International Journal of Mathematical, Engineering and Management Sciences
Vol. 11, No. 4, 1770-1791, 2026
https://doi.org/10.33889/IJMEMS.2026.11.4.072

An Efficient Cluster Head Selection Approach in IoT Using Hybrid Grey Wolf Optimization and Squirrel Search Algorithm

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(Received on December 11, 2025; Revised on March 20, 2026 & June 13, 2026 & June 26, 2026; Accepted on June 27, 2026)

Abstract
Internet of Things (IoT) involves a large number of interconnected sensor nodes, which sense, communicate, and become active in data processing in resource-constrained settings. This paper proposes a hybrid grey wolf optimization and squirrel search algorithm (GWO-SSA) for optimal cluster head (CH) selection in an IoT network to enhance energy efficiency, reduce delay, and prolong network lifetime. The proposed model integrates SSA into GWO to enhance exploration and exploitation balance, enabling efficient selection of CHs based on temperature, delay, energy, load, and cost function. Experimental results demonstrate that GWO-SSA significantly outperforms existing methods such as GA, ACO, PSO, IPSO, GWO, SSA, and BCO. The proposed approach reduces temperature by 11.93 % and delay by 32.82 % compared to GA, while achieving an energy efficiency improvement of 22.61%. Additionally, the number of alive nodes increased by 21.27%, indicating a substantial enhancement in network lifetime. Load handling capability is improved by 12.70 %, and the cost function is reduced by 15.35 %, confirming effective optimized performance. The GWO-SSA approach provides a robust, scalable, and energy-efficient cluster solution for an IoT environment. The significant improvements across multiple performance metrics validate the effectiveness of the hybrid approach, making it suitable for real-time and large-scale sensor network applications.

Keywords- Cluster head selection, Internet of Things (IoT), Grey wolf optimization (GWO), Squirrel search algorithm (SSA).

1. Introduction

The Internet of Things (IoT) is a rapidly developing technological system that connects physical equipment, sensors, and actuators into smart, interdependent networks that can independently communicate and make decisions (Fathimamary et al., 2026). These networks permit a diverse variety of applications in the real world, such as smart homes, industrial control, health, intelligent transportation, and precision agriculture (Subramanian & Ramkumar, 2024). Nevertheless, IoT nodes are usually resource-limited and have small battery capacity, computing power, and communication range, and energy-efficient network design and operation remain one of the long-standing research problems (Dhanalakshmi et al., 2026; Vijayakumari et al., 2026). In large-scale IoT systems, energy efficiency, delay in communication, temperature control, and load balancing have a direct impact on the network lifetime and reliability (Alshammri, 2025).

To overcome these challenges, clustering has become one of the best techniques for scalable IoT communication. In a clustered IoT network, a group of nodes is formed wherein a Cluster Head (CH) is in charge of aggregating and sending data to the sink or base station (Urooj et al., 2025). The CH selection process has a profound effect on the performance of the entire network: inefficient CH selection results in fast energy loss, delay, uneven load distribution, and temperature increase in hotspot areas. Hence, the choice of optimal CH nodes is critical in the improvement of network lifetime, energy saving, and stable functioning in the changing network conditions (Khan et al., 2022). Conventional CH selection approaches are based on probabilistic or distance-related criteria that do not always consider the multi-dimensional nature of IoT networks in terms of temperature variations, remaining power, communication distribution delays, and node workloads. These drawbacks encouraged the investigation of metaheuristic algorithms of optimization that are able to smartly deal with nonlinear, multi-objective, and complicated optimization issues by simulating natural or biological behavior (Jaiswal & Anand, 2021). Nevertheless, traditional methods can have a problem of premature convergence, small-scale capability, or failure to dynamically respond to network dynamics. GWO and SSA have become highly popular in the current swarm intelligence methods because of their simplicity, ability to converge, and a good balance between exploration and exploitation. Based on the rank of leadership and cooperative hunting behavior of grey wolves, GWO describes a hierarchical social system in which alpha (α), beta (β), delta (δ), and omega wolves are present. The three leading wolves direct the population towards the prey (optimal solution) by means of encircling, hunting, and attacking. GWO has a good ability to explore the world at its first stages, but it slows down convergence and can stagnate at local optima at subsequent iterations because of a decrease in population diversity. The SSA, on the contrary, emulates the foraging behavior of flying squirrels that fly between trees in search of food sources during the season. The wet seasonal adjustment and gliding distance control mechanism of SSA enables effective local utilization and agile flexibility to the fluctuations of the environmental conditions. Nonetheless, SSA by itself can be characterized by a certain lack of exploration in high-dimensional spaces, as well as being prone to parameter tuning. These two algorithms are complementary to each other, a good reason to have a hybrid one.

The global exploration of GWO can efficiently identify promising areas of the search space, and the precision of the best candidates can be improved by SSA. Through the synergizing of these mechanisms, the suggested Hybrid GWO-SSA model provides the convergence of global and local optimization, which has better stability and adaptability when evaluating Cluster Head selection in IoT contexts. The main goal of this study is to create an effective, adaptive, and energy-conscious CH selection algorithm for IoT networks, GWO-SSA. The presented study proposes a new hybrid GWO-SSA algorithm that aims at finding an ideal Cluster Head (CH) choice in IoT networks. The suggested algorithm is useful in integrating the global exploration of the GWO and the local exploitation of the SSA, which overcomes the typical problem of early convergence rampant in single metaheuristic algorithms. This hybridization ensures that there is an efficient and balanced search process to find the optimal solutions. Moreover, a multi-objective fitness is proposed in terms of a combination of important parameters, including residual energy, communication delay, node temperature, distance, and load. The proposed model, in contrast to the traditional ones, which tend to only consider energy efficiency, embraces temperature-aware and load-balanced clustering, which is better applicable to dynamic and resource-constrained IoT environments. The suggested approach has a better exploration-exploitation trade-off, which results in better convergence behavior and optimization. Consequently, it greatly minimizes energy usage and communication latency and maximizes the number of alive nodes and the overall network lifetime. It also enhances the stability of systems and the balancing of loads. Generally, the suggested hybrid GWO-SSA model shows better performance than the currently existing optimization and clustering methods, and it is a valuable, robust, scalable, and QoS-sensitive tool to manage the IoT network efficiently. The suggested hybrid solution optimize the choice of CH with the help of a multi-objective cost model depending on residual energy, communication delay, temperature, distance to the base station, and node load, which creates the conditions of minimum energy usage, balanced cluster creation, and a long-life cycle of the network. The contributions of the research work are carried out as follows,

- An innovative hybrid algorithm involving GWO and SSA is suggested to obtain an efficient balance in global exploration and local exploitation to solve the convergence stagnation and loss of diversity identified in single-algorithm methods.

- The five paramount IoT node parameters, including residual energy, delay, temperature, distance, and load, are used to design a comprehensive multi-objective cost function so that the CH can be optimally and adaptively chosen when the network is dynamic.
- The hybrid model proposes the periodic SSA-based local refinement of GWO leader solutions to maximize the accuracy of local search and ensure further stable and accurate CH selection.
- The model is tested in terms of important key performance metrics like average temperature, communication delay, residual energy, number of alive nodes, load distribution, and cost function that reveal significantly better results compared to traditional and standalone metaheuristics.
- The hybrid GWO-SSA achieves long network lifetime, equal energy consumption, and lower overheads, which makes it optimal in large-scale and practice-oriented IoT applications.

The remaining part of the paper is organized as follows: Section 2 provides related research on optimization-based CH selection schemes of IoT and WSN. Section 3 discusses the problem formulation of the research work. Section 4 discusses the fitness function for selecting optimal CH. Section 5 discusses the research methods. The results of the simulation, the comparison, and the evaluation of the performance are presented in Section 6. The paper concludes with the last Section 7, which gives the key findings and outlines the potential future research directions.

