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RESEARCH ARTICLE

Coverage Area Maximization Using MOFAC-GA-PSO Hybrid Algorithm in Energy Efficient WSN Design

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ABSTRACT Coverage area optimization is always a challenging task to configure an efficient Wireless Sensor Network (WSN). This article proposes an energy-efficient coverage area optimization technique of WSN using a novel hybrid algorithm, called MOFAC-GA-PSO (Minimum Overlapped Full Area Coverage using hybridized Genetic Algorithm-Particle Swarm Optimization) algorithm. The objectives of the article are maximization of coverage area, minimization of coverage hole as well as energy requirement. The above-mentioned three objectives had not been yet addressed combinedly with the existing literature. This limitation has been addressed in the proposed work with 100% area coverage. The result of the proposed algorithm is compared with the existing literature as well as with the individual meta-heuristic algorithms (i.e., GA and PSO) to prove the competence of the MOFAC-GA-PSO algorithm. To achieve the benefits of both optimizers, the GA was treated as a global optimizer while the PSO was treated as a local optimizer. The proposed research work achieves 100 percent area coverage with just 25 mobile WSN nodes, but the existing methodology can only provide a maximum of 91.26 percent of area coverage. In terms of energy efficiency, the network built by the proposed algorithm can last 11.06 days as contrasted to the performance of the existing paper, which is 6.33 days. So, a significant improvement concerning the maximization of coverage area as well as minimization of coverage hole, and energy requirement has been observed. Last, but not the least, a statistical analysis is carried out to justify the research for the required number of optimized WSN nodes.

INDEX TERMS Coverage area optimization, energy efficient WSN, hybrid algorithm, least movement consider first (LMCF), hexagonal structure, MOFAC-GA-PSO.

I. INTRODUCTION

A Wireless Sensor Node is a battery powered small device with limited computational, transmission and energy capacity. The situation where standard wireless communications networks are difficult or impossible to deploy, the Wireless Sensor Nodes can be deployed to form a collaborative and clustered Wireless Sensor Network(WSN) [1]. Depending on the sensors affixed to the WSN nodes, these WSN nodes collect a variety of physical measurements from

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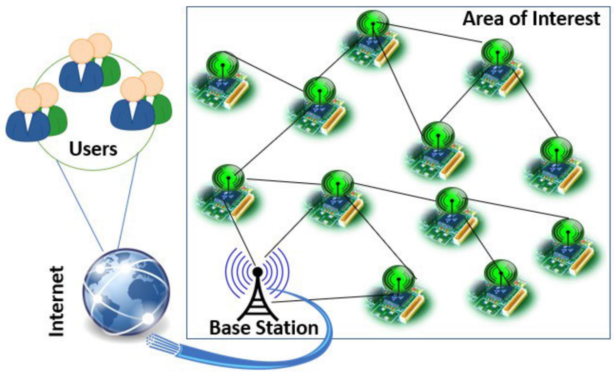


FIGURE 1. Structure of Wireless Sensor Networks [2].

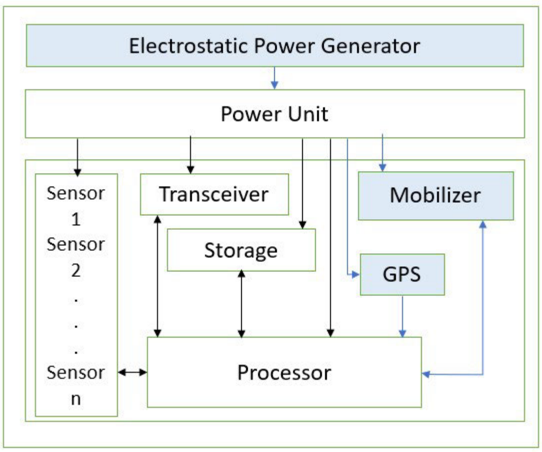


FIGURE 2. WSN node components with application-specific additional components (Power generator, GPS, Mobilizer) [7].

their surroundings, including noise intensity, air flow velocity, pollution level, pressure level, temperature, moisture, and surveillance data. After transforming the environmentally acquired data into electrical signals, the WSN nodes send and receive a limited amount of data to other nodes or sink nodes for further processing. The structure of the WSN network is depicted in Fig. 1.

Generally, the standard components of a Wireless Sensor Node include a micro-controller unit, a transceiver unit, a data storage unit, one or more sensors, and a battery stored power unit. Additionally, depending on the application, WSN nodes could contain other components like a GPS, an electrostatic power generator, and a mobilizer [3], [4], [5] to move the nodes as required. The components of the WSN node are shown in Fig. 2. The WSN has been applied for various purposes: environment monitoring, agriculture monitoring, medical surveillance, military surveillance, engineering surveillance, home automation, etc [6].

The key obstacles to developing WSN networks include limited battery energy, maximizing coverage area [8], limited processing capabilities, efficient deployment strategy [9], [10], [11], effective duty cycle optimization, and maintaining the quality of service. These issues are interrelated; for instance, efficient duty cycle optimization can decrease network energy consumption and boost quality of service, and an effective deployment strategy can minimise the number of WSN nodes needed to cover the maximum amount of ground while still improving network communication and coverage quality. Among the aforementioned challenges, this study took into account the issue of efficient deployment to maximize coverage area and to minimize network energy consumption by using and modifying hybridized meta-heuristic optimization algorithms [12].The work can be applied in a battlefield, ammunition factory, or precious mine where full area coverage is required without coverage holes, efficient connectivity needs to be provided.

The deployment of wireless sensor nodes involves scattering WSN nodes within the Area of Interest (AOI) in either planned or random manner. When wireless sensor nodes are deployed at random, there are more redundant nodes, high coverage perfection cannot be guaranteed, and there will be considerable costs as a result. However, the planned node deployment method may reduce unused nodes and achieve high coverage perfection.

In wireless sensor network, coverage refers to how well the region is tracked by the sensors that can detect objects, incidents, environmental data, etc. Three categories of coverage exist in wireless sensor networks: area coverage, boundary coverage, and target or point coverage [9], [13], [14], [15]. In the area coverage model, the challenge is to cover every point of the Area of Interest (AOI) with at least one sensor. Full area coverage is crucial when precision is greatly desired (such as in battlefield surveillance,Structural health monitoring, surveillance of highly sensitive areas like ammunition factory, nuclear power plan etc.). This study addresses the topic of full area coverage.

The sensing model in the context of area coverage can be either deterministic or probabilistic. According to Hossain et al. [16], the best coverage is obtained using the Boolean disc coverage model (deterministic sensing model). The work shows that the deterministic sensing model outperforms the probabilistic sensing model in terms of coverage.The comparison table of various mainstream coverage models has been given in Table no.1.

In this paper, the Boolean disk coverage model has been adopted. A sensor node in the Boolean disk coverage model only picks up those events that fall inside its sensing range r_s. The sensor does not monitor events outside its range. Eq. 1 would be used to describe the detection probability in the Boolean disk coverage model.

$$\text{Prob}\,(E_d(s,a)) = \begin{cases} 1, & \text{if } E_d(s,a) \leq r_s \\ 0, & \text{else} \end{cases} \tag{1}$$

here r_s stands for the sensor's sensing range and $E_d(s, a)$ is the Euclidean displacement between point a and sensor s.

TABLE 1. Comparison table of various coverage models [16].

Model Name	Type of sensing model	Obstacles/Environment dependency	sensing ability of nodes	Possibility of Degrading coverage area	Area coverage performance
Boolean disk coverage model	Deterministic	No	Uniforms in all directions	No (due to no uncertainty of detection in the sensing model)	Best
Shadow-fading sensing model	Probabilistic	Yes	Not uniform in all directions	Yes (due to uncertainty of detection in the sensing model)	Better
Elfes sensing model	Probabilistic	Yes	Not uniform in all directions	Yes (due to uncertainty of detection in the sensing model)	Good

The relation between the sensor's sensing range (r_s) and communicating range (r_c) is $r_c \geq 2 * r_s$.

In area coverage optimization, monitoring the Area of Interest (AOI) is a challenging task. Monitoring can be classified into two types: constant monitoring and periodic monitoring [17]. Although considerable energy will be used in continuous monitoring, it is necessary for extremely sensitive areas like a war, high alert zone, etc. In this article, constant monitoring is addressed. In some situations, such as on a battlefield, high coverage is another inherent necessity. So, to get a high coverage ratio and constant monitoring, sensor movement is necessary [18]. In this research, mobile sensor nodes have been taken into consideration. However, the challenge of adopting mobile sensor nodes is that the sensor's movement consumes a lot of energy. The total amount of sensor movement should be optimized to save energy. An efficient optimal placement strategy of WSN nodes is required to minimize the number of movements of sensors to build a WSN network that is energy-efficient [19], [20], [21], [22] and has the broadest possible coverage. The primary goals of the research are to maximize coverage area and to minimize the energy consumption of the network while using the fewest possible mobile WSN nodes.

Typically, the region covered by a WSN node is a circle with a radius equal to the node's sensing radius (r_s). As the coverage area of WSN nodes is circular even if WSN nodes are installed adjacently, a coverage hole will exist in the Area of Interest (AOI) during deployment, as shown in Fig. 3(a). The coverage hole makes the region uncovered and unconnected. This coverage hole issue is critical for full-area coverage. To solve the coverage hole issue, Banerjee et al., [23] proposed the Square Sub-region inscribed in Circle (actual range of WSN node), in 2022. Though the coverage hole problem had been solved it has been noticed that each Square Sub region's coverage area is 36.36 % smaller than the real sensing range (r_s), of a WSN node. Whereas each hexagonal region's coverage area is only 17.33 % smaller than the real sensing range (r_s), of a WSN node. Regarding the coverage hole problem, a hexagonal structure would be the best suitable strategy for maximizing coverage area while limiting the number of WSN nodes. Wang et al., [24] had shown that the number of sensor nodes required in hexagonal pattern deployment is least when compared to square, triangle pattern deployment.

The key factor in determining the total number of WSN nodes required to provide full area coverage is the degree of overlapping. The degree of overlapping, according to author's assumption, means how many WSN node's sensing ranges (r_s), overlaps with each other. When the optimal Euclidean distance between three nodes is $\sqrt{3}\ r_s$ then an optimal degree of overlapping ($D_{Overlap}$=1) is achieved which gives the full area coverage with the minimum number of WSN nodes. The optimum vertical and horizontal distance between the two sensor nodes will be $\sqrt{3}r_s$ and $\frac{3}{2}r_s$ respectively, Fig. 3(b).

