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ORIGINAL RESEARCH

Hybrid Sand Cat Swarm Optimization Algorithm-based reliable coverage optimization strategy for heterogeneous wireless sensor networks

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Abstract Network coverage plays an indispensable role in determining the Heterogeneous Wireless Sensor Networks (HWSNs) potentiality towards the process of monitoring the physical world with maximized service quality. This HWSNs possesses the limitations of complex deployment environments, poor node reliability and restricted energy which directly influences the transmission and data collection process of sensor nodes and minimizes the network performance. An efficient network coverage controlling mechanism need to be devised and implemented for improving the network service quality, lifetime, reducing energy consumption, and achieve rational utilization of limited resources. In this paper, a Hybrid Sand Cat Swarm Optimization Algorithm-based Reliable Coverage Optimization Strategy (HSCOARCS) is proposed for preventing the issue of coverage redundancy and coverage blind areas, and maximally optimize the sensor node deployment location to achieve reliable sensing and monitoring of target area. This proposed HSCOARCS is implemented over a HWSN coverage mathematical model which represents a problem of combinatorial optimization. The hybridization of Sand Cat Swarm Optimization Algorithm (SCSOA) is achieved for enhancing the speed of the global convergence with the initial population achieved using the method of Gaussian distribution. It targets on the optimization objectives that aids in minimizing the network costs and improve its coverage. The simulation results of the proposed HSSCSOA confirmed better network reliability of 21.38%, network coverage of 19.76%, and minimized energy consumption of 17.92% with different number of sensor nodes on par with the benchmarked schemes used for comparison.

Keywords Heterogeneous wireless sensor networks (HWSNs) · Network coverage · Sand Cat Swarm Optimization Algorithm (SCSOA) · Gaussian distribution

1 Introduction

Wireless Sensor Networks (WSNs) represents a new network and computing model which comprises of highly intelligent, expensive and tiny devices termed as sensor nodes in the network [1]. This WSNs consists of different sensor nodes which establishes a reliable network structure through the help of wireless communication technology [2]. It is useful for monitoring and detecting the events occurring in the core areas of target that includes the applications of smart home, mobile target tracking, military monitoring, environmental detection and urban monitoring [3]. However, weak sensing range and high network cost are two important limitations of the sensor nodes that introduces maximized degree of challenges during the process of routing in WSNs [4]. During the deployment of sensor nodes, redundancy need to be prevented for enhancing the objective of coverage in WSNs. Thus optimization of sensor nodes' coverage is a crucial issue in WSNs since the aspect of network coverage possesses a significant impact over the performable of the network [5]. This coverage

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optimization concentrates on the aspect of improving the network area of monitoring with just the least number of sensor nodes deployed in the network by minimizing the number of blond spots. The sensor nodes are typically dispersed at random throughout the entire region of monitoring such that events in the environment could be monitored in close for achieving reactive decision-making process [6]. But the random deployment of sensor nodes has the maximized probability of introducing redundancy and high node density which in turn results in poor network coverage [7]. This poor network coverage has the probability of further deteriorating the monitoring effectives in WSNs. In heterogeneous WSNs, the dimension of connectivity and coverage are potential twins of evaluation indicators which is highly useful for identifying whether the real time data could be facilitated to the users through the inter-cooperation of sensor nodes [8]. Diversified number of existing research contributed towards optimization of heterogeneous WSNs mainly concentrated on coverage and ignored or overlooked the aspect of network connectivity efficiency [9]. Hence, a reliable sensor node deployment methodology need to be practically developed and implemented for achieving better balancing of load during data transmission inside WSNs and at the same time increases the service quality and energy efficacy in WSNs [10].

The sensor nodes' coverage optimization represents a typical NP-hard problem since it has to handle the impact of coverage characteristics and network resources. Thus utilizing the classical mathematical optimization method such that gradient descent could not solve the problem effectively with efficiency [11]. From the recent years, the problem of sensor nodes' network coverage problem in WSNs have been explored by a quantifiable number of researchers using the swarm intelligent algorithms that includes simulated annealing algorithm (SA), artificial bee colony algorithm (ABC), particle warm optimization algorithm (PSO), genetic algorithm (GA), and so on [12]. These swarm intelligent algorithms are widely used for addressing the issue of sensor nodes' coverage optimization problem since it possesses only few limitations for the mathematical characteristic of the problem with maximized degree pf adaptation [13]. Inspite of above-mentioned swarm intelligent algorithms being successful in optimizing the problem of network coverage in WSNs in reality such that they focus on achieving approximate optimal solution compared to the best feasible solution. Further, the search methodologies adopted in the swarm intelligent algorithms are completely greedy. Most of the swarm intelligent algorithms used for sensor nodes' coverage optimization failed in handling the imbalance between local and global search process. Most of the utilized swarm intelligent algorithms faces the challenges that needed to be addressed for achieving rapid convergence of the algorithm, improved population diversity and preventing the solution from entering into the local point of optimality. The proposed research formulates and contributes a Hybrid Sand Cat Swarm Optimization Algorithm-based Reliable Coverage Optimization Strategy (HSCOARCS) for optimizing the coverage and connectivity of sensor nodes in WSNs.

1.1 Major contributions

The major contributions of the proposed HSCOARCS scheme is listed as follows.

- (i) It specifically used a Hybrid Sand Cat Optimization Algorithm (HSCOA) for improving the quality of the population such that maximized network coverage and connectivity is achieved.
- (ii) It also included into SCOA for improving the objective of faster convergence such that it prevents the algorithm from falling into a local point of optimality such that search space is widened during the aspect of sensor nodes' coverage optimization.
- (iii) It is proposed with the well-balanced potential of exploitation and exploration offered by SCOA which helped in better network coverage even under the existence of obstacles in the network.
- (iv) The performance evaluation is conducted using coverage ratio and connectivity efficiency with different number of iterations.

In addition, Fig. 1 presents the Overall View of the proposed HSCOARCS scheme contributed for guaranteeing Reliable Coverage Strategy in heterogeneous WSNs.

The remaining section of the paper is organized as follows. Section 2 presents the comprehensive review of the existing swarm intelligent algorithms-based sensor nodes' coverage optimization techniques contributed to the literature over the recent years with the merits and limitations. Section 3 details the WSN coverage model and the background of the adopted Hybrid SCOA algorithm used for achieving better sensor nodes' coverage optimization. Section 4 demonstrates the results and discussion of the proposed HSCOARCS scheme, and the benchmarked approaches evaluated in terms of network coverage and connectivity ratio with different number of iterations, Sect. 5 concludes the paper with major contributions and future scope of enhancement.

2 Related work

In this section, the comprehensive review of the existing swarm intelligent algorithms-based sensor nodes' coverage optimization techniques contributed to the literature over the recent years is presented with the merits and limitations.

Yao et al. [14] have proposed an improved coverage mechanism for WSNs using Virtual Force-directed Ant Lion

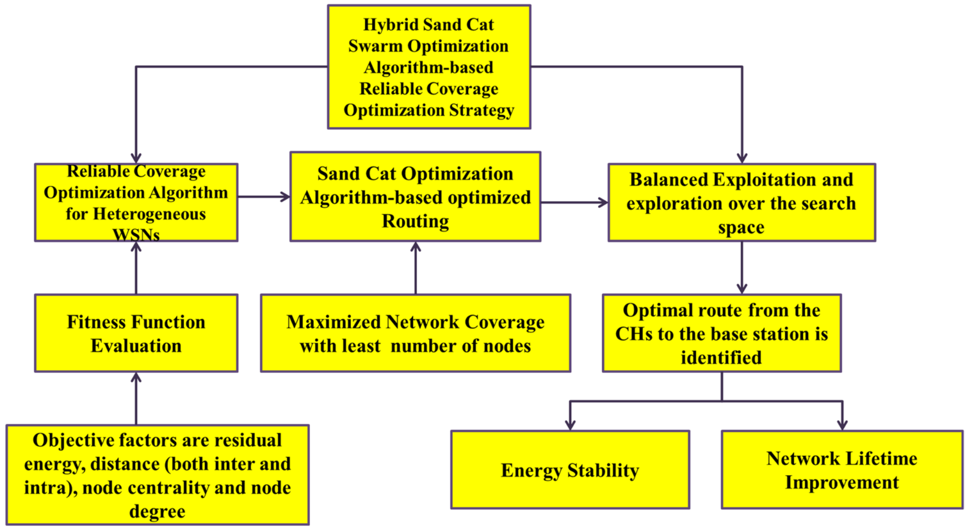

Fig. 1 Overall view of the proposed HSCOARCS scheme

Optimization (VF-IALO) algorithm. This ALO-based algorithm involves reassignment of ALs with dynamic reduction of number of ALs. It includes a factor for continuous ant arbitrary walk boundary reduction. It limits random walk range of ants to decrease the moving node distance during secondary positioning. It introduces virtual force incorporating force of neighbouring nodes, gravity of grid point along with repulsion of boundary. It updates the co-efficients representing weights of virtual force, AL as well as elite AL to dynamically modify the location of ant. It aids in preventing the algorithm from falling into local optimum, accelerating convergence speed as well as enhancing the overall optimization capability of the algorithm. Zhu and Wang [15] have dealt with the irregular node distribution that leads to issues of increased and incomplete coverage of areas that are monitored. To handle this challenge, an optimization model for dealing with network coverage is proposed along with coverage optimization scheme using Improved hybrid Weed algorithm (LRDE_IWO). Initially, in seed diffusion phase, it employs tangent function-based Standard Deviation (SD) of normal as step size of seed for balancing global and local searches of weed algorithm. To overcome the issue of early convergence, it uses a disturbance scheme which combines improved Levy flight and dynamic Random walk (LR) for seed breeding. In invasive weed phase, it involves Differential Evolution (DE) approach for optimising the operation and speeding up convergence. The proposed weed algorithm optimises coverage. The proposed scheme offers improved coverage rate, superiority as well as validity in contrast to standard schemes for optimising coverage in WSNs.

