

Optimal Cluster Selection Method Using Bat Algorithm

Supriya Gupta¹, Md. Amir Khusru Akhtar²

Usha Martin University, Ranchi, India.

¹Email id: supriyagupta000@gmail.com

Abstract: Clustering is an unsupervised learning strategy that involves splitting a data object or observation object into a subset, i.e., categorizing the data using observation learning rather than example learning and without the supervision of preexisting class label knowledge. The Bat Algorithm (BA) is a swarm intelligence optimization technique inspired by bats' ultrasonic echo location foraging activity; nevertheless, it is vulnerable to local minima and lacks precision. As a consequence of this study, the OCSA algorithm was devised and presented. The OCSA algorithm was developed using BAT algorithm and energy model parameters. The proposed algorithm is compared to the LEACH, and R-LEACH algorithms under various convergence factors. The findings show that the proposed OCSA algorithm's clustering effect outperforms other intelligent optimization methodologies. After which WCV is introduced and the results are compared with OCSA, LEACH, RLEACH and the result shows that WCV is beneficial for the network's lifetime.

Keywords: Bat algorithm, echo location, clustering, OCSA, LEACH, R-LEACH, swarm intelligence optimization, WCV.

1. Introduction

Clustering is a kind of unsupervised learning in which a data item or observation object is divided into subgroups. Observational learning will be utilized to classify data rather than example-based training, and no prior class label information will be employed (Madhulatha, 2012).

Bionics-based algorithms for swarm intelligence are now gaining popularity. People have successfully used biological world inspiration for practical problems, and they have also produced a variety of meta-heuristic swarm intelligence algorithms based on biological system behavior. The particle swarm optimization (PSO) algorithm is inspired by the swarm behavior of birds and fish (Wang, Tan, & Liu, 2018). The harmony search (HS) algorithm, which is inspired by the behavior of simulated musical instruments (Manjarres et al., 2013), and the bee colony algorithm (BCA) (Ebrahimzadeh & Mavaddati, 2014), are examples of such algorithms.

The Bat Algorithm (BA) is a swarm intelligence optimization approach inspired by the ultrasonic echo localization foraging behavior of bats. However, the strategy is not advised since it might get locked in local minimums and lacks extreme precision. As a result, an enhanced bat algorithm was suggested. On actual data sets, LEACH, and R-LEACH algorithms, together with the enhanced bat algorithm(OCSA), are compared in this work regarding the clustering impact that they produce under convergence factors. According to the findings of the simulations, the

clustering effect produced by the enhanced bat algorithm is better than that produced by existing intelligent optimization algorithms.

2. Related Works

Yao, Cao, and Vasilakos (2014) presented the WSN community with a data-gathering strategy that was delay-aware, energy-efficient, and lifetime-balanced. This technique includes decentralizing and centralizing the heuristic to make the algorithm scalable enough to employ a wide range of network activities. Han et al. (2013) proposed a method for facilitating data transmission in duty cycle WSNs. The authors Zhu et al. (2014), in their study, aimed to provide insights into difficulties associated with duty-cycled WSNs. In their research paper, Pushpalatha and Shivaprakasha (2020) suggested an energy-efficient WSN data aggregating technique based on compressed data. Joint routing, as well as compressed aggregation, were used by the authors Tirani & Avokh (2018) to cut down on the amount of energy consumed. This optimization issue has been solved by characterizing the optimum solution, which has shown that the problem is NP-complete. In addition, a formulation of mixed-integer programming that uses the greedy heuristic approach was provided as a way to get to both the optimal and near-optimal aggregation trees. It was done by providing the information in the form of a sentence.

2.1 WSN and WRSN

Throughout the last few years, the field of wireless sensor networks has drawn the attention of many academics worldwide (Yu et al., 2014; Mugunthan, 2021). The sensor nodes of a wireless sensor network are capable of both single-hop and multi-hop data storage and transmission (Huang et al., 2017). Random placement of sensor nodes in unattended locations monitors the surrounding physical environment and its immediate surroundings. WSNs find applications in various industries, including intrusion detection, security surveillance, health care, bridge monitoring, military installations, and many more industries (Kandris et al., 2020). The performance of WSNs is negatively impacted by various variables, including but not limited to battery constraints, network structure vulnerabilities, short life cycles, and concerns connected to security (Araujo et al., 2012). Since the invention of the technology known as wireless power transfer (WPT), the concept of wireless rechargeable sensor networks has become a practical application (WRSNs) (Jia et al., 2017). This solution solves the problems that wireless sensor networks (WSNs) often run into, such as cumbersome battery replacement and low energy storage capacity (Tuna & Gungor, 2016).

The WRSNs are responsible for conducting a variety of important studies and applications of research (Lin et al., 2019; Huong et al., 2020). In WRSN-related research conducted in recent years, the primary areas of concentration have been on the optimization of system performance as well as the scheduling of charging. Academics are often unconcerned about the security problems associated with WRSN. Malicious software programs or algorithms that replicate themselves maliciously may be implanted into a network, which can lead to its paralysis as well as the loss of data (Liu, Peng & Zhong, 2020). Because of the particulars surrounding rechargeability, the pre-warning and real-time application domains run the risk of suffering catastrophic effects due to

Denial of Charge (DOC) assaults that are launched against rechargeable sensor nodes (Lin et al., 2019). Because of the above factors, doing security-related tasks on WRSNs is necessary.

Since the primary function of a WSN is to collect data while using a minimum amount of resources efficiently, several research projects have been conducted in the field of energy-efficient data collection in WSN. It is because the WSN was designed to do this duty. The majority of the algorithms used for obtaining data are geared at reducing the issue of excessive energy use. LEACH is a hierarchical protocol, and the cluster heads (CHs) are the ones who are in charge of handling the node information (Kodali & Aravapalli, 2014). The CHs are the ones that collect the data and send it to the base station once it has been compressed (sink). To determine the CH, the stochastic method is used at each node.

2.2 Clustering

Clustering is an unsupervised learning approach. Therefore it does not need any previous class labeling information to categorize data. This method relies on observational learning instead of learning from examples (Hsu, Levine & Finn, 2018). The process of partitioning a data item or an observation object into distinct subgroups is called clustering. Each subset may be thought of as its cluster. The goal of the clustering process is to ensure that the items included inside a cluster are comparable to one another.

In contrast, the objects located between clusters are distinct from one another. The swarm intelligence optimization technique has a strong capacity for optimization. The clustering issue may also be seen as an optimization problem in which the goal is to locate the best possible clustering center within the available solution space. The solution space for the clustering issue is represented as a combined collection of several clustering centers. Finding the clustering center that most effectively partitions the data into the solution space is the objective of the clustering process. People can continuously explore the solution space thanks to an optimization strategy component of swarm intelligence algorithms. This technique can be found in the algorithms. It is done to determine which combinations of clustering centers are the most suitable.

As a consequence of this, the optimization method that is based on swarm intelligence is a viable option for addressing the clustering problem. The dynamic clustering approach described by Kuo et al. (2012) is based on the particle swarm algorithm as well as the genetic algorithm. This technique can do automated data clustering since it detects the data without first specifying the number of clusters to be performed.

2.3 WCV

Recently, many researchers have been researching to alleviate the energy limits. There have been a few studies (Zhong et al., 2017; Orumwense & Abo-Al-Ez, 2021) that have looked at the possibility of employing wireless charging vehicles (WCVs) that are fitted with resonance coils to deliver energy using the technique of wireless energy transfer (WET). WCVs lower the amount of energy lost, but they can also better respond to changes in the topology of the network (Sheng et al., 2019). In the process of data collection, data collection vehicles, also known as DCVs, are often utilized rather than installing static sink nodes or dynamic sink nodes to collect data through

multi-hop routing transmission. DCVs can collect data more efficiently (Rahmatizadeh, 2014). The combination of DCVs and multi-hop transmission distributes the burden of the sensor nodes more evenly. Still, it also minimizes the energy used by relaying and forwarding the data (Sheng et al., 2019).

In addition to DCVs and WCVs, dual-purpose vehicles, simultaneous data collecting, and wireless charging vehicles (DC-WCVs) are used to gather data and charge nodes in WRSNs. These vehicles are used in conjunction with DCVs and WCVs (Zhong et al., 2021). When it comes to WRSNs, the use of mobile vehicles that may either perform a single function or a combination of functions, such as collecting data and supplying energy, helps the network last longer, reduces the amount of energy it needs to operate and improves its overall performance, while also allowing for the achievement of optimization objectives (Wang et al., 2015). Nevertheless, no research has indicated which data gathering method and energy supplement is better appropriate for the various optimization aims.