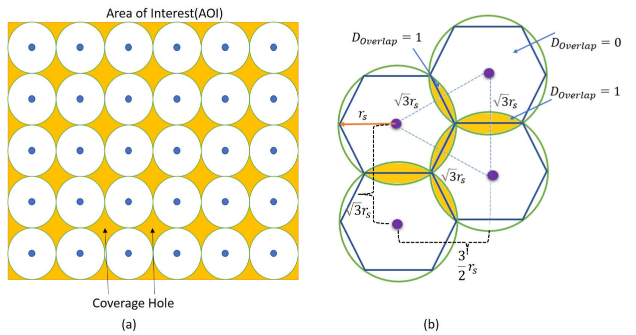


FIGURE 3. **(a) Coverage Holes in the AOI, when WSN nodes are deployed adjacently (b) Optimum vertical and horizontal distance between the two adjacent sensor nodes and optimum degree of overlapping.**

In this research, the whole Area of Interest (AOI) is clustered into a hexagonal grid network architecture, Fig 5(a). Here the Area of Interest(AOI) is clustered into 5 × 5= 25 hexagonal grids. So, the AOI is 225 × 260 m^2($\sum_1^5\left(\frac{3}{2}r_s\right) X\ \sum_1^5\left(\sqrt{3}\ r_s\right)$).

It is well understood that deployment strategies can be either planned or random. In case of planned deployment, the WSN will be installed in the center point of the circle inscribed within the hexagon grid. This would be the optimal position of the WSN node. But depending on the situation it is not always possible to place the WSN in the center of the hexagon grid. So random deployment is necessary for such a situation as a battlefield. In contrast to planned deployment, random deployment is more feasible in most of WSN applications [25].

In this study, the random deployment has been considered and random deployment strategy has been further classified into two categories: guided-random deployment and unguided-random deployment.

In guided-random deployment, a mobile WSN node will be aimed for para dropping inside the sensing radius (r_s) of each hexagonal grid cluster employing an unmanned aerial vehicle (UAV), helicopter, aircraft, etc.(Fig. 4(a)). Using equations 2

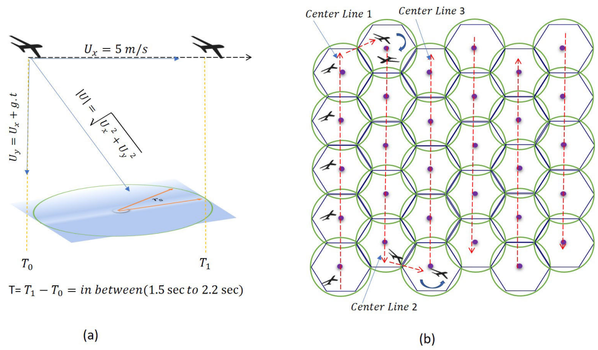


FIGURE 4. (a) Time interval in between two drop events (b) The red dotted lines represent the center lines in the guided-random deployment of WSN nodes in the (n_n) pattern within AOI.

to 4, it is possible to determine the time interval (T) between two drop occurrences if the UAV's speed is considered to be 5 m/sec and the sensing radius (r_s) of WSN is 30m.

$$U_x = 5\ \text{m/sec}; \tag{2}$$

$$U_y = U_x + g \cdot t; \quad |U| = \sqrt{U_x^2 + U_y^2} \tag{3}$$

$$x = |U| * T; \quad T = \frac{x}{|U|} = \frac{2 * r_s}{|U|} \tag{4}$$

here x is the maximum distance between two WSN nodes in a hexagonal grid structure. The x value will be 30.51m when T is 1.5 seconds, and 59.51m when T is 2.2 seconds. Consequently, if para dropping is carried out at intervals of 1.5 to 2.2 seconds, there is a high possibility that WSN nodes will be dropped into the desired hexagonal structure.

Depending on various factors like airflow, type of terrain, etc there is a chance that dropped WSN will not exactly be placed in the center of the circle but will be placed with the hexagonal structure. So, in guided-random deployment, it is assumed that wsn node can be placed randomly anywhere within a predefined (i.e., under guidance) circle of hexagonal grid which is very close to the center lines. The center lines are the lines that touch all the centers of the hexagonal grid. In this type of deployment, [26] the position of sensors can be decided according to the following Probability Density Function.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-m)^2}{2\sigma^2}} \tag{5}$$

where m is mean, σ is the standard deviation of sensor nodes distribution

To cover the whole AOI, para dropping should be continued to cover all the center lines, which can be called as (n_n) pattern, as shown in Fig. 4(b).

After placing the mobile WSN within the proximity of the predefined hexagonal grid point, the WSN will move linearly towards the center of that predefined hexagonal grid point, depicted in Fig. 5(a).Total energy loss has been calculated for every deployed WSN node. Once the WSN nodes take place at the center of the circle or hexagonal structure the WSN network will be established. Now the challenge is to decide whether all the neighboring nodes are connected or not. From the following theorem, it can be proved that all wsn nodes are well connected and able to transmit their data to adjacent nodes.

Theorem 1: All wsn nodes are well connected and able to transmit their data to adjacent nodes.

Proof: The AOI is clusterized into hexagonal grids. All the hexagonal grids are inscribed in a circle with radius r_s, Fig. 3(b). For any two arbitrary nodes s_i and s_j, placed into the center of hexagonal grids will have $\sqrt{3}\ r_s$, $\frac{3}{2}r_s$ vertical and horizontal distance respectively. For such distance, there can not have any coverage hole between the sensing range of wsn nodes. For such an arrangement of wsn nodes, the degree of sensing area overlapping is also minimum and it is denoted by the yellow region in Fig. 3(b). As there does not exist any coverage hole and the degree of overlapping is also minimum, so all adjacent wsn nodes will be well connected and able to transmit their data to adjacent nodes. If all adjacent nodes are connected then the full WSN network will be well connected also.

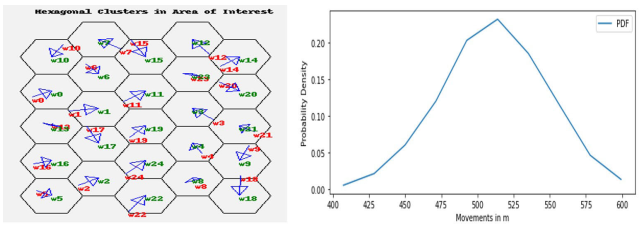
For unguided-random deployment mobile wsn nodes will be randomly para dropped inside the AOI. As a result, the wsn nodes can also be positioned densely, as depicted in Fig. 6(a). The WSN will move towards the center of that predefined hexagonal grid point, depicted in Fig. 6(b). After deployment of wsn nodes either by guided-random or unguided-random strategy the proposed hybrid MOFAC-GA-PSO algorithm will try to place those wsn nodes in the centre of hexagonal grid point so that a maximum area is covered, a network is formed with minimum number of wsn nodes movements.

The unguided random deployment experiment has been run a thousand times to approximate movements and energy loss during the movement. From the experiment, it is found that to cover an area of 225 × 260 m^2, using 25 WSN nodes the average movement is 499.28m, (median 500.696m) the standard deviation is 37.58. It is observed that the movements also follow the Gaussian distribution, as shown in Fig. 5(b).

From this experiment, it can be noted that in unguided-random deployment the average movement is 499.28 m. If any meta-heuristic algorithm can reduce the average movement to less than the average movement in a guided-random deployment strategy then that algorithm can be called an efficient algorithm. In this experiment using the proposed hybrid algorithm, MOFAC-GA-PSO, it is noticed that it gives better results (mean= 232.037m) in terms of movement.

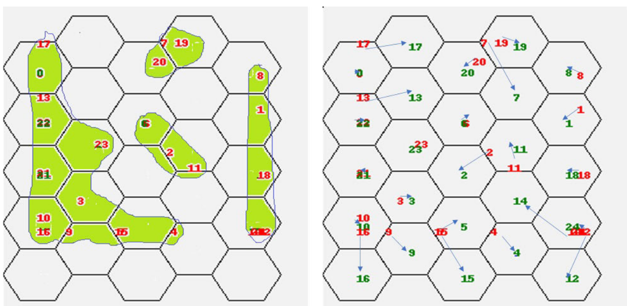
A. MOTIVATION AND CONTRIBUTION

In this article, coverage area maximization for an energy-efficient wireless sensor network has been accomplished. In order to achieve this, the Minimum Overlapped Full Area Coverage using Hybridized GA-PSO (MOFAC-GA-PSO) algorithm and the least movement



(a) (b)

FIGURE 5. **(a) In Unguided-random deployment, the movement of distributed WSN node (red color) towards the center of the hexagon grid (green color) is shown using the arrow (b) Number of movements needed to maximize coverage area follows the Gaussian distribution.**



(a) (b)

FIGURE 6. **(a) Wsn nodes position in unguided-random deployment (b) Wsn nodes' position after applying MOFAC-GA-PSO algorithm.**

consider first (LMCF) method have been utilised. The followings are the main objectives of this article:

- Maximizing the coverage area [27] by ensuring connectivity between sensor nodes with minimum overlapping while reducing the coverage hole in the Area of Interest (AOI).
- Minimizing consumed energy [28] in communication, sensing, and WSN node movements.

To fulfill the above-mentioned objectives followings have been contributed to this paper:

- The MOFAC-GA-PSO algorithm has been designed to extend the sustainability of the network by maximizing coverage area of interest and minimizing energy consumption in the WSN through the hybridization of the GA and PSO algorithms.
- To reduce the coverage hole, a HexGridClusterization method is proposed to partition the Area of Interest (AOI) into a hexagonal grid network architecture.
- The genetic algorithm (GA), with its powerful operators [29] (crossover, mutation, and selection), has been employed for its effective search capacity of discovering global optimized value. Therefore, the GA has been employed in this research to find the optimal solution for the specified problem.
- The entire population has been split into two equal groups. One group of populations is subjected to the GA algorithm. On the other group of populations, the PSO approach has been employed. The hybrid algorithm is based on the notion that a better population would provide a better result. The best solution obtained using GA and PSO are compared in this hybrid algorithm (see Fig. 8), and the best offspring or particles are sent back as the updated, higher-quality populations for subsequent generations.To get even better outcomes, the GA and PSO solution sets are compared.
- The MOFAC-GA-PSO algorithm is a combination of global as well as local optimizers. The hybridization property compensates weakness of the individual optimizer and gives a better result than the individual global and local optimizer. The global optimizer suffers from its late convergence to the global optimum value and takes more time to converge. On the other hand, the local optimizer may quickly converge to the local optimum value without reaching the global optimum value. To overcome the weakness of these global and local optimizers a hybrid algorithm has been designed. Here GA has been applied as a global optimizer and PSO has been applied as a local optimizer (FIGURE 8). To test the superiority of the proposed hybrid algorithm the result has been compared with individual GA and PSO algorithms and it is observed that the hybrid MOFAC-GA-PSO algorithm gives better results (Table 4 and Table 5).

