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RESEARCH ARTICLE

Vibrational Genetic Algorithm-Based Deployment of Wireless Sensor Networks With Heterogeneous Nodes in Irregularly Shaped Areas

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ABSTRACT Over the past few years, there has been a significant emphasis on improving the capabilities of Wireless Sensor Networks (WSNs) by making advancements in communication protocols, energy efficiency, optimal deployment, data analytics, and integration with emerging technologies, such as the Internet of Things and artificial intelligence. The deployment of WSN nodes can greatly enhance the effectiveness, scalability, and capability of different systems, resulting in cost reductions, enhanced performance, and improved safety in which the deployment of WSN involves determining the best positioning of sensor nodes to attain maximum coverage and connectivity while minimizing the number of nodes needed. WSNs often face challenges in deploying nodes effectively and Genetic Algorithms (GAs) offer a valuable approach for tackling this problem due to their ability to efficiently search large and complex solution spaces, such as those of complex network design, taking into account various constraints and objectives, which are common characteristics of real-world WSN deployment scenarios. The objective of this study is to use a new method, called the vibrational genetic algorithm, which can be used to optimize the placement of sensor nodes more efficiently. Apart from the other research, it is preferred to use heterogeneous sensor nodes to increase the coverage rate in an irregularly shaped area. The results of the experiments demonstrate that the proposed model offers an effective solution for achieving maximum coverage in application theaters that are more realistic and complex.

INDEX TERMS WSN deployment, coverage, genetic algorithm, heterogeneous nodes.

I. INTRODUCTION

Wireless sensor networks (WSNs) have become increasingly important in recent years due to the rapid advancements in micro-electromechanical technology. With the proliferation of smart devices and the Internet of Things (IoT), WSNs have emerged as a critical component in the collection and transmission of data in various applications. WSNs are composed of small, low-power, mobile sensors and they can be deployed in various environments to monitor physical and environmental conditions. Those sensors which can communicate with each other wirelessly can build a network to collect and transmit data in real-time. The increasing importance of WSNs is due to their ability to provide valuable information in a wide range of applications, including environmental monitoring, healthcare, and industrial automation. As such, there is a growing need for research and development in this field to further improve the capabilities and performance of WSNs [1], [2], [3], [4], [5], [6], [7].

The deployment of sensor nodes is important because it allows for the control of a specific area and the collection of data from different sources in real-time. When sensor

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FIGURE 1. Random distribution of sensor nodes.

nodes are deployed, it is possible to monitor and control various parameters such as temperature, humidity, pressure, and motion. These data can then be used to make informed decisions and improve the efficiency of various industries. In addition, WSNs can be used in remote or hazardous locations that can be difficult or dangerous for humans to access. Due to the nature of WSNs, the Random Deployment model is preferred, especially in uncontrolled areas. In this model, sensor nodes are randomly scattered in the area of interest, often by throwing them from an aircraft or dispersing them on the ground, as seen in Fig. 1. Although it has some considerable advantages such as easy and quick deployment, suitable for large-scale and inaccessible areas, and providing good coverage with a sufficient number of nodes; it has some critical disadvantages such as unpredictable node distribution which may lead to coverage gaps or redundant nodes, difficult to achieve optimal network connectivity, and requiring more nodes to ensure complete coverage. Therefore, some deterministic models in which sensor nodes are placed at predetermined locations based on a specific pattern or grid, providing optimal coverage and connectivity are preferred in many controlled areas.

The increasing importance of WSNs with rapidly advancing technology makes them a critical component of data collection and transmission in various applications. However, positioning sensor nodes may face some critical challenges, especially when using a random deployment model. While the random distribution model offers certain benefits, such as increased flexibility, it can also result in coverage gaps and unnecessary duplication of nodes due to the unpredictable distribution of nodes. This can make it difficult to achieve optimal network connectivity, and more nodes may be required to provide optimal coverage. Additionally, environmental factors, especially the structure of the terrain, vegetation, and obstacles in the area, have the potential to affect the connectivity and coverage of the sensor nodes. Obstacles, such as dense forests, hills, or buildings, can block the line of sight between nodes, weakening them or causing them to lose connections. This may reduce the effectiveness of WSNs by preventing sensor nodes' optimal coverage and reliable communication. In this context, this study focuses on the deployment of sensor nodes and the development of specific coverage optimization algorithms to overcome these problems. Such algorithms including evolutionary approaches can potentially offer a solution, particularly for effective deployment in uncertain and dynamic environments.

The objective of this study is to gain a comprehensive understanding of sensor node deployment issues and investigate novel optimization techniques applicable in this domain. To achieve this, the study will focus on addressing the following research inquiries:

Question 1: What are the strategies that can be used to address coverage gaps and the presence of unnecessary nodes for randomly distributed sensor nodes?

Question 2: What is the impact of different node types and environmental factors (such as the borders of the area of interest and the shape of the polygons) on the connectivity and coverage of sensor nodes?

Question 3: What are the ways in which evolutionary algorithms can be utilized to enhance the optimization of sensor node deployment?

These questions will form the framework of the research, and detailed discussions will be presented in the subsequent sections of the study. The rest of the paper is organized as follows: In Section II, WSN, which is the main subject of this study and the various subheadings under it are briefly defined. Then, the importance of these parameters in the design process was emphasized. Additionally, studies focusing on expanding the coverage area using evolutionary algorithms are reviewed and presented in the table in the same section. In Section III, the proposed model is introduced. In Section IV, experimental results for sensor node deployments are discussed into 2 subdivisions: Homogeneous and Heterogeneous node deployment using GA and VGA. In the last three sections (discussion, open issues future works and Conclusion) based on findings, some existing knowledge gaps in WSN coverage are expressed to direct researchers to those unexplored areas and potential breakthroughs in the field. It is finally concluded that heterogeneous nodes have the potential to exhibit better adaptability and flexibility compared to homogeneous nodes in real-world scenarios.

II. BACKGROUND

WSNs refer to large-scale distributed components including sensors, communication devices and gateways to monitor and record the physical conditions of the environment in a variety of applications. The most critical constraint in wireless sensor networks is energy, due to the fact that it is impossible to replace or charge the batteries of mobile sensors in the network [8]. The energy constraint in WSNs has caused two main challenges, leading to many studies:

1) Extending the Life of Sensors: To extend the useful life of sensors, it is necessary to reduce energy consumption.
2) Maximizing the coverage area: To maximize the coverage area, it is necessary to avoid intersecting/

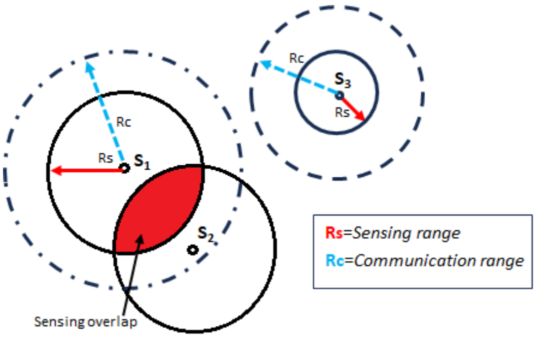

FIGURE 2. Ranges of nodes.

overlapping nodes as much as possible and cover the area with as few nodes as possible.

These two challenges can affect each other. For example, more sensors are necessary to maximize coverage, but it means an increase in energy consumption. Therefore, achieving a balance between the energy limitation and the coverage area maximization in WSNs is important.

A. COVERAGE IN WSNs

Sensor nodes are devices that transmit and receive data wirelessly. They generally work using radio frequency (RF) communication. When used within WSN, these nodes have coverage, which refers to the ability to detect events or objects within a specific region. In WSNs, the sensing range (R_S) and communication range (R_C) of the sensor nodes are critical. The sensing range refers to the distance at which the node can detect events or objects within the physical space surrounding it. This is called as "coverage". The communication range refers to the ability of the sensor nodes to communicate wirelessly with each other. It is called "connectivity" in the literature. These distances may vary depending on the strength and frequency of the signal transmitted from the sensor, the characteristics of the environment, and the communication protocol used. The distance between nodes S_1 and S_2 is shown in Fig. 2, since (R_S) is smaller than the distance R_C, they can communicate with each other. But, the coverage area of the two nodes intersects each other. On the other hand, since node S_3 is far from S_1 and S_2 by (R_C) and (R_S) distances, there is no overlapping. But, at the same time, it cannot communicate with both nodes. Both of the cases are not desired situation [9], [10], [11], [12].

