

Energy-Efficient Routing in IoT Sensor Networks Using a Squirrel Optimization Algorithm-Based Clustering Framework

Mohammad Ordouei*

Department of Computer, South Tehran Branch, Islamic Azad University, Tehran Iran,

ORCID ID: 0000-0002-0391-0638

*Corresponding author

Abstract: Energy efficiency remains a major challenge in Internet of Things (IoT) sensor networks due to the limited battery capacity of sensor nodes. Inefficient routing strategies often lead to unbalanced energy consumption and early node failure. This paper proposes an energy-efficient routing framework based on the Squirrel Optimization Algorithm (SOA).

In the proposed approach, SOA is employed to simultaneously optimize cluster head selection and routing path formation using a multi-objective fitness function considering residual energy, transmission distance, and network coverage. The algorithm balances exploration and exploitation to achieve optimal routing decisions while preventing premature energy depletion of critical nodes.

Simulation results demonstrate that the proposed SOA-based routing method significantly improves network lifetime, residual energy distribution, and convergence speed compared with the Genetic Algorithm (GA). The results confirm that SOA provides an effective and scalable solution for energy-aware routing in IoT sensor networks.

Keywords: IoT Sensor Networks, Energy-Efficient Routing, Squirrel Optimization Algorithm, Metaheuristic Algorithms, Network Lifetime

I. INTRODUCTION

The Internet of Things (IoT) has enabled the large-scale deployment of sensor networks in applications such as environmental monitoring, smart healthcare, intelligent transportation, and industrial automation. These networks consist of resource-constrained sensor nodes that operate with limited battery power, making energy efficiency a critical design concern. Since battery replacement or recharging is often impractical, extending network lifetime remains a fundamental challenge in IoT sensor networks [1].

Among various factors influencing energy consumption, routing plays a decisive role in determining network longevity and reliability. Inefficient routing strategies may lead to unbalanced energy usage, rapid depletion of critical nodes, and reduced network coverage. Therefore, energy-aware routing mechanisms that distribute communication load evenly among nodes are essential for improving overall network performance [2].

Clustering-based routing approaches have been widely adopted to reduce communication overhead and enhance scalability. In such methods, sensor nodes are grouped into clusters, and selected cluster heads are responsible for data aggregation and transmission to the base station. Although clustering can significantly reduce energy consumption, improper selection of cluster heads or routing paths may still result in premature node failures.

To address these challenges, metaheuristic optimization algorithms have been increasingly applied to routing and clustering problems in IoT sensor networks. These algorithms are capable of solving complex and non-linear optimization problems by efficiently exploring large search spaces. Popular approaches such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have demonstrated promising results; however, issues such as slow convergence and premature stagnation may limit their effectiveness [3].

The Squirrel Optimization Algorithm (SOA) is a relatively recent metaheuristic inspired by the dynamic foraging behavior of squirrels. Due to its balanced exploration–exploitation mechanism, SOA has shown improved convergence characteristics compared to traditional optimization algorithms. Despite its potential, the application of SOA to energy-efficient routing in IoT sensor networks has not been extensively investigated [4].

In this paper, an energy-aware routing framework based on the Squirrel Optimization Algorithm is proposed for IoT sensor networks. The proposed approach employs a multi-objective fitness function that jointly considers energy consumption and network coverage to achieve balanced energy utilization. Simulation results demonstrate that the proposed SOA-based routing approach outperforms conventional optimization algorithms in terms of network lifetime, energy efficiency, and convergence behavior[5].

Unlike traditional routing approaches, this study employs the Squirrel Optimization Algorithm (SOA) as the core optimization engine for both clustering and routing decisions. The proposed framework integrates cluster formation, cluster head selection, and routing optimization into a unified SOA-based process, ensuring algorithmic consistency throughout the network operation.

The main contributions of this paper are summarized as follows:

- A novel energy-aware routing framework based on the Squirrel Optimization Algorithm (SOA) is proposed for IoT sensor networks.
- A multi-objective fitness function is designed by jointly considering energy consumption and network coverage to achieve balanced energy utilization.
- The proposed routing strategy integrates clustering and optimized path selection to reduce communication overhead and prolong network lifetime.
- Extensive simulation results demonstrate that the proposed approach outperforms the Genetic Algorithm in terms of network lifetime, residual energy distribution, and convergence speed.

