EDK-LEACH: improving LEACH protocol-based machine learning in wireless sensor networks

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ABSTRACT

In wireless sensor networks (WSNs), many sensor devices are spread throughout the environment with the goal of collecting data and sending them to a base station (BS) for further studies. The issue of their limited battery power has aroused the interest of researchers, and several protocols were developed to optimize energy use and thus increase the network's lifetime. The present research enhances the well-known low-energy adaptive clustering hierarchy (LEACH) protocol with a new artificial intelligence (AI) protocol named energy distance K-means LEACH (EDK-LEACH). For this purpose, an innovative clustering strategy built on the machine learning K-means algorithm is used in WSNs to improve the cluster formation process and maximise network stability. By implementing an objective function that considers each node's residual energy and distance from the cluster centre when selecting the cluster head (CH) of each cluster, EDK-LEACH also eliminates the inherent randomness in LEACH during the CH election process. The proposed protocol has the advantage of ensuring better CH distribution throughout the network surface with a balanced load across all network nodes. In comparison with the known LEACH, the simulation results demonstrate the efficiency of our approach: the lifetime of the network is extended and the energy consumption is reduced.

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1. INTRODUCTION

Wireless sensor networks (WSN) have aroused the interest of both academics and industrialists. Their applications cover a wide range of industries, including agriculture, healthcare, smart buildings, the military and underwater technology [1]-[4]. A WSN is composed of several microelectronic devices called nodes which are distributed to collect real-time data. These nodes transmit specific physical parameters they sense from their environment to the base station (BS) via direct sensory communication or through other sensors. Following data receipt and processing, the BS provides information to the end user to make decision. An effective energy management is necessary due to the sensors' limited energy, the non-rechargeable and non-changeable batteries. Furthermore, long-distance data transmission uses more energy than multi-hop path transfer. These issues led scientists to focus on clustering as an approach of minimising use of energy and increasing network lifetime. By creating clusters and shortening transmission distances, clustering in WSN seeks to reduce the energy needed to carry information from the source to the destination. As a result, all nodes send straight their data directly to their cluster's head (CH). After data have been compiled, aggregated, and compressed [5]-[7], the CH forwards it to the nearby CH or the BS.

The most widely used clustering routing protocol is the well-known low-energy adaptive clustering hierarchy (LEACH), which selects cluster-heads randomly. Due to random selection, a low-energy node may be chosen to become CH. This node will rapidly consume its energy and dies, causing wholes region where nodes are unavailable and accelerating the "death" of the network in its entirety. Another disadvantage of LEACH is that it forms clusters based only on the distances between nodes and CHs, without considering other significant factors such as the optimal number of clusters or the manner they are distributed over the network. As a result, clusters differ in size, leading to unbalanced energy consumption. Consequently, two basic issues with the LEACH algorithm have been identified: ineffective CH selection and unoptimized clustering.

With the developments in artificial intelligence, the K-means is one of the unsupervised machine learning techniques that has been recently developed. It is employed in hierarchical routing protocols to more effectively segment the network into a given number of homogeneous clusters. This allows the energy consumption of the network’s nodes and CHs to be divided evenly and substantially decreased. In this work, to enhance clustering strategies’ performance, a new protocol called energy distance K-means LEACH (EDK-LEACH) that combines both the LEACH protocol and machine learning K-means algorithm is presented. Before to the CHs being elected, the area is divided into clusters using the K-means algorithm. The energy efficient objective function is then utilised to determine the CHs taking into account both the nodes’ remaining energy and distance from the centroid. This paper contributions are listed as follows:

- Initially, our protocol separates the network into K given clusters by applying the machine learning K-means algorithm.
- Next, the CH of each cluster is designed using an objective function that considers both the residual energy and the distance of each node from the cluster centre.
- Finally, we validate the effectiveness of the proposed protocol by comparing its simulations results with those known in the literature.

The rest of this work is organised as follows: section 2 provided an overview of various relevant existing works. Section 3 offers a thorough description of the proposed EDK-LEACH method. To confirm the effectiveness of our approach, section 4 contains the simulation parameters, displays and analyses the simulation results for various situations through comparison evaluation. Conclusions of the research study are finally outlined in section 5.

