Annals of Operations Research
https://doi.org/10.1007/s10479-023-05657-z

ORIGINAL RESEARCH

Machine learning for coverage optimization in wireless sensor networks: a comprehensive review

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Received: 25 June 2023 / Accepted: 13 October 2023

Abstract

In the context of wireless sensor networks (WSNs), the utilization of artificial intelligence (AI)-based solutions and systems is on the ascent. These technologies offer significant potential for optimizing services in today's interconnected world. AI and nature-inspired algorithms have emerged as promising approaches to tackle various challenges in WSNs, including enhancing network lifespan, data aggregation, connectivity, and achieving optimal coverage of the targeted area. Coverage optimization poses a significant problem in WSNs, and numerous algorithms have been proposed to address this issue. However, as the number of sensor nodes within the sensor range increases, these algorithms often encounter difficulties in escaping local optima. Hence, exploring alternative global metaheuristic and bio-inspired algorithms that can be adapted and combined to overcome local optima and achieve global optimization in resolving wireless sensor network coverage problems is crucial. This paper provides a comprehensive review of the current state-of-the-art literature on wireless sensor networks, coverage optimization, and the application of machine learning and nature-inspired algorithms to address coverage problems in WSNs. Additionally, we present unresolved research questions and propose new avenues for future investigations. By conducting bibliometric analysis, we have identified that binary and probabilistic sensing model are widely employed, target and k-barrier coverage are the most extensively studied coverage scenarios in WSNs, and genetic algorithm and particle swarm optimization are the most commonly used nature-inspired algorithms for coverage problem analysis. This review aims to assist researchers in exploring coverage problems by harnessing the potential of nature-inspired and machine-learning algorithms. It provides valuable insights into the existing literature, identifies research gaps, and offers guidance for future studies in this field.

Keywords Wireless sensor networks · Coverage optimization · Machine learning · Deep learning · Nature-inspired algorithms

Abbreviations

ACO	Ant Colony Optimization
AoI	Area of Interest
ABC	Artificial Bee Colony

Extended author information available on the last page of the article

ANN-PSO	Artificial Neural Network-Particle Swarm Optimization
ANN	Artificial Neural Networks
BPNN	Back Propagation Neural Network
BOA	Bat Optimization Algorithm
CH	Cluster Head
CFPA	Chaotic Flower Pollination Algorithm
DPSO	Democratic Particle Swarm Optimization
DE	Differential Evolution
Ex-GWO	Expanded Grey Wolf Optimization
FOA	Fruit Fly Optimization Algorithm
GA	Genetic Algorithm
GPS	Global Positioning System
GSO	Glowworm Swarm Optimization
GDMIP	Graph-based Dynamic Multi-Mobile Agent Itinerary Planning approach
GWO	Grey Wolf Optimization
I-GWO	Incremental Grey Wolf Optimization
HMCR	Harmony Memory Consideration Rate
HMS	Harmony Memory Size
HAS	Harmony Search Algorithm
ICS	Improved Cuckoo Search
IoT	Internet of Things
KF	Kalman Filter
LA	Learning Automata
ML	Machine Learning
MAC	Medium Access Control
MADIT	Mobile Agent Distributed Intelligence Tangle-based
MWSM	Mobile Wireless Sensor Network
PSO	Particle Swarm Optimization
PAR	Pitch Adjustment Rate
PSC	Probabilistic Sensing Coverage
QoS	Quality of Service
RoI	Region of Interest
SOM	Self-Organizing Map
SIR	Sensor Intelligence Routing
SN	Sensor Node
SCP	Smart Car Park
STCDRR	Spatial and Temporal Correlation-based Data Redundancy Reduction
SVM	Support Vector Machine
SI	Swarm Intelligence
TLBO	Teaching–learning-based optimization
TCO	Termite Colony Optimization
TPSMA	Territorial Predator Scent Marking Algorithm
WOA	Whale Optimization Algorithm
WSNs	Wireless Sensor Networks

1 Introduction

Networks play a crucial role in various aspects of human life, providing significant benefits and streamlining numerous complex tasks. Wireless sensor networks are cooperative systems composed of distributed and autonomous devices that monitor and observe environmental phenomena. The primary objective of these networks is to sense and collect data regarding physical environmental features, which are then transmitted to a central sink node for user analysis and inference. Often, a substantial number of nodes in the sensor network collaborate to monitor the target environment effectively. However, managing such a massive network poses challenges and requires efficient and scalable procedures (Chaturvedi et al., 2021; Jiang et al., 2020).

One important criterion for evaluating the monitoring capabilities of wireless sensor networks is network coverage, which refers to the installation of nodes to achieve optimal coverage over a monitoring area. The goal is to enhance the stability and effectiveness of information transmission. In wireless sensor networks, coverage optimization involves determining the optimal placement and configuration of sensors within the network to ensure sufficient coverage of the entire monitored area (Yick et al., 2008). This is critical to ensure the network can gather and process information from any point within the coverage region (Tarnaris et al., 2020). Several factors can influence the coverage of a wireless sensor network, including the range and sensitivity of the sensors, the number of sensors deployed, and the characteristics of the monitored environment. These factors must be carefully considered to select the best sensor network configuration for achieving optimal coverage (More & Patil, 2021).

One common approach to improving coverage in wireless sensor networks is using simulation tools to model the network's coverage under various configurations (Hammouti et al., 2018; Njoya et al., 2017; Tripathi et al., 2021). This aids in identifying the most suitable sensor locations and arrangements to ensure comprehensive coverage of the entire region. Additionally, algorithms can be employed to optimize the placement and configuration of sensors, or intelligent routing protocols can be developed to efficiently transfer data collected by the sensors to a central processing point for analysis. Coverage optimization is crucial in advancing wireless sensor networks by enabling efficient data collection and transmission from all locations within the coverage region.

Coverage optimization is a significant problem in wireless sensor networks (WSNs) that numerous algorithms have addressed. Optimization problems are prevalent in various domains of human life (Agushaka et al., 2023). In WSNs, coverage optimization involves strategically planning the placement of sensor nodes and communication strategies to optimize the coverage area while minimizing costs and energy consumption. Literature reports several approaches focusing on coverage optimization in WSNs, including: (1) Placement optimization: This approach aims to determine the optimal locations for sensor nodes to maximize coverage while utilizing the fewest nodes possible. (2) Communication range optimization: This approach involves adjusting the communication range of sensor nodes to expand coverage while minimizing energy usage (Ammari, 2010). (3) Routing optimization: This approach focuses on planning the routing strategy of sensor nodes to enhance coverage while minimizing energy consumption and network congestion (Abbasi & M. S. bin Abd Latiff et al., 2013). (4) Topology control: This approach involves modifying the network's topology, including the number and placement of nodes, to improve coverage and conserve energy (Mohd et al., 2019).

Designing WSNs can encounter challenges such as localization, deployment, data gathering, tracking, and communication coverage. The knowledge of the precise location of all sensor nodes deployed in the network is crucial for effective data collection. Location information enables the detection and recording of events within the network. Abdulwahid and Mishra (Abdulwahid & Mishra, 2022) emphasized the challenge of deployment, which is fundamental in designing a wireless sensor network monitoring system that leverages Internet of Things (IoT) technologies. While many studies aim to prolong the lifespan of wireless sensor networks by focusing on routing and deployment strategies, they often give less attention to ensuring adequate coverage of the target region. Therefore, as highlighted in this study, conducting a comprehensive assessment of coverage optimization in wireless sensor networks and exploring the potential benefits of combining machine learning and bio-inspired algorithms is imperative.

Connectivity and coverage are crucial considerations in wireless sensor networks (WSNs). Coverage can be defined as the ability of a sensor node to identify and monitor an object within the designated area. There are three types of coverage: area, point, and barrier. In area coverage, the objective is to ensure that every point in the monitoring area is covered by at least one operational sensor node. Depending on the network's specific requirements, such as in a battlefield scenario where precise knowledge of the observed region is necessary, full coverage with one sensor node per point or k (where $k \geq 1$) nodes might be needed. In other environmental applications, partial coverage may be acceptable for insufficient sensor nodes. Partial coverage can still increase energy efficiency and prolong the network's lifespan.

Point coverage involves monitoring a specific point or target, which can be stationary or in motion. Examples include observing the activity of an animal in a specific area or monitoring key locations on an enemy battlefield. Barrier coverage, on the other hand, focuses on detecting any signs of unauthorized activity outside a defined boundary. According to the Poisson point process model, full and partial coverage can be achieved by positioning a small number of sensors.

Connectivity, on the other hand, refers to the ability of the sensor nodes to establish communication paths with each other and the sink node. A network is fully connected when every sensor node can communicate with the sink node for data transmission and reception (Chaturvedi et al., 2021). It is essential to ensure both coverage and connectivity when deploying WSNs, as complete coverage without connectivity can lead to a degradation in the quality of service. In some applications, complete coverage is necessary to enable data collection and transmission to the central node. Connectivity can be categorized into two types: one-connectivity, where there is a single path connecting each sensor node to the processing nodes, and k-connectivity, where multiple paths exist between the sensor node and processing node (Lee & Shin, 2017). Considering both coverage and connectivity is crucial for successfully deploying and operating WSNs.

1.1 Related works

Numerous reviews and research articles have been published to address the wide range of coverage problems in wireless sensor networks (WSNs). In Table 1, we have compiled these studies, which directly or indirectly cover the topic, providing an overview of pioneering works that have examined or utilized nature-inspired algorithms for solving coverage problems in WSNs. To facilitate analysis, we have categorized these works based on different attributes, including coverage methods (theory, advantages, and limitations), bibliometric analysis, and machine learning. We delve into the theoretical underpinnings of the works,

Table 1 Summary of the existing survey articles on coverage problems in WSNs

References	Summary of the study	Coverage methods			Bibliometric analysis	Machine learning
		Theory	Pros	Cons		
Chen et al. (2019)	A genetic algorithm-based method for 2D sensing area coverage was presented	✓	✓	✓	✕	✕
Benghelima et al. (2022)	The authors reported optimal placement of SNs in WSNs using Whale Optimization Algorithm (WOA) for surveillance of fire incidents in a SCP with minimum number of nodes for coverage and connectivity	✓	✕	✓	✕	✕
Singh et al. (2021a)	The study focused on nature-inspired optimization algorithms for efficient and optimal coverage in WSNs	✓	✓	✓	✓	✕
Tian et al. (2016)	Improved genetic algorithm and binary ant colony algorithms were combined to address the issue of optimal coverage in WSNs	✓	✓	✓	✓	✕
Zheng et al. (2023)	An improved black hole algorithm for enhancing the longevity of WSNs was reported in the study	✓	✓	✕	✕	✕
Matos et al. (2022)	The authors reviewed optimization issues in WSNs and reported both the major and less common methods that are used to address coverage problems in WSNs	✓	✓	✓	✓	✕
Tripathi et al. (2018)	Presented a taxonomy of methods that could be applied to enhance maximum coverage and connectivity in wireless sensor networks	✓	✕	✓	✓	✕
Chelliah and Kader (2021)	The authors proposed hybrid tunicate swarm optimizer and salp swarm optimizer to solve connectivity and coverage problems in wireless sensor networks	✓	✓	✓	✓	✕
This work	Coverage optimisation: Theory, advantage, limitations, applications, bibliometric analysis are reported	✓	✓	✓	✓	✓

The ✓ and ✕ marks indicate whether the paper broadly covered said scope or not dissecting the core principles and methodologies they employ. We not only explore the foundations upon which these studies are built but also shed light on their practical implications and the advantages they bring to the field. Furthermore, we critically assess the limitations inherent in these approaches, offering a balanced perspective on their applicability and potential shortcomings. In addition, we employ bibliometric techniques to scrutinize the corpus of literature under review. By examining citation patterns, authorship trends, emerging topics and publication sources, we aim to uncover the broader scholarly landscape in which these works exist. This analysis not only provides insights into the impact and influence of these studies but also highlights emerging trends and gaps in the existing literature. In the realm of machine learning, we take a deep dive into the methodologies and algorithms employed by the included works. We also explore how machine learning techniques are leveraged to address the research questions at hand, highlighting the innovative approaches and breakthroughs achieved. Additionally, we consider the broader implications of machine learning in the context of the subject matter and assess the potential for future advancements in this domain. In essence, our categorization scheme serves as a comprehensive framework for dissecting and evaluating the collected works, allowing us to provide a nuanced and thorough analysis of their contributions to the field. By addressing the theory, advantages, limitations, conducting bibliometric analysis, and exploring the role of machine learning, we aim to provide a holistic understanding of the research landscape in question. Notably, none of the existing review or research articles have presented a comprehensive perspective by integrating nature-inspired algorithms, machine learning, and bibliometric analysis to tackle coverage problems in the domain of WSNs.

Existing studies have focused majorly on developing algorithms for data routing in wireless sensor networks to increase the network's lifespan, neglecting area coverage and connectivity challenges. The major contributions of this review is summarized as follows:

1. We present a summary of coverage optimization models in wireless sensor networks.
2. Identify and discuss existing approaches in solving coverage problems in wireless sensor networks.
3. A comprehensive discussion on the applications of machine learning algorithms in solving functional challenges in wireless sensor networks and nature-inspired techniques in solving coverage optimization problems in WSNs.
4. We identify research directions in coverage optimization in WSNs using machine learning and meta-heuristics algorithms.

1.2 Review scope

The coverage problem in wireless sensor networks (WSNs) is widely recognized as one of the most important issues in this domain. We conducted a bibliometric analysis to gain deeper insights into this problem, considering all the research publications that focus on coverage problems in WSNs. Our analysis revealed that the coverage problem in WSNs has garnered significant interest since 2003. We collected metadata from Scopus for 2280 research items addressing the coverage issue. The data showed an exponential growth in the number of research items, emphasizing the significance of this topic.

From 2003 to May 15th, 2023, our analysis identified 1189 original articles, 959 conference proceedings, 56 book chapters, 42 review articles, and 35 other items (such as editorials and comments), as illustrated in Fig. 1. China emerged as the leading contributor with 665 research articles, followed by India (431), the US (296), Taiwan (126), and Canada (98). Most of these studies have employed conventional approaches to tackle the coverage problem.

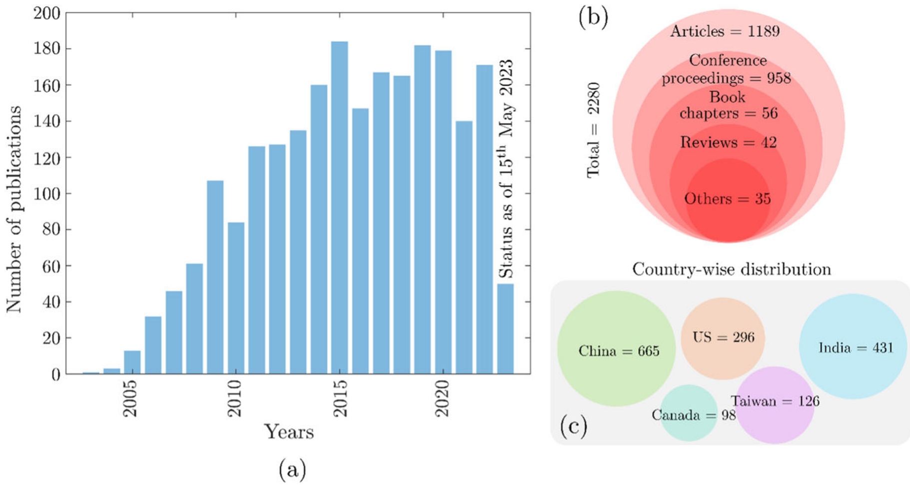


Fig. 1 **a** Number of publications (including research article, conference proceedings, book chapters, and review papers) in the last 20 years (from 2003 to 2023) on WSNs coverage problem (data from Scopus). **b** Categorization based on publication type, and **c** Country-wise distribution of publications (only top 5 countries)

Notably, there is a scarcity of review papers focusing on the coverage problem, highlighting the need for comprehensive overviews. No review paper has been published that specifically discusses the coverage problem using nature-inspired algorithms and machine-learning techniques.

1.3 Contributions and structure

This review paper is organized into eight sections. Section 1 discusses the introduction part, which introduces the coverage problem in WSNs. We also compared the existing review article and discussed the need for this review paper. Section 2 introduces the basic terminologies and theory of the coverage models and types of coverage in WSNs. In the first part of Sect. 2, we discussed frequently used sensing models such as the binary sensing model, probabilistic sensing model, shadow-fading sensing model, and Elfes sensing model. Lastly, we also discussed the finding of the bibliometric analysis. In the second part of Sect. 2, we discussed different types of coverage, such as area, target, and barrier coverage. We also performed a bibliometric analysis and discussed its findings. Section 3 discusses the widely used nature-inspired algorithms such as particle swarm optimization, ant colony optimization, artificial bee colony, genetic algorithm, teaching learning-based optimization, harmony search algorithms, and the corresponding bibliometric analysis. Section 4 discusses the functional challenges in WSNs from the machine learning aspect. Sections 5 and 6 discussed the pioneer studies on coverage problems using machine learning and deep learning, respectively. In Sect. 7, we highlighted the open research problem in WSNs. Finally, in Sect. 8, we concluded and discussed future work. Figure 2 illustrates the road map of the presented review.

