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INTERNET OF THINGS ENERGY EFFICIENT CLUSTER-BASED ROUTING USING HYBRID PARTICLE SWARM OPTIMIZATION FOR WIRELESS SENSOR NETWORK

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ABSTRACT

Specialized transducers in Wireless Sensor Networks (WSNs) that offer sensing services to the Internet of Things (IoT) devices have limited storage and energy resources. One of the most vital issues in WSN design is power usage, as it is nearly impossible to recharge or replace sensor nodes' batteries. A prominent role in conserving power for energy-constrained networks is served by the clustering algorithm. It is possible to reduce network energy usage and network lifespan prolongation by proper balancing of the network load with Cluster Head (CH) election. The single-hop inter-cluster routing technique, in which there is a direct transfer from CHs to the Base Station (BS), is done by the Low Energy Adaptive Clustering Hierarchy (LEACH). However, for networks with large-regions, this technique is not viable. An optimized Orphan-LEACH (O-LEACH) has been proposed in this work to facilitate the formation of a novel process of clustering, which can result in minimized usage of energy as well as enhanced network longevity. Sufficient energy is possessed by the orphan node, which will attempt to be cover the network. The proposed work's primary novel contribution is the O-LEACH protocol that supplies the entire network's coverage with the least number of orphaned nodes and has extremely high connectivity rates. A hybrid optimization utilizing Simulated Annealing (SA) with Lightning Search Algorithm (LSA) (SA-LSA), and Particle Swarm Optimization (PSO) with LSA (PSO-LSA) Algorithm is proposed. These proposed techniques effectively manage the CH election achieving optimal path routing and minimization in energy usage, resulting in the enhanced lifespan of the WSN. The proposed technique's superior performance, when compared with other techniques, is confirmed from the outcomes of the experimentations.

Keywords: *Wireless Sensor Networks, Internet of Things, Clustering, Low Energy Adaptive Clustering Hierarchy Protocol, Orphan-LEACH, Simulated Annealing, Lightning Search Algorithm and Particle Swarm Optimization.*

1 INTRODUCTION

A wide distribution of numerous sensor nodes within a specific area constitutes a Wireless Sensor Network (WSN). Processing data that is collected from the sensors for an area's event monitoring is the WSN's primary task. The area's data is gathered by the sensor nodes and transferred to a Base Station (BS) (also known as the sink) in a WSN. The efficacy of various civil and military applications like disaster management, security, and surveillance of combat fields, is substantially affected by the WSNs. Even so, constraints on storage, processing, communication, and energy are the sensor nodes' limitations. The duration of time till the desired points or area are no longer covered is defined as a WSN's network lifetime. A vital criterion for determining WSN efficacy is the lifetime of the network. The network sensor nodes' unbalanced usage of energy or high utilization of power is a major factor in the network lifetime's reduction. The reason being that every sensor node's power supply is a battery which, because of the coverage [1] area's conditions, maybe neither replaceable nor rechargeable. Due to this, prolongation of network lifespan can be achieved through the control and balancing of the network's energy usage. Therefore, the sensor nodes' energy usage must be accounted for by the networks' utilized algorithms.

A visualization of smart objects' (things) communication and integration is the Internet of Things (IoT). The latest innovations in applications and services have resulted from the IoT's dominance. IoT components constitute numerous objects like Radio Frequency Identification (RFID) tags, sensors, mobile phones, and so on, that are Internet-connected through wired and wireless networks. Data is sensed, collected, and transferred by the smart objects to fulfill users' diverse requirements. There can be communication between: (i) people and objects, and (ii) the objects themselves. There is the IoT's realization as a key solution for the acquisition of insight into the real world physical processes' diverse associated issues. Several deployment challenges have been posed by the IoT field's advancements in technology. A queried form or continuous methodology [2] can be utilized for the sensed data transmittal. But, for this to happen, the sensor nodes must communicate among themselves with energy efficiency. When there is the deployment of more objects in the IoT, the entire process will consume tremendous quantities of power. Hence, for making good use of environmental conservation and surveillance, decreasing operational costs, minimizing power usage, as well as lowering emissions and pollution, a prominent role is served in the IoT by green networking.

Network topology adjustments and regulation of the levels of nodal transmission power in the routing protocol will aid in the effective management of energy utilization. The minimization of the routing protocols' power utilization is aided by the clustering approach. There is an organization of the sensor nodes into clusters in a clustering architecture. Here, sensor nodes with smaller energies are employed for carrying out sensing tasks and for short distance-transfer of the sensed data towards their Cluster Head (CH). For removing correlated data from the cluster's members, a cluster's node is picked out as the CH. The CH's purpose is to minimize the amount of the aggregated data transferred to the BS. Extended network lifespan and energy efficiency enhancement is accomplished by the clustering approach [3] by minimizing the overall energy usage and balancing the nodes' energy usage during the

network's lifespan. This approach also has the ability to mitigate channel contention as well as packet collisions, and hence, provide better network throughput under high load conditions.

As a leading IoT technology, the WSN comprises diverse nodes that have sensing, computing, processing, and communicating abilities. Despite that, each sensor's limited sensing capability and battery capacity cause certain critical issues related to CH election, localization of nodes, and routing protocol planning in WSN. During its food search, the insect community's behaviour as its efforts to detect the optimal path of insects forms the basis for the Swarm Intelligence (SI) algorithm's [4] development. The extensibility, distribution, robustness, and adaptability of these algorithms make them compatible with the WSN's routing protocol requisites. Hence, there has been the development of numerous SI-based algorithms for routing protocols in WSN. The most frequently employed WSN routing protocol is the cluster routing protocol. This protocol's primary issue is the election of CH, which is, specifically, an NP-hard problem. The feasibility of SI in resolving NP problems makes its implementation with few parameters quite applicable.

Furthermore, simultaneous CH detection in multiple clusters is facilitated by its multi-objective optimization capability. Although the positioning problem's resolution is generally done with the Global Positioning System (GPS), this method's high energy usage, as well as unavailability in certain specific areas, make it infeasible for WSNs. An error optimization problem is considered to be part of the complex optimization problem. Therefore, SI algorithms can be used for resolution of node localization as this issue is also treated as an error optimization problem.

The hybrid SA-LSA and PSO-LSA techniques for IoT-based WSN have been proposed in this work. The investigation's remaining portion is arranged into the following sections. The associated literary works are detailed in Section Two. The different techniques utilized in this work are detailed in Section Three. Outcomes of the experimentations are discussed in Section Four, and the work is brought to an end in Section Five.

2 RELATED WORKS

With a focus on the conventional WSNs' issues like poor connectivity and low coverage, Wang [5] proposed an efficient and optimized WSN's design for dairy farming. Network nodes' implementation has taken into account two major issues in WSNs: connectivity and coverage. In WSNs, optimization of the node deployment is done by the PSO. It is demonstrated from the experimentations' outcomes that the proposed approach can enhance the WSNs' effective coverage, accomplish swift convergence speed, overcome the fixed sensor nodes' influence on layout optimization, and provide rapid and efficient realization of the WSN layout's global optimization. Meanwhile, the PSO algorithm is able to efficiently identify the optimal nodes that can be appended to the network and entirely connect the network through the addition of a small number of nodes so as to make the network effective as well as stable.

Genetic Algorithm (GA) - based clustering and PSO-based routing in WSN was utilized in the methodology presented by Anand& Pandey [6] for enhancement of the lifespan of a network. A GA will take into account energy and distance parameters for the election of the best CH. Data from the rest of the nodes are collected by this CH. Moreover, the PSO algorithm relies on optimal routing paths picked for each relay node for data delivery towards the BS. It is shown in the proposed procedure that the relay node will aid and enable communication between the sink and CH, that in turn, boosts the efficiency of energy. Eventually, the system will survive longer because of the improvement of the WSNs' Quality of Service (QoS). Outcomes of the simulated experiments demonstrated that, compared to other currently-used protocols, the proposed approach greatly raised the WSN's lifespan and minimized its energy usage.

The effective SA was exploited by Zhang et al., [7] for the proposal of a weighted Distance Vector (DV)-Hop technique. The effect of diverse known nodes on unknown nodes is initially identified by this algorithm, which will later weigh each known node's average distance. During this time, the adjacent nodes' average distance will be nearer to the network's real average distance. Eventually, the unknown nodes' location is found with the effective SA algorithm's utilization. The proposed positioning method was indicated to have higher precision when the outcomes of Matlab simulations were analyzed.

Grey Wolf Optimization (GWO), a novel intelligent computing approach, was propounded by Zhang & Liu [8] for WSN localization. Running simulations confirmed this proposed approach's practicability and validity. There was a discussion about the convergence performance and localization outcome and comparison with the standard PSO algorithm. This work hadalso analyzed the proposed approach's localization performance when it was subjected to diverse anchor node proportions and diverse communication radii. It is demonstrated from the experimentation outcomes that the proposed approach can achieve higher accuracy in localization and can save cost as it can accomplish the same accuracy with fewer anchor nodes anda smaller communication radius.

A combination of the elite selection and niche sharing mechanism, known as the Elite Niche PSO (ENPSO), was proposed by Xu et al. [9] to develop the robustness and convergence rate of the algorithm. Simulations were used to draw comparisons between the ENPSO's energy cost-optimized and those optimized by GWO and SA. It is demonstrated from the outcomes that, when the number of nodes is 100 with 10% CHs, ENPSO's energy cost-optimized smaller by 9.63% and by 19.54% compared to GWO and SA, respectively. It indicates that the proposed ENPSO's performance is superior to that of the other two algorithms and that it has better robustness and swifter rate of convergence.

Proposal for a novel energy-aware bio-inspired clustering scheme (PSO-WZ) was given by Zhang & Wang [10]. At the start of this work, there is random initialization of the CHs combination and allocation of non-CHs depending on the division rules. Afterward, the fitness function is employed for the selection process's guidance till attaining the maximum time. Two design angles: non-CHs and the overall network are utilized by this work to maximize energy conservation in each node as the division rule is in direct proportion to the

network topology and the node energy consumption distribution. Additionally, the Gini coefficient's introduction to the objective function in this work to balance the nodal energy load can help minimize node reduction and preserve the network coverage range. Based on the obtained results, further enhancement of the IoT's overall performance, network life cycle prolongation, and the ability to maintain more nodes alive over time is achieved by the proposed algorithm.

