Cluster Computing
https://doi.org/10.1007/s10586-024-04619-9

Metaheuristic algorithms and their applications in wireless sensor networks: review, open issues, and challenges

Essam H. Houssein[1] · Mohammed R. Saad[2] · Youcef Djenouri[3,4,5] · Gang Hu[6,7] · Abdelmgeid A. Ali[1] · Hassan Shaban[1]

Received: 29 February 2024 / Revised: 2 June 2024 / Accepted: 4 June 2024

Abstract

Metaheuristic algorithms have wide applicability, particularly in wireless sensor networks (WSNs), due to their superior skill in solving and optimizing many issues in different domains. However, WSNs suffer from several issues, such as deployment, localization, sink node placement, energy efficiency, and clustering. Unfortunately, these issues negatively affect the already limited energy of the WSNs; therefore, the need to employ metaheuristic algorithms is inevitable to alleviate the harm imposed by these issues on the lifespan and performance of the network. Some associated issues regarding WSNs are modelled as single and multi-objective optimization issues. Single-objective issues have one optimal solution, and the other has multiple desirable solutions that compete, the so-called non-dominated solutions. Several optimization strategies based on metaheuristic algorithms are available to address various types of optimization concerns relating to WSN deployment, localization, sink node placement, energy efficiency, and clustering. This review reports and discusses the literature research on single and multi-objective metaheuristics and their evaluation criteria, WSN architectures and definitions, and applications of metaheuristics in WSN deployment, localization, sink node placement, energy efficiency, and clustering. It also proposes definitions for these terms and reports on some ongoing difficulties linked to these topics. Furthermore, this review outlines the open issues, challenge paths, and future trends that can be applied to metaheuristic algorithms (single and multi-objective) and WSN difficulties, as well as the significant efforts that are necessary to improve WSN efficiency.

Keywords Metaheuristic algorithms (MAs) · Single-objective · Multi-objective · Wireless sensor network · Localization · Energy efficiency and clustering

1 Introduction

Wireless sensor networks (WSNs) are found in different areas of our lives, including medicine, engineering, industry, monitoring, and military purposes [1, 2]. WSNs have many challenges that must be addressed to improve the network's overall performance. These challenges include deployment, localization, placement of sink nodes, energy efficiency, and clustering. Deployment describes how to position sensor nodes in optimal locations to achieve a high percentage of area coverage rate [3]; Localization describes how to obtain the unknown positions of nonanchor nodes without using the global positioning system (GPS), achieving a low percentage of squared and localization errors [4]; Sink node placement describes how to better allocate the single or multiple sink nodes in the service area to reinforce the overall efficiency of the network regarding energy [5]; energy efficiency describes how to better use the limited power resources of sensor nodes to prolong the network lifespan [6]; and clustering describes how to divide the sensor nodes of the network into subparts and then assign a cluster head to each part to organize the routing mechanism and maintain the power usage of the entire network [7, 8].

The WSN challenges can be formulated as optimization challenges and solved using various metaheuristic algorithms. metaheuristic algorithms are the most common techniques used to address these challenges depending on their intelligent search mechanisms [9]. metaheuristic algorithms are classified into two main approaches in the

Extended author information available on the last page of the article

literature as follows: single-objective approaches (SO) [10] to deal with SO optimization problems and multi-objective approaches (MO) [11] to deal with MO optimization issues. Basically, metaheuristic algorithms are search algorithms to obtain the optimum solution to a given optimization issue. They extract their intelligent inspiration from nature and are found in different types [12, 13].

Various metaheuristic solutions are available to meet the numerous natures of optimization challenges related to WSN deployment, localization, sink node placement, energy efficiency, and clustering. Therefore, researchers must examine the current literature to determine the direction of the research society regarding the WSN methodologies used, the simulation tools used, and the pop-up searches of different geographical areas and diverse engineering fields. Additionally, the researchers proposed a broad problem with resource allocation in the WSN, which includes varied inputs and outputs, objectives, and limitations. The table of limitations will also provide a general overview of the numerous limitations considered when constructing the optimization model in WSNs. Taking into account the comprehensive overview of recent metaheuristic algorithms, this will help pave the way for research on optimization for WSNs [14]. Most of the articles that will be mentioned, discussed, and visualized in this review, whether in the metaheuristic solution scope or their applications in WSNs, have been picked up from very recent publications in the core of the field as a result of a Scopus search and based on our previous readings and experience in the point. The main contributions of this paper are organized as follows:

- Providing an overview of metaheuristic algorithms found in the literature, including the SO and MO approaches, as well as their evaluation criteria and applications in WSN challenges.
- Introducing a description of the WSN definition, categories, and architecture.
- Defining WSN challenges, including deployment, localization, placement of sink nodes, energy efficiency, and clustering.
- Providing a large list of recent studies related to metaheuristic algorithms and their applications in addressing WSN challenges including deployment, localization, sink node placement, energy efficiency, and clustering.
- Open issues, challenges and possible future research trends are also presented to illustrate the types of research issues related to metaheuristic algorithms and WSN challenges that need to be solved and given attention.

The rest of this paper is structured as follows: Sect. 2 will comprehensively cover the metaheuristic algorithms and their classifications. Section 3 will cover the definition and architecture of WSNs. Next, Sect. 4 will discuss the applications of metaheuristic algorithms in WSNs. Section 5 will cover open issues and challenges. Finally, the research review is concluded in Sect. 6.

2 Metaheuristic algorithms (MAs)

The concept of metaheuristic strategy involves applying various optimization techniques to develop, locate, or choose the optimal solution to an optimization issue, particularly when there is poor or partial information or limited computing capability. Specifically, metaheuristic algorithm employs metaheuristic algorithms to solve SO and MO optimization issues. Optimization is everywhere, be it engineering design or industrial design, business planning, etc. [15, 16]. Therefore, making the most of these resources is essential because time and money are always limited. Generally, metaheuristic algorithms are found in the literature in various categories, including bio-inspired algorithms [17], math-inspired algorithms [18], swarm-based algorithms [19], nature-inspired algorithms [20], biogeographic-stimulated algorithms [21], evolutionary algorithms [22], physics-based algorithms [23], human-base algorithms [24], and chemistry-based algorithms [25]. Under diverse and complex restrictions, most advances in the real world are non-linear and extremely multimodal. Several goals are often at odds. Even for a single goal, there may be no perfect solution. Generally, obtaining a flawless or even sub-optimal solution is difficult to undertake. metaheuristic algorithms, particularly in nature, emulate nature to clarify optimization problems. Therefore, to tackle realistic optimization issues, performance optimization techniques should be used; however, there is no guarantee that the best solution will be discovered, but they can at their best reach the sub-optimal one efficiently with respect to time and computer resources. In addition, new algorithms have been presented to investigate whether they can dominate these complex optimization issues. Based on the preceding considerations, the subsections that follow attempt to categorize the extant algorithms into two major categories: SO and MO metaheuristic algorithms [26].

2.1 Single-objective metaheuristic algorithms

The literature has many proposed SO metaheuristic algorithms, such as the neural network algorithm (NNA), which is inspired by biological nervous systems integrated with artificial neural networks to address various optimization issues. The proposed NNA was validated at Congress on Evolutionary Computation (CEC) 2015 and many engineering design issues, including pressure vessel design, welded beam design, speed reducer design, three-bar truss design, and gear train design. The experimental results demonstrated the super capacity of NNA compared to other competitors [27]. Similarly, the artificial electric field algorithm (AEFA) is inspired by Coulomb's law of electrostatic force to address various and complex optimization issues. The proposed AEFA is validated on 15 functions from CEC 2015 to test its applicability. The findings indicate that the suggested AEFA can outsmart metaheuristic techniques in the comparison of nonlinear optimization [28].

The seagull optimization algorithm (SOA) is suggested based on the combination of emigration and attacking procedures of seagulls in the wild. These procedures are theoretically defined and applied to encourage diversification and intensification within a specified search space. According to 44 benchmark routines from CEC 2005 and 2015, the efficacy of the SOA is compared with that of 9 familiar metaheuristics. Notably, the computational cost and convergence properties of the suggested algorithm have been investigated. Therefore, to demonstrate its usefulness, it is then used to address seven limited real-world manufacturing issues, including optical buffer design, pressure vessel design, speed reducer design, welded beam design, tension / compression spring design, 25 bar truss design and rolling element bearing design. The experimental findings indicate that the suggested method can solve restricted, complex problems on a large scale and is highly competitive compared to existing metaheuristic techniques [29]. Similarly, artificial ecosystem-based optimization (AEO) is a recent population-based optimizer based on the energy flow in an ecosystem on the earth according to the simulation of three procedures of alive organisms, including generation, exhaustion, and putrefaction. AEO is put through its paces on 31 benchmark routines from CEC 2014, and also eight real-world engineering design issues, including a three-bar truss, cantilever beam, tension/compression spring, pressure vessel, welded beam, speed reducer, rolling element bearing, and multiple disk clutch brake designs. Overall, the comparisons show that AEO's optimization performance beats that of other cutting-edge competitors. Furthermore, in terms of the convergence rate and the complexional effort, AEO outperforms other documented approaches, particularly for real-world engineering issues [30].

The artificial gorilla troops optimizer (GTO) is a contemporary metaheuristic model that considers inspiration from the social intelligence of gorilla troops in the wild. Diversification and intensification, also known as optimization procedures based on gorilla behavior, are performed by the algorithm using five unique operators. The model was mathematically modeled, implemented, and tested on 52 benchmark routines from CEC 2017. Furthermore, to test its applicability, it is used to address seven engineering issues, including frequency-modulated sound wave parameter estimation, circular antenna array design, spread spectrum radar polyphase code design, Cassini 2: spacecraft trajectory optimization, messenger: spacecraft trajectory optimization, Lennard–Jones (LJ) potential, and static economic load dispatch (ELD). The results indicate that the GTO surpass comparable models on most benchmark routines, notably on high-dimensional issues. The results show that the GTO outperforms other metaheuristics in terms of performance [31]. Furthermore, the orca predation algorithm (OPA) is a modern stochastic metaheuristic model that mimics the attitude of a smart carnivorous predatory dolphin known as orcas, with a high level of social interaction. Orcas, such as wolves, hunt with troops and have their hunting techniques. Instead of surging and gulping several fish, they employ their sonar to interact with each other and organize their strategies when they come across a swarm of fish. Members of the troop work together to herd a large group of fish to the surface and surround them in a controllable ball. Then, each takes turns blowing bubbles, flashing their white stomachs, and whipping their tails against the ball, shocking or killing the fish. The orca beats the edge of the shoal with its tail to collect food after the shoal is under control [32]. Therefore, to assess the performance of OPA, 67 non-constrained benchmark routines from CEC 2015 were used, followed by an evaluation of the algorithm's efficiency on five constrained engineering optimization issues, including welded beam, pressure vessel, speed reducer, tension / compression spring and three-bar truss designs. The test results show that OPA can produce more promising results with greater performance compared to other test models in various search landscapes [33].

The hunger games search (HGS) is presented in [34] with a clear structure, remarkable stability properties, and an extremely competitive ability to address limited and unconstrained issues more effectively. The HGS suggested is based on animal hunger-driven actions and behavioral preferences. This dynamic, fitness-based search method is based on the clear approach of "hunger" as the most important homeostatic motivation and reason for all animals' behaviors, decisions, and actions to make the optimization procedure more understandable and consistent for new users and decision-makers. The efficacy of HGS was demonstrated by comparing it with a complete selection of popular and sophisticated algorithms on 23 optimization routines from the CEC 2014 benchmark suite. Additionally, to illustrate the usefulness of the HGS, it was applied to many engineering issues, including the welded beam design, the i-beam design, and the multiple disk clutch brake. The experimental findings demonstrate that the method is adaptable and scalable, allowing it to be adapted to fit more optimization instances in both the architectural and application dimensions. Moreover, the mayfly algorithm (MA) is proposed to address optimization difficulties. The suggested method, which is based on the flight behavior and mating procedure of mayflies, combines the major benefits of swarm intelligence and evolutionary algorithms. Therefore, to assess the performance of the suggested approach, 38 mathematical test routines were used, including 13 test routines from the CEC 2017 benchmark suite, and the results were compared with those of seven popular and robust metaheuristic algorithms. The MA's performance is also evaluated using MO optimization convergence behavior and a real-world discrete flowshop scheduling issue. The comparison findings show that the proposed strategy is superior in terms of convergence rate and speed [35].

Therefore, to handle limited engineering optimization issues, the search and rescue optimization technique (SAR) was proposed. This metaheuristic model mimics human diversification during search and rescue efforts. SAR is tested by addressing 18 CEC 2010 benchmark routines and 7 constrained engineering design issues, such as speed reducer, three-bar truss, pressure vessel, welded beam, spring, tubular column, and reinforced concrete beam designs. The SAR performance is compared with that of some robust optimization techniques. According to statistical comparison outcomes, SAR outperforms or is highly competitive with the analyzed models on most of the tasks being studied [36]. Additionally, the turbulent flow of water-based optimization (TFWO) algorithm is proposed based on the natural search phenomenon. This method obtains global solutions to genuine benchmark routines of varying measures. Furthermore, to further study the efficacy of TFWO, it was used to address different types of nonlinear ELD optimization issues in energy systems, and reliability–redundancy allocation optimization (RRAO) for a highly protected gas turbine system, as two practical engineering optimization issues. The results of TFWO are compared with existing algorithms, which offer proof of the effective operation of the proposed TFWO algorithm with superior solution precision in addressing several real benchmarks and practical engineering issues [37]. Table 1 lists the above-mentioned works. Additionally, Fig. 1a illustrates the statistics for SO metaheuristic algorithm issuance and related studies from 2012 to 2021, according to information from Scopus databases. Also, Fig. 1b clarifies the distribution of SO metaheuristic algorithms in various research areas.

2.2 Multi-objective metaheuristic algorithms

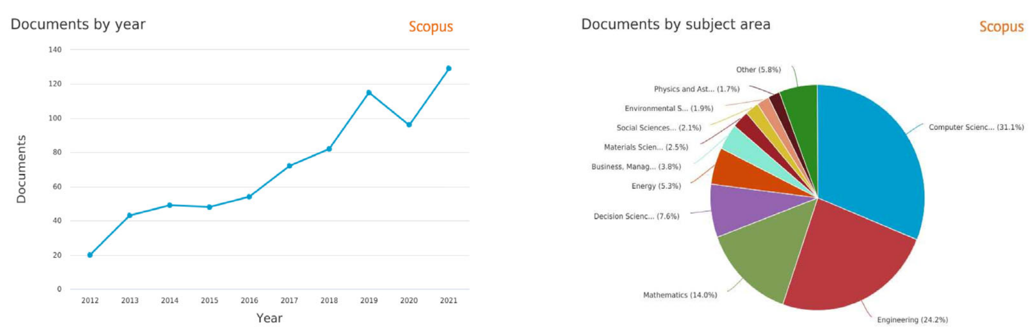
Different MO metaheuristic algorithms are proposed to deal with and address various MO optimization issues in different study fields [38, 39]. SO metaheuristic algorithms are modified to generate MO versions. Accordingly, an outer archive needs to be integrated with the algorithm and an efficient target selection technique. An outer archive to keep Pareto optimal (PO) solutions is needed, as here the concept of a single optimal solution to an issue does not exist because the objectives of MO issues conflict with each other and, consequently, multiple solutions to an MO issue are produced, which are known as PO solutions or alternatives [40]. These PO solutions achieve a trade-off. They are solutions where each bit of progress on one goal wreaks havoc on at least one other goal. The target selection technique can be performed by many procedures, such as an elitist non-dominated sorting mechanism [41], a roulette wheel selection mechanism [42], a grid-based approach [43], and a leader selection mechanism [44].

The literature has many proposed MO metaheuristic algorithms, such as the MO artificial bee colony (MOABC) algorithm, which was proposed in [45]. The MOABC employs a grid-based method to flexibly evaluate the Pareto front kept in an outer archive. The outer archive is used to manage individual flying behaviors and to structure bee colonies. The hired bees use the non-dominated solutions stored in the outer archive to adjust their route. In contrast, observer bees choose the food supplies of the hired bees to update their locations. The Pareto dominance principle is used to calculate the characteristics of these food supplies. The suggested method was assessed against existing contemporary methods on a set of typical investigation tasks. The experimental findings show that the suggested method is competitive compared to the other methods discussed in this study. Moreover, the MO artificial immune algorithm for fuzzy clustering based on multiple kernels (MAFC) is proposed in [46]. This method enhances the standard fuzzy C-Means method and solves some of its significant shortcomings, such as vulnerability to local optima convergence, which can cause poor grouping accuracy. Multikernel learning and MO optimization are combined in a grouping strategy that retains the dataset's geometric information. Furthermore, using kernel functions, the multikernel technique translates data from feature space to kernel space [47, 48]. MAFC is compared with robust literature approaches in studies using UCI and face datasets. According to the findings, MAFC is substantially more efficient for grouping and has a wider range of applications.

The MO water cycle algorithm (MOWCA) is introduced to tackle limited MO issues. MOWCA is based on simulating the natural water cycle mechanism. Here, several

Table 1 Recent single-objective metaheuristic models suggested in the literature

Metaheuristic algorithm	Author	Publication year	Inspiration	References
NNA	Ali Sadollah	2018	Biological nervous systems	[27]
AEFA	Anita	2019	Coulomb's law of electrostatic force	[28]
SOA	Gaurav Dhiman	2019	Migration and attacking behaviors of seagulls	[29]
AEO	Weiguo Zhao	2020	Flow of the ecosystem's energy on the earth	[30]
GTO	Benyamin Abdollahzadeh	2021	Gorilla troops' social intelligence	[31]
OPA	Yuxin Jiang	2022	Hunting behavior of orcas	[33]
HGS	Yutao Yang	2021	Hunger-driven actions and behavioural preferences of animals	[34]
MA	Konstantinos Zervoudakis	2020	Flight behavior and mating procedure of mayflies	[35]
SAR	Amir Shabani	2020	Investigation techniques of humans during search and rescue processes	[36]
TFWO	Mojtaba Ghasemi	2020	Phenomenon of natural search	[37]



(a) Histogram of single-objective metaheuristic algorithms publications.

