JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Analysis for the Optimal Number of Cluster Heads in a WSN.

[1]Neetika Bairwa, [2]Dr. Navneet Kumar Agrawal

[1]PhD Scholar, [2]Associate Professor and Head
[1,2] Electronics and Communication Engineering,
[1,2] College of Technology and Engineering, MPUAT, Udaipur, India

Abstract: Due to the variety of applications in monitoring and collecting data from diverse surroundings, Wireless Sensor Networks have attracted a lot of interest recently. Increasing network lifespan while retaining effective data collection is a major problem for WSNs. Clustering has become a potentially effective approach to dealing with this problem. In clustering, sensor nodes are grouped or clustered, and each cluster has a designated leader or cluster head who is in controller of gathering and transmitting data. The current research work focuses on the notion of clustering based on whale optimization and its influence on various parameters of assessment metrics. The research provided investigations on the appropriate number of cluster heads and their implications on stability region, network lifetime, utilization of energy, and throughput. According to the research's findings, the stability region is not significantly altered when the number of cluster heads rises. However, it was shown that as network throughput grows, network longevity diminishes.

IndexTerms **- Cluster heads, WSN, Whale optimization, clustering and nature inspired.**

I. Introduction

In the area of distributed systems and networking, Wireless Sensor Networks (WSNs) have become a well-known area of study and research. A WSN is made up of a lot of tiny, inexpensive sensor nodes that work together to collect and send data from the environment being watched. These sensor nodes can track physical phenomena like moisture, temperature, pressure, and illumination since they have sensing, data collection, processing, and wireless communication capabilities [1, 2].

One of a WSN's basic building blocks is a sensor node. It is made up of a sensing unit for gathering data related to the environment, a processing unit for processing the data, a storage unit for temporarily storing information, and a wireless communication module for sending data to additional sensor nodes or a base station. Since the power supply for these nodes is frequently constrained, energy-effective algorithms and protocols are required to increase the network's lifespan [3].

Clustering is a key strategy used in WSNs to increase network longevity and energy efficiency. Clustering entails grouping the sensing nodes into clusters, with a chosen leader or cluster head for each cluster. The cluster leaders are in charge of interacting with the base station and directing the actions of the nodes inside their specific clusters. Instead of directly connecting with the base station, the non-cluster head nodes, or cluster members, send their data to the cluster head. This method aids in lowering the energy needed for long-distance data transmission [4, 5].

WSN clustering has a number of benefits. By consolidating data at the cluster head and transferring it to the base station in a more power-efficient way, it first lowers total energy usage. Second, it offers a structured hierarchy that makes network administration and routing easier. In order to reduce redundant data transmission and save energy, the cluster heads can conduct data integration, data collection, and compression. Clustering also aids in load balancing since cluster leaders may divide jobs across the sensor nodes in their clusters, avoiding certain nodes from being overloaded with processing and sensing work [6, 7].

Clustering is also essential for increasing the network's lifespan. Clustering helps postpone the start of energy degradation in individual nodes by lowering the utilization of energy and distributing the energy use across the nodes. As a result, networks last longer, which makes it possible to gather and analyze data for longer in deployed environments [8].

In this research study, we explore the idea of clustering based on whale optimization in WSNs and look at how the number of cluster heads affects the growth of the stability region, network lifespan, throughput, and total energy consumption. Here, algorithm is examined with different number of CHs to evaluate how well they perform in terms of extending network longevity and energy efficiency and pinpoint the crucial elements that contribute to their efficiency.

II. Related Work

Vimalarani et al. updated an optimization algorithm that creates clusters in a centralized fashion, and the cluster leaders are chosen employing Particle Swarm Optimization in a distributed manner. Depending on the value of the threshold for which the multihop protocol for routing is utilized, data collected from all of the sensor nodes is combined by the head and transmitted directly to the base station via a relay node [9].

