Energy Optimization in Zigbee-Based Iot Networks Using Rainfall and Salp Swarm Metaheuristic Algorithms

BABANGIDA ZUBAIRU, AMINA NURA
Department of Computer Science,
Faculty of Natural and Applied Sciences,
Umaru Musa Yar'Adua University,
Katsina,
NIGERIA

Abstract: - Zigbee is a wireless communication protocol intended for short-range, low-power, and low-data-rate applications. It is frequently utilized in Internet of Things (IoT) devices, industrial controls, and home automation systems. Due to their low power consumption and use of a strong communication protocol to guarantee dependable data transfer, Zigbee devices are popular in Internet of Things applications and are appropriate for battery-operated devices. But even on these networks, energy usage can be very high, particularly when there is a lot of network traffic or when the deployment is vast. In IoT situations, this might result in shorter network lifetimes and more frequent battery replacements for battery-operated devices, which is both impractical and expensive. These issues show that in order to increase device lifespans and decrease energy waste, Zigbee-based IoT networks require energy-efficient solutions. There is a lack of comparative, device-level energy optimization studies in Zigbee-based IoT networks that jointly evaluate Rainfall Optimization and Salp sSwarm metaheuristic algorithms using multiple energy consumption metrics within a unified network framework. Reducing energy usage in Zigbee-based networks without sacrificing dependability and performance is the aim of this study. In order to reduce the average energy consumption, energy consumption per device, and energy consumption per connection, two optimization algorithms—Rainfall Optimization Algorithm (ROA) and Salp Swarm Algorithm (SSA) were optimized in this work. The findings indicate that both optimized algorithms were successful in reducing overall energy usage.

Key-Words: - IoT, optimization, metaheuristics, ROA, SSA, energy consumption.

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1 Introduction

Zigbee networks, which follow the IEEE 802.15.4 standard, are known for their power-saving capabilities and are suitable for applications that occasionally send data. However, it is essential to use sophisticated optimization techniques in order to enhance gadget performance and prolong battery life. In recent years, Zigbee networks have been used by many businesses in fields such as environmental management, industrial applications, and smart homes, which has led to concerns about their energy consumption.

In recent years, Zigbee networks have been used by many businesses in fields such as environmental management, industrial applications, and smart homes, which has led to concerns about their energy consumption. Particularly, meta-heuristic algorithms inspired by natural phenomena have been applied efficiently and extensively to various problems associated with Zigbee networks, namely algorithm optimization. There are case that need to tackle a problems from a complex optimisation that can be hard to resolve using the standard approaches but still reasonable solutions can be found, such as such algorithms as GA Genetic Algorithms, Particle Swarm Optimization PSO and Salp Swarm Algorithm SSA, Rainfall Optimization Algorithm ROA [15].

The research of [5] gives a systemic process for making IoT networks more energy-efficient. For reducing total power consumption and maximizing network lifespan, the major concept is intelligently selecting network Cluster Head (CH). The authors consider combined algorithms such as Simulated Annealing (SA) along with Whale Optimization Algorithm (WOA). This paper addresses the critical issue of power efficiency in Internet of Things (IoT) networks. The motivation for power savings is for network operation in the long term due to a large number of IoT devices being battery-powered and highly dispersed.

This study discusses the growing need for efficient energy management in smart cities, with a particular emphasis on home energy management systems (HEMS). With the growing integration of alternative power sources, it is increasingly essential to optimize power use in a sustainable and cost-effective manner.

For improved functionality of HEMS, this paper proposes a new method of integration of Deep Reinforcement Learning (DRL) with the Bacterial Foraging Metaheuristic Optimization (BFMO) algorithm [1].

