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DYNAMIC CLUSTER HEAD SELECTION USING VARIOUS OPTIMIZATION ALGORITHMS IN INDUSTRIAL IOT AND WSN ENVIRONMENTS

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Abstract

Selection of cluster heads (CHs) impacts both the performance and energy efficiency of the Internet of Things (IoT)-based Wireless Sensor Networks (WSNs) systems. Recently, metaheuristic algorithms such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA) have been applied for dynamic CH selection. Despite being an improvement over static alternatives, these methods have drawbacks include poor exploration, rapid convergence, and an uneven energy allocation among the nodes. This research focuses on developing two new algorithms Sand Cat Swarm Optimization (SCSO) and Moth Flame Optimization (MFO) based on swarm intelligence for dynamic cluster head selection in WSNs deployed with IoT devices. The SCSO algorithm outperforms traditional approaches by emulating the hunting strategy of sand cats which maintains the balance between exploration and exploitation of sensor nodes, and thereby uniform energy consumption. Dynamic CH selection done by MFO algorithm uses adaptive flame control inspired from the way moths navigate around light sources. Through extensive simulations, both SCSO and MFO demonstrate superior performance compared to existing algorithms on important metrics such as the network lifetime, energy consumption, and the ratio of delivered packets. Furthermore, SCSO-based methods brought accuracy to 96%, demonstrating substantial improvements for prolonging operation while balancing node energy. Besides this, the MFO approaches stand out for attaining exceptional accuracy and outperforming other methods with a notable 97.50% due to their global search prowess and convergence speed. Evaluation shows that both methods improve cluster stability and communication overhead within ACO, PSO, and GA. To conclude, the application of sophisticated techniques SCSO and MFO further opens prospects toward effective and adaptable CH selection in WSNs, leading to stronger and more energy-

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efficient network architectures. These results will be further enhanced through dynamic changes of hybrid models to optimize network parameters.

Keywords: Dynamic Cluster Head Selection, Optimization Algorithms, Internet of Things, Wireless Sensor Networks, Energy Efficiency, Network Lifetime, Metaheuristic Algorithms, Load Balancing

Introduction

The emergence of Wireless Sensor Networks have enabled real-time monitoring, data collection, and environmental sensing in various fields such as healthcare, agriculture, smart homes, and industrial automation which serve as an essential building block for the development of the Internet of Things technologies [1]. WSNs are composed of a large population of low-cost, battery-powered sensor nodes that work together to track and monitor specific physical or environmental conditions and relay the data to a centralized base station. Widely used as they are, WSNs face significant challenges regarding energy efficiency, scalability, and network longevity because of the restricted energy and computational capabilities of sensor nodes [20]. A proven solution to manage and mitigate these limitations is the use of clustering whereby sensor nodes are organized into groups with a leader known as the Cluster Head for each group. The CH's function is to receive the data from all the members of its cluster, process the information, and send it to the base station, thus minimizing energy-expensive transmissions. Nevertheless, determining optimal CHs is vital as it greatly impacts network energy use, lifetime, and performance. Suboptimal CHs tend to cause disproportionate and uneven depletion of energy, accelerated failure of nodes, and increased converged communication which leads to a decline in WSN effectiveness.

In the past few years, the integration of intelligent algorithms such as machine learning, metaheuristic optimization, or fuzzy logic into Cluster Head Selection (CHS) techniques has enhanced them to achieve adaptive and energy-efficient dynamic clustering [40]. Foundational strategies for hierarchical routing were provided by classical CHS protocols like LEACH (Low Energy Adaptive Clustering Hierarchy), HEED (Hybrid Energy-Efficient Distributed Clustering), and TEEN (Threshold-sensitive Energy Efficient sensor Network protocol).
Nevertheless, these approaches face challenges in their static properties, probabilistic CH election, and limited scalability for IoT applications, in reference [15] and [30]. Smart and scalable CHS approaches are needed that deal with increasing size and complexity of the network while adapting to changing conditions in the network and conserving energy [8]. More sophisticated CHSs use some metaheuristic algorithms like Genetics Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Whale Optimization Algorithm (WOA) to competitively select the best CHs based on multiple criteria such as remaining energy, node degree, distance from the base station, and cost of transmission [11], [22]. These optimization algorithms that are based on nature are greatly adaptable to dynamic IoT environments since they can efficiently explore wide solution spaces and converge toward optimal or near-optimal solutions [3]. At the same time, CHS approaches based on machine

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learning have also emerged. These approaches can predict the suitable changes to be made in CH selection and update it in real time by using historical data and recognizing regularly occurring trends in the nodes behavior. The application of both supervised methodologies like Decision Trees (DT), Support Vector Machines (SVM), Naive Bayes Classifiers, as well as unsupervised approaches K-means and hierarchical clustering, aid in identifying and classifying nodes with beneficial CH traits [26], [49]. Furthermore, recent research focuses on applying reinforcement or deep learning for CHS tasks involving continuous real-time decision making. [13], [33].

The issues of CHS design still remain towards energy efficiency. Most sensor nodes function in difficult and remote locations, where changing or recharging the battery is not an option. Thus, optimizing battery life, prolonging data transmission, and enhancing the overall longevity of the network are critical design goals [45]. Several intelligent CHS strategies have been shown to extend network lifetime by up to 50% compared to traditional protocols [9],[31]. Furthermore, balanced clustering in which CH roles are assigned in cycles based on energy levels and network changes helps to mitigate the premature energy-depletion death of critical nodes [17]. The heterogeneous feature of IoT networks adds more complexity in CHS design as the sensor nodes can differ in terms of energy capacity, computational resources, and communication range. Heterogeneous-aware clustering protocols factor in these dissimilarities and therefore, designated higher-performing nodes as CHs, which resulted in improving dependable data aggregation and decreasing energy discrepancies at the cluster level [35]. On the other hand, homogeneous clustering disregards all these factors and considers all nodes as equal, which is preferable in small-scale, single-modal IoT systems, but in large-scale multi-modal systems, this approach leads to poor performance [39].