2. RELATED WORKS

In WSNs, clustering is a very commonly employed topology management technique. It groups sensors to reduce transmission distance and improve network performance. Furthermore, it conserves bandwidth when communicating within clusters and reduces redundant message transfers between network nodes, specially in dense areas [8]. Several studies have focused on the geometric shape of clusters: circle or square of equal size [9]-[12], sector clustering [13]. Circular pathways are used to partition the network area into clusters, extending the life of WSN beyond that of traditional LEACH [12], [14], [15]. In some other works [10], [16], [17], the routing algorithm divides the network into regular hexagons where the nodes angle ratio, distance to the hexagon center and throughput optimization threshold function are considered in the CH selection phase. Considering a non-uniform partition, the authors in [18] suggested an energy-efficient adaptive double CH routing algorithm for WSNs, where, the network is partitioned, into several uneven sections, according to the remoteness of each sensor node to the BS. The study conducted in [19], has examined the efficiency of two cluster-based routing protocols: LEACH and energy-aware multi-hop multi-path hierarchical (EAMMH) routing techniques for homogeneous networks. The authors showed that EAMMH performs better in larger networks with a high node count, while LEACH performs better in smaller networks with fewer nodes. Panchal and Singh [20], authors have introduced an energy efficient hybrid clustering and hierarchical routing approach (EEHCHR) to deal with WSN problems. First, an adaptive hybrid clustering is applied for reducing node energy consumption. Next, energy-efficient fitness functions are used to select each CH, at last, hierarchical packet routing is suggested to preserve network energy. A new energy-aware density-based clustering and routing protocol (EA-DB-CRP) for collecting data in WSN is proposed in [21]. Its main goal is to eliminate setup overhead, minimize long-distance communications, and uniformly distribute power among sensor nodes. More precisely, the authors have presented a network model with empirical expressions for describing the most effective way to divide, into equal-size layers and sub-layers, the network area. In fact, the CH position is rotated in each sub-layer using a round robin algorithm. In order to ensure that each cluster contain the right number of nodes, they introduce the network density. They limit the cluster density by turning off nearby sensor nodes, and they use an effective merge algorithm to keep the number of cluster members from falling below a predefined threshold. Several studies explore the routing protocols in cluster-based WSNs with the goal of enhancing LEACH’s performance [11], [22]. These approaches have been based on fuzzy logic [11], [23], [24], genetic algorithms [25] or the social behavior of fish, birds, or ants when they move in a group searching for food. Among these algorithms are the particle swarm optimization (PSO) and ant colony optimization algorithm (ACO) [7], [26]-[31]. Liang *et al.* [28], the authors incorporated an Ant Colony method employing a CH close to the BS for receiving and sending data from a faraway CH so as to optimize the multi-hop routing protocol based on LEACH. In comparison to the LEACH protocol, this method can significantly increase the WSNs' lifespan and improve the energy efficiency by using a limited amount of energy. Five descriptors are used in the proposed model to evaluate each node's probability of becoming a CH wich are: location suitability, residual energy, density, compacting, and distance from the BS. To achieve all these goals, they use the fuzzy logic paradigm [32]. Kongsorot *et al.* [33] has focused on enhancing a fuzzy-based clustering protocol and has improved shuffled frog leaping algorithm (ISFLA), the objective was to preserve the lifetime of the network. The optimal CHs were chosen according to the energy threshold and an optimised fuzzy inference system (FIS), taking into account the separation between nearby CHs. Cluster creation and next-hop nodes (NHs) selection are also carried out. The testing outcomes showed that the proposed approach increases the number of data packets transferred to the BS and network stability. Panchal and Singh [34], the authors based their study on the fuzzy C-means (FCM) technique, the relative Euclidean distances of the nodes from the BS and cluster centroid, and the residual energy of the nodes, and have proposed an energy aware distance-based CH selection and routing (EADCR) protocol to increase the lifetime of the WSN. They also presented a novel clustering strategy in which an objective function that allows to select CHs. A relay node that will enable data transfer along the shortest path is then selected using a fuzzy system [11]. Artificial Intelligence includes machine learning among its subfields. Machine learning is essentially described as a machine's ability to simulate human behavior with a focus on pattern interpretation and analysis. Most machine learning algorithms belong to the following three categories: reinforcement learning, supervised learning, or unsupervised learning [35]. Recently, the application of machine learning methods in WSNs has been investigated to enhance performance network without requiring reprogramming. Consequently, many protocols have emerged [36]-[39] where K-means unsupervised machine learning was often implemented [40], [41]. Zhu *et al.* [42], an improved soft K-means (IS-K-means) clustering algorithm was introduced in order to increase network lifetime and balance energy consumption over all nodes in WSNs. This approach reassigns member nodes depending on their membership probability at the cluster boundary for maintaining a balance in the number of nodes per cluster. Extensive simulation results under several network circumstances demonstrated the good performance of the algorithm for small-scale WSNs. As a result, it can be efficiently employed in industrial control, smart agriculture, and health monitoring.

We have presented in this section several research works where different and varied improvements have been provided to the LEACH protocol using several approaches. Indeed, the use of machine learning algorithms within the LEACH protocol is one of the most effective. In this work, based on LEACH, we examine and propose an enhancement over unsupervised machine learning techniques of WSNs performances.

3. METHOD

Unsupervised machine learning, as used in computer science and artificial intelligence, describes machine learning scenarios in which the data are not labeled. Among the issues discussed is clustering, which seeks to identify a pattern in an unlabeled data collection. However, clustering is considered as the most popular unsupervised learning algorithm, which divides unlabeled data points, using an iterative process, into distinct, non-overlapping groups. It splits the area into K predetermined clusters with the goal of maximizing the intercluster distance and minimizing the distances between the nodes in the cluster and the cluster centroid. We highlight that the number of predefined clusters that need to be formed during the process is determined in this case by K. In the LEACH protocol, CHs are chosen regardless of the remaining energy in the sensors; it can happen that a node is selected if it is unable to gather and transmit data received from other cluster members to the sink [19]. Then based on Voronoi algorithm, clusters are formed. To remedy these disadvantages, the proposed EDK-LEACH algorithm starts by generating the clusters, and then chooses the CHs. In each of the K clusters of the WSN, the selection of the CH is based on two criteria: the remaining energy of the node and the distance separating the node and the cluster's centroids. As a result, this will allow the energy consumption balance among the network's sensors to be enhanced and the network's lifespan to be extended. The basic idea of our proposed method can be summarized in three steps. First of all, clustering is carried out using the K-means clustering algorithm. In a second step, CH selection is addressed. The nodes' remaining energy and their distances to the clusters center are taken into consideration at this stage. The EDK-LEACH introduces a new metric by designating the sensor node with highest score is designated as the CH rather than the nearest node to the centroid, EDK-LEACH. Finally, data transmissions from nodes to the CHs inside the clusters and from CHs to the BS, compose the last step.

