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Nature Inspired Algorithms for Internet of Things: A Comprehensive Survey

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Abstract: The Internet of Things (IoT) is permeating many aspects of our daily lives (AI) with the growth of intelligent services and applications powered by AI. Traditional AI algorithms require centralized data gathering and processing due to the enormous scalability of modern IoT networks and growing data privacy concerns, which may not be feasible in real-world application settings. IoT functioning depends on the Wireless Sensor Networks (WSNs) architecture. Nature-inspired algorithms are emerging as a viable solution to the pressing problems in Wireless Sensor Networks (WSNs), with worry about the limited sensor lifetime. Before any network configuration, it is important to carefully consider how to have the best possible network coverage. Optimal network coverage reduces the amount of redundant data that is sensed and also lowers the restricted energy consumption of battery-powered sensors. This article focuses on nature-inspired optimization algorithms for data aggregation, optimal coverage, sensor localization, energy-efficient clustering and routing, load balancing, fault tolerance, and security in wireless sensor networks (WSNs). We have briefly discussed the classification of optimization techniques as well as the WSN issue domains. The genetic algorithm (GA), differential evolution (DE), ant colony optimization (ACO), grey wolf optimization (GWO), particle swarm optimization (PSO), artificial bee colony (ABC), firefly algorithm (FA), cuckoo search (CS), lion optimization (LO) and crow search algorithm (CSA) are a few of the algorithms that take inspiration from nature.

Index Terms: *Nature-inspired Algorithms, Internet of Things, optimal coverage, data aggregation, energy-efficiency, localization, load balancing, fault tolerance, security*.

1. Introduction

The term "Internet of Things" (IoT) describes a network-like structure that links (unique) items and things. More and more sensors and gadgets are connected to wireless networks and, eventually, the Internet through integration into all kinds of items. A subclass of the Industry 4.0 standard is the Internet of Things (IoT). The Wireless Sensor Networks (WSNs) architecture is essential to the IoT's operation. WSN sensors have the ability to perceive, gather, and send data simultaneously [1]. To reduce the waste of the finite sensor battery life, all these operations must be completed efficiently. The sensor lifespan cannot be extended by providing external or since the majority of the sensors are placed in difficult-to-reach places [2–10]. The lifespan of the sensor node has been extended by extensive study. According to Liang et al. [11], the Huang method is an ideal energy clustering technique that ensures balanced energy depletion over the whole network, extending the system's lifespan. In order to increase the operating duration of the sensors, Cardei et al. [12] devised the TianD method groups the sensors into various maximum set covers that are disjoint in nature. Thus, the aforementioned algorithms do have significant drawbacks. Huang's technique is extremely complicated, and if communication data is excessively huge, it leads to block the channel. In comparison, the this method has a lesser level of complexity. However, while perceiving duplicate information, it is unable to identify the redundant node.

Sensing and overlapping information are the major problems in WSNs along with the energy restriction. In order to detect overlapping information, the sensors must be spaced apart at a suitable distance from one another in the sensing zone. However, if the sensors are set farther apart from one another, it will leave open spaces that are known as coverage holes or blind regions. A Coverage Configuration Protocol (CCP) was introduced by Wang et al. [13] that guarantees the coverage and connectivity. However, if there are a lot of sensors, the CCP algorithm performs poorly.

The burning issues that facing in WSNs are energy efficiency, Quality of Service (QoS), and security. All these difficulties are subject to trade-offs. For instance, we must sacrifice on network lifespan if we want strong QoS. The same is true for the each of these problems

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separately, there are several gaps. Therefore, we must concurrently optimize these security measures. Regarding solving each of these challenges separately, a lot of work has been done. However, when tackling difficulties in order to create a superior WSN. The choice of an appropriate algorithm is influenced by a number of variables, including the algorithm's behavior, the nature of the issue at hand, the timeframe, the resources at hand, and the level of precision that is sought. We first spoke about the issue domains in WSNs, and then we reviewed the optimization methods that are currently available to tackle them.

We divide the nature-inspired algorithms (NIAs) into five classes that are based on their characteristics such as natural evolution (NE), swarm intelligence (SE), biology, science, and others. NE based algorithms are constructed using the fundamental ideas of this theory. SE based algorithms are influenced by the group behaviour of animals including ants, bats, bees, fireflies, and cuckoos. The social behaviour of biological systems serve as the inspiration for the biologically based algorithms. The scientific notions provide the foundation of the science-based algorithms. Others include the algorithms that were motivated by other natural events. The classification of NIAs is shown in Fig. 1 [14].

- Numerous difficult issues in real life lack a true solution, requiring the use of optimization techniques to solve them. Many academics are encouraged to utilize NIA approaches to address complicated issues since nature is a tremendous source of inspiration and the way it approaches all real-life challenges. NIAs are those that draw their inspiration from the natural world, and these algorithms are frequently utilized today to solve challenging engineering challenges. The main goal of NIAs is to identify the overall best solution to a given issue [15,16].
- There are several NIAs that are extensively utilized in many applications, including Ant-Colony Optimization (ACO), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Firefly Algorithm (FA), Cuckoo search, Artificial bee colony algorithm, Leaping frog algorithm, Bat algorithm and Flower pollination algorithm, etc.[17]. Nature-inspired algorithms used in Internet of Things (IoT) , artificial neural networks (ANN), fuzzy systems (FS), evolutionary computing (EC), and swarm intelligence (SI),Digital filter designing , Image processing, Machine-learning(ML), Digital integrator and differentiator designing (DIDD), Face-recognition(FR) , and Wireless Sensor Networks (WSN) and they have been applied to solve many real-world problems.

