RESEARCH PAPER

SOA-ECCH: Sandpiper Optimization Algorithm based, Energy Conscious Cluster Head Selection for Smart City Internet of Things Networks

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ABSTRACT

In the recent years, the Internet of Things (IoT) has transformed many areas of society and improved human life by changing the way data is conveyed. IoT technology is now part of everyday life, transforming the way cities use resources, provide services, and allow individuals to interact with each other. The spread of IoT has resulted in more efficient and responsive urban systems, tailor-made services, and new ways of social interaction. Data from sensors and smart meters are utilized in intelligent cities to enhance public services, infrastructure, and utilities. WSNs are essential for gathering data in IoT systems over the long term. Data are delivered to the sink node through networks, and having strong connectivity between the sensor nodes is essential in IoT systems. Clustering techniques are popular in IoT to save power at the node level and enhance battery life. Improving the capacity and longevity of the clustered network depends on the careful selection of Cluster Heads (CHs). Over the past decade, studies on optimal Cluster Head selection have decreased energy consumption by a considerable amount. The wrong Cluster Head selection not only speeds up battery drain but also prolongs the network convergence time. To address this challenge, this research article proposes the Sandpiper Optimization Algorithm-based Energy-Conscious Cluster Head (SOA-ECCH) algorithm. It utilizes both distance constraints and residual energy levels to improve network performance and lifespan. The enhanced SOA-ECCH effectively minimizes energy consumption among network nodes while boosting network lifetime and throughput.

Keywords: Smart City, Internet of Things, Cluster Head, Energy-Conscious Cluster Head and sandpiper optimization algorithm.

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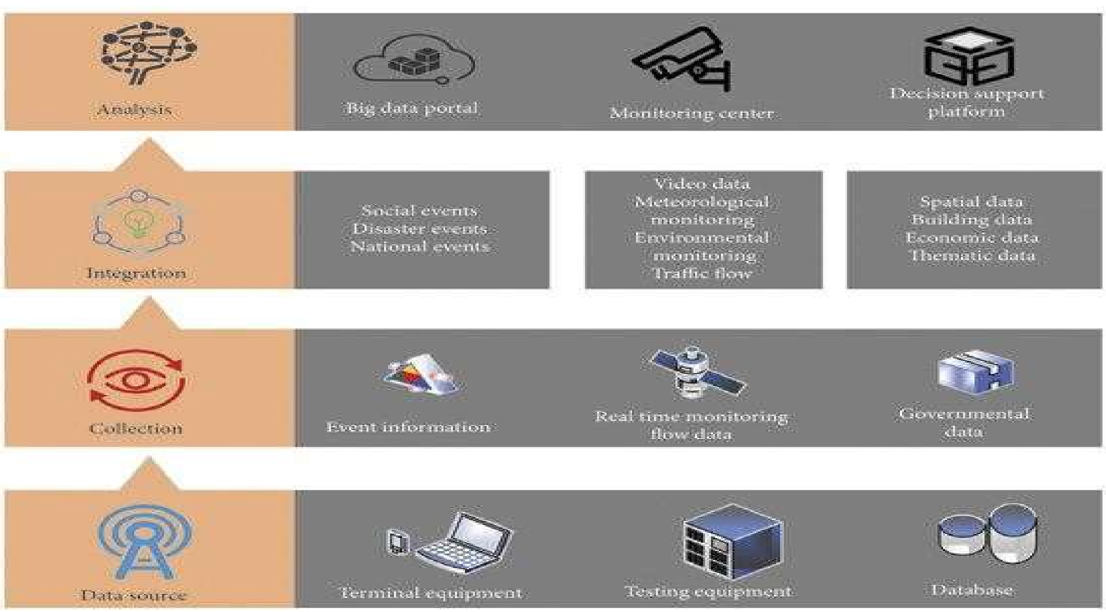
INTRODUCTION

A Smart City is a city that uses digital technology to enhance the life of its citizens. Smart cities are focusing on target, like modernizing public utilities, infrastructure, and services using digital governance. All these targets are met using the support of developments in Information and Communication Technology (ICT). With increasing metropolitan populations and speedy urbanization, contemporary urban planning techniques seek to minimize environmental degradation. Concurrently, these efforts leverage technology and creative planning to develop intelligent cities while providing equal opportunities for all citizens. This collective mechanism is generally called "smart cities" [1]. In a smart city, sensors are placed strategically across the city to track and manage a number of applications. Typical examples include automated road condition monitoring, tracking healthcare data, toll collection systems, traffic flow analysis, air quality monitoring, water resource management, intelligent electrical grids, public safety systems, waste management, and vehicle license plate recognition. Smart city governance is driven by data centers and analytics engines that crunch information gathered from sensors installed all over the city. These solutions facilitate the effective provision of core services via a network that integrates wireless devices, cameras, and other sensors. Furthermore, smart cities seek to minimize power consumption and ensure sustainability by creating infrastructure hubs using recycled materials and sustainable processes.

Figure 1: Smart city life cycle



The life cycle of a smart city is composed of four phases, as shown in Figure 1. In Stage 1, data are gathered from multiple sensors and networked devices. This phase is characterized by the identification and assessment of the sources of data. In Stage 2, data are cleaned, formatted, and analyzed at an initial level. In stage 3, decision-makers are communicated with through strong communication networks to use insights derived from the analysis for planning. In stage 4, the implementation occurs, where the findings are turned into implementable solutions with the goal of enriching the quality of life.

Smart cities provide a rich provisioning network for municipal officials and citizens by implementing sensors that obtain data and perform related operations [1, 2]. Wireless Sensor Networks (WSNs), facilitated by Internet of Things (IoT) applications, provide improved sensing capabilities and actuation. These WSN-based systems cover an extensive spectrum of studies, applications, and technological advancements, continuously enlarging the scope of IoT applications. This increasing research focus has driven the take-up of IoT network technologies, greatly attributed to access to affordable, flexible sensors and actuators [3–7]. IoT networks are constructed based on specialized sensor nodes, each of which broadcasts measured values to the cloud. This involves putting in environmental monitors that report periodically or even continuously to cloud servers using the Internet. The server uses the data received to decide the correct responses. In order to improve performance, sensors are organized under a central node known as the Cluster Head (CH) that makes communication with the servers [8, 9]. Every wireless sensor node usually comprises radio transceivers, processing units, sensing elements, and power components, and functions in a wireless communication system. A common WSN can be made up of hundreds or even thousands of such sensor nodes. Low energy usage and low device complexity are the main design objectives for these nodes, and there has to be a perpetual balancing act among communication requirements and data processing capacities [10, 11]. But resource limitation and heterogeneity in WSNs pose significant challenges to efficient network management particularly in smart city scenarios such as smart grids, intelligent transportation networks, and automated building complexes. Issues of concern are resource allocation, dynamic ad hoc topologies, maintenance of sensor nodes, and limited network and battery life. For resolving such issues, clustering is used a method used to group the nodes within the network [12]. A cluster is a subset of nodes that are chosen such that internal dissimilarities are reduced and network efficiency is improved [13]. Recent research indicates that hierarchical routing protocols are more energy-efficient and adaptable compared to flat routing protocols, especially in large-scale WSNs [14, 15].

