MINIMIZATION OF ENERGY HOLES USING BIO-INSPIRED ENERGY OPTIMIZATION TECHNIQUES IN WIRELESS SENSOR NETWORKS

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Abstract. Researchers currently face significant challenges in developing long-lived and energy-efficient clustering and routing protocols for wireless sensor networks (WSNs) in various domains, including military, agriculture, education, and environmental monitoring. WSNs have profoundly affected various aspects of human existence. Existing routing protocols have mainly focused on cluster head selection but have ignored critical elements of routing such as clustering, data aggregation, and security. Although cluster-based routing has played a significant role in solving these problems, there is definitely area for improvement in the cluster head selection process (Cluster Head) by integrating key features.

Biologically inspired algorithms are gaining recognition as a practical approach to addressing key issues in WSNs, including sensor lifetime and transmission range. Nevertheless, the wireless nature of sensor node batteries presents a challenge in replacing them when deployed in remote or unattended regions. Consequently, significant research efforts are underway to enhance the longevity of these nodes. The performance of a WSN relies on both device design and the architecture of its nodes. Maximizing device lifespan and range, minimizing energy consumption, and achieving optimal connectivity and high transmission rates are currently imperative goals.

Metaheuristic algorithms, including DE (Differential Evolution), GA (Genetic Algorithm), PSO (Particle Swarm Optimization), ACO (Ant Colony Optimization), SFO (Social Fish Optimization), and GWO (Grey Wolf Optimization), offer numerous benefits such as simplicity, versatility, and independence from derivative calculations. These algorithms effectively utilize the energy resources of wireless sensor networks (WSNs) by clustering nodes, leading to an increased overall network lifespan. This research paper focuses on the exploration of hybridization techniques, such as DE-GA, GA-PSO, PSO-ACO, PSO-ABC, PSO-GWO, and others, to enhance the energy efficiency of WSNs using bioinspired algorithms. It also addresses critical issues by accelerating the implementation process, enabling more efficient data transmission, and reducing energy consumption through the application of bioinspired hybrid optimization algorithms.

Keywords: WSNs; Bio-inspired Algorithms; WSN Architecture; WSN Optimization, Life Span, Sensor node, Optimal routing algorithm, energy minimization, Base Station.

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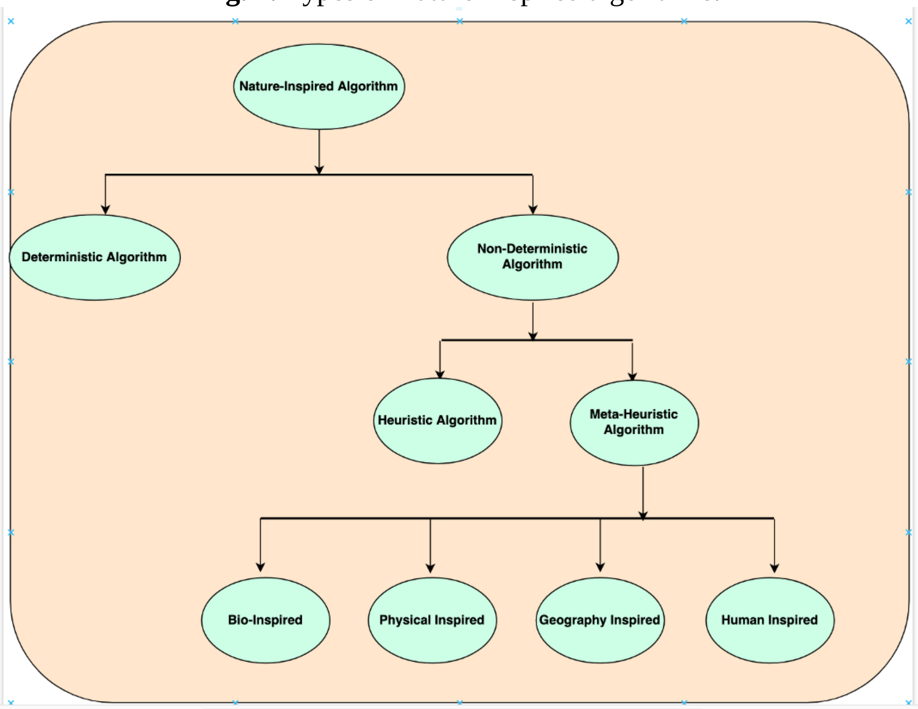
1 Introduction

A set of distributed deployed sensors which are used to monitor and capture the environment conditions is called Wireless Sensor Network (WSN). These sensors gather data and transmit it to multiple sensor nodes, which is used to monitor and record the physical conditions of the environment [1][3]. Managing energy consumption in wireless sensor network (WSN) is one of the most significant challenges. The power supply of a sensor node is provided by a battery. Batteries have limited energy and recharging the battery through flushing mechanism is very complicated and unpredictable. So it is necessary to control the energy usage of a sensor node without impacting the sensing capacity, coverage and performance. The design of sensor nodes and architecture of wireless sensor network defines the overall performance of network. It is always good to have that the sensor node lasts as long as possible and cover wide range of area with minimal consumption of energy. Also, it is important to have good connectivity and send the information as fast as possible. The main energy consumers are the controller, the radio front ends, memory, data transmission. Since most of the energy is consumed for communication, the best way is to use less energy by sending the fewer packets between the sensor and sink node.

WSNs face a variety of challenges that include accurate detection and unduplicated data. There are three significant important WSN concern which are Energy usage, security, and quality of service (QoS). Out of these issues, many involve negotiations, such as sacrificing network lifetime to improve the QoS. The security parameters follow a similar pattern. Dealing with these issues in isolation exposes several drawbacks. Consequently, to foster enhanced WSNs, it is imperative to tackle all these problems concurrently.