The rest of this paper is organized as follows:

A literature review is presented in Section II. The Section III,presents the Problem Formulation. Section IV explains the Solution Methodology, which demonstrates how the MOFAC-GA-PSO hybrid meta-heuristic algorithm helps to maximize coverage area, minimize consumed energy of the WSN. Section V includes a Result and Analysis that shows the coverage percentage, energy requirement, and the number of days the WSN network can endure. Section VI, presents a statistical analysis to justify the research work. In section VII, the Conclusion is drawn, along with the scope for further investigation.

II. LITERATURE REVIEW

The problem of maximizing coverage area, minimizing coverage hole, minimizing overlapping area and minimizing overall energy requirement with the fewest possible WSN nodes is covered in some literature. The efficient deployment strategy can address the above mentioned issues. It is known that efficient deployment strategy is a NP-complete challenge and so scientists are attempting to apply meta-heuristic algorithms to find ideal or nearly ideal solutions.

The performance of meta-heuristic algorithms depends on the implementations of various operators (crossover, mutation, selection for GA [29] and Update operator for PSO). Numerous researchers have used meta-heuristic algorithms to reduce energy consumption [28] and partition [27] the area of interest (AOI) to solve problems like efficient path planning, efficient communication, and efficient deployment.

It is also observed that hybridized meta-heuristic algorithms [30], [31] perform better in a variety of sectors than non-hybridized meta-heuristic algorithms.

Singh et al. [14] in 2016 uses an efficient deployment technique for a target point coverage problem using Simulated Annealing and Particle Swarm Optimization techniques to deploy sensor nodes at the optimal places to cover target locations in a region. It is claimed that efficient deployment technique can increase network lifespan.

Benatia et al. [32] in 2017 suggested a multi-objective genetic algorithm for the optimum WSN nodes deployment. The authors of this research demonstrated how the distance between the cluster head and the WSN node directly affects energy usage. A successful deployment strategy can optimize of the WSN lifespan.

Céspedes-Mota et al. [33] in 2018 developed a multi-objective differential evolution algorithm (MODEA) to enhance the sensor deployment strategy over the AOI in order to expand coverage area and decrease network energy consumption. Despite the research's encouraging findings, it fails to take into consideration how much energy is needed for data transmission and reception.

In 2016, Abo-Zahhad et al. [34] suggested a multi-objective energy-efficient deployment strategy for maximizing network coverage area and lifetime using mobile sensor nodes. The coverage area has been maximized by the rearrangement of mobile sensor nodes. According to the authors, the energy required for the movement of the sensor node is negligible when it is compared to the total lifetime of the WSN node.

In 2021, Banerjee et al. [35], presented various deployment strategies and proposed DE-QPSO meta-heuristic algorithm to build an energy-efficient WSN.

In 2019, Xiang et al. [10], used cuckoo search (CS) for movable wireless sensor nodes deployment to maximize area coverage and minimize energy usage. The authors focused on minimizing the number of WSN node migrations. The energy lost during movement will be minimised if the range of movements is decreased. The text does not, however, show how node mobility mechanisms and energy loss are related.

In 2020, considering mobile wireless sensor nodes ZainEldin et al. [36], suggested a deployment strategy using the IDDTGA meta-heuristic algorithm to discover the ideal positions of the WSN nodes and to address the issue of minimum coverage hole and maximum coverage area.

To ensure an optimum coverage area, network connectivity and minimum coverage overlap,in 2022, R. Christal Jebi et al. [37],developed a multi– objective grasshopper optimization method.

The Grey Wolf Optimizer (GWO) algorithm is used to address the issue of maximizing coverage and maintaining connectivity in WSN in 2022, Nematzadeh et al. [38].

In the article of Kumar et al. [25], various machine learning (ML) techniques in the field of WSN have been summarized. The Reinforcement learning (Q-learning), Semi-supervised hidden Markov model (HMM), and Artificial Neural Network(ANN) machine learning approach can be very useful to design a WSN network with a minimum number of sensor nodes to cover the AOI rapidly and dynamically assuring full connectivity among sensor nodes.The literature review has been summarized in the Table 2.

In Table 2, the Analysis column refers to the approach of the particular literature, Drawback column represents the weakness of the method used in the existing literature and Findings column suggests the strategy to overcome those drawbacks.The findings from Table 2 has been addressed in this proposed research work.According to the literature review, it is possible to develop an effective deployment strategy with a hybridized meta-heuristic algorithm for maximizing area coverage and minimizing network energy consumption. The efficiency of the network can be expressed in terms of coverage ratio, the number of WSN nodes necessary, the degree of overlapping, and the total energy consumption by the network.

III. PROBLEM FORMULATION

In this paper, the main problem can be defined as a combination of a maximization and a minimization problem. Firstly, the area coverage problem is a maximization problem, and secondly, the optimization of consumed energy for the movement of deployed nodes, sensing environmental data, and data transmission is a minimization problem. For both, the problem of WSN a modified meta-heuristic hybrid algorithm (MOFAC-GA-PSO) has been used. Both problems have been considered as non-linear problems.The first objective is to maximize the coverage area which is given below:

$$Obj_1 = \mathcal{M}ax\left(AOI \cap \left(\sum_{i=1}^{N}\sum_{j=1}^{M}\left(HexGrid_{r_s}(i,j)\right)\right)\right) \tag{6}$$

where AOI is the Area of Interest, HexGrid $r_s(i,j)$ represents the Hexagonal block at (i,j) location with r_s radius. The second objective is to minimize the total consumed energy which is given below:

$$Obj_2 = \mathcal{M}in\,(EN_{Total}) \tag{7}$$

where

$$EN_{Total} = EN_M + EN_S + EN_{Comm} \tag{8}$$

$$EN_M = wg_1 \cdot T_D; \quad EN_S = wg_2 \cdot r_s; \quad EN_{Comm} = wg_3 \cdot T_{Comm}^{Total}(k, r_c) \tag{9}$$

$$Where \quad wg_1 + \quad wg_2 + \quad wg_3 = 1 \tag{10}$$

Consequently, the formulated optimization problem is ex-pressed as

$$Obj_2 = \mathcal{M}in\Big(wg_1 \cdot T_D + wg_2 \cdot r_s + wg_3 \cdot E_{Comm}^{Total}\,(k, r_c)\Big) \tag{11}$$

TABLE 2. Analysis, Drawback and Findings of various Literature.

Ref. no	Year	Type of Coverage	Analysis	Drawback	Findings
[30], [31]	2014, 2021	NA	Hybridized meta-heuristic algorithms outperform non-hybridized meta-heuristic algorithms.	NA	The necessity of novel operators for hybrid meta-heuristics algorithms.
[14]	2016	Target point	Used Simulated Annealing approaches to address the target point coverage problem and deploy sensor nodes in the best positions to cover target sites over an area.	The Simulated annealing requires the careful tuning of numerous parameters which greatly impacts the quality of the outcomes.	Effective deployment methods can lengthen network lifetime.
[32]	2017	Area	Demonstrated several deployment tactics and suggested the DE-QPSO meta-heuristic algorithm to construct an energy-efficient WSN.	It encounters early convergence and the requirement for high memory in velocity updates.	Energy consumption is directly impacted by deployment strategy.
[33]	2018	Area	The deployment strategy over the AOI, using the MODEA algorithm increases the coverage area and minimizes energy consumption.	The differential evolution algorithm suffers from its sensitivity in choosing control parameters. Inappropriate parameter settings can lead to suboptimal results or slow convergence.	To increase the coverage area and minimize energy usage, hybridized meta-heuristic algorithms can improve.
[34]	2016	Area	The multi-objective, energy-efficient deployment technique uses mobile sensor nodes to maximize network coverage and longevity.	NA	Network coverage area and longevity can be improved by hybridized meta-heuristic algorithms.
[35]	2021	Area	Demonstrated several deployment tactics and suggested the DE-QPSO algorithm to construct an energy-efficient WSN.	It encounters numerous challenges including low-quality solutions and early convergence.	Network longevity can be improved by hybridized meta-heuristic algorithms.
[10]	2019	Area	Employed cuckoo search (CS) for the deployment of mobile WSN to increase coverage and reduce energy usage.	The 100 % coverage guarantee not given, high degree of overlapping, and the coverage hole problem exists	Chances of trapping in local optima in CS are reduced when hybridized algorithm is used.
[36]	2020	Area	Using IDDTGA meta-heuristic algorithm area coverage is maximized and issues of the smallest coverage hole have been addressed.	Drawbacks include sensitivity to operator choices and maintaining population diversity.	The hybridized meta-heuristic algorithm can determine the best locations of WSN nodes with minimal coverage holes and maximum area coverage.
[38]	2022	Area	The Grey Wolf Optimizer (GWO) algorithm is used to address the issue of maximizing coverage and maintaining connectivity in WSN.	Performance deteriorates in high-dimensional problems.	The issue of coverage optimization can be impacted by modified hybridized meta-heuristic techniques.

$$E_{Comm}^{Total}(k, r_c) = E_{tx}^{Total}(k, r_c) + E_{rx}^{Total}(k) \tag{12}$$

$$E_{tx}^{Total}(k, r_c) = E_{Electronic_{energy}}^{Total}(k) + E_{Amplifier}^{Total}(r_c) \tag{13}$$

$$E_{rx}^{Total}(k) = E_{Electronic_{energy}}^{Total}(k) * k \tag{14}$$

$$E_{Amplifier}^{Total}(k, r_c) = E_{SP}^{Total} * \{r_c\}^2 \tag{15}$$

T_D is the traveling distance. k is the data packet size. The r_c and r_s are the communication and sensing range of the WSN node respectively. Three weightage values wg_1,wg_2,and wg_3 are imposed to T_D, r_s,$E^{Total}_{Comm}(k,r_c)$ respectively. In the research work, there are three activities(moving, sensing, data communication) related to power consumption. Three weightage values (wg_1, wg_2, wg_3) have been distributed to indicate the priority of the moving, sensing, data communication activities respectively. Because these weightage values are the most speculative, they were randomised in this article such that the total weightage is 1, Eq. 10.

