Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/180304

Comparative Analysis of Energy-Efficient Clustering Algorithms for IoT Networks

Ahmed Gamal Soliman Soliman Deabes[1,*] , *Esraa M. Eid* [2] , *Hala Abd El-kader Mansour*[2], *and Michael Nasief*[2]

[1]Department of Electronics and Communication, Faculty of Engineering, Modern University for Technology and Information, Cairo, Egypt
[2]Department of Electronics and Communication, Faculty of Engineering, Shoubra, Benha University, Cairo, Egypt

Received: 1 Feb. 2024, Revised: 2 Mar. 2024, Accepted: 6 Mar. 2024
Published online: 1 May 2024

Abstract: The Internet of Things (IoT) is a crucial part of the future Internet. It can obtain and transfer data, making things more effective. The energy consumption of nodes is a challenge in IoT networks. Innovation in IoT is a dynamic and evolving field. The IoT plays a significant role in contributing to sustainable cities and economies. Clustering is an IoT data collection strategy that decreases energy usage by generating clusters out of IoT nodes. The Cluster Head (CH) supervises all Cluster Member (CM) nodes within each group, enabling the establishment of both intra-cluster and inter-cluster connections. Numerous algorithms are available to extend the IoT's remaining energy time, increase the number of nodes that are in an active state, and lengthen the network's lifespan. These algorithms use optimization and clustering approaches to improve the network's overall performance and energy efficiency. In this paper, a comparison between five algorithms is carried out, which are Low Energy Adaptive Clustering Hierarchy (LEACH), Artificial Fish Swarm Algorithm (AFSA), Genetic Algorithm (GA), Energy-Efficient Routing using Reinforcement Learning (EER-RL), and Modified Low Energy Adaptive Clustering Hierarchy (MODLEACH). According to the comparison between the five algorithms, the AFSA algorithm proved the highest efficacy, yet the GA algorithm remained superior in certain conditions.

Keywords: The Internet of Things- Cluster Head- Energy - Cluster Member.

1 Introduction

The IoT describes a network consisting of interconnected physical devices or items via the Internet, enabling them to interact and communicate amongst themselves and with users. This connectivity allows users to monitor and control these devices remotely [1]. The IoT is increasingly significant in smart homes, cities, industries, and other domains. With the IoT continually evolving, a growing variety of devices will gain the ability to connect and make use of its features. According to forecasts, the number of linked devices is predicted to reach 80 billion by 2030, equating to approximately 21 connected devices for each individual [2]. The expansion of IoT is shaping it to be the future technology of the coming years. IoT devices typically come equipped with sensors that collect and transmit data over the Internet for monitoring, control, or decision-making purposes. Most of this data is gathered in real-time to enable accurate decision-making regarding the device's condition [3]. IoT technologies can collect, measure, and analyze their surroundings, potentially leading to enhancements that improve the quality of life [4]. This situation simplifies communication between humans and objects through novel means facilitating the development of smart cities [5]. However, the network's inherent characteristics pose challenges, including reliability,

redundancy, and the presence of a diverse network with multiple nodes. These challenges can affect the performance of routing protocols at the network layer [6]. Hierarchical routing is an effective solution to enhance the longevity of IoT devices. Nodes are grouped into clusters, and each is managed by a node known as a Cluster Head [7,8]. As shown in Figure 1, the CHs serve as intermediaries connecting the nodes within the cluster around the central Base Station (BS). This intermediary role reduces the necessity for multiple communication hops and aids in conserving energy [9]. By utilizing clustering, the network enhances its scalability and network performance. Consequently, this leads to an

* Corresponding author e-mail: ahmed_deabes2009@yahoo.com

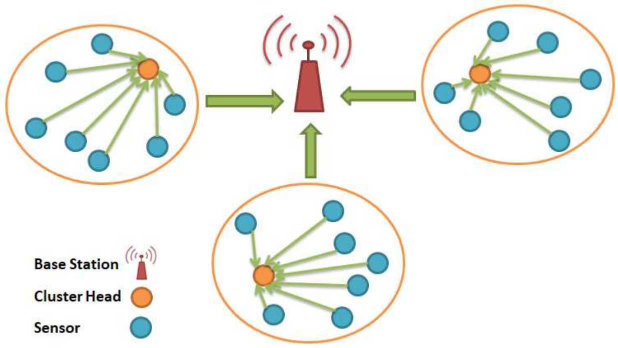

Fig. 1: The overview includes CHs and a BS.

extension of battery life and an increase in the overall lifespan of the network [10].

In a clustered network, several CM nodes are linked to a single CH node [11]. The CM nodes serve as standard network nodes and execute various tasks like transmitting data to the CH node. After the CH node receives and combines the data, it forwards them to the BS. Using a single-hop or multi-hop approach, depending on the specific application and network size, this routing approach reduces energy consumption and significantly minimizes communication among IoT nodes. The CH node is in charge of overseeing internal communication and data transfer within each cluster. [12].

Many algorithms aim to increase the lifespan and energy efficiency of IoT networks. This paper aims to compare five of these algorithms.

The first algorithm is the LEACH, which aids in reducing power consumption via clustering. A few CHs are chosen based on cluster rotation, and other nodes join these cluster heads to build clusters. Sent to the appropriate CH for aggregation, the CH subsequently relays the detected data to the BS [13].

The second algorithm is the Genetic Algorithm. It assesses all chromosomes by computing the fitness function encompassing three parameters: the cluster distance, the final node's energy depletion round, and the initial node's energy depletion round [14].