(b) Distribution of single-objective metaheuristic algorithms research areas.

Fig. 1 Single-objective metaheuristic algorithms researches achieved in the last decade (2012–2021) based on the Scopus database

non-dominated alternatives acquired by the suggested method are archived to demonstrate the MOWCA's exploratory ability compared with other efficient approaches in the literature. Furthermore, the resulting optimization outcomes are compared with other frequently used optimizers for limited engineering design issues to fully assess the resilience and efficiency of the suggested algorithm. Comparisons are presented in tabular, detailed, and graphical formats [49]. Additionally, the MO copy of a recently designed spotted hyena optimizer (SHO) known as MO spotted hyena optimizer (MOSHO) is introduced. MOSHO is used to address issues with multiple objectives. A fixed-sized archive is used in the suggested approach to save PO solutions. Furthermore, to imitate spotted hyenas' social and hunting activities, the roulette wheel mechanism is used to determine appropriate solutions from an archive. The proposed technique is investigated for 24 benchmark routines from CEC 2009 (MO CEC) and compared with six recently established metaheuristic approaches. Therefore, to demonstrate its applicability to real-world issues, the suggested method is applied to six constrained engineering design issues, including welded beam, multiple disk clutch brake, pressure vessel, speed reducer, gear train, and 25-bar truss designs. The experimental findings show that the suggested method outperforms the others in producing PO solutions with premium convergence [50].

In [51], the MO grasshopper optimization algorithm (MOGOA) was proposed, which selects the target from the archive using an appropriate selection method based on the probability of the roulette wheel. Also, the MO grey wolf optimizer (MOGWO) is presented to address MO difficulties [52]. Additionally, the proposed MOGWO is compared with two familiar metaheuristic algorithms, the MO evolutionary algorithm based on decomposition (MOEA/D) and MO PSO (MOPSO), on 10 MO benchmark challenges, including CEC 2009. The recommended optimization model beats other competing algorithms using descriptive and inferential statistical data. The MO slime mould algorithm (MOSMA) was created by merging the slime mould algorithm (SMA) with an auxiliary archive [53]. MOSMA applies the crowding distance method and elitist non-dominated sorting principles. Regarding Pareto proximity and reversed exponential distance in the decision zone, the recommended approach produced PO choices better than the familiar current approaches based on CEC 2020. The MO sine-cosine algorithm (MOSCA), presented in [54], has been used to solve MO engineering challenges involving spring designs, four-bar trusses, multi-plate disk brakes, gear trains and welded beam designs. According to the trial's findings, the suggested technique works better than other current algorithms. The MO volleyball premier league approach (MOVPL) is introduced in [55] to deal with global optimization problems that involve many target activities. Teams participating in an elite volleyball league inspired this optimization approach. Therefore, to assess how well the new technique performs, 10 MO benchmark test scenarios, including CEC 2009 with complex objectives, were conducted and compared with two familiar MO models, MOPSO and MOEA/D. According to the trial's findings, the MOVPL outperforms the two state-of-the-art optimization models on MO investigation routines. Meanwhile, MOMVO, a multi-verse optimizer-based MO approach, was evaluated in an 80-case study, including unconstrained MO investigation routines, restricted MO investigation routines, and MO engineering design issues in [56]. Reference [57] introduced the MO ALO (MOALO), which is used to address engineering optimization challenges. Unlike the non-dominated sorting genetic algorithm version 2 (NSGA-II) and the MO ant colony optimization (MOACO) approaches, the MO gravitational search algorithm (MOGSA) was developed in [58]. In [59], the MO WOA (MOWOA) is created and investigated for six IEEE CEC 2009 unrestricted bi-objective investigation challenges. The acquired outcomes indicated that the suggested optimization approach outperforms other familiar and currently developed methods. Similarly, MO moth flame optimization (MOMFO) with the same archiving process as MOWOA is introduced in [60].

One of the most well-known modern MO algorithms, the MOPSO, was created in [61]. In [62], the MO salp swarm approach (MSSA) is also introduced to address and resolve issues with MO optimization, such as airfoil design and marine propellers. It should be highlighted that both qualitative and quantitative findings supported the effectiveness of MSSA. Additionally, MO optimization challenges are addressed with the MO seagull optimization method (MOSOA). This method is based on the dynamic archive concept, which can cache non-dominated solutions. The roulette wheel selection mechanism is used to identify the most successful archival solutions by simulating seagull migration and attacking behaviors. The proposed approach is validated by running it through 24 test routines from CEC 2009 and evaluating its effectiveness compared to current MO techniques. The created method is investigated for six restricted structural engineering issues, including multiple-disk clutch brake, welded beam, pressure vessel, speed reducer, 25-bar truss, and gear train designs, to determine its suitability to solve real-world challenges. Empirical analyzes show that the suggested method outperforms other MO algorithms [63]. Furthermore, the MO GTO (MOGTO) is also suggested in [64] to solve concerns with MO optimization. The MOGTO stores the PO solutions it finds in an external repository. The archive was used to mimic the collective attitude of the gorilla groups in the MO search region. Using the CEC 2020 investigation suite, the proposed method is statistically and subjectively assessed to address different MO concerns. The ten well-known and effective optimization models that are contrasted with the suggested algorithm include MOPSO, NSGA-II, MOGWO, MOWOA, MOSCA, MOSMA, hybrid NSGAII-MOPSO, MOEA/D, MOPSO with ring topology and special crowding distance (MO_Ring_PSO_SCD), and improved MO manta-ray foraging optimization.

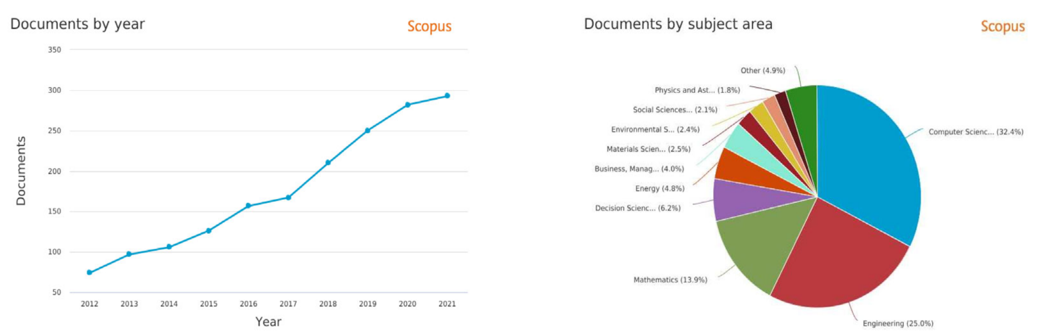
The suggested MOGTO can deliver outstanding results compared to previous optimization models with respect to Pareto set proximity, inverted generational distance in decision space (IGDX), and hypervolume (HV) indicators, according to simulation findings in the CEC 2020 investigation routines. Table 2 reports on the metaheuristic MO algorithms mentioned above with their various archiving processes. Furthermore, Fig. 2a illustrates the statistics for the issuance of MO metaheuristic algorithms and related studies from 2012 to 2021 based on information from the Scopus databases. Furthermore, Fig. 2b clarifies the distribution of MO metaheuristic algorithms in various research areas.

2.3 Evaluation criteria of metaheuristic algorithms

Metaheuristic algorithms are a class of adaptable and flexible search frameworks that draw their inspiration from physical or natural events. Additionally, because they utilize the idea of training a computer to think and select the best option from a range of options in a manner similar to

Table 2 Recent multi-objective metaheuristic models suggested in the literature

Metaheuristic algorithm	Author	Publication year	Archiving process	References
MOABC	Reza Akbari	2012	Grid-based approach	[45]
MAFC	Ronghua Shang	2019	Clone selection mechanism & Uniformity maintaining mechanism	[46]
MOWCA	Ali Sadollah	2015	Crowding distance mechanism	[49]
MOSHO	Gaurav Dhiman	2018	Roulette wheel selection mechanism	[50]
MOGOA	Seyedeh Zahra Mirjalili	2018	Roulette wheel selection mechanism	[51]
MOGWO	Seyedali Mirjalili	2016	Grid-based approach	[52]
MOSMA	Essam H. Houssein	2022	Elitist non-dominated sorting mechanism & Crowding distance mechanism	[53]
MOSCA	Mohamed A. Tawhid	2019	Elitist non-dominated sorting mechanism & Crowding distance mechanism	[54]
MOVPL	Reza Moghdani	2020	Leader selection mechanism	[55]
MOMVO	S. Mirjalili	2017	Leader selection mechanism	[56]
MOALO	Seyedali Mirjalili	2017	Roulette wheel selection mechanism	[57]
MOGSA	Hossein Hemmatian	2014	Uniform mutation operator & Elitist policy	[58]
MOWOA	Ishwar Ram Kumawat	2017	Grid-based approach	[59]
MOMFO	Vikas	2016	Grid-based approach	[60]
MOPSO	Carlos A. Coello	2004	Adaptive grid-based approach & Mutation operator	[61]
MSSA	Seyedali Mirjalili	2017	Roulette wheel selection mechanism	[62]
MOSOA	Gaurav Dhiman	2021	Roulette wheel selection mechanism	[63]
MOGTO	Essam H. Houssein	2022	Elitist non-dominated sorting mechanism & Crowding distance mechanism	[64]



(a) Histogram of multi-objective metaheuristic algorithms publications.

(b) Distribution of multi-objective metaheuristic algorithms research areas.

Fig. 2 Multi-objective metaheuristic algorithms researches achieved in the last decade (2012–2021) based on the Scopus database

that of a person, these algorithms are considered one of the most significant applications of artificial intelligence [65]. Various factors are used to evaluate the performance of these algorithms, including:

- The CEC test suite is a collection of test routines, including unimodal, multimodal, and composite issues, expressed in mathematical forms that are used to validate the algorithm by running the algorithm on it through the objective function for measuring both quantitative and qualitative performance of the algorithm, as well as how the algorithm performs compared to other algorithms in terms of achieving equilibrium between diversification and intensification, escapement of local optima, diversification capacity, and intensification capability [66, 67].

- Results of statistics based on CEC values, including mean, standard deviation, best, and worst. The mean is the average of the objective scores acquired from the implementation of the algorithm M times, the standard deviation represents the variation in the objective function scores acquired after the algorithm M times, the best denotes the lowest objective score, and the worst denotes the highest objective score [68].
- The Wilcoxon check is a type of statistical test that is used to statistically validate the algorithm's performance. It is considered a nonparametric statistical test and is conducted to establish the significance of the algorithm's output, with p-values typically less than 0.05. Furthermore, the Friedman rank test is also used and achieved [69].
- The convergence curve is a graphical test (diagram) that visualizes the relationship between the algorithm's capacity to maximize or minimize the objective function and the number of iterations. It also shows how quickly a solution can be reached [70].
- Engineering issues are a collection of traditional engineering issues that have various constraints that are addressed by utilizing metaheuristic algorithms, such as the welded beam design in SO optimization and the disk brake design in MO optimization. In fact, these issues are considered a type of constraint optimization test [71].

3 Wireless sensor networks (WSN)

WSN can be described as a system comprising a set of sensor nodes that are geographically scattered in some region of interest (ROI) to detect and sense some environmental parameters, such as temperature, humidity, sound, wind and pollution levels, among others [72, 73]; for momentary surveillance and feedback, as depicted in Fig. 3. These sensors gather data and deliver it to the sink node for processing and organizing. The sink node becomes in charge of transmitting the result information to the user through the Internet or satellite. WSNs are often composed of hundreds or thousands of nodes linked to each other. Processing, sensing, transmitter and receiver, and power units are the four major components of each sensor node (Fig. 4) [2]. GPS, packers, and power generators are examples of application-dependent plugins.

Analog to digital converters (ADC) and sensors are generally present in a sensing unit. The ADC transforms the analog signals produced by the sensors due to the observed phenomena into digital signals, which are subsequently sent to the processing unit. The processing unit, which is usually linked to a small storage unit, controls the tasks that permit the sensor node to operate with other nodes to achieve the sensor's specific duties. The node is connected to the network via the transceiver. One of the most essential parts of a sensor node is the power unit. Power scanning units, such as solar cells, may be used to assist power units. Therefore, it may be necessary to use the fill tool to shift the sensor nodes when performing certain operations. A matchbox module may be required in these subunits [2]. Moreover, the needed capacity might be as little as one cubic centimeter, allowing light to float in the air.

The Zigbee protocol (IEEE 802.15.4) communicates among nodes in WSNs. It features a bit rate of 250 kbps and a frequency of 2.4 GHz. Therefore, it employs a lower frequency to extend the radio range. Every node has a communication range R_c (usually $\leq$ 100 m) and a detection range R_s (the space to be tracked by the sensor) [74, 75]. WSN provides several advantages, including eliminating many cables, accepting additional devices at any time, and the flexibility to travel through the real section. It is accessible via a centralized screen and/or an architecture [76]. Industrial tracking, water quality tracking, landslide detection, air pollution tracking, forest fire detection, area tracking, health care monitoring, natural disaster prevention, and other applications are all possible with a WSN [77, 78].

The star, mesh, and tree are the three most prevalent topologies for WSNs that must be built correctly using

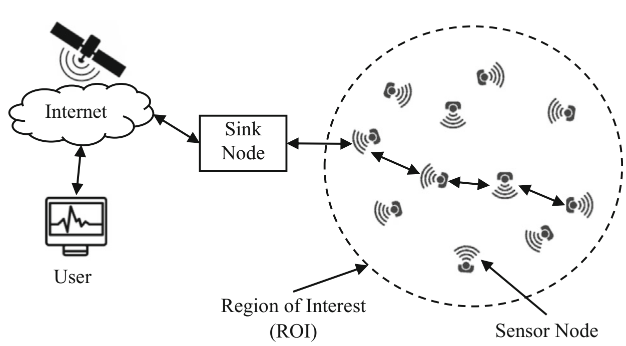


Fig. 3 Wireless sensors network environment

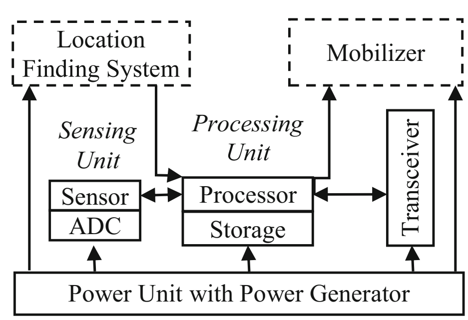


Fig. 4 Sensor node components

appropriate methodologies. Additionally, topology control is the most fundamental approach in dispersed techniques. Topology control is a distributed computing strategy that involves making changes to the fundamental network, which may be represented as a graph, to reduce the cost of dispersed techniques compared to modern topologies [79]. It is one of the most essential distributed algorithm approaches and is mostly used to create sensors and wireless ad-hoc networks. More recent arguments have been made to split topology control methods into two sub-strategies. First, topology-building techniques, such as A3 [80], EECDS [81], and CDS-Rule K [82], are responsible for the first network reduction. Second, topology maintenance techniques, such as SGTRot, DGTRec, and HGTRotRec, can achieve some adjustments to the first reduced topology when they cannot complete their role and maintain the reduced topology in terms of coverage and connectivity. Topology control's key goals are to lengthen network lifespan by preserving energy, decreasing interference among sensor nodes, and producing a well-linked topology.

Several methods are available to accomplish the topology building, which is followed by topology-building techniques, such as adjusting the sensor nodes' communication range; creating a communication framework; removing some nodes from the network; introducing additional nodes to the network to ensure connectivity; and clustering. However, the primary problem with topology-building techniques is that they initially lack a mechanism for deploying sensor nodes. Therefore, these techniques place sensor nodes at random, causing significant network damage, such as redundant areas, which happens when many sensor nodes are placed in the same ROI subarea. In this context, sensor node redundancy is one of the most frequent reasons for message collisions and transmitting multiple copies of the same data to the base (sink) node. In addition, blind areas (areas that do not have sufficient sensor nodes to detect or cover events) may appear due to the use of these techniques. However, the network administrator has no control over the placement of the sensor nodes and cannot rearrange them to reduce redundancy or blindness. Therefore, metaheuristic algorithms play a vital role in repositioning sensor nodes to reduce redundancy [83].

4 Applications of metaheuristic algorithms in WSNs

Because of their diverse uses and incorporation into more complicated network systems, WSNs are a stimulating subject of study. WSN difficulties are frequently related to its stringent limitations, such as deployment, localization, placement of sink nodes, energy efficiency, and clustering. The basic challenges of area coverage, node localization, sink node placement, energy efficiency, and clustering are examined and modeled as independent optimization issues in this survey [84, 85]. Meta-heuristic optimization algorithms are used to propose solution techniques. The relationship is also drawn with traditional optimization issues. WSN deployment, localization, placement of sink nodes, energy efficiency, and clustering concerns are represented as NP-hard [86]. As a result, metaheuristic algorithms are used to overcome or mitigate some of the shortcomings of these difficulties. As is known, the WSN is made up of a number of sensor nodes, each of which is emulated as a single search agent in the optimization process, and the method optimizes the goal, whether it is location or energy, after a given number of iterations.

