ofrim & Sacaleanu. 2010 [23] In this study, a highly effective strategy for lowering energy usage and extending the lifetime of wireless sensor networks was given. A scenario including network architecture, synchronization mechanisms, an energy model, and management of data transmission and scheduling is constructed to assess the effectiveness of network lifespan. According to the simulation results for the same wireless sensor network model, utilizing an adaptive scheduling algorithm significantly lengthens the network lifespan compared to using a non-adaptive scheduling model.

Khanna et al. [24] proposed GA-based optimization for multi hop sensor network to acquire minimum energy consumption. The network discovers the Hot-Spot problem since it requires multi-hop communication.

Hussain et al.[25]used GA to create data gathering clusters that were energy efficient. The suggested protocol is inefficient for broad area networks due to the random selection of CH and single-hop communication.

III. Different mathematical technique used in WSN deployment algorithms

We discovered two mathematical approaches or tools often used for designing planned deployment and re-deployment algorithms for WSNs in papers published in the last decade. We hope to provide the reader with the background and foundations of these mathematical approaches in this part.

A. Genetic Algorithms (GA)

GAs have been used to solve optimization problems in a variety of domains, including computer networking, industrial engineering, and machine learning. The paradigm of GAs is copying the natural selection as described in Darwin's Theory stating that "species whose individuals are best adapted survive; others go extinct". AGA can be especially effective in combinatorial and multi-objective optimization problems, in which deterministic optimization methods are not applicable [27]. In general, a GA has three basic components [28]:

i. A genetic representation of the problem's potential solutions. This is known as encoding, and it is based on the variables and constraint problem. Candidate solutions are classified in such a way that they can be decoded into a unique variables vector that belongs to the search space, allowing the constraints to be verified. Binary encoding, integer encoding, and real number encoding are some of the encoding methods used in GAs. The type of encoding method to choose is mostly determined by the nature of the optimization problem. The candidate solutions in the problem's search space are said to be in the phenotype space, while their genetic representation through encoding is in the genotype space.

ii. For evaluating candidate solutions, a fitness function is used.

iii. During the reproductive phase of the GA, stochastic genetic operators change the composition of the offspring. In a single iteration of a standard GA, five steps are completed. Creating an initial population of individuals or chromosomes is the first stage. During the reproductive phase of the GA, stochastic genetic operators change the composition of the offspring. In a single iteration of a standard GA, five steps are completed. Creating an initial population of individuals or chromosomes is the first stage. Each chromosome represents a different candidate solution to the problem that has been encoded. The initial population usually uniformly covers the problem's search space. Following the creation of the initial population, step two is completed, which involves evaluating the individuals in the population using a fitness function. The fitness function is a mathematical statement of what we want to maximize, and it is essentially a cost function. Fitness evaluation is used by GAs to eliminate the weakest members of the population and identify the fittest members.

As a result, a chromosome is said to be the fittest if it influences the fitness evaluation to a value that is closer to the ideal point than the others. The third step, known as parent selection, involves choosing chromosomes from the population to participate in the GA's reproductive phase. Parental choice is typically stochastic in nature and depends on the calculated fitness. The roulette wheel and tournament procedures are the two most often utilized methods of choosing parents. The final stage is to use the two genetic operators, crossover and mutation, on the parent chromosomes that have been chosen in order to create an offspring or child population. The main genetic operator is crossover, which is accomplished by randomly pairing each pair of individuals (parents) in the population.