Challenges of routing in Internet of Things have been tackled in this paper, considering energy efficiency. In this, classical routing mechanisms may not be appropriate for Internet of Things networks considering its special aspects. This is resolved by publishing a comprehensive taxonomy of routing algorithms of a metaheuristic type and abstracting it in an energy-efficient routing framework. Apart from presenting a reference point for comparing metaheuristic algorithms, it tries to address frequent problems arising in the process of evaluation. The detailed discussion sheds light on power-saving mechanisms, routing vulnerability, and pros and cons of utilizing metaheuristic in Internet of Things [11]. For improved system designs, energetic, the lead exploring and lead exploiting capacity of SSA results in improved performance and improved efficiency. Such metaheuristic strategies represent improvements in optimization of energy and new mechanisms for solving various complex problems in an effort to achieve improved energy. Metaheuristics Algorithms (particularly ROA and SSA), due to such factors as applicability and adaptability, can solve energy management problems in which there are various different criteria and constraints.

2 Review of Existing Literature

Zigbee is a widely used communication protocol for low-rate, low-power data communication. The standard is based on IEEE 802.15.4 standard and is being utilised in industries ranging from home automation, industrial automation, and medical systems. The standard can support a network of nodes in a mesh network, which can help in forwarding data using other nodes in order to reach more distant nodes, which in turn improves network stability and expandability. The power efficiency, security, and interoperability of a large number of various manufacturers of different devices is given priority in zigbee. Ullah, Anwar, Nadeem, Mahmood, Rehman, & Saba, (2023) provides an overview of all of these various applications for smart cities, along with the challenges of using IoT and machine learning in urban environments. The study further provides a comparison of various case studies of successful implementations of smart cities using IoT and machine learning technology. The result of this is that new technologies have the capability of transforming urban environments and making it possible for us to create more efficient, sustainable, and livable urban environments. For smart cities, however, there is a number of critical concerns which must first be resolved, such as data security, data privacy, power efficiency, and ethics

[19] introduced an energy-efficient routing protocol for LCF-ZBR (Low Formation of cluster ZigBee Routing). If a certain cluster head node is insufficient in its energy, an alternative is employed in an effort to conserve its residual energy so as not to lead to a failure of the cluster head node due to overuse. This is aimed at extending the network's lifespan. LCF-ZBR and ZBR power usage issues were simulated using NS2, and residual power, along with dead nodes, were compared. The results indicated a greater efficiency in the proposed routing protocol.

Comparative study of routing protocol of Internet of Things Network is conducted by [16]. In this study, routing protocols have been compared and classified based on number of parameters, such as power utilization, network operation time, reliability, efficiency. [12] conducted a comparative study of LaRa and Zigbee on power utilization. they detail LoRa and Zigbee based power utilization model which provides power utilization monitoring and power utilization measurements in cyclic sleep. With parameters such as data packets, data send rate, communication radius, experimental results demonstrate LoRa wireless sensor nodes can be used in real Internet of Things environments. They have lower power utilization compared to Zigbee sensor nodes. The power utilization of sleep periods recorded in LoRa is lower compared to Zigbee. The author of [6] proposed an Energy-Efficient Scheduling (EES) system which made use of power efficiency of ZigBee and data send capacity of Wi-Fi. Interference Avoidance (IA) algorithm for avoiding interference issue in developing these two technologies in a similar frequency band of 2.4 GHz is being used. The simulation makes use of Omnet++ simulator package Inet. The power utilization of device and gateway have been highly minimized due to its deployment. Performance of ZigBee is improved when Wi-Fi is active, and results demonstrate improved throughput maintaining constant power utilization and interference

The study of [20], in a quest for maximizing utilization of power, utilized a detailed experimental analysis in determination of an ideal balance and trade-off between network performance and power levels of transmissions. Packet delivery ratio (PDR) is accounted for in network performance. In a testbed of a real-world scenario in an outdoor and an indoor environment, there is an inclusion of a study of encrypted and unencrypted Zigbee using such parameters. One of the greatest contributions of this paper is reducing power utilization in a process of determination of an ideal power utilization of Zigbee, in which network performance is satisfactory in regards of PDR and determination of and quantifying a trade-off between current, power levels of transmissions, PDR, and assessment of energy utilization.