After running the proposed algorithm 1000 times, it is found that the maximum moving distance by all 25 mobile wsn is only 600.26 m. According to [39] the moving energy cost is 8.27 J per meter. The total moving energy cost of all 25 wsn nodes will be 4964.15 J (600.26m * 8.27 J). So the average moving cost for each wsn node is 198.57 J ($\frac{4964.15\ J}{25}$). According to [40], it is stated that minimum energy requirement for image sensing @20fps is 115 μW(0.000115 J). For 11.06 days of sense, the energy requirement by a single wsn node would be 109.89 J (0.000115 *3600*24*11.06). The energy requirement for sensing and moving a single wsn node is 308.46 J (198.57 J+109.89 J) or 85.68 mAh. The battery energy capacity of each mobilizer of the wsn node would be a minimum of 85.68 mAh. In this article it is considered that battery attached with the mobilizer will supply the required energy for moving and sensing operations of wsn nodes.

The article deals with two objective functions. The first objective is to maximize the coverage area which is denoted by Eq. 6 and the second objective is to minimize the energy which is denoted by Eq. 11. Both optimization problems are solved with the MOFAC-GA-PSO algorithm. After the problem formulation (see Eq. 6 - 15) and implementation of the hybrid algorithm to solve the coverage area optimization as well as the energy minimization problem, the efficient network is configured where the AOI has been covered by a smaller number of WSN nodes with minimum traversal of WSN mobile nodes. The durability of the network has been calculated in terms of Day-Life [41] and achieved a satisfactory result as mentioned in the result analysis part of the article.

IV. SOLUTION METHODOLOGY

In this section, for the maximization of coverage area with minimum overlapping while using the fewest possible mobile WSN nodes and to minimize WSN nodes movements the MOFAC-GA-PSO (Minimum overlapped Full Area Coverage using Hybridized GA-PSO) algorithm has been proposed and explained. The followings are the three algorithms that were developed to construct the MOFAC-GA-PSO algorithm.

A. HexGridClusterization Algorithm (for hexagonal clustering of the AOI with a minimum degree of overlapping and to generate six-coordinate points of the hexagonal cluster).
B. The LeastMovementConsiderFirst (LMCF) Algorithm (for determining the total allocation cost of all WSN nodes with the least amount of movement).
C. The hybridized GA-PSO Algorithm (for coverage area maximization and consumed energy minimization).

The proposed MOFAC-GA-PSO algorithm's block diagram, which is shown in Fig. 7, demonstrates how it interacts with the three other algorithms mentioned above.

The HexGridClusterization algorithm takes the boundary information of AOI, sensing range (r_s) of wsn node and it divides the AOI into hexagonal grid. The grid is constructed in such a way that Euclidean distances between three nodes is $\sqrt{3}\, r_s$. The optimum vertical and horizontal distance between the two sensor nodes will be $\sqrt{3}\, r_s$ and $\frac{3}{2}\, r_s$ respectively, Fig. 3(b). It provides the optimal positions of all adjacent wsn nodes. The horizontal spacing (HS_W) and vertical spacing (VS_H) between two adjacent hexagonal grid is initialized and number of row and column needed to fully cover the area is calculated in lines 3-4. To find out all the center position of all hexagonal grids two loops have been used (lines 6-8). Center position location is recorded in line 17. The six vertices of a hexagonal structure has been found through lines 20-24. The *HexMatrix* stores all the center positions of all hexagonal grids and it is returned finally (line 32).

The *HexMatrix* will have the optimum positions of all the hexagonal grids. The *HexMatrix* has been provided to GA-PSO algorithm so that the GA-PSO algorithm could have a prior knowledge of optimum position of wsn nodes, line 1. The GA-PSO algorithm will provide optimal position of all wsn nodes, line 2. In GA-PSO algorithm, nodes are deployed in a (n_n) pattern using the guided-random deployment strategy within AOI. Each chromosome in GA and each particle in PSO represents wsn nodes' movement path planning and represents a candidate solution, line 4. Total population is equally distributed among population of GA (P^{GA}_{size}) and PSO(P^{PSO}_{size}), line 4. The GA has been applied on P^{GA}_{size} population, line 6. Each chromosome of P^{GA}_{size} population, is evaluated using Eq. 11 and LMCF Algorithm, line 6(a). Based on fitness values the best chromosomes have been identified, line 6(b). To reproduce the offspring the crossover and mutation operators have been applied on current population, and population has been enlarged, line 6(c). Using tournament Selection operator best chromosomes are selected and population is updated for next iteration, line 6(d). The global best value,P^{GA}_{gbest}, is updated in line 6(e). The PSO has been applied on P^{PSO}_{size} population, line 7. Each particle is evaluated using Eq. 11 and LMCF Algorithm, line 7(a).To find a better position, the particles' positions inside the search area are modified depending on personal and societal information. The personal best position of each particle,$pbest_i$, and societal best position,$gbest_i$, is calculated in lines 7(a)-7(b).

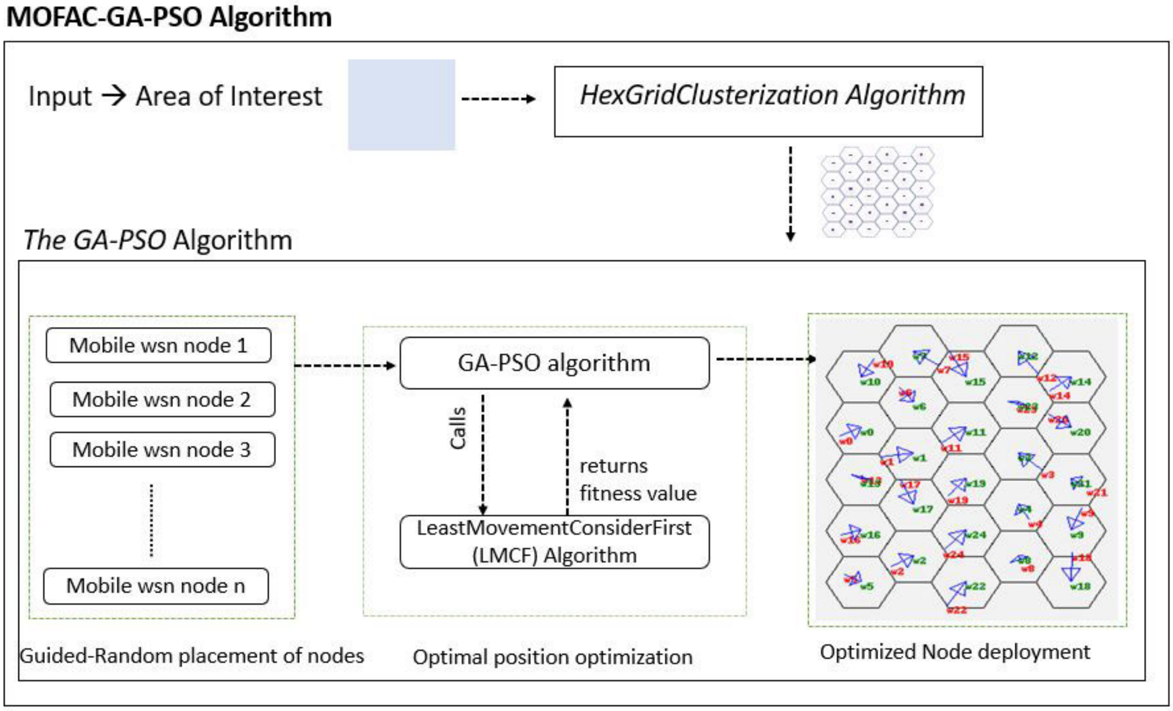


FIGURE 7. The block diagram of the MOFAC-GA-PSO algorithm.

Three components that are responsible for the alteration of velocity are Momentum (w_i), Cognitive information ($pbest_i$), and Social information($gbest_i$). The velocity of each particle has been calculated, line 7(c), and the position of each particle has been updated, line 7(d). The global best value in PSO,P^{PSO}_{gbest}, is updated in line 7(e). The best evaluated fitness value from GA,(P^{GA}_{gbest}), and PSO,(P^{PSO}_{gbest}), are compared and best of these two is chosen for next iteration operations, line 8. Eventually on termination condition (line 10) satisfied the GA-PSO algorithm provides the optimal or near-optimal position of wsn nodes with maximum area coverage, minimum coverage hole, minimum overlapping area, line 12.

The LMCF algorithm is founded on the principle that all mobile sensor nodes should have the lowest possible movement costs. The Euclidean distances between the present positions of the wsn nodes and the centers of hexagonal grids are contained in the CostMatrix. The fitness value is determined using this CostMatrix, keeping in mind that the lesser distance value has a higher priority for being chosen. The minimum row and column values are deducted from the row and column values in lines 3–4 to determine the least value. There will be at least one zero element in each row and column following subtraction. The zero elements intersecting of rows and columns are pointed out, in lines 7-18. These zero components represent a greater likelihood of the proper hexagonal grid association. The corresponding Euclidean distances are added to the fitness value, lines 19–20, and the fitness value is returned, line 21, if optimizeLocation.size() reaches the number of wsn nodes.

Once the wsn nodes takes their optimal or near-optimal position the wsn network has been established. Energy requirements by the network has been calculated using the formulae 8- 15. The schematic diagram of the GA-PSO algorithm is depicted in Fig. 8.

The challenges to implementing this work in real-time applications are heterogeneous sensor types, heterogeneous sensing range, communication range, environmental challenges like extreme heat or cold weather, and obstacles. The following assumptions have been made for the proposed algorithm:

- Sensors with omnidirectional sensing ability, are distributed in the AOI using the Unguided-random approach.
- In the MOFAC-GA-PSO algorithm, each sensor is encoded as a particle in the PSO algorithm and all sensors collectively create a single chromosome in the GA algorithm.
- Hexagonal grid points' locations are considered the optimal position of the WSN nodes.
- All of the WSN nodes will get position information of hexagonal grid points from the sink node.
- An external mobilizer unit is attached to every WSN sensor to move from one point to another.
- As time goes on, the WSN node's battery life decreases as a result of transmitting, receiving, sensing data, and sensor movement.