The third algorithm is the Artificial Fish Swarm Algorithm, which consists of three essential components: following behavior, swarming behavior, and search behavior [15]. In AFSA, individual fish enhance their positions by learning from the best-performing fish. This algorithm finds application in IoT networks by optimizing network resource allocation, routing strategies, and sensor node deployment, ultimately leading to improved efficiency and enhanced performance.

The fourth algorithm is Energy-Efficient Routing using Reinforcement Learning, in which devices can enhance their routing decisions by exchanging localized information within their vicinity. This optimization minimizes energy consumption by selecting the most efficient next-hop routes. The sender adds local data to the packet's header to achieve this. Any adjacent device that intercepts the packet can deduce this data from the header. The shared local data includes device identification, remaining energy levels, positional coordinates, and hop count. EER-RL comprises three key phases: network initialization and cluster head selection, the formation of clusters, and the transmission of data [16].

The fifth algorithm, the MODLEACH, adapts the LEACH algorithm. The objective of MODLEACH is to optimize the energy usage of IoT devices. It dynamically chooses cluster heads that manage communication within clusters to ensure that devices are evenly divided among energy-intensive activities [17].

The rest of this paper is structured as follows: A review of the relevant literature for the chosen cluster head method algorithms for IoT is provided in Section 2. Section 3 contains the specifics of the comparing algorithms. The performance study, MATLAB implementation, and simulation results of the algorithms are presented in Section 4. Conclusion and future work are presented in Section 5.

2 Literature review

In [18], the LEACH algorithm uses a cluster formation process where nodes autonomously select themselves as cluster heads, and this selection probability is directly related to their residual energy levels. The network's energy load is evenly distributed, and nodes assume the role of cluster heads when they have more energy remaining.

S. Bhatia, A. Kumar, and A. Shuhail [19] employ cluster head nodes designated for each cluster to relay information to the BS. The network comprises numerous sensor nodes organized into clusters through clustering. The selection of cluster heads within each cluster is based on the highest available energy and the shortest distance between nodes. The cluster head receives data collected by the other nodes within the cluster. Subsequently, this information is consolidated at the nearest cache node to the cluster heads. The metric employed to compute the distance between the cache node and the cluster head is referred to as Euclidean distance.

Also, S. Rabah, A. Zaier, and H. Dahman [20] utilized genetic algorithms within the base station to select the best IoT nodes from among the qualifying nodes, designating them as Cluster Heads. These chosen CHs are responsible for gathering data from the other nodes and relaying it to the BS, marking the completion of a single round. After each round, the BS reevaluates the energy levels of the IoT nodes, which may potentially lead to the formation of new clusters. The primary criterion for selecting CHs is their Fitness parameter determined by the qualifications of the IoT nodes.

In [21], The CHs are chosen using an optimized genetic algorithm for CH election. Node density, distance, energy, and the heterogeneous node's capability are the four criteria integrated into the GA-based CH selection process and used to create a fitness function. Reducing intra-cluster distance, effectively managing node energy within the cluster, minimizing hop count, and favoring the selection of competent nodes as CHs are some essential aspects that these criteria help optimize.

In [22], the artificial fish swarm algorithm draws inspiration from the social interactions observed in natural fish schools. The core concept behind AFSA involves replicating fish behaviors such as hunting, group formation, and tracking, all while incorporating a local search component to enable individual fish to reach their best. AFSA offers numerous advantages, such as rapid convergence, adaptability, and precision.

In addition, D. Mechta and S. Harous [23] introduced a setup phase that initiates each round. During this phase, the base station acquires location information and the remaining energy levels of all nodes within the network. This information enables the virtual division of the network area into zones, with the initial Cluster Heads selected as the nearest nodes to each zone's center. The formation of clusters is accomplished using the artificial fish swarm algorithm. For every group of CHs, initial clusters are created during this process, and every node is associated with the closest CH. Then comes the data aggregation phase, in which every CH gathers data from other nodes in its cluster. Finally, the data transmission phase unfolds, encompassing the direct transfer of data from each CH to the BS or potentially through other CHs.

Furthermore, Y. Serrestou, S Bouzid, M. Omri, and K. Raoof [24] introduced reinforcement learning for lifetime optimization, which efficiently manages energy consumption by dynamically selecting the optimal path to the sink node. This operates without requiring prior knowledge of the network. Through a discovery process, each node autonomously explores its neighboring nodes. Subsequently, the learning process empowers each node to make informed decisions about selecting the best forwarder based on factors like remaining energy, required energy, and hop count. This selection helps prevent node isolation, balances energy consumption across all sensor nodes, and ensures the successful delivery of packets.

The authors in [25] use the MODLEACH algorithm for cluster head selection, considering the sensor nodes' probability and present energy levels. This probability factor ensures an equitable chance for each sensor node to become a CH over the entire network lifespan. The algorithm within MODLEACH governs the process of CH selection. After the CH is designated, all nodes collaborate in transmitting data to the BS through the chosen CH. The CH is entrusted with aggregating this data, and the selection of CHs hinges on a predetermined threshold value. Sensors are assigned varying energy levels, with some starting at their maximum energy capacity.

This paper compares the algorithms (LEACH, GA, AFSA, EER-RL, and MODLEACH), and the MATLAB code will be implemented and tested.

3 Comparison of clustering algorithms

In this section, a brief explanation of each algorithm will be provided.

3.1 LEACH Algorithm

The LEACH employs a cluster-oriented routing approach to reduce overall energy usage in a network. LEACH groups deployed nodes in a region into clusters, each with a CH node. The communication process involves two main phases: the setup and steady-state phases.