[13] proposed a new system in 2024, which is a combination of two potent meta-heuristic algorithms, Sailfish Optimization (SFO), and Spotted Hyena Optimization (SHO). The dual algorithm employs SFO for its rapid explorations for best clustering and best Cluster Head election, and fine-grained explorations of SHO for maximizing effective routing paths. This new system improves network metrics such as network longevity, power usage, and Packet Delivery Ratio (PDR) drastically. This paper is a more improved dual-phased solution for clustering based, power-efficient routing in Wireless Sensor Networks (WSNs). This paper is a solution for a vital issue of balancing power usage and network functionality. With a new optimization mechanism, it clearly surpasses classical single-algorithm based solutions, delivering more worth and uniqueness.

The study of [9] reflects on power-saving technologies of ZigBee-based wireless sensor networks. The author begins describing technology aspects of ZigBee, for example, its protocol stack model and its various fields of usage, highlighting aspects of ZigBee network meshes. The article proceeds on this platform, highlighting defense-related fields in which mesh networks play a role. The article gives detailed study of the ZigBee protocol, along with its physical, MAC, and network layer design and implementation process. Besides, network methods in ZigBee networks, network process is summarized, and steps for establishing a new network have been elaborated. The outcome indicates a power usage reduction of 9.1%. Besides, Alhamdane, & Nickray (2024) have presented an in-depth account of past, current, and future advancement in environmental-friendly routing algorithms for wireless communication networks in this article. The article reflects on how these algorithms have evolved over time in an attempt to make wireless communication networks more sustainable and efficient.

A new energy consumption model for Wireless Sensor Networks (WSNs) is proposed by [4], taking each node's energy usage under account. The new proposed model is based on estimating energy usage on major functions involved in data forwarding and data sensing when a routing protocol is executed. Such functions involve wireless communication and are quantified for major contributions toward minimizing power usage and maximizing metrics. The new proposed model is verified on a system-on-chip (SoC)-based Texas Instruments CC2530 as a proof of concept. The new proposed energy model is, in turn, employed for analyzing energy usage in a case study of a Multi-Parent Hierarchical (MPH) routing protocol, along with five well-established routing protocols for sensor networks, which are Ad-hoc On-demand Distance Vector (AODV), Dynamic Source Routing (DSR), ZigBee Tree Routing (ZTR), Low Energy Adaptive Clustering Hierarchy (LEACH), and Power Efficient Gathering in Sensor Information Systems (PEGASIS). The experimental simulations have been conducted on a random network of two collector nodes, each of which is utilizing different wireless technologies, which includes Zigbee, Bluetooth Low Energy, and LoRa using WiFi. The paper aims for examining different routing protocols, such as reactive, proactive, hybrid, and energy-aware, on the proposed energy model. The outcomes of this study conclude a savings of 16%, 13%, and 5% in energy is exhibited by MPH routing in relation to AODV, DSR, and ZTR, respectively. The proposed MPH routing exhibits an increase in usage of just 2% and 3% in relation to respective energy-aware PEGASIS and LEACH. The proposed model is proven to have an excellent accuracy of 97% compared to actual network metrics. The proposed model is, in turn, verified on test cases for analyzing different major nodes for which usage of energy is quantified. Where [8] focused on a new enhanced new salp swarm algorithm (SSA), which is based on a new concept of getting inspiration from salp fish. Although results are promising, there have been a myriad of factors which have hindered its potential. The solution for this is proposed in SSA2. This paper describes a system of design based on using sensors for temperature, humidity, and gas data delivery to the ZigBee protocol. Upon receiving data, it is accumulated in the base station and forwarded for processing on the platform for SSA2. Any malfunction can be tracked and monitored.

Additionally, [3] addressed the issue of maximizing power usage and data dissemination speed in Wireless Underground Sensor Networks (WUSNs). The paper provides a power controlling of nodes in data dissemination using a new method based on the Salp Swarm Algorithm (SSA). The system attains enhanced balance between power utilization and spectral efficiency—the data dissemination rate—via maximum power levels. In maintaining efficiency, the paper considers ground condition variation in performance and recommends power adjustment of nodes. The simulation indicates that, in underground environmental change, in the SSA approach, network lifespan and operation time extend. [10], proposed enhanced Salp Swarm Algorithm as a new solution for power reduction in wireless sensor networks titled ES2A. ES2A systematically replaces dead, power-hungry nodes with more powerful nodes in place of just making them continue running till depletion. This extends network lifespan by power usage division among all nodes. ES2A is verified in trials, in comparison with more traditional methods, in power usage reduction and network lifespan increase. ES2A keeps more nodes active for a greater time by switching nodes in a smart way.

