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Internet of things multi hop energy efficient cluster-based routing using particle swarm optimization

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Abstract

The Internet of Things (IoT) is a collection of various sensors connected to the internet that share information. In a large-scale IoT network, data is collected through the wireless sensor network (WSN), and the aggregated data is sent from the sink to the next level of IoT for processing. Clustering is utilized to cut down on energy use, network redundancy, interference, and collision in WSN and improve network lifetime, scalability, and data aggregation. In addition, multi-hop communication is more effective for networks with sensors that cover a broad region. The Multi-Hop Low Energy Adaptive Clustering Hierarchy brings about a reduction to the transmission distance and prolongs the network lifetime. This particle swarm optimization (PSO) technique is effective for determining the most effective solutions for a particular problem. The particles in the PSO embody the candidate solutions tend to move through their solutions space (in several directions) in different velocities. A distributed multi-hop cluster-based routing algorithm that takes advantage of the PSO and the Lightening Search Algorithm is developed in this work. The proposed method optimizes the clustering process and achieves energy efficiency, as demonstrated by the experimental results. Reduced end-to-end delay and lower packet loss rate whereas the lifespan network and cluster count are improved.

Keywords IoT · Wireless sensor network · Clustering · Multi-hop low energy adaptive clustering hierarchy · Particle swarm optimization · Lightning search algorithm

1 Introduction

The Wireless Sensor Networks helps with the Internet of Things (IoT) platform. IoT has shown how the same technology may be used in environments including home monitoring, healthcare, and the environment. [1, 2]. A crucial issue in WSN is energy consumption. If the WSNs' energy is properly utilized, the network lifetime can be prolonged. In this network, any change in a node within the network can induce change to the topology, which further results in the overhead messages for maintenance of topology.

Some serious scaling difficulties can arise in a large-scale IoT network, as getting all of the nodes connected to the Internet, as well as each individual connection, might be a challenge. [3, 4]. To reduce scalability difficulties, the nodes are distributed into clusters, and a scluster head (CH) functions as the node's gateway to the cluster. Data is transmitted between the nodes in the cluster and the CH, which transfers the aggregated data to the gateway. Adapting the IoT architecture in all domains that include energy harvesting, home automation, environment, and biomedical fields is anticipated, and this will reach a realization immediately.

Clustering denotes an efficient and scalable network structure for the collaboration of sensor nodes made by grouping and gathering nodes within the hierarchy. There can be a high contribution made to hierarchical clustering in the WSNs for the overall system scalability, efficiency of

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energy, and network lifetime. Through the use of clusters, it may be efficient and also a good method of reducing the amount of messages sent to the base station by aggregating the data, as well as lowering energy consumption [5].

The clustering of networks into groups is studied extensively in transmissions of the sensed data within the WSN. Batteries are used to power the sensor nodes, which makes it difficult to replace or recharge them. The methods of clustering used in the WSNs support scalability and communication that conserves energy among the nodes to prolong network lifetime [6]. It has to be remarked that this varies from typical sensors, and the IoT network nodes will be required to be part of appliances equipped with a power supply that was continuous to complete specific types of intrinsic functionality aside from sensing alone.

For all IoT networks [7], when it comes to reducing the number of Internet connections rather than the number of communications that are energy efficient, reducing the actual number of Internet connections becomes the most important problem in terms of reducing the cost of network administration.

In most cases, the WSN sensor nodes are deployed randomly, and the BS is established at a distance. Thus, the nodes will require to expend more energy to deliver data to the BS. So, the sensor node energy runs out and dies fast. A Multi-Hop LEACH protocol attempts at distributing the load to all parts of the network to achieve balance, and it also considers the dissipation mode. Thus, it attempts to identify the distance, which is the lowest possible one and used by the CH to transmit data. In contrast, when compared to the Low Energy Adaptive Clustering Hierarchy, the MH-LEACH is both adaptable and varied in its design.