On the contrary, metaheuristic approaches are not tied to any specific problem. Because of their non-adaptive and non-greedy nature, they can be used as black boxes. These algorithms often tolerate temporary degradation of solutions to achieve global optima. Metaheuristic optimization algorithms are commonly called as nature-inspired algorithms as they are inspired from natural phenomena around us. There are four different categories of nature-inspired/metaheuristic algorithms: bioinspired, physically inspired, geographically inspired, and human-inspired. Within these categories, most algorithms are derived from biological systems.

Fig. 1. Types of Nature-Inspired algorithms.



The purpose of the optimization process is to determine the best solution for a problem. To achieve this goal, it is important to choose the right algorithm. However, some problems are so complex that it is difficult to find all solutions. Various metaheuristic algorithms that monitor the biological or organic behavior of animal or insect groups have been introduced in the literature.

These algorithms use deterministic or stochastic rules to solve various optimization problems.

Hybrid algorithms inspired by nature have been developed to address various limitations in wireless sensor networks (WSNs). Previous research efforts have implemented diverse metaheuristic algorithms to enhance the lifetime, stability, and overall performance of WSNs. The integration of hybridization techniques into optimization algorithms has proven beneficial in improving network lifetime, stable duration, throughput, number of dead nodes per iteration, and residual energy. However, there have been instances where these bio-inspired algorithms have produced incorrect solutions for real-time applications. Currently, important research problems revolve around convergence speed, multiple objective problems, dynamic problems, and handling the convergence of local optima. The combination of different algorithms requires a meticulous evaluation of multiple characteristics, resulting in enhanced accuracy and performance of WSNs.

Researchers have proposed the development and refinement of complex objective functions along with the utilization of suitable mathematical optimization techniques, or a combination thereof, to tackle challenging and ever-changing problems in WSNs. This paper primarily focuses on the significant role played by different hybrid metaheuristic approaches in improving the overall performance of WSNs. It includes a comparative analysis of these approaches and highlights the contributions made by researchers in this field. The paper also discusses and compares various techniques employed for cluster head selection. Additionally, it addresses the problems, open issues, and challenges encountered by bio-inspired optimization techniques, along with potential solutions.

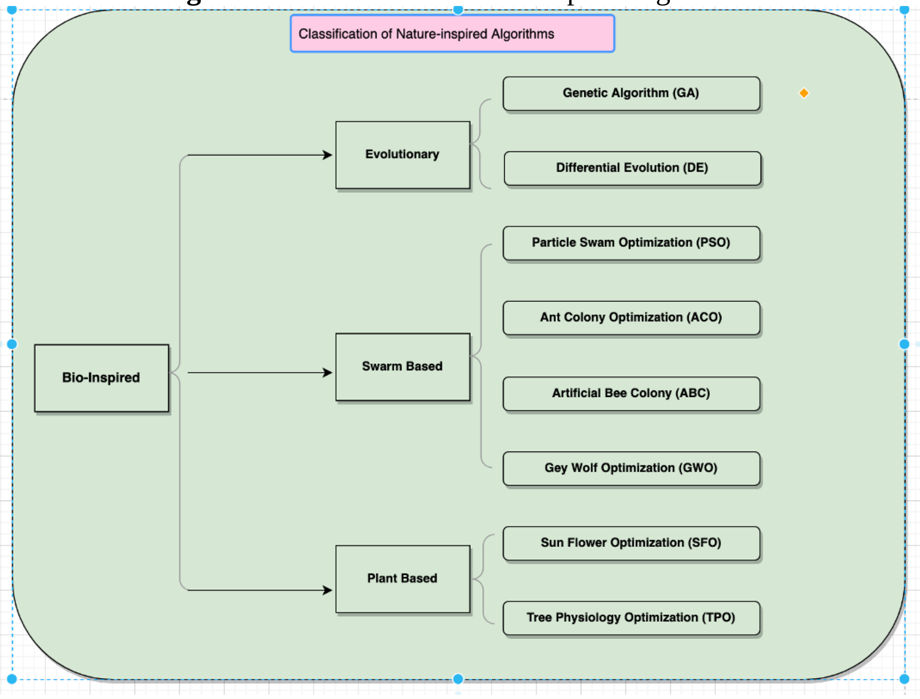
In this section, we will discuss the three primary categories of bioinspired algorithms: evolutionary algorithms, swarm-based algorithms, and plant-based optimization. The categorization is depicted in Figure 2.

Evolutionary techniques encompass genetic algorithms (GA) and differential evolution (DE). Genetic Algorithm is an evolutionary algorithm that provides solutions for optimization and search related problems. It employs principles inspired by natural selection, including selection, crossover, and mutation. Researchers additionally looked into combining other bio-inspired algorithms with GA. For instance, the Differential Evolution-Genetic Algorithm (DE-GA) combines the strengths of both algorithms, resulting in higher accuracy and reduced processing times. This hybrid technique benefits from an increased population vector size, which enhances accuracy and reduces time complexity. The selection of design parameters and utilization of improved hybrid methods can further enhance efficiency and prediction accuracy.

Among the swarm-based techniques, there are four distinct methods to consider. Notably, the genetic algorithm and particle swarm optimization (GA-PSO) demonstrate higher performance in terms of network lifetime and packet transmission rate. When compared to PSO, GA, and shortest path approaches, the hybrid GA-PSO method exhibits a 12-23% increase in network lifetime and a 9-16% improvement in packet delivery rate for large networks. Another hybrid optimization approach, Particle Swarm Optimization-Ant Colony Optimization (PSO-ACO), calculates the shortest path for data transmission from the cluster head to the base station. In a simulation involving 100 sensor nodes, this technique exhibits higher average residual energy, a larger number of active nodes, and improved throughput.

Furthermore, the hybrid approach known as Particle Swarm Optimization-Gray Wolf Optimization (PSO-GWO) enhances the consideration capability of PSO, preventing it from becoming stuck in local minima. Through this combination, the hybrid technique exhibits superior network performance when compared to other metaheuristic methods, including ABC, PSO, and GWO [1-7].