Large contributions have been made by hierarchical-based routing protocols towards minimum energy usage and, as a result, toward prolongation of the network lifespan. A Hybrid bio-inspired clustering-based Routing Protocol (HRP-CSSA) was proposed by Demri et al. [11], which utilized the Cuckoo Search (CS) Algorithm and the Simulated Annealing (SA) Algorithm. This proposed protocol would exploit the SA's benefit of avoiding getting captured in the local minima and the CS algorithm's effectivity in resolving global optimization. It is evident from the outcomes of the experiments that the HRP-CSSA achieves the best performance with regards to received data amount at the BS, network longevity, stability period, and energy usage.

The conventional Bat Algorithm's (BA) attributes were modified with the TLBO algorithm by Kadiravan&Sujatha [12] to put forward a BAT-TLBO algorithm to determine the network's proper node localization. Diverse scenarios with variations in anchor node density are used for the assessment of the BAT-TLBO algorithm. It is indicated from the simulation outcomes that, on average, the localization error of BA is 0.259, that of the Modified BA (MBA) is 0.541, and that of the BAT-TLBO is 0.219. Moreover, in comparison to other algorithms, the experimental outcomes also ensured that the BAT-TLBO algorithm has better localization performance regarding computation time, improved localization success ratio, and robustness.

3 METHODOLOGY

There is a discussion about the O-LEACH protocol, PSO, SA, LSA, SA-LSA, and PSO-LSA methods in this section.

3.1 Orphan-LEACH (O-LEACH) Protocol

Orphan Problem: After cluster formation, the nodes' random election of CH is concentrated in the work field's specific part. Due to this, nodes outside the network would not be covered (see Figure 1) in the field's remainder part. The BS will not be sent values that were received by the Orphan nodes. The Orphan node problem necessitates identifying a solution to allow these nodes to join the network's remainder portion. The Orphan LEACH presents two scenarios. In the first scenario, a cluster member can act as a gateway that permits the Orphan nodes' joining. The gateway node is treated as the connected Orphan's CH' since the gateway node must connect several Orphan nodes. Hence, Orphan nodes can deliver their data messages towards the CH'. The CH' will then carry out the aggregation of data and forward these messages towards the CH. The second scenario is for an uncovered area where the number of Orphan nodes is quite critical, and there is the creation of a sub-cluster if the number of a cluster member is more than the number of orphan nodes. A CH'

will be the first Orphan node which has arrived at the gateway (cluster member). The CH's [13] similar role is served by the CH'.

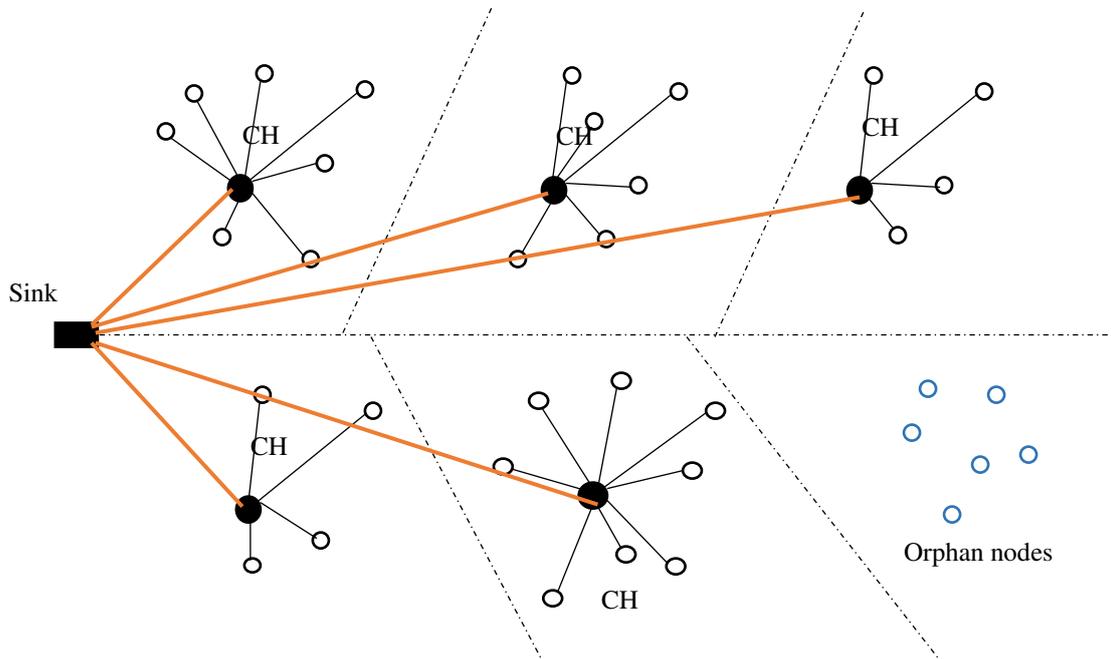


Figure 1 T round in O-LEACH with orphan nodes

Solution: Scenario 1

In round i , an area needs not to be covered by the CH, or CHs cannot cover it. These nodes are not within the CHs' reach, and a cluster member is known as Gateway (CH'). It is shown in Figure 2:

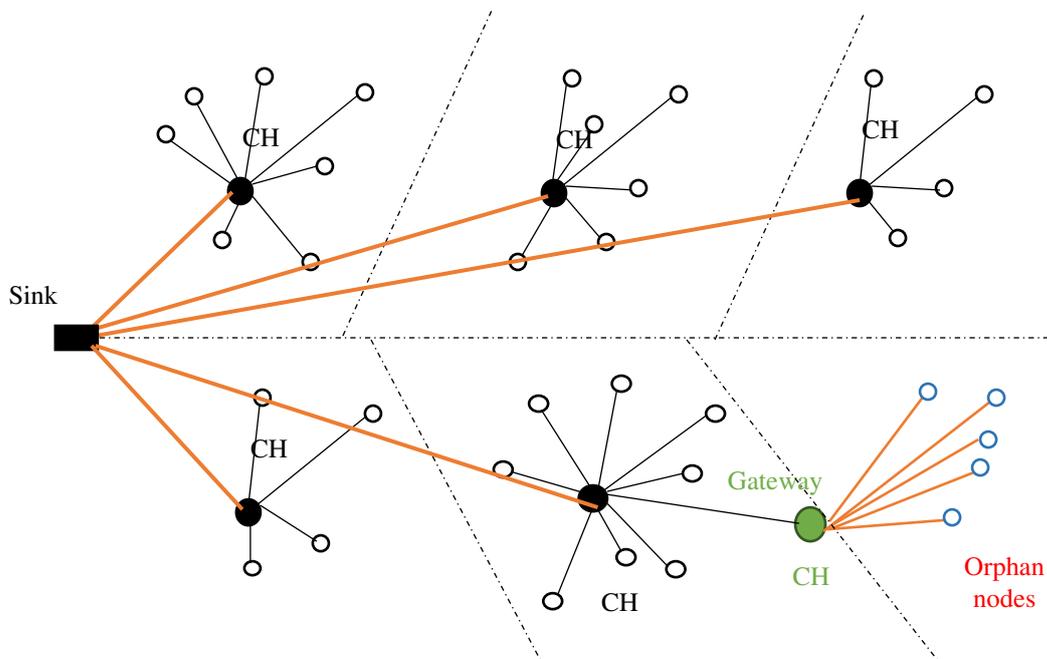


Figure 2 Solution with member gateway CH scenario 1

Setup Phase extension Orphan-LEACH:

The setup phase and the steady-state phase are displayed in Figure 3. With this phase setup, the cluster is permitted to organize by taking the orphan nodes into account.

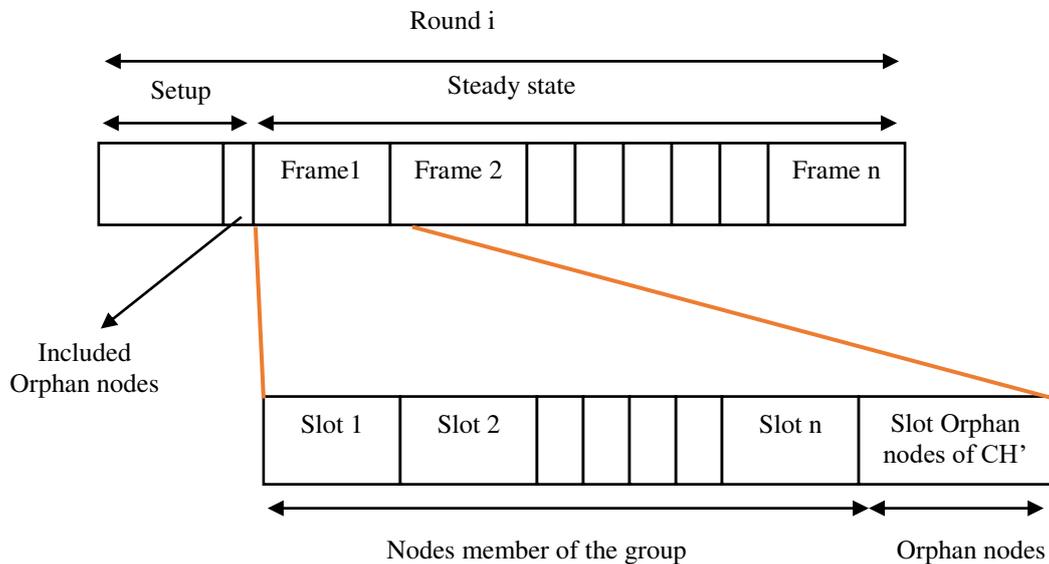


Figure 3 T round in Orphan-LEACH reserved slots

The initialization phase will comprise an election of CH nodes with a particular probability through a local decision taken by a node to turn into a CH. A timer is utilized for verification of the Orphan nodes' existence after the clusters have been formed. The CH will reserve two slots for gateway (CH') when it is a positive answer: a slot for gateway and a slot for Orphan nodes (compression and aggregation of data). The CH allocates every member node a slot, and Time Division Multiple Access (TDMA) is utilized to divide the time into various intervals (timeslot) allocated for every node. Therefore, even though an individual node has the channel's access (that is, it utilizes the bandwidth channel's whole range), it can only transfer its data only during its allocated time intervals.