2. Related Works

The related works play a crucial role in shaping and guiding research in IoT and WSN networks by providing a foundation of existing methodologies, highlighting their strengths and limitations, and identifying gaps that require further exploration. They offer insights into various cluster head (CH) selection strategies, metaheuristic and hybrid optimization techniques, and intelligent routing approaches, demonstrating how energy efficiency, network lifetime, and data delivery performance can be improved. Additionally, studies integrating deep learning, recurrent neural networks, and intrusion detection systems illustrate the potential of combining machine learning with optimization for secure and adaptive network management. By reviewing these works, researchers can benchmark performance metrics such as energy consumption, packet delivery ratio, delay, and throughput, while understanding the trade-offs between efficiency, reliability, and security. Moreover, the literature helps to identify underexplored areas, such as adaptive multi-objective optimization, large-scale heterogeneous networks, privacy-preserving mechanisms, and explainable AI in network decision-making. Overall, related works not only provide methodological guidance and validation frameworks but also inspire novel approaches to address the challenges of energy-efficient, secure, and intelligent IoT/WSN systems. Table 1 shows the comprehensive review of CH selection in IoT.

Table 1. A comprehensive review of energy-efficient cluster selection approaches.

References	Year	Application	Objective	Techniques	Findings	Limitations
Chouhan et al. (2024)	2024	IoT-based WSN	Energy-efficient CH selection	Taylor-PO + Deep Neuro-Fuzzy + TSGWO	Effective CH selection, multi-path routing, and improved network lifespan	High complexity; limited adaptability in dynamic networks
Jubair et al. (2022)	2022	VANET	Secure and reliable routing	QoS-based CH + AES & ECC	Higher message success rate; lower end-to-end delay	Only evaluated on NS2; limited real-world deployment
Elsayed et al. (2022)	2022	IoT	Intrusion detection & anomaly detection	MRMR feature selection + Enhanced LSTM	High accuracy (97–99%); multi-level attack detection	High computational requirement; centralized training
Jagdale et al. (2023)	2023	WSN / IoT	Data aggregation & energy efficiency	WCFO + Deep LSTM	Reduced prediction error, delay, and energy; improved PDR	Complexity in routing tree construction; dynamic adaptation is limited

Table 1 continued…

Krishnan et al. (2023)	2023	MANET	Multi-attack intrusion detection	CFA + Ensemble Deep Learning	Reduced IDS traffic and memory use; fast attack detection	Mobility and energy-aware optimization could be further improved
Dinesh et al. (2025)	2025	WSN	Energy-efficient CH selection & routing	CPSO + Attention-based RNN	Adaptive CH selection; intelligent routing; improved network lifespan	Centralized routing may not scale for ultra-large networks
Srivastava & Paulus (2023)	2023	WSN-IoT	Coverage hole-aware routing	MLO + LEO-DM + HD-RNN	Balanced clustering, optimized routing, improved PDR, and network longevity	Computationally intensive; limited real-time evaluation
Awad et al. (2024)	2024	WSN	IDS & energy-efficient CH selection	PDU-BDO + DHVNN	Enhanced accuracy, precision, and F1-score for IDS; optimized CH	Limited to the NSL-KDD dataset; real-time adaptability not tested
Jayaram & Satyanarayana (2025)	2025	IoT	Energy-efficient routing	Multi-layer clustering + CNN-GRU	Improved network lifetime, PDR, and reduced delay	Focused on energy efficiency; security is not addressed
Gupta et al. (2024)	2024	WSN	CH selection for energy efficiency	CIBOA	Optimized energy and distance; reduced network operation time	E-commerce-specific; generalizability limited
Siddiq & Ghazwani (2024)	2024	IoT-enabled WSN	Secure routing & intrusion detection	HODNN + MEECRP	Improved PDR, detection rate, reduced delay & energy use	Complexity in the hybrid model is resource-intensive
Nathiya et al. (2023)	2023	IWSN	Energy-efficient clustering & intrusion detection	MapDiminution + ANN-SA	Reduced energy consumption; high detection accuracy (97.57%)	Limited real-time deployment; scalability not discussed
Othmen et al. (2025)	2025	IoT-enabled healthcare	Efficient CH selection & routing	Fuzzy logic + PSO	Improved PDR, throughput, energy efficiency, and delay	Focused on healthcare, the generalized IoT deployment is not addressed
Mahmood et al. (2024)	2024	WSN-IoT	Dynamic clustering & energy-efficient routing	Mean Value & Min Distance + RNN-LSTM	Load balancing, reduced latency, optimized energy	Simulation-based evaluation; real-world traffic variability is missing
Saranya & Sudha (2025)	2025	WSN	CH selection & intrusion detection	HYBRID GWO-SSA + Blockchain + DL	Prolonged network lifetime, improved PDR, and removed malicious nodes	Blockchain overhead; complex deployment
Alzuwaini et al. (2025)	2025	Ultra-dense IoT networks	EE optimization & interference management	CSA + LSTM	Improved network data rate, energy efficiency, and user acceptance	High computation; complex small-cell deployment
Sapkota et al. (2025)	2025	IoT	Security & data management	Blockchain + LSTM Autoencoder + PBFT	High anomaly detection accuracy; low latency; storage optimization	Heavy resource requirement; integration complexity
Alsuwat & Alsuwat (2025)	2025	WSN	Multi-hop routing & energy efficiency	IQ-ABC + Fuzzy Logic	Reduced energy consumption; extended SN lifetime	Limited real-world deployment; dynamic topology challenges
Vankdothu & Hameed (2025)	2025	WSN-IoT	Congestion & interference-aware routing	Fuzzy C-means + Adaptive Quantum Logic + AKH	Improved PDR, reduced delay, optimal routing	Security and intrusion detection are not addressed
Rahman et al. (2025)	2025	SDN-IoT with Blockchain	Secure & efficient data transfer	SDN + BC + NFV	Plug-and-play integration; enhanced security & efficiency	The conceptual framework lacks full real-time testing

Based on the extensive review of recent literature, several research gaps can be identified in IoT- and WSN-based networks. Most existing works focus on either energy-efficient cluster head (CH) selection (Alsuwat & Alsuwat, 2025; Awad et al., 2024; Chouhan et al., 2024; Dinesh et al., 2025; Gupta et al., 2024), secure routing and intrusion detection (Elsayed et al., 2022; Jubair et al., 2022; Krishnan et al., 2023; Nathiya et al., 2023; Sapkota et al., 2025; Siddiq & Ghazwani, 2024), or hybrid deep learning for prediction and optimization (Jagdale et al., 2023; Jayaram & Satyanarayana, 2025; Sapkota et al., 2025; Saranya & Sudha, 2025; Srivastava & Paulus, 2023; Vankdothu & Hameed, 2025). While these approaches improve network lifetime, energy consumption, and security, they often consider only a subset of network performance metrics, such as energy, delay, or packet delivery ratio, without integrating multi-objective optimization that simultaneously addresses energy efficiency, security, reliability, and latency. Moreover, many methods rely on static or pre-defined clustering, limiting adaptability in dynamic or large-scale IoT environments (Chouhan et al., 2024; Jayaram & Satyanarayana, 2025; Mahmood et al., 2024). The majority of deep learning-based solutions (including LSTM, CNN-LSTM, and hybrid DNNs) (Elsayed et al., 2022; Jagdale et al., 2023; Jayaram & Satyanarayana, 2025; Sapkota et al., 2025) achieve high accuracy for routing, prediction, or intrusion detection but require extensive computational resources and centralized training, which may not be feasible for resource-constrained sensor nodes. Additionally, integration of blockchain or federated learning for secure, decentralized data processing remains limited, with only a few studies (Rahman et al., 2025; Sapkota et al., 2025; Saranya & Sudha, 2025) exploring these technologies in combination with CH selection or anomaly detection. Finally, very few approaches consider explainable AI or real-time adaptive decision-making to allow transparency and trust in critical applications such as healthcare, smart grids, and industrial IoT. These gaps indicate a need for holistic, scalable, and privacy-preserving frameworks that combine multi-objective swarm intelligence optimization, deep learning, and federated or distributed mechanisms for energy-efficient, secure, and reliable IoT/WSN networks.