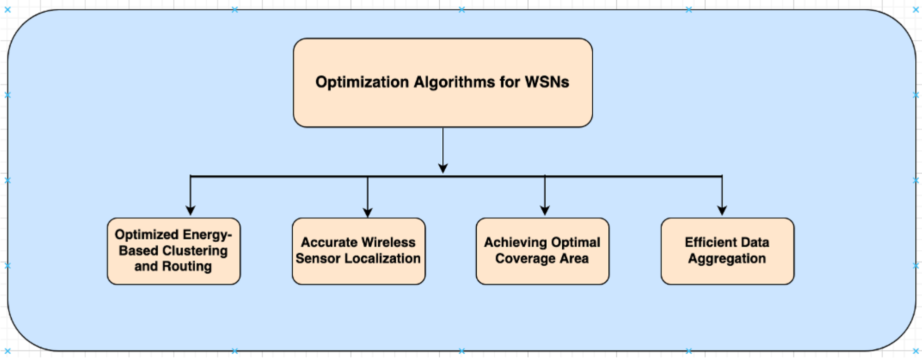
Fig. 2. Classification of Nature inspired algorithms



2 Challenges in Achieving Energy Efficiency and Load Balancing in WSNs

Resolving these challenges comprehensively necessitates a considerable investment of effort as well as time. As a result, researchers directed their attention towards tackling both challenges concurrently. One approach employed is the creation of a multi-objective function, which is subsequently optimized using a fitting algorithm or optimizer. The choice of an algorithm is influenced by several factors, including the problem's characteristics, time limitations, resource availability, and the desired level of precision. Figure 3 provides a overall representation of the diverse optimization problems encountered in WSNs, encompassing areas such as clustering, routing, area coverage, sensor localization, and data aggregation techniques.

Fig. 3. Optimization Algorithms for WSNs



2.1 Enhancing Energy Efficiency in Clustering and Routing for WSNs

Due to limitation of energy in sensors, ensuring energy efficiency in WSN infrastructure is crucial. The majority of sensor resources are allocated to data transmission, and as the duration of transmission increases, the energy consumption rises exponentially. Hence, multi-hop communication is necessary for efficient sensor data transmission.

The path or route that data packets take from source node to the sink node is called routing in Wireless Sensor Network. This process involves classifying sensors into cluster heads and non-cluster head nodes. The cluster heads are selected to collect data from non-cluster head nodes, which is then transmitted to sink node using the most optimal routing options available. It is important to note that choosing of cluster head plays an important character in this topic. The focus is to find the best possible way for data to travel in each iteration making sure to it moves quicky, keeping the network alive for longer period of time and reducing how far the sensors need to be communicate with each other.

2.2 Significance of Sensor Localization in WSNs

Positioning of sensor in the context of Wireless Sensor Networks (WSNs) refers to the process of determination and estimation of the physical locations of individual sensors within the network. It involves assigning spatial coordinates to each sensor node, allowing the network to have knowledge of their precise positions.

Distance measurement and location computation are two main components of Sensor localization. Various localization methods leverage existing knowledge of distances and locations to determine the positions of other nodes within the WSN. The hardest part of this area is to reduce the local error and improve the accuracy of the unknown location. An anchor node plays a crucial role in sensor localization, which is a node with a known position or coordinates, which can be determined either through the Global Positioning System or by pre configuration with its coordinates before deploying the WSN.

Therefore, sensor localization comprises two key elements: distance measurement and location computation. Different localization methods utilize available information on distances and positions to estimate the locations of nodes within the WSN. Improving precision and minimizing localization errors are significant challenges in this domain. The anchor node, have a known position determined or pre-programmed by GPS and act as a beacon during recording.

2.3Requirement of Optimal Coverage in WSNs

The need of maximum coverage in Wireless Sensor Networks (WSNs) refers to the need for achieving effective and efficient sensing coverage over the target area. Optimal coverage ensures that the sensing capabilities of the network are maximized, enabling comprehensive monitoring and data collection.

Deploying minimum number of sensor nodes to cover the entire area or the target area is the main aim of the optimal coverage of WSN. The mathematical shape of a sensor's detection zone are critical factors that determine its coverage scope in WSNs. In practical scenarios, the detection zone's shape tends to be irregular and complex due to topographical variations and structural obstacles. The main challenge lies in minimizing the overlap between sensing patches without leaving any gaps in detection.

Excessive overlap among sensing regions results in redundant information being detected by multiple sensors, leading to unnecessary battery consumption. To address this issue, one approach is to optimize the positioning of sensor nodes, which can be formulated as a single-objective optimization problem. However, by considering other network elements, we can transform the single objective into a multi-objective optimization problem within a WSN context. The purpose is to strike a equilibrium of minimizing redundancy and ensuring complete coverage by considering various objectives simultaneously.

2.4Requirement of Data Aggregation in WSNs

Data gathering is an important phase in WSNs as it helps conserve the limited resources of individual sensor nodes. In WSNs, each sensor monitors a specific area and transmits its local data to a central data collection sensor node. The data aggregation center leverages the collected data to make informed decisions, aiming to extend sensor lifetime by minimizing redundant sensing at overlapping or shared locations.

There are four primary types of data aggregation methods commonly used in WSNs: tree-based, cluster-based, grid-based, and chain-based. Each strategy offers unique benefits and trade-offs in terms of energy efficiency and network performance. Developing an optimal strategy for energy allocation, determining the minimum number of data aggregation points, and ensuring consistency in extended and complex WSNs are major concerns in this field of research. By addressing these challenges, we can enhance the overall efficiency and effectiveness of data aggregation in WSNs.

3 Prior Research and Literature Review

J.H. Holland [8] introduced Genetic Algorithm, a metaheuristic-based algorithm inspired by Charles Darwin theory of natural evolution and generative reproduction in humans. GA comprises several phases, including initialization, fitness evaluation, selection, crossover, and mutation. Extensions of GA, such as adaptive genetic algorithms and coarse-grained parallel genetic algorithms, have been applied to various tasks, including feature extraction, subset selection, computer-aided design (CAD), and optimization of the traveling salesman problem.