II. RELATED WORKS

Energy-efficient routing in IoT and wireless sensor networks has attracted significant research attention in recent years. Traditional clustering-based protocols such as LEACH aim to reduce energy consumption by rotating cluster head roles; however, random cluster head selection may lead to premature energy depletion of low-energy nodes[6]. To address these limitations, several studies have incorporated residual energy, distance, and communication cost into clustering decisions. Although these methods improve energy balance, their heuristic nature limits adaptability in large-scale and dynamic networks[7].

Metaheuristic optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Whale Optimization Algorithm (WOA) have been widely applied to routing and clustering problems. While these approaches demonstrate improved performance, issues such as slow convergence and premature stagnation remain challenging.

The Squirrel Optimization Algorithm (SOA) is a recent metaheuristic inspired by the foraging behavior of squirrels and offers an effective balance between exploration and exploitation. Despite its successful application in various optimization problems, its use in energy-aware routing for IoT sensor networks has been limited. Unlike existing approaches, this study proposes an SOA-based routing framework that explicitly integrates energy consumption and network coverage within a unified optimization process, resulting in improved energy balance and extended network lifetime.

which are reported in a classified form in Table (1) [8].

Table 1: Important factors for the development of IoT sensor networks and protocols

Factor	Explanation
Network connection rate	Nodes share their information with each other and the central unit through IoT communication. When a node fails, it causes the network topology to change or part of the information to be destroyed.
coverage area	The area where the sensor nodes have the capability of mining and collecting data.
Node deployment	How to place the nodes in the network in such a way that the desired goals are met.
fault tolerance	The ability of sensor nodes when encountering errors and stopping transmission caused by factors such as lack of energy, environment and physical damage.
Routing	A process in which the route of sending data from an origin to a destination is determined.
Network changes	Change in network topology due to movement of sensors.

Table (2) shows the characteristics, advantages and disadvantages of structure-independent protocols [9].

Table 2: characteristics, advantages and disadvantages of structure-independent protocols

Structure	Protocol	Characteristics	Advantages	Disadvantages
Clustering-based	LEACH[15]	It randomly selects the cluster head nodes and tries to balance the energy by rotating the network	1) Each node has an equal chance to become a cluster head. 2) Using TDMA to avoid collisions	1) It has a high chance for a node with low energy to become the cluster head 2) Some nodes do not have a cluster head in the coverage domain
Chain-based	PEGASIS[16]	1) Nodes are organized as a linear chain. 2) A greedy approach is used.	1) Energy distribution is uniform 2) Reducing the energy overhead by using the dynamic network structure	1) It is necessary to have global information about the coordinates of the nodes 2) Reducing the number of sending nodes
Tree-based	EADAT[17]	The nodes with the most remaining energy and the shortest path to the sink node are selected	1) Nodes with more residual energy have a higher priority to become an intermediate node 2) The average residual energy of each node rarely decreases.	1) The network density is considered in the central unit. 2) Load imbalance in the network
Grid-based	GRID[18]	A set of aggregators is assigned to each grid.	Ability to adapt to changes and change the coordinates of nodes	Nodes located in the same grid cannot communicate with each other.

A few similar researches have been done regarding energy-aware routing in IoT networks using meta-heuristic algorithms. In [10], a research has been done to design a multi-objective routing in IoT networks using genetic algorithm. In this routing, the two criteria of energy and time delay are the constraints considered for routing. The proposed method provides a real-time routing. In [11], an energy-aware routing in IoT networks using particle swarm algorithm is proposed. In this research, by using a multi-stage particle swarm algorithm, constraints such as connectivity and all-diffusion are considered. In [12], another method using neural networks is presented. This research tries to increase the



lifetime of the network by using clustering of sensor nodes. In [13], multi-objective routing in multimedia IoT networks with the ultimate goal of increasing network lifetime and using genetic algorithm is proposed. Also, in [14], a clustering-based routing method in IoT sensor networks using a hybrid algorithm of genetics and ant community is presented, in order to balance energy consumption in the entire network.