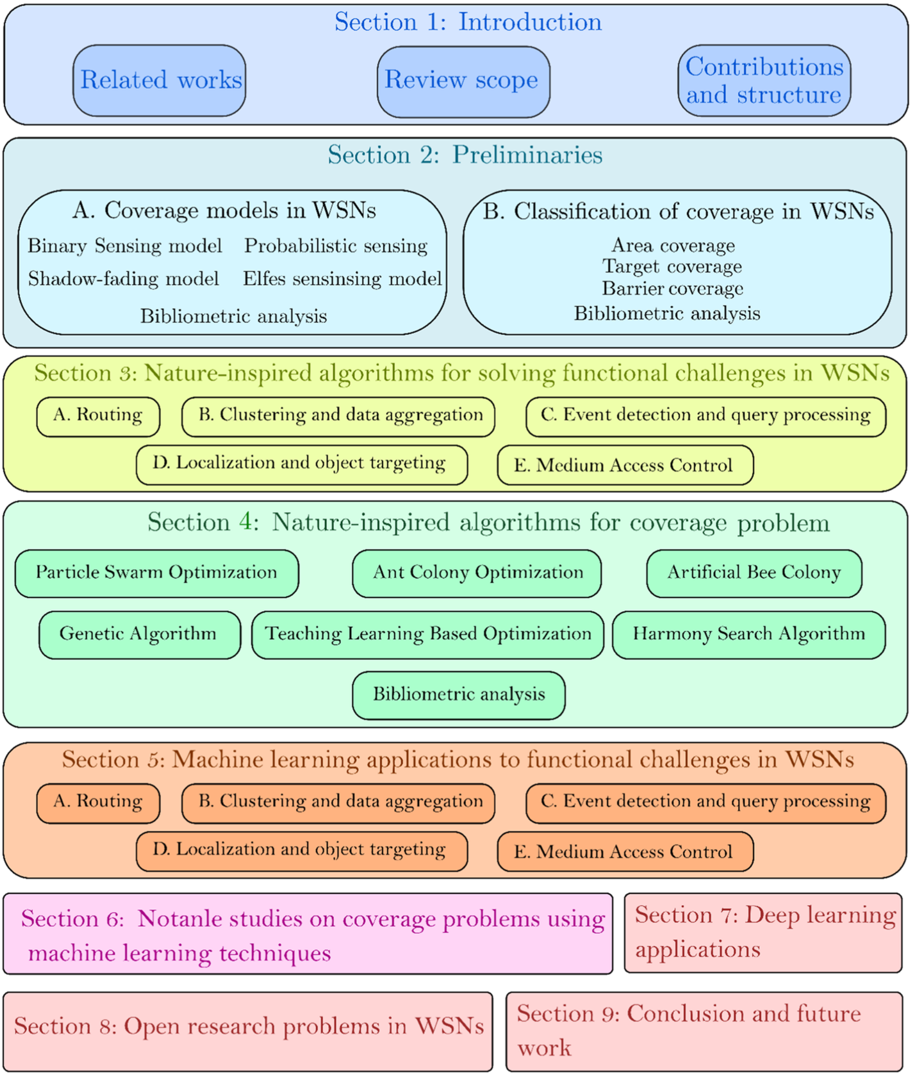


Fig. 2 Structure and contribution of the review paper

2 Preliminaries

In the field of wireless sensor networks, the majority of published articles have predominantly focused on energy-saving methods and routing protocols aimed at prolonging the network's lifespan. Conversely, coverage and connectivity, considered two crucial challenges in WSNs, have received comparatively less attention. However, coverage optimization is a critical issue in WSN due to its direct impact on the network's dependability and performance.

Achieving adequate coverage is essential for monitoring all relevant areas effectively. It enables efficient data collection and transmission, ensuring that the network functions optimally. Despite its significance, coverage optimization has been relatively overlooked in the scholarly literature of wireless sensor networks. To address this gap, further research is needed to develop strategies and algorithms focusing on coverage optimization. By emphasizing the importance of coverage and dedicating more attention to its optimization, researchers can enhance wireless sensor networks' overall performance and reliability. In this section, we present the key preliminaries, definitions, and terminologies related to coverage problems in the domain of wireless sensor networks (WSNs). These concepts serve as the foundation and background for our study.

2.1 Coverage models in WSNs

The WSNs coverage models measure the monitoring ability of the events that occur in the Region of Interest (RoI). The sensing range and communication range are typically necessary for the sensor node's coverage functionality. For each application, coverage and connection are constantly correlated. Figure 3 shows that the connectivity range (Rc) is always assumed to be twice as large as the sensing range (Rs).

It is assumed that at coordinates (x, y), there is a point P and at coordinates (x_i, y_i), there is a sensor node Si, and the Euclidean distance between point P and sensor node Si is given as:

$$d(Si, P) = \sqrt{(x_i - x)^2 + (y_i - y)^2} \tag{1}$$

A sensor node's overall sensitivity at point P is represented as:

$$(Si, P) = \frac{\delta}{(d(Si, P))^k} \tag{2}$$

From Eq. (2), δ, represents the coverage region while k represents the total number of sensor nodes in the coverage region.

The coverage models in the literature are categorized into the following two groups based on the likelihood that events would be detected in the RoI: binary coverage model and probabilistic coverage model (Abidin et al., 2014).

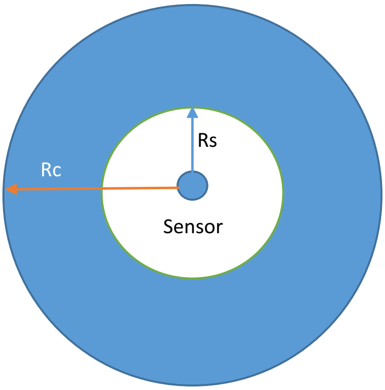
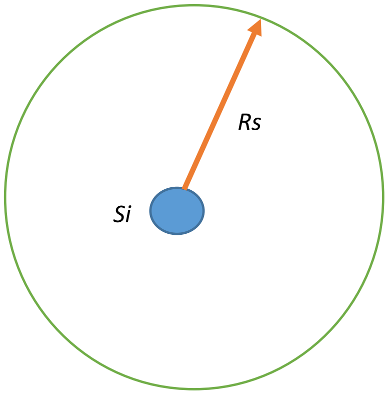


Fig. 3 Communication range (Rc) and Sensing range. *Source*: Nath et al. (2021)

Fig. 4 Binary sensing model



2.1.1 Binary sensing model

The binary or deterministic sensing model is regarded as the simplest sensing model as shown in Fig. 4. In this sensing model, a sensor node only senses the events that lie within the range of sensing and any events that are not within the coverage region are not captured (Abdollahzadeh & Navimipour, 2016; Amutha et al., 2020). If the position of P can be reached based on the sensing ability of the sensor node Rs, then, it may be argued that the sensor node covers this place; otherwise, it cannot. The equation for this coverage model is given as:

$$C_{xy}(Si) = \begin{cases} 1 & if\ d(Si,\ P) < Rs \\ 0 & othewise \end{cases} \tag{3}$$

where $d(Si,\ P)$ represents the Euclidean distance.

2.1.2 Probabilistic sensing model

The binary coverage model does not accurately represent the behavior of the sensor unit and calls for high precision. As a result, the likelihood of monitoring the events can be added to the binary coverage model to create the Probabilistic Sensing Coverage (PSC) model. In the probabilistic model, the more the distance among the sensor nodes, the more the ability of the nodes to sense eents decreases. This model, which posits that the detected event, the design of the sensor, and environmental variables are all stochastic in nature, is more realistic and complete than the binary model (Abdollahzadeh & Navimipour,2016; More & Raisinghani, 2017). The coverage model is expressed as follows:

$$C_{xy}(Si) = \begin{cases} 0, & if\ Rs + Re \le d(Si,\ P) \\ e^{-\delta\alpha^{\beta}} & if\ Rs - Re < d(Si,\ P) < Rs + Re \\ 1, & if\ Rs - Re \ge d(Si,\ P) \end{cases} \tag{4}$$

where Re represents the presence of unstable measure in sensor detection,$0 < Re < Rs$,$\alpha = d(Si,\ P) - (Rs - Re)$;$\delta$ and β are variables that show the measurement of detection probability when there is a distance of Rs from the target.$Rs - Re < d(Si,\ P) < Rs + Re$.

The diagrammatical representation of probabilistic sensing model is shown in Fig. 5.

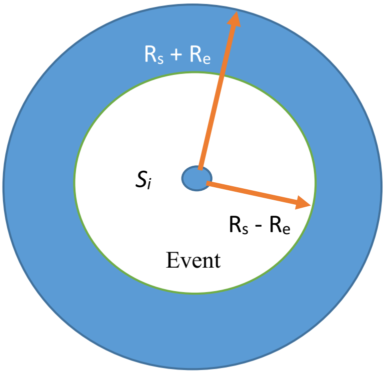


Fig. 5 Probabilistic sensing model

2.1.3 Shadow-fading sensing model

Shadowing in radio wave propagation is comparable to this sensing concept. The sensing capacity of each node in this sensing model varies with respect to the directions it can sense. This model takes into account the dependency of all the factors (obstacles such as foliage and building). In this sensing model, different directions have different sensing radius (Hossain et al., 2008). The likelihood that an event at a distance x from the node would be detected is determined by the log-normal shadowing path loss model expressed as:

$$P_{det}(x) = Q\left(\frac{10nlog_{10}(x/r_s)}{\sigma}\right) \tag{5}$$

where the path loss exponent expressed as $(2 \leq n \leq 4)$ is represented by n, the radius of sensing without fading is denoted by r_s, the fading parameter is represented by σ.

2.1.4 Elfes sensing model

This model gives the expression in Eq. (6) as the likelihood that a sensor will detect an event at a distance x.

$$p(x) = \begin{cases} 1,\ x \leq R_1 \\ e^{-\lambda(x-R_1)^{\gamma}} & ,\ R_{max} > x > R_1 \\ 0,\ x \geq R_{max} \end{cases} \tag{6}$$

where, R_1 indicates possibilities of uncertainty in sensed data and the parameters λ and γ are adjusted in line with the physical characteristics of the sensor. R_{max} is the maximum range the node can sense ((Hossain et al., 2008; Wang et al., 2015)).

2.1.5 Bibliometric analysis

We performed bibliometric analysis using Scopus data. We performed a query and extracted the keywords using WSNs and Sensing models. We found that a total of 885 research articles are published, which includes both WSNs and sensing models as author keywords. In total, these articles consist of 6000+ keywords which we filtered by the number of occurrences. We extracted those keywords that are repeated in at least five research publications, resulting in a total of 939 keywords that get clustered into 17 clusters (shown in 17 different colors) using

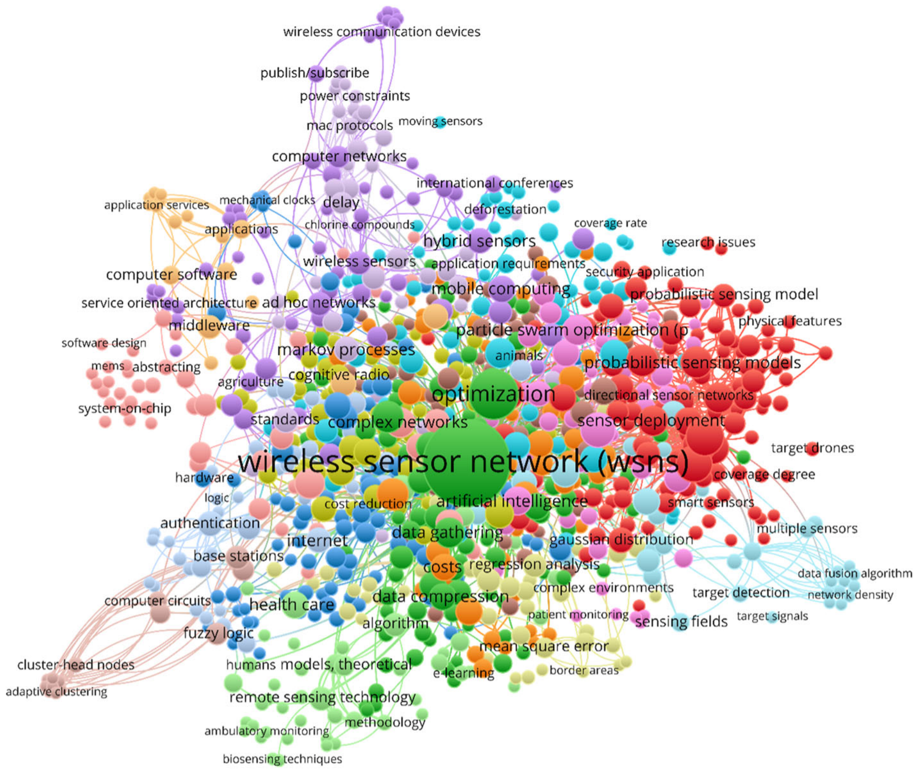


Fig. 6 Bibliometric analysis of keywords "WSNs" and "Sensing models."

the bibliometric clustering algorithm. These clusters form 17,885 links among them, with a total link strength of 21,810. We found that the total link strength associated with binary and probabilistic sensing models is high, indicating their wide usage. The illustration is given in Fig. 6.

2.2 Classification of coverage in WSNs

Coverage in WSNs is classified as follows:

2.2.1 Area coverage

The area coverage, which can also be regarded as blanket coverage monitors the RoI using a collection of sensor nodes that are deployed in wireless sensor networks. Figure 7 is an example of a WSN that is randomly deployed to monitor a given RoI. In the network, the sensing range of the sensor nodes are represented by circles. The arrow in the circle indicates the sensing radius of each sensor node represented by the circle.

The coverage optimization problem is assumed to begin with a two-dimensional domain of A-sized $W x H$ and a defined size of sensors. The entire set of sensors consist of k different types and the sensors that belong to type i have a predetermined sensing radius r_i. The main goal is to achieve an optimal deployment strategy for all the sensor nodes in the network such

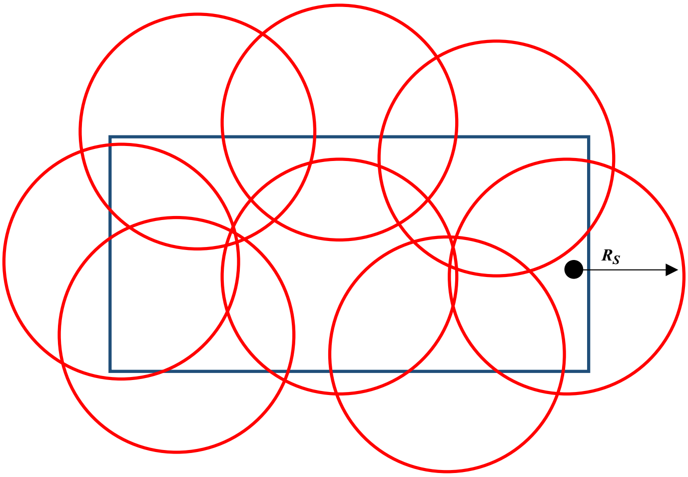


Fig. 7 Area coverage in a sensor network

that their coverage area denoted as coA on A is optimized. The $CoverageArea - coA$ of n sensor nodes regarded as the total coverage area casted on the domain A is optimized as:

$$coA = area\left(\bigcup_{i=1}^{k}\bigcup_{j=1}^{n_i} c_{r_i}(x_{i_j}, y_{i_j}) \cap A\right) \rightarrow max \tag{7}$$

$c_{r_i}(x_{i_j}, y_{i_j})$ shows the representation of the circle at (x_{i_j}, y_{i_j}) and r_i represents the radius. The $area(X)$ represents the area of the domain X. This coverage optimization problem is however NP-hard.

2.2.2 Target coverage

The target coverage, also referred to as point coverage monitors a particular targets in the RoI. Figure 8 shows a target coverage representation in which five targets are monitored by the deployed three sensor nodes in the RoI. As shown in Fig. 8, t_1, t_2, t_3, t_4 and t_5 represent targets in the network which shows the points sensor nodes are deployed to gather physical phenomenon from. S_1, S_2 and S_3 are sensor nodes that are deployed to monitor defined targets in the network. In the network, only one sensor node is deployed to cover targets t_1, t_3, and t_4. Two sensor nodes are deployed to cover targets t_2 and t_5 simultaneously. The S_1 is a sensor node that monitors the targets within its sensing radius which are t_1 and t_2. The energy utilization is minimized by the target coverage since it is only a particular location in the RoI that is monitored. Toloueiashtian et al. (Toloueiashtian et al., 2022) reported a model for solving point coverage problem in WSNs. However, as more sensor nodes are added to the sensory area, the algorithm become stuck in a local optimum.

However, in the network design that would be proposed in our subsequent studies, the network would be designed with a certain level of Quality of Service (QoS) for maximum coverage. Presence of holes affects the reliability, network coverage rate and QoS. In order to address these issues, more sensor nodes can be deployed in critical areas.

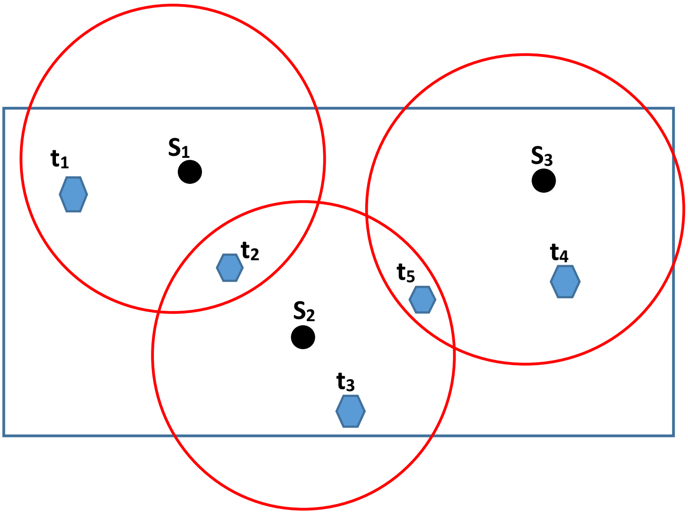


Fig. 8 Wireless sensor networks target coverage

2.2.3 Barrier coverage

The major focus of barrier coverage is on constructing a barrier that detects intrusion. In this classification of coverage, sensor nodes detect any intrusion that takes place along the barrier. Phenomena such as shadowing, interference, multipath losses and fading are common with radio waves propagation which eventually affect the strength and quality of the signal. Sensing range is a pivotal feature for predicting k-coverage probability (Nagar et al., 2023). Intrusion detection at border areas of critical network infrastrucuture is importance and demands a high level of accuracy. For accurate barrier coverage provisioning, at least one barrier must exist for every possible intrusion path. Maintaining this strategy can identify and prevent any intrusion attempts in a timely and safe manner (Singh et al., 2022a, 2022b).

