



Cluster Head Selection for Energy Balancing in Wireless Sensor Networks Using Modified Salp Swarm Optimization

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Abstract – In today's realm, Wireless Sensor Network (WSN) has been emerged as a prominent research topic due to the advances in the design of small and low cost sensors for an extensive sort of applications. A battery powers the sensor nodes that make up the WSNs. The restricted quantity of electricity available within WSN nodes is considered as one of the important research issues. Researchers have offered a variety of proposals from various angles to maximize the use of energy resources. Clustering nodes has shown to be one of the most effective ways for WSNs to save energy. The traditional Salp Swarm Algorithm (SSA) has a slow convergence rate and local optima stagnation, and thus produces disappointing results on higher-dimensional issues. Convergence inefficiency is caused by SSA's lack of exploration and exploitation. Improvements to the original population update method are made in this study, and a Modified Salp Swarm Algorithm (MSSA) is provided for achieving energy stability and sustaining network life time through effective cluster head selection throughout the clustering process. Furthermore, the performance of MSSA is validated and equated to other start-of-the art optimization algorithms under different WSN deployments. The suggested model outperforms competing algorithms in terms of sustained operation time, longevity of the network, and total energy consumption, as shown by the simulation results.

Index Terms – Wireless Sensor Network, Optimization, Clustering, SSA, LEACH, Network Life, Throughput.

1. INTRODUCTION

A Wireless Sensor Network (WSN) is an assembly of enormous number of economical sensor nodes that are randomly placed throughout a space and connected through

wireless signals. In mandate to process and share information, these nodes interact with one another and the base station (BS). Altogether sensor nodes in a WSN relate to data processing and sensing capabilities. The data is generally conveyed from the sensor nodes to the sink node either directly or hop-by-hop through one or more passable nodes. Routing protocols play a crucial role in transferring and receiving data between source, sink and intermediate nodes. The sensors are usually driven by batteries. It's tough to either substitute the battery or provide more energy once the sensors have been positioned in a specific field, such as the deep sea or the battlefield. As a result, conserving energy in WSN'S is the key challenge. Researchers have utilized wide diversified mechanisms for the purpose of achieving this goal. The use of low-power radio communication hardware [1], energy-aware Medium Access Control (MAC) layer procedures [2, 3], and so on are all examples of such approaches. Although there are several methods for reducing the sensor nodes' power consumption, clustering is the most effective. Clustering is the process of organising a network's nodes into smaller, more manageable groupings, or clusters, for purposes including balancing network load, improving service quality, and maximising efficiency [4]. The low energy adaptive clustering hierarchy (LEACH) protocol [5] uses clustering to make networks more resourceful in terms of how much energy they use. The data transmission energy loss occurs as a function of the distance from the node to the base station. Clustering helps to lower the transmission distance of nodes. The selection of Cluster Heads (CHs) plays a strategic role in

RESEARCH ARTICLE

controlling of energy consumption. LEACH protocol helps the nodes by selecting them as CHs either evenly nor probabilistically irrespective of the trait and state of the nodes that are selected. The traits include remaining energy of node, how much energy the node can consume and the number of co-nodes that are available. The CH selection need to be centralized by considered all nodes which are near to base station, but it is hard to find out the information in process of transmitting the data at base station. Using time division multiple access (TDMA), a novel method called low energy adaptive clustering hierarchy centralised (LEACH-C) [6] has emerged to gather data on energy consumption at individual nodes. This technique has wide range of information and supports the nodes in consuming of low power compared to the power consumed at base station. The process of clustering can be further improved by considering the centralization method. The network diagram is as shown in Figure 1.

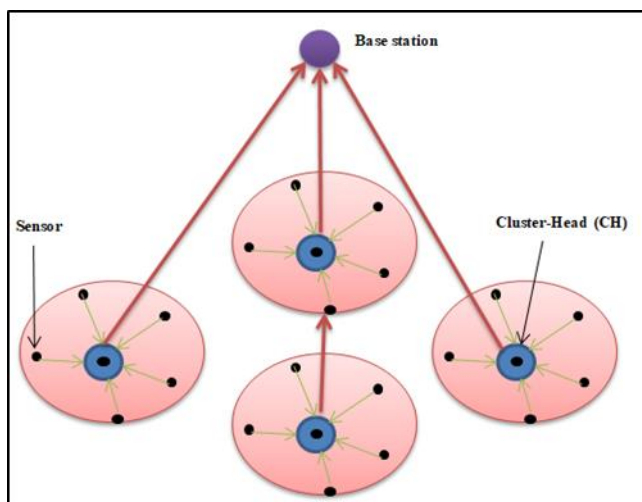


Figure 1 Clustering Model in WSN

Various optimization techniques evolved and are successfully used in variety of applications. Natural events have served as inspiration for a plethora of metaheuristic algorithms such as the migration of monarch butterflies [7], elephant herding optimization (EHO) motivated by the herding of elephants [8], beetle antennae search algorithm (BAS) inspired by the searching behaviour of longhorn beetles [9], crow search algorithm (CSA) [10] based on the brainpower of crows, the enhancement of soil by earthworms termed as earthworm optimization algorithm (EWA) [11], moth search (MS) [12] is created by taking phototaxis and Levy flights of moths into account are developed. Particle swarm optimization (PSO) algorithm is inspired by intelligence and movement of swarms. PSO is used in clustering for obtaining high rate of accuracy [13]. In [14], bee colony optimization (BCO) is used to improve the quality of clustering and increase network performance. In [15], the ant colony optimization (ACO) algorithm is applied to find the routes to the BS and to reduce

the power consumption. Inspired by the foraging habits of spider monkeys, the spider monkey optimization (SMO) is described as a swarm intelligence based method in [16]. Comparison of SMO and PSO is discussed in [17]. A reliable metaheuristic algorithm should find a global optimum solution that avoids local optima. Stability between exploration and exploitation is required for best results as reported by Subramanian et al., in [18]. Even with a stringent energy-saving strategy in place, nodes can quickly become drained if routing is not carefully tuned. To ensure the network's longevity, communication between nodes must be kept to a bare minimum. Cooperation between nodes is crucial to the operation of a WSN when several are deployed in close proximity across a wide region [19].

1.1. Problem Statement

The energy is the most essential deciding trait in the process of making clusters and picking the right CH. Given that energy scarcity is a key concern in WSNs, energy consumption dictates the efficacy of the majority of WSN applications. Nodes in a WSN can operate properly and efficiently only if they save energy. As routing protocols run on individual nodes and manage data and connections, they use energy and must be optimised to use as little as possible. This necessitates measures to shrink the overall size of sent and received data packets and the amount of power used by sensors. Once the clusters are formed, then CHs play a crucial role in transmitting the data from source nodes to destination nodes via the BS. The network's longevity and energy efficiency may be improved with thoughtful CH selection and rotation. To achieve greater lifetime and energy efficiency in WSN, the Modified Salp Swarm Algorithm (MSSA) for ideal selection of CH is presented in this study.

1.2. Organization of the Paper

Below is a breakdown of the succeeding sections of this paper's structure: Relevant literature to the issue statement is discussed in Section 2. Explaining the thinking underlying the LEACH clustering method is what Section 3 is all about. In Section 4, we went through the recommended method, network model, energy model, standard SSA, and MSSA. Findings and analysis are presented in Section 5. Findings and suggestions for further study are summed up in the paper's last section.

2. CORRELATED WORKS

Several effective optimization strategies for choosing CHs in WSNs have been discussed here. By fusing the Harmony Search and Squirrel Search Algorithms, Lavanya et al. [20] introduced an adaptive squirrel harmony search algorithm for optimal cluster CH selection through distance and energy. The authors of [21] suggested an energy-efficient cluster head selection technique based on particle swarm optimization that takes into account an effective particle encoding strategy and

RESEARCH ARTICLE

fitness function. Mann et al. [22] proposed a reformed artificial bee colony protocol to extend network life time. In [23], the authors suggest a novel optimization for improved CH selection based on energy stability, node distance reduction, and latency minimization by mingling the Grey Wolf Optimization (GWO) and Firefly (FF) algorithms. In [24], the authors introduced a GWO-inspired multilevel hybrid clustering methodology (MLHP). Here, cost-based decentralised clustering and GWO-based routing for data transfer are presented. The authors of [25] used ideas from nature to come up with a revolutionary SMO approach that makes traditional routing practices better in terms of how they use energy and how well they work. Optimal fixed packet sizes are determined by the radio characteristics and channel conditions of the transceiver in a system described by Madiha Razzaq et al. [26], which is a K-means clustering-based routing algorithm designed to lower power consumption and increase network longevity. Further, several power stages are explored for data broadcast from the CH to the cluster member and the base station.