In an attempt to minimize energy of sensors, [14] proposed a greedy algorithm based on prioritized minimal energy sensors and followed it by an utilization of a maximum number of nodes in a boycott. The proposed algorithm is predicted to perform well in comparison to previously published strategies. For constructing the usual arrays, an analytic approach which shows an optimal solution, all of the energies of sensors reduce to zero. The theoretical solution makes it clearer that modern light occurs in the linked ring of odd-size sets, which is difficult in comparison to taking non-disjoint cover sets. [18], gives a new, internet-of-things-enabled solution for domestic energy management systems. In a smart grid situation, a multi-object optimization strategy was published which considers two major objectives, which are cost of electricity usage and user satisfaction. In an attempt to demonstrate the capability of proposed strategy, results have been compared with results of PSO-based and BOA-based algorithms. The system efficiency is measured based on comparing simulation results with a standard home energy management system.

Furthermore, [15] presented an in-depth discussion of various optimization strategies in operation for addressing microgrid energy management problems. The paper summarizes and critiques various optimization strategies for addressing microgrid energy management problems, emphasizing forecasting, demand management, economic dispatch, and unit commitment. Since they can be applied and have been shown to be efficient in addressing the microgrid energy management issue, the results of the review showed that mixed integer programming strategies have been extensively employed.

The literature under study emphasizes there is a great benefit in using Zigbee networks in terms of energy efficiency, especially compared to other technologies and enhanced using hybrid metaheuristic algorithms. With different ways of minimizing energy consumption, considering network topology, and utilizing energy-harvesting solutions, there can be further improvements in systems based on Zigbee in functionality and lifespan.

Even though many metaheuristic algorithms have been implemented to enhance the energy efficiency of Zigbee-based Internet of Things networks, most of the existing work concentrates on the network-level metrics or on a single optimization technique. There are no studies though, which comparatively focus on the device-level energy optimization that incorporates the Rainfall Optimization Algorithm and Salp Swarm Algorithm together, using multiple metrics of energy consumption within a single integrated Zigbee network. The energy efficiency ratio and the connection-level energy of the network have also been overlooked. This work aims to fill these voids through a thorough, integrated, and comparative assessment of the ROA and SSA for energy optimization of Zigbee-based IoT networks.

3 Research Methodology

3.1 Network Model and Topology

The Zigbee network is modeled using a star topology with 10 IoT devices, where one device acts as the coordinator (central node) and the remaining nine devices are connected to it. The network is represented using an adjacency matrix A, where a value of 1 indicates a direct connection between devices, and 0 represents no connection.

Create the Adjacency Matrix

$$A = \begin{bmatrix} 0 & 1 & 1 & 1 & \cdots & 1 \\ 1 & 0 & 0 & 0 & \cdots & 0 \\ 1 & 0 & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 0 & 0 & \cdots & 0 \end{bmatrix}$$

The matrix A represents a star topology where the coordinator (device 1) is connected to all other devices, and each of the other devices is only connected to the coordinator.

Define Device Coordinates and Names

Assign Coordinates: Define the 3D coordinates for each device:

$$\mathbf{Coordinates} = \begin{bmatrix} 0.5 & 0.5 & 0.5 \\ 0.2 & 0.8 & 0.5 \\ 0.8 & 0.8 & 0.5 \\ \vdots & \vdots & \vdots \\ 0.3 & 0.3 & 0.5 \end{bmatrix}$$

Initialize Energy Consumption

Set Initial Energy Values: Define the initial energy consumption for each device:

$$\text{Initial Energy Consumption} = [1.5, 2.0, 1.2, 2.5, 1.8, 1.0, 1.3, 2.1, 1.9, 2.2]$$

Step 1: Define the Nodes (Devices) and Connections

In this case, we can assume the devices are connected in a certain topology, like a star, tree, or mesh network.