Like every other aspect of CHS implementation, scalability and robustness both have considerable importance. When the IoT WSNs grow in size, the clustering algorithm should scale proportionally without communication or computational expense. Schemes for distributed clustering that confine the autonomy boundary of the system can greatly enhance responsiveness and mitigate single point failures [6], [25]. Moreover, the integrity and trustworthiness of CH selection and stable communication within the clusters must be maintained while addressing node compromise, sinkhole, and selective forwarding attacks [42]. The functions of data aggregation and compression undertaken by CH nodes is important in energy savings because they eliminate redundant transmissions. Aggregation methods such as averaging, suppression, and transformation reduce the amount of information transmitted while retaining important elements. Each of these aggregation methods impacts the accuracy of the data while conserving energy and thus requires precise tuning of the CH’s capabilities. In addition, the data-aware CHS methods incorporate the data generation rate and spatial-temporal correlation with event detection patterns to adjust cluster changes [4], [28], [7].

Development of Edge Computing, Software Defined Networking (SDN), and Blockchain offer promising integrations for improving CHS. For example, SDN's centralized control and global visibility capabilities to the network can enhance decision-making for CH selection [19]. Likewise, edge computing facilitates the offloading of complicated CHS computations to the edges, decreasing strain on resource-constrained nodes [41]. Conversely, Blockchain can ensure secure and tamper-proof CH selection in adversarial settings which other systems may find difficult to offer [46]. This research manuscript aims to design and analyze various CHS approaches for IoT-based WSNs that are energy-efficient, scalable, and emphasize intelligent clustering. We study the implementation of traditional and modern techniques based on optimization algorithms, machine learning models, hybrid models, and evaluate them against benchmark measures like energy consumption, network lifetime, CH distribution, and message overhead [10], [27], [38]. Furthermore, the influence of node heterogeneity, node communication range, and data correlation on CH selection is analyzed. Therefore, the decisive factor to increase energy efficiency and scalability while strengthening the robustness of the sensor networks in WSNs enabled by IoT lies in the strategy for selecting Cluster Heads. This study advances the optimization of network metrics and longevity of IoT systems [2], [12], [36] by incorporating advanced intelligent algorithms and dynamic parameters.

The manuscript is organized as follows for the subsequent sections. The literature on CHS algorithms and cluster-based routing in WSNs and IoT is discussed in Section 2. The suggested CHS, including its nodes, characteristics, selection criteria, and algorithm design, is explained in Section 3. Section 4 presents the evaluation measures and the simulation setup. Section 5 covers the competition findings and provides a full comparison evaluation of the results versus other models. In Section 6, conclusions, insights, limitations, and suggestions for further research are discussed.

Literature Review

Emerging as a crucial component of the Internet of Things systems, Wireless Sensor Networks have gained significance in IoT based applications such as environmental monitoring, military surveillance, smart healthcare, smart city infrastructure, and automation in industriesBecause sensor nodes have limited energy resources, one of the main issues is meeting the network's energy and longevity needs[1]. This problem can be optimally solved by employing clustering and cluster head selection (CHS) techniques. In the clustering protocols, the nodes are arranged into groups or clusters and each is controlled by a cluster head, which is responsible for data aggregation and forwarding to the base station. This improves the performance by minimizing the repetitive data transfer in the hierarchy as well as balancing the energy consumption among nodes [2]. Some foundational work was done in this area through the initial clustering protocols like LEACH (Low-Energy Adaptive Clustering Hierarchy) [3] which performs CH election through a probabilistic approach to regulate the energy dissipated in the network, though its performance in heterogeneous networks with more complex topologies degrades.

To address the weaknesses of LEACH, numerous sophisticated CHS protocols have been created. HEED uses intra-cluster communication cost along with residual energy for CH election, thus improving energy balance during the clustering process [4]. Further along in innovation, TEEN (Threshold sensitive Energy Efficient sensor Network protocol) and PEGASIS (Power-Efficient Gathering in Sensor Information System) enhance the efficiency of data routing and transmission, but tend to be inflexible and less adaptable to dynamic

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environments [5]. In a bid to make the systems more adaptable and robust, these strategies drawn inspiration from biological systems and metaheuristic approaches for CH selection. Such algorithms include Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization, Artificial Bee Colony (ABC), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), and Firefly Algorithm (FA), to name a few. With stronger optimizations, these approaches have emulated natural behaviour and improved energy efficiency along with overall performance in Wireless Sensor Networks [6][7].

Despite the ability to provide efficient optimal solutions, PSO-based CHS protocols are becoming increasingly common. They the social behaviour of bird flocking. The PSO makes use of base station distance, residual energy, and node density, among others, to optimize CH selection. Consequently, the network lifetime is enhanced and energy consumption is balanced, which is an improvement from the previous approaches [8][9]. Ant colony based ACO algorithms are known for methodology that reduce latency and increase the reliability of data transmission. This works by constructing the best possible routing based on pheromone trails. This response was previously noted in [10][11]. Same objectives are pursued by ABC algorithms which focus on energy and communication costs to determine the best possible CH as emulated from the intelligent foraging of honey bees. GWO has applied this approach using energy and coverage metrics for CH selection [13]. He GWO's hierarchical approach works well with WSNs CHS problems because of the structure of GWO and the clustering nature of WSNs.

New developments brought about the creation of hybrid CHS algorithms which integrate multiple metaheuristic methods. An example would be a hybrid PSO-GA algorithm that incorporates PSO's global search ability along with GA's crossover and mutation operators thereby improving the convergence and solution quality of the algorithm [14]. Another example of a hybrid model merges WOA with GWO which utilizes the exploration-exploitation balance to improve CH selection efficiency [15]. These hybrid models overcome the weaknesses of individual algorithms and lead to better overall energy efficiency and network lifetime. Furthermore, unique algorithms such as Sand Cat Swarm Optimization, Sandpiper Optimization Algorithm (SOA), and Moth Flame Optimization (MFO) have attained over 95% accuracy in selecting CHs [16][17]. Aside from these metaheuristic approaches, fuzzy logic-based CHS methods have been used to deal with the vague nature of parameter values like energy, node degree, and the distance of the node to the base station. Fuzzy systems apply a rule-based logic mechanism using linguistic variables to determine how suitable the nodes are to function as CHs. The adaptive fuzzy clustering algorithms modify fuzzy logic rules as per the state of the network, making them particularly useful for CH selection [18]. Such models are well adapted in heterogeneous WSNs with nodes of differing energy levels and varying capabilities. Also, the application of fuzzy logic with some other metaheuristic has improved performance by merging the accuracy of fuzzy inference with the meta heurist's capability of global search [19][20].