Agrawal et al. suggested a clustering protocol that performs better than PSO since it takes residual energy into account and CH balancing elements into account when choosing CHs. The CH uses a greater amount of energy than the remaining sensor nodes due to its heavy load. As a result, it must be appropriately balanced. The network load is adequately balanced by the suggested protocol [10].

Elhabyan and Yagoub suggested a protocol that improves WSN energy efficiency by putting a cap on the total number of CHs and attempting to reduce that number. Simulation findings demonstrate that the suggested protocol can increase WSN's energy efficiency while also maintaining a reasonable data throughput [11].

Rambabu et al. proposed a clustering head selection mechanism for sensor networks. For the primary decision-making regarding cluster heads during the clustering process, a combination of the Artificial Bee Colony (ABC) and Monarchy Butterfly Optimization (MBO) algorithms is used. By retaining the trade-off between exploitation and exploration, the proposed algorithm replaces the employee bee phase of ABC with the mutated butterfly adjusting operator of MBO to prevent earlier trapping of options into a local optimal position and delayed convergence [12].

Lipare et al. designed the novel fitness function for routing to reduce the total distance traveled and the number of hops. A greater number of sensor nodes are allocated to the gateways distant from the workstation and a relatively smaller number to those close to it [13].

Kaddi et al. discussed the routing issue in WSNs, particularly focusing on the hierarchical routing utilizing the cluster concept. The authors solved the challenge of optimization, especially on vast networks, by forming clusters, and each cluster is led by a cluster leader who is in charge of gathering data from member nodes and transferring it to a master station [14].

Sharawi et al. suggested a population-based bat algorithm to extend the lifetime of the sensing network. The authors used a special fitness function to decrease intra cluster compression with the least amount of space between cluster nodes [15].

Sahoo et al. developed a technique for optimizing group imagination using a substitute technique along with sink mobility using the particle swarm algorithm, which maintains the reduced energy CH in conjunction with the closest CH with the shifting sink and the dimensions of the team. The algorithm focuses on heterogeneous WSNs [16].

Priyanka et al. created a circular network algorithm with random node positioning and an increase in node density closest to the workstation's position. Within the huge circular territory, a number of segments have been developed where WOA is employed to provide interactive CH voting in each sub-sector [17].

Gupta and Rout developed a method of optimization specifically designed to lengthen the lifespan of single-cluster networks, and it was later expanded to handle multi-cluster structures. The coupled problem of prolonging network longevity is then investigated by including energy-harvesting (EH) nodes. For cluster heads, EH nodes serve as specialized relay nodes, and a technique for maximizing network lifespan is proposed [18].

III. WHALE OPTIMIZATION TECHNIQUE (WOA)

A WOA method is used as a new dynamically influenced metaheuristic optimization methodology among swimming intelligent systems, as suggested by Mirjalili et al. [19]. The air bubble feeding activity is a distinctive eating strategy used only by humpback whales. They create columns and clouds that are available by breathing underwater. Prey is gathered by this enormous group of connected air bubbles. Later, in the water bubbles, the whale comes to the surface. By inhaling in and exhaling out, the target keeps creating bubbles as it rises, and as it gets closer to its prey, the target area gets smaller by constricting the bubbles around it. The attacking approach is explained mathematically by equations (1) and (2):

$$\vec{A} = \left|\vec{B} \cdot \overrightarrow{P^*}(t) - \vec{P}(t)\right| \tag{1}$$

$$\vec{P}(t+1) = \overrightarrow{P^*}(t) - \vec{Q} \cdot \vec{A} \tag{2}$$

where t is the present iteration, Q and B denote coefficient vectors, and P denotes the current location vector. The optimum solution location vector is the P^* value that was found. After each cycle, the value of P^* is revised if a better solution materializes. Equations (3) and (4) are used to calculate the coefficients Q and B.

$$\vec{Q} = 2\vec{v} \cdot \vec{a} - \vec{v} \tag{3}$$

$$\vec{B} = 2 \cdot \vec{a} \tag{4}$$

Vector $\vec{a}$ is a vector that is generated at random with a range of 0 to 1 and $\vec{v}$ declines linearly from 2 to 0 as the number of repetitions increases.