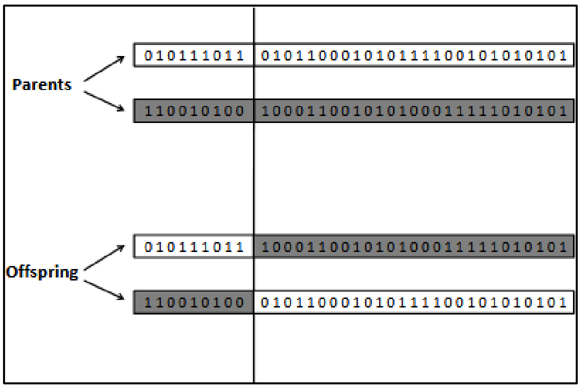


Figure 3.1: The process of crossover for binary encoding

Mutation, on the other hand, is a background operator that creates a new individual by altering a randomly chosen part of a selected parent. Both operators are responsible for directing a population of offspring toward new areas of the problem's search space. The same fitness function is also used to evaluate the offspring population. The fifth step in a GA is the selection step, which is choosing individuals from both the parent and off spring populations to form a new population. Selection is the driving force of the GA since it directs the search to promising region for search space. The several methods for selection, both stochastic and deterministic, such as age-based selection, fitness-based selection, and elitism. Steps two through five are repeated multiple times to produce iterations or generations, and the algorithm gradually converges on the fittest individual, which should represent an optimal solution to the problem. Although that outcome isn’t guaranteed. Pseudo Code of a General Genetic Algorithm is given by the following steps:

Pseudo Code of a General Genetic Algorithm:

Step 1: Put t ← 0
Step 2: Initialize P (t)
Step 3: Evaluate P (t)
Step 4: While (termination condition not met)
    Recombine P (t) to yield C (t)
    Evaluate C (t)
    Select P (t+1) from P (t) and C (t)
    t← t+1
  End

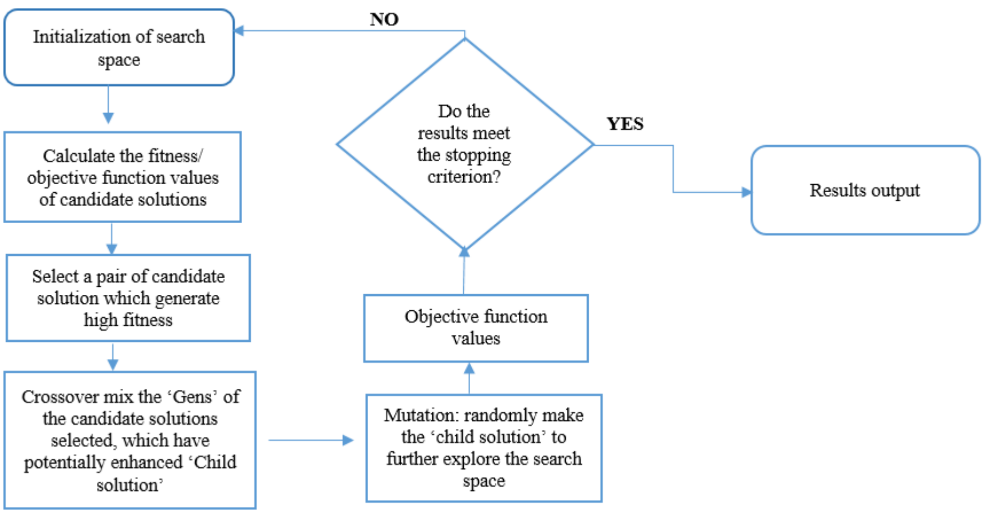


Figure 3.2 Flow Chart of GA

The algorithm can either terminate after a certain number of generations have been produced or after discovering an individual with fitness that corresponds to a satisfying solution to the problem. The algorithm can either terminate after a certain number of generations have been produced or after discovering an individual with fitness that corresponds to a satisfying solution to the problem. The general structure of GAs is expressed using pseudo code. One of GAs' most important advantages as an optimization tool is their capacity to handle combinatorial and multi-objective optimization issues. Because of this beneficial quality, GAs were used to create multi-objective deployment algorithms for WSN. One method for measuring fitness in multi-objective GAs or MOGAs is to add the weighted normalized cost functions of each objective separately, as shown in the following equation [33]

$$\text{Cost} = \sum_{i=1}^{N} W_i f_i 0 \leq f_i \leq 1, \qquad (3.1)$$

Where f_i is the i^{th} normalized cost function $(1 \leq N \leq i)$ and w is the weighting factor where

$$\sum_{i=1}^{N} w_i = 1 \qquad (3.2)$$

Another approach for fitness evaluation in MOGAs is the Rank-based Fitness assignment [34].It is dependent on the concept of praetor dominance, which can be described as follows: An individual is called Pareto domain which gives a set of objectives in a MOGA. If the first is not superior to these condition of the objectives, and there is at least one objective, the first is said to Pareto dominate the second where it is better. As a result, the optimal solution to the multi-objective optimization problem is represented by a set of non-dominated Pareto optimal individuals rather than a single individual. In Rank-based fitness assignment. Individuals are assigned ranks that are directly proportional to the number of individuals that dominate them.