Then Zhang et al. [16] have proposed an optimized Grey Wolf Algorithm (GWA) based on Simulated Annealing (SA) in which the nodes involve increased aggregation degree and reduced coverage rate when arbitrarily deployed. Initially, it establishes a mathematical model to handle coverage optimization in WSNs. Secondly, it includes SA in GWOA once siege behavior finishes and before GW is updated to improve global optimization capability and convergence rate of GWA. It is seen that the enhanced SA optimised GWA is applied to coverage optimization of WSNs. It offers improved optimization speed, network coverage and lifetime along with reduced energy consumption. Ma and Duan [17] have focussed on effectively increasing node coverage of WSN. Enhanced Butterfly Optimization Algorithm (H-BOA), a hybrid strategy is proposed. It introduces Kent Chaotic Map (KCM) for initialising population to assure unvarying search space. It also includes an inertial weight that is based on modified Sigmoid function to balance global as well as local search capacities. It uses elite-fusion as well as elite-based local mutation approaches to improve diversity. It involves perturbation that is based on normal distribution to lessen likelihood of algorithm dropping into premature convergence. It also introduces SA to assess the quality of solution and enhances algorithm's capability that is helpful in moving out of local optimum. The proposed scheme offers improved network coverage in contrast to optimization algorithms.

Liang et al. [18] have proposed Adaptive Cauchy Variant Butterfly Optimization Algorithm (ACVBOA) for efficiently enhancing network coverage in Soil Moisture WSNs (SMWSNs). It involves Cauchy variants as well as dynamic factors for enhancing global as well as local search capabilities of ACBOA. Further, it offers a coverage optimization model which includes node coverage along with network QoS. Performance is analysed in terms of fairness for certain population size and number of iterations. The proposed scheme offers improved convergence rate. Dao et al. [19] have proposed a system for offering ideal node coverage of unstable WSN distribution while performing arbitrary positioning depending on Enhanced Archimedes Optimization

Algorithm (EAOA). It collectively takes network coverage from numerous sub-areas. As AOA is inefficient in dealing with complex scenarios, EAOA adapts equations using reverse learning as well as multi-direction schemes. The proposed scheme offers better range of coverage as well as convergence speed.

Chawra and Gupta [20] have focussed on finding ideal wakeup schedule for nodes with acceptable coverage as well as connectivity demands. The existing schemes focus on only coverage or connectivity. Only a few mechanisms take both into consideration, hence do not offer an ideal solution and get struck into local minima. An enhanced Memetic Algorithm-based energy-efficient wakeup scheduling mechanism is propounded based on connectivity, energy, coverage and ideal wakeup schedule. It forms new mutation, crossover, as well as local search operators. The proposed mechanism better offers better results based on coverage ratio, ideal quantity of live nodes as well as network lifespan. The existing algorithms do not consider optimising energy or enhancing network coverage together with reducing equipment cost. Zulfiqar et al. [21] have proposed bio-stimulated algorithm that mimics the digestive system of ruminant animals. These animals consume huge quantity of raw food and produce ideal value of food which is filled with energy. The propounded algorithm focuses on enhancing network coverage offering optimized energy and node distribution that improves device lifespan. It enhances network coverage thus offering optimized energy value without increase in the quantity of sensors deployed in the network. It offers improved more network coverage and enhanced lifespan involving same equipment cost.

Hanh et al. [22] have designed a multi-Objective design for Maximizing lifetime with Target Coverage (MO-MMTC) that deals with fluctuation of energy among mobile nodes after every movement. Enhanced Non-dominated Sorting Genetic Algorithm II (ENSGA-II), a multi-population GA is proposed to handle this issue. It determines numerous ideal movement plans that offers optimised energy balance in mobile WSNs. It simultaneously reduces the total and maximal movement distance of sensors. A 2-phase framework is proposed for handling the issue. It uses geometrical computing schemes to handle the initial stages. Multi-objective optimization-based bi-population GA is proposed for dealing with relocation involving coverage constraints. Heterogeneous WSNs (HWSNs) demand sufficient network coverage along with connectivity. Zeng et al. [23] have proposed Improved Wild Horse Optimizer (IWHO) algorithm to deal with this issue. It improves population quality by using SPM CM during initialization. It hybridises WHO and Golden Sine Algorithm (Golden-SA) to enhance accuracy and offer quicker convergence. IWHO aids in escaping from local optimum as well as broadening search space by employing Opposition-Based Learning (OBL) and Cauchy variation. IWHO offers better optimization capacity. The proposed scheme offers improved sensor connectivity with coverage ratios.

Wang et al. [24] proposed an enhanced Grey Wolf Optimization Algorithm with multi-strategy for achieving efficient coverage and energy conservation in WSNs. This IGWOAMS was proposed as an energy efficient network coverage optimization solution which improved coverage area and minimized energy consumptions. This model used a sort-driven hybrid opposition-based learning and higher-order multinomial sensing models for addressing the number of obstacles in the network area. It was proposed a better approach for sustaining scalability and enhanced connectivity with the option of minimizing the node deployment costs in the network.

Ma et al. [25] proposed a Reptile Search algorithm-based network coverage optimization method This network coverage was proposed with the idea for tracking the movement of each optimal CHs in the network during each round of lifetime. It included the strategy of distribution estimation for comprehensive determination of all information associated with the sensor nodes deployed in the entire network. This RSA-based network coverage method when tested with different optimization test benchmarked function confirmed better convergence and optimal results. The experiments conducted using different influential factors and scenarios confirmed the efficiency of this approach in optimization the network coverage facilitated by the deployed sensor nodes using the random initialization of search agents.

Yue et al. [26] proposed a Monarch Butterfly Optimization Algorithm (MBOA)-based network coverage solution using the model that included the factors of coverage, energy consumptions and operational performance during the determination of optimal results. It facilitated potential sensor placement for guaranteeing required coverage in the network. It used the parameter of butterfly adjustment ratio as the iteration number for the objective of preventing local extremes, increasing the search space and rapid up the rate of convergence. It divided the population of search agents into particle swarm update, butterfly adjustment and migration for the process of attaining hybrid update mechanism. The This MBOA-based network coverage method when tested with different optimization test benchmarked function confirmed better convergence and optimal results. The results of this MBOA-based network coverage algorithm confirmed better results in terms of node utilization and minimized network expenses.

Kurian et al. [27] implemented a Hill Climbing and simulated annealing integrated the binary ant colony algorithm (HCSABACA) for addressing the issue of energy efficiency during the process of achieving maximized network coverage. This approach was modelled based on the concept of pheromone trails and foraging behaviour of ants while determining the location of sensor nodes deployed in the network. This method specifically adopted HC and SA for refining the solution that are determined initially during the inclusion of BACA over the initial part of the network lifetime. This hybridisation of HC and SA balanced the trade-off between exploration and exploitation such that superior solutions are only determined during the process of network coverage. The results of this HCSABACA approach confirmed better energy potential coverage in the two-dimensional network field (Table 1).