The rest of the paper is organized as follows. In Section 2 we have talked about the Optimization Algorithms in WSNs and WSN's challenge domains, which include the WSNs' primary challenges by classifying them into seven groups. In Section 3, we discuss optimal coverage in WSN and existing methods for achieving optimal coverage using NIAs. In Section 4 we discuss Data aggregation in WSN and existing methods for achieving optimal coverage using NIAs. In Section 5 we discuss Energy Efficient Clustering and Routing (EECR) in WSN and existing methods for achieving optimal coverage using NIAs. In Section 6 we discuss Sensor Localization in WSN and existing methods for achieving optimal coverage using NIAs. In Section 7 we discuss Load Balancing in WSN and existing methods for achieving optimal coverage using NIAs. In Section 8 we discuss Fault Tolerance in WSN and existing methods for achieving optimal coverage using NIAs. In Section 9 we discuss Security in WSN and existing methods for achieving optimal coverage using NIAs. In Section 10 describes Conclusion and Future Work.

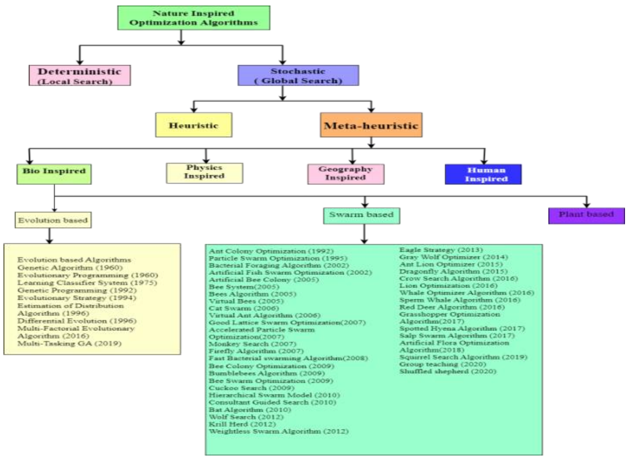

Fig. 1. The classification of optimization methods

2. Optimization Algorithms in WSNs

A model, a simulator, or an algorithm can all do an optimization. In this study, we assessed the possibility for WSN issue domain optimization using an algorithmic technique. Fig. 1 displays a thorough taxonomy of the optimization techniques typically employed in WSNs. Since 2000, there have been more than 100 algorithms that draw inspiration from nature. As a result, it is impossible to compile a taxonomy of all the current algorithms. For instance, 134 such algorithms are documented by Xing and Gao [88], while the online database Bestiary has more than 200 methods [89]. The most current and complete taxonomies or databases of algorithms drawn from nature can be found in [90].

There are predictable (local search) and chaotic (global search) optimization techniques. While stochastic techniques only provide a probability guarantee, predictable methods theoretically ensure that we will attain the global minimum or at least a local minimum.

Nevertheless, stochastic approaches are quicker than deterministic ones. Furthermore, stochastic approaches are appropriate for the construction of black boxes and poorly behaved functions. The deterministic technique, in contrast to stochastic methods, primarily focuses on the theoretical presumptions regarding the formulation of the issue as well as on its analytical features.

Additionally, heuristic and meta-heuristic algorithms are included in the classification of stochastic techniques. When it is challenging to identify an optimal solution, both types of algorithms are utilized to speed up the search for a global optimum.

Problem-dependent algorithms include heuristics. They are extremely likely to become trapped at local optimums as a result of their adaptability to the situation and hungry character, which prevents them from reaching the global optimum. Meta-heuristics algorithms, in contrast, are problem-independent algorithms. These algorithms' non-adaptive and non-greedy characteristics make it possible to employ them as a black box. In order to reach the global optima, these algorithms occasionally allow a brief worsening of the solution (using, for example, the simulated-annealing approach).

Meta-heuristic algorithms are also referred to as intelligent optimization algorithms or NIAs [91–93]. These algorithms were developed by drawing design cues from nature. The nature-inspired/meta-heuristic algorithms are further divided into four categories: bio, physics, geography, and human. The biological system is the primary inspiration for the bulk of NIAs. Consequently, a significant portion of NIAs are also biologically inspired Fig.2. The bio-inspired algorithms are further divided into three categories: plant-based, swarm-based, and evolutionary. The Darwinian principles of selection, inheritance, and variation, among others, serve as the foundation for the evolutionary algorithms [94]. Swarm algorithms, in contrast, are founded on collective intelligence [95,96].

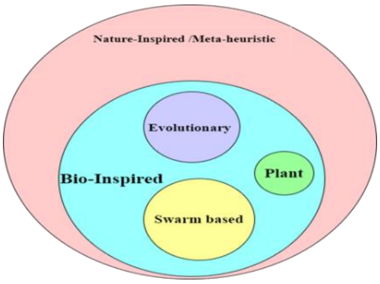

Fig.2. A Venn diagram for broadening an optimization method

. *WSN problem domains:*

We focused on the various WSN regions and looked at the potential for optimization, as shown in Fig.3.

- Optimal Coverage in WSNs: The definition of coverage in that area is locating a group of sensors to cover a designated target zone or all of the target points. It is necessary to use a minimum number of sensors to completely cover the area or all target points in order to achieve optimal coverage.
- Data Aggregation in WSNs: Data aggregation reduces the perception of duplicate information. It is an energy-efficient strategy for WSNs. Sensors collect local data while monitoring a location, and they either fully or partially process it before sending it to the center for data aggregation. The data aggregation center decides specifically to extend the sensor life by removing the detection of overlap or common locations based on the data obtained.
- EECR in WSNs: Since sensors have a limited quantity of energy, energy-efficient infrastructure is necessary. The transmission of the detected data uses up the majority of the sensor's energy. With increasing transmission length, the amount of energy required to transmit data grows exponentially. Due to this, multi-hop communication is used for data transfer in sensors. The path that data packets take from the source node to the sink is referred to as "routing" in WSNs. The sensors are first grouped in clusters. Then, for each group, a CH is chosen to gather all the information from the non-CH sensors. The best routing techniques are then used to send the collected data to the sink.
- Sensor Localization in WSNs: The process of locating sensor nodes is known as localization in WSN. A WSN is made up of lots of inexpensive nodes that are strategically placed throughout an area of interest to assess certain phenomena. The main objective is to determine the target's location. Estimating parameters related to the position between two nodes using distance and angle. Calculating a node's position based on the positions of anchor nodes and the information currently available. Localization algorithm: manipulating available information to localize other nodes in a WSN.
- Load Balancing: The network's inequitable load distribution leads to the formation of holes and a swift network collapse. When a specific set of sensor nodes are repeatedly chosen to serve as cluster heads, load balancing problems develop. As a result, such nodes will quickly disappear, leaving empty spaces throughout the entire network. Such gaps could harm the multi-hop communication that is the backbone of WSN communication, which could jeopardize the precision of the data that has been sensed.
- Fault Tolerance**:** Fault tolerance, also known as graceful degradation, refers to a system's capacity to carry on operating normally even if one or more of its components fails or develops a defect. Two key factors, such as node failures and/or communication failures,