The coverage areas of various nodes interact with crossing pathways in the region of interest to create a barrier path. There must be at least one barrier passage from one side of the border region to the other parallel side in order to guarantee barrier coverage. By monitoring every point along the barrier path in this manner, the deployed network would be able to identify any intrusion to the area of interest (Amutha et al., 2020). Barrier coverage is divided into two categories which are weak barrier coverage and strong barrier coverage. The quality of events detection on the boundary of the RoI determines this categorization. Figure 9 shows an illustration of strong barrier coverage. Strong barrier coverage provides continuous coverage and ensures that every event or intrusion since any crossing needs to traverse a barrier. Where there are some uncovered region or holes, it is regarded as weak barrier coverage as shown in Fig. 10. Unconvered regions in Fig. 10 means that there is no global barrier coverage in the network domain. In that case, sensitive events that take place within the region can go undetected.

In weak barrier coverage, the horizontal projections of sensing regions overlap and guarantee to detect movements only along the vertical traversing paths (Tripathi et al., 2018).

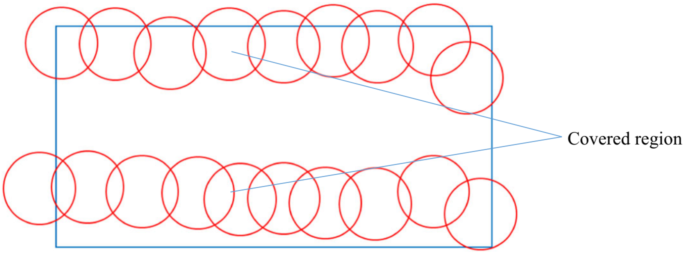


Fig. 9 Strong barrier cov + erage

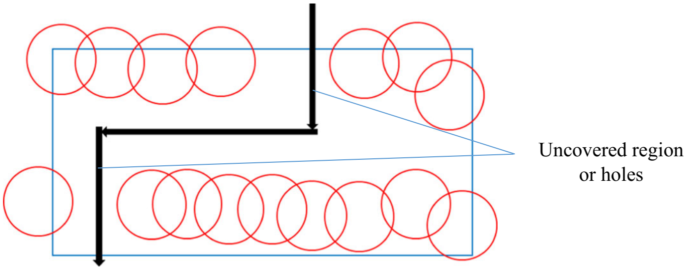


Fig. 10 Weak barrier coverage illustration

2.2.4 Bibliometric analysis

We performed bibliometric analysis using Scopus data. We performed a query and extracted the keywords using *WSNs* and *Coverage*. We found that a total of 1200+ research articles are published, which includes both WSNs and coverage as author keywords. In total, these articles consist of 9084 keywords which we filtered by the number of occurrences. We extracted those keywords that are repeated in at least five research publications, resulting in a total of 1000+ keywords that get clustered into 14 clusters (shown in 14 different colors) using the bibliometric clustering algorithm. These clusters form 46,033 links among them, with a total link strength of 102,851. We found that the total link strength associated with target and k-barrier coverage is high, indicating their wide usage. The illustration is as shown in Fig. 11.

3 Nature-inspired algorithms for solving functional challenges in WSNs

In the dynamic landscape of WSNs, the quest for effective and flexible solutions to a multitude of operational challenges has taken center stage. These challenges cut across a wide spectrum of problem areas, encompassing tasks such as optimizing energy consumption, improving data routing, enhancing network coverage, and bolstering resilience against ever-changing environmental conditions. It's in this demanding arena that nature-inspired algorithms have emerged as a beacon of promise. These algorithms, drawing inspiration from the intricate workings of the natural world, present a novel and innovative approach to addressing the intricate issues that permeate the world of WSNs. In this section, we embark on a journey to explore the transformative potential of nature-inspired algorithms, illuminating their practical

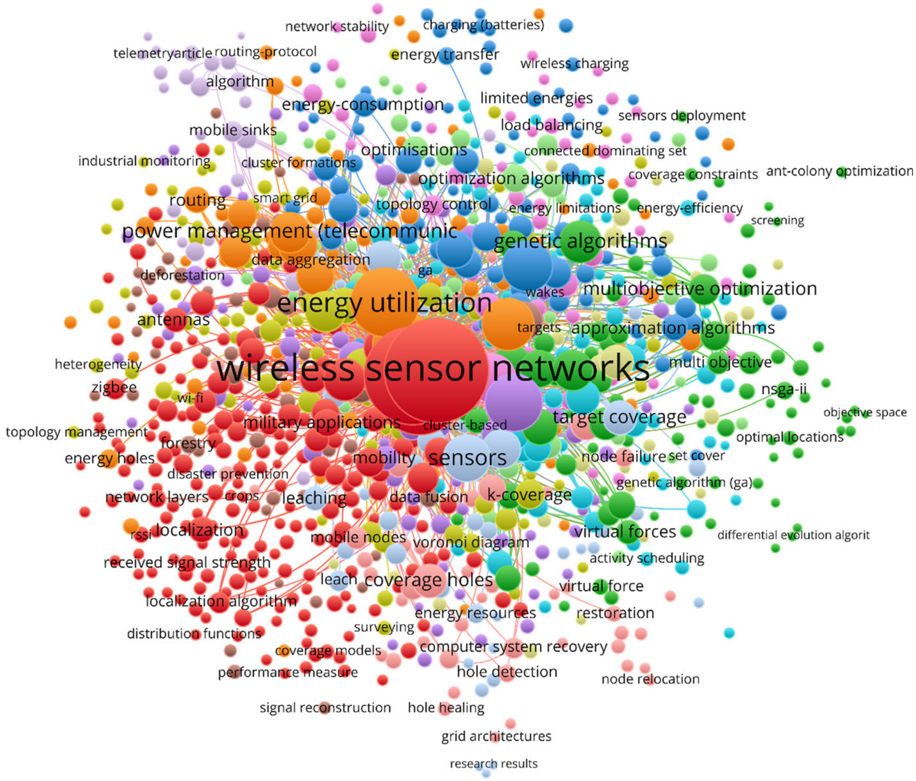


Fig. 11 Bibliometric analysis of keywords “WSNs” and “Coverage.”

applications across diverse problem domains within WSNs and showcasing their capacity to deliver solutions that are not only efficient but also adaptive and sustainable (Fan et al., 2023). These algorithms exhibit robustness and remarkable adaptability, rendering them highly suitable for tackling challenging problems within both theoretical research and engineering technology. Notable wireless network issues, including routing, clustering, data aggregation, event detection, and query processing, can be effectively addressed through the application of artificial simulations inspired by swarm intelligence-based solutions, drawing insights from the foraging behavior of ants, termites, and honey bees (Datta & Nandakumar, 2017; Singh et al., 2021b).

3.1 Routing

In Wireless Sensor Networks (WSNs), the task of finding the most efficient paths in terms of energy usage is of utmost importance. There have been various methods proposed in scientific literature to tackle this challenge. However, designing a routing technique that can work effectively across different scenarios while maintaining network integrity, connectivity, and inclusiveness is both complex and resource-intensive. These challenges fall into the category of Non-deterministic Polynomial-time (NP-hard) problems, which means they are computationally demanding and difficult to solve precisely within a reasonable amount of time. Given the complexity of NP-hard problems, it is appropriate to employ metaheuristic algorithms to find approximate solutions. Metaheuristic algorithms are a class of optimization techniques that take inspiration from natural processes or behaviors to find good solutions to difficult problems. They are particularly well-suited for addressing NP-hard problems because they can efficiently explore solution spaces without guaranteeing the absolute optimal solution.

Seyyedabbasi et al., as discussed in reference Wang et al. (2015), introduced a versatile architectural framework capable of performing routing tasks without incurring any additional cost. This architecture is designed to seamlessly integrate with a variety of metaheuristic algorithms. Its generic nature allows it to adapt and work effectively with different metaheuristic algorithms, making it suitable for various purposes and problem-solving scenarios. Routing is a critical challenge in WSNs, and finding an exact deterministic solution for it is currently not known. This implies that there is no straightforward, fixed method to solve the routing problem in WSNs with guaranteed optimality. Consequently, researchers have turned to nature-inspired optimization algorithms, such as those inspired by biological or physical processes, to discover cost-effective routing paths and other techniques to improve the performance of WSNs. These nature-inspired algorithms provide solutions that may not be optimal but are often close to it while being computationally feasible. They offer low-cost routing options and are one of the approaches used to tackle the complex routing problems in WSNs.

3.2 Clustering and data aggregation

In Wireless Sensor Networks (WSNs), clustering is a fundamental strategy where the network is divided into smaller groups known as clusters, each managed by a cluster head. The primary goal of clustering in WSNs is to aggregate data efficiently, potentially extending the network's lifetime by reducing energy consumption through data grouping. Within this clustering approach, a critical element is the Cluster Head (CH), chosen to handle the transmission of data from the cluster to a central point referred to as the sink node (Vellaichamy, et al., 2023). Cluster heads are responsible for coordinating data collection and aggregation within their respective clusters, making them crucial nodes in the network.

The network hierarchy consists of top-level nodes, which serve as cluster heads, and next-level nodes, responsible for data collection and relaying it to the cluster head for further processing. Communication within clusters is facilitated by neighbor nodes, forming the local communication backbone. While conventional clustering methods have been employed in the past, they may not consistently deliver efficient results in terms of energy usage and network performance. To address these limitations, clustering-based optimization techniques have gained prominence. These techniques utilize various optimization algorithms to determine the optimal clustering scheme that minimizes energy consumption and maximizes network efficiency (Feng et al., 2019a).

Data aggregation, particularly within heterogeneous sensor networks, holds significant importance for ensuring efficient network operation. The process of scheduling data aggregation is a critical aspect in achieving this efficiency, often accomplished through the application of optimization techniques such as Particle Swarm Optimization (PSO). PSO, drawing inspiration from the social behavior of animals, stands out as a widely adopted optimization method utilized to refine clustering schemes and bolster the performance of Wireless Sensor Networks (WSNs). In essence, the concept of clustering in WSNs involves the organization of sensor nodes into distinct clusters, each led by a designated cluster head. This clustering mechanism serves to streamline the management of data aggregation and transmission. The introduction of clustering-based optimization approaches, exemplified by the use of PSO, has paved the way for the development of more energy-efficient and performance-enhanced clustering strategies. Ultimately, these advancements contribute significantly to the overall effectiveness and reliability of WSNs (Singh et al., 2022a).

3.3 Event detection and query processing

Ensuring the precision and dependability of data gathered by sensor nodes constitutes a critical hurdle in the realm of Wireless Sensor Networks (WSNs). When the data within the network lacks reliability, it can yield far-reaching consequences, including the degradation of original data quality, adverse impacts on network performance, and a skewed portrayal of real-world events within the network's purview. As noted by Fan et al. in their work referenced in Abdollahzadeh and Navimipour (2016), they introduced an ingenious solution that employs a Particle Swarm Optimization (PSO) algorithm to optimize the initial weights and biases of a Back Propagation Neural Network (BPNN). This optimization methodology not only reduces the training time of the neural network but also bolsters its predictive accuracy. By elevating the efficiency and accuracy of data processing within sensor nodes, this approach substantially enhances the overall dependability of data collected by the network. Addressing the challenge of guaranteeing dependable and precise data collection in WSNs necessitates the incorporation of various key considerations and technologies:

3.3.1 WSN protocol design

Crafting WSN protocols that prioritize dependable and precise data collection by sensor nodes is paramount. This encompasses the formulation of communication strategies, data aggregation techniques, and error correction mechanisms aimed at elevating data quality.

3.3.2 Anomaly detection

Anomaly detection technology assumes a pivotal role in discerning abnormal or erroneous data points within the continuous flow of sensor data. The identification of anomalies empowers the network to take corrective actions to mitigate the impact of unreliable data.

3.3.3 Bio-inspired algorithms

Drawing inspiration from natural processes, bio-inspired algorithms have emerged as promising tools in confronting diverse challenges in WSNs. These algorithms exhibit particular efficacy in event detection and query processing, thereby enhancing the precision and dependability of real-world event identification within the network's monitoring domain.

In summation, assuring the accuracy and reliability of data collected by sensor nodes in WSNs is a multifaceted endeavor. It encompasses considerations in protocol design, the integration of anomaly detection technologies, and the application of bio-inspired algorithms to streamline data processing. These concerted efforts collectively yield more trustworthy data, ultimately elevating the overall performance and utility of WSNs for real-world applications.

3.4 Localization and object targeting

Accurate information localization stands as a pivotal element within the realm of Wireless Sensor Networks (WSNs). In the context of WSNs, localization pertains to the process of pinpointing the geographic coordinates of sensor nodes, a critical requirement for a multitude of applications. This localization process encompasses several key steps, including event location determination, data gathering from neighboring devices, and assessment of network coverage. Conventional techniques for localizing sensor nodes, such as relying on Global Positioning System (GPS) services and other established methods, often incur significant costs and energy expenditure. Consequently, researchers have introduced alternative localization approaches that enable nodes to ascertain their positions more efficiently. These approaches generally fall into two main categories: range-based and range-free techniques, as elaborated in reference (Singh et al., 2022b).

3.4.1 Range-based techniques

Range-based localization methods revolve around the measurement of distances or ranges between sensor nodes, employing techniques such as time-of-flight, signal strength, or angle of arrival. These measurements facilitate the estimation of node positions relative to one another through triangulation. However, it's worth noting that these methods may demand precise hardware and can consume substantial energy resources.

3.4.2 Range-free techniques

In contrast, range-free localization methods do not rely on exact distance measurements. Instead, they utilize proximity or connectivity information to approximate node positions. These techniques often prove more energy-efficient but may compromise on accuracy.

In the realm of localization algorithms, the primary objective remains the swift and precise determination of sensor node locations. However, within the context of WSNs, considerations surrounding energy efficiency and computational resources are paramount. Localization protocols must be thoughtfully designed to minimize energy consumption and computational overhead, ensuring the network operates efficiently and boasts an extended lifespan. One particular algorithm mentioned in the provided text is the Bat Optimization Algorithm (BOA). BOA stands as an exemplary instance of an optimization algorithm applied to address the challenge of node localization. Its aim is to enhance the accuracy and efficiency of node localization when compared to existing optimization algorithms. BOA achieves this by mitigating localization errors and reducing computational time, aspects of utmost importance in resource-constrained WSN environments.

In summation, the precision of information localization holds immense significance within WSNs, catering to a diverse range of applications. Traditional localization techniques often come with notable costs and energy consumption, prompting the development of alternative methodologies, including range-based and range-free approaches. The overarching objective of localization algorithms is to swiftly and accurately determine node positions, all while meticulously considering energy efficiency and computational resources. Algorithms such as BOA symbolize significant advancements in this field, offering heightened accuracy and reduced computing time for node localization in WSNs.

3.5 Medium access control

The efficiency of Wireless Sensor Networks (WSNs) plays a crucial role in ensuring their effective operation. To achieve this efficiency, it is imperative to carefully design the Medium Access Control (MAC) routing protocol, which is responsible for transmitting information to the sink node while utilizing low-cost communication links. A MAC protocol for data communication is essential among nodes within a WSN, as it is tasked with determining a reliable path for data transmission throughout the network. Many data communication protocols have been devised to maximize energy efficiency, evenly distribute the energy load across all nodes, and minimize power consumption in the network.

In a notable contribution, Vellaichamy et al. (as documented in reference Toloueiashtian et al., 2022) proposed a multi-criteria optimal bio-inspired MAC protocol. This innovative protocol was designed with the primary goals of enhancing the network's lifetime and prolonging the operational time of WSN-based applications. This research underscores the significance of developing MAC protocols that can effectively address the unique challenges and requirements of WSNs. It is important to note that designing MAC protocols for WSNs presents a complex problem that has garnered considerable attention from researchers in the field. This problem is regarded as NP-hard, meaning that finding optimal solutions can be extremely challenging and computationally intensive. Consequently, researchers have turned to optimization algorithms inspired by nature, such as genetic algorithms or particle swarm optimization, to explore efficient alternatives among various options (as indicated in reference Fan et al., 2023). These nature-inspired algorithms leverage principles from biology or natural phenomena to seek optimal or near-optimal solutions for MAC protocol design, thus mitigating the computational complexity of the problem.

In the context of WSNs, route optimization algorithms go beyond considering just the shortest path distance. They also take into account factors such as energy efficiency and network lifespan. This holistic approach to routing optimization ensures that data is transmitted not only efficiently but also with a focus on preserving the network's energy resources and overall longevity. In summary, the efficient design of MAC routing protocols and the incorporation of optimization algorithms are pivotal in achieving the desired performance and longevity of Wireless Sensor Networks.

Table 2 provides a summary of various bio-inspired algorithms utilized to tackle significant challenges within the realm of Wireless Sensor Networks (WSN). The selection of a specific bio-inspired algorithm depends on the particular problem at hand. Additionally, the survey reveals that multiple authors have employed diverse evaluation metrics to assess the effectiveness of their protocols and methodologies. Across several of the functional challenges discussed, two commonly used evaluation criteria are throughput and network lifetime.