In group formation, the neighboring nodes' messages are broadcast by the CH. The cluster membership is notified to the CH by the cluster member nodes. Hence, the cluster members (Gateway), which receive the Orphan nodes' messages, will demand a group membership. The gateway notifies the CH of the Orphan nodes' number. Assigning some TDMA slots to the Orphan nodes and the cluster members is permitted by the CH for their simultaneous data transmissions. As a result, the number of Orphan nodes must be lesser than or equivalent to the number of cluster members. Description of Orphan LEACH's sequence in the Setup Phase is given below.

Solution scenario2

When the number of Orphan nodes is more than the number of CH's cluster members, there will be the sub-clusters creation (as shown in Figure 4). CH' and Orphan nodes are the sub-clusters constituents. The first Orphan node (CH'), which has access to the gateway, is known as CH'. The Orphan nodes' neighbor is notified of the latest status of the CH' by the

CH' itself. The number of slots reserved for the Orphan nodes is notified to the CH' by the CH. The CH' has a similar role to the CH. The CH' will compress the Orphan nodes' received data, and later, via a Gateway, this data is aggregated to a CH.

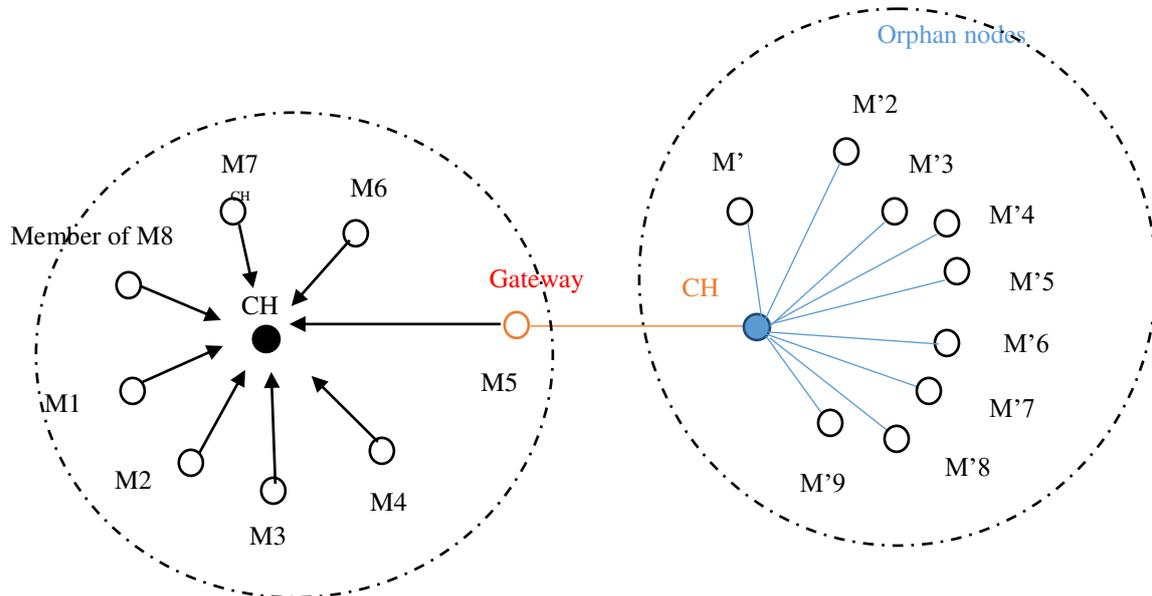


Figure 4 Setup Phase extension Orphan-LEACH scenario 2

Steady-state Phase: Data collection is permitted in this phase. The TDMA is utilized by the cluster's member nodes and the orphan nodes for their data transfer during their slots. Data from the neighboring members is collected by the CH' (gateway). The CH' (gateway) will merge and compress this data before delivering the CH's outcome. Slot 1 will contain the CH' (gateway) data, and Slot 2 will contain the Orphan nodes' aggregated data. Data from the cluster member nodes and Orphan nodes will be gathered, aggregated, and later transmitted to the BS by the CH.

3.2 Particle Swarm Optimization (PSO) Algorithm

Kennedy and Eberhart are the PSO, which is modeled on the bird flocks' social behavior. Every individual in a population is regarded as a multidimensional solution space's particles in this algorithm. The PSO will begin with the random initialization of a particle group in the population. Each particle presents a feasible solution, and its position in the search space will determine its fitness values. Within the solution space, every particle will traverse towards the randomly weighted average of the historical personal best position and the historical global best position and will identify the current global solution [14].

Suppose that for an n -dimension objective search space, the population will comprise of s particles. The i particle's position and velocity will be X_{id} and v_{id} , respectively, where, $1 \leq i \leq s$, $1 \leq d \leq n$. An objective function is used for the assessment of a particle's fitness. When a particle has a smaller fitness value, it will be nearer to the global solution than another particle. The i particle's historical personal best position where it had the smallest fitness is denoted as $pbest_{id}$ is, and the smallest of all $pbest_{id}$, $1 \leq i \leq s$, is denoted as $gbest_d$. For

every iteration k , Eq. (1) and Eq. (2) are utilized to update each particle's velocity v_{id} and position as below:

$$v_{id}(k+1) = \omega \times v_{id}(k) + c_1 \times rand_1 \times (pbest_{id} - X_{id}) + c_2 \times rand_2 \times (gbest_d - X_{id}) \quad (1)$$

$$X_{id}(k+1) = X_{id}(k) + v_{id}(k+1) \quad (2)$$

In these equations, the inertia weight that denotes the particle's inertia is indicated as ω , the acceleration constants are indicated as c_1 and c_2 , and random numbers that are uniformly distributed in $[0, 1]$ are indicated as $rand_1$ and $rand_2$.

3.3 Simulated Annealing (SA) Algorithm

SA is a metaheuristic algorithm that is utilized in materials. The concept of not ruling out the worse solution is employed in the SA. As the solution may not be the worst during the first few iterations [15], this concept is quite beneficial. Even though the criterion is not fulfilled by the solution, instead of rejecting the solution outright, it is rejected with a probability that is given in Eq. (3) below:

$$p = \exp\left(-\frac{\Delta E}{k_B T}\right) \quad (3)$$

Energy change in Eq. (4) is indicated in Eq. (5) as given below:

$$\Delta E = \gamma \Delta f \quad (4)$$

In this equation, the change in fitness function is denoted as Δf , and the inverse of the Boltzmann's constant is elected as c . Given below is the resultant probability upon substitution of energy change in Eq. (5):

$$p = \exp\left(-\frac{\Delta f}{T}\right) \quad (5)$$

Here, the energy levels' change is denoted as ΔE , the Boltzmann's constant is denoted as k_B , the temperature for controlling the process of annealing, denoted as T , is elected as the fitness function's average value, and the inverse of the Boltzmann's constant is elected as c . Therefore, an exponential function of the difference in fitness function and the temperature can be used for the probability's expression.

3.4 Lightning Search Algorithm (LSA)

Nature's phenomenon of lightning has influenced the development of the new metaheuristic algorithm known as LSA. This algorithm's key concept is a generalization from the hypothesis, which is associated with the step leader propagation's mechanism. Projectiles, which are a set of fast particles that traverse the search space in the form of a step leader's binary tree structure, are utilized by the LSA to execute a search. Evolutionary algorithms' utilized terms such as "chromosome", "individual," or "particle" share similarity with this concept of the projectile.

The following [16] elucidates the three projectile types incorporated by the LSA

- **Transition projectiles:** The step leaders' initial population is formed with these projectiles. Numbers that are randomly chosen from the standard uniform probability distribution are utilized for these projectiles' generation. This distribution's probability density function $f(x)$ is as per Eq. (6) below:

$$f(x) = \begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & x < a \text{ or } x > b \end{cases} \quad (6)$$

- **Space projectiles:** There are updates and evolution of these projectiles such that one of them turns into the leader. Eq. (7) is utilized to carry out the update mechanism.

$$p_j^s = p_i^s \pm \text{exprnd}(D) \quad (7)$$

In this equation, the new space projectile is denoted as p_j^s , the old space projectile is denoted as p_i^s , and a function that will generate numbers randomly from the exponential distribution is denoted as exprnd . The exponential distribution's probability density function is offered by Eq. (8) as below:

$$f(x) = \begin{cases} \frac{1}{\mu} e^{-\frac{x}{\mu}} & x > 0 \\ 0 & x \leq 0 \end{cases} \quad (8)$$

The assumption for the μ used in Eq. (8) is that it is the distance D between the lead projectile p^L and the p_i^s , as indicated in Eq. (9) below:

$$D = |p^L - p_i^s| \quad (9)$$

- **The lead projectile:** The best solution to projectile's representation. Update for this projectile will be by Eq. (10) as below:

$$p_{new}^L = p^L + \text{normrnd}(0, E_k) \quad (10)$$

In this equation, the updated lead projectile is denoted as p_{new}^L , the old lead projectile is denoted as p^L , and a function which will generate numbers randomly from the normal distribution with a mean μ and a standard deviation parameter σ is denoted as $\text{normran}(\mu, \sigma)$. Eq. (11) will offer the normal distribution's probability density function. σ parameter is utilized as a kinetic energy E_k variable, which will decrease exponentially with the iteration's progression, as indicated in Eq. (12). While the total number of iterations is denoted as T , the current iteration's number is denoted as t .