make sensor networks susceptible to failures. Low-cost sensor nodes frequently operate in harsh or even uncontrolled environments, making them susceptible to malfunctions. A deployed sensor network may experience numerous issues for a variety of reasons, including environmental effects, hardware flaws, and software problems, according to Chen et al. (2012)[18].

- Security: Security and privacy for IoT devices in IoT networks continue to be major problems since they open users up to a whole new level of threats and privacy worries. This is done so that they can monitor user activity as well as collect personal information. Several AI/ML algorithms have been implemented to solve security and privacy challenges due to their ability to identify and categorize risks and privacy bottlenecks in IoT networks. However, these traditional approaches have some drawbacks, such as the need for centralized IoT. Due to public data sharing, data collecting and user privacy exposure occur.

Each of these problem categories has first been briefly reviewed, and then the work done to address these problems using NIAs has been presented.

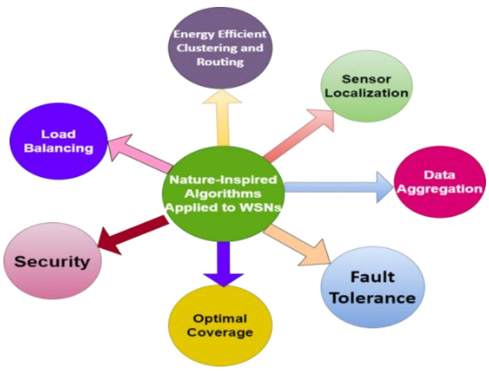

Fig. 3. WSNs Problem domains

3. Optimal Coverage in WSNs

Since coverage is vital, it becomes a key area of research for WSNs. Coverage in that area is defined as finding a set of sensors to cover a designated target zone or all of the target points. In order to achieve optimal coverage, a minimum number of sensors must be used to cover the whole region or all target points.

The form of the sensing region is one of the critical variables in a sensor's coverage in WSNs. We show four two-dimensional geometric-based sensing forms in Fig. 4(a) through (d). Since there are solid structures and rough terrain in real life, the sensing area has a complicated and irregular form. A typical illustration of the detecting geometry of a sensor in real life is shown in Fig. 4(c). But we frequently choose either a circular or a hexagonal form for computational and conceptual convenience. Due to its flexibility and lack of overlap, the hexagonal form is frequently used for analysis in WSNs, as seen in Fig. 4. (a). The round form is more common, nevertheless, because of its simplicity. As seen in Fig. 3, one drawback of the circular design is that it leaves a coverage hole (b). As seen in Fig. 3, this restriction is overcome by expanding the circle's radius (d). However, this creates a brand-new problem with overlapping zones. Due to these overlapping zones, duplicate information is sensed, wasting sensor battery power. However, if we carefully examined each of the three options to the actual sensing form, Fig. 4(d) emerges as the most accurate representation of Fig. 4. (c).

The only tough task in this issue area is to reduce these overlapping sensing zones without leaving a coverage hole. More duplicate information will be perceived by the sensors and, as a result, larger of the sensors' limited battery will be wasted the more the overlapping region. Placement of the sensor nodes may be optimized, to lessen this redundancy, which is a single-objective optimisation problem. By taking into account the additional network factors, we may convert the single objective to a multi-objective problem.

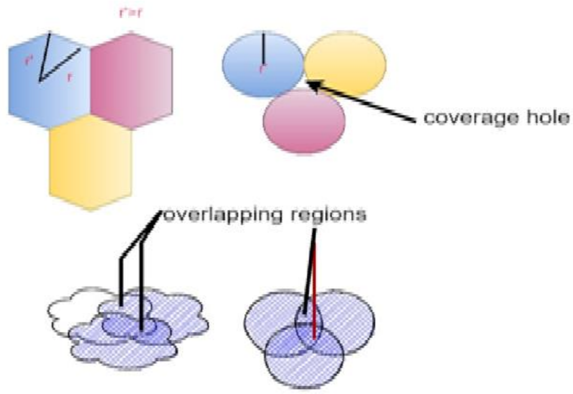

Fig 4. (a) Hexagonal coverage, (b) Circular coverage (radius=r) (c) Real time coverage (d) Circular with minimal over lapping (radius=r')

PSO's applicability in the reduction of coverage gaps for WSNs' close-to-optimal coverage is made possible by its centralized design [19, 20–27]. Several researches have suggested employing PSO to increase sensor coverage. Mendis et al. [26] used the conventional PSO to optimize the location of the movable sink node in WSNs. The literature suggests numerous modified or improved versions of PSO to address the various complexities and challenges in various applications. Ngatchou et al. [22] modified PSO by utilizing sequential PSO to position dispersed sonar sensors. Sequential PSO is frequently used for high dimension optimization and is frequently applied to the deployment of underwater sensors.