4 Nature-inspired algorithms for coverage problems

In this section, we explore the existing approaches that have been reported in addressing the coverage challenges of wireless sensor networks (WSNs).

The deployment strategy of sensor nodes plays a crucial role in determining the level of coverage achieved by the nodes in the target region and how the sensory data can be effectively communicated to the sink node. When evaluating the performance of a sensing network, the spatial distribution of nodes becomes a critical factor to consider.

Table 2 Summary of nature-inspired algorithms for solving functional challenges in WSNs

Functional challenge	Bio-inspired algorithms	Performance metrics	Remarks
Routing (Dayal & Bassoo, 2022; Seyyedabbasi et al., 2023)	Incremental Grey Wolf Optimization (I-GWO), Expanded Grey Wolf Optimization (Ex-GWO), Red-Deer Algorithm	(1) Network lifetime, (2) the alive node ratio in the network, (3) the packet delivery ratio and lost data packets, (4) routing overhead, (5) throughput, and (6) convergence behavior	The authors proposed a generic system architecture that combines the metaheuristic and network model to provide an adaptable system that can serve numerous purposes
Localization (Aldeen et al., 2023)	Particle Swarm Optimization	average localization error, normalized localization error and root-mean-square error	The authors adopted PSO technique for the selection of candidate nodes and their coordinates calculation
Clustering and data aggregation (Vellaichamy, et al., 2023)	Moth Flame and Salp Swarm Optimization algorithms	Energy consumption, throughput, end-to-end delay, latency, lifetime, and packet delivery rate	A combined bio-inspired algorithm that serves as a better substitute for energy-efficient routing for the WSN was provided. Minimal energy consumption was attained in terms of throughput, minimal latency, and maximum packet delivery
Event detection and query processing (Fan et al., 2023)	Particle Swarm Optimization	Detection accuracy and False positive rate	Improved particle swarm algorithm was combined with Back Propagation Neural Network to achieve events detection in WSNs
Localization and object targeting (Dev, 2023)	Hybrid Particle Swarm Optimization (PSO)-Grey Wolf Optimization (GWO) algorithm with Poor-for-Change strategy	Object localization error	In the proposed study, unknown node locations were estimated using traditional algorithms while in step 2, the hybrid nature-inspired algorithm with poor-for-change strategy was used for minimization of the localization error
Medium Access Protocol (Seyyedabbasi et al., 2023)	Incremental Grey Wolf Optimization (I-GWO) and Expanded Grey Wolf Optimization (Ex-GWO) algorithms	Network lifetime, alive node ratio in the network, packet delivery ratio and lost data packets, routing overhead, throughput, and convergence behavior	The proposed methods provide more efficient execution time and CPU power in time and space complexities

Deploying WSNs poses a significant challenge, and various algorithms and models have been proposed in the literature to solve this problem and maximize coverage and connectivity. One of the key issues addressed is optimization, which can be approached using single-objective or multi-objective methods. Single-objective optimization techniques focus on maximizing a specific performance indicator. However, in real-world applications, relying solely on single-objective optimization may lead to undesirable trade-offs. For example, optimizing coverage alone may result in a large number of sensor nodes, leading to increased energy consumption and reduced network lifetime.

To overcome this limitation, the recommendation is to employ multi-objective optimization techniques in WSN deployment. These techniques aim to simultaneously satisfy multiple objectives while considering various constraints and restrictions. By considering multiple objectives, such as coverage, energy efficiency, network lifetime, and connectivity, a more balanced and efficient deployment of sensor nodes can be achieved. By utilizing multi-objective optimization techniques, researchers and practitioners can find deployment strategies that strike a balance between coverage and other performance metrics, resulting in more robust and sustainable wireless sensor networks (Abdulwahid & Mishra, 2022).

The placement of sensor nodes is a critical challenge in the deployment of wireless sensor networks (WSNs). If the nodes are not strategically positioned, coverage holes can occur, where certain areas of the terrain are not monitored by any sensor node. These coverage holes lead to a lack of data collection and potential gaps in network connectivity. Achieving full connectivity among sensor nodes can be challenging due to the distance between them. When nodes are far apart, it becomes difficult to establish reliable communication links, resulting in increased energy consumption for sensing and communication tasks.

In a study by Akbar et al. (2019), the Fruit Fly Optimization (FOA) algorithm was compared with Particle Swarm Optimization (PSO) and the Territorial Predator Scent Marking Algorithm (TPSMA) to address the coverage holes problem. The performance of these algorithms was evaluated based on metrics such as energy consumption, coverage, and connectivity. Another study by Boualem et al. (2018) discussed deterministic and random deployment techniques for achieving coverage in wireless sensor networks. The researchers highlighted that random deployment can be effective in vast areas where human intervention is limited or impractical. On the other hand, deterministic deployment provides an alternative when human intervention is possible for troubleshooting, battery replacement, configuration adjustments, and node repositioning. The size of coverage within the network plays a crucial role in ensuring that an Area of Interest (AoI) is adequately monitored in most WSNs. By carefully considering deployment strategies and optimizing coverage, WSNs can effectively capture and monitor the desired areas of interest, leading to improved performance and reliable data collection.

Efficient mechanisms for deploying sensor nodes are crucial to maximize coverage rates in wireless sensor networks. However, previous studies have not fully addressed the impact of the increasing size of mobile agents as they move between nodes for data gathering. To tackle this issue, Alsboui et al. (2022) proposed a Graph-based Dynamic Multi-Mobile Agent Itinerary Planning approach (GDMIP). This method aims to handle node failures caused by diminishing energy levels and optimize travel routes for mobile agents, ensuring timely data transmission to processing nodes. In the context of Internet of Things (IoT) applications, Alsboui et al. (2020) introduced the Mobile Agent Distributed Intelligence Tangle-based architecture (MADIT). MADIT enables scalable and efficient IoT applications by facilitating local interactions among Internet-enabled devices. Computation is offloaded to resource-rich devices, thereby conserving energy usage. These approaches address specific challenges posed by wireless sensor networks and contribute to the development of protocols and tools tailored to their unique characteristics.

Wireless sensor networks present various challenges related to routing, scheduling, security, node clustering, localization, data aggregation, data integrity, fault detection, and coverage. Machine learning techniques offer promising solutions to enhance the capacity of wireless sensor networks to adapt to environmental changes (Alsheikh et al., 2014). However, there is a need to consider the limited resources of the network and select appropriate learning themes and patterns that effectively address the specific problem at hand. Additionally, further investigation is required to address coverage and connectivity issues in wireless sensor networks.

Researchers, such as Al-twalah et al. (2020), have explored the use of deep learning techniques to develop routing algorithms and improve wireless network performance. Deep learning, a subfield of machine learning based on artificial neural networks, allows for the simulation of human brain functions. By leveraging dynamic alternative paths and reducing data traffic, deep learning can optimize routing paths, enhance performance, and increase routing accuracy in wireless networks.

Ardakani (2021) introduced the MINDS protocol, which utilizes mobile agents for the collection of sensory data. MINDS aims to reduce network congestion, enhance data robustness, and minimize delay. The protocol divides the sensor network into data-centric clusters using the Hamming distance approach, with cluster-heads forming a tree-based data-centric communication infrastructure based on named data networking. Mobile agents traverse this tree-like infrastructure using a modified version of the Depth-First Search algorithm, considering hop count to optimize their movement. These studies demonstrate the ongoing efforts to develop innovative approaches and protocols to address deployment, routing, and performance challenges in wireless sensor networks. By incorporating machine learning techniques and optimizing resource utilization, these advancements contribute to the improvement of coverage, connectivity, and overall network efficiency.

In Bhatti's study (2018), a model was developed to address the localization issue in wireless sensor networks by mapping it onto various machine learning models. Unlike previous studies that treated localization as a classification problem, Bhatti's approach treated it as a regression problem. The study also explored the impact of deploying anchor nodes in a grid pattern rather than randomly throughout the network domain. Various network parameters such as anchor node population, network size, transmitted signal power, and wireless channel quality were considered. Simulations were conducted to analyze the performance of the localization models after defining feature vectors and mapping them onto regression models.

Nguyen et al. (2021) proposed an energy-efficient distributed algorithm for solving the target coverage problem in wireless sensor networks. The algorithm involved the rotation of a group of sensor nodes to monitor events based on cover sets and available energy for each time slot. To reduce control message overhead, a clustering approach based on target point locations was introduced. The study also presented a cover set construction algorithm to group sensor nodes that could collectively cover all target points within a cluster. However, classical machine learning or bio-inspired algorithms were not utilized in this particular study. Another study by Nguyen and So-In (2018) focused on a distributed deployment technique for improving barrier coverage in wireless sensor networks with mobile sensors. The technique allowed for the relocation of sensor nodes after the initial deployment. However, global optimization was not achieved through the use of soft computing strategies in this study.

The concept of "swarm" refers to a gathering of cooperating insects or flying objects that work together to achieve a common goal. Swarm intelligence (SI) refers to the collective intelligence exhibited by a group of units within a network. SI draws inspiration from the organization, communication, warning systems, army maintenance, and division of labor observed in social insects such as ants, wasps, termites, and bees. The adaptability and flexibility of these social insect colonies have led researchers to adopt swarm intelligence concepts for both inter-cluster and intra-cluster communication. Observations of individual insects within colonies, such as bee dancing, ant pheromone secretion, and specific signaling behaviors, have influenced the development of nature-inspired algorithms for wireless sensor networks.

These nature-inspired algorithms are widely used in the field, leveraging the concepts derived from swarm intelligence. By emulating the behaviors and interactions observed in social insects, these algorithms aim to improve the efficiency and performance of wireless sensor networks.

4.1 Particle swarm optimization

PSO is a popular intelligent optimization algorithm that is based on population. The search space is first initialized with a set of particles. With three indications of position, velocity, and fitness value, each particle represents a potential best-case scenario for solving the extremum optimization issue. The predefined fitness function is used to assess the benefits and limitations of the particle's position as it progresses across the solution space (Gou & Sun, 2021). Particles track their individual historical extremum and population extremum during each cycle, updating their velocity and position accordingly.

The original PSO model consists of a swarm of particles moving in an n-dimensional space, randomly generated within real-valued search space. In the PSO formulae, the subscript *(i, j)* denotes the *ith* particle in the *jth* dimension, and *j* is from *1* to *n* ($j \in 1,\ldots,n$).

Fan and Chiu in Fan and Chiu (2007) provided the foundation for the update formula given as follows:

$$V_{ij}(t+1) = \omega_t V_{ij}(t) + c_1 r_1 [p_{ij}(t) - x_{ij}(t)] + c_2 r_2 [g_{ij}(t) - x_{ij}(t)] \tag{8}$$

At each time step t, the old velocity is updated to generate the new velocity $V_{ij}(t+1)$.

In Eq. (8), the number of current iteration is represented by t; ω_t represents the weight of inertia. The inertia weight is a scaling factor associated with the velocity from the previous time step; V_{ij} is the velocity vector of the ith particle in the jth dimension at time t. c_1 and c_2 represent the learning factors which are also regarded as acceleration constants or control parameters; the random numbers between 0 and 1 are represented by r_1 and r_2. $p_{ij}(t)$ is the historical optimal position of particle i at dimension j. The randomness of particle movement is increased by these numbers. $x_{ij}(t)$ is the current position of the particle, and $g_{ij}(t)$ is the global optimal position of the current population. ω_t is defined as a linearly decreasing weight which is expressed as:

$$\omega_t = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{t_{max}} \times t \tag{9}$$

where t_{max} is the highest iterations number, ω_{max} and ω_{min} are the respective initial and final values of inertia weight. The inertia weight regulates how much of the previous velocity should be retained from the previous step. A larger inertia weight facilitates a global search, while a smaller inertia weight facilitates a local search. The velocity change informs the updating of the position of the particle as expressed in the formula given in Eq. (10) which shows that a new position is calculated as the sum of the previous position and the new velocity.

$$x_{i,j}(t+1) = x_{i,j}(t) + V_{i,j}(t+1) \tag{10}$$

Updating the position of particle i at dimension j given as $x_{i,j}(t+1)$ is dependent on the current position of particle i at dimension j and the new velocity vector represented as $x_{i,j}(t)$ and $V_{i,j}(t+1)$ respectively.

Many authors have attempted to solve many challenges of WSN on the basis of PSO technique and in collaboration with other classical algorithms. Olayode et al. (2021) applied an artificial neural network combined with particle swarm optimization (ANN-PSO) to solve the problem of traffic congestion at signalized road intersections. Sixu et al. (2022) introduced a fusion of artificial bee colony and particle swarm optimization techniques for clustering in WSNs. While an artificial bee colony was utilized to create the base station traversal path, PSO was employed to determine the cluster heads and sojourn sites of the base station. The resilience of the strain–displacement transfer connection was the main topic of earlier research projects that used single-objective optimization. Studies have demonstrated that using single-objective optimization, it is challenging to strike a compromise between resilience and accuracy. Zhao et al. (2019) highlighted a bi-objective optimal model for sensor nodes distribution scheme. Particle swarm optimization was combined with chaos optimization to solve coverage problem in wireless sensor networks (Zhao et al., 2022). The study represents all sensor locations as a particle position. However, multi-objective optimization was not considered in the study.

PSO suffers from the same issues as other meta-heuristic algorithms, including local optimal stagnation and poor convergence accuracy. Scholars will continue to explore the opportunities to improve the execution efficiency and global search ability of the algorithm.

4.2 Ant colony optimization

The ant colony optimization algorithm is a probabilistic technique that is modeled after how natural ants behave. The fundamental concept behind this swarm intelligence technique is similar to how ants use pheromone to determine the optimal path between two points. Figure 12 shows the concentration of ants' pheromone based on number of ants that follow a particular path.

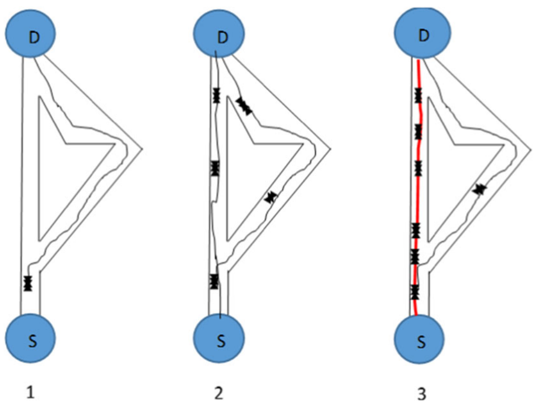


Fig. 12 Natural behavior of ants

In Fig. 12, **S** stands for the source ants start their search for food from while **D** stands for destination. As shown in Fig. 12, the search activities of the ants begin from step 1 and ants do not start emitting pheromone until they carry food from their destination. In step 2, the ants in the search space followed different paths to the destination and in step 3, as ants return to the source, the path that shows red line (pheromone) indicates the route more ants with food followed back to the souce.

Starting with a set of random solutions, the algorithm iteratively improves them until they satisfy a predetermined stopping condition. This is done after initializing settings and modeling the problem's search space. Based on a likelihood that is impacted by pheromone and heuristic, ants choose how to construct a solution. At the end of each iteration, when all the ants have offered a solution to the problem, the pheromone matrix is updated based on the quality of the solution, which is the corresponding cost. The best ant, or the one with the lowest cost (for the minimization problem), is stored at the end of an iteration (Khoshrangbaf et al., 2022).

4.3 Artificial bee colony

A novel heuristic technique called artificial bee colony optimization uses three bee groups in the colony: scouts, onlooker, and employed bees. Every bee in the search space indicates a position. The bee populations are used to determine the algorithm's ideal path. A scout bee is a bee that randomly hunts for food. An onlooker bee is a bee that chooses a food source while waiting in the dance area, whereas an employed bee goes to a food source that has already been visited. The locations of food sources suggest potential solutions to the optimization problem (Yue et al., 2016).

There are four steps in artificial bee colony optimization.

Initialization: if the population size is assumed to be *SN* and the first generated food source is N, the initial population $X_i = \{X_{i1}, X_{i2}, \ldots, X_{iD}\}(i = 1, 2, \ldots, N)$, with D given as the vector dimension. The initial population is randomly expressed as:

$$X_i = X_{min} + rand(0, 1) \bullet (X_{max} - X_{min}) \tag{11}$$

where X_{min} and X_{max} are the minimum and maximum values of the population. $rand(0, 1)$ is the numerical value between randomly produced (− 1, 1) which controls the producing range of X_{ij} neighborhood.

Population Updating: Each employed bee was assigned to a food source after the food sources were randomly placed in their initial location. Using Eq. (11), each employed bee then chooses a new food source that is nearby its existing assigned food source as expressed in Eq. (12).

$$V_{i,j} = X_{i,j} + rand(-1, 1) \bullet (X_{i,j} - X_{k,j}) \tag{12}$$

where $V_{i,j}$ is a candidate solution, $X_{i,j}$ is the current solution and $X_{k,j}$ is a neighborhood solution. $k \in \{1, 2, 3, \ldots, SN\}$, $j \in \{1, 2, 3, \ldots, D\}$ given D is the vector dimension and $rand(-1, 1)$ is the numerical value between randomly produced $(-1, 1)$. The neighborhood scope gradually decreases as the search approaches the optimum solution.

Bee Source Selection: In this phase, the employed bees move according to the income rate. High income rates food sources are more likely to be selected according to Eq. (13).

$$P_i = \frac{fit(X_i)}{\sum_{n=1}^{SN} fit(X_n)} \tag{13}$$

where $fit(X_i)$ is the fitness value of the solution i proportional to the nectar amount of the food source $n \in \{1, 2, 3, \ldots, SN\}$. SN is the number of food sources equal to the number of employed bees.