By immobilizing the prey, this hunting technique seems to aid in locating or catching the prey, and it can also serve to conceal the predator from the prey. The precise position of their prey can be predicted by humpback whales. They can therefore use air bubbles to enclose their prey. The whale hunting is regarded as the ideal point to reach in WOA. The finest response found or a point nearby it is thought of as the optimum point because the optimal solution to optimization issues is unknown. Whenever the best search agent has been identified, the best search agent is used to update the positions of other search agents.

Therefore, to update whale locations, determine a 50% likelihood of selecting either the spiral model or the declining encircling technique. The encircling and spiral position updates can be described by equation (5).

$$\vec{P}(t+1) = \begin{cases} \overrightarrow{P^*}(t) - \vec{Q} \cdot \vec{A} & if\ p < 0.5 \\ \overrightarrow{A'} \cdot e^{ck} \cdot \cos(2\pi k) + \overrightarrow{A^*}(t) & if\ p \geq 0.5 \end{cases} \tag{5}$$

The shape of the logarithmic spiral is determined by the constant c, a random number k that falls between [-1, 1], and a multiplicand (.) that multiplies each element individually.

Instead of using the most popular location, new search agent sites for global search are found around a randomly chosen search agent.

$$\vec{A} = |\vec{B} \cdot \vec{P}rand - \vec{P}| \quad (6)$$

$$\vec{P}(t+1) = \vec{P}rand - \vec{Q} \cdot \vec{A} \quad (7)$$

where $\vec{P}rand$ is a position vector representing a randomly chosen whale from the current population [20]

IV. PROPOSED MODEL

This section covers the information about network model, energy model, CH selection, and fitness function used for optimal CH election.

3.1 Network Model

The following factors are taken into account when building the network model:

- Every node is fixed in place and has a random position.
- The initial energy of every node in a homogeneous network is constant.
- The exact locations of the nodes themselves and one another are unknown.
- The nodes self-organize after deployment and don't need to be watched over.
- Each node periodically collects data and passes it to the appropriate cluster head. Any node is capable of acting as the cluster head.
- BS is located at the center of the network.

3.2 Energy Model

A straightforward radio model is used in this model to compute the energies of both receiver and transmitter [21]. The energy needed to send and retrieve the u bit packets of information over the distance l are expressed in equations (8) and (9) correspondingly.

$$E_{TX}(u,l) = \begin{cases} u * (E_{elec} + \varepsilon_{fs} * l^2), & l \le l_0 \\ u * (E_{elec} + \varepsilon_{mp} * l^4), & l > l_0 \end{cases} \quad (8)$$

$$E_{RX}(u,l) = l * E_{elec} \quad (9)$$

where E_{elec} is the amount of energy lost at the point of transmission and reception, l is the transmission distance, l_0 is the threshold transmission distance, ϵ_{fs} is the amplification energy for free space and, ϵ_{mp} is the amplified energy for multipath models.

3.3 Optimal CH Selection Process

It is believed that the intended algorithm is implemented on a collection of stationary nodes that are randomly placed throughout a sensor network. The basis of the suggested method's operation is a centrally managed algorithm imposed by the base station. The process runs in rounds. All nodes provide their initial energy and position data to the base station at the start of each setup phase. The base station then runs WOA to identify the cluster heads that provide the best fitness function values. There are N search agents (artificial whales) that are equivalent to temporary cluster heads $\{Ch = Ch_1 + Ch_2 + \ldots + Ch_n\}$.