Wireless Sensor Networks (WSNs) are applicable to a vast array of real-time situations. Every node in the network is powered by a battery, and wireless communication energy consumption depends on the position of the node. Energy consumption is directly proportional to the distance for which data need to be transmitted. As a result, energy consumption across nodes is uneven [16, 17]. The unevenness in energy distribution creates difficulty in sustaining network longevity and reliability. In WSN-based IoT systems, data exchange between nodes and sink nodes is mostly dependent upon routing mechanisms. Routing becomes more complicated as the network grows, and hence many routing protocols have been developed to enhance the overall network performance. These protocols are generally categorized on the basis of network structure, node involvement, operating modes, and clustering algorithms [18, 19]. Of these, clustering is a very efficient method for data transmission in WSN-based IoT systems since it helps in energy conservation. Clustering supports data aggregation, which reduces redundant transmission among cluster members (CMs) and the sink node [20]. During the clustering operation, the Cluster Head (CH) is responsible for identifying the best cluster members from a pool of candidates.

To improve the effectiveness of CH selection, a number of optimization algorithms are utilized. These are mathematical approaches that aim to find the optimal solution to a problem, usually presented as an objective function [21]. Iterative optimization techniques are applied to iteratively refine the solution over many iterations. A broad range of algorithms has been employed, such as Differential Evolution Algorithm (DEA), Harmony Search Algorithm (HSA), Cuckoo Search (CS), Whale Optimization Algorithm (WOA), and Honey Bee Mating Optimization (HBMO), among others. One common limitation of most of these methodologies is long convergence times, which are an aftermath of the high levels of iterations required to achieve optimal or near-optimal solutions.

RELATED WORKS

Optimized clustering of Wireless Sensor Networks (WSNs) means systematically clustering sensor nodes into clusters and choosing the Cluster Head (CH) with clearly defined optimization criteria in order to enhance overall network performance and efficiency. It reduces energy consumption significantly, minimizes communication overhead, improves data transmission reliability, and maximizes network lifetime.

Chaurasia et al. [22] presented a Route Search Algorithm combined with a meta-heuristic-based CH selection approach. The Cluster Head Selection Algorithm applies a clustering process based on an Energy Level Matrix function, taking into account various parameters including node density, inter-cluster formation, network topology, distance, and residual energy. The Route Search Algorithm is intended to find the best path between cluster heads and the base station for optimal transmission of data, thus enhancing both the network lifetime and data flow rate. Although this approach has its benefits, it also has some limitations, such as computational complexity, scalability issues, and difficulty in being used in heterogeneous network contexts.

Rami Reddy et al. [23] introduced an energy-efficient Improved Grey Wolf Optimization (GWO) algorithm for Cluster Head (CH) election in Wireless Sensor Networks (WSNs). The GWO algorithm is based on the social structure and hunting mechanism of grey wolves, and it has been widely applied to complex optimization problems. The algorithm starts by generating an initial population of candidate solutions, assessing their fitness with an objective function specified in advance, and sorting them into alpha, beta, and delta wolves as the best solutions. The rest of the wolves adapt their positions by moving toward and encircling these best solutions, balancing exploration and exploitation stages. The advanced version of GWO enhances this process by utilizing adaptive parameters, hybridation with other algorithms, and more efficient exploration exploitation mechanisms. In efficient CH selection in WSNs, the algorithm represents wolf locations as candidate CH configurations with the aim to balance energy consumption and network lifetime. The algorithm repeatedly refines wolf positions and recalculates the fitness scores until the algorithm settles on an optimum or near-optimum CH arrangement, hence improving overall network performance and efficiency. Main parameters taken into account in the process of selecting CH include intra-cluster distance, residual energy, distance from the sink node, and load-balancing factors for the CH node. Although the improved GWO provides higher throughput, stability, energy efficiency, and network lifetime, one of its drawbacks is high computational time of the fitness function in the CH selection process.

Samiayya et al. [24] developed the Hybrid Snake Whale Optimization (HSWO) algorithm for the optimal selection of Cluster Head (CH) for Wireless Sensor Networks (WSNs) to achieve maximum network lifetime. The HSWO methodology functions through three prominent phases: CH selection, system configuration, and path selection. The algorithm sets out to select the most optimal CH based on various factors such as latency and distance. In order to certify the efficacy of the HSWO approach, various performance parameters were examined, including network energy, throughput, energy efficiency, packet delivery ratio, computational cost, network lifetime, and computation time. The findings confirmed that HSWO enhances overall network efficiency as well as extends operating lifespan. Though, the approach has a significant limitation when it comes to computational complexity, especially while selecting the CHs, which could affect the scalability of the approach in highly dynamic or large-scale network settings.

Ramalingam et al. [25] proposed EECHS-ARO, which is an energy-efficient cluster head selection technique for wireless sensor networks (WSNs) used in the monitoring of livestock in particular. The technique utilizes the Artificial Rabbits Optimization (ARO) algorithm, which simulates the rabbits' foraging and hiding tendency to optimally manage exploration and exploitation while optimizing. This method solves the key issue of energy utilization in WSNs, where inefficient selection of cluster heads can contribute to early node death as well as a reduced network lifespan. Tested in MATLAB R2021a, EECHS-ARO was compared with well-known met heuristic optimization algorithms like Teaching-Learning-Based Optimization (TLBO), Ant Lion Optimizer (ALO), and Quasi-Oppositional Butterfly Optimizer (QOBOA). Performance results indicated that EECHS-ARO surpassed these algorithms by extending network lifetime to about 15%, enhancing the packet delivery ratio (PDR) by 5%, and lowering latency to 380 ms, in contrast to 430–495 ms in other approaches. The algorithm also demonstrated quicker convergence and postponed the appearance of dead nodes, which helped overall network reliability. The research highlights the efficacy of ARO in regulating energy-conscious clustering in WSNs and its feasibility for real-time implementation in the livestock sector, thus helping to develop smart agriculture technologies.

Arunachalam et al. [26] adapted the squirrel search algorithm (SSO-CHST) to utilize the gliding factor to choose the best cluster heads in WSN. The algorithm starts with a group of candidate cluster heads, or "squirrels," distributed randomly across the network. During the search process, the squirrels travel to various spots across the network to find potential cluster heads and adjust their options based on performance criteria. The gliding factor controls the smoothness of squirrel movement so that a transition to the optimal cluster heads is facilitated. With the inclusion of this factor, SSO-CHST maintains selection efficiency while ensuring a gradual process without making abrupt transitions and boosting convergence to the best cluster heads. This approach optimizes energy efficiency as well as network performance, ultimately extending the lifespan of the network. Yet, it did take into account certain simulation runs to pick the optimal CH. It is limited by computational complexity, scalability issues, slower convergence rate, potential to be trapped in local optima, and the need for significant changes in dynamic environments.