In WSN design, accurately determining the area of coverage of sensor nodes is a critical task for the application requirements, energy efficiency, cost, and overall performance of the network. Therefore, some different coverage strategies have been adopted depending on the shape of the deployment area or the type of application. Some coverage strategies commonly used in WSNs are as follows:

- **Area/Blanket Coverage:** It aims to distribute the sensor nodes over a certain geographical area and cover that region widely, as seen in Fig. 3(a). This is often used to understand or monitor the general characteristics of events in a region.

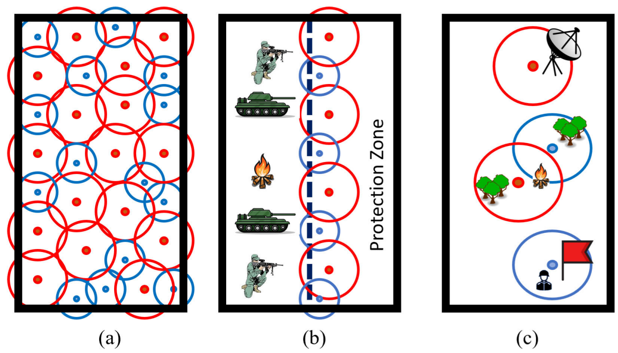

FIGURE 3. WSN coverage strategies, (a) Area coverage, (b) Barrier coverage, (c) Target coverage.

- **Barrier Coverage:** It aims to arrange the sensor nodes along a certain line, as seen in Fig. 3(b). For example, this method can be used for border security or to monitor the approach of irregular immigrants to the border.
- **Target/Point Coverage:** It aims to ensure more specific monitoring of the region only around a specific target or object, as seen in Fig. 3(c). For example, it can be used to track the movement of a specific object or to focus on an event in a specific area.

B. DESIGN CONSIDERATIONS FOR COVERAGE PROBLEM IN WSNs

In this part of the paper, we want to mention the following design issues for the coverage problem of WSNs:

1) OBJECTIVE FUNCTIONS

In coverage area problems, the selection of objective functions is of utmost importance as they will guide the design and optimization processes. The following objective functions are commonly employed in WSNs [9]: 1) Coverage, 2) Network Lifetime, 3) Energy consumption and 4) Cost. In WSNs, maximizing the coverage area is the fundamental goal. Some metrics such as coverage completeness, regularity, and redundancy are used to evaluate this process. Maximizing the lifetime of the network is another critical goal. This involves designing coverage algorithms that will keep the network can operate a longer period. Energy Consumption is another goal. Since sensor nodes have a limited network lifetime, it is important to design algorithms that maximize the coverage area while minimizing energy consumption. For each node, sensing intervals or duty cycles must be optimized to ensure balanced energy consumption and savings. Cost is the last goal to be ensured in WSN deployments. Total cost including hardware used, deployment of the nodes and the maintenance of the WSNs should be minimized.

2) HOMOGENEOUS VS. HETEROGENEOUS SENSOR NODES

Homogeneous WSN is a type of network consisting of sensor nodes with the same characteristics such as sensing range, energy capacity, and communication capabilities, as seen

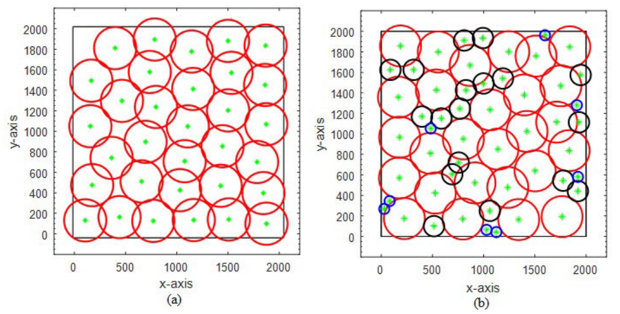

FIGURE 4. **Illustration of sensor nodes (a) Homogeneous (b) Heterogeneous.**

in Fig. 4(a). In homogeneous networks, sensor nodes often perform the same task, and this structural homogeneity simplifies network management. However, this brings some difficulties in some matters such as energy consumption and the balanced distribution of other resources. Heterogeneous WSN is a type of network consisting of sensor nodes with different characteristics for sensing range, energy capacity, computing power and communication capabilities. Heterogeneous networks include a variety of sensor nodes, making the network more flexible and customizable, as seen in Fig. 4(b). While sensor nodes that can perform different tasks improve the overall performance of the network; this heterogeneous structure of WSNs results in a more complex algorithmic structure in network management. Heterogeneous networks can offer benefits such as energy savings, task customization, and network lifetime [8].

3) DETERMINISTIC VS. RANDOM DEPLOYMENT

How the nodes are distributed to optimize the coverage area is another important issue. Node deployment strategies in WSN are generally divided into two main categories, based on deterministic and random methods. Deterministic node deployment strategies aim to place the nodes in a defined location by a specific algorithm or model, while random node deployment strategies determine the location of nodes randomly. Both methods have unique advantages and disadvantages [1], [13], [14], [15].

Deterministic node deployment strategies are often used to achieve specific goals such as balancing the energy use of the network, optimizing coverage, minimizing communication costs or optimizing against certain criteria. For example, optimal positioning of nodes using Voronoi diagrams can aim to provide homogeneous coverage in certain regions. On the other hand, random node deployment strategies focus on determining the overall distribution of the network by placing nodes randomly in a given area. The most important advantage of this strategy is the fast and simple implementation. However, problems such as energy imbalance and coverage gaps may arise with these methods [10], [16], [17], [18].

To optimize and minimize these problems, evolutionary algorithms, genetic algorithms or complex optimization methods can be used. These solutions contribute to more sustainable, energy-efficient, and reliable operation of the network.

4) STATIC VS. MOBILE WSNs

In static WSNs, sensor nodes remain in determinate positions and are typically used to monitor a specific area or to measure some environmental parameters such as air pollution. Against the static, in mobile WSNs, sensor nodes are mobile and are usually used to track the moving targets. Static WSNs often have a planned topology that facilitates their management. Even if mobile WSNs adapt better to dynamic environments, they involve more complexity in terms of energy consumption and node management.

5) DIRECTIONAL VS. OMNI-DIRECTIONAL WSNs

There are two different ways to communicate wirelessly in WSNs: Directional and Omnidirectional, and each has its uses and features [15]. Directional WSNs use antennas that focus the signal in a certain direction. This makes the contact range longer and reduces interference from areas that are not needed. This targeted method works very well when the sensor nodes need to talk to each other over longer distances or in a certain direction. This makes them perfect for tasks like monitoring the border or a specific area of the environment. Omnidirectional WSNs, on the other hand, use transmitters that send the signal evenly in all directions, covering a full circle. This wide range makes them good for uses that need to cover a large area, such as home automation, watching traffic in cities, or keeping an eye on crops in the field. Omnidirectional networks are easier to set up and keep up, but they may not have as much range and are more likely to get messed up than directed networks. Ultimately, the decision between directional and omnidirectional WSNs is based on the application needs, such as the coverage area, range, and the type of environment where they will be used.