Several schemes were energy-efficient, which were developed for the IoT, and this was a major challenge since the IoT was getting even more intricate owing to its large-scale technique. For achieving a green network IoT, the issues of energy efficiency were addressed by Rani et al. [9] by a proposal for another novel scheme of deployment. The scheme introduced: (1) a new hierarchical network design; (2) an energy-efficient IoT model; (3) an algorithm of minimum energy consumption transmission for implementing an optimal model. According to the simulation results, the novel system is more energy and flexibility efficient when compared to the previous WSN techniques that have historically been used.

In WSNs, multi-hop graph-based routing (MH-GEER) was developed by Rhim et al. [10] to balance consumption of energy and, moreover, seek to increase the network's lifespan. It dealt with the clustering of nodes as well as the selection of inter-cluster multi-hop routing protocols between them. During the clustering phase, centralized clusters emerged, as well as a distributed selection of CHs, such as the LEACH clustering system. This routing stage further built a new and dynamic multi-hop route among CHs and their BSs. The approach proposed was concerning exploring the levels of energy for the entire network by using the chosen subsequent hop in an intelligent and probabilistic manner. The evaluation proved the MHGEER to have minimized depletion of energy and also ensured network load balancing. With this protocol, compared to the standard LEACH protocol, which was a single-hop protocol, the network lifespan and stability were significantly increased.

Arioua et al. [11] proposed another new approach to clustering, combining the MTE and LEACH protocols. Communication to the network has been optimized via multi-hop rather than direct communication. The simulation results have demonstrated the multi-hop energy efficiency of this method. The proposed approach was effective in prolonging lifespan and providing a significant boost to the WSN's overall energy capacity. In a cluster-based multi-hop network, the authors proposed another EACBM protocol for routing: Toor and Jain [12] developed an alternative protocol for routing using heterogeneous WSNs in which the clustering along with multi-hop communication is used to reduce energy consumption. The SNs that were not part of any cluster or were no longer reachable were identified by using a notion of sub-clustering. The protocol was simulated and further compared to the current routing protocols (LEFCA, CEEC, SEP, and LEACH) in MATLAB, and the EACBM had been able to outperform concerning stability and network lifetime. It also provided better efficiency of energy in the heterogeneous WSNs.

A multi-hop mechanism of clustering in IoTs for minimalizing the need for network links was presented by Sung et al. [13]. More specifically, the proposed mechanism had the objective of choosing a minimal number of CHs. This problem had mapped into a problem of set cover that was NP-hard; it had to pursue a heuristic approach for being solved. Turkish et al. [14] proposed a set of energy-efficient strategies of routing, which were three in number, to design a novel PSO-based WSN based routing. The initial approach will maximize node energy using the lowest energy (the node that performs the worst) in WSNs. The second step will maximize the entire energy of WSN, and finally, the worst-performing node's energy is maximized. Results had compared to a new benchmark variant consisting of a protocol of LEACH known as the LEACH-Centralized Sleeping (CS). They proved that the strategy was able to maximize the overall energy of WSN for improving the network lifetime to a better level. They also proved an energy harvesting-aware protocol of routing could extend the WSN lifetime compared to a protocol that was not considered to be energy harvesting aware. Aghora et al. [21] proposed a Multi-tier MH-LEACH (MMR-LEACH) for increasing the lifetime of the WSN. In the proposed method a residual energy which functions as an intermediary between the CH and the base station, is used to choose a Vice CH. Because the CH is in charge of gathering and processing the data, as well as delivering it to the base station, there is less strain on the WSN, resulting in conservation of energy and prolonging the useful lifetime of the WSN.

Based on the works available in the literature, it is observed that various schemes for improving the energy efficiency of the LEACH protocol are available and similarly, techniques like graph-based, multi-tier are proposed for improving the MH-LEACH. Optimizing the MH-LEACH is addressed with swarm intelligence using PSO and Lightning Search Algorithm (LSA) metaheuristics. The principles of swarm intelligence have been best applied to the different dynamic systems needing self-organization, scalability, and robustness. At the time of ensuring the optimality of solutions has, this is not a very crucial factor. An innovative computational approach known as the Particle Swarm Optimization (PSO) includes the social behaviors of real-world species for computation [8]. The process of optimization, along with the objective optimizing fitness function, is a swarm intelligence technique. The approach employs a swarm to search in each particle and records its fitness value. Once the work is completed, the particles will be connected to their corresponding velocity. It helps the particles choose an ideal location by taking the cost of the fitness function of the particles. The PSO has better throughput and energy compared to the other heuristic and mathematic approaches. The LSA metaheuristic is based on the lightning phenomena. The LSA has good convergence, effective global exploration for solutions, robust and requires few parameter tunings.

