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ARTICLE

Accelerated Particle Swarm Optimization Algorithm for Efficient Cluster Head Selection in WSN

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ABSTRACT

Numerous wireless networks have emerged that can be used for short communication ranges where the infrastructure-based networks may fail because of their installation and cost. One of them is a sensor network with embedded sensors working as the primary nodes, termed Wireless Sensor Networks (WSNs), in which numerous sensors are connected to at least one Base Station (BS). These sensors gather information from the environment and transmit it to a BS or gathering location. WSNs have several challenges, including throughput, energy usage, and network lifetime concerns. Different strategies have been applied to get over these restrictions. Clustering may, therefore, be thought of as the best way to solve such issues. Consequently, it is crucial to analyze effective Cluster Head (CH) selection to maximize efficiency throughput, extend the network lifetime, and minimize energy consumption. This paper proposed an Accelerated Particle Swarm Optimization (APSO) algorithm based on the Low Energy Adaptive Clustering Hierarchy (LEACH), Neighboring Based Energy Efficient Routing (NBEER), Cooperative Energy Efficient Routing (CEER), and Cooperative Relay Neighboring Based Energy Efficient Routing (CR-NBEER) techniques. With the help of APSO in the implementation of the WSN, the main methodology of this article has taken place. The simulation findings in this study demonstrated that the suggested approach uses less energy, with respective energy consumption ranges of 0.1441 to 0.013 for 5 CH, 1.003 to 0.0521 for 10 CH, and 0.1734 to 0.0911 for 15 CH. The sending packets ratio was also raised for all three CH selection scenarios, increasing from 659 to 1730. The number of dead nodes likewise dropped for the given combination, falling between 71 and 66. The network lifetime was deemed to have risen based on the results found. A hybrid with a few valuable parameters can further improve the suggested APSO-based protocol. Similar to underwater, WSN can make use of the proposed protocol. The overall results have been evaluated and compared with the existing approaches of sensor networks.

KEYWORDS

Wireless sensor network; cluster head selection; low energy adaptive clustering hierarchy; accelerated particle swarm optimization

1 Introduction

Wireless Sensor Networks (WSNs) are comprised of many sensor nodes and at least one Base Station (BS). The four essential components of WSN power supply, communication, processing & sensing make up a sensor node's autonomous operation [1–3]. These sensors' primary job is to gather environmental data and transfer it to the BS, which is typically connected to the wired world [3]. The Information is subsequently processed, examined, and delivered to applications employed in various spheres of life in the modern era of technology. WSNs can be crucial in linking the real and virtual worlds by establishing this processing and communication in the physical world [4]. The wireless sensor system comprises the sensor node, cluster head, and sink node. A radio transceiver, another wireless communication device, an energy supply, a smaller microcontroller, and occasionally a battery are often provided to each node in the sensor network, affordable and power-saving sensor nodes that cooperate to build a network for monitoring the target region [5,6]. WSN gathers the necessary data and provides various sorts of evidence about the monitored environment of the sink node [7,8].

In a WSN, the CH problem refers to the challenge of selecting appropriate cluster heads among the sensor nodes in the network. CHs are responsible for aggregating data from their member nodes, performing data processing tasks, and transmitting the aggregated data to a base station or a higher-level node in the network. The selection of CH is crucial in WSNs because they play a significant role in energy efficiency, network scalability, and data aggregation. The main objectives in solving the CH problem are to achieve load balancing, prolong network lifetime, and ensure efficient data routing and aggregation. Some approaches exist to solve the CH problem in WSNs, such as Static Cluster Head Selection, Dynamic Cluster Head Selection, Distributed Cluster Head Selection, Hierarchical Cluster Head Selection, and Machine Learning-Based Approaches. The choice of approach depends on the specific requirements and constraints of the WSN application. When selecting a CH solution, it is important to consider factors such as energy efficiency, network scalability, data aggregation requirements, and network dynamics. APSO can address the CH problem in WSNs by optimizing the selection of CHs based on specific objectives and constraints [9]. Some general approaches to solving the CH problem in WSNs using APSO include Define the Optimization Objective, Formulate the Particle Representation, Define the Fitness Function, Initialize the Particle Swarm, Evaluate Fitness, Update Particle Positions and Velocities, Repeat Evaluation and Update, and Extract the Best Solution. It is important to note that the specific implementation details of APSO for solving the cluster head problem may vary depending on the objectives, constraints, and specific requirements of the WSN application. The choice of fitness function, particle representation, and update equations should be tailored to the problem. Furthermore, APSO can be enhanced or combined with other techniques, such as local search mechanisms, constraint handling strategies, or adaptive parameter control, to improve the optimization process further and achieve better results.

WSNs are widely used in various applications, including environmental monitoring, surveillance, and healthcare. However, one of the key challenges in WSNs is energy efficiency since limited-capacity batteries typically power sensor nodes. To address this challenge, researchers have proposed several techniques and mechanisms to reduce energy consumption, maximize throughput, and extend the network lifetime. Here is a discussion of some of the existing works in these areas.

Energy-Efficient Routing Protocols: Routing protocols play a crucial role in WSNs as they determine how data is forwarded from source nodes to the sink. Many energy-efficient routing protocols, such as LEACH (Low-Energy Adaptive Clustering Hierarchy), have been developed. These protocols employ techniques like data aggregation, clustering, and dynamic clustering to reduce energy consumption by minimizing the amount of data transmission and maximizing the use of sleep modes.

- Duty Cycling: Duty cycling is a technique where sensor nodes alternate between active and sleep states. In the active state, the nodes perform sensing, processing, and communication tasks, while in the sleep state, they conserve energy by turning off unnecessary components. Synchronization mechanisms are used to ensure nodes wake up and sleep at the same time, reducing idle listening and collisions.
- Data Aggregation and Compression: Data aggregation techniques aim to reduce redundant data transmission by merging and summarizing data at intermediate nodes before forwarding it to the sink. This reduces the number of transmissions and hence saves energy. Similarly, data compression techniques are employed to reduce the size of the data to be transmitted, thereby reducing energy consumption.
- Energy Harvesting Techniques: Energy harvesting techniques involve capturing energy from the environment, such as solar, wind, or vibration energy, to power the sensor nodes. By integrating energy harvesting mechanisms into WSNs, nodes can replenish their energy and extend their operational lifetime without relying solely on batteries.
- Cross-Layer Optimization: Cross-layer optimization techniques consider the interactions between different layers of the protocol stack to achieve energy efficiency and maximize throughput. By jointly optimizing parameters such as routing, medium access control, and physical layer parameters, these techniques can reduce energy consumption and enhance network performance.
- Sleep Scheduling: Sleep scheduling involves dynamically determining the sleep/wake-up schedule of sensor nodes to balance energy consumption and coverage requirements. By intelligently scheduling sleep periods, nodes can conserve energy while maintaining network connectivity and data collection capabilities.
- Energy-Efficient MAC Protocols: Medium Access Control (MAC) protocols control access to the shared wireless medium and play a vital role in energy efficiency. Various MAC protocols, such as SMAC (Sensor MAC) and TDMA-based protocols, have been proposed to reduce energy consumption by optimizing the node's active and sleep periods and minimizing idle listening and collisions.

When a CH is turned to be arbitrary, the energy consumption must be evenly distributed [10]. A WSN deals with several applications, such as military, health, and environmental monitoring [11,12]. WSN comprises a specific number of sensor nodes implemented in a fixed region with the connection of the significant node called CH (sink). Energy consumption and network lifetime are the two essential aspects that arise in WSNs when designing a convenient routing protocol model [13–15]. The main drawback of WSNs is their low energy usage because each sensor node only has a fixed range of energy that is exceedingly challenging to replace or recharge. The researchers have proposed various approaches to design a scheme that conserves the node's energy [16–19].

The motivations behind choosing an APSO approach for CH selection in WSNs are stated as follows: In WSNs, CH-based protocols are commonly used to enhance energy efficiency and network scalability. The CH selection process plays a crucial role in balancing the energy consumption among sensor nodes and prolonging the network lifetime. Traditional approaches for CH selection, such as random selection and fixed metrics, may not always result in optimal solutions. APSO is a variant of the Particle Swarm Optimization (PSO) algorithm that is specifically designed to improve convergence speed and solution quality. APSO incorporates acceleration coefficients to enhance the algorithm's exploration and exploitation abilities. It has been widely applied in various optimization problems due to its efficiency and effectiveness. The motivation behind choosing APSO for cluster head selection in WSNs is to leverage its capabilities to find near-optimal solutions quickly. By applying APSO, the algorithm can efficiently explore the solution space and identify the optimal cluster heads based on specific objectives, such as energy efficiency or network lifetime maximization. APSO can adaptively adjust the acceleration coefficients to balance the exploration and exploitation trade-off, leading to improved convergence speed and better-quality solutions. Overall, the motivation for selecting an APSO approach for CH selection in WSNs is to leverage its efficiency, effectiveness, and ability to find near-optimal solutions quickly, thereby enhancing energy efficiency, maximizing throughput, and extending the network lifetime in WSNs. APSO is a metaheuristic optimization algorithm that is used to solve complex optimization problems. It is an extension of the traditional PSO algorithm, specifically designed for WSNs. APSO incorporates several novel features that contribute to the existing body of knowledge in WSNs. The discussions of these aspects are given as follows:

- Velocity Updating Mechanism: APSO introduces a novel velocity updating mechanism that enhances the algorithm's exploration and exploitation capabilities. In traditional PSO, the velocity of particles is updated based on three components: the current velocity, the cognitive component (based on the particle's best position), and the social component (based on the global best position). APSO extends this mechanism by introducing an acceleration term that allows particles to move faster toward promising regions in the search space. This acceleration term is computed based on the particle's historical best position, which helps accelerate convergence and improve the overall search performance.
- Adaptive Inertia Weight: In PSO, the inertia weight controls the balance between the global and local exploration of the search space. APSO introduces an adaptive inertia weight scheme that dynamically adjusts the weight during the optimization process. This adaptation is based on the fitness values of the particles, allowing the algorithm to fine-tune the exploration and exploitation trade-off based on the problem characteristics. This adaptive mechanism enables APSO to handle different types of WSN optimization problems effectively.
- Hybrid Initialization Strategy: APSO incorporates a hybrid initialization strategy that combines random initialization and deterministic initialization. In WSNs, the initial positions of particles have a significant impact on the convergence behavior and solution quality. APSO addresses this by randomly initializing a portion of the particles and deterministically initializing the remaining particles based on problem-specific knowledge or heuristics. This hybrid approach leverages both exploration and exploitation to improve the algorithm's performance in WSN optimization.
- Local Search Mechanism: APSO integrates a local search mechanism to refine the solutions obtained by the particle swarm. After the global exploration and exploitation phases, APSO performs a local search around the best particle's position. This local search helps to fine-tune the solutions and overcome local optima. The specific local search method can vary depending on the problem domain, but common techniques include gradient-based optimization or local neighborhood search.

Application to Wireless Sensor Networks: APSO is specifically designed to solve optimization problems in wireless sensor networks. WSNs pose unique challenges due to resource constraints, dynamic network topologies, and energy limitations. APSO takes these factors into account and incorporates mechanisms to address them effectively. By considering the specific characteristics of WSNs, APSO aims to improve the network performance, energy efficiency, coverage, connectivity, and other relevant metrics. The novelty of APSO lies in its unique features, such as the velocity updating mechanism, adaptive inertia weight scheme, hybrid initialization strategy, local search mechanism, and its application to WSNs. These contributions enhance the algorithm's ability to handle optimization problems in WSNs and improve the overall performance and efficiency of the network. APSO expands the existing body of knowledge by providing a specialized optimization approach tailored to the unique requirements and challenges of WSNs. The scheme's issue has solely been the energy usage of the nodes and distance. The CH node could be chosen randomly to be far from the BS. The network is thus burdened by this cluster head, which reduces throughput while increasing routing overhead and energy usage. The network's lifespan can be improved with the least minor energy consumption and delay by choosing the optimum Cluster Head [20]. Therefore, a routing technique that uses less energy must be proposed for CH selection. The following contributions and motivations have been taken into consideration:

- To study the different routing models for improvements in lifetime and reducing energy consumption in WSN.
- To propose a clustering-based approach for WSN by targeting the APSO algorithm.
- To suggest an APSO-based LEACH protocol that chooses a suitable node as a CH to increase the network's lifetime.
- To evaluate the APSO algorithm's performance, contrast it with LEACH, NBEER, CEER, and CR-NBEER techniques regarding throughput, energy usage, and network lifetime.
- To further evaluate the proposed work with additional sensor routing protocols for checking the performance.
- To increase or decrease the number of nodes and to examine the node's performance.

The rest of this paper is structured as follows: The basis of our literature review is described in Section 2. The research's methodology is presented in Section 3. Our technique for efficient cluster head selection in wireless sensor networks using an APSO algorithm is described in Section 4. In Section 5, the experimental design and analyses are described. It brings the report to a close and suggests some additional research.

2 Related Work

This section elaborates and highlights the discussions of the existing state-of-the-art solutions. Most of the related works are presented here, as well as the concept and terminologies of the APSO and its features. It also discusses the main challenges and issues in WSN, especially when selecting the CH nodes. The majority of the authors have published their works in WSN for the best CH selection, and the work that is being proposed is the solution for the problems and issues in WSN.

Yang et al. [21] discovered that every business activity aims to increase the performance and profitability of the delivered services and end product. Because of this, company optimization becomes a crucial topic for these kinds of commercial activity. The support vector machine and metaheuristics have made significant progress and have several benefits. PSO, which can resolve challenging optimization problems, is one of the most important. Yang et al. used an upgraded Accelerated PSO and a non-linear Support Vector Machine (SVM) to tackle the business optimization problem. Initially employed for production optimization, the APSO-SVM has since been used for project scheduling and future forecasting. The parametric analysis and the suggested metaheuristic SVM were both carried out similarly. According to [22], WSNs are an emerging technology in various industries. A need of life is this technology. According to [23], a routing protocol must meet several criteria to support wireless sensor networks' distributed and dynamic architecture. A routing protocol is essential in WSNs to achieve a particular goal, such as greater network lifespan and power efficiency. Ensure efficient data transfer network connectivity and maximize network lifespan to create a better routing protocol.

When attempting to improve WSNs, it was discovered in [24] that modern, cutting-edge developments in digital electronics, wireless communication, and micro-electro-mechanical systems improved WSN performance. Information interchange across wireless sensor nodes was made possible by routing protocols and several other techniques. These communication techniques underpin the entire performance of WSNs. Based mostly on network structure, three classes of routing protocols were established. Geographical location, data-centric, and hierarchical routing techniques make up these groups. Due to clustering-based routing, clustering technology spirals into a dynamic path in communication. In WSNs, the most active area of research is power consumption. Geographic position protocol requires a wireless sensor network with high throughput and low power consumption. According to [25], the clustering mechanism in WSNs is a hot area of study for wireless networks. The node's location in the network can determine whether a cluster forms, as can several performance indicators. The cluster's nodes can be homogeneous or heterogeneous. An objective function is suggested in the suggested approach, and the function named objective function is used to build the Bat Algorithm (BA). The BA is used to calculate the distance between sensor nodes. The network's clustering is then done using distance. The outcomes of the suggested strategy are then contrasted with those of the fundamental algorithm. The results compared performance metrics such as residual energy, end-to-end delay, and network throughput while verifying the technique.

In [26], these authors concluded that the applications make wireless sensor networks an appealing research area. Tiny sensors can analyze and identify wireless broadcasts that are part of how WSNs operate. The fundamental challenge for a WSN is to provide a clustering protocol that is power efficient. The usage of clustering protocols improved the network lifespan. The biggest issue with clustering techniques was CH choice. Expert cluster design was presented for improved WSN performance. Their proposed method outperformed the current procedures in terms of performance. According to [27], energy preservation is the main issue with wireless sensors. Because of their inherent nature and variety of applications, all WSN nodes require a certain power that is challenging to change.