B. Particle Swarm Optimization

Swarm Intelligence is a branch of Artificial Intelligence (AI) that focuses on the collective behavior and properties of complex, self-organized, decentralized systems with a social structure, such as bird flocks, ant colonies, and fish schools. These systems consist of simple interacting agents organized in small societies, called swarms, which exhibit traits of intelligence, such as the ability to react to environmental threats and decision making capacities [29].Swarm Intelligence was utilized in the global optimization framework in the form of a set of algorithms introduced in [30] for controlling robotic swarms in 1989. Three important swarm intelligence optimization techniques, Ant Colony Optimization, Stochastic Diffusion, and Particle Swarm Optimization, were developed several years later (PSO). In this paper, we will only focus on PSO due to its emerging use in the development of deployment algorithms for WSNs.

In 1995, Eberhart and Kennedy [31] developed PSO as a stochastic global optimization algorithm based on social simulation models. The core idea of the PSO algorithm is to use a population (swarm) of search points (particles) that move stochastically in the boundaries of the optimization problem's search space. The nomenclature was inspired by similar models in social sciences and particle physics. The best position (i.e. the best solution) ever reached by each individual in the population, which is called experience, is retained in memory. This experience is then communicated to part or all of the swarm, directing its movement towards the search space regions where it is more likely to find the optimal solution. The convergence of the algorithms depends greatly on the chosen communication scheme.

The mathematical framework of PSO is as follows. Let $A \subset R^n$ (R^n is then dimensional space) be the search space and f : A → Y ⊆R be the objective function of the optimization problem, where Y is the corresponding value of f to any point in A. Assume that there are no further constraints in the problem and that are the conditions on either A or f. The swarm S is defined as a set of N particles, representing candidate solutions:

$$S = \{p_1, p_2, \dots \dots \dots \dots . p_N\} \qquad (3.3)$$

$$p_i = (p_{i1}, p_{i2}, \dots \dots \dots \dots \dots . . p_{in}) \in A, i = 1,2, \dots, N \qquad (3.4)$$

Where, N is a user defined parameter in the algorithm. The particles are assumed to move within A iteratively in order to visit all its regions. Pseudo Code of a Particle Swarm Optimization is given by the following steps:

Pseudo code of Particle Swarm Optimization:

Step 1: Put t ← 0
Step 2: Initialize S and Set M ≡ S
Step 3: Evaluate S and M; Define index g for best position
Step 4: While (termination condition not met)
    Update S using (18) and (19)
    Evaluate S
    Update M; Redefine index g
    t ← t+1
End While
Step 5: Print best position found