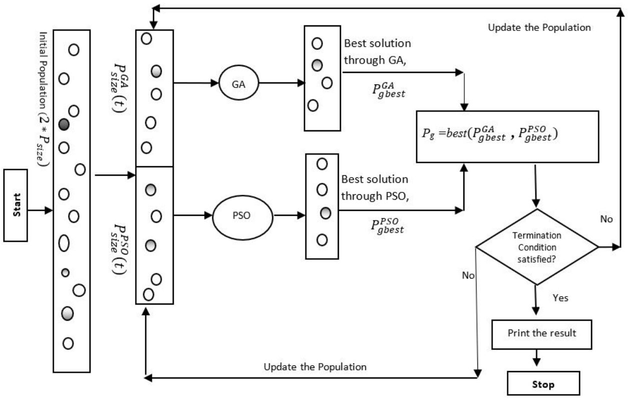


FIGURE 8. The schematic diagram of the GA-PSO algorithm.

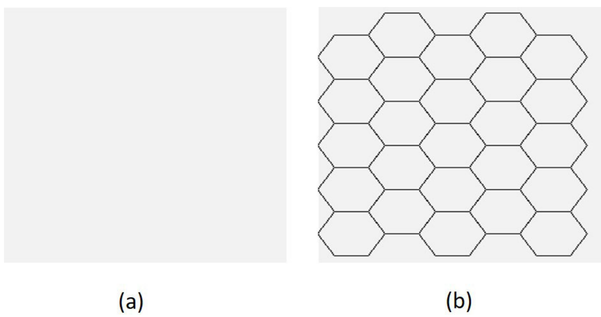


FIGURE 9. (a) The Area of Interest is 225 × 260 m^2 (b) The Area of Interest has been clustered into Hexagonal blocks using the HexGridClusterization algorithm.

- Sensor nodes are initially fully charged using 1J of battery power.

How the algorithm, MOFAC-GA-PSO, is achieving maximum area coverage is shown in Fig. 9 to Fig. 10. The HexGridClusterization algorithm does the clusterization of AOI into the hexagonal network for the minimization of the coverage hole and overlapping area, Fig. 9.

Fig. 10. shows how guided-random deployment of WSN nodes does not cover the total AOI and how the proposed algorithm optimizes the placement of WSN nodes to cover the AOI with minimal overlapping regions and no coverage holes.

Algorithm 1 HexGridClusterization Algorithm

Input : Boundary of AOI($startX$, $endX$, $sratY$, $endY$), Radius(R_s) of Hexagon, Starting position of the Hexagonal grid ($PositionX$, $PositionY$)
Output : $HexMatrix[N][M]$ containing the centers of the Hexagon grid, Points $[NxM]$ containing six co-ordinates of the hexagonal grid.
Initialize Horizontal Spacing (HS_W) and Vertical Spacing (VS_H) between two adjacent Hexagon clusters:
$HS_W = \frac{3}{2}R_s$; $VS_H = \sqrt{3}R_s$
Calculate the number of Rows (N) and Columns (M)
$N = \left\lceil \frac{(endY - startY)}{VS_H} \right\rceil$ $M = \left\lceil \frac{(endX - startX)}{VS_W} \right\rceil$
Find the centers of the Hexagonal structure with six coordinates
$HexMatrix$[N][M]={} : $prev_Y = PositionY$
for $row = 0$ To $N - 1$ **do**
$prev_X = PositionX$: $tempRow$=[]
for $col = 0$ To $M - 1$ **do**
if col %2 is 0 **then**
$HCenterY = prev_Y - \frac{VS_H}{2}$
End if
else
$HCenterY = prev_Y$
End else
$HCenterX = prev_x$
s = new structure()
$s.center = [\ HCenterX, HCenterY\ ]$
$\theta = \frac{\pi}{3}$
$sixPairs = []$
for $i = 1$ To 6 **do**
px = round ($\cos(\theta * i) * R + HCenterX$)
py = round ($\sin(\theta * i) * R + HCenterY$)
$sixPairs.add(\ px,\ py\ )$
End for
$s.points = sixPairs$
$tempRow.append(s)$
$prev_X = prev_X + HS_W$
End for
$prev_y = prev_y + VS_H$
$HexMatrix.append(tempRow)$
End for
$return$ ($HexMatrix$)

V. RESULT AND ANALYSIS

The hardware and software configuration of the machine is 11th Gen Intel(R) Core(TM) i5-11300H @ 3.10GHz, 16 GB RAM, 64-bit operating system, x64-based processor, and Simulation Platform (Python, Jupyter Notebook). Because of its low power and low-cost features, the IEEE 802.15.4 standard has been taken into consideration in this study. In order to handle the MAC, Network, and Application layers while maintaining secure networking (128 bit symmetric key encryption), IEEE 802.15.4 employs the ZigBee protocol [42], [43]. The maximum specified data rate for ZigBee is 250 kbit/s and the transmission distances vary from 10 to 100 meters, depending on the required output power and the surrounding conditions. The factors equivalent distribution, iterations, and maximum energy usage have all been taken into consideration while selecting the best result set out of all the results that were obtained. The input parameters have been chosen for the experiment settings are shown in Table 3. The criteria were chosen with the available literature in mind [44], [45].

Algorithm 2 LeastMovementConsiderFirst

1: **Input :** A N x N, $CostMatrix$.
2: **Output :** Fitness value (total allocation cost of all WSN nodes with the least amount of movement)
3: Find the smallest element in each row of the matrix and deduct Row minima from every element in that row:
  for $i = 0$ To $N - 1$ **do**
    for $j = 0$ To $N - 1$ **do**
      $RowMin$[i] =min{CostMatrix[i][j]}
      $CostMatrix$[i][j] =CostMatrix[i][j]−RowMin[i]
    End for
  End for
4: Find the smallest element in each column of the matrix and deduct Column minima from every element in that column:
  for $j = 0$ To $N - 1$ **do**
    for $i = 0$ To $N - 1$ **do**
      $ColMin$[j] =min{CostMatrix[i][j]}
      $CostMatrix$[i][j] = $CostMatrix$ [i][j]- $ColMin$ [j]
    End for
  End for
5: **While** *fitness value is Not found* **do**
6:   Select minimum number of covering rows & columns to cover all zeros in the $CostMatrix$
7:   **for** *each row*, i, **do**
8:     **if** count of Zero element in i^{th} row is 1 **Then**
9:       Find *column*,j, where element Zero is found and store row & column
10:         $coveringColumn.append(j)$
11:         $optimizeLocation.add([i, j])$
12:     **End if**
  End for
13:   **for** *each column*, j, except columns in $coveringColumn\ list$ **do**
14:     **if** count of Zero element in j^{th} column is 1 **Then**
15:       Find *row*,i, where element Zero is found and store row & column
16:         $coveringColumn.append(i)$
17:         $optimizeLocation.add([i, j])$
18:     **End if**
  End for
19:   **if** $optimizeLocation.size() == N$ **Then**
20:     **for** *each element*, E, in $optimizeLocation$ list **do**
      $R = E[0]$
      $C = E[1]$
      fitness =*fitness* + $CostMatrix[R][C]$
    End for
21:     *return* (*fitness*)
22:   **else**
    a. Subtract that least uncovered element, m, from each uncovered row
    b. Add m to each intersection element of the covered row and column
23:   **End if**
24: **End while**

Algorithm 3 GA-PSO Algorithm

1: **Input :** Width and height of AOI (Area Of Interest)
2: **Output :** Maximum area coverage with the optimized position of all WSN nodes
3: Initialize Max_{gen}, t, P_{cross},P_{mute},V_i,$C1$,$C2$
4: Generate the population as (2*P_{size}), and distribute the population among GA,PSO equally.
  $P^{GA}_{size}(t)$={$chrom^t_i$ i=1,2,. . .,P_{size} }
  $P^{PSO}_{size}(t)$={$swarm^t_j$ j=P_{size+1},P_{size+2},. . .,P_{size*2} }
5: **While** *exit condition is Not satisfied* **do:**
6: **Apply GA to the population** $P^{GA}_{size}(t)$ and to find the global best at the t^{th} iteration, P^{GA}_{gbest}
  a. For each chromosome, $chrom^t_i$, in $P^{GA}_{size}(t)$ determine the fitness value using the LMCF function and Eq.11 for area maximization and energy minimization, respectively.
  b. Identify the best chromosome (P^t_{cbest}) of the current generation (t), from $P^{GA}_{size}(t)$.
  c. Apply crossover & mutation operations to the current population $P^{GA}_{size}(t)$ to reproduce offspring and update the population as $P'^{GA}_{size}(t)$.
  d. Apply the Tournament Selection mechanism on $P'^{GA}_{size}(t)$ to update the next generation's (t+1) population, $P'^{GA}_{size}(t + 1)$
  e. Compare the P^t_{cbest} with earlier fittest chromosome P^{GA}_{gbest} and save better one in P^{GA}_{gbest}.
7: **Apply PSO to the population** $P^{PSO}_{size}(t)$ and to find the global best at the t^{th} iteration, P^{PSO}_{gbest}
  a. For each particle, p^t_i, in $P^{PSO}_{size}(t)$ determine the fitness value using the LMCF function and Eq.11 for area maximization and energy minimization, respectively and update $pbest_i$ of the particle, P^t_i, if its current fitness value is superior to its prior best fitness value.
  b. Identify the best particle of the current generation,t, $gbest_t$ (based on the particle's most recent best locations, $pbest_i$).
  c. Calculate each particle's velocity for next iteration (t+1): R^t_1=$Random(0, 1)$; R^t_2=$Random(0, 1)$;
  $S^t_i = (gbest_t - pbest_i) * \frac{(Max_{gen}-t)}{Max_{gen}}$: $w^{t+1}_i = e^{-e^{(S^t_i)}}$
  $V^{t+1}_i = w^{t+1}_i * V^t_i + C1 * R^t_1 * (pbest_i - P^t_i) + C2 * R^t_2 * (gbest_i - P^t_i)$
  d. Determine each particle's new position for the next generation (t+1). $P^{t+1}_i = P^t_i + V^{t+1}_i$
  e. Update the global-best value, P^{PSO}_{gbest} of $P^{PSO}_{size}(t)$ as $P^{PSO}_{gbest} = gbest_t$
8: **Compare** P^{GA}_{gbest} **and** P^{PSO}_{gbest} and update both the population $P^{GA}_{size}(t)$, and $P^{PSO}_{size}(t)$, with the best-compared value.
9: Increment the iteration number by 1. (t=t+1)
10: Terminate the loop according to the conditions:
  (**a**). $t > Max_{gen}$ (**b**). the population's diversity is not being observed for k (threshold) number of iterations
11: **End While**
12: Print the feasible solution and the global best position of all WSN nodes.