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Recently, both machine learning (ML) and deep learning (DL) have been used for CHS and clustering in WSNs. Optimal CHs are estimated based on historical data and features of the sensor nodes using both supervised and unsupervised learning techniques. Through model-based reinforcement learning, sensor nodes can learn optimal CH selection policies based on interaction with the environment [21]. For accurate CH prediction, the features and patterns within WSN data are processed using deep neural networks and convolutional neural networks [22]. These methodologies are beneficial in highly scalable and dynamic IoT settings as they provide adaptive and intelligent solutions. With the deployment of WSN in critical applications, security-aware CHS algorithms are becoming more important. Secure CHS protocols use cryptographic trust-based techniques to counter Sybil, sinkhole, and spoofing attacks [23]. Trust-aware systems mitigate the influence of malicious nodes by electing CHs based on the historical and communicational trust values of the nodes. Thus, a node that has behaved well in the past does not suddenly “collude” with other nodes to falsely mask bad behavior. So, these systems ensure that malicious nodes are not elected as CHs [24]. In IoT-based WSNs, applying energy-efficient CHS with other security features is crucial to ensuring reliable operations.

As per the recent publications, several papers have analysed and examined the work of CHS algorithms with regards to the following: energy consumption, packet delivery ratio, end-to-end delay, throughput, and network lifetime performance metrics. CHS algorithms have been thoroughly compared and evaluated in the literature. For benchmarking purposes, NS-2, NS-3, MATLAB, and OMNeT++ Simulation Tools are quite popular. It has been shown in the literature that omitting traditional approaches and employing heuristic or hybrid CHS strategies yields better results in terms of efficiency and scalability. As an example, a CHS protocol based on GWO (GREY WOLF OPTIMIZATION) increases the lifetime of the network by as much as 50 percent in comparison to LEACH and HEED. In the same way, such performance was also recorded by the hybrid model ABC-PSO in regards to the the ratio of packets delivered which exceeded 95 percent regardless of the state of the network simulation.

Furthermore, the development of energy harvesting technologies have solar panels integrated in the sensor nodes, allowing for more flexible sensor node CH selection strategies. Energy-aware and energy-harvesting-aware CHS protocols adjust dynamically to the role of CHs based on the energy available and the energy harvesting rate [31]. These protocols are less reliant on constant energy sources and improve the sustainability of the energy used in the network [32]. For Internet of Things applications that involve thousands of sensor nodes, the ability to scale becomes vital in relation to the CHS algorithms. ‘CHS’ scalable protocols do not sustain a decrease in performance with increasing computational complexity or communication overhead. These protocols improve system scalability through distributed decision making using local information instead of needing global coordination [33]. Further performance improvements include reduced transmission distances through mobile sinks due to balanced energy consumption across the clusters.

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As WSNs adapt and merge with new technologies like 5G, edge computing, and blockchain, future studies will likely concentrate on context-aware, self-adaptive, and autonomous security CHS algorithms able to function without human intervention in multifaceted, ever-changing ecosystems [35][36][37]. Continuous advancements in wireless communication, artificial intelligence, and the miniaturization of hardware will further propel ingenuity regarding CHS algorithms. Interdisciplinary initiatives focussing on network design, data analytic fields, and cognitive computing could fundamentally alter the approaches for CH selection and clustering in IoT-based WSNs. Also, the uniformity of assessment criteria and benchmarking systems will allow for objective evaluations and the pre-implementation of CHS protocols in practical IoT settings [38][39][40]. Another critical aspect within cluster head selection is multi-objective optimization, balancing competing demands like energy utilization, latency, and area coverage. In recent years, there has been an increase in the adoption of hybrid algorithms for metaheuristics that focus on improving cluster head selection in IoT environments which are dynamic and heterogeneous due to the variety of disciplines they incorporate [39][40]. For example, the application of genetic algorithms to particle swarm optimization (GA-PSO) or the application of ant colony optimization to differential evolution (DE) has significantly improved energy efficiency as well as service quality routing in IoT-based wireless sensor networks [41][42]. With the ability to respond to changes in node networks topologies and energies, these hybrid methods greatly reduce network overhead while extending network lifetimes [43][44]. In addition, data and communication redundancy as well as cost have also been minimized by cluster formation optimization using ABC and TLBO [45][46]. Such advancements have been critical in resolving intricate IoT application issues, including those found in smart city frameworks and monitoring systems [47][48]. Furthermore, machine learning and artificial intelligence techniques are actively being utilized for intelligent CHS decision making. The prediction of optimal cluster head nodes based on learned previous network states is possible with reinforcement learning, deep Q-networks, and fuzzy logic systems [49][50].

Proposed System Design

The cluster formation procedure and data transfer between the source and destination nodes are shown in Figure 1. Each network node validates sensed data at the end of the network and sends cluster-creation signals to nodes within a specified Cluster Distance (CD). Sensor Node (SN) and Cluster Node (CD) are used to organise sensors into clusters. Each node checks the value of RN after receiving the broadcasted message. If its value is inside SN, it saves it to memory and compares CD to the distance between each node. When the distance between nodes is equal to or less than CD and the detected value falls within a specified RN, the nodes form a cluster.