In [27], which talks about fuzzy logic-based clustering practices, it is said that fuzzy logic was used successfully in WSNs. Rajkumar et al. [28] proposed a hybrid energy-efficient centroid-based optimization to improve sensor network efficiency in WSN-aided IoT settings using ACO techniques. Arora et al. [29] suggested a self-organized tree-based energy balancing solution for wireless sensor networks utilising ACO, which will help with effective route selection for intra-cluster communication. To combine the findings of existing clustering protocols and reach the goal of energy efficiency, the authors of [30] developed a clustering routing protocol based on weighing and parameter optimization. This protocol uses weighting to take into account numerous clustering criteria related to energy consumption when selecting CHs, including distance from node to BS, number of neighbours, distance between adjacent nodes, and residual energy. Using the ebb and flow of the network's state, Zongfeng et al. [31] suggested a unique Ant colony method for building the transfer function and pheromone update rule of sensor nodes and for adaptively picking a data route.

Anupam et al. [32] looked at how well hierarchical and flat networks work as ways to route data in WSNs. Using the connectivity between neighbouring nodes and the remaining energy of mobile sensor nodes, Muqet et al. [33] proposed using LEACH a novel mobile energy-efficient connectivity-based routing technique for CH selection. Using fuzzy C means for cluster formation and the differential evolution method for cluster head CH selection, Sharma et al. [34] presented a hybrid energy-efficient clustering approach. A fresh search procedure of sparrow was proposed by Panimalar et al. [35]. The Sparrow Search's high-level search efficiency and the vivid potential of differential evolution approaches are coupled here to extend the lifetime of nodes. Dattatraya et al.

[36] suggested a unique fitness that may maximise both network lifetime and energy efficiency while choosing the best CH by merging the Fruitfly Optimization algorithm (FFOA) with the Glowworm Swarm Optimization (GSO). In order to pick the best set of CHs among the many that may effectively meet the coordination requirement, Rajpoot et al. [37] presented a multiple-attribute decision-making technique. To progress energy efficiency and network lifetime, [38] proposed a two-level hybrid optimization strategy that combined modified particle swarm optimization with a genetic algorithm. Nelder Mead optimised for low energy use using Grasshopper Santosh et al. [39] suggested NMGOA-MR, an algorithm based clustering with multihop routing, to increase the WSNs' longevity. Zhang et al. [40] came up with a clustered routing protocol based on ACO and the type-2 Mamdani fuzzy logic system (T2MFLS). Their goals were to spread out the load and make WSN last longer.

The increased energy consumption for data transmission is a problem shared by all the aforementioned protocols, which might eventually lead to the failure of individual nodes and the whole network. Therefore, an optimization-based routing protocol is required to determine the optimal CH that simultaneously minimizes latency and maximizes energy efficiency. This study is motivated by the need to construct a swarm-inspired optimizer that can efficiently address a variety of practical issues. Here we anticipated a unique metaheuristic algorithm called the modified salp swarm algorithm (MSSA), which is based on the foraging behaviours of salp swarms and may be used to address the issue of uneven energy consumption. Through its improved search efficiency and convergence rate, the suggested MSSA method is a significant improvement over previously proposed methods.

3. LEACH PROTOCOL

In order to outspread the service life of a WSN, LEACH employs a TDMA-based MAC protocol for cluster formation and maintenance [41]. It is a self-organising, adaptive clustering strategy that employs randomization to distribute energy load uniformly. Here, a large number of sensor nodes grouped into clusters. It is anticipated that every node has the same energy constraints and characteristics. The BS is permanently installed and physically separated from the sensors. Members of the cluster vote for the CH to ensure that energy is not wasted. Here, the majority of nodes broadcast to the CHs, which then gather and compress the data and send it to the base station. LEACH consists of two phases: the Set-up Phase and the Steady-State Phase. In the setup phase, cluster formation occurs. A total of three steps make up this phase. To become CHs for that round, the self-elected CH candidates first promote itself by forwarding an advertising message to other member nodes. Entire cluster-heads spread their advertisement message using same transmit energy. The next phase is for nodes to pick which CH they want to join and

RESEARCH ARTICLE

send a join-request message to that CH established on the received signal strength of the advertising message. The final step involves CHs sending their cluster members a message containing TDMA time slots. LEACH begins the steady-state stage after cluster establishment. This stage involves the actual communication. Cluster members initially communicate sensor interpretations to the CH. After that, the CH compiles the senses and sends the data to the BS. Only nodes with energy values that are equal to or higher than the sum of all nodes energies will take part in the CH selection process. However, the remaining energy, the location of the node are not taken into account when choosing the CH, it is done at random. Nodes that have been CHs in the past are ineligible to do so for B rounds, where B is the desired percentage of CHs. Thereafter, each node has a $\frac{1}{B}$ probability of resuming its role as the CH. After each round nodes generate numbers between 0 and 1 at random. Nodes that have random values that are less than the threshold $T_H(nd)$ become the CHs for the existing round. The threshold value is given as shown in Eq. (1).

$$T_H(nd) = \begin{cases} \frac{B}{1-B[r * \text{mod}(\frac{1}{B})]} & nd \in G \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Where G is the set of nodes that were not CHs in the previous round, B is the probability, nd is the given node, r is the current round.

4. PROPOSED ALGORITHM

In this MSSA is a Centralised nature inspired, energy aware clustering algorithm. This algorithm creates and distributes the cluster evenly by considering the high energy nodes as CHs. This algorithm is developed to prolong the network's life and use its energy more efficiently. Cluster head selection, the energy model, and the network model that make up this proposed MSSA are detailed below.

4.1. Network Model

Here we have considered a free space network model with the following assumptions.

- Nodes are distributed randomly.
- Position of all sensor nodes is fixed
- The BS is static.
- The BS might be positioned within or outside the considered area.
- All nodes are the same and have the same amount of energy.
- Data is always available for transmission to BS.
- Each node has the ability to become the leader of a cluster.

Matlab Programming environment is used to build the above network model. The locality of BS is fixed and can be positioned in the centre or elsewhere, it cannot be altered until simulation completion. The number of CHs was based on ten percentage of the overall quantity of nodes in the system. In other words, if there are 400 nodes, then there will be 40 CHs. If a node's energy falls beneath a certain threshold in the simulation, the node dies and is removed from the system.

4.2. Energy Model

For calculating the overall energy consumption during data communication, the radio energy model from [41] is utilised. For transmitting and receiving q -bit data packet the energy consumed by a node over a distance d are given by Eq. (2) and Eq. (3) respectively.

$$E_{Tx}(q, d) = \begin{cases} q \cdot E_{Elec} + q \cdot \epsilon_{fs} \cdot d^2, & d \leq t_0 \\ q \cdot E_{Elec} + q \cdot \epsilon_{mp} \cdot d^4, & d > t_0 \end{cases} \quad (2)$$

$$E_{Rx}(q) = q * E_{Elec} \quad (3)$$

Here, t_0 is the threshold distance as shown in Eq. (4), and E_{Elec} is the extent of per bit energy dissipated at the transmitter or receiver.

$$t_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \quad (4)$$

Here, free space model strengthening energy is ϵ_{fs} , and multipath model strengthening energy is ϵ_{mp} .

The BS picks an ideal number of nodes and makes them CHs based on their distance from the BS, their remaining energy, their energy consumption ratio, and whether or not they are eligible to be CHs. The proposed MSSA implementation focuses on the arbitrarily installed immobile nodes. It adopts M nodes that represent the CH search agents ($CH = CH_1, CH_2, \dots, CH_M$). Since moving a fixed sensor node would be impossible to simulate the Salps' movements in MSSA, we represent the search agent's spot (candidate CH) with the notation X_j^i . The best search agent from the best solution is used to determine the best CH. The quasi code of the suggested algorithm is presented in Algorithm 2. When the best search agent is found, MSSA's parameters are adjusted so that the other agents are in the best possible positions relative to it. The fitness function is the primary factor in the MSSA algorithm's hunt for prey, and thus it is the fitness function that ultimately decides which CH to select. The fitness function used in this analysis is defined in [42], as shown by Eq. (5).

$$f(CH_i) = p_1 * |N(CH_i)| + p_2 * \sum(CH_E) \quad (5)$$

Where parameters p_1 and p_2 can have any value between 0 and 1. $N(CH_i)$ is the set of nearby sensors for a particular

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cluster head CH_i , CH_E is the outstanding energy of neighbour node's. In order to become the CH, the best solution must have sufficient number of neighboring nodes, sufficient residual energy, and high enough fitness value. Once the selection is complete, the CHs will send out a message that details their identifier and their distance from the BS. CH will then wait for other cluster members to join. Each node measures distance from cluster heads. Nodes upon joining the cluster notifies the nearest CHs. If the node's distance to the CH is further than to the BS, it will broadcast directly with the BS. Else, it forms clusters based on Euclidean distance.