In all these researches, by using a meta-heuristic algorithm and by defining a suitable fitness function, it has been tried to realize the desired goals in routing such as increasing the network lifetime, reducing energy consumption, reducing time delay and other cases [15].

An overview of the genetic algorithm:

Nowadays, one of the prominent methods to solve a group of optimization problems is the use of methods known as optimization methods based on collective intelligence[16].

Evolutionary clustering algorithms, using evolutionary algorithms such as genetic algorithm, particle swarm optimization, ant colony optimization, etc., try to find the best possible solution for cluster construction. So that the resulting cluster has the minimum amount of energy consumption, the maximum amount of data sent to the well, etc. Algorithms are examples of popular algorithms in the field of IoT sensor network clustering based on evolutionary algorithms [17].

Genetic algorithm [18] is a special type of evolutionary algorithm that uses biological methods such as inheritance and mutation. In the genetic algorithm, a chromosome is a set of indicators that defines a proposed solution for the problem that the genetic algorithm is trying to solve. The genetic algorithm starts by generating a random initial population. After the initial population is generated, a percentage of chromosomes are randomly selected as squirrels from the current population[19].

Squirrel chromosomes combine and exchange information between each other to create two child chromosomes. Also, in order to create more optimal children, the mutation method can also be used. After this step, the new generation is evaluated using the fitness function. A new generation is produced from the population of the best children and the population of the old generation [20].

III. ARCHITECTURE

Proposed SOA Routing Algorithm

In the proposed model, each squirrel represents a candidate routing configuration. The position vector of a squirrel encodes selected cluster heads and routing paths.

The optimization objective is defined through a multi-objective fitness function:

- Residual Energy of Nodes
- Communication Distance
- Network Coverage

SOA iteratively updates squirrel positions using adaptive coefficient vectors to balance global exploration and local exploitation. During each iteration:

1. Candidate routing solutions are evaluated.
2. Best squirrels guide the population toward optimal routing paths.
3. Poor solutions are replaced to maintain diversity.

The algorithm terminates when convergence criteria or maximum iterations are reached.

IV. PROPOSED METHOD

Suggested algorithm:

First, we state the assumptions of the network:

- 1) The size of the sensors is all the same and they have limited energy and are distributed in a square area.
- 2) The mobile stations are periodically monitoring the field and move randomly in a non-repetitive path.
- 3) Mobile stations have unlimited energy.

- 4) The location and ID of the sensor nodes are known and fixed.
- 5) Sensors can adjust their transmission power to the desired station distance.
- 6) In each period, after changing the location of the stations and temporary stop, it is executed, processed and published.

Fitness Function Design

The fitness function combines energy efficiency and coverage performance:

$$\text{Fitness} = C1 \times \text{Coverage} + C2 \times (1 / \text{Energy Consumption})$$

where C1 and C2 are weighting coefficients controlling optimization priorities.

To enhance routing efficiency in IoT sensor networks, a multi-objective fitness function is employed in the proposed SOA-based routing framework. The fitness function considers both residual energy of sensor nodes and network coverage to ensure balanced energy consumption and reliable data transmission. By integrating these objectives into a unified optimization process, the proposed approach effectively avoids early energy depletion of critical nodes and improves overall network stability. This formulation enables SOA to achieve a better trade-off between exploration and exploitation during the routing optimization process.

The proposed method includes two phases of identifying the coverage sensors of each station and determining the most appropriate mobile station.

The first phase is to identify the coverage sensors of each mobile station.

Wireless sensor networks consist of a number of sensor nodes that are spread across the sensor field and are responsible for collecting location information, which has different functions depending on the type of environment. These control sensors, which have a specific coverage range and limited energy, sense the data from the environment, and the mobile stations that periodically and randomly move between these sensors receive the data from them and send it to the control center. They transmit or broadcast the desired commands or messages among them.

After the network is established and the sensors are placed, the mobile stations that enter the environment must identify themselves to the network sensors. The way the mobile station works to identify itself in the network is as follows:

First uses a message to identify its location. The identification includes the number of the mobile station and the location information, they all broadcast between the sensors within a few paces, so that the sensors that are within a few paces of that station receive their message (Figure 3).

