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Review

Bio-Inspired Hybrid Optimization Algorithms for Energy Efficient Wireless Sensor Networks: A Comprehensive Review

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Abstract: Researchers are facing significant challenges to develop robust energy-efficient clustering and routing protocols for Wireless Sensor Networks (WSNs) in different areas such as military, agriculture, education, industry, environmental monitoring, etc. WSNs have made an everlasting imprint on everyone's lives. The bulk of existing routing protocols has focused on cluster head election while disregarding other important aspects of routing including cluster formation, data aggregation, and security, among others. Although cluster-based routing has made a significant contribution to tackling this issue, the cluster head (CH) selection procedure may still be improved by integrating critical characteristics. Nature-inspired algorithms are gaining traction as a viable solution for addressing important challenges in WSNs, such as sensor lifespan and transmission distance. Despite this, the sensor node batteries cannot be changed when installed in a remote or unsupervised area due to their wireless nature. As a result, numerous researches are being done to lengthen the life of a node span. The bulk of existing node clustering techniques suffers from non-uniform cluster head distribution, an imbalanced load difficulty within clusters, concerning left-out nodes, coverage area, and placement according to a recent study. Metaheuristic algorithms (DE, GA, PSO, ACO, SFO, and GWO) have the advantages of being simple, versatile, and derivation-free, as well as effectively utilizing the network's energy resource by grouping nodes into clusters to increase the lifespan of the entire network. In this paper, we explore recently used hybridization techniques (DE-GA, GA-PSO, PSO-ACO, PSO-ABC, PSO-GWO, etc.) for bio-inspired algorithms to improve the energy efficiency of WSNs. This paper also discusses how critical issues can be addressed by speeding up the implementation process, how more efficient data can be transferred, as well as how energy consumption can be reduced by using bio-inspired hybrid optimization algorithms.

Keywords: hybridization; nature-inspired algorithms; energy utilization; WSNs

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1. Introduction

Wireless Sensor Networks (WSN) can detect, store, and transmit data in real-time. These tasks must be completed efficiently to avoid wasting the limited sensor battery life. We cannot extend the sensor's life by providing external or extra energy since most sensors are placed in difficult-to-reach locations. With a lot of work, the sensor node's lifespan has been prolonged. In addition to the energy limitation, WSNs confront a variety of problems, including precise sensing and non-redundant information. There are three types of WSN significant issues: energy efficiency, security, and service quality (QoS). Many of these concerns are subject to trade-offs such as network lifetime for a better QoS. The same is true for the security parameters. Individually solving these problems has taken a considerable amount of time and effort. When dealing with these problems separately, there are several flaws. As a result, to create better WSNs, we must address all of these problems at the same time.

On the other hand, meta-heuristics methods are problem-independent. They can be utilized as a black box since they are non-adaptive and non-greedy. These algorithms frequently allow temporary deterioration of the solution to reach the global optima. Meta-heuristic or intelligent optimization algorithms are sometimes known as nature-inspired algorithms. The natural environment serves as inspiration for these algorithms. There are four types of nature-inspired/meta-heuristic algorithms: bio-inspired, physics-inspired, geography-inspired, and human-inspired. Biological systems are the source of the great majority of nature-inspired algorithms. As a result, bio-inspired algorithms (biology-inspired) comprise a large portion of nature-inspired algorithms as shown in Figure 1.

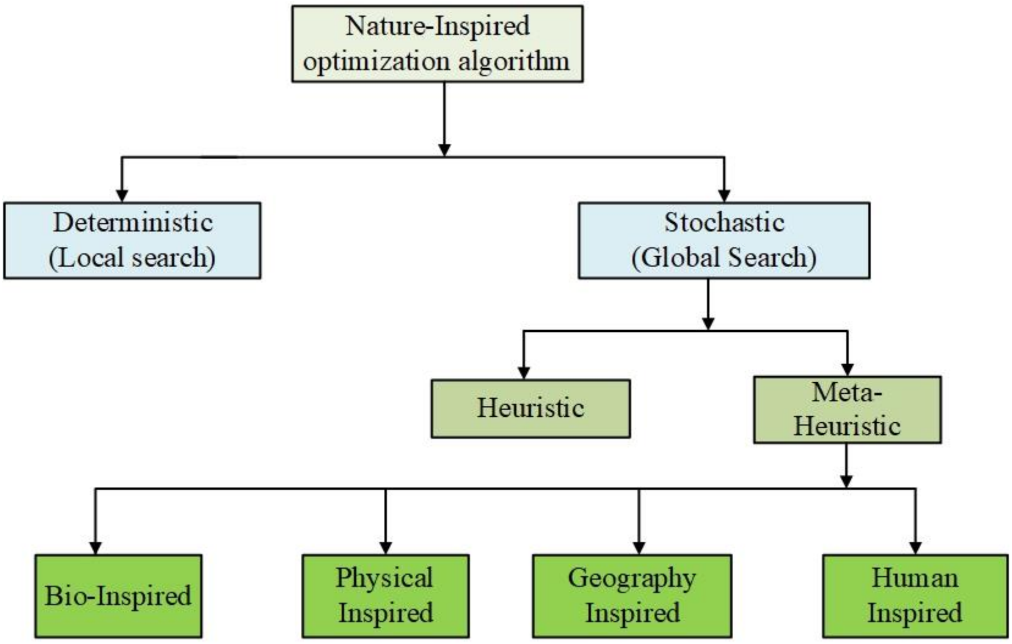

Figure 1. Classification of Nature-inspired Optimization Algorithm.

The goal of the optimization process is to discover the best solution to a given issue. The selection of an appropriate algorithm is critical for achieving this goal. However, certain issues are complicated, and finding all feasible solutions is challenging. Several meta-heuristic algorithms have been created in the literature to simulate the biological behavior of animal or insect groups by creating deterministic or random rules to be used in addressing various optimization issues.

Nature-inspired hybrid algorithms are designed to overcome different constraints in WSNs. Many researchers have implemented different meta-heuristic algorithms in the past to improve the lifetime, stability, and performance of the entire WSN. Hybridization techniques in optimization algorithms have helped in improving the network lifetime, stability period, throughput, number of dead nodes per iteration, and residual energy of the network. Sometimes, these bio-inspired algorithms evaluate incorrect solutions for some real-time applications. Convergence speed, multiple objective problems, dynamic problems, and local optima convergence are hot research problems nowadays. Hybridization of algorithms requires a large number of functions to be evaluated, resulting in more accuracy and improved performance of WSNs. Researchers have suggested the use of creating and optimizing a multi-objective function with a suitable mathematical function-based optimizer or hybridization technique to solve challenging, dynamic, and multi-objective problems in WSN. This paper mainly focuses on how different hybrid metaheuristic approaches play an important role in enhancing the overall performance of WSNs and their comparative analysis followed by contributions given by researchers in this field. We also discuss and compare various techniques to choose the cluster head. The problems, open issues, and challenges faced in Bio-inspired optimization techniques have been elaborated with various solutions followed by concluding remarks.