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (11)$$

$$E_k = 2.05 - 2 \exp\left(\frac{-5(T-t)}{T}\right) \quad (12)$$

There is the old projectiles' replacement by the updated space and lead projectiles and channel formation only if their energy (quality) is better than that of the old one. The procedure of forking is the LSA's other distinct property. There is the creation of an additional channel (a projectile in a new direction) from a successful projectile as its symmetrical copy in this procedure. The formation of new projectile p_j is given in Eq. (13), wherein the upper and lower bounds are denoted as a and b . Later on, there is an evaluation of the quality of p_j . While the two projectiles' best is retained in the population, exclusion (channel elimination) of the other is excluded. The application of this procedure is done on LSA at a very low rate.

$$p_j = a + b - p_i \quad (13)$$

3.5 Proposed SA-LSA Algorithm

LSA is regarded as the primary process in the hybrid SA-LSA algorithm. For the SA mechanism's introduction, LSA is included in the crossover and mutation operations for the population's further optimization. For each iteration, a specified number of individuals are elected by the crossover operation to go into a dependent pool on the crossover probability P_c . There is also the random election of two individuals from the pool to execute a two-point crossover to generate the same number of sub-individuals. Moreover, as per a smaller mutation probability P_m , the mutation operation is done for each individual's dimension. Simulated annealing will determine if the sub-individuals attained by the crossover and mutation operations can replace their parents.

There are two parts to the hybrid SA-LSA algorithm's implementation. At first, there is a generation of a better group focused on global search by the LSA algorithm's evolution. Secondly, SA is carried out by applying the crossover and mutation operations, which is focused on local search, for further enhancement of the solution's accuracy. The following [17] is the methodology of the SA-LSA:

Step 1: Initialization of the LSA's population, iteration, and channel time, along with the probabilities of crossover and mutation.

Step 2: Random generation of step leaders by Eq. (6). There is the encoding of transition projectiles by binary strings, representing the multilayer microwave absorber's design.

Step 3: The projectile energy E_{s1} is evaluated.

Step 4: The main loop is entered. There is also an update of the absorber's worst step leader, best step leader, and current best maximum reflection coefficient.

Step 5: If there is the maximum channel time attainment, there will be the elimination of the bad channel (solution) and its replacement with the best. Else, proceed to Step 6.

Step 6: The projectiles' direction is updated. Later, there is the ejection of space and lead projectiles through the utilization of Eq. (7) and Eq. (10) for sub-projectiles' generation.

Step 7: The sub-projectile energy E_P is evaluated.

Step 8: If $E_P < E_{sl}$, there is an update of the projectile position and energy and the occurrence of forking. Else, the original position is retained. Upon forking, two symmetrical channels are produced at the fork, and for entry into the next generation, only the better channel is chosen.

Step 9: There is the execution of the crossover operation, followed by the SA's execution.

Step 10: There is the execution of the mutation operation, followed by the SA's execution.

Step 11: If there is the maximum number of iterations, the output is considered the absorber's optimal design parameters. Else, return to Step 4 and enter the next generation search.

3.6 Proposed PSO-LSA Algorithm

The various benefits of PSO include quick convergence speed. However, it also has certain drawbacks like premature convergence and easily getting trapped in the local optima. The quick rate of convergence is an advantage of the classical LSA. However, low capability for resolving multimodal optimization problems, poor accuracy of the solution, premature convergence, and easily fall into local optimum are some of its drawbacks. There is a proposal for a hybrid PSO-LSA method for improvement of the LSA's search performance.

The proposed hybrid PSO-LSA algorithm's flowchart is illustrated in Figure 5.

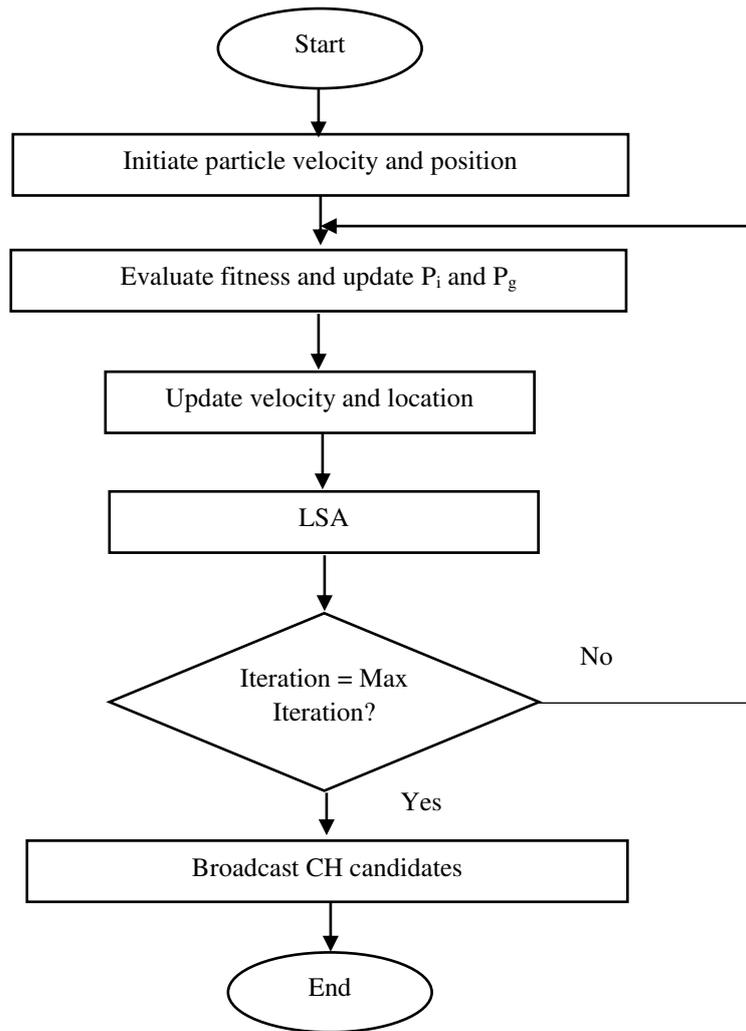


Figure 5 Proposed Hybrid PSO-LSA Method

4 RESULTS AND DISCUSSION

In this section, the LSA, O-LEACH, SA-LSA, and PSO-LSA methods are used. Experiments are carried out using 200 to 1000 number of nodes and 0 to 800 number of rounds. The number of clusters formed, average end to end delay, average packet loss rate, and lifetime computation, as shown in tables 1 to 4 and figures 6 to 9.

Table 1 Number of Clusters Formed for PSO-LSA

Number of nodes	LSA	O-LEACH	SA-LSA	PSO-LSA
200	15	15	15	16
400	26	24	25	26
600	41	40	42	43
800	47	45	46	48
1000	46	45	46	47

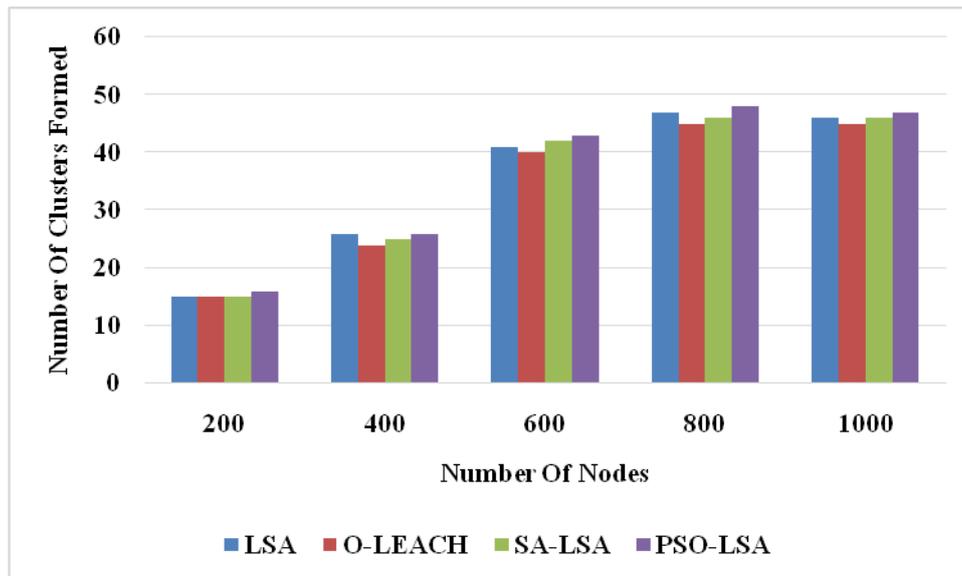


Figure 6 Number of Clusters Formed for PSO-LSA

From the figure 6, it can be observed that the PSO-LSA has a higher number of clusters formed by 6.45%, 6.45% & 6.45% for 200 number of nodes, by no change, 8% & 3.92% for 400 number of nodes, by 4.76%, 7.23% & 2.35% for 600 number of nodes, by 2.1%, 6.45% & 4.25% for 800 number of nodes and by 2.15%, 4.34% & 2.15% for 1000 number of nodes when compared with LSA, O-LEACH, and SA-LSA respectively.