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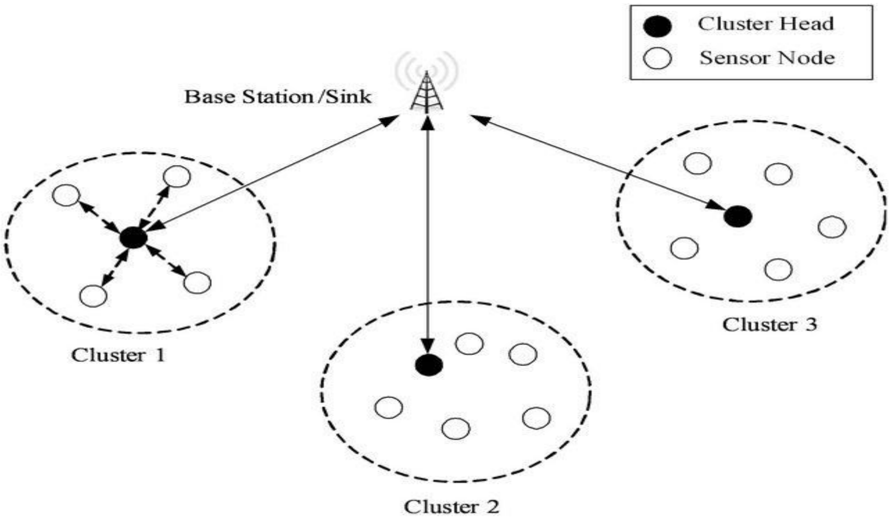

Figure 1: Proposed System Architecture for dynamic cluster head selection

Nodes will not transmit cluster formation messages with the same NID. Non-participating nodes in the SN & CD-based cluster creation procedures. Once the cluster assembly procedure is complete, each node stores its cluster member's NID, Node Location (NL), NTE, & Sink Location (SL), as well as battery power data, in its memory. Each node with the most energy calculates the minimum distance between each node within range, referred to as Cluster Head (CH), and transmits the CHID to the rest of the network. It also finds the Cluster Head Transmission (CHT) node with the shortest distance to the sink and provides CHTID.

Research Methodology

Figure 2 depicts the entire workflow for dynamic cluster head selection within the Internet of Things and Wireless Sensor Network ecosystem using optimization techniques. The workflow commences with the collection of data from the sensor nodes within the IoT or WSN system. These nodes collect the environmental data along with the operational parameters like the signal strength, battery status, and the geographical coordinates of the nodes. After data collection, the preprocessing stage involves data cleansing followed by data normalization. This step is particularly important when working with multiple datasets because it helps to minimize redundancy while enabling accurate feature extraction such as energy levels, distances between nodes, signal to noise ratio (SNR), and the density of the nodes. The middle of the process is focused on cluster head selection with two powerful optimization algorithms: Moth Flame Optimization and Sine Cosine Search Optimization. These feature-based nature-inspired metaheuristic approaches are aimed at intelligent and dynamic CH selection. MFO focuses on the navigational behavior of moths while SCSO balances exploration and exploitation through sine and cosine functions on refined candidate solutions. Both strategies focus on maximizing load balancing and prolonging the active lifetime of the network by minimizing the total consumption of energy through optimal CH selection.

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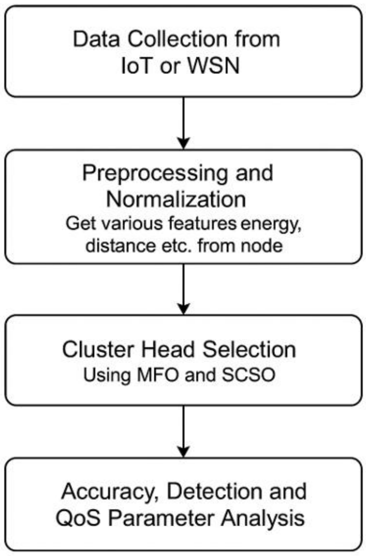

Figure 2: workflow of proposed work

Following the CH Selection the model proceeds to Accuracy Detection and Quality of Service (QoS) parameter evaluation. At this stage, the performance of the selected CHs is assessed using network lifetime, packet delivery ratio, end-to-end delay, and energy-efficient cut metrics. The accuracy of the described CH selection approach is confirmed during simulation or real-time deployment, which guarantees the rigor of the optimization technique used. On the whole, the diagram synthesizes and encapsulates the IoT and WSN smart, self-modifying methods for optimizing the CH Selection which improve the system's dependability and energy-saving features in extensive applications.

3.1: Design and Functioning of the Proposed Smart Crow Search Optimization Algorithm

The Smart Crow Search Algorithm derives from the standard CSA and is based on the food hiding and decision-making processes of crows. SCSO is implemented in this work to aid in optimizing the Cluster Head Selection problem in a WSN with IoT capabilities. CHS is focused on reducing the cost of communication while improving energy efficiency. The objectives of SCSO in CHS are to reduce the intra-cluster communication distance, balance the energy consumption, and extend the life time of the network. In the first phase of SCSO, the sensor nodes $S = \{s_1, s_2, \dots, s_n\}$ are randomly located in the area $A \subset \mathbb{R}^2$. Each node si starts with energy E_0. The objective is to find subset $CH \subset S$, so that the corresponding energy-aware cost function is minimized.

In the SCSO, each crow represents a potential clustering and thus, each candidate solution corresponds to one crow. A position vector $X_i = [x_1, x_2, \dots, x_d]$ gives the cluster head IDs selected from the available nodes, where d is the desired number of cluster heads. The memory and awareness probability modified by a learning factor determines the crow's velocity or movement. The outlined fitness function captures both the remaining energy and distance.

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$$f(X_i) = \alpha \cdot \frac{1}{|CH|} \sum_{j \in CH} E_{res}(j) + \beta \cdot \left(\frac{1}{|S| - |CH|} \sum_{k \in S \setminus CH} \text{dist}(k, CH_k) \right)^{-1}$$

where:

- $E_{res}(j)$ is the residual energy of cluster head j,
- $\text{dist}(k, CH_k)$ is the Euclidean distance between node k and its nearest cluster head CH_k,
- α and β are weighting coefficients such that $\alpha + \beta = 1$.