3.1. Cluster generation phase

This stage begins with applying K-means algorithm which is a simple technique used for splitting a certain data set into K predefined clusters [23], [42]. The fundamental concept is to define aleatory K centroids, as far as possible away from each other then associate each node of the WSN to the closest centroid. When every node is mapped to a cluster, the first stage and the initial grouping are finished. The next step consists of computing K new centroids, obtained from the previous step, and considered as the barycenters of the clusters. Once K new centroids are established, a new stage consisting of an association between the WSN's node set and allows the nearest new centroid needs to be performed. Finally, this loop is continuously executed until all K centroids converge gradually to a fixed position.

Let assume that the WSN is composed of N sensors namely S = {S_1, S_2, …, S_N}. The outputs of this phase are K clusters {C_1, C_2, C_3, ..., C_K} with K centroids {U_1, U_2, U_3, ..., U_K} respectively. N_i is the number of nodes in the C_i cluster, such as: $\sum_{i=1}^{K} N_i$= N

The sum of squares of the Euclidean distances from each sensor node in cluster C_k to the center U_k of the cluster is computed using in (1).

$$J(C_k) = \sum_{S_i \in C_k} \|S_i - U_k\|^2 \tag{1}$$

The distance square is calculated as (2):

$$J(C_k) = \sum_{S_i \in C_k} \|S_i - U_k\|^2 = \sum_{S_i \in C_k} [(S_{xi} - U_{xk})^2 + (S_{yi} - U_{yk})^2] \tag{2}$$

where (S_{xi}, S_{yi}) and (U_{xk}, U_{yk}) are respectively the coordinates of the node S_i and the centroid U_k.

The K-means's purpose consists to reduce the total Euclidean distance between the cluster's centroid and each of its members [25]. In other words, the objective function that this method aims to optimise is the squared error function given as (3).

$$J(C) = \sum_{k=1}^{K} \sum_{S_i \in C_k} \|S_i - U_k\|^2 = \sum_{k=1}^{K} \sum_{S_i \in C_k} [(S_{xi} - U_{xk})^2 + (S_{yi} - U_{yk})^2] \tag{3}$$

3.2. Cluster heads designation phase

The generation of homogeneous and balanced clusters is the key advantage of WSN clustering based on K-means. In fact, in LEACH, the node's position either the remaining energy are not considered when the CH is chose. A no-coverage area can then occur by selecting a low-energy node as the CH, which reduces the network's stability phase. For this reason, the overall energy efficiency of the network could decline. To address these issues, when the CH is chosen, our suggested protocol is designed in such a way that node's residual energy and its distance to the cluster's center are both considered.

We assign a score to each node S_i in the cluster C_k defined by the following (4).

$$Score(S_i) = \alpha . E_{res}(S_i) + (1 - \alpha) \frac{1}{d_{tocc}(S_i)} \tag{4}$$

Where $E_{res}(S_i)$ symbolizes the residual energy of the node S_i and $d_{tocc}(S_i)$ represents the distance between the node and the cluster's center. The node with the greatest score is designed to be CH of the cluster Ck. Due to the equal starting energy, the nearest node to the centre is chosen as the CH for the first round. The parameter α between 0 and 1 used to provide high importance and to prioritize the residual energy or the node's distance to the cluster center (in this paper α=0.5).

A node that is selected to be the CH must keep this position for as long as its residual energy exceeds the dynamic threshold, which is established by the cluster's average node energy. This condition is required to prevent the premature death of the CH, which would cause the network section to be disconnected. The CHis replaced by a new node, which is selected according to the scores produced by the objective function provided by (4) once its residual energy decreases below the dynamic threshold. Thus, with enough energy remaining in the network allowing continuous monitoring and reporting, even after each node's energy level drops below the initial threshold, the dynamic threshold ensures that CHs could be selected. As a result, this stage of our proposed algorithm makes the network far more resilient than it would be with traditional methods. The ideal number of clusters K_{opts} is initially 5% of all nodes [43] and is adjusted when nodes run out of energy.

3.3. Data transfer phase

This phase begins after the cluster generation and CHs designation phases. The time division multiple access (TDMA) technique will be applied by the CHs sensors [6], [25] to assign a specific time slot for data transmission to every member node within their clusters to prevent collisions. This implies that within a given time frame, the member nodes will transmit their packets respectively to its CHs. Indeed, when the sensor nodes are not transmitting or receiving during sleep mode, they can turn off their radios and activate them within the allotted time slots. Consequently, the TDMA technique can reduce nodes' energy loss, therefore prolonging their lifetime. Data gets received by the CH from its member nodes, which then aggregates, eliminates redundancy, and transmits the data to the BS. Table 1 presents a comparison between LEACH and the suggested EDK-LEACH. The EDK-LEACH protocol's organisational structure is shown in Figure 1.

Table 1. Comparison between the proposed EDK-LEACH and LEACH

LEACH	EDK-LEACH
Uses Voronoi diagram and a probability law.	Uses K-means and fitness function
Cluster heads selected before the cluster's formation.	Cluster heads designed after the cluster's formation
Residual energy of the nodes not considered while selecting CHs.	Residual energy of the nodes considered while selecting CHs.
The clusters's number differs from the ideal number since CHs are selected at random.	The clusters's number is set at optimal value.
Number of nodes inside different clusters varies significantly.	There is a uniform number of nodes within each cluster.
Disparities in the CHs' distribution over the network's area.	An even dispersion of CHs throughout the network's domain.