By Konstantinidis et al. [29] and optimized with a conventional GA, the sensor placement and power assignment have been modeled as a multi-objective problem. Poe and Schmitt [31] proposed a technique for sensor deployment using a large WSN. They use conventional GA. Three different deployment types have been studied and their benefits and drawbacks have been documented. Bhondekar et al. [30] used conventional GA to deploy nodes in fixed WSNs. Jia et al[28] .'s innovative network coverage technique uses traditional GA and is energy-efficient. According to their findings, the suggested strategy yields balanced performance and high network coverage rates. Li et al. [32] have presented DT-ACO, a powerful toolkit for optimizing sensor deployment. They have also recommended EasiNet, a hardware-based real-time WSN solution. Later, in Li et al. [33], they updated the EasiNet that was initially proposed. They could modify the deployment of sensors by removing extra sensors. An effective strategy for sensor placement utilizing ACO has been put out by Liao et al. [34]. The multiple-knapsack problem (MKP) has replaced deployment as the problem at hand. They asserted that the network had extensive lifespan and comprehensive coverage.

TABLE 1. NIOA FOR OPTIMAL COVERAGE

Nature-Inspired Algorithm (NIA)	***Applications of NIA in the WSNs problem domain***	***Reference***
GA [97]	Optimal coverage.	[98–101]
Genetic programming [104]	Optimal coverage	[105,106]
Evolutionary strategy [107]	Optimal coverage	[108,109]
Estimation of distribution algorithm [110,111]	Optimal coverage	[112,113]
Differential evolution [114]	Optimal coverage	[115–117]
ACO [120–123]	Optimal coverage	[124–127]
PSO [128–130]	Optimal coverage	[131–134]
Bacterial foraging algorithm [135–137]	Optimal coverage	[138–140]
Artificial fish swarm optimization [141,142]	Optimal coverage	[143–145]
Artificial bee colony [146–149]	Optimal coverage	[150–153]
Cat swarm [157,158]	Optimal coverage	159,160]
Firefly algorithm [163–165]	Optimal coverage	[166–168]
Bat algorithm [177]	Optimal coverage	[178–180]
Krill herd [181]	Optimal coverage	[182,183]
Gray wolf optimizer [184,185]	Optimal coverage	[186–188]
Ant lion optimizer [189]	Optimal coverage	[190,191]
LO [205]	Optimal coverage	[191,197]
Whale optimizer algorithm [198]	Optimal coverage	[199–201]
Salp swarm algorithm [202]	Optimal coverage	[203,204]

4. Data Aggregation in WSNs

Data aggregation is the second method for reducing the perception of duplicate information. In WSNs, it is an energy-efficient approach. While monitoring a location, sensors gather local data and transfer it to the data aggregation center either fully processed or partially processed. The data aggregation center decides specifically to increase the lifespan of the sensors by removing the sensing of overlap or common regions based on the data obtained.

The four data aggregation methods—tree-based, cluster-based, grid-based, and chain-based—can be generally categorized. There are examples of each of the four kinds in Fig. 5(a) to 5(d). Based on a tree architecture, the Tree-based data aggregation approach is used, in which the source node serves as the coordinator and the aggregator node is an intermediary node where the data is aggregated. The information is sent from the lower level nodes to the higher level nodes. The clustering architecture serves as the foundation for the cluster-based aggregation method. The network is initially separated into numerous clusters in this sort of data aggregation, and then Cluster Heads (CH) are chosen based on sensor metrics like sensor energy, etc. The CH initially aggregates the data locally within the clusters before delivering it to the sink. To prevent the CH from using too much energy, a new CH is chosen for every new cycle of data transmission. The network is initially separated into numerous sections in the Grid-based aggregation approach, and each area reports the presence of any new event. The grid aggregator node, commonly referred to as the center node, is where the data aggregation happens. In the chain-based aggregation approach, the lead node aggregates the data after the sensor node transfers the information to its neighbors.

The most difficult problems in this problem category include:

- To solve the optimum power distribution issue.
- When routing data, a minimum number of aggregate points must be found.
- Maintain consistency for dynamic, large-scale WSNs.

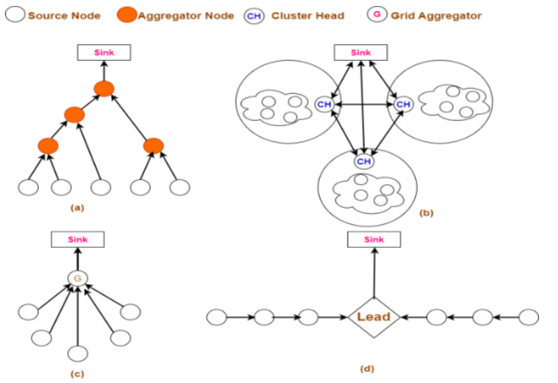

Fig 5. (a) Tree-based aggregation, (b) Cluster-based aggregation, (c) Grid-based aggregation and (d) Chain based aggregation.

In Dynamic Sensor Management Using Multi Objective Particle Swarm Optimizer [37] optimised the accuracy and time from the data aggregation aspect using the traditional PSO. They have assessed the broad applicability of the PSO for multi-objective optimisation. For efficient power distribution, Wimalajeewa and Jayaweera [35] have also employed limited PSO. ABC-PSO [36] used the PSO hybrid known as ACO and PSO for dynamic sensor management. Guo et al. [38] "published the multi-source temporal data aggregation technique (MSTDA) for data aggregation in WSNs". Linear Decision Fusion under the Control of Constrained PSO for WSNs [39] integrated the penalty function technique with the constrained PSO to improve accuracy. Islam et al. [40] have published a balanced data aggregation tree technique that is energy-efficient and based on GA. They asserted that the spanning tree-based method suggested significantly increases network lifespan. Al-Karaki et al's grid-based data aggregation and routing method [41] has been suggested for WSNs. They asserted that the suggested plan would lengthen network life and use less energy. Similar to the work of Islam et al. [40], Data aggregation trees based algorithm using GA in wireless sensor networks [43] used spanning trees and GA to construct a balanced data aggregation that is energy-efficient. They also observed an increase in network endurance. Despite this, Norouzi et al. [42] have presented an improved variant of the spanning tree-based data aggregation method. By utilizing the nodes' remaining energy, they prolong the network's lifespan.