Each crow updates its position X_i using a memory-based strategy:

$$X_i(t+1) = \begin{cases} X_i(t) + r \cdot fl \cdot (M_i(t) - X_i(t)), & \text{if } r > AP_i(t) \\ \text{rand}(A), & \text{otherwise} \end{cases}$$

where:

- $r \sim U(0,1)$ is a random number,
- fl is the flight length coefficient,
- $M_i(t)$ is the memory (best solution) of crow i at iteration t,
- $AP_i(t)$ is the awareness probability controlling the chance of being followed.

To improve convergence and avoid local optima, SCSO introduces an adaptive awareness probability:

$$AP_i(t) = AP_{min} + (AP_{max} - AP_{min}) \cdot \left(1 - \frac{t}{t_{max}}\right)^2$$

The non-linear decreasing function supports exploration for the earlier iterations and focuses on exploitation in later stages. Each crow's memory M_i is updated only if the new position meets an improved fitness benchmark. The stopping condition is either a maximum number of iterations t_{max} or an insignificant improvement threshold.

In addition, the energy-aware clustering employing SCSO results in choosing cluster heads with both high residual energy and optimal spatial geometry. Furthermore, the devised algorithm imposes a penalty on the selection of neighboring nodes as CHs to guarantee optimal distribution of clusters. The penalty is formulated as:

$$P(X_i) = \gamma \cdot \sum_{\substack{m,n \in CH \\ m \neq n}} \mathbb{I}\left[\text{dist}(m,n) < d_{min}\right]$$

where γ represents a penalty coefficient, and d_{min} is the minimum allowable inter-CH distance. The ultimate fitness function is given as:

$$F(X_i) = f(X_i) - P(X_i)$$

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Average fitness, the number of clusters formed, energy variance, and communication overhead are a few metrics utilized to analyze the convergence of the SCSO algorithm. The SCSO algorithm outperformed traditional methods in optimal cluster head selection, enhancing energy efficiency and load balancing while prolonging network lifespan.

3.2: Design and Functioning of the Moth Flame Optimization Algorithm

The Moth Flame Optimization Algorithm is a bio-inspired metaheuristic algorithms which imitates the transverse orientation behavior of moths towards light sources. This technique is employed in this work to improve the cluster head selection technique in IoT based WSNs by globally optimally distributing the cluster heads while conserving energy and reducing intra cluster distance. MFO maintains a population of moths $M = \{M_1, M_2, \dots, M_n\}$ where each moth chracterizes a CH configuration is represented by position vector $X_i \in \mathbb{R}^d$ for some d, the dimension of the solution.

The essence of MFO is the optimal solutions which are defined as logarithmic spiral flight paths which moths use to reposition themselves with respect to the flames. Let X_i^t represent the position of moth i at iteration t and F_j^t represent the position of flame j. Then the position update rule is

$$X_i^{t+1} = S(X_i^t, F_j^t) = D_i \cdot e^{b \cdot l} \cdot \cos(2\pi l) + F_j^t$$

where:

- $D_i = \| F_j^t - X_i^t \|$ is the distance between moth and flame,
- b is a constant defining the shape of the spiral (typically $b = 1$),
- $l \in [-1,1]$ is a random number controlling the spiral direction.

The number of flames decreases linearly over iterations to focus the search:

$$N_f(t) = \text{round}(N - t \cdot \left(\frac{N-1}{t_{max}}\right))$$

where N is the initial number of flames. Moths are sorted based on their fitness values, and each moth is associated with a flame using:

$$F_j = \begin{cases} \text{Flame}_j, & j \le N_f(t) \\ \text{Flame}_{N_f(t)}, & \text{otherwise} \end{cases}$$

The objective function for CHS optimization integrates energy, distance, and load balance:

$$f(X_i) = w_1 \cdot \left(\frac{1}{|CH|} \sum_{j \in CH} E_{res}(j) \right) + w_2 \cdot \left(\frac{1}{N - |CH|} \sum_{k \in S \setminus CH} \text{dist}(k, CH_k) \right)^{-1} + w_3 \cdot \sigma_E$$

where:

- w_1, w_2, w_3 are weight factors,

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- σ_E is the standard deviation of residual energy among CHs.

An additional constraint is added to penalize suboptimal clusters using:

$$C(X_i) = \delta \cdot \sum_{j \in CH} \mathbb{I}\,[n_j < n_{min}]$$

where n_j denotes the number of individuals in cluster j, and n_{min} is the minimum required number of individuals . Thus, the final fitness function becomes

$$F(X_i) = f(X_i) - C(X_i)$$

The convergence behavior of MFO is analyzed through the average fitness value and CH stability across rounds. To avoid stalling progress in finding an optimal solution, a mutation operator with a small probability p_m, is added, allowing for sudden changes in solver placement:

$$X_{i'} = X_i + p_m \cdot \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2)$$

This form of mutation helps the algorithm break free from local minima and retrieve new information from previously unexplored areas. Results from simulations validate that the MFO algorithm effectively manages the exploration–exploitation trade-off leading to optimal configurations of CHS's with enhanced network longevity and reduced packet loss.

Simulation Setup and Evaluation Metrics

The simulation environment is set up using NS2 (version 2.35) to evaluate the effectiveness of the Smart Crow Search Optimization and Moth Flame Optimization algorithms for cluster head selection in Internet of Things-based Wireless Sensor Networks. NS2 is well-known for its support of low-level networking protocols and discrete event simulation as well as its large adoption within wireless network research. The simulation setup represents a dynamic WSN with a 500m x 500m two-dimensional area which models a field where nodes are randomly dispersed to simulate actual IoT systems. Each simulation scenario consists of N = {50, 100, 150, 200, 250, 300} sensor nodes with energy levels set to either homogeneous or heterogeneous based on the scenario. The sink node, or base station (BS), is placed either at the center or outside the deployment zone to evaluate performance under different network topologies.