Table 2 Average End to End Delay for PSO-LSA

Number of nodes	LSA	O-LEACH	SA-LSA	PSO-LSA
200	0.0034	0.0034	0.0033	0.0032
400	0.0042	0.0043	0.0041	0.0039
600	0.0379	0.0378	0.037	0.0356
800	0.0642	0.0638	0.0619	0.0607
1000	0.1272	0.1258	0.1223	0.1189

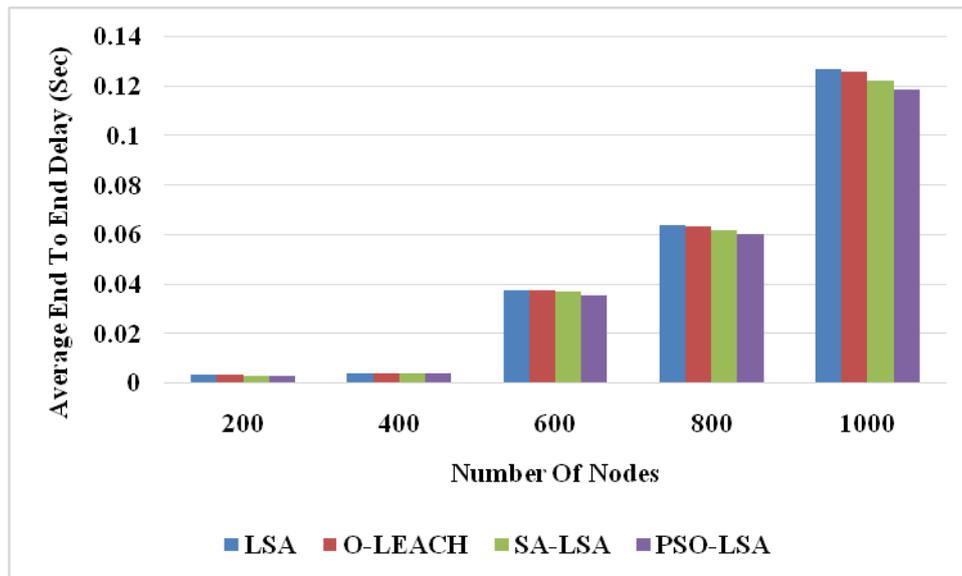


Figure 7 Average End to End Delay for PSO-LSA

From the figure 7, it can be observed that the PSO-LSA has lower average end to end delay by 6.06%, 6.06% & 3.07% for 200 number of nodes, by 7.41%, 9.75% & 5% for 400 number of nodes, by 6.25%, 5.99% & 3.85% for 600 number of nodes, by 5.6%, 4.98% & 1.96% for 800 number of nodes and by 6.74%, 5.64% & 2.82% for 1000 number of nodes when compared with LSA, O-LEACH and SA-LSA respectively.

Table 3 Average Packet Loss Rate for PSO-LSA

Number of nodes	LSA	O-LEACH	SA-LSA	PSO-LSA
200	11.22	11.34	11.07	10.54
400	18.32	18.13	17.51	17.13
600	18.79	18.53	18.08	17.71
800	19.58	19.53	18.86	18.3
1000	29.93	29.82	29.06	28.22

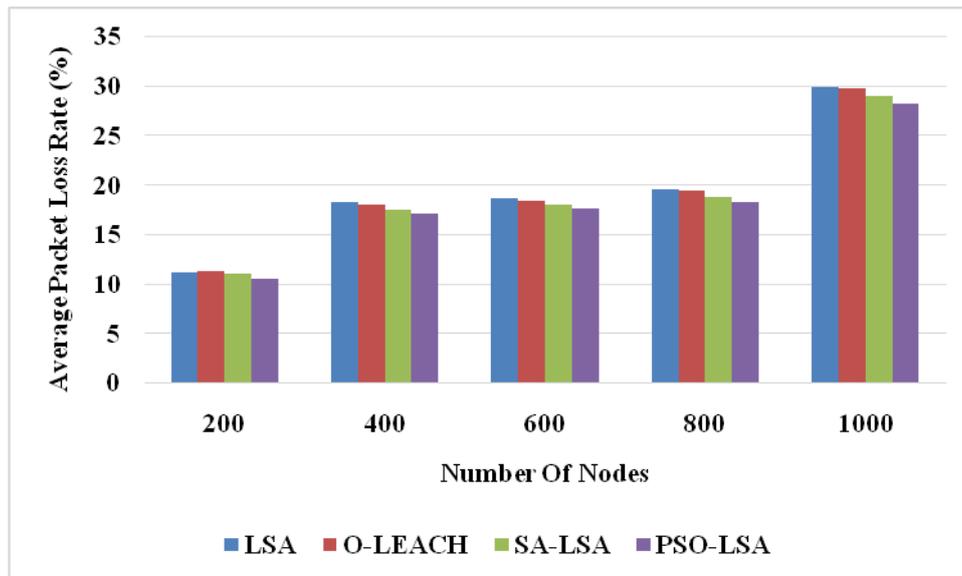


Figure 8 Average Packet Loss Rate for PSO-LSA

From the figure 8, it can be observed that the PSO-LSA has lower average packet loss rate by 6.25%, 7.31% & 4.91% for 200 number of nodes, by 6.71%, 5.67% & 2.19% for 400 number of nodes, by 5.91%, 4.52% & 2.07% for 600 number of nodes, by 6.75%, 6.5% & 3.01% for 800 number of nodes and by 5.88%, 5.51% & 2.93% for 1000 number of nodes when compared with LSA, O-LEACH and SA-LSA respectively.

Table 4 Lifetime Computation for PSO-LSA

Number of rounds	LSA	O-LEACH	SA-LSA	PSO-LSA
0	100	100	100	100
100	100	98	98	100
200	94	89	91	94
300	87	73	76	87
400	78	62	67	78
500	66	24	45	66
600	43	11	32	43
700	22	4	11	22
800	6	0	2	6

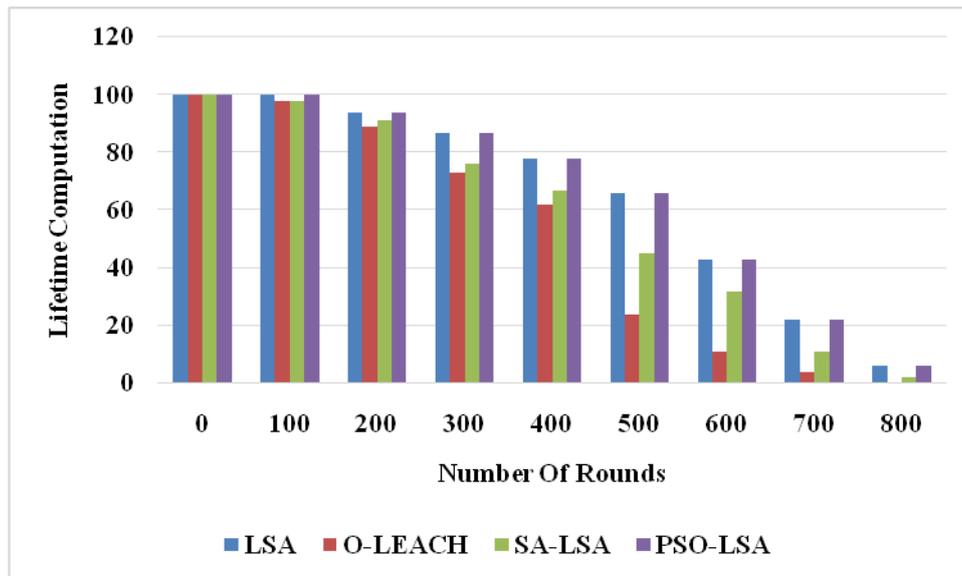


Figure 9 Lifetime Computation for PSO-LSA

From the figure 9, it can be observed that the PSO-LSA has higher lifetime computation by 2.02% & 2.02% for 100 number of rounds, by 5.46% & 3.24% for 200 number of rounds, by 17.5% & 13.49% for 300 number of rounds, by 22.86% & 15.17% for 400 number of rounds, by 93.33% & 37.84% for 500 number of rounds, by 118.51% & 29.33% for 600 number of rounds and by 138.46% & 66.67% for 700 number of rounds when compared with O-LEACH and SA-LSA respectively. The PSO-LSA has higher lifetime computation by no change for LSA, respectively.

5 CONCLUSION

WSN routing's primary design issue is coverage. Lower orphan nodes are used in this protocol to enhance the network's reliability as well as connectivity. More data is made available at the BS with values gathered by orphan nodes. This facilitates a better decision on the application and rapid response. The O-LEACH routing protocol for homogeneous WSNs can be optimized to minimize the isolated nodes and improve the sensor network's connectivity. Proposals of the hybrid SA-LSA and PSO-LSA techniques are given in this work for the minimization of the isolated nodes. Based on nature's lightning discharge phenomenon to the Earth, the classical LSA algorithm has a quick rate of convergence and also explores better solutions through replication of the lightning bifurcation process. Falling of the LSA into the local optimal solution is avoided through the SA's utilization. The algorithm has higher computational accuracy by adding crossover and mutation operations prior to SA's introduction. The design of absorbers capable of the maximum amount of vertically incident microwave energy absorption is achieved with the SA-LSA algorithm. When compared to other heuristic algorithms, thinner and less reflective absorbers are obtained by the SA-LSA algorithm. As the standard LSA suffered from poor convergence accuracy, there was the addition of a PSO technique for its accuracy improvement. PSO is an evolutionary computation technique that is SI-based, which does not utilize evolution operators like crossover and mutation. Its benefits like simplistic operation and local minima avoidance, make it an efficient global optimization algorithm. Experimental outcomes

demonstrate that the PSO-LSA has higher number of clusters formed by 6.45%, 6.45% & 6.45% for 200 number of nodes, by no change, 8% & 3.92% for 400 number of nodes, by 4.76%, 7.23% & 2.35% for 600 number of nodes, by 2.1%, 6.45% & 4.25% for 800 number of nodes and by 2.15%, 4.34% & 2.15% for 1000 number of nodes when compared with LSA, O-LEACH and SA-LSA respectively. In future work, the hybrid SA-LSA algorithm can solve this multi-objective problem and compare it with other algorithms to verify its performance. To implement various other meta-heuristic algorithms and to improve the computational complexity.

DECLARATIONS

We hereby declare that we are the sole author's of this article. To the best of my knowledge this article contains no material previously published by any other person except where due acknowledgement has been made.