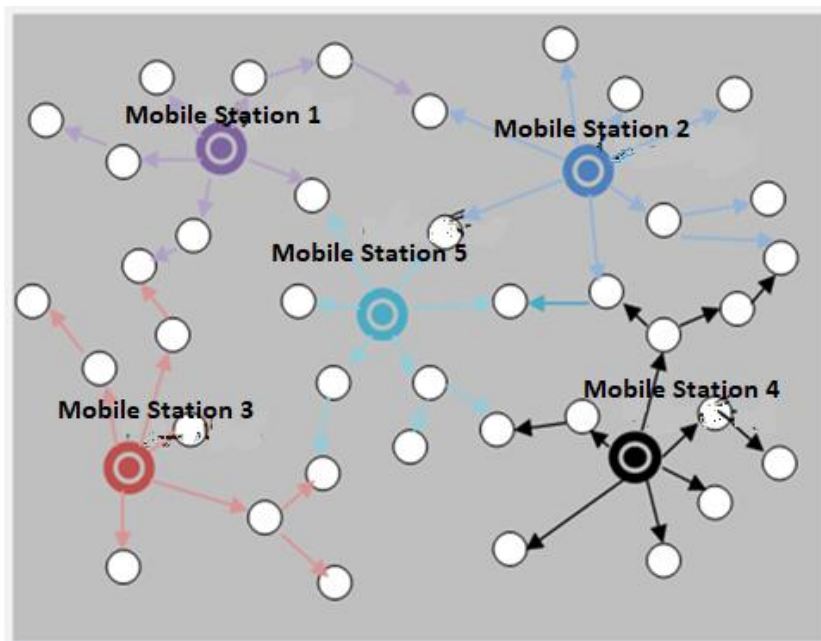


Figure 3: The first phase of sending an identification message through mobile stations



Then the sensors that receive the message, by examining the received messages, return a response message -that includes sensor number, location and cost- to the nearest sending station, and identify and introduce themselves as one of the sensors under control. then if each of this sensors receive a message from another station, it discards it.

In this way, the stations broadcast their location notification in the field and monitor the sensors that are adjacent or within a few steps of them. After sending the identification message and receiving the response message from the adjacent sensors, the mobile stations create an internal information table for themselves and according to the amount of data of each of their covering sensors, which indicates whether the sensory action is active or inactive. that is, it will record a value for it: it will take the value of zero for the inactive sensor and the value of one for the sensor that is active and sending data. Therefore, there will be a table for each of the mobile stations, which has a parameter of 0 or 1 for each sensor (Figure 4).