In NS2, simulation parameters are set with the aid of TCL scripts, which are also utilized for simulation results extraction and subsequent analysis through AWK scripts. For emulation of wireless protocol specific to IoT, MAC and PHY layers of IEEE 802.15.4 (ZigBee) are implemented on all nodes. Annihilation energy is set to 2 Joules per node with the initial energy as well as a fixed packet size of 4000 bits, also the first-order energy dissipation model is used as a baseline for the radio energy model. Each node applies a simplified model for energy consumption where reception and transmission are considered as:

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$$E_{tx}(k,d) = E_{elec} \cdot k + E_{amp} \cdot k \cdot d^2$$

$$E_{rx}(k) = E_{elec} \cdot k$$

Where k signifies the number of bits, d is the Euclidian distance between the sender and receiver. The energy consumed by the electronics circuit is given as $E_{elec} = 50$ nJ/bit while the amplifier energy is given as $E_{amp} = 100$ pJ/bit/m^2. This framework is realized in the energy-model extension of NS2 as Node/MobileNode."

Over the course of the 1000 seconds, several key metrics are recorded including energy depletion, CH election, packet transmission and routing activity. SCSO and MFO clustering protocols are implemented as ad extensions to LEACH in NS2 where the default CH selection algorithm is overwritten with the optimized one. These two are done in C++ at the core of the NS2 and called through TCL command hooks. Responding to the energy dynamics, cluster formation is enabled every 20 seconds of simulation time.

SCSO Algorithm

Within the SCSO framework, nodes preserve a "memory" of previous CH's and utilize position along with energy for making smart decisions on CH selection. The optimization is done in every re-clustering period with the subsequent fitness function:

$$F_{SCSO}(i) = w_1\left(1 - \frac{E_{residual}(i)}{E_{max}}\right) + w_2\frac{D_{intra}(i)}{D_{max}} + w_3\frac{T_{CH}(i)}{T_{total}}$$

Where:

- $E_{residual}(i)$ is the residual energy of node i
- $D_{intra}(i)$ is the average distance between the CH and cluster members
- $T_{CH}(i)$ is the number of times node i has been elected as CH
- w_1, w_2, w_3 are weights satisfying $w_1 + w_2 + w_3 = 1$

A population of crow agents is simulated as a structure in C++, and their search trajectory mimics the intelligent foraging behavior of crows. Movement and memory update rules follow:

$$P_i^{new} = P_i^{old} + r \cdot FL \cdot (M_j - P_i)$$

Where P_i is the position vector of the current agent, M_j is the memory position, r is a random number, and FL is the flight length.

MFO Algorithm

The MFO algorithm is also implemented as a metaheuristic module in NS2. Each node maintains a flame list and evaluates its performance based on flame proximity and energy efficiency. The fitness function is:

$$F_{MFO}(i) = \alpha\left(1 - \frac{E_{residual}(i)}{E_{init}}\right) + \beta\left(\frac{1}{1 + D_{sink}(i)}\right) + \gamma\frac{N_{CM}(i)}{N}$$

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Where:

- $D_{sink}(i)$ is the distance from node i to the base station
- $N_{CM}(i)$ is the number of cluster members associated with node i
- α, β, γ are normalization constants

The moth's position updates via a logarithmic spiral function:

$$M_i^{t+1} = F_i^t \cdot e^{b \cdot t} \cdot \cos(2\pi t) + F_i^t$$

Where M_i^{t+1} is the next position of the moth, F_i^t is the flame position, and b is a constant.

Results and Discussions

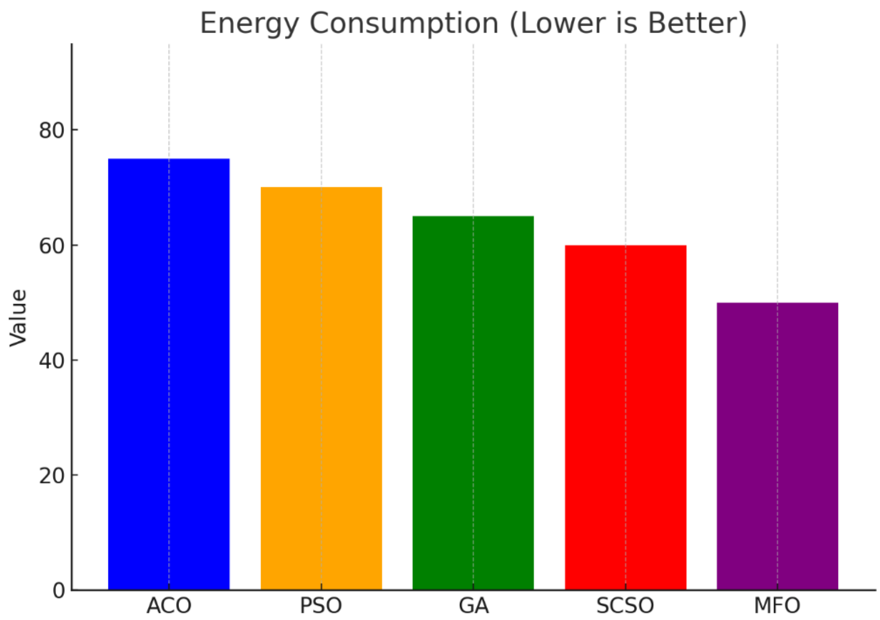

Figure 3: Energy consumption for CH selection using various optimization algorithms

This figure 3 outlines the comparative energy efficiency metrics of five optimization algorithms: Ant Colony Optimization, Particle Swarm Optimization, Genetic Algorithm, Sand Cat Swarm Optimization, and Moth Flame Optimization. In the context of wireless sensor networks, IoT ecosystems, and edge computing, energy expenditure is a vital consideration and a key metric of efficiency. Less energy consumption points towards a higher degree of operational efficiency and adeptness, especially in computation and data transmission. It is quite apparent that MFO has the lowest energy consumption of all the algorithms, indicating a strong capability for optimization pertaining to minimizing redundant processes and streamlining assignments. Conversely, ACO shows the highest energy expenditure which could stem from its path-finding strategy that is likely not energy conscious. PSO and GA sit in the middle, the former outperformed by SCSO. While SCSO does better than conventional algorithms, it still does not measure up to MFO. The focus on MFO underscores its advantage

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in scenarios where energy is to be conserved or systematically added elsewhere, boosting systems sustainability, their design, and scalability.