This paper has discussed the three main types of bio-inspired algorithms: evolutionary, swarm-based, and plant-based optimization. These groups are further subdivided, as indicated in Figure 2. Under the evolutionary techniques, Genetic Algorithm (GA) and Differential Evolution (DE) are placed. A GA is an evolutionary algorithm that generates solutions to optimization and search problems. To achieve the best results, it employs techniques that are influenced by natural selection. Selection, cross-over, and mutation are examples of such techniques. Researchers have also utilized hybridized GA with different bio-inspired algorithms. Differential Evolution-Genetic Algorithm (DE-GA) is more accurate and requires less time to complete. The technique works well in terms of accuracy and time complexity due to the rise in the population vector size. By carefully selecting the design parameters and employing superior hybrid methods, efficiency and forecast accuracy might be improved. Under the Swarm-based techniques, four different and unique techniques are listed. In terms of network lifespan and packet delivery ratio, the Genetic Algorithm-Particle Swarm Optimization (GA-PSO) method is found superior. When compared to the shortest path, PSO, and GA approaches, hybrid GA-PSO increased the lifetime from 12 percent to 23 percent, from 8 percent to 15 percent, from 5 percent to 13 percent, and packet delivery ratio from 9 percent to 16 percent, from 6 percent to 11 percent, and from 5 percent to 9 percent for large scale networks. Particle Swarm Optimization-Ant Colony Optimization (PSO-ACO) hybrid optimization technique evaluates the shortest path for data transfer from the cluster head to the base station. This proposed technique also evaluates more average remaining energy, a greater number of alive nodes, and better throughput when simulated by taking 100 sensor nodes. The particle Swarm Optimization-Grey Wolf Optimization (PSO-GWO) approach has enhanced the exploration ability by preventing PSO from falling into local minima. This hybrid technique also improved the performance of the network as compared to ABC, PSO, and GWO meta-heuristic methods [1–7].

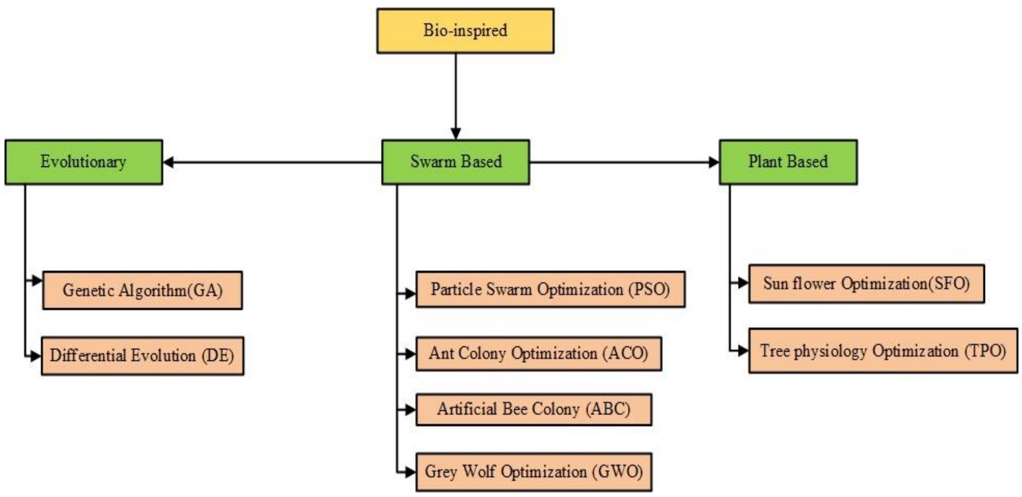

Figure 2. Taxonomy of Bio-inspired Optimization Techniques.

Similarly, different bio-inspired algorithms as shown in Figure 2, are hybridized with each other based on their contribution and limitations and have been discussed in the subsequent sections.

2. Problem Domains in Energy-Efficient and Load Balanced WSNs

Individually resolving these concerns has taken a substantial amount of time and effort; hence, researchers have focused on addressing both of these challenges at the same time. The development of a multi-objective function followed by its optimization with an appropriate optimizer or algorithm is one such technique. The behavior of the algorithm, the kind of issue, the time restriction, resource availability, and required accuracy are also known to influence the algorithm's selection. Figure 3 shows the various optimization problems in WSNs including clustering, routing, area coverage, sensor localization, and data aggregation techniques.

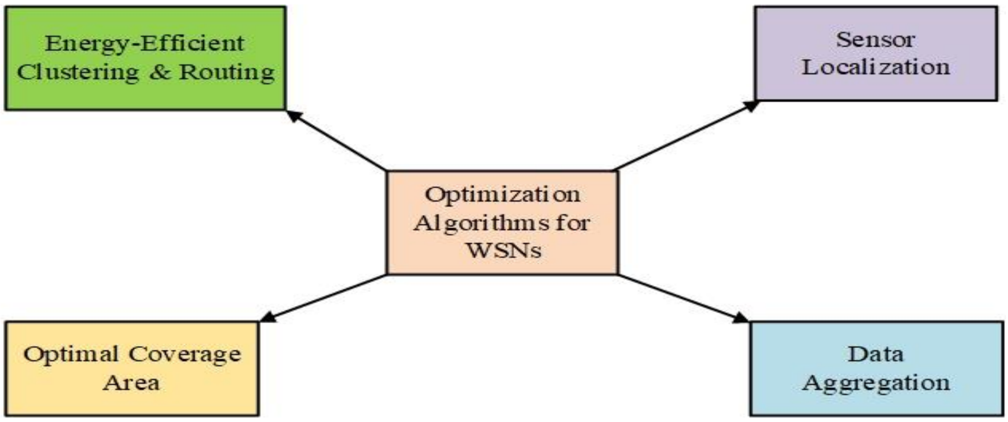

Figure 3. Problem domains found in the active research area of Wireless Sensor Network.

2.1. Energy Efficient Clustering and Routing in WSNs

Energy-efficient infrastructure is essential as sensors have a finite amount of energy. The bulk of sensor resources is used to transmit the detected data. As the transmission duration grows, the amount of energy required for data transmission increases exponentially. As a result, multi-hop communication is used in sensor data transfer. In WSNs, routing refers to the path traveled by data packets from the source node to the sink. In this, the sensors are first sorted into categories based on CH and Non-CH. The CH sensors are then chosen and collected from the non-CH sensors. This collected data are subsequently sent to the sink using the most efficient routing choices available. Owing to this process, it can be noticed that the selection of the CH is of high importance. The main issues in this domain are primarily the optimal routing path in each cycle, data maximization with increased network lifespan, and contact distance reduction.

2.2. Requirement of Sensor Localization in WSNs

Sensor localization is the process of estimating a sensor's location in a network. There are two parts to it, i.e., distance measurement and location computation. To localize the other nodes in the WSNs, several localization methods are utilized to use the existing knowledge about distances and locations. Minimizing the localization error and improving the precision of the unknown node position are the two most difficult problems in this sector. The anchor or beacon node has a known position that may be determined via the Global Positioning System (GPS) or automatically pre-programmed before deployment of a WSN.

2.3. Requirement of Optimal Coverage in WSNs

Optimal Coverage is prime in the development of a WSN and has become a hot issue in this field. Finding a collection of sensors to cover a specified target region or all of the target points is referred to as coverage in a given target area of WSN. Optimal coverage entails using the fewest number of sensors to cover the whole region or all of the target sites. The geometry of the detecting zone is one of the most important aspects of a sensor's coverage in WSNs. Due to topographical factors and solid buildings, the shape of the sensing zone is uneven and intricate in real life. The only difficulty in this area is to reduce the number of overlapping sensing patches with no detection void. The more overlapping regions there are, the more redundant information the sensors will detect, wasting more battery life. Optimizing the sensor node location, which is a single-objective optimization problem, is one way to remove redundancy. By including the other network elements, we may make a single aim multi-objective WSN.