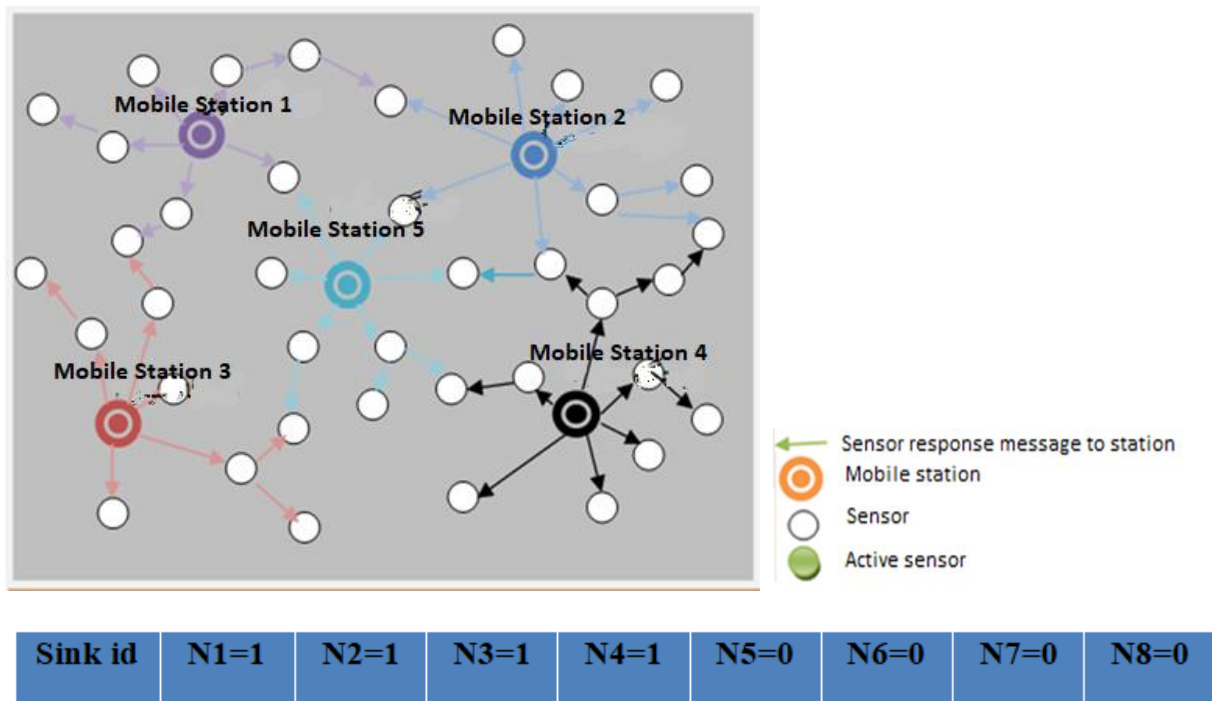


Figure 4: Creating a table with the identification of active and inactive sensors for each mobile station

s it can be seen, by creating such a table, a binary code will be considered for each of the stations, and with the calculation that is done with the objective function, the stations that have more active sensors in a certain period, as the most appropriate broadcasting station will be considered and the sensors that are not covering sensors of this station will be turned off at that stage and will help to save energy and increase their life span and the network.

This operation will be done in each period and in each period, the stations keep their path in each step so that they do not pass through it repeatedly in the next step. Other stations also do not cross at the desired places considering their crossing location. Otherwise, due to the operations repetition, the algorithm in question will not need to be optimized. And the energy consumed by the nodes to respond to sending messages from other stations will be reduced, which will lead to a reduction in the total lifetime of the network.

Phase two, determining the most appropriate mobile station in the routing algorithm:

Due to the dynamics of mobile stations and their number in the network, an optimal mechanism should be considered to manage the selection of mobile stations and information dissemination. The squirrel algorithm is one of the meta-innovative algorithms that are inspired by the way squirrels are hunted. In the wild, squirrels can find the coordinates of prey and then circle around it. Inspired by this behavior, this algorithm seeks to find the global optimal answer in the problem search space. Also, in this algorithm, each squirrel can be considered as an independent agent that seeks to find the right answer for the problem in the environment. Using this pattern in nature provides a framework based on collective intelligence.



The chipmunk algorithm starts its processing with a random initial population of possible answers. Each of these answers is considered as a squirrel. Each squirrel contains two features, coordinates and coding. We assume that each squirrel contains a vector of size n (n is the number of clusters in the network). Figure 5 shows the structure of each chip in the proposed algorithm.



Figure 5: The structure of each squirrel in the algorithm

Each house of the vector (Ci) represents the number of the cluster and Ni represents the number of the mobile station. A mobile station is randomly assigned to each cluster. The random population should be such a number that all possible situations are examined. The required number of population is equal to the permutations without repetition of the number of mobile stations. After completing the initial population creation stage, each of the squirrels is evaluated. In the proposed routing algorithm, two objective functions that measure the amount of energy consumption and coverage have been used. It is worth mentioning that the node that is selected as a mobile station should have a higher energy level than the usual sensor network nodes. The objective function related to energy consumption is defined in relation (1):

$$E_{TX}(k, d) = E_{TX}(K) + E_{TX-map}(k, d) \tag{1}$$

In this regard, d is the distance to be sent and k is the number of bits sent or received. This relationship can be rewritten as follow:

$$E_{Tx}(k, d) = \left\{ \begin{array}{ll} k.E_{elec}(k, d) + k.\epsilon_{friss} d^2 & \text{if } d < d_{crossover} \\ k.E_{elec}(k, d) + k.\epsilon_{two-ray-ap} d^4 & \text{else} \end{array} \right\} \tag{2}$$

In this regard, the amount of energy consumption for receiving or sending when the distance in the threshold area ($d_{crossover}$) is of the second order d, but if the distance is greater than the threshold value, then the amount of energy consumption has a relationship of the fourth order with the distance. E_{elec} is the amount of energy used for receiving/transmitting, ϵ_{friss} is the amplification factor and $\epsilon_{two-ray-ap}$ is another amplification factor.