6) TWO-DIMENSIONAL VS. THREE-DIMENSIONAL WSNs

In Two-Dimensional (2D) WSNs, sensor nodes are placed in a 2D plane. This distribution is used in scenarios where tracking or coverage can be represented well enough in 2D. Most of the existing work focuses on 2D WSN. However, in real-world application scenarios, there are obstacles, structures, etc. in the field. Due to the presence of objects, a 2D WSN design is not enough, and a Three-Dimensional (3D) WSN design is required. In 3D WSN, sensor nodes also extend into a three-dimensional space, namely, the height dimension. This distribution is used when the monitored environment or the observed events differ in three dimensions. The choice between 2D and 3D WSNs depends on the specific requirements of the application and the nature of the monitored environment. However, to find approximate solutions for real applications, the focus should be on 3D WSNs [19].

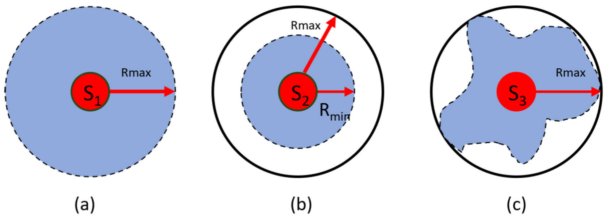

FIGURE 5. Node sensing models (a) Boolean disk sensing model (b) Elfes node sensing model (c) Shadow-fading sensing model.

7) CENTRALIZED VS. DISTRIBUTED APPROACHES

There are two methods for addressing connectivity issues in WSN topologies: centralized approaches and distributed approaches. The centralized approach refers to a management model in which all decision-making processes and control in WSNs are concentrated at one central station. In this model, a central authority or master station controls all sensor nodes in the network, processes data, and makes decisions. On the other hand, the distributed approach represents a management model in which decision-making processes and control are distributed across various nodes in the network. In this case, sensor nodes can process the data and make decisions locally, creating a more autonomous structure. The preferred approach depends on factors such as application scenario, energy efficiency, and reliability.

8) NODE SENSING MODELS

In WSNs, the term "sensing models" refers to the methods and mechanisms through which sensor nodes within the network perceive or measure environmental factors [19]. These models are important for both the design process and the evaluation of network performance. In the realm of WSN, there exist three widely recognized sensor models. Each of these models has its own unique characteristics and application area which make them suitable for various scenarios and requirements in WSN. Understanding these models is crucial for developing efficient, effective and accurate sensor networks, as they directly affect how the network interacts with and responds to its surroundings.

The *Boolean disk sensing model* refers to a simple logical model in which sensor nodes detect events as present or absent. This model assumes that the sensing area of a sensor node is circular with a sensing radius of, R_{max} as shown in Fig. 5(a). It is simple and has low complexity. *Elfes node sensing model* represents an approach in which sensor nodes detect events using probability distributions. Sensor nodes calculate the probability that a particular event occurs and report information based on these probabilities. This model offers a more realistic and flexible approach. R_{max} is the maximum sensing range of the sensor node and R_{min} is the point where the uncertainty in sensing begins. Consequently, it is probabilistic to detect an event that occurs between R_{max} and, R_{min} as seen in Fig. 5(b).

The *shadow fading sensing model* is a model used in WSNs to account for the impact of obstacles (such as buildings and foliage) on the sensing capabilities of sensor nodes. This model acknowledges that the sensing ability is not uniform in all directions, resembling the concept of shadowing in radio wave propagation. Employing the log-normal shadowing path loss model, it calculates the probability of an event occurring at a certain distance from the node being detected. The model realistically represents the irregular sensing pattern arising from obstacles' influence as seen in Fig. 5(c) and provides the capability to model sensing characteristics by considering environmental conditions.

Table 1 provides a comparison of sensing models. Consequently, the sensing model to be used must be selected based on the specific application requirements and environmental conditions. The Boolean Disk Model can be preferred in cases of simple and no need for detailed analysis requirements. Elfes and Shadow Fading models can be suitable for more complex environments and detailed analysis. In this study, the Boolean disk coverage model was utilized to detect whether the sensor covers the relevant point.

9) TARGET AREA MODELING

Target Area Modeling is a concept that aims to reflect more accurately real-world conditions such as irregular and different types of obstacles while solving the deployment problem of WSNs. Although most of the existing solutions only include a planar perspective, target area modeling provides a more realistic scenario by taking into account the unique physical characteristics and environmental obstacles of each target area. It considers various factors such as height, shape, and type of obstacles to determine appropriate locations where sensor nodes are to be placed. In this way, it is possible to determine the exact 3D locations of sensor nodes and the coverage and connectivity status of the network can be evaluated more precisely. This modeling aims to develop more optimized solutions for the effective deployment of WSNs, providing a more comprehensive and realistic perspective than the existing two-dimensional plane.

In this study, a different approach was adopted from existing studies in the literature and tried to provide a realistic perspective by distributing sensor nodes on real campus maps containing obstacles, lakes, and buildings.

10) DYNAMIC ENVIRONMENT

The operational areas of WSNs have dynamic conditions that undergo continuous changes. This variability may come from various factors, such as buildings, objects, and obstacles within the application area, which can undergo constant alterations. New buildings may be constructed, walls and obstacles may be added or removed, and tracked objects can change positions. The main aim of this model is to allow adjusting WSNs continuously changing environmental conditions, ensuring the efficient operations of nodes.

Given that this study is conducted on real campus maps, it adopts a dynamic modelling approach to address the instant

TABLE 1. Comparison of node sensing models.

Criteria	Boolean disk sensing model	Elfes sensing model	Shadow-fading sensing model
Degree of Certainty	Deterministic	Probabilistic	Probabilistic
Obstacle Dependency	Independent	Dependent	Independent
Node's Sensing Ability	Equal and Constant	Regional Variable	Random and Variable
Possibility of Degrading Coverage Area	No	Yes	Yes
Area Coverage Performance	High	Medium	Variable
Complexity	Simple	Moderate	Complex

changes in environmental conditions. This study focused on providing more realistic and applicable solutions for effective node deployment and optimization by considering these dynamic changes in environmental conditions.

C. THE GENETIC ALGORITHM

GA is known as a search and optimization algorithm that simulates evolutionary processes. GAs try to find the best solution in a search space using mechanisms such as natural selection, crossover, and mutation. GAs are commonly used to solve complex optimization problems such as node placement, mission scheduling, route optimization, and resource allocation [1], [16], [18], [20], [21].

The flowchart of GAs consists of the following steps:

1) Population Generation: First, a random population of solutions is created in the search space. This population contains a collection of potential solutions.
2) Selection: The best solutions are selected from the population. This selection imitates the natural selection mechanism. That is, solutions with a better fit are more likely to be selected than others.
3) Crossover: The selected solutions are subjected to the crossover process. Crossing produces new solutions by combining the genetic material of two solutions.
4) Mutation: Solutions obtained from crossover can be subjected to mutation. The mutation increases the variation in the solutions by making random changes.
5) Population Regeneration: New solutions are added to the population, and some old solutions are replaced with new ones.

This cycle, shown in Fig. 6, is repeated until a certain state or criterion is reached. GA uses these steps to ensure that a solution represents the best in the search space.

D. RELATED WORKS

The placement of sensors in WSNs has a critical impact on network performance, energy efficiency, and overall effectiveness. The difficulty in finding optimal sensor locations further complicates the task due to the NP-hard nature of the problem. Research in this field has generally focused on topics such as sensor placement, network performance, energy efficiency, coverage strategies, and sensor node selection. These topics include critical factors determining the application requirements, energy efficiency, cost, and overall performance of WSNs. In their study, Egwuche et al. reflected the increase in efforts to improve WSN performance and efficiency by performing bibliometric analysis [4].