In Bi-AntChain algorithm [44] give WSNs an effective ACO-based self-adaptive data aggregation mechanism. According to their research, the proposed method outperforms benchmark algorithms like LEACH and PEGASIS in terms of extending network longevity. Optimal aggregation tree using Ant-Aggregation Algorithm [45] provided a strategy for a successful way for WSNs to gather data. They argued that the suggested method saves energy. Data aggregation scheme based on ant optimization algorithm using bionic swarm intelligence [46] give a fresh method for aggregating multi-media data in wireless sensor and actor networks. They claimed that the performance was superior in terms of stability, precision, and network longevity when compared to earlier techniques like MEGA. An energy-efficient data aggregation technique based on ACO for WSNs was proposed by Yang et al.

TABLE 2. NIOA FOR DATA AGGREGATION

Nature-Inspired Algorithm (NIA)	***Applications of NIA in the WSNs problem domain***	***Reference***
GA [97]	Data aggregation	[98–101]
Multi-factorial evolutionary algorithm [118]	Data aggregation	[119]
ACO [120–123]	Data aggregation	[124–127]
PSO [128–130]	Data aggregation	[131–134]
Bee colony optimization [169]	Data aggregation	[170]
Cuckoo search [171–173]	Data aggregation	[174–176]
Ant lion optimizer [189]	Data aggregation	[190,191]
LO [205]	Data aggregation	[191,197]

5. EECR in WSNs

Since sensors have a tiny amount of energy, energy-efficient infrastructure is necessary. Most of the energy used by the sensor is used to transmit the data that was detected. Data transmission energy requirements increase exponentially with transmission length. As a result, multi-hop communication is used for sensor data transfer. The path that data packets take from the source node to the sink is referred to as routing in WSNs. The sensors are first grouped together in clusters. Then, for each group, a CH is chosen to gather all the information from the sensors. The gathered data is then sent through the best possible routing methods to the sink.

The most difficult problems in this problem category include

- Choosing high-energy CHs and the best routing option for each round.
- Maximization of network lifespan and data provided.
- Reduction of communication distance.

PSO has been used in several research to demonstrate EECR. For sensor node clustering in WSNs, Tillett et al. [49] applied the traditional PSO. In terms of energy-efficient clustering, they claimed that the PSO surpasses random search and simulated annealing. Following that, a split range PSO method for network clustering was suggested by [51]. They claimed that when there are a lot of mobile sensors, the suggested method is effective. Four of PSO's variants were used for energy-efficient clustering provided by HPSO-TVAC and PSOSSM [47]. According to their claims, the supervisor-student model PSO outperformed the other three algorithms. Graph theory and the PSO algorithm were used by Cao, et al. [48] for energy-efficient clustering in multi-hop WSNs. Latiff et al. [50] used the conventional PSO to move the BS within a clustered WSN. Overall, PSO usage reduces energy consumption and increases network lifespan.

GA-ILPs.

In GA-ILPs [55] a two-tier sensor network using a typical GA approach for energy-efficient clustering and routing, while Jin et al. [52] suggested a framework for optimisation of the sensor network. They claim that the recommended strategy outperforms the previously presented methods noticeably. Seo et al. [54For effective clustering in WSNs, [] introduced the Location-Aware 2-D GA (LA2D-GA) hybrid GA approach. They claimed that the LA2D performed better than its 1-D counterpart. Hussain and Islam [53] “developed a standard GA-based clustering and routing strategy that uses less energy”.

A novel ACO-based routing method for WSNs has been put out by Camilo et al. They had a small amount of communication difficulty and energy consumption. Additionally, a brand-new ACO-based routing technique with two routing stages was proposed by Salehpour et al. [58]. They asserted improved load balancing and relatively low power consumption. Ziyadi et al. [59] published an ACO-based clustering methodology for WSNs that takes energy considerations into account. It was claimed that the network's lifespan had extended. Later, Huang et al. [57] released an ACO-based Prediction routing method. It was a pioneer in its field. Low power consumption, increased network lifetime, and excellent load balancing were just a few of the advantages they listed. SensorAnt [56]suggested an ACO-based self-optimization algorithm for balancing energy consumption in WSNs. Low energy usage and packet loss, they said. A method for unequal clustering based on fuzzy data was published by Mao et al. For energy-efficient routing, ACO is utilised. They claimed that the new method outperformed a number of well-known algorithms, such as LEACH.

TABLE3. NIOA FOR EECR

Nature-Inspired Algorithm (NIA)	***Applications of NIA in the WSNs problem domain***	***Reference***
GA [97]	EECR	[98–101]
Estimation of distribution algorithm [110,111]	EECR	[112,113]
Differential evolution [114]	EECR	[115–117]
ACO [120–123]	EECR	[124–127]
PSO [128–130]	EECR	[131–134]
Bacterial foraging algorithm [135–137]	EECR	[138–140]
Artificial fish swarm optimization [141,142]	EECR	[143–145]
Artificial bee colony [146–149]	EECR	[150–153]
Cat swarm [157,158]	EECR	[159,160]
Monkey search [161]	EECR	[162]
Firefly algorithm [163–165]	EECR	[166–168]
Cuckoo search [171–173]	EECR	[174–176]

Bat algorithm [177]	EECR	[178–180]
Krill herd [181]	EECR	[182,183]
Gray wolf optimizer [184,185]	EECR	[186–188]
Dragonfly algorithm [192]	EECR	[193,194]
Crow search algorithm [195]	EECR	[196]
LO [205]	EECR	[191,197]
Whale optimizer algorithm [198]	EECR	[199–201]

6. Sensor Localization in WSNs

Calculating the position of each sensor in a network is a process known as sensor localization. There are two phases to it. As shown in Fig.6, The first one involves estimating the distance, and the second one involves calculating the position. The anchor or beacon node is the node whose location is preprogrammed into GPS or is known automatically during deployment. During the first stage, the relative distance between the anchor and the unknown node is determined. Using the data acquired in the first phase, the second step calculates the coordinates of the unknown node with respect to the anchor nodes. Various localization methods are used to alter the distances and locations of the other nodes in the WSNs in order to localize them [18] .Has a thorough examination of such methods.