The second objective function is related to the evaluation of the network coverage by the mobile station. Equation (3) calculates how to calculate this objective function:

$$COV_j = \sum_{i \in n} ((p_{ji} + a + e_i) - m_i) * y_{ij} \tag{3}$$

In relation (3), y_{ij} is a binary value that is extracted from the mobile station table. If the i-th sensor is active in station j, the value of this variable will be one, otherwise it will be zero. E_i is the amount of energy consumed by the i-th sensor, p_{ij} is the cost of the path of the i-th sensor to the j-th satellite station, a is the energy required to turn on a sensor, and m_i is the remaining energy of the i-th sensor. In this objective function, the greater the number of active sensors in the desired station, the greater its fitness function will be and hence it will have a greater chance of being selected.

In the proposed algorithm, it is an optimal answer that can achieve a compromise of both objective functions. In multi-objective optimization problems, the final evaluation relationship should be defined in such a way that the effects of each function are considered. The relation (3-4) expresses the final goal function of the research:

$$f_j = C_1 * COV_j + C_2 * \frac{1}{E_{TX}} \tag{4}$$

In the above relationship, the lower the amount of energy consumed, the higher the value of the evaluation function (reverse relationship), but the function of the amount of coverage has a direct relationship with the final evaluation function. The higher the value of this function, the higher the value of the evaluation function. The values of C_1 and C_2 are the influence coefficients that are calculated experimentally. For example, if we want to give more importance to the amount of energy consumption, then $C_2 > C_1$. If we don't want to make a difference between the two objective functions, then $C_2 = C_1$.

The evaluation stage of the squirrels is done for t generations and for each answer. After this step is completed, the coordinates of the squirrels are updated. Equation (3-5) shows how to calculate the coordinates of squirrels:

$$\begin{aligned} \vec{D} &= |\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)| \\ \vec{X}(t+1) &= \vec{X}_p(t) - \vec{A} \cdot \vec{D} \end{aligned} \tag{5}$$

In this relationship, t is the number of repetitions (generation), X_p is the coordinates and X is the coordinates of the squirrels. The values of A and C are coefficient vectors that are calculated as follows:

$$\begin{aligned} \vec{A} &= 2\vec{a}r_1 - \vec{a} \\ \vec{C} &= 2\vec{r}_2 \end{aligned} \tag{6}$$

The value of a is in the range [0 to 2] and r₁ and r₂ are randomly assigned. The proposed algorithm has an iterative structure; the number of repetitions depends on the number of generations or the value of the convergence threshold. When similar answers are found for different generations, the algorithm is no longer able to find another optimal answer. For this reason, it is better to stop the algorithm and report the result.

simulation:

All optimization procedures in clustering and routing stages are exclusively performed using the Squirrel Optimization Algorithm (SOA) to maintain methodological consistency.

Using the Matlab programming language, the proposed algorithm for customizing the squirrel algorithm for routing in IoT networks was tested and investigated in order to properly distribute energy consumption in networks with different numbers of nodes.

The main implementation parameters are listed in the table 3.

Table 3: Algorithm Code Simulation’s Main Parameters:

Parameter	Value
Size of each Squirrel	4
Number of Squirrels population	1000
Number of iterations	5000
Packet Length	4
Mutation rate in the nodes population	1%
Random Value generation function	Uniform
Matlab Version	2020

In the initial part of the program code, the main parameters are initialized. Then the coordinates of the network nodes are stored in two lists x and y. The population of squirrels is stored in a two-dimensional matrix. In each iteration of the algorithm, one percent of the population of answers (as weak answers) is removed and mutated answers replace them. Figure (6) shows the way of mutation in the proposed algorithm. In this figure, each antibody consists of four nodes, where node number one and four are the source and destination nodes, respectively. The other two nodes are intermediate nodes. In the bit replacement method, one of the nodes is randomly selected and its value is replaced with a random value. In Figure 6, the value 1 is replaced by 3.