Population Elimination: When a solution is abandoned because it has been stuck in a local optimum and shows no sign of improving after receiving continual limit cycle updates, the corresponding onlooker bees transform into scouting bees and generate a new solution at random using Eq. (13).

$$X_{ij} = X_{minj} + rand(0,\ 1)(X_{maxj} - X_{minj}) \tag{14}$$

The new solution replaces the old one and the optimum solution is generated accordingly. X_i represents the abandoned source. $j \in \{1, 2, 3, \ldots, D\}$, $rand(0,\ 1)$ is the numerical value between randomly produced (− 1, 1), and X_{max} and X_{min} are the maximum and minimum values.

4.4 Genetic algorithms

One of the most popular evolutionary algorithms, the genetic algorithm (GA), is widely used to solve different optimization problems (Gong et al., 2018). The initial population of the GA method is made up of potential solutions that were generated at random. The term "chromosome" refers to each distinct solution, which can be represented by a series of numeric values, symbols, or alphabets. The best few chromosomes are chosen from the initial population once it has been formed, and a new population is then established using those chromosomes. The fitness function that was derived assesses the chromosomes' quality. The success of a given problem's desired purpose is greatly impacted by the derivation of an effective fitness function. Two chromosomes (let's say, parent chromosomes) are chosen at random to pair during the crossover operation and produce two kid chromosomes when the new population is created. Then, to create better chromosomes, a mutation operation is performed on both of the child chromosomes. If it is determined that the kid chromosomes are superior to the parent chromosomes, they will take the place of the parent in the new population. Up until the termination requirement is met, the crossover and mutation operation is repeated.

4.5 Teaching–learning-based optimization

Teaching–Learning-Based Optimization (TLBO) is a population-based approach that moves toward the overall solution using a population of solutions. The population is regarded as a class of learners or a group of learners for TLBO. In TLBO, various design parameters will be comparable to various learning objectives provided to students, and the students' performance will be comparable to their "fitness," as in previous population-based optimization techniques (Rao et al., 2011). The teacher is considered as the best solution obtained so far.

There are two stages to the TLBO procedure. The "Teacher Phase" makes up the first section, while the "Learner Phase" makes up the second. Learning occurs during the "Teacher Phase," which refers to studying with the instructor, and the "Learner Phase," which refers to studying with other students.

4.5.1 Teacher phase

A skilled teacher raises the knowledge level of their students to that of the teacher. In reality, however, this is not feasible, and a teacher may only raise the class mean to a certain level based on the responses of the class. This proceeds in a random manner based on several variables.

Assuming T_i is the teacher at any iteration i and M_i is the mean, T_i will attempt to move mean M_i towards its own level, and the new mean will be T_i designated as M_{new}. The solution is thereafter updated based on the difference between the existing and the new mean expressed as:

$$Difference_{Meani} = r_i(M_{new} - T_F M_i) \tag{15}$$

4.5.2 Learner phase

The teacher's input and the students' interactions with one another are two separate ways that learners increase their knowledge. Random interactions between students occur through group discussions, official correspondence, presentations, etc. If the other student is more knowledgeable than the learner, the learner gains new knowledge. Learner modification is expressed as:

Algorithm 1: Pseudo-code for TLBO

$\boldsymbol{For\ i = 1; P_n}$
    Randomly select two learners $\boldsymbol{X_i}$ and $\boldsymbol{X_j}$, where $\boldsymbol{i \neq j}$
    $\boldsymbol{if\ f(X_i < f(X_j)}$
        $\boldsymbol{X_{new,i} = X_{old,i} + r_i(X_i - X_j)}$
    Else
        $\boldsymbol{X_{new,i} = X_{old,i} + r_i(X_j - X_i)}$
    End If
End For
Accept $\boldsymbol{X_{new}}$ if it gives a better function value.

Harmony search algorithm (HAS) The harmony search algorithm is a metaheuristic method that mimics musical improvisation. HSA is based on a musician's desire for the optimal notes that will provide the ideal harmony. The method used to find the best options in the given situation is similar to the method used by a musician seeking a pleasing harmony to the ear (Dubey et al., 2021).

There are three situations occurring, in which the pitch can be improved by a musician.

1. A stored pitch is performed from the musician's memory.
2. From the saved pitches, a nearby pitch is played.
3. Any random pitch that falls within the permitted range is played.

Algorithm 2: Pseudo code of the Harmony Search algorithm (HSA)

```
Begin,
  Define objective function f(x), x=(x1 ,x2 ,…,xd )T
  Define Harmony Memory Considering rate (HMCR)
  Define Pitch adjusting rate (PAR) and other parameters
  Generate Harmony Memory with random harmonies
      while (t< max number of iterations)
          while (i<=number of variables)
                if (rand<HMCR),
                 Choose a value from HM for the variable i
                   if (rand<PAR),
                      Adjust the value by adding certain amount
                   end if
                 else
                   Choose a random value
                 end if
            end while
               Accept the New Harmony (solution) if better
        end while
  Find the current best solution
end
```

The main components of HSA are harmony memory size (HMS), harmony memory consideration rate (HMCR), pitch adjustment rate (PAR), and stopping criteria (i.e., number of improvisation). These parameters are responsible for exploration and exploitation.

In the context of wireless sensor networks, energy efficiency refers to the deployment and utilization of the network with minimal energy consumption that guarantees long network lifespan. Self-organizing and self-adapting ability of swarm intelligence optimization algorithm make it suitable for the robustness and expandability of the network. The network becomes scalable when other nodes or particles can be added to the network or search space without compromising the lifespan of the network.

The fault tolerance metric of the algorithm shows that nodes in the network are distributed and there is no centralized control, even if a node fails, it will not affect the solution to the problem; that is, it will not affect the overall performance of the network. Convergence performance is dependent on the ability of the algorithm to acquire global extreme value while avoiding regional extreme value.

The comparison of different algorithmic requirements that influence the performance of the algorithms is given in Table 3. It can be deduced from the table that most of the swarm intelligence algorithms at relatively stable energy level, the network maintains good stability with high level of fault tolerance at different convergence level. Conventional PSO without any modification easily fall into local optimum while TLBO proves to survive in a complex active distribution environment. However, to improve the search rate and avoid premature convergence of swarm intelligence algorithms, the algorithms can either be improved with modified version or it is integrated with other algorithms to attain hybrid solutions.

Bibliometric analysis We used Scopus data for our bibliometric analysis. We ran a query and used WSNs, a Nature-inspired method, and Coverage to extract the keywords. We discovered that there are only 12 published research publications overall, with WSNs, nature-inspired algorithms, and coverage listed as author keywords. These articles include 120 keywords in total. In this instance, we took into account all the phrases that the bibliometric clustering method groups into 8 clusters (shown in 8 distinct colors) as shown in Fig. 13. These clusters have a total link strength of 1365 and 1316 linkages between them. We discovered that the

Table 3 Comparative analysis of performance metrics of different swarm intelligence algorithms

Algorithm	Energy efficiency	Scalability	Fault tolerance	Convergence performance	Algorithm performance parameters
Particle Swarm Optimization (Hanh et al., 2018; Morkevičius et al., 2023; Roshanzamir et al., 2022)	Good	Good	It can easily fall into local optimum	High	Variation of weight, learning factors, and the maximum value of velocity
Ant Colony Optimization (Kulkarni et al., 2016; Wang et al., 2020a)	Weak	Good	The solution accuracy is low when it is fed with a large volume of data	Low	Evaporation rate
Artificial Bee Colony (Saleem & Ahmad, 2022)	Good	Good	The population diversity is always insufficient	High	The limit value
Genetic Algorithm (GA) (Shahi et al., 2016)	Weak	Good	When the complexity is high, GA does not scale well	High	Mutation rate, crossover probability and selection method
TLBO (Rao et al., 2011; Tuo et al., 2017)	Weak	Weak	It can survive in a complex active distribution environment	High	No algorithm performance parameters, therefore simpler
HAS (Dubey et al., 2021; Tuo et al., 2017)	Good	Good	It provides good balance exploration and exploitation	Low	Pitch adjusting rate, the harmony memory consideration rate, and number of improvisations

Table 3 (continued)

Algorithm	Energy efficiency	Scalability	Fault tolerance	Convergence performance	Algorithm performance parameters
Lion Optimization Algorithm (LOA) (Liu et al., 2018; Singh et al., 2021c; Yazdani & Jolai, 2016)	Good	Good	Under different population sizes, LOA offers higher network coverage	Low	Population size
Cockoo Search Algorithm (Cheng & Xia, 2016; Gupta, 2018)	Good	Good	The convengence level of the algorithm varies according to different iterations	It varies according to iterations	Number of nests, mutation probability, and step size, total energy consumption and residual energy
Firefly Optimization Algorithm (Pakdel & Fotohi, 2021)	Weak	Weak	There is high tolerance level since it is the base station that determines how long a sensor node serves as a cluster head	High	Maximum relative load, and network lifetime
Grey Wolf Algorithm (Zhang et al., 2021; Wang et al., 2019a; Rajakumar et al., 2017)	Good	Good	It has strong adaptability and fast optimization speed. Its superior global optimization ability makes it withstand falling into local optimum	High	Computation time, percentage of localized node, and minimum localization error measures
Bat Optimization Algorithm (Mohar et al., 2022; Yang & Zhang, 2016)	Weak	Weak	It can easily fall into local optimum solution	It has a high convergence level	Mean localization error, number of localized nodes and computing time

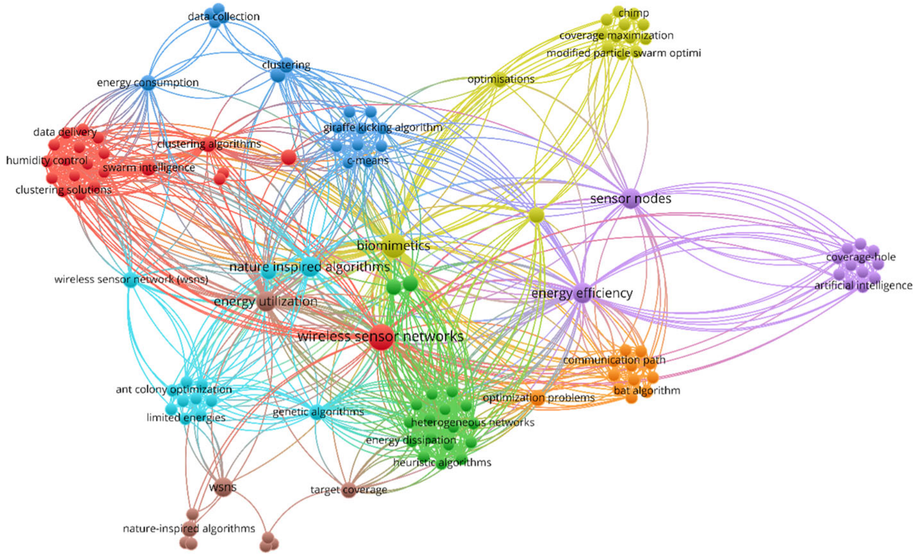


Fig. 13 Bibliometric analysis of keywords "WSNs", "Nature-inspired algorithm" and "Coverage."

genetic algorithm and particle swarm optimization had a high overall connection strength, indicating their widespread use.

5 Machine learning applications to functional challenges in WSNs

Machine learning techniques can be utilized in sensor networks to enable adaptation to changes in the monitoring environment, eliminating the need for frequent redesign. Designers of sensor networks often view machine learning as a toolbox comprising various tools and processes for creating prediction models. The field of machine learning holds immense potential for numerous applications, a fact acknowledged by experts in the field. Familiarity with these concepts provides valuable insights to scholars interested in integrating machine learning into their wireless sensor network designs. Given the versatility of machine learning algorithms, wireless sensor networks can leverage them in a wide range of applications. The following examples highlight some notable uses of machine learning in wireless sensor networks (Alsheikh et al., 2014).

5.1 Routing in WSNs

The design of a routing protocol for WSNs must take into account a number of design issues, including energy usage, scalability, fault tolerance, and data coverage. Nodes of sensors are designed with a limited amount of memory, bandwidth, and computing power. In wireless sensor networks, it is customary to characterize a routing problem as a graph G = (V, E), where V represents the set of all nodes and E denotes the set of channels that connect the nodes in a bidirectional fashion. According to this paradigm, the routing problem is the process of determining the lowest-cost route utilizing the available graph edges that starts at the source vertex and travels to all destination vertices. The originating node (i.e., a root node) and destinations are the vertices of this path, which is actually a spanning tree with the formula T = (V, E) (i.e., leaf nodes that do not have any child nodes). Even when the complete topology is known, solving such a tree with optimal data aggregation is discovered to be NP-hard.

A sensor network can use machine learning to learn from prior experiences, choose the best routing decisions, and adapt to the changing environment. Below are some of the benefits of machine learning applications for routing in WSNs.

- Ability to learn optimal routing path that is energy efficient and prolong the lifetime of the network based on the dynamics of the network.
- By breaking the network down into smaller groups or cluster, more manageable sub-routing problems, a common routing problem can be made less complex. To achieve low cost, effective, and real-time routing, nodes in each sub-problem create the graph structures by simply taking into account their local neighbors.

Machine learning protocols such as Self-organizing map (SOM) with "Sensor Intelligence Routing" (SIR), Reinforcement Learning based Geographic R (RLGR), and distributed regression framework have been developed specifically for routing in wireless sensor networks. SOM with SIR utilizes unsupervised machine learning to detect efficient routing paths. Reinforcement learning-based routing, on the other hand, offers routing enhancements by leveraging reinforcement learning techniques. One of the key advantages of using reinforcement learning for routing is that it can generate satisfactory routing solutions without prior knowledge of the network topology. However, a major drawback of reinforcement learning-based routing algorithms is their limited ability to anticipate future knowledge or look ahead. These algorithms typically require some time to discover the best paths, making them less suitable for highly dynamic environments.

5.2 Clustering and data aggregation in WSNs

In large-scale sensor networks, the direct transmission of all sensed data to the processing node is not energy efficient due to the limited energy level of sensor nodes. Instead, a more effective option is to forward the data to a cluster head, also known as a processing node, which aggregates data from other sensors within its group and transmits it to the sink or base station (Yue et al., 2016). This cluster-based data aggregation approach is illustrated in Fig. 14. Any malfunctioning node detected in the network is removed to prevent the generation of incomplete readings that could impact the overall accuracy of the network. Machine learning techniques play a crucial role in enhancing the performance of sensor node clustering and data fusion in wireless sensor networks:

- Cluster heads can compress data locally by using machine learning to efficiently extract similarity and dissimilarity (for instance, from malfunctioning nodes) in readings from numerous sensors. Machine learning approaches are utilized to effectively select the cluster head.
- Selecting the right cluster heads will significantly reduce energy usage and lengthen the network's lifespan.

Previous research has employed neural networks for large-scale network clustering, decision trees for cluster head selection, self-organizing maps for data aggregation, online data compression using learning vector quantization, data aggregation using principal component

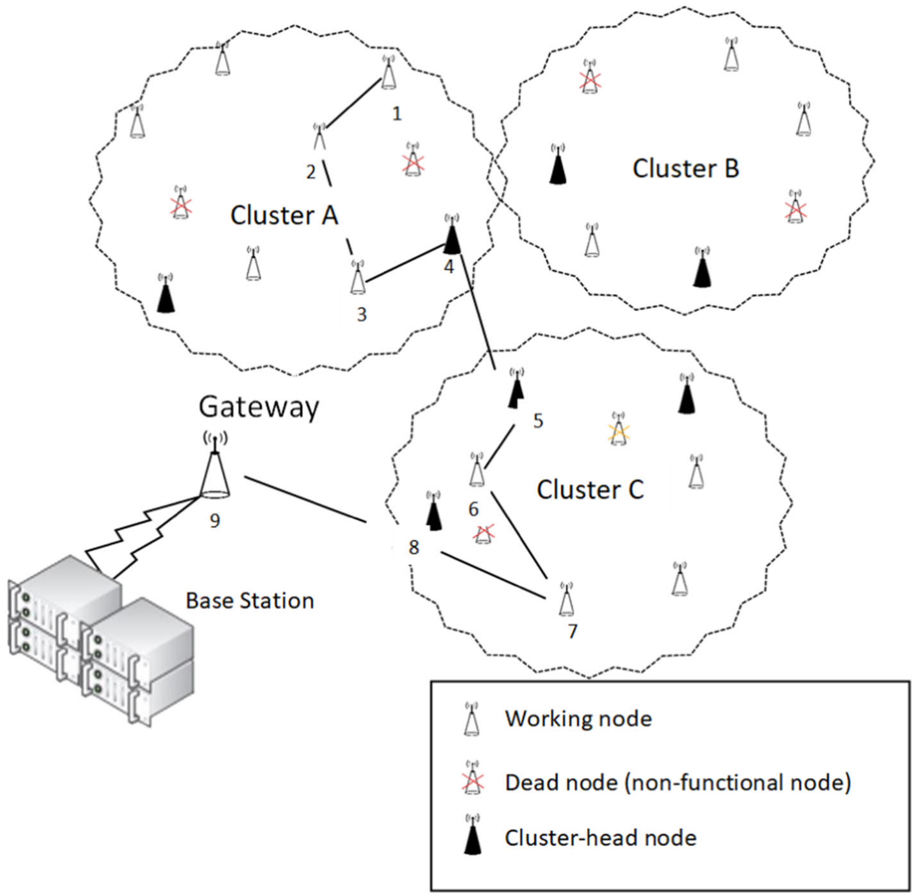


Fig. 14 Clustered architecture of data aggregation showing working nodes, dead nodes and cluster heads. Adapted from Ma and Duan (2022)

analysis, the k-means algorithm for collaborative data processing, decentralized learning for data latency and role-free clustering.