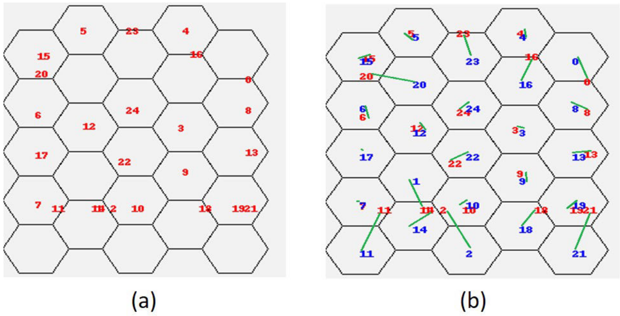


FIGURE 10. **(a) Guided-Random placements of WSN nodes (red color) (b) Using hybridized GA-PSO algorithm the optimal locations of the WSN nodes are indicated in blue color, while the green line indicates how far each node has moved linearly overall.**

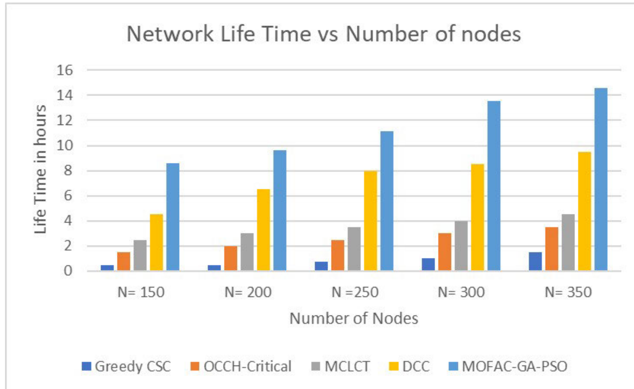


FIGURE 11. **Network Life-Time vs Number of nodes.**

TABLE 3. **Simulation Parameters.**

Different parameters	Values
Dimension of Area of Interest (AOI)	225 x 260 m^2
Initial energy per WSN node	1J
Total number of WSN nodes	25
Permissible "Data packet size" (k)	4096 bits
E_{sp}^{Total}	0.0013 pJ • bit^{-1} • m^{-2}
$E_{Electronic_{energy}}^{Total}$	50nJ/bit
Total initial energy	0.25E+14J
MAC Protocol	IEEE 802.15.4 standard
Sensor node type	ZigBee enabled wsn
Application protocol used	ZigBee protocol
Simulator used [45]	Python

The comparison results of various algorithms with the proposed MOFAC-GA-PSO algorithm are given in Table 4.

The average moving distance for each node using Guided-random Approach, GA, PSO, MOFAC-GA-PSO, and Cuckoo Search (CS) [10] is 19.97 m, 22.54 m, 18.11 m, 9.28 m, and 14.37 m respectively. From the result, it is noticed that concerning the number of movements by each node, the MOFAC-GA-PSO performs better than other algorithms. Concerning coverage area percentage and the existence of coverage holes, the MOFAC-GA-PSO algorithm performs better than the existing literature's outcomes ([10], [18]). The MOFAC-GA-PSO algorithm also provides 100% area coverage with minimum overlapping and without coverage holes using only 25 mobile WSN nodes. In the literature of Xiang et al.,2019, [10] only 91.26% coverage is achieved with a moderate percentage of coverage holes observed. In the literature of Ray et al., 2016, [18] only 83% coverage is achieved with a moderate percentage of coverage holes observed. The existing literature [10], uses 70% static WSN nodes and 30% mobile WSN nodes. As lots of static WSN nodes have been deployed randomly so the approach proposed in the literature [10] suffers from a heavily high degree of overlapping. The authors, Ray et al., [18], used mobile WSN nodes and it also suffers from a moderate degree of overlapping. So, a significant improvement has been noticed in the proposed MOFAC-GA-PSO algorithm.

In the research work of Xiang et al. [10], 11 WSN nodes have been used to cover a 100 × 100 m^2 area of interest. But it suffers from the following problems: it cannot provide a 100 percent coverage guarantee, the degree of overlapping is high, and the coverage hole problem is also present. In the proposed MOFAC-GA-PSO algorithm 25 WSN nodes have been used to cover more regions (225 × 260 m^2) and the above-mentioned problems have been addressed i.e., 100 percent coverage is guaranteed, the degree of overlapping is low, and the nonexistence of the coverage hole. With the help of Eq.nos, 7 to 15, the energy consumption by all WSN nodes is calculated and the results are enlisted in Table 4.

In the existing literature, [35], [44], the energy consumption of the wsn network has been only considered for data communication. In this research work, energy consumption for moving, sensing, and data communication by the wsn nodes has been considered. The wsn node consumes energy for moving and sensing from the battery attached to the mobilizer(85.6823 mAh capacity) and for data communication the energy is supplied from the battery (1 Joule) attached to the wsn node. The longevity of the network depends on the battery (1 Joule) attached to the wsn node. In this research work, we have tried to maximize the network's durability by minimizing the energy consumption for data communication. Continuous data communication is also not realistic to sustain for a long period. In reality, communication is triggered by the sensor like image sensor, motion sensor, smoke sensor, etc. So in this research work, the random time of communication has been considered to find the minimum energy consumption by the network. From Table 5, it can be seen that the suggested MOFAC-GA-PSO algorithm requires less energy than other algorithms and can operate for longer periods than other algorithms.

The proposed algorithm is compared with Greedy-CSC, OCCH-Critical, MCLCT, DCC [15] approaches by varing the number of nodes and the life time of the network is compared. It is observed that the MOFAC-GA-PSO works better than the others approaches [see Fig 11]. To compare with those approaches few parameters' values have been changed and one parameter has been introduced [see Table 6].

TABLE 4. Performance Evaluation of various approaches in terms of movements of WSN nodes.

Performance Index	Proposed Unguided-random Approach	Proposed Guided-random Approach			Cuckoo Search (CS) [10]	EEMRGSO [18]
		GA	PSO	MOFAC-GA-PSO		
Average moving distance/node	19.97 m	22.54 m	18.11 m	**9.28 m**	14.37 m	—
Number of mobile wsn nodes used	25	25	25	25	11	**100**
Number of static wsn nodes used	0	0	0	**0**	26	0
Percent of Area coverage	100	100	100	**100**	91.26	83
Dimension of area m x m	225 x 260	225 x 260	225 x 260	**225 x 260**	100 x 100	100 x 100
Existence of the coverage hole	No	No	No	**No**	Yes	**Yes**
Degree of Overlapping	low	low	low	**low**	high	**moderate**

TABLE 5. Comparison of various algorithms on energy consumption for data communication and day-life longevity.

Parameters	Yahya et al. [44]	Banerjee et al. [35]	Using proposed GA Algorithm	Using proposed PSO Algorithm	Using proposed MOFAC-GA-PSO Algorithm
Total Initial Energy (in pj)	1.0E+14	2.17E+14	0.25E+14	0.25E+14	0.25E+14
Nodes required to configure the WSN	100	49	25	25	25
Area of Interest (AOI) m x m	500x 500	850 x 650	225 x 260	225 x 260	225 x 260
Total consumed energy per sec (pj/sec)	794611026.24	1756090368	46484745.02	34863558.76	26147669.07
Total number of the day life	1.45	6.33	6.22	8.30	11.06

TABLE 6. Modified Simulation Parameters.

Parameter Type	Old Parameter	New Parameter
Area of Interest(AOI)	225 x 260 m^2	**225 x 250 m^2**
Initial energy per WSN	1J	-
Total number of WSN	Fixed(25)	**Variable**
Data packet size(k)	4096 bits	**1024 bits**
E_{sp}^{Total}	0.0013 pJ • bit^{-1} • m^{-2}	-
$E_{Electronic_{energy}}^{Total}$	50nJ/bit	-
Total initial energy	0.25E+14J	-
MAC Protocol	IEEE 802.15.4 standard	-
Sensor node type	ZigBee enabled wsn	-
Application protocol used	ZigBee protocol	-
Simulator used [45]	Python	-
Nature of energy consumption	Discrete	**Continuous**
Source of energy consumption	Data Communication, Sensing and Movement of node	**Data Communication**
DPOIs	NA	**30**

A. TIME COMPLEXITY OF PROPOSED MOFAC-GA-PSO ALGORITHM

The proposed MOFAC-GA-PSO algorithm consists of three algorithms. The HexGridClusterization Algorithm takes $O(n^2)$ time, LeastMovementConsiderFirst algorithm also takes $O(n^2)$ time. For hybridized GA-PSO algorithm,the complexity of GA is depends on chromosome-length, size of population, complexity [6], [46], [47] of the objective function and complexity of various genetic operators. In this article multi-point crossover, multi-point mutation operator is used on a single chromosome to expand the scope of search by involve random changes in gene location, swapping gene position, and inverting gene sequence positions. The roulette-wheel selection operator has been used. For the GA, G=number of generation; l=chromosome length; n=number of population Time complexity for crossover operator is $O(nl)$ Time complexity for mutation operator is $O(nl)$ The selection operator needs to sort the population, so its time complexity is $O(n.logn)$ The fitness function, LMCF algorithm, which has nested loop, requires $O(n^2)$ time..So the overall complexity of GA can be obtained as: $O(G.(nl + nl + n.logn + n^2) = O(G.n^2)$

For the PSO, I=number of iteration; L=particle length; n=size of swarm; Time complexity of Updation operator is $O(nL)$. The fitness function, LMCF algorithm, which has nested loop, requires $O(n^2)$ time. So, the overall complexity of PSO algorithm can be written as: $O(I.(nL+n^2) = O(I.n^2)$.