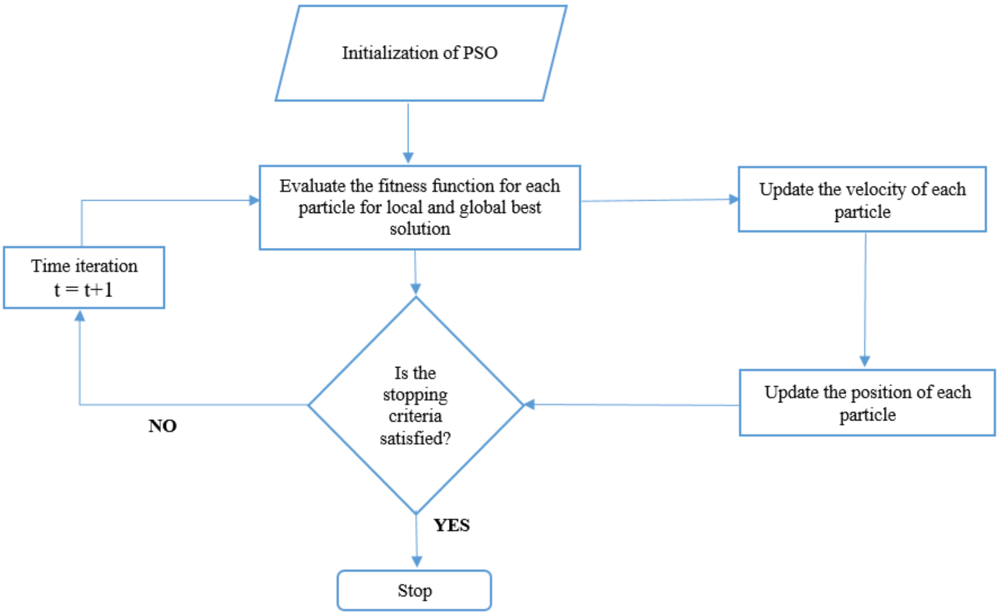


Figure 3.3: Flow chart of PSO

This is achieved by defining the velocity of each particle, which is used to adjust the particle's position in each iteration t of the algorithm, as follows:

$$v_i = v_{i1}, v_{i2}, \dots \dots . . v_{in}), i = 1,2 \dots \dots \dots . N \qquad (3.5)$$

In the algorithm, the particle velocity v_i also changes iteratively. The current position and velocity of the $i - th$ particle are denoted (t) and (t) respectively. The algorithm Keeps track of the best position for each particle in a memory set (i.e. best solution) it has ever reached during its search in A. The PSO memory set is defined as follows:

$$M = \{m_1, m_2, \dots \dots \dots m_n\} \qquad (3.6)$$

$$m = \{m_{i1}, m_{i2}, \dots \dots \dots m_{in}\} \in A, i = 1,2, \dots \dots \dots . . N \qquad (3.7)$$

Of course, determining the iteration, (t), depends on the objective function f. A teach given iteration, the best visited location in A by any particle in the swarm, i.e. the best position in M, is denoted (t). Particles are considered to communicate their experiences with one another, hence this term represents social behavior in PSO:

$$v_{ij}(t + 1) = v_{ij}(t)) + C_1R_1((m_{ij}(t)) - p_{ij}(t)) + C_2R_2(m_{gj}(t) - p_{ij}(t)) \qquad (3.8)$$

$$pij(t + 1) = pij(t) + vij(t + 1 \qquad (3.9)$$

For i=1,2,3,4…,N and j=1,2,3,4…….,n; R_1 and R_2 are random variables uniformly distributed between 0 and 1; C_1 and C_2 are weighting factors; also called the cognitive and social parameter respectively. In pseudo code, the steps of the PSO are provided. It should be noted that PSO has undergone many refinements to its earliest version, as represented by (8) and (9), to enhance its performance in more complicated optimization problems [32]. However, the main steps in its operation remain constant.

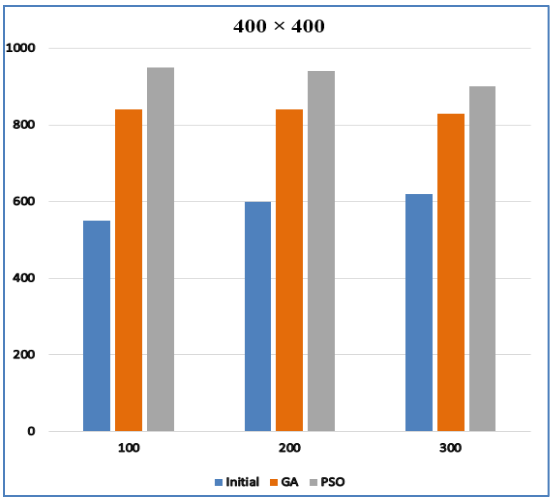
IV. Result

The proposed algorithm's results analysis using various parameters are shown in Table 4.1. Results are realized utilizing the thought-out parameters in Matlab R2015a. In this research, the proposed work was contrasted with already-in-use methodologies like GA and PSO. On coverage and the number of additional nodes, the impact of the number of static nodes deployed at random and the sensing ranges were examined. For performance evaluation, two simulation experiments were carried out. In the simulation environment, it was assumed that the sensor nodes were randomly deployed and the targets were uniformly located in 400 terrain ×400 terrain and 800 terrain × 800 terrain sensor field.