The search agent's initial spawn location is chosen at random, and when it does, the information of the nearby node is copied to its position. The base station uses this data to calculate the fitness value (residual energy, the separation between the nodes and the cluster head, and the distance between the cluster head and the base station), with the best fitness value then being considered for selection as the cluster head. Fitness function is crucial and is constructed as follows:

$$F = \alpha.\sum_{j=1}^{k} \frac{1}{E_r(Ch_j)} + \beta.\sum_{i=1}^{k}\left(\sum_{j=1}^{I_i} D(N_j, Ch_i)/N_i\right) + \Upsilon.\sum_{j=1}^{k}\left(D(BS, Ch_j)\right) \quad (10)$$

In equation (10) the values of α, β and Υ are 0.5, 0.25, and 0.25, respectively. After a number of iterations, the best cluster head is selected based on best fitness value. Then the base station transmits the cluster heads' IDs throughout the network after determining the best arrangement of cluster heads and the nodes they belong to. These cluster heads each function as a neighborhood control point for data transmission and collection.

V. PERFORMANCE EVALUTION

Performance evaluation metrics are employed in wireless sensor networks to evaluate the efficacy and efficiency of the network and the applications that are connected to it. The following metrics are frequently used to assess WSN performance:

- **Energy consumption**: The overall energy consumed during a given round can provide a good measure of the algorithm's energy efficiency, and it rises as the number of rounds grows.
- **Throughput**: The amount of data that is successfully transferred to the base station within a predetermined amount of time is known as throughput. High throughput characterizes a good sensor network.
- **Stability Region**: It describes how long the network can continue to function before the first sensor node runs out of power. For a network to operate sustainably, stability optimization is essential. The statistic can be calculated as the number of iterations until the first node fails.

- **Network Lifespan:** The amount of time a sensor network may continue to function until the last sensor node stops working or runs out of power is referred to as the network lifespan. It is an important performance indicator that measures how long the network will continue to function.

VI. RESULT AND ANALYSIS

The suggested protocol's performance metrices were analyzed and evaluated using MATLAB 2022a for different number of cluster heads. In Table 1, the different parameters are displayed that are used for simulations.

Table 1: Parameters used in suggested algorithm.

Parameters	Value
Sensing area	100*100 m^2
Sensing nodes	100
Position of base station	Center
Packet size	4000 bits
Initial energy	0.5 J
Transmit amplifier (ϵ_{mp})	0.0013 $pj/bit/m4$
Transmit amplifier (ϵ_{fs})	10 $pj/bit/m^2$
Tx/Rx Electronics (E_{elec})	50 nJ/bit
No. of CHs	5,10,15,20,25,30,35

The statistics and analysis of the suggested approach are presented in this section based on the performance measures described in Section 5. The data is then analyzed after the suggested algorithm has been performed by changing the number of cluster heads.

Figure 1 shows the initial, half, and final dead nodes in the network for the suggested algorithm, with CH numbers varying from 5 to 35 with an interval of 5. Our investigation, however, shows that the algorithm stability region that is the first node dead increases with the increment in CHs, but after 20 CHs it again decreases. Network lifespan performs better with fewer CHS, but it decreases as the number of CHS increases.

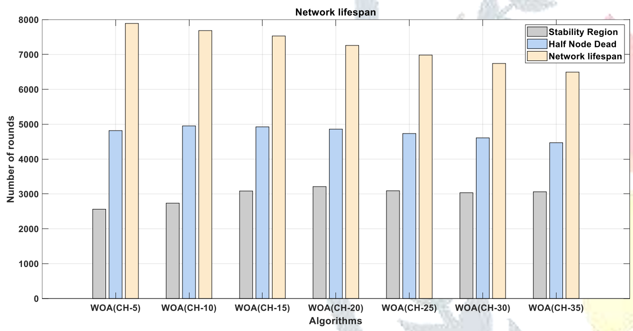

Fig-1: Comparison of stability region and network longevity.