Sensors in wireless sensor networks communicate with one another using several hops. The node's primary task is to acquire the data from the surroundings and transmit it via cluster to the BS for further evaluation. In cluster-based routing protocols, a node's function is switched every cycle for load balancing. This study recommended an RF-LEACH routing protocol that divided the network into clusters using CH selection and an RFCM with fuzzy logic as its foundation. The proposed method was effective compared to additional methods such as Fuzzy LEACH, FCM LEACH, and Fuzzy LEACH regarding load-balancing, increased network lifetime, and throughput. In [28], the most significant issue with wireless sensor networks was network longevity, developed through energy conservation. Three cluster heads were chosen for each cluster in a modified version of the k-means technique used for clustering. CHs employ a load distribution technique to switch out their role as the active CH to maximize network performance while conserving the sensor's energy. Due to its numerous cluster structures, the suggested technique performed better than existing clustering algorithms. According to [29], the proposed method's efficient routing configuration was the essential element that increased the wireless network's battery-operated lifetime. The sensors' power was constrained and unaltered to reduce energy utilization, which impacts network longevity. The diversity of the traffic and its impact on routing protocols were investigated. The study field included the sensor, power use, and connection heterogeneity. Diverse WSNs were not the main emphasis of traffic creation. There is a space for research there. Hierarchical clustering-based routing techniques were used in the research. An improved cluster head method was proposed in this paper to address traffic diversity. According to [30], this paper's advancements in wireless sensor networks focus on building small, multipurpose, low-power, and fast sensor components. WSN routing conundrums are handled at the network layer. Energy is the primary factor to be examined because radio communication consumes electricity. Energy supervision was a fundamental flaw with WSN. The network's major, most critical issue is with power. Power was necessary for sensors to function since it allowed them to do their jobs until more power was needed. Applications for many types of sensors were powered by ambient energy, which was the defining technology. It was suggested in this paper that MIEEPB would perform better than MODLEACH.

In [31], the network lifetime and energy consumption are major issues in WSNs. A Multi-Objective BA (MOBA) is used for the model routing and best cluster development in the WSNs. It chooses the appropriate node in the WSNs' energy efficiency. The energy usage is maximized by modeling the entry-linked distance and selecting the best node with the bat's noise parameter. This solution takes advantage of the LEACH clustering methodology, which extends the life of the WSNs and improves stability. By comparing the LEACH, the results generated using this method demonstrate the accuracy and conversion rate. As a result, various characteristics, such as throughput, energy consumption, and longevity, are used to analyze the effectiveness of the suggested strategy. The suggested method accomplishes this by choosing the most appropriate node, CH, and optimizing the WSN, which reduces energy usage and improves network lifetime and throughput. The energy efficiency of the WSNs is increased by following this protocol for all processes.

In [32], clustering is one of the finest techniques for reducing energy usage in WSNs. However, when hierarchal cluster-based WSNs are employed, they have some fundamental flaws, including the high and excessive energy consumption required to gather data from related sensor nodes and transfer upgraded data to the near BS. With these restrictions in mind, CH choices are vital in saving the sensor node's energy and prolonging the WSNs' lifetime. Based on PSO, the PSO-ECH algorithm is employed to resolve this problem. The fitness function and particles are both encoded by this approach. The protocol's characteristics are considered to determine the energy-efficiency distance between the cluster's energy from the sensor nodes and the sink's distance. Non-CH sensor nodes are considered when joining the CH depending on the obtained weight function. The suggested algorithm, which alters the number of CH and sensor nodes, has been used in various WSN scenarios. The generated outcomes were then contrasted with the present algorithms to prove the superiority of the new approach. These methods lead to the proposal of the CH, which uses PSO as the foundation for an effective function and effective particle depiction. The energy efficiency of a node, the distances to the sink, and the distances between the CHs are chosen for energy efficiency. The function of the weight is determined from these cluster development factors. The efficiency of the suggested algorithm has been demonstrated to be superior to the existing algorithm based on lifetime, energy consumption, and throughput by comparison with additional algorithms such as LDC, PSO-C, LEACH-C, E-LEACH, and LEAACH.

According to [13], sensor nodes in WSNs are dispersed randomly throughout their territories. Storage, power, and memory limitations were the sensor's key problems and storage space restrictions. The component of CH that provided consistently steady power in cluster-based protocols was the spin after each cycle. The cluster-based protocols were the main focus of this effort. LEACH extended the wireless sensor network's lifespan and improved performance. In this paper, a novel protocol named Node Ranked LEACH was proposed. The node rank algorithm enhanced the network lifespan. This technique chooses the CH for each cluster's connectivity and pathway speed between sensors. The proposed approach outperforms the arbitrarily selected method. This study made the case for improved performance when utilizing node-ranked-LEACH instead of LEACH. According to [33], this research advocated that advancements in wireless sensor networks focus on building small, multipurpose, low-power sensor components. The study of WSNs has become much more focused due to technological advancements. These nodes were arranged into a group known as a cluster, which gathers data from the place where it was deployed. Information from the cluster is used to interconnect with the BS. Communicating the information to CH takes much work. The LEACH was chosen for this task after being chosen by CHs based on doorsill value. Power efficiency has effectively increased the total distance and metrics of neighbor nodes by the LEACH. Energy and working nodes are counted using distance measurements. The evaluations demonstrated that the proposed model has enhanced performance compared to the present methods. See the proposed strategy for the sensor nodes installed arbitrarily in certain locations [34]. Nodes were key components in wireless sensor networks. These nodes had finite energy, storage, and computational capabilities. Because WSN energy is limited, it is necessary to build better routing protocols to increase energy utilization and improve network lifetimes. EECRP protocol was designed to improve network proficiency.

According to [19], the LEACH protocol's descendent should be used in single- and multi-hop scenarios. Numerous studies relating to the LEACH procedure have been conducted. This project included 60 LEACH protocols discussed and debated, including multi-hop and single-hop communication. Additionally, many factors were discussed, including overheads, scalability, and energy efficiency. Regarding LEACH changes, the development of the basic LEACH technique was noticeable. The primary goal of the newly developed protocol in WSNs was power efficiency. According to [35], sensor technology is vital in making the current systems smarter and easier to use. The WSNs have many sensors that can sense objects, perform calculations, and transmit data using radio frequencies. WSNs use communication technologies constantly in the modern day. Because of their flexibility, WSNs are simple to connect and create larger networks. It has a wide range of uses in communication from one location to another. Although it has several issues, the battery power is the most prominent. A hybrid protocol based on LEACH and additional clusters, such as LEACH-SOFM, LEACH-LVQ, and LEACH-FUZZY, is created to solve this issue. In comparison to the other two methods, LEACH-FUZZY produces great outcomes.

People who use communication technologies can employ WSNs anywhere in the globe. The IoT's WSNs hold the key. It has a huge impact on communication and a variety of uses. It is usually difficult to reduce energy usage; hence, LVQ, SOFM neural networks and FUZZY-C are used. In terms of applicability, all of these methods relate to LEACH. LEACH-FUZZY is the ideal choice in this instance because the goal is to increase lifetime.

In deployed WSNs, efficiently transmitting Information collected by sensor nodes with limited energy is a challenging problem. An appropriate cluster head selection strategy can efficiently solve this problem, but many factors must be considered, such as energy consumption, the coverage of cluster head nodes, and the number of cluster head nodes. Each factor profoundly impacts the performance of wireless sensor networks, and conflicts exist among them [36]. This paper proposes a Binary Multi-Objective Adaptive Fish Migration Optimization (BMAFMO) algorithm. The algorithm introduces the Pareto optimal solution storage strategy to improve the global search ability of the optimization algorithm and transform the continuous solution into a binary solution according to the sigmoid transformation function to solve the problem of cluster head node selection. The new algorithm was comprehensively tested using eight test problems and four test metrics. At the same time, the algorithm's reliability is tested by the rank sum test. The test results show that the BMAFMO algorithm obtained the best results in 78.13% of test problems compared with other algorithms. Finally, the BAMFMO algorithm is applied to solve the cluster head selection problem of WSN, and the simulation results show that the novel algorithm has better optimization ability than other heuristic algorithms [37,38].

The IoT and industrial IoT play a significant role in today's world of intelligent networks, and they essentially use a WSN as a perception layer to collect the intended data [39]. This data is processed as Information and sent to cloud servers through a base station; the challenge here is the consumption of minimum energy for processing and communication [40,41]. The dynamic formation of cluster heads and energy-aware clustering schemes help improve the lifetime of WSNs. In recent years, grey wolf optimization (GWO) has become the most popular feature selection optimizing, swarm intelligent, and robust metaheuristics algorithm that gives competitive results with impressive characteristics. Despite several studies in the literature to enhance the performance of the GWO algorithm, there is a need for further improvements in feature selection, accuracy, and execution time [42]. In this paper, they have proposed an energy-efficient cluster head selection using an improved version of the GWO (EECHIGWO) algorithm to alleviate the imbalance between exploitation and exploration, lack of population diversity, and premature convergence of the basic GWO algorithm. The primary goal of this paper is to enhance the energy efficiency, average throughput, network stability, and network lifetime in WSNs with an optimal selection of cluster heads using the EECHIGWO algorithm. It considers sink distance, residual energy, cluster head balancing factor, and average intra-cluster distance as the parameters in selecting the cluster head. The proposed EECHIGWO-based clustering protocol has been tested regarding the number of dead nodes, energy consumption, operating rounds, and average throughput. The simulation results have confirmed the optimal selection of cluster heads with minimum energy consumption, resolved premature convergence, and enhanced the network lifetime by using minimum energy levels in WSNs. The proposed algorithm, there is an improvement in network stability of 169.29%, 19.03%, 253.73%, 307.89%, and 333.51% compared to the SSMOECHS, FGWSTERP, LEACH-PRO, HMGWO, and FIGWO protocols, respectively [43,44].

In WSNs, sensors are deployed in a specific region to sense the environment's physical parameters. After sensing, data is processed and sent to the base station through a given route. Sensing and transmitting nodes consume much energy; hence, nodes die quickly, and hot spot problems occur. Henceforth, data transmission is done by a single route; thus, WSNs experience network overhead problems. Nowadays, the enhancement of WSNs' energy remains a challenging issue. Alternatively, efficient processes such as routing or clustering may be improved. Dynamic cluster head selection can be considered a vital decision approach for optimal path selection and saving energy. This paper proposed a meta-heuristic optimized cluster head selection-based routing algorithm for WSNs (MOCRAW) to minimize nodes' energy consumption and fast data transmission [45].

MOCRAW removes isolated nodes or hot-spot problems and provides loop-free routing with the help of the Dragonfly Algorithm (DA), wherein the decision is based on Local Search Optimization (LSO) and Global Search Optimization (GSO). This protocol exploits two sub-processes: the optimal Cluster Head Selection Algorithm (CHSA) and the Route Search Algorithm (RSA). CHSA uses the Energy Level Matrix (ELM). ELM is based on node density, residual energy, the distance between the Cluster Head (CH) and Base Station (BS), and inter-cluster formation. The inter-cluster discovers the optimum path between source and destination in RSA by levy distribution. MOCRAW performance is compared with other clustering and routing protocols on parameters such as the number of alive nodes, delay, packet delivery ratio, and average energy consumption. Simulation-based findings exhibit that the proposed methodology surpasses its peers and competitors in terms of energy efficiency [46,47].

Recently, the deployment of wireless sensor networks has become essential in revolutionary areas such as smart cities, environmental monitoring, smart transportation, and smart industries. The battery power of sensor nodes is limited, so their efficient utilization is necessary as the battery is irreplaceable for indoor Wi-Fi positioning technology [48]. Efficient energy utilization has recently been addressed as one of the essential issues by many researchers in WSN [49]. Clustering is a fundamental approach for efficient energy utilization in WSNs. The clustering method should adequately select optimal clusters with efficient energy consumption. Extensive modification in the clustering approaches leads to an increase in the lifetime of sensor nodes, which is a unique way to enhance network lifetime. As the technologies were taken to the next level, where multiple parameters need to be considered in almost every clustering application, multiple factors affected the clustering, and these factors were also conflicting. Due to the contradictory nature of these factors, it becomes difficult to coordinate among them for optimized clustering. In this paper, we have considered multi-attributes and made coordination among these attributes for optimal cluster head selection. We have considered Multi-Attribute Decision-Making (MADM) methods for CH's selection from the available alternatives by making suitable coordination among these attributes, and comparative analysis has been taken in LEACH, LEACH-C, EECS, HEED, HEEC, and DEECET algorithms. The experimental results validate that using MADM approaches, the proposed APRO algorithm proves to be one of the better exhibits for choosing the available CHs [50,51].

In the research of heterogeneous wireless sensor networks, clustering is one of the most commonly used energy-saving methods. However, existing clustering methods face challenges when applied to heterogeneous wireless sensor networks, such as energy balance, node heterogeneity, and algorithm efficiency. Among these challenges, a well-designed clustering approach can lead to extended node lifetimes. Efficient selection of cluster heads is crucial for achieving optimal clustering [52]. In this paper, they proposed an Enhanced Pelican Optimization Algorithm for Cluster Head Selection (EPOA-CHS) to address these issues and enhance cluster head selection for optimal clustering. This method combines the Levy flight process with the traditional POA algorithm, which not only improves the optimization level of the algorithm but also ensures the selection of the optimal cluster head. The logistic-sine chaotic mapping method is used in the population initialization, and the appropriate cluster head is selected through the new fitness function. Finally, they simulate 100 sensor nodes within a configured 100×100 m^2 area. These nodes were categorized into four heterogeneous scenarios: $m = 0$, $\alpha = 0$, $m = 0.1$, $\alpha = 2$, $m = 0.2$, $\alpha = 3$, and $m = 0.3$, $\alpha = 1.5$. They verified four aspects: total residual energy, network survival time, number of surviving nodes, and network throughput across all protocols. Extensive experimental research indicates that the EPOA-CHS method outperforms the SEP, DEEC, Z-SEP, and PSO-ECSM protocols [53–55].

Authors proposed the Age of Task-oriented Information (AoTI) for industrial tasks. It measures the time elapsed of the latest analyzed results before arriving at the receiver since the generation of any type of sampling data belonging to an industrial task. Considering the time-varying and wireless environments, they aimed to minimize the long-term AoTI for IWSN applications by jointly optimizing access selections and sampling frequencies for all sensors. They first formulated this problem as a Mixed Integer Nonlinear Programming (MINLP) problem and then transformed it into a Constrained Markov Decision Process (CMDP), which is further relaxed as an MDP using the Lagrangian method. Finally, they developed a Learning-based Access selection and Sampling frequency Control (LASC) algorithm and verified its superiority through extensive simulations [56,57].

3 Research Methodology

3.1 The Proposed Model

This article's major and primary goal is to select the appropriate and best CH node for transmitting data to the BS. Many researchers have employed a different method for CH selection to reduce the energy and maximize the throughput and network lifetime. This article provides a new APSO-based technique for CH selection efficiently to reduce energy consumption while increasing the throughput and lifetime of the network, as illustrated in Fig. 1.

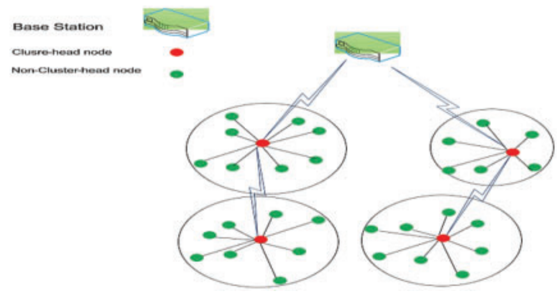


Figure 1: The proposed model in WSN for clustering

A fully distributed routing protocol LEACH does not require global knowledge. The following are a few of the primary advantages of LEACH: The LEACH protocol uses a clustering approach, which reduces communication between nodes and base stations and extends the network lifetime.

a) Using the data combining technique, CH reduces local associated data that lowers the crucial metric of energy utilization.
b) Distribute the TDMA agenda to the member nodes while allowing them to enter sleeping mode with the help of the CH. This improves the battery life of sensor nodes and mitigates intra-institution impacts.
c) According to [54], the protocol gives every sensor node an equal chance to designate a member node and the CH at least once frequently at some point in its existence. This random CH turn extends the longevity of the network.

The proposed approach was tested using a simulator named MATLAB version 2021a. The potential simulations were tested on various sensor nodes totaling 100 with 5, 10, and 15 cluster heads. Every sensor node was assumed to have a 5J (Joules) starting point energy. The values shown in Table 1 were considered and utilized as a case study during the simulation's running time. We looked at several network scenarios, and the following three are highlighted. Additionally, we have considered a sensing field with a 500 $\times$ 500 m^2 area for the overall ideal circumstances. Coming back to the question of how many nodes and other elements were grabbed, in this case, the BS location was 250, 250 (x, y) in the middle of the field. Also taken into consideration and proposed for WSN are three distinct scenarios with the numbers WSN-(1), WSN-(2), and WSN-(3). There are now different sensor node ranges and numbers for each WSN; for example, WSN-(1) had 100 sensor nodes, WSN-(2) had 100 (hundred) sensor nodes, and WSN-(3) had the same amount of sensor nodes as WSN-(1) and WSN-(2). The amount of CH selections varies between these scenarios, which is the fundamental distinction. We construct and evaluate the usefulness and presentation of the concern algorithm on various scenarios and a predetermined number of sensor nodes.