In the first experiment, the number of deployed static nodes varies from 100 to 300 to cover targets, whereas the sensing ranges of all nodes are fixed to 12 m. In the second experiment, for heterogeneous the number of deployed static nodes varies from 10 to 30 to cover targets, while the sensing ranges vary from 10 m to 20 m.

Table 4.1 Different parameters used for WSN deployment

SN	Parameter	Value
1	Network Area	400 x 400 and 800 x 800
2	Number of Nodes	100-300
3	Initial Energy of Nodes	1J



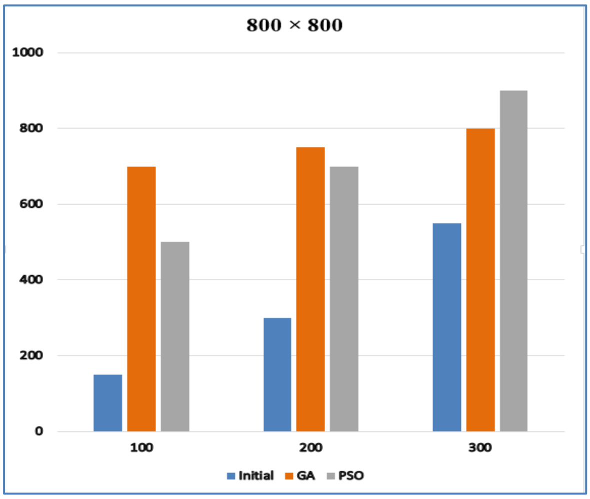
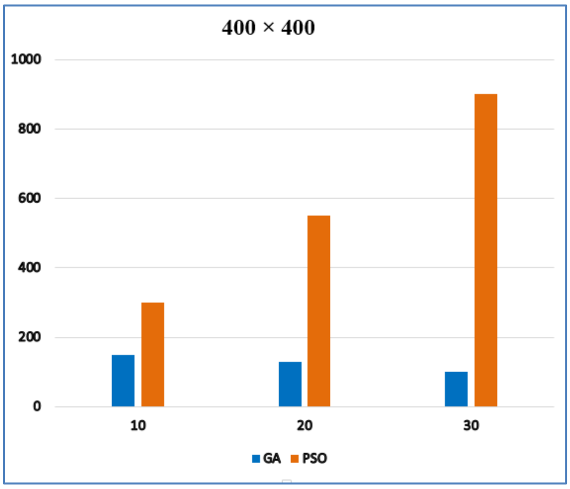


Figure - **4.**1 shows the lifetime of the initial state, GA and PSO during simulation. X axis represents nodes in the networks. Y axis represents Lifetime of network. The initial lifetime increases as the number of deployed nodes increases.



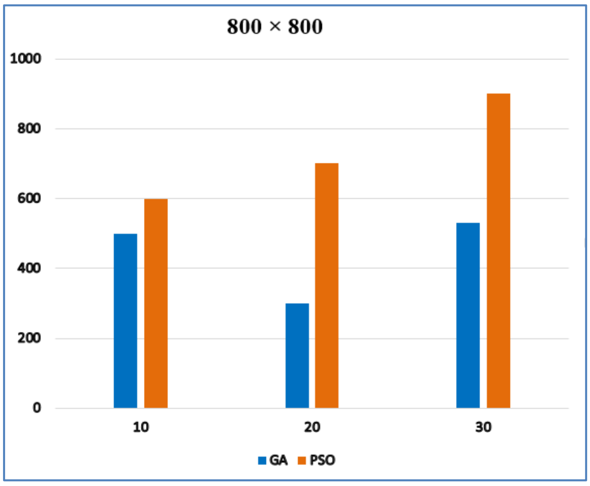


Figure - 4.2 shows the Time to take GA and PSO algorithm during simulation. X axis represents nodes in the networks. Y axis represents Time in second. GA is faster than PSO.