Al-Mousawi et al. explored WSN optimization using multiple evolutionary algorithms, focusing on routing, clustering, localization, and coverage. Their experiments, employing evolutionary algorithms, demonstrated improvements in sensor network capabilities, enhancing overall performance and efficiency [16]. Birtane et al. utilized a GA to maximize coverage area in a uniform space with homogeneous sensors. The proposed method to calculate the coverage area in the GA's fitness function showed high accuracy and reduced calculation time, providing a novel contribution to the literature [1]. Egwuche et al. conducted a comprehensive review, emphasizing WSN coverage optimization using machine learning and nature-inspired algorithms. Deep learning techniques have been identified as promising for enhancing coverage and network performance [4]. Elhoseny et al. tackled the K-coverage problem, proposing a K-scope model based on GA. The model aimed to extend WSN lifetime by optimizing energy consumption, demonstrating superior performance compared to other methods [20]. Hanh et al. developed a novel algorithm called MIGA to address the weaknesses of heuristic algorithms in their study. This algorithm is a combination of heuristic population initialization, a fitness function that calculates the full integral area, and Laplace and arithmetic crossover methods [18].

Idrees and Al-Yaseen proposed DiGALCO, a distributed genetic algorithm, to extend the lifetime of WSN and maintain the coverage area by optimizing virtual network division, cluster head selection, and sensor activity planning [22]. In their study, Idrees and Al-Yaseen proposed a new protocol called a distributed genetic algorithm (DiGALCO) to extend the useful life of the WSN and maintain the coverage area. DiGALCO tries to optimize the division of the virtual network into subareas, the selection of the cluster head in each subarea, and the planning of the sensor activity performed by each cluster head with a genetic algorithm (GA). Thus, it enables WSNs to operate longer and more efficiently [22]. Karatas developed a model using a multi-objective integer linear program and GA to position heterogeneous nodes to monitor critical areas. The model was designed to increase the monitoring area while considering technical features and constraints [23]. Khalaf et al. proposed a method to optimize WSN coverage using the bee algorithm. They simulated the proposed method in MATLAB and compared the results with the genetic algorithm. According to the results, the bee algorithm gave a more optimal coverage percentage and worked faster than the genetic algorithm [24].

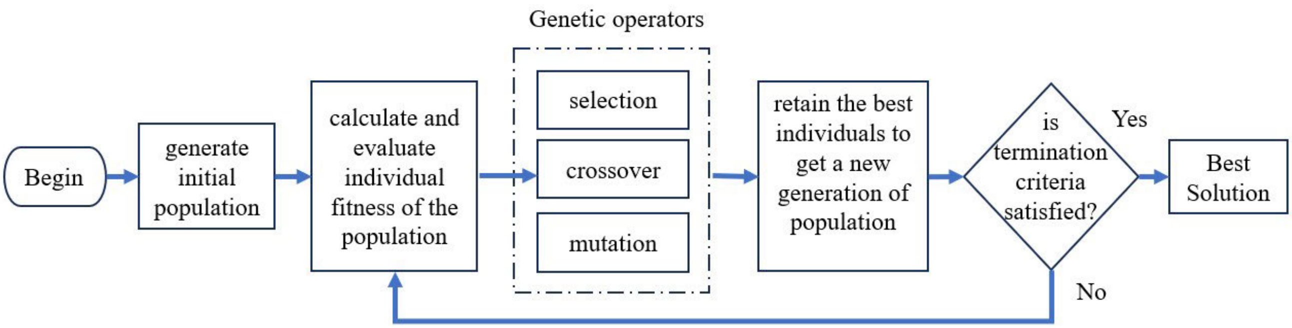

FIGURE 6. The flowchart of GA.

Patil and Suresha evaluated static, dynamic and energy-oriented node placement methods, comparing their performance on various parameters to identify optimal placement strategies [14]. Priyadarshi et al. reviewed coverage techniques in four main categories, providing a comparative analysis based on positive and negative aspects of computational techniques based on geometry, force, grid, and metaheuristics [15]. Tossa et al. proposed GAFACM, a GA-based algorithm to maximize coverage area in WSNs, addressing the problem of maximum coverage while considering connectivity between sensor nodes [11]. Wang et al. introduced an optimization model based on the whale algorithm to improve WSN coverage and network performance, incorporating the idea of reverse learning to optimize population distribution [25]. Wang et al. addressed the deployment optimization problem in WSNs with heterogeneous nodes, proposing novel approaches based on the Flower Pollination Algorithm (FPA) to achieve higher coverage rates and reduced costs while preserving population diversity [26]. Yarinezhad and Hashemi proposed collaborative PSO and collaborative PSO using fuzzy logic algorithms based on the PSO algorithm to solve sensor placement problems, demonstrating effectiveness in simple coverage scenarios, K-Coverage, and Q-Coverage [12]. Yoon and Kim introduced four approaches based on genetic algorithms for sensor distribution problems in WSNs, namely PGA, MGA, OPTGA, and OPTHA, providing comparative results to assess their effectiveness [27].

It can be understood that these studies mostly contributed to the advancement of WSN deployment methodologies, showing the diversity of approaches and techniques used to address the challenges associated with sensor placement in NP-hard scenarios. The studies focusing on increasing the coverage area using evolutionary algorithms are given in Table 2.

In the previous studies, it was carried out to increase the coverage area using GA. In this paper, a new approach 'Vibrational Genetic Algorithm' (VGA) which exists in the literature but has not been used in such studies is proposed to increase the coverage area to higher rates. VGA was first proposed by Hacıoglu et al. in their studies on the design of transonic airfoils [38], [39]. Later, it was used in studies such as continuous covering location problems [40], optimization of 3D wing geometries [41], path planning of autonomous unmanned aerial vehicles [42], and design of a single-stage hybrid rocket engine of a low-altitude sounding rocket [43].

Experimental results show that the performance increase in proposed VGA algorithms for GA has revealed valuable information for the optimization of coverage in WSNs, providing various perspectives on the effectiveness of homogeneous and heterogeneous node distribution strategies.

III. PROPOSED SYSTEMS

This study involves simulations which aim to expand the coverage area in WSNs. Simulations are conducted with sensor nodes that possess homogeneous and heterogeneous properties. Nodes are initially distributed throughout the area using a random deployment method, followed by adjusting their positions using GA and VGA algorithms. This iterative process continues until achieving the optimal node placement with the best coverage ratio according to the blanket/area coverage model, avoiding excessive overlapping or intersecting.

The research encompasses both regular and irregular-shaped areas. A regular area is defined as a geometric shape with known width and length, while simulations with irregular shapes were conducted on two different real university campus maps including lakes and buildings. The concepts used in the experiments are outlined in Table 3. In the literature, studies in this field often focus on regular areas because of the ease of area calculation. Therefore, this study aims to contribute to originality by working on real maps having irregularly shaped areas and including lakes and buildings. In designed simulation, experiments were performed using both homogeneous and heterogeneous sensor nodes. In sensor node placement, lakes or specific buildings were excluded from the region of interest, aiming for optimal coverage while considering different properties of nodes.

A. MEASURING WSN COVERAGE

This study aims to accurately depict real-world scenarios to assess and model the performance of WSNs in irregular terrains. Although WSNs are commonly deployed in

TABLE 2. Studies focusing on increasing the coverage area using evolutionary algorithms.

Paper	Type of Node	# of Sensor Types	# of Nodes	Target Area	Environment	Method	Coverage(%)	Year
[13]	Homogeneous	1	100	2D Square	Static	Ant-Lion	97.19	2018
[13]	Homogeneous	1	100	2D Square	Static	GA	91.47	2018
[13]	Homogeneous	1	100	2D Square	Static	PSO	86.53	2018
[18]	Heterogeneous	3	27-199	2D Square	Static	MIGA	—	2019
[24]	Homogeneous	1	32	2D Square	Static	BEE	97.87	2020
[25]	Homogeneous	1	50	2D Square	Static	Whale	95.80	2018
[27]	Heterogeneous	3	27-199	2D Square	Static	OPTHGA	—	2013
[28]	Homogeneous	1	40	2D Square	Static	Cheetah Optimizer	93.72	2023
[29]	Heterogeneous	3	63	2D Square	Static	CFPA	98.84	2016
[30]	Homogeneous	1	35	2D Square	Static	FOA	91.92	2023
[30]	Homogeneous	1	35	2D Square	Static	E-FOA	92.59	2023
[31]	Homogeneous	1	100	2D Square	Static	GWOVF	99.45	2023
[32]	Homogeneous	1	200-1200	Target model	Static	GA-TabuSearch	—	2022
[33]	Homogeneous	1	45	Target model	Dynamic	MuGWO	99.14	2022
[34]	Homogeneous	1	40	2D Square	Static	IGWO	97.50	2019
[34]	Homogeneous	1	55	2D Square	Dynamic	IGWO	100.0	2019
[35]	Homogeneous	1	20	2D Square	Static	Yin-YangPIO	99.51	2022
[36]	Homogeneous	1	45	Target Model	Static	IDDT-GA	97.25	2020
[37]	Homogeneous	1	45	2D Square	Static	IWHO	97.58	2023
[37]	Heterogeneous	2	20	2D Square	Static	IWHO	98.51	2023

TABLE 3. Experiment concepts.