Table 1: The experimental parameters

Parameter (s)	Value (s)
Nodes amount	100
BS position	(250, 250) (center)
Number of cluster head	5, 10, 15
Area size	500 m × 500 m
Technology	IEEE 802.15.4
Initial energy	5 Joules
Routing protocol	LEACH, APSO, NBEER, CR-NBEER & CEER
Data size	4000 bytes
Performance parameters	Energy consumption, Packet sent ratio, Network lifetime

3.2 Terminologies

The following terminologies are used in this article which are gives as:

S:	Denoted sensor nodes set, i.e., $S = [s1, s2, \ldots, sn]$.
C:	Denotation of CHs, i.e., $C = [CH1, CH2, \ldots, CH]$. where $m < n$.
Esi:	The sensor node si initial energy, $1 \leq i \leq n$.
dis (si, sj):	The distance between two sensor nodes si and sj.
lj:	The sensor nodes in the jcluster are denoted by lj.
TH:	TH represents the CH threshold energy.
Rmax:	Represents the CH communication range.
dmax:	It represents the highest range of sensor communication.
ECHj:	Represent the cluster head CHj current energy, $1 \leq j \leq m$.
Comm (si):	The set of nodes that are within the communication range of si
d0:	The threshold distance.

The routing mechanism used by LEACH is cluster or hierarchical-based. A single sensor node cannot sustain a WSN with an increase in the node's number. One node is chosen to serve as the CH in each cluster created by the cluster-based protocols. A threshold value determines the random selection of CHs. Many non-cluster nodes choose their CHs using this method while considering their separations. CH selection was founded on the primary LEACH protocols following the threshold determined [55]. This term can be calculated using Eq. (1).

$$T(n) = \frac{P}{1 - P * \left(r \bmod \frac{1}{P}\right)} : \text{ if } n \, \varepsilon \, G = 0 \tag{1}$$

The term P stands for the clustered heads' preferred number, G for sensors that did not participate in the CHs' selection during the $I = P$ rounds, and r for the current rounds. The whole WSN is divided into clusters using mLEACH, and every cluster consists of cluster nodes and CH nodes. The

LEACH protocol seeks to increase WSN energy usage. Once CH has been chosen, the other sensors communicate the data they have gathered with CH. Then, the CH distributes the acquired data to the BS in pieces.

The qualities listed below are present in LEACH. APSO is a sophisticated optimization technique that uses a population-based approach which is the author who invented this method. APSO starts with a random initialization. Initializing a collection of random particles forms the foundation of APSO's operational methodology, like other meta-heuristic techniques. This approach involves updating each particle's position and speed until it finds the best result in the examined space. The APSO carefully determined the optimal value by comparing the starting value to the desired value. The search is carried out to the final round to find the best value for the network. Only the most influential global solutions are found using APSO. It is a less complicated variation of PSO. Eq. (2) is used to decide the APSO's velocity.

$$\mathrm{Vi}^{t+1} = \mathrm{Vi}^{t} + \alpha \in +\beta(\mathrm{G}_{\mathrm{best}} - \mathrm{Xi}^{t}) \tag{2}$$

The $\in$ represents a value between 0 and 1 at random. Use the equation below to update the position vector APSO.

$$\mathrm{Xi}^{t+1} = \mathrm{Xi}^{t} + \mathrm{Vi}^{t+1} \tag{3}$$

The following mathematical formula has been applied to speed up convergence in a single step:

$$\mathrm{Xi}^{t+1} = (1-\beta)\,\mathrm{Xi}^{t} + \beta \mathrm{G}_{\mathrm{best}} + \alpha\varepsilon \tag{4}$$

APSO is, therefore, more straightforward and produces results quickly. One of the most crucial factors in enhancing the already employed approach is the effective node selection of the CH. The right choice of node will aid in the provision of an energy-efficient system, as well as the improvement of throughput, the extension of the network's lifetime, and the reduction of energy consumption. This article serves as a standard for additional research by getting the previously specified necessary criteria.

$$\mathrm{comm}\,(\mathrm{s_i}) = \mathrm{S_j} | \forall \mathrm{s_j} \varepsilon S^{dis}(\mathrm{s_i}, \mathrm{s_J}) \le \mathrm{d_{max}} \tag{5}$$

There are several ways to describe the lifetime of a network, such as the time that passes between the first placing of various nodes and a well-defined percentage of each node's existing energy or the time allocated to the primary node and other comparable nodes. The amount of rounds until the final node dies, typically termed a Final Node Death (FND), has been considered in this study. There are several approaches for the single node lifetime, which is given in Eq. (6).

$$\mathrm{L} = \frac{\mathrm{einitial}}{\mathrm{etotal}} \tag{6}$$

where *einitial* denotes the node's initial energy, *etotal* denotes the overall energy of the sensor nodes for receiving and transmitting and is given in Eq. (7) as:

$$e^{\mathrm{total}} = \mathrm{E_{TX}}\,(1, \mathrm{d}) + \mathrm{E_{RX}}(1) \tag{7}$$

3.3 Consumption of Energy

CHs use the energy to collect data and send it to the BS for specific rounds. In this instance, CHs obtain the Information, gather it, and then transfer it to the BS. The amount of energy consumed likewise increases with increasing number of rounds. The amount of data sent and the distance traveled affect the node's energy usage. The *d2xy* denotes the energy loss model in which the two axes *x* and *y* represent different angles and are used to represent the attenuation with distance. Therefore, a node's energy consumption is comparable to d^2 when propagation distance (d) is less than d^0, while it is comparable to d^4 when the broadcast distance (d) is more than d^0. The following equations provide a node's energy for l-byte data packet transmission:

$$E_{TX}(l,d) = l.E_{elec} + l.E_{elec}\varepsilon_{fs}d^2 \text{ if } d < d0 \tag{8}$$

$$= l.E_{elec} + l.E_{elec}\varepsilon_{mp}d^4 \text{ if } d > d0 \tag{9}$$

Whereas per byte energy usage by the sender and receiver is represented by E_{elec}. Similarly, ε_{fs} stands for amplifier energy for the free space and multi-path models [56].

Network Lifetime: It denotes the number of rounds a node takes until the first node dies, or FND, has been used to set the network lifetime, as mentioned previously. In a similar vein, network performance over time has also been researched.

Packet Receiving: It denotes the overall number of packets received at the destination, and till the network's final node dies, it is referred to as packet receiving. The performance of the network will be improved with more packets received.

APSO: The APSO algorithm was influenced by nature. Its design was influenced by the movement patterns of fish schools and bird flocks as they look for food and pave in three-dimensional space. A swarm, or NP, is a set amount of particles in APSO, every one of which offers a potential outcome. A particle in the search region with the coordinates $X_{i,d}$ and $X_{i,d}$, $1dD$ has a velocity of $X_{i,d}$, $1dD$, and its location is Pi, $1iNP$. The D dimension is the same for every particle. The function named fitness is used to check the quality of the results. Discovering the particle's position to assess the optimal fitness function is the main goal of the APSO. All particles in the search space are initially given random positions and speeds. Every particle discovers its individual best, known as P_{best}, and the collective best, known as G_{best}, during each iteration. Every particle updates its position $X_{i,d}$ and velocity $V_{i,d}$ using the following equations to determine its global best solution:

$$Vi^{t+1} = Vi^{t} + \alpha \in +\beta(G_{best} - Xi^{t}) \tag{10}$$

$$X_{i,d}(t+1) = X_{i,d}(t) + V_{i,d}(t+1) \tag{11}$$

Updating is carried out repeatedly until the best G_{best} value is discovered. The particle then assesses the fitness function and adjusts G_{best} to minimize the issue once it has the newly updated position:

$$Gbest = \begin{cases} Pi, \text{ if (fitness (Pi)} < \text{fitness} (G_{best})) \\ \text{Gbest, otherwise} \end{cases} \tag{12}$$

3.3.1 Energy and Network Model

APSO is an optimization algorithm inspired by the behavior of bird flocking and fish schooling. It is commonly used for solving optimization problems, including the efficient cluster head selection problem in WSNs. APSO consists of two key components: The energy model and the network model.

Energy Model

The energy model in APSO represents the energy consumption of individual particles (agents) in the swarm. In the context of WSNs, each particle corresponds to a candidate cluster head, and the energy model captures the energy consumption associated with the communication and computation tasks of the cluster heads.

Assumptions

- Each candidate cluster head has a limited energy supply.
- Energy consumption is primarily determined by communication and computation tasks.
- The energy consumption is proportional to the distance between cluster heads and their respective sensor nodes.
- Energy dissipation due to the transmission and reception of data packets follows a specific energy model, such as the Friis transmission equation or the log-normal shadowing model.

Parameters

- Energy capacity: The maximum energy available to each candidate cluster head.
- Energy dissipation rate: The rate at which energy is consumed during communication and computation tasks.
- Communication range: The maximum distance over which a cluster head can transmit and receive data.
- Energy threshold: The minimum energy level required for a candidate cluster head to remain active.

Relevance

- The energy model is crucial in APSO for efficient cluster head selection in WSNs. By considering energy consumption, APSO aims to identify the optimal set of cluster heads that maximizes network lifetime. The energy model helps in assessing the energy consumption of cluster heads, enabling the algorithm to select energy-efficient cluster heads and avoid premature energy depletion in the network.

Network Model

The network model in APSO represents the topology and connectivity of the WSN. It captures the relationships between sensor nodes and cluster heads, including the distance, signal strength, and communication links.

Assumptions

- WSN nodes are uniformly distributed in a given area.
- Communication links follow certain models, such as the radio propagation model or the path loss model.
- The distance between nodes and the signal strength primarily influences the network connectivity.

Parameters

- Node positions: The locations of the sensor nodes and the target area of the WSN.
- Signal strength: The strength of the wireless signal between nodes.
- Communication range: The maximum distance over which nodes can establish communication links.
- Quality of Service (QoS) requirements: The specific constraints or requirements of the WSN application, such as latency, reliability, or bandwidth.

Relevance

- The network model is essential in APSO for efficient cluster head selection. By considering the network topology and connectivity, APSO aims to identify a set of cluster heads that can establish reliable communication links with sensor nodes. The network model helps in assessing the quality of communication links, enabling APSO to select cluster heads that can effectively collect and aggregate data from the sensor nodes.

3.4 Proposed Algorithm

The creation stage of the cluster and the CH selection stage are the two stages of the suggested methodology. The APSO algorithm chooses the CH seen in Fig. 2. The distance and remaining energy of the nodes are the criteria for choosing the CH. In the first step, nodes communicate their location and amount of residual energy to the BS. The base station determines whether the nodes are eligible for the CH election based on the threshold value. The cluster creation stage begins following CH selection. We derive the weight function from the cluster formation based on numerous factors, including node degree of the CHs, distance, and energy. Before presenting the Linear programming formulation for the CH election problem, we describe the proposed APSO-based method for CH selection and the cluster formation stage. In Eq. (13), the terminologies used represent the complete module for the APSO algorithm with the nth stages starting from the Xi1 till the last nth.

$$P_i = [(X_{i1}(t), Y_{i1}(t)), (X_{i2}(t), Y_{i2}(t)), (X_{i3}(t), Y_{i3}(t)) \ldots\ldots\ldots, X_{id}(t), Y_{id}(t))] \tag{13}$$

For all particles, *D* is the number of dimensions *D*, which is equal and matches the number of CHs, m.

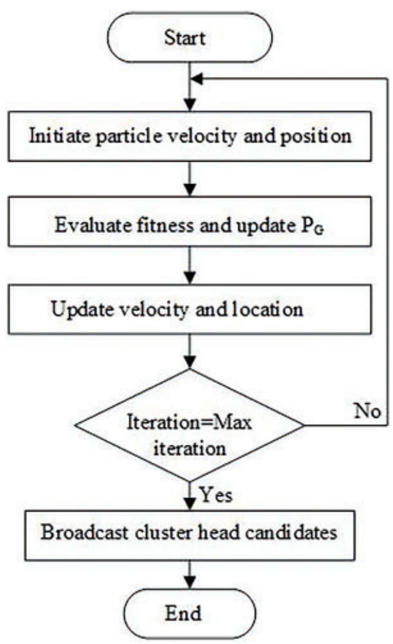


Figure 2: The proposed APSO

Advantages of the proposed algorithm

- APSO has no overlapping or mutation calculations, is intelligence-based, and can be used in engineering and scientific study.
- The particle's speed can be used to search.
- It can be utilized to choose the ideal node for CH.
- Energy consumption can be reduced by choosing the optimal node, CH.
- The network's throughput can be enhanced.
- The lifetime of the network can also be enhanced.

Average Intra-Clusters Distance (AICD): The AICD between each node and the CH that was chosen is expressed as $1/l\_j\_(i = 1)(l\_j)dis(s\_(i,)CH\_j)$, it is crucial to reduce AICD to reduce intra-cluster communications energy. Therefore, selecting the closest cluster head by the sensor node is necessary.

Average Sink Distance (ASD): According to the formula $1/ljdis(CH_j, BS)$, the ASD between a CH_j and the BS is equal to the number of sensor node *lj* in the CH_j. Each CH must transmit its gathered data to the BS during the data routing stage. Therefore, we must reduce the space between each CH and the BS to reduce energy usage. That's why the objective 1 and 2 are given as:

Objective 1:

$$\text{Minimize } f_1 = \sum\nolimits_{j=1}^{m} \left(\sum\nolimits_{i=1}^{lj} \text{dis}\left(s_i, CH_j\right) + \text{dis}(CH_j,\ BS)\right) \tag{14}$$

Energy Parameters: ECH_j stands for the initial energy for cluster heads nominated in an iteration from the usual nodes, CH_j, l_j, m. It makes sense to raise all of the nominated CHs' current energy when choosing the best cluster heads, which means we must minimize its reciprocal. Consequently, the following is our second goal.

Objective 2:

$$\text{minimizef1} = \frac{1}{\sum_{j=1}^{m} (CHj)} \tag{15}$$

Because these two objectives do not substantially conflict, it is crucial in our proposed APSO-based strategy to reduce the direct combination of the objectives above rather than minimizing them separately. There is then the best course of action. Thus, we utilize the fitness function below:

$$\text{Fitness} = \alpha \times f_1 + (1 - \alpha) \times f_2 \tag{16}$$

The following formula can be used to calculate the functions f_1 and f_2, where is α constant value and f_1 and f_2 are functions:

$$f_1 = \sum_{i=1}^{n} E\,(n_i) \Big/ \sum_{m=1}^{M} E\,(CH_m) \tag{17}$$

$$f_2 = \max_{m=1,2,\ldots M} \left\{ \sum_{i\epsilon m} d\left(n_{i,} CH_m\right) |C_m| \right. \tag{18}$$

where f_1 is the energy representative fraction, node energy $E(n_i)$ (excluding CH) is divided by the total energy $E(CH_m)$ of the cluster heads. The value f_2 is the ratio of the density and joined member nodes (n_i, CH_m) to the total number of nodes in the same cluster $|C_m|$. We intend to reduce the fitness value.

The cluster head selection will be more advantageous when the fitness value is low. Each iteration's velocity and location are updated based on Eqs. (18) and (19) separately.

Development of Cluster: A function *CH_Weight* called the weight function serves as the foundation for cluster formation. Use this *CH_Weight* to connect to each sensor node in the CH. The weight function depends on the factors listed below.