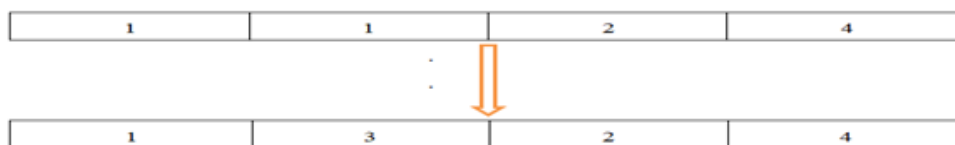


Figure 6: Mutation in the proposed Routing Algorithm

The aim of presenting the proposed algorithm is to optimize energy consumption in IoT sensor networks. Optimum energy consumption also increases the lifespan of the network. The proposed research algorithm has been compared with the routing method based on the genetic algorithm [21].

In this simulation, we consider the number of independent routings, considering the origin randomly and sending an information packet that contains 4000 bits, and the lifetime of the network before the first node is destroyed. The result of these comparisons is shown in table (4).

Table 4: Comparison of Squirrel Algorithm implementation in the first and second cases

Network Lifetime	First Case	1386
	Second Case	1914
Mean of energy consumption after 1386 round routing (joule)	First Case	0.0952
	Second Case	0.1069
Standard Deviation of energy remaining of all sensor nodes after 1386 round routing	First Case	0.089
	Second Case	0.080

To compare the mentioned two modes, three measures of network lifetime, average energy consumption and standard deviation of the remaining energy of all sensor nodes, after the death of the first node that occurs in each of the modes, have been considered. The better the distribution of energy consumption between network nodes, the lower the standard deviation of the remaining energy of network nodes. As can be seen, in the second case, with the reduction of the standard deviation, the average energy consumption has increased, so in this case, by establishing a proper balance between the two criteria of energy consumption and the proper distribution of energy consumption, the lifetime of the network has been increased. In the second case, although the average energy consumption has increased, but considering the energy of nodes participating in routing, nodes with more energy have actually been used for routing. This issue increases the lifespan of the network. To compare the speed of convergence of two algorithms, squirrel and genetics, to find the optimal solution, we have considered the average execution time of 100 independent executions of these algorithms on the sample graph. All test conditions are the same for the two methods, such as graph specifications, fitness function, and other items. The only difference between the two methods is the type of meta-heuristic algorithm, which in one method is the squirrel algorithm and in the other method, the genetic algorithm.

By the time of finding the optimal path and the average number of generations for two algorithms, it is shown in table (5).

Table 5: Comparison of Convergence Speed of Squirrel Algorithm and Genetic Algorithm on the Sample Graph

Algorithm	Average of Convergence Time(second)	Average of Number of Generation producing
Squirrel	0.82	856.29
Genetic	1.43	1413.51

Squirrel algorithm finds the optimal solution faster than the genetic algorithm and with a lower average generation number.

Table (6) shows the execution result and Figure (7) shows the distribution of energy consumption after each round of routing for two algorithms.

Table 6: Comparison of Squirrel and Genetic Algorithms on a Sample Graph

Network Lifetime	Squirrel	1914
	Genetic	1752
Mean of energy consumption after 1752 round routing (joule)	Squirrel	0.115
	Genetic	0.109
Standard Deviation of energy remaining of all IoT Network nodes after 1752 round routing	Squirrel	0.097
	Genetic	0.099