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Figures

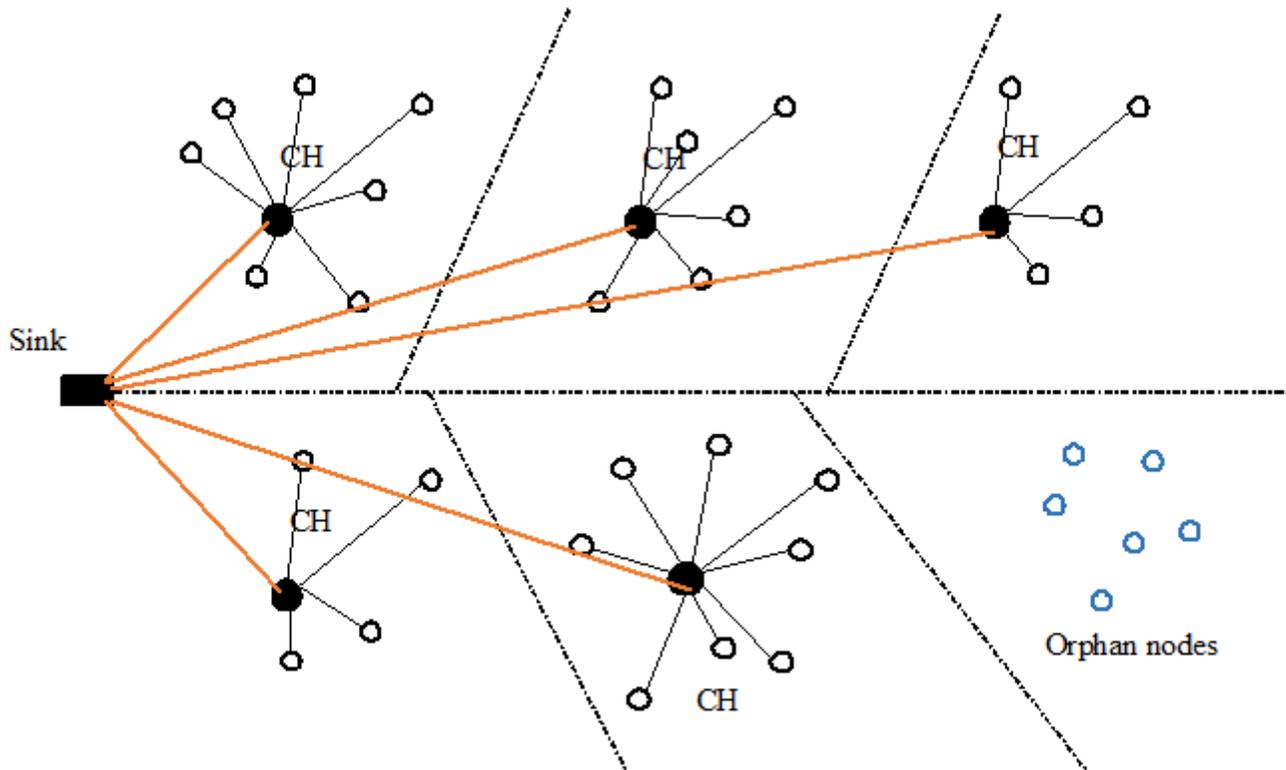


Figure 1

T round in O-LEACH with orphan nodes

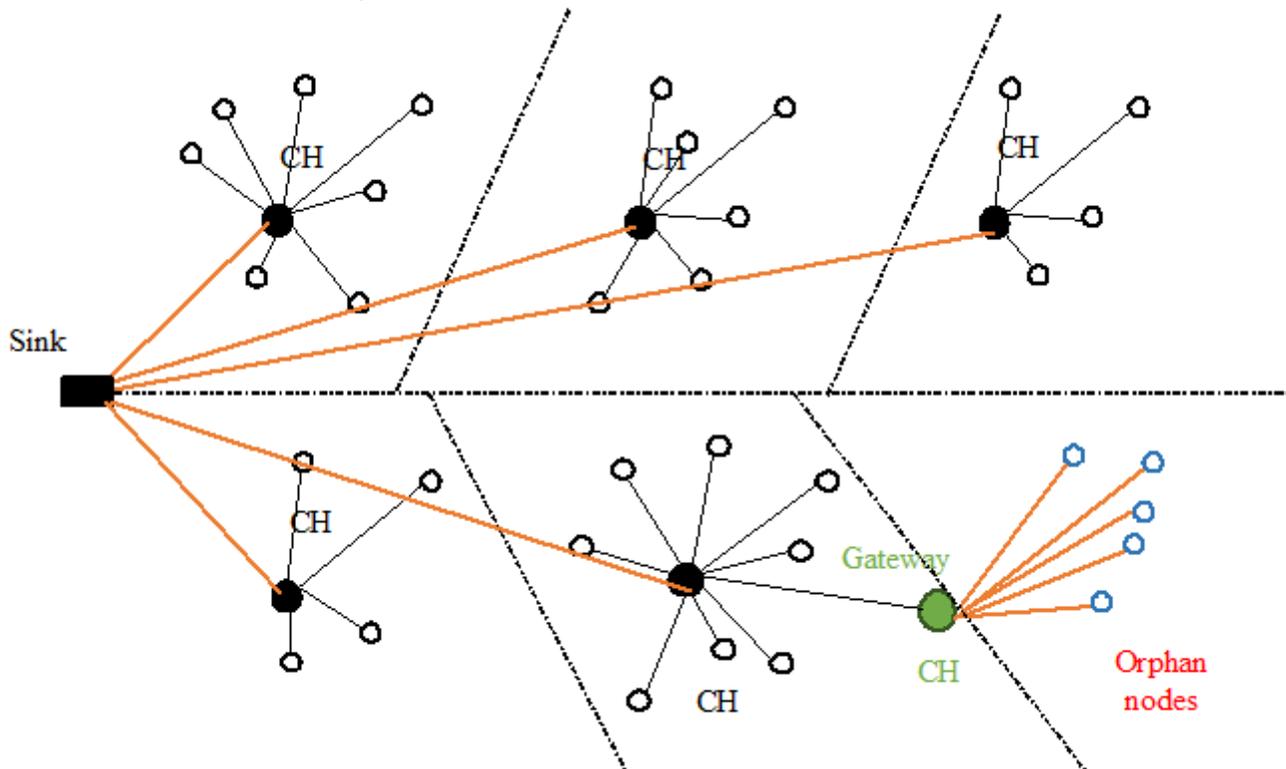


Figure 2

Solution with member gateway CH scenario 1

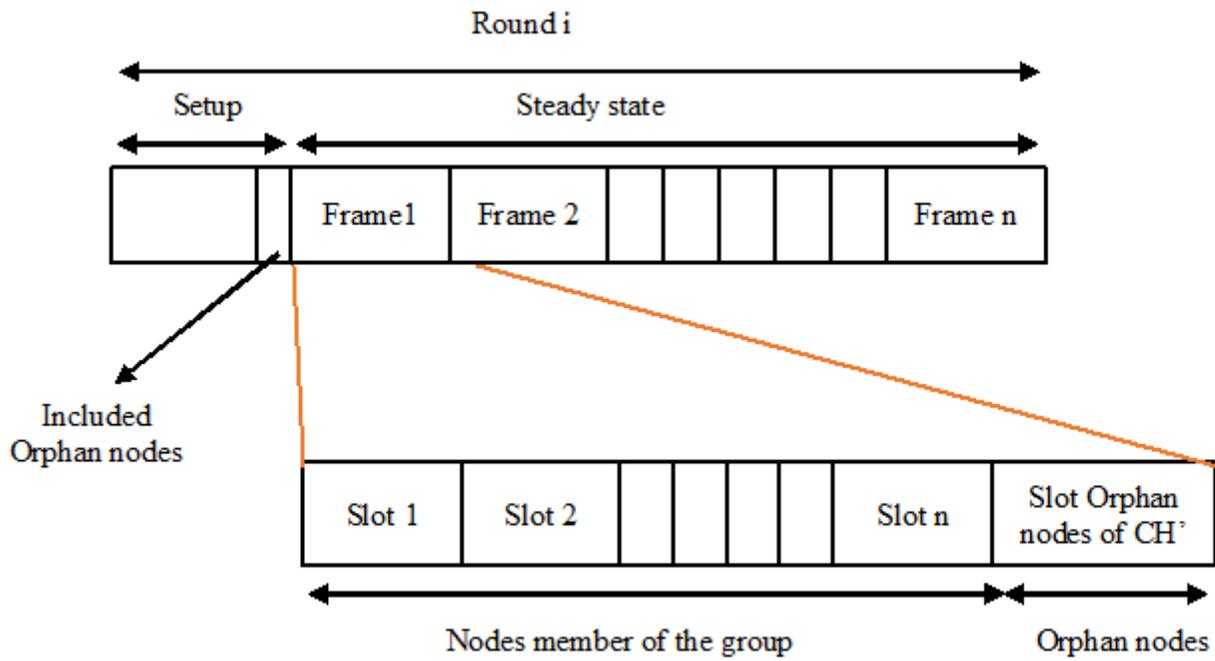