Cluster Head Remaining Energy: For communication, the sensor s_i needs to link with the CH_j, which must have the most energy left in its range. Thus,

$$CH\_weight(s_i, CH_j) \propto E_{residual}(CH_j) \tag{19}$$

Distance between CH & Sensor: Node s_i must join the nearest cluster head CH_j to use the least amount of energy. The energy usage will be at its lowest when the communication range is lower. Therefore,

$$CH\_weight\left(s_i, CH_j\right) \propto \frac{1}{dis(s_{i,}CH_j)} \tag{20}$$

Distance between BS & CH: Sending the gathered data to the BS is crucial for CHs. Therefore, these sensors must connect to the CH close to the BS. Therefore,

$$CH\_weight\left(s_i, CH_j\right) \propto \frac{1}{dis(CH_{j,}BS)} \tag{21}$$

Algorithm of the proposed APSO based protocol:

Input: particle initialization: All the sensor nodes are initialized with an initial energy Eo and an initial velocity o, and set sensor node: $S = (s_1, s_2, s_3, \ldots, s_n)$
Predefine swarm size: N_p
Number dimension of particle: $D = m$.
Output: cluster heads optimal positions, $CH = (CH_1, CH_2, CH_3, \ldots, CH_n)$
Step 1: initialized particle P_i, $\vee$ i, j, $1 = i = N_p, 1 = j = D = m$, numbers of CHs
$X_{i,j}(0) = (X_{i,j}(0), Y_{i,j}(0))$ //the deployed position of the sensor nodes//
Step 2: for i = 1 to Np ***do***
calculate *fitness* (*PGbest*) //using Eq. (17)
$PGest_i = P_i$
End for
Step 3: $Gbest = [bestk \mid Fitness(best_k) = \min(Fitness(best_i), \vee i, 1 = i = N_p)]$
Step 4: for t = 0 to T_R/*T_R = Max. number of iterations*/
for i=1 to N_p ***do***
update velocity and position of P_i using Eqs. (11) and (12)
calculate fitness
if *Fitness*(p_i) < *Fitness* (*Gbest*) ***then***
Gbest $= P_i$
end if
end for
for k = 1 to n
calculate *dis* $(X_{i,j}(t+1), s_k)$
$X_{i,j}(t+1) \vee (s_k \mid \min(dis(X_{i,j}(t+1), s_k)), \vee i, 1 = k = N_p)$

(Continued)

Algorithm of the proposed APSO based protocol (continued)

end for
end for
Step 5: restate steps 2–5 until maximum number of iterations are reached.
Step 6: Broadcast CH candidates: Eligible CH candidates are broadcasted by the base station.
Step 7: stop

3.5 Key Features for Applying the APSO in WSN

APSO is a variant of the PSO algorithm that aims to improve its convergence speed and exploration-exploitation balance. While APSO is designed for wireless sensor networks (WSNs), it can be applied to optimize WSN parameters or configurations. When using APSO to WSNs, the objective is typically to optimize specific parameters and configurations of the network to improve its performance. Here are some key features of APSO applying in WSN:

- Acceleration Mechanism: APSO introduces an acceleration mechanism that modifies the velocity update equation in the PSO algorithm. This mechanism enhances the search process by allowing particles to explore the search space more efficiently.
- Adaptive Parameters: APSO typically employs adaptive parameters to dynamically adjust the control parameters of the algorithm during the optimization process. These adaptive mechanisms help improve the algorithm's performance by fine-tuning the balance between exploration and exploitation.
- Local and Global Search: APSO combines both local and global search strategies. The local search focuses on exploiting the best solutions found by individual particles or their neighbors, while the global search allows for exploring the entire search space to discover potentially better solutions.
- Diversity Maintenance: APSO often incorporates mechanisms to maintain diversity within the particle population. This helps prevent premature convergence to suboptimal solutions and promotes a more thorough search space exploration.
- Convergence Speed: APSO aims to accelerate the convergence speed compared to standard PSO algorithms. By incorporating acceleration mechanisms and adaptive parameters, APSO can guide the particles toward promising solutions more quickly, reducing the number of iterations required to converge.
- Application to WSNs: APSO can be applied to various optimization problems in WSNs, such as node placement, energy optimization, coverage optimization, and routing. By formulating the specific objective function and appropriately defining the particle representation, APSO can help find optimized configurations or parameter values for WSNs.

It is worth noting that APSO is a dynamic and evolving field of research, and different variants and adaptations of the algorithm may exist. APSO's specific features and performance can vary depending on the implementation details and the problem being addressed.

3.6 Analysis of the Algorithm's Time & Space Complexity

APSO is a variant of the original PSO algorithm that introduces an acceleration term to enhance convergence speed. The complexity of APSO can be analyzed in terms of time complexity and space complexity. When analyzing the complexity of APSO, we can consider both the time complexity and the space complexity.

1. Time Complexity:

The time complexity of APSO depends on several factors, including the number of particles (N), the dimensionality of the problem (D), the maximum number of iterations (T), and the complexity of the fitness function being optimized. In each iteration, APSO updates the position and velocity of each particle based on its own best position and the global best position found so far. This process involves evaluating the fitness function for each particle, which can be computationally expensive depending on the complexity of the problem. Therefore, the time complexity of APSO can be expressed as O $(N * D * T * F)$, where F represents the time complexity of evaluating the fitness function.

2. Space Complexity:

The space complexity of APSO mainly depends on the number of particles (N) and the dimensionality of the problem (D). APSO requires storing the position and velocity vectors for each particle. Therefore, the space complexity of APSO can be expressed as O $(N * D)$. It is important to note that the time and space complexity analysis provided above is a general guideline and can vary depending on the specific implementation of APSO and the problem being solved. Additionally, the complexity of time and space can be influenced by various factors, such as the termination criteria, the topology of the swarm, and the complexity of the fitness evaluation function. APSO is a metaheuristic optimization algorithm that is commonly used to solve optimization problems. Its complexity, including time and space complexity, can vary depending on various factors such as the problem size, the number of particles, and the convergence criteria.

The time complexity of APSO is influenced by the number of iterations required to converge to an optimal solution. In each iteration, the algorithm evaluates the fitness function for each particle and updates their positions and velocities. The number of iterations needed to converge depends on the complexity of the problem and the convergence speed of the algorithm. Generally, the time complexity of APSO is considered to be moderate, as it involves several operations proportional to the number of particles and the problem size. The space complexity of APSO is determined by the memory required to store the particles and their positions, velocities, and personal bests. The space complexity is usually linear to the number of particles and the problem size. The algorithm also requires additional memory to store global best positions and other parameters. However, the memory requirements of APSO are typically not a limiting factor unless dealing with extremely large problem sizes or limited memory resources. When considering the scalability of APSO in larger WSN environments with thousands of nodes and varying network densities, several factors come into play, such as:

1. Number of particles: The number of particles in APSO is often chosen based on problem size and complexity. In larger WSN environments, increasing the number of particles may be necessary to explore the search space adequately. However, a larger number of particles can also increase the computational cost of evaluating fitness functions and updating particle positions, leading to increased time complexity.

2. Fitness function evaluation: In WSN environments, the fitness function evaluation can be computationally expensive, especially when considering thousands of nodes and varying network densities. The time required to evaluate the fitness function for each particle can significantly impact the scalability of APSO. Efficient techniques, such as parallel computing or approximation algorithms, can be employed to improve the scalability.

3. Convergence speed: The convergence speed of APSO is crucial for scalability in larger WSN environments. If the algorithm converges too slowly, it may not be practical to apply APSO to large-scale problems. Techniques such as adaptive parameter settings, dynamic population size, or hybridization with other optimization methods can be employed to enhance convergence speed.

4. Communication and coordination: In WSN environments, communication and coordination among nodes can affect the scalability of APSO. As the network density increases, the number of interactions and information exchanges between particles may also increase. Efficient communication protocols and strategies are required to handle large-scale WSN environments effectively.

3.7 Robustness of the Proposed APSO Algorithm under Dynamic Network Conditions

The APSO algorithm is a variation of the traditional PSO algorithm that aims to enhance its convergence speed and search efficiency. APSO introduces an acceleration coefficient to adjust the particle velocity, which helps accelerate the convergence process. In terms of the robustness of APSO under dynamic network conditions, including node mobility, node failures, and varying environmental conditions, APSO can exhibit varying degrees of robustness depending on how these factors are handled:

1. Node Mobility: APSO can be affected by node mobility in WSNs. If nodes move during the optimization process, the fitness landscape may change dynamically, affecting the convergence behavior of APSO. Strategies such as incorporating velocity constraints or adaptive mechanisms to handle node mobility can improve the robustness of APSO.

2. Node Failures: In the presence of node failures, APSO needs to handle the loss of information and adapt accordingly. Strategies such as dynamic topology maintenance, fault-tolerant mechanisms, or re-initialization of particles can help maintain robustness in the face of node failures.

3. Varying Environmental Conditions: APSO may encounter challenges when environmental conditions (e.g., noise, interference, or varying signal strengths) change during optimization. Robustness can be improved by incorporating mechanisms that adapt particle behavior or adjust the exploration and exploitation trade-off based on environmental conditions.

3.8 In-Depth Analysis of Energy Efficiency

Breakdown of Energy Consumption and APSO's Contribution: In the context of energy consumption in WSNs, APSO's contribution lies in optimizing the network's operational parameters, such as transmission energy, reception energy, and idle energy.

1. Transmission Energy: APSO can optimize the transmission power levels of the nodes to reduce energy consumption during data transmission. By finding optimal transmission paths and power levels, APSO can minimize the overall transmission energy expenditure.

2. Reception Energy: APSO can optimize the placement of nodes and the routing paths to reduce the reception energy. By considering the distances and quality of links, APSO can find energy-efficient routes that reduce the reception energy consumption.

3. Idle Energy: APSO can also contribute to reducing idle energy consumption by optimizing the sleep-wake schedules of nodes. By coordinating the activation and deactivation of nodes, APSO can minimize idle energy consumption in the network.

3.9 Security Implications of the Proposed APSO Algorithm

The APSO algorithm is a metaheuristic optimization algorithm inspired by the behavior of bird flocking or fish schooling. It has been widely used in wireless sensor networks (WSNs) for various applications, including data aggregation, routing, and energy optimization. While APSO can provide efficient solutions for optimization problems in WSNs, it also introduces certain DeFi security implications and vulnerabilities that need to be addressed [58]. Here are some security implications of the APSO algorithm in WSNs deployed in sensitive applications, along with potential security vulnerabilities and proposed mitigation strategies:

1. Data Confidentiality: APSO relies on the exchange of information among sensor nodes to find optimal solutions. This information exchange can potentially be intercepted by an adversary, leading to data confidentiality breaches. To mitigate vulnerability, encryption techniques such as symmetric or asymmetric encryption can be employed to protect the exchanged information and ensure confidentiality.

2. Data Integrity: APSO involves the transmission of control messages and optimization parameters among sensor nodes. An attacker can tamper with these messages, leading to compromised data integrity. Implementing message authentication mechanisms, such as digital signatures or message authentication codes (MACs), can help ensure the integrity of the exchanged messages and detect any tampering attempts.

3. Node Spoofing: In APSO, sensor nodes communicate and share information to optimize the network behavior collectively. However, an attacker can impersonate a legitimate sensor node and inject false information or manipulate the optimization process. Techniques such as public key infrastructure (PKI) or digital certificates can be used to verify the authenticity of sensor nodes and prevent node spoofing attacks.

4. Denial of Service (DoS): APSO relies on the cooperation and participation of all sensor nodes to achieve optimal results. An attacker can launch DoS attacks by disrupting the communication or compromising the functionality of specific sensor nodes, thereby affecting the overall optimization process. Implementing intrusion detection systems (IDS) and anomaly detection mechanisms can help identify and mitigate DoS attacks in WSNs.

5. Energy Depletion: APSO requires significant communication and computation among sensor nodes, which can result in increased energy consumption. This could lead to premature depletion of sensor node batteries, affecting the overall network performance. Energy-efficient routing protocols and optimization techniques should be employed to minimize energy consumption and prolong the network lifetime.

6. Physical Attacks: WSNs are often deployed in hostile environments where attackers can physically access sensor nodes. An adversary can tamper with or physically compromise sensor nodes, leading to various security breaches. Securing the physical environment through measures such as tamper-resistant packaging, intrusion detection sensors, and secure deployment locations can help mitigate physical attacks.

7. Key Management: APSO may require the use of cryptographic keys for secure communication and authentication. Establishing a robust key management scheme, including key distribution, key updates, and key revocation mechanisms, is crucial to prevent unauthorized access and ensure the security of the network.

3.10 Implementation Details of the APSO Algorithm

APSO incorporates an acceleration coefficient to improve the convergence speed and exploration capability of the optimization process. The major working concept of APSO in WSNs is to enhance the search capability and convergence speed of the traditional PSO algorithm. APSO achieves this by introducing an acceleration term that allows particles to take larger steps toward promising regions of the search space. Following is a detail of the major working concepts of the APSO algorithm in WSNs:

Particle Representation: Each particle in APSO represents a potential solution in the WSN. The particle's position and velocity capture the parameters or variables that need optimization. In the context of WSN, these parameters can include node positions, energy levels, routing paths, transmission power, or other network-related variables.

Swarm Initialization: APSO starts by initializing a swarm of particles randomly within the search space. The search space represents the feasible region for the optimization problem. Each particle is assigned an initial position and velocity.

Fitness Evaluation: The fitness of each particle is evaluated by calculating the objective function based on the particle's position. The objective function quantifies the performance of the WSN based on the optimization problem. It can consider metrics such as energy consumption, network coverage, communication overhead, or any other relevant performance criteria.

Velocity and Position Updates: The velocity and position of each particle are updated iteratively based on its own experience and the experience of the best-performing particles in the swarm. The velocity update equation in APSO incorporates an acceleration term, which allows particles to move larger toward promising regions.

Acceleration Term: The acceleration term in APSO is responsible for enhancing the search capability. It is calculated by multiplying the acceleration coefficients (c1 and c2) with random values and the differences between the particle's personal best position and the current position, as well as the global best position and the current position. The acceleration term guides the particles to explore the search space more efficiently and escape local optima.

Global Best Update: APSO keeps track of the best-performing particle in the swarm, known as the global best. The global best is updated whenever a particle discovers a better solution. This helps in guiding the swarm towards promising regions of the search space.

Termination Criteria: Termination criteria are defined to determine when the APSO algorithm should stop. Common termination criteria include reaching a maximum number of iterations, achieving a satisfactory solution, or when the improvement in the objective function becomes negligible. Once the termination criteria are met, the algorithm terminates, and the optimized solution is extracted.

Solution Extraction: After the APSO algorithm terminates, the optimized solution is extracted from the global best particle. This solution represents the optimal parameter settings for the WSN based on the defined objective function. By incorporating the acceleration term, APSO enables faster convergence and improved exploration of the search space, allowing for better optimization performance in wireless sensor networks. Furthermore, the following is a detailed implementation of the APSO algorithm, including pseudocode, parameter settings, and configuration details.

PSO Recap: PSO is a population-based optimization algorithm inspired by the social behavior of bird flocking or fish schooling. It uses a swarm of particles, each representing a potential solution in the search space. These particles move through the search space, adjusting their positions based on their own experience and the experience of the best-performing particles in the swarm.

APSO: APSO introduces an acceleration term to enhance the search capability and convergence speed of PSO. The acceleration term allows the particles to take larger steps toward promising regions of the search space. By incorporating the acceleration term, APSO can escape from local optima more effectively and explore the search space more efficiently. The implementation steps for APSO in WSN are discussed as follows:

Step 1: Define the Problem: Identify the specific optimization problem in WSNs that you want to solve using APSO. For example, it could be related to optimizing node placement, energy consumption, or routing.

Step 2: Formulate the Objective Function: Define an objective function that quantifies the performance of the WSN based on the optimization problem. The objective function could consider factors such as energy consumption, network coverage, communication overhead, or any other relevant metrics.

Step 3: Define Particle Representation: Determine how each particle in the APSO algorithm represents a potential solution in the WSN. The particle's position and velocity should capture the parameters or variables that need optimization.

Step 4: Initialize the Swarm: Initialize a swarm of particles randomly within the search space. Assign initial positions and velocities to each particle.

Step 5: Evaluate Fitness: Evaluate the fitness of each particle by evaluating the objective function using the particle's position.

Step 6: Update Particle Velocity and Position: Update each particle's velocity and position based on its own experience and the experience of the best-performing particles in the swarm. Incorporate the acceleration term to adjust the particle's movement towards promising regions.

Step 7: Update Global Best: Track the best-performing particle in the swarm (global best) and update it whenever a better solution is found.

Step 8: Termination Criteria: Define termination criteria, such as a maximum number of iterations or a satisfactory solution. Check if the termination criteria are met, and if not, go back to Step 5.

Step 9: Extract the Optimized Solution: Once the algorithm terminates, extract the optimized solution from the global best particle. This solution represents the optimal parameter settings for the WSN.

The considerations and extensions of APSO can be further defined as follows: Parameter Tuning: APSO, like other optimization algorithms, has parameters that need to be tuned for optimal performance, such as the acceleration coefficients and the number of particles. Constraint Handling: If there are constraints in the optimization problem, appropriate mechanisms should be incorporated to ensure that the particles satisfy those constraints during the position updates. Performance Evaluation: After obtaining the optimized solution, it is essential to evaluate its performance in the WSN and compare it with other algorithms or baseline methods.