The CH and member nodes inside each cluster are selected during the setup phase. During the steady-state phase, the CHs gather and consolidate data generated by their respective cluster members and subsequently relay this data to a central BS. This phase endures for a longer duration compared to the setup phase due to the data processing. As such, there is an increase in energy consumption during the steady-state phase. In the setup phase, the nodes designated as CHs for the current round are chosen independently and randomly, provided that their energy level exceeds a minimum threshold but remains above zero.

The creation of a random number (R_n) is necessary for a CH node to operate. where $R_n \in [0,1]$. The selection of the CH node selection of the CH node when $R_n \leq T(n)$, A threshold value obtained from Equation 1 is denoted by $T(n)$. The cluster's nodes receive a nomination from the CH node, chosen based on their proximity to the CH node.

$$t(n) = \begin{cases} \frac{p}{1-p\left(r \mod \frac{1}{p}\right)} & \text{if } n \in G, \\ 0 & \text{otherwise.} \end{cases}, \qquad (1)$$

where represents the group of nodes that have not been designated as *CH* nodes in the preceding selection rounds, is the current number of selection rounds, and the probability that a node will surpass every other node in the network to become a CH node is denoted by . The CH nodes selected for each cluster allocate time slots for data transmission using Time Division Multiple Access (TDMA). This system of data transmission orders for each CH node enables them to optimize their resting periods between transmissions.

3.2 Genetic Algorithm

The GA is an exploration technique that is rooted in the concepts of natural selection and genetics. Chromosomes and genes are the fundamental building components of a

GA. In a binary code chain, the optimization parameters are represented in bits. An objective function is employed in the evolutionary process to separate the most adapted individuals from each generation and reject the least suited. Once the problem has been represented using chromosomes, and an appropriate parameter has been selected to distinguish between effective and ineffective solutions, as determined by the objective function, the GA is poised to identify the solution. Figure 2. shows a general overview of the Genetic Algorithm. Here is a detailed explanation of how the GA algorithm works in IoT networks:

Initialization: The GA algorithm starts by generating the first population of potential solutions. These denote different routing pathways connecting the source and destination nodes.

Evaluation: Every potential solution undergoes an evaluation according to an objective function, which could involve minimizing energy consumption or maximizing the network's lifespan.

Selection: Using a selection operator, a subset of candidate solutions is chosen based on their fitness.

Crossover: In the realm of IoT sensor nodes, this procedure entails the selection of pairs of CHs and the creation of new offspring solutions through the utilization of a crossover operator.

Mutation: The new population of CHs for the subsequent iteration is formed from the offspring solutions with the most significant fitness values. This procedure is repeated until a halting requirement, such as a maximum number of iterations, is satisfied.

Replacement: The new candidate solutions are substituted for the least-fitting candidate solutions to create the CH.

Termination: The procedure persists until a termination criterion is satisfied.

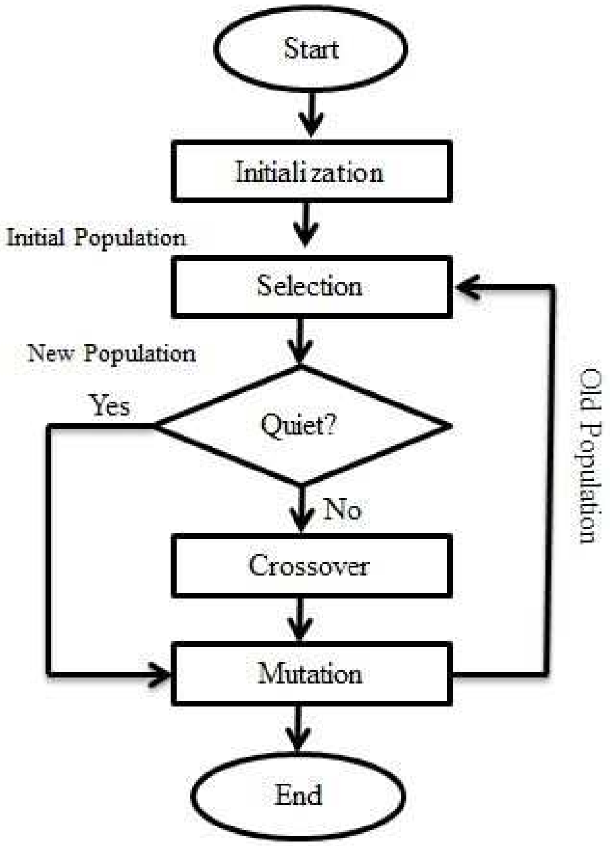

Fig. 2: Flow chart of Genetic Algorithm.

3.3 AFSA Algorithm

The fundamental principle of the AFSA is derived from the behavioral patterns observed in fish swarms. In the underwater environment, fish have a natural ability to locate areas with abundant prey. This situation arises from the individual's or group's search for nourishment through the fish. Subsequently, in the AFSA, artificial fish navigate towards regions of higher prey density, concentrating their efforts on capturing their targets. Figure 3. provides an overview of the AFSA Algorithm.