2.4. Requirement of Data Aggregation in WSNs

Data aggregation is the second strategy for decreasing redundant content detection and is also considered an energy-efficient approach in WSN. When sensors track a region, they capture local data and send them as fully processed or partially processed data to a data aggregation center. Based on the data collected, the data aggregation center makes a clear choice to extend the sensor lifespan by decreasing the sensing of overlap or common locations. There are four types of data aggregation strategies: tree-based, cluster-based, grid-based, and chain-based. The major concerns focus on addressing the challenge of optimum power allocation, identifying the least number of aggregation points while routing the data, and establishing consistency for wide-ranging and complicated WSNs.

3. Related Work

J. H. Holland [8] investigated the GA, a metaheuristic algorithm based on natural selection and generational reproduction of the fittest humans. Initialization, fitness, selection, cross-over, and mutation are the phases of the GA algorithm. Two extensions of GA are adaptive genetic algorithms and coarse-grained parallel genetic algorithms. They are utilized for a variety of tasks, including feature extraction, its sub-set selection, engineering designs of CAD, and the traveling salesman dilemma for optimization. The two most essential elements that determine the algorithm's efficiency are the fitness function and the number of iterations. By combining the parents you have chosen, you will be able to create new genetic algorithms from the current generation (often referred to as parents) to generate offspring in the subsequent generation. They have the advantage of being able to achieve faster convergence, have a simple implementation procedure, and are optimized for a wide range of functions. They have several drawbacks, such as a proclivity for concentrating on local optima rather than global optima. For decision-making issues, GA is inefficient and ineffective. M. Dorigo [9] studied the foraging technique of ant species used in ACO. The ants leave a pheromone, a route marker that may be followed by others, to indicate a good path. The constructive greedy heuristic approach for finding excellent pathways through networks eliminates issues. Authors use a simple phenomenon by using ants' pheromones as their path tracker by which they interact with each other. Edges and node weights are dynamically updated by the agent using the random probabilistic pheromone-based model. The used algorithm continuously repeats iterations to keep updating the path. Multiple paths are created from which the optimum path is to be selected.

D. Karaboga [10] studied an Artificial Bee Colony (ABC) algorithm, another metaheuristic algorithm that includes a food source, jobless, and employed FB. Honey bees benefit from forager feedback on food sources because it allows them to adapt and share knowledge. Employed, scout, and spectator bees are the three categories of bees. The food supply is the same as a feasible solution. The amount of nectar calculated is proportional to the solution's fitness in this algorithm. A specific operation is performed just once for a single unit of scouts, hired, and onlookers, and similarly for the other categories. D. Simon [11] studied a population-based evolutionary algorithm that, hypothetically and repeatedly, improves any mathematical function. It also improves the candidate solutions in terms of fitness function and provides a quality control technique. It is easily able to break out from local optima and obtain a fast convergence rate.

H. Shah-Hosseini [12] implemented an intelligent water drop (IWD) robust algorithm for fast convergence to the global optimization problem in WSN. In IWD, each water drop has a velocity and soil present in this journey. The velocity and the soil are determined by the quantity of soil and the time it takes to traverse the field, respectively. In its course, an IWD always favors low soil content. Each IWD passes through it, producing the best solution that is utilized to update the global best solution regularly. E. Rashedi [13] presented a Gravitational Search Algorithm (GSO) in which the active gravitational mass (GM), inertial mass (IM), location, and passive GM of each object are listed. GM and IM regulate the velocity of an object. The software navigates by modifying the mentioned masses until all of the masses are drawn to the heaviest mass, which is often considered the best choice.

X. S. Yang [14] presented a Bat Algorithm (BA) in which bats change their wavelength and rate of emission depending on how close they are to their prey. Echolocation is a method that is utilized to figure out where they are. They can tell the difference between loudness and the intensity of a pulse that should be within a specified range. A global optimization meta-heuristic approach was developed by employing bat echolocation with different pulse rates. As the bat gets closer to the location where the answer should be discovered, the frequency and strength of the pulse are modified. A. Kaveh [15] presented a Charged System Search (CSS) algorithm in which the charged particles are dispersed randomly. Well-charged particles can attract badly charged particles and vice versa. It is important to start with a modest level of investigation and gradually raise it. An examination of the global search space suggests an area in which the optimal answer is most likely to be discovered, which is subsequently exploited.

M. Clerc [16] performed an easy implementation in which the PSO algorithm can search through a huge number of potential solutions and find a suitable one over time. In a search space for candidate solutions, it also seeks the best response rather than utilizing gradients as other optimization algorithms do. The method searches the candidate solution space for the best-known solution, which is based on the particle's best-known location as well as the swarm's most advantageous position. S. Goel [17] proposed a Cuckoo Search (CS) algorithm that utilized levy flights for global search and quick convergence. Each cuckoo egg represents a fresh solution in this algorithm. The less-than-ideal cuckoos are replaced by better ones as time goes on. The eggs that survive act as solutions that are further handed down for the next iteration. With each iteration, a single algorithm iterates through the solutions in the search space, which helps in enhancing the quality of the solutions. Its purpose is to develop better and fresh ideas, the quality of which is determined by an objective function that is often maximized.

X. S. Yang [18] presented a robust Flower Pollination Algorithm (FPA) using levy flights. The cross-pollinators do global pollination, while local pollination is comparable to local search. Floral similarity influences reproduction with the fittest surviving and reproducing optimally in terms of numbers and fitness. This is an iterative approach that uses local and global pollination to find the best result. A. Sabry Eesa [19] studied the Cuttlefish Optimization Algorithm (COA) in which reflection and visibility are achieved by using the multiple layers of the fish. Pattern matching is simulated by visibility, whereas matching light is simulated by reflection. The algorithm uses reflection and visibility to try to hide the fish in the surroundings, and the resulting pattern is the global optimal solution. Global search with a random component is represented by the first two solution groups, while local search and solution comparison is represented by the last two.

S. Mirjalili [20] presented a Gray Wolf Optimization (GWO) algorithm that equilibriums the state of exploration and exploitation. It consists of a hierarchy of wolves i.e., alpha, beta, delta, omega. The three finest solutions will always lead you to the ideal search space, but we must strike a balance between exploration and exploitation. The basis of an optimization technique is a series of randomly generated solutions, which encircle the prey and pursue the target in the search space to find the global optimum. Mirjalili [21] emphasized exploration via global search. Every quest is an attempt to find the neighborhood's best solution. Encircling the prey is simulated by updating the location vector. The goal function determines the convergence behavior. Exploration of the search space for the best potential answer is based on the cycled position of search agents. S. Gao [22] presented a divided algorithm called as Improved Artificial Fish Swarm (IAFS) algorithm. It is based on searching a mathematical function, its swarming and chasing through various means, and finally its leaping behavior. Random behavior is strongly influenced by the visual scope. Swarming takes place only when the current function value is better than the prior one. One algorithm iterates repeatedly and updates the swarming behavior. To discover the global optimum or optimal solution, a fish simulation behavior is done through a randomized parallel algorithm. Y. Y. Hao [23] proposed an improved Glow-worm swarm optimization (IGSO) algorithm to enhance the performance of multi-dimensional problems and convergence rate. A population of glowworms with an identical quantity of luciferin is dispersed across the search space. The value of luciferin is determined by the glowworm's location. Brighter light in the field indicates more luciferin. To update the position of the glow-worm, a randomized algorithm based on parameter adaptation is used which is followed by the luciferin update.