Step 2: Create the Adjacency Matrix

The adjacency matrix represents the connections between devices. For example, if device 1 is connected to device 2, the matrix will have a 1 in the position (1,2) and (2,1).

Step 3: Visualize the Network

We will use the gplot function to visualize the network. This function takes the adjacency matrix and the coordinates of each node as input.

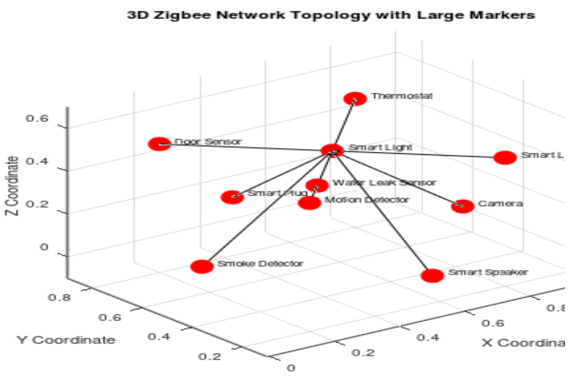

Fig. 1: Zigbee Network Topology with large markers

Zigbee is a wireless communication standard heavily used in home automation and IoT for its power efficiency and reliability. The network shows various smart devices, such as nodes, sensors, and actuators, which have connections between each other. One of these nodes, which is presumably a coordinator of Zigbee, is a point of connection for various nodes, a communication manager. The nodes have a location in a 3D space, which can be of interest in studying potential interferences or coverage. The network can be applied in home automation, security systems, power supply, and other contexts of IoT. The network can be depicted using an adjacency matrix and coordinate system for plotting in 3D. Plot connections between nodes and label each device according to its name.

$$\text{Plot}(C_i, C_j \mid a_{ij} = 1)$$

3.2 Detail the implementation of the SSA, ROA in Zigbee networks.

3.2.1 Device Coordinates and Naming

Each device in the network is assigned a unique 3D coordinate in the space to visualize the network topology. The coordinates are defined in a 3D Cartesian system to facilitate graphical representation. The devices are named according to typical home IoT devices, such as door sensor, motion detector, water leak sensor, smoke detector, smart light, smart lock, smart speaker, thermostat, SmartyPlug and camera.

3.2.2 Energy Consumption Initialization

Initial energy consumption values for each device are defined in joules. These values represent the energy required by each device under its standard operating conditions. For this study, hypothetical values are used for demonstration purposes.

3.3 Optimization Algorithms

Two optimization algorithms, Rainfall Optimization Algorithm (ROA) and Salp Swarm Algorithm (SSA), are employed to minimize the total energy consumption of the network.

3.3.1 Rainfall Optimization Algorithm (ROA)

- **Initialization:** ROA starts by generating an initial population of potential energy consumption solutions. Each solution is a variation of the initial energy consumption values.

Algorithm 1 Rainfall Optimization Algorithm (ROA)

Initialize population of raindrops P Initialize parameters: evaporation rate E, condensation rate C, precipitation rate P, maximum number of iterations max_iter $iteration < max\_iter$ Evaporation Calculate fitness for each raindrop Remove raindrops with fitness below threshold Condensation $i = 1$ to $|P|$ Update raindrop position x_i using:

$$x_i(t+1) = x_i(t) + C \cdot (x_{best} - x_i(t)) + rand() \cdot (x_{rand} - x_i(t)) \quad (1)$$

Precipitation Generate new raindrops using:

$$x_{new} = x_{best} + P \cdot rand() \cdot (x_{rand} - x_{best}) \quad (2)$$

Add new raindrops to population Increment $iteration$

Fig. 2: Rainfall optimization algorithm

- **Fitness Evaluation:** The fitness of each solution is evaluated based on the total energy consumption.
- **Update Mechanism:** The population is updated iteratively to converge towards the best solution, which is the one with the minimum total energy consumption.