The most difficult problems in this problem category include

- Localization error reduction to a minimum.
- Accuracy of the unknown node placement being improved

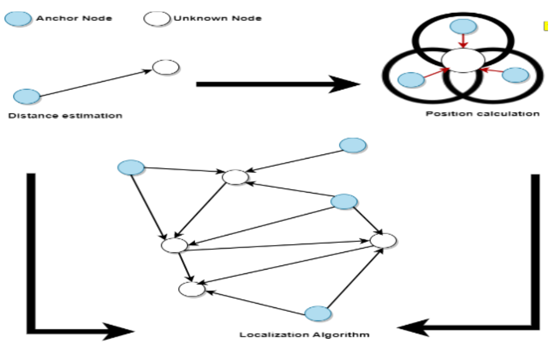

Fig. 6. Working of the localization system.

PSO Approach for the Localization of a WSN [62] used the conventional PSO to locate nodes precisely. They contend that the accuracy is superior when compared to the Gauss-Newton algorithm. Localization in WSN using PSO [63], who employed the same conventional PSO and claimed more accuracy compared to the simulated annealing approach. Later, Kulkarni et al. [61] reported on a thorough investigation of node localization. Results from the bacterial foraging algorithm and the PSO have been compared. They asserted that PSO and the bacterial foraging algorithm both speed up and enhance the accuracy of node location in WSNs.

GA for Node Localization in WSN [64] have utilised the traditional GA to place nodes in WSNs. The DV-Hop GA-based method for node localization WSNs has recently been adopted [66]. They claimed that the previously described method is outperformed by the DV-Hop GA-based technique. Tan et al. [65] for precise node localization in WSNs, the Distance Mapping Algorithm (DMA) was just recently introduced and coupled with the GA. They claimed that the recommended algorithm performed better in terms of accuracy and energy usage than earlier suggested techniques.

Qin et al. [67] “have suggested a revolutionary ACO-based beacon-based node localization technique. They claimed that they could localise items with great accuracy and little power”. Niranchana and Dinesh [69] have put out a node localization technique where the nodes are moved with ACO and predicted with interval theory.. Additionally, they reported very accurate localization. Furthermore, ACO was used to localize nodes in WSNs in the underground WSN localization method [68]. The trilateration positioning error function has been enhanced. They reported a higher level of localization accuracy in comparison to the earlier proposed localization methods. Adaptive mobile anchor localization algorithm based on ACO in WSN [70] have recently proposed ideas for the localization of mobile anchor nodes for WSNs.

TABLE 4. NIOA FOR SENSOR LOCALIZATION

Nature-Inspired Algorithm (NIA)	***Applications of NIA in the WSNs problem domain***	***Reference***
GA [97]	Sensor localization	[98–101]
Evolutionary programming [102]	Sensor localization	[103]
Genetic programming [104]	Sensor localization	[105,106]
Evolutionary strategy	Sensor	

[107]	localization	[108,109]
Estimation of distribution algorithm [110,111]	Sensor localization	[112,113]
Differential evolution [114]	Sensor localization	[115–117]
ACO [120–123]	Sensor localization	[124–127]
PSO [128–130]	Sensor localization	[131–134]
Bacterial foraging algorithm [135–137]	Sensor localization	[138–140]
Artificial fish swarm optimization [141,142]	Sensor localization	[143–145]
Artificial bee colony [146–149]	Sensor localization	[150–153]
Bees algorithm [154,155]	Sensor localization	[156]
Firefly algorithm [163–165]	Sensor localization	[166–168]
Cuckoo search [171–173]	Sensor localization	[174–176]
Bat algorithm [177]	Sensor localization	[178–180]
Gray wolf optimizer [184,185]	Sensor localization	[186–188]
Dragonfly algorithm [192]	Sensor localization	[193,194]
Whale optimizer algorithm [198]	Sensor localization	[199–201]
Salp swarm algorithm [202]	Sensor localization	[203,204]

7. Load Balancing in WSNs

- Uneven distribution of load in the network leads to the formation of holes and collapse of network in very short period of time. When a certain set of sensor nodes is regularly chosen to serve as cluster heads, load balancing problems arise. As a result, such nodes will expire quickly, leaving vacant spaces throughout the whole network. The communication of the WSNs, which are mostly based on multi-hop communication, can be affected by such gaps, which can also have an impact on the veracity of the sensed data.
- The load balancing measure shows the percentage of the network's total remaining energy after the first node fails. The performance of networks assessed using this measure has an inverse relationship, meaning the network with the least amount of leftover energy after the first node fails exhibits the best load balancing [71], [72]. In other words, if just a small percentage of a network's energy is left after the death of the first node, As a result, it denotes that the remaining living nodes have consumed the bare minimum of energy required to sustain life. Additionally, it indicates that they may pass away in the following round or a few rounds as opposed to dying in the initial node's round (in maximum). According to the aforementioned explanation, it is clear that the reason why all nodes die at the same time, or even within a short period of time, is because they all used the same amount of energy while operating. Consequently, each sensor node in the network is burdened with roughly the same volume of data packet traffic.
- Small clusters of sensor nodes can be formed in big sensor networks. A cluster head serves as the central coordinator for each cluster's nodes. By requiring the cluster head to collect data from cluster nodes and transfer it to the base station, cluster structure can extend the lifespan of the sensor network. Clustering provides several benefits, including decreasing the size of the routing table, conserving communication bandwidth, extending network lifetime, reducing data packet redundancy, and decreasing the rate of energy consumption, among others[73]. Additionally, load balancing with clustering can improve the scalability of a network.. Wireless sensor network with the different energy levels nodes can prolong the lifetime of the network and also its reliability. Spreading the load on the each node of the wireless sensor network leads to enhancing the network performance and also increases the life span of the network. Scheduling algorithm for wireless sensor networks to increase the life time network uses optimal scheduling algorithm for packet forwarding which determines the time slot for sending the packets for the nodes. The algorithm provides uniform packet loss probability for all the nodes. The algorithm uses balanced cost objective function for optimum scheduling. Load balancing show in fig (7)