4.3. Salp Swarm Algorithm

Being member of salpidae, salps are transparent and cylindrical in shape. In both appearance and behaviour, they resemble jellyfish. Salps create a reverse thrust by sucking water from the environment via their barrel-shaped bodies while moving [43]. Salp's bodily tissues are so fragile that they struggle to survive in the Test conditions. As a result, certain discoveries in the study of this species have only recently been made, the most noteworthy of which is salp group behaviour. Salps frequently form a flock known as a salp chain in heavy oceans. Mirjali et al. first came up with a mathematical model of the salp chains in 2017 [44]. Separating the Salp population into leaders and followers is the first step in developing the mathematical model for Salp chains. Followers, as described in [45], are salps that trail after the leading salp. Every salp location is formed to find sustenance in an $M \times K$ dimension examining space, where M is the resident salps size and K is the searching dimension, in this paper. As a result, i^{th} salp locus x_j^i in the j^{th} dimension can be represented as depicted in Eq. (6).

$$X_j^i = \begin{bmatrix} X_1^1 & X_2^1 & \dots & X_K^1 \\ X_1^2 & X_2^2 & \dots & X_K^2 \\ \vdots & \vdots & \ddots & \vdots \\ X_1^M & X_2^M & \dots & X_K^M \end{bmatrix} \quad (6)$$

Here $i = 1, 2, 3, \dots, M$ & $j = 1, 2, 3, \dots, K$

The optimum solution in terms of functionality is the food source FS, which is set to be placed in the seeking area and targeted by the group of salps. The updated leader location is calculated using the following equation Eq. (7).

$$x_j^1 = \begin{cases} FS_j + w_1 \left((ub_j - lb_j)w_2 + lb_j \right), w_3 \geq 0 \\ FS_j - w_1 \left((ub_j - lb_j)w_2 \right) + lb_j, w_3 < 0 \end{cases} \quad (7)$$

where x_j^1 spectacles the locality of the Salp front-runner in the j^{th} aspect, FS_j is the spot of the food source in the j^{th} aspect, ub_j points the upper margin in j^{th} aspect, lb_j points the lower margin in j^{th} aspect, and w_1, w_2 & w_3 are random numbers. The parameters w_2, w_3 are haphazard figures in interval $[0,1]$. Eq. (7) shows that the leader only streamlines its

position with respect to the food source. The parameter w_1 is a key part of SSA because it balances exploration and exploitation and is defined as follows in Eq. (8).

$$w_1 = 2 \exp \left(-\left(\frac{4L}{L_{max}} \right)^2 \right) \quad (8)$$

Where L is the recent repetition & L_{max} is the extreme number of repetitions. Each follower keeps track of the leader's spot by following other followers during each search phase. The location of follower Salps is adjusted toward the target using the following Eq. (9).

$$x_j^i = \frac{1}{2} (x_j^i + x_j^{i-1}) \quad (9)$$

here $i \geq 2$, and x_j^i, x_j^{i-1} indicate the respective positions of i^{th} & $(i-1)^{th}$ followers in j^{th} aspect.

The pseudocode and the flowchart diagram for the basic SSA method are presented in Algorithm 1, and Figure 2, respectively.

-
- 1: M : Population size
 - 2: L_{max} : Extreme number of iterations
 - 3: $L = 0$; Set the population size $x_i (i = 1, \dots, M)$ in the defined search space
 - 4: while($L < L_{max}$) do
 - 5: compute w_1 using Eq.(8) & set w_2, w_3 in the range of $[0,1]$
 - 6: for ($i = 1, \dots, M$)do
 - 7: if ($i = 1$) then
 - 8: if ($w_3 \geq 0$) then
 - 9: update leader position using first part of Eq. (7)
 - 10: else
 - 11: update leader position using second part of Eq. (7)
 - 12: end if
 - 13: else
 - 14: modernize the position of followers using Eq. (9)
 - 15: end if
 - 16: end for
 - 17: With Eq.(5) determine the individual salps, fitness value and assign the overall best solution of food source FS.
 - 18: increment value of L by one
 - 19: end while
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Algorithm 1 Pseudocode of Basic SSA Protocol



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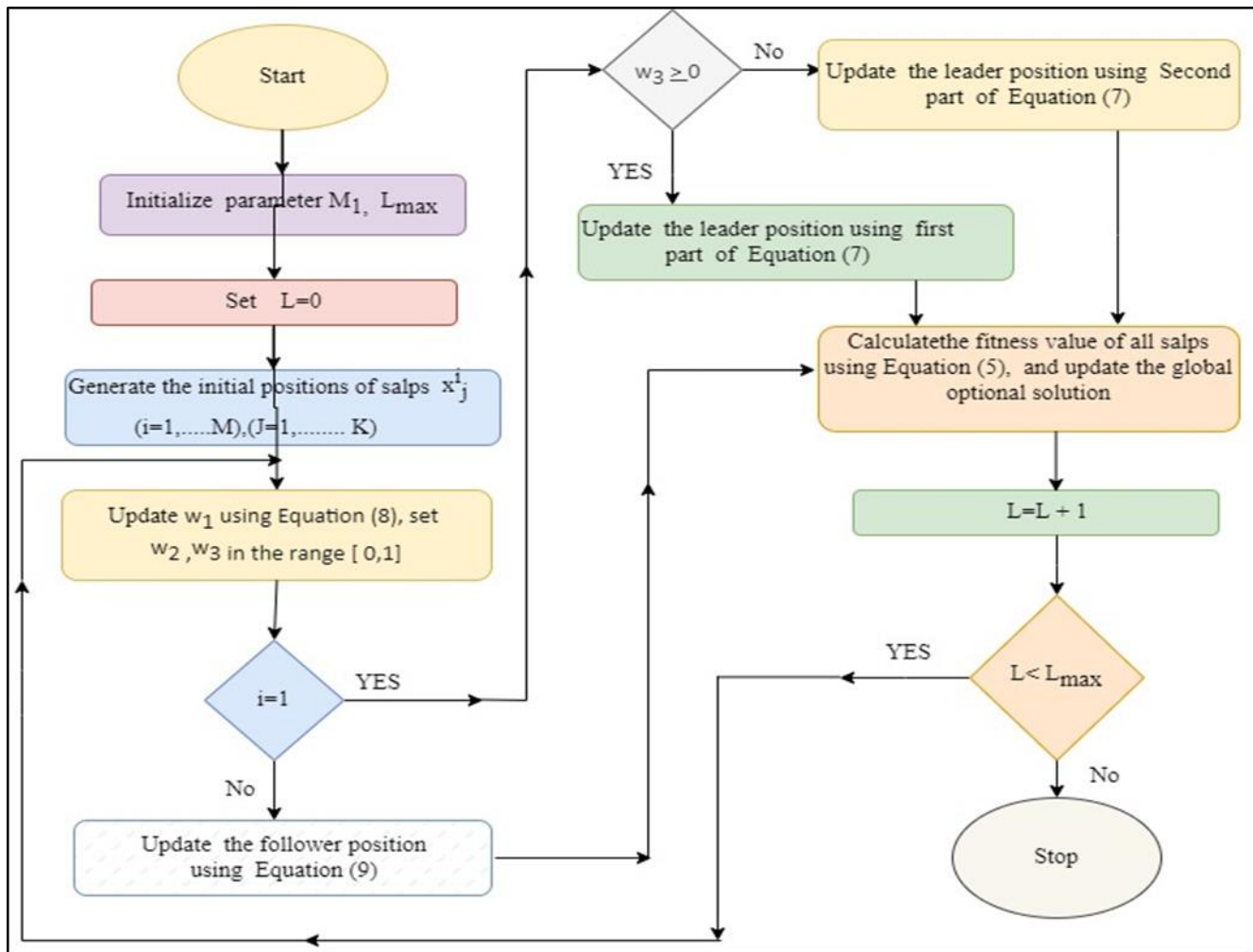


Figure 2 Flowchart of Basic SSA Protocol

4.4. Improved Salp Swarm Algorithm

Every salps position is streamlined using Equations (6) and (7), as described in [44]. The revised solution in SSA is primarily based on the recent best results. Based on the difference of upper and lower searching boundaries, the leader salp helps the follower salps in identifying the food source in basic SSA. As a result, in high-dimensional search spaces, the elementary SSA has complications such as slow convergence and local optima stagnation.

Some refinements to the original population update method are presented to boost its exploitation and exploration capabilities, leading to a more effective search strategy that avoids the pitfalls of blind searching. For this, we have adopted variable perturbation weight mechanism and the concept of local best information into the basic SSA to modernize the location of leader and follower salps. The following modified Eq. (10) is used to remodel the position of the leader toward the target.

$$x_j^i = \begin{cases} x_j^1 + w_1 \left((x_j^1 - x_j^s) * w_2 + lb \right) & \text{if } w_3 \geq 0.5 \\ x_j^1 - w_1 \left((x_j^1 - x_j^s) * w_2 + lb \right) & \text{if } w_3 < 0.5 \end{cases} \quad (10)$$

Eq. (11) is used to reorganize the postions of the follower Salps.

$$x_j^i = \frac{(x_j^i + x_j^{i-1})}{2} + w_1 (b_j^r - x_j^s) \quad (11)$$

Where, b_j^r is a haphazardly selected best local minimum in the j^{th} aspect, x_j^s is a arbitrarily selected salp in the j^{th} aspect and $r, s \in \{1, \dots, M\}$.