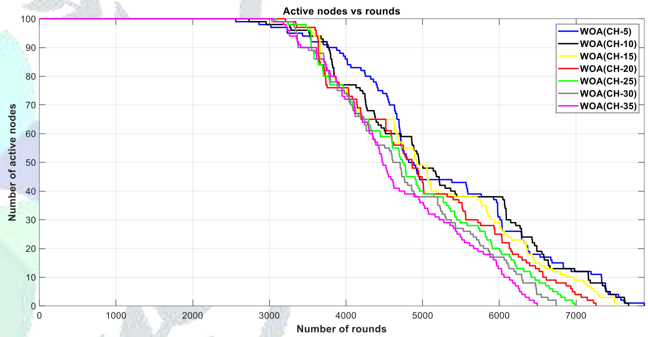

Fig-2: Comparison of various cases for active nodes versus rounds.

Figure 2 shows the number of active nodes versus iterations. According to Figure 1 and 2, the stability region is highest when the number of CHs is 20, and the network lifespan is highest when the number of CHs is 5.

Table 2 gives the comparison data for stability region and network longevity for all cases with CH numbers varying from 5 to 35. In Table 2, red numbers show the minimum value, and blue numbers show the maximum value.

Figures 3 and 4 show the maximum number of packets received by the base station with varying numbers of CHs. As shown in the figures, throughput increases continually with the increment in CHs. Table 3 gives information about the number of data packets received by the workstation.

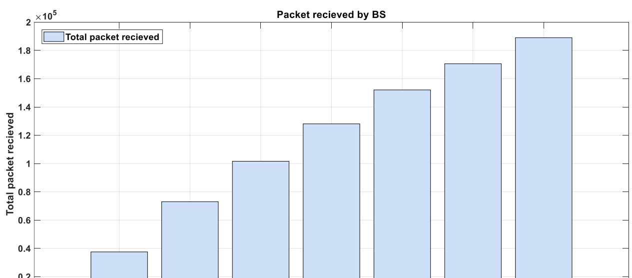

Fig-3: Packet received analysis.

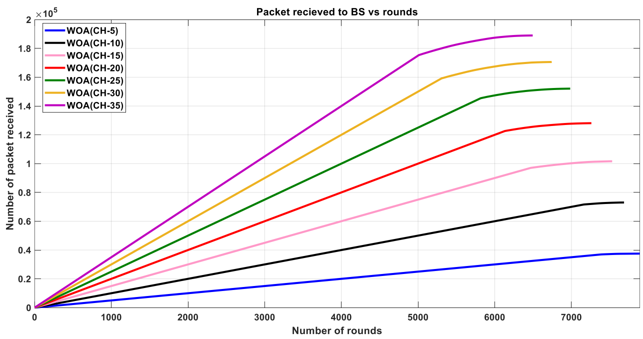

Fig-4: Packet received analysis.

Table 2: Comparative analysis of various parameters.

No. of CHs	Stability Region	Half dead nodes	Network lifespan
5	**2561**	4817	**7891**
10	2735	4951	7686
15	3083	4924	7531
20	**3210**	4859	7260
25	3089	4733	6984
30	3033	4608	6743
35	3060	4469	**6495**

Table 3: Comparative analysis of throughput.

Number of CHs	Throughput
5	**37515**
10	73005
15	101626
20	128079
25	152067
30	170566
35	**188990**

An algorithm's total consumption of energy may serve as a valuable measure of how resource-efficient it is, and as the number of iterations rises, so does the overall energy consumption. Energy use for the right clustering technique should be as minimal as possible. Figure 5 shows a comparative analysis of energy consumption. Data on total energy utilization versus iteration for several scenarios at 5000 rounds are shown in Figure 6.