The fitness criteria function and the number of iterations/cycles are main components of Genetic Algorithm. In each generation, new genetic algorithms, known as offspring, are generated by combining selected parents from the current generation. These algorithms offer benefits such as faster convergence, ease of implementation, and suitability for optimizing a wide range of functions. However, they also have limitations such as inefficiency in decision problems and tendency to meet to local optima instead of global optima.

[M. Dorigo (9)] studied the exploratory behavior of ant species and developed the algorithm called Ant Colony Optimization based on this technique. Ants leave pheromone trails that can be tracked by other ants and serve as markers of good paths. The constructive-greedy heuristic approach is used to find optimal paths in networks where ants interact with each other using their pheromone trails. The agent dynamically updates the weights of edges and nodes using a chance based probabilistic pheromone model. The algorithm iterateates the process to continuously update the paths, and the optimal path is selected from multiple generated paths.

[D. Karaboga (10)] has researched the Artificial Bee Colony algorithm, which is again metaheuristic-based algorithm which mimics honeybee behavior. The algorithm includes three types of bees: busy bee, unemployed bee, and scout bee. In nature, honeybee benefit from feedback about food sources to adapt and share knowledge. In the ABC algorithm, food sources represent feasible solutions, and the nectar amount is proportional to the fitness of the solution. Each category of bees performs specific operations, with a single unit assigned to scouts, employed bees, and spectators. The algorithm is able to escape the local optima and achieve a fast convergence rate.

[D. Simon (11)] did research on concept of biological evolution i.e., population-based evolutionary algorithm that iteratively improves mathematical functions and proposed solutions based on their fitness. The algorithm also incorporates a quality control technique. It demonstrates the ability as how to bypass local optima and achieve a fast convergence rate.

H. Shah-Hosseini [12] used the powerful Intelligent Water Droplet (IWD) algorithm to achieve rapid convergence while solving global optimization problems in WSNs. In the IWD algorithm, every water drop has a velocity and crosses the area where the water flows Interaction Ground Velocity and soil characteristics are determined by soil and the time required to get to the ground, travel by method, IWD consistently prefers areas with little soil. As every IWD is named, it creates quality solutions that are used to update quality solutions around the world.

The gravitational search algorithm (GSO) by E. Rashedi [13] that considers the active gravitational mass, location, passive GM and inertial mass (IM) for each object. the velocity of the object is controlled by the Gravitational Mass and Inertial Mass. The approach here is when all the objects try to get the heavier mass, which is considered as the best or optimal choice.

The Bat Algorithm, where bats change their wavelength and emission rate depending on their proximity to the target. Echolocation is used to determine their location, distinguishing between the loudness and intensity of pulses within a certain range. When bat echolocation is introduced with different pulse rates, a global optimization method was developed that is meta-heuristic. As the bat approaches the target location, the power, frequency of the pulse are adjusted. This was proposed by X. S. Yang [14].

The theory by A. Kaveh [15], the CSS algorithm, where the particles which are in the form of charge scattered arbitrarily. The rich charged particles attract the less charged particles and the poor charge particles attract the well charge particles. It is important to start with a careful exploration and gradually increase it. Identification of the global search space identifies the area where the optimal solution is likely to be found, and this region is then used.

M. Clerc [16] conducted a straightforward implementation of the PSO algorithm, enabling it to explore a lot of future solutions and gradually converge on a suitable one. Unlike other optimization algorithms that rely on gradients, the PSO algorithm searches for the best response within the search space of candidate solutions. It identifies the best-known solution by considering both the particle's previous best-known location and the swarm's most advantageous position.

Another researcher S. Goel [17] gave the Cuckoo Search algorithm, which utilizes random walk process to facilitate to meet rapidly and explore globally. In CS, each cuckoo egg is a new potential solution, and less potential cuckoos are gradually replaced by better ones over time. The surviving eggs is treated are passed down to next gradual iterations as a answer. The algorithm loops through the solutions in the search ing space, striving to enhance their quality iteratively. The primary aim is to generate novel and improved ideas, and their quality is assessed using an objective function typically optimized for maximization.

Again X. S. Yang [18] proposed an elastic flower pollination algorithm that integrates delivery flights. The algorithm incorporates both global and local pollination strategies, with cross-pollinators performing global and local pollination simulating local search. The reproductive success of flowers is determined by their flower similarity, allowing the most robust flowers to survive and reproduce optimally in terms of quantity and fitness. This iterative method combines local pollination and global pollination techniques to effectively determine the optimal solution.

A study on the Cuttlefish Optimization Algorithm by A. Sabry Eesa [19] , which incorporates the concept of reflection and visibility following the different layers of a fish. The visibility component emulates pattern matching, while reflection mimics the process of light matching. By using these mechanisms, the algorithm aims to hide the fish in its environment, in which the pattern that emerges representing the global optimal solution. The algorithm includes four solution groups, with the first two focusing on global exploration with a random element and the last two focusing on local search and solution comparison.

S. Mirjalili [20] presented the GWO, which aims to balance to explore and utilization. The algorithm uses alpha, beta, delta, and omega based on hierarchical structure of wolves. The three best solutions always guide the search towards the best possible area, where balancing exploration and utilization is crucial. The algorithm starts with a set of randomly generated solutions surrounding the prey and attempts to find the global optimum by navigating the search space. Mirjalili [21] emphasized exploration through global search, where each exploration attempts to find the best possible solution within the surrounding. The simulation updates a location vector to simulate the wolves' circumnavigation behavior, and the objective function determines the convergence behavior . The exploration of the search area for the most promising solution is based on the cyclic position of the search agents. An improved algorithm known as the improved artificial fish swarm mechanism by researcher S. Gao [22] presented an, which uses the swarming, hunting and random behavior to search for a mathematical function. The jumping behavior is influenced by the visual range, and swarming occurs only when the current function value exceeds the previous value. The algorithm iteratively updates the swarming behavior in search of the global optimum or optimal solution. The fish simulation behavior is implemented by a parallel random algorithm.