Sensor Node Type	Shape of Area to be covered	Algorithm	
Homogeneous Heterogeneous	Regular polygons such as squares or rectangles	GA	VGA
Homogeneous Heterogeneous	Irregular polygons with some excluding parts	GA	VGA

regular and unobstructed spaces, real-world applications often involve irregular landscapes with obstacles and structures. Consequently, this research is focused on gaining a better understanding of how WSNs function in such irregular environments and developing models that are specifically tailored to these conditions. The research introduces a novel approach to determining the coverage area, known as the Point Counting Method (PCM), which is thoroughly explained in the paper [1]. PCM is used as a fitness function, which evaluates the effectiveness of a potential solution to assess each chromosome in the population. It operates as follows:

1) *Determination of Reference Point Set:* A reference point set is selected for coverage analysis of the region of interest. These points are typically chosen randomly and distributed throughout the area.
2) *Determination of Sensor Nodes' Detection Range:* Each deployed sensor node has a detection range (Rs). This distance generally represents the maximum distance that a sensor node can cover.
3) *Determination of Coverage Status for Each Point:* To determine whether each point is covered by at least one sensor node, the Euclidean distance equation is used, as shown in Eq.1. The distance between each point and the sensor nodes is checked one by one. If the distance from the points to at least one node is less than Rs, the point is considered covered, as seen in Eq.2. Then, the number of covered points is calculated.
4) *Calculation of Coverage Area:* The total number of covered points is divided by the total number of points, and this ratio is used to calculate the percentage of the total coverage area. This indicates how much of a specific region is covered by sensor nodes.

$$D(P, S) = \sqrt{((Px - Sx)^2) + ((Py - Sy)^2)} \tag{1}$$

$$C(P, S) = \begin{cases} 1, & D(P, S) <= Rs \\ 0, & otherwise \end{cases} \tag{2}$$

The number of points thrown into the PCM can vary depending on the nature and complexity of the region. In this study, the number of points was determined as 20,000 to achieve a specific level of precision and accuracy. Using more points can increase the probability of obtaining more statistically reliable results [33]. As seen in Fig. 7(a) and Fig.7(b), it can be seen that 20,000 points placed in the area of interest completely cover the area. The number of 20,000 points is an example determined by experimental studies to enhance the resolution and positioning accuracy. However, it should be noted that while increasing the number of points improves accuracy, it also increases processing load and time.

The number of points can be increased or decreased depending on the specific application scenario. The characteristics and intended use of the area where PCM is applied will be influential in determining the number of points thrown. PCM provides a higher level of accuracy compared to other methods in the literature by offering faster and simpler calculations.

B. PROPOSED GENETIC APPROACH

In this study, a simulation was developed to monitor two different university campuses having lakes and buildings. The campus maps are irregularly shaped and borders are not linear. In simulation, heterogeneous sensor nodes with

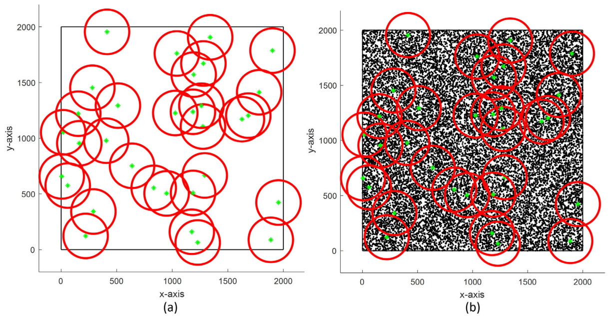

FIGURE 7. **(a) Node deployment, (b)Coverage calculation with PCM.**

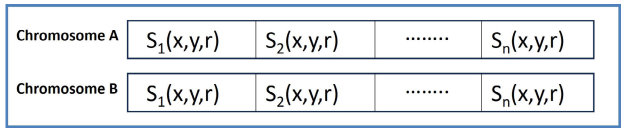

FIGURE 8. **Chromosome structure.**

different properties are used. Distributed sensor nodes are placed by avoiding lakes or desired buildings in the region of interest. On the contrary, sometimes, it can be aimed that the nodes should be placed to cover a defined target at the highest rate while the rest of the area is covered at a lower rate. In this kind of coverage task, WSNs require more planning and optimized node positioning.

To expand the coverage area, new approaches were integrated into GA. During the mutation stage of GA, small vibrations were applied to node positions to maximize local coverage in the search process. This approach promotes effective diversity, facilitating a quicker escape from local optima, and increasing the likelihood of reaching the global optimum. Detailed explanations will be given in the following sections.

In this paper, researches were carried out to increase WSN coverage. In previous studies, it has been understood that it is difficult to reach better solutions using random or traditional methods and evolutionary algorithms must be used for this purpose. In this context, a series of experiments with various parameters such as regular/irregular areas, and homogeneous/heterogeneous nodes were carried out to increase the coverage area and aimed to reach the most appropriate node distribution scheme.

1) CHROMOSOME DESIGN

In GA, chromosomes refer to possible solutions that represent the problem. Genetic operators are applied to these chromosomes to create new and improved solution candidates. The structure of the chromosome determines how the candidate solutions are represented. The length of the chromosome refers to the number of genes or parameters in a chromosome. In this study, the length of the chromosome is determined by the number of nodes distributed in the area of interest. The number of genes in each chromosome is equal to the number of nodes. Fig. 8 shows a chromosome consisting of heterogeneous nodes. The genes in the chromosome contain the location information (X-Y coordinates) of the distributed nodes and the coverage distance of the node. The fitness function is used to calculate the coverage of each chromosome within the relevant area.

2) PARENT SELECTION

After evaluating the fitness function, the tournament selection method is used to select the best individuals for generating new potential solutions. This method is a popular selection strategy in genetic algorithms that aims to reduce the impact of individuals with low fitness values on the algorithm.

To implement tournament selection, initially, N individuals are randomly chosen from the population, and the total number of these selections is referred to as the tournament size. A tournament is organized among the selected individuals, and at the end of this tournament, the individual with the best fitness or objective function is chosen as the accepted best individual and added to the new population [21]. This process can be expressed mathematically, as seen in Eq.3,

$$Fitness(I_t) = maxFitness(I_x) \Leftarrow x = 1, 2, 3 \ldots N \tag{3}$$

The selected best individuals then proceed to the crossover and mutation stages, contributing to the generation of new potential solutions. This approach helps to improve the quality of the population over time, gradually approaching better solutions.

3) CROSSOVER (BLX-α)

The study aims to find better solutions for the coverage area. The Blend (BLX-α) Crossover is used in the crossover phase of GA. BLX-α crossover is a recombination method in which two parental genes are crossed with each other. This approach generates offspring genes by blending them not only at key points but also at intermediate locations. In particular, BLX-α crossover outperforms other recombination methods. This makes it a more preferable choice for multi-dimensional optimization problems. BLX-α depends on the value of alpha, a hyperparameter. In the context of machine learning and optimization algorithms, a hyperparameter is a parameter that is not directly learned from the dataset but is crucial for algorithm configuration, the extent of genetic differences between two parents and typically assumes a value within the range of $0 < \alpha < 1$ [44], [45], [46].

$$C = P_1 + \alpha(P_2 - P_1) + \varepsilon \tag{4}$$

BLX-α crossover selects the value of a child gene C based on two parent genes P_1 and P_2 where $P_1 < P_2$. It is represented by the formula in Eq.4. ε is a randomly selected number within the range [-$\alpha(P_2$ -$P_1)$, $\alpha(P_2$-$P_1)$] and which introduces variation while generating the child gene based on the difference between the parent genes.