Abraham et al. [27] introduced FSA-CHS, an energy-aware cluster head selection protocol for wireless sensor networks (WSNs) that improves data transmission and saves energy through the use of the Flamingo Search Algorithm (FSA). The optimal cluster heads are chosen by the proposed mechanism based on the important parameters of residual energy, the distance to neighboring nodes, and the network topology in general. By choosing the most appropriate nodes as cluster heads, FSA-CHS reduces wastage of energy and distributes the communication burden over the network, thus increasing its lifetime. The algorithm allows the chosen cluster heads to have low energy usage and reliable communication, which increases performance and sustainability of the WSN. Nonetheless, the strategy has significant drawbacks, especially in extensive network environments where the computational cost is elevated as a result of the assessment of multiple candidate nodes under multiple parameters. Moreover, similar to most meta-heuristic algorithms, FSA-CHS is prone to being trapped in local optima, which may hinder the identification of actually energy-efficient solutions and thereby its efficiency in reducing energy consumption.

Ambareesh et al. [28] proposed the Hybrid Jarratt Butterfly Optimization (HJBO) algorithm for wireless sensor networks (WSNs) optimal path choice, leveraging cluster heads (CHs) for effective data transmission. The hybrid method combines the quick convergence ability of the Jarratt algorithm with the global search power of the Butterfly Optimization Algorithm (BOA), complemented by the FUZZY TOPSIS decision-making method. FUZZY TOPSIS is used to assess and choose the best cluster heads or routes of communication according to factors like energy usage, base station distance, and data reliability. The optimization starts with an initial population of candidate solutions in the form of butterflies, which is then improved using the Jarratt method to have a strong background. BOA subsequently iteratively refines these solutions by exploring the search space through a trade-off of exploration and exploitation. The Jarratt algorithm is re run in order to refine these outcomes and achieve fast convergence to the optimal solution. The hybrid strategy shows very high accuracy and efficiency in solving complicated optimization problems and can be applied to large-scale network installations. Yet this benefit is gained at the expense of added computational overhead, which can result in longer processing times and system resource consumption in large network deployments. Overall, HJBO represents a robust framework for improving energy efficiency, decreasing latency, and enhancing throughput in WSNs.

Jaya Pratha et al. [29] introduced a hybrid cluster head (CH) selection algorithm in wireless sensor networks (WSNs) to improve the energy stability and prolong network lifetime. The method follows the hybrid Partha Mutualism mechanism, where various objectives like residual energy, network cost, proximity of nodes, and coverage area are used to select the most appropriate CHs. Through the combination of exploration and exploitation, the algorithm sufficiently traverses the solution space while utilizing potential candidate solutions to optimize the formation of cluster heads. This equilibrium allows for the choosing of efficient and strategically located cluster heads, enhancing overall network performance. Though optimal, the hybrid CH selection technique suffers from greater computational complexity, a typical setback whenever several optimization approaches are combined. Moreover, the algorithm could also be challenged by scalability and responsiveness in dynamic or very large WSN settings, where topology or node status changes could adversely affect performance without real-time modification. Nevertheless, the work proposed is a great step toward more insightful and goal-oriented CH election in energy-limited WSNs.

Sindhuja et al. [30] proposed MOCHSAPGAN-AVO, a multi-objective cluster head selection algorithm for WSNs based on the African Vulture Optimization (AVO) algorithm. The algorithm integrates the advantages of Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) along with Adaptive Velocity Optimization (AVO) to solve the issues of energy-efficient and dependable cluster head (CH) selection. MOCHSAPGAN-AVO is formulated to optimally maximize multiple goals like network lifetime and minimizing energy usage. The optimization starts from an initial population of possible CH sets, which are assessed according to pre-specified multi-objective parameters. GA operations, including selection, crossover, and mutation, are performed to search the search space globally and produce fitter children. Parallel to this, PSO optimizes these solutions through social learning processes by particle position updates from their individual and neighborhood experience. Adaptive Velocity Optimization further optimizes the PSO process by changing particle velocities dynamically to enhance convergence behavior. This hybrid method efficiently combines GA's global search ability with PSO's local exploitation effectiveness, leading to an efficient and effective CH selection process. MOCHSAPGAN-AVO offers an effective model for balancing multiple performance objectives in WSNs, especially in applications requiring high reliability, data integrity, and long-lasting operation.

Cherappa et al. [31] suggested a power-aware clustering scheme for wireless sensor networks (WSNs) that combines rapid routing algorithms with the Adaptive Sailfish Optimization (ASFO) algorithm. Motivated by the hunting patterns of sailfish, ASFO optimally adjusts its optimization approach based on feedback from the network, facilitating timely adaptation in the choice of cluster head (CH) and routing path selection. The algorithm uses a two-pronged approach based on clustering and multi-hop routing to effectively broadcast information throughout the network. Its adaptive mechanism provides load-balanced distribution among CHs, decreasing the energy consumption and increasing network lifetime considerably. By dynamically adapting CH roles and routing decisions according to current network conditions, ASFO improves energy efficiency and operation reliability. Nevertheless, the algorithm's combination of sophisticated optimization and routing elements incurs increased computational overhead, resulting in higher processing times and more resource utilization. Additionally, ASFO can face performance bottlenecks in densely dynamic network conditions where frequent topological modifications necessitate prompt algorithmic response. In spite of these difficulties, ASFO provides a viable solution for intelligent and energy-saving data communication in WSNs, particularly in situations with dynamic clustering and adaptive routing needs.

In total, the literature reviewed emphasizes an open research issue in creating a wireless sensor network (WSN) cluster head selection algorithm that is energy-efficient, scalable, adaptive, and robust at the same time. Although many meta-heuristic and hybrid methods ARO, FSA, HJBO, hybrid mutualism, MOCHSAPGAN-AVO, and ASFO have been proven to excel in certain areas such as energy saving, convergence rate, or robustness, the majority of them experience drawbacks such as excessive computational complexity, decreased flexibility in changing environments, or poor scalability in larger networks. Hence, there exists an urgent need to propose a meta-heuristic-based CH selection algorithm that should be efficient in tackling major challenges: achieving maximum network lifetime and throughput, reducing energy consumption, speeding up convergence rates, and providing uniform coverage and connectivity under varying network conditions. Such an approach would provide a more pragmatic and balanced deployment strategy for real-world applications of WSN.

PROPOSED METHODOLOGY

MODEL FOR NETWORKS

First, the wireless sensor network (WSN) is installed with ‘n’ sensor nodes distributed randomly across an area of defined surface. Every sensor node is denoted by parameters like initial energy, processing power, and energy cost of data transmission. A central sink node is located at the center of the network to receive and send data transmissions. In this network, Cluster Head (CH) nodes serve as the central nodes by collecting data from the sensor nodes that belong to their own clusters. Upon data collection, every CH node accumulates the received data and sets up a communication link either with neighboring CHs or with the sink node centrally. This hierarchical transmission format enables CH nodes to transmit the aggregated data upstream in the network either intermediate processing by other CHs or straight to the sink node for final analysis. This approach greatly improves the data management efficiency by eliminating redundant transmissions and keeping the overall communication overhead low, thereby extending the lifetime of the network and saving energy.