T. Shankar [24] proposed a Harmony Search Algorithm (HSA) PSO-based hybrid algorithm to overcome the different local search constraints and exploration-exploitation trade-offs. This hybrid scenario also obtained a fast convergence rate in global search and has improved the lifetime of sensor nodes due to its dynamic capability and high search efficiency. S. Su [25] presented a GA-PSO hybrid approach that explores the distributed clustering levels for large-scale WSNs. At the lower level, GA is used in independent subgroups for a global search, and, at the upper level, the PSO algorithm is used for the local search of individuals. The proposed technique also reduces energy consumption and accelerates convergence speed.

J. Kapoor [26] proposed an improved protocol of LEACH which is inspired by Low-energy adaptive clustering with the collaboration of GA and Bacteria Foraging (BF) implementation to overcome the disadvantages of former conventional protocols. The proposed algorithms also reduce energy dissipation and improve the network's lifetime. B. Farnad [27] presented a new hybrid approach by combining GA, PSO, and Symbiotic Organisms Search (SOS) based on the natural selection phenomenon. GA creates and picks the best population for the future phases, PSO accumulates and updates experience for each appropriate solution, and SOS builds on prior phases and executes symbiotic interaction update phases in the real-world population. S. Potthuri [28] proposed DE-SA hybrid approach for best cluster head selection. It is utilized to extend the life of the network by delaying the death of cluster heads. The cluster head's remaining energy and the distance between the nodes are taken into account by the fitness function concerning the differential evolution and simulated annealing concept (DESA). In this technique, the authors have tried to keep the maximum no. of sensor nodes alive, as the network's lifetime is directly proportional to the number of nodes alive.

B. Pitchaimanickam [29] proposed Firefly Algorithm with Particle Swarm Optimization (HFAPSO) which is provided in the LEACH-C approach for selecting the optimal cluster head selection. The hybrid method optimizes firefly global search behavior and achieves optimal cluster head positioning using PSO. The suggested methodology's performance is measured by the number of live nodes, available energy, and performance. L. Nagarajan [30] proposed a Hybrid GWO-based Sunflower optimization (HGWSFO) technique for optimum CHS under particular factor constraints such as energy consumption and separation distance, to extend network longevity. Balancing the exploration-exploitation trade-off increases network performance in terms of total throughput, node residual energy, dead nodes, alive nodes, network survivability index, and convergence rate. Table 1 provides a comprehensive comparison of algorithms based on their strengths, drawbacks, performance influencing variables, and application areas.

Table 1. A comprehensive comparison of nature-inspired algorithms in WSNs.

Algorithm	Advantages	Nature of Solution	Disadvantages	Applications
Genetic Algorithm (GA) (J. H. Holland 1992) [8]	Enables us to explore a search space without losing partial solutions, explores various parts of the solution space simultaneously, and effectively combines novel combinations with existing information.	Based on natural selection and generational reproduction of the fittest humans, initialization, fitness, selection, cross-over, and mutation are all phases in the algorithm, follows a constructive greedy heuristic approach for finding excellent pathways.	More computational time, large complexity in network structure, difficulty in showing branching and looping. For decision-making issues, genetic algorithms are inefficient and ineffective.	Data clustering and mining, Traveling Salesman Problem (TSP), neural networks Wireless sensor networks, medical science, Vehicle Routing Problem (VRP).
Particle swarm optimization (PSO) (Kennedy and Eberhart 1995) [16]	PSO has a few parameters to adjust, it takes a small amount of time to compute, in terms of discovering global optima, PSO has a greater likelihood and efficiency.	The algorithm explores the candidate solution space for the best-known solution and is based on the best location of the entire swarm, as well as the particle's most known position.	The challenges faced in PSO are low-quality solutions, initial design parameters are quite difficult to define, and cannot perform in the problems of a non-coordinated system.	Price and load prognostication, volatile power management, ideal power flow, neuronal network training.
Ant colony optimization (ACO) (Dorigo et al. 1996) [9]	ACO can be used in dynamic applications, it can adjust to new distances and other changes, and it may also search for a large population at the same time.	Model-based on pheromones that are random and probabilistic, the agent dynamically updates the weight of nodes and edges (ant).	The probability distribution might change with each iteration, which is one of ACO's problems, ACO's theoretical analysis is complex, it will take an unknown amount of time to reach a point of convergence.	Job shop forecast problem, retro vehicle steering problem, antenna optimization, image dispensation.
Artificial bee Colony (ABC) Algorithm (Karaboga 2005) [10]	ABC has a simple structure. It also uses a few parameters, strong robustness.	The nutrition supply is comparable to a potential resolution, and the volume of nectar is proportional to the solution's suitability.	The challenges in ABC are slow speed of convergence and low QoS, and the precision of optimization is low.	Image Processing, Clustering and facts mining, fiscal communication problems, job forecasting.
Biogeography based optimization (BBO) (Simon 2008) [11]	Convergence occurs quickly, can easily break out from local optimum conditions.	Species extinction, migration, and speciation are all factors that influence the evolution of species.	Exploration of the solution space is inadequate, there is no way to save each generation's finest work, and many unworkable ideas are devised.	TSP, Feature Extraction.
Intelligent water drop (IWD) (Shah- Hosseini 2009) [12]	Simple to use, union to the comprehensive optimum is a foregone conclusion, Robust.	In terms of minimum direction and maximum velocity, we are looking for a global optimum.	For big enough iterations, the best solution is discovered, and probability is used to choose the next node.	Traveling Salesman Problem, multiple knapsacks, workflow scheduling.

Table 1. *Cont.*

Algorithm	Advantages	Nature of Solution	Disadvantages	Applications
Gravitational search algorithm (GSA) (Rashedi et al. 2009) [13]	Adjustable learning rate, algorithm with less memory, results are more consistent and precise.	The program navigates by modifying gravitational and inertial masses until the masses are drawn to the heaviest mass, which is the best option.	Intensely computational, the beginning population and its size have an impact on performance, in the most recent editions, searching is sluggish.	Renewable micro-grid, commercial consignment communication, regulator strategy, wireless sensor networks.
Bat algorithm (BA) (Yang 2010) [14]	Switching from exploration to exploitation is possible, offering control over parameters, using echolocation and frequency fluctuation, and frequency tweaking is possible.	The echo sounding of bats with different beat rates was used in a global optimization metaheuristic method.	A large variety of objective function evaluations are available, initial parameters have no values specified, and during iterations, the pace of convergence is mercurial.	Clustering cataloging, facts withdrawal, image processing.
Charged system search (CSS) (Kaveh and Talatahari 2010) [15]	During exploration, it is difficult to become imprisoned in the local minimum, simple to implement, initially, there are just a few settings to tweak.	An ideal explanation for optimization that mimics electrostatic services between particles and their dependency on distance.	The computation cost rises as the quantity of charged particles rises, only a few charged particles are required for preemptive convergence to occur.	Water dispersal networks, operational mutilation recognition.
Cuckoo Search (CS) (Goel et al. 2011) [17]	Convergence occurs quickly, and is simple to put into practice, global optimums are guaranteed if enough time is given, and Levy flights are used for worldwide searches.	Its purpose is to develop novel and better solutions, the quality of which is determined by an objective function that is often maximized.	It is possible to get stuck in a local optimum along the border, lack of effectiveness.	Exercise of neural system, conniving a wind turbine edge, statistics synthesis in wireless sensor networks.
Flower Pollination (FPA) (Yang 2012) [18]	Easily able to break out from local minima, fitness function made it easy to survive, robustness to issues involving continuous optimization.	Optimal reproduction and survival of the fittest in terms of numbers and fitness.	Flights on Levy might lead to domain exploration outside of the search space, it is not possible to use it for binary optimization, and there are no default values for the initial parameters.	Design pressure pitchers, image firmness, chart coloring.
Cuttlefish optimization (CFO) Algorithm (A. Sabry Eesa 2013) [19]	Can easily break out from local optimum conditions, ensured global optimal location, vigorous.	Two of the solution groups are for global search with a random component, while the other two are for local search with solution comparison.	Intensely computational, slow conjunctional.	Control systems, signal dispensation, information mining, biomedical engineering, power systems.
Grey wolf optimizer (GWO) (Mirajlili et al. 2014) [20]	Simple to contrivance, flexible, mountable, exploration, and extraction are in a state of equilibrium.	A collection of random solutions is used in the optimization process, with each result being a vector that reflects the parameter values.	Only single-objective issues are allowed, local optima stagnation occurs when there are a large number of variables, and performance suffers as a result.	Design and alteration of controllers, clustering, and robotics.