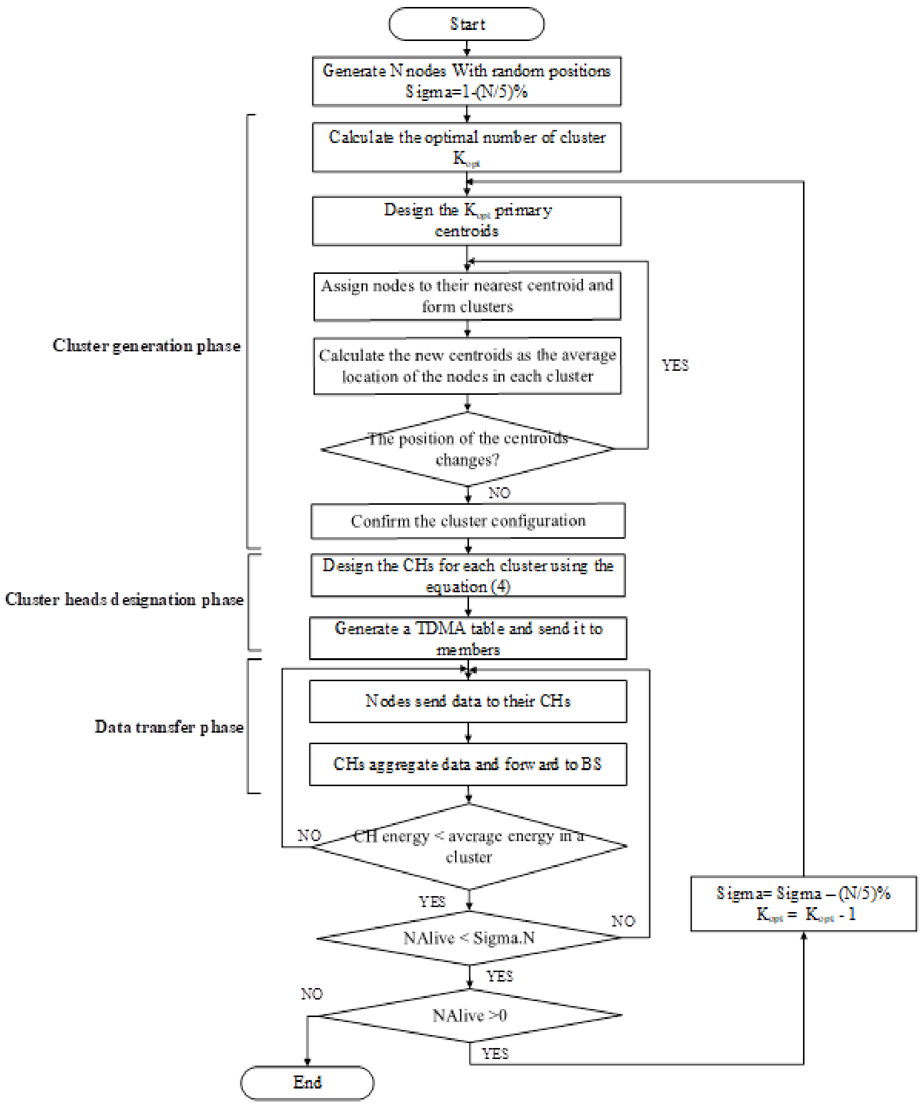


Figure 1. The EDK-LEACH protocol's operational program

4. RESULTS AND DISCUSSION

4.1. Assumption and simulation parameters

To make simulating these two protocols simpler, the following assumptions are made:

– The fixed location of the BS is known for all nodes.
– After deployment, sensor node locations are known and fixed.
– Nodes have to always forward the information.
– The BS memory, the processing capacity, and the power are all unlimited.

The first order radio model [6] is the energy model used in this work, and Table 2 lists the simulation settings.

Table 2. Network parameters for simulation

Parameter	Description	Value
N	Number of nodes	100
M×M	Network size	100×100 (m^2)
E_0	Initial energy of nodes	2 J
P	Percentage of cluster heads	5%
E_{TX}	Energy to transmit one bit	0.5 nJ/bit
E_{RX}	Energy to receive one bit	0.5 nJ/bit
E_{AG}	Aggregation energy	5 nJ
ε_{amp}	Amplification factor for free space model	10 pJ/bit/m^2
ε_{two_ray}	Amplification factor for free multi-path model	0.0013 pJ/bit/m^4
d_0	Crossover distance	87 m
k	Packet size	500 bytes
α	Weighting coefficient to elect CHs	0.5

4.2. Simulation results and analysis

In this section, we present computational results of our approach. The experimentations have been carried using MATLAB R (2018 a) to validate the effectiveness of the suggested EDK-LEACH algorithm for minimizing node power consumption, as well as extending network lifetime. Therefore, to demonstrate the relevance of the suggested protocol for WSNs, the simulation results were compared with the LEACH protocol results based on two important metrics: the number of alive nodes and the quantity of energy remaining in the network after each round. Primarily, 100 sensor nodes are randomly deployed to cover a 100 x 100 m^2 square area. Depending on the location of the BS, our algorithm has been tested in two distinct scenarios. In scenario 1, the BS is located in the center of the field at coordinates (50, 50), while in scenario 2, it is outside the sensing area at coordinates (50, 175). The graphs were generated by taking the average of 10 runs of each simulation.

The clustering of 100 randomly distributed sensor nodes within the area of interest is shown in Figure 2. Cluster generation using the Voronoi diagram and the K-means algorithm is depicted in Figures 2(a) and 2(b), respectively. As illustrated in Figure 2(a), with the LEACH protocol, there are more clusters than the optimal value, and the node distribution inside clusters is not regular. Figure 2(b) shows that with EDK-LEACH, the clusters' number is fixed at the ideal value and the CHs are evenly distributed around the BS. The protocol's energy efficiency is largely dependent on the CHs' number. A lower number of CHs means that the data transmission length from sensor nodes to the CH will be excessively long, resulting in increased energy consumption. Additionally, the CH will consume more power due to the excessive amount of data it receives and transmits. However, a large number of CHs will clearly increase both the overall network load and the energy consumption of each network cycle, but will decrease the efficiency of network data fusion, and will shorten the network lifetime. For these reasons, we applied the K-means algorithm and set the number of clusters to its optimal number. By eradicating the randomness of CH number and adjusting the ideal number of clusters with node death in WSNs, the network energy consumption will be reduced.