5.3 Event detection and query processing

It is assumed that in every large-scale sensor network, the functional requirements for event detection and query processing are present. This emphasizes the need for minimally human-involved event detection and scheduling. For efficient methods for query processing and event detection, machine learning fundamentally provides ways to restrict the scope of queries and assess the authenticity of events. The following benefits are believed to arise from the adoption.

- Learning algorithms make it possible to create effective event detection systems with a minimum amount of storage and processing power. Additionally, they can evaluate the correctness of such occurrences using straightforward classifiers.

- Machine learning enables the development of effective query processing techniques for WSNs to identify the search regions whenever a query is received without overwhelming the network.

The most basic methods depend on setting a rigid threshold value for the phenomena being monitored and alerting the system manager when it is exceeded. However, the event and query processing units in the majority of current WSN applications are frequently complex and call for more than a predetermined threshold value. Utilizing machine learning to create sophisticated event detection and query processing solutions is one of such growing technology. Event recognition using Bayesian algorithms, detection of forest fire using neural networks, k-nearest neighbors for query processing, decision trees for detection of distributed events during disaster, principal component analysis for query optimization, etc. are just a few examples of machine learning-based query processing and event detection solutions for wireless sensor networks.

5.4 Localization and objects targeting

Localization is the process of determining the geographic coordinates of the nodes and components of a network. Position awareness of sensor nodes is an essential feature because the majority of sensor network functions are frequently dependent on location. Deployment of Global Positioning System (GPS) hardware on each node is typically not feasible economically in a large scale network. After deployment, sensor nodes may experience changes in their placement with reasons such as due to movement. The advantages of using machine learning techniques to the process of localizing sensor nodes can be summed up as follows:

- Employing a small number of anchor points to transform nodes' relative coordinates into absolute ones. This will make it unnecessary to use range measurement equipment to get distance estimates.
- Machine learning can be used in monitoring and object targeting systems to group the surveillance environment into a smaller group of clusters where a unique location indicator is represented by each cluster.

Node localization using Bayesian network, location-aware activity recognition, neural networks localization, support vector machines localization, localization using support vector regression, localization based on decision tree, Gaussian processes of sensor placements, and spatial Gaussian process regression, self-organizing map localization, and reinforcement learning for path determination are some examples of machine learning applications for WSN localization that have been reported in literature (Wang et al., 2019b).

5.5 Medium access control

A variety of sensors work together in WSNs to convey data quickly. Because of this, creating MAC protocols for WSNs presents unique difficulties in terms of latency, energy usage, and other factors. Furthermore, in order to save energy, the duty cycle of the node (i.e., the percentage of time that a sensor node is active) must be managed. The Medium access control (MAC) protocols must be changed as a result to support the sensor nodes' efficient data transmission and reception (Rugwiro et al., 2019). Machine learning techniques have recently been applied to improve the performance of MAC protocols in WSNs, including:

- Adaptively calculating a node's duty cycle using machine learning and the network's transmission history. In particular, the nodes that can foresee when the transmissions of

the other nodes will end can swing to sleep mode for sometimes and wake up at the end of the transmission time of the other nodes. When constructing MAC protocols for WSNs, many aspects, such as consumption of energy and latency, are more crucial than fairness.
- Integrating the ideas of MAC protocols with machine learning to achieve safe data transport. These MAC layer security systems can iteratively learn random attack patterns and are independent of the planned application.

The Bayesian statistical model for MAC, the Neural Network-based MAC, reinforcement learning for management of duty cycle, and the adaptive MAC layer are examples of machine learning-based MAC developed protocols. Although machine learning approaches have been applied in numerous WSN applications, however many problems that bother on coverage optimization remains a challenge and require more research. The benchmarked performance metrics of machine learning techniques in solving the identified challenges in WSNs are given in Table 4.

Various machine learning algorithms have been applied to address many functional issues in wireless sensor networks. Analysis of studies carried out in Table 3 shows that supervised machine learning algorithms are applied in solving routing, localization, event detection and query processing functional problems in WSNs. Unsupervised machine learning algorithms are mostly applied to solve medium access control and data aggregation problems. Ensemble-based and reinforcement machine learning algorithms are also applied across many functional problems that are associated with wireless sensor networks. It can be concluded from the table that machine learning techniques offer rich potentials in the deployment and utilization of wireless sensor networks.

Our research has revealed that machine learning algorithms possess significant potential for effectively addressing the functional challenges encountered in Wireless Sensor Networks (WSNs). In the forthcoming section, we delve exclusively into the pivotal role of machine learning in tackling the intricate issue of coverage within WSNs.

6 Notable studies on coverage problem using machine learning techniques

Machine learning algorithms can be categorized into three main types: supervised learning, unsupervised learning, and reinforcement learning. Supervised learning algorithms rely on labeled datasets to classify data into different categories. Examples of supervised learning techniques include multiple regression, linear regression, logistic regression, Naive Bayes, classification using random forests, and support vector machines.

On the other hand, unsupervised learning techniques, such as K-means and hierarchical clustering, do not require labeled data. They focus on finding patterns and structures in unlabeled datasets. Unsupervised learning shares some similarities with reinforcement learning, as both approaches work with unlabeled data and incorporate the concept of rewards and punishments. Reinforcement learning is commonly used in gaming scenarios, where an agent explores its environment independently to acquire information.

Supervised machine learning algorithms have proven useful in solving various problems in wireless sensor networks. They can be employed for tasks like localization, defect detection and identification, coverage and connectivity optimization, routing strategies, and anomaly detection. Anomaly detection, for instance, utilizes machine learning to identify and flag faulty or defective nodes. Unsupervised learning techniques are primarily used to address clustering and dimensionality reduction challenges in wireless sensor networks.

Table 4 Recent studies and performance metrics of machine learning applications in solving functional challenges in WSNs

Functional challenges focus	Technique(s)	Contributions	Performance consideration
Routing (Kim et al., 2023)	Reinforcement learning	Buffer occupancy ratio, weighted average of received signal strength, and power consumption ratio cognitive metrics were formulated to handle various network scenarios	Multiple cognitive metrics, weighted moving average was used to prevent cognitive metrics from changing suddenly
Routing (Muriira et al., 2018)	Support vector machine and genetic algorithm	Adjustment of transmission rate in wireless sensor networks	Mean Absolute Error, Mean Square Error, and Root Mean Square Error served as the basis of comparison with other classification techniques
Medium Access Control (Richert et al., 2017)	improved variant of carrier sense multiple access	The study presented a modified version of MAC protocol in WSN to overcome the limitations of existing protocols in relation to reliability, energy efficiency, access delay, low, and high throughput	The average delay, throughput, and mean backoff were considered as the performance metrics
Medium Access Control (Su et al., 2023)	Markov decision process applied on mobile edge computing (MEC) network architecture	Markov decision process was adopted to design MEC-based network architecture for an eHealth system	The channel resources are allocated in the proposed protocol to minimize the probability of collision when the sensor nodes transmit data. The network performance is enhanced with the delivery ratio. There is lower collision rate and high transmission rate
Data Aggregation (Dash, et al., 2022; Manjarres et al., 2013)	Spatial and Temporal Correlation-based Data Redundancy Reduction (STCDRR) protocol	STCDRR was implemented to address the issue of data redundancy in WSNs and enhanced its smooth running	Time complexity, aggregation ratio, data accuracy, time complexity and energy consumption metrics were considered. ANOVA model and Bartlett test were carried out

Table 4 (continued)

Functional challenges focus	Technique(s)	Contributions	Performance consideration
Event detection and query processing (Kazmi et al., 2019; Zidi et al., 2018)	Grey Wolf Optimization, Support Vector Machine, and Differential Evolution	Minimizing congestion in WSNs by adjusting the transmission rate using support vector machine. The parameters of SVM are tuned using GWO and DE to reduce the classification error because of their potentials to generate better results than other methods of classification	Mean Absolute Error, Mean Square Error, and Root Mean Square Error served as the basis of comparison with other classification techniques
Events detection and objects targeting (Leela Rani & Sathish Kumar, 2021)	Pre-localization-based Kalman Filter (KF) for target detection and clique-based estimation for tracking the target trajectories	Minimizing energy consumption level and increasing accuracy of tracking using combined KF and clique-based approach	The target detection rate decreased when the distance between target and the sensor under consideration increased. Estimation error decreased with increase in radius
Event detection (Arora & Singh, 2017; Ismail et al., 2023)	Ensemble-Based Machine Learning	A lightweight ensemble-based ML approach for detecting cyber-attacks in WSNs was presented	Performance analysis was carried out on the basis of probability of false alarm, accuracy, probability of detection, processing time, probability of misdetection, average prediction time per sample, and model size
Localization and Detection (Gebremariam et al., 2023; Verde et al., 2021)	Artificial Neural Network	Detection and localization against multiple attacks using security localization based on optimized multilayer perceptron artificial neural network was presented	Performance comparison carried out using accuracy, precision, recall, and F1-measure shows that the proposed technique is effective in detection and localization

Table 4 (continued)

Functional challenges focus	Technique(s)	Contributions	Performance consideration
Localization (Goyal & Patterh, 2014; Han et al., 2020)	Cuckoo Search Algorithm	A distributed and iterative technique for efficient detection of sensor nodes location in WSNs	No weight coefficient was used to control the global search ability
Clustering (Bouarourou et al., 2023),	Improved ant clustering algorithm	A model that focuses on increasing the network's lifetime by performing cluster head selection, path construction from sink to cluster head tasks and thereby minimizing the load on the sensor nodes was presented	Hops count and residual energy level were used as basis of performance comparison

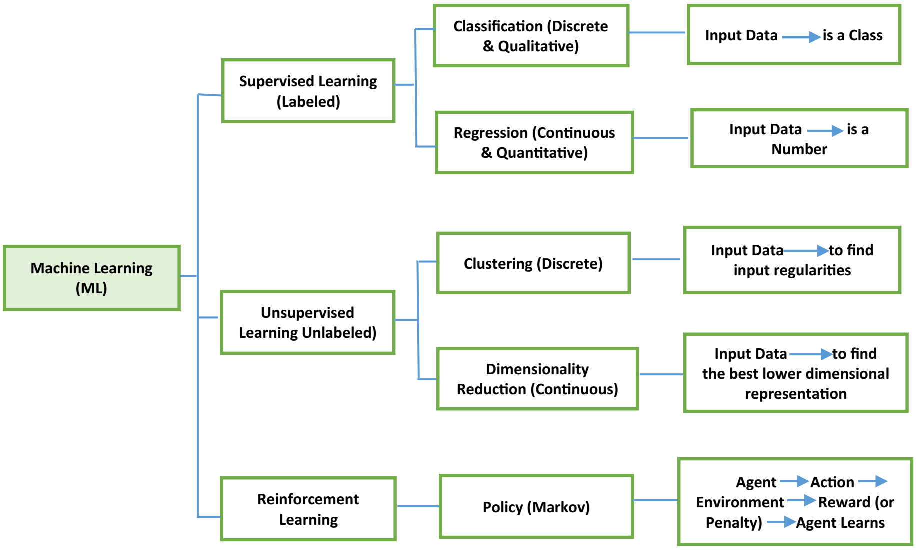


Fig. 15 Machine learning algorithms overview. *Source*: Rashidi et al. (2019)

Reinforcement learning, specifically using Q-learning, has shown promise in solving different problems in WSNs, including routing, coverage optimization, and quality-of-service (QoS) parameter management. By applying reinforcement learning principles, agents can learn and adapt their behavior based on received rewards, enabling them to make optimal decisions in dynamic environments.

Figure 15 provides an overview of the hierarchy of machine learning algorithms, including supervised learning, unsupervised learning, and reinforcement learning. Within supervised learning, there are further classifications such as classification and regression, which deal with discrete/qualitative and continuous/quantitative targets, respectively.

Machine learning has become an essential tool for data inference and decision-making in optimizing wireless sensor networks, contributing to extending their lifetime. This section reviews the applications of machine learning in wireless sensor networks. Coverage and connectivity challenges are critical in assessing the performance of a wireless sensor network within a given area. By controlling the coverage of the network, energy consumption of the master node can be improved, resulting in an extended lifecycle and reduced energy consumption (Ma et al., 2022; Madagouda & Sumathi, 2021).

While machine learning-based research in wireless sensor networks has addressed issues like energy efficiency, data transmission, and coverage optimization, challenges remain in machine learning-based edge computing, particularly in energy reduction. Tossa et al. (2022) proposed a genetic algorithm-based method to maximize coverage and connectivity in WSNs. However, their scheme lacks the ability to detect connectivity disruption during routing sessions. Xu et al. (2018) formulated a multi-objective coverage control optimization problem for wireless sensor networks, considering coverage rate, energy consumption, and energy consumption equilibrium. However, they did not incorporate learning techniques to enhance the performance of their algorithms.

To address uncertainties in detecting ranges, measuring parameters, and overlapping coverage among sensors, the artificial bee colony (ABC) algorithm has been proposed. Inspired by the behavior of honey bees, the ABC algorithm is a swarm-based intelligent approach. Extending network lifetime while maintaining full coverage of the area of interest is a crucial trade-off in deployment strategies (Boualem et al., 2018; Sun et al., 2018a).

Another prominent challenge in wireless sensor networks is deploying a minimal number of nodes to ensure connectivity and coverage in specific areas. In this regard, Sun et al. (2014) proposed an improved coverage control approach for WSNs. They used Ant Colony Optimization (ACO) to design the routing path and employed other techniques to create a relationship mapping model between sensor nodes and target nodes. The ant determines the state transition probability during the traversal search process based on the amount of data and heuristic information associated with each path.

Assume that there will always be a transition between any two points p.

$$p = \begin{cases} \frac{[r_{ij}(t)]^{\alpha}[\eta_{ij}(t)^{\beta}]}{(\sum_{S\subset \ allowed}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)^{\beta}])} s\epsilon allowed \\ 0S \notin allowed \end{cases} \tag{16}$$

where α is the informative heuristic factor that identifies the track's relative importance and highlights the part that the acquired information played in the ant's progress. The bigger it is, the more likely it is that other ants will follow it, and the more effectively the ants cooperate. β is the anticipated heuristic factor, which demonstrates the level of attention paid by an ant to heuristic information during path selection and illustrates the relative relevance of visibility. When the likelihood of a state change is close to 1, the value rises, turning the algorithm into a greedy one. $\tau_{ij}(t) and \eta_{ij}(t)$ represent the pheromone residual function and the heuristic function, respectively.

Guooor & Sharma (2021) proposed a node distribution method to tackle the coverage issue in wireless sensor networks. They employed Glowworm Swarm Optimization to achieve the desired network coverage. The routing in the network was based on essential force clustering, considering average power, minimum proximity distance, and sensor position to determine the route selection. However, the study did not consider the dynamics of glowworm movement and the evolution of decision-making in the decision space.

Kwon et al. (2020) emphasized intelligent IoT connectivity using deep reinforcement learning. Their strategy involved relay nodes making decisions based on limited information about the network as a whole. Lee and Shin (2017) presented a method for identifying signal points within overlapped sensor areas and installing sensors for tracing moving objects as part of an optimal sensor deployment strategy in WSNs. They utilized a support vector machine for signal categorization and the apriori technique for trilateration.

Liang et al. (2021) investigated a target coverage problem with sensors of limited mobility in Mobile Wireless Sensor Networks (MWSNs). The monitoring area was divided into sub-areas, each responsible for detecting/covering a different subset of targets. Liu et al. (2016) proposed an itinerary planning system for multiple mobile agents in wireless sensor networks that was faster and simpler compared to existing methods. Their model involved building a spanning tree of WSN nodes.

Liu and He (2014) presented an innovative deployment strategy based on ant colonies as a cost-effective solution to the grid-based coverage problem with guaranteed connectivity. The method employed a greedy migration mechanism that rapidly captured the coverage area and significantly reduced deployment costs. Ma and Duan (2022) introduced a hybrid butterfly optimization approach for improving node coverage in wireless sensor networks. They combined the grey wolf optimizer for node coverage and utilized the virtual force-directed particle swarm optimization algorithm and evidence theory.

An overview of various machine learning methods, including fuzzy logic, Artificial Neural Networks (ANN), evolutionary algorithms, swarm intelligence, and reinforcement learning, was provided in Kulkarni et al. (2011). The study conducted a comprehensive analysis of computational intelligence in WSNs and summarized the contributions of multiple scholars in this field. It also explained the hybridization of computational intelligence techniques to address various issues in WSNs. Bhatti (2018) utilized SVM regression and multiple regression models for localization in wireless sensor networks, considering localization as both a classification and regression problem. The author listed several disadvantages of applying machine learning in wireless sensor networks, among which includes, regression versus classification, size of training data set, and multivariate vs. univariate modeling. A brief descriptions of these advantages are highlighted below:

- *Regression vs. Classification*: In wireless sensor networks, the Support Vector Machine (SVM) is commonly used for node localization. However, since SVM is a classification technique, it requires mapping the localization problem into a classification problem. One popular approach is to divide the deployment area into cells (rectangular or square) and classify each node based on its membership in those cells.
- *Size of Training Data Set*: Machine learning algorithms require large training datasets to create an appropriate model and avoid underfitting or overfitting. A well-trained model captures the relevant features efficiently and can generalize well to unseen test data.
- *Multivariate vs. Univariate Modeling*: Localization in wireless sensor networks often involves estimating Cartesian coordinates (two or three dimensions). While most algorithms use multiple independent variables (predictors), they typically predict only one dependent variable. To address this, a simple solution is to train two separate machines to estimate each coordinate independently, allowing for multivariate modeling..