As new version of the Glow-worm swarm optimization algorithm by Y. Y. Hao [23] for better performance and convergence rate on multidimensional problems. A population of glowworms, each possessing the same amount of luciferin, is scattered throughout the search space. The position of the firefly tells the amount of luciferin, with brighter light indicating a higher luciferin levels. The glowworm's position is changed using a random method that depends on adjusting certain settings, and then its luciferin levels are updated.

A hybrid algorithm, Harmony Search Algorithm, based on Particle Swarm Optimization hybrid algorithm (PSOH) that considers the constraints of local area search and the exchange between exploration and exploitation. This combination achieves a quick search process to reach a favorable solution and extends the lifespan of the sensor by doing smart adjustments. Similarly, S. Su [25] gave a Genetic Algorithm and PSO hybrid approach for exploring scattered clustering layers in large-scale wireless sensor networks. This approach uses the Genetic algorithm at the lower level to perform global search in independent subgroups, while the PSO algorithm used for local search of individuals in higher level. Energy usage is reduced by this technique and helps increase in the speed.

LEACH algorithm was introduced by J. Kapoor [26] and integrated to the implementation of a Genetic Algorithm and Bacteria Foraging. This protocol aims to solve the limitations and drawbacks of traditional protocols. It was evident that the reduction in energy waste and increase the network lifetime.

A brand-new approach was introduced by combining GA, PSO and SOS which was based on the natural selection. The role of GA to create and select the best population, role of PSO is to gather, update for suitable solution. SOS builds on previous phases and performs update phases with symbiotic interaction within the population. This was presented by B. Farnad [27].

Another approach by S. Potthuri [28] with combination of Differential Evolution (DE) and Simulated Annealing (SA) came to the table which aimed to delay the consumption of cluster heads with the help of residual energy of cluster head and distance between the nodes. The main goal of this technique to increase the active nodes as these active nodes are directly proportional to network life.

One more approach came up with combination of firefly algorithm and particle swam optimization which was used inside LEACH -C algorithm for a better cluster head selection. Using this approach, global search process was faster using firefly, particle swam provided better selection of cluster head and the performance result showed increase in active nodes, energy which gave better performance. This was presented B. Pitchaimanickam [29].

Then new approach of algorithm came combining Grey Wolf Optimization with sunflower optimization technique where the best or optimal cluster head is selected considering energy consumption and distance between nodes. This technique was aimed to prolong the network life resulting the improved performance of parameters such as throughput, remining node energy, number of active and inactive nodes, network coverage. This theory was introduced by L. Nagarajan [30].

4 Examining Selected Bio-Inspired Algorithms: A Comprehensive Analysis

4.1Genetic Algorithm (GA)

John Holland was the first inventor of Genetic Algorithm in 1960. It is another version of heuristic algorithm which is used in modern concepts like machine learning and artificial intelligence. This algorithm uses the concept of natural process selection, its main purpose is to establish a global consensus for the optimization problem. In the context of genetic algorithms, two terms are used: "personal" and "population". While a person talks about the possibility of solving the problem, the public represents such a solution.

These contacts are found in the search area. Genetic algorithm uses various techniques such as initiation, selection, crossover and mutation to perform computations [31-33].

4.2Differential Evolution (DE)

Rainer Storm, Kenneth Price proposed Differential Evolution in the year 1997. From that time, Differential algorithm is mostly used in many fields such as engineering science, decision science, materials science, and energy. To wait. DE works as a population-based stochastic approach, where each solution is called a genome (chromosome). Chromosomes have mutation and recombination. Many terms are used in DE, including target, free, and orbital vector.

When all the trajectory vectors are generated, the algorithm chooses the optimal solution. Additionally, DE uses the desired selection of target vectors and trajectory vectors [34-36].

4.3PSO - Particle Swarm Optimization

In the year 1995, PSO algorithm, was originally introduced by J. Kennedy along with R. Eberhart. Swarm intelligence is the approach based on the combined behavior of movement of birds and animals, which is used to find the optimal solution to complex optimization problems. Swarm intelligence has two important characteristics: self-organized arrangement and task allocation among the members of the group. Self-organization involves local interactions between individuals without considering the global pattern. It includes elements such as positive and negative feedback, oscillations, and multiple interactions. Allocation of tasks or splitting the labor refers to the simultaneous execution of tasks by specialized member of the group. PSO utilize the concept of “profit from experience member of group”, the social behavior of group of birds or a group of fish, where each particle or bird has a position and a velocity. These particles can adjust their position by changing their speed to avoid enemy or find suitable environmental conditions. The flight experience of the particles or birds can influence the change in velocity of their group [37–39].

4.4ACO - Ant Colony Optimization

Marco Dorigo introduced a new algorithm called Ant Colony Optimization in 1992. Ant Colony is built concept that how the ant colonies or a big group of ants behave in complicated ways, in which the queen is the leadership role while the workers perform tasks such as foraging and defending the big ant group. The idea of ant colonies includes not just where they live, but also the rules they follow to work together and get tasks done. Ants navigate their environment effectively through cooperation, division of labor, and advanced communication systems. They are attracted to pheromone trails left by their conspecifics and show adaptability by quickly finding alternative routes when faced with obstacles. ACO is an optimization technique inspired by bio-semiotic communication among ants. In this method, every ant creates an affordable solution by using both of a heuristic function which does a smart guess and the path of pheromone trails, using a stochastic and greedy approach. ACO belongs to the category of SWO algorithms which is mostly used for graph search problems [40–42].

4.5ABC - Artificial Bee Colony

Back in 2005, Dervish Karaboga introduced an incredible algorithm called Artificial Bee Colony, which was based on the behavior of honeybees. Three key phases of ABC: the working, the observing, and the scouting bee phase, which monitors the movement of honeybees. The amount of busy bees matches to the count of food sources in busy phase. All solutions in this phase have the potential to generate new solutions. A partner, distinct from the current solution, is randomly selected. Probability values for all solutions are determined before the fence guest phase, similar to the fence guest phase. Solutions with higher fitness values hold a greater probability of success. A fitter solution can go through multiple iterations of the Onlooker phase.
In the Scout phase, the discarded solutions are used to set a predefined limit. When a specific iterations goes beyond the limit, the process enters the scouting phase and creates a new solution [10,43,44].