MO optimization is used to address a variety of real-world issues that have multiple objectives that must be met simultaneously. Studying MO optimization is undeniably an important topic for theorists and engineers to study [87, 88]. However, occasionally, issues with multiple objectives are in direct conflict with each other. As a result, finding the global ideal is practically impossible [89]. Unlike optimization for SO, in MO optimization, there are several optimal solutions, and the decision maker determines the viable options according to the order of priority given to various competing objectives. When the decision maker enforces the preference on several competing objectives, a MO optimization issue may be stated using various methodologies [90]. The most common method is to assign various weights to distinct objectives and then use an MO optimization algorithm to combine several objectives into one number of merits. In WSNs, objectives such as coverage vs. cost, throughput vs. rate of packet faults, delay vs. throughput, battery life vs. coverage, rate of packet faults vs. cost, and so on can clash [14].

A list of earlier investigations into metaheuristic algorithms and their use in WSNs will be presented in the following subsections.

4.1 Deployment challenge in WSNs using metaheuristic algorithms

In WSNs, deployment refers to the practical process of efficiently deploying sensor nodes (optimal distance among sensor nodes = $\sqrt{3}$ * detection range) to provide enough ROI coverage as shown in Fig. 5. Because WSNs have limited radio capacity, users must adopt and apply good node placement tactics to compensate for this. A good deployment ensures that deployment costs are reduced while WSN detection capabilities are improved. It can also

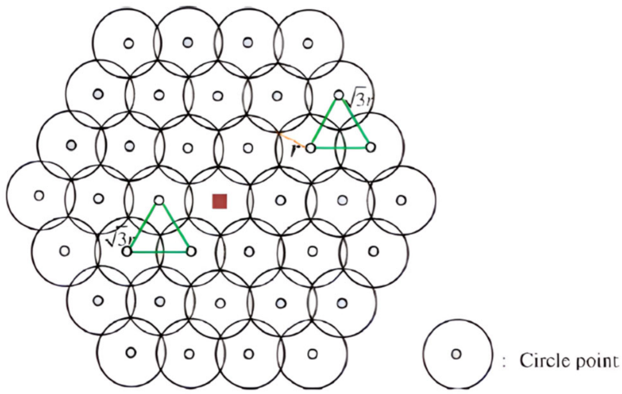


Fig. 5 Optimal sensor nodes deployment schema

increase the goodness of surveillance in WSNs by expanding the ROI.

Several metaheuristic algorithms have been designed in recent years to address tough and complex nonlinear situations. However, the deployment architecture for WSNs has received a lot of attention in recent years. For example, reference [91] presented two metaheuristic algorithms to overcome the deployment issue, namely an improved cuckoo search (ICS) and a chaotic flower pollination algorithm (CFPA). In previous studies, the two methods were able to perform better, with the aid of an insightful local search and the idea of computational flexibility. The experiments in 15 cases demonstrated a significant improvement in computational effort, solution quality, and reliability. The work in [92] developed a sensor deployment strategy based on glowworm swarm optimization (GSO) to improve coverage after random sensor deployment. Each sensor node is modeled as a single glowworm that releases a luminant material called luciferin, the intensity of which is proportional to the distance between the sensor node and its neighbors. A sensor node is drawn to neighbors with lower luciferin intensities and decides to travel towards one of them. As a result of the sensor nodes gravitating toward areas with lower sensor density, the sensing field's coverage is maximized. This deployment strategy demonstrated that it can offer enough coverage with minimal motion, implying a low energy travel distance.

The dense deployment and power assignment issue (d-DPAP) in WSNs was introduced in [93], a hybrid MOEA/D and a generalized subproblem dependent heuristic (GSH) was suggested. The d-DPAP was split into a series of numerical sub-problems utilizing this approach. Through the use of local knowledge and problem-specific information, the subproblems were optimized concurrently. Six d-DPAP-specific techniques, developed in accordance with the subproblems' goal preferences and a variety of WSN notions, are alternated deterministically utilizing the suggested GSH. The suggested hybrid problem-specific MOEA/D outperforms the general-purpose MOEA/D and NSGA-II in numerous WSN scenarios, according to simulation findings, offering a variety of high-quality near-optimal network architectures to aid in decision-making. Also mentioned was the MOEA/D-attitude GSH in the target space. The ant colony optimization (ACO) technique was introduced in [94] as a natural and inherent means of exploring the search space for the multiple-knapsack problem (MKP). The problem of sensor placement was studied in this work to obtain extensive coverage of the service zone and improve the lifespan of the network. The deployment challenge was modeled as the multiple knapsack problem in this work. This work presented a deployment technique based on the ACO algorithm to extend the life of the network while ensuring complete ROI coverage. The simulations suggest that the proposed technique can extend the useful life of the network. The artificial fish swarm algorithm (AFSA) was upgraded to the optimized artificial fish swarm algorithm (OAFSA) for use in the deployment of WSN in [95]. In this study, the network is seen as a group of stationary sensors. The scavenging and rearing attitudes of the original algorithm are passed down to the improved algorithm. Discussions and numerical simulations demonstrate that the OAFSA suggested schema outperforms the original AFSA in terms of WSN area coverage by improving network efficiency.

Reference [96] investigated the issue of maximum coverage deployment in WSNs. Specifically, how to deploy a given number of sensors with varying detection ranges in a particular domain such that their coverage is maximized. This is considered an NP-complete issue. This study offered a new genetic algorithm that improved on an existing genetic algorithm. Among the enhancements are the specification of a new overlapping notion for the objective function, the utilization of a heuristic approach to initialize the population, and the utilization of dynamic mutation. The suggested approach was tested in 15 instances built for this challenge. The experimental findings demonstrate that the suggested method was successful in all aspects of computational complexity, solution quality, and reliability. Furthermore, the virtual force algorithm (VFA) was used to address the issue of area coverage in WSN, and it was improved with the improved virtual force algorithm (IVFA) and the exponential virtual force algorithm (EVFA) to increase the efficiency of the WSN in terms of coverage rate, energy consumption of moving objects and convergence of the deployment strategy [97]. Coevolutionary PSO (CPSO) was combined with the virtual force algorithm (VFA) to deploy network sensor nodes in installation regions with no blind or duplicated sub-areas in order to achieve the highest feasible coverage ratio. The results showed that the hybrid algorithm (VFCPSO) beat the VF, PSO and VFPSO algorithms in terms of efficacy and computation time [98].

In [99], node deployment based on the bat algorithm (BA) was developed to improve the node coverage rate. Each bat provides a distinct solution for sensor node placement. Grid locations covered by one sensor node are eliminated for the residual sensor nodes in the BA-based node deployment. Eliminating points from the grid reduces the pressure on remaining nodes and eliminates the possibility of overlap. Simulations of node placement using BA and the fruit fly optimization algorithm (FOA) are also shown. To improve the coverage of the sensor nodes, the performance of several BA parameters such as the pulse emission rate, the maximum frequency, the loudness, the sensing radius and the points of the grid was adjusted in this study. In terms of mean coverage rate, calculation time, and standard deviation, the simulation results of node deployment according to the improved BA are also compared with node deployment based on BA and FOA. The findings indicated the efficiency of the improved BA, which produced a higher coverage rate than the BA and FOA algorithms. The artificial bee colony technique (ABC) was used in [100] to dynamically install stationary and mobile sensor networks in an effort to enhance efficiency by broadening the network coverage. To obtain more accurate findings when calculating the successfully covered region, a probabilistic detection strategy was taken into consideration. The program's performance was compared with that of the PSO, another swarm-based optimization method that was once employed in the WSN deployment. Based on the results obtained, the ABC algorithm might be recommended for dynamically deployed WSNs.

The region coverage issue was addressed using two metaheuristics, the genetic algorithm and particle swarm optimization, in [101]. This study adds an identical slowdown to the computation of the inertia weight as well as the effect of subpopulations' head individuals. It also introduces a new objective function and modifies the virtual force method. The suggested methods are thoroughly tested and evaluated against the state of the art for a similar issue without constraints. The findings of the experiments reveal not only which algorithms should be used in which situations but also shed light on parameter choices, the impact of heuristic initialization, and the impact of the virtual force algorithm in each situation. These findings have implications for future studies on connection and WSN lifespan issues related to hurdles in restricted region coverage. An energy efficient coverage optimization method utilizing the Voronoi glowworm swarm optimization K-means algorithm (Voronoi-GSO-K-means) was reported in [102]. Glowworm swarm optimization, Voronoi cell structure, and the K-means algorithm are used in this method to increase the coverage area while utilizing the fewest possible active nodes. For effective sensor deployment, this method takes into account the determination of the optimal sensing radius. By utilizing multi-hop transmission and the sleep-wake mechanism to decrease the energy consumed by the deployed sensor nodes. The simulation results showed that the suggested strategy can cover the area with an ideal number of active nodes. Eventually, the deployment challenge of a WSN is without a doubt a key issue because the tactics used will have a significant impact not only on the overall efficiency but also on the energy used by the sensors in such a system. This means that a solid deployment solution can not only improve performance, but also conserve energy, extending the lifespan of a WSN. Acquiring an optimal solution for most deployment challenges with limited computation resources remains a difficult research issue, particularly for hard NP optimization issues. Compared to extensive search and deterministic methods, metaheuristics offers an alternate approach to solving these optimization issues by searching for a near optimal solution while utilizing limited computation resources in a fair amount of time [103]. Table 3 lists the studies mentioned above. Furthermore, Fig. 6a illustrates the statistics for WSN deployment research publications related to metaheuristic algorithms from 2012 to 2021 based on information from the Scopus databases. Furthermore, Fig. 6b clarifies the various types of publications of WSN deployment research related to metaheuristic algorithms.

4.1.1 Evaluation criteria

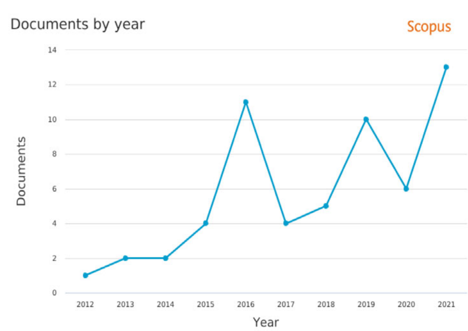
Gage proposed the coverage rate C_r in [104], which is defined as the ratio of the area covered by all sensor nodes to the entire ROI area. C_r is a measure of coverage quality. Because the entire area covered by the sensor nodes is measured in units, the coverage rate is always less than or equal to one, as computed by Eq. (1).

$$C_r = \frac{\bigcup_{i=1\ldots num} Z_i}{Z} \tag{1}$$

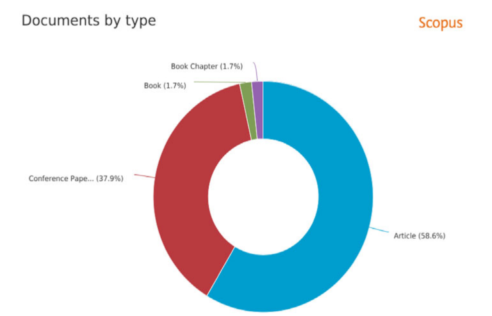
where Z_i is the area covered by the sensor node i, num is the total number of sensor nodes and Z is the total ROI area.

Table 3 Recent metaheuristic models used in the literature for the WSN deployment challenge

Metaheuristic algorithm	Author	Publication year	Network size (sensor nodes)	ROI	References
ICS & CFPA	Huynh Thi Thanh	2018	17–130	10,000 m^2	[91]
GSO	Wen-Hwa Liao	2011	50–200	10,000 m^2	[92]
MOEA/D-GSH	Andreas Konstantinidis	2011	25–250	2500–10,000 m^2	[93]
ACO	Wen-Hwa Liao	2011	10,000	Nodes are dispersed over a six-layer square area	[94]
OAFSA	Wang Yiyue	2012	50	2500 m^2	[95]
IGA	Dinh Thi Ha	2015	17–130	10,000 m^2	[96]
VFA & IVFA & EVFA	Jiming Chen	2007	50–200	10,000 m^2	[97]
VFCPSO	Xue Wang	2007	100 (20 Mobile, 80 Stationary)	10,000 m^2	[98]
BA	Satinder Singh Mohar	2021	50	2500 m^2	[99]
ABC	Celal Ozturk	2011	100 (20 Mobile, 80 Stationary)	10,000 m^2	[100]
GA & PSO	Huynh Thi Thanh	2020	23–130	10,000 m^2	[101]
Voronoi-GSO-K-means	Aparajita Chowdhury	2021	100, 200, 500, 1000	2500 m^2	[102]



(a) Histogram of metaheuristic algorithms publications used in the WSN deployment challenge.



(b) Research publication types for metaheuristic algorithms used in the WSN deployment challenge.

Fig. 6 Metaheuristic algorithms publications used in the literature for the WSN deployment challenge and their types achieved in the last decade (2012–2021) based on the Scopus database

4.2 Localization challenge in WSNs using metaheuristic algorithms

The node localization challenge in WSNs attempts to know the spatial location of each sensor node with an unknown location (target node/nonanchor) in ROI utilizing evolutionary methods as shown in Fig. 7, particularly metaheuristic algorithms [105, 106], rather than using global positioning systems (GPS) because it consumes a lot of energy, which is not commensurate with the limited energy resources of WSNs. In other words, if it is necessary to know the location of sensor nodes in the ROI without using any additional device such as GPS, it must utilize metaheuristic algorithms to perform localization. Localization is often beneficial for indicating the location of unexpected circumstances. Many recent studies have addressed the localization challenge in WSNs and solved it with new, enhanced, or hybrid metaheuristic algorithms [107, 108].

A brief series of studies related to localization challenges in WSNs employing metaheuristic techniques is described below. In [109], the current bat algorithm (BA) was upgraded to the modified bat algorithm (MBA) by

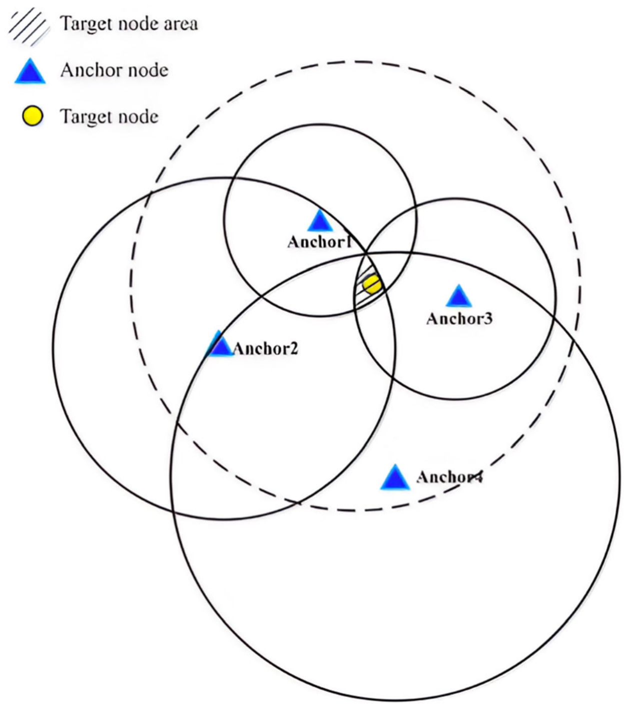


Fig. 7 Localization procedure for the target node/non-anchor using neighboring anchor nodes

combining it with the chemical movement of bacteria found in the bacterial foraging algorithm (BFO) [110] in an effort to identify the best solution in the direction where bat motion is not possible. Because the improved method searches the search space more effectively, it outperformed the original BA in terms of the success rate of localized nodes (low mean localization error) and computing performance. PSO was enhanced to MOPSO in [111], resulting in a modern localization technique known as the MOPSO localization algorithm (MOPSOLA). This technique was used to handle the MO difficulties related to localization in WSNs. There are MO difficulties that must be addressed, which are made up of a geometric topology limitation and a spatial distance limitation. The MOPSO technique was then used to identify the optima. The results of the simulation revealed significant advancements in terms of localization precision and convergence rate. According to elephant herding optimization (EHO), a modern way to address the issue of node localization in WSNs was proposed [112]. In general, the localization issue in WSNs is considered an NP-hard issue, and as a result, the EHO method is used as a metaheuristic algorithm capable of producing proper solutions when dealing with NP-hard situations. Additionally, for the first time in this study, the implementation of the EHO was described. The EHO method outperformed other state-of-the-art methods evaluated in the same issue scope in simulation outcomes.

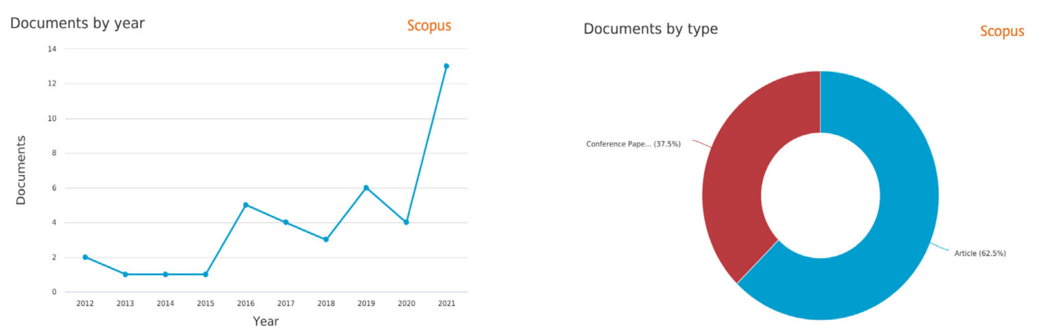
In [113] a better localization method was introduced called MAOADV-Hop based on the modified Archimedes optimization algorithm (MAOA) and DV-Hop to address the issue of the low localization precision of the distance vector hop (DV-Hop) localization technique in WSNs. This algorithm can achieve a dynamic equilibrium between localization precision and localization speed. In order to enhance the initial population variety and alter the rules for intensity and magnitude, the tent chaotic mapping and PSO were first incorporated into the AOA. This improved the algorithm's ability to achieve global convergence and accelerated convergence. To increase the localization accuracy of the method, the least square component of the DV-Hop localization technique is replaced by MAOA. Ultimately, MAOADV-Hop was compared with DE_DV-Hop, BOA_DV-Hop, and DV-Hop after being confirmed in four distinct network scenarios. According to the simulation findings, the suggested technique localizes the data faster than DE_DV-Hop and BOA_DV-Hop and with a lower localization error than DV-Hop, DE_DV-Hop, and BOA_DV-Hop. Furthermore, an analysis of the effectiveness of metaheuristic algorithms was performed, including the suggested Buffalo optimization algorithm (BOA), ant colony optimization algorithms, and opportunity routing algorithms in [114]. With these metaheuristic algorithms, the BOA's performance was compared. Throughput, packet forwarding rate, residual energy, packet loss rate, cost, and latency were among the performance parameters evaluated. The method was then turned into a hardware system for instantaneous monitoring of system performance. In the end, the thorough analysis of the effectiveness of metaheuristic algorithms in WSNs showed that the buffalo method offers improved performance and efficiency in WSN applications.