In the field of wireless networking, machine learning (ML) techniques are commonly used. Logistic regression models, for example, are utilized to assess the probability of network or process failures, which involves regression analysis. However, ML algorithms also come with their limitations and challenges. One such challenge is the need for hand-selected features to train the network, which can impact the model's performance. Overfitting is another issue that arises when there is a lack of available data. Additionally, utilizing more training data can lead to higher computing costs. To address these challenges, deep learning methods have been developed (Rameshkumar et al., 2023).

Qin and Chen (2018) proposed a differential evolution algorithm for area coverage in wireless sensor networks (WSNs). This technique aims to extend the lifespan of WSNs while ensuring effective coverage of the desired area. The continuous area coverage problem is transformed into a discrete point coverage problem, enabling the optimization process to be implemented.

Osamy et al. (2022) conducted an analysis of existing research trends in deployment, coverage, and localization problems in WSNs, with a focus on the application of artificial intelligence (AI) techniques to enhance network lifetime. The study reveals that in terms of coverage, 13% of the reported studies applied Evolutionary Computation, 29% utilized swarm intelligence, 10% employed Reinforcement Learning, 19% utilized nature-inspired algorithms, 6% applied Fuzzy Logic, and 19% utilized hybrid algorithms. These findings indicate that swarm intelligence is frequently applied to address the challenges in WSNs. Furthermore, it is noted that there is a growing research interest in incorporating computational intelligence techniques into various WSN applications to address coverage and connectivity maintenance, as highlighted in Sharma and Chauhan (2020).

7 Deep learning applications

Deep Learning, which is another subfield of AI, operates differently from traditional ML approaches. Unlike ML, DL doesn't treat all features equally. Instead, DL identifies the features that have a significant impact on the outcome and creates a combination of those features for the learning process. This characteristic of DL requires a substantial amount of data. DL models typically have hidden layers, or multiple layers, which contribute to their effectiveness. Unlike ML, where features are manually selected and provided to the model, DL automates both the feature selection and extraction process. DL achieves this by utilizing blocks and hidden layers, allowing the model to learn and determine the optimal combinations of features for the specific dataset being analyzed. This automated feature learning capability makes DL a preferred approach compared to traditional ML methods (Mao et al., 2018; Zhang et al., 2019).

By using numerous hidden layers or intermediate layers as shown in Fig. 16 between the input and the output layers, the DL approach eliminates the complex input data pre-processing.

In Fig. 16, I represents inputs to the network while *O* represents the output of the network while w represents varying weights from the input layer through the hidden layer. The inputs are features of the raw data that the system is processing.

In DL, the learning system directly receives raw, unprocessed data. The DL system then automatically extracts the required representations from the data for tasks such as classification or detection. Each layer in the DL model starts with the raw data and progressively extracts different features, amplifying the ones that are more crucial for decision-making while suppressing the less important ones. The layers are interconnected with varying weights

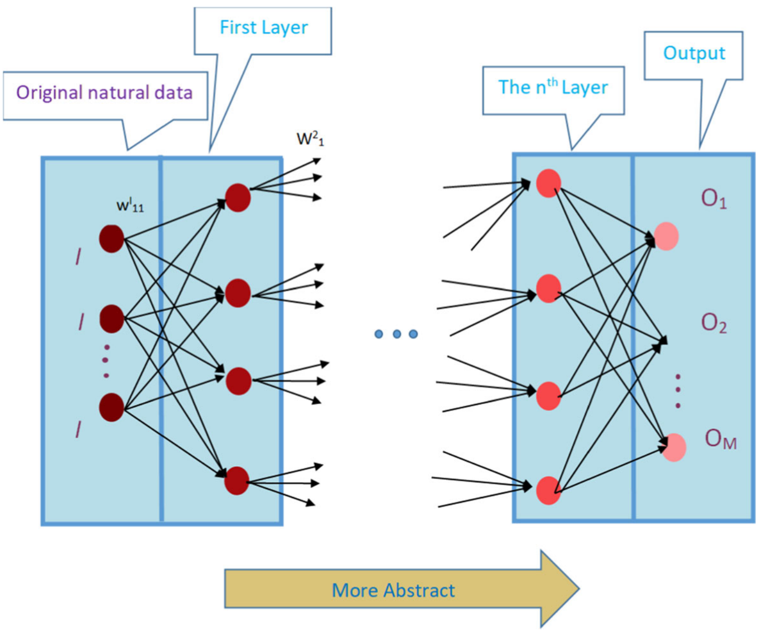


Fig. 16 Schematics of DEEP LEARNING

assigned to the connections. In the context of current research in wireless sensor networks, there is a strong focus on improving area coverage, as it is recognized as a critical factor that significantly influences network performance. Table 5 shows different machine learning algorithms that have been applied to address various challenges in WSNs.

Different machine learning techniques adopted different metrics in their applications to improve the services that are rendered on the network and authors choose different techniques to address different problems on the network. The survey reveals that deep learning and evolutionary algorithms are gaing increasing attention among scholars in solving notable problems that are associated with the design and deployment of wireless sensor networks. In its entirety, machine learning has find good place of application in the domain of WSNs.

In Binh et al. (2018), the Chaotic Flower Pollination Algorithm (CFPA) and the Improved Cuckoo Search (ICS) were introduced as nature-inspired algorithms to enhance area coverage in wireless sensor networks (WSNs). Researchers have been utilizing bio-inspired metaheuristic swarm intelligence techniques to improve the performance of WSNs, addressing issues such as expanding coverage, extending network lifespan, implementing routing protocols, and distributing sensor nodes. Metaheuristic algorithms have proven to be particularly effective in solving optimization problems in WSNs. Chowdhury and De (2021) explored the similarities between the behavior of glowworms and mobile sensor nodes and implemented the Glowworm Swarm Optimization (GSO) technique to expand coverage and increase network lifespan.

In Das et al. (2015), Das et al. presented the Termite Colony Optimization (TCO) algorithm, which was modified to achieve a balance between maximizing coverage area and minimizing the number of sensors used. TCO is a population-based metaheuristic method inspired by termite intelligence, offering improved efficiency and effectiveness compared to previous population-based algorithms in WSNs. Das et al. (2019) proposed a backup node system for ad hoc network coverage, aiming to improve energy efficiency by minimizing communication through the use of a triangulation approach. Backup nodes are strategically selected to provide backup coverage to existing nodes. Du et al. (2022) introduced a multi-level structure and competition mechanism in WSNs to enhance data exploration while balancing energy utilization. Dezfuli and Barati (2019) recognized energy consumption, network lifetime, and coverage as key challenges in WSNs. They proposed a grid-based approach using the evolutionary firefly algorithm to maximize network coverage. Deif and Gadallah (2017) emphasized the importance of creating dependable WSNs that maintain both coverage and connectivity to the sink(s) throughout their intended mission. A multi-agent based energy and fault-aware protocol was developed for challenging and remote areas in Dwivedi and Kumar (2020).

Fan et al. (2021) combined evolutionary computing and machine learning techniques, such as particle swarm optimization and neural networks, to achieve reliable data collection in WSNs. Lei et al. (2019) proposed a model for network coverage optimization and presented a technique based on the weed algorithm. However, the method's effectiveness in maintaining population diversity depends on the use of differential evolution. Guo et al. (2019) employed reinforcement learning-based routing to improve the lifetime of WSNs, but the study focused on flat routing suitable for small networks. Tripathi et al. (2021) provided a review of literature on WSN coverage and connectivity problems, identifying challenges in constructing geometries that preserve coverage and connection, as well as probabilistic-based techniques. Future research needs to bridge the gap between practical application requirements and existing work.

Table 5 Summary of machine learning algorithms applied to solve various problems in wireless sensor networks

Wireless sensor networks issues	Machine learning mechanism	Contributions of the algorithm
Localization (Kaur et al., 2023; Poggi et al., 2022)	K NN	It was possible to localize a free range network effectively using distance estimation
	Reinforcement learning	It is appropriate for dynamic networks where the details of the regions are unknown
Connectivity and coverage (Harizan & Kuila, 2019; Kori & Kakkasageri, 2022; Muruganandam et al., 2022)	Decision tree	Applied for efficient classification of distant and connected network nodes
	Deep learning and evolutionary algorithm	Minimum sensor nodes are required to ensure optimal connectivity and coverage
Anomaly and fault detection (Fan et al., 2021; Noshad et al., 2019; Regin et al., 2021; Tiegang & Junmin, 2020)	Random forest	Applied for classification of normal and faulty nodes
	Deep learning algorithm	Faults and online anomaly detection
Routing (Ghosh et al., 2020; Kim et al., 2023; Othman et al., 2023)	Random forest, decision tree, and evolutionary algorithm	Optimal data routing prediction and control of dynamic paths
Medium Access Control (MAC) (Hussien et al., 2023; Richert et al., 2017; Su et al., 2023)	Support vector machine	Efficient assignment of data routing paths
	Decision tree	Efficient assignment of data routing paths
	Deep learning	Automatic prediction of channels in time and reconfiguration of the network's dynamics
Data aggregation (Dash, et al., 2022; Mahboub et al., 2017; Wang et al., 2023)	K-means	Detection of available number of cluster heads
	Support vector machine	Detection of available number of cluster heads
	Reinforcement learning	Optimal selection of routing paths without the initial details of the network area
Congestion control (Ahmad et al., 2022; Kazmi et al., 2019; Liu et al., 2023)	Reinforcement learning	Detection of congestion and alternate paths in the network

Table 5 (continued)

Wireless sensor networks issues	Machine learning mechanism	Contributions of the algorithm
	Random forest, decision tree and SVM	Classification of normal and congestion nodes in large scale wireless sensor networks
	Evolutionary computation	Discovery and selection of alternative dynamic path to avoid congestion
	Principle & independent component analysis	Dimensionality reduction to control unnecessary sending of information
Target tracking (Ismail et al., 2023; Leela Rani & Sathish Kumar, 2021)	Deep learning	Efficient tracking of targets in different mobile ad hoc networks
	Support vector machine	Target classification in complex networks
	Decision tree	Target classification in complex networks
Event Detection (Balasubramanian & Govindasamy, 2020; Gebremariam et al., 2023)	Evolutionary computation	Effective management of duty cycles
	Deep learning	Effective management of duty cycles
Mobile Sink (Bouarourou et al., 2023; Soni & Shrivastava, 2018)	Evolutionary computation	Choosing the optimum route from mobile sink between rendezvous spots or sensor nodes
	Reinforcement learning	Selection of rendezvous points and optimal tour
	Random forest classifier	Selecting the optimal point and data forwarding routes in complex networks
Energy harvesting (Sarang et al., 2023; Zhang et al., 2020)	Support vector machine	Estimation of timely energy harvesting
	Deep learning	Estimation of timely energy harvesting
	Evolutionary computation	Estimation of harvested amount of energy

Hammouti et al. (2018) and Njoya et al. (2017) adopted a data-driven approach to build models that predict coverage likelihood in wireless networks, revealing limitations in stochastic geometry-based analytical expressions for coverage, which are applicable only to simple network scenarios. Nguyen et al. (2021) identified limited coverage as a key challenge in WSNs and proposed two algorithms, Particle Swarm Optimization (PSO) and Democratic Particle Swarm Optimization (DPSO), to address this issue. The challenge of falling into local optima remains a drawback, and traditional evolutionary computation methods may not fully solve this problem. Hong and Zhong (2014) presented a coverage optimization technique based on an enhanced artificial fish swarm algorithm, aiming to increase coverage rate, extend network service life, reduce running time, and improve sensor network optimization while considering wireless sensor features.

Jameii et al. (2016) proposed a coverage and topology management approach for heterogeneous WSNs using an adaptive multi-objective optimization framework based on learning automata (LA) and non-dominated sorting. The method aimed to maximize the number of active sensor nodes, achieve a high coverage rate in the monitoring area, and maintain a balanced energy usage while ensuring network connectivity. It should be noted that incorporating learning automata with genetic algorithms in this model may lead to increased energy consumption. On the other hand, Wang et al. (2022) introduced a dynamic optimization technique for routing in WSNs utilizing deep learning. However, it is important to note that their study did not specifically address coverage optimization.

In Table 6, a comprehensive overview of bio-inspired algorithms employed in the field of WSNs is presented. The review provides insights into the significant contributions and limitations associated with each of the listed algorithms. However, it should be noted that not all bio-inspired algorithms have potential applications in WSNs. The selection of algorithms for specific problems in wireless sensor networks depends on the relevant parameters that align with the problem domain and the specific algorithm under consideration. Literature research indicates that only three algorithms, namely particle swarm optimization, genetic algorithm, and ant colony optimization, are applicable across all problem domains in WSNs. Consequently, it is crucial to further investigate and explore the potential of various modifications and variants of these algorithms to determine their suitability for optimization purposes in the wireless sensor network field.

Various machine learning techniques and bio-inspired algorithms have been employed to address critical challenges in WSNs, as depicted in Table 7. Optimization algorithms can be broadly categorized as deterministic and stochastic methods for local search and global search, respectively. Deterministic algorithms aim to reach the global minimum based on theoretical assumptions and analytical properties, or at least achieve a local minimum. On the other hand, stochastic algorithms operate on the principle of probability. Stochastic algorithms typically offer faster responses compared to deterministic methods, making them more suitable for handling black box functions and unstable conditions. Stochastic algorithms are further classified into heuristic and meta-heuristic algorithms. Heuristic methods are problem-dependent, which can lead to being trapped in local optima and struggle to find global optima. In contrast, meta-heuristic methods are problem-independent algorithms that are non-greedy and non-adaptive in nature, enabling them to search for global optima. These meta-heuristic algorithms are often referred to as bio-inspired algorithms since they draw inspiration from biological systems.

In summary, coverage is a crucial quality parameter used in WSNs to evaluate the duration for which a node can effectively monitor a specific area. There are three main types of coverage issues in sensor networks: area coverage, target/point coverage, and barrier coverage. Area coverage focuses on monitoring all points within the observation area, target/point coverage

Table 6 Nature-inspired algorithms in wireless sensor networks

References	Algorithms	Nature of Optimization	Solution	Remark
Choudhury et al. (2020)	Particle swarm algorithm	Distributed constraints optimization	The centralized particle swarm optimization algorithm has recently been enhanced to include a decentralized set using a novel strategy	It is not established in the study whether the algorithms could be generalized to solve multi-objective continuous distributed constraint optimization problems
Rugwiro et al. (2019)	Ant Colony Optimization	Task scheduling and resource allocation	The objective is to reduce total task completion time and increase resource usage. A Deep Reinforcement Learning (DRL) algorithm that divides resources into state space and action space to reduce space complexity was presented	The proposed task scheduling and resource allocation process was not evaluated using real-time data
Rahmani et al. (2011)	Voronoi Diagram using Genetic Algorithm	Node placement for maximum coverage	The proposed approach divides the field into cells using voronoi diagram, and then deploys new mobile nodes to the holes in each cell using genetic algorithm	The network model can only run on heterogeneous sensors of random deployment
Toloueiashtian et al. (2022)	Whale optimization algorithm	Point coverage problem	The protocol presented in the study seeks to reduce the monitoring energy consumption of a point coverage network that monitors multiple targets while avoiding excessive overhead in information delivery	The algorithm becomes stuck in a local optimum as the number of sensor nodes within the sensory area increases. To overcome the local optimum challenge, it is important to combine the proposed protocol with local search algorithms (LSA)

Table 6 (continued)

References	Algorithms	Nature of Optimization	Solution	Remark
Narayan and Daniel (2022)	Sleep and wake up technique for WSNs	Coverage hole healing problem	The proposed protocol minimizes overlapping of nodes and coverage hole issues caused by random deployment of nodes	Sleep and wake up protocols are not efficient in time critical applications
Yue et al. (2016)	Artificial bee colony algorithm	Large-scale mobile wireless sensor networks data collection	The solution formulated mobile sink path optimization as a traveling salesman problem and used artificial bee colony technique to search for the shortest path of the mobile sink for efficient network data collection	Data fusion mechanism was not considered in the proposed protocol. There is therefore possibility of high data gathering latency A single mobile sink was considered in the study
Wang et al. (2020b)	Improved particle swarm optimization and genetic algorithm	Optimal coverage of multiple mobile sinks for WSNs	For several mobile sinks, a novel trajectory scheduling strategy based on coverage rate was proposed	A single-hop based trajectory scheduling method was adopted in the study. However, single-hop scheme is not efficient in a large-scale network
Qin and Chen (2018)	Differential evolution	Wireless sensor networks area coverage	The proposed protocol converts continuous area coverage into traditional discrete point coverage so that WSNs can implement optimization. The differential evolution's optimization goal is to maximize the least amount of energy	The sleep and wake up state strategy adopted in the study is not suitable for time critical application domain

Table 6 (continued)

References	Algorithms	Nature of Optimization	Solution	Remark
Guo et al. (2019)	Reinforcement learning algorithm	Lifetime optimization via routing	Residual energy, link distance, and hop count to the sink were considered as reward function factors for the reinforcement algorithm	The reinforcement learning-based routing is a flat routing protocol which is basically not fit for complex networks. The proposed protocol was not tested with real WSN testbed
Wang et al. (2019a)	Improved grey wolf optimizer	Node coverage optimization in WSNs	The relationship between global search and local search is balanced by designing nonlinear convergence factor in the algorithm. The population diversity is attained by introducing dynamic variation strategy to improve the efficiency of the algorithm to jump out of local optimum	Though the protocol is an improvement on grey wolf optimizer, it has a longer running time which will mean higher computational cost
Deif and Gadallah (2017)	Ant Colony Optimization	Sensor nodes deployment	The study proposed ant colony optimization algorithm and local heuristic search for sensor nodes deployment in WSNs. Network reliability metric was considered in the proposed protocol	The reported protocol did not discuss coverage and connectivity in the study. Most of the time, deploying sensor nodes randomly does not ensure maximum coverage and connectivity