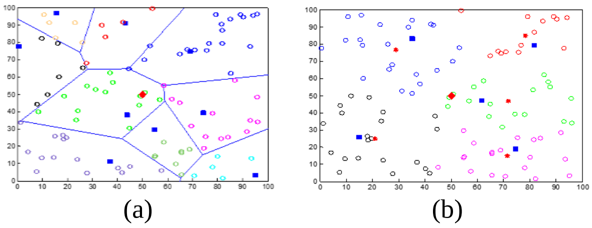
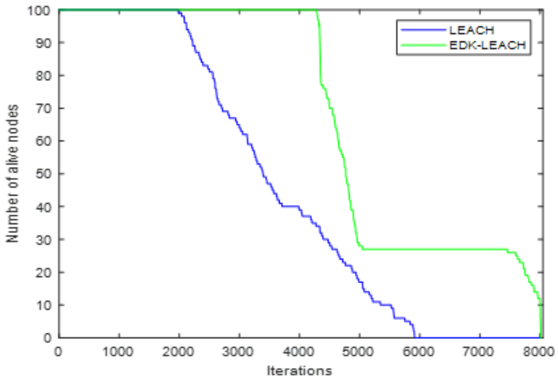


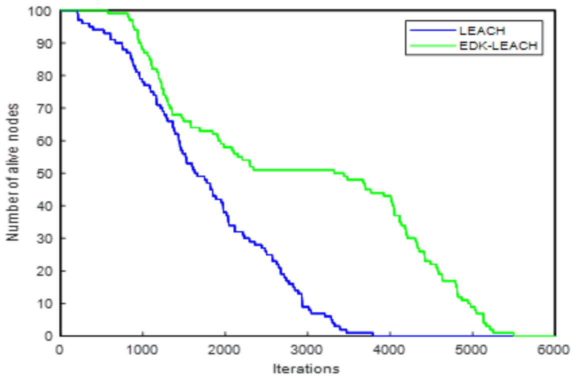
Figure 2. Clustering using (a) voronoi diagram and (b) K-means algorithm

4.2.1. Alive nodes for rounds of each scenario

Figure 3 illustrates how the number of alive nodes declines with iterations. Figures 3(a) and 3(b) show the network lifetimes when the BS situated in the center of the surface and outside the area respectively. The two figures show that the EDK-LEACH approach outperformed the LEACH technique in terms of energy performance. Furthermore, considering these two different scenarios, the network lifetime has been analyzed in terms of first node dead (FND) and last node dead (LND). In scenario 1, Figure 3(a) shows that the first node died in EDK-LEACH is at 4285 versus 1983 rounds in LEACH. The last node died in the proposed protocol at more than 8000 rounds, in LEACH at 6851 rounds although. The stability period is extended and the results confirmed that EDK-LEACH protocol outperforms LEACH protocol by 116% in scenario 1 and 177% in scenario 2. It is clear that when the BS is located outside the network area, nodes deplete more energy because of the great transmission distances. Table 3 displays the statistics for each alive node vs. round scenario. Considering the simulation results and Table 3, it can be asserted that the EDK-LEACH protocol outperforms LEACH protocol.



(a)



(b)

Figure 3. Alive nodes vs. iterations (a) BS (50,50) and (b) BS (50,175)

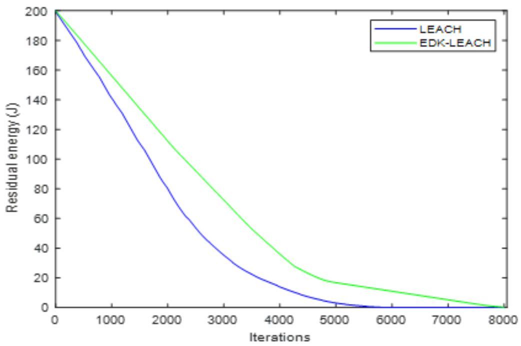
Table 3. Comparison of network lifetime protocols

BS position	% Dead nodes	LEACH	EDK-LEACH	EDK-LEACH rate
	1 (FND)	1983	4285	116%
(50; 50)	50 (HND)	3398	4771	40%
	100 (LND)	5913	8010	35%
	1 (FND)	208	577	177%
(50; 175)	50 (HND)	1663	3439	107%
	100 (LND)	3791	5497	45%

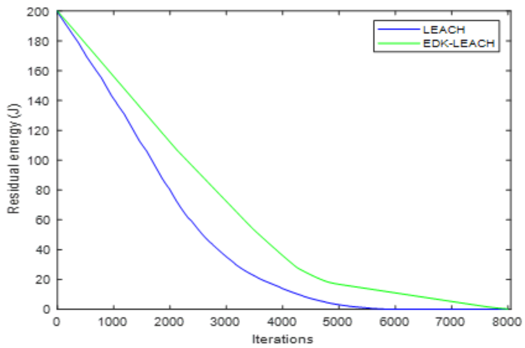
4.2.2. Energy consumed vs. rounds

The residual energy evaluation for the two protocols is shown in Figure 4. Figures 4(a) and 4(b), demonstrates the effectiveness performance of EDK-LEACH protocol comparing to the LEACH protocol. In EDK-LEACH, the energy decreases gradually, whereas in LEACH, it lowers abruptly. When the BS is located in the center of the studied area, Figure 4(a) shows that 860 rounds in LEACH and 1141 rounds in EDK-LEACH use 25% of the energy. In other words, LEACH used 0.058 J every round while EDK-LEACH used 0.043 J. In Figure 4(b), where the BS is located at the coordinates (50,175), the total amount of energy is utilized in 3791 rounds in LEACH and 5497 rounds in EDK-LEACH. Thus, for LEACH, each round uses 0.052 J of energy, while with EDK-LEACH, each round uses 0.036 J of energy. We can observe that EDK-LEACH improves the total residual energy consumption by 35% and 45% compared to LEACH when the BS is at (50,50) and (50,175), respectively. Table 4 provides the percentages of energy used vs. rounds for the two protocols at different BS locations. In terms of energy consumption, the simulation results and data in Table 4 show that the suggested approach performs better than LEACH.