Table 1. *Cont.*

Algorithm	Advantages	Nature of Solution	Disadvantages	Applications
Whale optimization algorithm (WOA) (Mirjalili and Lewis 2016) [21]	Exploration via global search is emphasized by the global optimizer, there are fewer settings that may be changed, simple to put into practice.	Starts with a random solution, then updates its position using a randomly selected search engine or the best approach so far.	Low rate of merging, low precision, and randomness affects the convergence phase.	Workflow planning of creation sites, image segmentation, optimal power flow problem
H-HSA PSO Algorithm (T. Shankar 2016) [24]	Searches at a higher rate, allowing for speedier exploration and exploitation, moving from one place to another in quest of the best answer is a dynamic capacity.	At each level, the starting settings are modified. The goal is to provide an energy-efficient cluster head selection that also demonstrates high HSA search efficiency and dynamic PSO capabilities, extending sensor node lifespan.	Convergence rates start to drop in high-dimensional problems, it is tough to fine-tune the basic settings, its full potential, and restrictions have yet to be determined.	Feature selection, training neural networks, economic dispatch problems.
H-GA PSO Algorithm (Shengchao Su 2017) [25]	In large-scale WSNs, it is effective for distributed clustering, the algorithm's convergence speed will be significantly increased, over time, you will come up with suitable answers.	The algorithm looks for the most well-known solution in the candidate solution space is determined by the particle's finest position as well as the most appropriate position of the entire swarm.	Dependent on the initial parameters such as location, inadequate speed, and acceleration, in a high dimensional space, it is possible to fall into the trap of local optima.	Clustering, robotics neural network training.
H-GA BFO Algorithm (J. Kapoor 2017) [26]	Obtained optimal coverage with a minimum no. of nodes in large-scale WSNs, reduced average power consumption i.e., increases the lifespan of the entire network.	Energy and Physical parameter are to be initialized, during iterations, if the node is dead, calculate NCH energy. The route is updated after one algorithm repeats repeatedly.	Dependency of fitness functions on various parameters, is difficult to implement on large scale WSNs.	Biomedical engineering, wireless sensor networks.
Improved Artificial fish swarm (IAFS) (S. Gao 2018) [22]	Ability to make a proper junction, suppleness, present with great precision and fault tolerance.	A randomized parallel method that models fish behavior to get the worldwide finest or topmost solution.	Each fish's visual range is unique and cannot be generalized, there is a discrepancy between global and local minima.	Job scheduling, image processing, clustering.
Improved Glowworm swarm optimization (IGSO) (Y. Y. Hao 2018) [23]	For many peaks, an adaptive local judgment is made, for issues with a constant domain, this method works well. The process used less memory during iterations.	To update position, a distributed algorithm based on luciferin apprise uses the statistics accessible in the nearby vicinity.	For high-dimensional issues, performance is poor, convergence occurs gradually, and Inadequate local search capability.	Positioning numerous mobile signal bases, communal transport report systems, and wireless sensor networks.

Table 1. *Cont.*

Algorithm	Advantages	Nature of Solution	Disadvantages	Applications
H-GA PSO SOS Algorithm (B. Farnad 2018) [27]	In the real-world population, it runs symbiotic interactions to update stages. Superior in terms of convergence, success rate, and execution speed.	Searching the solution with logarithmic spirals which is a deterministic dynamical system. Natural selection inspired the notion of merging three evolutionary algorithms.	Improve search performance by introducing randomization, initial parameter selection has a significant impact on performance.	Job scheduling, data mining, path planning, statistics synthesis in wireless sensor networks.
H-DE SA Algorithm (S. Potthuri 2018) [28]	Extend the lifespan of the network by extending the cluster heads' death, improved the selection rate of genes of DNA microarrays.	Iteratively improves a potential solution based on an evolutionary process to optimize a problem.	Low convergence rate, randomness during the selection of initial parameters, and less robustness.	Multidimensional global optimization problems over continuous spaces, training of integer weight neural networks.
H-FF PSO Algorithm (B. Pitchaimanickam 2020) [29]	Flexible, scalable, providing parameter control statistics, not easily trapped in the local minima.	Set the FF and PSO parameters to their default values. Calculate your fitness level based on the amount of light you are exposed to after initializing the parameters. Update the velocity and position of the population.	Initial characteristics such as position, velocity, and acceleration showed randomness. Difficult to implement on large scale WSNs.	Automatic data clustering, machining parameter optimization, optimal power flow.
F-GWO SFO Algorithm (L. Nagarajan 2021) [30]	Automates the setting of a collection of parameters in such a way that the weight is evenly distributed. In comparison to previously employed algorithms, it also enhances the stability and energy efficiency of WSNs.	An array of random solutions is used in the optimization process. The energy consumption and separation distance are considered for selecting optimal CHs.	Low solving precision. The unpredictability of the starting input determines the convergence phase. In a high-dimensional space, it is possible to fall into the trap of local optima.	Engineering design problems, design and controllers tuning, robotic and path planning.

4. Analysis of Considered Bio-Inspired Algorithms

Recent advances in bio-inspired optimization algorithms seek to solve the issues of classical optimization methods, which are potentially providing solutions to tackle complicated optimization problems. Below are some important algorithms selected from a large number of nature-inspired algorithms. Based on the merits of these algorithms and their linkages to self-organization, the following algorithms play an important role in the hybridization of algorithms in WSN research.

4.1. Genetic Algorithm (GA)

GA was proposed by John Holland in 1960. It is an adaptive heuristic algorithm used in machine learning and artificial intelligence. This algorithm is based on natural selection and is also focused on generating optimal global solutions for optimization problems. Individual and population are two basic terms used in GA. In terms of GA, the individual is considered as a possible solution for a given problem, and a group of these possible solutions is considered as a population. Such a population of individuals is maintained within a search space. Initialization, selection, cross-over, and mutation are some important operators used by GA [31–33].