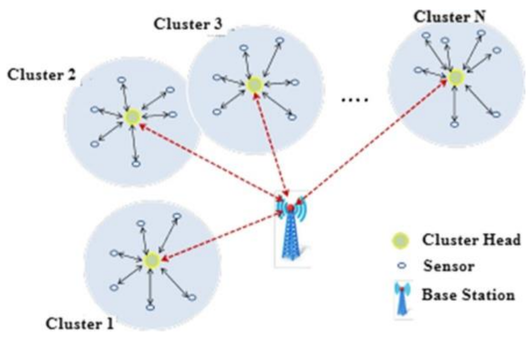

Fig.7. Load balancing

The authors of [74] created cluster-based load balancing strategies with a variety of mobile sinks using a modified multi-hop layered model. RPs and RNs are employed in delay-tolerant applications to achieve the goal of optimal energy use through the use of a heuristic algorithm. Kuila and Jana [75] proposed an energy-efficient load-balanced clustering algorithm with O(n log m) time. Under the EELBCA, load balancing and energy efficiency are both covered. A GA-based load-balanced clustering technique for WSNs was suggested by Kuila et al. in [76]. The method can be applied to both equal and unequal sensor node loads, and it builds clusters in a way that reduces the maximum load on each gateway. The method has faster convergence and better load balancing than the traditional GA that Goldberg introduced in [77]. The PSO-based algorithm introduces the concept of load balancing to protect the clustered WSNs' energy [78]. All chosen cluster heads' energy consumption is balanced by accounting for the routing overhead of the CHs. The average cluster distance and the CH's lifespan are taken into account when creating a fitness function. In multi-hop communication, load balancing is done by assigning smaller nodes to the heavily loaded cluster heads that serve as intermediate relays for data to the BS. The results of the simulation show that the proposed effort would result in better results in terms of dead nodes, network life, and total data packets sent.

TABLE 5: NIOA FOR LOAD BALANCING

Nature-Inspired Algorithm (NIA)	***Applications of NIA in the WSNs problem domain***	***Reference***
GA [97]	Load balancing	[98–101]
ACO [120–123]	Load balancing	[124–127]
PSO [128–130]	Load balancing	[131–134]

8. Fault Tolerance

- Hundreds or even thousands of tiny, inexpensive, and low-power sensor nodes make up the WSN in most cases. These nodes work together to complete a job by communicating wirelessly despite having limited memory, computing power, and storage space. The most common applications for these networks are military surveillance, environmental monitoring, industrial process control, and fire prevention. The deployment of WSNs in such vast regions increases the likelihood of sensor node failure in the network, which may lead to a system disturbance and ultimately end in system collapse [80]. The failure issue may be caused by a variety of factors, including the environment's influence, battery depletion, physical damage, radio interference, etc. The demand to make the WSNs more dependable grows as their acceptance and range of applications do. As a result, fault-tolerant WSNs are created [79]. The ability of a network to continue operating even when certain sensor nodes fail is known as fault tolerance in WSNs. Because the battery life is short and it's challenging to recharge or replace the failed node, In order to enhance coverage and connection, sensor nodes are placed densely across the target region. The network lifetime will be impacted if all sensor nodes operate constantly since this accelerates battery consumption. Due to the vulnerability of sensor nodes to failure, WSNs applications must think about some important characteristics like security, availability, fault tolerance, and dependability, among others. Therefore, one of the most current research directions in wireless sensor networks is fault-tolerance [81].
- Fault detection and recovery are the two key processes in dealing with WSN issues. The goal of fault detection is to identify the network's functional failure and determine whether or not it will soon be exceeded. Defect recovery, which enables the system to go past the discovered fault, comes next after fault detection. Several flaws, including power drain and failure Self-diagnosis is a form of detection method that allows a sensor node to recognize in connections. Cooperative diagnosis is a different approach that addresses issues that call for cooperation. Between a group of diagnostic sensor nodes [82]. The most widely used method of fault recovery relies on duplicating faulty components. Sensing data is sent to a base station in monitoring systems. As a result, even if certain sensor nodes are unable to transmit data, the deployed redundant nodes in that area still provide the base station with sufficient data. Additionally, supplying If some links along a route fail, multiple pathways routing increases the dependability of the route [81].

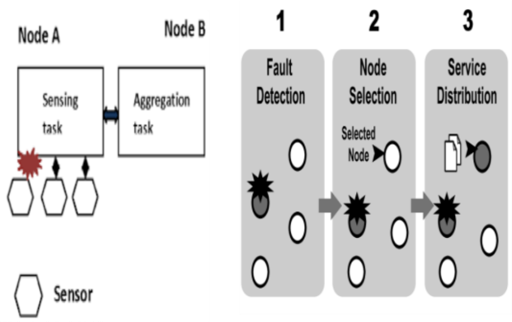

Fig 8. Fault tolerance in WSN

- Li et al. [83] published a method for fault tolerance in WSN that makes use of an immunity mechanism. Using a multi-path routing system as its foundation. It is a more trustworthy and effective suggestion. The proposed method is based on the guiding idea of the artificial ant. These artificial ants use the network's pheromone data to enhance network functionality. Li et al. [84] published a fault-tolerant method for maximizing coverage in WSNs. This method investigates the transmission stability and dependability, two fundamental aspects. It develops reliable packet transport methods using a synthetic immune system. It facilitates the efficient deployment of network nodes and guarantees full network coverage fault-tolerance show in fig. (8)