The Energy Conscious Cluster Head (CH) Selection Algorithm is utilized by the sink node to select the best CH node in a Wireless Sensor Network (WSN). The selection follows the Sandpiper Optimization Algorithm (SOA) to identify the most appropriate node in terms of energy efficiency and distance. Upon selection, the Cluster Head is tasked with creating the cluster and acting as the mediator between sensor nodes and the sink. The SOA-ECCH protocol revolves around CH formation and its corresponding cluster members. Every communication round, the sink node triggers the SOA to choose the best CH from among the alive nodes. The iteration and energy-efficient selection involves analyzing a fitness function that takes into consideration of the candidate nodes' residual energy. By repeated assessment, the node with the best fitness score is chosen as the CH for that iteration. After being chosen, the CH takes charge of managing its cluster. Once the Sandpiper Optimization Algorithm (SOA) selects the most energy-efficient Cluster Head (CH), the remaining active nodes automatically become Cluster Members (CMs) to efficiently route data through this optimized CH, minimizing overhead and maximizing network lifetime.

ENERGY MODEL OF SOA- ECCH PROTOCOL

The SOA-ECCH protocol uses conventional channel architecture to transport data. The nodes energy can be spent by while sending and receiving a packet. It has the energy consumption involved in transmitting and receiving data packets. The upper half of the diagram depicts the transmission process. Here, data packets are fed as input to a transmission unit and subsequently processed by an amplifier unit. The total energy consumed during transmission, denoted as E_{TX}, is explicitly defined by the formula:

$$E_{TX} = E_{elec} + E_{amp} \tag{1}$$

where, E_{elec} represents the electronic energy consumed by the transceiver circuitry. E_{amp} represents the energy consumed by the power amplifier to boost the signal to a sufficient level for wireless propagation.

The energy consumed during reception, E_{RA}, is shown to be solely:

$$E_{RA} = E_{elec} \tag{2}$$

where, E_{elec} signifies the electronic energy used by the receiver's circuitry

Table 1: Algorithm steps for Energy Conscious Cluster Head selection based on the Sandpiper Optimization Algorithm (SOA-ECCH)

Procedure SOA_ECCH_Round(Nodes, Sink, SOA_Parameters):

1. Initialize Packet Counters: packets_to_CH = 0, packets_to_sink = 0.
2. Identify Alive Nodes: Create a list of all nodes with energy > 0.
3. If no alive nodes, return failure.
4. // Cluster Head Selection Phase (using SOA)
   Call Select_Cluster_Head_SOA(Nodes, Sink, SOA_Parameters) to get CH_idx.
   If CH_idx is -1 (no CH selected by SOA), return failure.
5. // Data Transmission Phase
   Simulate Data Transmission:
   a. Nodes send data to the selected CH, consuming energy.
   b. CH aggregates data and sends to the Sink, consuming energy.
   c. Update node energies and increment packets_to_CH, packets_to_sink.
6. Update Node Status: For each node, if energy <= 0, set status to 'dead'.
7. Return Selected_Cluster_Head_Index, Updated_Nodes, Packets_Transmitted_to_CH, Packets_Transmitted_to_Sink.

End Procedure

Procedure Select_Cluster_Head_SOA(Nodes, Sink, SOA_Parameters):

1. Initialize Sandpiper Population: Randomly select 'Population_Size' alive nodes as initial sandpipers (candidate CHs).
2. Initialize Best Solution: Set best_fitness_overall = Infinity, best_CH_overall_idx = -1.
3. // SOA Iteration Loop
   For iteration = 1 to Max_Iterations:
   a. Filter and Re-initialize Sandpipers: Remove dead nodes from sandpiper population; if population size drops, add new random alive nodes to maintain 'Population_Size'.
   b. Evaluate Fitness: For each sandpiper, calculate its fitness using the ECCH Fitness Function (combining residual energy and inverse distance to Sink).
   c. Update Best Solution: If current best sandpiper's fitness is higher than best_fitness_overall, update best_fitness_overall and best_CH_overall_idx.
   d. Update Sandpiper Positions: Apply SOA movement rules (e.g., move towards current best CH, or explore randomly) to generate new candidate positions. Map new positions to valid alive nodes.
4. // Final Cluster Head Selection
   If best_CH_overall_idx is valid (alive and found by SOA), return best_CH_overall_idx.
   Else (SOA failed or best CH died), return a randomly selected alive node as fallback.

End Procedure

Procedure ECCH_Fitness_Function(Node, Sink, Weights):

1. Calculate Normalized Residual Energy: Energy_Factor = Node.current_energy / Node.initial_energy.
2. Calculate Inverse Distance to Sink: Dist_Factor = 1 / (Distance(Node.position, Sink.position) + epsilon).
3. Combine Factors: Fitness = (Energy_Factor * Weights.Energy) + (Dist_Factor * Weights.Distance_to_Sink).
4. If Node.current_energy <= 0, set Fitness = -Infinity.
5. Return Fitness. End Procedure

Energy Conscious Cluster Head Election based on the Sandpiper Optimization Algorithm (SOA-ECCH)

SOA-ECCH, an optimization methodology for sandpipers that considers energy consumption while selecting cluster heads. The sink is located at the center of the network. The sink performs the SOA for choosing the most suitable Cluster Head (CH). This approach leverages the Sandpiper Optimization Algorithm (SOA), inspired by the foraging behavior of sandpipers, to identify the most suitable nodes for cluster head roles. Colonies are places where seabirds like sandpipers live together. They use their intelligence to find and eat food in these areas. Sandpiper has two different phases namely migrating phase and attacking phase. During the migrating phase, sandpipers migrate from one place to another place in search of food sources with three behaviors. They are as follows: avoiding collision with neighbor sandpiper, flying together in the direction of best neighbor and update flying position with the best sandpiper.

The Migrating phase is used to explore the optimal position and residual energy of potential Cluster Heads. During the attacking phase, sandpipers have three behaviors. They are as follows: sandpipers attack other birds, change its speed to attack prey using its wings and usually forming a spiral pattern. The Migrating phase is used to optimal selection of Cluster Head based on optimization. SOA evaluates potential cluster heads based on criteria such as node energy levels, network topology, iteratively refining the selection to maximize network lifetime and minimize energy consumption. Once cluster heads are selected, they collect and aggregate data from sensor nodes, reducing the amount of data transmitted directly to the base station and conserving energy.

The proposed energy-aware CH selection approach increased throughput and lifetime of network. The objective of SOA-ECCH is to ensure both cluster formation and CH selection prolonged the network lifetime. The modified Sandpiper Optimization Algorithm (SOA) has two main phases. They are the startup phase and the exploration and exploitation phase.

In the startup phase, the algorithm generates a different population of candidate solutions randomly within a defined range. In the exploration and exploitation phase, SOA refines these solutions by mimics the foraging behavior of sandpipers. This involves iteratively updating the candidate solutions based on their fitness evaluations and adjusting their positions to explore new areas and exploit promising regions in the solution space. This two-phase approach ensures a detailed search for optimal or near-optimal solutions to complex optimization problems.