3. Problem Formulation

According to the network, IoT involves integrating a range of sensors and tiny devices. These provide clients with information about the monitored environmental elements. In the cited IoT, there are more sensors overall. These require electricity, and batteries cannot be taxed for replacement because doing so would shorten their lifespan. The more the node counts, the shorter the network's expected lifespan. On the other hand, better energy preservation results in a longer lifespan, which may be achieved by using a clustering process. The task of creating a cluster involves overcoming the aforementioned shortcomings among sensing devices in the network that is based on cluster-organizing IoT by using a topology-control technique from the clustering scheme. By choosing the leader of each group based on various criteria, clustering is a method for grouping the SNs. Clusters are the collective nouns for groups, and CHs are the collective nouns for group leaders. The cluster nodes will pass the data to their CH after deciding on the optimal CH. The combined data will be forwarded by the CH to the central BS. This is because entire nodes in a cluster—aside from the CH—are prohibited from using their energy to establish a single line of communication with the BS. The IoT consists of $'N'$ number of groups represented by $C_i(i = 1,2,3,\ldots..N)$. Every cluster is the owner of any number of nodes. Any cluster's SNs are represented by S_{ij}. Here, $i = 1,2,\ldots\ldots N$ and $j = 1,2,\ldots\ldots. M$ are not identical for a certain cluster, and j can differ from cluster to cluster. Every cluster has a certain node identified as the CH. The WSN-IoT features impact the greater cluster node as the CH. Instead of all S_{ij}, a total of $'N'$ CHs only interact with the BS. The IoT integrated with WSN complicates the CH selection process as it is necessary to consider the features of the latter, as well as the energy consumption of the latter. The clustering strategy must be effectively designed to provide maximum energy storage so that the network lifetime is increased.

4. Fitness Functions

The IoT network consists of a number of nodes. These nodes have limited storage, processing, and battery power. The sensor nodes of a network detect the data, which is constantly relayed to the BS. Because of the above-mentioned factors, the probability of the BS becoming overloaded is higher, and it will contribute to the higher probability of SNs within the IoT network malfunctioning, redundancy of data, and the rise in temperature. In order to resolve these problems, the nodes within the IoT network are grouped into a number of clusters, and one optimum node is picked as a CH within each cluster. The CHs are chosen depending on the energy and temperature of the nodes, the load of the network, the delay incurred to reach the BS through the nodes, and the distance between the BS and the CH. The longevity of the IoT network is to be enhanced through the selection of the most appropriate CH. Important information, such as energy, distance, and latency, is essential in the selection of the appropriate CH in a WSN. The features of the IoT network should be considered. In other words, as the current experiment is a combination of WSN and IoT, it is necessary to incorporate the temperature and load of the smart devices with the properties of WSN. In selecting the CH of the WSN-IoT platform, the distance, energy, delay, load, and temperature are first calculated in this experiment. It is only possible to have a functional network when latency, distance, temperature, and load are low, and energy is high. Consequently, the proposed fitness is a maximizing function, as is demonstrated in the equations below (Reddy & Babu, 2019),

$$F_1 = f^{energy}/f^{load} + f^{energy}/f^{temperature} \tag{1}$$

$$F_2 = \frac{\alpha}{f^{dis\tan ce}+(1-\alpha)}.F_1 \tag{2}$$

$$F_3 = \frac{\beta F_2+(1-\beta)}{f^{delay}} \tag{3}$$

The suggested objective model, where the constants α and β have values of 0.9 and 0.3, respectively. The five parameters that were calculated as a result of this experiment are represented mathematically as follows.

4.1 Distance

The distance between BS and IoT devices is computed as follows:

$$f^{dis\tan ce} = \frac{f^{dis\tan ce}(m)}{f^{dis\tan ce}(n)} \tag{4}$$

where, $f^{dis\tan ce}(m)$ denotes the distance between CH and the typical node, and between CH and BS of networks described as follows,

$$f^{dis\tan ce}(m) = \sum_{i=1}^{N}\|S_i - CH_i\| + \sum_{j=1}^{M}\left\|CH_j - BS\right\| \tag{5}$$

$f^{dis\tan ce}(n)$ denotes the distance between two usual nodes that take values between 1 and 0, which are described as follows,

$$f^{dis\tan ce}(n) = \sum_{i=1}^{N}\sum_{j=1}^{M}\left\|S_i - S_j\right\| \tag{6}$$

where, S_i is the position of i^{th} sensor node. CH_j is the position of j^{th} cluster head. BS is the base station.

4.2 Energy

Energy is a term used for network utilization that takes values between 1 and 0, and it is determined as follows:

$$f^{energy} = \frac{f^{energy}(m)}{f^{energy}(n)} \tag{7}$$

where, $f^{energy}(m)$ and $f^{energy}(n)$defined as follows,

$$f^{energy}(m) = \sum_{j=1}^{M} nE(j) \tag{8}$$

$$nE(j) = \sum_{\substack{i=1 \\ i \in j}} (1 - E(S_i) * E(CH_j))\, ; 1 \leq j < M \quad (9)$$

$$f^{energy}(n) = M \times \underset{i=1}{\overset{N}{Max}} \left(E(S_i)\right) \times \underset{j=1}{\overset{M}{Max}} \left(E(CH_j)\right) \quad (10)$$

where, $E(S_i)$- is the energy of i^{th} sensor node ($E(S_i) > 0$). $E(CH_j)$- energy of j^{th} cluster head ($CH_j \epsilon C_j$). C_j is the set of nodes in the cluster j.

4.3 Delay

Network efficiency is enhanced by sending data packets from the source to the destination in a short time. Thus, both the transmission delay (T_t) and the propagation delay (T_p) must be taken into account when calculating the delay in sending packets to their destination. The following equation, which takes values between 0 and 1, is used to compute the latency of IoT devices during data transfer from the SN to the BS. The delay, which takes into account both the transmission and the propagation delay, is normalized as follows,

$$f^{delay} = \frac{Max\,(CH_j)_{j=1}^{M}}{N} \quad (11)$$

where, $Max(CH_j)_{j=1}^{M}$ is the total number of CHs of WSN, and N is the total number of devices. Delay $(T_t + T_p)$ is associated with the cluster head j.

4.4 Temperature and Load

In order to determine the optimal CH, the sensor node load and temperature must be minimized. The best CH should be found by reducing the temperature of sensor nodes and network load. Temperature and load are two of the most important parameters that directly affect the energy consumption, reliability, and lifetime of IoT networks. In the simulation, the generated temperature and load values from the sensor nodes are transmitted to the ThingSpeak cloud platform for real-time visualization and monitoring using the MQTT (Message Queuing Telemetry Transport) protocol (Chandrasekaran et al., 2025). It offers cloud-based services to collect, store, analyze, and visualize IoT sensor data. The platform allows for continuous monitoring of the node conditions and efficient analysis of the network performance. The platform also seamlessly integrates with MATLAB for advanced data analytics, signal processing, and predictive modeling directly on the collected sensor data.