4) MUTATION (NONUNIFORM)

The mutation process is applied to the offspring created as a result of the crossover process. The mutation is applied to increase diversity, exploring various combinations of genetic material and potentially finding better solutions. In studies focusing on expanding coverage, when only GAs are employed, Non-Uniform Mutation is utilized during the mutation phase. As the name suggests, this mutation method aims to enhance the algorithm's flexibility by breaking free from the constraints of the original mechanism and generating a new search mechanism. This method relies on the mutation rate being variable. In other words, the mutation rate changes based on a specific factor, such as iteration count or generation count. Initially, a low mutation rate is set, and then, after each generation or iteration, the mutation rate is increased, thereby increasing the probability of gene alterations. In this way, it initially allows the algorithm to explore a broad search space with a low mutation rate and then focus on more specific search areas with a higher mutation rate, enabling access to better solutions [47].

Create an offspring for each individual in the t-th generation population through non-uniform mutation as follows: if $X_i^t = \{x_1, x_2, \ldots x_k\}$ represents a chromosome (where t is the generation number), and when x_k (original gene value) is selected for mutation, the result is the vector $X_i^{t+1} = \{x_1', x_2', \ldots x_k'\}$. ($x_k'$ is the new gene value obtained after mutation) UpperBound(UB) and LowerBound(LB) are the lower and upper bounds of x_k, representing the limits of the values that the genes can take. ξ is a random number. The function $\Delta(t, y)$, as the value t increases, provides a result within a specified interval [0,y] such that $\Delta(t, y)$ approaches zero. This property causes the operator to explore the solution space initially equally (when t is small) and, later on, very locally [48]. The mathematical representation of this approach is provided by Eq.5:

$$x_k' = \begin{cases} x_k + \Delta(t, UB - x_k) & \xi = 0, \\ x_k + \Delta(t, x_k - LB), & \xi = 1 \end{cases} \tag{5}$$

To overcome the limitations of random mutations in evolutionary algorithms, the dynamic Non-Uniform Mutation operator is widely used in the literature. This method gives better results compared to other mutation methods and it accelerates the convergence process. This is because Non-Uniform Mutation allows better solutions by focusing on more specific search areas.

5) VIBRATIONAL MUTATION

The Vibrational Genetic algorithm (VGA) is a method that increases the convergence performance of GA because it provides search/finding with effective diversity. It is implemented as a Vibrational Crossover or Vibrational Mutation. The applied vibration is expected to increase the diversity of the solution and improve local searches. In this study, vibration was used within a certain probability in the mutation step after the crossover process of GA.

VGA is a type of genetic algorithm that involves a unique mutation process inspired by the concept of vibration at the molecular level. In traditional GA, a mutation is a random change in one or more genes of an individual in the population to preserve genetic diversity and prevent premature convergence. In VGA, the mutation process is influenced by the idea of molecular vibrations, in which molecules vibrate at certain frequencies depending on their structure and environment. This algorithm assumes that similar vibration patterns are present in the search space of optimization problems. By giving vibrations to the individual's genes, the algorithm increases the chance of finding better solutions by exploring new areas in the search space. The pseudocode and the steps of VGA are presented in Algorithm 1.

Algorithm 1 Pseudocode of VGA

```
Set initial parameters.
Generate the initial population.
while termination criteria not met do
    Evaluate the fitness of every individual.
    Select parents for breeding based on their suitability.
    Perform crossover on parents to create offspring.
    Apply vibrational mutation to offspring.
    Evaluate the suitability of the offspring.
    Replace the individuals with the least fitness value in
    the population with offspring (update population).
end while
Show best solution
```

In this study, one or more chromosome genes are probabilistically moved in a random direction and amount in a certain band range by using vibrational mutation. This method allows the coverage area to expand and the sensor nodes to be placed more effectively in the area of interest. The effects of applied vibration vary depending on the amount and frequency of mutation. Increasing the amount of mutation increases the improvement of the coverage area, especially in cases where overlaps are high. However, it should be taken into consideration that in this case, the positions of the nodes will change excessively. Increasing the mutation frequency expands the search area and increases the possibility of finding better solutions. However, high frequency lengthens the search process. It has been observed that this algorithm has been used in various optimization problems, including function optimization, machine learning, and engineering design, and has produced successful results. However, it may not suit the characteristics of every optimization problem.

6) TERMINATION CRITERIA

Algorithm termination criteria define the conditions under which the algorithm should be stopped or terminated. An ideal termination criterion should indicate that the algorithm is sufficiently optimized and prevent excessive consumption of processing resources. Various criteria can be used to terminate GAs as follows:

TABLE 4. Homogeneous sensor node deployment concept properties.

Properties	Values
Target Model	2D Square
Environment	Static
Dimensions of Area	2000x2000
Number of Points Distributed	20000
Type of Nodes	Homogeneous
Sensing Radius of Nodes	200
Number of Nodes	32

- Maximum Number of Generations; GA typically evolves the population within a loop. Terminating the algorithm after a certain number of generations is a criterion for obtaining predictable results and preventing continuous operation.
- Fitness Threshold; The algorithm can be terminated when the fitness values of the obtained solutions fall below a certain threshold or reach a specific fitness level.
- No Change Termination; The algorithm can be terminated if there is no significant change in consecutive generations. This criterion ensures stopping when the algorithm begins to optimize and changes are minimized.
- Achieving a Target Value; Terminate the algorithm when a specific target value is reached. This criterion is commonly used for GAs that work towards a particular objective.

Since each problem and application are different, choosing the most appropriate termination criterion depends on problem-specific information, computational resources, and optimization objectives.

IV. EXPERIMENTAL RESULTS

Our experiments were carried out with different concepts in Table 3. All parameters used in our experiments were determined through numerous tests conducted as part of our doctoral research, utilizing different sets of parameters. The findings that led to related determinations were detailed in our previous work [1]. The concept properties in Table 4 were used in the experiments conducted by distributing homogeneous nodes over a uniform area.

Based on the parameters of the identified concept, a series of experiments were carried out using the genetic parameters in Table 5 to realize the simulation scenario. These experiments are designed to evaluate the performance of the identified concept in a simulation environment and understand its responses to specific scenarios. Each experiment was conducted to understand how the concept behaved against its specified specifications and to identify its potential strengths and weaknesses. The results obtained provide important information on the performance of the concept determined.

Fig.9(a) shows the placement of 32 nodes with homogeneous characteristics and randomly distributed with r = 200. Under normal conditions, if these nodes were placed deterministically, they would cover the entire area. However, as a result of the random distribution, a significant number of nodes overlap and intersect. Based on these observations, it is clear that random deployment of nodes poses challenges for coverage optimization.

TABLE 5. Experiment parameters.