A population-based method is used by the SOA-ECCH, a meta-heuristic optimization technique. In a Wireless Sensor Network, sandpipers are considered nodes that collect data. The data collection nodes are first dispersed at random per Equation (3) during the startup step, particularly in the context of initializing candidate solutions with random values within a specified range, helping to ensure a diverse set of starting points for the optimization process. In Search space definition of decision variables are done by sandpiper locations. Therefore, the sandpiper positions stand for energy consumption. Both the exploratory and misappropriation stages are separate from one another in the process of finding new Cluster Head candidate solutions.

$$C_{i,j} = hob_j + rand\left(std_j - p_j\right) i = 1,2,3,\dots.p, j = 1,2,\dots,q \tag{3}$$

The sandpiper decision variable numerical value is shown by the variable i which also denotesits position in the search space. In the search space, the variable q indicates the overall count of sandpipers. Here, p stands for the total number of choice factors. To symbolize a real number between zero and one, the symbol rand is used. The j[th] decision variables upper and lower limits are denoted by std_j and hob_j accordingly. The target function generates many possible solutions by using the chosen variables. Equation (4) represents these numbers.

$$\begin{bmatrix} U_1 \\ U_i \\ U_n \end{bmatrix}_{n\times 1} = \begin{bmatrix} U(C_1) \\ U(C_i) \\ U(C_n) \end{bmatrix}_{n\times 1} \tag{4}$$

The objective function vector, U, represents the numerical values of each sandpiper goal, denoted as U_i. The position of each person determines a possible solution to the goal function in SOA. Both the ideal member placement and the prospective solution may vary to the iterations.

EXPLORATORY PROCESS

Sandpipers hunt in a coordinated manner, employing techniques such as tree climbing and intimidation. While waiting for prey to fall, some sandpipers hide behind trees to remain out of sight. Once prey, like a fallen apple, lands, the sandpipers quickly pursue and attack it. The effectiveness of sandpipers in exploring and solving problems depends on their positions within the search area. The population of sandpipers aims to identify the most optimal position. As one group climbs the tree to explore higher areas, another group stays below, waiting for the dust to settle and evaluate the findings. A mathematical representation of the sandpiper position may be found in Equation (5).

$$C_i^{rep1}: C_{i,j}^{rep1} = x_{i,j} + rand\left(dist_j - I . x_{i,j}\right), \text{for } i = 1,2,\dots \tfrac{q}{2} \text{ and } j = 1,2,\dots,p \tag{5}$$

After descending from the tree, the sandpipers are randomly distributed within the search area. They then move through the search space based on their random positions. This migration process can be evaluated using Equations (6) and (7).

$$dist^G: dist^G = hob_j + rand\left(std_j\ hob_j\right) i = 1,2,\dots p \tag{6}$$

$$C_i^{rep1}: C_{i,j}^{rep1} - \begin{cases} C_{i,j} + rand.\left(dist_j^G - I. C_{i,j}\right), U_{dist} < U_i \\ C_{i,j} + rand.\left(x_{i,j} - dist_j^G\right), else , \end{cases} \tag{7}$$

where C_i^{rep1} Specifies the updated location of the sandpiper at the i[th] position $C_{i,j}^{rep1}$ occupies the

j^{th} dimension where the sandpiper is located; the numerical value of objective function named ran ranges from zero to one; The optimal participant in the searching space is denoted as dist, indicating its specific position. The $dist_j^G$ symbol "j" denotes j^{th} dimension, whereas "I" represents randomly chosen integer values in a set.

MISAPPROPRIATION PROCESS

When a sandpiper encounters or is attacked by a predator, it shifts its position within the search area to a safer location. This behavioral response is mathematically modeled to represent such changes. When threatened, a sandpiper moves to a safer area. Equations (8) and (9) are used to determine the current positions of the sandpipers, followed by a local search that places them randomly but close to these positions.

$$\mathrm{hob}_j^{loc} = \frac{\mathrm{hob}_j}{n}, \mathrm{std}_j^{loc}, \text{where } z = 1,2, \ldots n \quad (8)$$

$$c_i^{rep2} : c_{i,j}^{rep2} = c_{i,j} + (1 - 2\,\mathrm{ran}).\left(\mathrm{hob}_j^{loc} + \mathrm{ran}\,.\left(\mathrm{std}_j^{loc} - \mathrm{hob}_j^{loc}\right)\right) \quad (9)$$

To find the number of candidate Cluster Heads (CHs), Equation 10 is used. It determines the number of candidate CH nodes for the internal optimization loop based on a target percentage of active nodes in the network

$$num_{candidate_{chs}} = \max(1, \mathrm{round}(P_{CH_{target}} \times num_{alive_{nodes}})) \quad (10)$$

where $P_{CH_{target}}$ represents the target percentage of Cluster Heads, $num_{alivenodes}$ represents the total number of currently alive nodes.

$$\mathrm{Energy}_{factor} = \frac{E_{current}}{E_{initial}} \quad (11)$$

The inverse distance factor is calculated using the following equation. It prioritizes nodes closer to the sink during the Cluster Head (CH) selection process by assigning higher values to shorter distances. Here, ϵ is a small positive constant used to prevent division by zero.

$$\mathbf{Dist_{factor}} = \frac{1}{d_{sink} + \epsilon} \quad (12)$$

The overall fitness of a node as a Cluster Head (CH) for the Sandpiper Optimization Algorithm (SOA) is evaluated by combining weighted energy and distance factors.

This fitness value is computed using the following equation.

$$F = \left(\mathrm{Energy}_{facor} \times w_{energy}\right) + \left(\mathrm{Dist}_{factor} \times w_{dist\_to\_sink}\right) \quad (13)$$

EXPERIMENTAL RESULTS

The performance of the proposed SOA-ECCH technique is implemented using MATLAB 2013a and includes increasing number of sensor nodes ranging from 100, 200 and 300. The area of the nodes is 100×100 m². The initial energy per node is 0.5 J. The transmission energy is E_{TX} = 50 n J / bit. The reception energy is E_{RX} = 50 n J / bit. The amplification energy E_{amp} = 10 p J / bit / m² (short range) and E_{amp} = 0.0013 p J / bit / m² (long range). The packet size is 4000 bits. The base station of the network is located at (50, 50). The simulation runs for 2500 rounds. Here, the metric are considered for evaluating the performance of the method. They are as follows: a) Number of alive nodes, b) Cumulative energy consumption, c) overall cumulative packets, d) cumulative inter cluster packets, e) network traffic rate and f) network lifetime comparison.