3.11 Extending the APSO Algorithm to Address the Multi-Objective Optimization Problems

APSO is a metaheuristic optimization algorithm inspired by the behavior of bird flocking or fish schooling. It has been applied to various optimization problems, including WSNs. In the context of WSNs, APSO can be extended to address multi-objective optimization problems such as latency minimization, coverage optimization, and energy conservation.

1. Latency Minimization:

Latency in WSNs refers to the delay between data generation at the sensor nodes and its reception at the sink node or base station. Minimizing latency is crucial for time-sensitive applications, such as real-time monitoring or event detection. APSO can be extended for latency minimization in WSNs by considering the following:

a. Routing Optimization: APSO can optimize the routing paths in the network to minimize the overall latency. The fitness function can incorporate latency as a metric, and the particles can search for optimal routes that minimize latency while satisfying other constraints, such as energy efficiency.

b. Transmission Scheduling: APSO can also optimize the scheduling of data transmissions to minimize latency. By considering factors like channel availability, interference, and data priorities, APSO can find efficient transmission schedules that reduce latency.

2. Coverage Optimization:

Coverage optimization in WSNs aims to ensure that the sensor nodes adequately cover the sensing area. APSO can be extended to optimize coverage in the following ways:

a. Node Placement: APSO can optimize the placement of sensor nodes to achieve better coverage. The fitness function can be based on coverage metrics such as area coverage, connectivity, or target detection probability. The particles can explore the search space to find optimal node locations that maximize coverage.

b. Power Optimization: APSO can optimize the transmission power levels of the sensor nodes to achieve the desired coverage. By adjusting the transmission power of each node, APSO can balance energy consumption while ensuring sufficient coverage.

3. Energy Conservation:

Energy conservation is a critical concern in WSNs due to the limited power resources of sensor nodes. APSO can be extended to conserve energy in the following ways:

a. Sleep Schedule Optimization: APSO can optimize the sleep schedule of sensor nodes to minimize energy consumption. By determining the optimal time for nodes to sleep and wake up, APSO can reduce idle listening and unnecessary data transmission, leading to energy savings.

b. Data Aggregation: APSO can optimize the aggregation of sensor data to minimize the amount of transmitted data. By intelligently aggregating and compressing data at intermediate nodes, APSO can reduce the number of transmissions, thereby conserving energy. By extending APSO for WSNs, it is possible to address latency minimization, coverage optimization, and energy conservation. Thus, the proposed APSO algorithm has the features and ability to perform well according to the mentioned parameters.

3.12 Case Studies & Simulations Based on Real-World Deployment Scenarios in APSO

APSO is a metaheuristic algorithm that has been widely used for optimization problems. It can be extended to address multiple conflicting objectives, such as latency minimization, coverage optimization, and energy conservation in Wireless Sensor Networks (WSNs). In this discussion, I will provide an overview of APSO and then present some case studies or simulations based on real-world deployment scenarios to demonstrate its practical applicability in WSNs. Case studies and simulations:

a. Latency Minimization: In a WSN deployment scenario where minimizing latency is crucial, APSO can be used to optimize the placement of sensor nodes to reduce communication delays. The fitness function can be defined as a combination of the latency experienced by each node and the overall network performance. By running simulations with different APSO configurations and objective weights, it is possible to find the optimal trade-off between latency and other performance metrics.

b. Coverage Optimization: For WSNs aimed at maximizing coverage, APSO can be utilized to determine the optimal deployment locations for sensor nodes. The fitness function can incorporate coverage metrics such as sensing range, overlap detection, and connectivity. By applying APSO with multiple objectives and Pareto-based techniques, the algorithm can identify a set of solutions that provide the best compromise between coverage and other objectives.

c. Energy Conservation: Energy efficiency is a critical concern in WSNs due to the limited power resources of the sensor nodes. APSO can be employed to optimize energy consumption by finding the best node placement and transmission power levels. The fitness function can consider energy-related metrics such as residual energy, transmission distance, and energy consumption rate. By applying APSO with multi-objective optimization, the algorithm can identify solutions that achieve a balance between energy conservation and other objectives.

3.13 Quantitative Analysis of the APSO Algorithm

APSO extends the lifetime of a network by efficiently optimizing the network's parameters or configurations to maximize its performance or minimize certain objective functions. APSO achieves this by combining traditional PSO with an acceleration mechanism. To understand how APSO contributes to prolonging network operation, let's discuss its key features and advantages compared to other existing methods:

1. Exploration and Exploitation: APSO strikes a balance between exploration and exploitation in the search space. It uses a population of particles, each representing a potential solution, to explore the solution space and exploit promising regions. By doing so, APSO avoids getting trapped in local optima and enhances the chances of finding the global optimum, leading to improved network performance.

2. Acceleration Mechanism: APSO introduces an acceleration mechanism that enhances the convergence speed of the algorithm. The acceleration factor modifies the velocity update equation of PSO, allowing particles to move faster toward better solutions. This acceleration mechanism helps APSO to converge quicker and find optimal or near-optimal solutions more efficiently, which is crucial for prolonging network operation.

3. Dynamic Inertia Weight: APSO employs a dynamic inertia weight that adjusts the impact of particle velocity on its movement. By adaptively changing the inertia weight during the optimization process, APSO can effectively balance exploration and exploitation. Initially, a higher inertia weight promotes exploration to cover a wider search space. As the optimization progresses, the inertia weight decreases, favoring exploitation to refine the solutions. This dynamic adjustment improves the optimization efficiency, contributing to prolonging network operation.

4. Robustness and Stability: APSO exhibits robustness against noise and perturbations in the network environment. It is less likely to be affected by local optima or premature convergence compared to other optimization methods. By maintaining diversity within the population of particles, APSO can escape suboptimal solutions and adapt to changes in the network conditions. This robustness ensures the network's continued operation even under varying circumstances, thereby extending its lifetime.

5. Distributed and Parallelized Implementation: APSO can be implemented in a distributed and parallelized manner, which is advantageous for large-scale networks. By dividing the optimization process into multiple sub-processes running concurrently, APSO can handle complex optimization problems more efficiently. This parallelization capability improves the scalability of APSO and enables its application to real-world networks, contributing to prolonged network operation. APSO extends the lifetime of a network compared to other existing methods by efficiently optimizing its parameters or configurations. Its exploration and exploitation capabilities, acceleration mechanism, dynamic inertia weight, robustness, and distributed implementation all contribute to prolonging network operation. By finding better solutions and adapting to changing conditions, APSO enhances the network's performance, stability, and efficiency, thereby extending its useful lifetime.

3.14 Adaption of APSO for Specific User Requirements and Application Domains

The APSO algorithm can be adapted and customized for specific user requirements and application domains in wireless sensor networks (WSNs) by exploring different parameter settings or modifications. Here are some ways to optimize the APSO algorithm for particular use cases in WSNs:

1. Objective Function Design: The objective function used in APSO determines the optimization goal. In the context of WSNs, the objective function should be tailored to the specific requirements of the application domain. For example, if energy efficiency is a critical factor, the objective function could incorporate energy consumption metrics or consider the network lifetime. By defining an appropriate objective function, the APSO algorithm can be customized to optimize the desired performance criteria.

2. Particle Initialization: The initial positions and velocities of particles in APSO play a crucial role in convergence and exploration. Customizing the initialization process can improve the algorithm's performance. For instance, in WSNs, the initial particle positions can be intelligently distributed to cover the sensor field effectively or focus on certain regions of interest. Similarly, setting initial velocities based on domain-specific knowledge can aid in faster convergence.

3. Parameter Tuning: APSO has several parameters, such as acceleration coefficients, inertia weight, and maximum velocity limits, that influence the algorithm's behavior. These parameters need to be optimized for specific use cases in WSNs. For example, the acceleration coefficients can be adjusted to balance exploration and exploitation based on the desired trade-off between global and local search capabilities. The inertia weight can be dynamically adjusted during the optimization process to control the convergence rate. Fine-tuning these parameters through experimentation and domain knowledge can enhance the algorithm's performance.

4. Constraint Handling: In WSNs, there are often constraints related to energy consumption, communication range, and connectivity. Customizing the APSO algorithm to handle these constraints is crucial. One approach is to incorporate penalty functions or constraint-handling techniques into the objective function to guide the search process while satisfying the constraints. This adaptation ensures that the solutions generated by APSO are feasible and practical for the given WSN application.

5. Neighbourhood Topology: APSO utilizes a neighborhood topology to facilitate information exchange among particles. Choosing an appropriate neighborhood structure can significantly impact the algorithm's performance. In the context of WSNs, different neighborhood topologies can be explored based on the network architecture and communication capabilities. For example, a ring or star topology can be suitable for homogeneous WSNs, while a grid or hierarchical topology may be more appropriate for heterogeneous WSNs. Adapting the neighborhood topology can enhance the APSO algorithm's ability to explore the search space effectively.

6. Hybrid Approaches: APSO can be combined with other optimization techniques or algorithms to leverage their strengths and address specific challenges in WSNs. For instance, incorporating local search methods, such as gradient-based algorithms, can enhance the exploitation capabilities of APSO. Hybrid approaches can also involve integrating APSO with machine learning techniques to learn and adapt to the changing network conditions dynamically. Overall, customizing and adapting the APSO algorithm for specific user requirements and application domains in WSNs involves tailoring the objective function, particle initialization, parameter tuning, constraint handling, neighborhood topology, and exploring hybrid approaches. By considering these factors, the APSO algorithm can be optimized to achieve better performance and meet the specific demands of WSN applications.

4 Simulation Results

Three scenarios with various cluster head selections, including 5, 10, and 15, were used in this research investigation. The effectiveness of the suggested algorithm is based on data packets sent, energy consumption at the base station, and the network's lifetime, which is in contrast with the LEACH, CEER, NBEER, and CR-NBEER protocols. The simulation has 100 nodes with different levels of energy. The nodes are dispersed over a network area of 60 by 60 and 500 by 500 m. The sign of the simulation parameters is determined by 0.1. The results of the algorithm employed for the suggested network scenario for five CH selections are displayed in Table 1. This demonstrates that the proposed APSO base efficient clustering protocols outperform the traditional LEACH algorithm regarding CH selection, average energy consumption, and packets transmitted to the BS. The base station (BS) sites are 200 m from the 100 sensor nodes in this research project. The data size is 4000 bytes, with 5, 10, and 15 CHs out of the 100 sensor nodes. The proposed simulation parameters are listed in Table 1.

Figs. 3 and 4 show that the APSO-based proposed protocol chooses 5 CHs, whereas the LEACH chooses just 3 CHs, utilizing 0.1359 and 0.1441 J/bytes of energy for each byte, respectively. The suggested protocol outperforms the default LEACH protocol. Compared to APSO, the proposed protocol transmits 1636 packets to the BS, but LEACH's 682 packets are surprisingly low. The selection of CH of the proposed algorithm and the convergence performance of the two protocols for energy consumption, node lifetime, and packets delivered to the base station are shown in Figs. 5 and 6, and the numbers show that the proposed method uses less energy than the current LEACH protocol while having a higher network lifetime and packet-transmitted ratio. Fig. 7 also depicts the throughput of the suggested APSO-based and LEACH methods. This scenario's simulation time is 26 s.

Figs. 3 and 4 compare the proposed APSO-based protocols and the LEACH protocol. It can be seen that 100 nodes for each algorithm were used to compare their performance based on throughput, dead nodes & energy consumption. Following a thorough study, the LEACH and the suggested method were instructed to obtain 5 CHs out of every 100 nodes. It was discovered that the proposed approach chose five nodes as CHs while LEACH chose just three. The proposed technique also reduced the LEACH's 51 dead nodes to 29.

The energy consumption ratio decreased from 0.1441 J/byte to 0.1359 J/byte. Additionally, the network's throughput has increased from 682 to 1636 bytes. It similarly depicts the CH selection scenario. There were nodes scattered around a 500 × 500 m^2 space. It also displays the CH selection for the proposed and current LEACH protocols on the x and y-axes. The figure shows the proposed technique as having the most nodes connected to CH, whereas the existing LEACH shows the fewest nodes connected to CH. The comparison of energy usage between the suggested approach and traditional LEACH is demonstrated. The y-axis shows the detailed energy used, while the x-axis shows the complete rounds. The graph illustrates that conventional LEACH's energy consumption is slowly rising, as shown by the green line, but the proposed technique's energy consumption is decreasing, as indicated by the blue line.

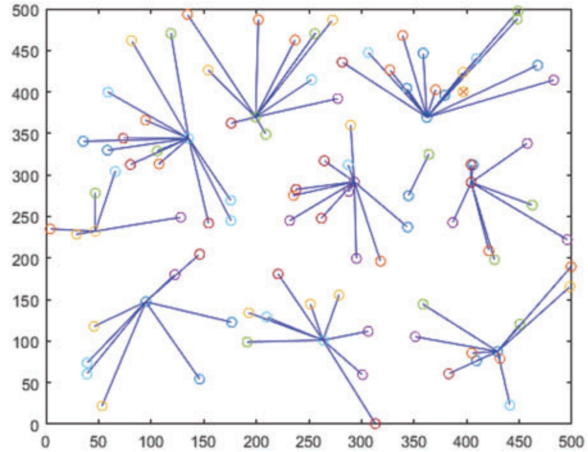


Figure 3: Cluster head selection

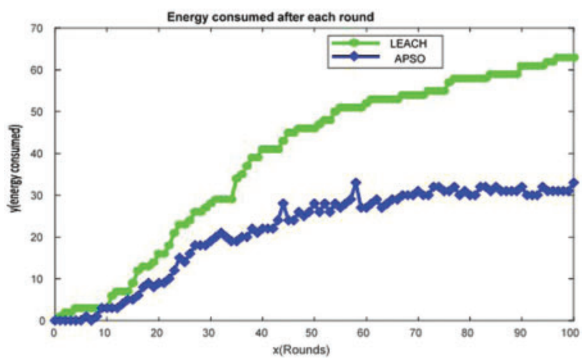


Figure 4: Comparison of the performance of energy consumption

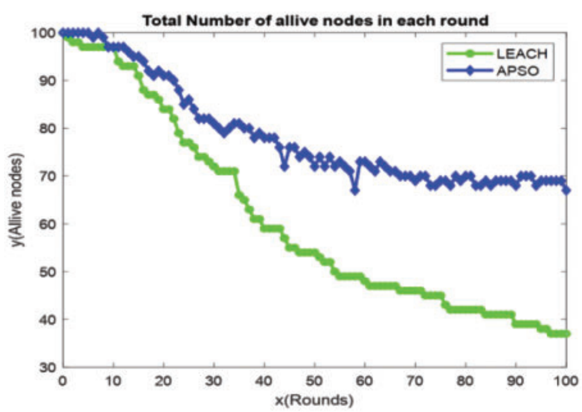


Figure 5: Alive nodes for APSO and LEACH

Fig. 5 displays the total amount of active nodes. Both protocols start their simulations with the same number of alive nodes. After performing the specified rounds, the amount of alive nodes for the suggested protocol steadily increases while the LEACH for the selected scenario decreases. This demonstrates that the current LEACH cannot accomplish the acquired energy usage due to the large number of dead nodes. In contrast, the proposed protocol has a substantially more significant amount of living nodes than the current LEACH. Demonstrates that the suggested method is proficient in achieving the determined energy consumption. The throughput ratio is also displayed.

The packet-transmitted ratio for the specified rounds is demonstrated in Fig. 6. The amount of rounds is represented on the x-axis, while the packet transmitted ratio is shown on the y-axis. Both the LEACH and the suggested APSO-based method's ratios are provided. While the suggested APSO-based protocol's packet transmitted ratio is above 1600 bytes, LEACH's is between 400 and 600. Demonstrates that the APSO-based proposed protocol has a substantially greater packet-transmitted ratio than the current LEACH protocol. Similar to Fig. 7, which details the throughput of both strategies; the suggested technique exceeds 1600 bytes, whereas LEACH has a throughput of 600 to 800 bytes.