2.4 Bat Algorithm

The bat algorithm, often known as the BA, is an example of a swarm intelligence system. It was developed by Pan, Dao, and Chu (2015) and is based on the foraging behavior of bats using ultrasonic echo localization. Because of its few parameters, straightforward concept, and straightforward code, it has found widespread use. However, similar to other methods of random searching, it suffers from the issues of low convergence accuracy and easy premature convergence, which are especially problematic when dealing with high-dimensional data. It is particularly true for rather expansive search spaces.

Zhu et al. (2020) designed a brand-new chaotic bat swarm algorithm to enhance the rate of convergence of the bat algorithm as well as its accuracy. The inclusion of the chaotic component and the second-order oscillation mechanism improved the system's dynamic parameter mechanism and its update speed. The addition of the chaotic component brought about these enhancements. To avoid premature convergence, Yong et al. (2018) came up with several innovative update functions for the pulse's emissivity, velocity, loudness, and location. A one-dimensional perturbed local search was yet another strategy used to improve the effectiveness and precision of local searches.

3. Proposed Model – Bat Algorithm Based OCSA Algorithm

In the context of this research paper, a paradigm is proposed in which sensor node classification is carried out in a manner that is both global and deterministic. The proposed OCSA algorithm has been developed using BAT algorithm and energy model parameters. First, the clustering algorithm's parameters, other than the number of clusters, are fixed. The cluster number is altered from the lowest to the greatest value (max). The data is then partitioned by cluster number. The cluster validity indices are then applied to the data split created in the previous step for assessment. The values influence the selection of the cluster number. Moreover, a comparative analysis is also executed to analyze the enhanced performance of the proposed system.

The network that is being considered is homogenous. It is broken up into rings to ensure that data processing during transmission to the sink or base station is carried out in an organized fashion with the primary vision of reducing energy consumption and increasing the lifespan of the network. The sensor nodes that make up the provided network are dispersed randomly, and each node that makes up the network can determine the distance between itself and other nodes located nearby. The nodes can interact with one another inside their clusters; however, communication between the nodes is limited by the boundaries of the clusters.

The network is structured into rings and clusters, and the nodes that have been randomly placed are of a static type. We make use of the free space model $e_f d^2$ and multipath fading model $e_m d^4$ here at Energy Radio Two, which is a paradigm for analyzing energy usage. Both archetypes depend on the amount of distance that separates the receiver and the transmitter.

E_{TX} : required energy utilization for packet transmission.

E_{elec} : is electronic energy that counts on the filtering, modulation the digital coding and spreading of the signal.

E_{RX} : required energy utilization for packet receiving.

d_0 : is equal to the square root of the dividing EDA free space model by multipath fading model (Elshrkawey, Elsherif & Wahed, 2018).

Because the selection of the clustering heads is so important, the Bat Algorithm, which takes its cues from the natural world, will be used in this research paper. Because of their extraordinary skill, known as echo localization, bats have been a source of motivation for computer scientists. This skill enables them to target their prey or other insects accurately, but it also helps them be aware of their surroundings even when it is dark. They do this by delivering a loud pulse that causes an echo, which helps them establish awareness of their surroundings (Yang, 2010).

Table 1. Radio Energy Model Values

E_{elec}	$50 * 0.000000001$
E_{mp}	$0.0013 * 0.0000000000001$
E_{fs}	$10 * 0.0000000000001$
d_0	$\text{sqrt}(E_{fs}/E_{mp})$