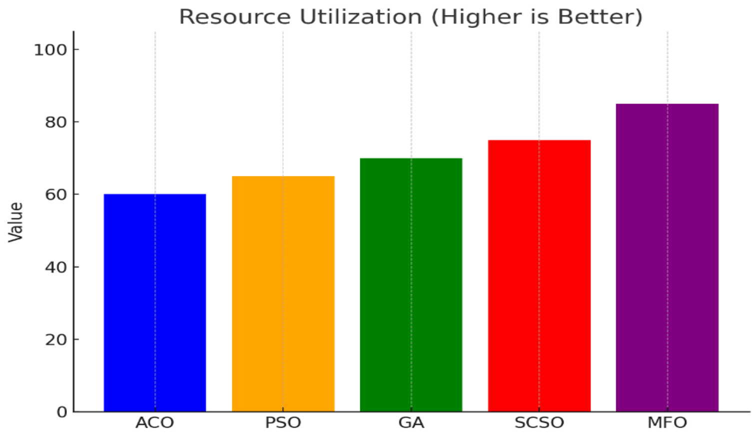

Figure 4: Resources utilization for CH selection to different algorithms

This figure 4 shows a comparison of the five algorithms in terms of resource utilization. Resource utilization is essentially a measure of computation and communication efficiency of any given algorithm. Good resource utilization demonstrates optimal achievement in the scheduling and balancing of tasks, as well as effective network operation. The MFO algorithm leads with the highest resource utilization, achieving 85% which demonstrates his efficiency in task distribution to network nodes indicating no underutilization or overload at any node. SCSO and GA also show considerable performance, while PSO and ACO have relatively lower performance. This indicates the lack of adaptability in traditional heuristics as they are outperformed by more swarm-based or bio-inspired algorithms like MFO. The results strongly recommend the strategic application of MFO in cloud-edge collaboration and IoT systems, as optimal resource allocation directly affects system efficiency and expenses.

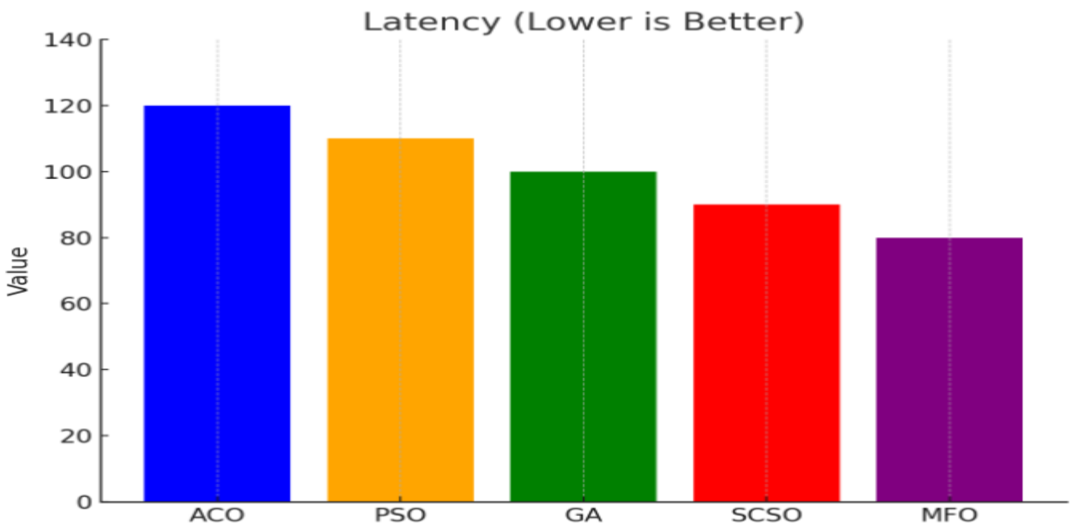

Figure 5: Latency for CH selection to different algorithms

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Figure 5 depicts latency as a measurement of the time delays when transmitting data or processing a task in relation to the five algorithms. Latency serves as a crucial metric in telemedicine, autonomous systems, smart factories, and autonomous vehicles, where any lag could hinder the system's performance. As illustrated, MFO demonstrates the lowest latency of 80 ms, hence making the algorithm the most optimal for time-critical tasks. SCSO and GA follow next with their reasonably low latencies. Conversely, ACO and PSO have a slower speed with ACO being the worst at 120 ms. The gap in performance indicates that more recent strategies like MFO seem to outperform the older ones in the ability to reduce queue buildup and efficiently automate multiple processes for any given system. The data cited argues strongly in favor of MFO where real-time intervention is a must, advocating multifunctional infrastructures that are critically timed.