4.6GWO - Gray Wolf Optimization

Mirjaliali Mohammad and Lewis presented Grey Wolf Optimization as a meta-heuristic method In 2014. This innovative technique refers the way grey wolves interact and work together in their group and how they go about hunting for food. Grey wolves live in well-structured packs consisting of approximately 5 to 12 members. The pack members are categorized into four distinct groups: α-wolves, β-wolves, δ-wolves, and ω-wolves.
The α-wolves hold the leadership roles within the pack, making decisions regarding hunting, rest, activity hours, and other crucial aspects. The remaining members of the pack follow the lead of the α-wolves. The β-wolves, on the other hand, are the main contenders for the alpha position in the pack's second level. The δ-wolves play a vital role in gathering food and safeguarding the pack during times of danger. Occupying the bottom of the pack hierarchy are the ω-wolves, which consist of scouts, elders, and guardians. These ω-wolves often serve as scapegoats and are typically the last to partake in meals.

The hunting process of the GWO algorithm encompasses several crucial phases, including:

─ Searching for the food
─ Track, pursue, and approach the prey
─ Chase and bother their prey until it stops moving.
─ Engaging with the target prey [45–48].

5 Maximizing Results with Selective Bio-Inspired Hybrid Algorithms

Current metaheuristic methods have several limitations, such as slow convergence and limited accuracy. In recent years, researchers have increasingly focused on swarm intelligence algorithms. Because of their simplicity in nature, adaptability, non-derivative mechanism, and ability to avoid local optimality metaheuristic algorithms are used mostly. The rapid development of swarm intelligence algorithms reflects the characteristics and trends of scientific progress. In this research topic, we tried to investigate novel hybridization approaches for nature-inspired algorithms with the aim of increasing algorithm resilience and improving simulation analysis and statistical results.

5.1A Combined Approach of Genetic with Differential Evolution (GA-DE) Algorithm

Genetic Algorithm (GA) is effective in solving nonconvex and nonlinear prob-lems. GA uses several operators, including initialization, selection, and crossover. In GA-DE hybrid, the mutation process is done by differential evolution (DE), which is particularly suitable to solve the real world problems which lacks differentiation and continuity. The composite approach of GA-DE provides better global optimal solutions [49,50].

The design procedure for the algorithm GA-DE can be summarized as follows:

1. Selection of control variables for the sensor nodes.
2. Initialization of the population of sensor nodes.
3. Evaluate the fitness parameter of sensor nodes using the localization function.
4. Use the roulette wheel pairing method for selection.
5. Perform crossover operations with GA.
6. Apply mutation operation using DE.
7. For upcoming generation, selection of new population.
8. Steps four, five, six, and seven should be repeated.
9. Get the estimated location.

5.2GA with PSO Algorithm: A Hybrid Approach

The main purpose of hybrid approach of GA-PSO algorithm is to enhance the selection of cluster head and optimize the routing between the deployed sensor nodes and the base station node. The method consists of two steps. In the preliminary stage, the Particle Swarm

Optimization algorithm selects the best individual vector or member from the population. In the secondary phase, these best individuals are subjected to genetic operations such as selection, crossover, and mutation performed by the genetic operators. Through the combination of GA and PSO, hybridization leverages those strengths of two algorithms. As a result, convergence rate is better and the problem of local optima is better handled [51,52]. The main contributions of the two algorithms are summarized in Table 2.

Table 1. Contribution of GA and PSO algorithms

Algorithms	GA	PSO
Operators used	Selection, cross-over, mutation	Inertia, cognitive, social
Ability to search global optima	High	Low
Implementation	Complex	Simple
Trapped on local optimum	Occasional	Common
Computer efficiency	Moderate	High

This hybrid method takes the advantages of both algorithms by taking advantage of the fast convergence rate of PSO and overcoming the tendency of GA to get stuck in local optima. The main goal of this PSO-GA combination method is to gradually increase the number of good individuals across generations.
The algorithm GA-PSO follows the following design procedure:
- Initialization
- Generate initial population.
- Selection
- Crossover
- Mutation
- Propagation
- Generate next generation population.
- Repeat the above steps until the number of generations is reached or evaluated.

Small and Large networks use the hierarchical sensor network model used in PSO, GA and PSO with GA methodologies. In the hierarchical wireless sensor network structure, each cluster consists of a base station node and a relay node, where the relay node can serve as the cluster head. An assumption is that the base stations have the known information about routing paths and that the average data volume of each relay node. After each generation, the residue energy of each relay node is filled, and the current energy is used to determine the next routing path. For lager sensor networks, when compared the shortest path method, the PSO , the GA, and the hybrid PSO with GA approach, it was found that the hybrid PSO-GA strategy has the highest network lifetime and packet transmission rate.

5.3ACO with PSO Algorithm: A Hybridized Approach

The primary purpose of combining ACO and PSO approach is to enhance data aggregation between clusters in WSNs while increasing the overall network lifetime in comparison to alternative optimization strategies. With this strategy, ACO is responsible for localized updates, while PSO contributes more on better global results. There is a 6% positive improvement in network lifetime and performance compared to alternative optimization techniques such as ant colony optimization, cuckoo search, and flower pollination, when ACO with PSO combined approach is used.

The algorithm of ACO-PSO can be outlined as follows:
1. Begin by initializing the number of deployed wireless sensors in the network.
2. Incorporate the energy-level consideration in path selection process. If the energy level (E) of sensor node is greater than 0, proceed to the next step. Otherwise, repeat the process mentioned in step 2. Once a sensor node has sufficient energy, select a cluster head (CH) and proceed to get a new optimal path using ACO-PSO algorithm.
3. Based on the energy consumption of the sensor node, If a dead node is identified, evaluate it. Else, repeat the step 2 process. This step ensures that the algorithm considers the energy consumed by the sensor nodes and accounts for potential energy depletion issues.
4. The performance of the network is evaluated using different parameters to assess its efficiency and effectiveness.