Figure 3

T round in Orphan-LEACH reserved slots

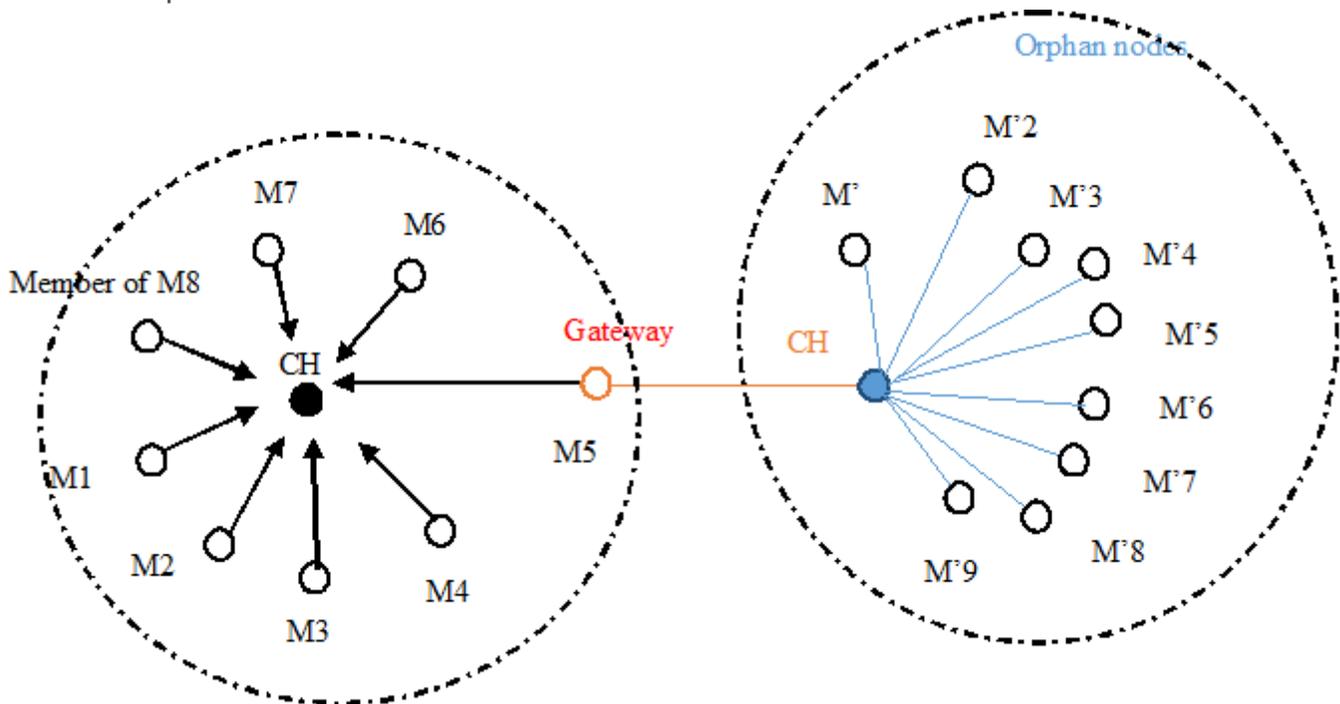


Figure 4

Setup Phase extension Orphan-LEACH scenario 2

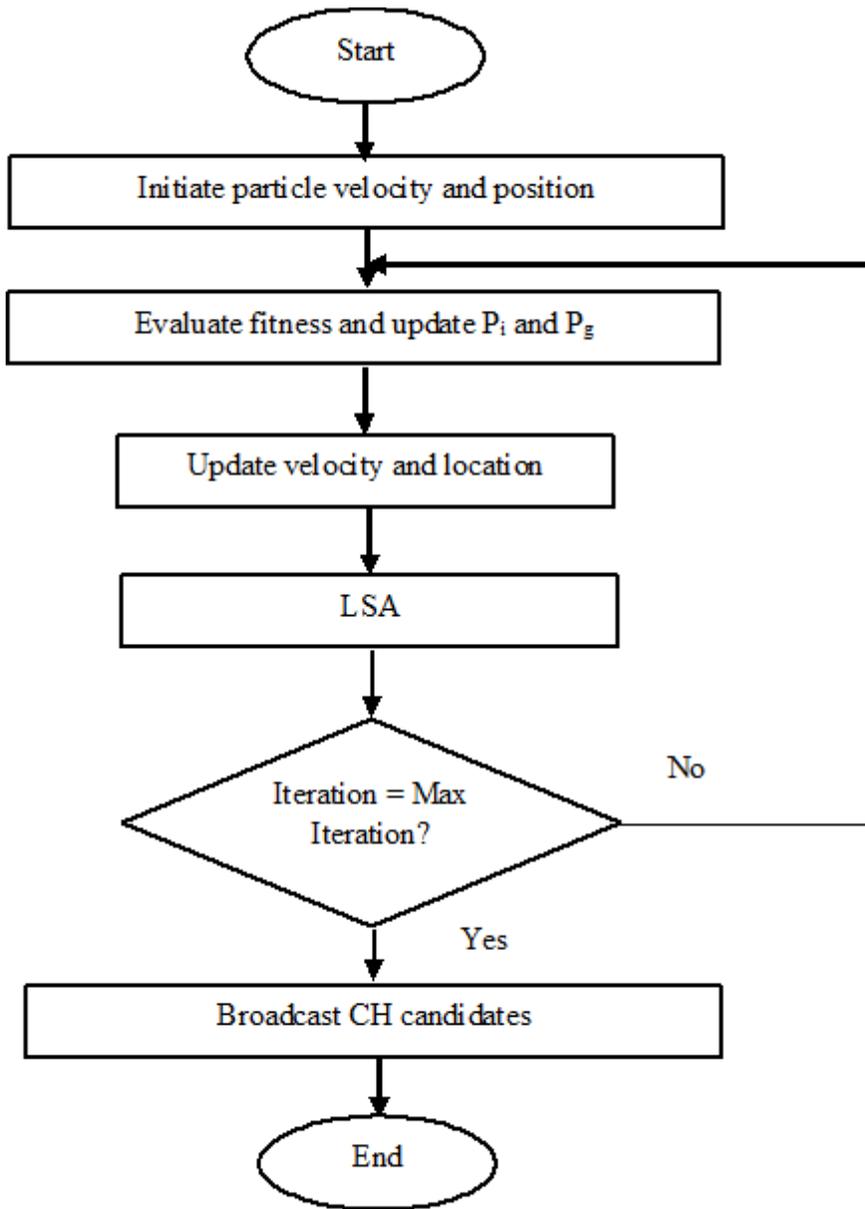


Figure 5

Proposed Hybrid PSO-LSA Method

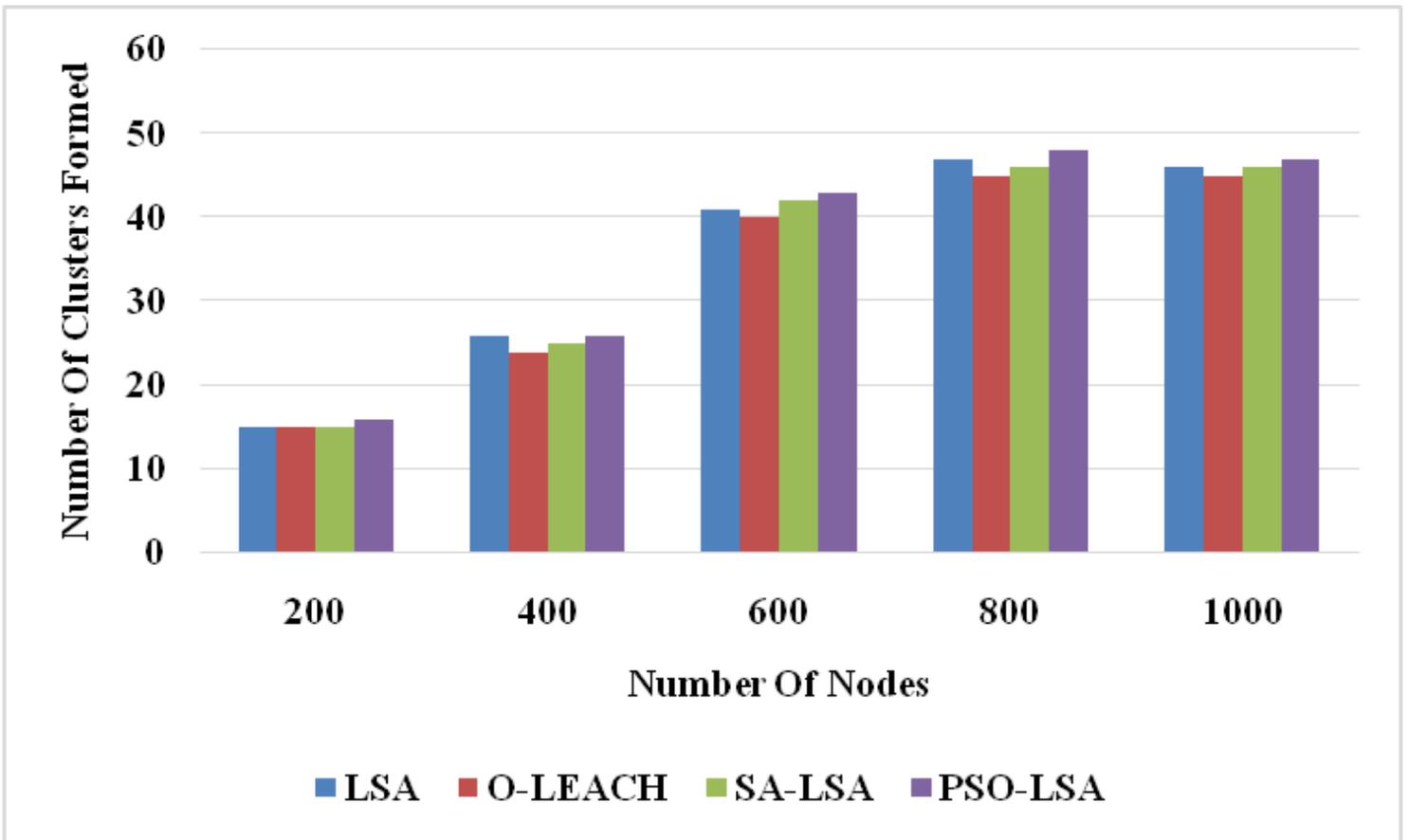


Figure 6