Genetic Parameters	Value
Population size	100
Number of genes	Number of nodes
Crossover method	BLX-α
Probability of Crossover	0.8
Mutation method	Nonuniform
Probability of Mutation	0.3
Vibrational Mutation method	Random +/-5
Probability of Vibration	0.1
Iteration	1000

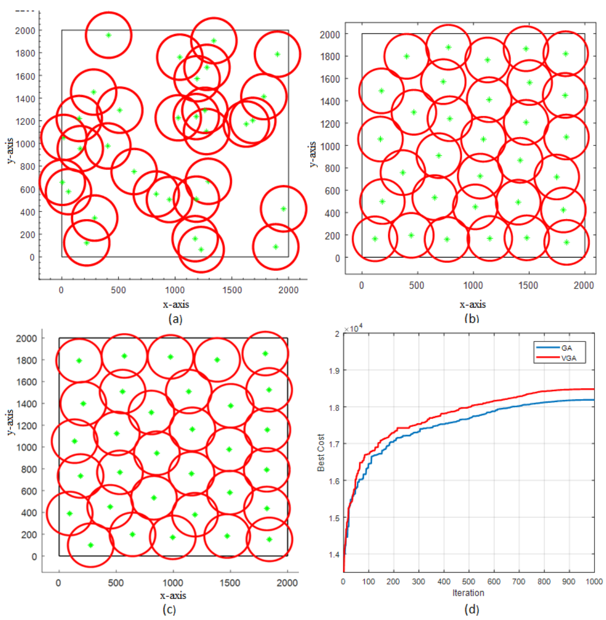

FIGURE 9. Homogeneous node placement, (a) Random, (b) GA, (c) VGA and (d) Best Cost-Iteration Graph.

Based on the findings obtained, GA and VGA were employed to improve the distribution of nodes to reach the maximum coverage area. The use of GA and VGA aims to achieve a more balanced distribution of nodes, ultimately optimizing the coverage area. This approach is considered vital to overcome the difficulties posed by randomly deployed nodes and to improve the overall performance of the sensor network in terms of coverage area optimization.

The nodes distributed with GA can be seen in Fig.9(b), and the nodes distributed with VGA can be seen in Fig.9(c). It can be seen that the nodes are not evenly distributed with GA, there are coverage gaps, and some nodes overflow from the area. On the other hand, It has been observed that the nodes deployed with VGA are more evenly distributed and have a positive effect on expanding the coverage area. Fig.9(d) shows the comparative best cost-iteration graph of the two algorithms. Table 6 shows the results for these two cases.

TABLE 6. GA and VGA results for homogeneous nodes.

Method	Points Covered	Coverage(%)	Time(sec)	Error(%)
Random	12310	61.55	0.10	38.78
GA	18187	90.93	808.08	9.07
VGA	18480	92.40	995.23	7.60

TABLE 7. Heterogeneous sensor node deployment concept properties.

Properties	Values
Target Model	2D Square
Environment	Static
Dimensions of Area	2000x2000
Number of Points Distributed	20000
Type of Nodes	Heterogeneous
Number of Type	3
Sensing Radius of Nodes	r1=50, r2=100, r3=200
Number of Nodes	n1=8, n2=18, n3=27

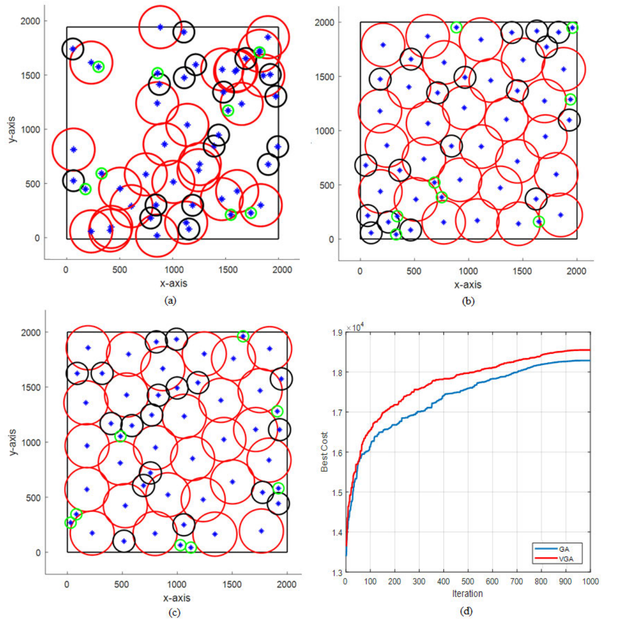

FIGURE 10. Heterogeneous node placement, (a) Random, (b) GA, (c) VGA and (d) Best Cost-Iteration Graph.

In the second concept experiments in Table 3, extensive experiments were carried out using heterogeneous nodes with different detection ranges in the ROI area (a regular square-shaped area) with the characteristics in Table 7. In this context, the performances of GA and VGA algorithms were compared. GA parameters used in this experiment were used as in Table 5.

The placement of randomly distributed heterogeneous nodes is shown in Fig.10(a). Due to the overlap and intersection of randomly distributed nodes, the coverage rate is 61.02%. However, the deployed nodes were supposed to fully cover of the area under normal conditions.

The node locations resulting from the expansion of coverage area using GA Fig.10(b) and VGA Fig.10(c) are presented. The results obtained from both GA and VGA

TABLE 8. GA and VGA results for heterogeneous nodes.

Method	Points Covered	Coverage(%)	Time(sec)	Error(%)
Random	12204	61.02	0.11	38.98
GA	18268	91.34	1129.03	8.66
VGA	18550	92.75	1262.17	7.25

TABLE 9. A real campus Map1 concept properties.

Properties	Values
Target Model	Irregular Polygonal Shape
Environment	Dynamic
Number of Points Distributed	20000
Type of Nodes	Heterogeneous
Number of Type	3
Sensing Radius of Nodes	r1=5, r2=10, r3=20
Number of Nodes	n1=10, n2=20, n3=30

TABLE 10. A real campus Map2 concept properties.

Properties	Values
Target Model	Irregular Polygonal Shape
Environment	Dynamic
Number of Points Distributed	20000
Type of Nodes	Heterogeneous
Number of Type	3
Sensing Radius of Nodes	r1=5, r2=8, r3=10
Number of Nodes	n1=8, n2=15, n3=30

indicate a more balanced placement of heterogeneous nodes, particularly with the impact of the vibrational mutation in VGA. This balanced placement enhances the effective utilization of the coverage area, leading to more efficient coverage in the target areas. Fig.10(d) and Table 8 depict the outcomes for these two scenarios.

Experiments were initially conducted on regular 2D square areas using homogeneous and heterogeneous node distributions. Subsequently, trials were carried out on two real campus maps having irregular polygonal shapes, a scenario relatively scarce in the literature. These two distinct campus maps fully meet the dynamic environment definition, having lakes and varying conditions. Here, the objective is to deploy sensor nodes in a way that allows to monitor the campuses. Therefore, the final goal is to achieve traceability suitable for any other complex geographical structures and variable environmental conditions as in the campuses.

Our primary focus is on a real university campus map. Table 9 presents the properties of the concept related to the target area and can be observed in Fig.11(a). In Fig.11(b), a total number of 60 heterogeneous sensor nodes are placed using random distribution on this campus map. The coverage ratio of these nodes is measured as 36.86%. When the same nodes were deployed using GA, it was observed that the rate increased to 90%. (Fig.11(c)). Similarly, when deployed using VGA, it was observed that the coverage ratio is higher than the two previous rates at 91.78% (Fig.11(d)).

In Fig.12(a), a real university campus map with a pond is illustrated. Our goal is to monitor and secure areas outside

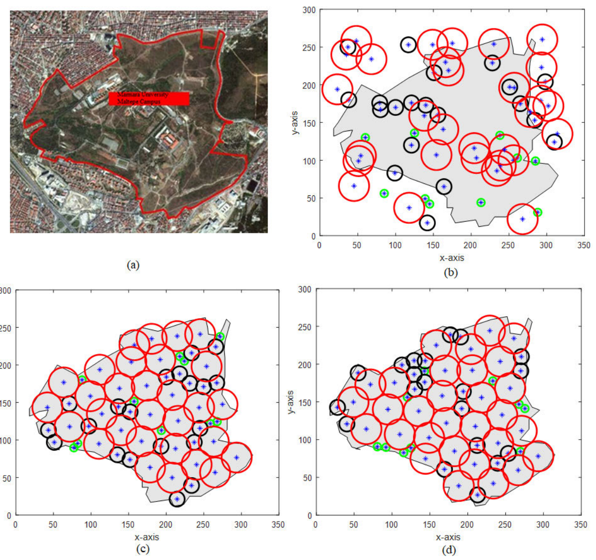

FIGURE 11. Sensor node deployment on a real campus map1, (a) Campus Map1, (b) Random, (c) GA and (d) VGA.