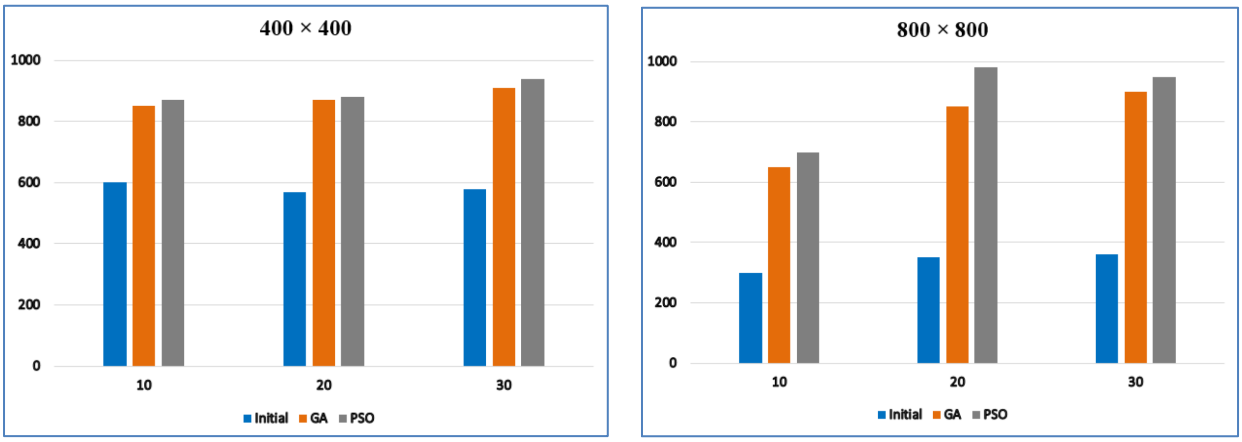


Figure -4.3 Shows the lifetime of the initial state, GA and PSO during simulation For Heterogeneous node. X axis represents Heterogeneous nodes in the networks. Y axis represents Lifetime of network. The initial lifetime increases as the number of deployed nodes increases.

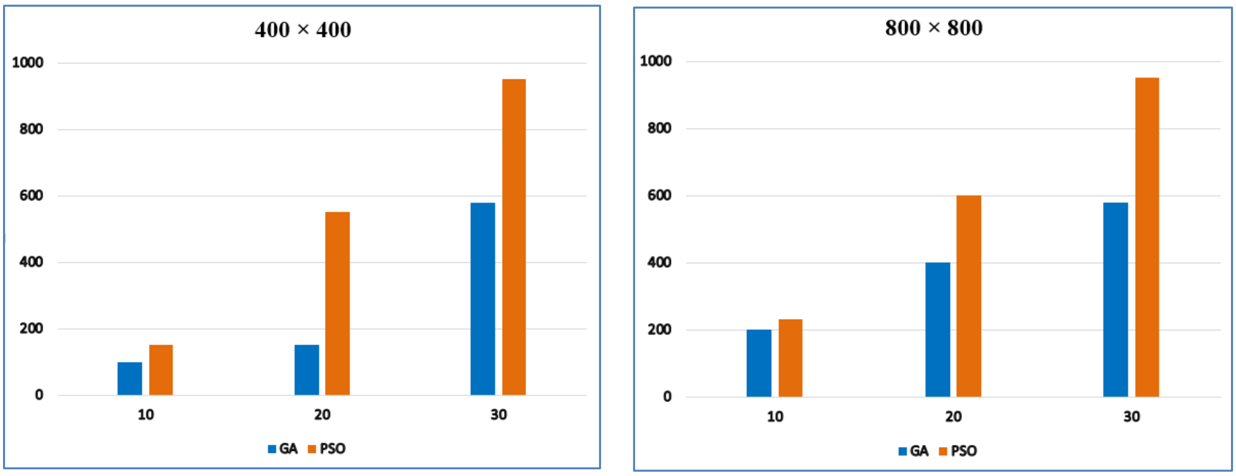


Figure - 4.4 shows the Time taken part of the initial state, GA and PSO during simulation For Heterogeneous node. X axis represents Heterogeneous nodes in the networks. Y axis represents Time in second. The initial lifetime increases as the number of deployed nodes increases.