Consequently, the overall time complexity of proposed MOFAC-GA-PSO algorithm can be expressed as: $O(n^2 + n^2 + G.n^2 + I.n^2)$. In [47], the authors proposed methodology also has the n^2 time complexity for similar WSN network. The content pertaining to the suggested article will be found at the URL "https://tinyurl.com/skdabj".

TABLE 7. Statistical analytical data of various approaches.

Performance Index		Unguided-random Approach	Proposed Guided-random Approach		
			GA	PSO	MOFAC-GA-PSO
Measurements of movements by all 25 WSN nodes in meter	Minimum	385.866	410.081	371.513	207.867
	Maximum	613.034	635.437	567.201	290.099
	Average	499.279	563.473	452.615	232.037
	Median	500.6965	576.322	451.724	226.91
	Standard Deviation	37.582	47.187	32.746	18.275

TABLE 8. Confidence levels of the number of movements for various approaches.

Various approaches	Mean	SD	The range for a 68% confidence level		The range for a 95% confidence level		The range for a 99% confidence level	
			From	To	From	To	From	To
Guided-random Approach	499.28	37.58	461.7	536.86	424.12	574.44	386.53	612.03
GA	563.47	47.19	516.29	610.66	469.1	657.85	421.91	705.03
PSO	452.62	32.75	419.87	485.36	387.12	518.11	354.38	550.85
MOFAC-GA-PSO	232.04	18.28	213.76	250.31	195.49	268.59	177.21	286.86

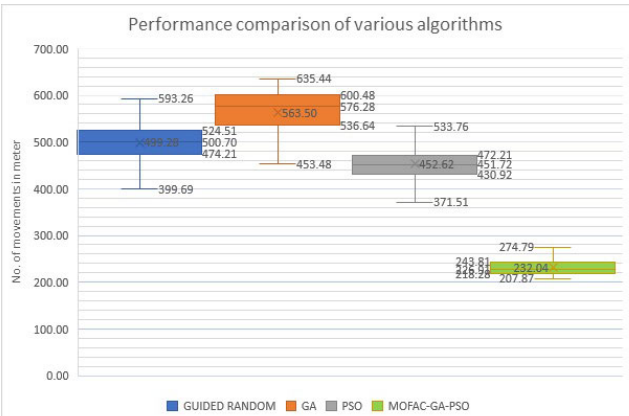


FIGURE 12. The performance comparison of various algorithms using Box & Whisker plot to identify the better result providing algorithm, MOFAC-GA-PSO, among other algorithms.

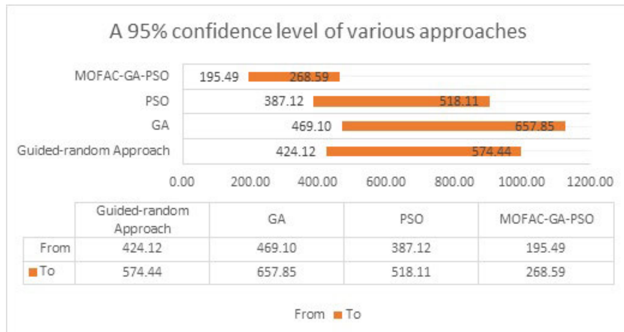


FIGURE 13. Range of node movement with a 95% confidence level of different methodologies.

VI. STATISTICAL ANALYSIS

Using guided-random and unguided-random deployment strategies the mobile WSN nodes have been deployed in the AOI. The goal was to ensure maximum coverage with minimum sensor movements (to minimize energy consumption). This simulation was done for 1000 separate runs to remove simulation errors due to randomization. The program has been run 1000 times to evaluate the performance using unguided-random deployment, and it has been found that the deployed WSN nodes require 613.034m, 385.866m, and 499.279m movements in maximum, minimum, and average, respectively, to reach the hexagonal grid locations, as shown in Table 7. In the proposed MOFAC-GA-PSO algorithm, it has been found that the deployed WSN nodes require 290.099m, 207.267m, and 232.037m movements in maximum, minimum, and average, respectively, to reach the hexagonal grid locations, as shown in Table 7.

For all parameters (minimum, maximum, average, median, standard deviation) of movement measurement, it can be observed that the proposed MOFAC-GA-PSO algorithm brings the lowest value among all other algorithms. So, it can be said that the proposed MOFAC-GA-PSO algorithm performs better than all other methods (GA, PSO). Performance comparison, in terms of the movement measurements, is shown in Fig. 10.

After running the experiment 1000 times when the frequency distribution is plotted then it takes the form of normal distribution. When a frequency distribution is normally distributed, it can be calculated the likelihood of an event happening, by standardizing the scores, which are referred to as the Z scores. The Z score [48] provides information on confidence levels on how closely a value relates to the mean and how far away from the mean a particular data point is. Three confidence levels (68%, 95%, and 99%) or Z scores of various approaches have been calculated and enlisted in Table 8. It can be stated with 68% confidence that in the MOFAC-GA-PSO algorithm, the movements will lie between 213.76m and 250.31m. To achieve 68% confidence the other approaches like the Guided-random approach, GA, and PSO, need [461.70m to 536.86 m], [516.29m to 610.66m], [419.87m to 485.36m] the number of movements respectively. The MOFAC-GA-PSO algorithm shows lower values compared to other algorithms. The 95% confidence level of various approaches has been plotted in Fig. 13 and from the figure, it can be noticed that the range [195.49m to 268.59m] for the MOFAC-GA-PSO algorithm is the lowest one. Therefore, with the assistance of statistics, it is possible to state that the node's movements can be reasonably predicted to fall between the range of 195.49m to 268.59m with a 95% confidence level, and the MOFAC-GA-PSO algorithm performs well in comparison to other algorithms.

VII. CONCLUSION

The primary goals of the research are to maximize the coverage area of the WSN network with minimum overlapping and minimal consumed energy. To achieve these goals a hybrid meta-heuristic algorithm, MOFAC-GA-PSO has been designed. The efficiency of WSN has been measured in terms of the percentage of area coverage, the degree of overlapping, the number of WSN nodes used, and total consumed energy of the network. The overall area coverage is compared with the existing pieces of literature and it has been observed that the proposed research work provides 100% area coverage with only 25 mobile WSN nodes whereas the existing methodology can provide a maximum of 91.26% of area coverage. When compared to the current literature, the suggested approach has the lowest degree of overlapping. In terms of energy efficiency the network built by the proposed algorithm can last 11.06 days as contrasted to the performance of the existing paper, which is 6.33 days. So theoretically, the suggested algorithm produces a good result in terms of both coverage area maximization and consumed energy minimization. The scenario can be made more realistic in the future by using fuzzy logic to include uncertainty in experimental outcomes. The limitations of the proposed work are that the obstacles are not considered in the path of communication and all WSN nodes have been assumed as homogeneous sensors with the same sensing range. The proposed MOFAC-GA-PSO method will be extended in a future research to cover area with obstacles using a periodic monitoring technique considering heterogeneous sensors using various machine learning algorithms to cover the AOI rapidly and dynamically.

REFERENCES

[1] S. Verma, S. Zeadally, S. Kaur, and A. K. Sharma, "Intelligent and secure clustering in wireless sensor network (WSN)-based intelligent transportation systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 13473–13481, Aug. 2022.

[2] M. R. Senouci and A. Mellouk, "1-wireless sensor networks," in *Deploying Wireless Sensor Networks*, M. R. Senouci and A. Mellouk, Eds. Oxford, U.K.: Elsevier, 2016, pp. 1–19.

[3] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: A survey," *Comput. Netw.*, vol. 38, no. 4, pp. 393–422, 2002.

[4] B. A. Akgül, M. F. Hasoğlu, and B. Haznedar, "Investigation and implementation ultra-low power PIC-based sensor node network with renewable energy source and decision-making unit," *Wireless Sensor Netw.*, vol. 10, no. 2, pp. 41–58, 2018.

[5] S. Azar, A. Avokh, J. Abouei, and K. N. Plataniotis, "Energy- and delay-efficient algorithm for large-scale data collection in mobile-sink WSNs," *IEEE Sensors J.*, vol. 22, no. 7, pp. 7324–7339, Apr. 2022.

[6] D. Sah, C. Shivalingagowda, and D. P. Kumar, "Optimization problems in wireless sensors networks," *Soft Comput. Wireless Sensor Netw.*, vol. 2018, pp. 41–62, Sep. 2018.

[7] S. Srivastava, M. Singh, and S. Gupta, "Wireless sensor network: A survey," in *Proc. Int. Conf. Autom. Comput. Eng. (ICACE)*, Oct. 2018, pp. 159–163.

[8] A. Anurag, R. Priyadarshi, A. Goel, and B. Gupta, "2-D coverage optimization in WSN using a novel variant of particle swarm optimisation," in *Proc. 7th Int. Conf. Signal Process. Integr. Netw. (SPIN)*, Feb. 2020, pp. 663–668.

[9] M. Farsi, M. A. Elhosseini, M. Badawy, H. A. Ali, and H. Z. Eldin, "Deployment techniques in wireless sensor networks, coverage and connectivity: A survey," *IEEE Access*, vol. 7, pp. 28940–28954, 2019.

[10] T. Xiang, H. Wang, and Y. Shi, "Hybrid WSN node deployment optimization strategy based on CS algorithm," in *Proc. IEEE 3rd Inf. Technol., Netw., Electron. Autom. Control Conf. (ITNEC)*, Mar. 2019, pp. 621–625.

[11] Z. Wang, H. Xie, D. He, and S. Chan, "Wireless sensor network deployment optimization based on two flower pollination algorithms," *IEEE Access*, vol. 7, pp. 180590–180608, 2019.

[12] A. Banerjee, S. Chattopadhyay, M. Gavrilas, and G. Grigoras, "Optimization and estimation of reliability indices and cost of power distribution system of an urban area by a noble fuzzy-hybrid algorithm," *Appl. Soft Comput.*, vol. 102, Apr. 2021, Art. no. 107078.

[13] J. Roselin, P. Latha, and S. Benitta, "Maximizing the wireless sensor networks lifetime through energy efficient connected coverage," *Ad Hoc Netw.*, vol. 62, pp. 1–10, Jul. 2017.