In [115] an intrusion detection system (IDS) was presented to protect the integrity, security, and confidentiality of Internet of Things (IoT) networks and their data. State-of-the-art IDSs have limited detection capabilities and considerable communication and device overhead, making them unsuitable for IoT applications that require secure and timely processing. In [116] a method was suggested for efficiently encrypting data streams in a 5 G-enabled IoT context and establishing their proof of hardness and security against quantum attacks, eavesdropping, selected plaintext attacks, chosen ciphertext attacks, and public key attacks. In [117] a hybrid latency and power-aware strategy was developed for B5G-IoT networks (HLPA B5G-IoT) to decrease latency with minimal overhead on battery-constrained IoT nodes while also providing a power-efficient solution for B5G-IoT-edge networks. In [118] an energy-efficient binary PSO-based routing and clustering method was described that employs an intuitive matrix-like particle representation. In addition, a unique particle update approach and an efficient linear transfer function were suggested, outperforming previously used particle update strategies and several traditional transfer functions. Detailed testing confirmed that the proposed routing and clustering technique outperforms existing algorithms in terms of network longevity. Furthermore, the study in [119] suggested a distance-based, stable connected dominating set approach employing an MA GWO (DBSCDS-GWO) to achieve a stable, balanced, and energy-efficient CDS-based WSN. Similarly, utilizing GWO, the study in [120] offered a new approach to optimum placement of vision sensors for maximum coverage of the predefined surveillance area. The monitoring space is divided into priority areas (PAs), impediments, and possible camera placement sites. The authors of [121] used MA biogeography-based optimization to solve the challenge of efficiently allocating data relay burden to numerous cluster heads (CHs) and situating mobile sinks (MS) near these multiple CHs. Likewise, the authors of [122] suggested an event-based efficient deployment algorithm (EEDA) for relocating redundant sensors to the event site to obtain full coverage. They partition the deployment region into small square cells, allowing individual cells to be efficiently monitored rather than treating the entire scenario as a single entity. IoT devices vary in nature and can connect sensors to simple, restricted devices. Software and hardware threats are a serious concern in this field. These attacks may result in breaches of privacy, confidentiality, and malware. To address this issue, a new security technique was developed in [123]. Moreover, in [124] a novel load balancing strategy was developed that uses biogeography-based optimization (LB-BBO) to reduce sensor node energy usage while maximizing WSN lifetime. LB-BBO balances equal and unequal loads using two distinct target functions.

Reference [125] suggested an MO evolutionary method that simultaneously considers the localization precision and some topological limitations brought on by connection implications throughout the evolutionary process. The suggested strategy was evaluated utilizing various network settings and sensor arrangements, and its normalized localization error performance was compared with that of another Metaheuristic Algorithm called SAL, which is based on simulated annealing. The findings demonstrated the usefulness and stability of the suggested MO method, which in all cases outperforms SAL and produces high accuracy gains. Moreover, an efficient cuckoo search (CS) technique for node localization was presented in [126]. This method allowed the population to quickly approach the global optimal solution based on the alteration of the step size, and the fitness score of each solution was used to create the mutation probability to prevent local convergence. Additionally, the method confined the population to a specific range to avoid wasting resources on pointless searches. Numerous tests were performed to determine how node density, anchor density, and communication range affected the mean localization error and the localization success rate of the suggested method. To achieve the same localization objective using the same network deployment, a comparison research was also carried out. Experimental findings demonstrated that the suggested CS algorithm, when compared with the traditional CS method and the PSO, may not only enhance the convergence rate but also decrease the mean localization error. Furthermore, in [127], the distributed weighted search-based localization method (WSLA) and its refinement algorithm (WSRA) for WSN were proposed. In practical applications, WSLA and WSRA need to run repeatedly to perform node location and location exploration. Each node determines its location and type based on the distribution of its optimal computed locations in each iteration of the WSLA after first obtaining the location and distance information of its 1-hop neighbors and utilizing weighted 2-D logarithmic search to determine its optimal computed location. Analysis of the WSLA experiment findings revealed various inaccuracies, leading to the eventual proposal of the geometrically based WSRA. The simulation results demonstrated that WSLA and WSRA have low computing complexity and comparatively good localization precision. The application of metaheuristic algorithms for the optimal determination of the positioning of sensor nodes was explored in [128]. In terms of computation time, number of localized nodes, and localization precision, the performance of metaheuristic algorithms such as the firefly algorithm (FA), FPA, PSO, and GWO for localization issues in WSN was analyzed. In contrast to FA, PSO, and GWO, the comparison study revealed that FPA is more adept at finding the nodes' locations by decreasing the inaccuracy of the location. Butterfly optimization algorithm (BOA), a Metaheuristic Algorithm, is also applied in [129] to suggest a modern node localization strategy. The suggested technique is tested using simulations on sensor networks of varying sizes, from 25 to 100–50 nodes, whose distance estimations are tainted by Gaussian noise. A few well-known schemes, including the PSO algorithm and FA, are used to compare the performance of the innovative scheme that has been suggested. Based on the modeling findings, the suggested node localization scheme outperforms current PSO-based and FA-based node localization techniques in terms of consistency and precision. Ultimately, the study in [130] provided a review of the most common localization approaches to minimize localization errors. Establish a new taxonomy of approaches used in this subject, such as

Table 4 Recent metaheuristic models used in the literature for the WSN localization challenge

Metaheuristic algorithm	Author	Publication year	Network size (sensor nodes)	ROI	Localization measurement Technique	References
MBA	Sonia Goyal	2016	30 anchor/170 non-anchor	40,000 m^2	Received Signal Strength (RSS)	[109]
MOPSOLA	Ziwen Sun	2015	32 anchor/128 non-anchor	10,000 m^2	Received Signal Strength (RSS)	[111]
EHO	Ivana Strumberger	2018	100 anchor/900 non-anchor	10,000 m^2	Received Signal Strength (RSS)	[112]
MAOADV-Hop	Mangmang Cheng	2022	20 anchor/80 non-anchor	10,000 m^2	Distance Vector Hop (DV-Hop)	[113]
BOA	G. Hemanth Kumar	2022	Hardware system	Hardware system	Opportunity routing algorithm	[114]
MOEA	Massimo Vecchio	2012	20 anchor/180 non-anchor	Uniformly placing 200 nodes in $T = [0,1] \times [0,1] \subset \mathbb{R}^2$	Received signal strength (RSS)	[125]
CS	Jing Cheng	2016	40 anchor/360 non-anchor	10,000 m^2	Received signal Strength (RSS)	[126]
WSLA & WSRA	Yingbiao Yao	2015	8 anchor/92 non-anchor	100 nodes are deployed in a square region of $1 \times 1, x_i, y_i \in [0,1]$	Received signal strength (RSS)	[127]
FA & FPA & PSO & GWO	Ranjit Kaur	2017	15 anchor/50 non-anchor	10,000 m^2	Received signal strength (RSS)	[128]
BOA	Sankalap Arora	2017	35 anchor/150 non-anchor	10,000 m^2	Received signal strength (RSS)	[129]



(a) Histogram of metaheuristic algorithms publications used in the WSN localization challenge.

(b) Research publication types for metaheuristic algorithms used in the WSN localization challenge.

Fig. 8 Metaheuristic algorithms publications used in the literature for the WSN localization challenge and their types achieved in the last decade (2012–2021) based on the Scopus database

machine learning, mobile anchors, metaheuristics, and mathematical models. The authors present their various algorithms in this later section, including genetic optimization, ant colony optimization, particle swarm optimization, firefly optimization, bat optimization, flower pollination optimization, artificial bee colony optimization, grey wolf optimization, fish swarm optimization, and others. Furthermore, a comparison of various metaheuristic-based localization optimization techniques was performed. Finally, a detailed examination of performance characteristics such as precision, energy use, convergence rate, and number of localized nodes was provided. Table 4 lists the studies mentioned above. Furthermore, Fig. 8a illustrates the statistics for WSN localization research publications related to metaheuristic algorithms from 2012 to 2021 based on information from the Scopus databases. Furthermore, Fig. 8b clarifies the various types of publication of WSN localization research related to metaheuristic algorithms.

4.2.1 Evaluation criteria

The performance of the used localization techniques is assessed using Eq. (2), which determines the localization error *LE*. The estimation error between the true node coordinates and the estimated node coordinates is known as *LE*.

$$LE = \frac{\sqrt{(a' - a)^2 + (b' - b)^2}}{R_c} \times 100\% \quad (2)$$

where (a', b') are the estimated coordinates of the node, (a, b) are the true coordinates of the node and R_c refers to the communication range of the node.

4.3 Sink node placement and energy efficiency challenge in WSNs using metaheuristic algorithms

Identifying the best location for the sink (base) node in any WSN environment is crucial, since base node placement is one of the typical and trending problems in WSNs. Since the goal is to collect data for real-time monitoring, rapid action may be taken when necessary. The aforementioned base node, which is responsible for processing and interpreting the gained data, is one of the most significant sensor nodes used in a WSN. It functions as a hub between the administrator and the network sensor nodes. In addition, it is responsible for managing the entire network. Obtaining the optimal base node position in a WSN is difficult, since doing so is essential to the network's longevity and maintaining the highest level of network activity. Most researchers resort to search algorithms, especially metaheuristic algorithms, whether SO or MO, to determine the optimal location of the base node in various WSN scenarios [131, 132]. In fact, determining the optimal base node position will positively affect the power usage of the entire network, consequently prolonging the network lifespan as the number of message hops from the sensor node to another to reach the base node will be decreased as a result of using Prim's greedy algorithm [133] in finding the minimum spanning tree (MST) [134] via establishing the shortest communication routes from the sensor nodes to the determined base node. Furthermore, the central place of the base node, as shown in Fig. 9, which is followed in many WSN scenarios by the suggested P-Median Problem (PMP) model [86, 135], will not exist because the coordinates of the base node will be determined according to other criteria such as the number of neighbors, neighbors' residual energy, number of active nodes around the base node, the distance from the center of the ROI, etc.

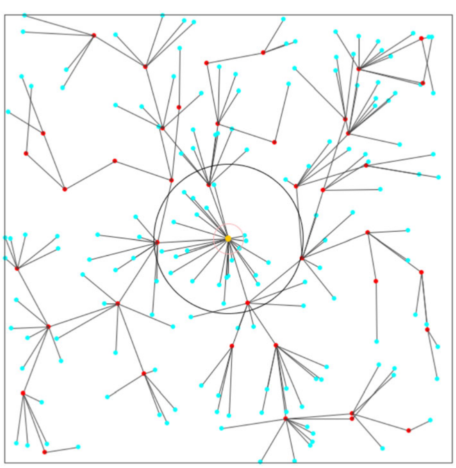


Fig. 9 Central location of the sink node in a WSN of 200 sensor nodes and ROI = 360,000 m^2

The literature has several works which address the issue of base node allocation and energy usage in WSNs, such as the work in [5], in this study, the HHO metaheuristic model was used to address the optimal base node location issue, and the Prim's shortest route technique was used to rebuild the network by taking the shortest communication lines from the base node to the remaining sensor nodes. HHO outperformed other familiar techniques such as FPA, PSO, SCA, GWO, WOA, and MVO. In this study, the simulation outcomes of various network sizes, with single and multiple base nodes, demonstrated the sufficiency of the strategy used in terms of localization error and power usage, thus prolonging the network's lifespan in an efficient manner. Reference [136] proposed a strategy based on the cat swarm optimization (CSO) algorithm [137] to handle the challenge of identifying the location of the base node. Compared with PSO, the authors argue that the new technique demonstrates efficacy by prolonging the life of the network. Furthermore, the use of the greedy method to efficiently create minimal transmission pathways from the base node to the remaining sensor nodes contributed significantly to reducing the power consumption of the transmission and receiving process of the gathered data.

In [138], another implementation of PSO in this scope was provided. Researchers suggested an energy-aware topology control protocol that utilizes a technique to select the optimal location of the base node in the entire network to extend the lifespan of the network. To validate the potential of the suggested solution to reduce the power consumption of sensor nodes, it is compared with various topology creation methods. The simulation results showed that the suggested technique was superior in terms of functional network lifespan, number of topology, and number of active nodes during the topology creation and maintenance stages of the topological control protocols. Srinivasa et al. in [139] used a PSO-based algorithm (PSO-MSPA) to best locate base nodes in WSNs, and the findings show that the suggested technique outperforms the exhaustive grid search technique. In [140], an MOPSO was used to address a variety of optimization issues related to WSNs and their general applicability in various industries to discover the optimal coordinates of the base node in WSNs with consistent nodes. The authors focused on determining the ideal location of the base node in relation to the relay nodes to extend the lifespan of the network. In [141], an adaptive PSO (APSO) was presented for the optimal allocation of base nodes in WSNs. Based on the data, APSO beats PSO in terms of obtaining an extended network lifespan for a significant amount of operating time. In addition to PSO, a classic metaheuristic approach, a genetic algorithm (GA) [142], has been applied in [143] for optimal base node allocation. The study claimed to have achieved the optimal base position in short generations using several mutations and crossover tuning.

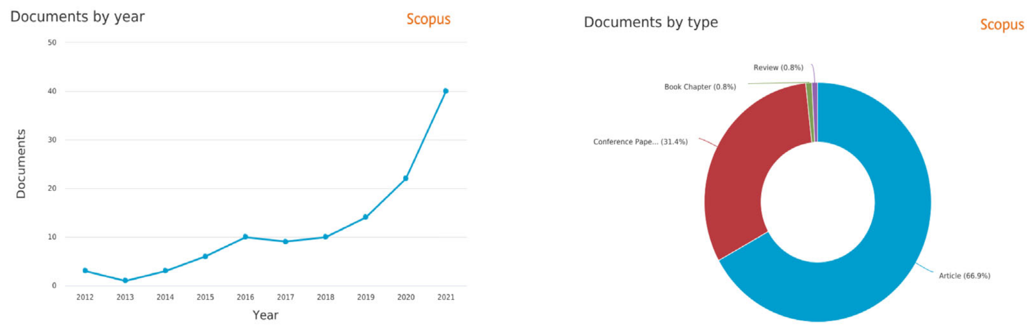
In [144], another cutting-edge metaheuristic approach was presented called ant colony optimization (ACO) for base node allocation. The authors used ACO to discover the optimal communication route with a technique to increase the single base lifespan of the WSN in this study. This study claimed to have obtained greater results than the energy-oriented method [145]. The study in [146] described another implementation of ACO to increase the useful life of heterogeneous WSNs. The authors suggested a procedure for determining the greatest coverage of the sensor network by constructing the optimal route on the building graph. Similar to this, reference [147] suggested an ACO-based method to develop an energy-efficient solution to improve WSN longevity and reduce packet loss. The authors of [148] used fuzzy logic in an ACO-based method to construct a heuristic rule for route categorization to improve the overall energy efficiency of the network. Similarly, the findings of [149] confirm the usefulness of ACO in tackling optimization challenges in WSNs. In addition to ACO, the authors of [126] used another well-constructed method, CS [150], for sensor node localization in WSNs. In this paper, the CS method was changed using a mutation technique to improve its global search capability. On the basis of comprehensive experimental research, the suggested technique demonstrates that it may successfully expand sensor node coverage while reducing localization errors. When tackling the best base node localization issue in large-scale WSNs, a modern swarm intelligence-based metaheuristic approach was devised in [72]. To reduce energy usage and increase network longevity, the authors used the MOWOA to address the issue of selecting the smallest number of base nodes that can feed the entire network in the case of large-scale WSNs. The suggested approach outperformed other familiar MO algorithms such as MOGOA [151], MSSA [62], MOGWO and MOPSO in a range of network sizes, according to a specified number of trials. Brainstorm optimization (BSO) [152], a powerful swarm-based Metaheuristic Algorithm, was used in [131] to deploy base nodes in WSNs in the best possible way. The findings revealed that BSO was able to arrange base nodes in networks with longer lifetimes and greater energy efficiency compared to PSO and grid search-based techniques.

The authors of [153] employed GWO to address the issue of the central base node location of the topology creation methods. The qualitative and quantitative performance of the established approach was further assessed by contrasting it with the topology control methods. Based on several tests with various network sizes and deployment circumstances, it was determined that the proposed model was effective in terms of energy usage, the number of active nodes, and the time needed to build a smaller topology. Unlike previous research, the study conducted in [154] discovered that GWO produced worse results compared to chicken swarm optimization (CSO) [155], while building the little active nodes for the WSN procedure. The study claimed that, based on practical findings, CSO exceeds GWO in terms of demonstrating the capacity to create a smaller set of active nodes with significantly higher energy. In the relevant literature, several additional strategies have also been published. To enhance the lifespan of the network, the authors of [156] created an ideal clustering topology, energy-conscious cluster head rotation, and a routing protocol. PSO recruitment created a deactivation strategy to regulate excessive particle transformation by keeping copies of the position vectors of particles with higher valuation outcomes. In a similar vein, an effective method for allocating N base nodes in a 2-D space was presented in [157]. However, studies in [86] and [135] suggested using the PMP model to identify the base node. Additionally, in [135], the authors showed that the ROI center is the best place for a base node of WSN, although the finding was only applicable for nodes that were distributed equally. According to [158], the location of the junction node was chosen to minimize power usage by maximizing the weight of the data streams.