By comparing Figure 4.1, Figure 4.2, Figure 4.3, Figure 4.4 it is shown that

1. 40% improvement in the result was observed in 400 X 400 terrain and up to 150% increase was observed in 800 X 800 terrain.
2. On a 400 X 400 terrain, both the PSO and GA have comparable performance, however on 800 X 800 terrain PSO has performed better.
3. GA has consistently outperformed the PSO algorithm in speed. PSO works better on larger terrain.

The results of applying GA and PSO to the sensor node deployment problem show that the PSO method is superior in terms of accuracy and iteration in locating the best solution. The PSO algorithm also performs better than the widely used straightforward methods. On a small scale, there is no distinguishable difference between the two methods. Where practical solutions that are close to ideal can only be produced by genetic algorithms on a medium and large scale. The PSO method is simple to use and has a high calculation accuracy

Table 4.2 Summary of the result

Algorithm	Simulation area	Improved
Genetic algorithm	400 x 400	20%
	800 x 800	120%
Particle swarm optimization	400 x 400	22%
	800 x 800	130%

As can be seen, selecting a WSN deployment technique depends on a number of criteria. The targeted RoI, whether a distributed or centralized strategy is necessary, the degree of sensor mobility (if any) in the WSN, and whether the deployment has one or more objectives are some of these aspects. In some WSN applications, the degree of complexity in the deployment strategy also influences the outcome. Whether the WSN is placed in an area with obstacles or one without them is the targeted RoI. It also depends on whether the RoI is intended to be static or dynamic over the WSN's lifetime.

Overall the results indicate that both GAs and PSO can be used in the optimization of parameters during model identification The GA approach is faster in terms of computational effort, though it should be emphasized that neither algorithm takes an enormous amount of time to determine its result. The GA determines values that are closer to the known values than the PSO in terms of model parameter accuracy.

Finally, it appears that the GA takes less generations to reach its final parameter values than the PSO. As a result, it must be concluded that the GA technique is superior to the PSO approach for process modeling. Biologically techniques such as PSO and Genetic Algorithms have proven to be efficient solutions to optimization challenges. In general, each instance of an optimization problem requires some type of trial-and-error adjustment. Furthermore, any meta-heuristic should not be examined in isolation; the use of hybrid techniques should be considered. Furthermore, the selection of a suitable goal function is a fundamental implementation issue for both systems.

However, there are limitations to this approach like increase in terrain size, increases time complexity and reducing the randomness of the algorithm can lead to better convergence. This approach can be further improved by employing different routing algorithms to conserve energy. The network's lifespan will be extended as a result. Despite the fact that we may not always get the optimum solution because we are employing evolutionary algorithms, we can be sure that the issue will have a workable solution.

V. Conclusion

Because of the rapid development of smart cities, WSNs are playing an increasingly important part in our daily lives. When sensor nodes are dispersed and need to stay active to acquire and send data from one site to another, deployment challenges in WSNs become critical. The operational region is often where a high number of sensor nodes are deployed. As a result, attaining the lowest number of sensor nodes that can surround the whole field of interest is critical for research. This study examines the present state of the art in the domain of node deployment in WSNs. The two methods suggested for this classification are genetic algorithms and particle swarm optimization. In addition, a detailed comparison of the advantages and pitfalls of these techniques is presented. The latter technique is justified by the necessity to satisfy different (sometimes conflicting) goals, such as reducing energy usage or load balancing across nodes, increasing network connectivity, minimizing the number of deployed nodes or the fault tolerance of the network and the network lifetime or the network traffic. However, it may be important to relax some constraints in order to reduce the search space and arrive at a near-optimal solution in a reasonable amount of time. Because a real test of the proposed approaches is often impossible in this situation, we must rely on simulations to demonstrate their efficacy.

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