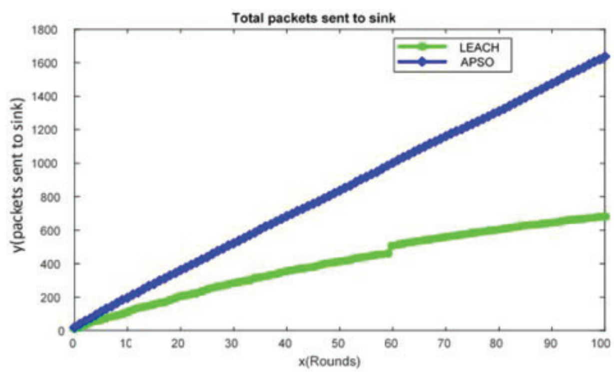


Figure 6: Packet sent ratio of APSO and LEACH

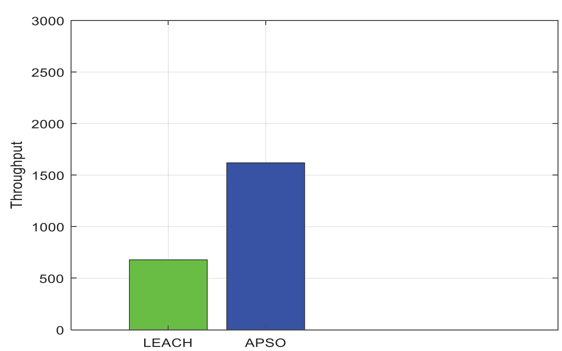


Figure 7: Throughput of the network by APSO and LEACH

Similar to the first situation, Fig. 8 shows CH selection, while Fig. 9 demonstrates that the suggested APSO-based method picks 6 CHs, whereas the LEACH elects only 4 CHs for the second scenario of 10 cluster head selection. Meanwhile, LEACH uses 0.1003 J/byte of energy, and the proposed technique uses 0.0521 J/byte. The suggested method outperforms the LEACH method. Compared to the APSO-based proposed protocol, which has transmitted 1655 packets to the BS, & the LEACH has just sent 722, which is a significantly lower number. Figs. 10–12 illustrate the convergence performance of the two algorithms for the energy consumptions, node lifetime, and packets transmitted to the BS, while Fig. 13 displays the cluster head selection nodes of the suggested method. These values demonstrated that the proposed method uses less energy, has a higher network lifetime, and has a much higher throughput ratio than the current LEACH protocol.

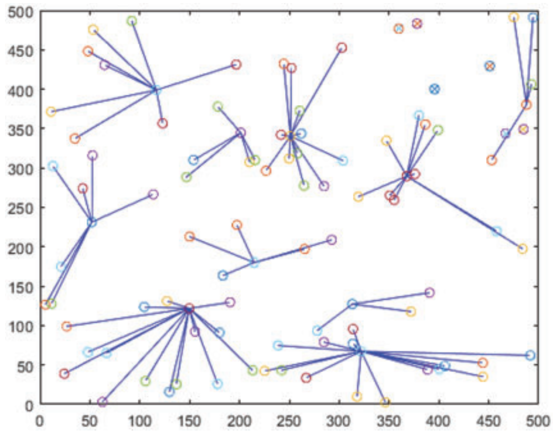


Figure 8: Cluster head selection

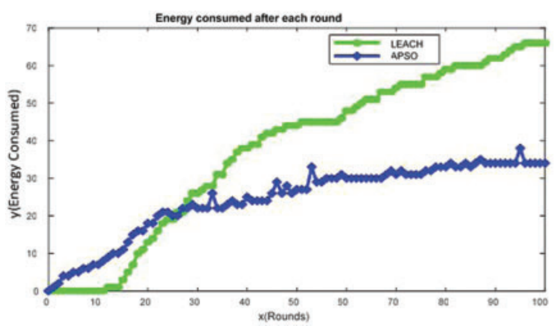


Figure 9: Comparison of the performance of energy consumption

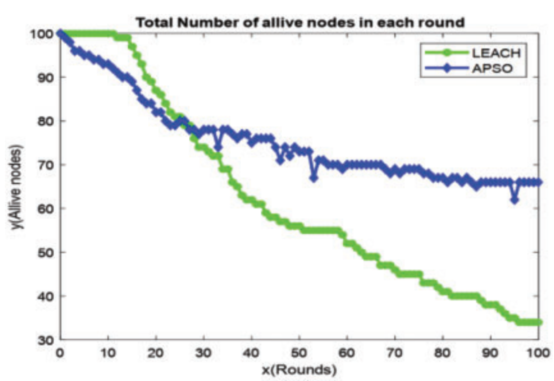


Figure 10: Alive nodes for APSO and LEACH

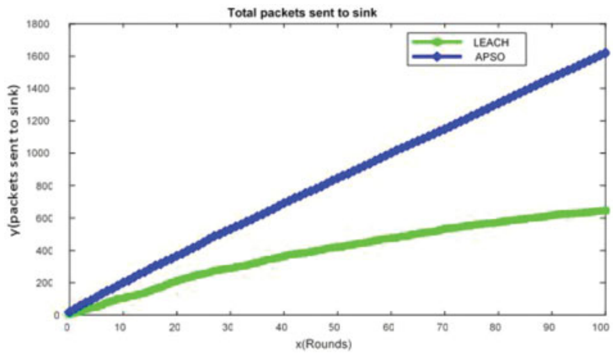


Figure 11: Packet sent ratio of APSO and LEACH

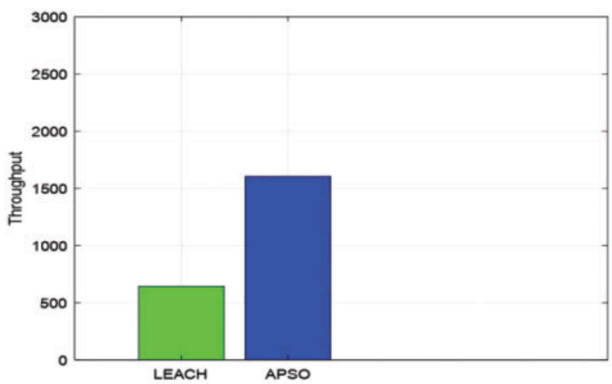


Figure 12: LEACH & APSO throughput evaluations

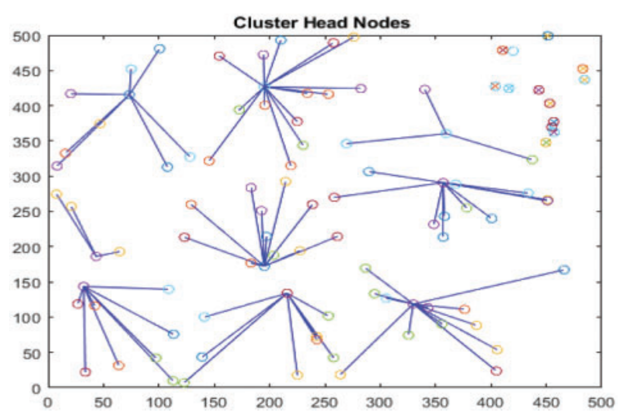


Figure 13: Cluster head selection

These compare energy usage between the suggested approach and traditional LEACH. The y-axis details the energy used, while the x-axis shows the overall amount of rounds. The graph illustrates that the energy consumption of the conventional LEACH is slowly rising, as shown by the green line, but the proposed technique's energy consumption is reducing, as indicated by the blue line.

Fig. 10 shows the overall number of active nodes in the network. Both protocols start with the same amount of nodes that are alive. After the specified rounds, the number of live nodes for the suggested protocol steadily increases while the LEACH for the selected scenario decreases. This demonstrates that the current LEACH cannot accomplish the acquired energy usage due to the vast number of dead nodes. In contrast, the proposed protocol has a substantially higher amount of live nodes than the current LEACH. This demonstrates that the suggested method can achieve the determined energy consumption. In Fig. 11, the throughput ratio is displayed.

Fig. 11 demonstrates the packet transmitted ratio for the specified rounds. The amount of rounds is represented on the x-axis, while the packet transmitted ratio is shown on the y-axis. Both the LEACH and the suggested APSO-based method's ratios are provided. While the suggested APSO-based protocol's packet transmitted ratio is above 1600 bytes, LEACH's is between 400 and 600. This demonstrates that the APSO-based proposed method has a substantially higher packet-transmitted ratio than the current LEACH protocol. As Fig. 12 describes the throughput of both strategies, the suggested technique has a throughput above 1600 bytes, while LEACH has a throughput between 600 and 800 bytes.

Moreover, Figs. 13 and 14 demonstrate that the suggested APSO-based method picks 6 CHs, whereas the LEACH selects only 3 CHs for the third scenario of 15 CH selections. Compared to LEACH, which uses 0.1734 J/byte of energy, the suggested approach uses 0.0911 J/byte. The recommended protocol outperforms the default LEACH protocol. Compared to the APSO-based proposed method, which transmitted 1730 packets to the BS, LEACH just sent 659 packets, a minimal number. Fig. 14 illustrates the convergence performance of the two methods for energy consumption, node lifetime, and packets transmitted to the BS.

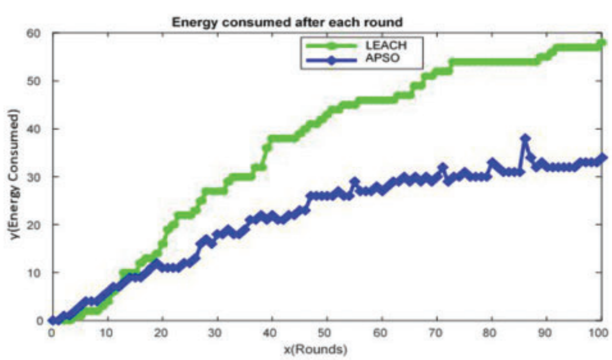


Figure 14: Comparison of the performance of energy consumption

Fig. 15 displays the selection of CH nodes of the suggested method. These numbers show that the recommended method uses less energy, has a higher network lifetime, and has a higher throughput ratio than the current LEACH protocol. Fig. 16 compares the proposed APSO-based and LEACH methods in terms of throughput. This scenario's simulation time is 16 s. The figure compares the proposed APSO-based protocols and the LEACH protocol. It can be seen that 100 nodes for each algorithm were used to compare their performance based on energy consumption, dead nodes &

throughput. Following a thorough study, the LEACH and the suggested method were instructed to obtain 15 CHs out of every 100 nodes. It was discovered that the proposed approach chose six nodes as CHs, while LEACH chose just 3 CHs. The suggested technique also helped to reduce the dead nodes from LEACH's 58 to just 34, which is another improvement. The energy consumption ratio decreased from 0.1734 J/byte to 0.0911 J/byte. The network's capacity has also increased from 659 bytes to 1730 bytes.

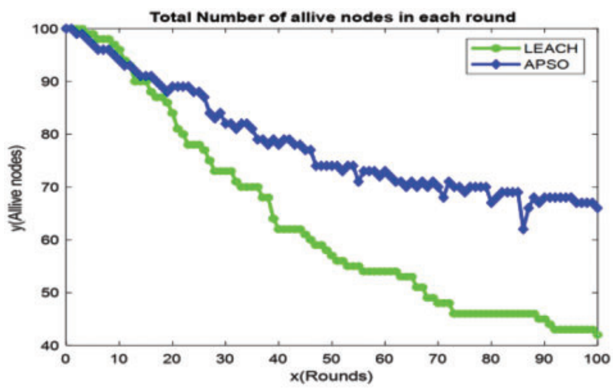


Figure 15: Alive nodes for APSO and LEACH

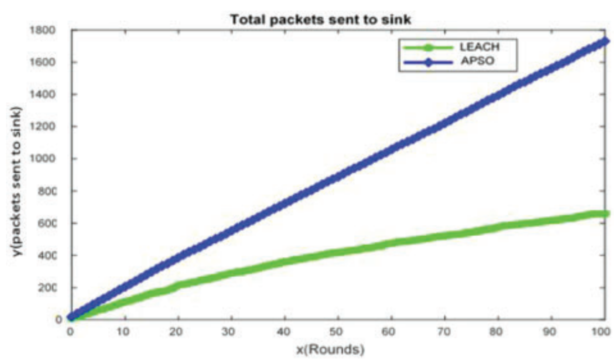


Figure 16: Packet sent ratio of APSO and LEACH

Fig. 14 compares the energy used by the suggested approach and that of traditional LEACH. The y-axis details the energy used, while the x-axis shows the overall amount of rounds. The generated diagram illustrates that the conventional LEACH energy consumption is gradually rising, as shown in the green line, but the proposed technique's energy consumption is reducing, as indicated by the blue line. Additionally, Fig. 14 displays the suggested APSO-based and LEACH algorithms throughput. This scenario's simulation time is 17 s. Fig. 14 compares the proposed APSO-based protocols and the LEACH protocol. It can be seen that 100 nodes for each algorithm were used to compare their performance based on energy consumption, dead nodes & throughput. Following a thorough investigation, 10 CHs out of 100 nodes were to be obtained using LEACH and the suggested approach. It was discovered that the proposed approach chose six nodes as CHs, while LEACH chose just 4 CHs. A further benefit of the presented technique was that it reduced the LEACH's 62 dead nodes to just 32. The energy consumption ratio decreased from 0.1002 J/byte to 0.0520 J/byte. Furthermore, the network's throughput is also enhanced from 722 bytes to 1655 bytes.

Fig. 15 illustrates the overall number of active nodes in the network. Both protocols start with the same amount of alive nodes. After performing the specified rounds, the amount of alive nodes for the suggested protocol steadily increases while the LEACH for the specified scenario decreases. This demonstrates that the current LEACH cannot accomplish the acquired energy usage due to the large number of dead nodes. In contrast, the proposed protocol has a substantially higher amount of living nodes than the current LEACH. This demonstrates that the suggested method can achieve the determined energy consumption.

Fig. 16 demonstrates the packet transmitted ratio for the specified rounds. The amount of rounds is represented on the x-axis, while the packet transmitted ratio is shown on the y-axis. Both the LEACH and the suggested APSO-based method's ratios are provided. The LEACH packet sent ratio ranges from 600 to 800 bytes, whereas the APSO-based proposed protocol has a packet sent ratio of over 1700 bytes. This demonstrates that the proposed APSO-based protocol has a substantially higher packet-transmitted ratio than the current LEACH protocol. Similar to Fig. 16, which details the throughput of both strategies, the suggested technique has a throughput above 1700 bytes, while LEACH has a throughput between 600 and 800 bytes. In Fig. 17, the throughput ratio is displayed. According to Fig. 17, LEACH has a throughput of 600 to 800 bytes per second, while the proposed technique has a throughput of more than 1700 bytes per second. Table 2 shows the comparative analysis of both LEACH and proposed APSO protocols. Apart from the LEACH, other schemes, NBEER, CEER, and CR-NBEER, are also evaluated with the proposed APSO algorithm, which is shown in Figs. 18–20, respectively.