3 Proposed Hybrid Sand Cat Swarm Optimization Algorithm-based Reliable Coverage Strategy (HSCOARCS)

3.1 Network coverage model of WSNs

Let us consider an area of monitoring which is represented using a two-dimensional region with the dimension $M \times N$. In this area of monitoring, number of sensor nodes are deployed randomly which is represented using $N_{S(i)} = \{n_1, n_2, \ldots \ldots .., n_m\}$. If the sensor nodes in this monitoring area are heterogeneous in nature with different radius of sensing (R_s) and communication radii which is equivalent to R_c and $R_c \geq 2R_s$. At the same time, the sensor nodes is determined to move such that the position cam be instantly updated. Then the Euclidean distance between the random sensor node and targeted sensor node is represented using Eq. (1)

$$d\left(N_{S(i)}, T_{O(i)}\right) = \sqrt{\left(x_{(i)} - x_{(j)}\right)^2 + \left(y_{(i)} - y_{(j)}\right)^2} \quad (1)$$

where, $(x_{(i)}, y_{(i)})$ and $(x_{(j)}, y_{(j)})$ represents the random sensor nodes coordinates and targeted sensor nodes coordinates.

$$p\left(N_{S(i)}, T_{O(i)}\right) = \begin{cases} 0 & R_s > d\left(N_{S(i)}, T_{O(i)}\right) \\ 1 & R_s \leq d\left(N_{S(i)}, T_{O(i)}\right) \end{cases} \quad (2)$$

Then the probabilities related to the joint perception of random and targeted sensor nodes is determined based on Eq. (3)

$$\mathrm{P}\left(\mathrm{N_{S(i)}}, \mathrm{T_{O(i)}}\right) = 1 - \prod_{I=1}^{m} p\left(N_{S(i)}, T_{O(i)}\right) \quad (3)$$

At this juncture, the coverage ratio being a significant indicator of heterogeneous WSN problem of deployment is computed based on Eq. (4)

$$\mathrm{F_1} = \mathrm{Cov} = \frac{\sum_{\mathrm{j=1}}^{\mathrm{M \times N}} \mathrm{P}\left(\mathrm{N_{S(i)}}, \mathrm{T_{O(i)}}\right)}{\mathrm{M \times N}} \quad (4)$$

The degree to which the sensor nodes' coverage gets evaluated depends on coverage efficiency The maximized coverage efficiency represents that only few numbers of sensor nodes are used for achieving the same coverage area. The coverage efficiency is computed based on Eq. (5)

$$CoV_{Eff} = \frac{\bigcup_{i \leq i \leq m} N_{S(Area(i)}}{\sum_{1 \leq i \leq m} N_{S(Area(i)}} \quad (5)$$

where, $N_{S(Area(i)}$ represents the area enveloped by each of the i^{th} sensor nodes deployed in the network of area $\mathrm{M \times N}$.

$$p\left(T_{O(i)}, T_{O(J)}\right) = \begin{cases} 0 & R_s > d\left(N_{S(i)}, T_{O(i)}\right) \\ 1 & R_s \leq d\left(N_{S(i)}, T_{O(i)}\right) \end{cases} \quad (6)$$

The ratio of connectivity which represents the proportion of connected paths to the number of maximized connected paths determined between the sensor nodes is determined based on Eq. (7)

$$\mathrm{F_2} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{m} p\left(T_{O(i)}, T_{O(J)}\right)}{n(n-1)/2}. \quad (7)$$

In this situation, the number of paths determined between two specific sensor nodes is determined to be $n(n-1)/2$.

Hence, the objective function for the proposed model depending on sensor node coverage and connectivity is determined based on Eq. (8)

$$\mathrm{Max\ f}\left(\mathrm{F_1}, \mathrm{F_2}\right) = \mathrm{W_1 F_1} + \mathrm{W_2 F_2} \quad (8)$$

Such that $\mathrm{W_1} + \mathrm{W_2} = 1$

$$\sum_{j=1}^{M \times N} \mathrm{P}\left(\mathrm{N_{S(i)}}, \mathrm{T_{O(i)}}\right) \leq \mathrm{M \times N}$$

$$p\left(N_{S(i)}, T_{O(i)}\right) \geq 0$$

$$p\left(T_{O(i)}, T_{O(J)}\right) \geq 0$$

In this context, the weights [28–31] associated with $\mathrm{W_1}$ and $\mathrm{W_2}$ related to two functions F_1 and F_2 after several number of experiments is determined to be 0.8 and 0.2, respectively.

3.2 Primitives of Sand Cat Swarm Optimization

The adopted Sand Cat Swarm Optimization (SCSO) algorithm mimics the foraging nature of Sand Cats (SCs) that are found in deserts. It is efficient in identifying noise of low frequency to localise prey, be it under or above the ground. It determines the prey by taking optimal value seen in exploration space. The Search Agent (SA) constantly examines

Table 1 Summary of the existing swarm intelligent algorithms-based sensor nodes' coverage optimization techniques

Authors	Mechanism	Features	Demerits
Yao et al. [14]	Virtual Force-directed Ant Lion Optimization (VF-IALO) algorithm	• Includes a factor for continuous ant arbitrary walk boundary reduction • Limits random walk range of ants to decrease the moving node distance during secondary positioning • Introduces virtual force incorporating force of neighbouring nodes, gravity of grid point along with repulsion of boundary	It concentrated only on the achievement of network coverage but ignored connectivity
Zhu and Wang [15]	Improved hybrid Weed algorithm (LRDE_IWO)	• Focuses irregular node distribution that leads to issues of increased and incomplete coverage of areas • Uses a disturbance scheme which combines improved Levy flight and dynamic Random walk (LR) for seed breeding	It was nor able to handle the issue of imbalance realized between the process of exploration and exploitation during the optimization of sensor nodes coverage
Zhang et al. [16]	Optimized Grey Wolf Algorithm (GWA)	• Establishes a mathematical model to handle coverage optimization • Includes SA in GWOA once siege behavior finishes, and before GW is updated to improve global optimization capability and convergence rate of GWA	It has the possibility of getting stuck into the local point of optimality such that it determines only approximate results during the optimization process
Ma and Duan [17]	Hybrid strategy enhanced Butterfly Optimization Algorithm (H-BOA)	• Introduces Kent Chaotic Map (KCM) for initialising population to assure unvarying search space • Includes an inertial weight that is based on modified Sigmoid function to balance global as well as local search capacities • Uses elite-fusion as well as elite-based local mutation approaches to improve diversity	The coverage network model considered for implementation possesses a room of improvement which still has the possibility of enhancing network coverage and connectivity
Liang et al. [18]	Adaptive Cauchy Variant Butterfly Optimization Algorithm (ACBOA)	• Involves Cauchy variants as well as dynamic factors for enhancing global as well as local search capabilities of ACBOA • Offers a coverage optimization model which includes node coverage as well as network QoS	It delivers a poor rate of convergence and utilized maximized number of factors during the process of optimization
Dao et al. [19]	Enhanced Archimedes Optimization Algorithm (EAOA)	• Collectively takes network coverage from numerous sub-areas • Adapts equations using reverse learning as well as multi-direction schemes	The use of reverse learning only targeted on optimization rather than minimizing the network cost
Chawra and Gupta [20]	Enhanced Memetic Algorithm-based energy-efficient wakeup scheduling mechanism	• Based on connectivity, energy, coverage and ideal wakeup schedule • Forms new mutation, crossover, as well as local search operators	The coverage network model considered for implementation possesses a room of improvement which still has the possibility of enhancing network coverage and connectivity
Zulfiqar et al. [21]	Bio-stimulated algorithm based on digestive system of ruminant animals	• Focuses on enhancing network coverage offering optimized energy and node distribution that improves device lifespan • Enhances network coverage thus offering optimized energy value without increase in the quantity of sensors deployed in the network	The fitness function considered for achieving,maximized sensor nodes' coverage optimization need to be comprehensive since the ignorance of some impact factors results in moderate network coverage

Table 1 (continued)

Authors	Mechanism	Features	Demerits
Hanh et al. [22]	Multi-Objective design for MaxiMizing lifetime with Target Coverage (MO-MMTC)	• Determines numerous ideal movement plans that offers optimised energy balance in mobile WSNs • Simultaneously reduces the total and maximal movement distance of sensors	The factors considered for evaluating the potential of the network coverage model is not comprehensive
Zeng et al. [23]	Improved Wild Horse Optimizer (IWHO) algorithm	• Improves population quality by using SPM CM during initialization • Hybridises WHO and Golden-SA to enhance accuracy and offer quicker convergence	The aspect of integrating WHO and SA also possesses a room of enhancement in stablishing a well-balanced trade-off between local and global searching process
Wang et al. [24]	An enhanced Grey Wolf Optimization Algorithm with multi-strategy for achieving efficient network coverage	• This IGWOAMS was proposed as an energy efficient network coverage optimization solution which improved coverage area and minimized energy consumptions • This model used a sort-driven hybrid opposition-based learning and higher-order multinomial sensing models for addressing the number of obstacles in the network area	It still need to utilize more number of impactful factors for the purpose of fitness function evaluation process
Ma et al. [25]	Reptile Search algorithm-based network coverage optimization method	• This network coverage was proposed with the idea for tracking the movement of each optimal CHs in the network during each round of lifetime • It included the strategy of distribution estimation for comprehensive determination of all information associated with the sensor nodes deployed in the entire network	The network coverage achieved during the adoption of RSA algorithm still possesses a room of improvement, and hence a well balance between the local and global searching process becomes indispensable
Yue et al. [26]	Monarch Butterfly Optimization Algorithm (MBOA)-based network coverage solution	• It facilitated potential sensor placement for guaranteeing required coverage in the network • It used the parameter of butterfly adjustment ratio as the iteration number for the objective of preventing local extremes, increasing the search space and rapid up the rate of convergence	The degree of energy efficiency achieved by this approach is marginal, and hence requires phenomenal improvement in the rate of coverage and solution diversity
Kurian et al. [27]	Hill Climbing and simulated annealing integrated the binary ant colony algorithm (HCSABACA)	• This approach was modelled based on the concept of pheromone trails and foraging behaviour of ants while determining the location of sensor nodes deployed in the network • This method specifically adopted HC and SA for refining the solution that are determined initially during the inclusion of BACA over the initial part of the network lifetime	The computational complexity incurred by this approach is considerably high due to the inclusion of HC and SA even though they are essential for better exploration and exploitation of search space

search space based on position updates, finally gets nearer to location of optimal value. It includes prey search and attack schemes. The scheme designed to handle the search for prey simulates SCs foraging for prey. The SC population is given by,

$$\vec{P}_{t+1} = \vec{r}.\left(\vec{P}_t^b - rand(0,1).\vec{P}_t^c\right) \quad (9)$$

where,

$\vec{P}$—Position vector of SA; t—Present iteration; $\vec{P}_b$—Position of best candidate; $\vec{P}_c$—Current position of SA; r—Range of SCs' sensitivities to low frequency noise

$$\vec{r} = \vec{r}_c \times rand(0,1) \quad (10)$$

where, $\vec{r}_c$—Common sensitivity range linearly decreased from 2 to 0

$$\vec{r}_c = s_M - \left(\frac{s_M \times Itr_{Curr}}{Itr_{max}}\right) \quad (11)$$

where, Itr_{Curr}—Current iteration; Itr_{Max}—Maximum iterations; $s_M = 2$.