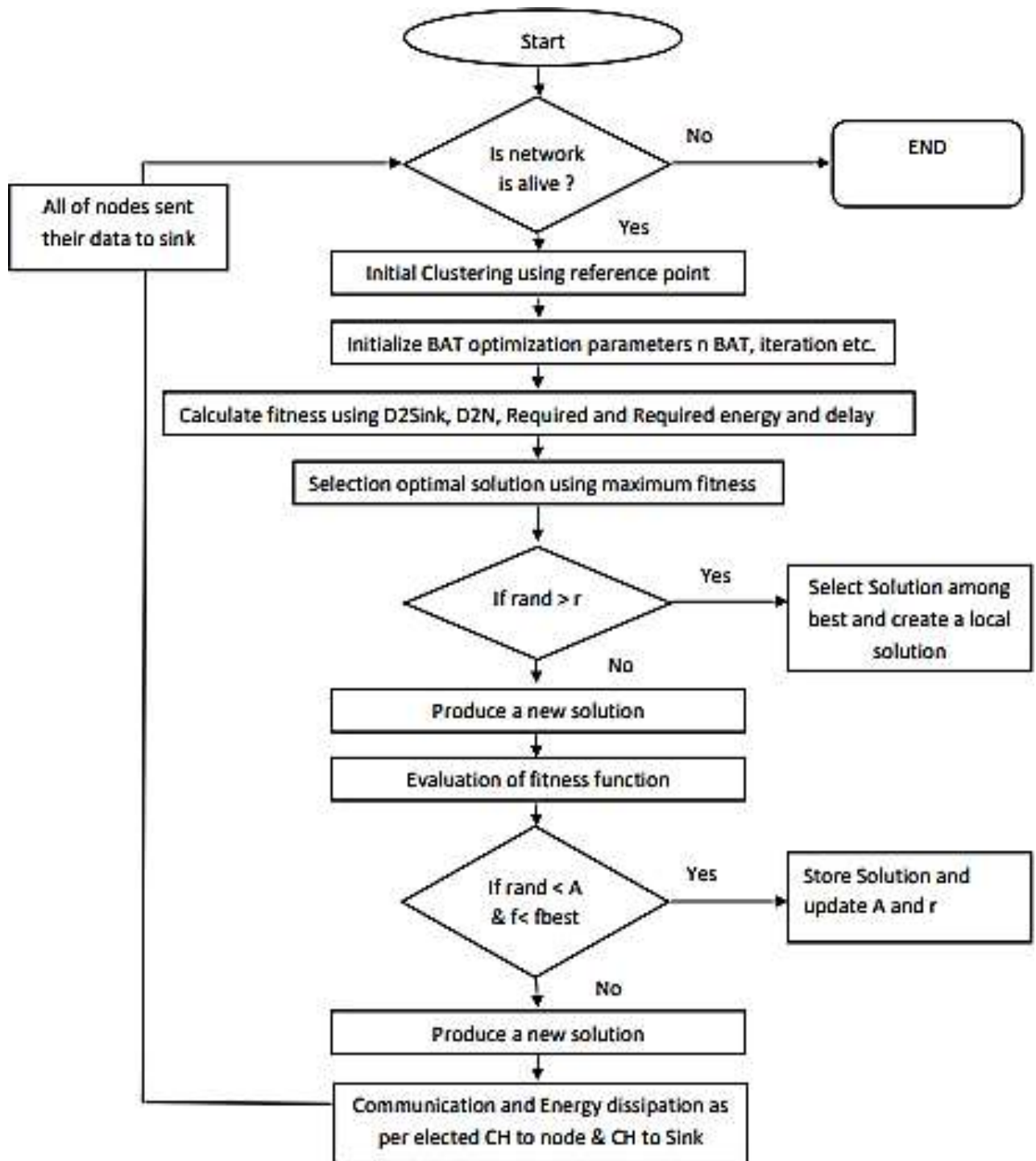
Table 2. Network Structure values

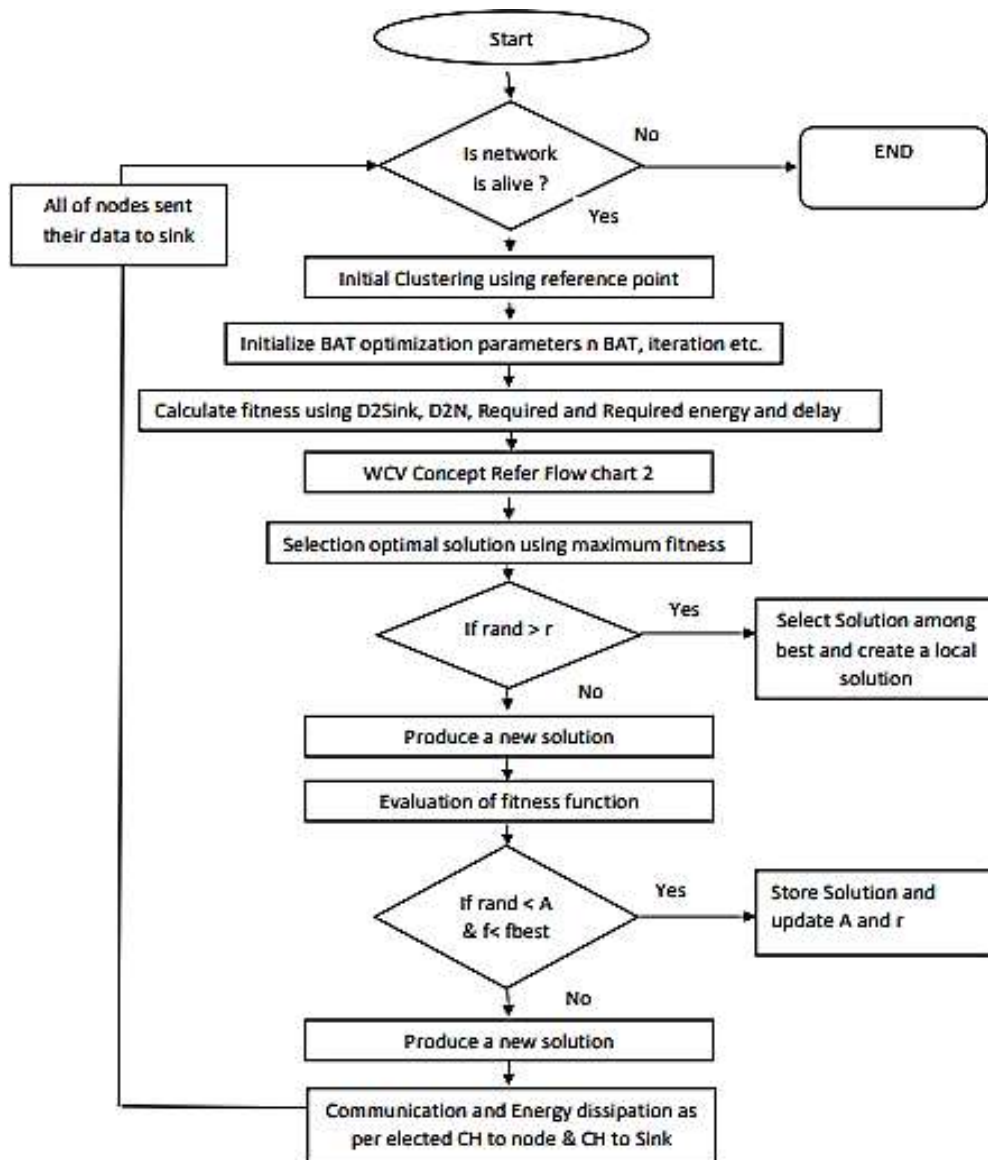
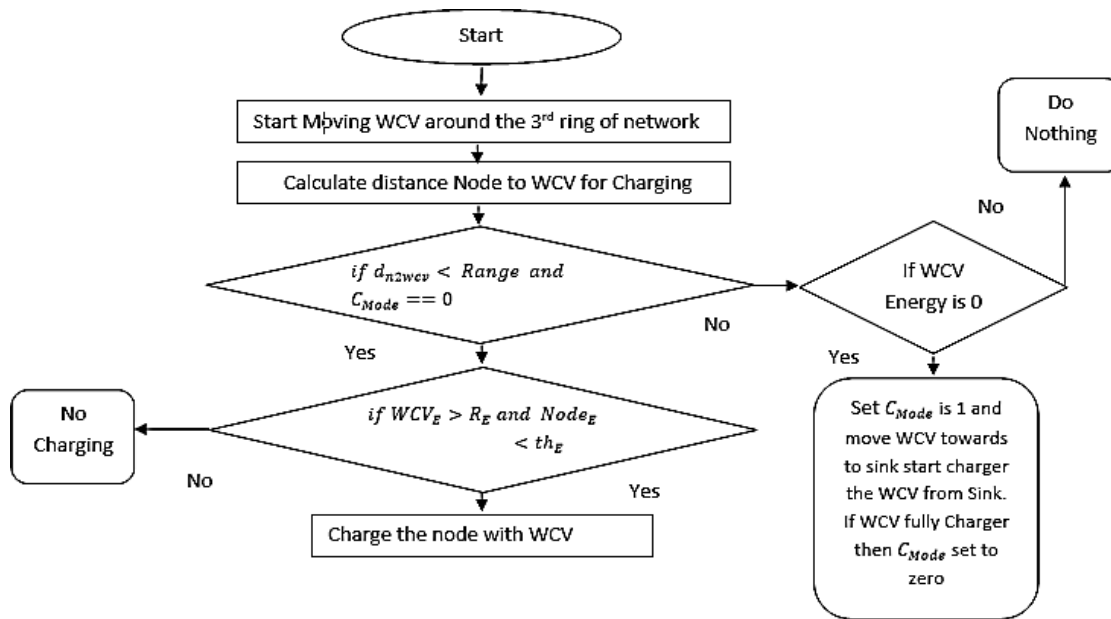
No of Circle	4
Area	100

Node	100
Packet	8*500

Flow Chart

- 1. $A=0.5$; Loudness (constant or decreasing) for BAT
- 2. $r=0.5$; Pulse rate (constant or decreasing) for BAT
- 3. D2Sink Distance from Node to Sink
 - 1. D2N Distance from Node to Node
 - 2. fbest Overall Best fitness value for BAT
 - 3. f Calculate fitness for current solution
 - 4. CH Cluster head





4. Results

Algorithm 1: Cluster Heads Selection and Energy dissipation

Input: No of Nodes, Initial Energy, XY node location, No of Circle, No of CH in each Circle,

Notations:

- CH = Cluster Head,
- nC = No of Circle,
- N = No of Nodes,
- l = No of Packets,
- c= speed of light,
- C_E = Charging Energy
- d_{n2wcv} = Distance node to WCV
- R_E = Required energy for charging
- th_E = Energy threshold for check required node for charging
- C_{Mode} =Charging mode or not

Output: Dead node, alive node, Energy consumption

1. for nC do

(a) for N do

(i) Calculate distance to sink

$$d_{\text{sink}} = \left[\sum_{i=1}^n \sqrt{(\text{Node}_{(x_i, y_i)} - \text{Sink}_{x_j, y_j})^2} \right]$$

(ii) Calculate delay

$$\text{delay} = l * \frac{d_{\text{sink}}}{c}$$

(iii) Calculate distance to Node d_{mean} using

$$d_{\text{mean}} = \text{mean} \left[\sum_{i=1}^n \sqrt{(\text{Node}_{(x_i, y_i)} - \text{Node}_{x_j, y_j})^2} \right]$$

(iv) Calculate required energy for communication E_{required} using

$$E_{\text{required}} = l * E_{\text{elec}} + l * E_{\text{mp}} * d^2 \text{ if } d_0 < d_{\text{sink}}$$

$$E_{\text{required}} = l * E_{\text{elec}} + l * E_{\text{fs}} * d^2 \text{ if } d_0 > d_{\text{sink}}$$

(v) Calculate residual energy E_{residual} using

$$E_{\text{residual}} = \text{Node residual energy}$$

(vi) Start moving WCV around 3rd ring of network

(vii) WCV charging Concept calculate distance node to WCV i.e. d_{n2wcv} using

$$d_{n2wcv} = \sqrt{(\text{Node}_{(x_i,y_i)} - \text{WCV}_{(x_j,y_j)})^2}$$

(viii) if $d_{n2wcv} < \text{Range} \ \&\& \ C_{\text{Mode}} == 0$

1. if $\text{WCV}_E > R_E \ \&\& \ \text{Node}_E < \text{th}_E$

2. $\text{Node}_E = \text{Node}_E + C_E$

(ix) if $\text{WCV}_E < 0$

1. $C_{\text{Mode}} = 1$

2. WCV move towards to sink and WCV_E charger from sink until fully charger

(x) if $\text{WCV}_E \rightarrow$ fully Charger

1. $C_{\text{Mode}} = 0$

(xi) Calculate delay

$$\text{delay} = l * \frac{d_{\text{sink}}}{c}$$

(xii) Calculate distance to Node d_{mean} using

$$d_{\text{mean}} = \text{mean} [\sum_{i=1}^n \sqrt{(\text{Node}_{(x_i,y_i)} - \text{Node}_{(x_j,y_j)})^2}]$$

(xiii) Calculate required energy for communication E_{required} using

$$E_{\text{required}} = l * E_{\text{elec}} + l * E_{\text{mp}} * d^2 \text{ if } d_0 < d_{\text{sink}}$$

$$E_{\text{required}} = l * E_{\text{elec}} + l * E_{\text{fs}} * d^2 \text{ if } d_0 > d_{\text{sink}}$$