This algorithm is versatile for tracking purposes and operates without the need for prior knowledge of the objective function's value during IoT optimization. It consistently delivers robust and effective results without being overly sensitive. A detailed description of each phase follows. The first component pertains to the searching behavior of the fish, allowing them to explore their aquatic environment freely in search of food. When a significant food source is located, the fish quickly

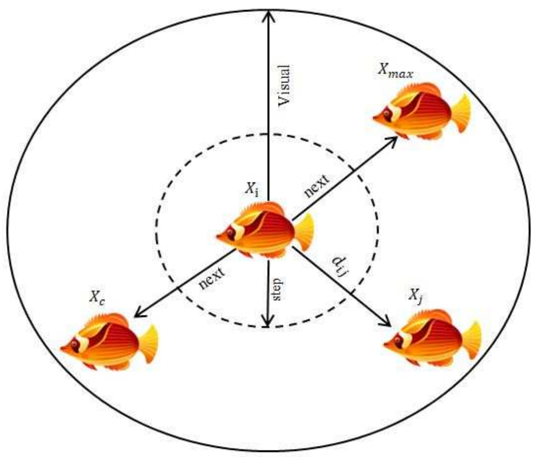

Fig. 3: The vision of the AFSA algorithm.

converge towards it. This behavior can be computed using Equation 2, where X_n Represents the central position of the artificial fish (AF).

$$X_j = X_i + AF\text{visual} \cdot \text{Rand} \tag{2}$$

Here, $X_i$represents the current state of AF and X_j is selected randomly from within its observable range. The larger the AF_{visual} value, the simpler it becomes to detect the AF. In Equation 3, if Y_j is less than Y_i, it signifies the boundary of the problem's last iteration, and the AF moves forward. At time t, $X_i^{(t+1)}$ represents the state of the AF.

$$X_i^{(t+1)} = X_i^t + \left(\frac{X_j - X_i^t}{\|X_j - X_i^t\|}\right) \cdot \text{AFstep} \cdot \text{Rand} \tag{3}$$

The second component involves the swarming behavior of the fish. Fish can procure food while in motion, ensuring survival and avoiding potential threats. To avoid clustering with their peers, they adhere to three principles: cohesion, alignment, and movement along the same path as other groups, as defined by Equation 4.

$$X_i^{(t+1)} = X_i^t + \left(\frac{X_c - X_i^t}{\|X_c - X_i^t\|}\right) \cdot \text{AFstep} \cdot \text{Rand} \tag{4}$$

The third component pertains to the following behavior. When one fish's movement pattern identifies a richer food source, other fish promptly become aware of it. In this context, X_i represents the current state of the AF, and the AF scans its vicinity for d_i values less than AF_{visual}, examining X_j using Y_j If Y_j surpasses Y_i, has a higher concentration of nutrients (resulting in a higher cost function value) with less congestion. Equation 5 calculates the distance between nodes and, representing the length of the connecting line. Equation 6 supplies the median value for the expected number of nodes allocated to each cluster.

$$ED(q,p) = \sqrt{\sum_{m=1}^{d} (q_m - p_m)^2} \tag{5}$$

$$\mu = \frac{N-K}{K} \tag{6}$$

Here, K represents the number of clusters, N signifies the total count of IoT nodes, and μ stands for the average number of IoT nodes per cluster.

3.4 EER-RL Algorithm

EER-RL enhances routing decisions among devices by fostering the exchange of localized data with nearby nodes, resulting in the more efficient selection of subsequent hops and reduced energy consumption. When a packet is transmitted, it contains a network. Any nearby device capable of overhearing the transmission can extract this data. EER-RL comprises three primary stages: network setup and cluster head election, cluster formation, and data transmission.

The initial stage in the network setup and cluster head election procedure involves calculating the device's initial Q-value using the locally acquired data from the network configuration phase. Upon receiving a message from the BS containing its position coordinates, each device stores the base station's position and computes its initial Q-value using Equation 7 and Equation 8, considering the hop count and initial energy level. As each device has a distinct energy level, a threshold distance is established between the BS and the cluster heads to minimize network overhead and assist IoT sensors far from the BS in finding a CH.

$$Q = \begin{cases} \frac{1}{N_h}, & \text{if } E_{\min} = E_{\max}, \\ p\left(\frac{E_r - E_{\min}}{E_{\max} - E_{\min}}\right) + (1-p)\frac{1}{N_h}, & \text{if } E_{\min} \neq E_{\max}. \end{cases} \tag{7}$$

$$N_h \approx \frac{D_{\text{link}}}{\text{TXrange}} \tag{8}$$

where p indicates the number of companions, N_h indicates the distances between the nodes, E_r is the receiver energy, $E_{\min}$ is the lowest energy and $E_{\max}$ is the most energy. D_{link}denotes the distance of the link between the nodes. In the second stage of cluster formation, following the election of cluster heads, each CH sends an invitation message to all devices within its transmission range during the second stage of cluster creation. Each CH sends an invitation message containing its ID, coordinates, and starting Q-value. When non-CH devices hear these invitation messages, they utilize the data to choose which cluster to join based on variables like distance. They then submit a request and their local details to the assigned CH. When a device is positioned at the intersection of multiple clusters and gets multiple invites, it can join the cluster with the nearest channel.

In the third stage, the energy consumption model accounts for energy usage by both the sender and receiver following packet transmission. The sender typically incurs higher energy consumption as it needs to amplify the signal over a distance and transmit packets across the network. This energy consumption model is employed to compute the energy expended during packets' sending or receiving and keep the residual energy updated. Equation 9 illustrates the energy consumption model.

$$\begin{cases} E_{\text{TX}}(k,d) = E_{\text{elec}} \times K + E_{\text{amp}} \times k \times d^m \\ E_{\text{RX}}(k) = E_{\text{elec}} \times K \end{cases} \tag{9}$$

$E_{\text{TX}}(k,d)$ represents the energy expended by the sender and $E_{\text{RX}}(k)$ indicates the energy used by the receiver. Here, d^m signifies the distance between nodes, k denotes the energy coefficient, E_{elec} stands for the initial energy and E_{amp} represents the current energy level of each node.