SIMULATION OUTCOME OF 100 SENSOR NODES

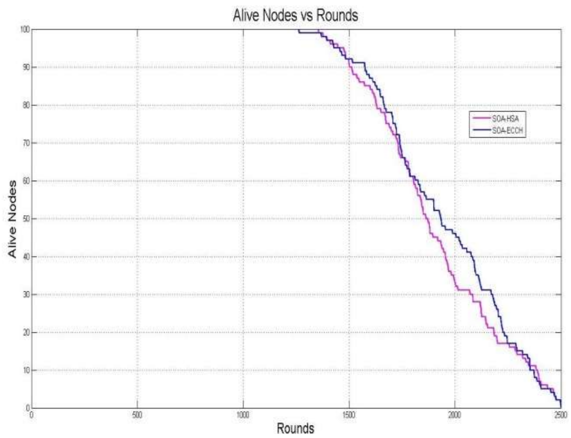


Figure 2: Alive Nodes vs Rounds

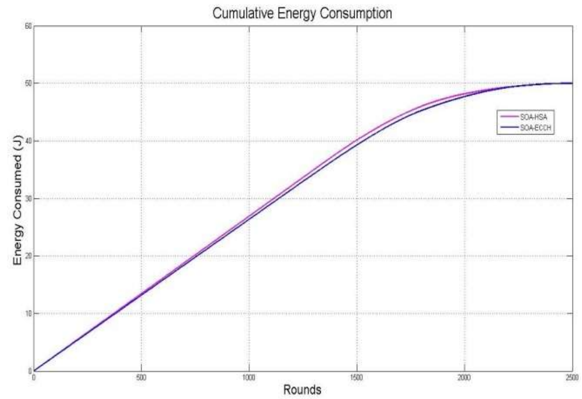


Figure 3: Cumulative Energy Consumption vs Rounds

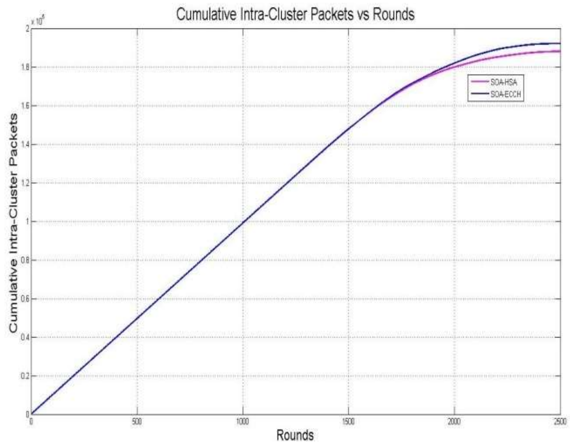


Figure 4: Overall Cumulative Packets vs Rounds

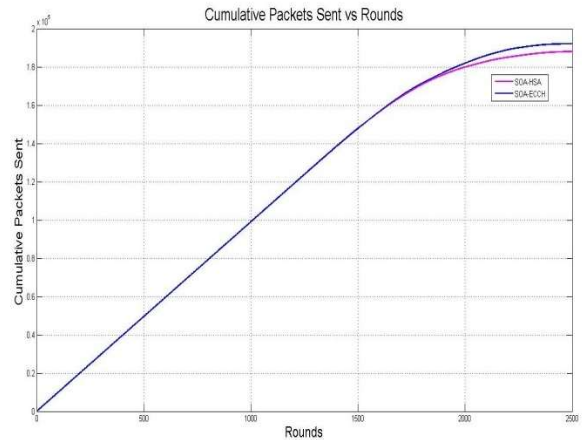


Figure 5: Overall Cumulative inter-cluster Packets vs Rounds

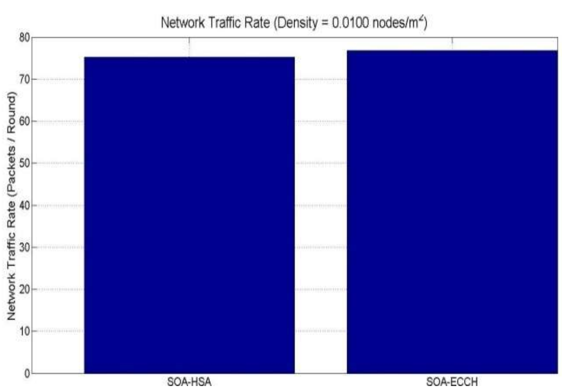


Figure 6: Network Traffic Rate vs Rounds

Table 1: Summary of Collected Data for 100 sensor nodes

METRIC	Hybrid SOA-HSA	Hybrid SOA-ECCH
Total Rounds (All Dead)	2500	2500

First Node Dead	1317	1349
Last Node Dead	2499	2499
Network Traffic Rate (pkt/round)	77.83	79.12
Cumulative Intra-Cluster Packets	197076	199946
Cumulative Inter-Cluster Packets	2698	2798

To critically assess the operational efficacy of the proposed techniques, a comprehensive evaluation of the hybrid SOA-HSA and hybrid SOA-ECCH algorithms was carried out. While both algorithms successfully sustained network operations up to 2,500 simulation rounds. Regarding the stability period of the network, the First Node Dead (FND) was observed at round 1,317 for hybrid SOA-HSA, whereas the hybrid SOA-ECCH algorithm prolonged this threshold to round 1,349, yielding a commendable 2.43% improvement in stability. Though both algorithms experienced the Last Node Dead (LND) at round 2,499, the hybrid SOA-ECCH framework consistently worked a larger volume of active nodes throughout the operational time, thereby enhancing overall system reliability. The hybrid SOA-ECCH algorithm exhibited highly efficient throughput metrics; it registered a network traffic rate of 79.12 packets per round compared to 77.83 packets per round for hybrid SOA-HSA, marking a 1.66% improvement. This trend of enhanced performance is further substantiated by the cumulative intra-cluster packet delivery, which escalated from 197,076 packets to 199,946 packets (representing a 1.46% gain), and the cumulative inter-cluster packet transmissions, which progressed from 2,698 packets to 2,798 packets, reflecting a notable 3.71% advancement. These augmented packet delivery rates thoroughly validate that the hybrid SOA-ECCH algorithm establishes a highly optimized cluster-head election mechanism and robust routing pathways. Consequently, these findings establish that the hybrid SOA-ECCH algorithm shows superior energy preservation, seamless traffic management, and an improved lifespan, suitable for resource-constrained smart Internet of Things (IoT) and Wireless Sensor Network (WSN) environments.