Number of Clusters Formed for PSO-LSA

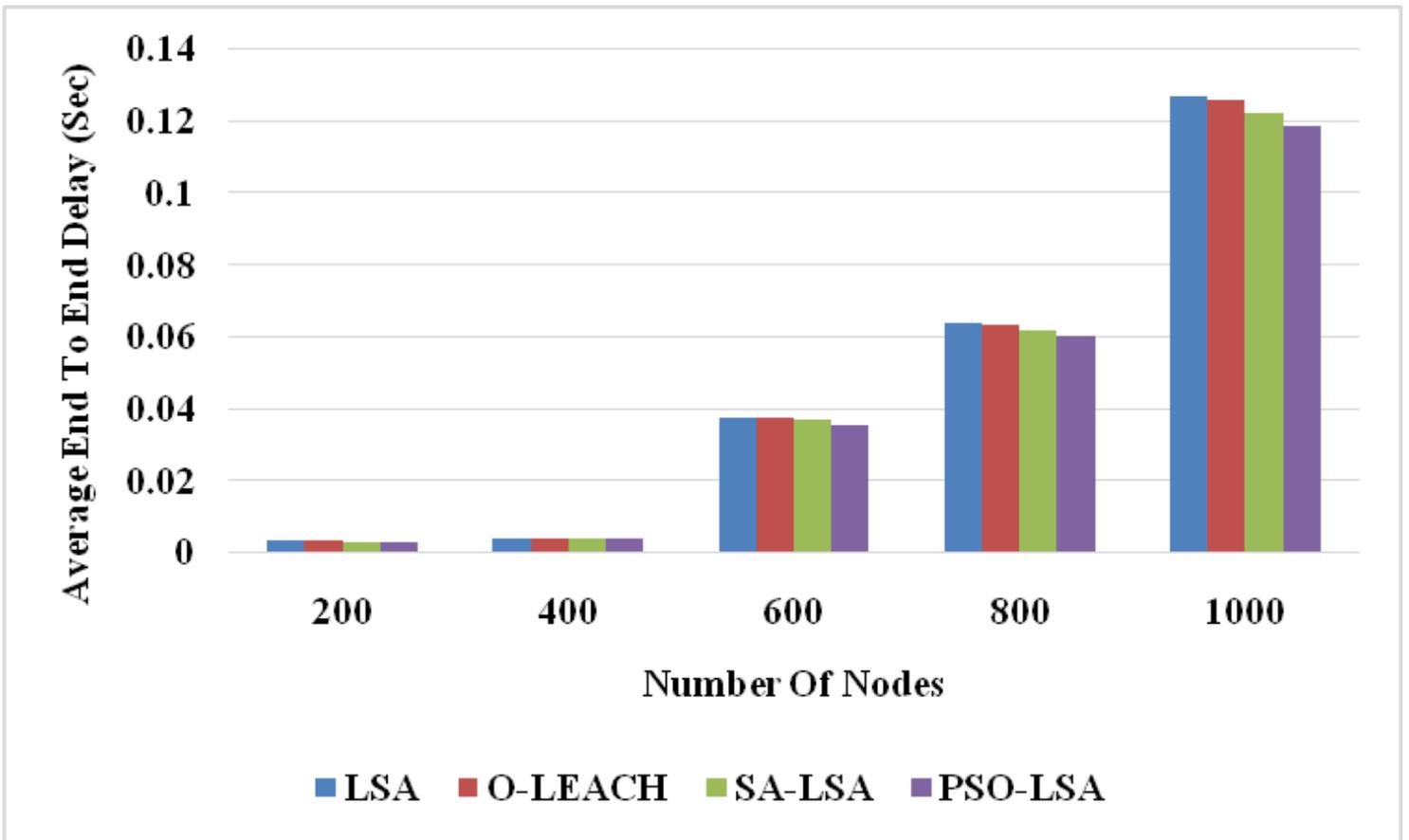


Figure 7

Average End to End Delay for PSO-LSA

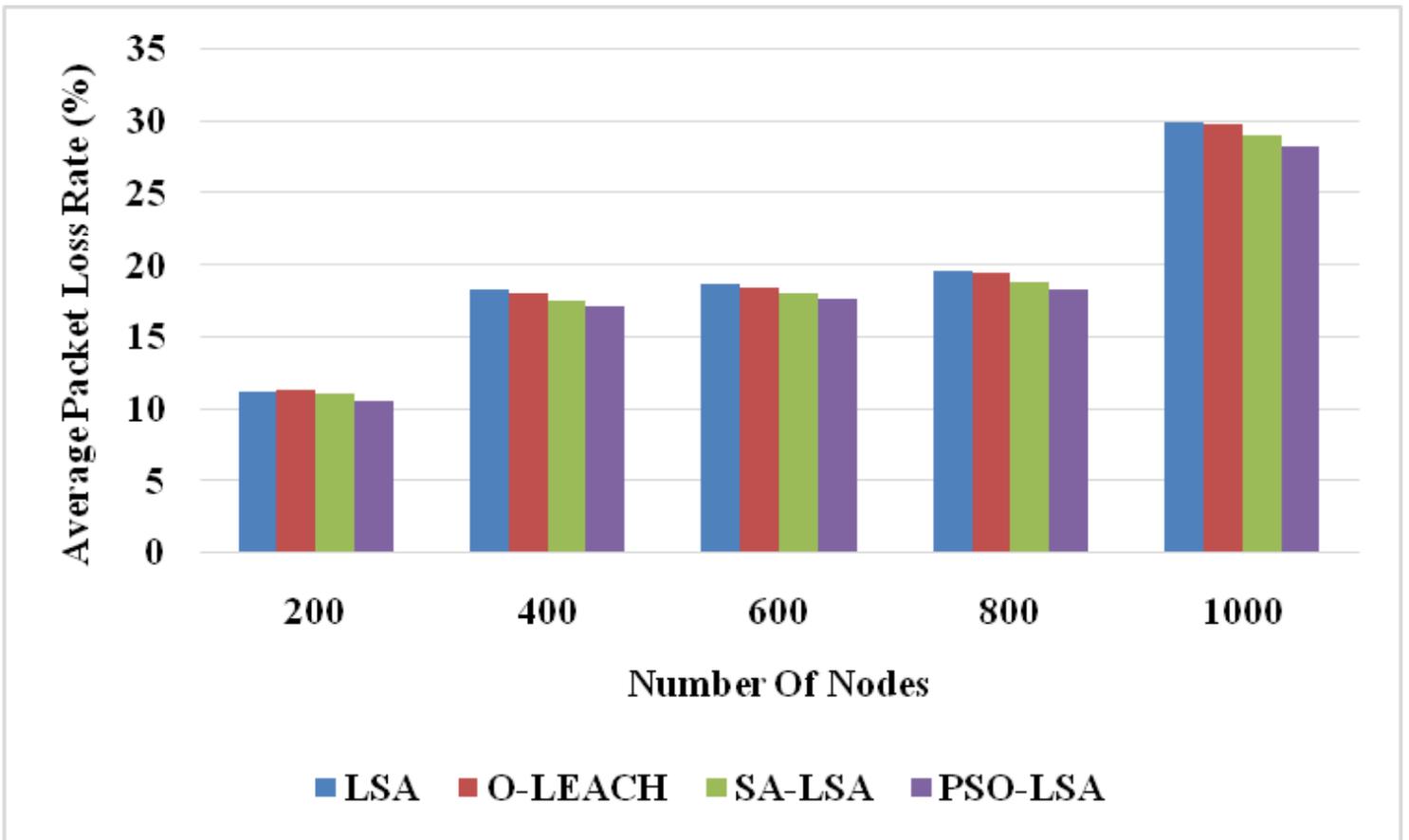


Figure 8

Average Packet Loss Rate for PSO-LSA

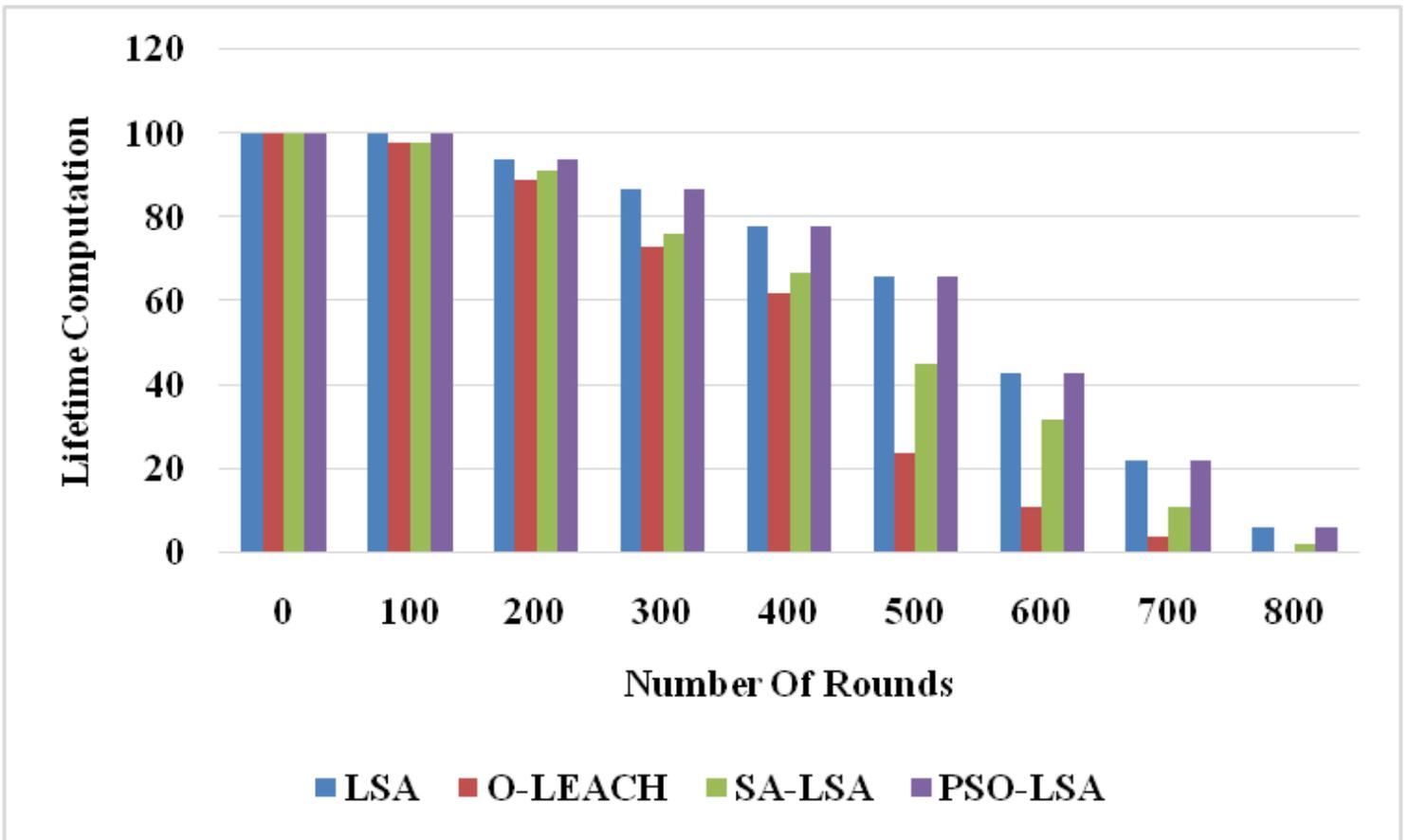


Figure 9

Lifetime Computation for PSO-LSA