3.5 MODLEACH Algorithm

The MODLEACH algorithm is a modified iteration of the widely used LEACH algorithm. In the next round, a predefined threshold for CH formation exists. If the current cluster has effectively conserved energy and maintains a level exceeding the specified threshold, It will carry over into the next round as a CH. The utilization of this algorithm significantly contributes to energy conservation that would otherwise be consumed in routing packets for the establishment of new CHs and clusters. However, if the energy level of the CH dips below a specific threshold, the algorithm selects a replacement CH. To further control energy usage during cluster formation, the algorithm introduces two distinct power levels enhancing signal strength based on the nature of the transmission. Three forms of transmission are in a clustered network: transmission from the CH to the BS, transmission between clusters, and intra-cluster transmission.

Transmission inside a cluster includes all types of communication within its members. In this type of communication, data is sensed by member nodes and sent to the CH. Inter-cluster transmission refers to the data exchanged between two CHs, whereas CH-to-BS transmission is the direct data transmission from a CH to the BS.

The energy requirements for inter-cluster or CH-to-BS communication differ from those for intra-cluster communication. While the amplification energy is uniform for all transmissions, employing lower energy levels for intra-cluster communication instead of CH-to-BS transmissions can result in substantial energy savings. Moreover, incorporating multiple power levels can reduce the packet drop rate.

MODLEACH employs a routing algorithm that guides a node, serving as a CH, to utilize high-power amplification. Once the node transitions to a cluster member in the subsequent round, the routing algorithm switches it to low-level power amplification.

4 Performance Evaluation

This section contrasts the simulation findings with the LEACH, GA, AFSA, EER-RL, and MODLEACH algorithms. The experiment resulted in three outputs: the number of live nodes, delay, and residual energy. The first part describes the simulation environment and then the simulation results.

Table 1: Simulation set up

parameters	Values
Size of a data packet	1024 byte
E_{fs}	$10\,P^{J/\text{bit}/\text{m}^2}$
E_{elec}	50 nJ/bit
E_{mp}	$0.0013\,P^{J/b/m^4}$
E_{DA}	5 nJ/b/message
Distance threshold (d_o)	$\sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}\,m$

Table 2: Presents specifications for four cases.

Cases	Radius	No. of Nodes	Eo	p
1	400 m	300	Eo=0.5J	0.05
2	500 m	300	Eo=1J	0.05
3	500 m	300	Eo=1.5J	0.03
4	500 m	400	Eo=0.5J	0.05

4.1 Simulation Environment

The performance of the compared algorithms is examined and evaluated using the MATLAB simulator. The primary and essential parameters are shown in Table 1.

The experiment involved four variables: the number of nodes, initial energy, number of clusters, and network radius, with one variable changed while the other variables were constant. An extensive set of sixty experiments resulted in three outputs in each experiment: the number of live nodes, delay, and residual energy. In 900 rounds, simulations were conducted. The base station is located at the center of the grid. Due to the faster transmission rate of IoT nodes, the packet size is 1024 bytes. The network features a circular layout with a radius of 200m, 300m, 400m, 500m, and 600m, with a The network comprises 100, 200, 300, 400, and 500 IoT nodes, each with initial node energy (Eo) of 0.5J, 1J, 1.5J, 2J, and 2.5J. The Number of Clusters (No = p * n) where n denotes the number of nodes, and p takes values of 0.03, 0.04, 0.05, 0.06, and 0.07, representing a percentage of the total number of network nodes in use. Specifications for four cases out of the sixty experiments will be presented in Table 2.

4.2 Experimental Results

The sections below exhibit the live nodes, defined as the count of nodes that are currently active in the network; the delay, defined as the average end-to-end latency; the residual energy, defined as the uses less energy and has more incredible remaining energy; and the lifetime defined as the period that the network is active.

4.2.1 Alive nodes

Figures 4, 5, 6, and 7 depict the number of alive sensor nodes in each round for four cases. As depicted in the

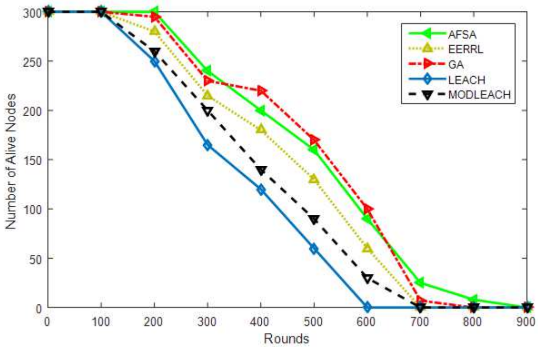

Fig. 4: shows the number of nodes alive in the 1st case.

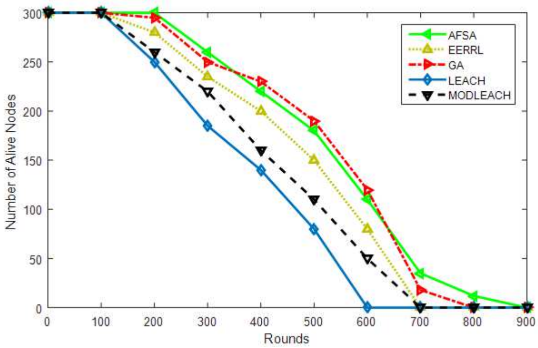

Fig. 5: shows the number of nodes alive in the 2nd case.

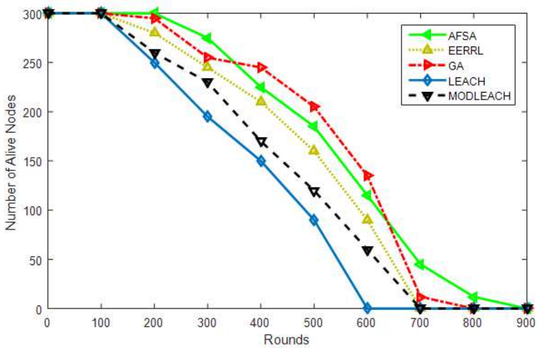

Fig. 6: shows the number of nodes alive in the 3rd case.

figure, AFSA is energy-saving, but in some cases, GA performs better. The LEACH, EER-RL, and MODLEACH algorithms consume amounts of energy. The last node of the AFSA algorithm dies in 900 rounds, but in the GA algorithm, it dies in 800 rounds, and in the EERRL algorithm and MODLEACH algorithm, it dies in 700 rounds, and the LEACH algorithm dies in 600 rounds.