The pseudocode and the flowchart diagram for the proposed MSSA method are shown in Algorithm 2, and Figure 3, respectively. At first, the best local solutions are set to be the same as the first population that is made, and the best fitness values are set to be the results of the fitness function, as shown in Eq. (5). New locations for the salps that follow the

RESEARCH ARTICLE

leader are calculated by means of Eq. (11), and the leader's position is updated with Eq. (10).

After each new position is made, its fitness function is recorded and its viability is checked. By comparing the newly discovered best local optimum to the stored global ideal, the proposed MSSA detects a new global optimum. A predetermined number of generations ends the iteration. In this way, the proposed MSSA protocol is able to outperform the basic SSA in finding the optimal CH.

1: M : Population size

2: L_{max} : Extreme number of iterations

3: $L = 0$; Set the population size $x_i (i = 1, \dots, M)$ in the defined search space

4: while($L < L_{max}$) do

5: compute w_1 using Eq.(8) & set w_2, w_3 in the range of [0,1]

6: for ($i = 1, \dots, M$)do

7: if ($i = 1$) then

8: if ($w_3 \geq 0.5$)then

9: update leader position using first part of Eq.(10)

10: else

11: update leader position using second part of Eq.(10)

12: end if

13: else

14: modernize the position of followers via Eq.(11)

15: end if

16: end for

17: With Eq.(5) determine the individual salps, fitness value and assign the overall best solution of food source FS.

18: increment value of L by one

19: end while

Algorithm 2 Pseudocode of MSSA Protocol

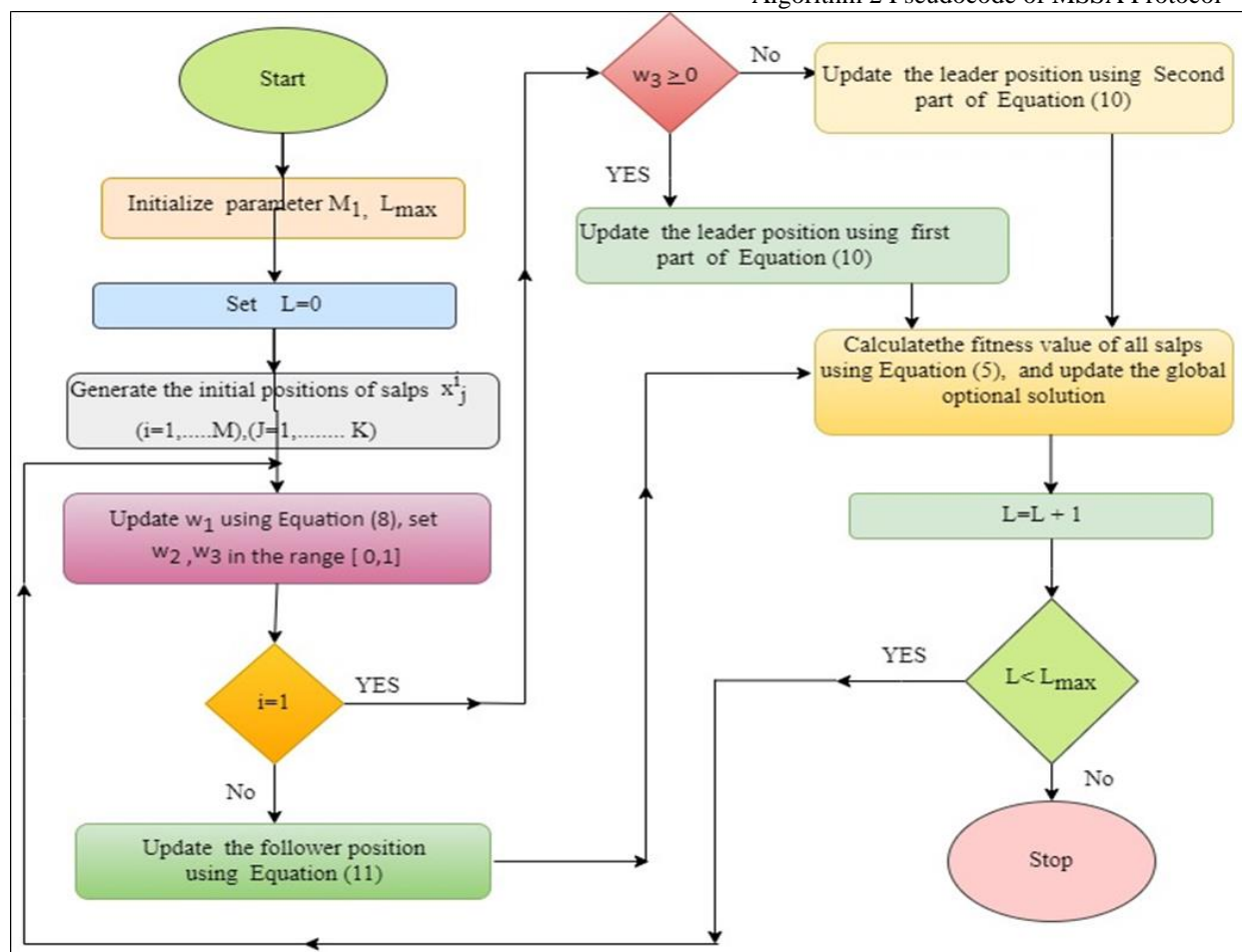


Figure 3 Flowchart of Proposed MSSA Protocol

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5. PERFORMANCE ANALYSIS AND DISCUSSION

5.1. Simulation Setup

In this part, a comparison of the accuracy and processing time of the proposed MSSA-LEACH method against those of five existing algorithms LEACH, genetic algorithm (GA), PSO, whale optimization algorithm (WOA), and SSA is performed under diverse conditions. Matlab R2021a was used to test the algorithm and display the results. The hardware specifications included a 4GB RAM, Windows 10 Pro, and an Intel core i3-4005U processor. In simulations, we created clusters with a probability of 0.1, or 10% of overall nodes. For a network with 500 nodes, there will be 50 clusters. The experiments were executed with a variety of sensor nodes placed in a 100 m by 100 m area, fluctuating their figures from 100 to 500 and 10 to 50 CHs. We have considered node survival rate, amount of energy used, and the lifespan of the network over time as performance indicators. During our simulation, we took into account populations of 20 search agents and ran the proposed algorithm 100 times. Table 1 gives an insight into the list of simulation aspects under consideration.

Table 1 Network Simulation Aspects

Factor	Value
Field Deployment	100 m × 100 m
Sensor nodes	100-500
BS Position	(50,50) (100,100), (50,200)
Nodes Initial energy	0.5J
Transmission/Reception energy per bit (E_{Elec})	50 nJ/bit

Cluster Heads (CHs)	10-50
Packet size	4000 bits
Message size	2000 bits
Data aggregation energy cost	5 nJ/bit
L_{max} , number of iterations	100
Number of search agents	20
Amplification energy for free space model (ϵ_{fs})	10 pj/bit/m ²
Amplification energy for multipath model (ϵ_{mp})	0.0013 pj/bit/m ⁴
p_1	0.7
p_2	0.3
d_0	87.7m

The sensing area in each of the three cases we investigated (WSNs #1, #2, and #3) was 100 m × 100 m, and the BS location ranged from the middle (50, 50) to the edge (100, 100) and beyond (50, 200). In the case of WSN#1, 200 nodes and 20 cluster heads are reflected. Additionally, WSN#3 and WSN#2 consist of 500 nodes with 50 cluster heads and 400 nodes with 40 cluster heads, respectively.

5.2. Analysis of Alive Nodes

For a WSN#1 network, Figure 4 plots the number of living nodes against the number of iterations for the WOA, SSA, PSO, LEACH, GOA, and GA algorithms, as well as the proposed MSSA. Corresponding result values from Figure 5 are presented in Table 2. It can be seen from the illustration that, when compared to other algorithms, the MSSA consistently has more active nodes in any given time window.