Further, SCs observe low-frequencies of 2 kHz. At the end of prey search, the algorithm attacks it, and the attack method for SCs population is shown below.

$$\vec{P}_{rand} = \left|rand(0,1).\vec{P}_t^b - \vec{P}_t^c\right| \quad (12)$$

$$\vec{P}_{t+1} = \vec{P}_t^b - \vec{r}.\vec{P}_{rand}.\cos\theta \quad (13)$$

where, θ—Random angle in range [0, 360]; cos θ—Values in range [−1, 1]; $\vec{P}_{rand}$—Random location produced by best and current locations.

Every member in population moves in varying circular directions. Every SC selects an arbitrary angle. SCs circumvent local optimum traps while moving toward prey location. Random angle in Eq. (5) facilitates influencing hunt as well as direction of search of SA.

3.3 Exploration and exploitation

SCSO balances exploration as well as exploitation stages using dynamic factor ($\vec{R}$) that is given by,

$$R = 2 \times \vec{r}_c \times rand(0,1) - \vec{r}_c \quad (14)$$

where, '$\vec{r}_c$'—Linearly decreases from 2 to 0 with increase in number of iterations.

The updated description of location of each SC during exploration and exploitation stage is given by:

$$\vec{P}_{t+1} = \begin{cases} \vec{r}.\left(\vec{P}_t^b - rand(0,1).\vec{P}_t^c\right), |R| > 1 \\ \vec{P}_t^b - \vec{r}.\vec{P}_{rnd}.\cos\theta, |R| \le 1 \end{cases} \quad (15)$$

where, SA attacks prey when |R| < 1; else SA globally searches for promising solutions.

Every SC has its own search radius in exploration stage, thereby preventing the algorithm from dropping into local ideal solution.

4 Discussion

SCSO has the ensuing features:

- It has a simple structure involving less number of factors that is easy for implementation
- It considers position of ideal solution as prey. It does not lead to search stagnation by following angle
- It is capable of balancing exploration as well as exploitation stages to increase the algorithm's convergence accuracy
- It retains location of global optimal solution in every iteration, and decrease of population quality has no impact on prey location
- Every member in the population moves in diverse directions which guarantees that the algorithm can move toward prey offering increased convergence accuracy

SCSO has some demerits:

- In case of multi-peak functions, it easily falls into local optimal solutions which demands enhancement approaches to be included to reinforce transition amid exploration as well as development stages of algorithm and assign a sensible sensitivity range lessening approach
- Quality of arbitrarily produced populations is diminished as they are in want of diversity
- There are chances for presence of insufficient communication among individuals along with global optimal solution which guides the population to cause search stagnation

Algorithm 1: SCSO Algorithm

Initialize population
Determine fitness function
Set r, r_c, R
while ($t \le itr_{max}$)
for (every agent)

Obtain an arbitrary angle 'θ' in the range [0°, 360°]
if (|R| ≤ 1) then
Update location of SA using Eq. (13)
else
Update location of SA using Eq. (9)
end /*if*/
end /*for*/
t=t+1
end /*while*/

4.1 Stochastic difference-based SCSO with elite collaboration

4.1.1 Non-linear periodic modification approach

For population-based optimization schemes like SCSO, a stable shift amid global exploration as well as local exploitation (R) is essential for optimising the algorithm. In early iterations, improved global exploration capability is vital for maintaining diverse population distributions. In later iterations, improved local exploitation ability is indispensable for ensuring fine exploitation in local scale and accelerating algorithm convergence.

'R' aids in finding the switch between exploitation and exploration, and indicates algorithm's capability to determine the finest. This arbitrary value lies in the range $\left[-2r_c, 2r_c\right]$, where '$\vec{r}_c$' drops from 2 to 0 by using linear iteration.

When |R| > 1, location of SC is modified at present and prey arbitrary locations amid present and prey locations conforming to algorithm's global detection stage
When |R| ≤ 1, cat targets the prey conforming to algorithm's local exploitation

From Eq. (11), it is evident that '$\vec{r}_c$' decreases linearly in single-period. As this process is iteratative, it becomes erratic with natural rule which demands several rounds of co-operative prey capture for population, leading to linear conversion of varying range of 'R'. So the algorithm involves a non-linear periodic modification approach for '$\vec{r}_c$' to define prey hunting performed by the population. Precisely, a logarithmic function that is used to represent non-linear periodicity is shown below:

$$\vec{r}_c = S_M - S_M \times \ln\left[1 + \frac{itr_c}{itr_{max}}(e-1)^3\right] \tag{16}$$

where, t—Present amount of iterations; itr_{max}—Maximum quantity of iterations; e—Natural constant; $S_M = 2$.

Based on Eq. (6), the value of 'R' decays slowly in initial iterations which is faster in later iterations. The population performs sufficient global exploration as well as improves population diversity in initial iteration; in latter iteration, algorithm may converge faster to attain a balanced and steady switch among global exploration (initial iteration) and local exploitation (late iterations). It improves accuracy of optimization as well as algorithm's convergence speed.

4.1.2 Pseudo-oppositional and pseudo-reflection learning schemes

OBL improves diversity of population, accuracy as well as convergence speed of smart optimization algorithms using synchronised consideration of candidate entities along with opposition solutions. In correlation model, location of entity (i) in d-dimensional space is given by $X_i = (X_i^1, X_i^2 \ldots X_i^d)$; $x_{i,j} \in \left[L_j, U_j\right]$

$\left[L_j, U_j\right]$—Range values in j-dimensional space; $X_i' = \left(x_i'^1, x_i'^2 \ldots x_i'^d\right)$—Entity's opposing point; $X_i'' = \left(x_i''^1, x_i''^2, \ldots x_i''^d\right)$—Entity's Pseudo-Opposite Point (POP); $X_i''' = \left(x_i'''^1, x_i'''^2, \ldots x_i'''^d\right)$—Entity's Pseudo-Reflection Point (PRP)

$$x_i'^j = L_i + U_j - x_i^j \tag{17}$$

$$x_i''^j = \text{rand}\left[\frac{L_i + U_j}{2}, x_i'^j\right] \tag{18}$$

$$x_i'''^j = \text{rand}\left[x_i^j, \frac{L_i + U_j}{2}\right] \tag{19}$$

The PRP is always closer to Candidate Solution (CS) when compared to POP, and may be locally exploited completely in CS' neighbourhood. In case, the POP is away from the location of CS, then wider global exploration can be obtained and unexplored space of CS can be opened.

When |R > 1|, the prey may escape from encirclement, and hence the SC should enlarge search range to seize prey. To handle this, PO Learning (POL) scheme is included in location update phase of global search. As POP is distant from CS location, once PO solution of present solution in the area far from CS is generated, the entity may attain a broader global search and increase the area not examined by CS. This improves the population diversity and holds the original and POS into population of ensuing generation by using greedy selection approach. Let '$X_{i,old}^{t+1}$' be the location update in global search. After including POL, the location update is given by,

$$X_i^{t+1} = \begin{cases} X_{i_{t+1}}^{Old} \\ f\left(X_{i_{t+1}}^{Old}\right) < f\left(X'''_{i_{t+1}}\right) \\ X'''_{i_{t+1}} \\ f\left(X_{i_{t+1}}^{Old}\right) \geq f\left(X'''_{i_{t+1}}\right) \end{cases} \tag{20}$$

$$X'''_{i_{t+1}} = \left(X'''_{i,1.Old_{t+1}} \ldots ..X'''_{i,1d.Old_{t+1}}\right) \tag{21}$$

$$X'''_{i,j.Old_{t+1}} = rand\left[X_{i,j_{t+1}}^{Old}, \left(\frac{L_i + U_j}{2}\right)\right] \tag{22}$$

By including POL and PRL schemes in local exploitation and coalescing diverse search approaches of entities, it accelerates search efficacy of SCSO algorithm and enhances universal convergence capability.