This approach involves utilizing the LSA and the PSO to improve the MH-LEACH protocol's performance. In the PSO, LSA, and MH-LEACH protocols, go on to Sect. 2 for further information. Section 3 describes the results and the discussion, and Sect. 4 contains the conclusion.

2 Methodology

This section provides details of the Particle Swarm Optimization, the Lightning Search Algorithm, and the Multi-Hop LEACH.

2.1 Multi-hop low energy adaptive clustering hierarchy (MH-LEACH)

For this work, a multi-hop communication protocol was used to transmit data from nodes to CHs (intra-cluster routing) and from the CH to the BS which is the destination. The CH combines the data in order to conserve leftover energy. A threshold value of d is specified. The distance between the cluster's CH and BS must be less than or equal to the threshold value; the CH will then send the aggregated data through single-hop transmission. If not, the CH must locate the cheapest next hop and utilize it as a relay node [15]. Additionally, this node is chosen depending on its distance and leftover energy. The relay cluster node is further chosen using minimum cost for sending data to its BS and for inter-cluster routing, which is established as soon as a selection is made.

In Multi-Hop LEACH, CH is farther than the threshold distance and can create special routing to choose the shortest route. The MHT-LEACH, according to its own model, envisions the implementation of three stages to create the pathways between the CH and its BS. They are [16]:

- *Phase 1*: An assumption is made that the CH is voted in a setup phase as in MH-LEACH protocol. Then after, every CH will construct another routing table by broadcasting an announcement message to every other CH.
- *Phase 2*: Based on the do, the CHs are divided into two groups: the first is external, which includes the CHs that are placed at a distance more than or equal to the do; and the second is internal, which includes the CHs that are located at a distance less than or equal to the do. The next is internal, which contains all nodes in the distance less than do.
- *Phase 3*: The internal transmission of data from the CH to the BS is determined by the distance between the CH and the BS. Every CH will create a new routing table based on the announcement message in order to choose the next hop to the BS when it receives it.

2.2 Proposed particle swarm optimization (PSO)

The PSO algorithm [17] is initialized with random solutions, which are referred to as particles, in order to determine the outcome of optimization. For every particle, there will be a velocity and position, and each of them indicate an available solution to optimization and a route to look for. Every time the algorithm iterates, the particle will alter its velocity to give the greatest possible experience. That best possible experience is then designated as the pbest, and the second-best experience is designated as the gbest. The PSO uses an objective function to evaluate candidate solutions and operates on the fitness values. The fitness function for each particle will compute, and its fitness value (the best solution) will be computed and further stored. The current optimum fitness value is known as pbest. The PSO also optimizes the population that is the best obtained by any particle among neighbors in the same location, known as the lbest. For each generation, both velocity and position are updated by Eqs. (1):

$$V_{pd}^{k+1} = \omega V_{pd}^{k} + c_1 r_1 \left(pbest^k - X_{pd}^k\right) + c_2 r_2 \left(gbest^k - X_{id}^k\right)$$
$$X_{pd}^{k+1} = X_{id}^{k} + V_{pd}^{k+1} \tag{1}$$

wherein ω denotes inertia weight, that ranges between 0.2 and 0.9; k represents number of iterations; V_{pd}^k describes velocity determined in d-th dimension of its p-th particle; X_{id}^k denotes the actual location of d-th dimension belonging to the p-th particle; the pbest and the gbest denote the remembrance of the particle; c_1 and c_2 denote the cognizance, as well as the social factor; r_1 and r_2 indicates the random functions that are distributed uniformly in [0, 1].

PSO method utilizes several candidates in the search space at the same time. Every candidate solution will be assessed by an objective function that is optimized for every iteration in the algorithm and determines the solution and its fitness. Every candidate solution is considered a particle that flies through the fitness landscape, which finds the maximum or minimum in the objective function. For the first part of the process, the PSO will choose a solution in the search space at random. [18]. The flowchart of PSO is shown in Fig. 1.