Table 2 Live Nodes Detailing in WSN#1 with BS at Middle (50, 50)

Amount of Alive nodes	LEACH	GA	PSO	WOA	GOA	SSA	MSSA
200	1042	4329	5492	5713	6279	6979	7153
180	1162	4709	5971	6335	7099	8321	8460
160	1216	4914	6201	6764	7571	8765	8952
140	1238	5172	6562	7132	8019	9328	9605
120	1280	5377	6776	7501	8302	9940	10341
100	1318	5598	7013	7808	8632	10309	10742
80	1338	5882	7394	8013	8905	10815	11320
60	1386	6306	7620	8386	9365	11193	11695
40	1451	6487	7898	8677	9687	11478	12027
20	1490	6582	8114	8946	9775	11681	12250



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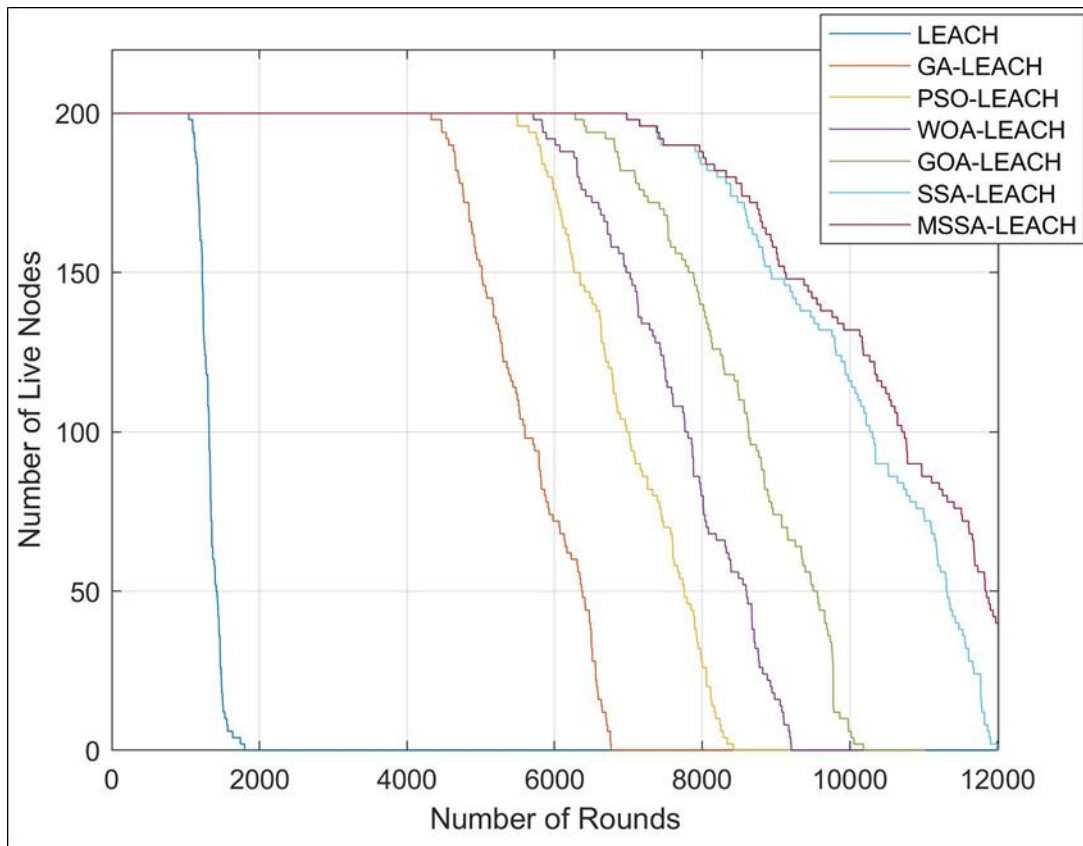


Figure 4 WSN#1 with BS at Middle-(50,50)

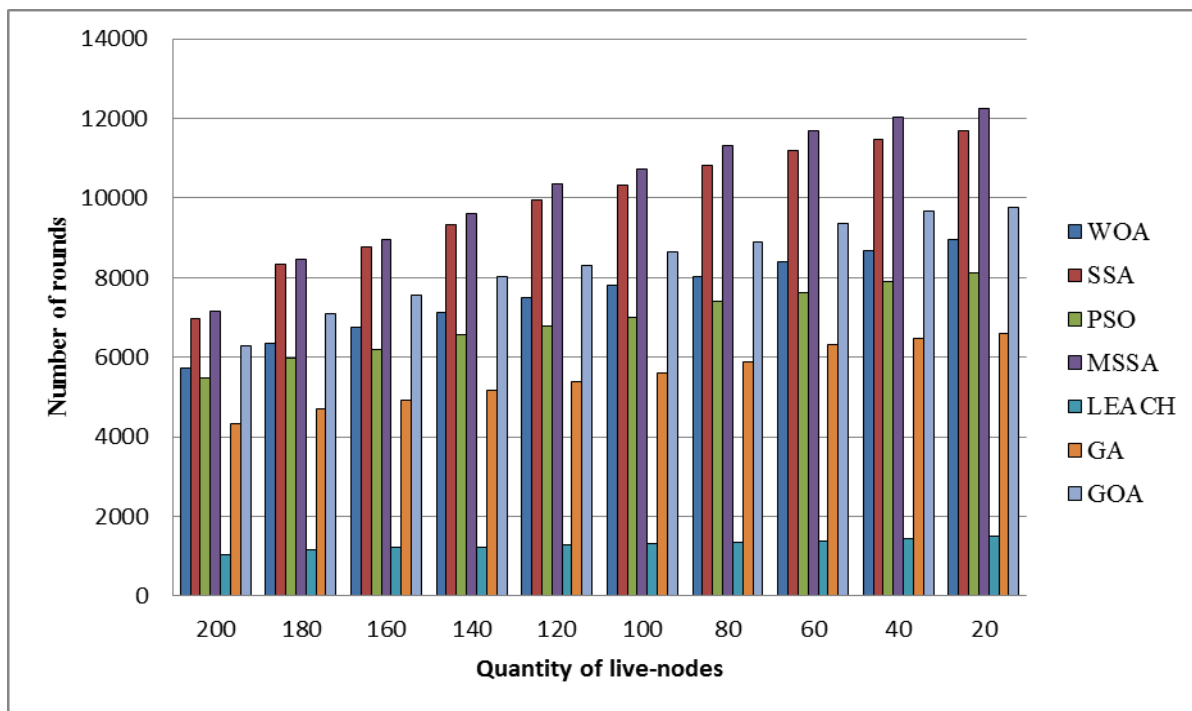


Figure 5 Quantity of Live-Nodes vs. Number of Executions in WSN#1 with BS at Middle-(50, 50)



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5.3. Performance Analysis of Total Energy Consumption

The total energy utilized by WSN#3, WSN#2, and WSN#1 at 6000 rounds for various algorithms under different conditions is depicted in Figures 8, 7, and 6 respectively. And the values for each are organized in Table 5, Table 4, and Table 3. Here simulations are performed by considering BS at Middle (50,

50), Edge (100, 100) & outward (50, 200). We can see how the overall amount of energy used by various algorithms in WSNs #1, #2, and #3 varies with regard to the placement of the BS in Figures 9, 10, and 11. In light of the above, it can be inferred that the suggested MSSA algorithm is more effective and uses less energy than competing methods.

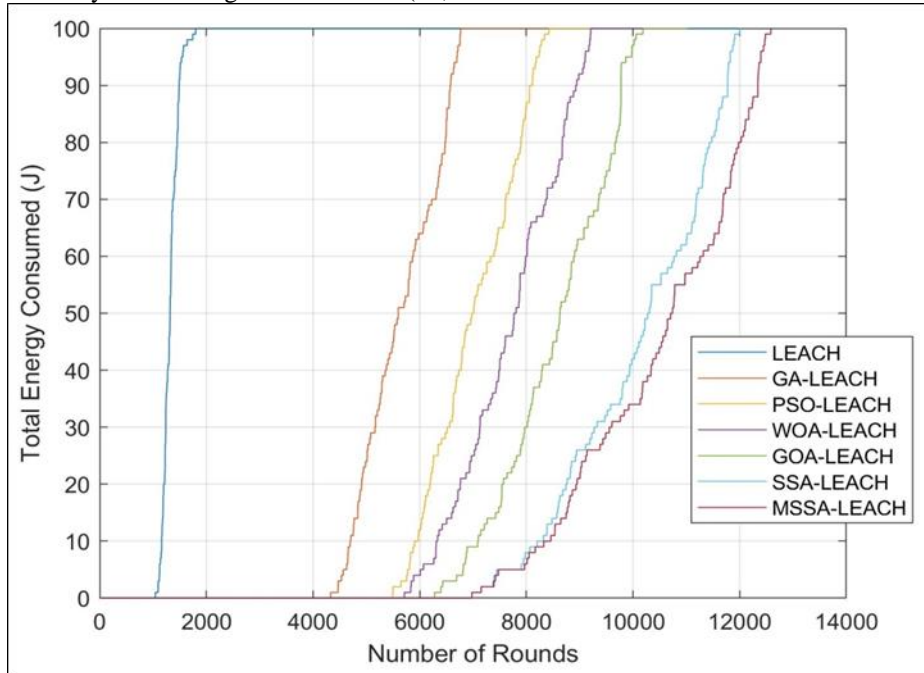


Figure 6 Overall Energy Consumed Under WSN#1 with BS at Middle-(50,50)