Figure 5 summarizes the results of this research work to known results of the literature in histogram graphs. We can see, our suggested protocol outperforms LEACH protocol in terms of death nodes in Figure 5(a) and energy consumption in Figure 5(b). These results can be explained by better clustering and the optimal choice of CHs.

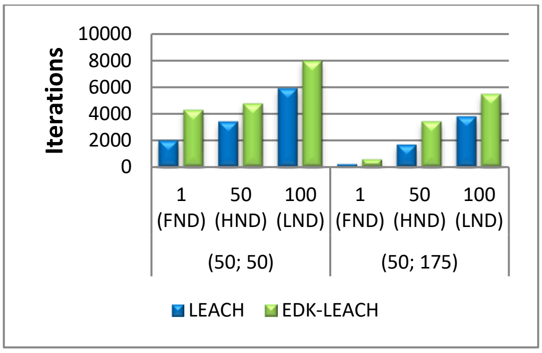


(a)

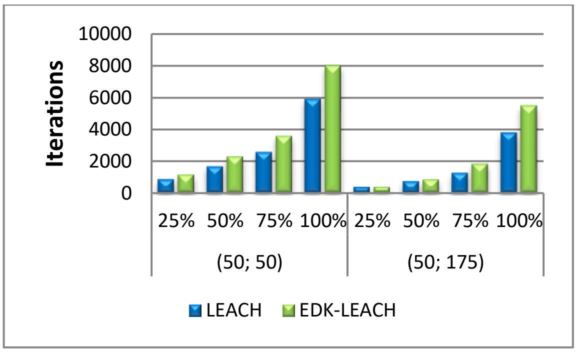


(b)

Figure 4. Residual energy vs. iterations (a) BS (50,50) and (b) BS (50,175)



(a)



(b)

Figure 5. Comparative results of EDK-LEACH and LEACH protocols (a) death nodes and (b) energy consumption

Table 4. Comparison of network energy consumption of protocols

BS position	Energy consumption (%)	LEACH	EDK-LEACH	EDK-LEACH rate
(50; 50)	25%	860	1141	33%
	50%	1677	2297	37%
	75%	2581	3586	39%
	100%	5913	8010	35%
(50; 175)	25%	378	385	2%
	50%	739	834	13%
	75%	1273	1832	44%
	100%	3791	5497	45%

5. CONCLUSION

In this research, an EDK-LEACH protocol is proposed. It is a K-means unsupervised machine learning based technique. LEACH, is a known protocol where clusters are constructed after CH selection using a probabilistic algorithm. However, our proposed EDK-LEACH clustering approach uses the K-means algorithm to create clusters and then, an objective function is used to design the CHs. The K-means clustering algorithm forms homogenous clusters with a uniform distribution of CHs over the network area, and determine the optimum number of clusters. Moreover, the number of clusters is adjusted as the nodes deplete their energy and the objective function considers two different parameters: the sensor's energy level and its distance from the cluster center. Consequently, by carrying out these processes, the load can be evenly distributed throughout all of the network's sensors. The experimentation results of our protocol were compared with the known results of LEACH, and showed on one side that the network lifetime has increased by more than 177% when the BS is in the center of the network and, by 116% when the BS is outside the network in other side. Machine learning applications to WSN are still an emerging field of study. Open issues can be considered as news research areas. As an extension of this current work, future research could investigate real-time implementation and integrate more machine learning-based algorithms for developing more energy efficient protocols.

REFERENCES

[1] V. Krishnaswamy and S. K. S. Manvi, “Clustering and data aggregation scheme in underwater wireless acoustic sensor network,” *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 17, no. 4, pp. 1604–1614, Aug. 2019, doi: 10.12928/TELKOMNIKA.V17I4.11379.

[2] M. Abdulkarem, K. Samsudin, F. Z. Rokhani, and M. F. A Rasid, “Wireless sensor network for structural health monitoring: a contemporary review of technologies, challenges, and future direction,” *Structural Health Monitoring*, vol. 19, no. 3, pp. 693–735, May 2020, doi: 10.1177/1475921719854528.

[3] K. G. Omeke *et al.*, “DEKCS: A dynamic clustering protocol to prolong underwater sensor networks,” *IEEE Sensors Journal*, vol. 21, no. 7, pp. 9457–9464, Apr. 2021, doi: 10.1109/JSEN.2021.3054943.

[4] P. M. Vishweshwaraiah, P. N. Siddegowda, and S. Rudraswamy, “Maximizing wireless sensor network lifetime through energy-efficient routing,” *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 31, no. 3, pp. 1442–1450, 2023, doi: 10.11591/ijeecs.v31.i3.pp1442-1450.

[5] S. Firdous, N. Bibi, M. Wahid, and S. Alhazmi, “Efficient clustering based routing for energy management in wireless sensor network-assisted internet of things,” *Electronics (Switzerland)*, vol. 11, no. 23, 2022, doi: 10.3390/electronics11233922.