4.1.3 Stochastic variation (SV) with elite collaboration

Elite collaboration approach is employed in heuristic algorithms. PSO employs dimensional elites as well as population elites for population guidance. Ideal guidance is repetitious and does not offer significance to intelligence of population. The GWO algorithm performs association of 3 ideal GW positions. The chosen Elites have similar weights which mean that every elite has similar location update for GW. The selected elites do not involve any weight variation as every elite has similar role weight on location update of GW leading to non-ideal location update of elite collaboration. Hence, an elite association approach involving elite weights is proposed to differentiate elite entities' roles on updating population location. Furthermore, the elite approach overcomes the challenge pertaining to communication lack amid population entities during iterations and prevents the algorithm from dropping into local optimum solutions.

There is a likelihood that the elite association may fail in latter iterations when elite locations are comparatively uniform. T-distribution-based random disparity is included to increase the arbitrariness of elite association approach. Elite SCs are chosen for adaptation and they collaborate to generate a fresh SC location to direct the process of searching. Elite SCs are allocated varying weights depending on the value of the objective function. Smaller the cost, greater is the weight. Weights are assigned as shown below:

$$W_{gb}^1 = \frac{1}{2} - \frac{f(X_{gb}^1)}{2\left(f\left(X_{gb}^1\right) + f\left(X_{gb}^2\right) + f\left(X_{gb}^3\right)\right)} \tag{23}$$

$$W_{gb}^2 = \frac{1}{2} - \frac{f(X_{gb}^2)}{2\left(f\left(X_{gb}^1\right) + f\left(X_{gb}^2\right) + f\left(X_{gb}^3\right)\right)} \tag{24}$$

$$W_{gb}^3 = \frac{1}{2} - \frac{f(X_{gb}^3)}{2\left(f\left(X_{gb}^1\right) + f\left(X_{gb}^2\right) + f\left(X_{gb}^3\right)\right)} \tag{25}$$

$$X_{lead} = \frac{W_{gb}^1 . X_{gb}^1 + W_{gb}^2 . X_{gb}^2 + W_{gb}^3 . X_{gb}^3}{3} \tag{26}$$

where, W_{gb}^1, W_{gb}^2, W_{gb}^3—Elite weights; X_{lead}—Global optimal solution location following collaboration of elites.

Variation of locations of optimal solution after collaboration of elites using SV strategy is given by,

$$X'_{lead} = X_{lead} + X_{lead}.t_{itr} \tag{27}$$

where, X'_{lead}—Optimal location of solution after variation; t(itr)—Present amount of iterations for t-distribution of freedom degrees.

SV with collaboration of elites guides the search by using 'X'_{lead}' instead of ideal solution ($\overrightarrow{X}_b$) in Eqs. (1) and (5). At the beginning of iteration, t-distribution moves to Coasey distribution which is smoother. The t-distribution operator takes huge values involving increased probability along with huge steps of location variation. The algorithm involves improved universal exploration capability. In latter iterations, t-distribution looks like typical normal distribution which is more focused. The operator takes small values involving high probability. Further, step size of position variation is lesser as it is favourable for algorithm convergence.

Algorithm 2: SCOA

```
Initialize population
Determine fitness function
Set r, r_c, R
While (t ≤ itr_max)
for (Every agent)
Mutate present ideal solution
Modify ideal solution using Eq. (22)
Obtain an arbitrary angle 'θ' in the range [0°, 360°]
if (|R| ≤ 1) then
Modify SA location depending on Eq. (23)
else
Modify SA location depending on Eq. (20)
end /*if*/
end /*for*/
  t+ = 1
end /*while*/
```

4.2 The classical seagull optimization algorithm

Recently, SOA is studied by several scholars [7, 8]. SA represents a seagull in search space. Every SA slowly approaches global optimal solution by mimicking migration as well as attacking behaviours.

4.2.1 Migration behaviour

It aids SOA to widely explore the whole search space. In this stage, SA satisfies the ensuing conditions:

- **Avoiding Collisions:** Collision avoidance deals with increasing the distance amid neighbouring SAs to overcome collisions as shown in Eqs. (28) and (29).

$$C_{SA} = A.L_{SA}^{Itr} \tag{28}$$

$$A = f_c - \left(itr \left(\frac{f_c}{Itr_{Max}} \right) \right) \tag{29}$$

where, SA = 1,2,… Size; Size—Population size; Itr—Present iteration; L_{SA}^{Itr}—Present location of SA; C_{SA}—Location of SA after evading collision; Itr_{Max}—Maximum quantity of iterations; f_c—Constant; A—Movement of SA.

During every iteration, ‘A’ decreases linearly from ‘f_c’ to 0.

- **Direction of Best SA:** Once collision is avoided, SAs move along best SA as shown in Eqs. (30) and (31).

$$D_{SA} = B\left(L_{Best}^{Itr} - L_{SA}^{Itr}\right) \tag{30}$$

$$B = 2.A^2.r \tag{31}$$

where, L_{SA}^{Itr}—Best SA in population; D_{SA}—Direction of best SA; B—Responsible for balancing exploration as well as exploitation; r—Random number in range [0,1]]

- **Searching for best SA:** The SA updates the location depending on best SA.

$$Dist_{SA} = \left|C_{SA} + D_{SA}\right| \tag{32}$$

where, $Dist_{SA}$—Distance between SA and best SA.

4.2.2 Attacking behaviour

As seagulls attack the prey around them, flight trajectory approaches a spiral curve. In the planes (X, Y, Z), attacking behaviour is observed as shown below.

$$X' = rad.Cos(k) \tag{33}$$

$$Y\prime = rad.Sin(k) \tag{34}$$

$$Z' = k.rad \tag{35}$$

$$rad = u.e^{kv} \tag{36}$$

$$L_{SA}^{Itr} = Dist_{SA}.X'.Y\prime.Z' \tag{37}$$

where, k—Arbitrary number in range [0, 2π] signifying attack angle; rad—Spiral flight trajectory radius; u and v—Constants which describe spiral flight trajectory shape; L_{SA}^{Itr}—Best solution that updates the location of other SAs.

4.3 SOA based on gaussian distribution (GD)

SOA is an efficient optimizer that is capable of handling challenging problems with more number of constraints. But in case of Chemical Dynamic Optimization Problems (CDOPs), SOA finds it tedious to approximate optimal control flight. GD-based SOA (GSOA) is propounded for CDOPs. GSOA offers an initialization concept which depends on GD and Dimension-Order Mutation Operator (DOMO) that effectively enhances the capability of SOA to handle CDOPs.

4.3.1 GD-based initialization

Practically, control mechanism must have continuity, and the one with minor fluctuation is found to be in-line with features of CDOP [9, 10]. SOA is based on the concept of conventional random initialization to produce primary population that makes every region in search space to have a particular probability for producing initial entity. Nevertheless, this concept is not applicable for solving CDOPs as the idea involves some amount of blindness as well as uncertainty. It produces chaotic entities and it is observed that the variance amid neighbouring dimensions in the entity is huge. Such entities are not typically in-line with the endurance of CDOP. To enhance the quality of preliminary population, an initialization concept based on GD is proposed. This concept efficiently employs the features of GD to produce initial population that can significantly enhance the population quality.

The steps are detailed below.

SA initialization

$$L_{SA} = \left(l_{SA}^1, l_{SA}^2 \ldots .l_{SA}^N\right) \tag{38}$$

Initially, ‘l_{SA}^1’ is arbitrarily produced in control domain[U_{min}, U_{max}] using Eq. (39).

Next, ‘l_{SA}^2’ is produced using Eq. (40)

Let, φ^2_{SA}—Random number produced from a GD having mean $\mu = l^1_{SA}$

Standard deviation, $\sigma = \frac{U_{max} - U_{min}}{10}$

If $\varphi^2_{SA} \notin [U_{min}, U_{max}]$

Equation (30) is used for producing 'l^2_{SA}'.

'φ^2_{SA}' continues to be an arbitrary number produced from a GD having mean $\mu = l^1_{SA}$ and 'σ' has the same value, till $\varphi^2_{SA} \notin [U_{min}, U_{max}]$

Similarly, $l^3_{SA}, l^4_{SA} \ldots .l^N_{SA}$ are produced in sequence.

$$l^1_{SA} = (U_{max} - U_{min}) \cdot rd + U_{min} \tag{39}$$

$$\begin{cases} I^I_{SA} = \varphi^I_{SA} \\ \varphi^I_{SA}\ N\left(l^{I-1}_{SA}, \left(\frac{U_{max} - U_{min}}{10}\right)^2\right) \end{cases} \tag{40}$$

where, $SA = 1, 2, \ldots . Size;$ Size—Size of population; $I = 2, 3, \ldots . N;$ N—Search space dimension; l^I_{SA}—Value of the 'l^{th}' dimension of SA

$$L_{SA} = \left(l^1_{SA}, l^2_{SA} \ldots .l^N_{SA}\right)$$

l^I_{SA}—'I^{th}' dimension of SA; U_{max}, U_{min}—Upper and lower bounds of control domain; r—Arbitrary number in the range [0,1]; φ^2_{SA}—Arbitrary number produced from a GD using $\mu = l^{I-1}_{SA}$

An arbitrary number produced from GD $N(\mu, \sigma^2)$ has increased probability to be within $[\mu - 3\sigma, \mu + 3\sigma]$

Assign the value of 'σ', initialization based on GD cannot avoid producing huge quantity of chaotic initial entities but also has reduced probability in generating entities with huge fluctuation to circumvent missing possible best individual with huge fluctuation.