5. Research Methods

5.1 Grey Wolf Optimization (GWO)

The GWO is an optimization technique for solving real-world problems (Mirjalili et al., 2014). The GWO mimics the hunting behavior and social leadership of grey wolves in nature. Grey wolves are at the top of the food chain, and they mostly prefer to live in a pack. In this algorithm, the population is divided into four groups: alpha (α), beta (β), delta (δ), and omega (ω). In the GWO, the hunting behavior is guided by α, β, and δ.the ω wolves follow these three wolves. In every iteration, the first three best wolves are considered as α, β, and δ, and the rest of the grey wolves are assumed to be ω and required to encircle α, β, and δ with the hope of obtaining better solutions. The following is used for position updates,

$$X(t+1) = X_p(t) - A.D \quad (12)$$

$$D = \left|C.X_p(t) - X(t)\right| \quad (13)$$

where, t is the present iteration, A and C are coefficient vectors, X_p is the position vector of the prey, and X is the position vector of a grey wolf. The vectors A and C are considered as follows:

$$A = 2a.r_1 - a \tag{14}$$

$$C = 2.r_2 \tag{15}$$

where, a decrease linearly between 2 and 0 in a sequence of iterations. r_1, r_2 are random vectors in [0,1]. To come up with a mathematical simulation of the hunting pattern of the grey wolves, we assume that α, β, and δ know more about the possible location of the prey. We therefore store the first three best solutions that we have found to date and commit the rest of the search agents to update their positions based on the position of the best search agent. In the same respect, the following formulas are suggested, which are defined as follows,

$$D_\alpha = |C_1.X_\alpha - X| \tag{16}$$

$$D_\beta = |C_2.X_\beta - X| \tag{17}$$

$$D_\delta = |C_3.X_\delta - X| \tag{18}$$

X_α shows the position of the δ, C_1, C_2 and C_3 are random vectors and X indicates the position of the current solution. In the end, the final position of the current solution is calculated as follows:

$$X_1 = X_\alpha - A_1.(D_\alpha) \tag{19}$$

$$X_2 = X_\beta - A_2.(D_\beta) \tag{20}$$

$$X_3 = X_\delta - A_3.(D_\delta) \tag{21}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{22}$$

X_α shows the position of the α, X_β shows the position of the β, X_α shows the position of β, A_1, A_2 and A_3 are random vectors and t indicates the number of iterations. With decreasing A Half of the iterations are dedicated to exploration ($|A| \geq 1$) and the others are devoted to exploitation ($|A| < 1$). The vector C contains random values in $[0,2]$. This component provides random weights for prey to stochastically emphasize ($C > 1$) or deemphasize ($C < 1$) that the effect of prey on defining the distance. This assistance of GWO in showing a more random behavior through optimization, choosing exploration, and escaping local optima.

5.2 Squirrel Search Algorithm (SSA)

The SSA is a biomimetic metaheuristic optimization process created to address complex optimization problems, that is, the foraging and gliding of flying squirrels (Jain et al., 2019). This algorithm is especially useful for balancing exploration and exploitation, which is why it applies to dynamic and distributed systems. Examples: Squirrels in the wild show intelligent foraging behavior. They find quality food sources (nuts or acorns), move between trees to get the best locations, and change their movements with seasonal variations and weather. These behaviors are converted to an optimization context using SSA: The search space candidate solutions are represented by the squirrels. Food sources are associated with the best solution to the fitness function that maximizes or minimizes the fitness. The model built on gliding and seasonal adjustments is used to model local and global search behavior to support search and exploitation of the search space by the algorithm. As stated above, FSs have a few FSs, and the location of each of them can be identified with a vector. The range of all FSs can be presented in the following matrix:

$$FS = \begin{bmatrix} FS_{1,1} & \cdots & FS_{1,d} \\ \vdots & \ddots & \vdots \\ FS_{n,1} & \cdots & FS_{n,d} \end{bmatrix} \tag{23}$$

where, $U(0,1)$ represents an arbitrarily distributed value that ranges between $[0,1]$ and FSL and FSU represent, correspondingly, the i^{th} FS's upper and lower boundaries in the j^{th} idea.

$$FSi = FSL + U(0,1) \times (FSU - FSL) \tag{24}$$

where, $FS_{i,j}$ denotes the j^{th} dimension of the i^{th} FS. According to Equation (2), the initial positions of every FS are distributed evenly. To determine the position fitness of each FS, the values of the choice variation, also referred to as the Solution vector, are entered into a pre-existing fitness function. Then the output values are stored in the assigned array, which is defined as follows,

$$f = \begin{bmatrix} f_1([FS_{1,1}, FS_{1,2}, \dots, FS_{1,d}]) \\ f_2([FS_{2,1}, FS_{2,2}, \dots, FS_{2,d}]) \\ \vdots \\ \vdots \\ f_n([FS_{n,1}, FS_{n,2}, \dots, FS_{n,d}]) \end{bmatrix} \tag{25}$$

The favorite food source of the FSs is defined by the fitness score of the position; an optimal food source is a hickory tree, the average one an acorn tree, or a complete lack of food source (an FS on a regular tree). Also, this information demonstrates the likelihood of survival of the FS. The one-dimensional array is sorted in increasing order when the values of the position of each FS are logged against fitness. The FS has been reported as having a poor health value on the hickory tree. The following three most preferable FS will be transferred to hickory trees, which are supposed to be situated on acorn trees. It is expected that the FSs that make it will be found on common trees. When, more haphazardly, they grow tired of daily energy, it is even expected that some squirrels will use the way of the hickory nut tree. The surviving squirrels visit acorn trees (to satisfy their daily need for energy). Predators always influence the FS strategy of hunting. This natural response is simulated in the position update mechanism in case a predator exists.

5.3 Proposed Hybrid GWO-SSA

All the IoT nodes in the suggested structure are regarded as potential CHs. A fitness measure of candidate CHs is based on residual energy, proximity to the base station, and neighboring nodes as well as the load that the CH carries. The efficiency of any CH to gather and transmit data, to manage balancing energy consumption throughout the network, etc., is a major requirement. A cluster is made up of one CH, which gathers information from member nodes and transmits the information to the base station, thus saving on communication overhead and energy. GWO is used to initiate the optimization process and determine promising CHs when simulating the leadership structure of grey wolves (alpha, beta, and delta) and its prey hunting behavior. GWO also has a high global search capability that enables the algorithm to search various parts of the solution space, thus avoiding early convergence. The best CH solutions, which had been acquired via GWO, are then optimized with the use of SSA, which simulates the foraging and gliding behavior of the squirrels so that it can optimize local search. SSA optimizes the spatial arrangement of candidate CHs and decreases the risk of entrapment in local optima, and speeds up convergence. The hybrid GWO-SSA algorithm will perform the exploration with a GWO-based approach and the exploitation with an SSA-based approach; every iteration of the algorithm will result in the evaluation of candidate CHs using the fitness function and the updating of the alpha, beta, and delta solutions. This is repeated until convergence is met or the highest number of repetitions is met.

After the optimal CHs have been detected, regular nodes will be linked to the closest CH based on distance and energy factors, and data transmission will be arranged based on energy-saving TDMA provisions. The presented hybrid strategy has a number of strengths compared to traditional strategies. It is also dynamic with topological changes and node movement, thus ensuring uniform performance of the network. The algorithm achieves a balance between global exploration and local exploitation through the combination of GWO with SSA and has the ability to deliver energy-efficient CH selection and long network lifetime. Also, it can be applied to massive deployments of IoT, as it takes into account various parameters, including residual energy, distance of communication, and network load. The resulting GWO-SSA model introduces a powerful framework and a methodological process for CH selection in IoT networks subject to energy-consumption and dynamism constraints. The proposed hybrid method offers a trade-off between exploration and exploitation, resulting in energy efficiency, load balancing, and network lifetime. It is also scalable and flexible to changing conditions of the network, which is why it can be used in the context of a large-scale IoT implementation and guarantees high performance and stability of the network. Algorithm 1 discusses the pseudocode for the proposed hybrid GWO-SSA method. **Figure 1** shows the flowchart of the proposed hybrid GWO-SSA CH selection method.