[6] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, “Energy-efficient communication protocol for wireless microsensor networks,” in *Proceedings of the Hawaii International Conference on System Sciences*, IEEE Comput. Soc, 2000, p. 223. doi: 10.1109/hicss.2000.926982.

[7] S. Sharmin, I. Ahmedy, and R. Md Noor, “An energy-efficient data aggregation clustering algorithm for wireless sensor networks using hybrid PSO,” *Energies*, vol. 16, no. 5, p. 2487, Mar. 2023, doi: 10.3390/en16052487.

[8] A. Shahraki, A. Taherkordi, Ø. Haugen, and F. Eliassen, “Clustering objectives in wireless sensor networks: a survey and research direction analysis,” *Computer Networks*, vol. 180, p. 107376, Oct. 2020, doi: 10.1016/j.comnet.2020.107376.

[9] N. C. Wang, Y. L. Chen, Y. F. Huang, C. M. Chen, W. C. Lin, and C. Y. Lee, “An energy aware grid-based clustering power efficient data aggregation protocol for wireless sensor networks,” *Applied Sciences (Switzerland)*, vol. 12, no. 19, p. 9877, Sep. 2022, doi: 10.3390/app12199877.

[10] T. Lechani, V. Tourtchine, and S. Amari, “A new modification of LEACH for efficient energy in WSN,” *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 20, no. 3, pp. 1495–1506, Dec. 2020, doi: 10.11591/ijeecs.v20.i3.pp1495-1506.

[11] V. Sivasankarareddy, G. Sundari, C. Rami Reddy, F. Aymen, and E. C. Bortoni, “Grid-based routing model for energy efficient and secure data transmission in wsn for smart building applications,” *Applied Sciences (Switzerland)*, vol. 11, no. 22, p. 10517, Nov. 2021, doi: 10.3390/app112210517.

[12] A. Sher *et al.*, “Monitoring square and circular fields with sensors using energy-efficient cluster-based routing for underwater wireless sensor networks,” *International Journal of Distributed Sensor Networks*, vol. 13, no. 7, p. 155014771771718, Jul. 2017, doi: 10.1177/1550147717717189.

[13] F. A. Mohammed, N. Mekky, H. H. Suleiman, and N. A. Hikal, “Sectored LEACH (S-LEACH): an enhanced LEACH for wireless sensor network,” *IET Wireless Sensor Systems*, vol. 12, no. 2, pp. 56–66, Apr. 2022, doi: 10.1049/wss2.12036.

[14] M. Arghavani, M. Esmaeili, M. Esmaeili, F. Mohseni, and A. Arghavani, “Optimal energy aware clustering in circular wireless sensor networks,” *Ad Hoc Networks*, vol. 65, pp. 91–98, Oct. 2017, doi: 10.1016/j.adhoc.2017.07.006.

[15] A. R. Tarawneh, B. Malahmeh, and A. Al-Odienat, “Improved LEACH protocol for increasing network lifetime based on circular patches clustering,” *Universal Journal of Applied Science*, vol. 7, no. 1, pp. 8–17, Apr. 2020, doi: 10.13189/ujas.2020.070102.

[16] H. Zhang, “A WSN clustering multi-hop routing protocol using cellular virtual grid in IoT environment,” *Mathematical Problems in Engineering*, vol. 2020, pp. 1–7, Nov. 2020, doi: 10.1155/2020/8886687.

[17] C. S. Fan, “HIGH: a hexagon-based intelligent grouping approach in wireless sensor networks,” *Advances in Electrical and Computer Engineering*, vol. 16, no. 1, pp. 41–46, 2016, doi: 10.4316/AECE.2016.01006.

[18] C. Tang, “A clustering algorithm based on nonuniform partition for WSNs,” *Open Physics*, vol. 18, no. 1, pp. 1154–1160, Dec. 2020, doi: 10.1515/phys-2020-0192.

[19] T. Salam and M. S. Hossen, “Performance analysis on homogeneous LEACH and EAMMH protocols in wireless sensor network,” *Wireless Personal Communications*, vol. 113, no. 1, 2020, doi: 10.1007/s11277-020-07185-6.

[20] A. Panchal and R. K. Singh, “EEHCHR: energy efficient hybrid clustering and hierarchical routing for wireless sensor networks,” *Ad Hoc Networks*, vol. 123, no. 1, p. 102692, Dec. 2021, doi: 10.1016/j.adhoc.2021.102692.

[21] K. A. Darabkh, S. M. Odetallah, Z. Al-qudah, A. F. Khalifeh, and M. M. Shurman, “Energy-aware and density-based clustering and relaying protocol (EA-DB-CRP) for gathering data in wireless sensor networks,” *Applied Soft Computing Journal*, vol. 80, pp. 154–166, Jul. 2019, doi: 10.1016/j.asoc.2019.03.025.

[22] T. M. Behera *et al.*, “Energy-efficient routing protocols for wireless sensor networks: Architectures, strategies, and performance,” *Electronics (Switzerland)*, vol. 11, no. 15, p. 2282, Jul. 2022, doi: 10.3390/electronics11152282.

[23] A. A. hussian Hassan, W. M. Shah, M. F. I. Othman, and H. A. H. Hassan, “Evaluate the performance of K-Means and the fuzzy C-Means algorithms to formation balanced clusters in wireless sensor networks,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 2, pp. 1515–1523, Apr. 2020, doi: 10.11591/ijece.v10i2.pp1515-1523.

[24] S. Lata, S. Mehfuz, S. Urooj, and F. Alrowais, “Fuzzy clustering algorithm for enhancing reliability and network lifetime of wireless sensor networks,” *IEEE Access*, vol. 8, pp. 66013–66024, 2020, doi: 10.1109/ACCESS.2020.2985495.