4.2. Differential Evolution (DE)

DE was proposed by Rainer Storm and Kenneth Price in 1997. Ever since this algorithm has been widely used in different areas like engineering science, decision sciences, material sciences, energy, etc. DE is a population-based stochastic approach in which each solution is referred to as a genome or chromosome. Each chromosome goes through mutation and recombination. DE uses terms such as target vector, donor vector, and trail vector. Only after all trail vectors have been generated is a superior solution chosen. This method also does greedy selection between the target and trail vector [34–36].

4.3. Particle Swarm Optimization (PSO)

J. Kennedy and R. Eberhard proposed PSO in 1995. It is a swarm intelligence approach that uses the collective behavior of birds and animals to solve optimization issues. Self-organization and division of work are two essential characteristics of swarm intelligence activity. Interactions in self-organization are carried out only based on local knowledge, with no regard for the global pattern. Positive and negative feedback, oscillations, and numerous interactions are all part of it. Tasks done concurrently by specialized persons are referred to as division of labor. The social behavior of PSO is modeled by bird flocking and fish schooling, in which each particle/bird has a position and velocity. To escape predators or find optimal environmental conditions, these particles may alter their location by changing their velocity. The velocity of the particles may be changed by modifying the particle's/or bird's group's flying experience [37–39].

4.4. Ant Colony Optimization (ACO)

In 1992, Marco Dorrigo suggested ACO. Ant colonies are socially complicated, with the queen as the leader and the workers hunting for food and defending the colony. Ant colonies refer to not only the physical structure in which ants reside but also the social principles by which they organize themselves and the job they accomplish. Ants have been able to use their surroundings because of their cooperation and division of work, as well as their well-developed communication systems. Ants are attracted to the pheromone trails made by other ants. If there is any obstacle on the way then ants quickly find the shortest diversion. Ant colony optimization is an optimization method that takes inspiration from the bio-semiotic communication between ants. Each constructs a solution using a stochastic greedy method using a combination of a heuristic function and pheromone trail following. ACO is related to the class of algorithms known as swarm optimization used to solve the graph search problems [40–42].

4.5. Artificial Bee Colony (ABC)

Dervish Karaboga proposed ABC in 2005, drawing influence from honey bees. The employed bee phase, spectator bee phase, and scout bee phase are the three periods in which bee movement is recorded in ABC. In the employed phase, the number of employed bees is equal to the number of food sources. During the employed bee phase, all solutions have the possibility of developing a novel solution. A partner is chosen at random, but the partner and the present solution should not be the same. As in the onlooker phase, the probability value of all solutions is determined before the onlooker phase. A solution with a greater fitness value has a better chance of succeeding. A fitter solution may undergo the onlooker bee phase more than once. In the scout bee phase, we have to find an abandoned solution based on the value of the limit. If some iterations exceed the defined limit, the process enters into the scouting phase and generates a new solution randomly [10,43,44].

4.6. Gray Wolf Optimization (GWO)

Mirjaliali Mohammad and Lewis presented GWO as a meta-heuristic method in 2014. The social hierarchy and hunting methods of grey wolves inspired this algorithm. These wolves lived in well-structured packs, with several wolves ranging from 5 to 12. The members of the pack are divided into four categories i.e., α-wolves, β-wolves, δ-wolves, and

ω-wolves. Alpha wolves are the leaders of the pack and the rest of the pack follow alpha. Alpha wolves are in charge of making decisions regarding hunting, sleeping, and waking up times, among other things. There are beta wolves who are the greatest contenders to be alpha at the second level. Delta wolves are present in the pack to supply food and to protect the pack in times of danger. Omega wolves (Scouts, Elders, and Caretakers) are at the bottom of the food chain, serving as scapegoats and the last to eat. The following are the main phases in the GWO hunting process: (1) searching for prey; (2) tracking, pursuing, and approaching the prey; (3) encircling and tormenting the prey till it finally comes to a halt; (4) taking on the prey [45–48].

5. Selective Bio-Inspired Algorithms with Hybrid Optimization

The present meta-heuristic techniques have several drawbacks, including sluggish convergence and limited accuracy. Scholars have progressively turned their attention to the swarm intelligence algorithm in recent years. Swarm intelligence algorithms are widely used because of their simplicity, adaptability, non-derivation mechanism, and avoidance of local optimality. The features and trends of scientific growth are reflected in the rapid development of swarm intelligence algorithms. In this paper, we are looking at some new hybridization approaches to nature-inspired algorithms to make the algorithm more resilient and enhance simulation analysis and outcomes statistics.

5.1. Hybrid GA-DE Algorithm

GA includes solutions regarding non-convex and nonlinear problems. As we know, different operators like initialization, selection, and cross-over are used by GA. In hybridization of GA-DE, mutation operation is performed by DE. DE also solves non-differential and non-continuous real-world problems. So, hybridization of GA-DE would be able to provide better global optimal solutions [49,50].

The design procedure for the GA-DE algorithm is:

- First sensor node control variables are selected like genes;
- Initialize the population of sensor nodes;
- Using the localization function, calculate the fitness of sensor nodes;
- Use the roulette wheel selection method for mating;
- GA performs cross-over operations;
- Mutation operation is performed by DE;
- Select a new population for the upcoming generation;
- Repeat steps four, five, six, and seven;
- Print estimate of location.

In the performance research of a hybrid GADE localization algorithm with localization function, the hybrid technique's precision and time complexity in the context of varying population vector sizes with localization function are reported. In comparison, when the size of the population vector grows larger, the accuracy improves and the time complexity performance improves. Additionally, when the hybrid GADE localization algorithm employs the average localization function instead of the basic localization function, it outperforms the better competition in terms of temporal complexity and accuracy.

5.2. Hybrid GA-PSO Algorithm

The fundamental goal of hybrid GA-PSO is to enhance cluster head selection and routing between deployed nodes and the base station. There are two steps to the proposed method. In the first phase, the PSO algorithm holds passed population and fittest individuals. In the second phase, these fittest individuals are operated by the GA operators who are selection, cross-over, and mutation. Hybridization of GA and PSO combines the merits of both algorithms, which provide us better convergence rate and avoid the problem of local optima [51,52]. The major contribution of both algorithms has been shown in Table 2.

Table 2. Combination of GA-PSO techniques in WSNs.

Algorithms	GA	PSO
Operators used	Selection, cross-over, mutation.	Inertia, cognitive, social.
Ability to search global optima	High	Low
Implementation	Hard	Simple
Trapped on local optimum	Sometime	Often
Computer efficiency	Low efficient	Highly efficient

This method combines the benefits of both algorithms, such as PSO's rapid convergence rate and GA's problem of trapping in local optima. The primary purpose of this PSO-GA strategy is to steadily raise the number of decent people across generations.

The design procedure for the GA-PSO algorithm is:

- Initialization;
- Generation of the initial population;
- Selection;
- Cross-over;
- Mutation;
- Growth;
- Generation of a new population;
- Repeat until no. of generation (Ng) evaluates.

The hierarchical sensor network model is used in the PSO, GA, and PSO-GA approaches for small and large size networks. In a hierarchical WSN paradigm, each cluster contains one base station and one relay node. In this WSN configuration, the relay node serves as the cluster head. The most significant assumption is that base stations offer routing pathways and that each relay node's average data volume is known. Each relay node's leftover energy is replenished at the end of each generation, and current energy is utilized to determine the next routing path. When comparing the shortest path method, PSO approach, GA approach, and hybrid PSO-GA approach for large-scale networks, we observed that the hybrid PSO-GA strategy has the best network lifespan and packet delivery ratio.