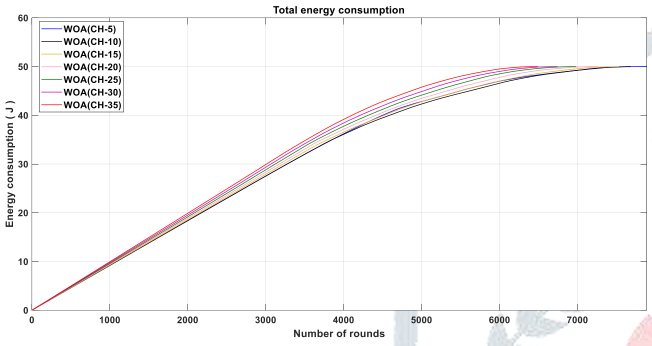

Fig -5: Analysis of energy consumption.

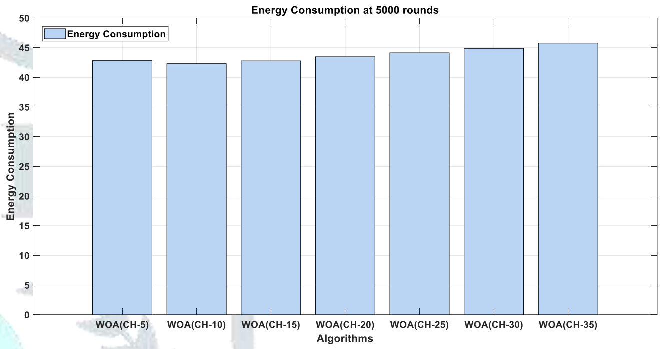

Fig -6: Analysis of energy consumption.

Table 4 gives the data on total use of energy versus iteration for different cases at 5000 rounds. Energy consumption at 5000 rounds is minimum when the number of cluster heads is 10, and energy consumption is maximum when CHs are 35. Here, blue numbers show the best value and red numbers show the worst value of energy consumption in a network.

Table 4: Comparative analysis of energy consumption at 5000 iterations.

Number of CHs	Energy consumption
5	42.824
10	**42.315**
15	42.783
20	43.477
25	44.142
30	44.881
35	**45.775**

VII. Conclusion

In this paper, using different numbers of cluster heads to apply clustering algorithms in sensor networks has produced insightful results. With this study, we desired to examine the effects of various CH numbers on the functionality of the WSN. The study's findings presented a number of significant conclusions. First, we found that adding more CHs led to a subsequent increase followed by a decrease in the stability region. Second, there was a clear correlation between the number of CHs and energy use. We discovered that more CHs use more energy since they receive data from the sensing nodes and then retransmit signals to the base station. A balance must be struck, though, since having too many CHs can result in higher control costs and lower energy effectiveness. Furthermore, it is observed that the number of packets transmitted increases with the increment in CH numbers.

In the future, results will be further explored by analyzing other parameters such as fault tolerance, node balancing, and security issues in real-world deployment.

References

[1] Heinzelman, W. R., Chandrakasan, A., & Balakrishnan, H. 2000. Energy-efficient communication protocol for wireless microsensor networks. In Proceedings of the 33rd annual Hawaii international conference on system sciences. IEEE. 10.

[2] Sun, Z. G., Zheng, Z. W., & Xu, S. J. 2009. An efficient routing protocol based on two step cluster head selection for wireless sensor networks. In 2009 5th International Conference on Wireless Communications, Networking and Mobile. IEEE. 1-5.

[3] Chniguir, A., Farah, T., Jemaa, Z. B., & Belguith, S. 2021. Performance Evaluation of Clustered Routing Protocols for Heterogeneous Wireless Sensor Networks. International Journal of Electronics and Communication Engineering, 15(3): 110-115.

[4] Lindsey, S., & Raghavendra, C. S. 2002. PEGASIS: Power-efficient gathering in sensor information systems. In Proceedings, IEEE aerospace conference, 3: 3-3.

[5] Sadhana, S., Sivaraman, E., & Daniel, D. 2021. Enhanced Energy Efficient Routing for Wireless Sensor Network Using Extended Power Efficient Gathering in Sensor Information Systems (E-PEGASIS) Protocol. Procedia Computer Science, 194: 89-101.