SIMULATION OUTCOME OF 200 SENSOR NODES

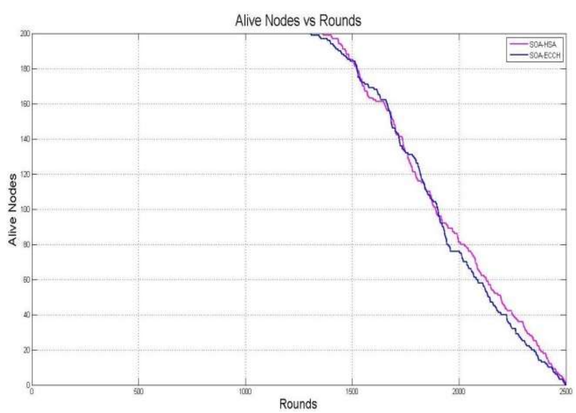


Figure 7: Alive Nodes vs Rounds

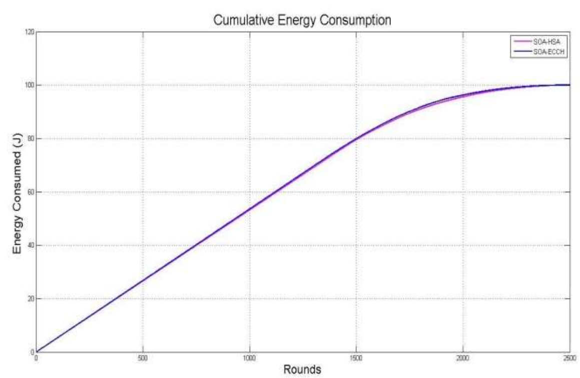


Figure 8: Cumulative Energy Consumption vs Rounds

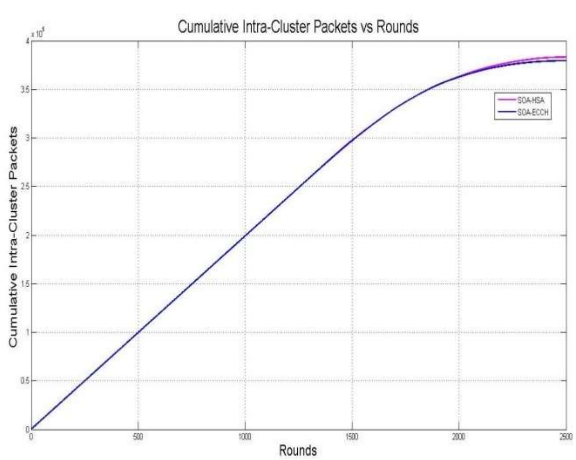


Figure 9: Overall Cumulative Packets vs Rounds

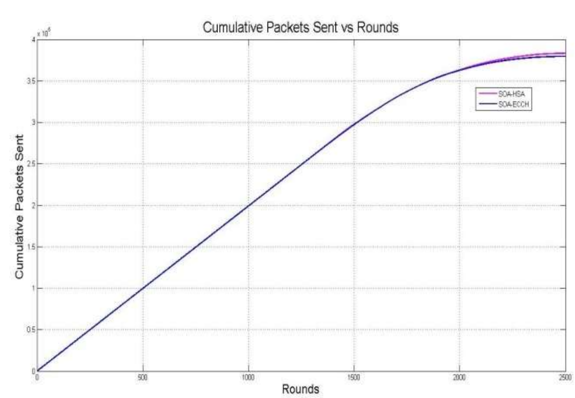


Figure 10: Overall Cumulative inter-cluster Packets vs Rounds

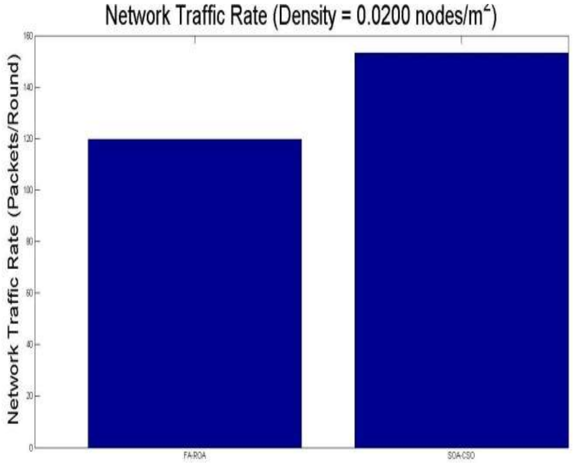


Figure 11: Network Traffic Rate vs Rounds

Table 2: Summary of Collected Data for 200 sensor nodes

METRIC	Hybrid SOA-HSA	Hybrid SOA-ECCH
Total Rounds (All Dead)	2500	2500
First Node Dead	1294	1297
Last Node Dead	2500	2500
Network Traffic Rate (pkt/round)	153.34	156.64
Cumulative Intra-Cluster Packets	387368	389968
Cumulative Inter-Cluster Packets	2699	2799

To critically assess the operational efficacy of the proposed techniques, a comprehensive evaluation of the hybrid SOA-HSA and hybrid SOA-ECCH algorithms was carried out until network operations up to 2,500 simulation rounds. Regarding the stability period of the network, the First Node Dead (FND) was observed at round 1,294 for hybrid SOA-HSA, whereas the hybrid SOA-ECCH algorithm prolonged threshold to round 1,297, yielding a valuable 0.23% improvement in stability. Though both algorithms experienced the Last Node Dead (LND) at round 2,500, the hybrid SOA-ECCH framework consistently enhances overall system reliability. The hybrid SOA-ECCH algorithm exhibited highly efficient throughput metrics; it registered a network traffic rate of 156.64 packets per round compared to 153.34 packets per round for hybrid SOA-HSA, marking a 2.15% improvement. This trend of enhanced performance is further substantiated by the cumulative intra-cluster packet delivery, which escalated from 387,368 packets to 389,968 packets (representing a 0.67% gain), and the cumulative inter-cluster packet transmissions, which progressed from 2,699 packets to 2,799 packets, reflecting a notable 3.71% improvement. These augmented packet delivery rates validate that the hybrid SOA-ECCH algorithm establishes a highly optimized cluster-head election mechanism and robust routing pathways. Consequently, these findings establish that the hybrid SOA-ECCH algorithm shows superior energy preservation, seamless traffic management, and an improved lifespan, suitable for resource-constrained smart Internet of Things (IoT) and Wireless Sensor Network (WSN) environments.