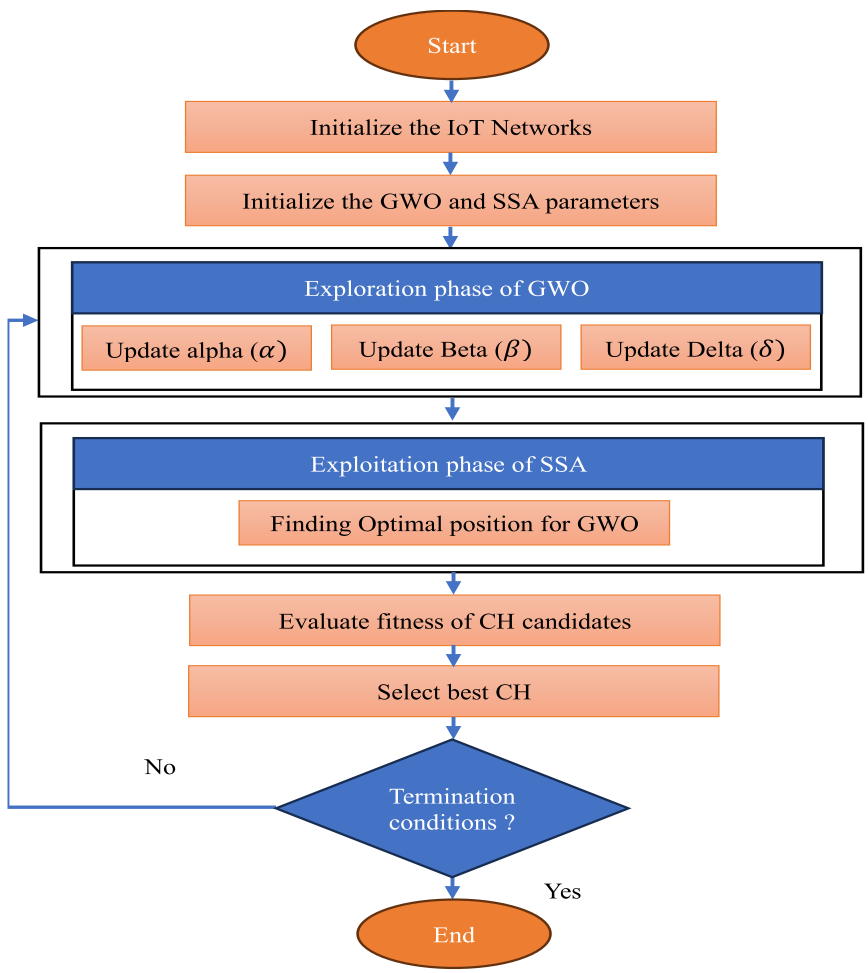

Figure 1. Flowchart of the proposed hybrid GWO-SSA method.

Algorithm 1: Hybrid GWO-SSA
Input: Objective function $f(x)$, energy, delay, temperature, load, Number of search agents (N), and Max_iter
Output: Best solution (Optimal CH set)
Begin
1) Initialize the IoT network with N sensor nodes
2) Initialize population $X_i(i = 1\ to\ N)$ randomly for GWO and SSA
    a. //Each X_i represents a candidate CH selection
3) Evaluate the fitness of each X_i using the objective function f
4) Identify the best solution for Alpha, Beta, and Delta
5) While $(iteration < Max\_iter)$
    // GWO PHASE
    For each search agent X_i
        Update the position of X_i based on Alpha, Beta, and Delta
    End For

    // SSA PHASE
    Classify updated agents into Hickory tree, Acorn tree, and Normal trees
    For each agent X_i
        If X_i is normal, then move towards the nearest Acorn solution
        Else if X_i is Acorn then move towards Hickory
        Else, retain current position
        End if
    End For
    Generate a random probability P
    If $(P < predator\_threshold)$:
        Randomly relocate some agents
    If $seasonal\_condition$ satisfied:
        Randomly reinitialize part of the population
    Ensure all X_i remain within search bounds
    Evaluate the fitness of all X_i

    Update the position of Alpha(best), Beta, and Delta
6) End While
7) Return Alpha (Optimal CH selection)

6. Experimental Results and Analysis

The selection of the optimal CH between nodes ideally reduces each node's energy consumption. The CH selection is based on a novel hybrid GWO-SSA, which is employed using MATLAB 2020R with an Intel i7 processor and 16 GB RAM on Windows. During simulation, 100 nodes' load and temperature are uploaded to ThingSpeak. IoT device factors are considered when simulating latency, distance, energy, temperature, and load. **Table 2** shows the parameter settings of CH selection algorithms. Standard parameter settings that are found in the literature are used to set all algorithms in order to maintain fairness. Population size and the number of iterations are maintained the same in all methods. Also, the choice of parameters is made within acceptable ranges and checked by initial experiments to guarantee stable performance. The parameters of the IoT network with static values required for the simulation are shown in **Table 3**. The optimum CH is selected using a hybrid GWO-SSA based on performance indicators, including temperature, load, the number of active nodes, residual energy, and cost function, to prolong the life of the network. The network is also modeled as consisting of stationary sensor nodes that have small amounts of energy, processing power, and communications bandwidth, and this is a realistic model that captures the actual implementation of IoT and WSN systems with little mobility. Base Station (BS) is supposed to be fixed and resource-rich (unlimited energy), because in most cases, it is a central point of data collection. Heterogeneity of nodes is not taken into consideration, though they are homogeneous in initial energy values, so that efficiency in the CH selection is fair, whereas energy consumption is modeled after a common communication paradigm. The clustering mechanism is used where nodes communicate with CHs, and CHs relay aggregated information to the BS, which minimizes redundancy and communication overhead. Moreover, distance, delay, temperature, and load parameters are also added to reflect natural working conditions. Temperature indicates heating of a device during constant operation, and load indicates load management by CHs. These are the typical assumptions used in the research of IoT and WSN and are necessary to simplify the model of the system and maintain its practical applicability. The suggested hybrid GWO-SSA method is compared with several cutting-edge optimization methods, including GA (Nandan et al., 2021), ACO (Shi & Zhang, 2021), PSO (Senthil et al., 2021), IPSO (Bao, 2022), GWO (Jaiswal & Anand, 2021), SSA (Arunachalam et al., 2021), and BCO (Subramanian & Ramkumar, 2024).

- **Temperature:** During the sending and receiving of data from the SN to the CH, the temperature of the SN will rise in both the SN and the CH. Temperature is measured in degrees Celsius (C).
- **Load:** The CH often keeps the IoT network's load stable. The cluster's SNs provide the data to the CH. The CH transmits the compiled data to the BS. From one iteration to the next, the load on the CH fluctuates. To improve the network's effectiveness, the CH's load has to be lower.
- **Alive node:** The alive node metric is crucial to the network's long-term viability. Live nodes began to perish as the number of repetitions progressively rose as a result of energy loss. As the number of active nodes falls, the cluster head is under more strain, gets hotter, and performs worse.
- **Residual energy:** One of the most important criteria for gauging the effectiveness of the IoT network is residual energy. The nodes' initial energy level will be high. If there aren't adequate energy-aware processes, the energy starts to drop as the number of repeats rises. The network as a whole performs poorly because the nodes' energy levels drop quickly.
- **Delay:** Network performance is enhanced by sending packets from source to destination in the shortest amount of time possible. As a result, both the transmission delay T_t and Propagation delay (T_p) must be taken into account when calculating the delay in sending packets to their destination.

The management and operation of the IoT networks are dependent on effective CH selection. Cluster-based architectures are also common in order to enhance the network efficiency and scalability of the IoT systems in cases where the latter often involve a vast number of different devices connected with each other and have a limited number of resources. The energy consumption, the aggregation of the data, the communication overhead levels, and general system reliability, among other aspects of network performance, depend on the selection of CHs in these designs. Like other optimization strategies, the aim of CH selection with Hybrid GWO-SSA in an IoT network is to enhance scalability, network performance, and energy efficiency. The Hybrid GWO-SSA algorithm integrates the hunting behavior and leadership hierarchy of grey wolves and the foraging and gliding behavior of flying squirrels to address the cluster head selection optimization problem. GWO is proficient in global search of the search space, while SSA is proficient in local search and solution improvement. Hybridization improves convergence rate, preserves population diversity, and minimizes the possibility of premature convergence, resulting in more efficient and reliable cluster head selection in IoT networks. CH is also necessary in the successful arrangement and management of the interconnected devices in IoT networks.

Clustering is often used to scale the IoT networks to ensure they are more energy efficient. The task of CHs is to collect data from diverse IoT devices within their cluster. These data are collected and forwarded to a centralized sink or gateway. There is reduced data traffic and energy consumption since not every device has to be directly connected to the gateway. CH is used as a routing node within its clusters and decides on the optimum paths. Such routing enables efficient data transmission and reduces latency and power consumption. The IoT networks are able to scale more effectively due to the use of CHs. The more devices are added, the more CHs can be added to form new clusters and decrease the administrative load. Therefore, selecting an appropriate CH is a very important decision that may influence the performance, efficacy, and overall effectiveness of the network. The following section addresses the execution of the proposed solution and compares it to some of the developed solutions in the section. The performance outcomes are received in various rounds: 100, 500, 1000, 1500, and 2000. The next sub-sections talk about the capability of the proposed novel Hybrid GWO-SSA cluster selection method.