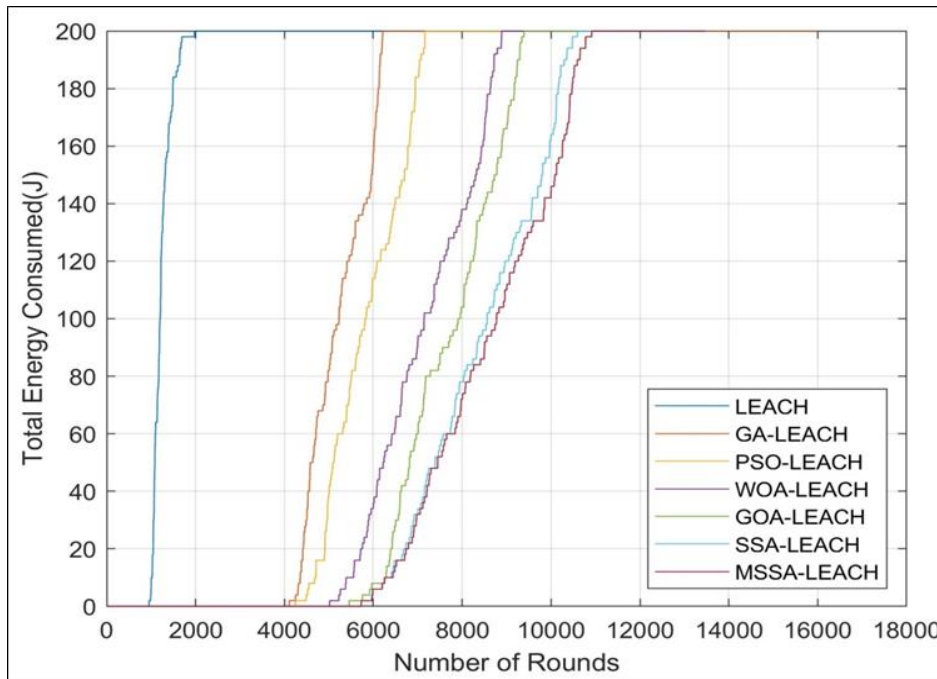


Figure 7 Total Energy Consumed Under WSN#2 with BS at Edge-(100,100)



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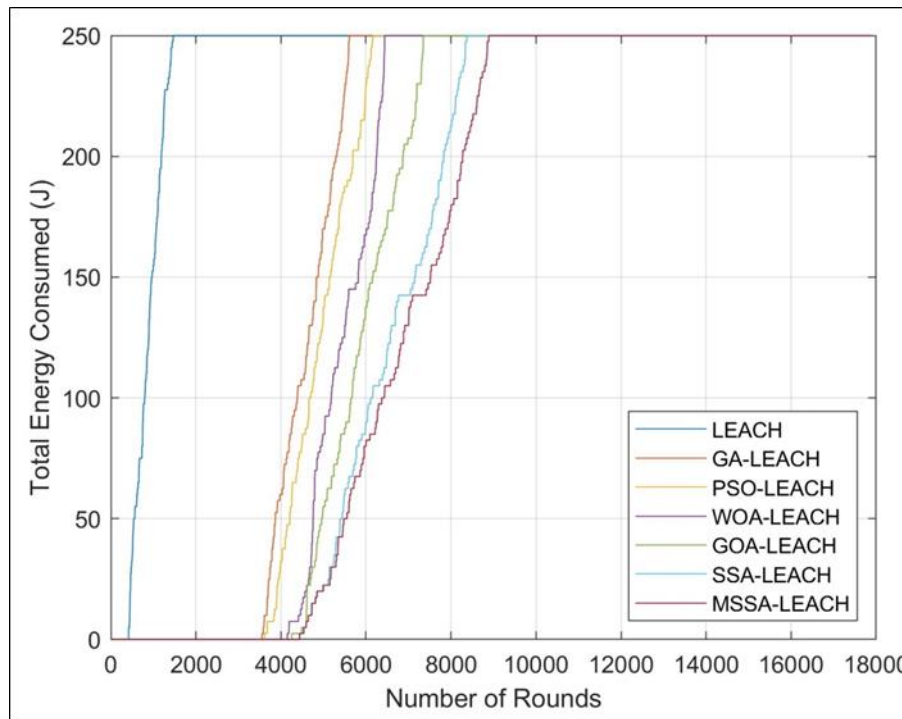


Figure 8 Total Energy Consumed Under WSN#3 with BS at Outward-(50,200)

Table 3 Overall Energy Consumed at Round 6000 in WSN#1 with 200 Nodes & 20 CHs

SPOT OF BS-(X,Y)	WOA	SSA	PSO	MSSA	LEACH	GA	GOA
BS-Outward(50,200)	100	52.85	100	47.14	100	100	76.42
BS-Middle(50,50)	5.00	0	8.88	0	100	47.77	0
BS-Edge(100,100)	20.55	3.88	53.33	2.79	100	100	4.44

Table 4 Overall Energy Consumed at Round 6000 in WSN#2 with 400 Nodes & 40 CHs

SPOT OF BS-(X,Y)	WOA	SSA	PSO	MSSA	LEACH	GA	GOA
BS-Outward(50,200)	164.61	86.15	200	81.53	200	200	133.84
BS-Middle(50,50)	9.23	0	15.38	0	200	10.61	0
BS-Edge(100,100)	36.92	7.69	116.92	4.61	200	161.53	10.76



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Table 5 Overall Energy Consumed at Round 6000 in WSN#3 with 500 Nodes & 50 CHs

SPOT OF BS- (X,Y)	WOA	SSA	PSO	MSSA	LEACH	GA	GOA
BS-Outward(50,200)	166.66	88.88	225.92	81.48	250	250	137.03
BS-Middle(50,50)	7.40	0	12.96	0	250	111.11	0
BS-Edge(100,100)	35.18	7.40	129.62	3.70	250	174.07	9.25