3.3.2 Salp Swarm Algorithm (SSA)

- **Initialization:** SSA initializes a population of candidate solutions similar to ROA.
- **Fitness Evaluation:** Solutions are evaluated based on their total energy consumption.
- **Update Mechanism:** The population is updated based on the best solution found so far, with adjustments to improve energy efficiency.

1 Salp Swarm Algorithm (SSA)

Algorithm 2 Exploration and Exploitation

Initialize the population of salps
Evaluate the fitness of each salp
while stopping criteria not met **do**
  Sort the salps based on fitness
  Update the positions of salps in the exploration phase
  Update the positions of salps in the exploitation phase
  Evaluate the fitness of each salp
end while
Return the best salp as the solution

Position Update Rules

Exploration Phase:

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \alpha \cdot (\mathbf{x}_{\text{best}}(t) - \mathbf{x}_i(t))$$

Exploitation Phase:

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \beta \cdot (\mathbf{x}_j(t) - \mathbf{x}_i(t))$$

Figure 3: Salp Swarm optimization algorithm

3.4 Performance Metrics

The performance of the optimization algorithms is assessed using the following metrics:

3.4.1 Total Energy Consumption:

This measure includes the total energy consumed by all devices in the network and the energy needed to run different Internet of Things devices, keep network connections open, and send data. Excessive aggregate energy usage might cause device batteries to drain more quickly, shortening the network's lifespan and dependability. As a result, reducing overall energy usage is essential, especially in networks where devices are meant to operate for extended periods of time without frequent battery changes or recharging.

3.4.2 Average Energy Consumption per Device

Average energy consumption per device in a Zigbee network is the average energy consumption of each individual device over a certain time period. Controlling energy consumption is crucial since many Internet of Things devices have short battery lives and Zigbee networks are frequently utilized for low-power wireless communication between them. For many Internet of Things applications, such as industrial monitoring, smart homes, and environmental sensing, high average energy consumption per device may necessitate frequent battery replacements or recharging.

3.4.3 Energy Consumption per Connection

Energy Per Connection is a term for power usage in maintaining and keeping communication connections between networked devices. Each connection in a network based on Zigbee is a data communication path between devices. Devices have to be active in order to send and receive signals, so there is a requirement for power in keeping these connections active. This is especially so in a network based on a mesh, in which devices pass on data continuously in an attempt to expand it. High power usage per connection can reduce device lifespan drastically, especially in networks made of a large number of connections. This is a critical issue in Internet of Things implementations in which devices have to be active for a lengthy period of time. Reducing power usage per connection is, therefore, imperative in aggregate efficiency.

3.4.4 Energy Efficiency Ratio

The ratio of total energy consumption to the number of connections, indicating how efficiently energy is used relative to network communication load.

3.5 Mathematical model (Rainfall Optimization Algorithm)

The mathematical model for ROA is made to effectively search the space and use mechanisms inspired by nature to converge to an optimal solution. Below is the mathematical model:

3.5.1 Initialization

A population of raindrops P is initialized within the search space. The algorithm parameters are defined as follows:

- Evaporation rate: E
- Condensation rate: C
- Precipitation rate: P
- Maximum number of iterations: max_iter

3.5.2 Fitness Evaluation and Evaporation

In order to simulate evaporation, each raindrop x_i is assessed using an objective function f(x), and those with fitness values below a predetermined threshold are eliminated from the population.

3.5.3 Condensation (Position Update of Raindrops)

The best-performing raindrop and a randomly chosen raindrop from the population determine where the other raindrops move. A raindrop's most recent location is provided by:

$x_i(t+1)=x_i(t)+C\cdot (x_{best}-x_i(t))+rand()\cdot (x_{rand}-x_i(t))$------------------(1)

where:

- x_{best} represents the best-performing raindrop (optimal solution so far).
- x_{rand} is a randomly selected raindrop.
- rand() is a uniformly distributed random number in [0,1].