(xiv) Calculate residual energy E_{residual} using

$$E_{\text{residual}} = \text{Node residual energy}$$

(b) CH_{best} = Apply BAT optimization algorithm

(c) Evaluation of fitness

$$\text{fitness} = w1 * \frac{1}{d_{\text{sink}} + d_{\text{mean}}} + w2 * \frac{E_{\text{residual}}}{E_{\text{required}}} + w3 * \frac{1}{\text{delay}}$$

(d) Perform energy consumption CH to sink

$$E_{\text{Cos}} = l * E_{\text{elec}} + l * E_{\text{mp}} * d^2 \text{ if } d_0 < d_{\text{sink}}$$

$$E_{\text{Cos}} = l * E_{\text{elec}} + l * E_{\text{fs}} * d^4 \text{ if } d_0 > d_{\text{sink}}$$

(e) Perform energy consumption CH to Node

$$d_{\text{node}} = \sqrt{[\sum_{i=1}^n \sqrt{(\text{Node}_{(x_i, y_i)} - \text{CH}_{x_j, y_j})^2}]}$$

$$E_{\text{Cos}} = l * E_{\text{elec}} + l * E_{\text{mp}} * d^2 \text{ if } d_0 < d_{\text{node}}$$

$$E_{\text{Cos}} = l * E_{\text{elec}} + l * E_{\text{fs}} * d^4 \text{ if } d_0 > d_{\text{node}}$$

(f) end

2. end

Algorithm 2: BAT optimization algorithm

Input: No of Population **N**, Maximum iteration **mIter**, pulse rates **r** loudness **A** and frequency **f_{min}** and **f_{max}**

Notations:

- v = velocity
- x = Solution for CH Node,
- fnew = New calculate fitness value,
- fbest = Best fitness value
- £ = [-1, 1] is a random number,

Output: Optimal CH cluster head

1. Generate random CH Nodes x i.e. 1 to N,

2. for t do

(a) Generate new solution using

$$f_i = f_{\text{min}} + (f_{\text{max}} - f_{\text{min}}) * \text{rand}$$

$$v = v + (x_i - x_*) * f_i$$

$$x_i = v + x_i$$

(b) if (rand > r)

(i) Update solution using best solutions

$$x_i = x_* + \epsilon * A$$

(c) Calculate fitness function for selection of best cluster

$$\text{fitness} = w1 * \frac{1}{d_{\text{sink}} + d_{\text{mean}}} + w2 * \frac{E_{\text{residual}}}{E_{\text{required}}} + w3 * \frac{1}{\text{delay}}$$

(d) end

(e) if (rand < A, and fnew > fbest)

(i) Selection of best solutions

(f) end

end

$$d_{\text{node}} = \left[\sum_{i=1}^n \sqrt{(\text{Node}_{(x_i, y_i)} - \text{WCV}_{x_j, y_j})^2} \right]$$

4.1 Simulation and Discussions

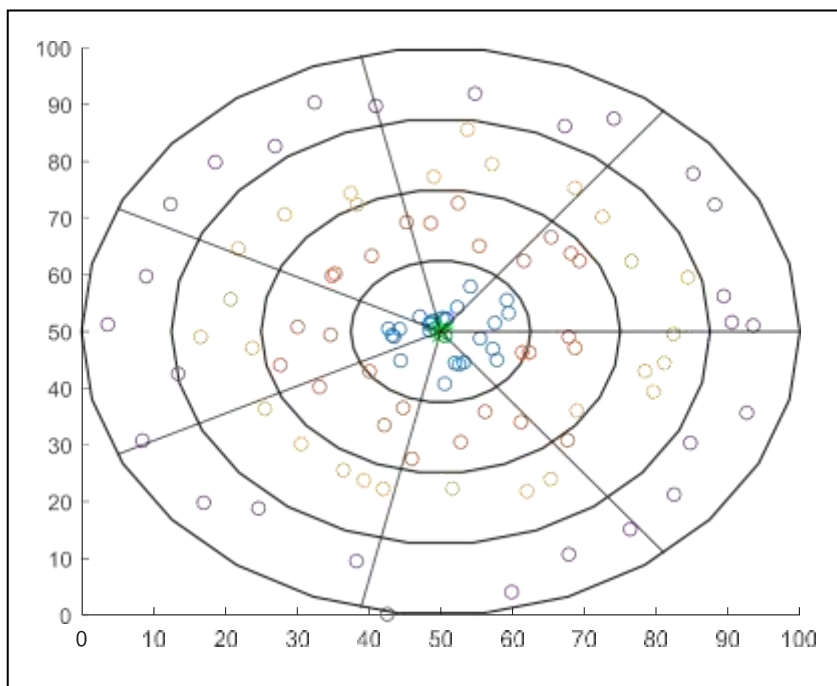


Figure 1. The Network Structure

The topology of the network, which can be seen in the figure that can be seen above (Figure 1), is shown as being split into the shape of rings, each of which clusters around a reference point. The nodes are distributed randomly. Within a space of 100X100, there are 100 nodes set up.

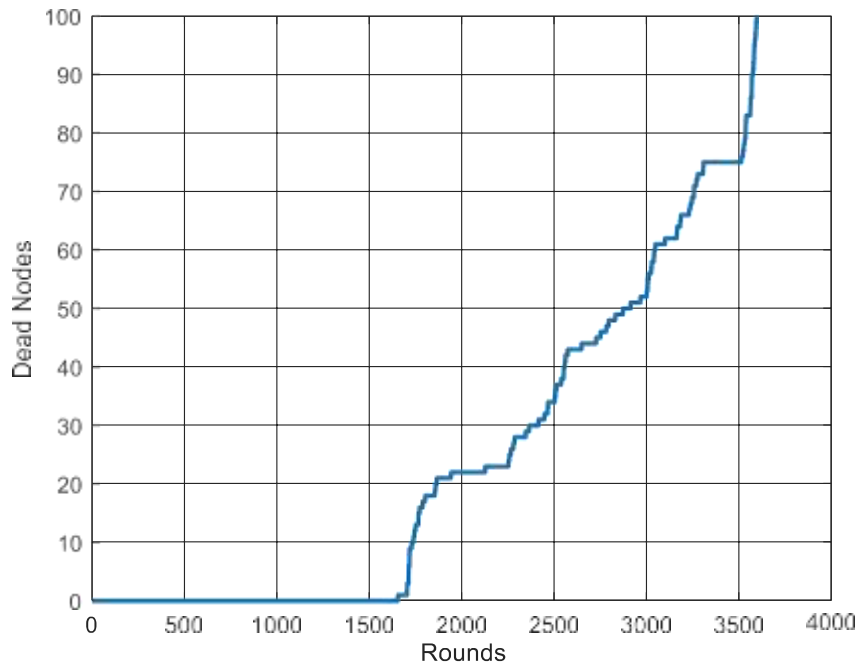


Figure 2. Dead Nodes

The total number of dead nodes is shown in the figure that may be seen above (Figure 2). When we talk about rounds, we're referring to the number of times that communication occurs. We have seized 400 nodes, and we are approaching the 1000th round in which all nodes will perish. It displays the number of dead nodes concerning the rounds.

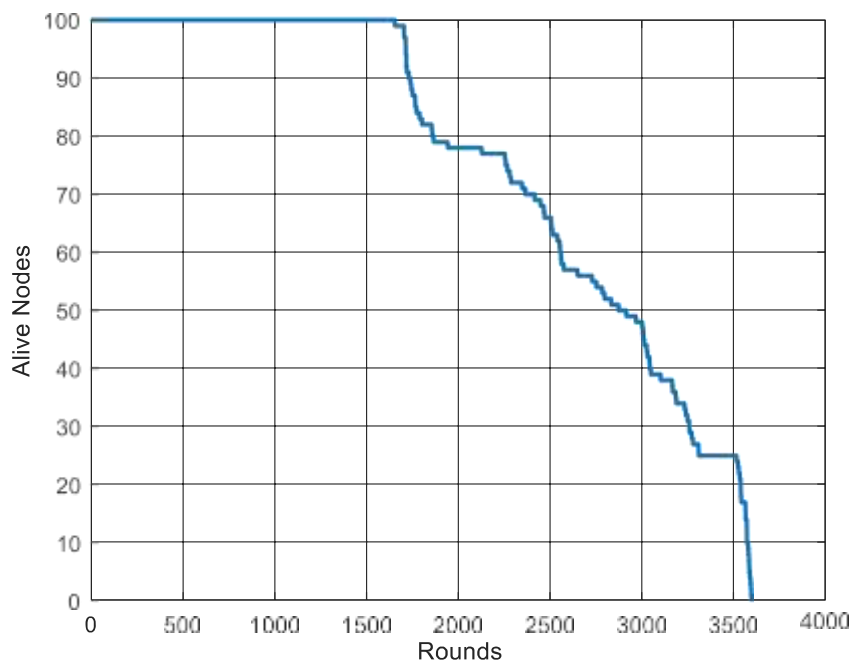


Figure 3. Alive Nodes

The length of time that the network will remain stable is shown in the figure that was just shown (Figure 3). The figure demonstrates that the network can remain stable for 300 cycles.