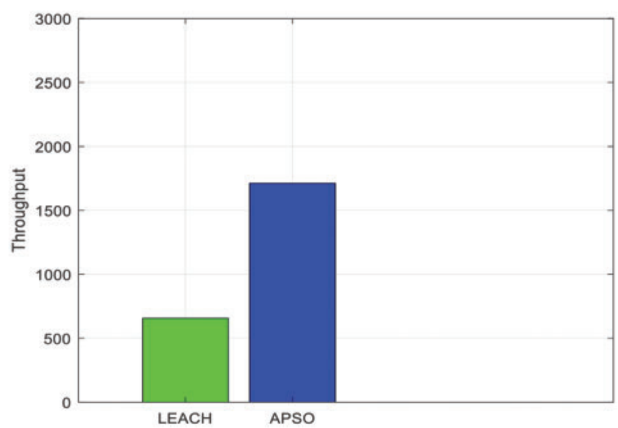


Figure 17: Throughput of the network by APSO and LEACH

Table 2: Comparative analysis for 15 CH selection

Algorithms	Cluster_H	Alive nodes	Packet sent ratio (Byte)	Avg energy consumption (J/byte)	Dead nodes
APSO	5	100	1636	0.1359	29
LEACH	3	100	682	0.1441	51

(Continued)

Table 2 **(continued)**

Algorithms	Cluster_H	Alive nodes	Packet sent ratio (Byte)	Avg energy consumption (J/byte)	Dead nodes
NBEER	3	100	650	0.1399	40
CR-NBEER	4	100	680	0.1499	45
CEER	3	100	677	0.1977	35
Comparative analysis for 10 CH selection					
Algorithms	Cluster_H	Alive nodes	Packet sent ratio (Byte)	Avg energy consumption (J/byte)	Dead nodes
APSO	6	100	1655	0.0521	32
LEACH	4	100	722	0.1003	62
NBEER	5	100	721	0.1000	50
CR-NBEER	4	100	700	0.1212	35
CEER	3	100	698	0.1021	44
Comparative analysis for 15 CH selection					
Algorithms	Cluster_H	Alive nodes	Packet sent ratio (Byte)	Avg energy consumption (J//byte)	Dead nodes
APSO	6	100	1730	0.0911	34
LEACH	3	100	659	0.1734	58
NBEER	5	100	650	0.0999	55
CR-NBEER	3	100	600	0.1200	40
CEER	4	100	644	0.9999	39

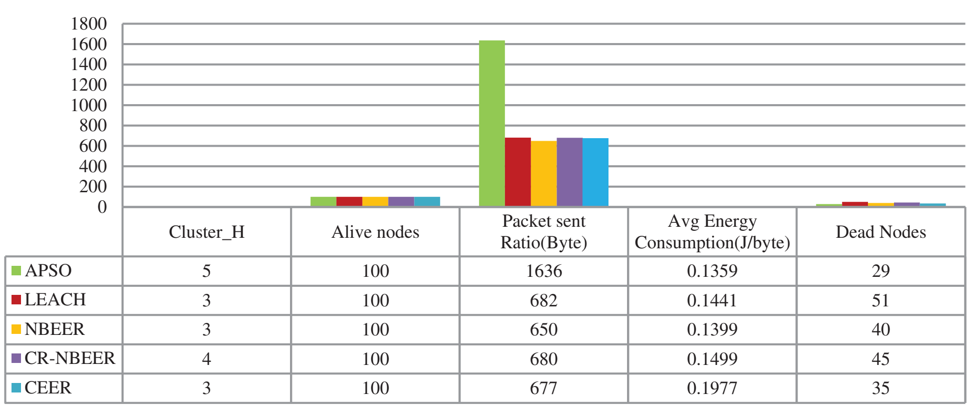
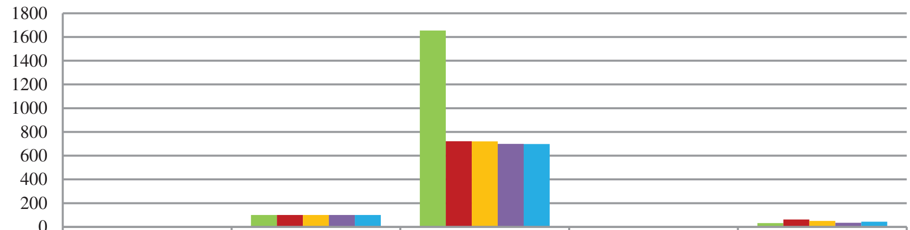
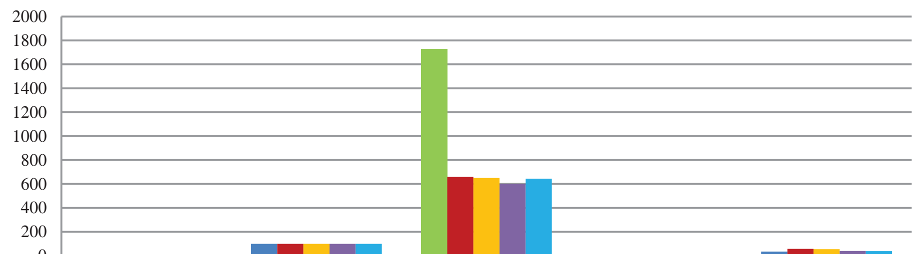


Figure 18: Comparative analysis for 15 CH selection



	Cluster_H	Alive nodes	Packet sent Ratio(Byte)	Avg Energy Consumption(J/byte)	Dead Nodes
APSO	6	100	1655	0.0521	32
LEACH	4	100	722	0.1003	62
NBEER	5	100	721	0.1	50
CR-NBEER	4	100	700	0.1212	35
CEER	3	100	698	0.1021	44

Figure 19: Comparative analysis for 10 CH selection



	Cluster_H	Alive nodes	Packet sent Ratio(Byte)	Avg Energy Consumption(J//byte)	Dead Nodes
APSO	6	100	1730	0.0911	34
LEACH	3	100	659	0.1734	58
NBEER	5	100	650	0.0999	55
CR-NBEER	3	100	600	0.12	40
CEER	4	100	644	0.9999	39

Figure 20: Comparative analysis for 15 CH selection

Apart from the LEACH, the proposed APSO has also been evaluated and compared with three other senior protocols, which are NBEER [59], CR-NBEER [60], and CEER [61] routing protocols. From the expanded evaluations, it has further been observed and concluded that the proposed APSO performed better. The values of new schemes are NBEER, CR-NBEER, and CEER, which are evaluated with the APSO and are shown in Table 2. Further evaluations for the robustness of the proposed APSO algorithm under dynamic network conditions such as node mobility, node failures, and varying environmental conditions are given in Figs. 21–29, respectively. The new evaluations have been carried out to analyze the proposed work for real-world WSN applications where network topology may frequently change. Multiple new parameters have been deployed such as transmission energy, reception energy, and idle energy. Also, the proposed scheme has been tested for its efficiency and impact on these energy constraints. For evaluations, the proposed work APSO is evaluated with NBEER, CR-NBEER, CEER, and LEACH. With 10 rounds of each, the new method has been implemented for evaluations.

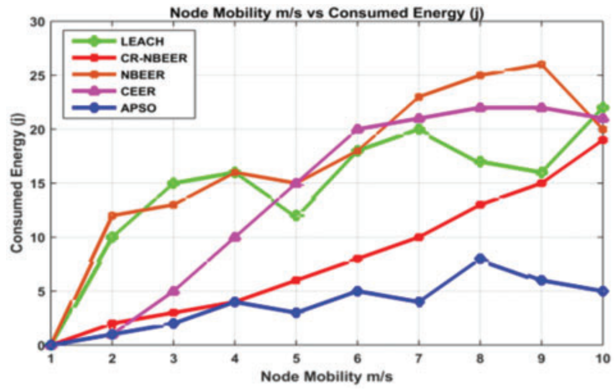


Figure 21: Node mobility *vs*. energy consumption

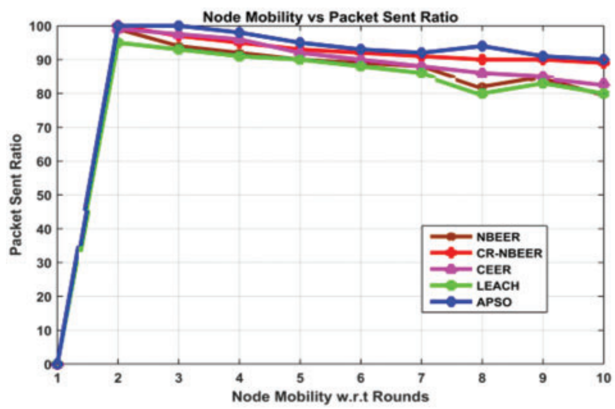


Figure 22: Node mobility *vs*. packet sent ratio

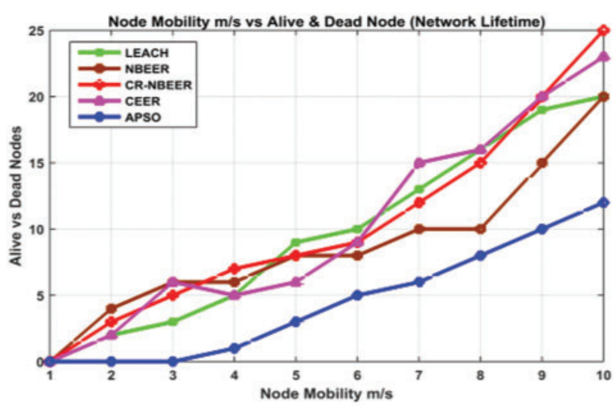


Figure 23: Node mobility *vs*. dead nodes

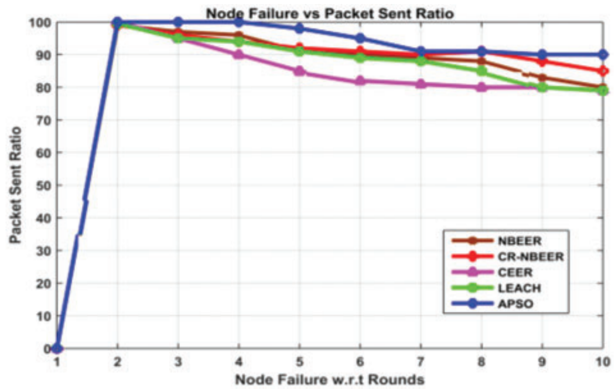


Figure 24: Node failure *vs*. packet sent ratio

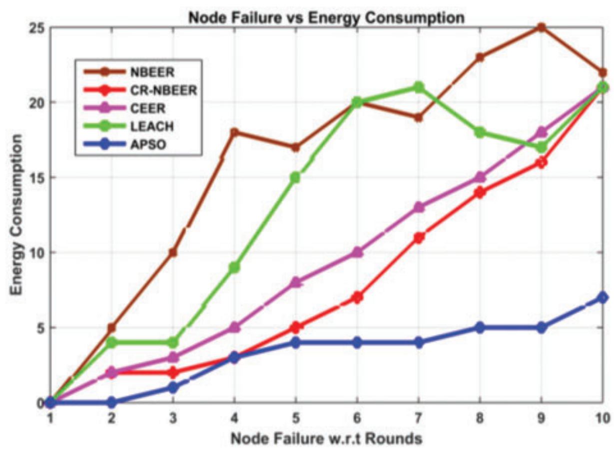


Figure 25: Energy consumption *vs*. node failure

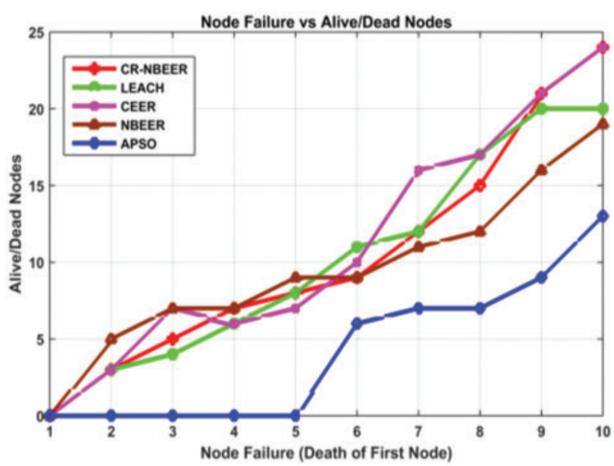


Figure 26: Node failure *vs*. dead nodes

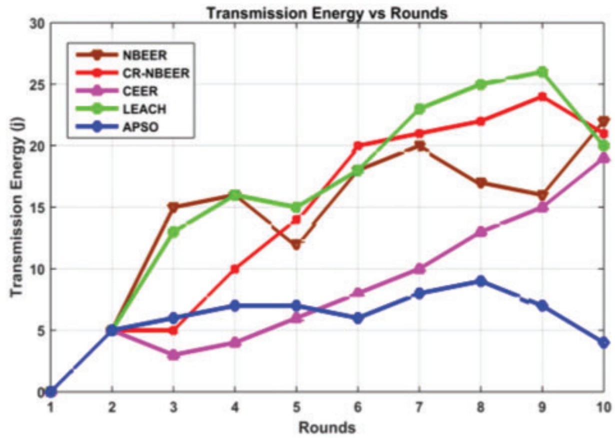


Figure 27: Transmission energy *vs*. rounds

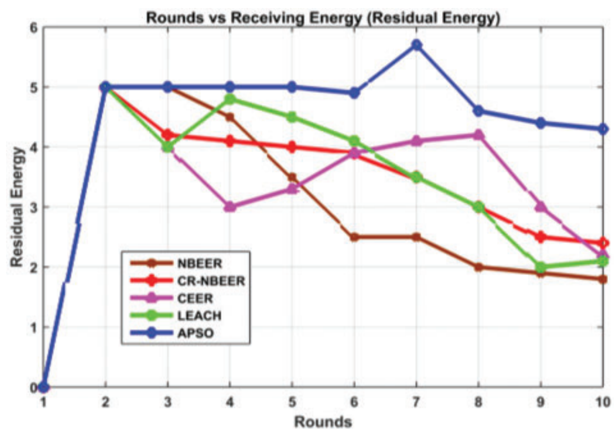


Figure 28: Rounds *vs*. residual energy

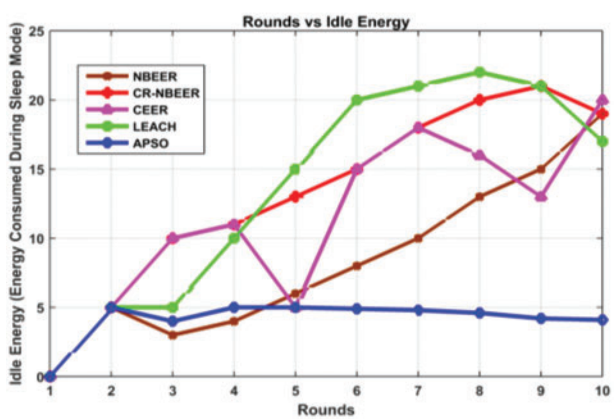


Figure 29: Idle energy *vs*. rounds

From additional simulations and generating multiple results, it was concluded that the proposed APSO algorithm can work under different conditions and network environments. Furthermore, this illustrates that the scheme can obtain the best performance among all other existing schemes based on throughput, energy consumption, packet sent ratio, and different mobility factors.

5 Conclusion

The concept of WSN is a smart communication among nodes, and the sensor nodes embedded in this network are the major and primary reasons for the Internet of Things (IoT). In the current scenario, the proposed work is presented in WSN with the collaboration of the APSO, which is an extended version of PSO. APSO is used for fair optimization in the network to select the fair and equal CH among all the nodes in the WSN. The goal of the analysis is to increase the network lifetime, which has been accomplished. The goal of objective 3 is to increase the network's throughput.

The throughput of the existing network has been enhanced from the level of 682 to 1636 kbps, in which 682 is the LEACH value, whereas 1636 is the value of the APSO-based proposed method. With the efficient routing techniques, this throughput has been enhanced. The highest possible throughput ratio (packet sent ratio) has been achieved. It has been discovered that the APSO-based suggested method has changed the outcomes of the current LEACH method after choosing a suitable node to serve as the CH and maximizing throughput. The current protocol has been changed to decrease energy consumption and increase the throughput and lifetime of networks. By obtaining the necessary findings, the proposed protocol's results have been compared to those of the current LEACH, and it has been discovered that the proposed protocol has increased network throughput while extending the network lifetime and consuming less energy than the existing LEACH, CEER, NBEER, and CR-NBEER. As a result, it has been determined that all the goals have been accomplished. Similar conclusions have been reached with the suggested APSO-based protocol, which is more effective than the current traditional LEACH methodology and can be used for upcoming research projects. The leach protocol can be improved by utilizing several optimization methods. A hybrid with a few valuable parameters can further enhance the suggested APSO-based protocol. Similar to that, UWSN can make use of the proposed protocol.

This concept can be further expanded in the future, and more simulation parameters can be included, such as latency, routing overhead, probability of connectivity, network congestion, and transmission loss. The concept can also be tested with other optimizations, such as the Whale Optimization Algorithm (WOA), Enhanced Differential Evolution (EDE). The network scalability for nodes and geography can also be tested to check the performance of the increasing and decreasing nodes.

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Availability of Data and Materials: Not applicable.

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References

[1] M. Shyjith, C. Maheswaran, and V. Reshma, "Optimized and dynamic selection of cluster head using energy efficient routing protocol in WSN," *Wirel. Pers. Commun.*, vol. 116, pp. 577–599, 2021. doi: 10.1007/s11277-020-07729-w.

[2] Z. Ur Rehman, A. Iqbal, B. Yang, and T. Hussain, "Void hole avoidance based on sink mobility and adaptive two hop vector-based forwarding in underwater wireless sensor networks," *Wirel. Pers. Commun.*, vol. 120, pp. 1417–1447, 2021. doi: 10.1007/s11277-021-08518-9.

[3] T. Hussain, Z. U. Rehman, A. Iqbal, K. Saeed, and I. Ali, "Two hop verification for avoiding void hole in underwater wireless sensor network using SM-AHH-VBF and AVH-AHH-VBF routing protocols," *Trans. Emerg. Telecomm. Technol.*, vol. 31, pp. e3992, 2020. doi: 10.1002/ett.3992.

[4] S. K. Gupta and P. Sinha, "Overview of wireless sensor network: A survey," *Telos*, vol. 3, no. 1, pp. 5201–5207, 2014.