The suggested technique involves the use of a genetic algorithm to optimally combine clustering and selection of cluster head based on the energy, which provides more energy conservation and faster path selection for the network. Nodes are represented as particles, and residual energy in the nodes, latency, and numbers of hops all contribute to the fitness.

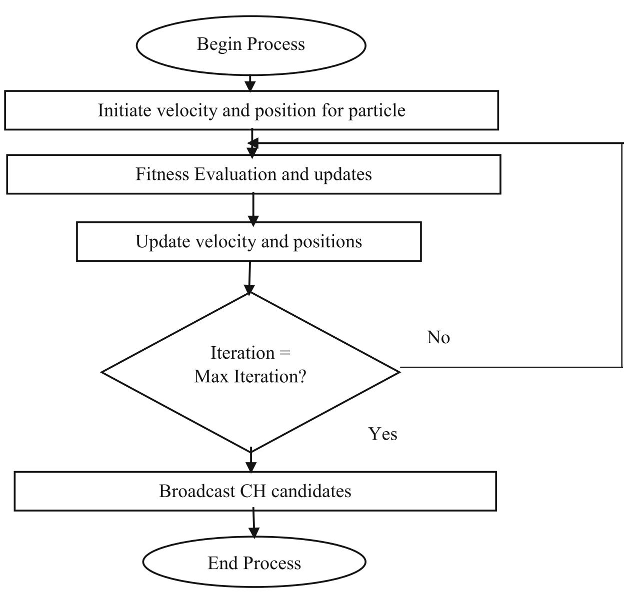

Fig. 1 Flowchart for particle swarm optimization (PSO)

2.3 Proposed lightning search algorithm (LSA)

The algorithm behind the Lightning Search has been built around the physical presence of lighting and has incorporated the sinuous attributes and mathematical probability of lightning discharge from a thunderstorm. This method has been derived from the step leader propagation mechanism that incorporates a concept known as projectiles. It is the starting population size that is strikingly comparable to the particle utilized in a particle swarm optimization algorithm. To conclude, a solution is whatever the leader is bringing to the table with his or her enthusiasm and the present step [19, 20].

The Lightning Search Algorithm can explain as:

- *The projectile model*: LSA consists of three projectiles: the transition projectile, the space projectile, and the lead projectile. The transition results in the formation of the initial step leader population for problem solving. Exploration and leadership are attempted by space, and the lead projectile is tasked with finding the most optimal answer.
- *The transition projectile*: When a stepped lead is being formed, the earlier stages of creation are used, and a transition projectile which is $P^T = [P_1^T, P_2^T, ..., P_N^T]$ will be ejected from its thunder cell randomly. Thus, this may be modeled to be a random number taken from a probability distribution which is standard and uniform in Eq. (2):

$$f(x^T) = \begin{cases} \dfrac{1}{b-a} & \text{for } a \le x^T \le b \\ 0 & \text{elsewhere} \end{cases} \tag{2}$$

  wherein x^T denotes the arbitrary number providing solutions, and ‘a’ and ‘*b*’ are the lower and upper bounds in solution space. For the population of the N are the stepped leaders $SL = [sl_1, sl_2, ..., sl_N]$, N denotes a random projectile for meeting solution dimensions.
- *The space projectile*: The space projectile position $P^S = [P_1^S, P_2^S, ..., P_N^S]$ at step + 1 may be modeled to be a arbitrary number that is attained from an exponential distribution along with a shaping parameter μ as per Eq. (3):

$$f(x^s) = \begin{cases} \dfrac{1}{u} e^{-x^s/\mu} & \text{for } x^s > 0 \\ 0 & \text{for } x^s > 0 \end{cases} \tag{3}$$

  So, both position and direction of P_i^s at step + 1 is represented as in Eq. (4):

$$P_{i\_new}^s = P_i^s \pm \exp \ \text{rand}(\mu_i) \tag{4}$$

  wherein the exp rand denotes the exponential random number, μ_i is measured to be the distance between the lead projectile pL and space projectile P_i^s is considered.