3.5.4 Precipitation (Generation of New Raindrops)

To improve exploration, new raindrops are created depending on the best answer and solutions chosen at random. A freshly formed raindrop's location is determined by:

$x_{new}=x_{best}+P\cdot rand()\cdot (x_{rand}-x_{best})$------------------(2)

3.5.5 Population Update and Iteration

The population is repeated. By mimicking the dynamics of real rainfall, this mathematical model successfully strikes a balance between exploration and exploitation, making ROA a reliable optimization method for resolving challenging optimization issues.is expanded to include the newly formed raindrops. Until a convergence condition is met or the maximum number of iterations max_iter) is achieved, the operation

3.6 Mathematical model (Salp Swamp Algorithm)

A metaheuristic optimization algorithm called salp Swamp is bio-inspired that imitates the foraging and movement patterns of salps in the ocean. The salps are guided toward the best answer in a multidimensional search space by the algorithms two main stages, exploration and exploitation.

3.6.1 Initialization

A population of salps, denoted as PPP, is randomly initialized within the search space. The position of each salp is represented as X={x1, x2,...,xn} in an mmm-dimensional search space. The algorithm parameters are defined as follows:

- α: Exploration coefficient that controls the movement of the leader salp.
- β: Exploitation coefficient that regulates the movement of follower salps.
- max_iter: Maximum number of iterations.

The fitness of each salp is evaluated using an objective function f(x) and the population is sorted based on fitness values.

3.6.2 Iterative Optimization Process

At each iteration, the salps are divided into two categories:

1. **Leader Salp**: The first salp in the sorted population, responsible for exploration.
2. **Follower Salps**: The remaining salps, which update their positions based on the preceding salp.

3.6.3 Exploration Phase.

The leader salp updates its position relative to the best-known solution as follows:

$x_i(t+1)=x_i(t)+\alpha\cdot (x_{best}(t)-x_i(t))$--------------(1)

where:

- $x_{best}(t)$ is the best solution found so far.
- α is a dynamically adjusted coefficient that facilitates exploration.

3.6.3 Exploitation Phase.

Follower salps adjust their positions relative to their preceding salp to enhance convergence:

$x_i(t+1)=x_i(t)+\beta\cdot (x_j(t)-x_i(t))$-----------------(2)

where:

- $x_j(t)$ represents the preceding salp in the chain.
- β is a control parameter that fine-tunes movement toward the optimal solution.

3.6.4 Stopping Criteria

The iterative process continues until one of the following conditions is met:

- The predefined maximum number of iterations (max_iter) is reached.
- The algorithm converges to an optimal or near-optimal solution.

3.6.5 Solution Selection

Upon termination, the salp with the best fitness value is selected as the final solution.

4. Results, discussion and Comparison

4.1 Energy Consumption per Connection:

To determine how efficiently energy is used relative to network connectivity

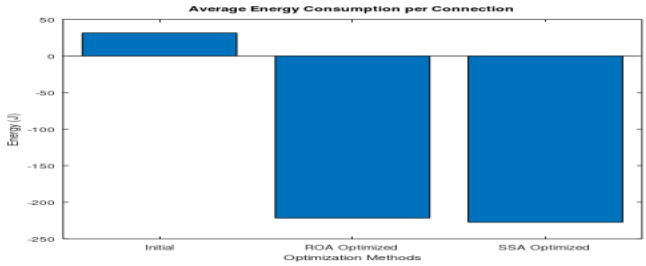

Fig. 4: Average energy consumption per connection

The average energy usage for each link for Initial, ROA Optimized, and SSA Optimized is displayed in a graph. The system with the greatest average energy usage per connection was the initial state, which represents the system prior to any optimization. Similar degrees of energy reduction have been attained by the ROA Optimized and SSA Optimized approaches, both of which demonstrate a notable drop in energy use. By lowering power usage and increasing efficiency, the optimization techniques appear to have saved energy, as indicated by the negative values on the y-axis. With SSA being more efficient, these techniques appear to be promising means of enhancing the zigbee network's energy efficiency due to their significant reduction in energy consumption.

4.2 Average Energy Consumption per Device

To assess whether optimization leads to a more balanced energy distribution.