Table 2. Parameters settings.

Algorithm	Parameter	Value	Description
GA	Population Size (N)	30	Number of candidate solutions
	Crossover Rate (P_c)	0.8	Probability of crossover
	Mutation Rate(P_m)	0.01	Probability of mutation
	Maximum iterations (Max_Iter)	100	Number of iterations
ACO	Number of Ants (N)	30	Number of ants
	Pheromone Factor (α)	1	Influence of pheromone
	Heuristic Factor (β)	2	Influence of heuristic
	Evaporation Rate (ρ)	0.5	Pheromone evaporation
PSO	Population Size (N)	30	Number of particles
	Inertia Weight (w)	0.7	Controls exploration/exploitation
	Cognitive Coefficient (c_1)	1.5	Personal learning factor
	Social Coefficient (c_2)	1.5	Global learning factor
GWO	Population Size (N)	30	Number of wolves
	Control Parameter (α)	$2 \rightarrow 0$	Linearly decreasing
	Coefficient Vectors (A, C)	Dynamic	Position update factors
SSA	Population Size (N)	30	Number of squirrels
	Gliding Constant (d_g)	1.9	Controls movement
	Predator Probability (P_{dp})	0.1	Predator presence
	Seasonal Constant (S_C)	0.5	Seasonal monitoring
BCO	Population Size (N)	30	Number of bacteria
	Chemotaxis Steps (N_c)	10	Movement steps
	Swim Length (N_s)	4	Swimming length
	Reproduction Steps (N_{re})	4	Reproduction phase

Table 3. IoT parameters.

Parameter	Value
The IoT area of sensing	100*100 m^2
Number of nodes	100
Free space model energy	10 pJ/bit/m^2
CH (%)	5–10 %
Packets size	5000 bits
The initial energy	1 J
Transmission energy	50 nJ/bit
Power amplifier energy	0.0013 pJ/bit/ m^2
Energy for data aggregation	5 nJ/bit/signal
Number of rounds	2000

6.1 Performance Results Based on Temperature

The temperature of sensor nodes (SNs) is likely to affect the IoT network performance because higher temperatures result in higher energy usage and possible reduction of the node reliability. The IoT network is affected negatively because the nodes become hot, and the energy consumed by the nodes increases. Hence, low temperature is an essential aspect of an IoT network. The analysis of the proposed approaches versus the traditional ones in terms of the temperature of the devices at time during the CH section of a suitable quantity of rounds appears in **Figure 2**. Simply put, the reduced average temperatures of IoT devices at a particular time ensure stability in the network. The mean temperature is first reduced to a drastic extent, and then rises slowly up to about two thousand. Upon comparing the suggested and the existing methods, it is realized that the suggested method possesses a low temperature.

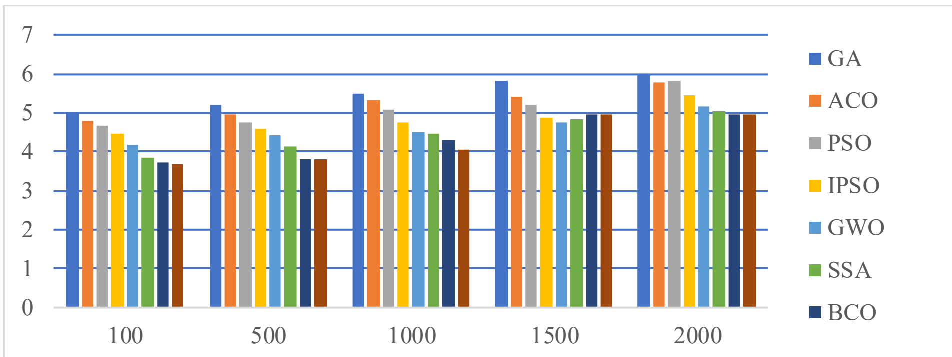

Figure 2. Performance results based on temperature.

6.2 Performance Results based on Delay

A network's performance is facilitated by the efficient transmission of packets of data between the source and destination. In this experiment, transmission delay (T_t) is the delay required for CH to transmit a packet of data to the outbound connection. The bandwidth on the network is 1 Mbps, and the size of the data packets is 4KB. The propagation delay (T_p) means that when CH transfers a data packet onto the channel, we cannot yet say that the data packet has arrived at the BS before the final bit of the data packet has actually passed through the entire link. The two key factors influencing the propagation delay are distance and speed. When the CH is distant with respect to the base station and the speed of the signal is low, the propagation delay is high. The propagation delay is very small, which results in a large delay period. The delay of the network requires (T_t) and (T_p) to know the speed, which is said to be 2.1 × 10^8 m/sec. **Figure 3** depicts a performance study of the delay of the proposed model as compared to the delay of the current models. Unlike other existing models, the transmission delay and the propagation delay are not significant in **Figure 3**. The delay that is experienced by the current architecture in transferring packets between CH and BS is usually longer. The proposed novel Hybrid GWO-SSA model maintains a lower delay time by maintaining the optimal distance between CH and BS since the distance between the ideal CH and the BS is minimal.

6.3 Performance Results based on Energy

IoT devices that are inaccessible require energy to enhance their durability. IoT nodes require more energy levels to sustain the IoT network. The amount of energy consumed is measured during the experiment when SN transmits the data packet to CH and vice versa, when CH transmits the data packets that it has received to the base station. There is more calculation required when the load is high and the distance between CH and the base station is long, consuming more energy. The suggested paradigm has a good balance between

CH, load, and delay. **Figure 4** depicts the performance analysis of the CH selection of the IoT network regarding the normalized energy until the final round. The power level of the IoT devices needs to be increased until the final stage of the CH selection process. In both the proposed and conventional methods, the energy rate is high and declines with an increase in the number of rounds.

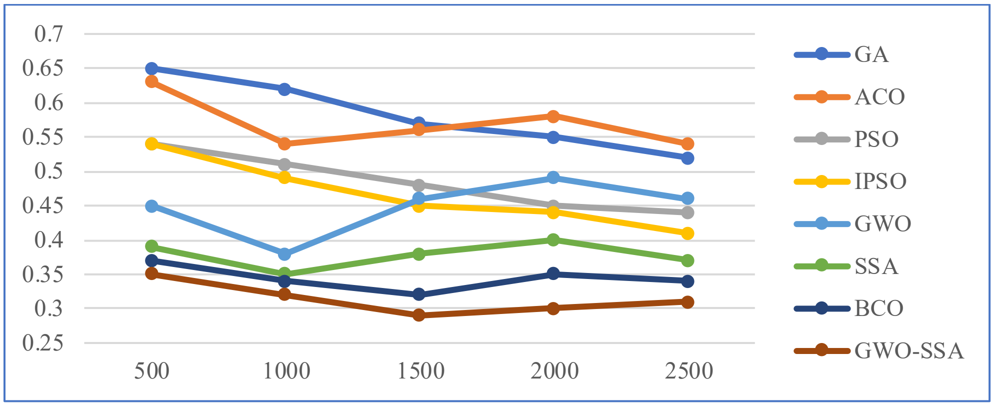

Figure 3. Performance results analysis based on delay.