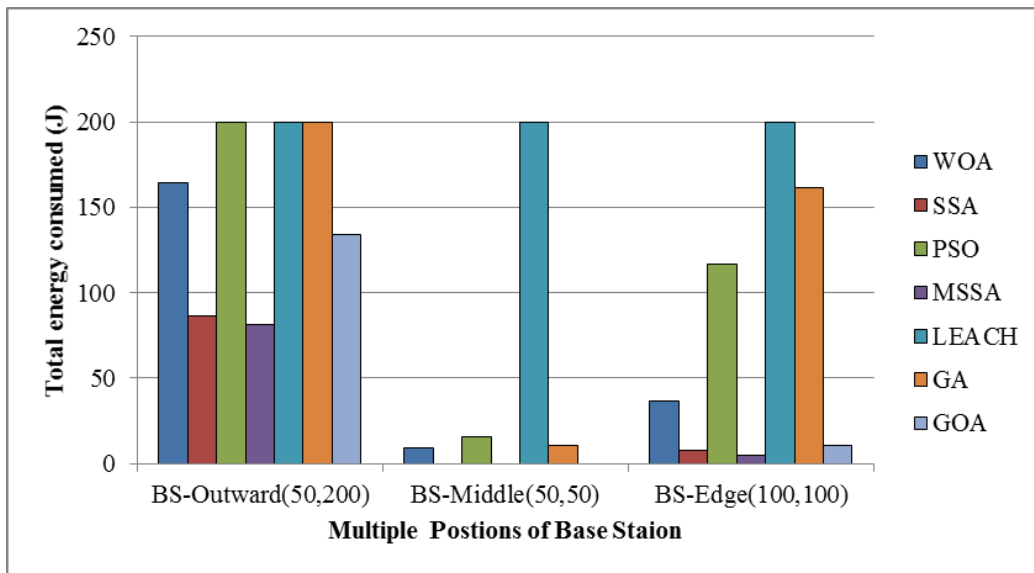


Figure 9 Overall Energy Consumed in WSN#1 for Various Positions of BS

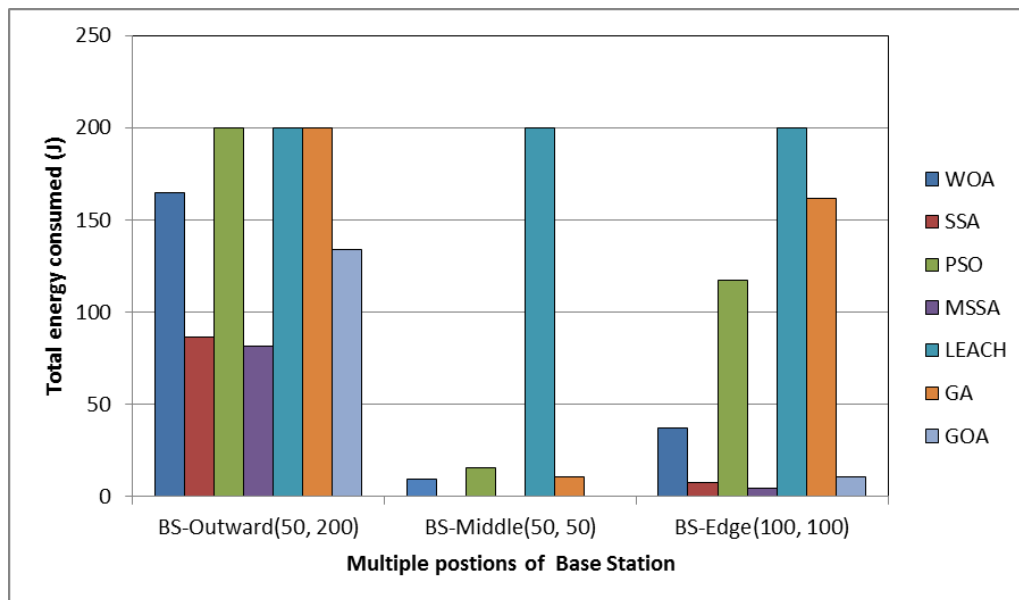


Figure 10 Overall Energy Consumed in WSN#2 for Various Positions of BS



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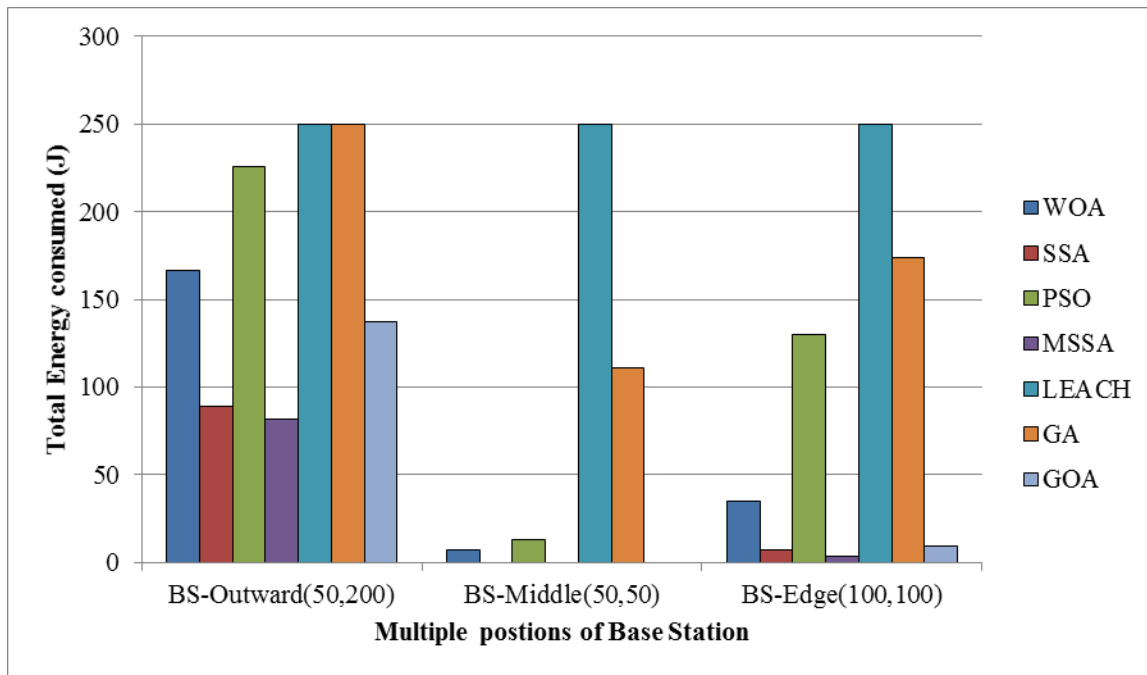


Figure 11 Overall Energy Consumed in WSN#3 for Several Positions of BS

5.4. Performance Analysis of Network Lifetime

We have run the proposed algorithm under different scenarios for observing the network life time performance. Simulations are carried out by fluctuating the figure of nodes with different positions of BS. We have compared various algorithms in WSNs #1, #2, and #3 based on network life time with different positions of BS, as presented in Figures 12, 13, & 14 respectively. The respective values of Network life time for the mentioned network scenarios are detailed in Tables 6, 7, & 8. WOA has a network life time of 9273 rounds, SSA has 12045 rounds, PSO has 8500 rounds,

LEACH lasts around 1818 rounds, GA & GOA have network lifetime of 6818 & 10273 rounds respectively, and MSSA has a network life of 12727 rounds, which clearly overtakes other Protocols in the WSN#1 scenario with BS sited in the interior position. Across all three WSN situations shown in Figures 12, 13, and 14, the network longevity is longest when the BS is in the midspot of (50, 50) and shortest when it is at the external spot of (50, 200). Even when the amounts of nodes, CHs, and BS positions are all changed, the MSSA maintains its superior performance compared to other mentioned algorithms.

Table 6 Network Life Time in WSN#1 with Varying Positions of BS

SPOT OF BS- (X,Y)	WOA	SSA	PSO	MSSA	LEACH	GA	GOA
BS- Outward(50,200)	5773	7227	5500	7454	1273	5000	6364
BS-Middle(50,50)	9273	12045	8500	12727	1818	6818	10273
BS- Edge(100,100)	8000	9227	6500	9545	1773	5773	8409



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Table 7 Network Life Time in WSN#2 with Varying Positions of BS

SPOT OF BS-(X,Y)	WOA	SSA	PSO	MSSA	LEACH	GA	GOA
BS-Outward(50,200)	6210	7895	5947	8158	1368	5368	6947
BS-Middle(50,50)	10474	14000	9474	14737	2000	7421	11789
BS-Edge(100,100)	8895	10579	7158	10895	1947	6210	9263

Table 8 Network Life Time in WSN#3 with Fluctuating Spots of BS

SPOT OF BS-(X,Y)	WOA	SSA	PSO	MSSA	LEACH	GA	GOA
BS-Outward(50,200)	6389	8222	6055	8722	1444	5500	7222
BS-Middle(50,50)	11000	14889	9889	15444	2000	7722	12500
BS-Edge(100,100)	9278	11111	7278	11389	1944	6333	9778

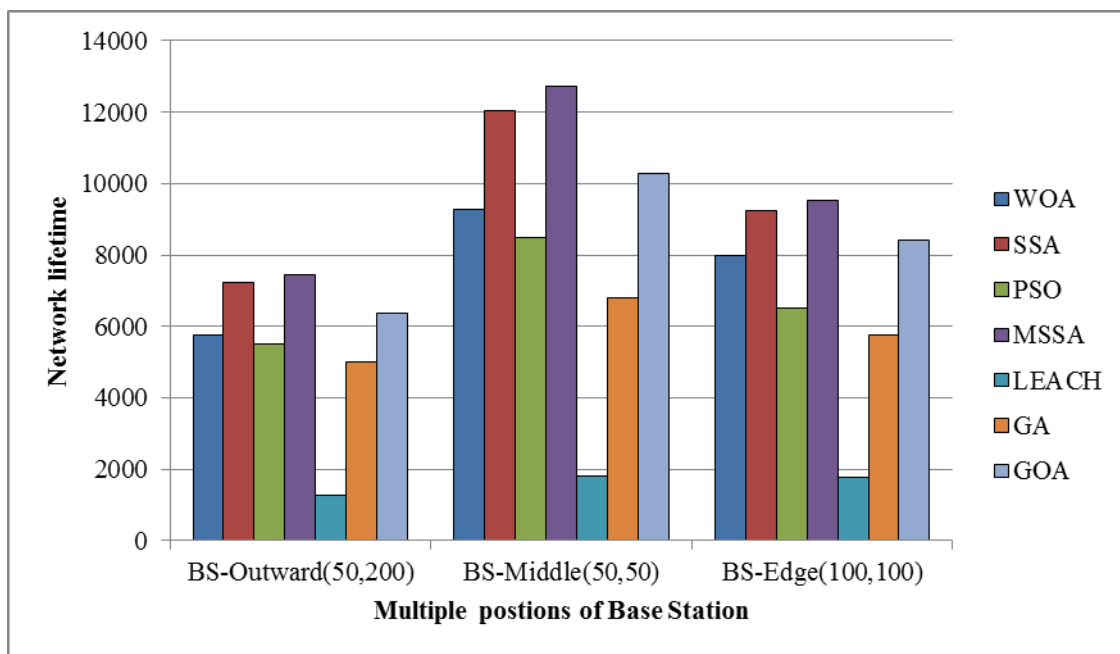


Figure 12 Associations of Network Lifespan in WSN#1 with Changeable Base Station Spots