In case $P^s_{i\_new}$ can give an ideal solution at step + 1 and projectile energy P^s_i is higher than its step leader E_{sl_i}, then in that case, P^s_i will be updated as $P^s_{i\_new}$. If not, it will be unchanged until the subsequent step.

- *The lead projectile*: A random integer from a typical normal distribution modelled the Lead Projectile PL as it moved closer to the target, according to the Eq. (5):

$$f\left(x^L\right) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\left(x^L-\mu\right)^2/2\sigma^2} \tag{5}$$

The lead projectile generated randomly will lookout in several directions from its current position that is defined using a shape parameter (μ_L). The projectile is the ability to exploit and is defined.

by a scale parameter (σ_L). This scale parameter σ_L will decrease exponentially while progressing towards the Earth or while identifying its best solution. So, the actual location of pL which is at step+1 is written as per equation (6):

$$P^L_{new} = P^L + norm\ r\ and(\mu_L, \sigma_L) \tag{6}$$

wherein normrand denotes the normal and random number that is generated using a normal distribution function. In case p_L new has a good solution which is at step + 1 a, d projectile energy $E^L_{p\_i}$ is more than step leader E_{sl_i},then P^L updates to P^L_{new}. Else, they do not change until the subsequent step.

- *The forking procedure*: This is a crucial characteristic of the stepped leader, which has two symmetrical branches that occur at the same time. There are two methods in which forking can be accomplished. First and foremost, symmetrical channels are created since, according to Eq. (7), nuclei collision for the projectile is accomplished by utilizing its opposite number.

$$\overline{P}_i = a + b - P_i \tag{7}$$

wherein $\overline{P}_i$ and P_i denote the opposed and the original projectiles falling in a 1-Dimensional system in which a and b are border confines. For maintaining the size of the population, a forking leader will choose $\overline{P}_i$ or P_i having a better fitness value. In the next type, there is a channel that is taken to appear in the position of a successful step leader tip since the redistribution of energy for an unsuccessful leader is made after several trials of propagation.

2.4 Pseudocode for lightning search algorithm

```
Initialize the populations (random solutions); Direction for each dimension in the population is initialized.
While (until termination) do
        Compute the fitness for each solution
        Sort the population
        Define the best and worst population
        Update the energy
        Update the direction for each dimension
        For each I=1: N where N = Pop
                If (pop (i) = = leader solution) then
                        Update the position of pop
                Else if (pop (i) = = Space solution) then
                Update the position of pop
                End if
                If (Pop (i) is not improvised) then
                        Initialize new pop
                End if
        End for
End while
OUTPUT: Best Step Leader
```

3 Results and discussion

The approaches' effectiveness was tested with the use of the Matlab software. Table 1 contains the simulation parameters. This experiment works well when working with networks between 200 and 1000 nodes. An investigation of the performance of Multi-Hop Leach as well as the proposed PSO and Lightning Search based methods is performed. This evaluation measures the average packet loss ratio, the average end-to-end latency, and the number of clusters that are created, as well as the length of time these clusters exist. Tables 2, 3, 4 and 5 and Figs. 2, 3 display the number of clusters, the average end-to-end latency (seconds), and the packet loss rate (percent). They also indicate the life expectancy, where the proportions of nodes that are still alive are shown.

In the case of a rise in the number of nodes, the Number of Clusters is raised. Clustering revealed the three search algorithms—Lightning Search Algorithm, Multi-hop LEACH, and PSO—created clusters that were almost identical in number are shown in Table 2 and Fig. 2. With the use of the Lightning Search Algorithm, it is shown that when the network performance increases, the packet loss and end-to-end delay decrease.

An increase in the number of nodes increases the amount of time it takes for an End to End Delay (seconds). In comparison to the Multi-hop LEACH and PSO, the Lightning Search Algorithm has a notable impact on the End-to-End Delay. Looking at Table 3 and Fig. 4, the Lightning Search Algorithm offers an end-to-end latency that is better by 5.71% and 2.89% at various nodes (200) than the Multi-hop LEACH and PSO. The time taken from one node to the next in the chain (end-to-end delay) for Lightning Search Algorithm is shorter by 4.68% and 2.41% than Multi-hop LEACH and PSO, respectively, at a thousand nodes. The Lightning Search Algorithm, as suggested, picks pathways based on factors such as residual energy in nodes and the amount of hops between each node. The result is that the overall latency is lower than that of Multi-hop LEACH and PSO.