SIMULATION OUTCOME OF 300 SENSOR NODES

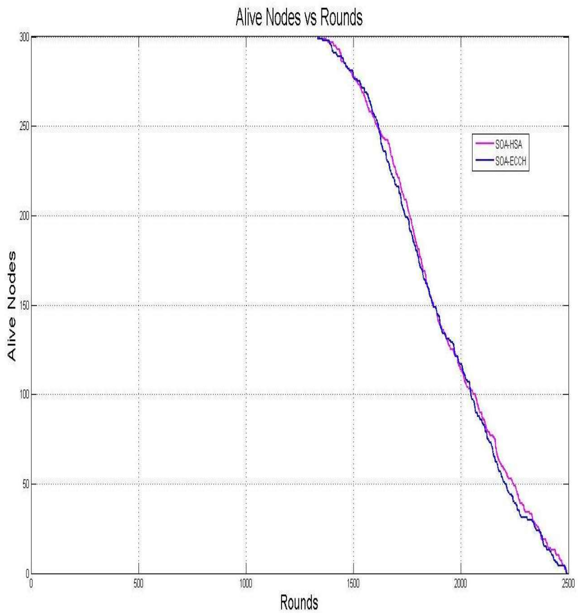


Figure 12: Alive Nodes vs Rounds

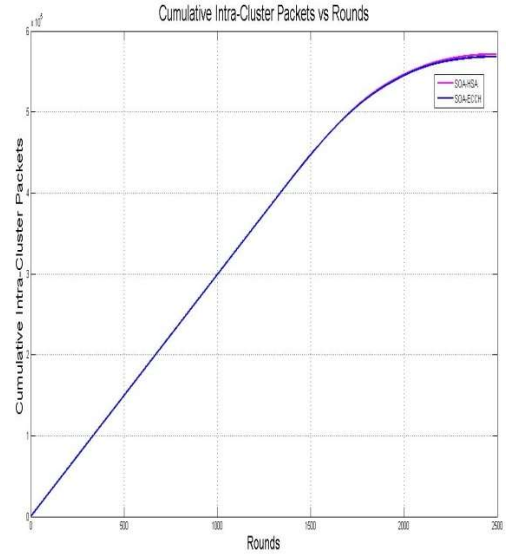


Figure 13: Overall Cumulative Packets vs Rounds

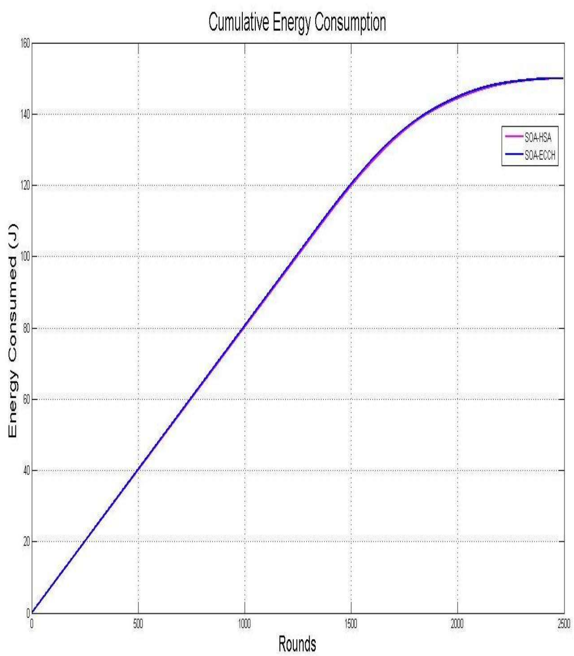


Figure 14: Cumulative Energy Consumption vs Rounds

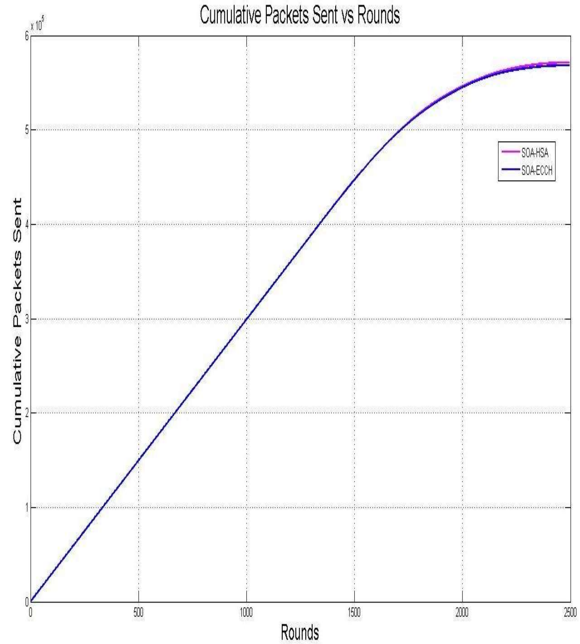


Figure 15: Overall Cumulative inter-cluster Packets vs Rounds

Table 3: Summary of Collected Data for 300 sensor nodes

METRIC	HYBRID SOA-HAS	HYBRID SOA-ECCH
Total Rounds (All Dead)	2499	2499
First Node Dead	1290	1390

Last Node Dead	2499	2499
Network Traffic Rate (pkt/round)	230.27	236.97
Cumulative Intra-Cluster Packets	585533	587500
Cumulative Inter-Cluster Packets	2698	2799

To critically assess the operational efficacy of the proposed techniques, a comprehensive evaluation of the hybrid SOA-HSA and hybrid SOA-ECCH algorithms was successfully sustained network operations up to 2,499 simulation rounds; the comparative analysis clearly highlights the performance superiority of the hybrid SOA-ECCH paradigm across all evaluation parameters. Regarding the stability period of the network, the First Node Dead (FND) was observed at round 1,290 for hybrid SOA-HSA, whereas the hybrid SOA-ECCH algorithm prolonged this threshold to round 1,390, yielding a highly significant 7.75% improvement in stability. Though both algorithms experienced the Last Node Dead (LND) at round 2,499, the hybrid SOA-ECCH framework consistently enhances overall system reliability. The hybrid SOA-ECCH algorithm exhibited highly efficient throughput metrics; it registered a network traffic rate of 236.97 packets per round compared to 230.27 packets per round for hybrid SOA-HSA, marking a 2.91% improvement. This trend of enhanced performance is further substantiated by the cumulative intra-cluster packet delivery, which escalated from 585,533 packets to 587,500 packets (representing a 0.34% gain), and the cumulative inter-cluster packet transmissions, which progressed from 2,698 packets to 2,799 packets, reflecting a notable 3.74% advancement. These augmented packet delivery rates rigorously validate that the hybrid SOA-ECCH algorithm establishes a highly optimized cluster-head election mechanism and robust routing pathways. Consequently, these findings establish that the hybrid SOA-ECCH algorithm shows superior energy preservation, seamless traffic management, and an improved lifespan, suitable for resource-constrained smart Internet of Things (IoT) and Wireless Sensor Network (WSN) environments.

CONCLUSION

In summary, the evaluation across network scenarios confirms that the Sandpiper Optimization based Energy Conscious Cluster Head Selection (Hybrid SOA-ECCH) algorithm provides substantial improvements in optimizing Smart City Internet of Things (IoT) networks, delivering real benefits in enhanced throughput and extended network lifetime over the hybrid SOA-HSA variant. Throughout the evaluations, hybrid SOA-ECCH consistently prolonged the network stability phase, delaying the First Node Dead (FND) threshold across all test scenarios achieving up to a 7.75% extension in stability during peak traffic loads. While both protocols managed to maintain overall network connectivity until nearly identical final rounds (concluding between 2,499 and 2,500 rounds), the hybrid SOA-ECCH framework consistently sustained a larger active node population during intermediate operational phases, minimizing cumulative energy consumption and proving its superior energy efficiency. Furthermore, data throughput metrics rigorously validate the routing efficiency of the hybrid SOA-ECCH paradigm. It consistently demonstrated escalated network traffic rates across all scenarios, handling up to 236.97 packets per round and yielding sustained throughput gains. This is further substantiated by significant increases in cumulative intra-cluster packet delivery (reaching up to 587,500 packets) and a predictable 3.7% advancement in cumulative inter-cluster packet transmissions, which implies highly optimized multi-hop communication and enhanced network robustness. This balanced performance is corroborated by the Load Balance Factor at round 2,000, where hybrid SOA-ECCH more evenly distributes the workload across the deployed nodes. Ultimately, these findings establish that hybrid SOA-ECCH guarantees superior node survivability, seamless traffic handling, and exceptional network longevity, rendering it a highly scalable and promising routing infrastructure for energy-aware WSNs within smart city deployments.

Ultimately, these collective findings establish that hybrid SOA-ECCH guarantees superior node survivability, seamless traffic handling, and exceptional topological stability under variable traffic loads, rendering it a highly scalable, resilient, and promising routing infrastructure for energy-aware WSNs within smart city deployments.

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