[14] D. P. Singh and B. Pant, "An approach to solve the target coverage problem by efficient deployment and scheduling of sensor nodes in WSN," *Int. J. Syst. Assurance Eng. Manage.*, vol. 8, no. 2, pp. 493–514, Jun. 2017.

[15] S. P. R. Banoth, P. K. Donta, and T. Amgoth, "Target-aware distributed coverage and connectivity algorithm for wireless sensor networks," *Wireless Netw.*, vol. 29, pp. 1815–1830, Jan. 2023.

[16] A. Hossain, P. K. Biswas, and S. Chakrabarti, "Sensing models and its impact on network coverage in wireless sensor network," in *Proc. IEEE Region 10 3rd Int. Conf. Ind. Inf. Syst.*, Dec. 2008, pp. 1–5.

[17] M. Srinivas, P. K. Donta, and T. Amgoth, "Efficient algorithms for point and area sweep–coverage in wireless sensor networks," in *Proc. 6th Int. Conf. Wireless Commun., Signal Process. Netw. (WiSPNET)*, Mar. 2021, pp. 315–320.

[18] A. Chowdhury and D. De, "Energy-efficient coverage optimization in wireless sensor networks based on Voronoi-Glowworm Swarm Optimization-K-means algorithm," *Ad Hoc Netw.*, vol. 122, Nov. 2021, Art. no. 102660.

[19] A. Naeem, A. R. Javed, M. Rizwan, S. Abbas, J. C. Lin, and T. R. Gadekallu, "DARE-SEP: A hybrid approach of distance aware residual energy-efficient SEP for WSN," *IEEE Trans. Green Commun. Netw.*, vol. 5, no. 2, pp. 611–621, Jun. 2021.

[20] R. Kumar, U. Venkanna, and V. Tiwari, "EOMCSR: An energy optimized multi-constrained sustainable routing model for SDWSN," *IEEE Trans. Netw. Service Manage.*, vol. 19, no. 2, pp. 1650–1661, Jun. 2022.

[21] D. Zhai, C. Wang, R. Zhang, H. Cao, and F. R. Yu, "Energy-saving deployment optimization and resource management for UAV-assisted wireless sensor networks with NOMA," *IEEE Trans. Veh. Technol.*, vol. 71, no. 6, pp. 6609–6623, Jun. 2022.

[22] S. H. Sackey, J. A. Ansere, J. H. Anajemba, M. Kamal, and C. Iwendi, "Energy efficient clustering based routing technique in WSN using brain storm optimization," in *Proc. 15th Int. Conf. Emerg. Technol. (ICET)*, 2019, pp. 1–6.

[23] A. Banerjee, S. K. De, K. Majumder, D. Dash, and S. Chattopadhyay, ''Construction of energy minimized WSN using GA-SAMP-MWPSO and K-mean clustering algorithm with LDCF deployment strategy,'' *J. Supercomput.*, vol. 78, no. 8, pp. 11015–11050, May 2022.
[24] Y. Wang, Y. Zhang, J. Liu, and R. Bhandari, ''Coverage, connectivity, and deployment in wireless sensor networks,'' in *Recent Development in Wireless Sensor and Ad-Hoc Networks*. New Delhi, India: Elsevier, 2015, pp. 25–44.
[25] D. P. Kumar, T. Amgoth, and C. S. R. Annavarapu, ''Machine learning algorithms for wireless sensor networks: A survey,'' *Inf. Fusion*, vol. 49, pp. 1–25, Sep. 2019.
[26] R. Priyadarshi, B. Gupta, and A. Anurag, ''Wireless sensor networks deployment: A result oriented analysis,'' *Wireless Pers. Commun.*, vol. 113, no. 2, pp. 843–866, Jul. 2020.
[27] M. H. Mousa and M. K. Hussein, ''Efficient UAV-based MEC using GPU-based PSO and Voronoi diagrams,'' *Comput. Model. Eng. Sci.*, vol. 133, no. 2, pp. 413–434, 2022.
[28] M. A. Alqarni, M. H. Mousa, and M. K. Hussein, ''Task offloading using GPU-based particle swarm optimization for high-performance vehicular edge computing,'' *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 34, no. 10, pp. 10356–10364, Nov. 2022.
[29] M. K. Hussein and M. H. Mousa, ''Efficient computation offloading of IoT-based workflows using discrete teaching learning-based optimization,'' *Comput., Mater. Continua*, vol. 73, no. 2, pp. 3685–3703, 2022.
[30] A. Khattak, M. Z. Asghar, Z. Ishaq, W. H. Bangyal, and I. A. Hameed, ''Enhanced concept-level sentiment analysis system with expanded ontological relations for efficient classification of user reviews,'' *Egyptian Informat. J.*, vol. 22, no. 4, pp. 455–471, Dec. 2021.
[31] W. H. Bangyal, J. Ahmed, and H. T. Rauf, ''A modified bat algorithm with torus walk for solving global optimisation problems,'' *Int. J. Bio-Inspired Comput.*, vol. 15, no. 1, pp. 1–13, 2020.
[32] M. A. Benatia, M. Sahnoun, D. Baudry, A. Louis, A. El-Hami, and B. Mazari, ''Multi-objective WSN deployment using genetic algorithms under cost, coverage, and connectivity constraints,'' *Wireless Pers. Commun.*, vol. 94, no. 4, pp. 2739–2768, Jun. 2017.
[33] A. Céspedes-Mota, G. Casta nón, A. F. Martínez-Herrera, L. E. Cárdenas-Barrón, and A. M. Sarmiento, ''Differential evolution algorithm applied to wireless sensor distribution on different geometric shapes with area and energy optimization,'' *J. Netw. Comput. Appl.*, vol. 119, pp. 14–23, Oct. 2018.
[34] M. Abo-Zahhad, N. Sabor, S. Sasaki, and S. M. Ahmed, ''A centralized immune-Voronoi deployment algorithm for coverage maximization and energy conservation in mobile wireless sensor networks,'' *Inf. Fusion*, vol. 30, pp. 36–51, Jul. 2016.
[35] A. Banerjee, V. Das, A. Biswas, S. Chattopadhyay, and U. Biswas, ''Development of energy efficient and optimized coverage area network configuration to achieve reliable WSN network using meta-heuristic approaches,'' *Int. J. Appl. Metaheuristic Comput.*, vol. 12, no. 3, pp. 1–27, Jul. 2021.
[36] H. ZainEldin, M. Badawy, M. Elhosseini, H. Arafat, and A. Abraham, ''An improved dynamic deployment technique based-on genetic algorithm (IDDT-GA) for maximizing coverage in wireless sensor networks,'' *J. Ambient Intell. Humanized Comput.*, vol. 11, pp. 4177–4194, Jan. 2020, doi: 10.1007/s12652-020-01698-5.
[37] R. C. Jebi and S. Baulkani, ''Mitigation of coverage and connectivity issues in wireless sensor network by multi-objective randomized grasshopper optimization based selective activation scheme,'' *Sustain. Comput., Informat. Syst.*, vol. 35, Sep. 2022, Art. no. 100728.
[38] S. Nematzadeh, M. Torkamanian-Afshar, A. Seyyedabbasi, and F. Kiani, ''Maximizing coverage and maintaining connectivity in WSN and decentralized IoT: An efficient metaheuristic-based method for environment-aware node deployment,'' *Neural Comput. Appl.*, vol. 35, no. 1, pp. 611–641, Jan. 2023.
[39] Y.-C. Wang, ''A two-phase dispatch heuristic to schedule the movement of multi-attribute mobile sensors in a hybrid wireless sensor network,'' *IEEE Trans. Mobile Comput.*, vol. 13, no. 4, pp. 709–722, Apr. 2014.
[40] J. Lin, R. Özgün, P. O. Pouliquen, A. G. Andreou, C. M. Andreou, and J. Georgiou, ''A 3-pin 1 V 115 μw 176 $\times$ 144 autonomous active pixel image sensor in 0.18 μm CMOS ,'' in *Proc. IEEE Int. Symp. Circuits Syst. (ISCAS)*, May 2011, pp. 1568–1571.
[41] Y. H. Robinson, R. S. Krishnan, K. L. Narayanan, Y. Reeginal, G. V. Rajkumar, and P. S. R. Malar, ''Hybrid data forwarding technique for enhanced lifetime in wireless sensor networks,'' in *Proc. 5th Int. Conf. Trends Electron. Informat. (ICOEI)*, Jun. 2021, pp. 657–660.
[42] M. D'Arienzo, M. Iacono, S. Marrone, and R. Nardone, ''Estimation of the energy consumption of mobile sensors in WSN environmental monitoring applications,'' in *Proc. 27th Int. Conf. Adv. Inf. Netw. Appl. Workshops*, Mar. 2013, pp. 1588–1593.
[43] J. Kabara and M. Calle, ''MAC protocols used by wireless sensor networks and a general method of performance evaluation,'' *Int. J. Distrib. Sensor Netw.*, vol. 8, no. 1, Jan. 2012, Art. no. 834784.
[44] Y. A. Yahya, S. Raed, A. M. H. Darghaoth, and S. A. Majeed, ''Secure routing protocol for wireless sensor networks: Survey,'' in *Proc. 8th Int. Eng. Conf. Sustain. Technol. Develop. (IEC)*, Feb. 2022, pp. 155–160.
[45] P. K. Donta, T. Amgoth, and C. S. R. Annavarapu, ''An extended ACO-based mobile sink path determination in wireless sensor networks,'' *J. Ambient Intell. Humanized Comput.*, vol. 12, no. 10, pp. 8991–9006, Oct. 2021.
[46] P. K. Donta, T. Amgoth, and C. S. R. Annavarapu, ''Delay-aware data fusion in duty-cycled wireless sensor networks: A Q-learning approach,'' *Sustain. Comput., Informat. Syst.*, vol. 33, Jan. 2022, Art. no. 100642.
[47] D. K. Sah, K. Cengiz, P. K. Donta, V. N. Inukollu, and T. Amgoth, ''EDGF: Empirical dataset generation framework for wireless sensor networks,'' *Comput. Commun.*, vol. 180, pp. 48–56, Dec. 2021.
[48] D. Wu, X. Ma, and D. L. Olson, ''Financial distress prediction using integrated Z-score and multilayer perceptron neural networks,'' *Decis. Support Syst.*, vol. 159, Aug. 2022, Art. no. 113814.

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