The quantity of energy spent by the network is increasing as it moves closer to the number of rounds, which leads to the depletion of the battery resources and, as a result, a decrease in the number of nodes that are still alive.

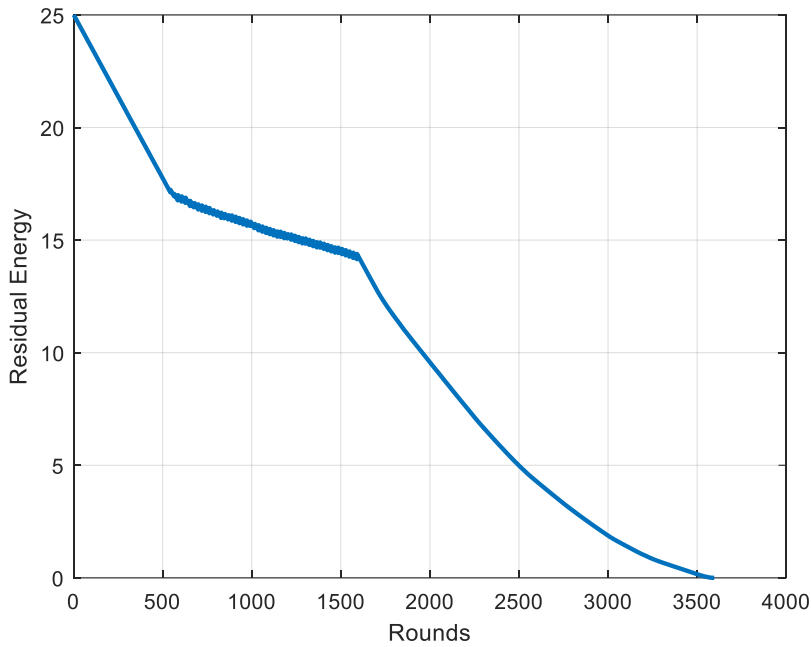


Figure 4. Residual Energy

The relationship between the rounds and the residual energy is shown in the figure that can be seen above (Figure 4). It demonstrates that during the 0th round, the residual energy is at its highest and that by the 1000th round, the whole network will have died out. As the network continues to advance toward further rounds, the amount of remaining energy is continually reduced.

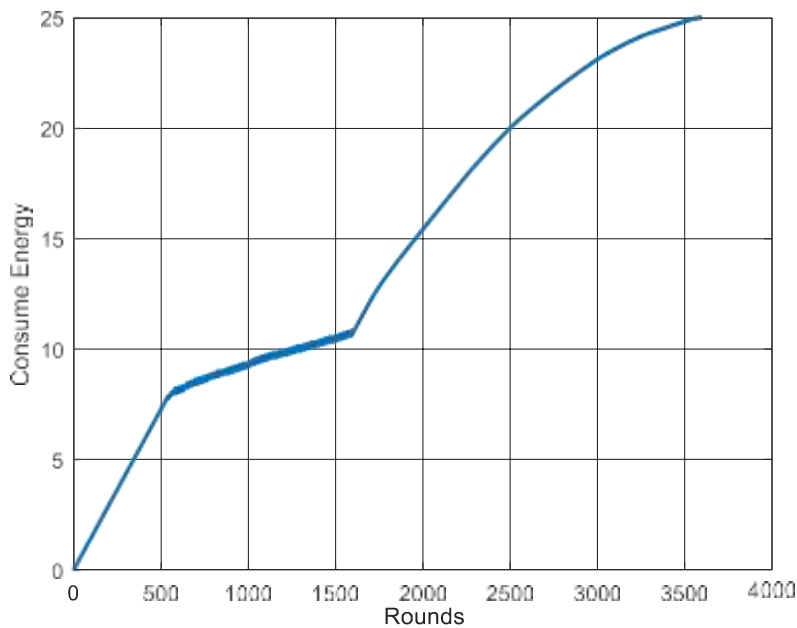


Figure 5. Consumed Energy

The overall usage of the network's available energy is shown in the figure that can be seen above (Figure 5). It is evident from this that the energy used is rising at an accelerating pace. It becomes asymptotic as the network approaches the 1000th round since the residual energy is also used up by the time the network reaches the 1000th round, as shown in Figure 4.

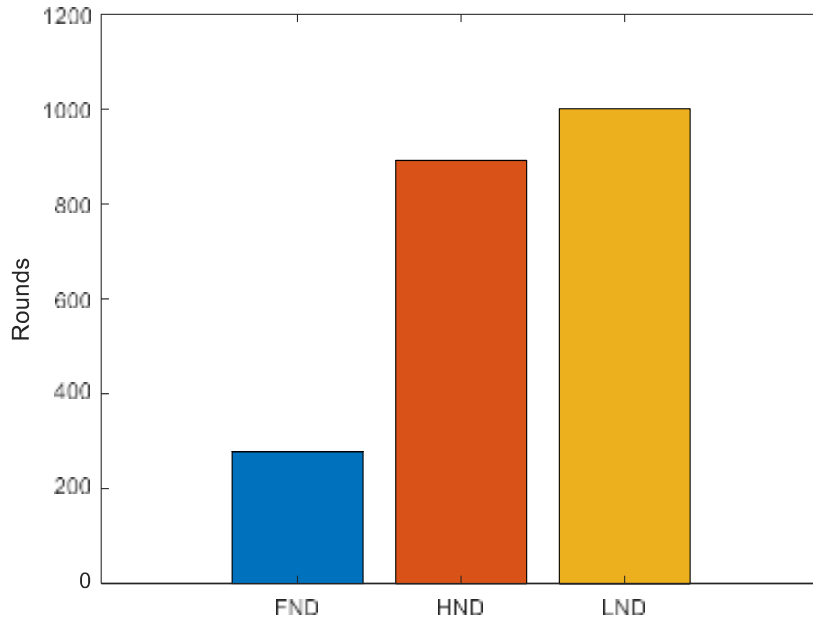


Figure 6. FND, HND, LND

The preceding figure (Figure 6) illustrates the round in which the (FND) First node in the network passes away. This information is shown as a blue notation in the bar graph; more specifically, the first node of the network passes away at around the 300th round. The second bar in the graph depicts the point in time when fifty percent of the network's nodes have died (HND). After the 900th cycle, almost half of the nodes will perish. Around the 1000th cycle, the last nodes are eliminated (abbreviated LND).

4.2 Comparative Analysis of OCSA with LEACH and R-LEACH

The outcomes of the proposed cluster head selection technique OCSA are being compared on a few parameters. The findings indicate that OCSA is superior to both LEACH and R-LEACH in terms of these parameters.

The comparative study of the parameter of no dead nodes is shown in Figure 7, which illustrates the progression of the number of rounds. Compared to LEACH and R-LEACH, the performance of OCSA is much higher. Compared to the OCSA, LEACH and R-LEACH have a much higher number of rounds, resulting in a significantly higher number of dead nodes.