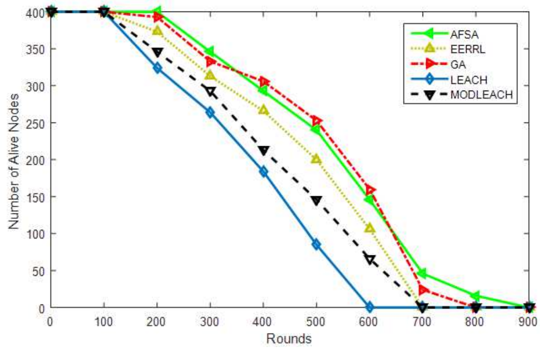

Fig. 7: shows the number of nodes alive in the 4th case.

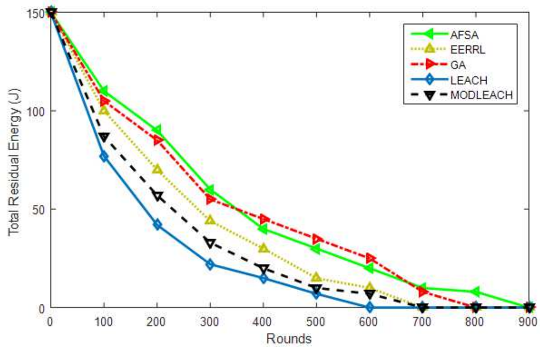

Fig. 8: depicts the total remaining energy in the 1st case.

4.2.2 Residual energy

Figures 8, 9, 10, and 11 present the overall remaining energy during each round for four cases. It can be seen that AFSA is generally energy-conserving, but in some cases, GA performs better. The selection of CH aims to improve performance based on distance, residual energy, the degree of IoT nodes, and the uniform distribution of clusters. The LEACH, EER-RL, and MODLEACH algorithms consume much energy during their operation and have the least energy remaining after 900 rounds.

4.2.3 Delay

One of the essential criteria for assessing network performance is transmission delay. In Figures 12, 13, 14, and 15, the performance of five algorithms is compared based on average end-to-end latency. AFSA performs the best, although GA outperforms others in some instances. The algorithm introduces a delay due to the re-selection of optimal CH nodes based on criteria. Notably, the LEACH, EER-RL, and MODLEACH algorithms exhibit significant differences.

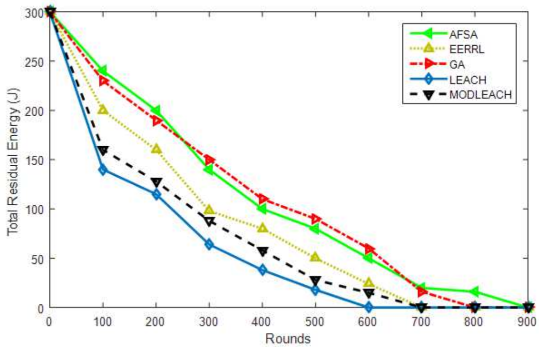

Fig. 9: depicts the total remaining energy in the 2nd case.

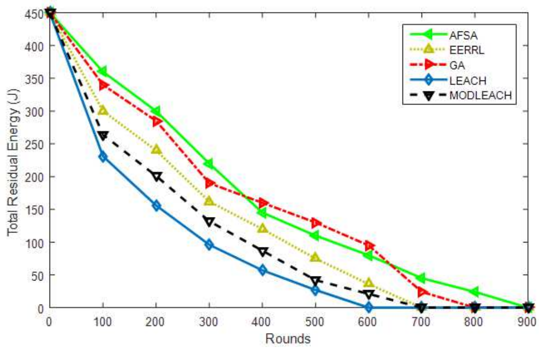

Fig. 10: depicts the total remaining energy in the 3rd case.

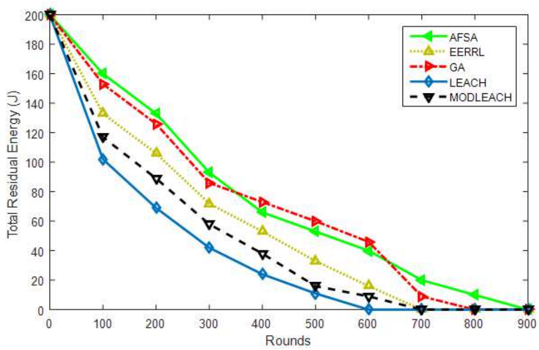

Fig. 11: depicts the total remaining energy in the 4th case.

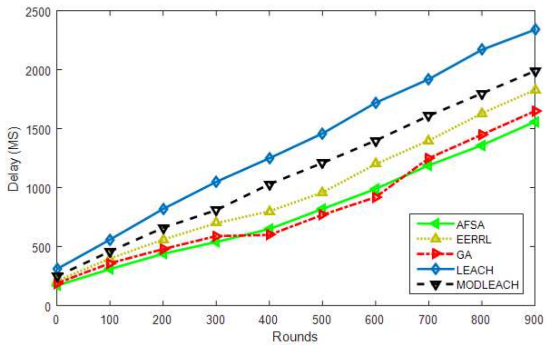

Fig. 12: Delay vs. rounds in the 1st case.