By following this step-by-step procedure, the ACO-PSO algorithm can optimize the cluster head selection and the energy consumed in wireless sensor networks, ultimately improving network performance.

To improve data aggregation between clusters, a hybrid ACO-PSO approach is used. Extensive research shows and proves the proposed approach significantly extends the network lifetime compared to alternate methods and strategies. The wireless sensor network is divided into multiple clusters, with each cluster having a selected cluster head. Tree-based data aggregation, which uses short-distance links, retrieves sensor data directly from the cluster heads. There is reduction in size of the packets that transmit over the network by using the compressive sensor network. The shortest path between the sink nodes and the cluster nodes is determined by hybrid ACO and PSO algorithm Researchers normally use the MATLAB simulation software tool for simulations, facilitating the comparison of the proposed approach with established technologies like GSTEB. This comparison involves evaluating stability duration, network lifespan, average remaining energy (residual energy), and throughput to assess performance differences.

5.4The Integrated PSO-GWO Algorithm: A Hybridized Approach

The purpose of PSO and GWO combination is to get better optimal results using a fewer iteration. By using respective strengths of both algorithms which results in enhances efficiency. The advantages of this hybrid algorithm include simplicity, fast convergence, and high exploitability. Combining the strengths of PSO with the robust exploration capability of GWO, greater stability is achieved and improved performance with more optimal solutions is demonstrated [53-55].

The algorithm PSO-GWO is as follows:

1. Initialize the total population and the values of A, C, and a to their default settings.
2. Create the members or individuals for population.
3. Check the fitness of every member or individual.
4. Compute the values of α, β, and δ by arranging them in descending sequence.
5. Compute the parameters under nonlinear control to update the values of A and C.
6. Reevaluate the fitness values using the positions of the individuals.
7. Revise and update the values of α, β, and δ.

Although the PSO algorithm approach is commonly used to solve real-world problems, we need to take preventive steps so that the algorithm does not struck in small and local solutions. GWO algorithm is introduced to avoid this and to support the PSO algorithm. By using the exploration capability of GWO, certain particles are directed to positions enhanced by the GWO method instead of random positions. Incorporating the GWO method alongside PSO increases the runtime of the algorithm. The algorithm PSO-GWO includes nonlinear control parameters that address the inadequacy of the control parameters of other algorithms. This guarantees a more even combination of local and global search capabilities, lowering the chances of getting stuck in specific solutions during the search.

6 Exploring Recent Literature: A Comparative Analysis

We conducted a comprehensive analysis of various methods and standards mentioned in recent papers for cluster head selection [56]. The evaluation encompassed a range of metrics, including data packet loss, network lifetime, energy utilization, throughput, delay, and overhead. Data packet loss refers to the failure of one or more data packets to reach their actual destination. Network lifetime is determined by factors such as the number of live nodes, connectivity, and sensor coverage. The assessment of energy in Wireless Sensor Networks (WSNs) is based on the energy consumed by packets received at the destination. Throughput represents the efficient transmission or reception of actual information over a communication channel. Delay measures the time taken for packets from sensor nodes to reach the sink and is directly related to the number of hops. Overhead quantifies the total energy consumed for data transmission within a specific time frame.

By considering these metrics, we gained valuable insights into the performance and suitability of different methods for cluster head selection.

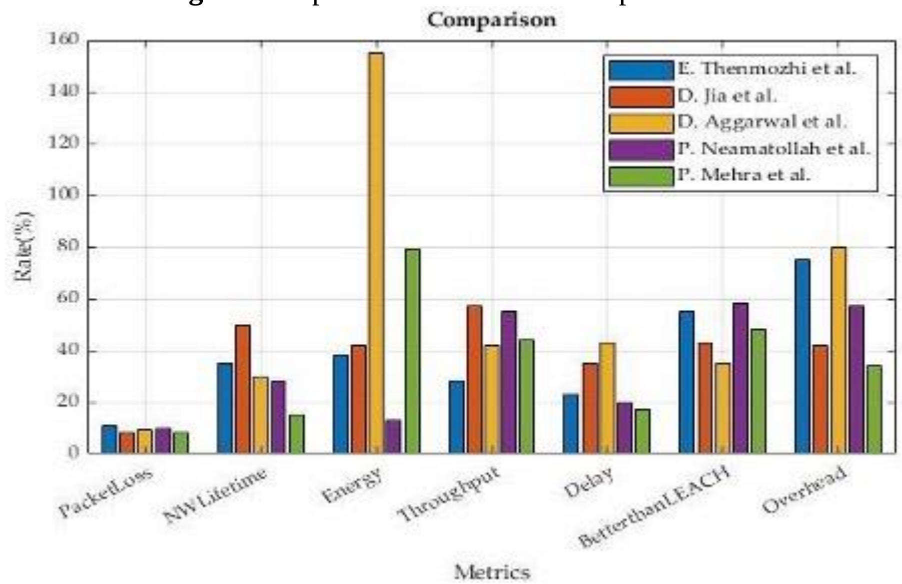
Table 2. Comparative Analysis of Conclusions in Recent Literature