Table 6 (continued)

References	Algorithms	Nature of Optimization	Solution	Remark
Nguyen et al. (2017)	Distributed deployment algorithms	Barrier coverage in mobile sensor networks	The proposed protocol first constructed clusters in the network area before using heuristics method to assign sensor nodes to cluster	The technique focuses on the distributed sensor deployment with mobile sensor nodes which is not applicable in all types of wireless sensor networks
Mehta and Malik (2018)	Swarm intelligence algorithm	Healing of coverage holes in wireless sensor networks	Ensembling of particle swarm optimization with gravitational search algorithm to attain global optimization was carried out. Different node's density and sensing range was utilized for results validation	The hole coverage area detection and healing discussed in the study does not guarantee network connectivity. New algorithms can be designed to detect obstacles in the communication path of the nodes
Xu et al. (2015)	Hybrid multi-objective evolutionary algorithms, namely Hybrid-MOEA/D-I and Hybrid-MOEA/D-II were proposed and applied	WSN coverage optimization	In order to account for the coverage rate, energy consumption, and energy consumption equilibrium, the coverage control problem in WSN was modeled as a multi-objective problem. Hybrid GA and DE were applied to increase the population variety	Learning strategies were not applied to improve the performance of the proposed algorithms. Also the proposed algorithms cannot address complex real world scenarios of WSN coverage problem

Table 6 (continued)

References	Algorithms	Nature of Optimization	Solution	Remark
Tarnaris et al. (2020)	Genetic algorithm and the particle swarm optimization algorithm	Area coverage in WSNs	Genetic and particle swarm optimization algorithms were applied to area coverage and area k-coverage optimization in WSNs	Proper multi-objective schemes that guarantee optimal results and coverage maximization were not reported. Reliable WSN applications are designed to address connectivity preservation, energy conservation, and other performance metrics which are multi-objective in nature
Zhao et al. (2022)	PSO and Chaos Optimization algorithms	Coverage optimization in WSNs	The proposed algorithm encoded all sensor locations as a particle position. Sensors approach their optimal positions via PSO strategy and higher coverage rate is attained by employing variable domain chaos optimization	Constrained optimization of the coverage, multi-objective optimization, and energy-saving of WSNs were not reported in the study
Dezfuli and Barati (2019)	Distributed energy efficient algorithm, firefly algorithm	Wireless sensor networks coverage	The study focused on attaining network area coverage with minimum number of nodes. The network area was grouped into cells. The firefly algorithm selects the most active suitable node in each cell based on the coverage radius and the remaining energy level while deactivating other nodes	In the algorithm, there is increased network lifetime and minimal energy consumption. However, in time critical application, this algorithm is not suitable as sensitive phenomenon may emerge in the deactivated period of the nodes

Table 6 (continued)

References	Algorithms	Nature of Optimization	Solution	Remark
Njoya et al. (2017)	Stochastic physics-based optimisation algorithm	Sensor nodes deployment and target coverage	With the aim of reducing the number of deployed sensors while retaining coverage of all target regions, a physics-based heuristic was implemented for effective sensor node deployment in wireless sensor networks	The method does not support connectivity among the deployed sensor nodes
Mini et al. (2014)	Particle swarm optimization and artificial bee colony algorithms	Sensor nodes deployment and target coverage problems in WSNs	Optimal sensor nodes deployment was carried out. The sensing range of the sensors was pre-specified to maintain maximum possible network lifetime with the required coverage level	Probabilistic coverage in wireless sensor networks was not discussed in this scheme of sensor deployment and scheduling
Binh et al. (2018)	Chaotic Flower Pollination and Improved Cuckoo Search and optimization algorithms	Area coverage maximixation in WSNs	The proposed hybrid scheme was presented to solve maximum area coverage making use of a given set of sensor nodes	The proposed algorithms were implemented with very simple assumptions which may not offer optimal results with more complicated assumptions. Area coverage maximization in Mobile Wireless Sensor Networks (MWSNs) environments can be investigated using the proposed protocol
Tossa et al. (2022)	Genetic algorithm	Area coverage maximixation	The proposed algorithm aims at maximizing coverage in the area of interest and minimizing coverage outside the area of interest with constraints to ensure connectivity while taking into account the overlapping region	The issues of connectivity disruption, routing of the detected data and energy efficiency were not addressed in the study

Table 7 Summary of studies on machine learning and bio-inspired algorithms in wireless sensor networks design

Authors	Machine learning technique used	Bio-inspired technique used	Major focus
Sun et al. (2018b)	Regression	×	Network Connectivity
Chang et al. (2016)	Regression	×	Network Connectivity
Kim et al. (2015)	SVM	×	Network Connectivity
Feng et al. (2019b)	SVM & Decision Tree	×	Network Connectivity
Elghazel et al. (2015)	Random Forest	×	Network Coverage
Yang et al. (2016)	Bayesian	×	Network Coverage
Huang et al. (2019)	K-means & C-means	×	Network Connectivity
Ancillotti et al. (2017)	K-means & C-means	×	Network Connectivity
Chen et al. (2016)	Reinforcement	×	Network Coverage & Connectivity
Xu et al. (2018)	Reinforcement	×	Network Coverage & Connectivity
Chowdhury and De (2021)	×	Voronoi-Glowworm Swarm Optimization	Network Coverage
Das et al. (2015)	×	Termite colony optimization	Network Coverage
Wang et al. (2020b)	×	×	Network Coverage
Guo et al. (2019)	Reinforcement learning-based		Network lifetime enhancement
Kapoor and Sharma (2021)	×	Glowworm swarm optimization	Routing protocol
Liu and He (2014)	×	Ant colony optimization with greedy algorithm	Node deployment
Ma and Duan (2022)	×	butterfly optimization algorithm	Coverage Optimization
Narayan and Daniel (2022)	×		Coverage Optimization
Khoshrangbaf et al. (2022)	×	Ant Colony Optimization Algorithm	Coverage Optimization
Qin and Chen (2018)	×	Differential Evolution	Coverage Optimization
Yue et al. (2016)	×	Artificial Bee Colony	Data Collection
Abidin et al. (2015)	×	Termite Colony Optimization	Coverage Optimization

involves monitoring a specific set of points, and barrier coverage emphasizes monitoring intruder movement within a designated area of interest. When a sensor node's detection range covers a location within the area of interest, it is considered to be providing coverage for that location. The level of coverage varies depending on the proximity of the sensor node to the target site. Table 4 highlights that machine learning and bio-inspired techniques have predominantly been utilized to address connectivity issues with the objective of extending the network's lifespan. However, further research is required to explore the application of machine learning and bio-inspired techniques for area coverage in wireless and ad hoc sensor networks. Evolutionary algorithms may lack intellectual advancement, thus deep learning with its more sophisticated learning structure holds promise in this context.

8 Open research problems in WSNs

The research challenges in wireless sensor networks (WSNs) are extensive and diverse. Many of the proposed protocols and solutions for addressing connectivity and area coverage problems in WSNs are tailored for homogeneous sensor nodes. However, the consideration of heterogeneity is crucial in the design of WSNs. It is an open research area that requires further exploration to develop algorithms that can effectively operate on heterogeneous nodes without compromising efficiency.

Another significant challenge lies in the development of meta-heuristic algorithms that can be applied to various optimization problems. As the complexities of problems evolve, there is a need for new optimization techniques to find solutions. This can be achieved through the proposal of novel algorithms or enhancements to existing algorithms. It may also involve combining different optimization approaches, such as classical algorithms, meta-heuristics, or machine learning algorithms, to tackle the evolving challenges effectively. This area of research holds promise for addressing the dynamic and diverse optimization requirements in WSNs.

In the existing literature (Matos et al., 2022), there are numerous research issues in wireless sensor networks (WSNs) that still require further in-depth studies. Some of these research areas include energy efficiency, coverage optimization, clustering techniques, network lifetime, reliability, throughput, latency, network security, load balancing, and the application of machine learning algorithms, among others. An open research area is the utilization of machine learning algorithms to determine the minimum number of sensor nodes required for monitoring a given region of interest.

Routing as one of the NP-hard problems in WSN can be solved using optimization methods. Bio-inspired algorithms can be utilized to find reliable and efficient routing paths in WSN with the potential to reduce energy usage and thereby increase the network's lifespan. In a large scale WSN, the network is designed to allow sensors nodes to transmit sensory data to a sink node that is farther away in multi-hop routing scheme. This strategy is not reliable because of energy constraints and the limited transmission range. It is therefore important to design optimal mechanisms in transmitting the collected data to the sink node. The deployment of WSNs to attain global coverage is a critical consideration for large scale sensor networks. To overcome this challenge, WSNs should be designed to allow sensors to efficiently coordinate their local interactions for the achievement of global goals such as throughput, efficiency, scalability and coverage. The limited transmission range of sensors especially in cases where the network is deployed in large area of interest does not present deterministic polynomial algorithm as a viable solution. This motivated the development of metaheuristic bio-inspired algorithms for routing in WSNs. Swarm Intelligence, evolutionary algorithms and other nature-inspired phenomenon in which self-organization and collective intelligence can emerge are increasingly applied in the domain of sensor networks in order to optimize the network performance.

Clustering is the most widely used technique for efficiently managing network energy consumption and scalability in order to increase network lifespan. This technique allows grouping sensors into clusters and making a node to serve as a Cluster Head (CH) in each cluster. Each CH performs the task of collecting data from the cluster members, process and transfer the processed data to the sink node. When using nature-inspired algorithms to address clustering issues in WSNs, the nature-inspired optimization algorithm can use each node's trust factor to determine which node should serve as the cluster leader. Organizing sensor nodes into clusters can eliminate transmission of redundant data which leads to efficient utilization of energy and ultimately enhances the scalability and overall performance of the network. Conventional clustering methods, however, might not always offer the best solution in terms of network efficiency and energy usage. Therefore, developing optimization algorithms that optimize the clustering process that minimizes energy consumption and maximizes network performance is key. The second method for reducing redundant content detection is data aggregation, which is also regarded as an energy-efficient solution in WSN. When sensors monitor a region, they collect local data and send it to a processing center call sink node either unprocessed or partially processed. The sink node decides to decrease the sensing of overlap or common data in order to prolong the network lifespan based on the collected data.

Data aggregation harvests the most important content of information received from two or more nodes in the network in order to avoid the possibilities of same data sensed and transmitted from different nodes. This contributes to network performance optimization and PSO with its variants offer potentials of efficiency in WSNs data aggregation. Data aggregation minimizes communication overhead by reducing redundant data. One observation from the literature is the lack of reporting data aggregation strategies in coverage optimization algorithms when there is overlapping coverage within the sensing region by sensor nodes. In subsequent studies, it is essential to address this issue and incorporate data aggregation strategies to filter redundant data in the overlapping regions of the network. Furthermore, there is a need to investigate the level of signal interference and establish the relationship between the communication range and packet collision.

Accurate detection and collection of events within the network domain is important in achieving the purpose of deploying the network. With the goal of accurate event detection and data gathering in mind, anomaly or malicious data are bound to emanate from the sensing region of the network. This occurrence offers great threat to the smooth operations of the network. Nature-inspired algorithms with its variants can be developed to address this challenge to enhance convergence rate and execution time against existing techniques.

The data gathered by the sensor nodes would be useless until the location from where the data have been collected from is determined. Localization of sensor nodes in WSNs plays a vital role in many applications. Finding the coordinates of all target nodes using anchor nodes is the primary goal of the localization problem. The Global Positioning System (GPS) can be utilized to locate sensor nodes, which can serve as a substitute for the localization problem. However, as WSNs are made up of numerous sensor nodes, installing a GPS device on each node would increase the cost and complexity of the overall network as well as the amount of power needed.. In recent times, researchers are investigating nature-inspired algorithms such as particle swarm optimization, bat optimization, salp swarm optimization and firefly algorithms in solving optimization problems in WSNs. These optimization algorithms are based on behaviour and searching ability of various natural systems to determine the food source. These algorithms are suitable for solving localization problems because of frequency tuning, automatic zooming, and parameters control features that they possess.

A MAC protocol for data communication is essential among nodes within a WSN, as it is tasked with determining a reliable path for data transmission throughout the network. Many data communication protocols have been devised to maximize energy efficiency, evenly distribute the energy load across all nodes, and minimize power consumption in the network. The lifespan of the network can be improved by designing bio-inspired MAC protocols to provide reliable paths for data collection in WSNs since they are based on the collective behavior of social individual communities.

It is also noted in the literature that achieving the global optimal value becomes challenging with certain machine learning algorithms, such as PSO and K-means, as they tend to converge to regional optimal values, impacting coverage performance. The issue of convergence into local optimal solutions has not been adequately addressed by the widespread application of metaheuristic algorithms (Ikotun et al., 2023). Therefore, it is necessary to explore different variants of particle swarm optimization and investigate their effectiveness in area coverage optimization in WSNs, aiming to improve the solution quality of PSO. Additionally, bio-inspired algorithms are emerging as suitable methods for solving critical problems in WSNs and warrant further investigation. Overall, these research gaps highlight the need for further studies to delve deeper into these areas and develop innovative approaches to address the challenges in WSNs effectively.

The optimization of coverage for mobile sensor nodes is still an ongoing research area due to the dynamic nature of the network topology. As the nodes move, encounter obstacles, or change their positions, the coverage needs to be continuously optimized. In this regard, there is a need to develop new algorithms that enable the sensors to adapt and remain functional even when they encounter obstacles in the region of interest. These algorithms should take into account the changing environment and optimize the deployment of sensor nodes to ensure optimal coverage.

To avoid arbitrary deployment of nodes and achieve efficient coverage, it is recommended to design algorithms that can predict the maximum number of sensor nodes that can be deployed within a region of interest. By accurately estimating the required number of nodes, the deployment can be optimized, and redundant or insufficient coverage can be avoided. This prediction algorithm should consider factors such as the size of the region, the density of events to be monitored, and the capabilities of the sensor nodes. By addressing the challenges of coverage optimization for mobile sensor nodes and developing predictive algorithms, the efficiency and effectiveness of wireless sensor networks can be significantly improved. Further research is needed in this area to explore novel approaches and algorithms that can adapt to the dynamic nature of mobile sensor networks and optimize coverage in real-time scenarios.

It is important to add that in attempts to solve area coverage maximization problem in WSNs, classical algorithms should be designed to estimate the amount of time that is needed to specify the optimal sensor nodes' placement within the network domain which in turn guarantees quality of service features in WSNS (Das et al., 2015). Bio-inspired algorithms are problem-independent. They can be utilized as a black box since they are non-greedy and non-adaptive. These methods frequently allow temporary deterioration of the solution to reach the global optima. These algorithms are scalable, adaptive, and robust and they are very similar to their corresponding natural systems. Multi-objective optimization is the most suitable method that can guarantee quality of service in WSNs due to a large number of factors.

9 Conclusion and future work

A review of the State of the Art of the WSN critical issues is presented, as well as bio-inspired algorithms and machine learning applications to optimize the performance of WSNs. Bibliometric analysis of research works carried out in the domain is also presented. Coverage issues and sensing models associated with WSNs were discussed. Optimization issues across different domains of WSNs applications at the intersection of bio-inspired and machine learning algorithms such as energy, routing, localization, events detection and medium access control protocols were reviewed.

Area coverage is a crucial problem in wireless sensor networks (WSNs) and is considered fundamental in this domain. The design of the network must effectively measure events within the target region. Different WSN area coverage models have specific requirements, restrictions, and goals. By maximizing the area coverage of WSNs, the cost and energy consumption of sensors can be reduced, enabling more efficient data gathering. The objective of area coverage optimization strategies is to find the optimal sensor locations that maximize the coverage area for each sensor across a given domain. Based on our survey, we observed that researchers in this field have primarily focused on addressing routing and clustering challenges. Swarm intelligence methods have been widely applied, while other artificial intelligence (AI) techniques are less commonly used, possibly due to their compatibility with the nature of the problem or their specific characteristics. An important open research area is the exploration of cross-layer approaches that leverage machine learning methods to achieve area coverage in WSNs.

WSNs are deployed either in 2-D or 3D environments. The practical applications scenarios of WSNs require that the sensor nodes are deployed in three-dimensional region of interest. However, our study did not consider the dimensionality of WSNs (Tripathi et al., 2018). Mobile sinks move continuously over the network in a more or less random fashion. The effects of mobile sensors as well as mobile sink on the resiliency of the network was not considered in the study. In the solution approaches of WSNs networks, the network is either deployed as a centralized or distributed system. The survey carried out in this study did not not consider the network to either be a centralized or distributed system. The outlined limitations associated with the study are open grounds for improvement in subsequent studies in the domain of WSNs.

During our extensive review, we identified several gaps, including low search precision, slow convergence, and susceptibility to local optima during data gathering and transmission within the region of interest. Further studies are necessary to address these gaps in the domain of wireless sensor networks. In addition to the techniques explored in existing literature, deep learning techniques hold promise for improving coverage and enhancing network performance. Furthermore, hybridizing the reported heuristic algorithms with other nature-inspired algorithms can be explored to test for potential improvements and establish meaningful comparisons with alternative methods. Future study can formulate a general mathematical coverage optimization model that is energy-efficient in wireless sensor networks.

Acknowledgements The authors wish to acknowledge the funding support by the North-West University postdoctoral fellowship research Grant (NWU PDRF Fund NW.1G01487).

Funding Not Applicable.

Data availability Data is available from the authors upon reasonable request.

Declarations

Conflict of interest The authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

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