4.3.2 DOMO based on GD

In case of CDOPs' solution, SOA is likely to drop into local optimum as population evolution is directed by best SA. In complex search space involving high dimensions, the chosen SA may drop into local optimum leading to deprived population quality. To enhance algorithm's capability for handling CDOPs, DOMO based on GD is proposed. Mutation is a common enhancement approach used in optimization algorithms that can efficiently improve efficiency of algorithms to move out of local optimum as well as accuracy [11–13]. Focussing on the features of CDOPs, GD-based DOMO performs dimension-wise Gaussian mutation on best SA based on dimension order to enhance algorithm's global search performance. For a DOP named 'max J', the steps of GD-based DOMO are listed below:

- $L^{Itr}_{Best} = \left(l^{itr}_{Best,1}, l^{itr}_{Best,2}, \ldots .l^{itr}_{Best,N}\right)$ shows the best SA at 'itr^{th}' iteration, and performance index is represented as 'J^{itr}_{Best}'. $L^{itr}_{nb} = \left(l^{itr}_{nb,1}, l^{itr}_{nb,2}, \ldots .l^{itr}_{nb,N}\right)$ signifies fresh best SA.
- For L^{itr}_{Best}", the 'l^{th}'dimension mutates to produce mutated SA $L^{itr,1}_{Mut} = \left(l^{itr,1}_{Mut}, l^{itr,2}_{Best}, \ldots .l^{itr,N}_{Best}\right)$. The value '$l^{itr,1}_{Mut}$' of the $I = 1^{st}$ dimension of '$L^{itr,1}_{Mut}$' is determined using Eq. (36). If $l^{itr,1}_{Mut} > U_{max}\left(l^{itr,1}_{Mut} < U_{min}\right)$, set $l^{itr,1}_{Mut} = U_{max}\left(l^{itr,1}_{Mut} = U_{min}\right)$. The remaining dimensions of '$L^{iter,1}_{Mutant}$' are equal to values of conforming dimensions of 'L^{itr}_{Best}'.
- Determine performance index 'J^{itr}_{Best}' of '$L^{itr,1}_{Mut}$'. If $J^{itr,1}_{Mut} > J^{itr}_{Best}$, set $l^{itr}_{nb,1} = l^{itr,1}_{Mut}$. If $J^{itr,1}_{Mut} \le J^{itr}_{Best}$, set $l^{itr}_{nb,1} = l^{iter,1}_{Best}$
- For 'L^{itr}_{Lest}', the '2^{nd}' dimension mutates to produce mutated SA, $L^{itr,2}_{Mut} = (l^{iter,1}_{Best}, l^{itr,2}_{Mut}, \ldots .l^{itr,N}_{Best})$. Value of '$l^{itr,2}_{mut}$' of $I = 2^{nd}$ dimension of '$L^{itr,2}_{Mut}$' is computed using Eq. (41). If $l^{itr,2}_{Mut} > U_{max}\left(l^{itr,1}_{Mut} < U_{min}\right)$, set $l^{itr,2}_{Mut} = U_{max}\left(l^{itr,1}_{Mut} = U_{min}\right)$. Values of residual dimensions of '$L^{itr,2}_{Mut}$' are equal to values of conforming dimensions of 'L^{itr}_{Best}'.
- Determine performance index '$J^{itr,2}_{Mut}$' of '$L^{itr,2}_{Mut}$'. If $J^{itr,2}_{Mut} > J^{itr}_{Best}$, set $l^{itr,2}_{nb} = l^{itr,2}_{Mut}$. If $J^{itr,2}_{Mut} \le J^{itr}_{Best}$, set $l^{itr,2}_{nb} = l^{itr,2}_{Best}$.
- Likewise, in relation to dimension order, perform mutation of residual dimensions of 'L^{itr}_{Best}'. Lastly, the fresh best SA $L^{itr}_{nb} = \left(l^{itr,1}_{nb}, l^{itr,2}_{nb}, \ldots .l^{itr,N}_{nb}\right)$ is got.

$$\begin{cases} L^{itr,I}_{Mut} = \alpha^{itr}_I \\ \alpha^{itr}_I\ N\left(l^{itr,I}_{Best}, \left(\frac{U_{max} - U_{min}}{G}\right)^2\right) \\ G = 500 - \left(490 - itr\left(\frac{490}{Itr_{Max}}\right)\right) \end{cases} \tag{41}$$

where, $I = 1,2, \ldots N;$ N—Search space Dimension; $l^{itr,I}_{mutant}$—Value of 'I^{th}' dimension of mutated SA $\left(L^{itr,I}_{Mut}\right)$; $l^{iter,I}_{best}$—Value of 'I^{th}' dimension of best SA $\left(P^{itr}_{Best}\right)$; itr—Present iteration; Itr_{Max}—Maximum quantity of iterations; α^{itr}_I—Random number produced from GD using $\mu = L^{itr,I}_{Best}$

$$\sigma = \frac{U_{max} - U_{min}}{G}$$

Moreover, Fig. 2 presents the clustering process included into the process of the proposed HSCOARCS scheme.

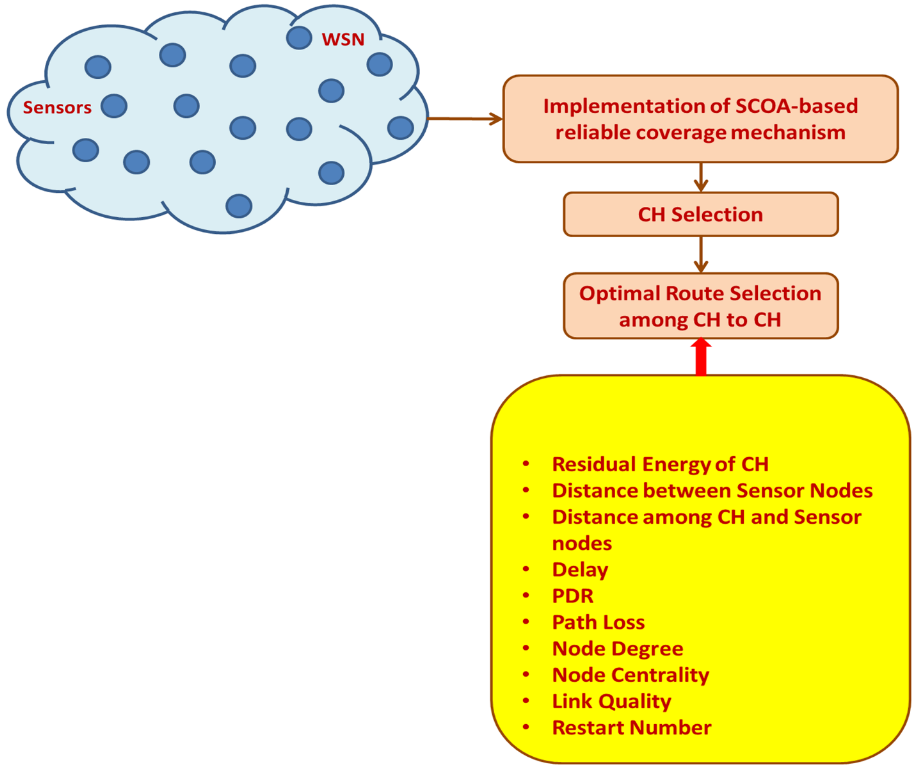

Fig. 2 Clustering process adopted in the proposed HSCO-ARCS scheme

Table 2 Algorithmic parameters used to implement of the proposed HSCOARCS scheme and the benchmarked approaches

Parameters used	Values
Monitoring area	100 m × 100 square meters
Number of sensor nodes	50
Distribution of sensor nodes	Random
Size of the data packets 0	512 Bytes
Sensing Radius of sensor nodes	10 m
Number of iterations	200
Initial energy of nodes	0.5 Joules and 2.0 Joules (Type 1 and 2)

Table 3 Parameter configurations for simulation experiment-1

Parameters used	Values
Monitoring area	100 m × 100 square meters
Radius for sensing	10 m
Number of iterations	200
Number of sensor nodes	50

5 Results and discussion

The simulation experiments of the proposed HSCOARCS scheme and the benchmarked approaches are conducted using the environment which has the configuration of Windows 10 Professional, 64-bit OS, Intel(R) Core (TM) i5-4210H CPU @2.90 GHz, 8 GB. This implementation of the proposed HSCOARCS scheme is conducted using the simulation software of MATLAB 2016a. The benchmark approaches used for comparing the proposed HSCOARCS scheme are ACVBOA, IWHOCOS, EBOA and SAOGWA mechanisms. The number of fitness evaluations considered in the experiment are unified to make the comparison fair between each of the implemented algorithms [32–34]. The number of fitness evaluations considered by each of the implemented algorithms is 30,000 [35, 36]. Table 2 presents the algorithmic parameters considered during the implementation of the proposed HSCOARCS scheme and the benchmarked approaches.