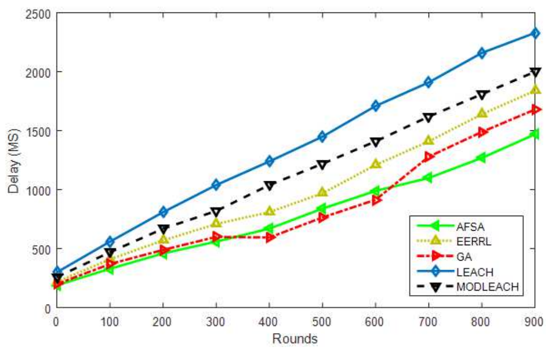

Fig. 13: Delay vs. rounds in the 2nd case.

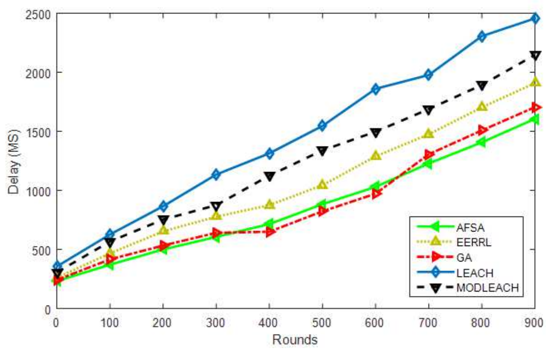

Fig. 14: Delay vs. rounds in the 3rd case.

5 Conclusion and future works

The IoT denotes a network of physical objects interconnected to the Internet, facilitating communication and information sharing. This paper focuses on the challenges facing the Internet of Things regarding energy consumption. Forming clusters from IoT nodes is a data collection strategy in IoT known as clustering, which effectively reduces energy usage. In this paper, the LEACH, GA, AFSA, EER-RL, and MODLEACH algorithms were compared, and MATLAB code was implemented and tested for the count of active nodes per round, the residual energy for each round, and the average end-to-end delay. The AFSA algorithm was the most effective when the five algorithms were compared, although the GA algorithm still performed better in some situations. The results were compared for further research

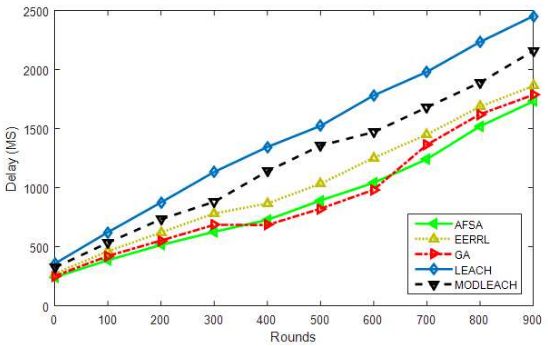

Fig. 15: delay vs. rounds in the 4th case.

on the performance evaluation of artificial intelligence to select the best result value for clustering techniques.

References

[1] A. Hameed and A. Alomary, "Security issues in IoT: A survey," 2019 Int. Conf. Innov. Intell. Informatics, Comput. Technol. 3ICT 2019, pp. 1–5, 2019.

[2] L. Chettri and R. Bera, "A Comprehensive Survey on Internet of Things (IoT) Toward 5G Wireless Systems," IEEE Internet Things J., vol. 7, no. 1, pp. 16–32, 2020.

[3] J. Chase, "Introduction The Evolution of the Internet of Things From connected things to living in the data, preparing for challenges and IoT readiness," Texas Instruments, vol. 1, pp. 1–7, 2020.

[4] A. Sarkeshikian, M. Shafia, A. Zakery, and A. Aliahmadi, "Simulation of stakeholders' consensus on organizational technology acceptance (case study: Internet of Things)," Kybernetes, vol. 50, no. 8, pp. 2367–2396, 2020.

[5] M. Hamzei and N. Jafari Navimipour, "Toward Efficient Service Composition Techniques in the Internet of Things," IEEE Internet Things J., vol. 5, no. 5, pp. 3774–3787, 2018.

[6] M. Sadrishojaei, N. J. Navimipour, M. Reshadi, and M. Hosseinzadeh, "A new clustering-based routing method in the mobile internet of things using a krill herd algorithm," Cluster Comput., vol. 25, no. 1, pp. 351–361, 2022.

[7] D. Valencia, "A Non-threshold-based Cluster-head Rotation," 2018 IEEE Glob. Commun. Conf., pp. 1–6, 2018.

[8] M. Amirinasab, S. Shamshirband, A. T. Chronopoulos, A. Mosavi, and N. Nabipour, "Energy-efficient method for wireless sensor networks low-power radio operation in internet of things," Electron., vol. 9, no. 2, 2020.

[9] R. Aslani and M. Rasti, "A Distributed Power Control Algorithm for Energy Efficiency Maximization in Wireless Cellular Networks," IEEE Wirel. Commun. Lett., vol. 9, no. 11, pp. 1975–1979, 2020.

[10] A. Dhumane, S. Chiwhane, K. Mangore Anirudh, and S. Ambala, Cluster-Based Energy-Efficient Routing in Internet of Things, vol. 311. Springer Nature Singapore, 2023.

[11] V. Rajaram and N. Kumaratharan, "An optimized clustering using hybrid meta-heuristic approach for wireless sensor networks," Int. J. Commun. Syst., vol. 33, no. 18, pp. 1–12, 2020.

[12] T. M. Behera, S. K. Mohapatra, U. C. Samal, M. S. Khan, M. Daneshmand, and A. H. Gandomi, "Residual energy-based cluster-head selection in WSNs for IoT application," IEEE Internet Things J., vol. 6, no. 3, pp. 5132–5139, 2019.