[6] Liu, T., & Li, F. 2009. Power-efficient clustering routing protocol based on applications in wireless sensor network. In 2009 5th International Conference on Wireless Communications, Networking and Mobile Computing,1-6.

[7] Tripathi, M., Battula, R. B., Gaur, M. S., & Laxmi, V. 2013. Energy efficient clustered routing for wireless sensor network. In 2013 IEEE 9th International Conference on Mobile Ad-hoc and Sensor Networks, 330-335.

[8] Manjeshwar, A., & Agrawal, D. P. 2001. TEEN: A Routing Protocol for Enhanced Efficiency in Wireless Sensor Networks. In ipdps, 1:189.

[9] Vimalarani, C., Subramanian, R., & Sivanandam, S. N. 2016. An enhanced PSO-based clustering energy optimization algorithm for wireless sensor network. The Scientific World Journal, 2016.

[10] Agrawal, D., Wasim Qureshi, M. H., Pincha, P., Srivastava, P., Agarwal, S., Tiwari, V., & Pandey, S. 2020. GWO‐C: Grey wolf optimizer‐based clustering scheme for WSNs. International Journal of Communication Systems, 33(8): e4344.

[11] Elhabyan, R. S., & Yagoub, M. C. (2014, September). Energy efficient clustering protocol for WSN using PSO. In 2014 Global information infrastructure and networking symposium (GIIS),1-3.

[12] Rambabu, B., Reddy, A. V., & Janakiraman, S. 2022. Hybrid artificial bee colony and monarchy butterfly optimization algorithm (HABC-MBOA)-based cluster head selection for WSNs. Journal of King Saud University-Computer and Information Sciences, 34(5):1895-1905.

[13] Lipare, A., Edla, D. R., & Kuppili, V. 2019. Energy efficient load balancing approach for avoiding energy hole problem in WSN using Grey Wolf Optimizer with novel fitness function. Applied Soft Computing, 84, 105706.

[14] Kaddi, M., Banana, A., & Omari, M. 2021. ECO-BAT: A New Routing Protocol for Energy Consumption Optimization Based on BAT Algorithm in WSN. Computers, Materials & Continua, 66(3).

[15] Sharawi, M., Emary, E., Saroit, I. A., & El-Mahdy, H. 2014. Bat swarm algorithm for wireless sensor networks lifetime optimization. Int. J, 3(5): 654-664.

[16] Sahoo, B. M., Amgoth, T., & Pandey, H. M. 2020. Particle swarm optimization based energy efficient clustering and sink mobility in heterogeneous wireless sensor network. Ad Hoc Networks, 106, 102237.

[17] Priyanka, B. N., Jayaparvathy, R., & DivyaBharathi, D. 2022. Efficient and dynamic cluster head selection for improving network lifetime in WSN using whale optimization algorithm. Wireless Personal Communications, 123(2): 1467-1481.

[18] Gupta, A. D., & Rout, R. K. 2022. A WOA Based Energy Efficient Clustering in Energy Harvesting Wireless Sensor Networks. Amity Journal of Computational Sciences, 5(2).

[19] Mirjalili, S., & Lewis, A. 2016. The whale optimization algorithm. Advances in engineering software, 95: 51-67.

[20] Baidar, L., Rahmoun, A., Lorenz, P., & Mihoubi, M. 2019. Whale optimization approach for optimization problem in distributed wireless sensor network. In Proceedings of the 9th International Conference on Information Systems and Technologies,1-7.

[21] Yassein, M. O. B., A. Al-zou'bi, Khamayseh, Y. M., & Mardini, W. 2009. Improvement on LEACH Protocol of Wireless Sensor Network (VLEACH). J. Digit. Content Technol. its Appl., 3(2): 132-136.