5.3. Hybrid ACO-PSO Algorithm

The main aim of ACO-PSO hybridization is to improve inter-cluster data aggregation in WSNs. This proposed technique also improves the network's lifetime over many optimization techniques. In this approach, ACO results in local updates, and PSO gives a better outcome for global updates. The combination of ACO–PSO enhances the durability and performance by 6% over previously used optimization techniques like an ant colony, cuckoo search, flower pollination, etc.

The design procedure for the ACO-PSO algorithm is:

- Step 1. Initialize the number of wireless sensors;
- Step 2. Calculate the energy level for each sensor node;

If $E > 0$, there will be a selection of CH otherwise, go to Step 2 again. After CH selection, implement the ACO-PSO algorithm to find a new path.

- Step 3. Calculate the energy dissipation for each sensor node.

If a dead node is found, evaluate otherwise, go to Step 2. For different parameters, evaluate the performance of the network.

Hybrid ACO-PSO-based data aggregation is used to increase the inter-cluster data aggregation. Extensive investigation shows that the suggested approach significantly increases network lifespan when compared to previous strategies. It divides the sensor network into several pieces, referred to as clusters, with cluster heads chosen for each cluster. Then, using short-distance connections, tree-based data aggregation is used to acquire sensory data directly from cluster heads. The use of compressive sensing decreases the size of the packets that are sent across the sensor network. The ACO-PSO algorithm determines the shortest path between the sink and cluster heads. For simulation, the MATLAB simulation tool is generally utilized by researchers. It helps in comparing the proposed approach's performance to that of existing technology, GSTEB, in terms of stability period, network lifespan, residual energy (average remaining energy), and throughput.

5.4. Hybrid PSO-GWO Algorithm

The aim of hybridizing PSO and GWO is to obtain more optimal results with a lesser number of iterations. This approach successfully merged the powerful merits of both algorithms to get better efficiency. Simplicity, fast convergence speed, and high exploitation ability are some of the advantages of this algorithm. When these merits of PSO collaborated with GWO of high exploration ability, it enables higher stability and shows better performance with more optimal solutions [53–55].

The design procedure for the PSO-GWO algorithm is as follows:

- Set the overall population and the A, C, and a value to their defaults;
- Create people for the population;
- Find the fitness value of each individual;
- Calculate the value of α, β, and δ by shortening the order according to size;
- Calculate nonlinear controlled parameters and update the value of A and C;
- Detect the location of individuals and again calculate fitness values;
- Update the values of α, β, and δ.

The PSO approach has been utilized to address almost any real-world problem. However, there must be a mechanism to reduce the chances of the PSO algorithm catching itself at a local minimum. Recommended techniques to reduce the likelihood of falling into a local minimum have introduced the GWO algorithm to support the PSO algorithm. To avoid risks, the GWO algorithm's exploration ability is employed to send certain particles to sites that are somewhat enhanced by the GWO method rather than random positions. Since the GWO method is used in addition to the PSO algorithm, the running duration is also increased. The PSO–GWO algorithm incorporates nonlinear control parameters. Other algorithms have inadequate nonlinearity in their control parameters, resulting in a lack of balance between local and global search abilities and an easy fall into local optimum throughout the search phase.

6. Comparative Analysis Based on Recent Literature

A comparison of the various methodologies and criteria utilized in recent articles to choose the cluster head has been conducted. Each of the measures has been explained in terms of percentage, utilization, and progress [56]. These measures are packet loss, network lifetime, energy, throughput, delay, and overhead. Packet loss occurs when one or more data packets fail to arrive at their intended destination. Network lifetime is based on the number of alive nodes, connectivity, and sensor coverage. The energy of WSNs is evaluated based on the packet received at the destination. Throughput is the actual amount of information that is efficiently sent/received via a communication channel. Delay is the time taken by the packets from sensor nodes to sink and is proportional to the number of hopes. Overhead is the total amount of energy consumed to transmit the data for a given time.

Table 3 compares several approaches offered by notable scholars in terms of parameters employed, tools used, and difficulties handled.

Table 3. Comparative analysis of various conclusions based on recent literature.

Reference	Parameters Used	Tool Used	N/w Life	Energy Efficiency	QoS Increased	Security	Results
Thenmozhi et al. [57]	Residual energy, node's capability assembly compactness, node's gradation	MATLAB	√	√	√	×	The overall delay is reduced by 23%. The rate of packet loss is reduced by 11%. Residual energy improved by 38%.
Jia et al. [58]	Area Coverage, life rotation, dynamic nodes, average remaining energy.	MATLAB	√	√	×	×	In comparison to LEACH and DEEC, network lifespan increased by 50% and 30%, respectively. Clustering overhead was reduced by 42%.
Aggarwal et al. [59]	Remoteness to the sink, enduring energy, sensor node concentration	MATLAB	√	√	×	×	Network lifetime increased by 30%. In comparison to LEACH and EAUCF, prolonged energy increased by 155.18% and 35.75%, respectively.
Neamatollah et al. [60]	Residual energy, gradation of the sensor node, distance SNs to BS.	MATLAB	√	√	×	×	The network's lifespan has increased by 28%. The overhead of clustering was decreased by 57%. A 13% reduction in energy utilization.
Mehra et al. [61]	Residue power, base station's remoteness, concentration of the SNs.	MATLAB	√	×	×	×	In comparison to LEACH, network lifespan raised by 15%, 11.38% with BCSA, and 8.1% with CAFL. Energy conservation raised by 79%.
Jeong et al. [62]	Concentration, centrality, overhead, average delay	MATLAB	√	√	×	×	In comparison to LEACH, there is a 42.7% increase in power and local distance.
Krishna et al. [63]	N/w lifetime, throughput, distance between SN to CH, number of neighboring nodes.	MATLAB	√	√	×	×	Average left overpowers and alive nodes improved by 62%. Overall, this is a 45% improvement over LEACH.
Azad et al. [64]	Remaining energy, the route followed between sensor nodes and sink. Number of neighbor nodes.	MATLAB	√	√	√	×	TOPSIS has a 151.2% percent longer network lifespan than LEACH. Overall, 40% better than LEACH.
Behra et al. [65]	Network's coverage, Total number of sensor nodes, entire network energy consumption, energy degeneracy.	MATLAB	√	√	√	×	Packet loss rate reduces by 8%. Throughput has increased by 60%, lifetime has increased by 63%, and residual energy has increased by 61%.
Tamizharasi et al. [66]	Usual enduring energy number of the active nodes, entire nominated cluster head.	NS2	√	√	×	×	In comparison to 19% for LEACH, 5% of the increase in energy utilization. Increase in the number of living nodes with a longer lifespan.

During comparative analysis, researchers implemented different deterministic and probabilistic approaches. These techniques performed well in terms of increasing network longevity and energy efficiency but failed spectacularly in terms of improving QoS and security. A comparison of the various methodologies and performance metrics is shown in Figure 4.