When the number of nodes increases, packet loss occurs more frequently. Packet loss rate is lower using the Lightning Search Algorithm than Multi-hop LEACH and PSO. Table 4 and Fig. 5 demonstrate that the average packet loss rate percentage for the Lightning Search Algorithm is superior, with the loss rate being reduced by 6.72% and 3.76%, respectively, when compared to Multi-hop LEACH and PSO, when applied to many nodes 200. At a number of nodes of 600, the Lightning Search Algorithm performs better than Multi-hop LEACH and PSO in terms of average packet loss rate percentage, decreasing loss rate by 5.29% and 2.94%, respectively, compared to the latter. For Lightning Search Algorithms the average rate of loss for packets is improved by lowering loss by 5.62% and 3.22% correspondingly compared to Multi-hop LEACH and PSO for certain nodes of 1000. The proposed approach has an increased ability to find the optimum path avoiding packet loss. The fact that the packet loss is much reduced as compared to the Multi-hop Leach method is clearly seen from the result of the clustering and end-to-end latency.

When the number of nodes rises, the Lifetime—Percentage of nodes alive decreases, yet the Lightning Search Algorithm raises the Lifetime—Percentage of nodes alive more than Multi-hop LEACH and PSO. Table 5 and picture 5 demonstrate that the Lightning Search Algorithm performs much better than Multi-hop LEACH and PSO in terms of Lifetime computation-Percentage of nodes surviving at multiple rounds 200, with a difference of 5.46% and 3.24%, respectively. At a number of rounds 400, the Lightning Search Algorithm outperforms Multi-hop LEACH and PSO in terms of lifetime computation-percentage of nodes alive by 22.86% and 15.17%, respectively. With Lightning Search Algorithm, Lifetime computes a percentage that is 138.46% and 66.67% better than the Multi-hop LEACH and PSO at 700 rounds. In

Table 1 Simulation parameters

Parameter	Values
No. of nodes	200–1000
Simulation part (m)	1000 × 1000
Transmission assortment (m)	100
Traffic model	CBR
Size of packets in bytes	512
Simulation interval	3000 s
Bandwidth	2Mbps

Table 2 Number of clusters formed for lightning search algorithm

Number of nodes	Multi-hop leach	PSO	Lightning search algorithm
200	15	15	15
400	24	25	26
600	39	40	41
800	44	46	47
1000	44	45	46

Table 3 Average end to end delay (sec) for lightning search algorithm

Number of nodes	Multi-Hop Leach	PSO	Lightning search algorithm
200	0.0036	0.0035	0.0034
400	0.0045	0.0044	0.0042
600	0.0406	0.0391	0.0379
800	0.0678	0.0656	0.0642
1000	0.1333	0.1303	0.1272

Table 4 Average packet loss rate % for lightning search algorithm

Number of nodes	Multi-hop leach	PSO	Lightning search algorithm
200	12	11.65	11.22
400	19.2	18.74	18.32
600	19.81	19.35	18.79
800	20.95	20.24	19.58
1000	31.66	30.91	29.93

Table 5 Lifetime computation—percentage of nodes alive for lightning search algorithm

Number of rounds	Multi-hop leach	PSO	Lightning search algorithm
0	100	100	100
100	98	98	100
200	89	91	94
300	73	76	87
400	62	67	78
500	24	45	66
600	11	32	43
700	4	11	22
800	0	2	6