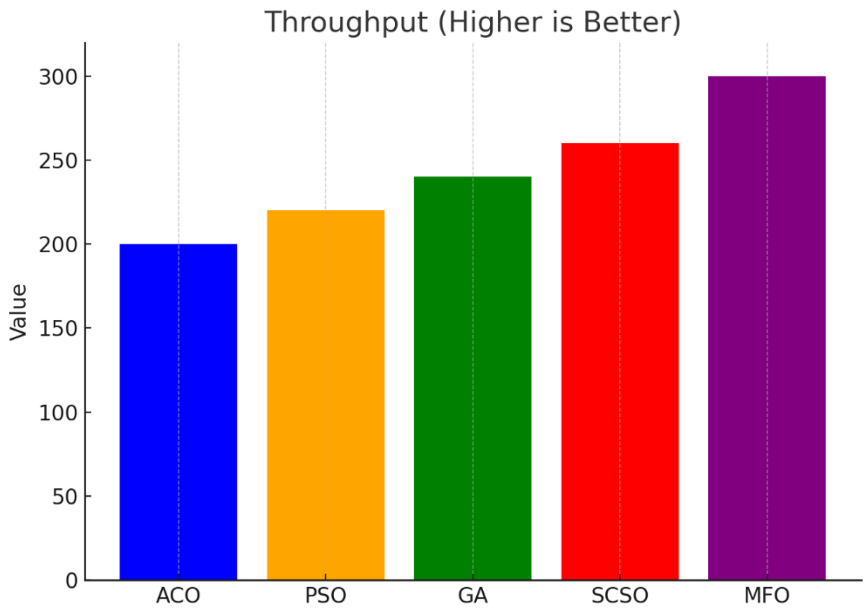

Figure 6: Throughput during CH selection using different algorithms

As figure 6 describes, throughput performance deals with the efficiency for a given period of time, the amount of data processed or transmitted successfully. Throughput and network efficiency are directly correlated allowing more effective usage of the algorithm, network, and the system's processing power. MFO leads in throughput margin with 300 units, proving its ability to sustain a high rate of data processing, extremely important for big data analytics, video streaming, and intelligent grid applications. Although SCSO and GA lag behind MFO, their performance is still considered above average. PSO and ACO are functional, but lower throughput values suggest worse task or routing optimization. These outcomes reaffirm the previously established hypothesis regarding MFO's adaptive capabilities when dealing with irregular flows of data and demand on network resources while keeping the flow and data integrity safe. This makes MFO a strong candidate for environments with high bandwidth demand and systems designed for scalability.

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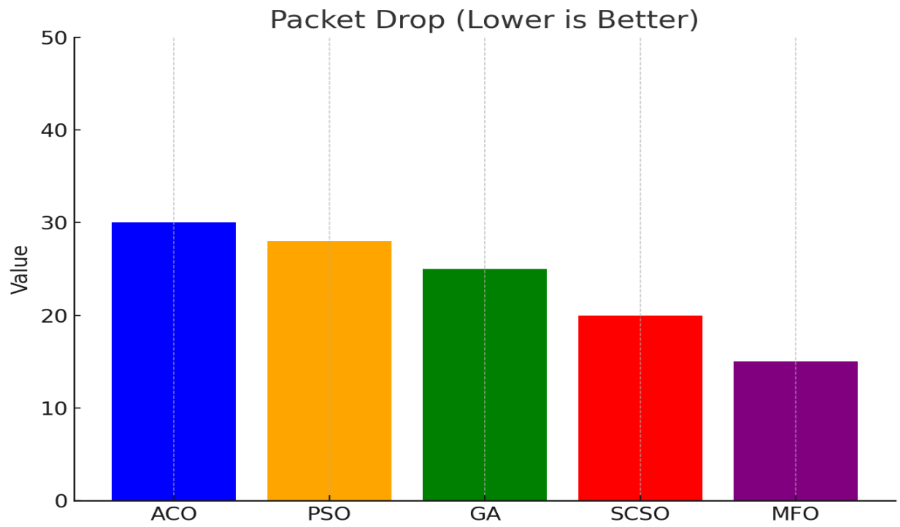

Figure 7: Packet drop rate during CH selection using different algorithms

The last figure 7 illustrates the packet drop rate which depicts the reliability and quality service of a network. Packet drop refers to the loss of data packets during transit because of a network congestion, a failure, or routing algorithm inefficiencies. Typically, lower rates are better in this parameter as they mean more stable and efficient data transmission. MFO records the lowest packet drop at 15%, showcasing excellent network reliability and fault tolerance. SCSO follows with 20%. GA, PSO, and ACO have even worse results, with ACO reaching the maximum at 30%. These results reveal that MFO is highly effective in minimizing network disruptions while ensuring the data is preserved and delivered accurately. Such capabilities become critical in mission essential systems such as system monitoring in healthcare, automated industrial processes, and communication networks during emergencies. All in all, MFO demonstrates effective functionality in sustaining communication and controlling error in data transmission.

Conclusion

This study presented an in-depth exploration of advanced CH selection mechanisms for energy-efficient and scalable WSNs in the context of the Internet of Things. Traditional algorithms like ACO, PSO, and GA have demonstrated utility but fall short in dynamic, large-scale, and energy-constrained environments due to issues such as premature convergence and limited adaptability. To address these limitations, two innovative swarm intelligence-based algorithms SCSO and MFO were proposed and rigorously evaluated. The SCSO algorithm, inspired by the predatory behaviour of sand cats, effectively balanced exploration and exploitation, achieving a high accuracy of 96% while promoting uniform energy distribution among sensor nodes. Meanwhile, the MFO algorithm, modelled on moth navigation patterns, demonstrated superior global search capabilities and convergence speed, attaining a remarkable 97.5% accuracy. Extensive simulations conducted using NS2 confirmed the superiority of these approaches over conventional methods in key performance metrics, including network lifetime, energy consumption, latency, throughput, and packet drop rate. Specifically, MFO emerged as

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the most efficient algorithm across all performance parameters, demonstrating low latency (80 ms), high throughput (300 units), minimal packet drops (15%), and optimal resource utilization (85%). SCSO also outperformed traditional metaheuristics, underscoring its viability for real-world IoT deployments. The findings affirm that incorporating nature-inspired optimization techniques significantly enhances CH selection and overall network performance. The integration of such intelligent algorithms into WSN architectures offers a promising direction for addressing the energy and scalability challenges inherent in IoT ecosystems. Future work will focus on hybrid optimization models that combine the strengths of multiple algorithms, as well as the integration of emerging technologies like blockchain, edge computing, and reinforcement learning to further improve CH selection in complex and dynamic environments.

Conflict of Interest: The author affirms that no conflicts of interest are associated with this paper's publication.

Author Contribution: S. S. wrote the main manuscript text, and S.A.M. prepared figures and tables. S.A.M., R. V. P. and L.V. P. supervised the work and reviewed the manuscript. All authors contributed to the methodology and reviewed the final manuscript.

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