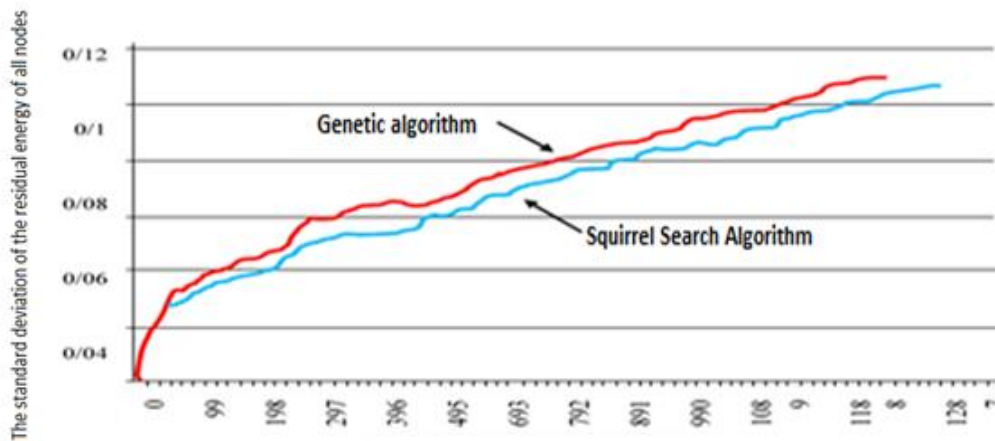


Figure 7: How energy consumption is distributed after each round of routing

Table (6) and Figure (7) show the fact that the distribution of energy consumption in the squirrel algorithm is better than the genetic algorithm. By spending more energy, the squirrel algorithm tries to distribute energy properly, which ultimately leads to an increase in lifespan. However, the squirrel algorithm tries to delay the death of the first node and increase its lifetime by sacrificing more energy. This causes the death of other nodes to happen more rapidly with the continuation of the network's life and assuming that the dead nodes are not replaced. Figure (8) shows the life cycle of the entire network

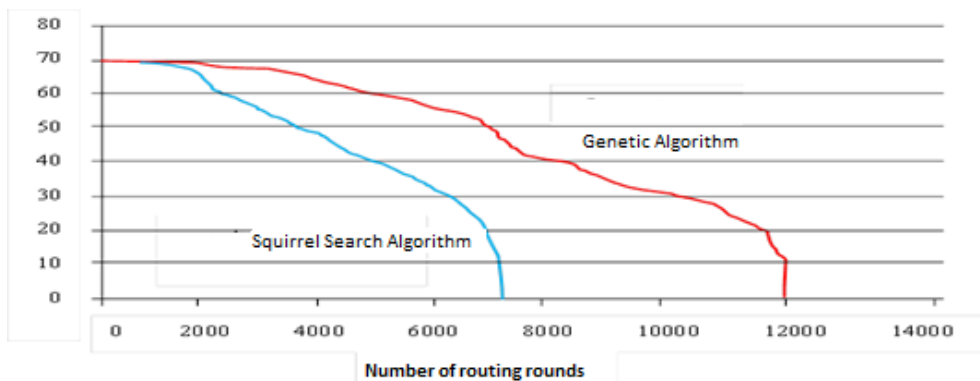


Figure 8: Life cycle of the entire network

Performance Analysis

The simulation results indicate that the proposed SOA-based routing approach consistently achieves superior performance compared to the benchmark Genetic Algorithm. Specifically, SOA demonstrates a slower rate of energy depletion and a more balanced residual energy distribution among sensor nodes. This behavior confirms that routing decisions are effectively distributed toward nodes with higher remaining energy, thereby preventing early exhaustion of critical nodes.

Moreover, the faster convergence of SOA highlights its ability to identify near-optimal routing paths with reduced computational overhead. As a result, the proposed approach significantly enhances network lifetime and improves overall energy utilization efficiency in IoT sensor networks.

V. CONCLUSION AND FUTURE WORKS

The proposed unified SOA-based framework successfully integrates clustering and routing optimization within a single metaheuristic model, leading to improved energy balance and extended network lifetime.

This paper presented an energy-efficient routing approach for IoT sensor networks based on the Squirrel Optimization Algorithm. By employing a multi-objective fitness function that considers both energy consumption and network coverage, the proposed method achieves balanced energy utilization and extends network lifetime. Simulation results

demonstrate that the proposed SOA-based routing framework outperforms conventional Genetic Algorithm-based routing in terms of energy efficiency, residual energy balance, and convergence speed.

Future work will focus on incorporating additional performance metrics such as end-to-end delay and security constraints, as well as validating the proposed approach in large-scale and highly dynamic IoT environments

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