5.1 Comparative results investigation of simulation experiment-1

In this simulation experiment 1, the performance of the proposed HSCOARCS scheme and the baseline approaches are compared based on improvement in coverage ratio as specified in Eq. (4) which is considered as the objective function of the problem. The algorithms were ren for thirty time independently for preventing the possibility of the algorithm from being struck into local point of optimality. In specific,

Table 4 Comparison between initial and optimized coverage ratio achieved by the proposed HSCOARCS scheme during simulation experiment-1

Number of sensor nodes	Initial coverage ratio (%)	Optimized coverage ratio (%)
50	81.32	97.96

Table 5 Comparison between coverage ratio and coverage efficiency achieved by the proposed scheme and the benchmarked approaches during simulation experiment-1

Compared Algorithms	Coverage ratio (%)	Coverage efficiency (%)
SAOGWA	88.14	58.54
EBOA	93.84	61.94
IWHOCOS	95.16	66.19
ACVBOA	94.18	64.72
Proposed HSCOARCS	**97.96**	**72.64**

Bold indicates the proposed approach performance

Table 3 highlights the parameter settings considered during the implementation of the proposed HSCOARCS scheme and the benchmarked approaches.

In this results investigation, the coverage maps that are initially covered by the sensor nodes deployed randomly in the monitoring area identified that the number of sensors nodes that overlap is more, but with the optimization of the proposed HSCOARCS scheme it started decreases. It also clearly demonstrated that the sensor nodes are evenly distributed in the entire area of monitoring.

Further Table 4 depicts the ratio of initial coverage ratio achieved by the proposed scheme and the coverage ration achieved by the same after the employed of the optimization process.

The above-mentioned results confirmed that the initial coverage ratio and optimized coverage ratio confirmed during the implementation of the proposed HSCOARCS scheme are 81.32% and 97.96%, respectively. Thus the improvement in the coverage ratio offered by the proposed HSCOARCS scheme is 16.64%. This improvement in coverage ratio achieved by the proposed HSCOARCS scheme is mainly due to the following reasons that the region possesses more amount of energy voids and seems to be clustered at the beginning since there were a greater number of redundant sensors in the region. But the sensor nodes distributions is visualized to be obviously uniform after the optimization process which eventually improved the coverage ratio to the expected level. Thus the proposed HSCOARCS scheme is effective in achieving better coverage optimization in WSNs.

Further Table 5 exemplars the coverage ratio and coverage efficiency achieved by the proposed HSCOARCS approach on par with the baseline approaches used for comparison. From the result, it is transparent that the best optimization results are achieved during the employment of the proposed HSCOARCS approach compared to the baseline approaches, since it employed balanced local and global strategies that helped in better optimization process. The results of the proposed HSCOARCS approach on an average confirmed an improved coverage ratio and coverage efficiency of 5.13 and 9.81% after thirty independent runs.

From the results, it is also observed that the proposed HSCOARCS approach outperformed the other compared baseline algorithms in terms of coverage ratio and coverage efficiency. In specific, the coverage ratio and coverage efficiency confirmed by the proposed HSCOARCS approach is higher than the worst SAOGWA scheme by 9.82 and 14.1%, respectively. On the other hand, the coverage ratio and coverage efficiency confirmed by the proposed HSCOARCS approach is higher than the best SAOGWA scheme by 2.82 and 6.45%, respectively.

Furthermore, Fig. 3 portrays the coverage convergence curves related to the proposed HSCOARCS approach and the baseline approaches used for comparison. This plots clearly highlighted that the proposed HSCOARCS approach confirmed a better coverage ratio independent to the number of iterations. In particular, the coverage efficiency achieved by the proposed HSCOARCS approach is 72.64% which is comparatively better than the worst SAOGWA algorithm by 14.1%. This improvement introduced by the proposed HSCOARCS approach demonstrated its efficacy in minimizing the degree of redundancy in the sensor coverage.

In addition, the excellence of the proposed HSCOARCS approach over the baseline approaches are verified with to sensors coverage optimization. In this experimentation, the parameters are kept constant with those that of the benchmarked approach for guaranteeing fairness during the investigation process. The experimental result of this investigation is presented in Tables 6, 7, 8, and 9, respectively.

5.2 Comparative results investigation of simulation experiment-2

In general, categorizing the types of sensors is always difficult in a complex sensor coverage environment, and hence in real environments a greater number of the heterogeneous WSNs is often covered. In this simulation experiment 2, two different sensor types were randomly deployed throughout the entire area of monitoring. Then the proposed HSCOARCS approach is employed for optimizing the coverage of the heterogeneous WSNs. In particular, Table 10 portrays the sensor parameter settings considered during the employment of the proposed HSCOARCS scheme with two different types of sensors.

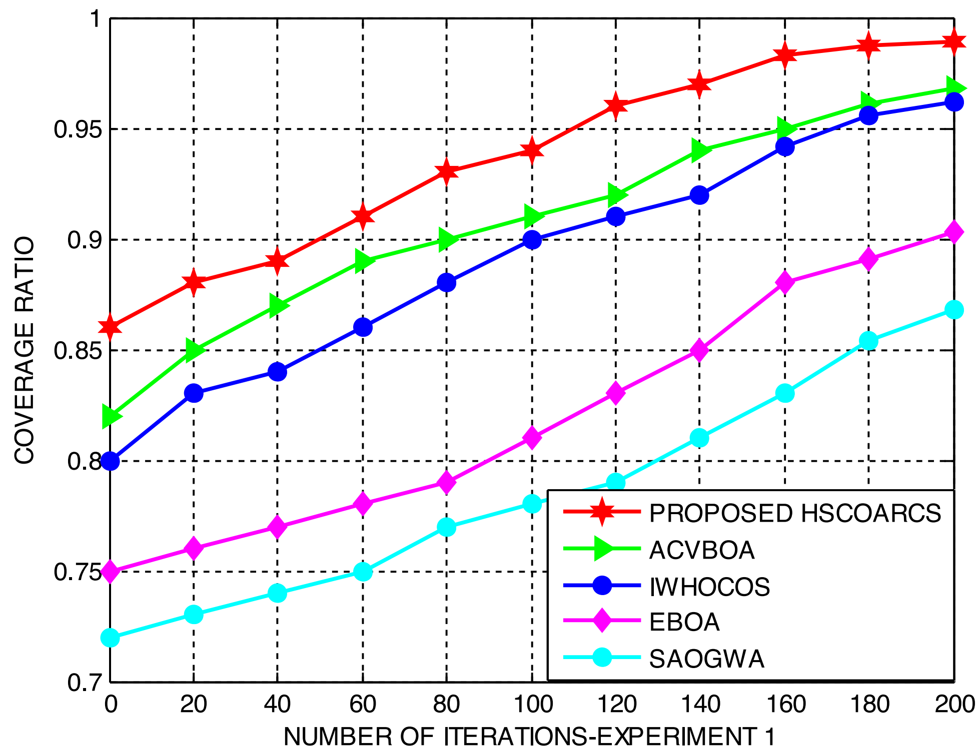

Fig. 3 Coverage convergence curves of the proposed HSCOARCS approach and the baseline approaches with different iterations

Table 6 Experimental results comparing the proposed HSCOARCS approach and ACVBOA scheme

Methods used for comparison	Coverage ratio (%)
ACVBOA	92.38
Proposed HSCOARCS	97.96

Table 7 Experimental results comparing the proposed HSCOARCS approach and ACVBOA scheme

Methods used for comparison	Coverage ratio (%)
IWHOCOS	95.16
Proposed HSCOARCS	97.96

Table 8 Experimental results comparing the proposed HSCOARCS approach and ACVBOA scheme

Methods used for comparison	Coverage ratio (%)
EBOA	93.84
Proposed HSCOARCS	97.96

Table 9 Experimental results comparing the proposed HSCOARCS approach and ACVBOA scheme

Methods used for comparison	Coverage ratio (%)
SAOGWA	88.14
Proposed HSCOARCS	97.96

Table 10 Sensor parameter settings used by the proposed HSCOARCS scheme with two different types of sensors-simulation experiment-2

Parameters used	Values
Monitoring area	100 m × 100 square meters
Number of iterations	200
Number of sensor nodes (/Type 1, Type 2)	30
Radius of communication (Type 1)	25 m
Radius of communication (Type 2)	20 m
Sending radius (Type 1)	12 m
Sending radius (Type 2)	10 m

Then Table 11 demonstrates the comparison between initial and optimized coverage ratio achieved by the proposed HSCOARCS scheme during Simulation Experiment-2. This experimentation is conducted over the monitoring area which comprises of two different types

Table 11 Comparison between initial and optimized coverage ratio achieved by the proposed HSCOARCS scheme during simulation experiment-2

Number of sensor nodes	Initial coverage ratio (%)	Optimized coverage ratio (%)
30	86.18	98.76

Table 12 Comparison between initial and optimized connectivity ratio achieved by the proposed HSCOARCS scheme during Simulation Experiment-2

Number of sensor nodes	Initial connectivity ratio (%)	Optimized connectivity ratio (%)
30	21.56	24.78

Table 13 Sensor parameter settings used by the proposed HSCOARCS scheme with obstacles-simulation experiment-3