[5] L. C. Mutalemwa and S. Shin, "Investigating the packet delivery reliability of source location privacy protocols in WSNs," in *Korea Commun. Soc. Conf. Proc.*, Mapo-gu, Seoul, South Korea, 2020, vol. 8, pp. 621–623.

[6] L. C. Mutalemwa, M. Kang, and S. Shin, "Controlling the communication overhead of source location privacy protocols in multi-hop communication wireless networks," in *2020 Int. Conf. Artif. Intell. Inf. Commun. (ICAIIC)*, Fukuoka, Japan, 2020, pp. 55–59. doi: 10.1109/ICAIIC48513.2020.9065284.

[7] B. M. Sahoo, H. M. Pandey, and T. Amgoth, "GAPSO-H: A hybrid approach towards optimizing the cluster based routing in wireless sensor network," *Swarm Evol. Comput.*, vol. 60, pp. 100772, 2021. doi: 10.1016/j.swevo.2020.100772.

[8] T. Hussain, B. Yang, H. U. Rahman, A. Iqbal, F. Ali and B. shah, "Improving source location privacy in social internet of things using a hybrid phantom routing technique," *Comput. Secur.*, vol. 123, pp. 102917, 2022. doi: 10.1016/j.cose.2022.102917.

[9] Y. Zheng, Y. Wang, and J. Liu, "Research on structure optimization and motion characteristics of wearable medical robotics based on improved particle swarm optimization algorithm," *Future Gener. Comput. Syst.*, vol. 129, pp. 187–198, 2022. doi: 10.1016/j.future.2021.11.021.

[10] K. Ramesh and D. K. Somasundaram, "A comparative study of clusterhead selection algorithms in wireless sensor networks," arXiv preprint arXiv:1205.1673, 2012.

[11] J. Wang, Z. Xu, X. Zheng, and Z. Liu, "A fuzzy logic path planning algorithm based on geometric landmarks and kinetic constraints," *Inf. Technol. Control.*, vol. 51, pp. 499–514, 2022. doi: 10.5755/j01.itc.51.3.30016.

[12] X. Zhang, S. Yao, W. Xing, and Z. Feng, "Fuzzy event-triggered sliding mode depth control of unmanned underwater vehicles," *Ocean Eng.*, vol. 266, pp. 112725, 2022. doi: 10.1016/j.oceaneng.2022.112725.

[13] A. Al-Baz and A. El-Sayed, "A new algorithm for cluster head selection in LEACH protocol for wireless sensor networks," *Int. J. Commun. Syst.*, vol. 31, pp. e3407, 2018. doi: 10.1002/dac.3407.

[14] D. Bhattacharyya, T. H. Kim, and S. Pal, "A comparative study of wireless sensor networks and their routing protocols," *Sens.*, vol. 10, pp. 10506–10523, 2010. doi: 10.3390/s101210506.

[15] M. Elhoseny, R. S. Rajan, M. Hammoudeh, K. Shankar, and O. Aldabbas, "Swarm intelligence-based energy efficient clustering with multihop routing protocol for sustainable wireless sensor networks," *Int. J. Distrib. Sens. Netw.*, vol. 16, no. 9, 2020. doi: 10.1177/1550147720949133.

[16] R. Kaur and D. Kumar, "A review on a novel approach for data collection in WSN," *Int. J. Comput. Technol.*, vol. 16, no. 3, pp. 6213–6218, 2017. doi: 10.24297/ijct.v16i3.6093.

[17] H. U. Khan, M. Sohail, F. Ali, S. Nazir, Y. Y. Ghadi and I. Ullah, "Prioritizing the multi-criterial features based on comparative approaches for enhancing security of IoT devices," *Phys. Commun.*, vol. 59, pp. 102084, 2023. doi: 10.1016/j.phycom.2023.102084.

[18] D. Mehta and S. Saxena, "MCH-EOR: Multi-objective cluster head based energy-aware optimized routing algorithm in wireless sensor networks," *Sustain. Comput.: Inf. Syst.*, vol. 28, pp. 100406, 2020. doi: 10.1016/j.suscom.2020.100406.

[19] S. K. Singh, P. Kumar, and J. P. Singh, "A survey on successors of LEACH protocol," *IEEE Access*, vol. 5, pp. 4298–4328, 2017. doi: 10.1109/ACCESS.2017.2666082.

[20] B. Pitchaimanickam and G. Murugaboopathi, "A hybrid firefly algorithm with particle swarm optimization for energy efficient optimal cluster head selection in wireless sensor networks," *Neural Comput. Appl.*, vol. 32, pp. 7709–7723, 2020. doi: 10.1007/s00521-019-04441-0.

[21] X. S. Yang, S. Deb, and S. Fong, "Accelerated particle swarm optimization and support vector machine for business optimization and applications," in *Netw. Digital Technol.: Third Int. Conf., NDT 2011*, Macau, China, Jul. 11–13, 2011, pp. 53–66.

[22] D. Mahmood, N. Javaid, S. Mahmood, S. Qureshi, A. M. Memon and T. Zaman, "MODLEACH: A variant of LEACH for WSNs," in *2013 Eighth Int. Conf. Broadband Wireless Comput., Commun. Appl.*, Compiegne, France, 2013, pp. 158–163. doi: 10.1109/BWCCA.2013.34.

[23] N. A. Pantazis, S. A. Nikolidakis, and D. D. Vergados, "Energy-efficient routing protocols in wireless sensor networks: A survey," *IEEE Commun. Surveys Tutorials*, vol. 15, pp. 551–591, 2012. doi: 10.1109/SURV.2012.062612.00084.

[24] A. K. Yadav and P. Rana, "Cluster based routing schemes in wireless sensor networks: A comparative study," *Int. J. Comput. Appl.*, vol. 125, pp. 31–36, 2015.

[25] T. M. Behera, U. C. Samal, and S. K. Mohapatra, "Energy-efficient modified LEACH protocol for IoT application," *IET Wirel. Sens. Syst.*, vol. 8, pp. 223–228, 2018. doi: 10.1049/iet-wss.2017.0099.

[26] N. K. Chaubey and D. H. Patel, "Energy efficient clustering algorithm for decreasing energy consumption and delay in wireless sensor networks (WSN)," *Energy*, vol. 4, pp. 8652–8656, 2016.

[27] S. Mondal, P. Dutta, S. Ghosh, and U. Biswas, "Energy efficient rough fuzzy set based clustering and cluster head selection for WSN," in *2016 2nd Int. Conf. Next Gener. Comput. Technol. (NGCT)*, Dehradun, India, 2016, pp. 439–444. doi: 10.1109/NGCT.2016.7877456.

[28] S. Periyasamy, S. Khara, and S. Thangavelu, "Balanced cluster head selection based on modified k-means in a distributed wireless sensor network," *Int. J. Distrib. Sens. Netw.*, vol. 12, pp. 5040475, 2016. doi: 10.1155/2016/5040475.

[29] D. Sharma, A. P. Bhondekar, A. Ojha, A. Shukla, and C. Ghanshyam, "A traffic aware cluster head selection mechanism for hierarchical wireless sensor networks routing," in *2016 Fourth Int. Conf. Parallel, Distrib. Grid Comput. (PDGC)*, Waknaghat, India, 2016, pp. 673–678. doi: 10.1109/PDGC.2016.7913207.

[30] M. M. Warrier and A. Kumar, "An energy efficient approach for routing in wireless sensor networks," *Procedia Technol.*, vol. 25, pp. 520–527, 2016. doi: 10.1016/j.protcy.2016.08.140.

[31] V. Krishnaveni and S. Varadhaganapathy, "Energy efficient cluster formation in wireless sensor networks based on multi objective Bat algorithm," *Int. J. Adv. Res. Sci. Eng.*, vol. 5, pp. 1–9, 2016.

[32] P. S. Rao, P. K. Jana, and H. Banka, "A particle swarm optimization based energy efficient cluster head selection algorithm for wireless sensor networks," *Wirel. Netw.*, vol. 23, pp. 2005–2020, 2017. doi: 10.1007/s11276-016-1270-7.

[33] A. Krishnakumar and V. Anuratha, "An energy-efficient cluster head selection of LEACH protocol for wireless sensor networks," in *2017 Int. Conf. Nextgen Electron. Technol.: Silicon Softw. (ICNETS2)*, Chennai, India, 2017, pp. 57–61. doi: 10.1109/ICNETS2.2017.8067897.

[34] J. Shen, A. Wang, C. Wang, P. C. Hung, and C. F. Lai, "An efficient centroid-based routing protocol for energy management in WSN-assisted IoT," *IEEE Access*, vol. 5, pp. 18469–18479, 2017. doi: 10.1109/ACCESS.2017.2749606.

[35] M. Mittal and S. Kumar, "Performance evaluation of LEACH protocol based on data clustering algorithms," in *Proc. 2nd Int. Conf. Commun., Comput. Netw.*, Chandigarh, India, 2019, pp. 135–144.

[36] J. Wang, Y. Liu, S. Rao, X. Zhou, and J. Hu, "A novel self-adaptive multi-strategy artificial bee colony algorithm for coverage optimization in wireless sensor networks," *Ad Hoc Netw.*, vol. 150, pp. 103284, 2023. doi: 10.1016/j.adhoc.2023.103284.

[37] M. Hajare, V. Biradar, and J. A. Shaikh, "Energy efficient underwater sensor networks routing protocol utilizing advanced particle swarm optimization," in *2023 4th Int. Conf. Emerg. Technol. (INCET)*, Belgaum, India, 2023, pp. 1–6. doi: 10.1109/INCET57972.2023.10170464.

[38] K. P. R. Krishna and R. Thirumuru, "Energy efficient and multi-hop routing for constrained wireless sensor networks," *Sustain. Comput.: Inf. Syst.*, vol. 38, pp. 100866, 2023. doi: 10.1016/j.suscom.2023.100866.
[39] D. Han *et al.*, "LMCA: A lightweight anomaly network traffic detection model integrating adjusted mobilenet and coordinate attention mechanism for IoT," *Telecommun. Syst.*, vol. 84, pp. 549–564, 2023. doi: 10.1007/s11235-023-01059-5.
[40] H. U. Khan, A. Hussain, S. Nazir, F. Ali, M. Z. Khan and I. Ullah, "A service-efficient proxy mobile IPv6 extension for IoT domain," *Inf.*, vol. 14, pp. 459, 2023. doi: 10.3390/info14080459.
[41] H. U. Khan, F. Ali, Y. Alshehri, and S. Nazir, "Towards enhancing the capability of IoT applications by utilizing cloud computing concept," *Wirel. Commun. Mob. Comput.*, vol. 2022, pp. 1–14, 2022. doi: 10.1155/2022/2335313.
[42] S. Chauhan, M. Singh, and A. K. Aggarwal, "Investigative analysis of different mutation on diversity-driven multi-parent evolutionary algorithm and its application in area coverage optimization of WSN," *Soft Comput.*, vol. 27, pp. 1–27, 2023. doi: 10.1007/s00500-023-08090-3.
[43] B. A. Kumar, N. Labhade-Kumar, B. P. Rajkumar, and K. D. Sagar, "Adaptive hybrid bird swarm optimization based efficient transmission in WSN," *J. Pharm. Negat. Results*, vol. 14, pp. 480–484, 2023.
[44] U. K. Siddamallappa, V. R. Sonawane, and N. Gandhewar, "Feature selection using MFCM (modified fuzzy C-mean) & classification using APSO (accelerated particle swarm optimization)," *Math. Stat. Eng. Appl.*, vol. 72, pp. 366–374, 2023.
[45] M. Hajare, V. Biradar, and J. A. Shaikh, "Robust opportunistic routing solutions for under water sensor networks," in *2023 4th Int. Conf. Emerg. Technol. (INCET)*, Belgaum, India, 2023, pp. 1–9. doi: 10.1109/INCET57972.2023.10169982.
[46] W. Zheng, F. Meng, N. Liu, and S. Huang, "A game model for analyzing wireless sensor networks of 5G environment based on adaptive equilibrium optimizer algorithm," *Sensors*, vol. 23, pp. 8055, 2023. doi: 10.3390/s23198055.
[47] H. Fei, B. Zhang, Y. Liu, M. Yan, Y. Lu and J. Zhou, "A novel chaotic elite adaptive genetic algorithm for task allocation of intelligent unmanned wireless sensor networks," *Appl. Sci.*, vol. 13, pp. 9870, 2023. doi: 10.3390/app13179870.
[48] R. Fei, Y. Guo, J. Li, B. Hu, and L. Yang, "An improved BPNN method based on probability density for indoor location," *IEICE Trans. Inf. Syst.*, vol. 106, no. 5, pp. 773–785, 2023. doi: 10.1587/transinf.2022DLP0073.
[49] W. M. Zheng, L. D. Xu, J. S. Pan, and Q. W. Chai, "Cluster head selection strategy of WSN based on binary multi-objective adaptive fish migration optimization algorithm," *Appl. Soft Comput.*, vol. 148, pp. 110826, 2023. doi: 10.1016/j.asoc.2023.110826.
[50] M. R. Reddy, M. R. Chandra, P. Venkatramana, and R. Dilli, "Energy-efficient cluster head selection in wireless sensor networks using an improved grey wolf optimization algorithm," *Comput.*, vol. 12, no. 2, pp. 35, 2023. doi: 10.3390/computers12020035.
[51] A. Srivastava and P. K. Mishra, "Load-balanced cluster head selection enhancing network lifetime in WSN using hybrid approach for IoT applications," *J. Sens.*, vol. 2023, pp. 1–29, 2023. doi: 10.1155/2023/4343404.
[52] S. Chaurasia, K. Kumar, and N. Kumar, "MOCRAW: A meta-heuristic optimized cluster head selection based routing algorithm for WSNs," *Ad Hoc Netw.*, vol. 141, pp. 103079, 2023. doi: 10.1016/j.adhoc.2022.103079.
[53] Z. Wang, J. Duan, H. Xu, X. Song, and Y. Yang, "Enhanced pelican optimization algorithm for cluster head selection in heterogeneous wireless sensor networks," *Sensors*, vol. 23, no. 18, pp. 7711, 2023. doi: 10.3390/s23187711.
[54] S. Ambareesh, H. Kantharaju, and M. Sakthivel, "A novel fuzzy TOPSIS based hybrid jarratt butterfly optimization for optimal routing and cluster head selection in WSN," *Peer Peer Netw. Appl.*, vol. 16, pp. 2512–2524, 2023. doi: 10.1007/s12083-023-01517-6.
[55] S. M. H. Daneshvar and S. M. Mazinani, "On the best fitness function for the WSN lifetime maximization: A solution based on a modified salp swarm algorithm for centralized clustering and routing," *IEEE Trans. Netw. Serv. Manag.*, vol. 20, pp. 4244–4254, 2023. doi: 10.1109/TNSM.2023.3283248.

[56] J. John and P. Rodrigues, "A survey of energy-aware cluster head selection techniques in wireless sensor network," *Evol. Intell.*, vol. 15, pp. 1109–1121, 2022. doi: 10.1007/s12065-019-00308-4.

[57] C. Ying, Z. Zhao, C. Yi, Y. Shi, and J. Cai, "An AoTI-driven joint sampling frequency and access selection optimization for industrial wireless sensor networks," *IEEE Trans. Vehicular Technol.*, vol. 72, pp. 12311–12325, 2023. doi: 10.1109/TVT.2023.3267479.

[58] W. Li, J. Bu, X. Li, H. Peng, Y. Niu and Y. Zhang, "A survey of DeFi security: Challenges and opportunities," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 34, pp. 10378–10404, 2022. doi: 10.1016/j.jksuci.2022.10.028.

[59] S. M. Shah *et al.*, "Advancements in neighboring-based energy-efficient routing protocol (NBEER) for underwater wireless sensor networks," *Sensors*, vol. 23, no. 13, pp. 6025, 2023. doi: 10.3390/s23136025.

[60] A. Hussain *et al.*, "CR-NBEER: Cooperative-relay neighboring-based energy efficient routing protocol for marine underwater sensor networks," *J. Mar. Sci. Eng.*, vol. 11, pp. 1474, 2023. doi: 10.3390/jmse11071474.

[61] S. M. Shah, T. Hussain, B. Shah, F. Ali, K. Zaman and K. S. Kwak, "CEER: Cooperative energy-efficient routing mechanism for underwater wireless sensor networks using clusters," *Comput. Syst. Sci. Eng.*, vol. 45, pp. 2587–2602, 2023. doi: 10.32604/csse.2023.034489.