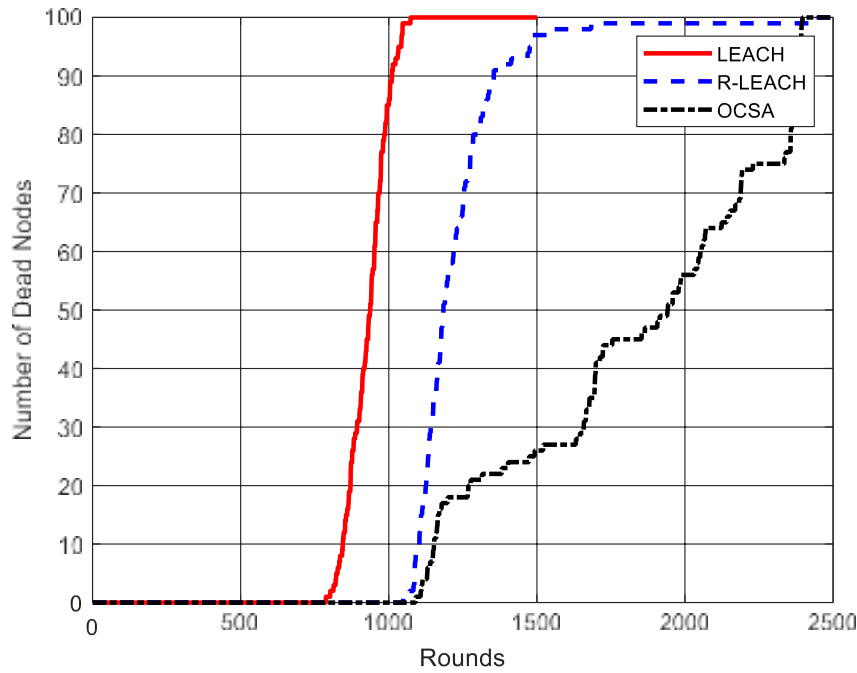


Figure 7. Number of Dead Nodes

The comparison of the characteristics of living nodes and residual energies is shown in Figures 8 and 9.

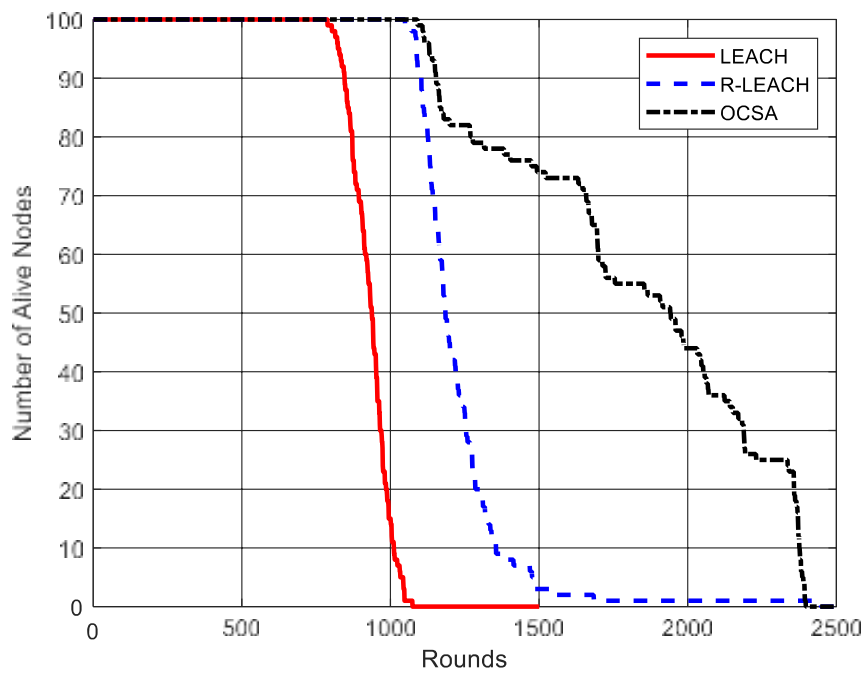


Figure 8. Number of Alive Nodes

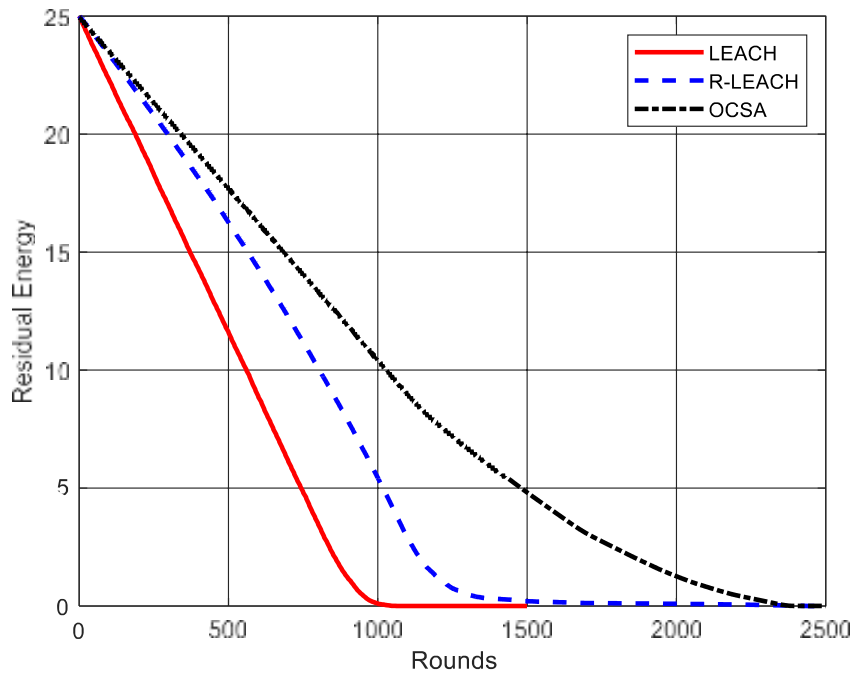


Figure 9. Residual Energy

First node dead (FND), final node dead (LND), and half node dead (HND) are shown in Figure 10. (LND).

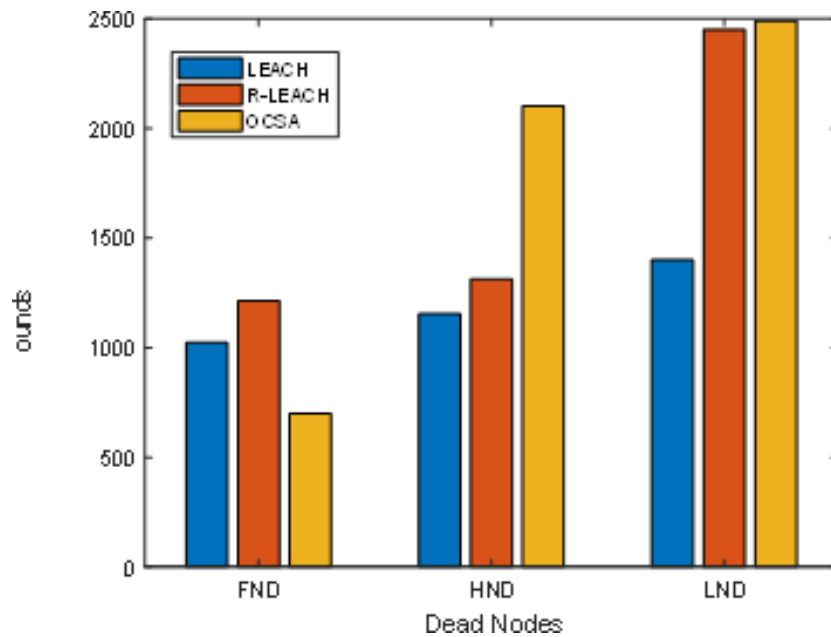


Figure 10. FND, HND, LND

The relative values of the figure are provided in the table 3 that can be seen below.

Table 3. FND, HND, LND Relative Values

Technique	FND	HND	LND
Leach	1022	1153	1400
R-Leach	1213	1312	2450
OCSA	700	2102	2490

Parameter	Value
Node	100
Initial Energy	0.25
Area	100x100 m
Sink Location	X=50, Y=50
Packet	2000 bits