Comparative Analysis of Conclusions in Recent Literature							
Reference	**Utilized Parameters**	**Methodology and Tools Utilized**	**N/W Life**	**Energy Efficiency**	**QoS increased**	**Security**	**Outcomes /Results**
	Residual energy, node's capability						
Thenmozhi et al. [57	Compactness of assembly and node gradation	MATLAB	√	√	√	X	"The overall delay experienced a reduction of 23%. The rate of packet loss saw a decrease of 11%. There was an improvement of 38% in residual energy."
Jia et al. [58]	Coverage Area, Lifespan Rotation, Dynamic Nodes, Average Remaining Energy.	MATLAB	√	√	X	X	In comparison to LEACH and DEEC, network lifespan increased by 50% and 30%, respectively. Clustering overhead was reduced by 42%.
Aggarwal et al. [59]	Distance from the sink, Longevity of Energy, Concentration of Sensor Nodes.	MATLAB	√	√	X	X	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]	Remaining energy, varying levels of sensor response node, distance SNs to BS.	MATLAB	√	√	X	X	Network lifetime increased by 28%. Clustering overhead was reduced by 57%. Energy usage was reduced by 13%.
Mehra et al. [61]	Remaining power, base station's remoteness, concentration of the SNs.	MATLAB	√	X	X	X	Compared to LEACH, network lifetime increased by 15%, 11.38% for BCSA and 8.1% for CAFL. Energy savings increased by 79%.
Jeong et al. [62]	Concentration, centrality, overhead, average delay	MATLAB	√	√	X	X	Compared to LEACH, performance and local distance increased by 42.7%.
Krishna et al. [63]	N/w lifetime, throughput, distance between SN to CH, number of neighboring nodes	MATLAB	√	√	X	X	On average, left overheads and live nodes improved by 62%. Overall, this is a 45% improvement over LEACH.

Azad et al. [64]	Residue energy, the path taken from one sensor node to the sink, and the count of neighboring nodes	MATLAB	√	√	√	X	TOPSIS extends the network lifespan by 151.2% compared to LEACH, demonstrating an overall improvement of 40% over LEACH.
Behra et al. [65]	Coverage of the network, the total count of sensor nodes, entire network energy consumption, energy degeneracy.	MATLAB	√	√	√	X	Packet loss rate has decreased 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	√	√	X	X	In contrast to LEACH's 19% figure, there's a 5% rise in energy consumption. Additionally, the count of active nodes with extended lifespans has increased.

In this analysis, the researchers employed various deterministic and probabilistic strategy. It looked successful in improving network longevity and energy efficiency. However, they showed significant shortcomings in improving quality of service (QoS) and security. Figure 4 shows a comparison of the different WSN parameters which was used for analysis.

Fig. 4.: Comparison of different WSN parameters



7 Open Issues and Challenges

7.1Network Robustness

The availability of working sensors decides how long the network will continue to work. Because of processing constraints and capacity of the nodes, it becomes a challenging task to optimize the transmission cost, data collection, withstand the workload to prolong their operational lifespan. The clustering optimization, which selects the most energy-efficient path for routing, can significantly contribute to extend the network lifetime [67].

7.2Unveiling the Dynamic Nature of the Network

Sensor nodes are traditionally considered static by many researchers. However, it is critical to address the dynamic nature of wireless sensor networks (WSNs) due to various factors, such as varying network sizes, sensor node mobility, topology changes, and unforeseen operational issues. In certain scenarios, even node or sink mobility can be challenging, requiring clusters to dynamically adapt and evolve over time [68].

7.3 Secure Data Transmission

The Cluster Head (CH) assumes the responsibility of collecting and aggregating data in WSNs. As clustering involves capturing highly sensitive data from potentially hostile environments, it is imperative to ensure that the data is transmitted securely without any malicious intent, tampering, or unauthorized modifications. Safeguarding the network from hostile attacks is of utmost importance, and it is crucial to employ robust authentication procedures. WSNs are susceptible to various types of attacks involving denial of service and data manipulation, which can lead to disconnection of nodes, Cluster Heads, or even the entire network [69, 70].

7.4 Continual replacement of dynamic cluster heads across iterations

Cluster head rotation (CH) was often overlooked. However, recent studies have recognized the importance of accounting for CH rotation by considering the required parameters such as capture rate and remaining energy. This is especially important in challenging and hazardous environments where sensor node failure is possible. Sensor node malfunctions can lead to inaccurate acquisition results, incorrect data processing, and improper data transmission. Investigation on Cluster Head rotation aims to address these issues, but also brings the concern that the overall network lifetime may be reduced [71].

7.5 Improvement in QoS

Wireless Sensor Networks (WSNs) serve as the foundation for advanced technologies such as the Internet of Things (IoT) and the Internet of Everything (IoE). These technologies heavily depend on the quality of experience (QoE) and quality of service (QoS) as essential prerequisites. However, when it comes to selecting Cluster Heads (CH) in WSNs, critical criteria such as bandwidth, response time, end-to-end delay, throughput, and reliability are often overlooked or given minimal consideration. Consequently, for cluster-based protocols in real-time IoT applications, it becomes imperative to consider and prioritize these QoS characteristics to ensure optimal performance and user satisfaction [72].

7.6 Inter-CH and CH-SN Distance Analysis

The energy consumption of individual members of a wireless sensor network (WSN) is affected by the position and placement of the cluster head (CH) within a zone. Clusters with a larger intra-cluster distance tend to consume more energy compared to clusters with a smaller intra-cluster distance. It is important that a clustering method takes this factor into account and forms clusters such that the intra-cluster distance is smaller than the inter-cluster distance [73, 74].

8 Conclusion

The intention of this study was to conduct a thorough examination of bioinspired hybrid optimization algorithms with the aim of enhancing the energy efficiency of wireless sensor networks (WSNs). A wide range of advanced and new techniques based on bioinspired optimization algorithms have been suggested to tackle different challenges in WSNs, including data aggregation, sensor placement, routing, and coverage area. The main focus of our research was to search and contrast the latest hybrid and conventional approaches used in the development of resilient and energy-efficient WSNs, while taking into account important parameters such as packet loss, energy consumption, throughput, delay, and overhead.

In this review, we have also addressed some outstanding problems and obstacles in designing WSNs using bio-inspired optimization techniques. These include network stability, the dynamic nature of networks, secure transmission, and methods for improving quality of service (QoS). It is evident that further investigation and extensive experimental work in this research area is critical to develop resilient and energy-efficient WSNs.

By leveraging the potential of bio-inspired optimization techniques, we can pave the way for innovative solutions that optimize energy consumption, enhance network performance, and tackle the complex requirements of modern WSN applications. This review serves as a foundation for future research and serves as a guide for scholars and professionals in the domain of Energy-Efficient WSNs.

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