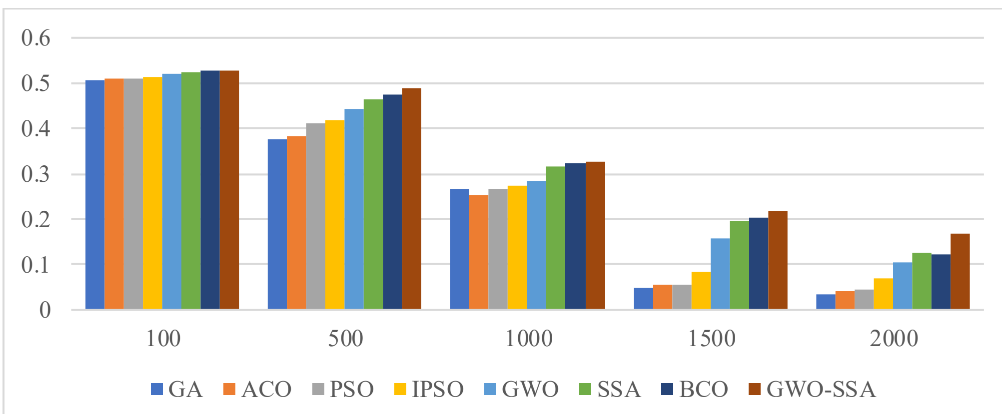

Figure 4. Results analysis based on normalized network energy.

6.4 Performance Results based on the Number of Alive Nodes

The number of living nodes will reduce as the number of iterations increases. The power decreases with the repetition of the same, and the nodes are killed. When the number of active nodes is greater, the load is evenly distributed among all CHs, and the delay time is minimized. The number of active nodes plays an important role in increasing the life of the network. **Figure 5** compares the proposed model and current models according to the number of active nodes. The active nodes are absent in GA, ACO, and PSO. Nevertheless, IPSO retained 2 nodes, GWO retained 5, SSA retained 12, and the proposed hybrid GWO-SSA retained 17. The proposed solution has better CH selection, load management, residual energy, and delay time than the rest of the existing models, which enhances live node numbers.

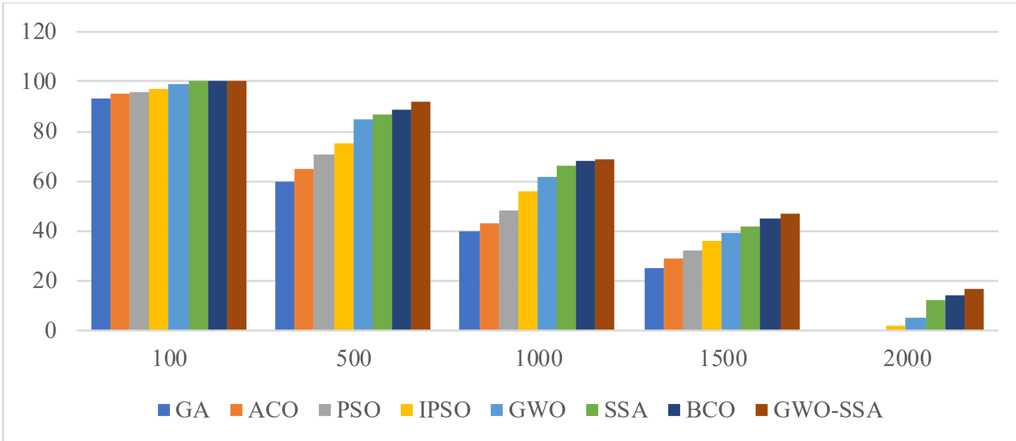

Figure 5. Results analysis based on the alive node.

6.5 Performance Results based on the Number of Loads

The CH is usually in charge of the load of the IoT network. The CHs should be loaded less to enhance the IoT network performance. Depending on the measurement of load, the proposed model is compared to the existing models in terms of its performance. The performance study of the load versus the number of rounds is shown in **Figure 6**.

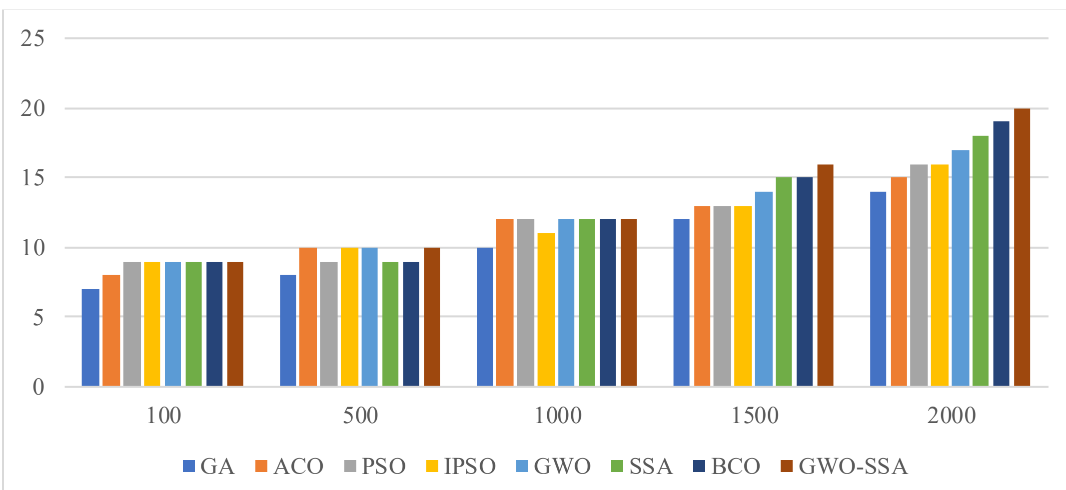

Figure 6. Results analysis based on load.

In this instance, the mean load of the 10 cluster heads to be selected for each instance is being calculated. The average load must be minimized to keep the network stable. **Figure 6** shows that the load of the proposed method is not significant, approximately 1,500 rounds. The sharp increase in load happens in the 2000th round, though. Because of the packet transfer between the CH and the BS, and the optimal distance between the node and CH, and CH and BS, the degree of load of the suggested novel hybrid GWO-SSA model is the lowest.

6.6 Performance Results based on the Cost Function

The IoT network's cost function needs to converge in earlier iterations to increase performance. **Figure 7** compares the proposed model with other current models in terms of the cost function's convergence ratio at various iterations. **Figure 7** makes it evident that, in the proposed model, the cost function converges with the best fitness value at the third iteration, in contrast to other current models, where the cost function converges with the worst fitness value at later iterations. The way hybrid GWO-SSA explores the solution space is comparable to how bacteria explore the environment for nutrition. This increases the possibility of discovering global optima by allowing it to quickly examine a variety of areas inside the search space.

6.7 Statistical Performance Analysis

The statistical analysis is important in the validation of the performance and reliability of the optimization algorithms, particularly stochastic approaches like GWO, SSA, and hybrid ones. As the algorithms rely on random initialization and probabilistic search processes, a single run of the simulation cannot provide a precise picture of the real performance of the model. Consequently, to achieve robustness and reproducibility, the given method is tested on 30 incremental runs with various random starting points. Temperature, delay, energy, number of alive nodes, load, and cost function are some of the performance metrics recorded per run. The resulting final results are then summarized in the form of statistical values or measures such as mean (average) and standard deviation, which give an indication of the central tendency as well as variability of the performance of the algorithm. A smaller standard deviation (SD) is a sign of more consistent and stable results, whereas the mean value is a representation of overall effectiveness.

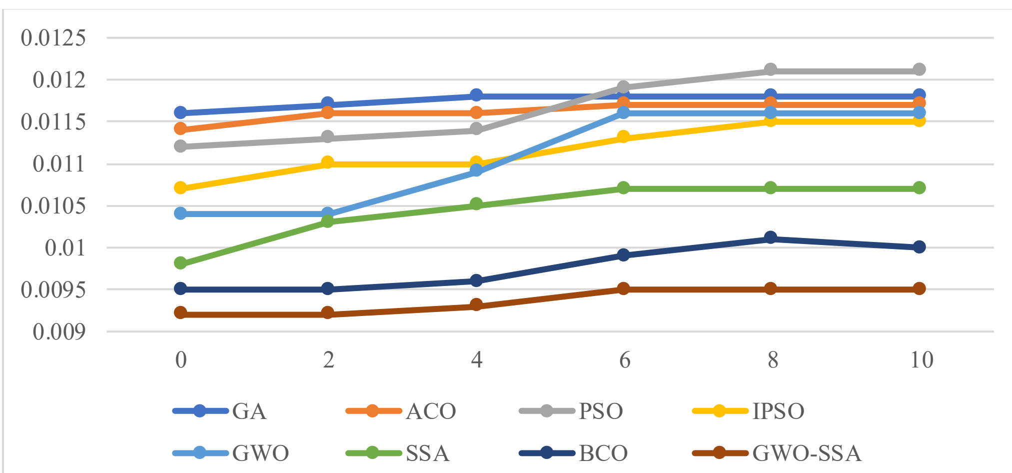

Figure 7. Results analysis based on the cost function.