Comparative Analysis of WCV with OCSA, LEACH, and R-LEACH

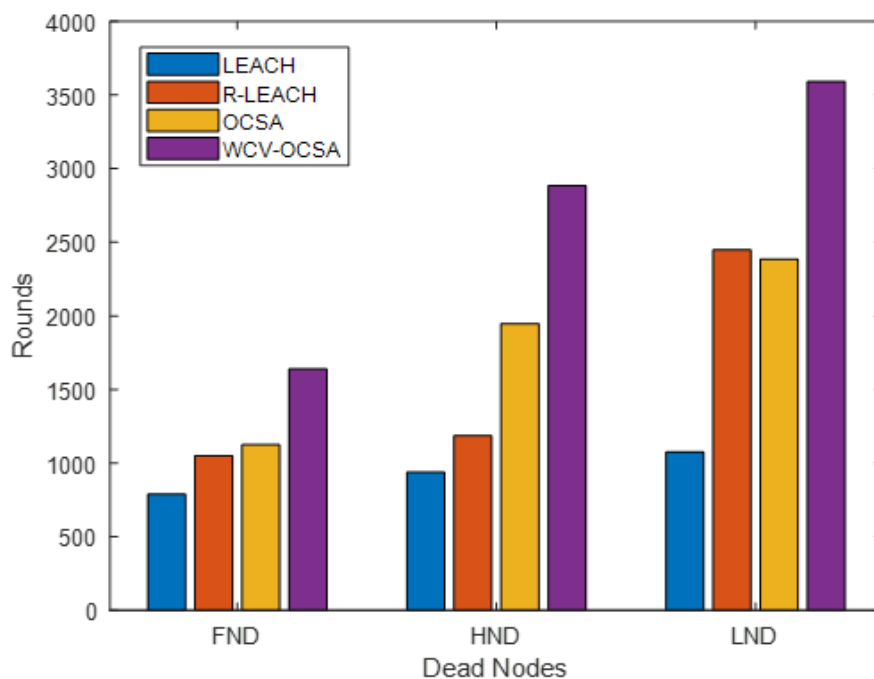


Figure 11. Comparative results with introduction of WCV

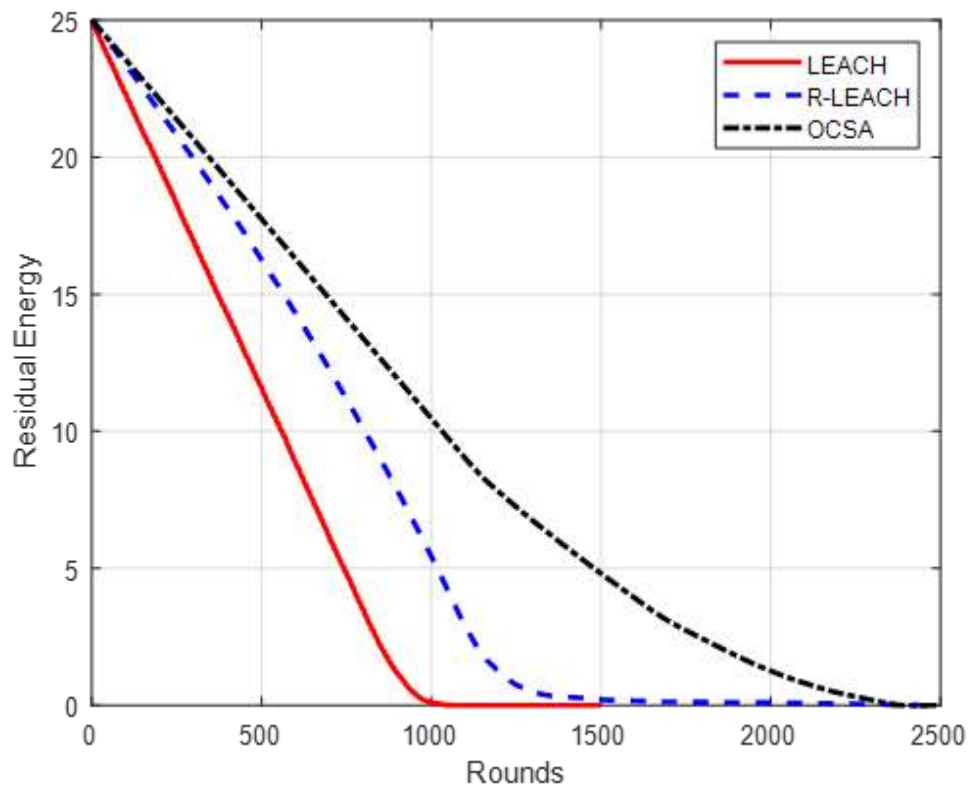


Figure 12. Residual Energy

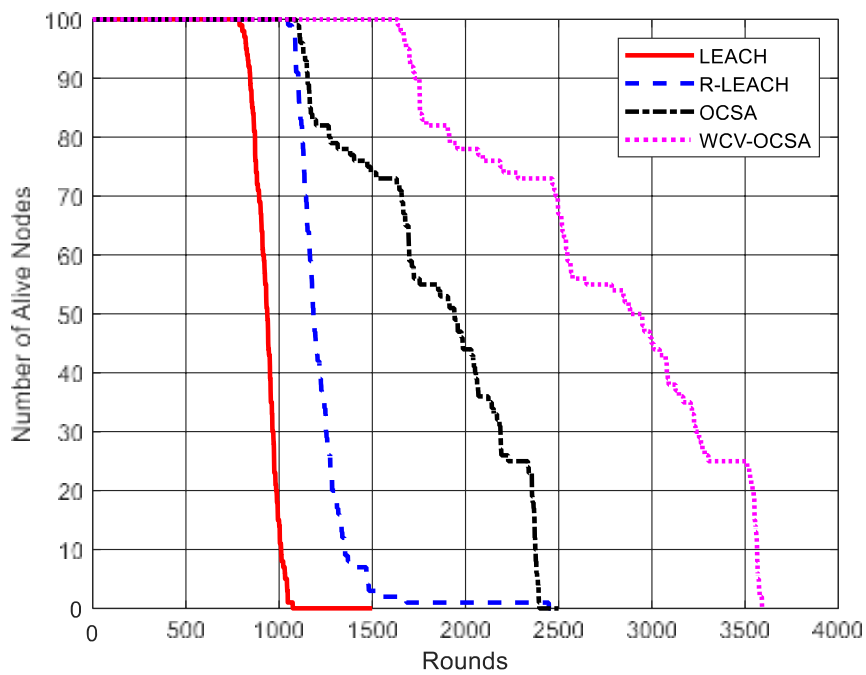


Figure 13. Number of Alive Node

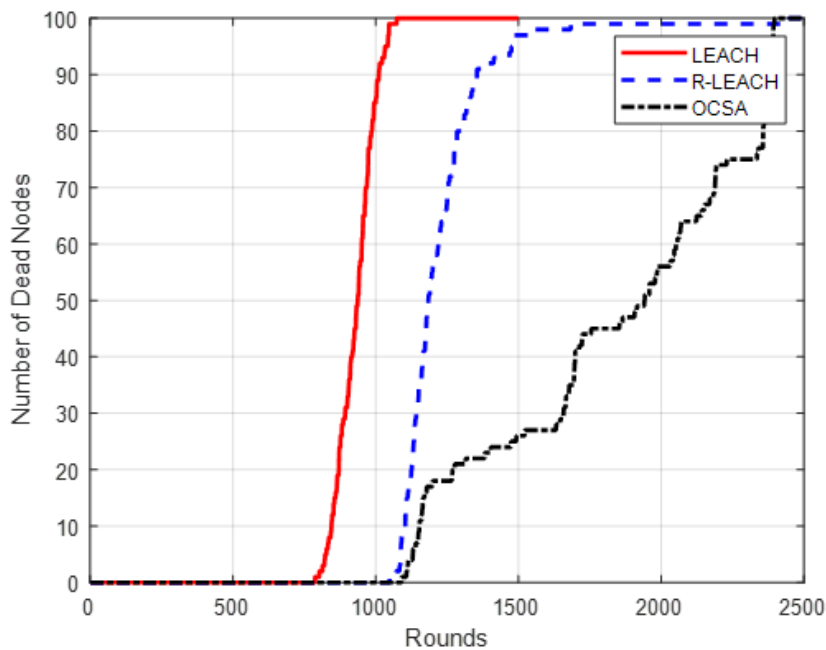


Figure 14. Number of Dead Nodes

The energy value of the nodes and the network's lifespan are two of the most important considerations concerning WSN. The traditional method of clustering, known as LEACH, as well as the modified version of LEACH, known as R-LEACH, is only effective for small networks. As the number of rounds increases, more communication is required, and the proposed algorithm OCSA is more effective at conserving energy. Along with the fitness function, the parameters, which include the distance to the sink, residual energy, consumed energy, alive nodes, dead nodes, FND, HND, and LND, all work for networks of a reasonable size. Since there have been more than a thousand rotations, the network's lifespan can no longer be considered significant. In conjunction with the appropriate clustering of CH selection, the inclusion of a wireless charging vehicle (WCV) in future works will increase the network's lifespan.