In [159], PSO was used to create a clustering-based technique to increase the lifespan of WSNs. By assigning a small number of sensor nodes, the suggested system handles all cluster heads (CHs), whose energy is gruellingly rapid. Additionally, another distributed strategy was created to prevent CHs from dying quickly as a consequence of the overall power exhaustion. The suggested strategy was thoroughly modeled, with the results compared with various current schemes to determine its strength. An energy-efficient self-stabilizing structure control technique for WSN was presented in [160]. Each node's transmission energy was decreased to preserve network connectivity while making the most possible energy savings. This research also suggested an approximation approach for the minimally weighted connected dominant set, which creates a virtual network of energy-efficient sensors. This backbone serves as an effective means of routing. The results of the simulations demonstrated the effectiveness of the suggested solution and validated the accuracy of the algorithm. Additionally, [161] suggested an energy-efficient clustering and tree-based routing protocol based on a hybrid ACO and PSO architecture. Clusters were first created based on available energy, and to further enhance inter-cluster data aggregation, hybrid ACOPSO-based data aggregation will be put into use. The thorough investigation revealed that the proposed strategy greatly extends the longevity of the network compared to alternative methods. Moreover, in [64], the MOGTO was also employed in large-scale WSNs to identify the possible fewest base nodes with the lowest localization error, which would nourish the entire network and prolong the lifespan of the network. On the basis of simulation outcomes in large-scale WSNs, the MOGTO can achieve the smallest number of base nodes and diminish the network's power usage. Eventually, the work in [162] improved the WOA to WOTC, which is based on a discrete copy of the original method in which the location of each whale is recomputed and expressed in binary sequence. In addition, a novel objective function was presented to target two key goals: minimizing the number of active nodes and maintaining a low power usage rate inside these nodes in order to overcome topology control issues and extend the lifespan of WSNs. In this study simulations were carried out using the Attaraya simulator [163]. Subsequently, the experimental findings revealed that, according to the number of neighbors and their residual energies for active nodes, the final architecture of the WSN generated by WOTC was superior to the A3 topology building technique. Table 5 lists the studies mentioned above. Furthermore, Fig. 10a illustrates the statistics for WSN base node placement and energy efficiency research publications related to metaheuristic algorithms from 2012 to 2021 based on information from the Scopus databases. Furthermore, Fig. 10b clarifies the various types of publication of WSN base node placement and energy efficiency research related to metaheuristic algorithms.

Table 5 Recent metaheuristic models used in the literature for the WSN base node placement and energy efficiency challenges

Metaheuristic algorithm	Author	Publication year	Network size (sensor nodes)	ROI	References
HHO	Essam H. Houssein	2020	100–500 & 1000–5000	360,000 & 1,000,000 m^2	[5]
CSO	Vaclav Snasel	2016	100–600	40,000 m^2	[136]
PSO	Mohamed Mostafa Fouad	2015	100–700	360,000 m^2	[138]
PSO-MSPA	C. Srinivasa Rao	2016	300	40,000 m^2	[139]
MOPSO	MN Rahman	2011	676	1,000,000 m^2	[140]
APSO	Mohamed Mostafa Fouad	2016	100–900	360,000 m^2	[141]
GA	Soumitra Ghosh	2016	17	904,401 km^2	[143]
ACO	Fengchao Chen	2013	100 & 370	10,000 & 360,000 m^2	[145]
ACO-MNCC	Ying Lin	2011	200–1000	2500 m^2	[146]
ACO	Ahmed M. Shamsan	2012	100	360,000 m^2	[147]
DD-ACO-Fuzzy	Jose V. V. Sobral	2013	100	360,000 m^2	[148]
ACO	Jingjing Zhang	2011	100	250,000 m^2	[149]
MOWOA	Mohammed M. Ahmed	2019	1000–10,000	1,000,000 m^2	[72]
BSO	Eva Tuba	2018	300	40,000 m^2	[131]
GWO	Mohamed Mostafa Fouad	2015	100, 300, 500, 700, 900	360,000 m^2	[153]
GWO & CSO	Mohamed Mostafa Fouad	2019	100–1000	360,000 m^2	[154]
SPSO	Hidehiro Nakano	2010	1000	250,000 m^2	[157]
PSO	Md Azharuddin	2016	300–600	250,000 m^2	[159]
Hybrid ACOPSO	Supreet Kaur	2018	100	10,000 m^2	[161]
MOGTO	Essam H. Houssein	2022	1000–10,000	1,000,000 m^2	[64]
WOTC	Mohammed M. Ahmed	2017	100–1000	360,000 m^2	[162]



(a) Histogram of metaheuristic algorithms publications used in the WSN base node placement and energy efficiency challenges.

(b) Research publication types for metaheuristic algorithms used in the WSN base node placement and energy efficiency challenges.

Fig. 10 Metaheuristic algorithms publications used in the literature for the WSN base node placement and energy efficiency challenges and their types achieved in the last decade (2012–2021) based on the Scopus database

4.3.1 Evaluation criteria

The network lifetime is defined as the total number of rounds till the last node is alive. The last node death (LND) can be determined by charting the number of dead nodes versus the number of rounds. Network lifetime also increases as energy efficiency improves.

4.4 Clustering challenge in WSNs using metaheuristic algorithms

Clustering is regarded as one of the most primitive strategies for extending the lifespan of WSNs [164]. However, the strategy of cluster head (CH) selection for power control with the goal of extending network life anticipation remains a serious challenge in WSNs. The main idea of clustering in WSNs is to divide the sensor nodes of the network into subparts and then assign a CH to each part. These CHs will be in charge of package transmission of gathered data from sensor nodes to the base node and receiving the controlling instructions from the base node to the sensor nodes rather than transmitting and receiving via the sensor nodes. This will reduce the number of message hops among sensor nodes and rationalize the power usage of the whole network, as the operation of transmitting and receiving data via each sensor node in the network will expend a huge amount of power, consequently decreasing the network lifespan, and this is absolutely not desirable to happen [165, 166]. Figure 11 illustrates the concept of clustering in WSNs.

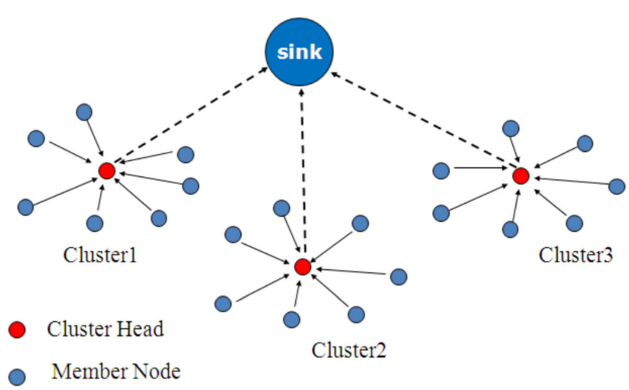


Fig. 11 Clustering concept in WSNs

A brief series of studies related to clustering challenges in WSNs employing metaheuristic techniques is described below. In [7], a hybrid grey wolf and crow search optimization algorithm-based optimal CH selection (HGWCSOA-OCHS) method was presented for increasing network lifespan expectation by focusing on latency reduction, distance decreasing among nodes, and power stability. The GWO was hybridized with the CSO to address the challenge of precocious convergence, which hinders it from effectively discovering the search zone. This combination of the GWO and CSO algorithms in the CH selection procedure maintains the equilibrium between the degree of diversification and intensification in the search zone. The suggested HGWCSOA-OCHS scheme's outcomes were compared with tested CH selection techniques with ABC, FA, firefly cyclic GWO (FCGWO), and GWO. By equalizing the proportion of active and inactive sensor nodes in the network, the suggested HGWCSOA-OCHS strategy confirmed reduced energy usage and increased network lifespan expectancy. In [167], an efficient tunicate swarm butterfly optimization algorithm (TSBOA) for choosing CHs was devised in order to achieve effective data transmission among sensor nodes. The suggested TSBOA was created by combining the tunicate swarm algorithm and the butterfly optimization method. As a result, the CH was chosen based on objective parameters such as inter-cluster distance, intra-cluster distance, node energy usage, anticipated energy, connection lifespan, and latency. The deep long-short-term memory classifier was used to forecast energy by taking into account the preliminary energy of nodes. The suggested TSBOA outperformed utilizing criteria like superfluity energy and packet generation (throughput), which were 0.1118 J and 82.101 percent, respectively.

Reference [168] described a novel strategy for extending the network lifespan based on an enhanced PSO, which is a Metaheuristic Algorithm for selecting target nodes. The proposed protocol considers both energy economy and transmission distance, and relay nodes are employed to reduce the CHs' excessive power usage. The proposed protocol produces better dispersed sensors and a well-balanced clustering structure, which increases the network's lifespan. The suggested protocol was compared with comparable protocols by adjusting a variety of factors, such as network space size, number of nodes, and base station position. The simulation outcomes demonstrated that the suggested protocol exceeds other comparable protocols in a variety of conditions. Therefore, to choose the best meeting places, a new method called PSO-based selection (PSOBS) was proposed in [169]. Using PSO, the suggested method was able to locate optimal or near-optimal rendezvous places for efficient network resource management. In the suggested method, the weight magnitude was generated for each sensor node according to the number of data packets received from other sensor nodes. The suggested method was compared with the weighted rendezvous planning based selection (WRPBS) method in terms of validation measures like power usage, throughput, hop count, and number of rendezvous spots. The simulation outcomes revealed that PSOBS outperformed WRPBS, but had a higher packet loss rate. The study in [170] developed an energy efficient CH selection method based on WOA clustering (WOA-C). As a result, the suggested approach aids in the selection of energy-aware CHs according to the objective function that takes into account the superfluity energy of the node and the total of surrounding nodes. The stability of the suggested algorithm overall, energy efficiency, throughput, and network longevity were assessed. Additionally, the effectiveness of WOA-C was validated compared with other common modern routing techniques such as Low-Energy Adaptive Clustering Hierarchy (LEACH). Numerous simulations proved the higher efficiency of the suggested algorithm in terms of residual energy, network lifespan, and extended stability duration.

In [171], the metaheuristic algorithms indicated by the harmony search algorithm (HSA) and the PSO were combined to handle local search issues with slow convergence and diversification-intensification trade-offs for each other individually, as well as to extend the WSN lifespan by developing an energy-efficient CH selection methodology. The suggested hybrid HSA-PSO algorithm outperformed the PSO, HSA, and LEACH algorithms in terms of throughput and superfluity energy reduction by 29.00 percent and 83.89 percent, respectively. A clustering-based routing technique for WSNs was suggested in [172]. Seven goal functions are presented for the MO metheuristic algorithm known as NSGA-II, which was used for clustering. Using the MO model was intended to achieve numerous objectives simultaneously. While attempting to reduce communication costs between the goal functions and CH and sink, as well as CH and non-CH, it was also tried to avoid selecting CHs exclusively from nodes close to the sink, and it was also taken into account for clusters to contain as many nodes as feasible. Each solution pointed out a new network architecture in the set of solutions produced by the NSGA-II. According to certain of the target functions, each solution in the solution set is the optimal solution. The sink was specified to mimic each solution in a set of solutions based on a specific situation and to select one that meets the needed criteria. In the suggested technique, the NSGA-II as well as the emulation and evaluation of the acquired solutions are carried out in an environment with adequate operational and power supplies. According to the findings, the proposed technique may extend network life five times longer than LEACH, the most well-known clustering technique. Additionally, it is seen that the suggested strategy increases the amount of packets reaching the sink twice more than LEACH, even if it extends the network's lifespan. Compared with LEACH, the data provided by the suggested technique contains information on larger areas.

The study in [173] offered a performance comparison of PSO and GA using a novel target function with the goal of simultaneously lowering the distance between clusters and improving the use of network power. In addition, the familiar cluster-based techniques designed for WSNs, LEACH, and LEACH-C, the latter being an upgraded copy of LEACH, as well as the classic K-means clustering technique, were compared. The simulation findings showed that the suggested protocol employing the PSO algorithm is more efficient and can fulfilll a longer network lifespan and more data throw at the base node than its competitors. Two techniques, GP-LEACH and HS-LEACH, were proposed in [174], based on GA and HSA. The energy usage was reduced by splitting the network and employing metaheuristic algorithms (GA and HSA) for the optimum selection of CH based on WSN node location information and superfluity energy. The MATLAB simulation findings revealed that the suggested techniques were more effective and extended the network's lifespan. The work in [175] was concerned with the selection of the ideal path in routing, which enhances network lifespan and energy efficiency. Several metaheuristic approaches, particularly PSO, were applied efficiently, albeit with poor local optima. The PSO and Tabu search algorithms were used to develop the proposed method. The results demonstrated the high adequacy of the suggested Tabu PSO by increasing the number of clusters created, the proportion of active nodes, and lowering the average packet loss rate and average end-to-end delay.

The work in [176] introduced a unique hybrid GWO-based sunflower optimization (HGWSFO) method for optimum CH selection given specific factor limitations like energy expenditure and separation distance, hence increasing network lifespan. Sunflower optimization (SFO) was used for a larger search (diversification), in which changing the step size parameter gets the plant closer to the Sun in search of global redaction, boosting diversification efficiency. GWO was used for a narrow search (intensification), with the parameter coefficient dimensions necessary to ensure intensification. This balances the diversification-intensification trade-off, extends network lifespan, increases energy efficiency, and improves network performance in terms of total throughput, node superfluity energy, alive nodes, lifeless nodes, network livability index, and convergence rate. Ultimately, due to technological advancements and the need for machine-to-machine connectivity, WSNs play a larger role than other wireless networks. In this context, many WSN-based applications must be implemented effectively in terms of energy and connectivity. To do this, many devices at different levels must interact. This may be accomplished by grouping these devices together, also known as clustering. Cluster-based routing is the best solution to support fault tolerance, load balancing, and reliable communication to extend WSN performance parameters. These performance values are obtained at the expense of a shorter lifespan for CH. To address the constraints of the clustering-based hierarchical method, an effective CH selection method and an improved routing technique are required to develop an effective solution for larger networks. To prolong the duration of network stability, a fuzzy-enhanced FPA-based threshold-sensitive energy-efficient clustering technique (EFPA-FIS) was developed in [177]. The suggested method beat competitive clustering methods in terms of stability duration, power usage, and system lifespan, according to analysis and simulation findings. Two well-known optimization issues, energy-efficient clustering and routing, have been extensively explored to increase the lifespan of WSNs. The work in [178] gives formulations of these issues using linear and nonlinear programming (LP and NLP), followed by two suggested algorithms based on PSO. The MO target function and an effective particle encoding strategy were used in the development of the routing algorithm. The clustering approach is provided while taking load balancing into account for node energy rationalization. Comprehensive testing is done with them to show the suggested algorithms' superiority in terms of network lifespan, energy usage, dead sensor nodes, and transmission of all data packets to the base node. The outcomes are then compared with those obtained with the existing algorithms. Table 6 lists the studies mentioned above. Furthermore, Fig. 12a illustrates the statistics for WSN clustering research publications related to metaheuristic algorithms from 2012 to 2021 based on information from the Scopus databases. Furthermore, Fig. 12b clarifies the various types of WSN clustering research publications related to metaheuristic algorithms.

4.4.1 Evaluation criteria

Throughput TP is defined as the number of packets transmitted from the source to the destination per unit of second. Equation (3) shows how it is computed.

$$TP = \frac{\delta}{t} \tag{3}$$

where δ denotes successfully transferred packets and t denotes time.

5 Open issues and challenges

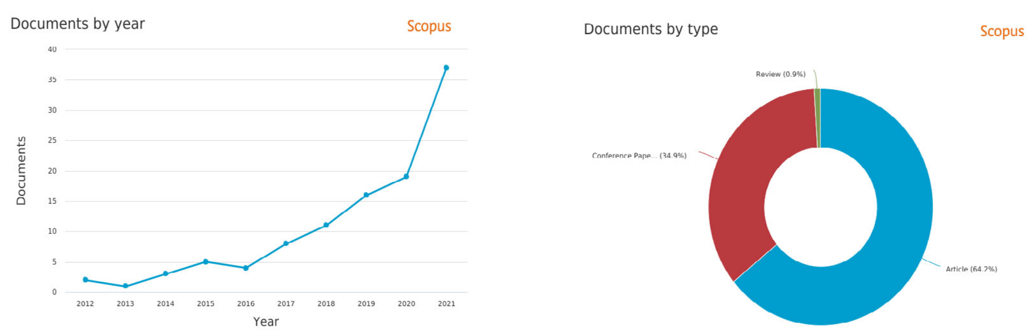
This section includes open issues, challenge paths, and future trends that can be applied to metaheuristic algorithms (SO and MO) and WSN difficulties, as well as significant efforts that are necessary to improve WSN efficiency. Despite the favorable outcomes of the examined literature, there are still certain limitations and challenges regarding SO and MO approaches to improving WSN efficiency that must be addressed. The review found numerous important difficulties, as well as future trends, prospective research areas, and challenges, which are mentioned below.