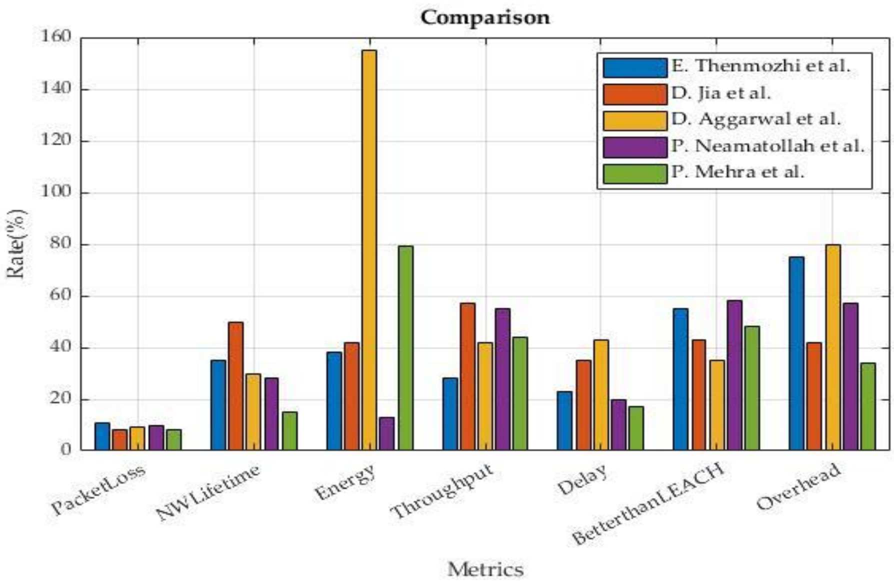

Figure 4. Comparison of the various methodologies and performance metrics [57–61].

In Figure 4, researchers tried to reduce the packet loss and overhead. Moreover, they have made an effort to enhance the lifetime of the network i.e., it depends on energy consumption. Thenmozhi et al. [57] reduced the packet loss by 11%. In comparison to LEACH and DEEC, network lifespan increased by 50% and 30%, respectively, to Jia et al. [58]. In comparison to LEACH and EAUCF, Prolonged Energy increased by 155.18% and 35.75%, respectively, to Aggarwal et al. [59]. Neamatollah et al. [60] and Mehra et al. [61] also improved the overall performance with a high reduction in delay and overhead, respectively.

In Figure 5, researchers tried to improve the lifespan of the network by taking energy and throughput into their account. The authors also compared their results with the existing algorithms. Jeong et al. [62] and Krishna et al. [63] improved in energy and overall performance by 43% and 45%, respectively, as compared to LEACH. Azad et al. [64] improved the maximum energy residual and network longevity, according to the results. Behra et al. [65] and Tamizharasi et al. [66] also boosted the maximum energy and network longevity. The algorithm improved the life of the network and preserved residual energy in the search space.

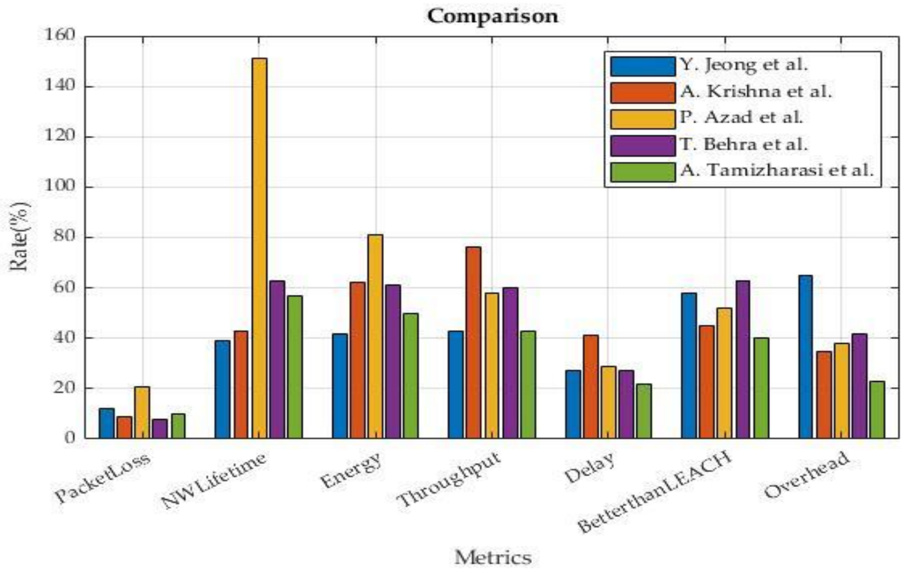

Figure 5. WSNs performance comparison based on recently reviewed articles [62–66].

7. Open Issues and Challenges

Following a thorough examination of the above-discussed literature, we have formulated various outstanding concerns and obstacles with WSNs.

7.1. Network Stability

The network's survival is contingent on the presence of active sensors. Due to the limited processing capabilities of nodes, optimizing transmission costs, data gathering, and load tolerance of nodes to extend their life is a difficult challenge. Clustering optimization, which involves selecting the best energy path for routing, can assist in extending the network's lifespan [67].

7.2. Network's Dynamic Character

Sensor nodes have long been thought to be stationary by many researchers. However, because of variable network sizes, sensor node moves, topology changes, and unanticipated operational problems, it is necessary to address the dynamic character of WSN. Even node or sink mobility might be difficult, necessitating clusters to alter over time [68].

7.3. Secure Data Transmission

The CH is in-charge of data gathering and compilation. Because clustering in WSN captures extremely sensitive data from a hostile environment, it must be conveyed without any malicious intent, attack, or change. It is important to avoid hostile attacks on the network and critical to use stringent and powerful authentication procedures. WSNs are vulnerable to a variety of attacks, including denial of service and manipulation, which can cause nodes, CHs, or whole networks to be disconnected [69,70].

7.4. Cluster Head Replacement during Iterations

Most previous methods ignore the CH rotation, which might be included further in recent studies by employing relevant parameters such as coverage rate and residual energy. These nodes are used in tough and dangerous environments where sensor node failure is a possibility. Sensor nodes that are malfunctioning can result in inaccurate sensing results, wrong data processing, and inappropriate data transmission. The research on CH rotation might result in a reduction in the lifetime of networks [71].

7.5. Improvement in QoS

WSN is the backbone of cutting-edge technologies like the Internet of Things (IoT) and the Internet of Everything (IoE), which rely on the quality of experience (QoE) and QoS as prerequisites. When choosing CH in WSN, several criteria like bandwidth, latency, end-to-end delay, throughput, and dependability are almost completely neglected. As a result, in cluster-based protocols for real-time IoT applications, these QoS characteristics must be taken into account [72].

7.6. Distance from CHs to CHs and CHs to SNs

The energy consumption of its members is determined by the position and positioning of CH in a zone. Clusters with a greater intra-cluster distance spend more energy than clusters with a smaller intra-cluster distance. This must be taken into account by a clustering method, and a cluster should be established so that intra-cluster distance is less than inter-cluster distance [73,74].

8. Conclusions

This study provides a comprehensive review of Bio-inspired Hybrid Optimization Algorithms for Energy-Efficient Wireless Sensor Networks (WSN). Various advanced techniques in bio-inspired optimization algorithms have been proposed till now, to solve the problem domains in WSN such as data aggregation, sensor location, and routing and coverage area. We have aimed to discuss and compare various newly adopted, hybrid, and conventional methodologies for establishing a robust energy-efficient WSN wherein parameters like packet loss, energy, throughput, delay, and overhead have been utilized. Various open issues and challenges in WSN development using bio-inspired optimization techniques such as network stability, network dynamic character, secure transmission lines, methods to improve QoS, etc., have been addressed through this review. Further investigation and extensive experimental work in this research field will aid in advancing and developing robust Energy-Efficient WSNs.

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