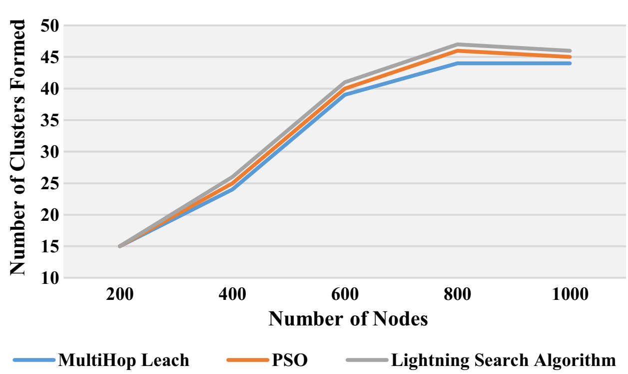

Fig. 2 Number of clusters formed for lightning search algorithm

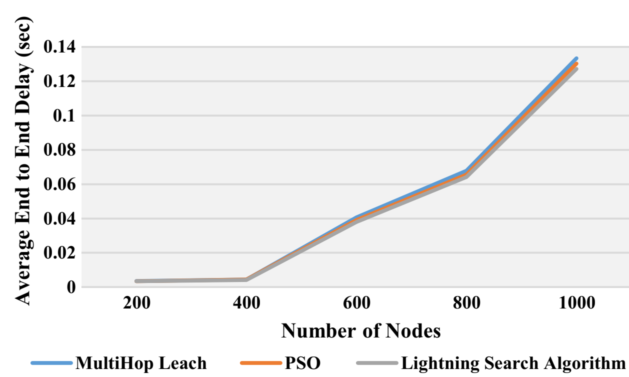

Fig. 3 Average end to end delay (sec) for lightning search algorithm

addition, the proposed Lightning Search Algorithm optimizes routing based on the residual energy in nodes as well as the number of hops; energy conservation in the nodes is achieved, resulting in a longer network lifetime.

4 Conclusion

With the Internet of Things (IoT), items that are separated are now able to communicate and operate on an entirely new platform that is accessible everywhere. The PSO is very effective and has a global capacity of fitness used by every particle in the swarm. Results have proven that the actual clusters formed for this Lightning Search Algorithm will be better by about 8% and further by about 3.92%

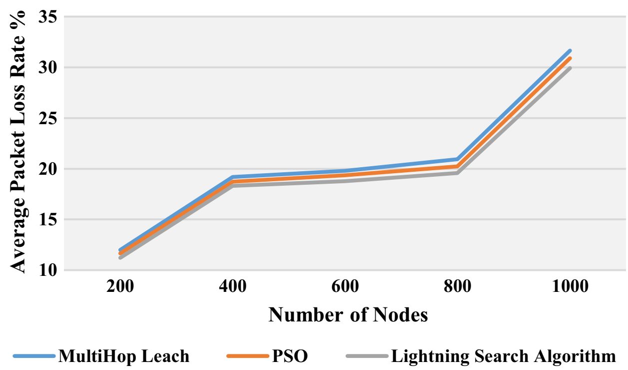

Fig. 4 Average packet loss rate % for lightning search algorithm

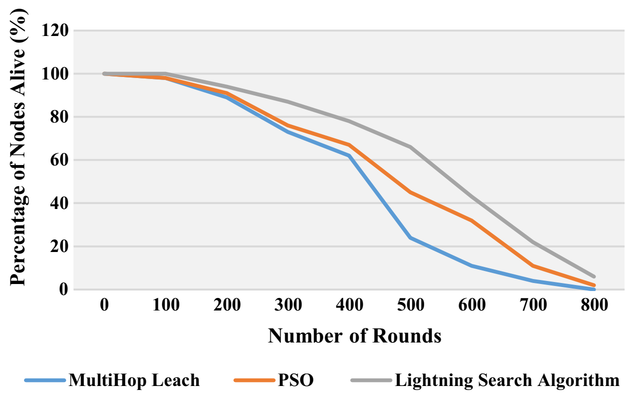

Fig. 5 Lifetime—percentage of nodes alive for lightning search algorithm

compared to the Multi-hop LEACH and the PSO at the number of nodes which is 400. The Lightning Search Algorithm's clusters are, on average, around 5% better and may be up to 2.47% better than the Multi-hop LEACH's clusters at 600 nodes. For the Lightning Search Algorithm, the calculated number of clusters was better by 4.44% and additional by 2.19% than the Multi-hop LEACH and the Particle Swarm Optimization at 1000 nodes. With this proposed Lightning Search Algorithm, the network lifespan is enhanced.

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