[25] A. Younes, U. A. Badawi, T. H. Farag, F. A. Alghamdi, and A. Ben Salah, “A genetic algorithm to find the minimum cost paths tree with bandwidth constraint in the computer networks,” vol. 13, no. 10, pp. 7472–7476, 2018.

[26] M. Gamal, N. E. Mekky, H. H. Soliman, and N. A. Hikal, “Enhancing the lifetime of wireless sensor networks using fuzzy logic LEACH technique-based particle swarm optimization,” *IEEE Access*, vol. 10, pp. 36935–36948, 2022, doi: 10.1109/ACCESS.2022.3163254.

[27] Y. Zhai, L. Xu, and Y. Yang, “Ant colony algorithm research based on pheromone update strategy,” in *Proceedings - 2015 7th International Conference on Intelligent Human-Machine Systems and Cybernetics, IHMSC 2015*, IEEE, Aug. 2015, pp. 38–41. doi: 10.1109/IHMSC.2015.143.

[28] H. Liang, S. Yang, L. Li, and J. Gao, “Research on routing optimization of WSNs based on improved LEACH protocol,” *Eurasip Journal on Wireless Communications and Networking*, vol. 2019, no. 1, p. 194, Dec. 2019, doi: 10.1186/s13638-019-1509-y.

[29] W. Ding and W. Fang, "Target tracking by sequential random draft particle swarm optimization algorithm," in *2018 IEEE International Smart Cities Conference, ISC2 2018*, IEEE, Sep. 2018, pp. 1–7. doi: 10.1109/ISC2.2018.8656985.
[30] X. Cheng, C. Xu, X. Liu, J. Li, and J. Zhang, "LEACH protocol optimization based on weighting strategy and the improved ant colony algorithm," *Frontiers in Neurorobotics*, vol. 16, Mar. 2022, doi: 10.3389/fnbot.2022.840332.
[31] K. Chinnaiah and K. N. Rao, "Swarm energy efficient power efficient gathering in sensor information systems protocol in wireless sensor networks," *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 31, no. 1, pp. 459–469, 2023, doi: 10.11591/ijeecs.v31.i1.pp459-469.
[32] A. Hamzah, M. Shurman, O. Al-Jarrah, and E. Taqieddin, "Energy-efficient fuzzy-logic-based clustering technique for hierarchical routing protocols in wireless sensor networks," *Sensors (Switzerland)*, vol. 19, no. 3, p. 561, Jan. 2019, doi: 10.3390/s19030561.
[33] Y. Kongsorot, P. Musikawan, P. Muneesawang, and C. So-In, "An enhanced fuzzy-based clustering protocol with an improved shuffled frog leaping algorithm for WSNs," *Expert Systems with Applications*, vol. 198, p. 116767, Jul. 2022, doi: 10.1016/j.eswa.2022.116767.
[34] A. Panchal and R. K. Singh, "EADCR: energy aware distance based cluster head selection and routing protocol for wireless sensor networks," *Journal of Circuits, Systems and Computers*, vol. 30, no. 4, p. 2150063, Mar. 2021, doi: 10.1142/S0218126621500638.
[35] R. Chandra Gangwar and R. Singh, "Machine learning algorithms from wireless sensor network's perspective," in *Wireless Sensor Networks - Design, Applications and Challenges*, IntechOpen, 2023. doi: 10.5772/intechopen.111417.
[36] M. Mittal, R. P. de Prado, Y. Kawai, S. Nakajima, and J. E. Muñoz-Expósito, "Machine learning techniques for energy efficiency and anomaly detection in hybrid wireless sensor networks," *Energies*, vol. 14, no. 11, p. 3125, May 2021, doi: 10.3390/en14113125.
[37] H. K. Prajapati and R. Joshi, "Performance analysis of LEACH with deep learning in wireless sensor networks," *International Journal of Electronics and Telecommunications*, vol. 68, no. 4, pp. 799–805, Nov. 2022, doi: 10.24425/ijet.2022.143888.
[38] M. S. Qamar and I. ul Haq, "Wireless sensors networks energy optimization using LEACH and ANNs." 2023. doi: 10.20944/preprints202307.0053.v1.
[39] P. Y. Kong, "Distributed sensor clustering using artificial neural network with local information," *IEEE Internet of Things Journal*, vol. 9, no. 21, pp. 21851–21861, Nov. 2022, doi: 10.1109/JIOT.2022.3181596.
[40] S. El Khediri, W. Fakhet, T. Moulahi, R. Khan, A. Thaljaoui, and A. Kachouri, "Improved node localization using K-means clustering for wireless sensor networks," *Computer Science Review*, vol. 37, p. 100284, Aug. 2020, doi: 10.1016/j.cosrev.2020.100284.
[41] M. Wu, Z. Li, J. Chen, Q. Min, and T. Lu, "A dual cluster-head energy-efficient routing algorithm based on canopy optimization and K-Means for WSN," *Sensors*, vol. 22, no. 24, p. 9731, Dec. 2022, doi: 10.3390/s22249731.
[42] B. Zhu, E. Bedeer, H. H. Nguyen, R. Barton, and J. Henry, "Improved Soft-K-means clustering algorithm for balancing energy consumption in wireless sensor networks," *IEEE Internet of Things Journal*, vol. 8, no. 6, pp. 4868–4881, Mar. 2021, doi: 10.1109/JIOT.2020.3031272.
[43] W. B. Heinzelman, "Application-specific protocol architectures for wireless networks," Ph.D. dissertation, Massachusetts Institute of Technology, Cambridge, MA, USA, 2000. [Online]. Available: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.27.5727&rep=rep1&type=pdf

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