Parameters used	Values
Monitoring area	100 m × 100 square meters
Dimension of the obstacle	20 m × 20 m
Number of iterations	200
Number of sensor nodes (/Type 1, Type 2)	30
Radius of communication (Type 1)	25 m
Radius of communication (Type 2)	20 m
Sending radius (Type 1)	12 m
Sending radius (Type 2)	10 m

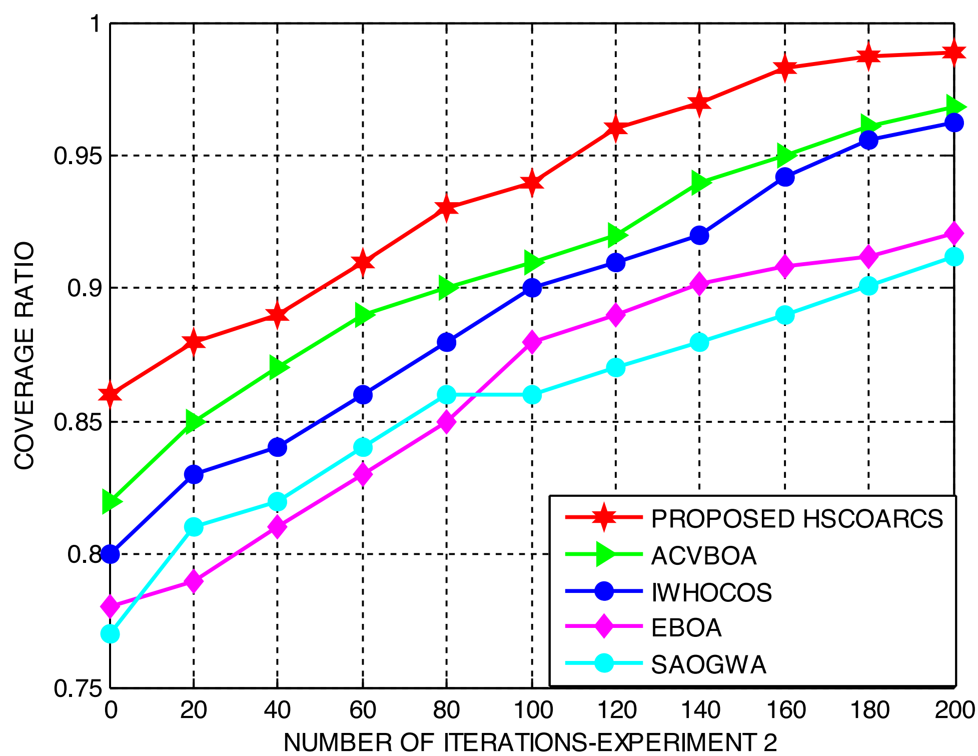

Fig. 4 Coverage convergence curves of the proposed HSCOARCS approach and the baseline approaches with different iterations (Experiment-2)

of sensors deployed randomly in the network. This result clearly confirmed a better optimized coverage ratio of 98.76%, which is a significant improvement of 12.58% over the initial coverage ration visualized at the initial stage.

On the other hand, the proposed HSCOARCS scheme confirmed a better optimized connectivity coverage ratio of 21.56%, which is a significant improvement of 3.22% over the initial connectivity ratio realized at the initial stage. In contrast to simulation experiment 1, the proposed HSCOARCS scheme achieved better network connectivity while concentrating on the improvement of network coverage. In the initial stage, some of the sensors were not connected and hence the initial connectivity ratio was 21.56%. But after the inclusion of the proposed HSCOARCS scheme-based optimization, the connectivity ratio is 24.78% which is realized as a potential improvement of 3.22% better than the baseline approaches (Table 12 and Fig. 4).

5.3 Comparative results investigation of simulation experiment-3

This simulation experiment is conducted for simulating a more realistic simulation environment by including an

Table 14 Comparison between initial and optimized coverage ratio achieved by the proposed HSCOARCS scheme under obstacles during simulation experiment-3

Number of sensor nodes	Initial coverage ratio (%)	Optimized coverage ratio (%)
30	88.76	98.18

Table 15 Comparison between initial and optimized connectivity ratio achieved by the proposed HSCOARCS scheme under obstacles during simulation experiment-3

Number of sensor nodes	Initial connectivity ratio (%)	Optimized connectivity ratio (%)
30	17.19	21.52

obstacle of dimension 20 m × 20 m around monitoring. This simulation experiment 3 is mainly conducted for evaluating the potential of the proposed HSCOARCS scheme towards the objective of coverage optimization under the presence of obstacles in the monitoring area. Table 13 depicts the sensor parameters setting considered during the implementation of the proposed HSCOARCS scheme for achieving simulation experiment 3.

Then Table 14 and 15 demonstrates the comparative improvement in the coverage and connectivity ratio achieved by the proposed HSCOARCS scheme before and after optimization process. The results from Table 14 clearly highlighted that the proposed HSCOARCS scheme ensured an optimized coverage ratio of 98.18%, which is a significant improvement of 9.62% over the initial coverage ratio visualized at the initial stage.

On the other hand, the proposed HSCOARCS scheme in the presence of obstacles (Table 15) also confirmed a better optimized connectivity coverage ratio of 21.52%, which is a significant improvement of 4.33% over the initial connectivity ratio realized at the initial stage.

In addition, Fig. 5 demonstrates the curves of coverage convergence confirmed by the proposed HSCOARCS approach and the baseline approaches with different iterations under the presence of obstacles in the network**.** The proposed HSCOARCS approach even under the existence of obstacles enveloped better network coverage ratio with optimized connectivity such that least number of sensor nodes are able to cover the network with their capability of sensing radius.

6 Conclusion

The proposed HSCOARCOS achieved better coverage optimization by addressing the issue of coverage redundancy and coverage blind areas, and maximally optimize the sensor node deployment location to achieve reliable sensing and monitoring of target area. This proposed HSCOARCOS is implemented over a HWSN coverage mathematical model which represents a problem of combinatorial optimization. The hybridization of Sand Cat Swarm Optimization

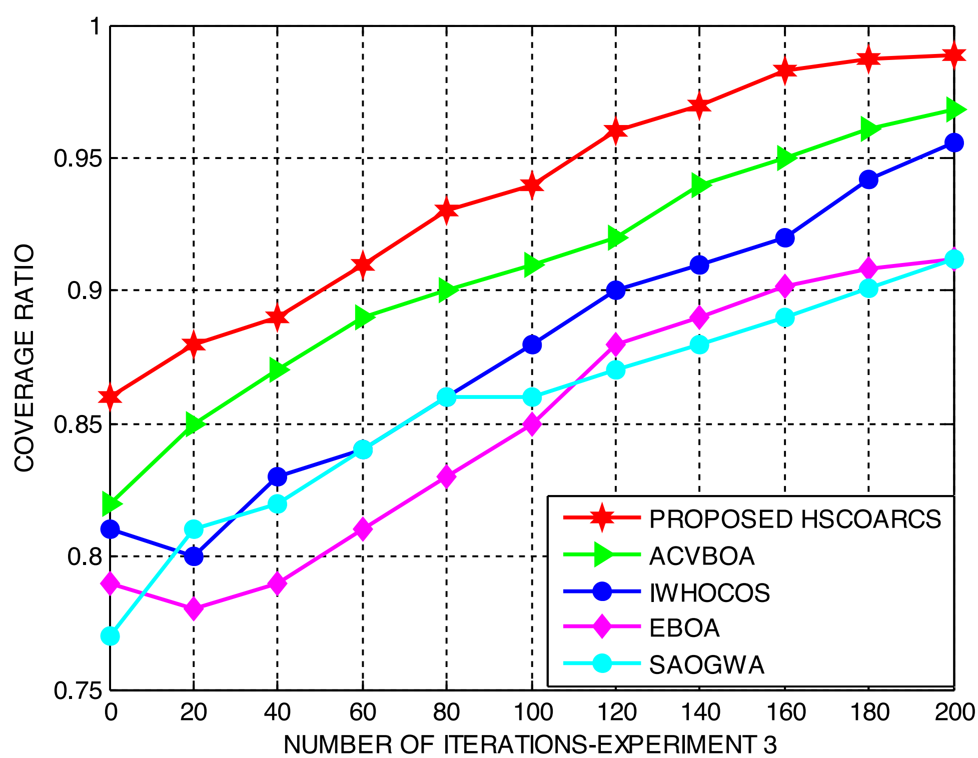

Fig. 5 Coverage convergence curves of the proposed HSCOARCS approach and the baseline approaches with different iterations (experiment-3)

Algorithm (SCSOA) is achieved for enhancing the speed of the global convergence with the initial population achieved using the method of Gaussian distribution. It targets on the optimization objectives that aids in minimizing the network costs and improve its coverage. The simulation results of the proposed HSSCSOA confirmed better network reliability of 21.38%, network coverage of 19.76%, and minimized energy consumption of 17.92% with different number of sensor nodes on par with the benchmarked schemes used for comparison.

7 Future scope of improvement

The proposed CH selection approach can be improved based on security through the process of utilizing multi-criteria decision-making models which plays and indispensable role in trust computation. Further homomorphic encryption algorithms can be used for ensuring the confidentiality of data transmitted from the selected CHs to the sink node.

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Declarations

Conflict of interest The authors declare that there is no competing interest.

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