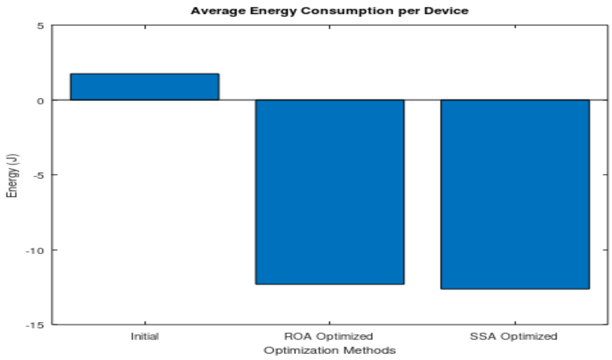

Fig. 5: Average energy consumption per device

The average energy consumption of each gadget is compared on the graph. When compared to the initial state, the energy consumption has significantly decreased as a result of the optimization techniques. The significant reduction in energy usage attained by ROA and SSA techniques implies that they are viable strategies for enhancing the system's energy efficiency.

4.3Total Energy Consumption

To evaluate the reduction in energy use after optimization.

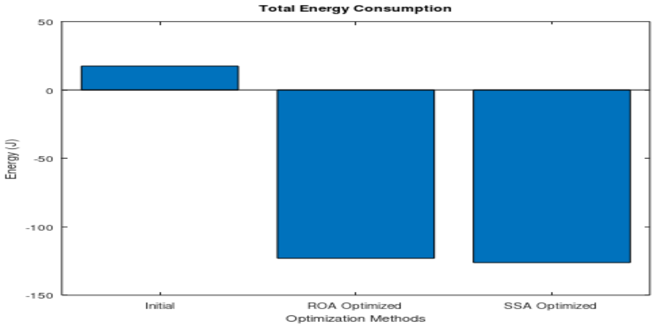

Fig. 6: Total energy consumption

The graph indicates that SSA Optimized and ROA Optimized techniques have both been successful in lowering overall energy usage. These approaches appear to be promising for increasing the energy efficiency of the zigbee devices, based on the significant reduction in energy consumption that they have brought about.

4.4 Energy Efficiency Ratio:

To evaluate overall energy efficiency improvements.

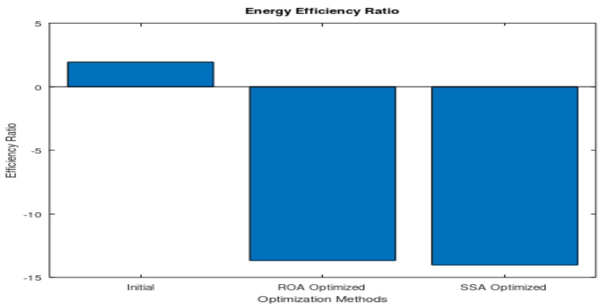

Fig. 7: Energy efficiency Ratio

The graph demonstrates that increasing the energy efficiency ratio has been successful for both SSA Optimized and ROA Optimized approaches. These methods provide a significant boost in efficiency, indicating that they hold promise for optimizing the energy consumption of devices in zigbee network.

5 Conclusion

The role of the ROA and SSA in the improvement of the energy efficiency of Zigbee-based IoT networks has been established in this work. All of the techniques applied to the devices and the network as a whole resulted in energy savings with a concomitant improvement in the efficiency of the networks. Of the two techniques, SSA was the most proficient at energy efficiency and is likely the best candidate for deployment in IoT networks where energy efficiency is a primary concern. The IoT energy efficiency improvement strategies presented in the work provides a benchmark for the optimal utilization of ROA in conjunction with SSA, thereby filling a void in the existing body of work and promotes the sustainable utilization of IoT networks, improving the overall network efficiency and functioning.

Feature work

Creating and validating new energy optimization algorithms, offering thorough comparisons of current methods, introducing new energy efficiency metrics, and providing workable solutions that improve network longevity and dependability, the study "Energy Optimization in Zigbee Networks" advances the field. These additions could greatly increase Zigbee networks' energy efficiency, which would increase their viability for a variety of Internet of Things applications.

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BIOGRAPHIES OF AUTHORS

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