5.1 Open issues

- The first open issue we noticed in the articles we reviewed was the use of 1-D and 2-D approaches to deploy sensor nodes in simulation environments, but in particular genuine environments of heterogeneous domains with obstacles, the conventional 1-D and 2-D placement techniques of sensor nodes deteriorate the efficiency of coverage appreciation and optimization. These 1-D and 2-D techniques also fail to address several difficult problems that emerge as a result of particular observation and monitoring needs. When

Table 6 Recent metaheuristic models used in the literature for the WSN clustering challenge

Metaheuristic algorithm	Author	Publication year	Network size (sensor nodes)	ROI	Sink node position	Initial energy of node	References
HGWCSOA-OCHS	P. Subramanian	2020	1000	160,000 m^2	[200, 200]	0.5 J	[7]
TSBOA	Jesline Daniel	2021	100	10,000 m^2	[0.5, 0.5]	0.6 J	[167]
PSO	Yuan Zhou	2016	100 & 400 & 1000	10,000 & 10,000 & 40,000 m^2	[50, 175] & [50, 200] & [100, 350]	2 J	[168]
PSOBS	Shamineh Tabibi	2019	20 & 30	10,000 m^2	Mobile Sink	0.5 J	[169]
WOA-C	Ashwin. R. Jadhav	2017	100 & 500	10,000 m^2	[50, 100] & [50,200]	0.5 J	[170]
Hybrid HSA-PSO	T. Shankar	2016	100	20,000 m^2	[50, 150]	0.5 J	[171]
NSGA-II	Gokce Hacioglu	2016	100	10,000 m^2	Center of ROI	0.5 J	[172]
PSO & GA	N. M. Abdul Latiff	2007	100	250,000 m^2	[250, 575]	[5 J for 20% of Nodes, 2 J for other 80% of Nodes]	[173]
GA & HSA	Mohammad Karimi	2012	100	10,000 m^2	[50, 50]	0.5 J	[174]
Tabu PSO	K. Vijayalakshmi	2019	600	10,000 m^2	[50, 50]	0.5 J	[175]
HGWSFO	Lavanya Nagarajan	2021	100	40,000 m^2	Center of ROI	0.5 J	[176]
EFPA-FIS	Nitin Mittal	2020	100	10,000 m^2	[50, 50]	0.25 J, 0.5 J, 1 J	[177]
PSO	Pratyay Kuila	2014	200–700	250,000 m^2	[500, 250]/ WSN#1, [250,250]/ WSN#2	2 J	[178]



(a) Histogram of metaheuristic algorithms publications used in the WSN clustering challenge.

(b) Research publication types for metaheuristic algorithms used in the WSN clustering challenge.

Fig. 12 Metaheuristic algorithms publications used in the literature for the WSN clustering challenge and their types achieved in the last decade (2012–2021) based on the Scopus database

sensor nodes are placed in a 3-D area rather than utilizing traditional 2-D placement methodologies, for instance, object surveillance, tracking of moving objects, and human activity monitoring may be optimally covered.

- Due to gaps between simulation outcomes and applications, the second open issue is how to apply

metaheuristic-based algorithms to a real WSN deployment system. Although the metaheuristic algorithm can find better results than the topology construction algorithm or the rule-based algorithm, it is typically more complex than these two algorithms for the challenge of deployment in WSNs. Therefore, when we wish to use the metaheuristic algorithm in the real world, it is more challenging to implement than conventional deployment methods (such as A3, EECDS, and CDS-Rule K). Our finding is that some tools and libraries for metaheuristic algorithms have been released recently, which could make it simpler to develop a metaheuristic algorithm. Therefore, a crucial study area will be how to implement a metaheuristic algorithm to improve a WSN's performance and offer a more comfortable atmosphere.
- Although the coverage gap was taken into account in a number of reviewed articles related to the WSN deployment challenge, the majority of them concentrated on ways to reduce the number of coverage gaps. In fact, they are unsure whether there are enough sensors deployed to cover every target in the ROI. According to our observations, the metaheuristic algorithm must first determine how many sensors are required to cover all the targets in the ROI in order to solve the coverage gap issue; Under this useful and meaningful condition, the optimal or suitable deployment solution can then be found rather than continuously adding resources (sensors) to meet the requirement.
- Most of the reviewed articles were evaluated using metaheuristic algorithms to WSN challenges in basic geographic environments, including flat areas or areas with a few barriers. In the real-world setting, many more considerations are required, such as signal interference, varying sensor lifetimes, or uncharted geographic terrain. Multiple factors being taken into account at once, or the so-called MO optimization approach in WSNs, is a promising research trend. The accuracy of the results will generally decline in studies that do not take into account the geographical environment, and there will be a difference between simulation results and real-world applications. As a result, a crucial open issue will be how to increase the accuracy rate of the outcomes, particularly when real-world applications are involved.
- The setup of WSN simulation parameters such as the sensing range, the communication range, the initial energy, the number of nodes, the deployment area, the location of the sink node, the number of multiple sink nodes, the routing protocol and the sensor node model are different from one article to another in the articles reviewed. This causes some difficulty in determining the performance evaluation between articles, such as the coverage ratio in the deployment articles, the localization error in the location articles, and the energy usage rate in the energy articles.
- Another limitation in some publications is the use of initial random deployment techniques such as A3, EECDS, and CDS-Rule K (topology building techniques) rather than LFD, GSO, and VF techniques that diminish the existence of redundant and blind areas in the ROI.
- In general, an optimization issue has input parameters, outputs, constraints, and a target function. In most WSN optimization issues, these constituent pieces can be mixed in a variety of ways, resulting in a wide range of optimization issues. As a result, no one-solution metaheuristic algorithm (no free lunch theorem) exists that may provide an optimal solution to many optimization difficulties linked to WSN.
- Similarly, the setup of execution parameters for the metaheuristic algorithms that are used in the articles reviewed, including the number of solutions, solutions lower bound, solutions upper bound, maximum number of cycles, and default parameters, is different from one article to another, especially for articles that use the same metaheuristic algorithm, such as PSO and ACO. Also, this causes some difficulty in determining the performance evaluation between articles in the same WSN issue.
- From the optimization concept point of view, articles that make some improvements to metaheuristic algorithms such as improved GA, improved CS, chaotic FPA, multiobjective PSOLA, optimized BA, optimized AFSA, hybrid ACOPSO, and hybrid HSA-PSO have a lack of CEC benchmark evaluations for these improved methods, and this is considered a challenge and a lack of flexibility.
- In the articles reviewed, the time complexity achieved by metaheuristic algorithms to address WSN challenges is large compared to other algorithms, as is the computational cost.

5.2 Challenges of metaheuristic algorithms in WSNs

- Address different WSN scenarios from the existing ones in the literature, including large-scale WSNs (more than 1000 nodes) and 3-D placement approaches.
- Employing multi-objective metaheuristic algorithms in WSN issues more extensively, as WSNs have many competing objectives such as quality of service vs. network/battery life, throughput vs. packet error rate,

coverage vs. cost, delay vs. quality of service, coverage vs. network/battery life, and so on.
- Employing many-objective optimization approaches in addressing various WSN issues, as these approaches can address and solve more than three objectives (no. of objectives > 3) at the same time.
- Although they can offer a high-performance solution to an optimization problem, hyperheuristic algorithms have not yet been used in research on WSN difficulties. Therefore, using hyper-heuristic-based algorithms to solve WSN problems may prove to be a fruitful research direction.

5.3 Future trends

- Remote sensing has numerous novel and intriguing application areas thanks to WSNs' flexibility, fault tolerance, high sensing quality, rapid deployment, and low cost features. This wide range of potential applications will make WSNs a crucial component of our lives in the future. However, to realize sensor networks, it must be possible to work within the limitations imposed by variables such as fault tolerance, scalability, cost, topology change, environment, hardware, and power usage. Modern wireless ad hoc networking strategies are needed because these restrictions are quite strict and unique to WSNs.
- Designing the technologies required for various layers of WSNs, such as distributed query processing, scalable coordination architectures, information networking architectures, mathematical frameworks, task management planes, and data dissemination protocols.
- WSNs will be crucial to the Internet of Things, and the data they gather will likely turn into what is known as big data. How to effectively obtain the felt data is the crucial factor we need to address. In more detail, we need to think about the data routing path from the sensor nodes to the base nodes or from one sensor node to another sensor node. Furthermore, one area that deserves more attention from a practical point of view is data flow optimization.
- Handling huge-dimensional data: A large volume of data is generated by multiple sensing devices. Furthermore, the "curse of dimensionality" arises when the dimensions and size of data expand. As a result, smart infrastructure is required for data processing, analysis, and storage in order to automate numerous processes. However, in a non-stationary environment, when the data is not static, some additional procedures are necessary. These key measures will assist metaheuristic approaches in solving several satisfactorily dynamic situations.
- Covering some other swarm based applications such as block-chain and big data.

6 Conclusion

Metaheuristic algorithms are a fascinating and essential topic of scientific inquiry due to their exceptional capacity to tackle any optimization or search issue in engineering or industry in general. In addition, these algorithms can produce many plausible solutions and are responsible for determining the optimal one. In this review, we enumerated the many sources of inspiration for metaheuristic algorithms, whether SO or MO, and discussed the presence of these algorithms in WSNs and the associated issues. These algorithms demonstrate a competent capability to solve WSNs' challenges, such as deployment, localization, sink node placement, energy efficiency, and clustering. Furthermore, we emphasized the definitions of these terms and the structural clarification of the WSN. Additionally, we advocate the development of additional metaheuristic algorithms, both new and enhanced, to address and solve more challenges in real-world applications. Furthermore, it is abundantly evident that metaheuristic algorithms are among the effective paradigms that are helpful in providing trustworthy and durable solutions for WSN-based systems. There are three ways to convey this review. First, a review of the range of metaheuristic algorithm types and their corresponding assessment standards. The second fold documents and discusses the use of metaheuristic algorithms in WSNs for deployment, localization, sink node placement, energy efficiency, and clustering. The final fold outlines the challenges, outstanding concerns, and future directions pertaining to WSNs and metaheuristic algorithms. Generally, the research categorized the various metaheuristic solutions used to address optimization issues related to WSNs via SO and MO approaches. Therefore, considering the proposed SO and MO metaheuristic solutions for WSNs, it is reasonable to predict that this work will pave new study areas in SO and MO optimization for WSNs.

Author Contributions Essam H. Houssein: Supervision, Methodology, Conceptualization, Formal analysis, Investigation, Visualization, Writing—review and editing. Mohammed R. Saad: Investigation, Data Curation, Resources, Writing—original draft. Youcef Djenouri: Data Curation, Resources, Formal analysis, Writing—review and editing. Gang Hu: Data Curation, Resources, Formal analysis, Writing—review and editing. Abdelmgeid A. Ali: Supervision, Writing—review and editing. Hassan Shaban: Methodology, Conceptualization, Formal analysis, Writing—review and editing. All authors read and approved the final article.

Funding Open access funding provided by The Science, Technology & Innovation Funding Authority (STDF) in cooperation with The Egyptian Knowledge Bank (EKB).

Data Availability Data sharing is not applicable to this article as no data sets were generated or analyzed during the current study.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Human Participants or Animals This article does not contain studies with human participants or animals carried out by any of the authors.

References

1. Matin, M.A., Islam, M.M.: Overview of wireless sensor network. Wirel. Sensor Netw.-Technol. Protoc. **1**(3) (2012)
2. Akyildiz, I.F., Weilian, S., Sankarasubramaniam, Y., Cayirci, E.: A survey on sensor networks. IEEE Commun. Mag. **40**(8), 102–114 (2002)
3. Sangwan, A., Singh, R.P.: Survey on coverage problems in wireless sensor networks. Wirel. Pers. Commun. **80**(4), 1475–1500 (2015)
4. Rudafshani, M., Datta, S.: Localization in wireless sensor networks. In: 2007 6th International Symposium on Information Processing in Sensor Networks, pp. 51–60. IEEE (2007)
5. Houssein, E.H., Saad, M.R., Hussain, K., Zhu, W., Shaban, H., Hassaballah, M.: Optimal sink node placement in large scale wireless sensor networks based on Harris' Hawk optimization algorithm. IEEE Access **8**, 19381–19397 (2020)
6. Rezaei, Z., Mobininejad, S.: Energy saving in wireless sensor networks. Int. J. Comput. Sci. Eng. Surv. **3**(1), 23 (2012)
7. Subramanian, P., Martin Sahayaraj, J., Senthilkumar, S., and Stalin Alex, D.: A hybrid grey wolf and crow search optimization algorithm-based optimal cluster head selection scheme for wireless sensor networks. Wirel. Pers. Commun. 113(2):905–925 (2020)
8. Ved Prakash, Deepti Singh, Suman Pandey, Samayveer Singh, and Pradeep Kumar Singh.: Energy-optimization route and cluster head selection using m-pso and ga in wireless sensor networks. Wirel. Pers. Commun. 1–26 (2024)
9. Spall, J.C.: Introduction to Stochastic Search and Optimization: Estimation, Simulation, and Control, vol. 65. Wiley, London (2005)
10. Zielinski, K., Laur, R.: Constrained single-objective optimization using differential evolution. In: 2006 IEEE International Conference on Evolutionary Computation, pp. 223–230. IEEE (2006)
11. Bowerman, R., Hall, B., Calamai, P.: A multi-objective optimization approach to urban school bus routing: formulation and solution method. Transp. Res. Part A: Policy Pract. **29**(2), 107–123 (1995)
12. Simon, D.: Evolutionary Optimization Algorithms. Wiley, London (2013)
13. Houssein, E.H., Saad, M.R., Hussain, K., Shaban, H., Hassaballah, M.: A review of metaheuristic optimization algorithms in wireless sensor networks. In: Metaheuristics in Machine Learning: Theory and Applications, pp. 193–217 (2021)
14. Iqbal, M., Naeem, M., Anpalagan, A., Qadri, N.N., Imran, M.: Multi-objective optimization in sensor networks: optimization classification, applications and solution approaches. Comput. Netw. **99**, 134–161 (2016)
15. Houssein, E.H., Sayed, A.: Dynamic candidate solution boosted beluga whale optimization algorithm for biomedical classification. Mathematics **11**(3), 707 (2023)
16. Hussain, K., Salleh, M.N.M., Cheng, S., Shi, Y.: Metaheuristic research: a comprehensive survey. Artif. Intell. Rev. **52**, 2191–2233 (2019)
17. Binitha, S., Siva Sathya, S., et al.: A survey of bio inspired optimization algorithms. Int. J. Soft Comput. Eng. **2**(2), 137–151 (2012)
18. Tanyildizi, E., Demir, G.: Golden sine algorithm: a novel math-inspired algorithm. Adv. Electr. Comput. Eng. **17**(2), 71–78 (2017)
19. Yang, X.-S.: Swarm-based metaheuristic algorithms and no-free-lunch theorems. Theory New Appl. Swarm Intell. **9**, 1–16 (2012)
20. Fister Jr, I., Yang, X.-S., Fister, I., Brest, J., Fister, D.: A brief review of nature-inspired algorithms for optimization (2013). arXiv preprint arXiv:1307.4186
21. Kumar, A., Bawa, S.: Generalized ant colony optimizer: swarm-based meta-heuristic algorithm for cloud services execution. Computing **101**(11), 1609–1632 (2019)
22. Bäck, T., Schwefel, H.-P.: An overview of evolutionary algorithms for parameter optimization. Evol. Comput. **1**(1), 1–23 (1993)
23. Can, Ü., Alataş, B.: Physics based metaheuristic algorithms for global optimization. Am. J. Inf. Sci. Comput. Eng. (2015)
24. Razmjooy, N., Khalilpour, M., Ramezani, M.: A new meta-heuristic optimization algorithm inspired by FIFA world cup competitions: theory and its application in PID designing for AVR system. J. Control Autom. Electr. Syst. **27**(4), 419–440 (2016)
25. Siddique, N., Adeli, H.: Nature-Inspired Computing: Physics- and Chemistry-Based Algorithms. Chapman and Hall/CRC (2017)
26. Ishibuchi, H., Nojima, Y., Doi, T.: Comparison between single-objective and multi-objective genetic algorithms: performance comparison and performance measures. In: 2006 IEEE International Conference on Evolutionary Computation, pp. 1143–1150. IEEE (2006)
27. Sadollah, A., Sayyaadi, H., Yadav, A.: A dynamic metaheuristic optimization model inspired by biological nervous systems: neural network algorithm. Appl. Soft Comput. **71**, 747–782 (2018)
28. Yadav, A.: AEFA: artificial electric field algorithm for global optimization. Swarm Evol. Comput. **48**, 93–108 (2019)
29. Dhiman, G., Kumar, V.: Seagull optimization algorithm: theory and its applications for large-scale industrial engineering problems. Knowl.-Based Syst. **165**, 169–196 (2019)