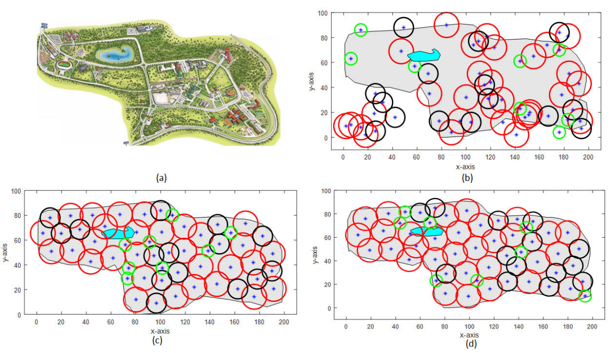

FIGURE 12. Sensor node deployment on a real campus map2, (a) Campus map2, (b) Random, (c) GA and (d) VGA.

the buildings on this campus using sensor nodes. The target region presents a dynamic environment with obstacles and structures. Table 10 presents the properties of the concept related to the target area. Therefore, the objective during the relocation of randomly placed nodes on the campus map is to ensure avoiding the pond area.

In this context, a total of 53 heterogeneous sensor nodes were randomly distributed on the relevant map, as shown in Fig.12(b). The coverage ratio of the randomly distributed nodes was measured as 49.31%. When deployed using GA, the positions of the nodes are as depicted in Fig.12(c), resulting in a coverage ratio of 90.91%. Subsequently, in the same scenario, the deployment using VGA achieved a coverage ratio of 92.35%, and the nodes were placed as illustrated in Fig.12(d).

A. PARAMETER SETTINGS AND EXECUTION ENVIRONMENT

All algorithms were implemented in Matlab and run on a machine with an Intel(R) Core(TM) i7-8700 CPU @ 3.20GHz, 32 GB memory and Nvidia GeForce GTX 1070 Ti graphics card.

V. DISCUSSION

Expanding the *coverage area* of a WSN system while simultaneously *reducing the number of sensor nodes* is a crucial aspect of network efficiency and cost-effectiveness. This can be achieved through optimized sensor placement, a method that emphasizes strategic planning and intelligent positioning of sensor nodes to maximize their coverage footprint. This approach involves the use of sophisticated algorithms (i.e., genetic algorithm) designed to identify the most efficient and effective locations for placing sensor nodes. These algorithms take into account a variety of critical factors, including the range of signal transmission, possible physical obstructions in the environment, and specific areas of high interest or importance. Taking these elements into account, algorithms can determine optimal placement positions that ensure maximum coverage and functionality of the sensor network.

The methods for sensor placement optimization not only guarantee thorough monitoring of the environment but also lead to significant cost reductions by decreasing the number of sensors needed to achieve desired coverage rates. As such, it represents a key strategy in the ongoing development and refinement of WSN systems, with the aim of delivering more efficient, reliable and cost-effective solutions for various WSN applications. Many coverage protocols are based on ideal models that do not accurately reflect real-world conditions. This paper suggests considering **realistic system modelling** using more realistic factors, such as irregular-shaped areas and subareas that do not need to be controlled, such as buildings, lakes, and barriers. Furthermore, the use of **heterogeneous sensor nodes** is also one of the discriminative features of the proposed method, which benefits from using a mixture of different types of sensor nodes. This diversity improves the performance, efficiency, and reliability of the network, making it suitable for various applications and environments. It also optimizes resource use, adds flexibility, and improves scalability.

As one of the main focus of the paper, the advantages of evolutionary algorithms are very critical. Specifically, the paper focused on the use of a new model **Vibrational Genetic Algorithm (VGA)** to address WSN coverage problems. GAs are adept at handling complex optimization challenges, which is particularly useful in environments with large search spaces and numerous possible solutions. Their robustness in dynamic settings, capability for parallel execution, and effectiveness in multi-objective optimization are highlighted. These features are essential to balance coverage, energy use, network lifespan, and data accuracy in WSNs.

The coverage rate of the proposed algorithm is widely recognized as the main performance metric. Nonetheless, the rate is intricately connected to both the quantity and capabilities of the used sensors. Hence, it is crucial to examine the solution visually in order to interpret the quality of the models. Despite our coverage rates being lower than a few of previous works, this can be attributed to the characteristics of the node types they employed.

VI. OPEN ISSUES AND FUTURE WORKS

This section has been carefully prepared to effectively identify and address existing knowledge gaps in WSN coverage. Its main purpose is to direct researchers to unexplored areas and potential breakthroughs in this field. It is intended to serve as a comprehensive review for future research efforts by highlighting open issues. Furthermore, this section plays an important role in promoting a broader perspective among new researchers. It achieves this by highlighting several open issues and suggesting possible future work, thereby sparking interest and innovation in this dynamic field of research.

Our research focuses primarily on areas structured as regular (flat) and irregular-shaped surfaces. However, in diverse environments, these areas often take on a three-dimensional (3D) shape. This complex 3D structure presents an intriguing avenue for future research, where we can model these environments more accurately. Therefore, the determination of coverage areas needs to be modified to accommodate the distinct shapes and sizes of these 3D surroundings. To address such challenges, the utilization of GA approaches is recommended in the paper. These methods should be employed similarly to existing models, but with necessary modifications to the coverage area calculations to accommodate the 3D aspect.

Additionally, our initial model proposes the use of omnidirectional boolean sensor models. However, it is important to note that in real-world scenarios, these sensors may exhibit varied coverage areas and shapes, diverging from uniformly structured designs. This variability necessitates a more nuanced approach. Therefore, integrating these diverse sensor models into system design is crucial, allowing a more realistic and effective representation of sensor behavior and coverage in complex environments.

In the final analysis, the incorporation of mobile sensor nodes offers a promising solution to compensate for the limitations of fewer static nodes. These mobile nodes have the unique capability to navigate the environment, effectively covering blind spots or areas that temporarily require increased surveillance. This mobility significantly improves the flexibility and adaptability of the sensor network. Furthermore, the use of directional antennas presents another advantageous strategy. These antennas can significantly extend the reach of individual sensors, enabling them to cover larger areas more efficiently compared to their omnidirectional counterparts. This extended reach not only improves the overall effectiveness of the sensor network but also reduces the need for a higher density of nodes. Integration of mobile sensor nodes and the utilization of directional antennas represent pivotal, yet unresolved, issues in this field. Their potential to revolutionize sensor network efficiency and coverage makes them compelling topics for ongoing research and development. Addressing these open issues could lead to substantial advances in the design and implementation of more robust and efficient sensor networks, tailored to the dynamic demands of varied environments.

VII. CONCLUSION

The effective placement of sensor nodes is crucial to determine the overall effectiveness of a wireless sensor network system. If the nodes are placed suboptimally, it can cause a series of problems, such as insufficient coverage, imbalances in energy consumption, and considerable delays in data collection and transmission. These difficulties can have a negative impact on response times and, consequently, the overall performance of the network. The main objective of this research is to improve the coverage area of a specific number of different types of (heterogeneous) sensor nodes in WSNs. The proposed method involves the optimization of a novel and modified variant of the genetic algorithm, called the vibrational genetic algorithm, to achieve the best or nearly the best positioning of the nodes.

The experimental results have shown great potential, indicating that the suggested system surpasses conventional genetic algorithm methods, particularly in terms of efficiency and effectiveness. One notable characteristic of this proposal is its evaluation of real-world situations. This involves conducting tests in irregular-shaped 2D areas that include regions that are not needed to monitor, such as lakes, seas, and buildings. These tests have proven that heterogeneous nodes exhibit better adaptability and flexibility compared to homogeneous nodes, particularly in practical applications. This discovery emphasizes the potential of the proposed approach to tackle complex challenges in the deployment of wireless sensor networks in real-world scenarios.

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