[13] L. Hu, G. Hong, J. Ma, X. Wang, and H. Chen, "An efficient machine learning approach for diagnosis of paraquat-poisoned patients," Comput. Biol. Med., vol. 59, pp. 116–124, 2015.

[14] S. R. Nabavi, V. Ostovari Moghadam, M. Yahyaei Feriz Hendi, and A. Ghasemi, "Optimal Selection of the Cluster Head in Wireless Sensor Networks by Combining the Multiobjective Genetic Algorithm and the Gravitational Search Algorithm," J. Sensors, vol. 2021, 2021.

[15] M. Sadrishojaei, N. Jafari Navimipour, M. Reshadi, M. Hosseinzadeh, and M. Unal, "An energy-aware clustering method in the IoT using a swarm-based algorithm," Wirel. Networks, vol. 28, no. 1, pp. 125–136, 2022.

[16] V. K. Mutombo, S. Lee, J. Lee, and J. Hong, "EER-RL: Energy-Efficient Routing Based on Reinforcement Learning," Mob. Inf. Syst., vol. 2021.

[17] D. Mahmood, N. Javaid, S. Mahmood, S. Qureshi, A. M. Memon, and T. Zaman, "MODLEACH: A variant of LEACH for WSNs," Proc. - 2013 8th Int. Conf. Broadband, Wirel. Comput. Commun. Appl. BWCCA 2013, pp. 158–163, 2013.

[18] H. R. Farahzadi, M. Langarizadeh, M. Mirhosseini, and S. A. Fatemi Aghda, "An improved cluster formation process in wireless sensor network to decrease energy consumption," Wirel. Networks, vol. 27, no. 2, pp. 1077–1087, 2021.

[19] S. Bhatia, A. Kumar, A. Kumar, and A. S. Alshuhail, "Performance analysis of energy efficient improved LEACH protocol in IoT networks," IET Commun., no. May, pp. 1–17, 2022.

[20] S. Rabah, A. B. Zaier, and H. Dahman, "New Energy Efficient Clustering Method Based on Fuzzy Logic and Genetic Algorithm in IoT Network," Proc. 17th Int. Multi-Conference Syst. Signals Devices, SSD 2020, pp. 29–33, 2020.

[21] A. S. Nandan, S. Singh, R. Kumar, and N. Kumar, "An Optimized Genetic Algorithm for Cluster Head Election Based on Movable Sinks and Adjustable Sensing Ranges in IoT-Based HWSNs," IEEE Internet Things J., vol. 9, no. 7, pp. 5027–5039, 2022.

[22] X. Li, B. Keegan, and F. Mtenzi, "Energy efficient hybrid routing protocol based on the artificial fish swarm algorithm and ant colony optimisation for WSNs," Sensors (Switzerland), vol. 18, no. 10, 2018.

[23] D. Mechta and S. Harous, "Clustering in WSNs based on artificial fish swarming Algorithm," 2019 15th Int. Wirel. Commun. Mob. Comput. Conf. IWCMC 2019, pp. 161–167, 2019.

[24] S. E. Bouzid, Y. Serrestou, K. Raoof, and M. N. Omri, "Efficient Routing Protocol for Wireless Sensor Network based on Reinforcement Learning," 2020 Int. Conf. Adv. Technol. Signal Image Process. ATSIP 2020, pp. 6–10, 2020.

[25] Z. Pang, W. Zhang, S. Wang, J. Luo, and H. Chen, "Energy-Efficient Improvements in Mod-LEACH Protocol on Optimal Cluster Heads Selection," Proc. - IEEE 2018 Int. Congr. Cybermatics 2018 IEEE Conf. Internet Things, Green Comput. Commun. Cyber, Phys. Soc. Comput. Smart Data, Blockchain, Comput. Inf. Technol. iThings/Gree, pp. 1765–1769, 2018.

Ahmed Gamal Soliman Soliman Deabes is a teaching assistant at Modern University for Technology and Information (MTI). He received his M.Sc. from Benha University in 2019 and his B.Sc. from Modern University for Technology and Information (MTI) in 2013, and the University of Wales, U.K., in 2014. He works part-time as a teaching assistant at the American University in Cairo (AUC). His research interests include the Internet of Things, machine learning, and Embedded Systems.

Esraa M. Eid got her B.Sc. degree in Electrical Engineering and Communication from Benha University in 2008 and her M.Sc. in Communication Engineering in Multicast Security in Long Term Evolution (LTE) Networks from Benha University in 2014 and she got her Ph.D. in Communication Engineering in Multiple Access Techniques in Mobile Next Generation Network from Benha University in 2019. She is currently an Assistant professor at Electrical Engineering Department, Electronic and Communications Division, Faculty of Engineering at Shoubra, Benha University. Her research interests include Mobile communication, machine learning, IoT.

Hala Abd El-kader Mansour is Professor & Head of Electronics & Communication session, Faculty of Engineering, Benha University, where she has been since 1980. She also currently serves as Head of Communication & Computer Engineering Department - Credit Hours, Faculty of Engineering, Benha University. She has done many investigations in the area of digital signal processing & digital design. She has more than 80 published papers.

Michael Nasief is lecturer in the Electrical Engineering Department, Electronic and communications division, Faculty of Engineering (Shoubra), Benha University. He got his Ph.D., M.Sc. and B.Sc. from Benha University in 2013, 2008, 2002 respectively. He works also as the consultant of the Egyptian Development Fund 'EDF' under the Cabinet of Ministries, Egypt since 2014. His research interests include Signal Processing, Speech Coding, Embedded systems, IoT.