5. Conclusion

As per the literature review, many scholars have pointed out that clustering is an important barrier that must be overcome in the near future. Meta-heuristic swarm intelligence algorithms are rapidly finding applications in clustering because of their tremendous optimization skills. These abilities enable the algorithms to choose the clustering centers that are the most effective effects. The bat algorithm has the drawback of being prone to becoming stuck in local minima, and the accuracy of the optimization it produces is not very great. By bolstering the bat algorithm, this research significantly improves the OCSA algorithm's capacity for global optimization as well as local optimization. As a result, the proposed OCSA algorithm can better tackle the clustering issues. The suggested system has been put into action and put through its paces, and the promising results have been based on those efforts. The search results may be unpredictable with many different types of random search algorithms. This issue is present in the enhanced bat algorithm presented in this study, and further work will be required moving forward. Because it has high accuracy and

a low standard deviation, the OCSA algorithm described in this work may be used in the scenario in which there is a known number of clusters.

6. References

- [1] Araujo, A., Blesa, J., Romero, E., & Villanueva, D. (2012). Security in cognitive wireless sensor networks. Challenges and open problems. *EURASIP Journal on Wireless Communications and Networking*, 2012(1), 1-8.
- [2] Ebrahimzadeh, A., & Mavaddati, S. (2014). A novel technique for blind source separation using bees colony algorithm and efficient cost functions. *Swarm and Evolutionary Computation*, 14, 15-20.
- [3] Elshrkawey, M., Elsherif, S. M., & Wahed, M. E. (2018). An enhancement approach for reducing the energy consumption in wireless sensor networks. *Journal of King Saud University-Computer and Information Sciences*, 30(2), 259-267.
- [4] Han, K., Luo, J., Liu, Y., & Vasilakos, A. V. (2013). Algorithm design for data communications in duty-cycled wireless sensor networks: A survey. *IEEE Communications Magazine*, 51(7), 107-113.
- [5] Hsu, K., Levine, S., & Finn, C. (2018). Unsupervised learning via meta-learning. *arXiv preprint arXiv:1810.02334*.
- [6] Huang, J., Hong, Y., Zhao, Z., & Yuan, Y. (2017). An energy-efficient multi-hop routing protocol based on grid clustering for wireless sensor networks. *Cluster Computing*, 20(4), 3071-3083.
- [7] Huong, T. T., Binh, H. T. T., Le Nguyen, P., Long, D. C. T., & An, V. D. (2020, July). Optimizing charging locations and charging time for energy depletion avoidance in wireless rechargeable sensor networks. In *2020 IEEE Congress on Evolutionary Computation (CEC)* (pp. 1-8). IEEE.
- [8] Jia, J., Chen, J., Deng, Y., Wang, X., & Aghvami, A. H. (2017). Joint power charging and routing in wireless rechargeable sensor networks. *Sensors*, 17(10), 2290.
- [9] Kandris, D., Nakas, C., Vomvas, D., & Koulouras, G. (2020). Applications of wireless sensor networks: an up-to-date survey. *Applied System Innovation*, 3(1), 14.
- [10] Kodali, R. K., & Aravapalli, N. K. (2014, February). Multi-level LEACH protocol model using NS-3. In *2014 IEEE International Advance Computing Conference (IACC)* (pp. 375-380). IEEE.
- [11] Kuo, R. J., Syu, Y. J., Chen, Z. Y., & Tien, F. C. (2012). Integration of particle swarm optimization and genetic algorithm for dynamic clustering. *Information Sciences*, 195, 124-140.
- [12] Lin, C., Shang, Z., Du, W., Ren, J., Wang, L., & Wu, G. (2019, April). CoDoC: A novel attack for wireless rechargeable sensor networks through denial of charge. In *IEEE INFOCOM 2019-IEEE Conference on Computer Communications* (pp. 856-864). IEEE.
- [13] Lin, C., Sun, Y., Wang, K., Chen, Z., Xu, B., & Wu, G. (2019). Double warning thresholds for preemptive charging scheduling in wireless rechargeable sensor networks. *Computer Networks*, 148, 72-87.
- [14] Liu, G., Peng, B., & Zhong, X. (2020). A novel epidemic model for wireless rechargeable sensor network security. *Sensors*, 21(1), 123.

- [15] Madhulatha, T. S. (2012). An overview on clustering methods. arXiv preprint arXiv:1205.1117.
- [16] Manjarres, D., Landa-Torres, I., Gil-Lopez, S., Del Ser, J., Bilbao, M. N., Salcedo-Sanz, S., & Geem, Z. W. (2013). A survey on applications of the harmony search algorithm. *Engineering Applications of Artificial Intelligence*, 26(8), 1818-1831.
- [17] Mugunthan, S. R. (2021). Wireless rechargeable sensor network fault modeling and stability analysis. *Journal of Soft Computing Paradigm (JSCP)*, 3(01), 47-54.
- [18] Orumwense, E. F., & Abo-Al-Ez, K. (2021, December). A Charging Technique for Sensor Nodes in Wireless Rechargeable Sensor Networks for Cyber-physical Systems. In 2021 International Conference on Electrical, Computer and Energy Technologies (ICECET) (pp. 1-6). IEEE.
- [19] Pan, T. S., Dao, T. K., & Chu, S. C. (2015). Hybrid particle swarm optimization with bat algorithm. In *Genetic and evolutionary computing* (pp. 37-47). Springer, Cham.
- [20] Pushpalatha, S., & Shivaprakasha, K. S. (2020). Energy-efficient communication using data aggregation and data compression techniques in wireless sensor networks: A survey. In *Advances in communication, signal processing, VLSI, and embedded systems* (pp. 161-179). Springer, Singapore.
- [21] Rahmatizadeh, R. (2014). Energy efficient routing towards a mobile sink using virtual coordinates in a wireless sensor network.
- [22] Sheng, Y., Liu, W., Li, Y., Zhong, P., & Duan, G. (2019). A Comparison of Mobile Vehicles for Data Collection and Wireless Charging. *International Journal of Performability Engineering*, 15(8), 2249.
- [23] Tirani, S. P., & Avokh, A. (2018). On the performance of sink placement in WSNs considering energy-balanced compressive sensing-based data aggregation. *Journal of Network and Computer Applications*, 107, 38-55.
- [24] Tuna, G., & Gungor, V. C. (2016). Energy harvesting and battery technologies for powering wireless sensor networks. In *Industrial Wireless Sensor Networks* (pp. 25-38). Woodhead Publishing.
- [25] Wang, C., Li, J., Ye, F., & Yang, Y. (2015). A mobile data gathering framework for wireless rechargeable sensor networks with vehicle movement costs and capacity constraints. *IEEE Transactions on Computers*, 65(8), 2411-2427.
- [26] Wang, D., Tan, D., & Liu, L. (2018). Particle swarm optimization algorithm: an overview. *Soft Computing*, 22(2), 387-408.
- [27] Yang, X. S. (2010). A new metaheuristic bat-inspired algorithm. In *Nature inspired cooperative strategies for optimization (NICSO 2010)* (pp. 65-74). Springer, Berlin, Heidelberg.
- [28] Yao, Y., Cao, Q., & Vasilakos, A. V. (2014). EDAL: An energy-efficient, delay-aware, and lifetime-balancing data collection protocol for heterogeneous wireless sensor networks. *IEEE/ACM transactions on networking*, 23(3), 810-823.
- [29] Yong, J., He, F., Li, H., & Zhou, W. (2018, May). A novel bat algorithm based on collaborative and dynamic learning of opposite population. In 2018 IEEE 22nd International Conference on Computer Supported Cooperative Work in Design ((CSCWD)) (pp. 541-546). IEEE.

- [30] Yu, S., Zhang, B., Li, C., & Mouftah, H. T. (2014). Routing protocols for wireless sensor networks with mobile sinks: A survey. *IEEE Communications Magazine*, 52(7), 150-157.
- [31] Zhong, P., Li, Y. T., Liu, W. R., Duan, G. H., Chen, Y. W., & Xiong, N. (2017). Joint mobile data collection and wireless energy transfer in wireless rechargeable sensor networks. *Sensors*, 17(8), 1881.
- [32] Zhong, P., Xu, A., Zhang, S., Zhang, Y., & Chen, Y. (2021). EMPC: Energy-Minimization Path Construction for data collection and wireless charging in WRSN. *Pervasive and Mobile Computing*, 73, 101401.
- [33] Zhu, C., Yang, L. T., Shu, L., Leung, V. C., Hara, T., & Nishio, S. (2014). Insights of Top- k Query in Duty-Cycled Wireless Sensor Networks. *IEEE Transactions on Industrial Electronics*, 62(2), 1317-1328.
- [34] Zhu, L. F., Wang, J. S., Wang, H. Y., Guo, S. S., Guo, M. W., & Xie, W. (2020). Data clustering method based on improved bat algorithm with six convergence factors and local search operators. *IEEE Access*, 8, 80536-80560.