TABLE 6: NIOA FOR FAULT TOLERANCE

Nature-Inspired Algorithm (NIA)	***Applications of NIA in the WSNs problem domain***	***Reference***
GA [97]	Fault tolerance	[98–101]
ACO [120–123]	Fault tolerance	[124–127]
PSO [128–130]	Fault tolerance	[131–134]

9. Security

- Compared to other networks or wired networks, the WSN is not secure. It is easily agitated by its surroundings. As a result, hackers may easily steal the needed data. A huge number of nodes that are densely placed either inside the phenomena or extremely close to it make up a wireless sensor network. In order to collaboratively monitor physical or environmental factors, such as temperature, sound, vibration, pressure, motion, or pollution, at several locations, it uses geographically dispersed autonomous devices. Security is required to maintain the integrity and confidentiality of sensitive information because wireless sensor networks may operate in hostile environments.
- WSNs place a high priority on security, which differs significantly from typical security measures. This is due to two main causes. First off, these gadgets are subject to significant limitations in terms of their energy, computational, and communicational capacities. In addition, there is a possibility of physical assaults such node capture and manipulation. Due to their lack of data storage and power, sensor networks also impose significant resource limitations. These two pose significant challenges to the application of conventional computer security methods in a wireless sensor network.
- In addition, the WSN-IoT devices are more prone to various security threats due to their interaction through internet. A serious communication between two interconnected devices can be hacked easily if it is going on through internet because of so many adversaries. A more serious issue is that devices in WSN-IoT may be compromised and perform malicious attacks such as packet dropping or packet modifications to disrupt normal operations of an IoT. Because of the openness of the deployed environment and the transmission medium, WSN-IoT suffer from There are many types of attacks, such as sinkhole attacks, DoS attacks, hijack attacks and tampering attacks.
- The authors of [85] advocated cryptography-based encryption for IoT medical picture security. This approach is based on a cryptography model with optimization. Security is necessary because medical data is accessible via the cloud and other open systems. This approach uses hybrid swarm optimization and grasshopper optimization to address security issues, relying on encryption and decryption. Grasshopper optimization is based on the concept of a particular class of bug. Grasshoppers frequently reduce agricultural productivity. This strategy requires less memory and is less unpredictable. For encryption and decryption operations, this approach is faster. Tests conducted under a variety of circumstances, including those with and without assaults, are used to evaluate the performance of the suggested algorithm. Cryptography-based solutions, however, are not more reliable, particularly in a cloud-based environment.
- The authors present a dragon particle swarm optimization (dragon PSO) strategy in [86]. The two techniques on which this strategy is based are the dragonfly algorithm and particle swarm optimization. This system was developed to address privacy and security concerns in the cloud-based environment. The proposed approach aims to select the optimal value for satisfying the k-anonymization criterion. The strategy then creates a secure, highly functional database. In terms of information loss and classification precision, this technique is assessed. The simulation results demonstrated that the suggested privacy preservation approach outperformed other existing systems. However, security and privacy are separate and require more consideration when handled separately.
- An ant colony optimization method for secured routing (ACOSR) for WSN was suggested by the authors in [87]. In order to identify malicious nodes in the network, the technique used in this model, which is based on trust perception, evaluated the node trust value from its behavior. Ant colony routing serves as the basis for assessing trust. This technique is used to counter the black hole attack and other malicious assaults. This technique also reduces the energy consumption of WSN networks by distributing the remaining energy among all nodes. In terms of packet loss ratio, end-to-end

latency, and data throughput, the simulation results demonstrated that the suggested approach is superior. Instead of using complex networks, this technique is tested in a real-world scenario.

Table 7.NIOA for Security

Nature-Inspired Algorithm (NIA)	***Applications of NIA in the WSNs problem domain***	***Reference***
GA [97]	Security	[98–101]
ACO [120–123]	Security	[124–127]
PSO [128–130]	Security	[131–134]
Firefly algorithm [163–165]	Security	[166–168]

10. Conclusion and Future work

- With rapid increase in the number of AI-based systems and solutions that make it easier to optimize services in the WSN space. Now that AI methods and WSNs have integrated, the IoTs can benefit and systems can learn, monitor activities, and aid in decision-making. We have addressed a review of "optimal coverage, data aggregation, energy-efficient clustering and routing, sensor localization, load balancing, fault tolerance, and security challenges in WSNs". In optimal coverage, we have discussed with few examples and mention some algorithms to achieve optimal coverage in WSNs. Similarly, data aggregation is addressed that reduces the perception of duplicate information. Moreover, we have discussed selecting CHs and the best routing option for each round in terms of energy-efficient clustering and routing, as well as maximizing network lifespan and data provision and minimizing communication distance. We also have discussed reducing localization error to a minimum. The issue of load distribution that leads to the formation of holes and a swift network collapse. Fault detection and recovery are the two crucial processes for dealing with WSN issues. Security is a more serious issue in WSN-IoT devices that have to perform sinkhole attacks, DoS attacks, hijack attacks, tampering attacks, and malicious attacks such as packet dropping or packet modifications to disrupt normal operations of an IoT. In order to increase the security of WSN-IoT devices, we addressed privacy and security concerns in this paper. In this paper, we have provided few NIAs to solve the issues.

For resolving practical issues, multi-objective optimization methods are used with hybrid optimization approaches. We also need to focus on hybrid systems to solve the problems encountered by WSN and deliver better results. These hybrid systems can offer new insights for finding the best WSN solutions. This idea may also be broadened to take into account the multi-objective minimal energy network connection setback for wireless sensor networks.

Declarations

The authors have no material competing interests, either financial or otherwise. Moreover, the authors have no declared conflicting interests that are pertinent to the subject matter of this study.

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