Table 4 presents the statistical findings of the application of various optimization algorithms in terms of temperature, delay, and energy based on means and standard deviation. As can be observed, the proposed method of GWO-SSA has the lowest temperature (4.288) of any other method, which means that it is effective in terms of thermal management and minimizes the overheating of sensor nodes. Conversely, traditional algorithms like GA (5.494) and ACO (5.248) have higher temperature values, which is likely to cause more rapid degradation of hardware equipment and less reliable networks. Equally, as regards communication delay, the proposed technique has the lowest mean delay value (0.314) and a very small standard deviation (0.02), which indicates efficiency as well as stability in data transmission. The improvement is considerable in comparison with GA (0.582) and PSO (0.484), which shows the efficiency of the hybrid model in reducing the latency with the most efficient CH placement. In the energy metric, the proposed GWO-SSA is the best in terms of mean value (0.347), which demonstrates improved energy preservation and balanced energy consumption among nodes. This is a major critical consideration in the network lifetime extension. The fact that gradual improvement took place between GA (0.247) and GWO-SSA (0.347) indicates that the hybrid optimization is effective in terms of energy resources management. In general, the reduced values of standard deviation prove that the offered model gives similar and stable results in numerous runs.

Table 4. Statistical analysis for temperature, delay, and energy.

Method	Temperature		Delay		Energy	
	Mean	SD	Mean	SD	Mean	SD
GA	5.494	± 0.36	0.582	± 0.05	0.247	± 0.19
ACO	5.248	± 0.37	0.570	± 0.03	0.249	± 0.19
PSO	5.106	± 0.43	0.484	± 0.04	0.258	± 0.19
IPSO	4.830	± 0.34	0.466	± 0.05	0.272	± 0.18
GWO	4.598	± 0.33	0.448	± 0.04	0.301	± 0.17
SSA	4.461	± 0.43	0.378	± 0.02	0.326	± 0.16
BCO	4.346	± 0.54	0.344	± 0.02	0.330	± 0.16
GWO–SSA	4.288	± 0.57	0.314	± 0.02	0.347	± 0.15

Table 5. Statistical analysis for number of alive nodes, loads, and cost function.

Method	Number of alive nodes		Number of loads		Cost function	
	Mean	SD	Mean	SD	Mean	SD
GA	43.6	± 34.5	10.2	± 2.6	0.01175	± 0.00008
ACO	46.4	± 35.7	11.6	± 2.7	0.01162	± 0.00010
PSO	49.4	± 36.8	11.8	± 2.6	0.01167	± 0.00037
IPSO	53.2	± 36.3	11.8	± 2.5	0.01117	± 0.00030
GWO	58.0	± 36.0	12.4	± 2.8	0.01108	± 0.00053
SSA	61.4	± 35.5	12.6	± 3.2	0.01045	± 0.00033
BCO	63.2	± 35.3	12.8	± 3.6	0.00977	± 0.00024
GWO–SSA	**65.0**	**± 35.0**	13.4	± 3.9	0.00937	± 0.00014

Table 5 shows the statistical comparison of the network lifetime (alive nodes), load distribution, and cost function. The GWO-SSA proposed approach has the greatest number of active nodes (65.0), which implies a considerable increase in network lifetime. On the contrary, GA (43.6) and ACO (46.4) indicate a steep reduction in active nodes, which is indicative of ineffective use of energy. The capability of GWO-SSA to preserve the number of active nodes proves the capability of the system to extend the network operation. The proposed method has the highest mean value (13.4) in load distribution, meaning that there is a higher load distribution between cluster heads. The distributed load will also minimize congestion and premature failure of nodes with a heavy load, thus increasing the stability of the entire network. In the case of the cost function, the ultimate optimization goal, the proposed GWO-SSA has the lowest value (0.00937), and the standard deviation (0.00014) is very low. This proves that the hybrid model converges faster and, at the same time, has stable performance over the iterations. The cost decrease is very high when compared to GA (0.01175) and PSO (0.01167).

The proposed hybrid GWO-SSA algorithm has a time complexity that is dependent on the size of the sensor nodes (N), Population size (P), Number of cluster heads (M), and iterations (T). Fitness evaluation and specifically distance calculation is the most computationally challenging step, and it needs. $O(NM)$ is involved, although other parameters play a role $O(N)$. In every iteration, both GWO and SSA revise all solutions that have a cost of $O(P)$. Therefore, the complexity per iteration is totaled as $O(P.N.M)$, and over (T)iterations, it becomes: $O(T.P.N.M)$. Since $M \ll N$. The algorithm is efficient and scalable and offers a fair tradeoff between optimization performance and cost of computation.

6.8 Compared with SOTA Methods

The suggested hybrid GWO-SSA algorithm is compared to various state-of-the-art optimization algorithms, such as GA (Nandan et al., 2021), ACO (Shi & Zhang, 2021), PSO (Senthil et al., 2021), IPSO (Bao, 2022), GWO (Jaiswal & Anand, 2021), SSA (Arunachalam et al., 2021), and BCO (Subramanian & Ramkumar, 2024). The traditional algorithms, GA and ACO, have the advantage of good global search; however, they tend to be slow at convergence and are more computationally expensive. Likewise, PSO and IPSO converge quickly but can easily result in premature convergence and can get stuck in local optima, particularly in more complicated IoT clustering cases. Standalone GWO has good exploration capability as the leadership hierarchy, but in subsequent cycles, it does not perform local exploitation efficiently, and hence, it refines inefficiently. SSA, conversely, can provide good local search based on adaptive gliding and seasonal monitoring strategies, but has poor global coverage in high-dimensional space. BCO is more efficient at achieving balance optimization, although it can be more complex and slower to adjust itself to dynamic network conditions. The suggested hybrid GWO-SSA, on the other hand, is a combination of GWO and SSA so that a better balance between exploration and exploitation is obtained. The GWO component is effective in the process of search space exploration to determine viable areas, whereas the SSA component optimizes these solutions by local exploration. The synergy eliminates the chances of premature convergence and increases solution accuracy. Consequently, the hybrid approach has better performance in energy efficiency, decreased delay, enhanced load balancing, regulated temperature, more alive nodes, and expanded network lifetime, which is more appropriate in dynamic IoT surroundings than the current approaches.

7. Conclusions

This paper proposes an effective and dynamic CH selection algorithm for an IoT network with a hybrid GWO-SSA. The hybrid model is a useful combination of the exploration capacity of GWO and the exploitation capacity of SSA to overcome the main limitations of dynamic clustering, including unequal energy loss, an increase in temperature, and unequal load distribution. The algorithm incorporates residual energy, delay, temperature, distance, and load into a multi-objective cost function and, therefore, is used to select the optimal CH under different network conditions. The results of the simulation demonstrate that the hybrid GWO-SSA algorithm performs significantly better on network performance metrics such as energy usage, number of alive nodes, communication delay, and cost reduction than traditional and standalone metaheuristics. Besides, SSA incorporation of the local intensification step allows the algorithm to respond quickly to network topology variations and remain stable. Generally, the suggested GWO-SSA framework is an addition of a scalable, energy-efficient, and thermally stable clustering mechanism that can be used in large-scale IoT deployments, paving the way for future developments of secure, intelligent, and distributed optimization-based IoT management systems.

Conflicts of Interest
There is no conflict of interest between authors.

Acknowledgments
Nil.

AI Disclosure
The author(s) declare that no assistance is taken from generative AI to write this article.

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