30. Zhao, W., Wang, L., Zhang, Z.: Artificial ecosystem-based optimization: a novel nature-inspired meta-heuristic algorithm. Neural Comput. Appl. **32**(13), 9383–9425 (2020)
31. Abdollahzadeh, B., Soleimanian Gharehchopogh, F., Mirjalili, S.: Artificial gorilla troops optimizer: a new nature-inspired metaheuristic algorithm for global optimization problems. Int. J. Intell. Syst. **36**(10), 5887–5958 (2021)
32. Ford, J.K.B.: Killer whale: Orcinus orca. In *Encyclopedia of marine mammals*, pp. 650–657. Elsevier (2009)
33. Jiang, Y., Qing, W., Zhu, S., Zhang, L.: Orca predation algorithm: a novel bio-inspired algorithm for global optimization problems. Expert Syst. Appl. **188**, 116026 (2022)
34. Yang, Y., Chen, H., Heidari, A.A., Gandomi, A.H.: Hunger games search: visions, conception, implementation, deep analysis, perspectives, and towards performance shifts. Expert Syst. Appl. **177**, 114864 (2021)
35. Zervoudakis, K., Tsafarakis, S.: A mayfly optimization algorithm. Comput. Ind. Eng. **145**, 106559 (2020)
36. Shabani, A., Asgarian, B., Salido, M., Gharebaghi, S.A.: Search and rescue optimization algorithm: a new optimization method for solving constrained engineering optimization problems. Expert Syst. Appl. **161**, 113698 (2020)
37. Ghasemi, M., Davoudkhani, I.F., Akbari, E., Rahimnejad, A., Ghavidel, S., Li, L.: A novel and effective optimization algorithm for global optimization and its engineering applications: turbulent flow of water-based optimization (tfwo). Eng. Appl. Artif. Intell. **92**, 103666 (2020)
38. Gunantara, N.: A review of multi-objective optimization: methods and its applications. Cogent Eng. **5**(1), 1502242 (2018)
39. Heena, N., Shelbi Joseph, S., Shailesh, B.B.: Emcp: evolutionary multi-objective clustering protocol for prolonged lifetime of heterogeneous iot networks. J. Supercomput. **80**(4), 5224–5254 (2024)
40. Ngatchou, P., Zarei, A., El-Sharkawi, A.: Pareto multi objective optimization. In: Proceedings of the 13th International Conference on Intelligent Systems Application to Power Systems, pp. 84–91. IEEE (2005)
41. Mishra, B.S.P., Dehuri, S. and Cho, S.B.: Swarm intelligence in multiple and many objectives optimization: a survey and topical study on eeg signal analysis. In: Multi-objective Swarm Intelligence, pp. 27–73. Springer (2015)
42. Timothy Marler, R., Arora, J.S.: Survey of multi-objective optimization methods for engineering. Struct. Multidiscip. Optim. **26**(6), 369–395 (2004)
43. Knowles, J.D., Corne, D.W.: Approximating the nondominated front using the pareto archived evolution strategy. Evol. Comput. **8**(2), 149–172 (2000)
44. Chen, J., Huang, H., Tian, S., Youli, Q.: Feature selection for text classification with Naïve–Bayes. Expert Syst. Appl. **36**(3), 5432–5435 (2009)
45. Akbari, R., Hedayatzadeh, R., Ziarati, K., Hassanizadeh, B.: A multi-objective artificial bee colony algorithm. Swarm Evol. Comput. **2**, 39–52 (2012)
46. Shang, R., Zhang, W., Li, F., Jiao, L., Stolkin, R.: Multi-objective artificial immune algorithm for fuzzy clustering based on multiple kernels. Swarm Evol. Comput. **50**, 100485 (2019)
47. Yang, X., Zhang, G., Jie, L., Ma, J.: A kernel fuzzy c-means clustering-based fuzzy support vector machine algorithm for classification problems with outliers or noises. IEEE Trans. Fuzzy Syst. **19**(1), 105–115 (2010)
48. Zhang, D.-Q., Chen, S.-C.: Clustering incomplete data using kernel-based fuzzy c-means algorithm. Neural Process. Lett. **18**(3), 155–162 (2003)
49. Sadollah, A., Eskandar, H., Kim, J.H.: Water cycle algorithm for solving constrained multi-objective optimization problems. Appl. Soft Comput. **27**, 279–298 (2015)
50. Dhiman, G., Kumar, V.: Multi-objective spotted hyena optimizer: a multi-objective optimization algorithm for engineering problems. Knowl.-Based Syst. **150**, 175–197 (2018)
51. Mirjalili, S.Z., Mirjalili, S., Saremi, S., Faris, H., Aljarah, I.: Grasshopper optimization algorithm for multi-objective optimization problems. Appl. Intell. **48**(4), 805–820 (2018)
52. Mirjalili, S., Saremi, S., Mirjalili, S.M., Coelho, L.S.: Multi-objective grey wolf optimizer: a novel algorithm for multi-criterion optimization. Expert Syst. Appl. **47**, 106–119 (2016)
53. Houssein, E.H., Mahdy, M.A., Shebl, D., Manzoor, A., Sarkar, R., Mohamed, W.M.: An efficient slime mould algorithm for solving multi-objective optimization problems. Expert Syst. Appl. **187**, 115870 (2022)
54. Tawhid, M.A., Savsani, V.: Multi-objective sine-cosine algorithm (mo-sca) for multi-objective engineering design problems. Neural Comput. Appl. **31**(2), 915–929 (2019)
55. Moghdani, R., Salimifard, K., Demir, E., Benyettou, A.: Multi-objective volleyball premier league algorithm. Knowl.-Based Syst. **196**, 105781 (2020)
56. Mirjalili, S., Jangir, P., Mirjalili, S.Z., Saremi, S., Trivedi, I.N.: Optimization of problems with multiple objectives using the multi-verse optimization algorithm. Knowl.-Based Syst. **134**, 50–71 (2017)
57. Mirjalili, S., Jangir, P., Saremi, S.: Multi-objective ant lion optimizer: a multi-objective optimization algorithm for solving engineering problems. Appl. Intell. **46**(1), 79–95 (2017)
58. Hemmatian, H., Fereidoon, A., Assareh, E.: Optimization of hybrid laminated composites using the multi-objective gravitational search algorithm (mogsa). Eng. Optim. **46**(9), 1169–1182 (2014)
59. Kumawat, I.R., Nanda, S.J., Maddila, R.K.: Multi-objective whale optimization. In: Tencon 2017–2017 IEEE Region 10 Conference, pp. 2747–2752. IEEE (2017)
60. Nanda, S.J., et al.: Multi-objective moth flame optimization. In: 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI), pp. 2470–2476. IEEE (2016)
61. Coello Coello, C.A., Pulido, G.T., Lechuga, M.S.: Handling multiple objectives with particle swarm optimization. IEEE Trans. Evol. Comput. **8**(3), 256–279 (2004)
62. Mirjalili, S., Gandomi, A.H., Mirjalili, S.Z., Saremi, S., Faris, H., Mirjalili, S.M.: Salp swarm algorithm: a bio-inspired optimizer for engineering design problems. Adv. Eng. Softw. **114**, 163–191 (2017)
63. Dhiman, G., Singh, K.K., Soni, M., Nagar, A., Dehghani, M., Slowik, A., Kaur, A., Sharma, A., Houssein, E.H., Cengiz, K.: Mosoa: a new multi-objective seagull optimization algorithm. Expert Syst. Appl. **167**, 114150 (2021)
64. Houssein, E.H., Saad, M.R., Ali, A.A., Shaban, H.: An efficient multi-objective gorilla troops optimizer for minimizing energy consumption of large-scale wireless sensor networks. Expert Syst. Appl. **212**, 118827 (2023)
65. Wong, W.K., Ming, C.I.: A review on metaheuristic algorithms: recent trends, benchmarking and applications. In: 2019 7th International Conference on Smart Computing and Communications (ICSCC), pp. 1–5. IEEE (2019)
66. Liang, J.J., Qu, B.Y., Suganthan, P.N.: Problem Definitions and Evaluation Criteria for the cec 2014 Special Session and Competition on Single Objective Real-Parameter Numerical Optimization. Computational Intelligence Laboratory, Zhengzhou University, Zhengzhou China and Technical Report, Nanyang Technological University, Singapore **635**, 490 (2013)
67. Zhang, Q., Zhou, A., Zhao, S., Suganthan, P.N., Liu, W., Tiwari, S., et al.: Multiobjective Optimization Test Instances for the cec 2009 Special Session and Competition. University of Essex, Colchester, UK and Nanyang technological University,

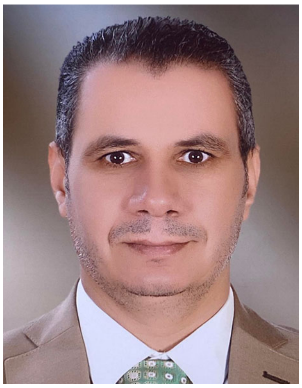
Singapore, special session on performance assessment of multi-objective optimization algorithms, technical report **264**, 1–30 (2008)
68. García, S., Molina, D., Lozano, M., Herrera, F.: A study on the use of non-parametric tests for analyzing the evolutionary algorithms' behaviour: a case study on the cec'2005 special session on real parameter optimization. J. Heuristics **15**(6), 617–644 (2009)
69. Zimmerman, D.W., Zumbo, B.D.: Relative power of the Wilcoxon test, the Friedman test, and repeated-measures anova on ranks. J. Exp. Educ. **62**(1), 75–86 (1993)
70. Azad, S.K.: Monitored convergence curve: a new framework for metaheuristic structural optimization algorithms. Struct. Multidiscip. Optim. **60**(2), 481–499 (2019)
71. Mailler, R., Lesser, V.: Solving distributed constraint optimization problems using cooperative mediation. In: Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems, 2004. AAMAS 2004, pp. 438–445. IEEE (2004)
72. Ahmed, M.M., Houssein, E.H., Hassanien, A.E., Taha, A , Hassanien, E.: Maximizing lifetime of large-scale wireless sensor networks using multi-objective whale optimization algorithm. Telecommun. Syst. 1–17 (2019)
73. Kanoosh, H.M., Houssein, E.H., Selim, M.M.: Salp swarm algorithm for node localization in wireless sensor networks. J. Comput. Netw. Commun. **2019** (2019)
74. Yick, J., Mukherjee, B., Ghosal, D.: Wireless sensor network survey. Comput. Netw. **52**(12), 2292–2330 (2008)
75. Silva, I., Guedes, L.A., Portugal, P., Vasques, F.: Reliability and availability evaluation of wireless sensor networks for industrial applications. Sensors **12**(1), 806–838 (2012)
76. Zhao, G.: Wireless sensor networks for industrial process monitoring and control: a survey. Netw. Protoc. Algor. **3**(1), 46–63 (2011)
77. Zhou, Yu., Xiao, C., Zhou, G.: Multi-objectivization-based localization of underwater sensors using magnetometers. IEEE Sens. J. **14**(4), 1099–1106 (2013)
78. Rathi, S., Gupta, R., Ormsbee, L.: A review of sensor placement objective metrics for contamination detection in water distribution networks. Water Sci. Technol.: Water Supply **15**(5), 898–917 (2015)
79. Wang, Y.: Topology control for wireless sensor networks. In: Wireless Sensor Networks and Applications, pp. 113–147. Springer (2008)
80. Wightman, P.M., Labrador, M.A.: A3: a topology construction algorithm for wireless sensor networks. In: IEEE GLOBECOM 2008-2008 IEEE Global Telecommunications Conference, pp. 1–6. IEEE (2008)
81. Yuanyuan, Z., Jia, X., Yanxiang, H.: Energy efficient distributed connected dominating sets construction in wireless sensor networks. In: Proceedings of the 2006 International Conference on Wireless Communications and Mobile Computing, pp. 797–802. ACM (2006)
82. Jie, W., Cardei, M., Dai, F., Yang, S.: Extended dominating set and its applications in ad hoc networks using cooperative communication. IEEE Trans. Parallel Distrib. Syst. **17**(8), 851–864 (2006)
83. Kulkarni, R.V., Venayagamoorthy, G.K.: Bio-inspired algorithms for autonomous deployment and localization of sensor nodes. IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.) **40**(6), 663–675 (2010)
84. Sahoo, B.M., Pandey, H.M., Amgoth, T.: A genetic algorithm inspired optimized cluster head selection method in wireless sensor networks. Swarm Evol. Comput. **75**, 101151 (2022)
85. Sahoo, B.M., Pandey, H.M., Amgoth, T.: Gapso-h: a hybrid approach towards optimizing the cluster based routing in wireless sensor network. Swarm Evol. Comput. **60**, 100772 (2021)
86. Efrat, A., Har-Peled, S., Mitchell, J.S.B.: Approximation algorithms for two optimal location problems in sensor networks. In: 2nd International Conference on Broadband Networks, 2005, pp. 714–723. IEEE (2005)
87. Coello, C.A.: An updated survey of ga-based multiobjective optimization techniques. ACM Comput. Surv. **32**(2), 109–143 (2000)
88. Zhou, A., Bo-Yang, Q., Li, H., Zhao, S.-Z., Suganthan, P.N., Zhang, Q.: Multiobjective evolutionary algorithms: a survey of the state of the art. Swarm Evol. Comput. **1**(1), 32–49 (2011)
89. Deb, K.: Multi-Objective Optimization Using Evolutionary Algorithms, vol. 16. Wiley, London (2001)
90. Andersson, J.: A Survey of Multiobjective Optimization in Engineering Design. Department of Mechanical Engineering, Linktjping University, Sweden (2000)
91. Binh, H.T.T., Hanh, N.T., Van Quan, L., Dey, N.: Improved cuckoo search and chaotic flower pollination optimization algorithm for maximizing area coverage in wireless sensor networks. Neural Comput. Appl. **30**(7), 2305–2317 (2018)
92. Liao, W.-H., Kao, Y., Li, Y.-S.: A sensor deployment approach using glowworm swarm optimization algorithm in wireless sensor networks. Expert Syst. Appl. **38**(10), 12180–12188 (2011)
93. Konstantinidis, A., Yang, K.: Multi-objective energy-efficient dense deployment in wireless sensor networks using a hybrid problem-specific moea/d. Appl. Soft Comput. **11**(6), 4117–4134 (2011)
94. Liao, W.-H., Kao, Y., Ru-Ting, W.: Ant colony optimization based sensor deployment protocol for wireless sensor networks. Expert Syst. Appl. **38**(6), 6599–6605 (2011)
95. Yiyue, W., Hongmei, L., Hengyang, H.: Wireless sensor network deployment using an optimized artificial fish swarm algorithm. In: 2012 International Conference on Computer Science and Electronics Engineering, vol. 2, pp. 90–94. IEEE (2012)
96. Ly, D.T.H., Hanh, N.T., Binh, H.T.T., Nghia, N.D.: An improved genetic algorithm for maximizing area coverage in wireless sensor networks. In: Proceedings of the Sixth International Symposium on Information and Communication Technology, pp. 61–66 (2015)
97. Chen, J., Li, S., Sun, Y.: Novel deployment schemes for mobile sensor networks. Sensors **7**(11), 2907–2919 (2007)
98. Wang, X., Wang, S., Ma, J.-J.: An improved co-evolutionary particle swarm optimization for wireless sensor networks with dynamic deployment. Sensors **7**(3), 354–370 (2007)
99. Mohar, S.S., Goyal, S., Kaur, R.: Optimized sensor nodes deployment in wireless sensor network using bat algorithm. Wirel. Pers. Commun. **116**(4), 2835–2853 (2021)
100. Ozturk, C., Karaboga, D., Gorkemli, B.: Probabilistic dynamic deployment of wireless sensor networks by artificial bee colony algorithm. Sensors **11**(6), 6056–6065 (2011)
101. Binh, H.T.T., Hanh, N.T., Nghia, N.D., Dey, N., et al.: Metaheuristics for maximization of obstacles constrained area coverage in heterogeneous wireless sensor networks. Appl. Soft Comput. **86**, 105939 (2020)
102. Chowdhury, A., De, D.: Energy-efficient coverage optimization in wireless sensor networks based on Voronoi–Glowworm swarm optimization-k-means algorithm. Ad Hoc Netw. **122**, 102660 (2021)
103. Tsai, C.-W., Tsai, P.-W., Pan, J.-S., Chao, H.-C.: Metaheuristics for the deployment problem of wsn: a review. Microprocess. Microsyst. **39**(8), 1305–1317 (2015)