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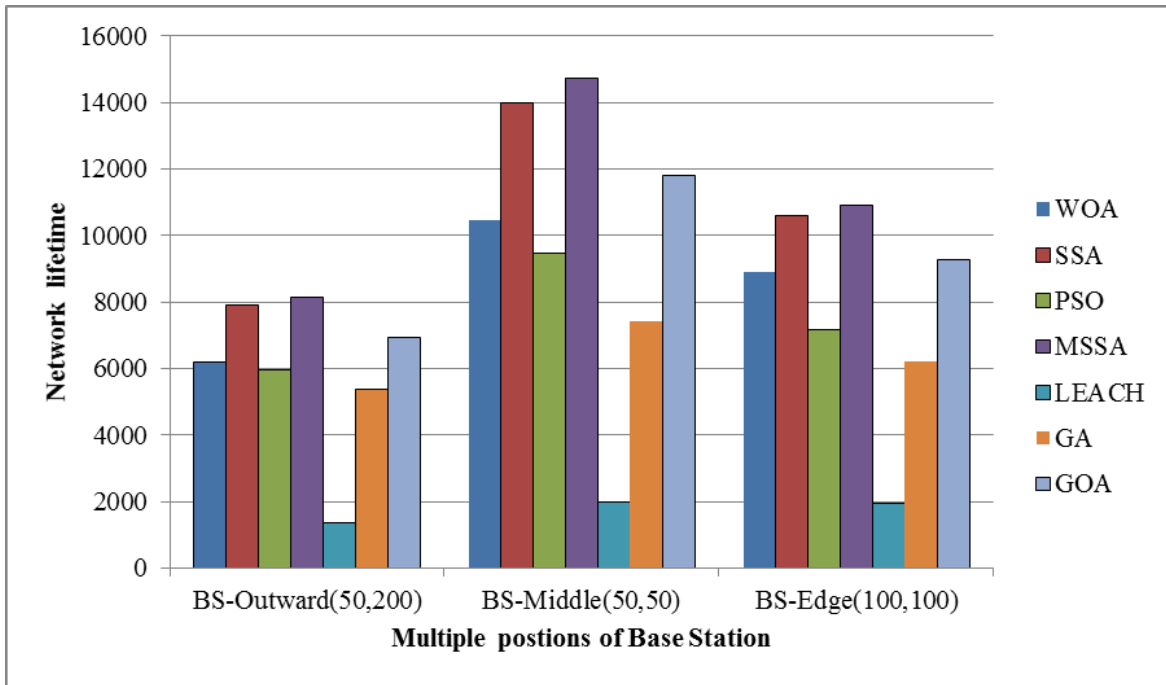


Figure 13 Associations of Network Lifespan in WSN#2 with Changeable Base Station Spots

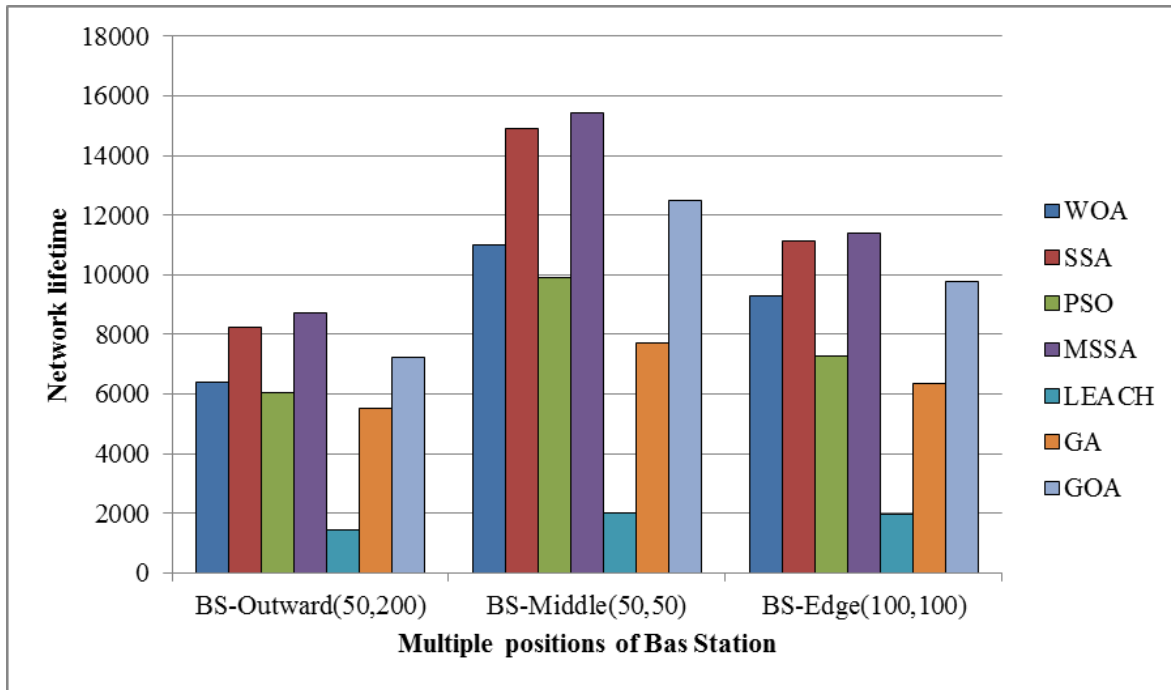


Figure 14 Associations of Network Lifespan in WSN#3 with Changeable Base Station Spots

5.5. Performance Analysis of Throughput

The throughput comparisons of the suggested technique against current methods with varied positions of BS are detailed in Figure 15 for WSN#2, and the related values are

detailed in Table 9. The simulation results show that MSSA outclasses the other six methods in throughput, regardless of BS placement. The network with more nodes and a BS at the centre (50, 50) has higher throughput.

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Table 9 Assessment of Throughput Performance in WSN#2 with Different BS Locations

SPOT OF BS-(X,Y)	WOA	SSA	PSO	MSSA	LEACH	GA	GOA
BS-Outward (50,200)	1973623.43233	2179744.6956	1766498.4323	2779175.7369	14477	1682000.432	2085228.695
BS-Middle (50,50)	2934681.43233	3543656.6956	2705614.4323	4518144.3369	254676	2183303.432	3227189.695
BS-Edge (100,100)	2558913.43233	2947192.6956	2119503.4323	3757661.8369	228142	1941637.428	2742332.695

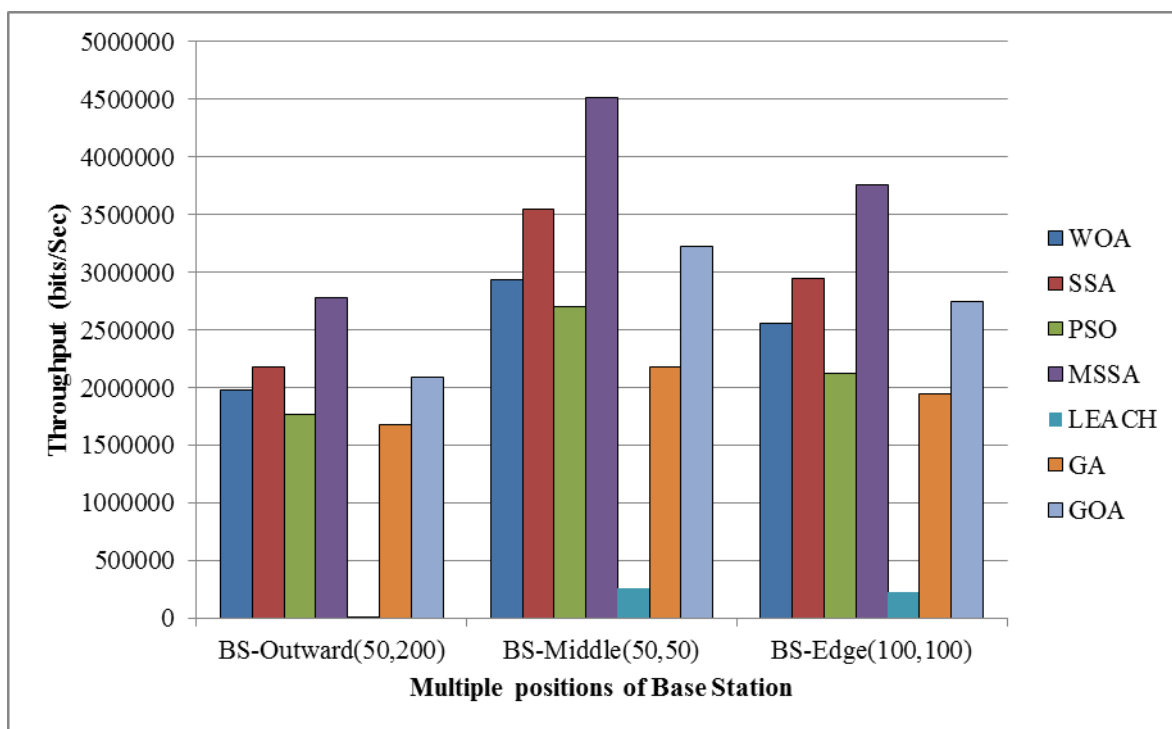


Figure 15 Assessment of Throughput in WSN#2 with Wavering Spots of BS

6. CONCLUSION

To extend the useful life of WSNs, we developed a new variant of SSA called MSSA. In early searching, the suggested method prevents premature convergence, improves exploitation, and avoids local optima. Using MSSA, our proposed protocol builds balanced clusters and chooses the best CH within each cluster established on a fitness function that reflects the residual energy of each node as well as the sum of the energies of the nodes in its vicinity. Comparisons are made between MSSA and other modern standard routing protocols, including LEACH, GA, WOA, GOA, and SSA

using a number of metrics, including network lifetime, throughput, and total energy. In future research, we want to syndicate the suggested MSSA scheme with both traditional and novel machine learning approaches to improve the effectiveness of CH selection and the stability of networks.

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