104. Gage, D.W.: Command Control for Many-robot Systems. Technical report, Naval Command Control and Ocean Surveillance Center Rdt And E Div San Diego CA (1992)
105. Lavanya, D., Udgata, S.K.: Swarm intelligence based localization in wireless sensor networks. In: International Workshop on Multi-disciplinary Trends in Artificial Intelligence. Springer, pp. 317–328 (2011)
106. So-In, C., Permpol, S., Rujirakul, K.: Soft computing-based localizations in wireless sensor networks. Pervasive Mob. Comput. **29**, 17–37 (2016)
107. Mohar, S.S., Goyal, S., Kaur, R.: A survey of localization in wireless sensor network using optimization techniques. In: 2018 4th International Conference on Computing Communication and Automation (ICCCA), pp. 1–6. IEEE (2018)
108. Cheng, L., Chengdong, W., Zhang, Y., Hao, W., Li, M., Maple, C.: A survey of localization in wireless sensor network. Int. J. Distrib. Sens. Netw. **8**(12), 962523 (2012)
109. Goyal, S., Patterh, M.S.: Modified bat algorithm for localization of wireless sensor network. Wirel. Pers. Commun. **86**(2), 657–670 (2016)
110. Muller, S.D., Marchetto, J., Airaghi, S., Kournoutsakos, P.: Optimization based on bacterial chemotaxis. IEEE Trans. Evol. Comput. **6**(1), 16–29 (2002)
111. Sun, Z., Tao, L., Wang, X., Zhou, Z.: Localization algorithm in wireless sensor networks based on multiobjective particle swarm optimization. Int. J. Distrib. Sens. Netw. **11**(8), 716291 (2015)
112. Strumberger, I., Beko, M., Tuba, M., Minovic, M., Bacanin, N.: Elephant herding optimization algorithm for wireless sensor network localization problem. In: Doctoral Conference on Computing, Electrical and Industrial Systems. Springer, pp. 175–184 (2018)
113. Cheng, M., Qin, T., Yang, J.: Node localization algorithm based on modified archimedes optimization algorithm in wireless sensor networks. J. Sens. **2022** (2022)
114. Kumar, G.H., Ramesh, G.P.: Node localization algorithm for detecting malicious nodes to prevent connection failures and improve end-to-end delay. Comput. Commun. **190**, 37–47 (2022)
115. Kaushik, A., Al-Raweshidy, H.: A novel intrusion detection system for internet of things devices and data. Wirel. Netw. **30**(1), 285–294 (2024)
116. Kaushik, A., Vadlamani, L.S.S., Hussain, M.M., Sahay, M., Singh, R., Singh, A.K., Indu, S., Goswami, P., Kousik, N.G.V.: Post quantum public and private key cryptography optimized for iot security. Wirel. Pers. Commun. **129**(2), 893–909 (2023)
117. Kaushik, A., Al-Raweshidy, H.S.: A hybrid latency-and power-aware approach for beyond fifth-generation internet-of-things edge systems. IEEE Access **10**, 87974–87989 (2022)
118. Kaushik, A., Goswami, M., Minkush Manuja, S., Indu, D.G.: A binary pso approach for improving the performance of wireless sensor networks. Wirel. Pers. Commun. **113**, 263–297 (2020)
119. Kaushik, A., Indu, S., Gupta, D.: A grey wolf optimization approach for improving the performance of wireless sensor networks. Wirel. Pers. Commun. **106**, 1429–1449 (2019)
120. Kaushik, A., Indu, S., Gupta, D.: A grey wolf optimization based algorithm for optimum camera placement. Wirel. Pers. Commun. **105**, 1143–1167 (2019)
121. Kaushik, A., Indu, S., Gupta, D.: Adaptive mobile sink for energy efficient wsn using biogeography-based optimization. Int. J. Mob. Comput. Multimedia Commun. **10**(3), 1–22 (2019)
122. Kaushik, A., Yakkali, R.T., Indu, S., Ahmed, F., Gupta, D., Nayar, R., Yadav, S.: A self-configurable event coverage approach for wireless sensor networks. Int. J. Mob. Comput. Multimedia Commun. **10**(2), 1–18 (2019)
123. Singh, R., Hussain, M.M., Sahay, M., Indu, S., Kaushik, A., Kumar Singh, A: Loki: a lightweight lwe method with rogue bits for quantum security in iot devices. In: Information and Communication Technology for Intelligent Systems: Proceedings of ICTIS 2020, vol. 2, pp. 543–553. Springer (2021)
124. Kaushik, A., Gupta, D., et al.: A novel load balanced energy conservation approach in wsn using biogeography based optimization. In: AIP Conference Proceedings, vol. 1884. AIP Publishing (2017)
125. Vecchio, M., López-Valcarce, R., Marcelloni, F.: A two-objective evolutionary approach based on topological constraints for node localization in wireless sensor networks. Appl. Soft Comput. **12**(7), 1891–1901 (2012)
126. Cheng, J., Xia, L.: An effective cuckoo search algorithm for node localization in wireless sensor network. Sensors **16**(9), 1390 (2016)
127. Yao, Y., Jiang, N.: Distributed wireless sensor network localization based on weighted search. Comput. Netw. **86**, 57–75 (2015)
128. Arora, S., Kaur, R.: Nature inspired range based wireless sensor node localization algorithms. Int. J. Interact. Multimedia Artif. Intell. **4**, 7–17 (2017)
129. Arora, S., Singh, S.: Node localization in wireless sensor networks using butterfly optimization algorithm. Arab. J. Sci. Eng. **42**(8), 3325–3335 (2017)
130. Lalama, Z., Boulfekhar, S., Semechedine, F.: Localization optimization in wsns using meta-heuristics optimization algorithms: a survey. Wirel. Pers. Commun. **122**(2), 1197–1220 (2022)
131. Tuba, E., Simian, D., Dolicanin, E., Jovanovic, R., Tuba, M.: Energy efficient sink placement in wireless sensor networks by brain storm optimization algorithm. In: 2018 14th International Wireless Communications and Mobile Computing Conference (IWCMC), pp. 718–723. IEEE (2018)
132. Strumberger, I., Minovic, M., Tuba, M., Bacanin, N.: Performance of elephant herding optimization and tree growth algorithm adapted for node localization in wireless sensor networks. Sensors **19**(11), 2515 (2019)
133. Bang Ye, W., Chao, K.-M.: Spanning Trees and Optimization Problems. Chapman and Hall/CRC, UK (2004)
134. Cheriton, D., Tarjan, R.E.: Finding minimum spanning trees. SIAM J. Comput. **5**(4), 724–742 (1976)
135. Luo, J., Hubaux, J.-P.: Joint mobility and routing for lifetime elongation in wireless sensor networks. In: Proceedings IEEE 24th Annual Joint Conference of the IEEE Computer and Communications Societies, vol. 3, pp. 1735–1746. IEEE (2005)
136. Snasel, V., Kong, L., Tsai, P.-W., Pan, J.-S.: Sink node placement strategies based on cat swarm optimization algorithm. J. Netw. Intell. **1**(2), 52–60 (2016)
137. Chu, S.-C., Tsai, P.-W., Pan, J.-S.: Cat swarm optimization. In: Pacific Rim International Conference on Artificial Intelligence. Springer, pp. 854–858 (2006)
138. Fouad, M.M., Snasel, V., Hassanien, A.E.: Energy-aware sink node localization algorithm for wireless sensor networks. Int. J. Distrib. Sens. Netw. **11**(7), 810356 (2015)
139. Banka, H., Jana, P.K., et al.: Pso-based multiple-sink placement algorithm for protracting the lifetime of wireless sensor networks. In: Proceedings of the Second International Conference on Computer and Communication Technologies, pp. 605–616. Springer (2016)
140. Rahman, M.N., Matin, M.A.: Efficient algorithm for prolonging network lifetime of wireless sensor networks. Tsinghua Sci. Technol. **16**(6), 561–568 (2011)
141. Fouad, M.M., Snasel, V., Hassanien, A.E.: An adaptive pso-based sink node localization approach for wireless sensor networks. In: Proceedings of the Second International Afro-European Conference for Industrial Advancement AECIA 2015, pp. 679–688. Springer (2016)

142. Holland, J.H.: Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence. MIT Press, Cambridge (1992)
143. Ghosh, S., Snigdh, I., Singh, A.: Ga optimal sink placement for maximizing coverage in wireless sensor networks. In: 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), pp. 737–741. IEEE (2016)
144. Dorigo, M., Birattari, M., Stutzle, T.: Ant colony optimization. IEEE Comput. Intell. Mag. **1**(4), 28–39 (2006)
145. Chen, F., Li, R.: Sink node placement strategies for wireless sensor networks. Wirel. Pers. Commun. **68**(2), 303–319 (2013)
146. Lin, Y., Zhang, J., Chung, H.S.-H., Ip, W.H., Li, Y., Shi, Y.-H.: An ant colony optimization approach for maximizing the lifetime of heterogeneous wireless sensor networks. IEEE Trans. Syst. Man Cybern., Part C (Appl. Rev.) **42**(3), 408–420 (2011)
147. Shamsan Saleh, A.M., Ali, B.M., Rasid, M.F.A., Ismail, A.: A self-optimizing scheme for energy balanced routing in wireless sensor networks using sensorant. Sensors **12**(8), 11307–11333 (2012)
148. Sobral, J.V., Rabelo, R.A., Araujo, H.S., Baluz, R.A., Holanda Filho, R.: Automated design of fuzzy rule base using ant colony optimization for improving the performance in wireless sensor networks. In: 2013 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), pp. 1–8. IEEE (2013)
149. Zhang, J., Gao, L.: Clustering routing algorithm for wsn based on improved ant colony algorithm. In: 2011 International Conference on Electrical and Control Engineering, pp. 2924–2928. IEEE (2011)
150. Yang, X.-S., Deb, S.: Cuckoo search: recent advances and applications. Neural Comput. Appl. **24**(1), 169–174 (2014)
151. Saremi, S., Mirjalili, S., Lewis, A.: Grasshopper optimisation algorithm: theory and application. Adv. Eng. Softw. **105**, 30–47 (2017)
152. Shi, Y.: Brain storm optimization algorithm. In: International Conference in Swarm Intelligence, pp. 303–309. Springer (2011)
153. Fouad, M.M., Hafez, A.I., Hassanien, A.E., Snasel, V.: Grey wolves optimizer-based localization approach in wsns. In: 2015 11th International Computer Engineering Conference (ICENCO), pp. 256–260. IEEE (2015)
154. Fouad, M.M., Hafez, A.I., Hassanien, A.E.: Optimizing topologies in wireless sensor networks: a comparative analysis between the grey wolves and the chicken swarm optimization algorithms. Comput. Netw. **163**, 106882 (2019)
155. Meng, X., Liu, Y., Gao, X., Zhang, H.: A new bio-inspired algorithm: chicken swarm optimization. In: International Conference in Swarm Intelligence, pp. 86–94. Springer (2014)
156. Li, H., Liu, Y., Chen, W., Jia, W., Li, B., Xiong, J.: Coca: constructing optimal clustering architecture to maximize sensor network lifetime. Comput. Commun. **36**(3), 256–268 (2013)
157. Nakano, H., Yoshimura, M., Utani, A., Miyauchi, A., Yamamoto, H.: A sink node allocation scheme in wireless sensor networks using suppression particle swarm optimization. Sustain. Wirel. Sens. Netw. (2010)
158. Bogdanov, A., Maneva, E., Riesenfeld, S.: Power-aware base station positioning for sensor networks. In: IEEE INFOCOM 2004, vol. 1. IEEE (2004)
159. Azharuddin, Md., Jana, P.K.: Particle swarm optimization for maximizing lifetime of wireless sensor networks. Comput. Electr. Eng. **51**, 26–42 (2016)
160. Ben-Othman, J., Bessaoud, K., Bui, A., Pilard, L.: Self-stabilizing algorithm for efficient topology control in wireless sensor networks. J. Comput. Sci. **4**(4), 199–208 (2013)
161. Kaur, S., Mahajan, R.: Hybrid meta-heuristic optimization based energy efficient protocol for wireless sensor networks. Egypt. Inform. J. **19**(3), 145–150 (2018)
162. Ahmed, M.M., Houssein, E.H., Hassanien, A.E., Taha, A., Hassanien, E.: Maximizing lifetime of wireless sensor networks based on whale optimization algorithm. In: International Conference on Advanced Intelligent Systems and Informatics, pp. 724–733. Springer (2017)
163. Wightman, P.M., Labrador, M.A.: Atarraya: a simulation tool to teach and research topology control algorithms for wireless sensor networks. In: Proceedings of the 2nd International Conference on Simulation Tools and Techniques, pp. 1–10 (2009)
164. Sahoo, B.M., Amgoth, T., Pandey, H.M.: Particle swarm optimization based energy efficient clustering and sink mobility in heterogeneous wireless sensor network. Ad Hoc Netw. **106**, 102237 (2020)
165. Kumarawadu, P., Dechene, D.J., Luccini, M., Sauer, A.: Algorithms for node clustering in wireless sensor networks: a survey. In: 2008 4th International Conference on Information and Automation for Sustainability, pp. 295–300. IEEE (2008)
166. Vellela, S.S., Balamanigandan, R.: Optimized clustering routing framework to maintain the optimal energy status in the wsn mobile cloud environment. Multimedia Tools Appl. **83**(3), 7919–7938 (2024)
167. Daniel, J., Francis, S.F.V., Velliangiri, S.: Cluster head selection in wireless sensor network using tunicate swarm butterfly optimization algorithm. Wirel. Netw. **27**(8), 5245–5262 (2021)
168. Zhou, Y., Wang, N., Xiang, W.: Clustering hierarchy protocol in wireless sensor networks using an improved PSO algorithm. IEEE Access **5**, 2241–2253 (2016)
169. Tabibi, S., Ghaffari, A.: Energy-efficient routing mechanism for mobile sink in wireless sensor networks using particle swarm optimization algorithm. Wirel. Pers. Commun. **104**(1), 199–216 (2019)
170. Jadhav, A.R., Shankar, T.: Whale optimization based energy-efficient cluster head selection algorithm for wireless sensor networks (2017). arXiv preprint arXiv:1711.09389
171. Shankar, T., Shanmugavel, S., Rajesh, A.: Hybrid hsa and pso algorithm for energy efficient cluster head selection in wireless sensor networks. Swarm Evol. Comput. **30**, 1–10 (2016)
172. Hacioglu, G., Kand, V.F.A., Sesli, E.: Multi objective clustering for wireless sensor networks. Expert Syst. Appl. **59**, 86–100 (2016)
173. Latiff, N.A., Tsimenidis, C.C., Sharif, B.S.: Performance comparison of optimization algorithms for clustering in wireless sensor networks. In: 2007 IEEE International Conference on Mobile Adhoc and Sensor Systems, pp. 1–4. IEEE (2007)
174. Karimi, M., Naji, H.R., Golestani, S.: Optimizing cluster-head selection in wireless sensor networks using genetic algorithm and harmony search algorithm. In: 20th Iranian Conference on Electrical Engineering (ICEE2012), pp. 706–710. IEEE (2012)
175. Vijayalakshmi, K., Anandan, P.: A multi objective tabu particle swarm optimization for effective cluster head selection in wsn. Clust. Comput. **22**(5), 12275–12282 (2019)
176. Nagarajan, L., Thangavelu, S.: Hybrid grey wolf sunflower optimisation algorithm for energy-efficient cluster head selection in wireless sensor networks for lifetime enhancement. IET Commun. **15**(3), 384–396 (2021)

177. Mittal, N., Singh, U., Salgotra, R., Bansal, M.: An energy-efficient stable clustering approach using fuzzy-enhanced flower pollination algorithm for wsns. Neural Comput. Appl. **32**(11), 7399–7419 (2020)

178. Kuila, P., Jana, P.K.: Energy efficient clustering and routing algorithms for wireless sensor networks: particle swarm optimization approach. Eng. Appl. Artif. Intell. **33**, 127–140 (2014)



Essam H. Houssein (Member, IEEE) received Ph.D. degree in computer science, in 2012. He is currently a Professor of Artificial Intelligence at the Faculty of Computers and Information, Minia University, Minia, Egypt. He is the founder and chair of the Artificial Intelligence Research (AIR) Group, Egypt. He has published more than 200 scientific research articles in prestigious international journals. His research interests include Meta-heuristics Optimization Algorithms, WSN, Bioinformatics, Internet of Things, Artificial Intelligence, Image Processing, and Data Mining. He serves as a reviewer for more than 100 journals, such as Elsevier, Springer, and IEEE.

Mohammed R. Saad received Ph.D. degree in computer science, in 2023. He is currently a lecturer at the Faculty of Computers and Information, Luxor University, Luxor, Egypt.

Youcef Djenouri is an Associate Professor at University of South-Eastern Norway, and a senior researcher at NORCE (Norwegian Research Center) from 2023. He was a research scientist at SINTEF, and a postdoc researcher at NTNU, and SDU. His research interests include AI, smart city applications, security and privacy. Dr. Youcef Djenouri published more than 170 research papers in top conferences and journals such as ICDM, ICDE, ACM KDD, IEEE TIST, IEEE TII, IEEE TCYB, and others. He is also in the list of 2% most outstanding researchers according to Stanford statistics. Dr. Youcef Djenouri is an Associate Editor in IEEE Transactions on Computational Social Systems, Neural Processing Letters, Discover AI journal, and Editorial Board in Applied Intelligence. He also organized workshops in top conferences such as ICDM, KDD, DSAA, and PAKDD.

Gang Hu was born in China in April 1979. He is a professor of Computer Engineering and Applied Mathematics at Xi'an University of Technology. He received his master's degree in applied mathematics from the Northwestern Polytechnical University and his doctorates in Mechanical Engineering from Xi'an University of Technology, respectively. He started his career as a Lecturer at Xi'an university of technology, Xi'an, China, in 2002 and taught a variety of courses of Applied Mathematics at undergraduate and graduate level. His research interests are in Artifcial Intelligence, Computational Intelligence, Geometry Optimization, Computation Geometry, CAD/CAM, Image Processing and Applied Mathematics and his works have been published in many different journals. He is a member of Chinese Computer Federation, a member of the CSIAM. He served as a program committee member for numerous international conferences.

Abdelmgeid A. Ali is a Professor in Computer Science Department, Minia University, El Minia, Egypt. He has published over 80 research papers in prestigious international journals, and conference proceedings. He has supervised over 60 Ph.D. and M. Sc. Students. Prof Ali is a member of the International Journal of Information Theories and Applications (ITA). Prof Ali interests are Information Retrieval, Software Engineering, Image Processing, Data security, metaheuristics, IOT, Digital Image Steganography, Data Warehousing.

Hasssn Shaban received his Ph.D. degree in Computer Science. Currently work as lecturer at Computer Science Dept., Faculty of Computers and Information, Minia University, Egypt. His research interests include wireless sensor networks, security, optimization, metaheuristics.

Authors and Affiliations

Essam H. Houssein[1] · Mohammed R. Saad[2] · Youcef Djenouri[3,4,5] · Gang Hu[6,7] · Abdelmgeid A. Ali[1] · Hassan Shaban[1]

✉ Essam H. Houssein
essam.halim@mu.edu.eg

✉ Mohammed R. Saad
m.saad@fci.luxor.edu.eg

Youcef Djenouri
youcef.djenouri@usn.no

Gang Hu
hugang@xaut.edu.cn

Abdelmgeid A. Ali
a.ali@mu.edu.eg

Hassan Shaban
hassanshaban@mu.edu.eg

1 Faculty of Computers and Information, Minia University, Minia, Egypt

2 Faculty of Computers and Information, Luxor University, Luxor, Egypt

3 University of South-Eastern Norway, Kongsberg, Norway

4 NORCE Norwegian Research Center, Oslo, Norway

5 IDEAS NCBR, Warsaw, Poland

6 Department of Applied Mathematics, Xi'an University of Technology, Xi'an 710054, China

7 School of Computer Science and Engineering, Xi'an University of Technology, Xi'an 710048, China